Are Crypto Anti-Money Laundering Policies Effective?[*]

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Abstract

We evaluate four major types of crypto enforcement actions. First, OFAC sanctions against the Tornado Cash mixer resulted in a 60% decline in volume, increased obfuscation costs by 33 bps, doubled detection probability, and shifted usage toward more traceable swaps and bridges. Second, other OFAC sanctions against individuals, while rare, left over 100,000 BTC and 155,000 ETH stuck on-chain. Third, $1.34 billion in Tether is frozen, pushing criminals to costlier DeFi services. Fourth, overseas exchange acceptance of sanctioned funds declines only after U.S. DOJ settlements. Overall, anti-money laundering policies appear effective, though our findings suggest areas for substantial policy improvement.

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Whereas the traditional banking sector has well-established anti-money laundering (AML) procedures, policies, and protocols in the crypto arena are relatively nascent and in flux. There is a general lack of understanding regarding whether crypto AML policies are enforced, useful, and effective in accomplishing their goals. What are the economic magnitudes of their impact? Through which channels do they operate? What substitutes emerge in response? Answering these questions could help inform policy design and enforcement priorities. Recent changes in the regulatory and enforcement environment provide an empirical testing ground to examine the implementation and efficacy of different forms of AML enforcement protocols.

Money laundering is the process of moving and concealing the origins of illicit proceeds to integrate them into the legitimate financial system and enable their unrestricted use. Anti-money laundering laws are deeply ingrained in the modern financial system, particularly following September 11, 2001, as controls to reduce terrorist financing and other criminal capital flows. The theoretical motivation from the Becker (1968) crime model suggests that to deter crime, one needs to increase the likelihood of being caught and the fine when punished. The goal of AML policies and their enforcement is to increase the probability of detecting both criminals and money launderers, and to punish to the extent that it results in the forfeiture and possible fine of funds (Ferwerda, 2009).

Evaluating the effectiveness of aspects of the AML framework is difficult because of the limited availability of reliable and detailed data. Chong and Lopez-De-Silanes (2015) outline two contrasting views on whether AML laws matter: A) the conventional view, which holds that AML laws reduce crime by blunting their profitability, and B) the skeptics' view, which emphasizes that efforts are best spent on targeting the root sources of crime and not on regulating money services.[1] A firm's reputational risk may also serve as a sufficient deterrent to money-laundering activities. Levi, Reuter, and Halliday (2017) detail how there is little reliable data to evaluate AML efforts and that regulation is largely unguided by data analysis. Within the cryptocurrency environment, we compile a large amount of detailed data on illicit funds that is typically private within banks and not available for researchers

[1]Consistent with this view, Cuéllar (2002) argues that there is a tenuous relationship between AML regulations and reducing crime, despite the large costs of implementation, reduction in privacy, and negative externalities such as reducing access to the banking system. Pol (2020) argues that there are few outcome metrics to measure AML effectiveness, criminals keep up to 99.95 percent of criminal proceeds, and that the policies actually enable all forms of serious criminal activity.

or large-scale outside analysis.

In this paper, we empirically evaluate the effectiveness of crypto AML policies and procedures by utilizing a number of regulatory and court orders as policy shocks. We process 5.16 TB of Ethereum transaction and event data as of August 14, 2025 to trace the flow of illicit funds through the blockchain. We then examine how centralized and decentralized exchanges (DEXs) interact with illicit flows before and after government sanctions. Specifically, we analyze two sets of policies: policies targeting *services*, including the high-profile 2022 Tornado Cash ban and U.S. Department of Justice (DOJ) settlements with exchanges, and policies targeting *individual users*, including sanctions by the U.S. Treasury's Office of Foreign Assets Control (OFAC), stablecoin seizures, and the $10,000 reporting threshold.

Our findings show that Tornado Cash, an Ethereum mixer that obfuscates the origin of funds, handles considerable criminal flows from more sophisticated cyber-criminal gangs, with the Lazarus Group from North Korea being the largest identified user. Before the August 2022 U.S. sanctions against Tornado Cash, Western centralized exchanges received 3.99% of Tornado Cash outflows on average, a proportion that declined to 2.14% in the twelve months following the ban, representing a 46.20% reduction. Flows to overseas centralized exchanges did not decline immediately after the ban but began to fall by the end of 2023, after which bridges became the dominant destination for Tornado Cash outflows. For funds that do reach exchanges post-ban, they take, on average, 0.17 additional hops and incur 33 basis points in incremental transaction costs from obfuscation techniques, compared to a pre-ban baseline of approximately 50 basis points, as shown in a difference-in-differences design. The probability of correctly matching transactions from the largest mixer user during a given week also doubles after the ban (from 10.15% before the sanctions to 21.10% afterward), indicating that the decline in volume renders the mixer less useful for obfuscation. Additionally, the reduction in transaction volumes is more pronounced for Western exchanges relative to overseas exchanges.[2] DeFi swaps and bridges take flows directly after leaving Tornado Cash, indicating that there is likely no concern for DEXs to reject their transaction.

Additionally, we analyze the flow of hackers over the pre-ban and banning period, and find that in a

[2]We use Western exchanges to refer to Coinbase, Crypto.com, Gemini, and Kraken because they are some of the largest exchanges that can be accessed from North America and Europe over the 2020 to 2025 sample period.

difference-in-differences design, their flows to Tornado Cash decrease by 30%. Rather than using other mixers, they typically move money through DeFi swaps and bridges, outlets that obfuscate transactions for standard tracing tools, but are nevertheless traceable. Additionally, we examine the recent Bybit hack by North Korea and find that the funds did not utilize Tornado Cash. After a long series of obfuscating transactions, the majority of flows use the Thorchain bridge to move to Bitcoin and are stored across multiple different wallets that are mostly viewable on the blockchain. Overall, the ban on Tornado Cash seems effective in that it increases transaction costs on criminal flows, and hackers switch to traceable methods where it is at least potentially possible to freeze funds.

Another potentially important enforcement mechanism is the freezing of individual criminal assets. We examine all addresses on the OFAC sanctions list, which includes 380 Bitcoin addresses and 60 Ethereum addresses. Although sanctions are often imposed too late and after funds have left addresses, sanctions nonetheless prove effective in trapping some assets on-chain. We find that approximately 195,000 Bitcoins and 420,000 ETH have passed through these sanctioned addresses, with 51.28% of the Bitcoin and 36.90% of the Ethereum flows remain seemingly stuck on their respective blockchains.

We next turn to an examination of stablecoin seizures. Tether and Circle have historically complied with the law enforcement or court order requests for stablecoin freezes, though not necessarily redemption. The GENIUS Act, signed on July 18, 2025, codifies this precedent into law as it requires stablecoin issuers to comply with U.S. law enforcement requests for asset seizure.[3] In total, we find that over $1.34 billion Tether and $93.12 million USDC have been frozen. Of this, $608.65 million is frozen in addresses that appear in the traced criminal network. However, stablecoin seizures appear extremely small relative to the underlying criminal flows. We also analyze other related addresses to the criminal freeze and find that their share of flows to DeFi services after freezes increases by approximately 25%, presumably to obfuscate their flows. This indicates that, in addition to costing the criminals their funds, seizures can impose additional costs on criminals in the form of more costly and less regulated services.

We then consider whether U.S. DOJ settlements with exchanges deter illicit behavior. We first

[3] See Congress website for more details about the Guiding and Establishing National Innovation for U.S. Stablecoins Act of 2025, or GENIUS Act.

revisit the 2022 Tornado Cash sanctions and observe that outflows from Tornado Cash to overseas exchanges did not immediately decline following the sanctions. Indeed, Binance did receive considerable sanctioned funds from Tornado Cash after sanctions were enacted and flows persisted all the way until Binance settled with the DOJ in November 2023. These findings support that the claims in the DOJ settlement that Binance ignored AML monitoring procedures and are inconsistent with claims that Binance was unfairly persecuted. A reduction in sanctioned flows to Binance becomes evident only after the exchange reached settlement agreements. Similar to Binance, OKX continues to receive large amounts of sanctioned Tornado Cash flows after the 2022 ban, but experience a sharp decline in flows four months prior to OKX's February 2025 DOJ settlement.

Finally, we compare the deposit patterns of criminal and other users using a bunching design. We find that tainted deposit addresses disproportionately use round-number amounts, being about 12–13 percentage points more likely to use deposit amounts exactly divisible by $500 or $1,000. Tainted users show additional bunching in round-number bins just under the $10,000 reporting threshold for suspicious activity, at Western (but not overseas) exchanges. Thus, criminals do appear to have some concern for this reporting threshold, though it is not clear if this threshold is an effective mechanism to detect criminal behavior.

Overall, it appears that sanctions, seizures, and fines have been effective tools for freezing funds, keeping funds trapped on-chain, moving funds to more transparent avenues, and increasing costs for criminals. Our findings suggest practical areas for industry improvement, enforcement, and policy to deter money laundering. First, more aggressive seizures and bans seem warranted. Actions against individual users are used relatively infrequently and often too late, only after funds are off-ramped. Second, self-policing appears ineffective given the wide range of practices by crypto exchanges in handling criminal flows. Only after settling federal charges did overseas exchanges significantly decrease their flows in OFAC-sanctioned addresses. Additionally, overseas exchanges still handle significant tainted crypto flows. Third, more attention should be paid to DeFi. Criminals do not appear to be concerned that these services will reject their transactions, and criminals are much less cautious with money coming out of DeFi services, suggesting that they believe the money is mostly viewed as clean

money.

We speak to ongoing policy debates. First, as of November 2025, Senate committees are deliberating new digital asset legislation that would determine whether DeFi services should be exempt from AML requirements.[4] Arguments to exempt DeFi from AML requirements are that compliance is too onerous for DeFi startups, that exemptions are necessary because builders will simply move to jurisdictions with weaker laws, or that the ecosystem will self-enforce.[5] Our findings show that mixers obfuscate substantial criminal flows from foreign actors, and that self-policing by the industry has been ineffective. Similar to how our findings indicate that the ban on Tornado Cash in combination with actions on international crypto exchanges reduced criminal flows through these entities, DeFi services could be required to reject sanctioned funds or face consequences similar to the sanctions imposed on Tornado Cash.[6] Second, on April 7, 2025, a DOJ order by Deputy Attorney General Todd Blanche stated that the DOJ "will no longer target virtual currency exchanges, mixing and tumbling services, and offline wallets for the acts of their end users or unwitting violations of regulations," but will instead hold accountable individuals who cause harm to digital asset investors or use digital assets for various forms of organized crime. At the same time, the U.S. government seems to be taking a more aggressive stance on drug cartels and foreign actors such as North Korea and Iran. Given that we find that the enforcement policies on services have been historically effective, the DOJ's goal of pursuing organized crime, including foreign actors, may be substantially impeded without targeting mixing and tumbling services.[7] Our findings suggest that Congress should consider legislation that will ban mixers and other technologies that specialize in laundering funds from criminal actors.

[4] The Responsible Financial Innovation Act, released by the Republican-led Senate Banking Committee on September 5, 2025, proposes a conditional exemption for non-custodial DeFi developers and protocols from AML obligations, whereas the Democratic Counterproposal, released by Senate Democrats on September 9, 2025, rejects such exemptions and would require DeFi platforms serving U.S. users to register with FinCEN and comply with the Bank Secrecy Act.

[5] Major industry participants have advanced self-regulation proposals asserting that the crypto ecosystem can effectively police itself. Examples include Gemini's Proposal for a Self-Regulatory Organization (2018), Coinbase's Digital Asset Policy Proposal (2021), and the INATBA's proposal on DeFi Self-Regulation (2025).

[6] Our paper also gives a roadmap indicating that monitoring by DeFi contract and exchanges is feasible. In particular, smart contracts could require that the string of prior transactions does not include sanctioned addresses, though the specific criteria would need to evolve over time to prevent exploitation by criminal actors.

[7] Additionally, the judge issuing the ruling that OFAC did not have the authority to ban code noted that "OFAC's concerns with illicit foreign actors laundering funds are undeniably legitimate. Perhaps Congress will update IEEPA, enacted during the Carter Administration, to target modern technologies like crypto-mixing software."

Related Literature. Our paper relates to two main strands of literature. First, in addition to the literature outlined above, we further contribute to the literature on crime and money laundering. El Siwi (2018) notes that recognizing "money is the lifeblood of organized crime" led to the adoption of the AML regime in Italy. Mirenda, Mocetti, and Rizzica (2022) show how organized crime utilizes cash and shell companies to obfuscate transactions entering the banking system. Moore, Clayton, and Anderson (2009) survey the economic structure of online crime and recommend more private data sharing and police enforcement focused on online gangs.[8] Chong and Lopez-De-Silanes (2015) find that money laundering regulations are associated with lower levels of proxies for money laundering across countries. Fracassi, Lee, and Roukny (2025) examine cross-country differences in AML compliance and their impact on international economic activity. Campbell-Verduyn (2018), Al-Tawil (2022), and Wronka (2023) overviews money-laundering laws and procedures, the potential challenges of application to cryptocurrencies, and the variation of policies across countries. Levi (2015) surveys the literature on how organized crime is financed and notes that what is known has been primarily limited to prosecuted case records. Our paper focuses on understanding the efficacy of money-laundering methods in the crypto space, where criminal activities can actually be partially measured and the regulatory landscape is rapidly evolving.

Second, there is a literature examining dark market activity in the crypto space. Meiklejohn, Pomarole, Jordan, Levchenko, McCoy, Voelker, and Savage (2013), Sokolov (2021), and Amiran, Jørgensen, and Rabetti (2022) examine the role of Bitcoin in the Silk Road (2011-2013), ransomware, and terrorism financing. Foley, Karlsen, and Putniņš (2019) find that 46% of non-exchange-related Bitcoin activity from January 3, 2009 to April 2017 is associated with darknet websites from 27 million Bitcoin users. Makarov and Schoar (2025) find substantially less in dark-market activities, Bitcoin mixers, and other criminal activities from 2009-2025.[9] They also highlight the high degree of interconnectedness

[8] Leukfeldt, Kleemans, Kruisbergen, and Roks (2019) find that technological knowledge for cybercrime in the Netherlands is often gained through a smaller set of technically skilled enablers in online marketplaces. Draca and Machin (2015) survey a growing literature on the economic incentives for crime. In terms of externalities of policies, Agca, Slutzky, and Zeume (2020) study how AML enforcement impacts lending by U.S. banks. Dirty money also distort macroeconomic capital allocations (Tanzi, 1996; Quirk, 1996).

[9] Chainalysis (2024) also provides a survey and examples of various types of criminal activity and calculates a total of $24.2 billion in 2023 through wallets directly identified with various identified for illegal activity though they note that their procedure undercounts. They seemingly do not count flows not other closely related addresses.

between Bitcoin clusters of illicit markets such as Hydra Market and centralized exchanges, which they note poses challenges for KYC and AML procedures. Griffin and Mei (2025) map the flows of pig butchering scams by tracing the flows and showing how criminal flows are entering centralized exchanges and how these exchanges are allowing inducement payments to potential victims. Cong, Harvey, Rabetti, and Wu (2025) show that 43 ransomware gangs carried out 2,690 attacks from May 2019 to July 2021. Cong, Grauer, Rabetti, and Updegrave (2023a) provide a useful overview as well as concrete examples of various crypto investment scams, Ponzi schemes, ransomware, money laundering, and dark markets.[10] We provide the first examination of AML laws. We also extend the literature by utilizing a comprehensive database of various types of criminal activity, and the analysis also leads to a fuller understanding of which laws might be effective and how criminals evade detection.

1. Data, Background, and Methodology

This paper arranges a group of data sets into a unified framework for following illicit funds. We do this by collecting data on transaction flows in Bitcoin and Ethereum. Transaction-level data is then enriched with attribution labels to assign addresses and flows to specific actors. Tracing methodologies further organize these transactions so that we can consistently follow specific funds that originate from an illicit address and track their flows to subsequent destinations. This section describes the process of developing our datasets, the background of crypto AML policies, and the tracing methodology.

1.1 Data

We primarily use two types of data: blockchain transaction data and attribution data. Blockchain transaction data is sourced from the Bitcoin and Ethereum blockchains. Importantly, the fields include the blockchain address of the sender and receiver, which allows us to construct paths of flows between addresses. We study both Bitcoin and Ethereum, with greater emphasis on Ethereum because that is where Tornado Cash, a high-profile mixer, exists. We analyze the Bitcoin blockchain for

[10] This literature also fits within a larger literature of other types of nefarious trading activity in crypto, including price manipulation (Gandal, Hamrick, Moore, and Oberman, 2018; Griffin and Shams, 2020), pump-and-dump schemes (Li, Shin, and Wang (2025), Hamrick, Rouhi, Mukherjee, Feder, Gandal, Moore, and Vasek (2021)), scams (Phua, Sang, Wei, and Yu, 2025), insider trading (Félez-Viñas, Johnson, and Putnins, 2022), and wash trading (Pennec, Fiedler, and Ante, 2021; Cong, Li, Tang, and Yang, 2023b) as briefly surveyed by Griffin and Kruger (2024).

an analysis of additional OFAC addresses, the Bybit hack, and for additional robustness tests. We use data from coingecko.com on end-of-day cryptocurrency prices to convert Ethereum and Bitcoin values to dollars.[11]

Beyond routine cryptocurrency transfers, blockchain users can also invoke specialized functions. We process data emitted from common functions, which allows us to follow funds that are swapped or bridged. Swapping is typically when an address uses a service such as a decentralized exchange to change one type of cryptocurrency to another on the same blockchain. Bridging is when an address deposits tokens into a service on one blockchain and receives that amount on another blockchain, net of any fees. We process data on swaps and bridges to further follow relevant funds. On Google Cloud BigQuery, our current mode of access, the total Ethereum blockchain amounts to over 5 TB of data.[12]

We use a rich set of sources for attribution data. First, we use data from online sources, such as blockchain.com and etherscan.io, to label addresses that belong to known entities. We focus on service providers such as centralized exchanges, decentralized exchanges, bridges, or mixers. Second, we collect all sanctioned addresses by OFAC, as well as all Ethereum-based addresses where the stablecoin issuers of Tether and USDC have seized assets. Third, we use and extend the data collected in Griffin and Mei (2025) to other types of illicit actors. Data on illicit actors originates mainly from law enforcement reports, lawsuits, and reports by victims. We use this dataset on illicit actors and their tainted flows solely to analyze the share of inflows to Tornado Cash that originate from illicit actors, to decompose stablecoin freeze events into categories of identifiable illicit addresses, and to examine whether tainted flows are more likely to utilize round-number increments.

1.2 Crypto AML Policy Background

After the terrorist attacks on September 11, 2001, the U.S. extended the existing anti-money laundering framework of the Bank Secrecy Act and increased cooperation across countries through new in-

[11] When converting cryptocurrency value to dollars, we assume prices for the stablecoins Tether, USDC, and DAI are always $1. This subset of currencies constitutes the vast majority of cryptocurrencies we see used in our sample.

[12] The Ethereum blockchain data consists of two primary tables on Google Cloud BigQuery: the *transactions* table (2.59 TB), which records transaction-level details such as sender, recipient, ETH value transferred, and contract interactions; and the *logs* table (2.57 TB), which stores all smart contract event logs, including token transfers, swaps, and other contract events, emitted during transaction execution.

ternational initiatives from the Financial Action Task Force (FATF). Anti-money laundering laws and enforcement may be the primary means of deterring activity in important settings such as terrorism and crimes committed by foreign nationals, where authorities may not have the ability to apprehend criminals in non-cooperative nations. Many of the basic principles are being questioned by a crypto industry born as an alternative financial system that is growing in size and political influence.

Cryptocurrency's appeal seemingly lies in its potential as an alternative financial system free from regulation. However, to interact with the global banking system, centralized crypto exchanges must authenticate the identities of new users through anti-money laundering and know your customer (AML/KYC) processes. Most exchanges purport to monitor transactions through know your transaction (KYT) policies to avoid receiving funds from known criminals. Since investors need trust in order to deploy capital and for meaningful investments to occur, the crypto ecosystem also has an incentive to root out bad actors as it seeks to be an alternative means of raising capital for legitimate entrepreneurial activity. The trade-off is that monitoring can be costly, reputational risk may be less pertinent in the crypto world, and lax monitoring may lead to more transactions and fees for the crypto intermediaries.

The regulatory and enforcement environment is in flux. On August 8, 2022, OFAC sanctioned Tornado Cash in response to its use by hackers sponsored by the Democratic People's Republic of Korea (DPRK) and thus prohibited the U.S. financial system from accepting related funds. A lawsuit challenging the sanctions, with the financial backing of large players in the crypto industry, argued that such a precedent would put undue responsibility on developers to prevent criminals from using their services.[13] The ban was lifted on November 26, 2024, when an appellate judge ruled that Tornado Cash's immutable smart contracts are not "property" and thus OFAC did not have authority to ban their use.[14,15] On a separate track, the U.S. DOJ prosecuted and fined large international crypto exchanges such as Binance (November 21, 2023) and OKX (February 24, 2025) for their lax AML proce-

[13] As reported by Reuters and discussed in a Coinbase blog post.

[14] More information can be found in this court ruling.

[15] When the Fifth Circuit ruled, Paul Grewal, Chief Legal Officer at Coinbase, remarked that: "Privacy wins. Today the Fifth Circuit held that U.S. Treasury's sanctions against Tornado Cash smart contracts are unlawful. This is a historic win for crypto and all who cares about defending liberty. Coinbase is proud to have helped lead this important challenge." More information can be found here.

dures. As part of their settlements, the exchanges agreed to more rigorous monitoring procedures and DOJ oversight. We use these shocks to study how users and exchanges respond to AML enforcement actions.

1.3 Methodology

We use blockchain data to construct a network of related addresses and analyze their characteristics in order to understand how the network responds to AML regulations. In this subsection, we describe the methodology used to identify related addresses, with *tracing* serving as the primary tool, and gas and deposit address clustering utilized.

1.3.1 Crypto Tracing

Tracing organizes transaction-level data into a framework that delineates the path of transaction flows of subsequent addresses. Tracing algorithms are an area of growing academic research (Anderson, Shumailov, and Ahmed, 2018; Möser and Narayanan, 2019; Tironsakkul, Maarek, Eross, and Just, 2022) and are commonly used by law enforcement, through service providers like Chainalysis and TRM Labs, to follow capital flows. We apply a suite of bulk tracing algorithms used and more fully described by Griffin and Mei (2025) in the context of pig butchering scams.[16] When tracing a given address, the first step is to collect all inflows. If outflows exist, then the tracer follows outflows to the next address. The goal is to follow tainted outflows to their end destination. Importantly, if tainted outflow funds are commingled in a downstream address that contains flows from other sources, then the forensic researcher must choose how to follow subsequent outflows. We follow commingled funds on a "first-in-first-out" (FIFO) basis, a well-established and accurate process for following specific fund transfers in cryptocurrency transaction-level data (Anderson, Shumailov, and Ahmed, 2018). We terminate a trace when it reaches an identified service such as an exchange, an unidentified large address with more than 2,000 transactions, five hops, or dust-level amounts under 0.00001 ETH, which avoid incorporating flows from other unrelated entities. By using tracing, we seek to only follow flows that are highly likely

[16] These tracing algorithms have been developed and maintained by Integra FEC. The algorithms are essentially a program with a series of steps to follow crypto fund flows to stopping points such as centralized exchange hot wallets. There are separate algorithms per blockchain for tracing funds forward and tracing funds backward.

to be controlled by reported criminal addresses, instead of implicating all downstream addresses and their respective funds. Consequently, traced funds will always follow strictly less than the initial inflow to the originating source.

In the next section, we trace all outflows from Tornado Cash and OFAC-sanctioned addresses. We also backtrace all funds entering Tornado Cash and OFAC-sanctioned addresses to their originating source. For services like Uniswap, Wrapped ETH, and bridge contracts, we only follow specific funds that are linked to traced transactions.

1.3.2 Gas and Deposit Address Clustering

In addition to tracing, we use two clustering methods to extend our network to find addresses that are highly likely to be related to an address of interest: gas clustering and deposit address clustering heuristics. Gas clustering arises when two addresses may share the same "funding" address, or the first instance of receiving a small amount of Ether, the native currency of Ethereum. The rationale is that all addresses need Ether because blockchain transaction costs can only be paid in Ether. Therefore, we associate the first funder as a way to link potentially related addresses. This idea is incorporated in services like Etherscan, the most popular service to view Ethereum transactions, where they display the first gas funder for every wallet. Deposit address clustering arises when two exchange deposit addresses receive funds from the same sender. The rationale is that deposit addresses are sensitive information like a bank account number, and therefore, if one sender transfers funds to two different deposit addresses, then it is likely that the two deposit addresses are linked, as discussed in Victor (2020).[17] Common gas funders and deposit address senders can then be used to link one address of interest to another in their nearby network. We exclude any gas funders or senders that have more than 2,000 transactions, and exclude any contracts to avoid linking clusters through services. We use gas funding to define related addresses to serve as a "treated" group for stablecoin seizures and deposit address clustering to measure inflows to potentially tainted addresses.

[17] On most centralized exchanges, each deposit address is linked to a specific customer account, and users can often generate new deposit addresses at no cost. These addresses are sensitive because if tainted funds are traced to one, law enforcement can subpoena the exchange, which may then be legally obligated to disclose the customer's identity.

