Crypto Capture of Foreign Aid[*]

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Abstract

We investigate whether cryptocurrencies have become a conduit for laundering diverted foreign aid. Using World Bank disbursement data (2018–2024) linked to on-chain Bitcoin forensics, off-chain exchange records, and web traffic, we combine network analysis with a stacked difference-in-differences design to trace illicit flows of funds form the staggered disaster-related aid disbursements. Web traffic provides a geographic measure of crypto transaction activity. We document a sharp post-disbursement reorientation of crypto flows consistent with the classic placement-layering-integration capital flow sequence in money laundering. Activity shifts from regulated exchanges toward tax-haven platforms and anonymous channels. In the disbursement month, anonymous transaction volume on tax-haven exchanges increases by approximately 169%, and the creation of new anonymous wallets (harder to trace) rises by approximately 660%, whereas there is no significant response in identified wallets (easy to trace). The effects are concentrated in the immediate aftermath of disbursement, persisting for one to two months before dissipating. Off-chain data corroborate the on-chain evidence, showing short-lived increases in trading activity concentrated in lightly regulated jurisdictions. Our estimates imply an average leakage of at least 5 cents per dollar of foreign aid. Overall, our findings suggest that cryptocurrencies have emerged as an increasingly important alternative to offshore banking for concealing the diversion of foreign aid. Our results also highlight the advantages of blockchain forensics for tracing, quantifying, and potentially recovering diverted public funds.

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1 Introduction

Foreign aid is intended to support development and welfare, yet substantial amounts are often siphoned off by elites for private gain (e.g., Reinikka and Svensson (2004)). Recent evidence shows large sums of aid ultimately end up in secret offshore accounts controlled by recipient-country elites (Andersen, Johannesen and Rijkers (2022)). The Panama Papers leak of 2016 exposed the vast hidden wealth that leaders have stashed in shell companies and tax havens (International Consortium of Investigative Journalists (2016)). In response, international scrutiny of traditional tax havens has intensified in recent years, raising the risks and barriers for corrupt actors trying to hide stolen funds (e.g., stricter compliance enforcement and information-sharing agreements). This prompts a relevant question: as conventional offshore avenues face greater oversight, are corrupt elites turning to cryptocurrencies as a new conduit for laundering diverted aid?

Cryptocurrencies enable fast, decentralized, and pseudonymous transfers that are difficult to trace (Amiram, Jørgensen and Rabetti (2022)). Funds can be split across thousands of new anonymous wallets and easily "off-ramped" through a growing network of cryptocurrency exchanges, many of which are based in jurisdictions with lax regulation. These jurisdictions often host exchanges with weaker Know-Your-Customer (KYC) enforcement ((2021)Financial Action Task Force (FATF) (FATF)). Such features have attracted illicit actors: for instance, an estimated 46% of Bitcoin transactions (valued at around $76 billion annually) involve illegal trade, and about one-quarter of users participate in illicit activity (Foley, Karlsen and Putnins (2019)). However, whether foreign aid funds are being diverted and laundered through cryptocurrency remains an open and under-researched question. We posit that the rise of crypto may enable a form of "crypto capture" of aid, analogous to classic elite capture, but through digital offshore channels.

In this paper, we provide what we believe is the first systematic evidence that cryptocurrencies are being used to launder proceeds from the diversion of foreign aid. First, we introduce the concept of "crypto capture" of foreign aid and provide systematic evidence that cryptocurrencies are being used to launder diverted aid, extending prior work on elite capture and illicit offshore finance. We construct a novel dataset combining World Bank project-level aid disbursements with forensic on-chain Bitcoin data, where wallet addresses are clustered and tagged to known entities such as exchanges (platforms for trading crypto and fiat), mixers[1] (services that obfuscate transaction origins), and payment processors (intermediaries for crypto payments). This enables real-time tracking of aid-related flows through the crypto ecosystem. Focusing on large, plausibly exogenous disbursements to developing countries, we exploit the timestamped, transparent nature of blockchain data to examine high-frequency changes in crypto flows and structures around these events, providing a quasi-natural experiment on aid and laundering.

Additionally, we develop a novel, multi-method empirical strategy that combines blockchain network analysis, panel regressions, and jurisdictional profiling to uncover laundering behavior. Conceptually, we interpret the evidence through the classical laundering framework of placement, layering, and integration, while emphasizing the distinct informational roles of on-chain and off-chain activity. On-chain data capture the movement and routing of assets across wallets and exchanges, whereas off-chain data identify where economically meaningful trading or internal reallocation occurs within exchange platforms. This distinction allows us to separate transient passage through the network from points of settlement or redistribution.

We first use high-resolution network analysis to map the flow of diverted aid through cryptocurrency channels. We provide visual characterizations of network changes around the five largest aid disbursements in our sample, directed to countries such as Indonesia, Pakistan, and Nigeria. Directed graphs reveal a sharp post-aid reorientation: flows shift from regulated exchanges to tax-haven platforms following disbursements. By clustering nodes by business type, we document that crypto flows not only to tax havens but also to mixers and other intermediaries. This pattern gradually reverses over the following months. The global distribution shows that the obfuscation occurs immediately after disbursement and is consistent with a layered laundering pattern operating through crypto markets.

Moreover, our analysis demonstrates how blockchain forensics can complement traditional approaches to tracing illicit finance, contributing to a growing literature that exploits on-chain transparency to study financial misconduct [2]. A key challenge is that blockchain data are pseudonymous and do not reveal users' geographic locations. To assign country-level variation to inherently borderless on-chain activity,

[1]Cryptocurrency mixers (also referred to as tumblers) are services that deliberately obfuscate the transaction history of digital assets by pooling funds from multiple users and redistributing them in a manner that breaks the on-chain link between sending and receiving addresses. While mixers can, in principle, be used for benign privacy-preserving purposes, they are widely documented as mechanisms for laundering illicit proceeds and evading monitoring, and they feature prominently in enforcement actions and regulatory guidance related to cryptocurrency-based money laundering.

[2]See Cong, Grauer, Rabetti and Updegrave (2023); Harvey and Rabetti (2024); Griffin and Kruger (2024); Foley et al. (2019); Griffin and Shams (2020); DeSimone, Jin and Rabetti (2024); Gefen, Rabetti, Sun and Zhang (2024); Griffin and Mei (2024) for related work

we use web traffic to cryptocurrency exchange platforms as a proxy for each country's share of global crypto engagement, and interact this share with aggregate Bitcoin transaction data to construct implied country-level outcomes. We then estimate a stacked difference-in-differences design that exploits the staggered timing of large aid disbursements. We restrict traffic to a short time horizon around each disbursement event and exclude episodes with overlapping shocks to ensure clean identification. To strengthen exogeneity, we focus on disaster-related aid flows, which are more plausibly unanticipated and less susceptible to political endogeneity than development or budget-support disbursements. We find a pronounced increase in anonymous transactions following aid inflows, with no comparable response among identified users. A similar pattern emerges for new wallet creation, consistent with laundering actors using fresh addresses to fragment and cycle funds.

We further incorporate off-chain data from centralized cryptocurrency exchanges that record activity in their private ledgers, including order execution and internal balance reallocation. These data allow us to distinguish transient on-chain routing from economically meaningful exchange usage and sharpen the interpretation of the layering stage. While on-chain activity rises broadly across exchange types, off-chain activity responds selectively in lightly regulated, tax-haven exchanges. Because off-chain volume is recorded only when assets are actively used within an exchange's private ledger, this pattern indicates that such venues are not merely transit points but sites where internal reallocation or redistribution occurs. At the same time, the response is short-lived, suggesting that the reallocation associated with layering is rapid rather than persistent. Using a benchmark-adjusted log-ratio design, we isolate abnormal post-disbursement growth on opaque platforms relative to compliant ones. The concentration of these effects in countries with poorer institutional quality, together with their rapid dissipation, is consistent with brief reallocation behavior rather than persistent changes in household or firm activity. Taken together, the on-chain and off-chain evidence suggests a coherent laundering pattern in which funds enter the crypto ecosystem through regulated platforms, are subsequently routed and internally reallocated through anonymous channels in lightly regulated venues, and then exit toward potential integration endpoints.

Together, the evidence suggests a sequence consistent with the classical stages of laundering. In the placement stage, fiat-denominated aid funds appear to enter the crypto ecosystem through regulated, non-tax-haven exchanges that possess the banking access and liquidity needed for large-scale fiat-to-crypto conversion. Consistent with this mechanism, our on-chain analysis documents statistically significant increases in inflows to non-tax-haven exchanges in the disbursement month. In the subsequent layering stage, funds appear to be withdrawn, fragmented across wallets, and routed through offshore or lightly regulated platforms to reduce traceability. Here, tax-haven exchanges emerge as central nodes: we find sharp increases in transaction volume, transaction frequency, and the creation of new anonymous wallets at these exchanges immediately following aid disbursements, indicating intensive routing and address-level reshuffling. Finally, in the integration stage, we document significant outflows from exchanges of all types following disbursement, consistent with funds exiting the exchange layer and moving toward two complementary endpoints: off-ramping through tax-haven channels, as evidenced by the concentration of transaction activity in offshore jurisdictions rather than regulated ones, and long-term storage in anonymous wallets that shield holdings from disclosure requirements. Together, these patterns suggest that laundered funds neither return to nor are detectable within the formal, regulated economy.

Our findings are robust across a wide range of alternative specifications and samples. We obtain similar results when using all aid disbursements instead of disaster-related aid only, when excluding geographically proximate countries to rule out regional spillovers, and when weighting transaction volumes by web visit duration rather than visit counts. We further address endogeneity concerns by instrumenting aid with countries' historical aid shares and governance quality, obtaining IV estimates that are comparable in magnitude and statistically stronger than the baseline results. Finally, extending the analysis to geopolitical events, we find suggestive evidence that aid disbursements are associated with shifts in crypto activity around national elections, consistent with diverted funds being repurposed for political uses.

Related Literature Our study bridges several strands of literature in economics and finance. In development economics, a foundational question concerns the extent to which foreign aid benefits intended recipients. Seminal work by Reinikka and Svensson (2004) documents substantial local capture of education aid in Uganda, while Werker, Ahmed and Cohen (2009) further links aid flows to political-economy distortions, particularly in weak-institutional contexts. Andersen et al. (2022) provides evidence of elite capture via offshore banking. More recently, traffic has turned to digital channels: Cavallo, Corbacho, Fernandez-Valdovinos, Ocampo and Singh (2024) demonstrates that cryptocurrency markets can function as platforms for capital flight by matching domestic demand for foreign exchange with offshore supply, while Gomez and Zhang (2024) shows that trading volumes surge in response to geopolitical events, indicating crypto's growing role in cross-border capital exodus. We extend this literature by identifying a new, real-time digital destination for diverted aid-cryptocurrencies-thereby highlighting how capital flight has evolved in the digital era. Our methodological contribution lies in applying blockchain transaction data as a forensic tool, complementing more traditional audits or banking records in tracing diversion at high frequency.

We also contribute to the literature on cryptocurrencies and illicit finance. Gandal, Hamrick, Moore and Oberman (2018) and Foley et al. (2019) reveal the scale of criminal activity in early crypto markets, ranging from drug trades to market manipulation. Our study builds on this foundation by focusing on a specific mechanism: how diverted public funds, such as foreign aid, are laundered through crypto. We find that such laundering increasingly exploits opaque corners of the ecosystem-e.g., mixers and offshore platforms- consistent with Foley et al. (2019)'s observation that criminal actors adapt to privacy-enhancing technologies. Moreover, our network analysis offers empirical support for "layering" pathways documented in industry reports such as Chainalysis (2021), and aligns with academic tracing efforts like Ron and Shamir (2013) and Sokolov (2021) on ransomware and money laundering.

Finally, our study relates to a nascent literature that leverages blockchain transparency for economic inference. Makarov and Schoar (2020) uncover cross-border arbitrage flows among exchanges, while Amiram et al. (2022) show that suspicious on-chain activity can predict terrorist attacks. More recently, Cong et al. (2023) and Cong, Harvey, Rabetti and Wu (2025) propose frameworks for tracking cybercrime on blockchains. Our work differs from prior literature in applying forensic techniques to aid diversion and strengthening identification via event-study designs. Broadly, we contribute to the study of illicit financial flows (IFFs), tax evasion, and capital control circumvention (e.g., Zucman, 2013; Regner, 2020). These insights inform ongoing policy debates on crypto regulation: while crypto enables crime, its traceability provides regulators with a unique enforcement lever. Our findings support a regulatory model that combines oversight with technical capacity, echoing calls for smart regulation, such as those in Cumming, Johan and Pant, 2019; Budish, 2025.

The remainder of the paper is organized as follows. Section 2 provides institutional background on foreign aid disbursement and the features of cryptocurrencies that make them attractive for laundering. Section 3 describes the data sources and construction of our on-chain and off-chain samples. Section 4 presents the empirical analysis, organized in three parts: network analysis of crypto flows around major disbursements (Section 4.1), on-chain transaction analysis using a stacked difference-in-differences design (Section 4.2), and off-chain exchange-level analysis (Section **??**). Section 5 concludes with a discussion of policy implications and directions for future research.

2 Institutional Background

International aid flows are vulnerable to capture by political and economic elites in recipient countries. When large aid disbursements arrive, especially in countries with weak governance, there is an opportunity for officials or their associates to misappropriate a portion of the funds. Traditional methods for concealing diverted funds often involve routing money to offshore bank accounts in jurisdictions known for bank secrecy (e.g., Switzerland, Cayman Islands) or to shell companies in tax havens (such as Panama or the British Virgin Islands). Anderson, Fang, Moon and Shipman, 2022 provide evidence consistent with this behavior: using bank data, they find that foreign aid disbursements coincide with significant increases in deposits in offshore financial centers linked to the recipient country. Their estimates imply that a non-trivial share of each aid dollar (potentially as much as 7.5 cents, according to some estimates) may be diverted to offshore accounts rather than reaching its intended beneficiaries.

However, the risks and costs associated with such offshore laundering schemes have increased in recent years. The 2016 Panama Papers leak, released by International Consortium of Investigative Journalists, 2016, and subsequent Paradise Papers and related exposés, led to greater enforcement of anti-tax-evasion measures and international cooperation in tracking illicit flows. Banks in traditional havens came under pressure to strengthen compliance measures, and the veil of secrecy surrounding shell corporations was partially lifted. Consequently, corrupt actors began seeking alternative methods to move illicit funds with a lower risk of detection.

2.1 Cryptocurrencies as a Modern Laundering Conduit

Cryptocurrencies offer a new channel for potentially laundering money, including stolen aid. In principle, converting misappropriated funds into cryptocurrency can be achieved by routing funds through crypto exchanges or peer-to-peer markets, thereby transforming identifiable bank transfers into pseudonymous crypto holdings. If executed skillfully, this process can obfuscate the origin of the money. Several features make crypto attractive for this purpose:

Pseudonymity: Bitcoin and most cryptocurrencies do not explicitly record the real-world identity of address holders. While all transactions are public on the blockchain, users can create new addresses at will, making it challenging to trace who controls a given address (especially if one uses many addresses to fragment funds).

Ease of Cross-Border Transfer: Crypto can be sent across borders instantly without relying on the banking system. This means capital flight or fund transfers can bypass reporting by banks or wire services.

Lack of Central Intermediary: No central authority can freeze or scrutinize transactions on the blockchain, unlike bank transfers, which pass through regulated institutions. This feature of censorship resistance might appeal to those transferring illicit wealth.

Exchange Ecosystem in Lenient Jurisdictions: The proliferation of cryptocurrency exchanges worldwide provides entry and exit points for fiat currency. Notably, many exchanges are based in jurisdictions with relaxed regulatory oversight (e.g., Seychelles, Malta, offshore British territories). On such platforms, enforcement of customer identification and AML may be lax, effectively providing a pseudo-offshore bank within the crypto ecosystem.