2. Tornado Cash Sanctions

Tornado Cash is the most well-known mixer on Ethereum and the most widely used money laundering service by illicit actors, particularly in hacks and smart contract exploits. We begin by examining how other crypto actors interact with this service, focusing on flows into and out of Tornado Cash to better understand how both centralized and decentralized exchanges respond to transactions involving this well-known service. On August 8, 2022, the U.S. Treasury Department sanctioned Tornado Cash, prohibiting the U.S. financial system from accepting related funds. This ban was lifted on November 26, 2024, when a U.S. judge ruled that smart contracts or computer code could not be sanctioned, as they do not constitute the property of a foreign national or entity. We use this regulatory timeline to study how crypto activity interfaces with Tornado Cash across two main periods: before the ban and during the ban. We also show some time-series analysis after the ban, though there is limited history and more reduced activity. We begin with an overview of aggregate fund flows, then address three key questions: (1) Do user flows to Tornado Cash decline following the sanctions? (2) Has criminal inflow to Tornado Cash decreased? (3) Are centralized exchanges effective in enforcing sanctions?

2.1 Overview of Flows

We first provide an overview of Tornado Cash flows. Panel A of Figure 1 shows the type of identifiable addresses that use Tornado Cash. To keep the visualization exercise manageable, the figure samples the 2,500 largest nodes within the Tornado Cash network. To the left of the center Tornado Cash node, we notice that many of the addresses that remit funds to Tornado Cash are recognizable hacks and illicit organizations, including the Lazarus Group. Among paths entering Tornado Cash, many are intertwined in more complicated networks, while outgoing paths are more discernible. Users appear to funnel more money from decentralized exchanges (i.e., Uniswap, 1inch) than from centralized exchanges. Further, Tornado Cash withdrawals are commonly funneled back to DeFi within one hop. Funds also move to centralized exchanges. If exchanges enforced sanctions, then we should expect this flow to cease after sanctions.

2.2 Do User Flows to Tornado Cash Decline Following the Sanctions?

Figure 2 shows the time series of all flows to Tornado Cash, along with totals traced from reported criminal flows. The August 2022 ban seems to have been effective in reducing volume to the mixer. Before the ban, Tornado Cash was handling more than 100,000 ETH ($400 million) per month, but after the ban by October 2022, volume was less than 40,000 ETH ($50 million) per month, or a more than 60% decline.[18] Interestingly, the mixer becomes more attractive for criminals with a large volume, as it is easier to plausibly deny that the outflows one receives are different from the input transactions. The volume in the mixer stays low until the ban is lifted. Nevertheless, the volume post-ban does not rise to pre-ban levels.

We also plot the weekly tainted criminal address activity as a percentage of the total activity, as shown by the red line in Figure 2. The total flows vary widely, but at times show a sizable fraction of the flows due to criminal activity. In the six months following the sanction, an average of 26.49% of inflows to Tornado Cash are due to criminal flows, more than double the 11.79% observed in the six months prior. This percentage rose further in 2024, reaching an average of 49.62% between March and October. The decline in late 2024 is likely more of a by-product of our data reporting since reported criminal addresses are gathered with a considerable lag, as previously discussed. Nevertheless, the numbers are likely understated because our sample likely does not capture the entirety of criminal activity. Further, criminal flows are coming from sources that either cannot be or which we have not previously traced, including Tornado Cash itself, bridges, and the Wrapped Ether contract. When one examines the total flows into Tornado Cash as a fraction of the total flows for which there could be attribution, the percentage of the flows that originates from criminal activity jumps considerably.[19]

2.3 Is Tornado Cash Less Anonymous Following the Sanctions?

Although Tornado Cash is designed to sever the link between deposits and withdrawals, when liquidity is low, large flows may be more detectable. We investigate how the ban on Tornado Cash affected this

[18] Brownworth, Durfee, Lee, and Martin (2024) and Cristodaro, Kraner, and Tessone (2025) also show the decline in Tornado Cash volume after sanctions were imposed.

[19] Of the identified tainted flows to Tornado Cash, Figure IA.1 plots the top 50 individual senders featuring the North Korean Lazarus Group as first.

aspect of anonymity by estimating, for each week, the probability that a one-ETH withdrawal can be matched to the largest depositor. Perfect attribution is inherently difficult given Tornado Cash's core function of obfuscating transaction flows, so we estimate expected withdrawals by spreading each depositor's inflows across future days according to a declining schedule.

For every depositor, we first observe the daily amount entering Tornado Cash. We predict expected outflows by distributing each depositor's daily inflows into future daily withdrawals using a declining schedule modeled as a Pareto decay function, $f(\Delta) = (1 + \frac{\Delta}{\tau})^{-\alpha}$, where $\alpha = 0.3534$ and $\tau = 30$ days.[20] This declining function assumes that each depositor withdraws a larger fraction of their deposited funds shortly after making the deposit, with the fraction declining progressively for withdrawals made in later periods. By applying this withdrawal projection to each individual depositor's daily inflows, we obtain predicted daily withdrawal amounts for each depositor, which, when aggregated across all depositors on a weekly basis, closely match the actual observed weekly withdrawal totals.

Given that each predicted withdrawal is directly associated with the original depositor, we can calculate the probability of correctly attributing a randomly selected one-ETH withdrawal during week t to the top depositor as follows:

$$\text{Prob (Detection)}_t = \frac{\text{predicted withdrawals by the top depositor in } t}{\text{predicted withdrawals in } t}.$$

We calculate this probability weekly and report its ten-week rolling average, as shown by the blue line in Figure 2. Following the August 2022 U.S. Treasury sanctions, the average probability of matching withdrawal transactions to the top depositor significantly increased from 10.15% before the sanctions to 21.10% afterward. This increase primarily resulted from the sharp decline in total inflows after the sanctions, which caused the top depositor's share to become more prominent. Note that there are additional ways to track transactions, such as transaction reporting, timing differences, and transaction

[20] We test six different withdrawal distributions and find that the Pareto distribution with parameters $\alpha = 0.3534$ and $\tau = 30$ days provides predicted weekly withdrawal amounts that most closely match the actual Tornado Cash outflows. Additionally, Béres, Seres, Benczúr, and Quintyne-Collins (2021) document that approximately 70% of Tornado Cash users of the linked deposit-withdraw pairs withdraw their funds within one day of deposit, consistent with the rapid withdrawal schedule implied by our estimated distribution. We discuss our methodology in Internet Appendix Section B.

clustering, which our basic method does not employ, but further detailed analysis of certain transactions might further increase the probability of detection. Thus, the sanction not only reduced Tornado Cash's overall usage but also made it less effective at obscuring fund source identities.

2.4 Has Criminal Inflow to Tornado Cash Declined?

In this subsection, we examine if criminal users of Tornado Cash change their behavior around the sanctions. We focus on the flows of technically sophisticated hackers because we observe that hackers or other technical exploits account for most of the criminal inflows into Tornado Cash (as seen in Figure IA.2).[21] We use data on 5,867 unique hacker reports, identified from addresses labeled as contract exploits, stolen funds, or illicit actors. For each report in our dataset, we trace monthly flows both to Tornado Cash as well as to all other destinations on Ethereum. We construct a panel dataset where the unit of observation is the flows from each labeled hack, to each destination, per month.[22] To formally test the effect of the ban, we estimate a difference-in-differences analysis on hacker flows. We define the traced flows going to Tornado Cash as the treatment group, while those going to all other services as the control group. Specifically, we estimate a regression of the form as follows:

$$\log(1 + \mathit{TaintedFlows})_{i,d,t} = \sum_{t \neq \mathit{July2022}} \beta_t \times \mathbb{1}(\mathit{Month} = t) \times \mathit{Tornado}_d + \delta \times \mathit{Tornado}_d + \mu_i + \gamma_t + \varepsilon_{i,d,t}$$

where $\log(1 + \mathit{TaintedFlows})_{i,d,t}$ is the log of one plus the amount of ETH traced from hacker report i to destination d in month t, $\mathbb{1}(\mathit{Month} = t)$ is an indicator for calendar month t, $\mathit{Tornado}_d$ is an indicator equal to one if the destination is Tornado Cash, and zero otherwise, and μ_i and γ_t are hacker report and month fixed effects, respectively. Figure 3 plots the estimated DiD coefficients (β_t), which capture how the difference in inflows between Tornado Cash and other destinations evolves in each month compared to the baseline month. After the ban in August, we find that Tornado Cash usage

[21] We choose to focus on hackers because this group has shown more technological sophistication and has used Tornado Cash before the sanctions. Importantly, we cannot simply take a sample of each user that have a transaction history with Tornado Cash because Tornado Cash users have a tendency to rotate wallets and avoid re-using the same wallet in the future. Therefore, for many users, usage will mechanically decline after the first transaction.

[22] This is a balanced panel in that if the reported hacker address i does not send any flows to destination d in month t, then we encode this as zero. The alternative would be to have an unbalanced panel with missing data.

falls significantly and remains approximately 26% lower for about a year.

2.5 Are Centralized Exchanges Effective in Enforcing Sanctions?

After OFAC sanctioned Tornado Cash, money services businesses, including exchanges, were prohibited from processing transactions associated with it. To assess whether exchange users responded to these restrictions, we trace the flows exiting Tornado Cash to determine whether users avoided transferring those funds to centralized exchanges.

We identify and follow transaction paths from Tornado Cash to their eventual destinations. Figure 4 summarizes these paths using Sankey diagrams that visualize outflows from Tornado Cash before and after the August 8, 2022 sanction. Flows originate from Tornado Cash, pass through intermediate hops, and ultimately reach centralized exchanges in blue, decentralized exchanges in red, bridges in purple, or wrapped ETH in gray. When flows reach a decentralized exchange, we continue to follow the funds in the new cryptocurrency to identify their final destinations. Before the ban, we observe relatively large direct flows to centralized exchanges. After the ban, we observe a sizable shift, with fewer flows reaching centralized exchanges and more funds routed through DEXs and bridges.

Figure 5 compares these paths in a time series. The bars in each sub-panel represent a monthly distribution that together displays the share of Tornado Cash outflows that terminate in Western centralized exchanges (Panel A), overseas centralized exchanges (Panel B), and cross-chain bridges (Panel C). Throughout the paper, we include Coinbase, Crypto.com, Gemini, and Kraken as Western exchanges, primarily because these are the main exchanges that can be accessed from the United States. All other exchanges are included as overseas exchanges. Blue bars represent flows that move directly from Tornado Cash to the destination, while yellow bars indicate flows that are first routed through a decentralized exchange before reaching the final destination. The red line shows the average number of hops in each path, and the blue line shows the average duration in days between the exit from Tornado Cash and arrival at the destination.

We find that flows to Western centralized exchanges decreased significantly after the ban. The average monthly share of outflows to Western exchanges declined from 3.99% in the twelve months

before the ban to 2.14% in the twelve months after, a 46.20% reduction. This difference is statistically significant at the 1% level (t-statistic = 3.57, p-value = 0.0017). The decline is driven specifically by the reduction in direct flows to Western centralized exchanges. The share of direct flows fell from 2.60% to 0.78% over the same period, a 69.80% reduction, which is statistically significant at the 0.1% level (t-statistic = 5.86, p-value < 0.001). The dollar-weighted share of paths that routed through DEXs also increased, but it is not statistically significant. Overseas centralized exchange flow also falls by the end of 2023, and bridges become the dominant destination for Tornado Cash flows. These paths also have more costly characteristics in that they require more hops and are more likely to use a DEX after the ban. We compare transaction costs before and after the sanctions were imposed, split by Western and overseas exchanges. The transaction costs include transaction gas fees paid and costs from swaps.[23] While paths previously required an average of 50 basis points before the ban, the paths that entered Western exchanges averaged 1.71% (or 171 basis points) in transaction costs during the ban. However, costs have only increased from 38 to 66 basis points for overseas exchanges.[24]

Table 1 formally tests whether transfer paths to Western centralized exchanges became more complex and costly after the Tornado Cash ban, using a difference-in-differences regression that compares Western exchanges (treatment group) and overseas exchanges (control group). Western exchanges are treated because the OFAC sanction is a U.S. action, and compliance is expected to be more strictly enforced by exchanges with U.S. regulatory exposure. The regressions are estimated at the path-exit level, where each path represents a sequence of transfers originating from a single withdrawal from Tornado Cash that passes through one or more intermediate hops. Each path can have multiple exits, where each exit is a distinct cash-out event to an exchange and is counted separately. We find that the dollar-weighted average path that terminated in domestic exchanges used 0.29 more hops, required about 120 more days, and incurred between 77-87 basis points in additional transaction cost, which are both significant at the 1% level. Users, therefore, are increasingly unwilling to take funds from Tornado Cash to Western centralized exchanges. Those that do incur almost twice as much cost compared

[23] For Tornado Cash paths, we follow swapped funds through Uniswap, 1inch, 0x, fixedfloat, paraswap, and curve.fi, which accounts for 85% of the Tornado Cash outflows to DEXs.

[24] Figure IA.3 visualize the transaction cost comparison.

to transaction paths before the ban.

More broadly, we also test whether paths from Tornado Cash incurred more cost to reach centralized exchanges, regardless of jurisdiction. We compare the characteristics of paths leaving Tornado Cash and entering centralized exchanges to all tainted paths from the traced network to centralized exchanges. The results presented in Table 2 show that Tornado Cash outflows incurred 0.12 more average hops, required 130 more days, and 33 basis points in additional cost compared to other tainted paths after the sanctions were imposed.

In summary, the study of Tornado Cash shows how various crypto players interact with a service known to handle dirty money. We briefly note that Tornado Cash handles considerable criminal flows from more sophisticated cyber-criminal gangs, and we explore this in more detail in Section 7. The main takeaway is that the Tornado Cash inflow has declined after the sanctions. A large share of the remaining flows to Tornado Cash is associated with reported crimes. However, when considering flows of reported hackers, we find that criminal flows to Tornado Cash have declined. Tornado Cash outflows increasingly do not enter centralized exchanges in a straightforward manner, and those that do incur greater cost, likely in an effort to obfuscate the source of capital. Overall, the ban appears to have reduced the effectiveness of the mixer.

3. OFAC Sanctions

The U.S. Treasury Department's Office of Foreign Assets Control (OFAC) began listing digital currency addresses on its sanctions list in 2018. These sanctions target individuals linked to international crime varying widely, including North Korea's Lazarus Group, Hezbollah, the Sinaloa cartel, etc. The list further includes cryptocurrency exchanges and other cryptocurrency-related services associated with illicit activity, such as mixers or malware vendors. Once an address is sanctioned, U.S.-based entities are legally prohibited from transacting with it. In this section, we evaluate whether these sanctions are effective at inhibiting the flows of these designated addresses.

3.1 Are OFAC-Sanctioned Addresses Able to Convert to Fiat?

There are 28 days during which OFAC issued sanction orders, and these capture 380 Bitcoin addresses and 60 Ethereum addresses. These addresses belong to many different illicit actors spanning multiple criminal professions related to dark markets, terrorism, ransomware, mixers, and others (as shown in Figure IA.4). The bulk of these sanctions occurred between 2022 and 2024.[25]

In Figure 6 Panel A, we plot the sanctioned Bitcoin (left) and Ethereum (right) addresses. Each bubble represents a sanctioned address, with the bubble size proportional to the address's total lifetime inflow in dollars. The scatterplots illustrate sanction timing by plotting the address age at the time of last transaction, or the number of days between an address's first and last transactions (x-axis), and age at the time of sanctions, or number of days between the first transaction and the sanction date (y-axis). Addresses positioned directly on the 45-degree line were last used to transact exactly on the sanction date, which means users halted all activity after sanctions. In contrast, if an address is far above the 45-degree line, then sanctions are applied significantly after the last active date. The darker red shaded triangular regions highlight addresses that are sanctioned for more than one year and for more than two years after the last transaction date. Bitcoin addresses exhibit significant lags in sanction timing. Specifically, 80.80% of sanctioned Bitcoin addresses have no transactions after they are sanctioned, but 47.47% ceased activity more than one year before sanctions. On average, they are sanctioned 409.13 days after their last transaction. Ethereum addresses, by contrast, tend to be sanctioned during active use, averaging sanctions 52.14 days before their last recorded transaction. Only 26.53% of Ethereum addresses are sanctioned one year after their last activity. These timing differences suggest that sanctions on Ethereum addresses are more likely to be effective, as they are often imposed while addresses are still active. Since Bitcoin sanctions typically occur after the funds have been moved, the funds only stop criminals from reusing the address, but are generally not actually

[25] On October 14, 2025, OFAC sanctioned 146 individuals and entities within the Prince Group Transnational Criminal Organization, including Cambodian national Chen Zhi, for operating online investment scams and forced-labor compounds in Cambodia. The DOJ unsealed an indictment against Chen Zhi and seized approximately 127,000 Bitcoin worth $15 billion, which was added to the OFAC list in October 14, 2025 (even though the seizure took place in July 2024). These addresses are not included in our analyses because our last date of analyses was August 14, 2025, which is precedes the event by two months.

freezing funds.

In Figure 6 Panel B, we plot the balances of sanctioned addresses and the destinations of their trace outflows with Bitcoin in the left subpanel and Ethereum in the right subpanel. The bars show the balances of these addresses over time and their subsequent destinations, indexed by months since sanctions. In Bitcoin, the total flow that has passed through these transactions totals more than 195,000 Bitcoin. We find that the balance in these addresses seldom stays in the sanctioned wallet.[26] Instead, balances commonly flow to other downstream wallets that reach popular exchanges such as Binance or HTX, and other service providers such as Hydra, a now-defunct Russian dark marketplace. After the sanctions, the eventual destination of these addresses is mostly unchanged, likely because the sanctions occur much later than the last transaction date. In Ethereum, we find that prior to sanctions, these addresses have also established accounts with a few centralized exchanges, such as Bitfinex and Binance. Sanctions are more likely to occur when there is still a balance in the wallet, as shown by the light blue bars. After being sanctioned, approximately 150,000 Ethereum were sent to Tornado Cash, providing a direct channel for money launderers to plausibly avoid sanctions. A similar amount was sent to other Ethereum wallets and remained on-chain.

In summary, the sanctioned addresses received over 420,000 Ethereum and 195,000 Bitcoin. Valued at prices at the time funds entered the sanctioned addresses, these amounts correspond to about $1.55 billion and $4.25 billion, respectively. Of these total inflows, close to 155,000 ETH (36.90%) and 100,000 BTC (51.28%) remain on-chain. Using prices at the time of deposit, sanctioned entities off-ramped funds to centralized exchanges and mixers: $524.62 million to Binance, $456.61 million to Tornado Cash, $323.17 million to Hydra, $147.22 million to HTX, and the remainder $253.02 million to other exchanges. Of these, only the flows to Tornado Cash occur after sanctions; all other funds exited the Ethereum and Bitcoin blockchains before sanctions through well-established centralized exchanges.[27]

[26] The light blue stacked bars at the top of each bar indicate the BTC still held in sanctioned wallets, i.e., the running balance. These bars are often barely visible because the BTC is typically transferred out quickly after arrival.

[27] Figure IA.5 and Figure IA.6 show the total inflow to sanctioned addresses and their services of choice, as well as the dollarized value of the respective amounts stuck on-chain in event time. Panel A of both figures plots the Bitcoin and Ethereum outflows over calendar time, respectively. Importantly, the large inflows to Tornado Cash during the middle of 2022 correspond to a series of hacks targeting DeFi platforms in the Ethereum network. The largest of these was the Axie

The assets that remained on-chain are effectively frozen, as sanctioned entities have been unable to transfer these funds through centralized exchanges and convert them into fiat currency. Thus, sanctions, though used relatively infrequently, appear effective in that they sever these actors from the traditional financial system. The remainder have either already entered centralized exchanges or a mixer service such that the on-chain path can no longer be traced. Naturally, sanctions would be more effective if they could be used more often, enforced sooner, or before a centralized exchange accepts the funds. Discouraging the use of mixers would also help make sanctions more effective since mixers are a preferred method to avoid sanctions.

4. Freezing Stablecoins

The risk of asset seizure is a critical consideration in money laundering schemes. Stablecoin issuers like Tether (USDT) and Circle (USDC) have the technical ability to freeze these assets and prohibit specific users from future transactions with that stablecoin. However, stablecoin issuers have historically not been held to the standards of traditional banks, and "the absence of a regulated financial institution, subject to AML/CFT obligations can limit authorities' collection of and access to information. It can also reduce the effectiveness of preventive measures" (U.S. Department of the Treasury, 2024). In this section, we consider how illicit flows respond when the expected probability of asset seizure may increase due to related freezes.

Figure 7 presents statistics on 1,798 Ethereum addresses that were blacklisted from future interactions with Tether.[28] In total, we find that $1.34 billion in Tether was held, and therefore frozen, at the time these addresses were blacklisted. Interestingly, only $109 million are destroyed, indicating that freezes often may not lead to distributions. Panel A plots the cumulative number of blacklisted addresses (red line) and the cumulative dollar value of Tether frozen (stacked bars) over time. Colored segments denote freezes that overlap our traced network; unfilled, transparent segments are outside of the traced networks. Of the $1.34 billion frozen, $603.14 million overlaps our traced network. Within

Infinity Ronin bridge hack perpetrated by the Lazarus Group. See here for further details on this hack.

[28] We drop instances where an address was added to the list of frozen assets and then later removed. To be consistent with the tracing framework that conservatively excludes large addresses, we only keep frozen addresses with less than 2,000 transactions. This ensures that we do not trace paths associated with shadow exchanges.

this overlap, pig-butchering is the most common scam type ($235.53 million), followed by impersonation ($158.01 million) and phishing ($129.54 million).[29] To gauge the scale of Tether freezes, we use the $94.6 billion of inflows to pig-butchering-associated reported addresses over 2021-2023 documented by Griffin and Mei (2025) as a benchmark. The $1.34 billion frozen corresponds to only 1.42% of that figure. Because pig-butchering scam is just one component of the broader criminal ecosystem, the relevant denominator is likely considerably larger. Therefore, the Tether freezing activity is small in scale relative to the underlying criminal flows.

In Panel B of Figure 7, we plot the activity of the addresses leading up to the asset seizure. These seizures have a wide variety in the number of days active and balance at the time of being frozen. We see that many were active for years prior to being frozen. However, most of them cease activity upon seizure, with a few exceptions using USDC and Ether.

We also examine USDC freeze events and find that they are relatively uncommon compared to Tether freezes (as shown in Figure IA.7). Nevertheless, similar patterns emerge where wallets with frozen USDC largely cease all other activity, with a few exceptions.[30] In summary, we find that $1.34 billion Tether and $93.12 million USDC have been frozen. Of this, $608.65 million is frozen in addresses that appear in the traced network.

4.1 How Do Related Addresses React to Asset Freezes?

In this subsection, we consider how related addresses react when shocked by a plausibly random seizure, and if higher risk leads to higher costs. Figure 8 plots flows in the hours immediately before and after the freeze. Bars above zero indicate inflows and bars below zero indicate outflows. Hatched bars denote flows that arise from token swaps rather than simple transfers. In Panel A, we see that frozen addresses react immediately: within the first hour, they swap USDC into DAI, and in the following hours, they move out ETH and DAI, in part because they were unable to move any frozen Tether. We then examine addresses related to the frozen ones through gas clustering, as described in the methodology section. Panel B documents a similar response over the next 24 hours, with both

[29] Table IA.1 presents more details on the 396 frozen addresses that also appear in this network.
[30] Table IA.2 presents the statistics on the frozen USDC addresses found in our traced network.

USDC and TUSD swapped into DAI and a rise in transaction activity in the hours after the freeze.[31] These observations are consistent with a rapid shift away from assets that can be frozen. USDC and TUSD, like Tether, can be frozen by their issuers, whereas DAI does not have a freeze function.[32] The evidence suggests that freezes are effective and that coordination by stablecoin issuers is important for enforcement.[33] We formally test this behavior of increased transaction volume using a difference-in-differences framework. The outcome variables are transaction value and transaction count. The treated group consists of the frozen addresses and their related counterparts, while for every treated address, the control group is a random sample of 20 addresses that also received Tether in the preceding three days. We find that the related addresses transferred an average of 466% more dollar flow in 1.36 greater number of transactions in the 24 hours after a freeze than the control group, indicating that the market participants may be concerned that additional funds may be frozen.[34]

Next, we further investigate whether treated addresses shift their activities toward DeFi services after their Tether balances are frozen. To formally test it, we employ a difference-in-differences design at the group-cohort-month level. Each cohort represents one seizure event and consists of a treatment group and a control group. The treated group consists of the frozen address and its related addresses identified via gas clustering. For every freeze event, the control group is a random sample of 20 addresses that received inflows of at least $100 within the seven days prior to the freeze. For each treatment and control group within every cohort, we define the dependent variable *DeFi Share* as follows:

$$DeFi\ Share_{g,c,t} = \frac{\sum_{i \in g} DeFi\ flows_{i,g,c,t}}{\sum_{i \in g} All\ flows_{i,g,c,t}},$$

where $DeFi\ flows_{i,g,c,t}$ denotes the dollar amount transferred to DeFi services by address i in treatment or control group g in cohort c in month t. Then, we run a regression of the form:

[31] TUSD refers to TrueUSD, a U.S. dollar–backed stablecoin that can also be frozen by its issuer.