Early evidence suggested that illicit actors quickly recognized the advantages of cryptocurrencies. Investigative reports documented surges in Bitcoin usage in countries facing capital controls or sanctions, as elites sought to move wealth discreetly. Academic work corroborates these patterns: Foley et al., 2019 shows that by the late 2010s, billions of dollars in illicit transactions flowed through Bitcoin annually, with even more opaque cryptocurrencies, such as Monero and Zcash, attracting users seeking greater anonymity. These developments highlight an ongoing cat-and-mouse dynamic between launderers and regulators.

At the same time, blockchain transactions leave immutable digital trails, and advances in blockchain forensics have increasingly pierced this veil of anonymity. Specialized analytics firms cluster addresses, tag known entities, and identify transaction patterns linked to exchanges, darknet markets, or criminal networks. Such tools have enabled both academic and law-enforcement breakthroughs, including evidence that on-chain activity predicts terrorist financing (Amiram et al., 2022) and the identification of laundering hubs such as the SUEX exchange.

In our setting, these forensic methods allow us to study otherwise hidden flows of misappropriated aid. By linking blockchain addresses to exchanges, mixers, and wallet types, we test whether aid disbursements are followed by signatures consistent with diversion—namely, spikes in anonymous activity, rapid creation of new wallets, and the movement of funds from regulated on-ramps to offshore or lightly monitored platforms.

3 Data Acquisition and Processing

Our analysis requires combining data from diverse sources: foreign aid disbursement records, on-chain crypto transaction data (with address identification), and off-chain exchange activity data. Variable descriptions are listed in Table A.1. Below, we describe each in turn, along with our data processing methods.

3.1 Foreign Aid Data

We construct a high-frequency dataset of foreign aid disbursements, with a focus on World Bank aid. We use the World Bank's Project Database (via its API) to obtain detailed information on project loans and grants provided by the International Development Association (IDA) and the International Bank for Reconstruction and Development (IBRD). For each World Bank project, we extract approval dates and commitment amounts, and, critically, we use disbursement records that indicate when funds are actually disbursed. Our main aid variable, denoted *Aid*, measures the total amount of World Bank aid disbursed to a given country in the 90-day period leading up to date t. In practice, we aggregate disbursements on a rolling quarterly basis (90 days) to align with our analysis frequency.

Focusing on World Bank aid (as opposed to all Official Development Assistance (ODA)) has a key advantage: the timing of the disbursement data.[3] Most aid datasets (e.g., OECD ODA statistics) are annual and do not reveal precisely when within the year funds were transferred. By contrast, World Bank projects provide more granular disbursement dates. This is crucial for our identification strategy, as we aim to observe crypto flows within narrow windows around aid events. We restrict our sample period to

[3]IDA alone constituted 12–14% of total gross Official Development Assistance disbursements to IDA-eligible countries between 2010 and 2019. See https://www.oecd.org/content/dam/oecd/en/publications/reports/2022/03/comparing-multilateral-and-bilateral-aid_7b441bde/81686d2f-en.pdf. IBRD operates on a similar scale to IDA, but its lending is not considered ODA because it provides non-concessional loans, primarily to middle-income countries.

April 2018 through March 2024, which reflects the period for which we have both aid data and reliable crypto transaction data.

One concern is that aid disbursements may not be exogenous – aid is typically disbursed in response to economic needs or shocks in the recipient country (e.g., disaster relief following a hurricane). If so, a surge in crypto activity after an aid disbursement might be driven by other concurrent factors. To mitigate this, we control for country-by-time fixed effects and aid lags in our regressions and perform event-study checks for pre-trends. Additionally, drawing on insights from Kraay, 2012, Kraay, 2014, and Andersen et al., 2022, we note that World Bank aid disbursements have institutional features (such as multi-year project cycles and predetermined release schedules) that impart some quasi-randomness in timing. While we are cautious in interpreting our results as establishing causality, these features support our interpretation that spikes in crypto activity closely following aid disbursements are likely effects of those disbursements rather than coincident shocks.

Table 1, Panel A reports the top 15 recipients by disbursed amount. Aid is concentrated among a small number of large recipients: India, Indonesia, and Colombia alone account for roughly 16 percent of total disbursements, and the top 15 countries together represent half of all disbursed funds. Recipients span South Asia, Sub-Saharan Africa, Latin America, and Eastern Europe, providing broad geographic variation for identification. Panel B describes the regulatory environment of countries in our sample. Approximately 45 percent of sample countries are classified as tax havens, 70 percent as crypto-friendly jurisdictions, and the others maintain stringent regulatory frameworks—a distribution that motivates our heterogeneity analysis by regulatory type.

3.2 On-Chain Data and Blockchain Forensics

The core of our analysis is based on on-chain Bitcoin transaction data. Bitcoin is the dominant cryptocurrency, and we can leverage the public availability of its full transaction ledger. We obtained Bitcoin blockchain data for the period 2018–2024, including information on every transaction and the addresses involved. On top of this raw data, we apply identification and clustering techniques to label addresses and group them into wallets (user clusters).

Our identification strategy builds on the framework of Amiram et al., 2022 and on other research in blockchain analytics. It consists of two main steps:

Address Attribution: First, we attribute addresses to known entities using public and forensic sources, including WalletExplorer and open-source blockchain investigations. These sources identify addresses associated with exchanges, mixers, gambling platforms, darknet markets, payment processors, and related services, enabling us to tag transactions involving these services.

Addresses attributed to known services are classified as non-anonymous at the service level, meaning the platform is observable on-chain. This does not identify the underlying end user. Importantly, wallets interacting with identified services remain classified as anonymous unless they themselves can be attributed to a known service, even when transacting with exchanges, including those in tax-haven jurisdictions.

Wallet Clustering: Individual blockchain addresses are highly fragmented, as users can generate many addresses. To recover user-level entities, we apply a union–find clustering algorithm to the transaction graph. Following standard practice (Ron and Shamir, 2013), addresses that appear jointly as inputs in the same transaction are clustered and treated as controlled by a single entity. Applying this and related heuristics yields wallet clusters corresponding to users or services, and prior work shows that aggregate exchange and flow patterns are robust to alternative clustering rules (Makarov and Schoar, 2025).

We then classify each wallet into one of five categories—Exchange, Mixer, Gambling, Dark Market, or Other Service—using attribution data. Wallets that cannot be matched to known services are labeled as anonymous. Throughout the analysis, anonymity is defined on-chain: anonymous wallets are those not attributable to identifiable services, rather than unidentified individuals. We compare activity involving anonymous versus identified wallets, where post-disbursement increases in anonymous activity are indicative of heightened anonymity-seeking behavior.

Identification Under Incomplete Wallet Labeling: We acknowledge that our labeling does not cover the full universe of wallets. This limitation introduces classification noise rather than systematic mislabeling: unidentified wallets remain unlabeled rather than being incorrectly assigned.

Identification relies on a stacked difference-in-differences design that exploits within-entity changes in the timing of aid disbursements. As long as labeling is unrelated to the timing of aid events, incomplete coverage does not bias the estimates; rather, it attenuates the estimated effects toward zero.

Table 2 summarizes the cryptocurrency transaction platforms in our on-chain data. Panel A reports account counts and 24-hour trading volumes across 15 platforms. The sample spans major centralized exchanges (Binance, Kraken, Huobi), privacy-enhancing services (CoinJoinMess), and smaller or specialized platforms. CoinJoinMess accounts for 77 percent of all new accounts but only 2 percent of trading volume, consistent with its role as an anonymization tool rather than a trading venue. By contrast, Binance, Kraken, and Huobi collectively represent 82 percent of total volume. Panel B reports the geographic distribution of exchange activity by domicile. Trading volume is heavily concentrated in jurisdictions with favorable regulatory environments: Malta, Singapore, and the Seychelles together account for 72 percent of total 24-hour volume, while the United States contributes only 3 percent. This pattern underscores the tendency of crypto trading infrastructure to cluster in tax-haven or crypto-friendly jurisdictions.

3.3 Off-Chain Exchange Data

While on-chain data captures the movement of Bitcoin between addresses, it does not directly reveal trades or transactions occurring within exchanges (for example, two customers trading Bitcoin on Coinbase's order book leave no trace on the public blockchain aside from their deposit/withdrawal transactions). To complement our analysis, we collect off-chain data on exchange activity from CoinMarketCap's API and other aggregate sources.

The off-chain dataset includes quarterly figures on trading volume and transaction counts for a large set of cryptocurrency exchanges worldwide. We compile statistics for exchanges that account for the majority of global trading volume and categorize them by geography and regulatory environment. Specifically, we group exchanges into the same jurisdictional categories as above: tax haven-based vs. non-haven, regulated vs. unregulated, crypto-friendly vs. not friendly. These designations draw on exchange registration information and indices of crypto regulatory openness.

Some summary statistics from our exchange classification highlight why this distinction matters: roughly 45% of active crypto exchanges in our sample are located in jurisdictions classified as tax havens, about 18% in strongly regulated countries, and about 70% in what can be termed "crypto-friendly" countries (those that actively promote crypto business or lack strict regulations). There is considerable overlap among these categories (for example, many tax haven jurisdictions are also crypto-friendly due to low regulation). The key point is that a significant portion of crypto trading infrastructure is based in places that could serve as new "offshore" havens for illicit flows.

Using CoinMarketCap data, we focus on off-chain transaction counts (trades or transfers) and exchange volumes around aid events. If, for example, a large aid disbursement to Country X is followed by a spike in trading volume on exchanges in the Cayman Islands, this would be consistent with elites in Country X converting aid money into crypto via those exchanges. We also examine the activity ratio between different groups of exchanges (e.g., tax haven vs. non-haven) around aid events to assess whether relative shifts occur.

Lastly, we incorporate a case study within off-chain data for a specific exchange of interest: Huobi. Huobi was one of the largest exchanges, and during our sample moved its headquarters from Seychelles to Singapore (May 2021). There are indications that Huobi, being large and at times loosely regulated, may have served as a platform of choice for certain money-laundering operations.[4] We therefore analyze whether results are driven by specific exchanges like Huobi or are broad-based.

4 Empirical Analysis

We begin with an illustrative network analysis (Part I), then present econometric results using on-chain data (Part II) and off-chain exchange data (Part III).

4.1 Part I: Network Dynamics and Crypto Flows

Network Graphs Around Aid Disbursements: We construct directed network graphs to visualize cryptocurrency flows before and after major aid disbursements. In these graphs, each node represents a cluster or service (e.g., a particular exchange or mixer), and directed edges represent Bitcoin flows between nodes. The size of a node reflects its centrality or total volume handled, and the thickness (weight) of an edge corresponds to the volume of transactions flowing along that link. We differentiate nodes by type using color.

Figure 1 illustrates the network of the five largest aid disbursements in our sample, with summary statistics provided in Table 3. Panel A represents the direct network, while Panel B illustrates the aggregated network by service category. We plot three snapshots in Panel A: (a) the network of Bitcoin flows

[4]See https://cointelegraph.com/news/research-binance-and-huobi-received-over-52-of-total-28b-illicit-btc-in-2019

among major services in the one month before the disbursement, (b) the network in the one month after the disbursement, and (c) the network six months after the disbursement. Figure 1 Panel A reveals a significant structural shift in the flow of funds:

Before aid disbursement, transaction networks are dominated by non-haven exchanges, with substantial inflows and outflows reflecting routine activity such as trading and remittances. Tax-haven exchanges and mixers are present but play a relatively minor role.

Immediately after disbursement, the network reconfigures sharply. Transaction flows surge toward tax-haven exchanges, which become central nodes for redistribution. New wallets become active, and mixers intensify their role as intermediaries, channeling funds from regulated exchanges into offshore platforms. This pattern is consistent with a layered laundering strategy: funds enter the crypto system through monitored exchanges, move through self-hosted wallets and mixers to obscure provenance, and are then parked or cycled through offshore exchanges.

Six months later, the network partially reverts toward its pre-disbursement structure. While tax-haven exchanges remain active, the initial spike in obfuscation-related flows subsides, and non-haven exchanges regain relative prominence. This suggests that concealment activity is front-loaded, with rapid redistribution occurring shortly after aid receipt and normalization thereafter.

Figure 2 visualizes these dynamics by comparing networks one week before, one week after, and six months after major aid disbursements. The results reveal a pronounced but short-lived reallocation of transaction flows toward opaque intermediaries immediately following aid events.

We replicate this analysis for a major World Bank disbursement to Nigeria in May 2019 ($24.4 billion), shown in Figure A.1. The patterns are qualitatively similar: mixers and tax-haven exchanges intensify immediately after disbursement, new nodes appear, and activity attenuates over time without fully returning to baseline.

Overall, the network evidence provides a visual complement to our regression results. It shows how aid disbursements are followed by a rapid, temporary reorientation of crypto flows from transparent to opaque venues, consistent with concealment and laundering behavior documented in law enforcement and forensic studies.

We analyze global redistribution patterns around the five largest aid disbursements in Appendix B. Cryptocurrency volumes spike briefly in tax havens and on U.S. exchanges, but U.S. spikes often occur without parallel increases offshore, indicating that U.S. platforms mainly serve as regulated entry points for fiat-to-crypto conversion rather than final destinations for redistributed aid.

4.2 Part II: On-Chain Transaction Analysis

4.2.1 Web Traffic

A central empirical challenge in studying cryptocurrency activity is the absence of reliable geographic identifiers in on-chain data. Blockchain transactions do not reveal users' country of origin, and exchange-level data typically aggregate activity across multiple jurisdictions. To address this limitation, we use web traffic to cryptocurrency exchange platforms as a proxy for country-level engagement with cryptocurrency trading.[5]

Web visits and time spent on crypto transaction platforms capture information acquisition, account access, and transaction execution behavior that typically precedes or accompanies trading activity. While web traffic does not directly measure realized on-chain transactions, it provides a high-frequency, geographically attributable signal of trading intent and participation. We therefore interpret web traffic as an informative proxy for country-level crypto engagement rather than as a direct measure of transaction volume.

We construct three country–month measures of web traffic. First, total visits capture the absolute intensity of engagement with crypto-related platforms. Second, total visit duration measures the depth of engagement, reflecting the amount of time users spend monitoring prices, accessing accounts, or executing transactions. Because duration data are not fully observed for all country–platform pairs, we approximate missing duration measures by multiplying the number of visits by the global average time spent per visit in that month. This approach preserves cross-country variation in visit intensity while anchoring duration estimates to observed global browsing patterns.

Third, we construct a visits ratio, defined as a country's share of global visits to crypto-related websites in a given month. Unlike level measures, the visits ratio captures a country's relative position in the global distribution of crypto-related traffic. We use this ratio to scale global Bitcoin transaction volume and transaction frequency, thereby constructing implied country–month measures of transaction volume and activity that combine global market conditions with country-specific engagement intensity.

[5] Examples include tax-haven-domiciled exchanges such as HTX (`https://www.htx.com/`) and regulated exchanges such as Kraken (`https://www.kraken.com/`).

4.2.2 Stacked Difference-in-Differences Design

Foreign aid disbursements occur at different points in time across countries and may repeat within the same country. To accommodate this staggered and recurrent treatment structure, we employ a short-horizon stacked difference-in-differences (DiD) design at the country–month level. This approach allows us to flexibly estimate dynamic treatment effects around each disbursement episode while avoiding contamination from later or overlapping aid events.

When multiple aid disbursements occur within a short window for the same country, we treat closely spaced disbursements as a single episode. Specifically, if two or more disbursements occur within three months of each other—within our post-treatment window—we combine them into a single shock and define the event time as the first month of the initial disbursement. This aggregation ensures that post-treatment periods are not mechanically re-treated and prevents overlapping episodes from biasing dynamic estimates.

Control countries are selected to be untreated over the entire episode window. Specifically, for each treated episode, the control group consists of countries that do not receive any World Bank aid disbursement during a twelve-month pre-treatment period, the treatment month itself, and the three-month post-treatment period. The same event window is used both to construct the stacked event-study design and to impose the no-aid requirement on control countries. This restriction ensures that control observations are not contaminated by contemporaneous or near-contemporaneous aid shocks and that estimated dynamics reflect within-country deviations around the treated episode relative to genuinely untreated countries over the full analysis window.

Formally, let c index countries and t index months. We define an "episode" e as a treated country-month pair corresponding to an aid disbursement event, and stack multiple episodes using the standard stacked DiD approach. For each episode e, the treated unit is the disbursement country $c(e)$, and event time is defined as

$$k \equiv t - t_e,$$

where t_e denotes the month of the disbursement. We estimate event-time coefficients over a symmetric window $k \in \{-K, \dots, L\}$ and omit $k = -1$ as the reference period.

For the baseline analysis, we focus on disaster-related aid disbursements (e.g., earthquakes and other natural disasters), which are plausibly unanticipated and therefore less likely to be confounded by forward-looking behavior or pre-existing trends. This restriction strengthens the interpretation of the estimated dynamics as responses to unexpected aid shocks. In robustness checks, we extend the analysis to the full set of aid disbursements and obtain qualitatively similar results. We further exclude geographically adjacent countries to rule out spillovers from regional disaster exposure or cross-border effects of aid flows. Together, these exercises indicate that our findings are not sensitive to sample selection and are driven by within-country responses to aid receipt rather than correlated regional shocks.

We analyze two country–month measures of web traffic: (i) total visits to crypto websites, (ii) total time spent on those websites. Then to map web traffic into implied country-level on-chain activity, we construct geo-adjusted measures of Bitcoin transaction outcomes by interacting a country's visits ratio with global on-chain aggregates. Specifically, we study three implied outcomes: (i) Bitcoin transaction volume, (ii) Bitcoin transaction frequency, and (iii) the number of newly created Bitcoin accounts.

Formally, for an on-chain global aggregate G_t (e.g., total transaction volume, total transaction frequency, or total number of new accounts worldwide), we define the implied country-level outcome as

$$\widetilde{Y}_{ct} \;=\; \text{VisitsRatio}_{ct} \times G_t.$$

These geo-adjusted outcomes capture changes in implied country-level activity that can arise either from shifts in a country's relative share of crypto-related traffic or from changes in the global level of on-chain activity.

For each outcome Y_{cpt} (web-traffic measures) or $\widetilde{Y}_{cpt}$ (geo-adjusted on-chain measures), where c indexes countries, p indexes platforms, and t indexes months, we estimate the following stacked difference-in-differences specification:

$$Y_{cpt} = \sum_{\substack{k=-K \\ k\neq -1}}^{L} \beta_k \cdot \mathbf{1}\{c = c(e)\}\mathbf{1}\{t - t_e = k\} \;+\; \alpha_{cp} \;+\; \gamma_t \;+\; \varepsilon_{cpt}. \tag{1}$$

Here, α_{cp} denotes country$\times$platform fixed effects that absorb all time-invariant differences in baseline platform usage and adoption within each country. Month fixed effects γ_t absorb global shocks common to all countries and platforms, such as worldwide Bitcoin price movements, market-wide traffic cycles, and major news events. The coefficients β_k trace the dynamic response of outcomes in treated country–

platform pairs relative to controls at event time k, normalized to the pre-disbursement period $k = -1$. Standard errors are clustered at the country$\times$platform level.

Another reason we focus on a relatively short event window and exploit high-frequency monthly variation is to mitigate concerns that our estimates capture slow-moving structural changes, such as improvements in internet infrastructure following aid disbursements. Large-scale investments in digital infrastructure typically require substantial planning and implementation time and are therefore unlikely to generate immediate changes in online behavior. In contrast, our estimates reveal sharp increases in web traffic during the disbursement month, which dissipate quickly thereafter. This timing pattern is difficult to reconcile with gradual expansions in internet access and instead points to a rapid behavioral response following the receipt of aid.

We do not estimate regressions at the daily frequency because disbursement activity is highly intermittent at that horizon. Daily data exhibit a large mass of zero observations, implying that the one-period lag of disbursements is zero for the vast majority of observations. As a result, the lagged disbursement regressor would contain little informative variation, undermining both the statistical power and the economic interpretation of the dynamic specification. We therefore aggregate the data to the quarterly level, which smooths high-frequency intermittency, preserves economically meaningful variation in disbursement amounts, and yields a well-defined and interpretable lag structure.

4.2.3 Results

Web Traffic. To assess whether foreign aid disbursements are accompanied by changes in online engagement with crypto markets, Figure 3 and Figure 4 plot stacked event-study difference-in-differences estimates for total visits to cryptocurrency-related websites and total time spent on those websites, respectively.

Table 4 reports the corresponding stacked DiD regression estimates. In the disbursement month ($k = 0$), total visits increase by approximately 11,000–11,800 visits, while total visit duration rises by about 127–187 minutes across specifications, with all estimates statistically significant at the 1% level. The effects remain positive and statistically significant at $k = 1$ and $k = 2$, though with smaller magnitudes, and attenuate by $k = 3$, where coefficients become economically small and statistically insignificant.

The pattern is robust across the baseline sample, a clean-control specification excluding nearby countries, and the full set of aid disbursements. The sharp, short-lived increase in web traffic suggests a rapid surge in information-seeking and platform engagement following aid receipt, rather than gradual changes driven by slow-moving factors such as improvements in internet infrastructure. This increase in web traffic provides a complementary demand-side signal that closely aligns with the observed spikes in on-chain and off-chain crypto activity.

The "all disbursements" specification yields fewer observations than the disaster-only baseline despite encompassing a broader set of treatment events. Expanding the treatment definition introduces episodes with multiple treated countries in the same month, which are dropped by our requirement of exactly one treated country and at least five controls per episode. Additionally, many new disbursement episodes fall outside the joint on-chain and web-traffic coverage window, contributing few usable observations after merging. These two forces more than offset the mechanical increase in the number of candidate episodes.

Anonymous vs. Identified Transactions To quantify heterogeneity by anonymity status and exchange jurisdiction, Table 5 and Table 6 report stacked difference-in-differences estimates of the dynamic response of transaction frequency and transaction volume around aid disbursements.[6] Complementary evidence is provided in Figure 5 and Figure 6, which plot stacked event-study estimates using geo-adjusted measures that scale global Bitcoin activity by each country's web-traffic share.

We begin with tax-haven exchanges. In Panel A of Table 5, transaction frequency for anonymous addresses increases by approximately 167% in the disbursement month ($k = 0$), compared with a 64% increase for identified addresses. A similar pattern appears for transaction volume in Table 6: anonymous transaction volume rises by about 169% at $k = 0$, while identified volume increases by roughly 95%. In both cases, the anonymous response remains positive and statistically significant through $k = 1$ and $k = 2$, then dissipates by $k = 3$, whereas the identified response is smaller and often becomes statistically insignificant beyond the contemporaneous month. These results indicate that the post-aid surge in activity on tax-haven exchanges is disproportionately concentrated in anonymous channels, consistent with strategic obfuscation via fragmented transfers and intermediary wallets.

We then turn to non-tax-haven exchanges. Although overall responses are also positive at $k = 0$, anonymity gaps remain pronounced. Transaction frequency for anonymous addresses increases by approximately 328% at disbursement, compared with a 112% increase for identified addresses. Similarly,

[6] Outcomes are specified as $\log(1 + y)$. Coefficients are converted to percentage changes as $100 \times (\exp(\beta) - 1)$.

transaction volume increases by about 346% for anonymous addresses, compared with 151% for identified addresses. These effects persist through $k = 1$ and $k = 2$ and attenuate by $k = 3$. Taken together, the evidence suggests that aid receipt is followed by a rapid but short-lived escalation in crypto activity across exchange jurisdictions, with a consistently stronger response in anonymous transactions, pointing to a reallocation toward more opaque transaction channels immediately after disbursement.

New Wallet Creation We next examine whether aid disbursements are followed by the creation of new wallets, a salient extensive-margin response commonly associated with laundering strategies that rely on fresh identifiers to reduce traceability. Figure 7 plots stacked event-study estimates for the geo-adjusted number of newly created Bitcoin accounts, and Table 7 reports the corresponding stacked DiD estimates by exchange jurisdiction and anonymity status.

Across specifications, the response in anonymous wallet creation is immediate, large, and highly statistically significant. In the disbursement month ($k = 0$), the number of new anonymous accounts increases by approximately 660% on tax-haven exchanges and by more than 3,300% on non-tax-haven exchanges. These effects remain sizable and statistically significant at $k = 1$ and $k = 2$, but attenuate and become statistically indistinguishable from zero by $k = 3$. In contrast, the creation of newly identified accounts exhibits only modest responses: contemporaneous increases at $k = 0$ amount to roughly 12–15%, are an order of magnitude smaller than those for anonymous accounts, and show no meaningful persistence.

This extensive-margin pattern closely mirrors the transaction-level findings. Rather than scaling up activity through pre-existing, identified accounts, aid episodes are associated with rapid entry into the crypto ecosystem via newly created anonymous wallets. The combination of a sharp surge in anonymous wallet creation and muted responses among identified accounts is consistent with intentional reshuffling behavior aimed at obscuring provenance and facilitating subsequent layering of transactions.

Time Pattern and Persistence The dynamics imply that responses are front-loaded and short-lived. Across implied transaction volume, transaction frequency, and new-account creation, the estimated effects peak at $k = 0$ and remain elevated through $k = 1$ and $k = 2$, but attenuate markedly by $k = 3$, where coefficients are smaller and often statistically insignificant. This temporal profile is consistent with relatively immediate laundering or concealment behavior following aid receipt: actors appear to react quickly in the disbursement quarter and shortly thereafter, with limited persistence beyond two to three quarters.

Importantly, because the geo-adjusted outcomes decompose implied country-level activity into a web-traffic share component and a global activity component, the findings are consistent with a mechanism in which aid episodes coincide with increased absolute engagement that moves with broader global market conditions, rather than a durable reallocation of global traffic toward recipient countries. In other words, the post-disbursement spikes reflect a rapid intensification of implied activity among treated countries relative to contemporaneous controls, with effects that fade as the episode window closes.

Leakage Ratio To quantify the economic magnitude of aid-linked cryptocurrency activity, we translate the estimated semi-elasticities from the stacked event-study regressions into dollar-valued transaction volumes and express them as a ratio of foreign aid disbursements. The mapping proceeds in four steps: (i) defining a pre-disbursement baseline, (ii) converting estimated percentage changes into level changes, (iii) valuing crypto activity in U.S. dollars, and (iv) scaling by the size of the aid disbursement.

Our regression outcomes are specified as $\log(1 + y)$, where y denotes geo-adjusted cryptocurrency transaction volume measured in Bitcoin units. To recover level changes, we first construct a counterfactual baseline $\bar{y}^0$ using the average geo-adjusted transaction volume for the same segment (anonymous transactions on tax-haven exchanges) in the pre-disbursement window ($k = -3$ to $k = -2$) for treated-country – exchange cells. This baseline captures typical transaction activity in the absence of aid receipt and provides the reference point for translating estimated percentage responses into economic magnitudes. In our baseline specification, the pre-disbursement mean is $\bar{y}^0 = 1{,}271$ BTC.

The leakage calculation focuses on the estimated response of anonymous transaction volume on tax-haven exchanges. This choice is guided by both institutional considerations and the empirical patterns documented above. As shown in Panel A of Table 6, tax-haven exchanges exhibit the largest and most precisely estimated responses in the anonymous segment. Identified transactions display substantially smaller and less persistent responses. Given weaker regulatory oversight in tax-haven jurisdictions and the reduced traceability of anonymous transactions, activity in this segment represents the most plausible channel through which aid-linked funds can be concealed, fragmented, or rerouted outside formal monitoring frameworks.

We therefore base the headline leakage estimate on the contemporaneous response at $k = 0$. This choice is motivated by two considerations. First, the event-study estimates indicate that the largest response occurs immediately at disbursement, while effects in later months attenuate rapidly. Second, focusing on $k = 0$ minimizes mechanical inflation arising from repeated routing or multi-hop transfers across periods, which would disproportionately affect cumulative measures constructed over longer post-treatment windows. As such, the $k = 0$ estimate provides a conservative measure of impact-period exposure.

From the stacked event-study estimates, anonymous transaction volume on tax-haven exchanges increases by approximately 169% in the disbursement month. Given the $\log(1+y)$ specification, the implied contemporaneous change in Bitcoin-denominated transaction volume is approximated by

$$\Delta y \;=\; (\exp(\hat{\beta}) - 1) \times (1 + \bar{y}^0),$$

which is numerically close to $(\exp(\hat{\beta}) - 1) \times \bar{y}^0$ given the large baseline level. Applying the estimated 169% increase yields an implied increase of approximately $2{,}148$ BTC in anonymous transaction volume at $k = 0$.

To convert Bitcoin-denominated transaction volumes into U.S. dollar values, we multiply the implied change in Bitcoin volume by the average Bitcoin price over the sample period. Taking the average Bitcoin price during our sample period ($21,763), the estimated increase in anonymous transaction volume corresponds to approximately $46.7 million in additional cryptocurrency value transacted in the disbursement month.

We define the leakage ratio as the ratio of the value of disbursement-linked cryptocurrency transactions to the size of the foreign aid disbursement. Letting ΔCryptoValue denote the estimated dollar value of additional anonymous transactions on tax-haven exchanges and Aid denote the average aid disbursement, the leakage ratio is given by

$$\lambda \;=\; \frac{\Delta\text{CryptoValue}}{\text{Aid}}.$$

With an average disbursement size of $305 million, the implied impact leakage ratio is approximately 0.153. That is, the contemporaneous increase in anonymous transaction activity on tax-haven exchanges corresponds to roughly 15.3% of the average aid disbursement.

Because cryptocurrency transaction volume reflects gross flows, this estimate should be interpreted as a measure of transaction-value exposure rather than a direct estimate of diverted funds. In particular, if each dollar is routed m times on average through anonymous tax-haven channels, observed transaction volume will mechanically exceed the underlying amount of resources being reallocated. To assess the sensitivity of the leakage estimate to repeated routing, we report a simple turnover adjustment under which the implied leakage ratio is approximately λ/m. As a baseline, we set $m = 3$, which corresponds to light but non-trivial reshuffling of funds and yields a conservative lower bound on exposure. Under this calibration, the implied leakage ratio is about 5.1%. For completeness, we also report alternative values $m \in \{2, 5\}$, yielding leakage ratios of approximately 7.7% and 3.1%, respectively. Together, these bounds provide a transparent and conservative range that accounts for plausible degrees of transaction layering, while preserving the central finding that a non-trivial share of aid disbursements is associated with contemporaneous activity in the most opaque segment of the crypto ecosystem.

4.3 Off-Chain Transaction Analysis

To complement the on-chain analysis, we examine off-chain exchange activities, which are recorded by centralized exchanges in different jurisdictions. Off-chain data are particularly valuable for capturing transactional behavior that occurs within exchange platforms, such as order matching, deposits, and internal transfers, which do not appear on public blockchains. While on-chain data traces the movement of crypto assets across wallets, it cannot distinguish between speculative transfers, custodial holdings, or active trading. Off-chain records thus provide critical confirmation that observed blockchain flows are tied to real economic activity, enabling a fuller picture of post-aid fund mobilization.

Our empirical strategy adopts a lead-lag framework to examine changes in off-chain crypto exchange activity surrounding foreign aid disbursements. We construct two dependent variables. The first is the logarithmic level change in exchange volume, capturing the absolute difference between post-aid and pre-aid quarters. The second is a logarithmic relative ratio, which compares volumes on suspect platforms (such as those located in tax havens) to volumes on a benchmark group of regulated exchanges. Specifically, we define this ratio as the change in the log of the exchange volume ratio between a haven platform and the benchmark: Coinbase, Kraken, and Gemini, between two adjacent quarters. This benchmark-adjusted measure provides a more nuanced lens into jurisdiction-specific behavioral shifts by filtering out common macro trends. Formally, we compute this as $\log\left(\frac{EX\_Haven_t}{Benchmark_t}\right) - \log\left(\frac{EX\_Haven_{t-1}}{Benchmark_{t-1}}\right)$, where EX_Haven_t is the off-chain volume of a given suspect exchange in quarter t, and $Benchmark_t$ is the aggregate volume of the benchmark platforms. This formulation allows us to isolate cases where off-chain activity grows disproportionately on potentially complicit platforms, providing indirect evidence of abnormal responses to aid flows.