[32] While Tether and USDC can be frozen by their respective stablecoin issuers, the DAI smart contract does not have the functionality to restrict future usage. Notably, the issuer of DAI has recently shifted its focus to a new stablecoin with built-in seizure capabilities.

[33] In the U.S., the GENIUS Act was signed on July 18, 2025, which requires stablecoin issuers to comply with U.S. law enforcement requests for asset seizure. Our analysis shows that seizures can be an effective tool and that this condition for stablecoin issuers is important; otherwise, criminal flows may move to stablecoin issuers who do not allow freezes.

[34] The estimated coefficients are plotted in Figure IA.8. Table IA.3 tabulates results.

$$DeFi\ Share_{g,c,t} = \sum_{t \neq t_{freeze}} \beta_t \times \mathbb{1}(Month = t) \times Treat_g + \mu_c + \gamma_t + \varepsilon_{g,c,t}$$

where μ_c are cohort fixed effects, and γ_t are month fixed effects. Figure 9 plots the coefficients by event time, and Table 3 tabulates the coefficients. Overall, we find that the share of flows to DeFi services by frozen addresses and those linked to them increases by approximately 25% following Tether's freezing of their assets. This is evidence in support of the idea that the asset seizures as part of AML enforcement can incentivize affected entities to turn to more costly and less regulated services, such as DeFi protocols, potentially to obfuscate their flows.

4.2 What Money Laundering Patterns are Associated with Asset Seizure?

After observing that asset seizure leads related addresses to use more costly obfuscation services, a natural economic question is whether greater obfuscation efforts are associated with a lower probability of seizure. We consider the dollar-weighted probability that Tether freezes an address in our traced network. We sort paths into quintiles based on two metrics: total transaction cost and the duration of the path. Total transaction cost includes the transaction cost fees paid at each hop and sums the total fees paid for each hop on the path. It also calculates the spread lost from swaps where one cryptocurrency is converted into another cryptocurrency.[35] The spread is calculated based on the dollar value of crypto of input compared to the amount received as output. Duration of the path is calculated as the time leaving an origin compared to the time when funds were received at a centralized exchange.

We find that the paths most likely to contain a frozen address fall into the highest quintiles of both transaction cost and path duration, with a freeze probability of 7.8%. In contrast, paths in the lowest cost and shortest duration quintiles have only a 0.4% chance of containing a frozen address.[36] One must be careful in evaluating this test because it reflects only a correlation and not a causal relationship. A key endogeneity concern is that law enforcement may focus more heavily on sophisticated actors who have obtained larger illicit proceeds. These entities may delay their actions because they are aware that

[35] For reported address flows, we follow swapped funds through Uniswap, 1inch, Tokenlon and curve.fi, which accounts for 92% of the DEX activity.

[36] Figure IA.9 illustrates how paths are grouped and reports each group's corresponding freeze probability.

depositing large sums too quickly could attract attention. As a result, they may be unable to pool with the faster, low-cost transaction paths used by smaller actors, and instead must store funds on-chain for longer periods, increasing their exposure to detection.

5. U.S. Settlements with Exchanges

The most critical money laundering defense is services where on-chain funds can be converted into fiat currency and reintegrated into the traditional financial system. For most users, exchanges offer the deepest liquidity and greatest breadth of features for offboarding on-chain funds. Exchanges are also the best-positioned players with rails to the traditional financial system to correctly perform know-your-transaction monitoring. However, some exchanges have historically maintained weak compliance processes, which create opportunities for money launderers to convert crypto into fiat undetected.

On November 21, 2023, as part of a settlement with the U.S. DOJ, Binance admitted to ignoring KYC and AML procedures, pleaded guilty to anti-money laundering and sanctions violations, and paid over $4.3 billion in penalties. The company's founder and CEO resigned and was sentenced to federal prison.[37] At the time, Attorney General Merrick Garland stated, "Binance became the world's largest cryptocurrency exchange in part because of the crimes it committed. Now it is paying one of the largest corporate penalties in U.S. history." On May 17, 2024, the DOJ appointed two independent compliance monitors to oversee Binance for a three-year term. Similarly, on February 24, 2025, OKX pleaded guilty to violating U.S. anti-money laundering laws.[38] We use these announcements to evaluate whether Tornado Cash flows to these exchanges changed following the settlements.[39]

We first test whether Binance stopped receiving flows leaving Tornado Cash after Tornado Cash was sanctioned. Figure 10 presents data in the same format as Figure 5, but focuses specifically on flows to Binance compared to all other overseas exchanges around November 2023. The blue and yellow bars plot the monthly share of Tornado Cash outflows reaching Binance and all other overseas exchanges,

[37] See here for the DOJ press release on Binance settlement.

[38] See here for the DOJ press release on OKX settlement.

[39] Customers may choose not to remit funds to these exchanges either because of the announcement effect, or due to direct tighter post-plea compliance measures that deter future transactions.

with yellow denoting paths that swapped through a DEX. In 2023 and before the DOJ settlement with Binance, Binance received an average of 3.98% of all Tornado Cash outflows to overseas centralized exchanges. In the months after the DOJ's settlement with Binance and before the Tornado Cash ban was lifted in November 2024, this share declined sharply to 0.75%, representing an 81.29% reduction, which is statistically significant at the 0.1% level (t-statistic = 5.61). The decline is even larger when measured after the start of the compliance monitorship in June 2024, falling further to 0.54%. In contrast, flows to other overseas exchanges also declined but less dramatically, from 11.80% before the settlement to 7.64% post-settlement. This is primarily due to Tornado Cash users redirecting their funds toward bridges at the same period, as shown in Figure 5.

Additionally, the red line in Panel A shows that addresses that continued to reach Binance did so with more intermediate hops after the monitorship began. We formally test this pattern using a dynamic difference-in-differences framework, with estimated monthly coefficients plotted in Panel B. The outcome variable is the number of intermediate hops for transfer paths from Tornado Cash to centralized exchange destinations. The treatment group consists of flow paths to Binance, and the control group consists of flow paths to other overseas centralized exchanges. The estimates show no significant change in the number of hops immediately after the settlement, but a clear increase following the start of the compliance monitorship. This pattern suggests that users who continued sending Tornado Cash flows to Binance began adopting more complex routing paths to obscure the origin of funds, and that users became more hesitant to send funds to Binance. Notably, the number of hops declined after the Tornado Cash ban was lifted, consistent with reduced incentives for concealment once the sanction was removed.

We next evaluate similar tests around the DOJ settlement with OKX and find similar results. After OFAC sanctioned Tornado Cash in 2022, we continue to observe sizable flows from Tornado Cash entering OKX (as seen in Figure IA.10). In the year before the OKX settlement, OKX accounted for an average 1.53% of Tornado Cash outflows. Interestingly, flows from Tornado Cash fell four months prior to the DOJ settlement with OKX in February 2025. By February 2025, the Tornado Cash flows to OKX were nearly nonexistent. In a formal test, we find that the flows declined by 99.03% (t-statistic

= 3.515, p-value = 0.0048) after the settlement. Over the same window, the combined share to other overseas exchanges fell from 4.84% to 3.04%, which is not statistically significant.

Overall, the fact that outflows from Tornado Cash to overseas exchanges did not decline sharply after Tornado Cash sanctions but only after the exchanges settled or neared settling with the DOJ indicates that the crypto industry does not always self-police and that regulatory enforcement can be effective at ensuring compliance.

6. Deposit Patterns by Tainted Deposit Addresses

Data collected as part of the Bank Secrecy Act is a cornerstone of the anti-money laundering policies of the U.S. Treasury's Financial Crimes Enforcement Network (FinCEN) (Cuéllar, 2002; Gao, Pacelli, Schneemeier, and Wu, 2023). In 2023, more than 15% of all FBI investigations were directly linked to reports of suspicious transactions.[40] Under these policies, any deposit of $10,000 or more must be reported under a Currency Transaction Report (CTR), and any suspicious transactions, such as repeated deposits, deposits just under the threshold, or funds of questionable origin, must be reported under a Suspicious Activity Report (SAR). Crypto exchanges are also required to report suspicious transactions as part of their money service business license. If criminals are concerned with such reporting, they might structure their deposits to avoid detection. In this section, we test whether tainted deposit addresses are more likely to use round-numbered transaction amounts or to bunch just below the $10,000 threshold. We categorize deposit addresses by whether they are tainted by traced criminal flows and study their transaction patterns relative to untainted addresses.

6.1 Use of Round Numbers

A natural starting point is to examine whether illicit actors favor round-numbered deposit amounts, which could reflect deliberate behavioral structuring or simple heuristics (Nigrini, 2018). Figure 11 plots two distributions: the distribution of transaction counts for illicit flows in red and the distribution of all other flows in blue. The other flows likely contain considerable illicit flows as well, though mixed in with more non-illicit activity. Note that the y-axis is on a logarithmic scale. Bins

[40] Source: FinCEN Year in Review.

divisible by $1,000 are represented by squares, and bins divisible by $10,000 are shown as triangles. Round-number bins, depicted by these shapes, are noticeably elevated compared to neighboring bins, reflecting the general tendency to use round numbers. When comparing illicit actors to others, the red illicit markers are almost always above their corresponding marker for other flows after $1,000 because illicit actors generally use larger transaction sizes. However, the separation between illicit and other flow markers becomes especially pronounced at round-number values, suggesting tainted addresses use round numbers more frequently.

To formally test whether tainted deposit addresses are more likely to use round numbers, we estimate regressions where the dependent variable is an indicator equal to one if the deposit amount is exactly divisible by 500 or 1000. The independent variable, *Tainted*, is an indicator equal to one if the deposit address receives funds from a reported illicit actor or criminal address. Columns (1) and (3) of Table 4 show that tainted deposits are significantly more likely to use round numbers. Specifically, tainted addresses are 13 percentage points more likely to deposit amounts divisible by 500, and 12 percentage points more likely to deposit amounts divisible by 1000. Columns (2) and (4) add an interaction term between the tainted indicator and a Western exchange dummy to test for differential behavior across jurisdictions. The interaction terms are small and statistically insignificant, indicating that the use of round-numbered deposit amounts does not differ systematically between Western and overseas exchanges.

To account for the fact that tainted deposit addresses tend to use larger transaction sizes, we repeat the analysis using only deposits greater than $100 and find similar results (as shown in Table IA.4). As an additional robustness test, we examine whether the effect is specific to round-number values by testing deposit amounts that are close but not exactly divisible by round numbers. If the results are truly driven by round-number behavior, we should not observe similar effects when the dependent variable captures non-round-number amounts. We redefine the dependent variable to capture deposits that leave a remainder of 1, 499, or 999 when divided by 500 or 1000. Across these specifications, the coefficients on the tainted indicator are either statistically insignificant or extremely small in magnitude (as shown in Table IA.5). These findings support the interpretation that tainted

addresses specifically favor round-numbered deposit values.

6.2 Bunching around the Reporting Threshold

Beyond round-number effects, we also study whether tainted addresses exhibit strategic behavior around the $10,000 reporting threshold. We begin by plotting the distribution of deposit transaction sizes within a narrow window around the $10,000 threshold in Panel A of Figure 12. The figure displays the density of deposits for tainted (red) and untainted (blue) addresses, using solid circles for flows divisible by $100 and hollow circles otherwise. High-order polynomials are fitted separately for each group, with dashed lines corresponding to bins not divisible by $100. The distribution is shown separately for Western and overseas exchanges.

The results reveal several important patterns. First, there is a clear spike in the frequency of deposits exactly at the $10,000 threshold, as shown in Figure 11. Second, there is more bunching right below the threshold than right above it, as supported by the discontinuity between the dashed lines to the left and right of the $10,000 threshold. This pattern holds for both tainted and untainted flows, as indicated by the overlapping blue and red dashed lines, and it appears in both Western and overseas exchanges. Third, when focusing on round-number bins below the threshold, tainted flows bunch at these numbers more than untainted flows, though mainly at Western exchanges. This is most evident at deposit amounts such as $9,900, $9,800, and $9,500.

To formally test the illicit actors' behavior of bunching below the threshold, we adopt a design conceptually similar to Goncalves and Mello (2021) and leverage the sharp $10,000 reporting cutoff and round-number clustering to test for differential bunching behavior across tainted deposit addresses and all other deposit addresses. Specifically, we estimate the following regression form separately for every $10 deposit bin k in the $9,500–$10,500 window:

$$\mathbb{1}(d \in k)_{d,k,i,e,t} = \alpha + \beta^k \times \mathit{Tainted}_i + \gamma_e + \eta_t + \varepsilon_{d,k,i,e,t}$$

where $\mathbb{1}(d \in k)$ is an indicator variable equal to one if deposit d falls into bin k, and $\mathit{Tainted}_i$ is an indicator for whether deposit address i is tainted by illicit flows. The coefficient β^k captures the difference

in the probability that a tainted deposit address uses a specific deposit amount (bin k) relative to an untainted address. All regressions include exchange fixed effects to account for time-invariant exchange-specific characteristics, and year-month fixed effects to control for common temporal shocks. The regressions are estimated separately for Western and overseas exchanges.

The regression results are presented in Panel B of Figure 12, with green markers corresponding to Western exchanges and purple markers to overseas exchanges. The estimates reveal several patterns. First, at the $10,000 threshold, the coefficients are positive for both Western and overseas exchanges, indicating that tainted deposit addresses are more likely to use this exact amount compared to untainted ones. However, the effect is notably smaller in Western exchanges, suggesting that bunching at the threshold is mitigated in Western exchanges. Second, at deposit amounts immediately below the threshold, such as the $9,990 and $9,980 bins, the coefficients are negative, implying that tainted addresses are less likely to use these slightly sub-threshold amounts relative to untainted users. This effect is again weaker in Western exchanges, indicating that illicit actors are more likely to use these near-threshold values when interacting with Western exchanges than with overseas ones. Third, within Western exchanges, the coefficients are positive and statistically significant at round-number bins below the threshold, including $9,900, $9,800, and $9,500, suggesting that illicit actors exhibit stronger bunching at below-threshold round-number deposits in Western exchanges. Together, these results are consistent with the patterns in Panel A that illicit actors favor round-numbered deposit sizes and bunch just below the reporting threshold at Western exchanges.

Critics of CTR and SAR reporting argue that these requirements generate unnecessary busywork and produce a volume of reports too large to be meaningfully analyzed (Cuéllar, 2002). Overall, while the requirements appear to influence deposit patterns, their ability to effectively discriminate between tainted activity does not appear as an extremely strong pattern. Effort spent on the $10,000 threshold might be more effectively applied to monitoring criminal flows.

7. Aggregate Trends

The previous sections explore an arsenal of anti-money laundering regulations implemented to deter illicit financial flows between 2020 and 2025. These actions have increased the cost of money laundering and may have heightened expectations regarding the probability of asset seizure. This section explores what substitutes are available to users as the costs of money laundering increase.

Figure 13 compares two cohorts: (i) hackers active before the ban, and (ii) those who started moving the funds after the ban. We plot the traced dollar flows of each group to various destinations, highlighting sizable shifts in blue and entirely new top destinations in red. The pre-ban group relied heavily on Tornado Cash. By contrast, the post-ban group uses Tornado Cash at lower rates and shifts to other major services. We see that Wrapped Ether experiences the largest jump. Hackers appear to convert their stolen Ether into Wrapped Ether, possibly as an intermediary step before onward transfers. Among the newly popular destinations, Thorchain stands out the most. Thorchain is a bridging protocol that enables cross-chain transfers without going through centralized intermediaries. Hackers likely hope that moving funds across different blockchains via bridges will obscure the trail and make their activities more difficult to trace. Furthermore, hackers do not seem to widely use identified non-KYC exchanges, as these are relatively short-lived and only handle relatively small crypto deposits (as shown in Figure IA.11). Our results indicate that while the ban on Tornado Cash reduced its usage, hackers adapt quickly and adopt other mixing or bridging services once any single laundering route becomes riskier.

North Korean hackers are an emblematic example that encapsulates how the environment has evolved. Not only were North Korea prolific users of Tornado Cash before the software was sanctioned, but a high-profile North Korea hack was also the precipitating event that led to the 2022 sanctions.[41] In February 2025, North Korea is alleged to have stolen $1.4 billion from the exchange Bybit, marking the largest crypto heist in history.[42] Figure 14 plots these flows, with stolen funds initially exiting

[41] North Korea hacked Harmony Bridge and used Tornado Cash to launder the funds in June 2022, and Tornado Cash was sanctioned in August 2022. Details are available in the OFAC Press Release.

[42] Details are available in this FBI Press Release.

Bybit on Ethereum and being forwarded by hackers through Ethereum-based wallets and services, represented in the center. Within Ethereum, we see $42.8 million sent to OKX, but the majority of funds, or $968.15 million, we traced through Thorchain to addresses on the Bitcoin blockchain, likely to minimize seizure risk. We calculate the transaction costs of this operation: transfers on Ethereum cost $12 thousand, using Thorchain to bridge to Bitcoin incurred $3.79 million (42 basis points), and subsequent Bitcoin transfers added another $67 thousand in miner fees, for a combined $3.87 million. Notably, North Korea seems to have substituted from Tornado Cash, a service with relatively low cost (30 basis points), to bridges, which are more costly. The excessive splitting into over 34,000 transactions was likely an attempt to cheaply obfuscate their flows. Additionally, speed appeared to be a priority, given that, after thousands of transactions, the Ethereum proceeds were bridged to Bitcoin within 24 hours following the hack. Once on the Bitcoin blockchain, the funds continue to circulate through a wide network. Approximately $98.7 million has been deposited in Freebitco.in, a Bitcoin-based wallet and gambling service. However, the vast majority of funds otherwise remain dormant on the Bitcoin blockchain.[43]

The Bybit hack illustrates that storing assets in Bitcoin, despite the structural disadvantages of blockchain transparency and the price volatility of floating cryptocurrencies, can be preferable to the relatively high risk of asset seizure on Ethereum. While it was technically feasible to route the stolen funds through a mixer, the limited liquidity in such protocols is unlikely to support the laundering of over $1 billion within a short time horizon without attracting enforcement action. Instead, the hackers bridged the funds into Bitcoin, which, owing to its decentralized design and the more limited reliance on custodial intermediaries, offers greater protection against seizure. The North Korean cyber criminals may be assessing opportunities to exchange Bitcoin for fiat currency or real-world goods. Ultimately, the episode highlights that, without substantial liquidity in mixers, even high-profile and extremely sophisticated attacks like this are potentially traceable.

[43] Figure IA.12 plots the cumulative tainted BTC associated with said hack, and the corresponding inflows to Freebitco.in deposits.

8. Conclusion

We provide the first empirical investigation of money laundering policies in the crypto arena. We observe decreased illicit volume following the sanctioning of Tornado Cash, other OFAC designations, and major exchange settlements. We also find evidence that users respond to these restrictions by switching to higher-cost methods. Tornado Cash users, for instance, incur higher transaction costs when attempting to access centralized exchanges, and addresses linked to stablecoin freezes show increased reliance on decentralized exchanges. Sanctions appear effective in making it more difficult for sanctioned entities to find destinations to off-board funds. Overall, our findings indicate that crypto asset freezes and anti-money laundering enforcement have been costly to criminals.

Nevertheless, our analysis indicates many areas for improvement. Even though OFAC sanctions keep funds on-chain, few addresses and dollar amounts are sanctioned, and often, too late. Additionally, while overseas exchanges see reduced sanction-related flows after enforcement actions, they continue to receive illicit volume and have not experienced a substantial reduction in tainted flows from other forms of criminal activity, such as scamming. The sanctions against Tornado Cash were also insufficient to deter some overseas exchanges until additional fines were assessed against exchanges, indicating that multiple enforcement actions may be necessary to plug enforcement weak spots. Therefore, reputational risk and the goodwill of exchanges to stop crime do not appear to be effective deterrents in the crypto space. Reducing flows to the Tornado Cash mixers led to greater blockchain transparency; thus, if mixer popularity increases as sanctions are lifted, then efforts to freeze criminal proceeds may be substantially more difficult. Additional research should also consider the costs and benefits of monitoring. Our research demonstrates how the blockchain makes tracing and monitoring more straightforward than in other contexts, such that large-scale monitoring could be automated for reasonable costs. We hope additional research will further analyze crypto crime and enforcement to help enact reasonable policies that both facilitate legitimate capital formation and deter crime.

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Figure 1. Tornado Cash Transaction Networks

This figure visualizes flows involving Tornado Cash. It illustrates the network of flows involving Tornado Cash, with senders positioned on the left and receivers on the right. Edges concave down represent flows moving from left to right (e.g., the curve moves as if going from 9 o'clock to 3 o'clock), while edges concave up indicate flows moving from right to left (e.g., from 3 o'clock to 9 o'clock). This is a sample constructed by selecting the largest 2,500 nodes within 5 hops from Tornado Cash and keeping connected paths. This was selected to reflect the largest ∼10,000 edges related to Tornado Cash.

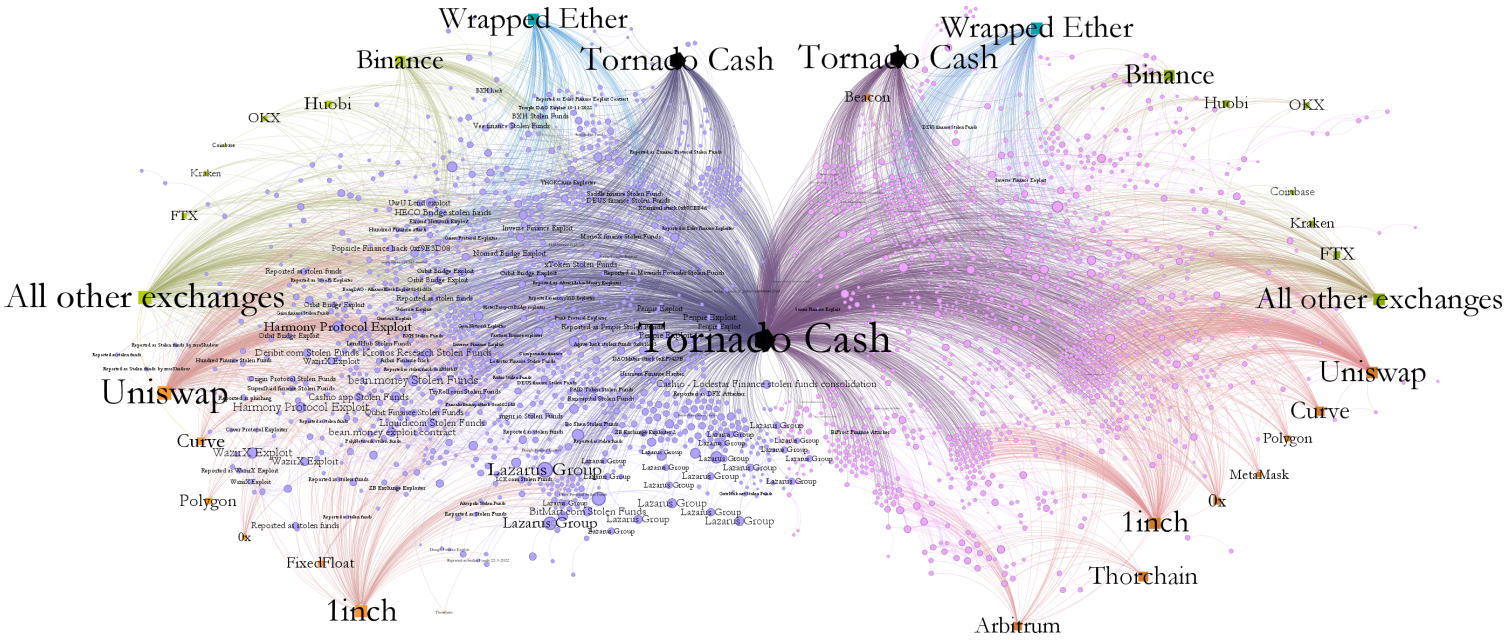


Figure 2. Inflows to Tornado Cash

This figure shows the total inflows and traced criminal inflows to Tornado Cash from 2021 to 2024. The bars indicate the monthly total inflows to Tornado Cash. The different shades in the bars represent the inflows from the top one depositor (dark blue), the top two to five depositors (blue), and all other depositors (light blue). The red line represents the percentage of traced criminal inflows from all scam types. The blue line shows the probability of matching the withdrawal transaction to the top depositor. This probability is estimated using a forward projection approach that allocates each depositor's inflows to future days according to a Pareto decay function; the weekly predicted outflows are then used to calculate the share attributable to the top depositor. While the bars are based on monthly totals, the percentages and probabilities shown in the lines are computed at weekly frequency and plotted as ten-week rolling averages. The dashed vertical lines indicate the period during which Tornado Cash was sanctioned by the U.S. Treasury, beginning on August 8, 2022, and lifted on November 26, 2024.