4.3.1 Tax Havens vs. Non-Havens

Panel A of Table 8 examines the effect of lagged foreign aid on off-chain transaction activity, comparing tax haven countries with non-haven counterparts. The results reveal a robust, statistically significant positive relationship between foreign aid and transaction growth on exchanges domiciled in tax havens. Specifically, a 1% increase in foreign aid is associated with a 2.39 percentage point increase in transaction count growth and a 0.39 percentage point increase in volume ratio, with both estimated effects significant at the 1% level. By contrast, the effects in non-haven countries are either statistically insignificant (for transaction counts) or near zero (for transaction ratios), and the differences across the two groups are themselves significant. These findings imply that aid disbursements are followed by disproportionately elevated trading activity in tax haven-based exchanges. The result complements our on-chain evidence by demonstrating that the off-chain response to foreign aid is not uniform across jurisdictions but is instead concentrated in more opaque regulatory environments.

4.3.2 Unregulated vs. Regulated Countries

We further stratify exchanges based on the regulatory environment of their host countries. As shown in Panel B of Table 8, foreign aid is associated with a sizable increase in off-chain transaction activity in unregulated jurisdictions: a 1% increase in aid corresponds to a 0.37 percentage point rise in volume ratio, a highly significant effect. In contrast, the effect in regulated countries is considerably smaller, approximately 0.03 percentage points. The magnitude of the difference is substantial, with the response in unregulated settings being over ten times larger. These findings suggest that even outside of formal tax havens, the degree of regulatory oversight-particularly with respect to KYC/AML enforcement—plays a critical role in determining whether exchanges are used as conduits for rapid fund movement. The result reinforces the interpretation that it is not cryptocurrency itself, but rather the institutional and regulatory context in which it operates, that governs its use for potentially opaque or illicit purposes.

4.3.3 Crypto-Friendly vs. Not Friendly

We also examine whether the effect of foreign aid differs by the overall crypto stance of a country-specifically, whether it is broadly "crypto-friendly", characterized by permissive regulation and policies that actively attract crypto businesses. As shown in Panel C of Table 8, aid disbursements are followed by a statistically significant increase in off-chain volume on exchanges located in crypto-friendly jurisdictions: a 1% increase in aid corresponds to a 0.39 percentage point increase in transaction ratio. In contrast, there is virtually no effect in countries classified as crypto-unfriendly. This divergence aligns closely with the findings in Panels A and B. Indeed, many crypto-friendly countries (e.g., Malta, parts of Southeast Asia) also qualify as tax havens or operate in regulatory grey zones. Thus, this result reinforces the conclusion that institutional openness to crypto-often coupled with limited oversight—facilitates the rapid redirection of aid-linked funds into loosely monitored exchange platforms.

To ensure our findings are not driven by broader market cycles, we re-estimate our regressions excluding a potentially important outlier period following the 2021 crypto boom (1 May 2021 to 1 September 2021). The results remain robust and consistent with our main specification—see Appendix Table A.3.

These off-chain results not only corroborate our earlier on-chain findings but also help address an important identification concern: could the observed on-chain spikes merely reflect speculative movement of cryptocurrencies—such as wallet rebalancing or internal transfers—rather than actual exchange usage? The fact that exchange-reported transaction counts increase precisely in the jurisdictions and periods where on-chain activity rises suggests otherwise. It indicates that the on-chain surges are indeed accompanied by real economic engagement with crypto exchanges, most plausibly through deposit and trading behavior. This lends further credibility to the interpretation that foreign aid is followed by the conversion of fiat into crypto assets, channeled through platforms in lightly regulated or strategically positioned jurisdictions.

Appendix D presents the off-chain transaction analysis, including a case study of the Huobi Effect in Singapore, to examine whether the documented patterns in on-chain activity are corroborated by jurisdiction-level transaction data and whether specific exchange-level events shape the cross-country distribution of post-aid crypto flows. Together, the results reinforce the interpretation that aid disbursements generate measurable behavioral responses at both the platform and jurisdiction level, with tax-haven and semi-offshore venues serving as the primary conduits through which funds are routed and ultimately stored outside the formal regulated economy.

4.3.4 Institutional Quality Heterogeneity

We examine whether the relationship between foreign aid and crypto flows varies with the recipient country's institutional quality. Specifically, we interact aid with measures such as the World Bank's CPIA governance score, an index of corruption control, and domestic financial depth (measured by credit-to-GDP). The rationale is that weaker institutions, which are more susceptible to corruption, may exhibit greater crypto capture. Consistent with this hypothesis, the results in Table 9 show that the effect of aid on crypto flows is significantly larger in countries with below-median governance indicators (e.g., a low control of corruption score). In contrast, in countries with stronger institutions, the aid-to-crypto relationship is weaker or statistically insignificant, suggesting that institutional strength may mitigate the diversion of aid into crypto channels.

4.4 Robustness Checks and Extenstions

This section presents a series of robustness checks and extensions that further probe the validity and scope of our main findings based on on-chain transaction data. These analyses address potential endogeneity in aid allocation, explore alternative sources of exogenous variation, and examine whether the relationship between foreign aid and crypto activity extends to politically salient periods such as national elections.

4.4.1 IV Analysis

To further address potential endogeneity in aid allocation, we complement our baseline estimates with an instrumental variables (IV) strategy. Aid disbursements may be systematically directed toward countries with weaker institutions, higher corruption risk, or limited financial oversight—precisely the environments in which diversion into opaque financial channels is more likely. As a result, reduced-form estimates may confound the causal effect of aid with underlying governance characteristics.

Consistent with this concern, heterogeneity results in Table 9 show that the relationship between aid and crypto activity is substantially stronger in countries with below-median governance indicators, such as weak control of corruption or shallow financial systems, and markedly weaker in countries with stronger institutions. To disentangle these channels and isolate plausibly exogenous variation in aid flows, we implement an instrumental variables strategy that exploits cross-country differences in historical aid exposure interacted with time-invariant measures of institutional quality.

Formally, our instruments are defined as:

$$\mathrm{IV}_{1t} = \sum_i w_i \cdot \mathrm{Aid}_{it}, \quad \mathrm{IV}_2 = g_i$$

where w_i is the historical share of aid received by country i, Aid_{it} is the daily aid disbursed to country i, and g_i is a time-invariant indicator of governance quality (e.g., the inverse of a corruption index). This specification exploits plausibly exogenous variation in aid shocks across countries with differing levels of institutional strength.

We estimate a two-stage least squares (2SLS) model using quarterly panel data. In the first stage,

$$\log(\mathrm{Agg\_Aid}_t) = \alpha + \boldsymbol{\beta}^\top \mathbf{IV}_{it} + \mathbf{X}_t' \gamma + \delta_c + \delta_t + \varepsilon_{it},$$

we regress the logarithm of disbursed foreign aid on a set of instruments $\mathbf{IV}_t$. δ_c and δ_t denote aid recipient country and year-quarter fixed effects, respectively. In the second stage, we estimate:

$$\log(Y_t) = \alpha + \lambda \cdot \log\left(\widehat{\mathrm{Agg\_Aid}}_{t-\mathrm{lag}}\right) + \mathbf{X}_t' \boldsymbol{\theta} + \delta_c + \delta_t + \epsilon_{it},$$

where the outcome Y_{it} is a measure of crypto activity, such as total on-chain transaction volume. Standard errors are clustered at the level of aid recipient countries.

To support the validity of our instrumental variables strategy, we examine both the relevance and exclusion restriction assumptions. In terms of relevance, the first-stage estimates pass standard weak identification tests, including the Cragg-Donald and Kleibergen-Paap statistics. The interaction between historical aid shares and governance quality significantly improves the prediction of current aid disbursements. Regarding the exclusion restriction, overidentification tests suggest that the instruments are jointly valid. Neither instrument is expected to influence the outcome variables directly, apart from their effect through foreign aid. These findings support the interpretation that the instruments affect crypto activity only through their impact on aid flows.

Consistent with our main findings, our IV estimates indicate that aid shocks cause meaningful increases in crypto activity on platforms associated with illicit use (see Table 10 Panel A). For example, aid shocks lead to a 6.0% increase in transactions involving anonymous wallets on tax haven-linked exchanges. A one standard deviation increase in lagged aid is associated with a 0.51 log-point rise in anonymous transactions on tax-haven exchanges (approximately a 65.97% increase). Crypto inflows rise by 4.7%, while outflows increase by 7.5%. These patterns are consistent with the layering phase of money laundering, in which funds are rapidly moved across wallets to obscure their origin. We also find corroborating evidence along the extensive margin. Following aid disbursements, the creation of new anonymous wallets increases by 7.3%, and outflows conducted through these newly established wallets rise by 10.6% (see Table 10 Panel B). These effects are substantially larger than those estimated using OLS, suggesting that OLS estimates may understate the true relationship due to attenuation bias or endogeneity in aid allocation.

The results provide evidence supportive of a systematic association between foreign aid and illicit crypto flows. The effects are concentrated in countries with weak governance, consistent with the idea that institutional quality shapes the extent to which aid may be diverted into digital financial channels. Moreover, the findings illustrate the potential of blockchain-based data to shed light on hidden financial activity and underscore the importance of institutional safeguards in preserving the integrity of aid disbursement.

4.4.2 Election-Related Crypto Activity

We extend our analysis to explore how blockchain-based forensic methods can shed light on political cycles, focusing in particular on national elections. As a case study, we examine Brazil, one of the largest recipients of foreign aid in our sample and a country that experienced heightened political uncertainty in the period surrounding the 2018 general election. The first-round election was held on October 7, 2018, followed by a runoff on October 28 after no candidate obtained an absolute majority; Jair Bolsonaro won the runoff and was subsequently elected president.

From a theoretical perspective, the period leading up to major elections in aid-recipient countries may alter the incentives of political and economic elites. Rather than solely accumulating or concealing resources, actors may seek to actively deploy funds to finance politically salient activities—such as vote-buying, campaign-related expenditures, or the consolidation of political support—while attempting to avoid detection. In this context, cryptocurrency networks may provide an attractive channel for transferring and mobilizing funds in a manner that obscures identity and transaction provenance. We therefore examine whether crypto activity in Brazil exhibits systematic changes around the election period.

As shown in Table 11, we document pronounced increases in crypto transactions in the months preceding the election, concentrated almost entirely among anonymous wallets and newly created accounts, with no comparable surge observed in the post-election period. This pattern suggests heightened reliance on opaque transaction channels during the run-up to the election rather than a persistent shift in crypto usage.

Importantly, this analysis is descriptive and not intended to establish a causal link between crypto flows and electoral outcomes. Nevertheless, the timing and composition of the observed pre-election surge are consistent with the possibility that funds—potentially including diverted aid resources—are redeployed during election periods for politically salient purposes.

The Brazil case illustrates how blockchain-based forensic data can be used to study the interaction between political cycles and illicit financial activity. While exploratory and outside the paper's core identification strategy, these results highlight the broader applicability of our approach to political economy settings in which covert financial flows may play an important role.

Appendix E shows the sampling-based robustness checks, including excluding the DeFi boom period, to ensure that our findings are not driven by exceptional market-wide dynamics. Together, the results reinforce the interpretation that the documented post-aid increases in crypto activity reflect behavioral responses to aid disbursements rather than spurious correlations or sample-specific artifacts.

4.5 The Laundering Patterns

The on-chain and off-chain evidence is consistent with a layered laundering pattern operating through cryptocurrency markets following foreign aid disbursements. We interpret the observed dynamics within the classical framework of placement, layering, and integration, while emphasizing the distinct informational roles of on-chain and off-chain activity. On-chain data captures the movement and routing of assets across wallets and exchanges, whereas off-chain data identifies where economically meaningful trading or internal reallocation occurs within exchange platforms. This distinction helps separate transient passage from points of settlement or redistribution.

Placement (Entry into Crypto). The placement stage involves the initial conversion of fiat-denominated aid funds into cryptocurrency. Large-scale fiat-to-crypto conversion typically requires access to banking infrastructure and liquid on-ramps, which are most readily available on regulated, non-tax-haven exchanges. Consistent with this mechanism, the on-chain analysis documents statistically significant increases in inflows to non-tax-haven exchanges in the disbursement month. These contemporaneous inflows are consistent with initial entry into the crypto ecosystem via compliance-compatible platforms that facilitate fiat on-ramping, rather than through opaque venues.

Layering (Obfuscation via Transfers). Once funds enter the crypto system, subsequent transfers are used to reduce traceability and obscure origin. This layering stage typically involves withdrawals from regulated exchanges to self-hosted wallets, fragmentation across multiple addresses, and routing through offshore or lightly regulated platforms. Our evidence points to tax-haven exchanges as central nodes in this process. The on-chain analysis shows sharp increases in transaction volume, transaction frequency, and the creation of new anonymous wallets at tax-haven exchanges immediately following aid disbursements, indicating intensive routing and address-level reshuffling.

The off-chain evidence sharpens this interpretation. While on-chain activity rises broadly across exchange types—reflecting movement of funds through the network—off-chain activity responds selectively in lightly regulated, tax-haven exchanges. Because off-chain volume is recorded only when assets are actively used within an exchange's private ledger, this pattern indicates that these venues are not merely transit points but sites where internal reallocation or redistribution occurs. At the same time, the response is short-lived, suggesting that the reallocation associated with layering is rapid rather than persistent.

Integration (Realization or Storage). The final stage involves either converting crypto holdings into usable forms or storing them for future use. Although direct conversion back into fiat or ultimate asset use is not observable in our data, we document significant outflows from tax-haven exchanges following aid disbursements. Combined with the off-chain activities in tax haven exchanges, these outflows are consistent with funds exiting exchanges after internal reallocation and being routed toward potential integration endpoints. Such endpoints may include long-term storage in private wallets, conversion into stablecoins, or further transfers through intermediaries that facilitate eventual re-entry into the formal economy.

5 Conclusion

This study provides systematic evidence that foreign aid disbursements trigger short-lived but substantial laundering activity in cryptocurrency markets. Using on-chain and off-chain transaction data from 2018–2024, we show that aid flows to developing countries — especially those with weak institutions — produce sharp post-disbursement surges in Bitcoin transactions involving anonymous wallets on exchanges in tax-haven jurisdictions.

Our forensic analyses reveal a laundering mechanism in which aid-linked funds first enter through regulated exchanges, then quickly shift into anonymous wallets and are routed through offshore platforms, mirroring the classic placement-layering-integration sequence. Anonymous transaction volume rises by about 169% in tax haven exchanges in the first month after disbursements, driven by new wallet creation and higher transaction frequency, but not observed among identified users.

These effects are most pronounced in countries with poor governance, financial opacity, and weak corruption control, suggesting strategic exploitation by elites. From a policy perspective, the findings highlight that stricter oversight of traditional offshore finance may have displaced illicit flows into crypto, while also showing that blockchain forensics can detect such behavior in near-real time.

Future work could expand beyond Bitcoin to include privacy-enhancing coins and multi-chain ecosystems, where laundering activity may be harder to detect. Linking blockchain analytics to leaked datasets or government audit reports could further strengthen causal attribution. More broadly, our approach opens new avenues for studying illicit financial flows, tax evasion, and regulatory arbitrage in a rapidly digitizing global financial system.