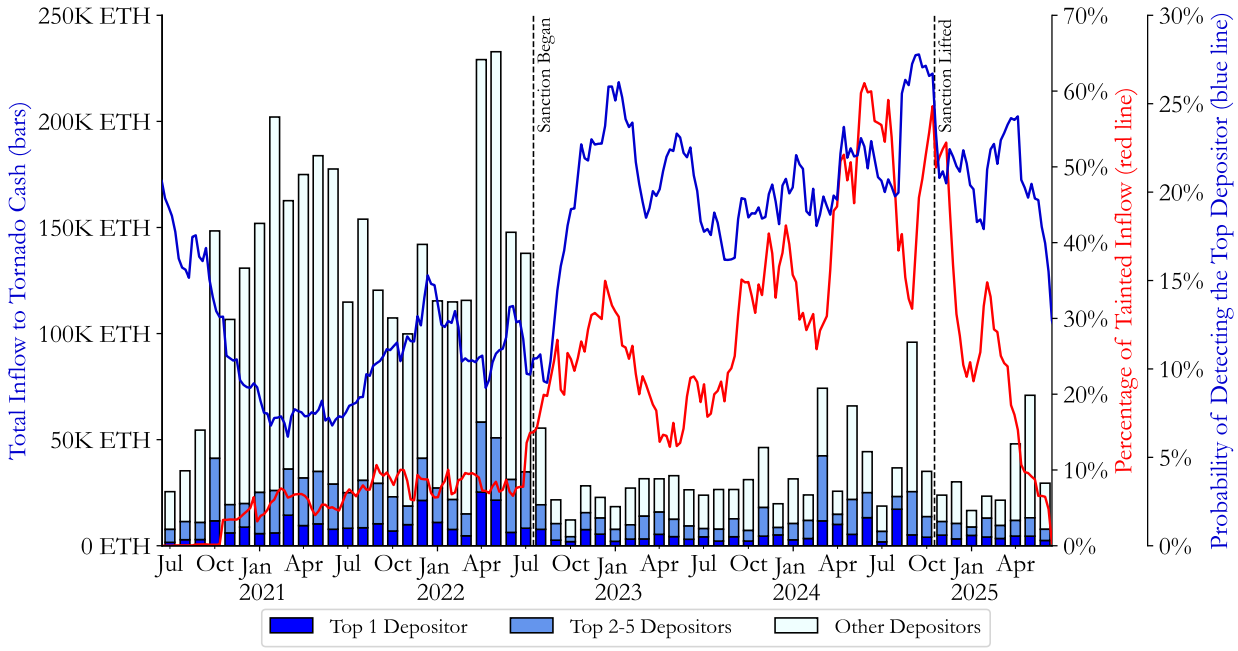


Figure 3. Effects of U.S. Treasury Sanctions Against Tornado Cash on Hacker Flows
This figure examines the change in hacker flows around the U.S. Treasury sanctions on Tornado Cash. It plots the monthly difference-in-differences coefficients from the regression

$$\log(1 + \mathit{TaintedFlows})_{i,d,t} = \sum_{t \neq \mathit{July2022}} \beta_t \times \mathbb{1}(\mathit{Month} = t) \times \mathit{Tornado}_d + \delta \times \mathit{Tornado}_d + \mu_i + \gamma_t + \varepsilon_{i,d,t}$$

where $\log(1+TaintedFlows)_{i,d,t}$ is the natural logarithm of one plus the amount of ETH traced from reported hacker address i to destination d in month t. Hacker report and month fixed effects are included. Standard errors are double-clustered by hacker report and month. The vertical dashed line marks the August 8, 2022 sanction of Tornado Cash.

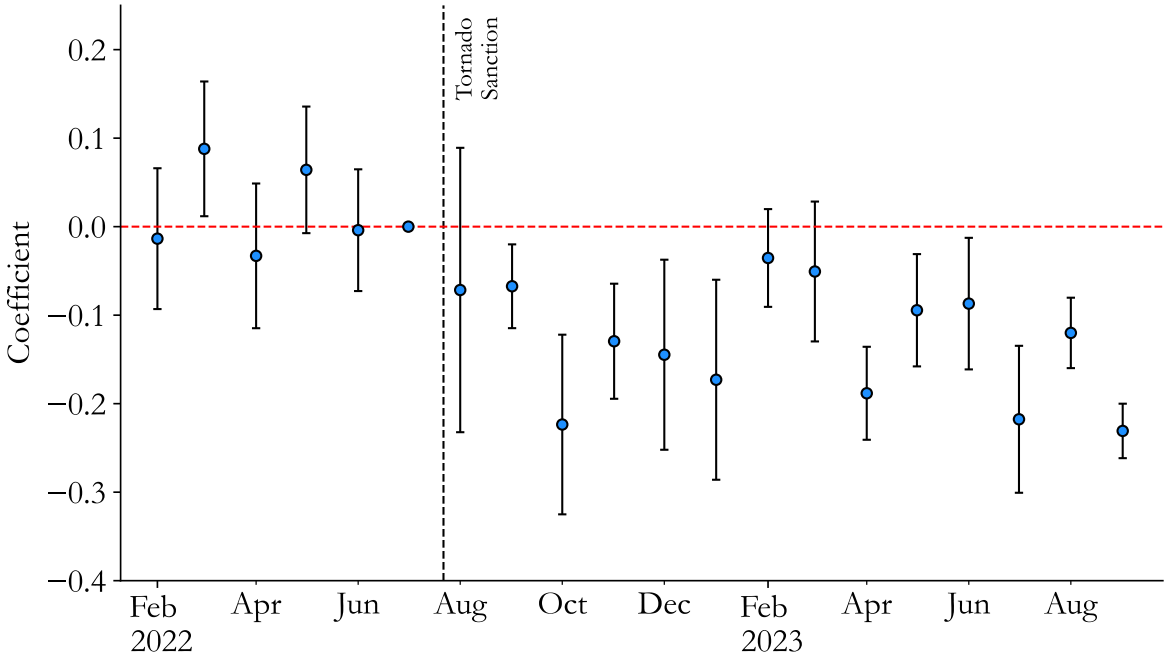
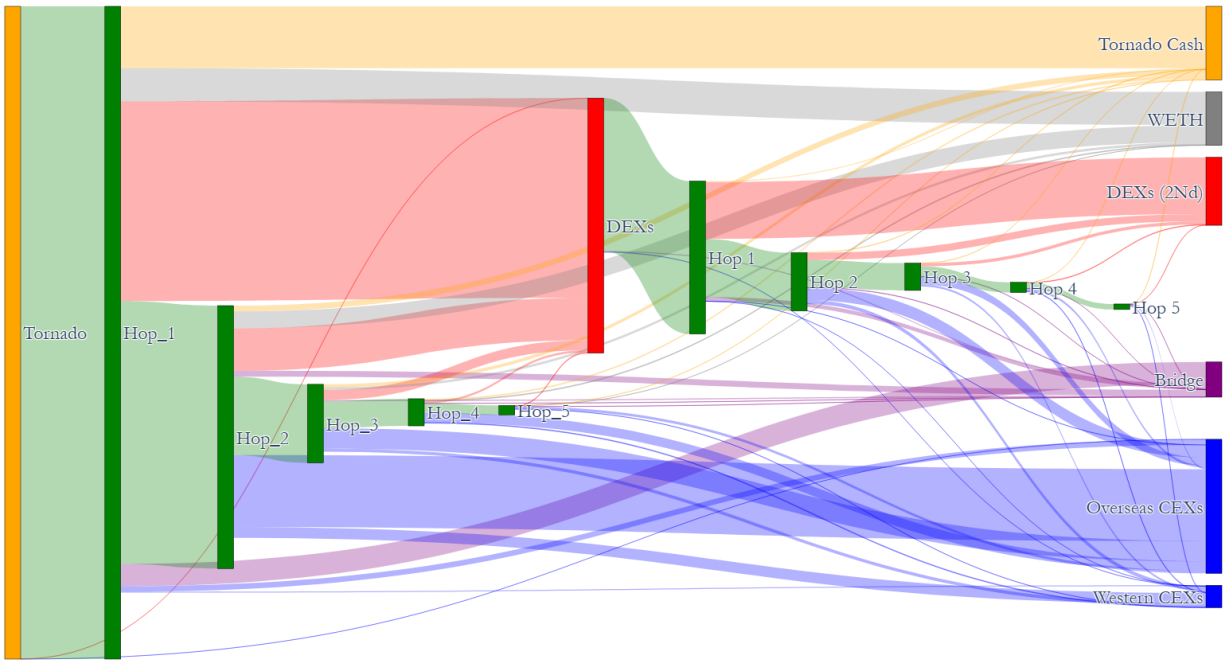


Figure 4. Tornado Cash Outflows to Destinations by Intermediate Hop

This figure visualizes Tornado Cash outflows and their destinations before and after the Tornado Cash ban on August 8, 2022, using Sankey diagrams. Panel A shows outflows before the ban, and Panel B shows outflows after the ban. In each diagram, flows originate from Tornado Cash on the left and proceed through intermediate hops (e.g., Hop 1, Hop 2, shown in green) before reaching final destinations on the right. Flows into centralized exchanges (CEXs) are shown in blue, decentralized exchanges (DEXs) in red, blockchain bridges in purple, and wrapped ETH (WETH) in gray. When flows arrive at a DEX, funds are traced through additional hops to identify their ultimate destinations after swaps. The width of each flow indicates the relative volume of funds moving along that path. Western exchanges are Coinbase, Crypto.com, Gemini, and Kraken, and all other exchanges are included as overseas exchanges.

Panel A: Before Tornado Cash Ban



Panel B: After Tornado Cash Ban

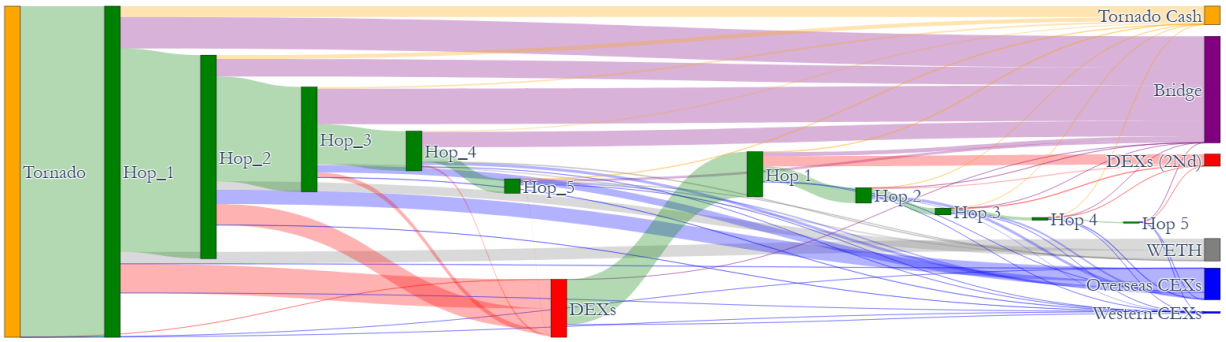


Figure 5. Effects of Tornado Cash Ban on Its Outflows to Different Destinations

This figure examines the effects of the Tornado Cash ban on its outflows to different destinations. It shows Tornado Cash outflows to Western exchanges in Panel A, overseas exchanges in Panel B, and bridges in Panel C. In each panel, bars represent the percent of monthly outflows to the destination category: blue bars represent flows that moved from Tornado Cash to the destination without passing through any decentralized exchanges (DEXs), while yellow bars represent flows that were first sent from Tornado Cash to DEXs, and then arrived at exchanges after being traced through DEXs. The red line plots the average number of hops before funds arrive, and the dark blue line plots the average number of days for transfers. Western exchanges are Coinbase, Crypto.com, Gemini, and Kraken, and all other exchanges are included as overseas exchanges. Two black vertical dashed lines mark the sanction of Tornado Cash on August 8, 2022, and its lifting on November 26, 2024.

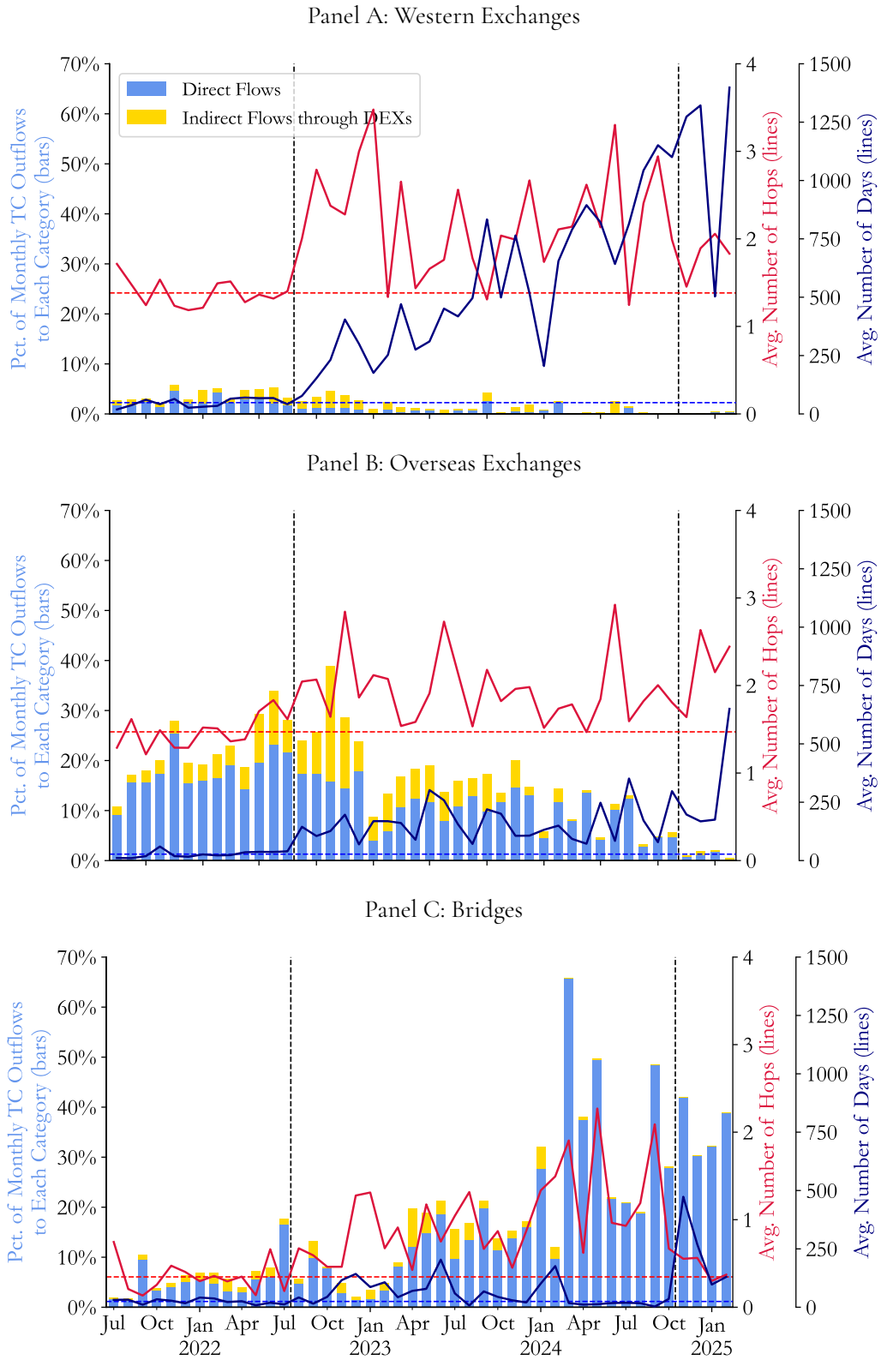
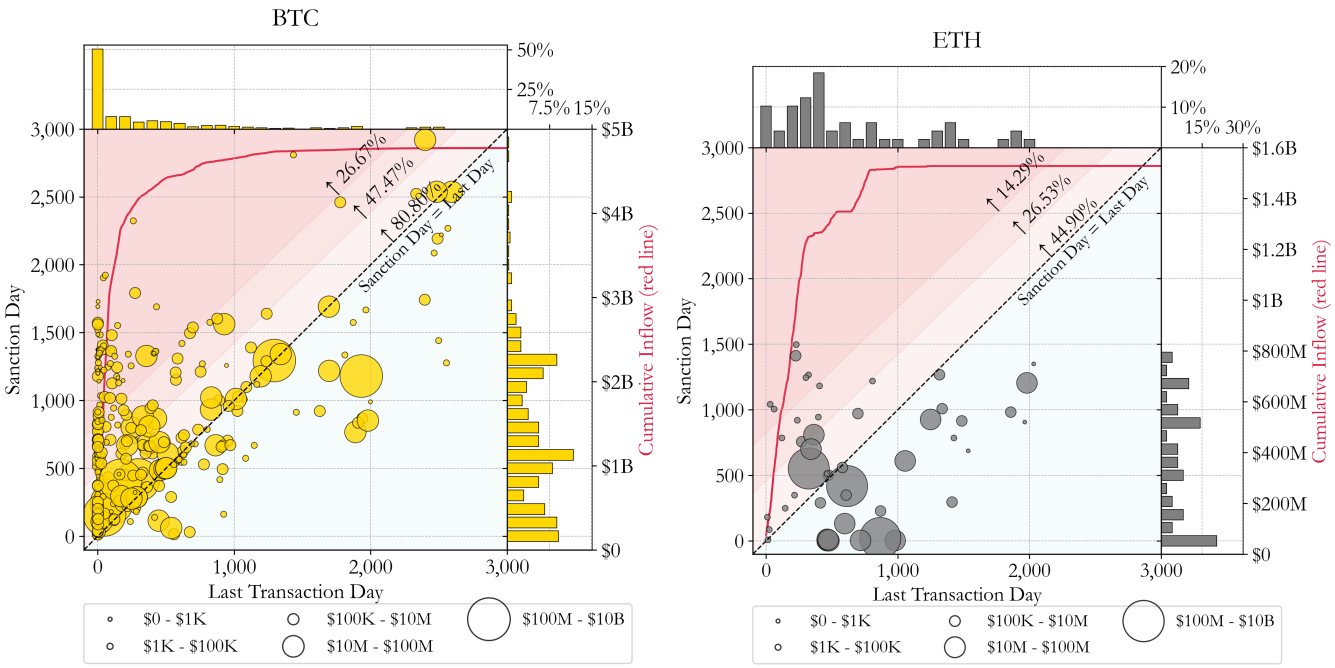


Figure 6. Effect of OFAC Sanctions

This figure plots OFAC sanction activity. Panel A shows scatterplots for BTC and ETH sanctioned addresses, with the x-axis indicating the number of days between the first and last transaction, and the y-axis showing the number of days between the first transaction and the sanction date. Dot size reflects total lifetime inflow, and the red line (rightmost axis) shows cumulative inflow. Histograms along the top and right display the percentage of addresses by last transaction day and sanction day, respectively. The shaded triangles show the timing of sanctions: addresses above the 45-degree line were sanctioned after their last transaction, while those below were sanctioned before. Darker red triangles highlight addresses sanctioned with a delay of more than 1 year and more than 2 years after their last transaction, respectively. Annotated percentages indicate the share of addresses in each group. Panel B plots destinations of flows leaving addresses sanctioned by OFAC, indexed by months since sanctions were imposed. Assets in the wallet correspond to those assets in the sanctioned address, whereas the assets on-chain are those that have been forwarded in the corresponding blockchain, but have yet to reach a known service.

Panel A: Sanctioned Day versus Last Transaction Day



Panel B: Balance Traced from Sanctioned Addresses to End Destinations

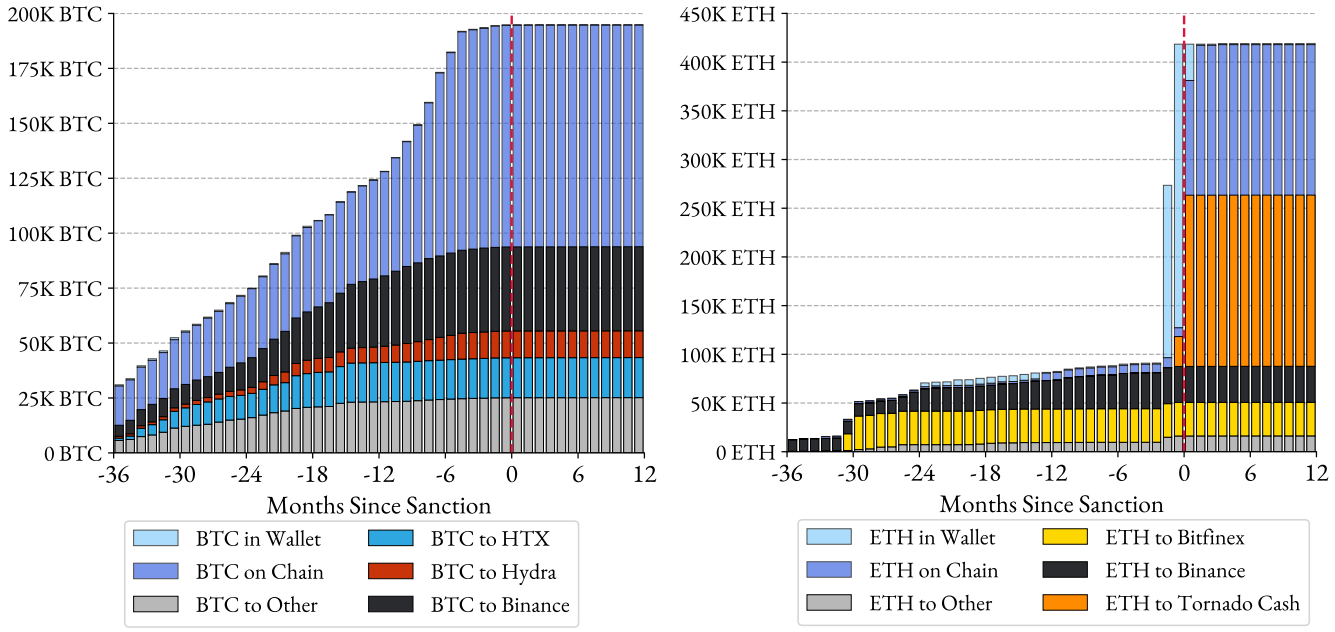
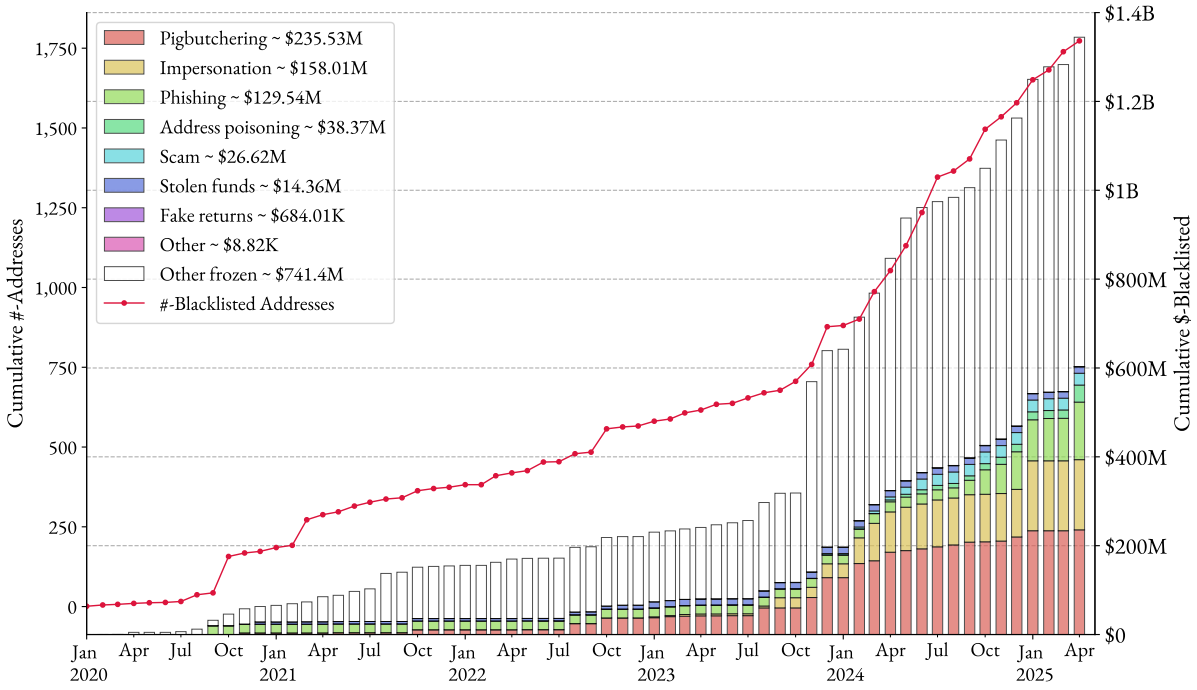


Figure 7. Tether Freezes

This figure presents the scope of Tether freezes and the pre-seizure activity of frozen addresses. Panel A summarizes enforcement scale over time: the red line (left axis) plots the cumulative number of blacklisted addresses, while the stacked bar (right axis) shows the cumulative dollar value of Tether frozen. Colored segments of each bar indicate frozen addresses appearing in the traced network of reported criminal flows and show the corresponding scam type, while white segments indicate addresses outside that network. Panel B illustrates inflow trajectories for frozen addresses prior to seizure. This panel plots a select sample of frozen addresses that have received more than $10K in total inflows. The horizontal axis reports the number of days each address was active prior to being frozen, and the vertical axis (log scale) shows the total dollar inflow to that address. Each dot represents a transfer event, with dot size reflecting the cumulative inflow received by the address at that point in time. Multiple dots forming a line represent inflow trajectories for a single address. Red crosses mark the date each address was frozen.