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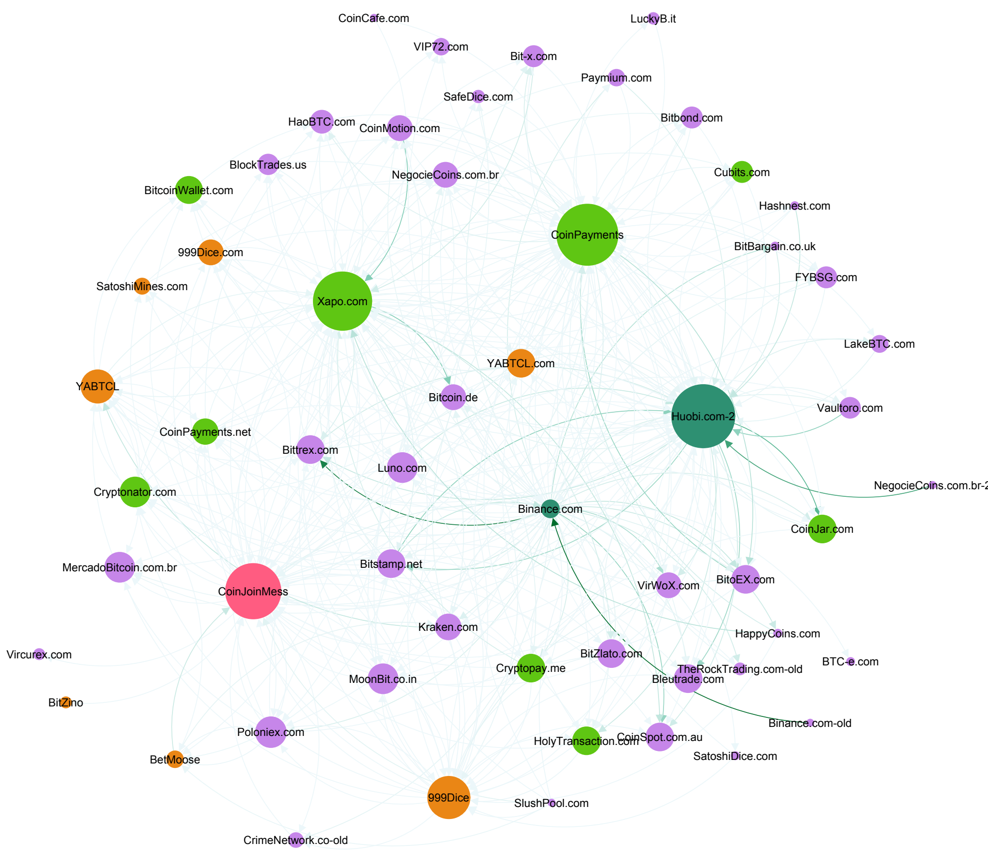
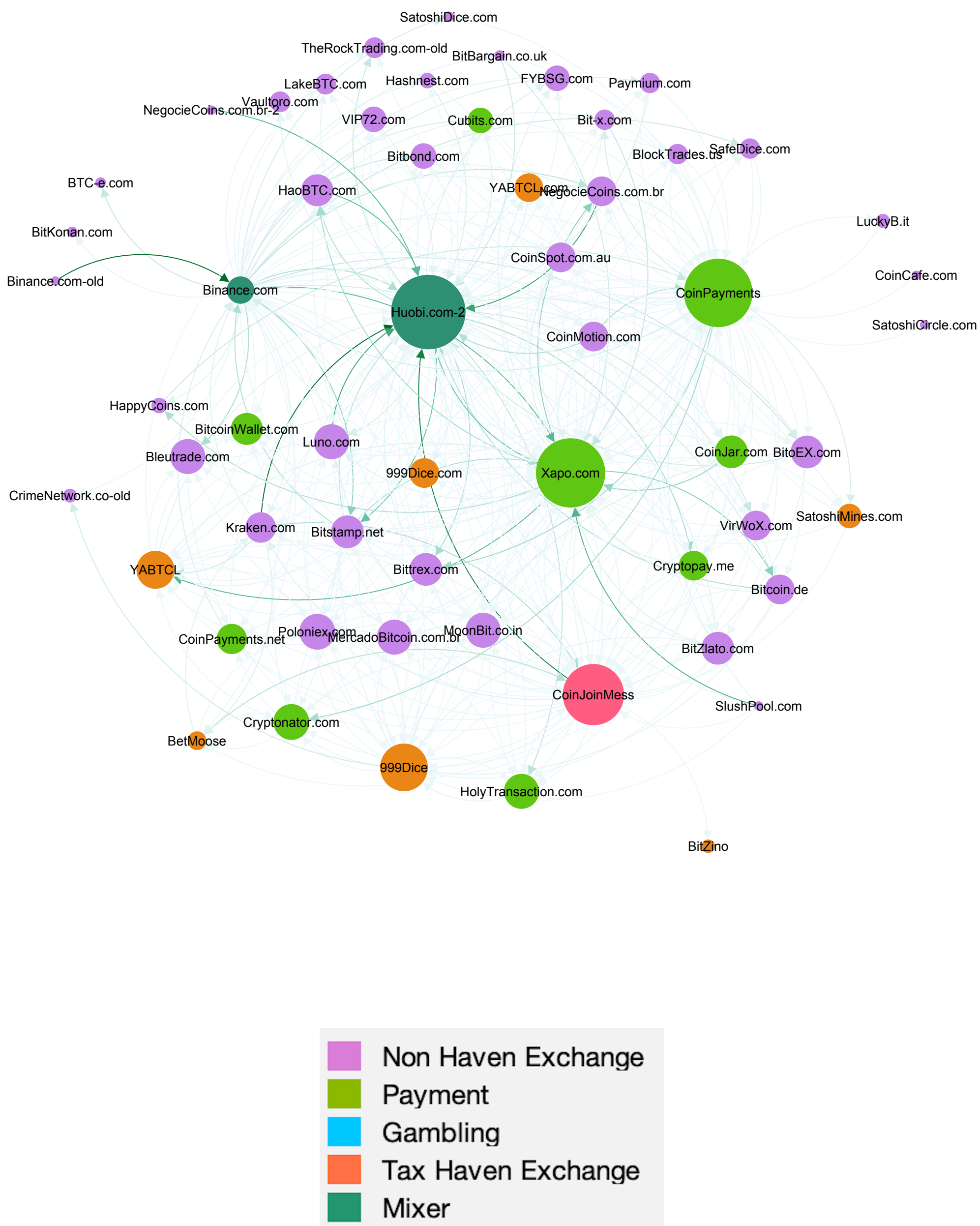
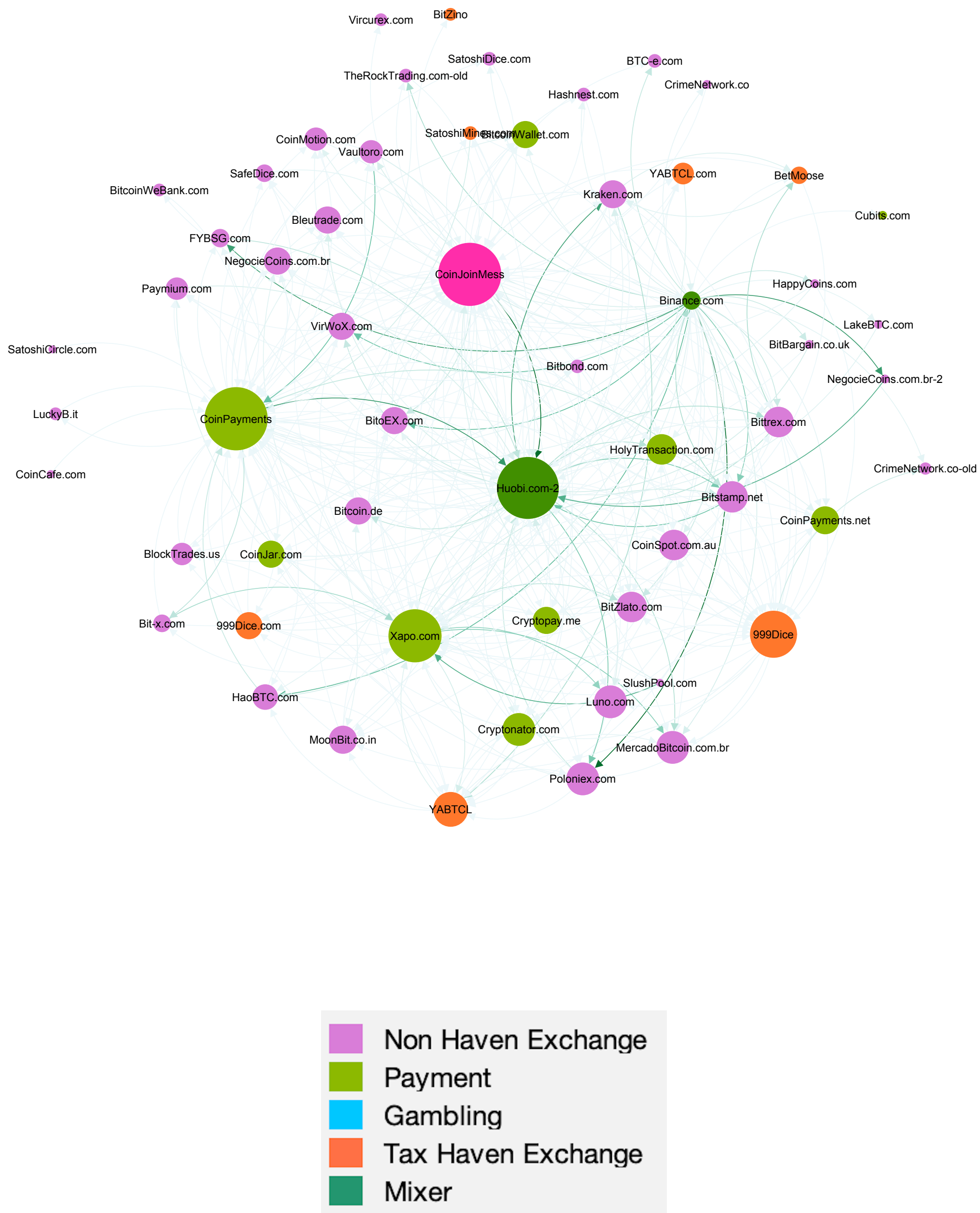
Figures

Figure 1. Network Analysis Around Top Five Aid Disbursements. Larger nodes represent higher centrality, and darker edges indicate greater volume. The panels show the networks one month before, one month after, and six months after the major aid disbursements. Colors distinguish service categories: non-tax-haven exchanges (purple), tax-haven exchanges (orange), payment platforms (blue), mixers (pink), and gambling/others (green).



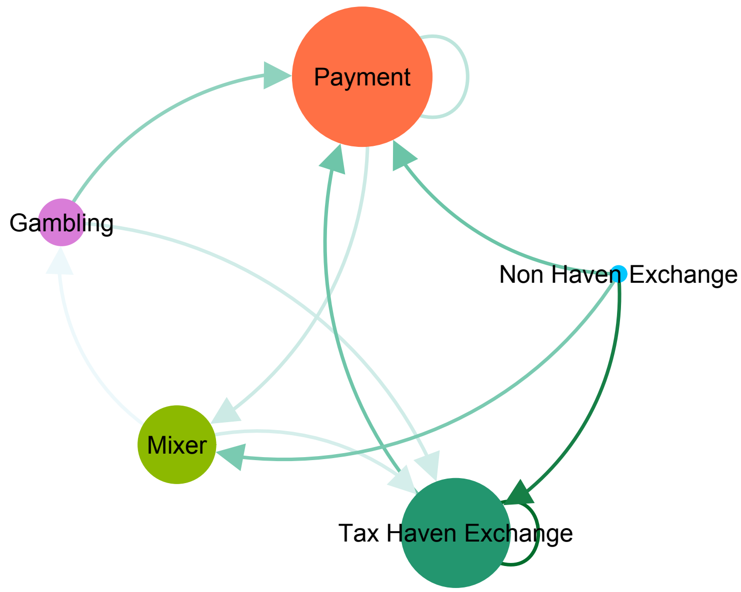
(a) Network One Month Before Aid


SatoshiDice.com
TheRockTrading.com-old
BitBargain.co.uk
LakeBTC.com
Hashnest.com
FYBSG.com
Paymium.com
Vaultoro.com
NegocieCoins.com.br-2
VIP72.com
Cubits.com
Bit-x.com
BlockTrades.us
SafeDice.com
Bitbond.com
BTC-e.com
HaoBTC.com
YABTCL.com
NegocieCoins.com.br
LuckyB.it
BitKonan.com
CoinSpot.com.au
CoinCafe.com
Binance.com-old
Binance.com
CoinPayments
Huobi.com-2
SatoshiCircle.com
CoinMotion.com
HappyCoins.com
BitcoinWallet.com
Luno.com
CoinJar.com
BitoEX.com
Bleutrade.com
999Dice.com
Xapo.com
CrimeNetwork.co-old
SatoshiMines.com
Kraken.com
Bitstamp.net
VirWoX.com
YABTCL
Cryptopay.me
Bittrex.com
Bitcoin.de
Poloniex.com
MercadoBitcoin.com.br
MoonBit.co.in
CoinPayments.net
BitZlato.com
CoinJoinMess
SlushPool.com
Cryptonator.com
BetMoose
999Dice
HolyTransaction.com
BitZino
Non Haven Exchange
Payment
Gambling
Tax Haven Exchange
Mixer

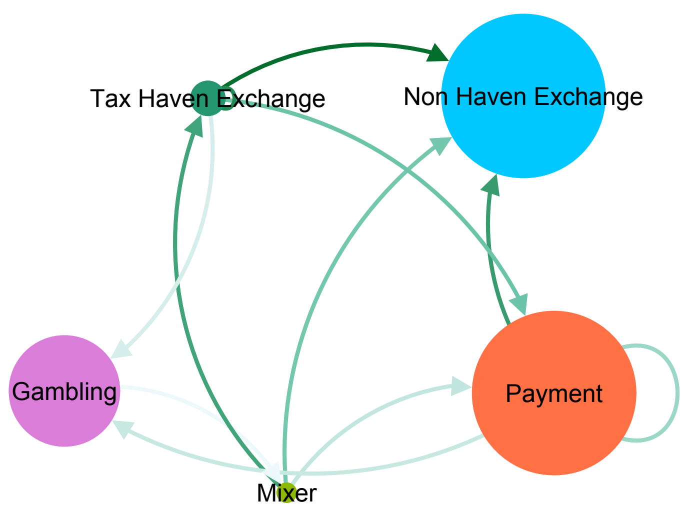


Vircurex.com
BitZino
SatoshiDice.com
BTC-e.com
TheRockTrading.com-old
CrimeNetwork.co
Hashnest.com
CoinMotion.com
SatoshiMines.com
BitcoinWallet.com
Vaultoro.com
SafeDice.com
YABTCL.com
BetMoose
BitcoinWeBank.com
Kraken.com
Bleutrade.com
Cubits.com
FYBSG.com
NegocieCoins.com.br
CoinJoinMess
Paymium.com
HappyCoins.com
Binance.com
VirWoX.com
LakeBTC.com
BitBargain.co.uk
SatoshiCircle.com
Bitbond.com
NegocieCoins.com.br-2
LuckyB.it
CoinPayments
BitoEX.com
Bittrex.com
HolyTransaction.com
CoinCafe.com
CrimeNetwork.co-old
Huobi.com-2
Bitstamp.net
Bitcoin.de
CoinPayments.net
CoinSpot.com.au
BlockTrades.us
CoinJar.com
Bit-x.com
999Dice.com
BitZlato.com
Cryptopay.me
Xapo.com
999Dice
SlushPool.com
HaoBTC.com
Luno.com
Cryptonator.com
MoonBit.co.in
MercadoBitcoin.com.br
Poloniex.com
YABTCL
Non Haven Exchange
Payment
Gambling
Tax Haven Exchange
Mixer

Figure 2. Clustered Network Analysis Around Top Five Aid Disbursements. Larger nodes represent higher centrality, and darker edges indicate greater volume. The figures show changes in network structure around the largest aid disbursements, comparing one week before vs. one week after, and one week before vs. six months after. Colors distinguish service categories: non-tax-haven exchanges (purple), tax-haven exchanges (orange), payment platforms (blue), mixers (pink), and gambling/others (green).



(a) Network Difference One Week Before and After the Top Five Aids



(b) Network Difference One Week Before and Six Months After the Top Five Aids

Figure 3. Stacked DiD: Foreign Aid and Total Web Visits to Crypto-Exchange Websites. This figure plots stacked difference-in-differences estimates of the dynamic response of total web visits to cryptocurrency-related websites around foreign-aid disbursement events. Event time k is measured in months relative to the disbursement month ($k = 0$), with $k = -1$ omitted as the reference period. The outcome is the total number of visits aggregated at the country-month level. The specification includes country fixed effects and month fixed effects, and standard errors are clustered at the country level. Error bars denote 95% confidence intervals.

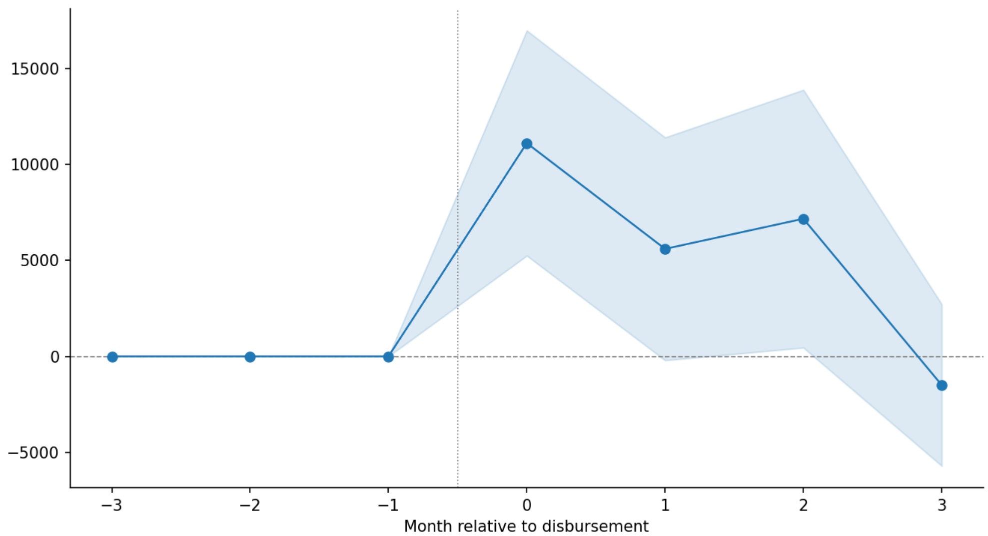


Figure 4. Stacked DiD: Foreign Aid and Total Time Spent on Crypto-Exchange Websites. This figure plots stacked difference-in-differences estimates of the dynamic response of total time spent on cryptocurrency-related websites around foreign-aid disbursement events. Event time k is measured in months relative to the disbursement month ($k = 0$), with $k = -1$ omitted as the reference period. The outcome is the total visit duration (in seconds), aggregated at the country-month level. The specification includes country fixed effects and month fixed effects, and standard errors are clustered at the country level. Error bars denote 95% confidence intervals.

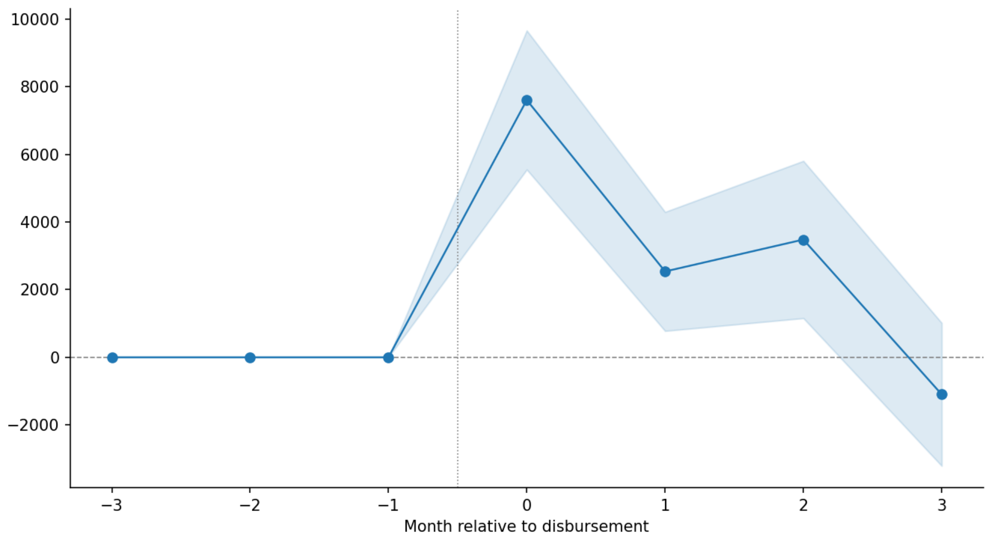


Figure 5. Stacked DiD: Foreign Aid and Geo-Adjusted Bitcoin Transaction Frequency. This figure plots stacked difference-in-differences estimates of the dynamic response of geo-adjusted Bitcoin transaction frequency around foreign-aid disbursement events. Event time k is measured in months relative to the disbursement month ($k = 0$), with $k = -1$ omitted as the reference period. The outcome is constructed by interacting a country's visits ratio with global Bitcoin transaction frequency, yielding an implied country-level measure of transactional activity. The specification includes country fixed effects and month fixed effects, and standard errors are clustered at the country level. Error bars denote 95% confidence intervals.

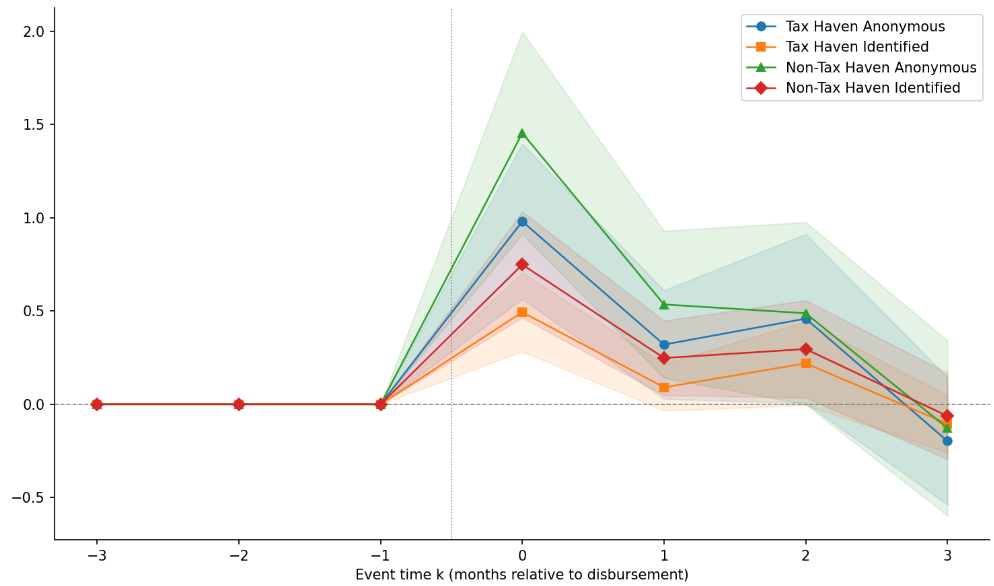


Figure 6. Stacked DiD: Foreign Aid and Geo-Adjusted Bitcoin Transaction Volume. This figure plots stacked difference-in-differences estimates of the dynamic response of geo-adjusted Bitcoin transaction volume around foreign-aid disbursement events. Event time k is measured in months relative to the disbursement month ($k = 0$), with $k = -1$ omitted as the reference period. The outcome is constructed by interacting a country's visits ratio with global Bitcoin transaction volume, yielding an implied country-level measure of transactional activity. The specification includes country fixed effects and month fixed effects, and standard errors are clustered at the country level. Error bars denote 95% confidence intervals.

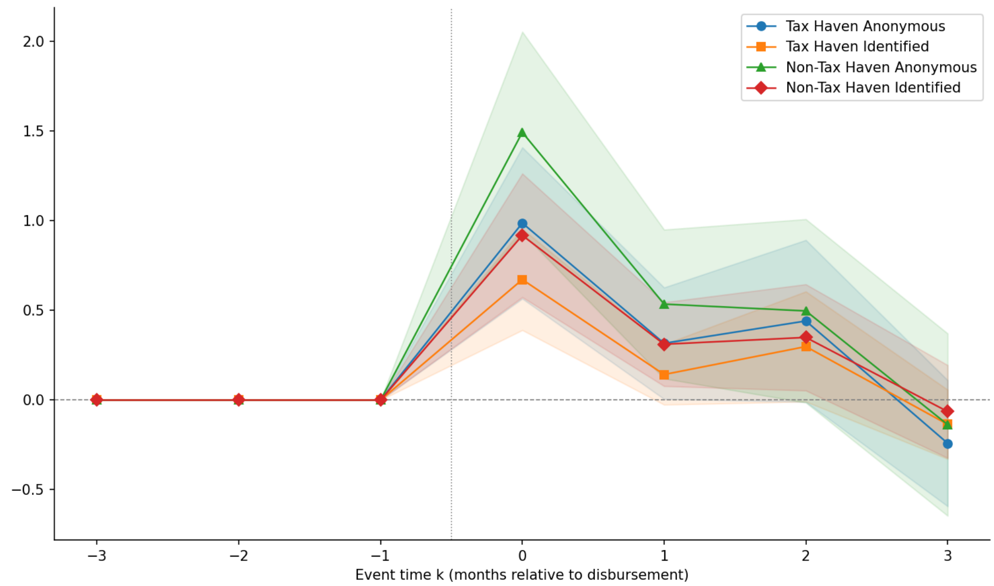
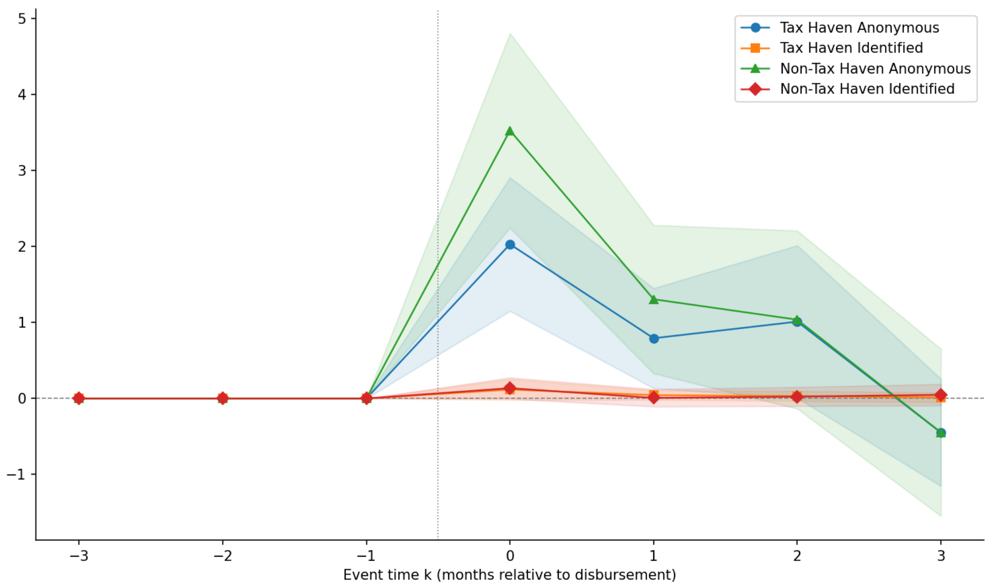


Figure 7. Stacked DiD: Foreign Aid and Geo-Adjusted Number of New Bitcoin Accounts. This figure plots stacked difference-in-differences estimates of the dynamic response of the geo-adjusted number of newly created Bitcoin accounts around foreign-aid disbursement events. Event time k is measured in months relative to the disbursement month ($k = 0$), with $k = -1$ omitted as the reference period. The outcome is constructed by interacting a country's visits ratio with the global number of newly created Bitcoin accounts, yielding an implied country-level measure of account adoption. The specification includes country fixed effects and month fixed effects, and standard errors are clustered at the country level. Error bars denote 95% confidence intervals.



Tables

Table 1. Overview of Aid Recipients. This table summarizes key statistics on aid distribution by country and region, organized in two panels.

Panel A. Top 15 Recipient Countries by Disbursed Aid Amount

Country	Disbursed Amount (in millions)	Fraction
India	8,968.22	0.06
Indonesia	7,726.85	0.05
Colombia	7,116.32	0.05
Ukraine	6,750.47	0.04
Philippines	6,541.72	0.04
Nigeria	5,206.00	0.03
Bangladesh	4,892.92	0.03
Morocco	4,584.78	0.03
Pakistan	4,345.55	0.03
Ethiopia	3,740.17	0.02
Argentina	3,506.50	0.02
Turkiye	3,416.46	0.02
Ecuador	3,373.90	0.02
Egypt, Arab Republic of	3,326.24	0.02
Kenya	3,198.90	0.02
Total	**76,694.99**	**0.50**

Panel B. Regional and Regulatory Distribution

Regulatory Type	Tax Haven	Regulated	Crypto Friendly
Proportion	0.45	0.18	0.70

Table 2. Overview of Crypto Transaction Platforms. This table summarizes key statistics on crypto platform features, organized in two panels.

Panel A. Distribution of Platforms by Number of New Accounts and Volume

Platform	# Accounts (k)	% Accounts	Volume 24h (k)	% Volume
CoinJoinMess	31,404.07	0.77	1,579.36	0.02
Binance	2,135.84	0.05	28,254.06	0.34
Kraken	2,050.89	0.05	20,808.49	0.25
CoinPayments	1,855.92	0.05	539.19	0.01
Luno	1,633.95	0.04	1,164.35	0.01
Huobi	1,229.52	0.03	19,029.29	0.23
Bittrex	495.58	0.01	3,482.29	0.04
YABTCL	16.92	0.00	1.75	0.00
999Dice	13.77	0.00	4.21	0.00
Bitstamp	13.17	0.00	5,639.09	0.07
Xapo	13.12	0.00	670.07	0.01
BetMoose	1.14	0.00	1.20	0.00
HitBTC	0.10	0.00	2.99	0.00
Cex	0.02	0.00	7.42	0.00
BitZino	0.01	0.00	0.06	0.00
Total	40,864.02	1.00	83,300.68	1.00

Panel B. Top Countries by Crypto Exchange Volume

Country	Volume 24h (in thousands)	Fraction
Malta	71,954.47	0.33
Singapore	60,677.21	0.27
Seychelles	26,541.83	0.12
South Korea	12,887.99	0.06
Hong Kong	11,673.39	0.05
UAE	10,125.61	0.05
USA	6,096.03	0.03
Australia	5,757.90	0.03
Estonia	3,793.66	0.02
Cayman Islands	2,792.98	0.01
Total	212,200.07	0.97

Table 3. Top Five Disbursements by Date and Amount. We present the aggregate network dynamics for the five dates with the largest foreign aid distributions between April 2018 and March 2024. This analysis captures the significant impact of these top aid distribution events on the overall network.