Panel A: Cumulative Freezes Over Time



Panel B: Activity of Frozen Addresses Prior to Seizure

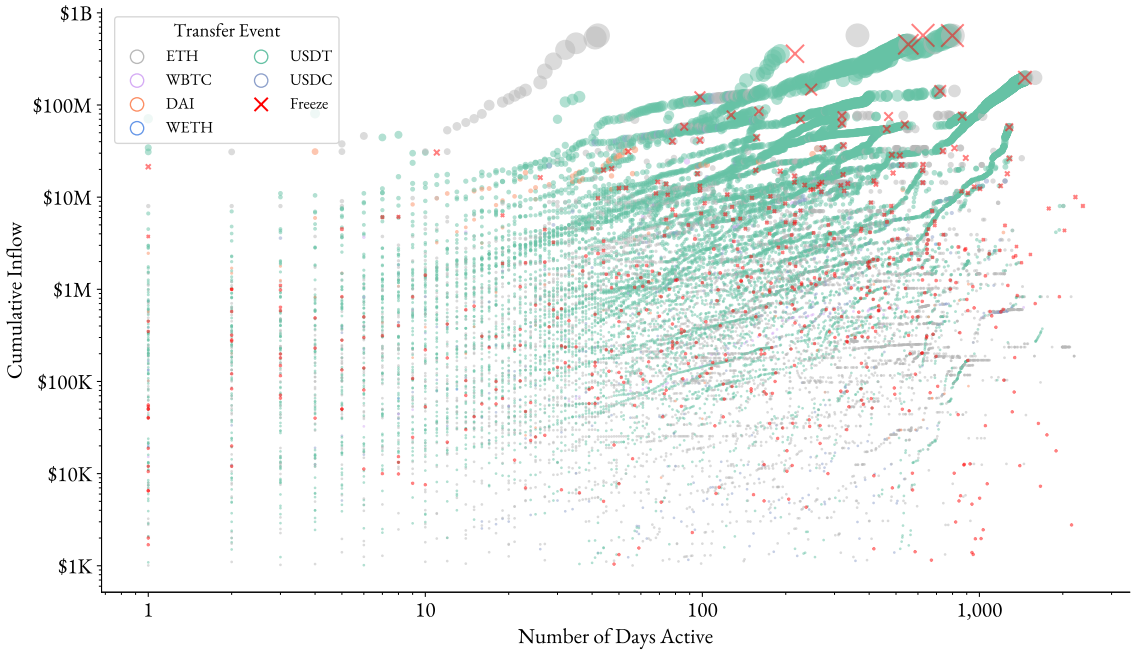


Figure 8. Tether Seizure: Immediate Effects

This figure presents inflows and outflows indexed by the hours prior to and after the Tether freeze for the targeted addresses and the addresses clustered around them. For both panels, inflows and outflows are reflected in the left-hand y-axis, and these flows are broken into their corresponding cryptocurrency, here denoted by the corresponding colors. Inflows are represented by upward-pointing bars, and outflows are likewise represented by downward-pointing bars. Hatched sections correspond to amounts swapped. On the opposite y-axis, the running balance is represented. Panel A shows the flows corresponding to the frozen addresses, which cannot forward Tether after the frozen date, marked here by the dotted vertical line at the zero hour. Panel B shows the outflows of addresses related to but excluding the addresses that were frozen. These additional addresses were clustered using a conservative common-funder heuristic.

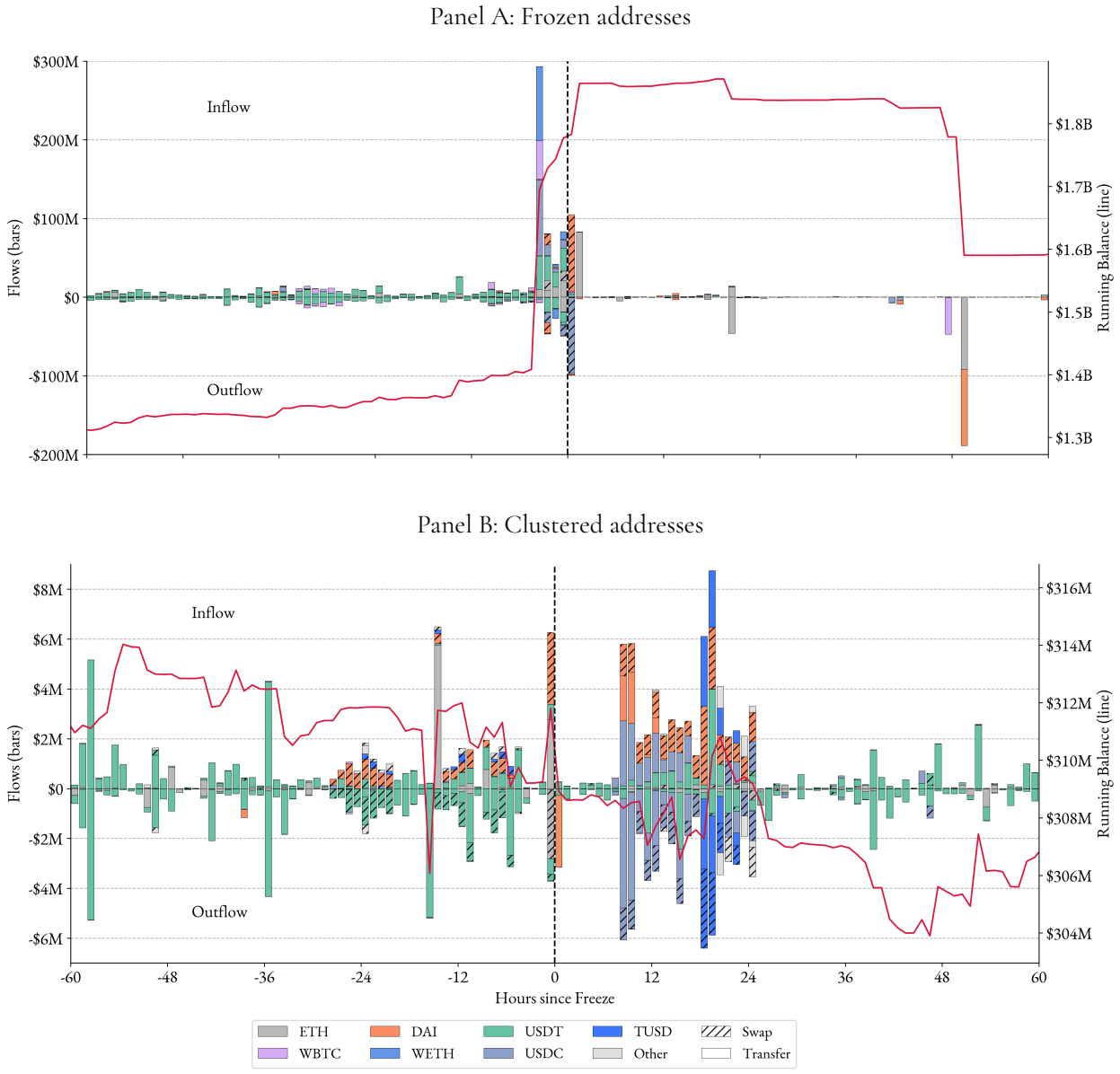


Figure 9. Tether Seizure: Long-Term Effects

This figure examines whether blacklisted addresses and their related addresses increase their use of DeFi services following an asset freeze. It plots coefficients from a difference-in-differences regression of the DeFi share of outflows at the group-cohort-month level. Each cohort represents one seizure event and consists of a treatment group and a control group. The treated group consists of the frozen address and its related addresses. For every freeze event, the control group is a random sample of 20 addresses that received inflows of at least $100 within the seven days prior to the freeze. Specifically, the following regression is estimated.

$$\textit{DeFi Share}_{g,c,t} = \sum_{t \neq t_{freeze}} \beta_t \times \mathbb{1}(\textit{Month} = t) \times \textit{Treat}_g + \mu_c + \gamma_t + \varepsilon_{g,c,t}$$

where $\textit{DeFi Share}_{g,c,t} = \frac{\sum_{i \in g} \textit{DeFi flows}_{i,g,c,t}}{\sum_{i \in g} \textit{All flows}_{i,g,c,t}}$ and it denotes the share of flows sent to DeFi services for the treatment or control group g in cohort c in month t. The regression includes the cohort fixed effects and event time fixed effects and is weighted by total transaction value. The sample period is 12 months before and after the freeze date of each cohort. Standard errors are clustered by asset seizure cohort and event time.

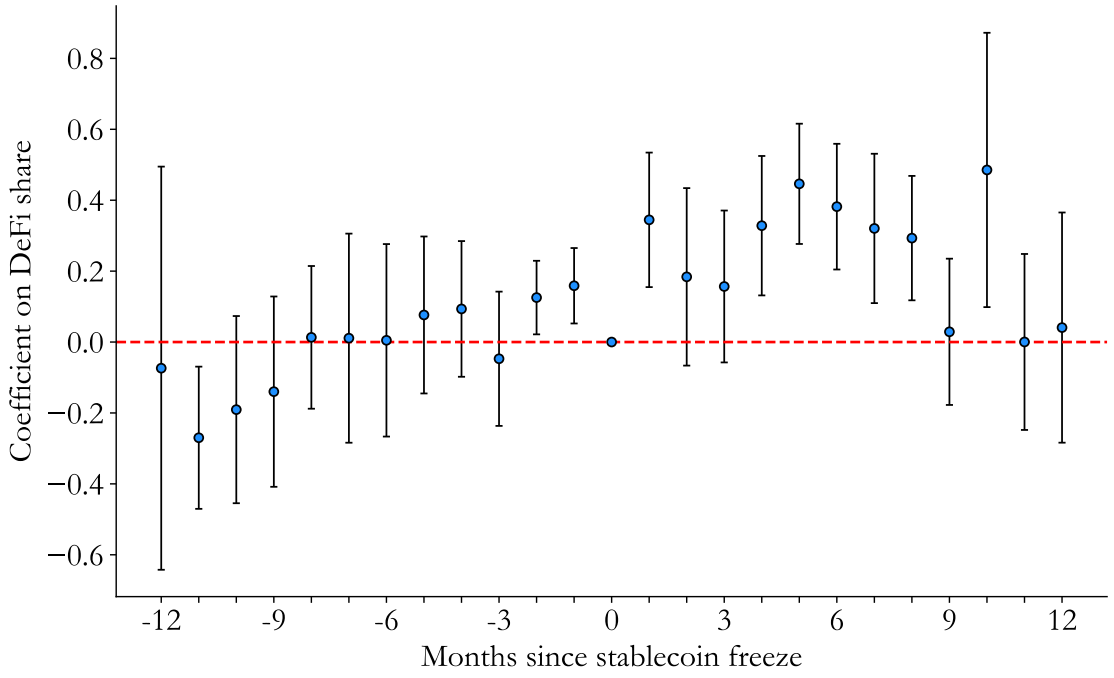
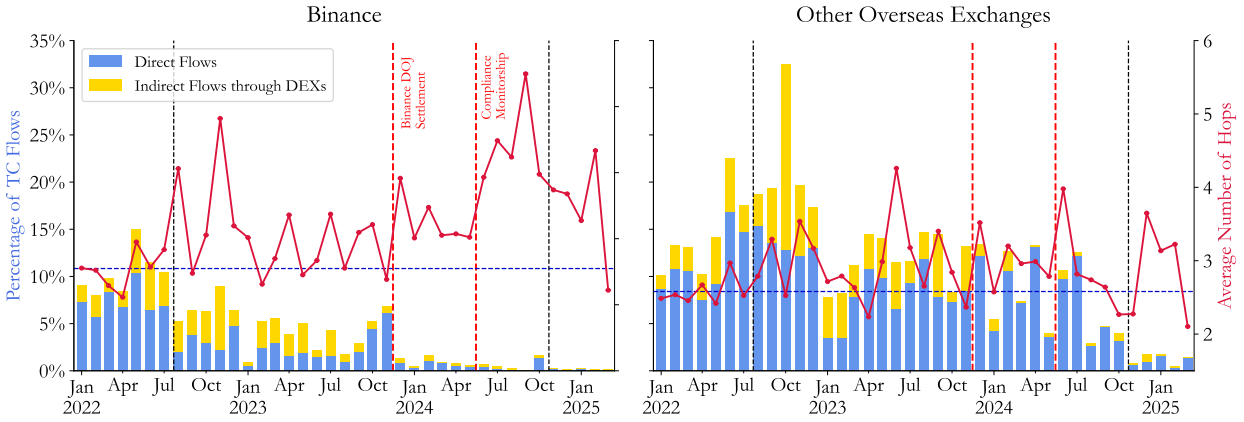


Figure 10. Tornado Cash Outflows to Binance around Binance Settlement

This figure examines the effects of the Binance DOJ settlement and subsequent compliance monitorship on Tornado Cash outflows. Panel A presents Tornado Cash outflows to Binance (left subpanel) and to other overseas exchanges (right subpanel). In each subpanel, bars represent the percent of monthly outflows to the destination category: blue bars represent flows that moved from Tornado Cash to the destination without passing through any decentralized exchanges (DEXs), while yellow bars represent flows that were first sent from Tornado Cash to DEXs, and then arrived at exchanges after being traced through DEXs. The red line shows the average number of hops before reaching the destination. Panel B compares the number of hops for transfers from Tornado Cash to Binance versus other overseas exchanges using a difference-in-differences regression, with the estimated coefficients plotted over time. Year-month fixed effects and exchange fixed effects are included. Standard errors are clustered by exchanges. Western exchanges are Coinbase, Crypto.com, Gemini, and Kraken, and all other exchanges are included as overseas exchanges. Two red vertical dashed lines indicate key regulatory events at Binance: the DOJ settlement on November 21, 2023, and the announcement of the compliance monitorship on May 17, 2024. Two black vertical dashed lines mark the Tornado Cash sanction on August 8, 2022, and the lifting of the sanction on November 26, 2024.

Panel A: Tornado Cash Outflows



Panel B: DID Analysis on Number of Hops

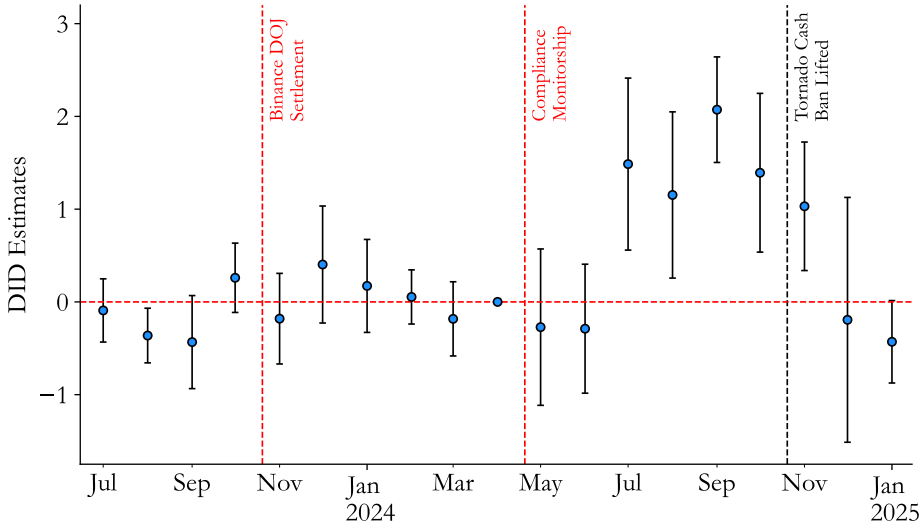


Figure 11. Round Number Deposits by Tainted Deposit Addresses in Exchanges

This figure plots the distribution of transaction sizes for all exchanges split into bins of $100. Red dots show illicit flows, and blue dots show all other flows. Right-bound bins divisible by $10,000 are triangles, $1,000 are squares, and all others are circles.

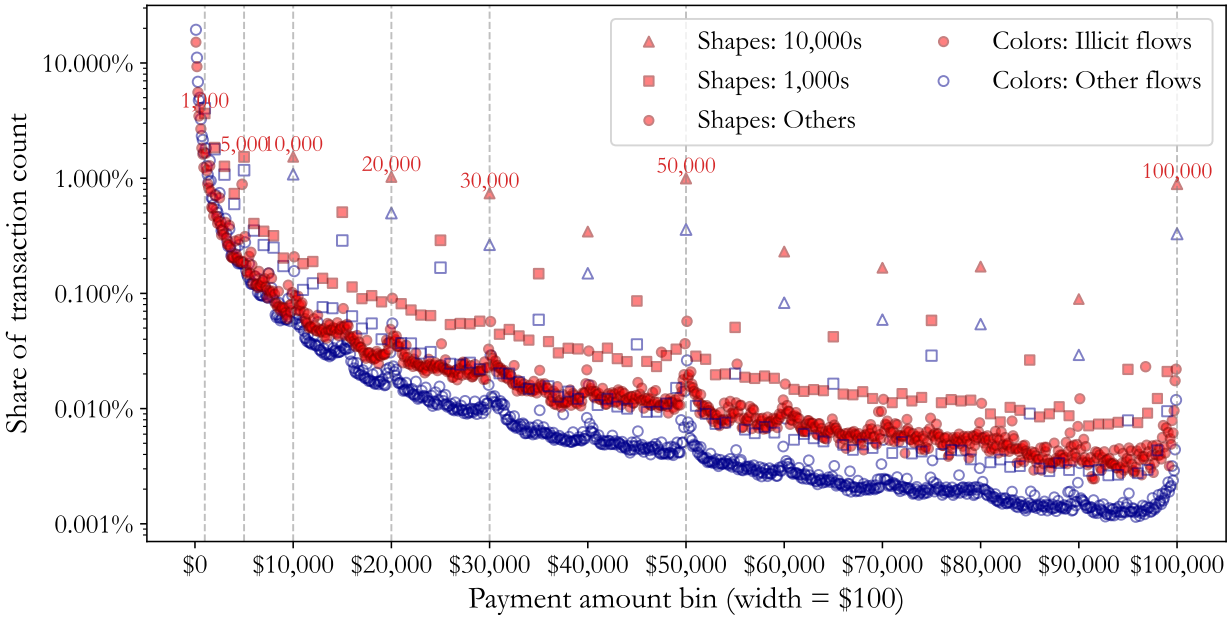


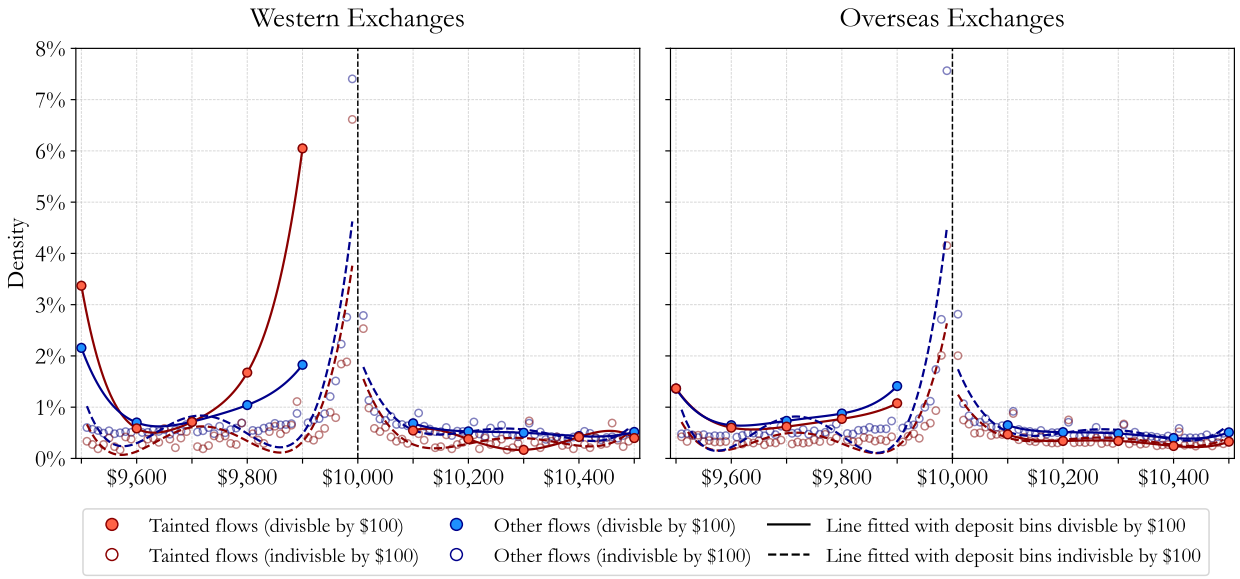
Figure 12. Deposit Bunching in Western Exchanges

This figure investigates deposit bunching around the $10,000 threshold. Panel A plots the density of deposit transactions within bins ranging from $9,500 to $10,500, with the y-axis representing the percentage of total transactions in this range. The $10,000 bin precisely captures the round number; bins to its left are left-inclusive (e.g., $9,990-$9,999.99), while bins to its right are right-inclusive (e.g., $10,000.01-$10,010). The left subpanel displays data for Western exchanges, and the right subpanel for Overseas exchanges. Solid red (blue) circles represent tainted flows (other flows) divisible by $100, with hollow red (blue) circles denoting tainted flows (other flows) indivisible by $100. Panel B presents the estimated coefficient β^k from the regression

$$\mathbb{1}(d \in k)_{d,k,i,e,t} = \alpha + \beta^k \times Tainted_i + \gamma_e + \eta_t + \varepsilon_{d,k,i,e,t},$$

run for each deposit bin k. Here, $\mathbb{1}(d \in k)$ is an indicator for a deposit d falling into bin k, and $Tainted_i$ is an indicator for whether deposit address i is tainted. β^k thus captures the differential probability of a tainted deposit occurring in bin k relative to a non-tainted deposit, after controlling for exchange fixed effects and year-month fixed effects. The regressions are run separately for Western (green) and Overseas (purple) exchanges, with vertical bars indicating 95% confidence intervals. Standard errors are clustered by exchange-time.

Panel A: Deposit Frequency around $10,000 Threshold



Panel B: Deposit Bunching Regressions

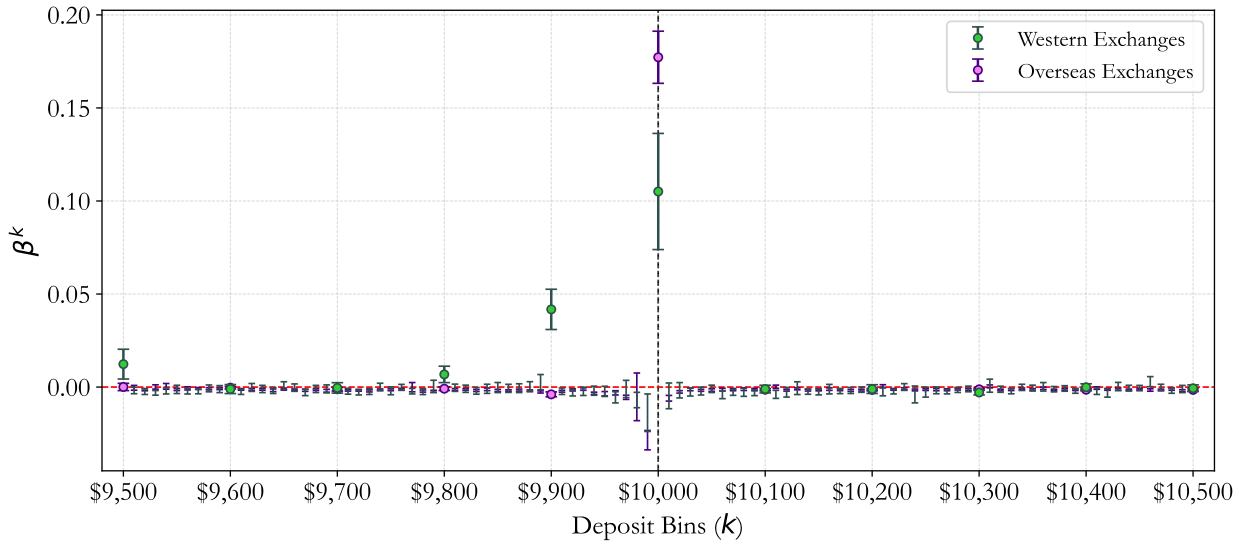


Figure 13. Effects of Tornado Cash Ban on Hacker Flows Destinations

This figure examines the change in hacker flows around the Tornado Cash ban. It displays flows of reported hackers to various destinations for hackers who started moving criminal funds before (left) and after (right) the ban. It highlights sizable shifts in blue and entirely new top destinations in red.

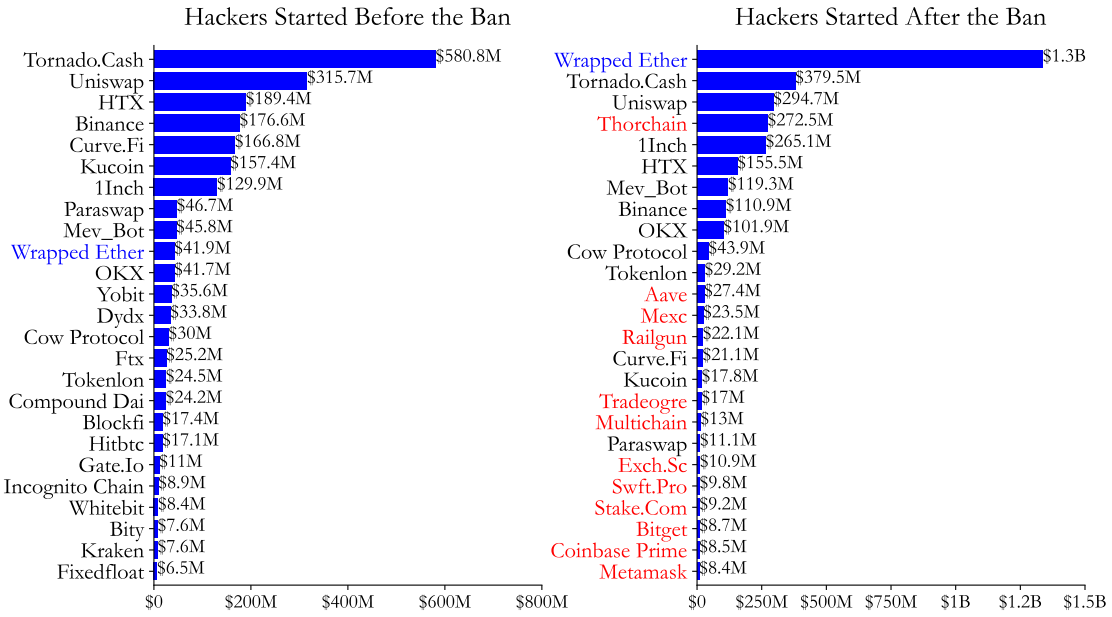


Figure 14. Bybit Hack and Flows to Bridge

This figure shows the flows of proceeds of the $1.4 billion theft from Bybit in February 2025. The left-hand side shows funds exiting Bybit and being forwarded through Ethereum by the hackers to the different services represented in the center. On the right-hand side of Thorchain are Bitcoin addresses, representing addresses downstream of bridge transactions. Concave down edges represent flows from a node on the left to another node on the right, and vice versa for concave up edges. Edges are colored by the total $-amount, and nodes are colored by the corresponding type: service, reported hacker, ETH wallet, BTC wallet, and BTC transaction. On Ethereum, we find about $1B is bridged through Thorchain, and traced over $42.8M to the OKX Web3 service, $7.1M to Mayachain, $4.6M Lifi, $4.5M to 1inch, and $4.5 to other destinations. On the Bitcoin blockchain, we traced $98.7M of the bridged funds to Freebitco.in, and $1.9M to other exchanges. Last updated in August 2025.

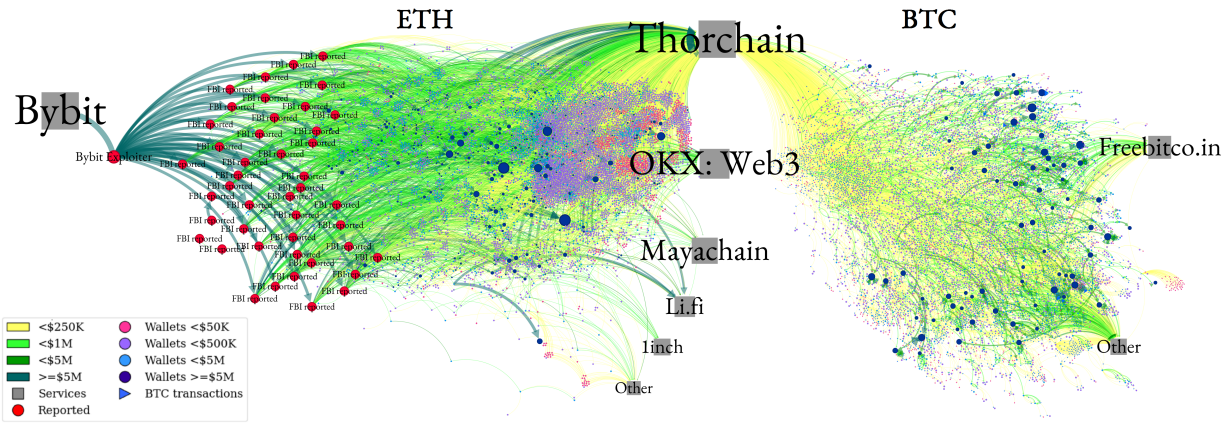


Table 1. Effects of the Tornado Cash Ban: Western versus Overseas Exchanges

This table presents the results of difference-in-differences regressions examining the effects of the Tornado Cash ban on criminal behaviors and transaction costs. It compares Tornado Cash outflows to Western (treatment group) with those to overseas exchanges (control group). The outcome variables are the number of intermediate hops (columns 1–2), the number of days to exit to an exchange (columns 3–4), and transaction costs, measured in decimals (columns 5–6). Regressions are estimated at the path-exit level, where each "path" corresponds to transfers originating from a single withdrawal of funds that pass through one or more intermediate hops before exiting to an exchange. Each path may include multiple exits, with each exit representing a cash-out event to an exchange and counted separately. The number of days is measured from when the funds initially leave Tornado Cash until they ultimately reach the exchange at each path exit. Transaction cost is expressed in decimal form (0.05 denotes 5%) by summing transaction cost fees paid at each hop and the spread lost from swaps, then dividing by the funds ultimately deposited into exchanges. Tornado Cash was sanctioned on August 8, 2022, and a path exit is assigned a post variable of one if the funds reached an exchange after this date. Western exchanges are Coinbase, Crypto.com, Gemini, and Kraken, and all other exchanges are included as overseas exchanges. All regressions are dollar-weighted by the amount of funds entering exchanges. Exchange fixed effects and year-month fixed effects are included as indicated. Standard errors, clustered by path, are reported in parentheses. The sample period covers March 1, 2022, to December 31, 2023.

Dep. Variable:	Number of Hops		Number of Days		Transaction Cost	
	(1)	(2)	(3)	(4)	(5)	(6)
Treat × Post	0.285***	0.285***	117.8***	121.7***	0.00875***	0.00770***
	(0.0992)	(0.108)	(22.27)	(22.14)	(0.00260)	(0.00265)
Treat	-0.157***		32.06***		0.00108	
	(0.0452)		(7.006)		(0.000681)	
Exchange FE		✓		✓		✓
Year-Month FE	✓	✓	✓	✓	✓	✓
Observations	132,050	132,040	132,050	132,040	132,050	132,040
Adjusted R^2	0.0868	0.195	0.179	0.276	0.0318	0.0578
Dep. Var. Mean	1.741	1.741	86.93	86.91	0.00545	0.00545
Dep. Var. Std	1.111	1.111	172.7	172.7	0.0262	0.0262

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2. Effects of the Tornado Cash Ban: Tornado Cash Outflows vs. Criminal-Address Outflows

This table presents the results of difference-in-differences regressions examining the effects of the Tornado Cash ban on its outflows versus criminal flows to exchanges. It compares Tornado Cash outflows to exchanges (treatment group) with flows originating from reported criminal addresses to exchanges (control group). The outcome variables are the number of intermediate hops (columns 1–2), the number of days to exit to an exchange (columns 3–4), and transaction costs, measured in decimals (columns 5–6). Regressions are estimated at the path-exit level, where each "path" corresponds to transfers originating from a single withdrawal of funds that pass through one or more intermediate hops before exiting to an exchange. Each path may include multiple exits, with each exit representing a distinct cash-out event to an exchange and counted separately. The number of days is measured from when funds initially leave the source (Tornado Cash or a criminal address) until they ultimately reach the exchange at that path exit. Transaction cost is expressed in decimal form (0.05 denotes 5%) by summing transaction cost fees paid at each hop and the spread lost from swaps, then dividing by the funds ultimately deposited into exchanges. Tornado Cash was sanctioned on August 8, 2022, and a path exit is assigned a post variable of one if the funds reached an exchange after the ban. All regressions are dollar-weighted by the amount of funds entering exchanges. Exchange fixed effects and year-month fixed effects are included as indicated. Standard errors, clustered by path, are reported in parentheses. The sample period covers March 1, 2022, to December 31, 2023.

Dep. Variable:	Number of Hops		Number of Days		Transaction Cost	
	(1)	(2)	(3)	(4)	(5)	(6)
Treat × Post	0.169***	0.122**	131.3***	133.2***	0.00326***	0.00332***
	(0.0464)	(0.0475)	(6.270)	(6.255)	(0.000638)	(0.000639)
Treat	0.168***	0.192***	23.85***	20.95***	0.00384***	0.00349***
	(0.0299)	(0.0300)	(1.942)	(2.044)	(0.000400)	(0.000420)
Exchange FE		✓		✓		✓
Year-Month FE	✓	✓	✓	✓	✓	✓
Observations	608,713	608,713	608,713	608,713	608,713	608,713
Adjusted R^2	0.0427	0.0549	0.118	0.136	0.00565	0.00712
Dep. Var. Mean	1.583	1.583	17.68	17.68	0.00114	0.00114
Dep. Var. Std	1.527	1.527	69.28	69.28	0.0189	0.0189

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3. Share of Value to DeFi Services after Asset Seizure
This table examines whether blacklisted addresses and their related addresses increase their use of DeFi services following an asset freeze. It presents the results from a difference-in-differences regression of the DeFi share of outflows, measured as the ratio of funds sent through DeFi services relative to total outflows. Specifically, the following regression is estimated.

$$\textit{DeFi Share}_{g,c,t} = \sum_{t \neq t_{freeze}} \beta_t \times \mathbb{1}(\textit{Month} = t) \times \textit{Treat}_g + \mu_c + \gamma_t + \varepsilon_{g,c,t}$$

where $\textit{DeFi Share}_{g,c,t} = \frac{\sum_{i \in g} \textit{DeFi flows}_{i,g,c,t}}{\sum_{i \in g} \textit{All flows}_{i,g,c,t}}$ and it denotes the share of flows sent to DeFi services for the treatment or control group g in cohort c at month t. Each cohort represents a freeze date. The treated group consists of the frozen addresses and their related counterparts. For every treated address, the control group is a random sample of 20 addresses that received inflows of at least $100 within the seven days prior to the freeze. The first regression includes the cohort fixed effects, and the second adds event time fixed effects, and both are weighted by total transaction value. The sample period is 12 months before and after the freeze date of each cohort. Standard errors are clustered by asset seizure cohort and month.

Dep. Variable:	DeFi Share	
	(1)	(2)
Treat × Post	0.266***	0.244***
	(0.0737)	(0.0773)
Treat	-0.169**	-0.164*
	(0.0797)	(0.0873)
Post	-0.0365	
	(0.0333)	
Cohort FE	✓	✓
Event Time FE		✓
Observations	10,187	10,187
Adjusted R^2	0.561	0.572
Dep. Var. Mean	0.337	0.337
Dep. Var. Std	0.334	0.334

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4. Use of Round Number Deposits by Tainted Deposit Addresses

This table presents regression results examining the relationship between tainted deposits and the likelihood of transactions being exact multiples of 500 or 1000. Specifically, the following regression is estimated.

$$\mathbb{1}(\text{Divisible by 500})_{i,e,t} = \alpha + \beta_0 \times \textit{Tainted}_i + \beta_1 \times \textit{Tainted}_i \times \textit{Western}_{i,e} + \gamma_e + \eta_t + \varepsilon_{i,e,t}$$

where d represents the deposit transaction value; $\mathbb{1}(\text{Divisible by 500})$ is a binary indicator that takes a value of 1 if the transaction value is divisible by 500; $\textit{Tainted}_i$ is a binary indicator equal to one if deposit address i is identified as tainted; and $\textit{Western}_{i,e}$ is a binary indicator equal to one if deposit address i is on an exchange e that is classified as a Western exchange. All regressions control for exchange fixed effects (γ_e) and year-month fixed effects (η_t). Standard errors are clustered by exchange.

Dep. Variable:	$\mathbb{1}$(Divisible by 500)		$\mathbb{1}$(Divisible by 1000)	
	(1)	(2)	(3)	(4)
Tainted	0.129***	0.111***	0.121***	0.104***
	(0.008)	(0.015)	(0.007)	(0.015)
Tainted × Western		0.020		0.019
		(0.017)		(0.016)
Exchange FE	✓	✓	✓	✓
Year-Month FE	✓	✓	✓	✓
Observations	88,580,957	88,580,957	88,580,957	88,580,957
Adjusted R^2	0.040	0.040	0.028	0.028

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

For Online Publication

Internet Appendix for "Are Crypto Anti-Money Laundering Policies Effective?"

A. Ethereum Tracing

We trace funds to their end destinations. A trace path is terminated if it triggers any of the following criteria: (i) the flows enter an identified service, such as an exchange; (ii) the flows enter an unidentified but large address with more than 2,000 transactions; (iii) the path reaches five hops; or, (iv) traced amounts diminish to be less than 0.00001 ETH or token quantities, which are known as *dusting* transactions.[44] The most commonly triggered criteria are (i) and (ii). In the case of (i), we present results on the most common end destinations. By halting at exchanges, services, or unidentified large addresses, we avoid incorporating flows from other unrelated entities that these large addresses may have received. The tracing algorithm also handles cases where tainted flows re-enter another reported address without double-counting the ultimate destinations. The tracing procedure is more fully described along with considerable robustness tests on parameters in Griffin and Mei (2025).

B. Relationship between Mixer Effectiveness and Volume

We are interested in considering how a mixer's effectiveness may vary as a function of each pool's volume. Specifically, consider the exercise of following a very large sum of illicit flows to a mixer such that it is the largest inflow of that day. A researcher would be interested in watching the mixer's outflows and asking what the probability is that any outflow the next day is linked to the prior large inflow. We argue that mixers are less effective when they have low volume and that effectiveness can be measured based on the following observations, starting from basic observations to more complex considerations.

Observation 1. *Suppose there is a pool of funds that has received inflows from N senders and has zero outflows. Sort the inflow deposits from largest to smallest, where the largest is first, into a set $\{x_1, x_2, ..., x_N\}$. For any given outflow, then the probability that this outflow belongs to the largest depositor is $x_1 / \sum_n x_n$.*

We interpret this basic fraction as the unconditional probability that a given outflow is linked to a given inflow over the lifetime of the pool. It is clear that a large volume, $\sum_n x_n$, is linked with a lower probability of successfully guessing a correct relationship.

We next consider the impact of outflows over time. Béres et al. (2021) and our own empirical results suggest that most users withdraw funds within a week. Thus, we consider a corresponding outflow of user n at time $t = 1$, $y_{n,t+1}$ to be a function of time since the previous inflow.

Observation 2. *Expected outflows are a function of amount and time of inflows, $y_{n,t+1} = f(x_{n,t})$.*

Next, we consider strategic behavior from the perspective of a mixer user seeking to conceal their transactions. Between the trade-off of removing funds quickly or slowly, a user would rather remove funds quickly so that they can offload funds to their final location. Storing funds on-chain for longer may generally expose a user to greater seizure risk, especially because researchers need time to disentangle the preceding web of transactions. Most importantly, a strategic user should take the behavior of all other users as given. Withdrawing funds too quickly would create an anomaly if it does not match other user behaviors.

[44] Dusting transactions may obfuscate tracing by creating many more paths for a researcher to follow.

Observation 3. *A strategic user concealing their funds and seeking to minimize anomalies would mimic the withdrawal rate of all other users.*

We model individual withdrawal in two steps. First, we fit a distribution on future daily outflows over the next 30 days based on each day's total inflows. We minimize the mean squared error between predicted aggregate outflows and actual outflows and find that a Pareto distribution with $\alpha = 0.3534$ best fits the aggregate data. Next, we predict the outflow of each user over the next 30 days and find the user with the largest fraction of expected outflows, or $\theta_{1,t} = y_{1,t} / \sum_n y_{n,t}$

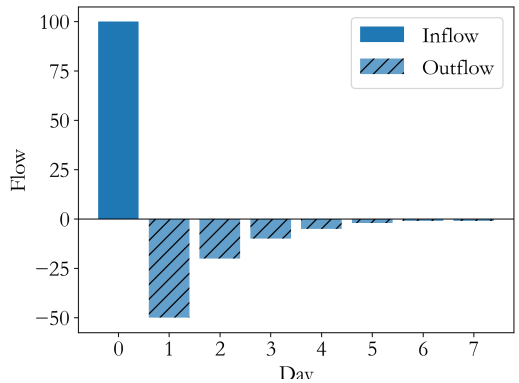
In this exercise, we model the predicted outflows based on the inflows of each user and find the user that has the highest predicted outflow. The share of expected outflows $\theta_{n,t}$ is the probability that any given dollar of outflow is related to user n, assuming all outflows follow the same distribution. If a user withdraws money faster, then it would increase their actual $y_{n,t}$ and raise the probability that a random dollar is related to that user. Thus, our measure is a lower-bound estimate of probability for the sub-sample that withdraws more quickly. As inflow declines, then a given user with a large amount of funds to launder would have a larger $\theta_{n,t}$, such that investigating a random withdrawal is more likely to be associated with the large user.

We summarize this approach with the following diagram. In the first panel, we plot an example of the modeled outflow for a single user in blue. Denote this as $\hat{y}_{1,t}$. The second panel adds the inflows and predicted outflows of two more users in green and orange, or $\hat{y}_{2,t}$ and $\hat{y}_{3,t}$. We proxy probability of detection at time t as:

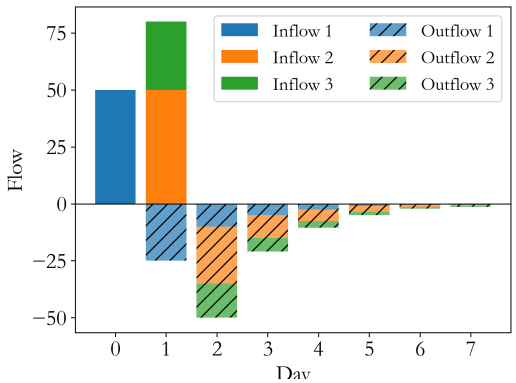
$$\text{Prob(detection)}_t = \frac{\max_i \hat{y}_{i,t}}{\sum_i \hat{y}_{i,t}}$$

In this highly stylized exhibit in Panel (b), at time $t = 2$, that would be the dollar value of hashed orange divided by the sum of hashed blue, hashed orange, and hashed green.

(a) Modeled flow for a single user



(b) Modeled flow for three users



C. Additional Figures and Tables

Figure IA.1. Top Tornado Cash Related Scams
This figure shows the total amounts deposited by the top 50 reported addresses into Tornado Cash. Each horizontal bar represents an individual reported Ethereum address and is colored according to its scam category. Hatches indicate in which hop of the backward trace the reported addresses forwarded the funds for depositing to Tornado Cash.

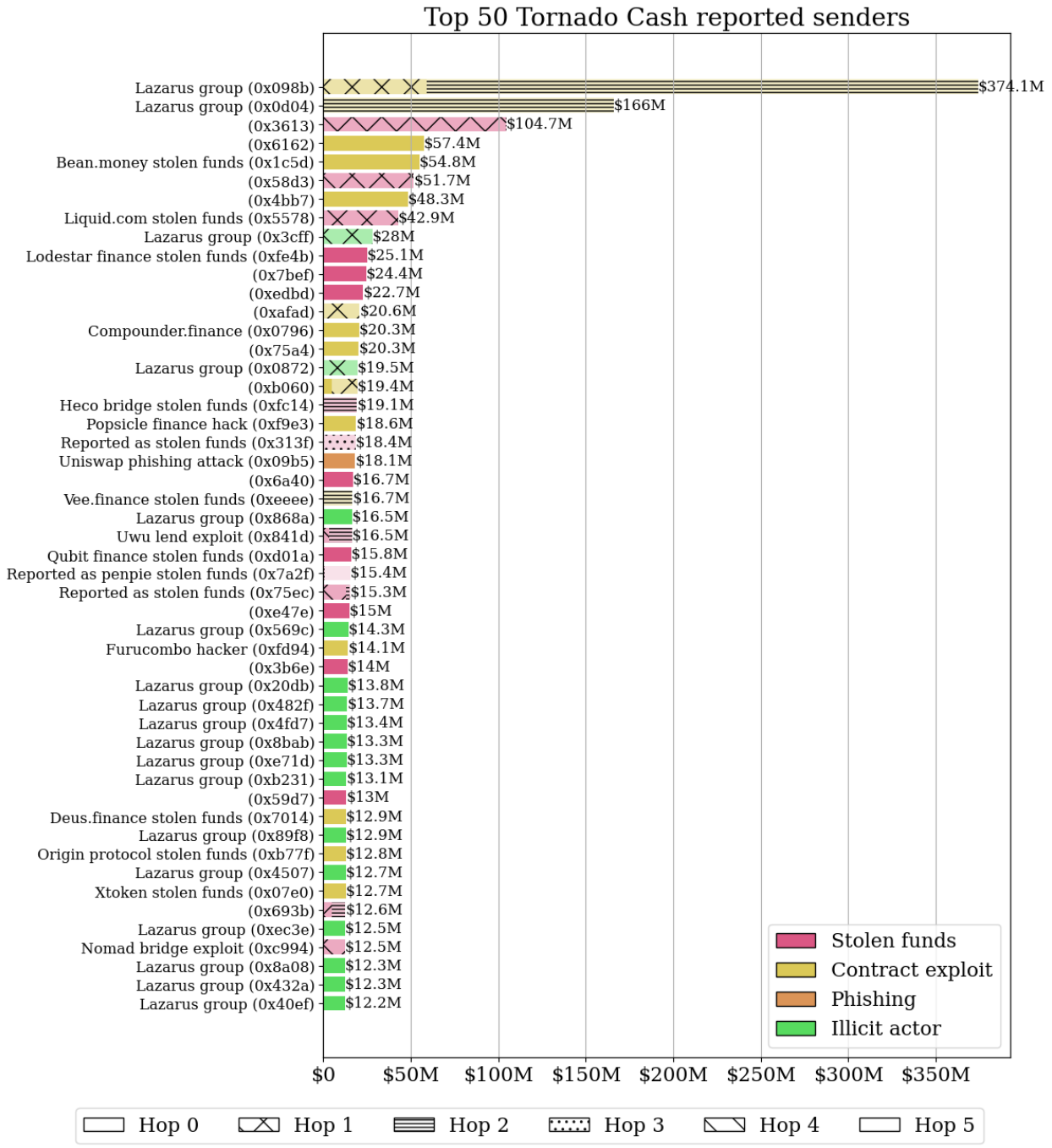
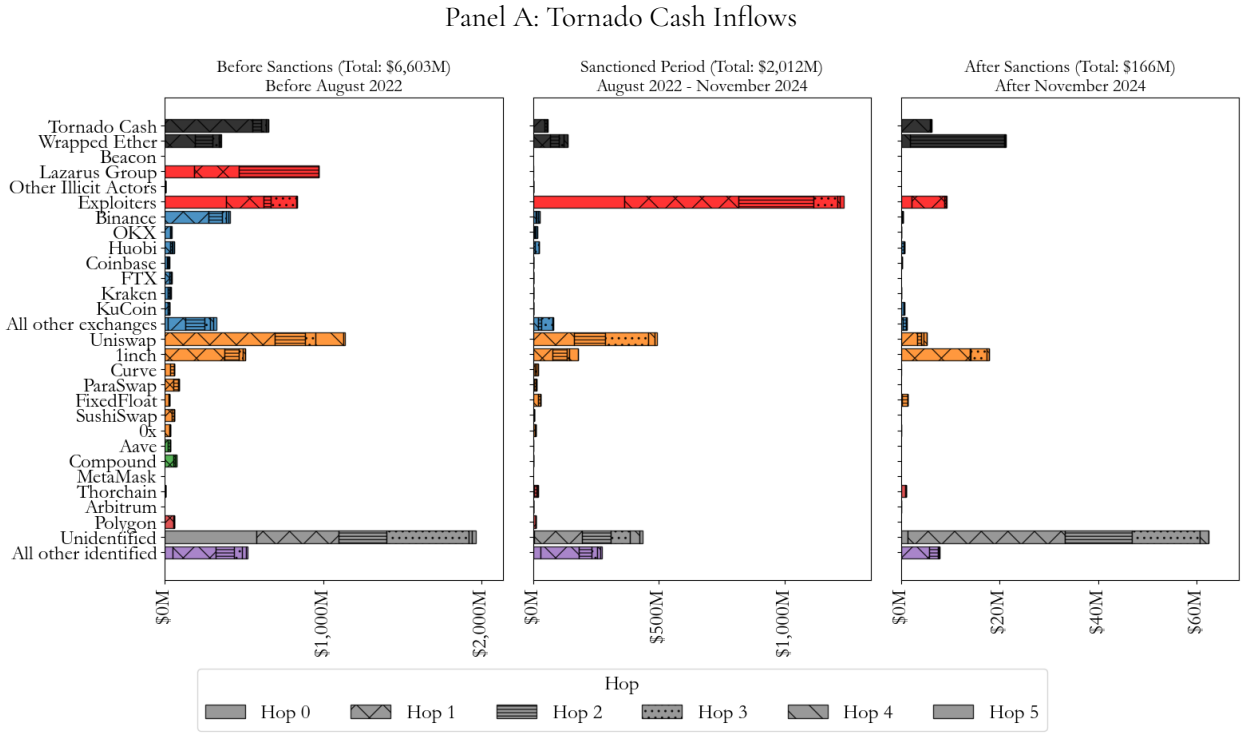


Figure IA.2. Destinations of Tornado Cash Outflows

This figure shows Tornado Cash inflows (Panel A) and outflows (Panel B) by hop. The y-axis lists the various entities found in each corresponding trace, and the hatches stand for the hops in each trace. The left panels are before the ban, the center panels are during the ban, and the right panels are after the ban was lifted. Hatches indicate hop distance from Tornado Cash.