Date	Disbursed Amount (in millions)	Receiving Countries
2023-07-25	1,507.40	Tajikistan, Ukraine
2023-11-28	1,443.43	Turkiye, India
2022-12-05	1,386.16	Indonesia, Romania
2020-12-17	1,347.77	Kiribati, Cote d'Ivoire, Nigeria, Uganda, Malawi, Papua New Guinea, Dominican Republic, Uzbekistan, Pakistan, Bosnia and Herzegovina
2023-12-18	1,301.26	Senegal, Sierra Leone, Burkina Faso, India, Albania, North Macedonia, Ukraine, Turkiye

Table 4. Stacked DiD: Foreign Aid and Web Traffic. Stacked DiD. Event time k is months relative to disbursement; $k = -1$ is omitted. Specification absorbs Country×Platform fixed effects and Month fixed effects. Standard errors clustered by Country×Platform. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

	Baseline		**Clean Control**		**All Disbursements**	
Event k	**Total Visits**	**Total Visit Duration (Sec.)**	**Total Visits**	**Total Visit Duration (Sec.)**	**Total Visits**	**Total Visit Duration (Sec.)**
$k = 0$	11,114.582***	7,611.046***	11,493.678***	7,758.452***	11,773.780***	11,209.333***
	(2,993.897)	(1,049.826)	(2,903.031)	(1,112.920)	(2,943.405)	(1,320.615)
$k = 1$	5,601.193*	2,539.079***	7,688.443**	2,766.091***	904.645	3,104.221***
	(2,962.446)	(898.134)	(3,169.776)	(934.579)	(1,017.379)	(830.231)
$k = 2$	7,172.187**	3,482.853***	6,691.472**	3,698.250***	5,871.198**	3,594.383***
	(3,427.360)	(1,186.927)	(3,014.518)	(1,199.914)	(2,512.977)	(938.031)
$k = 3$	-1,492.938	-1,098.231	364.567	-665.968	1,467.704	561.410
	(2,150.487)	(1,079.440)	(2,693.716)	(1,127.734)	(1,132.090)	(775.409)
Country×Platform FE	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓
Obs.	107,310	107,310	103,886	103,886	49,392	49,392
Adj. R^2	0.0032	0.0119	0.0039	0.0142	0.0165	0.0555

Table 6. Impact of Foreign Aid on Transaction Volume across Tax Haven and Non-Tax Haven Crypto Exchanges. This table reports stacked difference-in-differences estimates of the dynamic response of geo-adjusted Bitcoin transaction volume to disaster-related World Bank aid disbursement events. The dependent variable is $\log(1+y)$, where y denotes the geo-adjusted number of transactions; coefficients are interpretable as approximate log-point changes relative to the omitted period $k=-1$. Event time k is measured in months relative to the disbursement month. Columns distinguish transactions by anonymity status (All, Anonymous, Identified) and by exchange jurisdiction (Tax Haven, Non-Tax Haven). Controls include the two-quarter lagged aid amount and the one-quarter lagged global Bitcoin transaction volume. The specification absorbs Country×Platform fixed effects and Month fixed effects. Standard errors, reported in parentheses, are clustered at the Country×Platform level. *$p<0.1$, **$p<0.05$, ***$p<0.01$.

	Crypto Exchanges in Tax Haven			Crypto Exchanges in Non-Tax Haven		
	All	Anonymous	Identified	All	Anonymous	Identified
	Panel A: All Transactions					
$k=0$	1.003***	0.988***	0.673***	1.514***	1.494***	0.919***
	(0.218)	(0.215)	(0.144)	(0.290)	(0.286)	(0.176)
$k=1$	0.323**	0.317**	0.143*	0.544**	0.536**	0.312***
	(0.160)	(0.159)	(0.086)	(0.214)	(0.212)	(0.119)
$k=2$	0.450*	0.441*	0.299*	0.505*	0.497*	0.350**
	(0.234)	(0.230)	(0.157)	(0.263)	(0.261)	(0.151)
$k=3$	-0.242	-0.241	-0.135	-0.139	-0.137	-0.064
	(0.181)	(0.179)	(0.099)	(0.261)	(0.259)	(0.132)
Controls	✓	✓	✓	✓	✓	✓
Country×Platform FE	✓	✓	✓	✓	✓	✓
Obs.	53,655	53,655	53,655	53,655	53,655	53,655
Adj. R^2	0.01	0.01	0.01	0.01	0.01	0.01
	Panel B: Inflows					
$k=0$	0.910***	0.886***	0.628***	1.350***	1.317***	0.861***
	(0.197)	(0.193)	(0.136)	(0.260)	(0.255)	(0.165)
$k=1$	0.279*	0.269*	0.124	0.482**	0.467**	0.288**
	(0.143)	(0.140)	(0.080)	(0.191)	(0.187)	(0.113)
$k=2$	0.406*	0.392*	0.295*	0.463*	0.451*	0.336**
	(0.211)	(0.206)	(0.152)	(0.236)	(0.232)	(0.144)
$k=3$	-0.219	-0.218	-0.117	-0.116	-0.113	-0.057
	(0.163)	(0.161)	(0.091)	(0.234)	(0.232)	(0.125)
Controls	✓	✓	✓	✓	✓	✓
Country×Platform FE	✓	✓	✓	✓	✓	✓
Obs.	53,655	53,655	53,655	53,655	53,655	53,655
Adj. R^2	0.01	0.01	0.01	0.01	0.01	0.01
	Panel C: Outflows					
$k=0$	0.910***	0.903***	0.487***	1.357***	1.348***	0.625***
	(0.198)	(0.196)	(0.108)	(0.262)	(0.260)	(0.124)
$k=1$	0.281**	0.279*	0.074	0.485**	0.482**	0.192**
	(0.143)	(0.143)	(0.064)	(0.192)	(0.191)	(0.081)
$k=2$	0.401*	0.397*	0.197*	0.461*	0.459*	0.234**
	(0.208)	(0.207)	(0.111)	(0.236)	(0.235)	(0.105)
$k=3$	-0.217	-0.217	-0.109	-0.117	-0.117	-0.025
	(0.163)	(0.162)	(0.078)	(0.235)	(0.234)	(0.099)
Controls	✓	✓	✓	✓	✓	✓
Country×Platform FE	✓	✓	✓	✓	✓	✓
Obs.	53,655	53,655	53,655	53,655	53,655	53,655
Adj. R^2	0.01	0.01	0.01	0.01	0.01	0.01

Table 5. Impact of Foreign Aid on Transaction Frequency across Tax Haven and Non-Tax Haven Crypto Exchanges. This table reports stacked difference-in-differences estimates of the dynamic response of geo-adjusted Bitcoin transaction frequency to disaster-related World Bank aid disbursement events. The dependent variable is $\log(1 + y)$, where y denotes the geo-adjusted number of transactions; coefficients are interpretable as approximate log-point changes relative to the omitted period $k = -1$. Event time k is measured in months relative to the disbursement month. Columns distinguish transactions by anonymity status (All, Anonymous, Identified) and by exchange jurisdiction (Tax Haven, Non-Tax Haven). Controls include the two-quarter lagged aid amount and the one-quarter lagged global Bitcoin transaction volume. The specification absorbs Country×Platform fixed effects and Month fixed effects. Standard errors, reported in parentheses, are clustered at the Country×Platform level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	Tax Haven Exchanges			Non-Tax Haven Exchanges		
	All	Anonymous	Identified	All	Anonymous	Identified
Panel A: All Transactions						
$k = 0$	0.985***	0.981***	0.494***	1.464***	1.455***	0.749***
	(0.213)	(0.212)	(0.108)	(0.278)	(0.277)	(0.145)
$k = 1$	0.321**	0.320**	0.091	0.539***	0.536***	0.248**
	(0.149)	(0.149)	(0.064)	(0.202)	(0.201)	(0.102)
$k = 2$	0.462**	0.459**	0.219*	0.492**	0.488*	0.296**
	(0.232)	(0.231)	(0.115)	(0.251)	(0.249)	(0.133)
$k = 3$	-0.198	-0.197	-0.105	-0.129	-0.128	-0.063
	(0.174)	(0.174)	(0.078)	(0.241)	(0.240)	(0.118)
Controls	✓	✓	✓	✓	✓	✓
Country×Platform FE	✓	✓	✓	✓	✓	✓
Obs.	53,655	53,655	53,655	53,655	53,655	53,655
Adj. R^2	0.01	0.01	0.01	0.01	0.01	0.01
Panel B: Inflows						
$k = 0$	0.859***	0.852***	0.440***	1.332***	1.320***	0.679***
	(0.187)	(0.185)	(0.098)	(0.255)	(0.253)	(0.132)
$k = 1$	0.268**	0.266**	0.071	0.484***	0.479***	0.218**
	(0.133)	(0.132)	(0.058)	(0.186)	(0.185)	(0.094)
$k = 2$	0.393**	0.389**	0.196*	0.444*	0.439*	0.275**
	(0.200)	(0.198)	(0.104)	(0.229)	(0.227)	(0.124)
$k = 3$	-0.182	-0.181	-0.095	-0.123	-0.122	-0.059
	(0.158)	(0.157)	(0.070)	(0.224)	(0.223)	(0.108)
Controls	✓	✓	✓	✓	✓	✓
Country×Platform FE	✓	✓	✓	✓	✓	✓
Obs.	53,655	53,655	53,655	53,655	53,655	53,655
Adj. R^2	0.01	0.01	0.01	0.01	0.01	0.01
Panel C: Outflows						
$k = 0$	0.915***	0.913***	0.362***	1.266***	1.259***	0.521***
	(0.197)	(0.196)	(0.084)	(0.241)	(0.240)	(0.104)
$k = 1$	0.285**	0.284**	0.052	0.467***	0.465***	0.167**
	(0.131)	(0.130)	(0.048)	(0.172)	(0.171)	(0.073)
$k = 2$	0.429**	0.428**	0.152*	0.449**	0.447**	0.207**
	(0.214)	(0.213)	(0.082)	(0.215)	(0.214)	(0.093)
$k = 3$	-0.169	-0.169	-0.071	-0.092	-0.091	-0.024
	(0.155)	(0.154)	(0.059)	(0.202)	(0.201)	(0.088)
Controls	✓	✓	✓	✓	✓	✓
Country×Platform FE	✓	✓	✓	✓	✓	✓
Obs.	53,655	53,655	53,655	53,655	53,655	53,655
Adj. R^2	0.01	0.01	0.01	0.01	0.01	0.01

Table 7. Impact of Foreign Aid on New Bitcoin Accounts across Tax Haven and Non-Tax Haven Crypto Exchanges. This table reports stacked difference-in-differences estimates of the dynamic response of geo-adjusted Bitcoin accounts creation to disaster-related World Bank aid disbursement events. The dependent variable is $\log(1 + y)$, where y denotes the geo-adjusted number of transactions; coefficients are interpretable as approximate log-point changes relative to the omitted period $k = -1$. Event time k is measured in months relative to the disbursement month. Columns distinguish transactions by anonymity status (All, Anonymous, Identified) and by exchange jurisdiction (Tax Haven, Non-Tax Haven). Controls include the two-quarter lagged aid amount and the one-quarter lagged global Bitcoin transaction volume. The specification absorbs Country×Platform fixed effects and Month fixed effects. Standard errors, reported in parentheses, are clustered at the Country×Platform level. $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	Crypto Exchanges in Tax Haven			Crypto Exchanges in Non-Tax Haven		
	All	Anonymous	Identified	All	Anonymous	Identified
	Panel A: All Transactions					
$k = 0$	2.029***	2.029***	0.117*	3.525***	3.525***	0.136*
	(0.448)	(0.448)	(0.070)	(0.653)	(0.653)	(0.071)
$k = 1$	0.792**	0.792**	0.044	1.305***	1.305***	0.008
	(0.335)	(0.335)	(0.032)	(0.498)	(0.498)	(0.058)
$k = 2$	1.011**	1.011**	0.032	1.037*	1.037*	0.025
	(0.512)	(0.512)	(0.034)	(0.597)	(0.597)	(0.064)
$k = 3$	-0.446	-0.446	0.014	-0.446	-0.446	0.048
	(0.360)	(0.360)	(0.032)	(0.561)	(0.561)	(0.072)
Controls	✓	✓	✓	✓	✓	✓
Country×Platform FE	✓	✓	✓	✓	✓	✓
Obs.	53,655	53,655	53,655	53,655	53,655	53,655
Adj. R^2	0.01	0.01	0.01	0.01	0.01	0.01
	Panel B: Inflows					
$k = 0$	1.898***	1.898***	0.027*	3.429***	3.429***	0.064
	(0.421)	(0.421)	(0.015)	(0.636)	(0.636)	(0.058)
$k = 1$	0.734**	0.734**	0.025	1.263***	1.263***	0.011
	(0.319)	(0.319)	(0.018)	(0.486)	(0.486)	(0.049)
$k = 2$	0.932**	0.932**	-0.002	0.995*	0.995*	0.022
	(0.474)	(0.474)	(0.013)	(0.579)	(0.579)	(0.048)
$k = 3$	-0.437	-0.437	0.007	-0.449	-0.449	0.028
	(0.343)	(0.343)	(0.013)	(0.549)	(0.549)	(0.056)
Controls	✓	✓	✓	✓	✓	✓
Country×Platform FE	✓	✓	✓	✓	✓	✓
Obs.	53,655	53,655	53,655	53,655	53,655	53,655
Adj. R^2	0.01	0.01	0.01	0.02	0.02	0.02
	Panel C: Outflows					
$k = 0$	1.960***	1.960***	0.092	3.255***	3.255***	0.066
	(0.430)	(0.430)	(0.068)	(0.601)	(0.601)	(0.049)
$k = 1$	0.759**	0.759**	0.017	1.224***	1.224***	0.014
	(0.313)	(0.313)	(0.029)	(0.453)	(0.453)	(0.041)
$k = 2$	0.978**	0.978**	0.034	0.980*	0.980*	0.006
	(0.490)	(0.490)	(0.030)	(0.547)	(0.547)	(0.038)
$k = 3$	-0.398	-0.398	0.007	-0.376	-0.376	0.023
	(0.335)	(0.335)	(0.025)	(0.507)	(0.507)	(0.048)
Controls	✓	✓	✓	✓	✓	✓
Country×Platform FE	✓	✓	✓	✓	✓	✓
Obs.	53,655	53,655	53,655	53,655	53,655	53,655
Adj. R^2	0.01	0.01	0.01	0.01	0.01	0.01

Table 8. Effect of Foreign Aid on Quarterly Difference in Off-chain Transaction and Ratio Compared with Benchmark Platforms (Coinbase, Kraken, and Gemini). "With" refers to jurisdictions classified as Tax Haven, Unregulated, or Crypto-Friendly, depending on the panel. "Without" refers to Non-Haven, Regulated, or Not Friendly jurisdictions. Columns 1-3 report the effect on transaction; columns 4-6 report the effect on volume ratios. We control the two-quarter lagged foreign aid amount and one-quarter lagged BTC volume, cluster the standard error by the aided country, and add time and aided country fixed effects. Coefficients are multiplied by 100. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

	Lead - Lag			**Lead - Lag Ratio**		
	With	Withoutn	Δ	With	Without	Δ
Panel A: Tax Haven vs. Non-Haven						
Foreign Aid$_{lagged}$	2.39***	1.51	0.88***	0.39***	−0.03	0.42***
	(0.55)	(1.16)	(0.31)	(0.11)	(0.14)	(0.02)
Controls	✓	✓		✓	✓	
Country FE	✓	✓		✓	✓	
Time FE	✓	✓		✓	✓	
Obs.	1,727	1,727		1,727	1,727	
Adj. R^2	0.29	0.21		0.39	0.14	
Panel B: Unregulated vs. Regulated						
Foreign Aid$_{lagged}$	2.38***	1.97***	0.41***	0.37**	0.03***	0.34***
	(0.64)	(0.55)	(0.05)	(0.16)	(0.01)	(0.08)
Controls	✓	✓		✓	✓	
Country FE	✓	✓		✓	✓	
Time FE	✓	✓		✓	✓	
Obs.	1,727	1,727		1,727	1,727	
Adj. R^2	0.25	0.19		0.29	0.21	
Panel C: Crypto-Friendly vs. Not Friendly						
Foreign Aid$_{lagged}$	2.41***	1.47**	0.94***	0.39**	−0.00	0.39***
	(0.64)	(0.58)	(0.03)	(0.16)	(0.00)	(0.08)
Controls	✓	✓		✓	✓	
Country FE	✓	✓		✓	✓	
Time FE	✓	✓		✓	✓	
Obs.	1,727	1,727		1,727	1,727	
Adj. R^2	0.25	0.37		0.29	0.50	

Table 9. Heterogeneity Analysis of the Impact of Foreign Aid on Volumes Based on CPIA, Domestic Credit, Control for Corruption, and Disclosure Levels. The *High* group consists of observations where the dimension value exceeds the median, while the *Low* group includes those with values below the median. The results indicate that countries with lower levels of CPIA, domestic credit, control over corruption, and disclosure experience a more pronounced increase in crypto volumes in response to foreign aid. In contrast, the effects in the *High* group are either smaller or statistically insignificant. We control the two-quarter lagged foreign aid amount and one-quarter lagged BTC volume, cluster the standard error by the aided country, and add time and aided country fixed effects. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	CPIA		Domestic credit		Control corrupt		Disclosure	
	High	Low	High	Low	High	Low	High	Low
Foreign Aid $_{lagged}$	0.03	0.03***	0.02	0.03***	0.02**	0.03***	0.01	0.12***
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.04)	(0.04)
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Country FE	✓	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓
# Obs	267	701	736	605	696	691	53	152
Adj. R^2	0.35	0.29	0.30	0.28	0.46	0.29	0.40	0.45