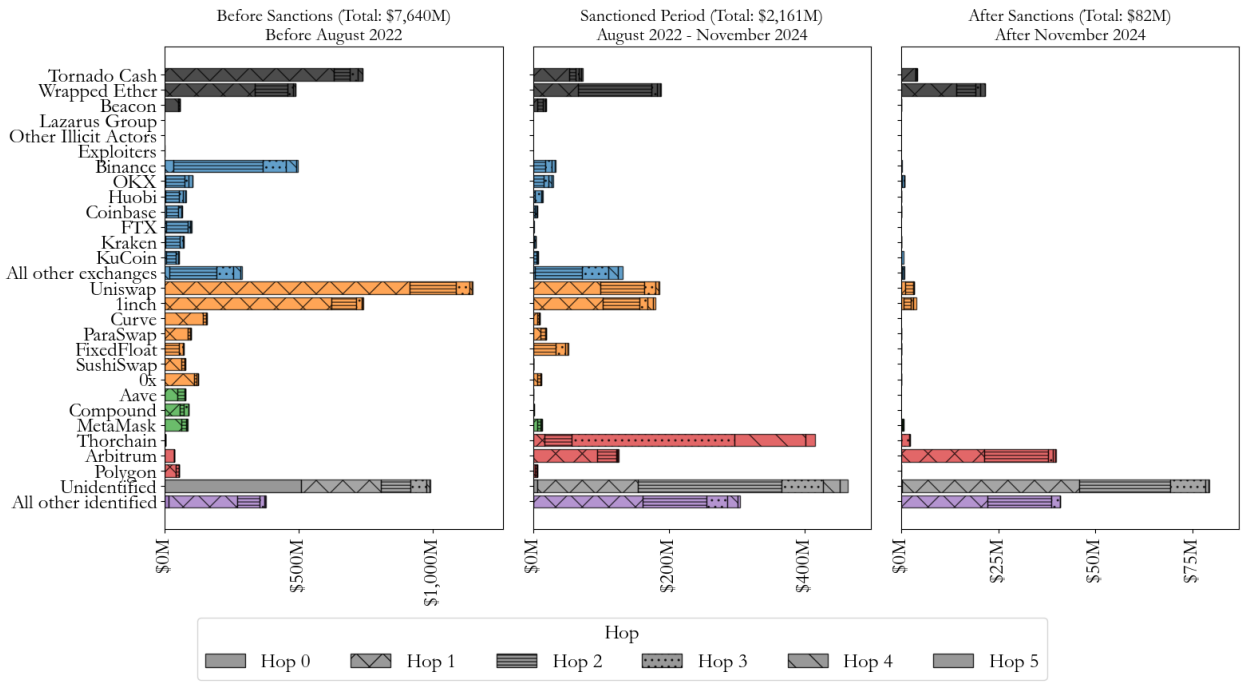


Figure IA.3. Transaction Costs of Moving Funds from Tornado Cash to Exchanges
This figure compares the transaction costs of moving funds from Tornado Cash to domestic and overseas centralized exchanges (CEXs) before and after the Tornado Cash ban, which was imposed on August 8, 2022. Transaction costs are first calculated for each individual path from Tornado Cash to the destination, and then aggregated by weighting each path's cost by the amount of funds moved into the respective exchanges. The classification of a path as pre-ban or post-ban is based on the end date of the path. Blue bars represent domestic exchanges and orange bars represent overseas exchanges. The 95% confidence intervals are shown.

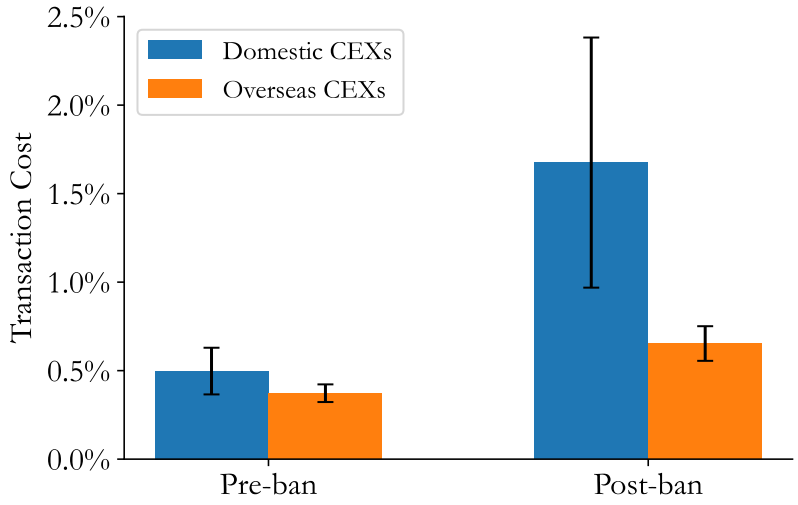
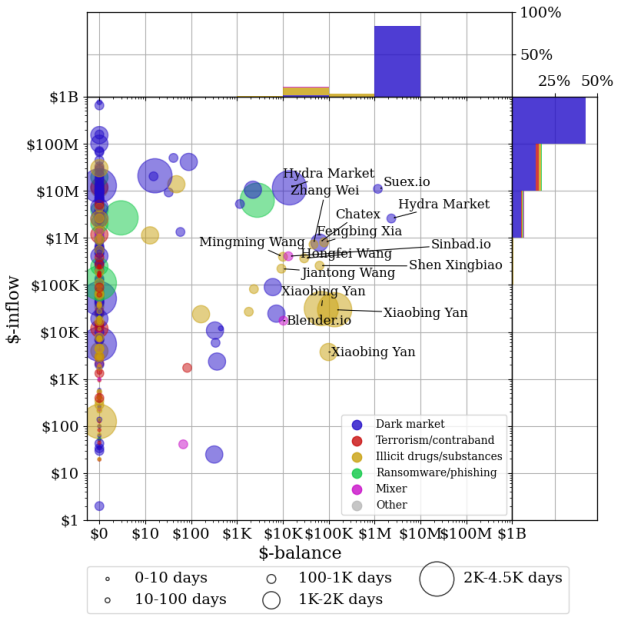


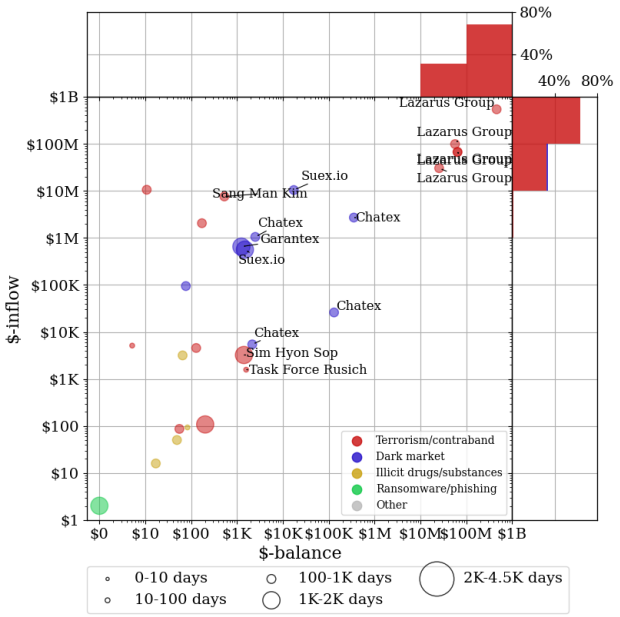
Figure IA.4. Balance of OFAC-Sanctioned Addresses

This figure shows two scatter plots for the BTC (Panel A) and ETH (Panel B) sanctioned addresses and the corresponding illicit activity represented by each unique color. The x-axis represents the remaining balance in each address during the sanction day, and the y-axis represents the lifetime inflow to each address. Size is proportional to the number of days each address is active. Panel C plots the cumulative number of sanctioned addresses on the left y-axis and the cumulative number of sanction orders on the right y-axis. Significant sanction orders are indicated accordingly.

Panel A: BTC



Panel B: ETH



Panel C: OFAC-Sanctioned Addresses

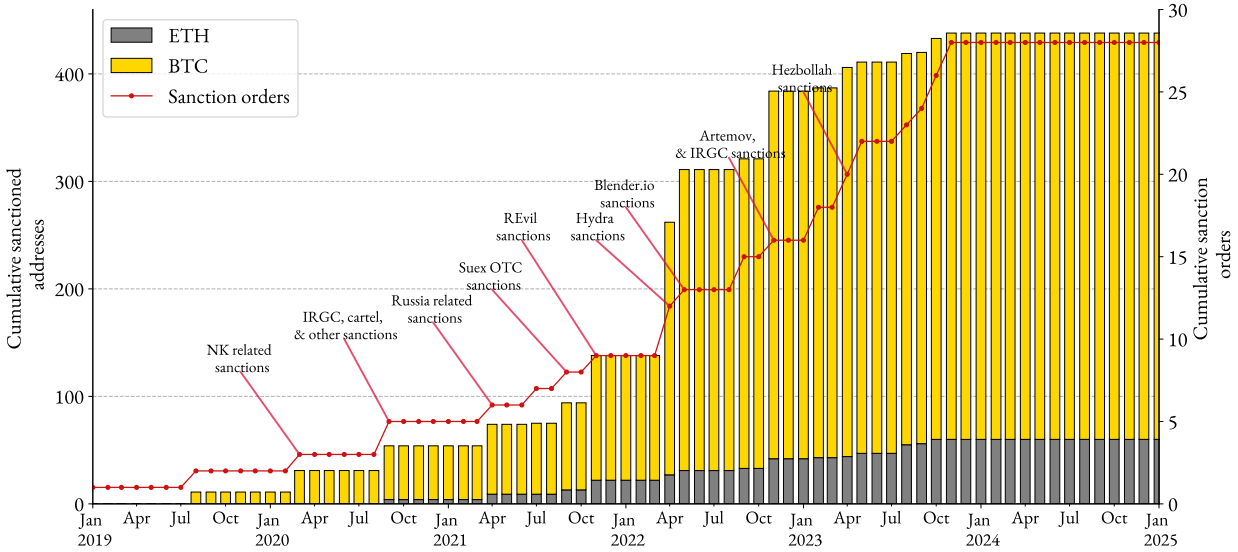
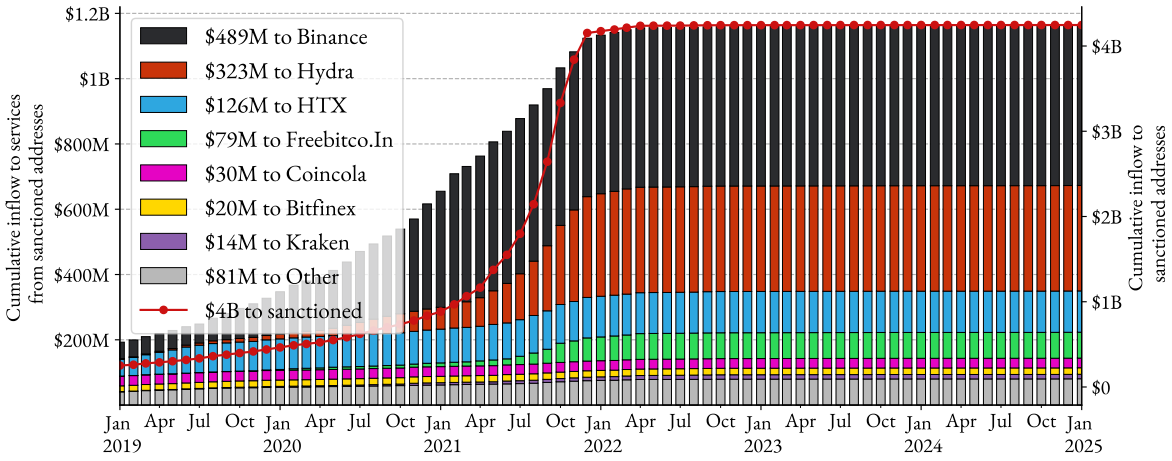


Figure IA.5. OFAC BTC Addresses Sanctioned Totals

This figure plots the dollar amounts Bitcoin sanctioned addresses forward to services and other addresses on-chain. Panel A plots the cumulative total dollar amount off ramped to each individual service, reflected in the left-hand y-axis. The right-hand y-axis corresponds to the cumulative inflow to the actual sanctioned addresses. Panel B plots the same inflows to services plus the remaining amount on-chain, with the x-axis in event time. Dollarization in Panel B is calculated using the monthly average price of Bitcoin for each individual address. Fluctuations on the on-chain balance are therefore due to price fluctuations.

Panel A: Trace Destinations



Panel B: Dollarized Balance

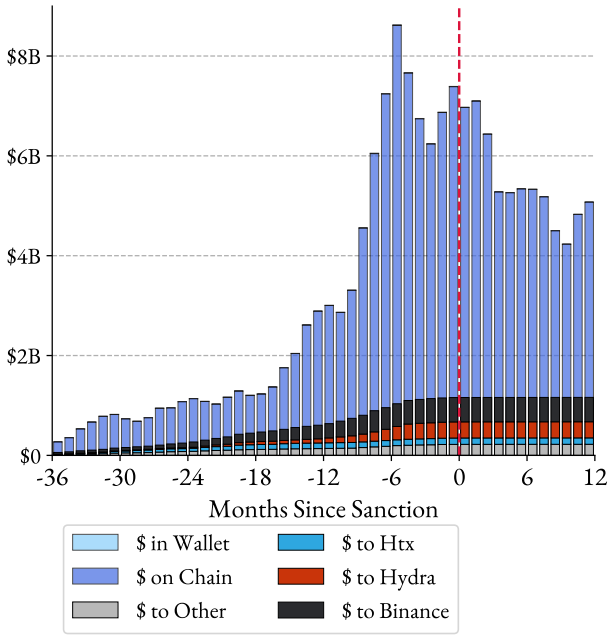
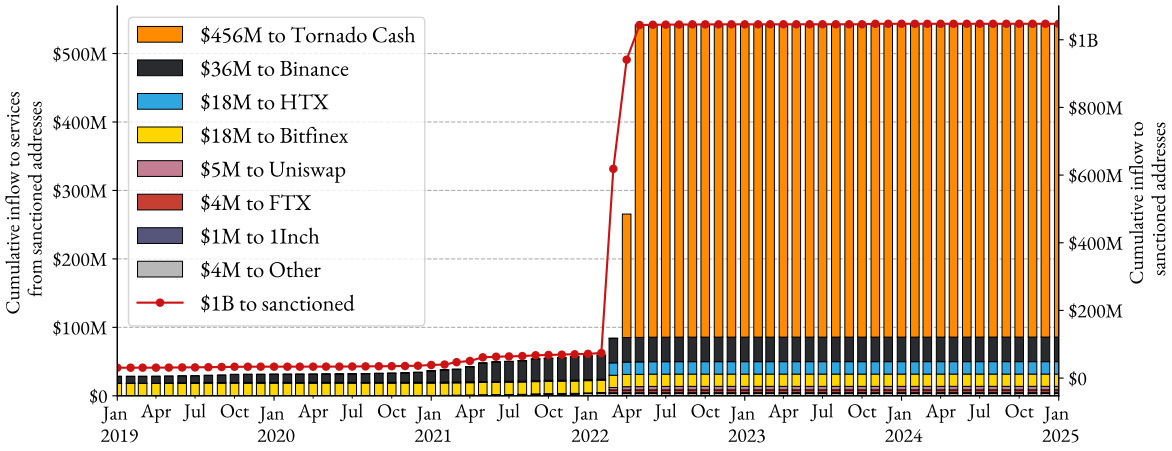


Figure IA.6. OFAC ETH Addresses Sanctioned Totals

This figure plots the dollar amounts Ethereum sanctioned addresses forward to services and other addresses on-chain. Panel A plots the cumulative total dollar amount off ramped to each individual service, reflected in the left-hand y-axis. The right-hand y-axis corresponds to the cumulative inflow to the actual sanctioned addresses. Panel B plots the same inflows to services plus the remaining amount on-chain, with the x-axis in event time. Dollarization in Panel B is calculated using the monthly average price of Ethereum for each individual address. Fluctuations in the on-chain balance are therefore due to price fluctuations.

Panel A: Trace Destinations



Panel B: Dollarized Balance

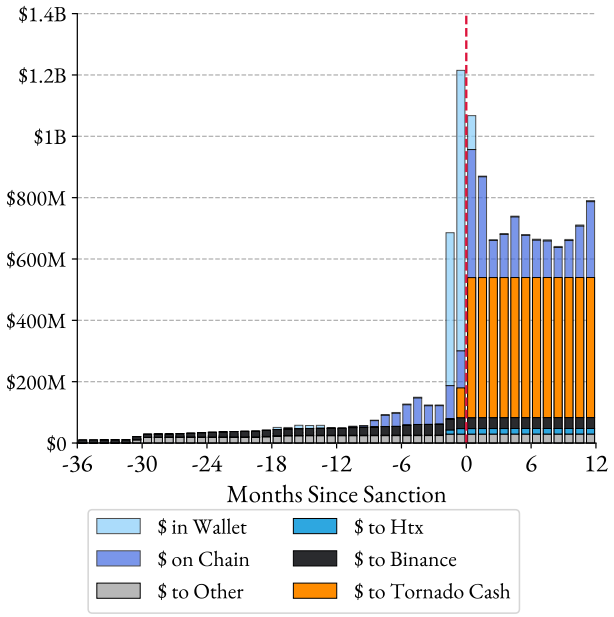
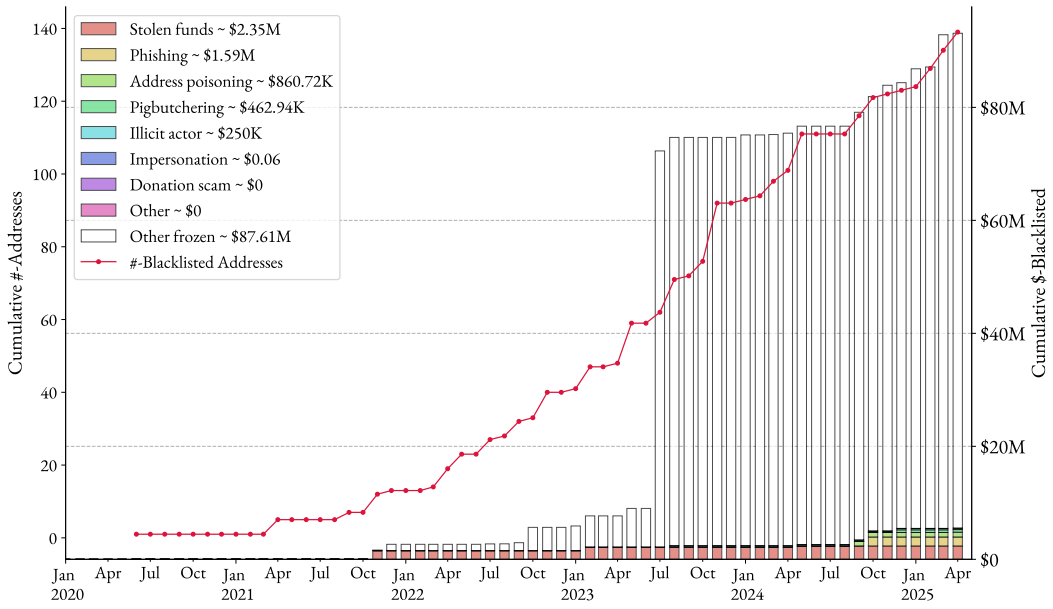


Figure IA.7. USDC Freezes

This figure presents the scope of USDC freezes and the pre-seizure activity of frozen addresses. Panel A summarizes enforcement scale over time: the red line (left axis) plots the cumulative number of blacklisted addresses, while the stacked bar (right axis) shows the cumulative dollar value of USDC frozen. Colored segments of each bar indicate frozen addresses appearing in the traced network of reported criminal flows and show the corresponding scam type, while white segments indicate addresses outside that network. Panel B illustrates inflow trajectories for frozen addresses prior to seizure. This panel plots a select sample of frozen addresses that have received more than $10K in total inflows. The horizontal axis reports the number of days each address was active prior to being frozen, and the vertical axis (log scale) shows the total dollar inflow to that address. Each dot represents a transfer event, with dot size reflecting the cumulative inflow received by the address at that point in time. Multiple dots forming a line represent inflow trajectories for a single address. Red crosses mark the date each address was frozen.

Panel A: Cumulative Freezes Over Time



Panel B: Activity of Frozen Addresses Prior to Seizure

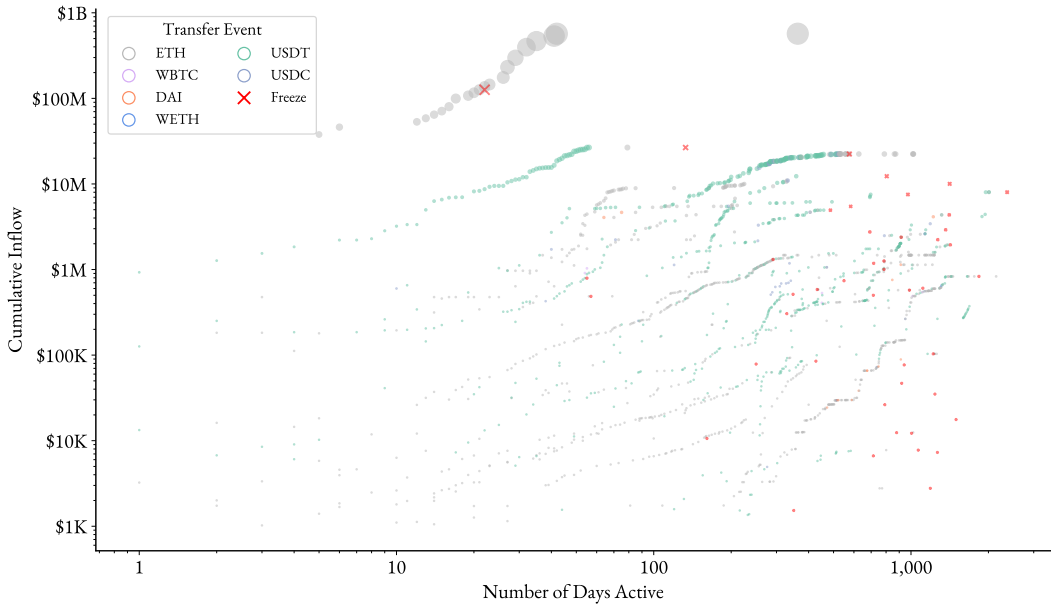


Figure IA.8. Effects of Tether Seizure on Transaction Volume by Hours
This figure presents results from a dynamic difference-in-differences regression that tests whether frozen addresses and their related addresses increase transaction volume after the account has been frozen by Tether. Related addresses to the frozen ones are found through gas clustering. The treated group consists of the frozen addresses and their related counterparts, while for every treated address, the control group is a random sample of 20 addresses that also received Tether in the preceding three days. Specifically, the following regression is estimated:

$$y_{i,t} = \sum_{t \in [-24,24]} \beta_t \times \mathbf{1}(Hour = t) \times Treat_i + \mu_i + \gamma_t + \varepsilon_{i,t}$$

where $y_{i,t}$ denotes the transaction volume or transaction count of address i in hour t, $Post_t$ is a binary variable that equals one for hours after the freeze, μ_i are address fixed effects, and γ_t are event time fixed effects. Standard errors are clustered by cohort, address, and event time. The top panel plots the regression coefficients when transaction dollar volume is the dependent variable, and the bottom panel presents the number of transactions.

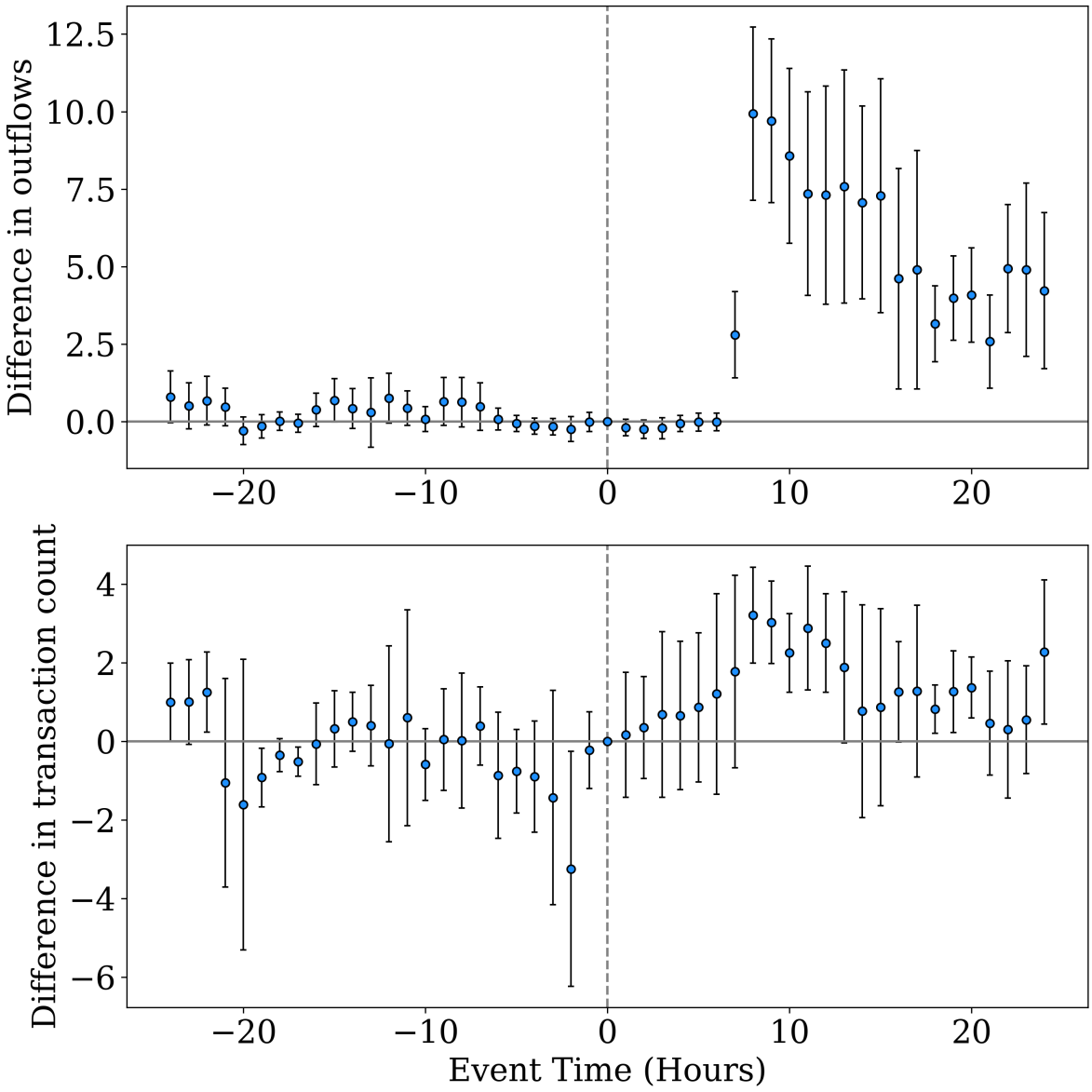


Figure IA.9. Risk of Seizure versus Transaction Cost and Speed

This figure examines how transaction costs and exit speed correlate with the risk of account freezing for funds originating from reported criminal addresses. The sample includes all identified transfer paths from reported criminal addresses to exchanges. Each path is categorized along two dimensions: quintiles of transaction costs (x-axis) and quintiles of the number of days required to exit to an exchange (y-axis). For each cell, the height of the bar indicates the probability that at least one address along the path was subsequently frozen by Tether (z-axis). The probabilities are calculated as weighted averages across paths belonging to the category, weighted by the dollar amount of funds entering exchanges. Transaction cost is expressed as a percentage by summing transaction cost fees paid at each hop and the spread lost from swaps, then dividing by the funds ultimately deposited into exchanges.

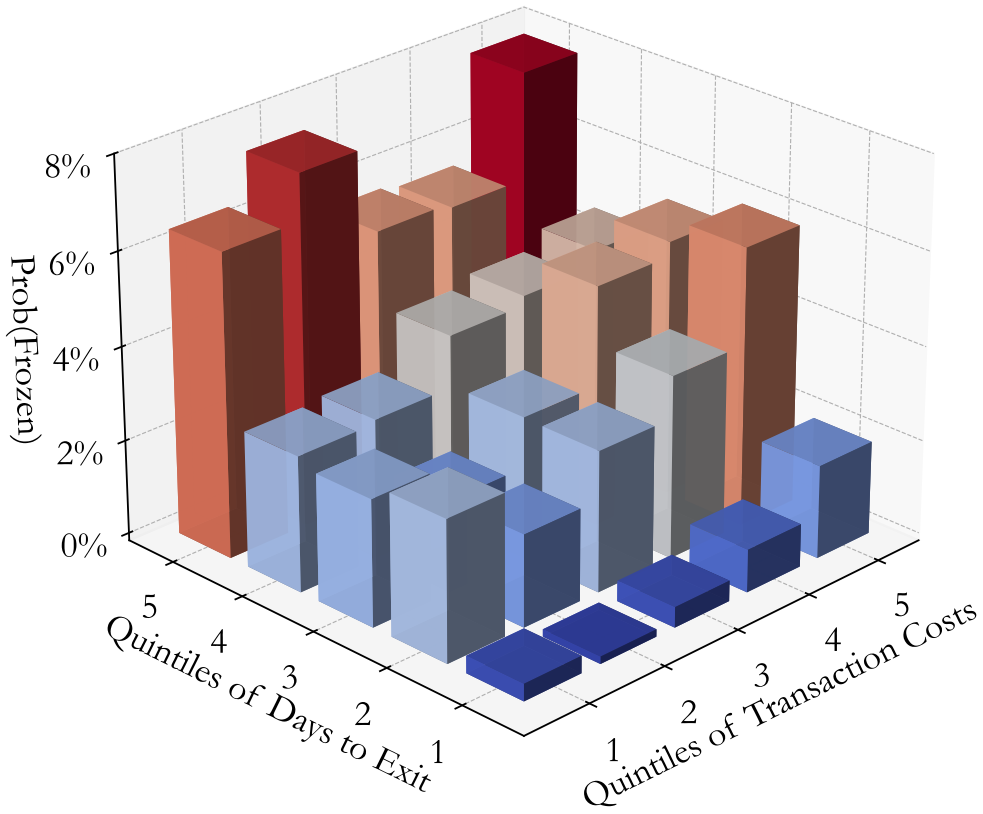


Figure IA.10. Tornado Cash Outflows to OKX around OKX Settlement

This figure examines the effects of the OKX DOJ settlement on its acceptance of Tornado Cash flows. It presents Tornado Cash outflows to OKX (left subpanel) and to other overseas exchanges (right subpanel). In each subpanel, bars represent the percent of monthly outflows to the destination category: blue bars represent flows that moved from Tornado Cash to the destination without passing through any decentralized exchanges (DEXs), while yellow bars represent flows that were first sent from Tornado Cash to DEXs, and then arrived at exchanges after being traced through DEXs. The red line shows the average number of hops before reaching the destination. Western exchanges are Coinbase, Crypto.com, Gemini, and Kraken, and all other exchanges are included as overseas exchanges. Binance is excluded from the overseas exchanges because it also had a settlement with the DOJ during the test window. The red vertical dashed line marks February 24, 2025 when OKX settled with the U.S. DOJ. Two black vertical dashed lines mark the Tornado Cash sanction on August 8, 2022, and the lifting of the sanction on November 26, 2024.

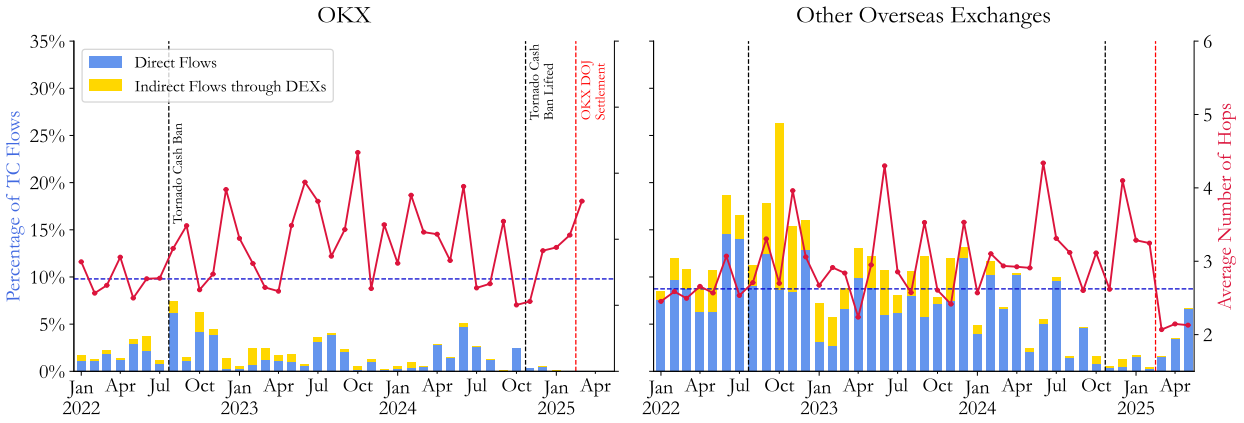
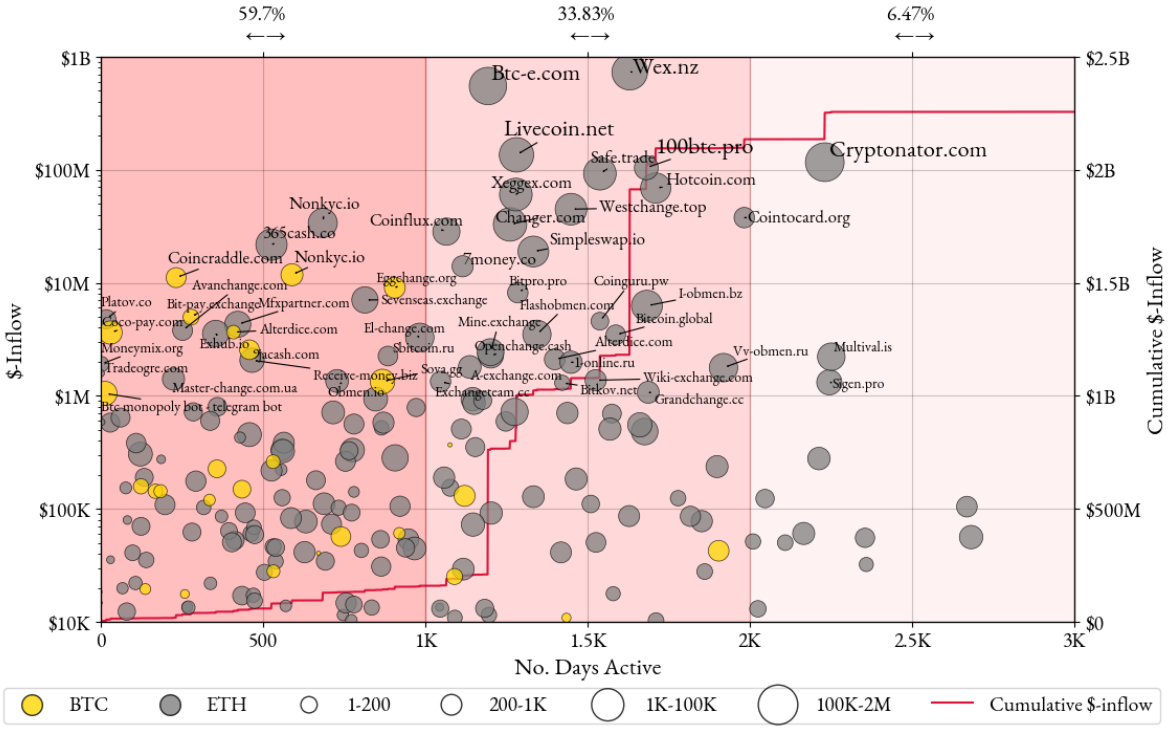


Figure IA.11. Non-KYC Exchanges

This figure displays the activity of identified Non-KYC exchanges. Panel A plots the total $-inflow in the left y-axis, and days active for each individual exchange in the x-axis. Each exchange is colored according to its corresponding blockchain, and the size corresponds to the total number of transactions. The cumulative $-inflow is reflected in the right y-axis. The background shaded area corresponds to the percentage of exchanges in that area. Panel B plots the time series for the same exchanges, with the left y-axis plotting the monthly $-inflow, and the right y-axis plotting the cumulative $-inflow. Top Non-KYC exchanges are colored accordingly.

Panel A: Non-KYC Exchange Inflow and Days Active



Panel B: Non-KYC Exchange Inflow Timeseries

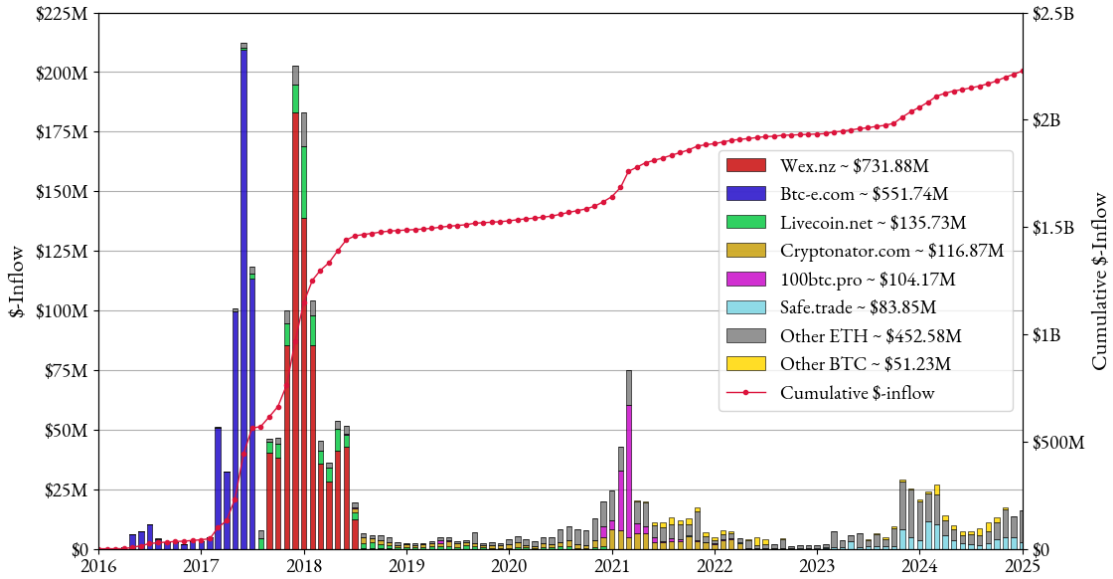


Figure IA.12. Tainted Freebitco.in Deposits

This figure presents the tainted BTC of the Bybit hack and the related traced deposits into Freebitco.in. The tainted BTC corresponds to the total amount laundered through Thorchain, while the tainted BTC associated to Freebitco.in corresponds to that same amount which is also connected to some deposit to said exchange. We also plot both the full amount of these deposits and the conservative amount we traced. The cumulative amounts are represented as a stacked plot reflected in the left y-axis. The right y-axis plots the scattered tainted deposits to Freebitco.in.

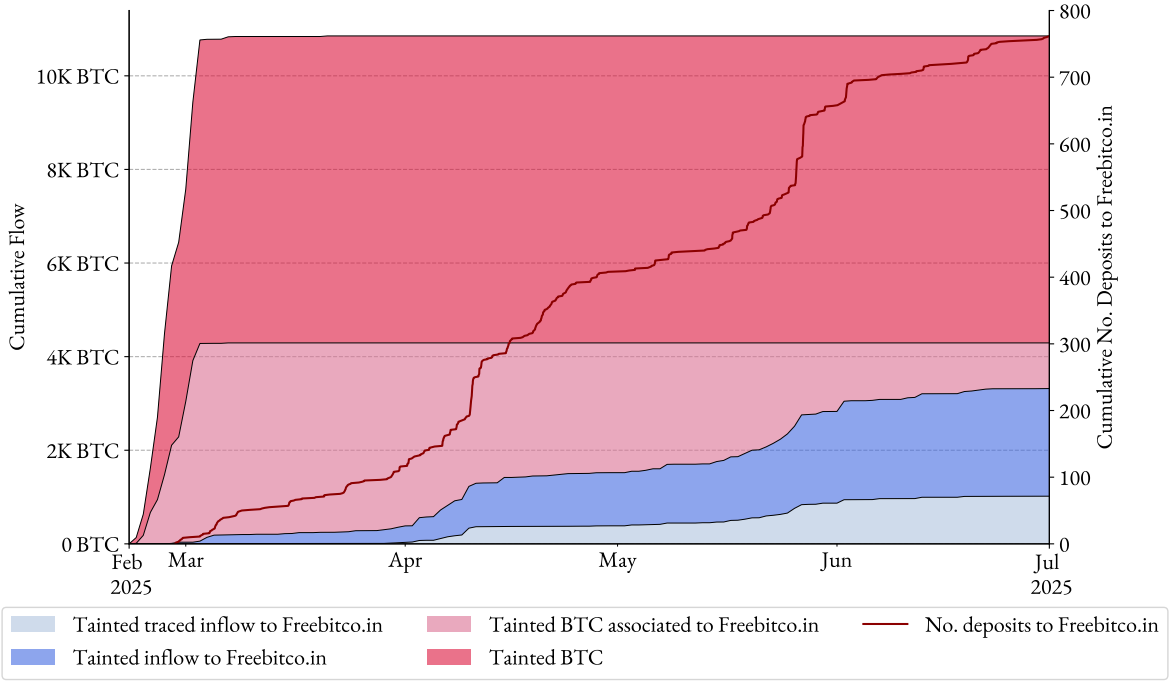


Table IA.1. USDT Freezes Summary Statistics

This table summarizes USDT freezing statistics for blacklisted addresses overlapping with the traced criminal network. The leftmost column lists each scam category. Column (1) reports the number of origin addresses in that category where the downstream path reaches at least one blacklisted address. Column (2) shows the number of blacklisted addresses downstream of those origins. Column (3) reports the total dollar outflow from the origin addresses. Column (4) reports the dollar amount traced to these blacklisted addresses from origin addresses; this value may exceed the origin outflow in column (3) because a blacklisted address may aggregate flows from multiple origin categories. Column (5) shows the total dollar value frozen in these blacklisted addresses. Column (6) reports the dollar value of stablecoins destroyed by issuers after freezing. The last row presents the aggregate overlap; the columns do not sum because one blacklisted address may appear in multiple paths downstream of reported addresses.

	(1)	(2)	(3)	(4)	(5)	(6)
Category	# associated origins	# blacklisted addresses	$ origin outflow	$ traced to blacklist	$ total blacklisted	$ total destroyed
Impersonation	1,589	63	1.52M	2.60M	228.54M	8.44M
Pigbutchering	853	182	4.13B	344.50M	401.57M	52.59M
Address poisoning	331	112	18.71K	11.88K	132.87M	10.34M
Scam	281	134	515.35M	104.57M	301.84M	24.30M
Phishing	58	150	21.04M	3.12M	230.46M	28.91M
Stolen funds	35	37	161.98M	86.03M	95.10M	13.57M
Illicit actor	14	17	52.26M	3.88M	26.40M	3.30M
Fake returns	8	11	26.15M	1.98M	56.01M	0.51M
Fake project	6	11	78.09M	4.88M	59.60M	0
Contract exploit	2	2	180.90K	3.79M	0	0
Donation scam	1	1	9.35K	99.99	0	0
Sim swap	1	1	50.04K	8.20K	25.91K	0
Total	3,179	396	4.99B	555.38M	603.14M	109.06M

Table IA.2. USDC Freezes Summary Statistics

This table summarizes USDC freezing statistics for blacklisted addresses overlapping with the traced criminal network. The leftmost column lists each scam category. Column (1) reports the number of origin addresses in that category where the downstream path reaches at least one blacklisted address. Column (2) shows the number of blacklisted addresses downstream of those origins. Column (3) reports the total dollar outflow from the origin addresses. Column (4) reports the dollar amount traced to these blacklisted addresses from origin addresses; this value may exceed the origin outflow in column (3) because a blacklisted address may aggregate flows from multiple origin categories. Column (5) shows the total dollar value frozen in these blacklisted addresses. The last row presents the aggregate overlap; the columns do not sum because one blacklisted address may appear in multiple paths downstream of reported addresses.

	(1)	(2)	(3)	(4)	(5)
Category	# associated origins	# blacklisted addresses	$ origin outflow	$ traced to blacklist	$ total blacklisted
Pigbutchering	56	8	$13.51M	$8.97M	$462.94K
Scam	20	7	$682.36K	$1.38M	$2.63K
Phishing	17	8	$31.04K	$34.99K	$2.05M
Address poisoning	8	3	$0.80	$7.31	$860.72K
Impersonation	7	7	$0.98	$1.46	$596.01K
Illicit actor	6	6	$2.99M	$1.49M	$250.00K
Stolen funds	3	6	$1.13M	$4.02M	$2.35M
Fake project	3	3	$450.84K	$1.65M	$0
Donation scam	1	1	$0	$99.99	$0
Total	121	30	$18.8M	$17.54M	$5.51M

Table IA.3. Effects of Tether Seizure on Transaction Volume

This table presents results from a difference-in-differences regression that tests whether frozen addresses and their related addresses increase transaction volume after the account has been frozen by Tether. Related addresses to the frozen ones are found through gas clustering. The treated group consists of the frozen addresses and their related counterparts, while for every treated address, the control group is a random sample of 20 addresses that also received Tether in the preceding three days. Specifically, the following regression is estimated:

$$y_{i,t} = \sum_{t \in [-24,24]} \beta_t \times Treat_i \times Post_t + \mu_i + \gamma_t + \varepsilon_{i,t}$$

where $y_{i,t}$ denotes the transaction volume or transaction count of address i in hour t, $Post_t$ is a binary variable that equals to one for hours after the freeze, μ_i are address fixed effects, and γ_t are event time fixed effects. Standard errors are clustered by cohort, address, and event time. This table correspond to results in Figure IA.8.

Dep. Variable:	log(Transaction Volume)	Transaction Count
	(1)	(2)
Treat × Post	4.666***	1.360***
	(0.474)	(0.252)
Address FE	✓	✓
Event Time FE	✓	✓
Observations	9161730	9161730
R^2	0.699	0.501
Number of Clusters	49	49

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table IA.4. Use of Round Number Deposits by Tainted Deposit Addresses (Sub-sample)
This table presents regression results examining the relationship between tainted deposits and the likelihood of transactions being exact multiples of 500 or 1000. Specifically, the following regression is estimated.

$$\mathbb{1}(\text{Divisible by 500})_{i,e,t} = \alpha + \beta_0 \times Tainted_i + \beta_1 \times Tainted_i \times Western_{i,e} + \gamma_e + \eta_t + \varepsilon_{i,e,t}$$

where d represents the deposit transaction value; $\mathbb{1}(\text{Divisible by 500})$ is a binary indicator that takes a value of 1 if the transaction value is divisible by 500; $Tainted_i$ is a binary indicator equal to one if deposit address i is identified as tainted; and $Western_{i,e}$ is a binary indicator equal to one if deposit address i is on an exchange e that is classified as a Western exchange. All regressions control for exchange fixed effects (γ_e) and year-month fixed effects (η_t). Standard errors are clustered by exchange. This sample only includes deposits greater than $100.

Dep. Variable:	$\mathbb{1}$(Divisible by 500)		$\mathbb{1}$(Divisible by 1000)	
	(1)	(2)	(3)	(4)
Tainted	0.132***	0.112***	0.127***	0.107***
	(0.009)	(0.016)	(0.008)	(0.014)
Tainted × Western		0.022		0.021
		(0.018)		(0.017)
Exchange FE	✓	✓	✓	✓
Year-Month FE	✓	✓	✓	✓
Observations	70,302,800	70,302,800	70,302,800	70,302,800
Adjusted R^2	0.041	0.041	0.028	0.028

Standard errors clustered by exchange in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table IA.5. Use of Non-Round Number Deposits by Tainted Deposit Addresses

This table presents regression results examining the relationship between tainted deposits and the likelihood of transactions having a remainder of 1, 499, or 999 when divided by round numbers. Specifically, the following regression is estimated.

$$\mathbb{1}(d \bmod C = R)_{d,i,e,t} = \alpha + \beta_0 \times Tainted_i + \beta_1 \times Tainted_i \times Western_{i,e} + \gamma_e + \eta_t + \varepsilon_{d,i,e,t}$$

where d represents the deposit transaction value; $\mathbb{1}(d \bmod C = R)$ is a binary indicator that takes a value of 1 if the transaction value d leaves a remainder R when divided by C (where C is either 500 or 1000, and R is either 1, 499, or 999); $Tainted_i$ is a binary indicator equal to one if deposit address i is identified as tainted; and $Western_{i,e}$ is a binary indicator equal to one if deposit address i is on an exchange e that is classified as a Western exchange. All regressions control for exchange fixed effects (γ_e) and year-month fixed effects (η_t). Standard errors are clustered by exchange. This sample only includes deposits greater than $100.

Dep. Variable:	$\mathbb{1}(d \bmod 500 = 1)$	$\mathbb{1}(d \bmod 500 = 499)$	$\mathbb{1}(d \bmod 1000 = 1)$	$\mathbb{1}(d \bmod 1000 = 999)$
	(1)	(2)	(3)	(4)
Tainted	0.0016	0.0008*	0.0016	0.0007*
	(0.0017)	(0.0004)	(0.0018)	(0.0003)
Tainted × Western	-0.0007	-0.0001	-0.0008	-0.0000
	(0.0018)	(0.0005)	(0.0018)	(0.0004)
Exchange FE	✓	✓	✓	✓
Year-Month FE	✓	✓	✓	✓
Observations	88,580,957	88,580,957	88,580,957	88,580,957
Adjusted R^2	0.0031	0.0277	0.0008	0.0188

Standard errors clustered by exchange in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$