Table 10 Panel A: IV Analysis: Impact of Foreign Aid on Transaction Frequency across Tax Haven and Non-tax Haven Crypto Exchanges. This table shows the effect of foreign aid on the one-quarter lagged total number of transactions (by all addresses, anonymous, and non-anonymous addresses) across crypto exchanges in tax haven and non-tax haven jurisdictions. Both dependent and independent variables are transformed using the natural logarithm. We control the two-quarter lagged foreign aid amount and one-quarter lagged BTC volume, cluster the standard error by the aided country, and add a time-fixed effect. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

	Crypto Exchanges in Tax Haven			All Crypto Exchanges		
	All Wallets	Anonymous	Identified	All Wallets	Anonymous	Identified
	All Transactions					
Foreign Aid $_{lagged}$	0.06**	0.06**	−0.00	0.02	0.02	−0.01
	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Controls	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓
Obs	4,441	4,441	4,441	4,441	4,441	4,441
R-squared	0.80	0.79	0.96	0.88	0.86	0.95
	Inflows					
Foreign Aid $_{lagged}$	0.04**	0.05**	−0.02	0.02	0.02	−0.01
	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)
Controls	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓
Obs	4,441	4,441	4,441	4,441	4,441	4,441
R-squared	0.79	0.74	0.95	0.78	0.74	0.95
	Outflows					
Foreign Aid $_{lagged}$	0.07***	0.07***	0.04**	0.02	0.02	−0.01
	(0.03)	(0.03)	(0.02)	(0.01)	(0.01)	(0.01)
Controls	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓
Obs	4,441	4,441	4,441	4,441	4,441	4,441
R-squared	0.80	0.80	0.86	0.92	0.91	0.94

Table 10 Panel B: IV Analysis: Impact of Foreign Aid on New Bitcoin Accounts across Tax Haven and Non-tax Haven Crypto Exchanges. This table shows the effect of foreign aid on the quarterly difference in the on-chain number of new accounts (by all addresses, anonymous, and non-anonymous addresses) across crypto exchanges in tax haven and non-tax haven jurisdictions using IV analysis. Both dependent and independent variables are transformed using the natural logarithm. We control the two-quarter lagged foreign aid amount and one-quarter lagged BTC volume, cluster the standard error by the aided country, and add a time-fixed effect. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

	Crypto Exchanges in Tax Haven			All Crypto Exchanges		
	All Wallets	Anonymous	Identified	All Wallets	Anonymous	Identified
			All Transactions			
Foreign Aid $_{lagged}$	0.07**	0.07**	−0.32**	0.00	0.00	−0.27**
	(0.03)	(0.03)	(0.14)	(0.02)	(0.02)	(0.13)
Controls	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓
Obs	4,441	4,441	4,441	4,441	4,441	4,441
R-squared	0.88	0.88	0.38	0.90	0.90	0.54
			Inflows			
Foreign Aid $_{lagged}$	0.04	0.04**	−0.55***	−0.00	−0.02	−0.84***
	(0.03)	(0.02)	(0.19)	(0.01)	(0.01)	(0.29)
Controls	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓
Obs	4,441	4,441	4,441	4,441	4,441	4,441
R-squared	0.89	0.81	−0.25	0.88	0.48	−1.20
			Outflows			
Foreign Aid $_{lagged}$	0.10***	0.10***	0.13	0.00	0.00	0.26
	(0.04)	(0.04)	(0.14)	(0.02)	(0.02)	(0.18)
Controls	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓
Obs	4,441	4,441	4,441	4,441	4,441	4,441
R-squared	0.86	0.86	0.56	0.91	0.91	0.36

Table 11. Effect of Foreign Aid on Crypto Transaction Around Election in Brazil This table shows the effect of foreign aid on the quarterly difference in the on-chain transactions (by all addresses, anonymous, and non-anonymous addresses) around the election in Brazil in 2018. The estimation covers a 10-month window before and after national elections. Both dependent and independent variables are transformed using the natural logarithm. We control the two-quarter lagged foreign aid amount and one-quarter lagged BTC transaction volume, cluster the standard error by the aided country, and add time fixed effects. Coefficients are multiplied by 100. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

	10-Month Period Before Election			10-Month Period After Election		
	All Wallets	Anonymous	Identified	All Wallets	Anonymous	Identified
Panel A: Transaction Frequency						
Foreign Aid $_{lagged}$	3.90***	4.03***	1.59***	-0.07	-0.07	-0.15
	(0.30)	(0.30)	(0.20)	(0.37)	(0.37)	(0.22)
Controls	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓
Obs	345	345	345	597	597	597
Adj. R^2	0.572	0.573	0.657	0.646	0.648	0.448
Panel B: New Accounts Creation						
Foreign Aid $_{lagged}$	5.06***	5.06***	-7.00***	-0.21	-0.21	-1.85
	(0.38)	(0.38)	(0.50)	(0.78)	(0.78)	(1.88)
Controls	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓
Obs	345	345	345	597	597	597
Adj. R^2	0.566	0.566	0.567	0.630	0.630	0.160

Appendix: Crypto Capture of Foreign Aid

Agarwal, Jin, Prasad, and Rabetti – March 2026

Appendix

A Network Analysis: Nigeria

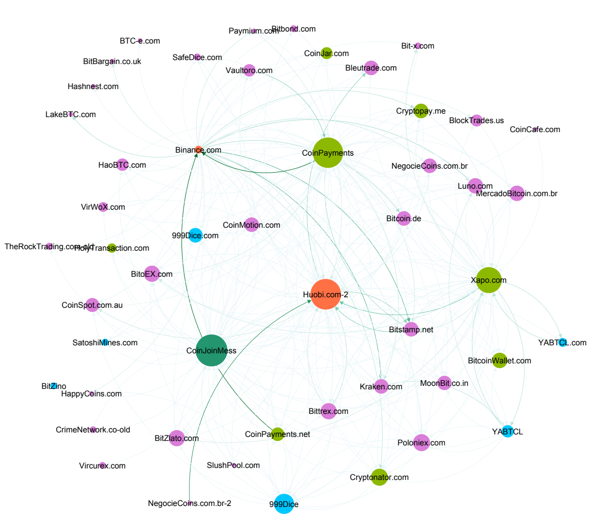
This appendix provides a visual, case-based illustration of how crypto transaction networks evolve around large foreign-aid disbursements, focusing on Nigeria as a representative high-volume recipient country. Nigeria experienced several large World Bank disbursement episodes during our sample period and features a diverse ecosystem of regulated exchanges, offshore platforms, and intermediary services, making it well suited for network-based analysis.

The figures construct directed transaction networks using wallet- and platform-level on-chain data aggregated over short event windows around the five largest aid disbursements to Nigeria. Nodes represent crypto platforms or services (exchanges, payment platforms, mixers, gambling services, and others), and directed edges represent aggregated transaction flows between nodes within the event window. Node size reflects platform centrality in the transaction network, while edge width is proportional to transfer volume. Platforms are color-coded by service category and jurisdictional status, with particular emphasis on tax haven versus non-tax haven exchanges.

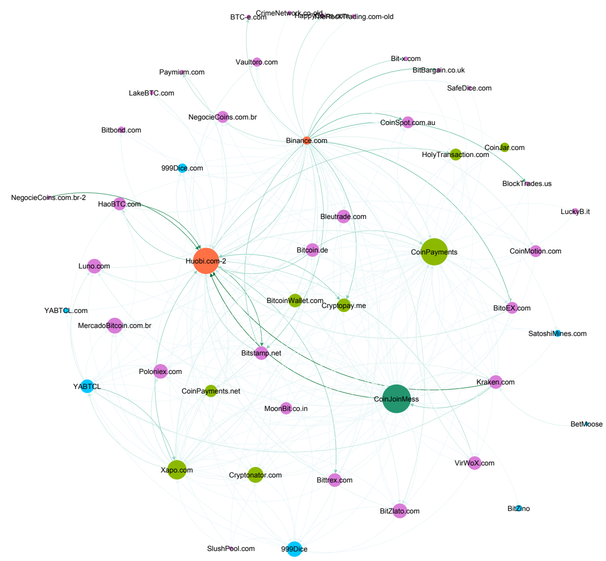
Figure A.1 plots the average network structure one month before, one month after, and six months after the largest aid disbursement events. Relative to the pre-disbursement period, the post-disbursement network exhibits a marked increase in transaction volume and connectivity, particularly toward tax haven exchanges and among exchange-to-exchange links. This pattern is consistent with a temporary intensification of intermediary activity following aid receipt. Six months after disbursement, overall network density and flow intensity decline, with the structure reverting toward pre-disbursement levels.

Figure A.2 presents network-difference graphs that directly contrast transaction flows before and after the largest aid episode. The left panel highlights changes between one week before and one week after the disbursement, while the right panel compares one week before to six months after. These difference plots emphasize that the post-aid surge is concentrated in short-run increases in flows involving exchanges—especially offshore platforms—rather than persistent, long-run reconfiguration of the network.

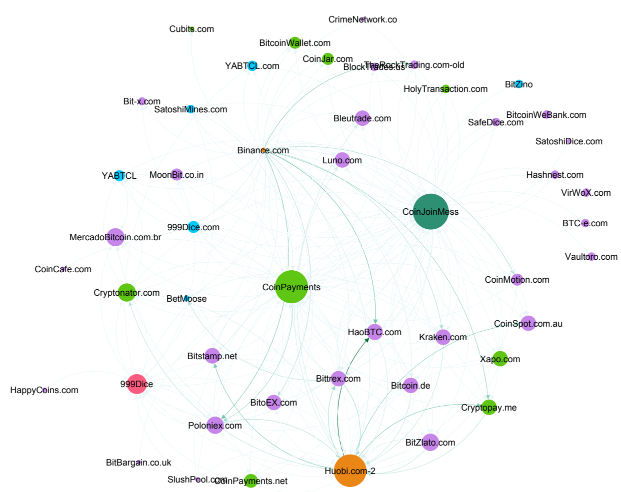
Figure A.1. Network Analysis: Largest Aid (Nigeria). The figures show the average network one month before, one month after, and six months after the top five disbursement dates. The width of arrows represents transfer magnitudes; node sizes represent platform centrality. Non-tax haven exchanges are purple, tax haven exchanges are orange, payment platforms are blue, mixers are pink, and gambling/others are green. Compared to the pre-disbursement period, post-disbursement networks exhibit greater transfer volume toward tax havens and intensified flows among exchanges, while six months later, the network reverts to lower activity.



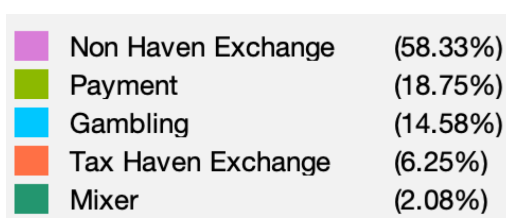
(a) One month before the aid



(b) One month after the aid

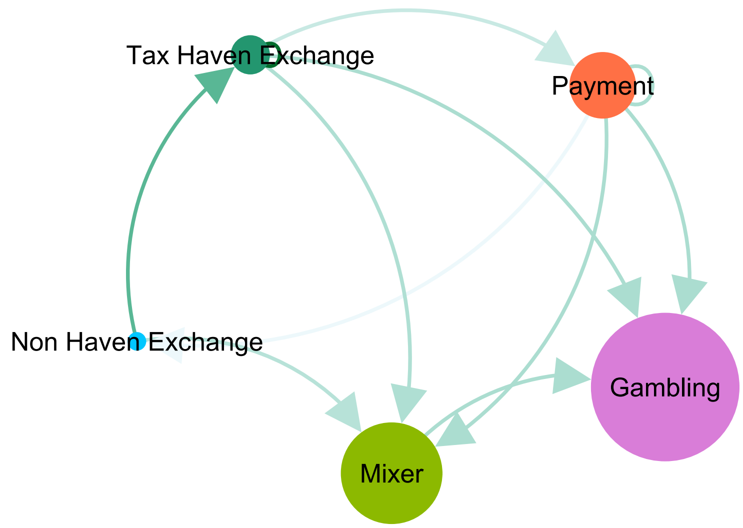


(c) Six months after the aid

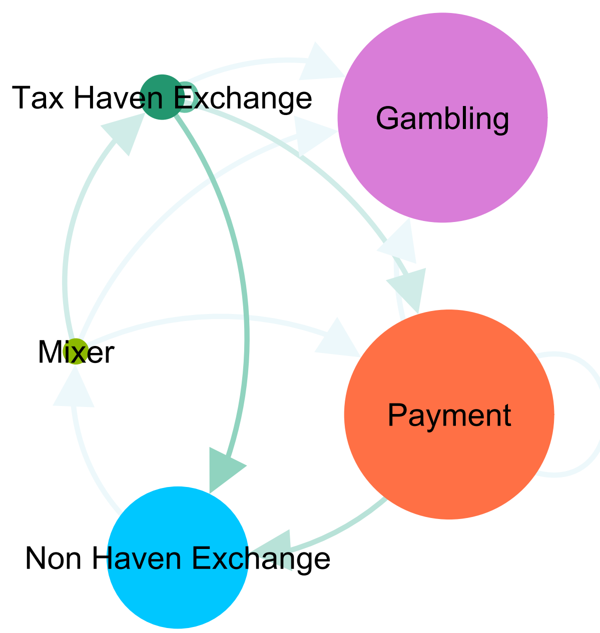


Service Category Color Legend

Figure A.2. Network Differences: Largest Aid (Nigeria). These plots show the differences in network structures before and after major aid disbursements. The left panel compares one week before and one week after the largest aid event, while the right panel compares one week before and six months after. Color coding follows the same convention: non-tax haven exchanges (purple), tax haven exchanges (orange), payment platforms (blue), mixers (pink), gambling and others (green).



Network Difference One Week Before and After the Largest Aid



Network Difference One Week Before and Six Months After the Largest Aid

B Global Redistribution Patterns

Figure A.3 presents global patterns in cryptocurrency volumes across major jurisdictions surrounding the top five foreign aid disbursement dates. In tax haven exchanges such as the Cayman Islands, Luxembourg, Malta, and Singapore, we observe a sharp but short-lived increase in volume within the first ten days following the receipt of aid. As a credible benchmark for detecting abnormal activity in offshore exchanges, the United States also exhibits an immediate rise in volume following aid receipt.

To unpack the distinctive role of U.S. exchanges, we compare weekly volumes between the United States and a composite of tax haven jurisdictions in Figure A.4. Spikes in U.S. volume, defined as weeks in which volume exceeds both twice the eight-week rolling average and a fixed threshold (150,000 Bitcoins), frequently occur in the absence of any corresponding increase among tax haven exchanges. This lack of co-movement suggests that U.S. exchanges serve a structurally different purpose in the transaction pipeline. Specifically, rather than serving as endpoints for redistributed aid, U.S. platforms appear to function as strategic entry points that facilitate initial fiat-to-crypto conversion under regulatory oversight.

Figure A.3. Global Volume Shifts Around Top Five Foreign Aid Disbursement Dates. This figure shows changes in cryptocurrency volumes across jurisdictions surrounding the largest foreign aid disbursements. Notably, transaction activity increases significantly on U.S.-based exchanges immediately following aid inflows. These platforms, such as Coinbase and Kraken, serve as strategic fiat-to-crypto on-ramps, providing regulated liquidity and establishing a verifiable on-chain origin for transactions. While initially transparent, aid-linked flows often transition from compliant exchanges to self-hosted wallets, offshore exchanges, or mixers, complicating traceability. The observed patterns highlight the dual role of regulated platforms: enabling legitimate access to crypto markets while also offering a launch point for subsequent obfuscation strategies.

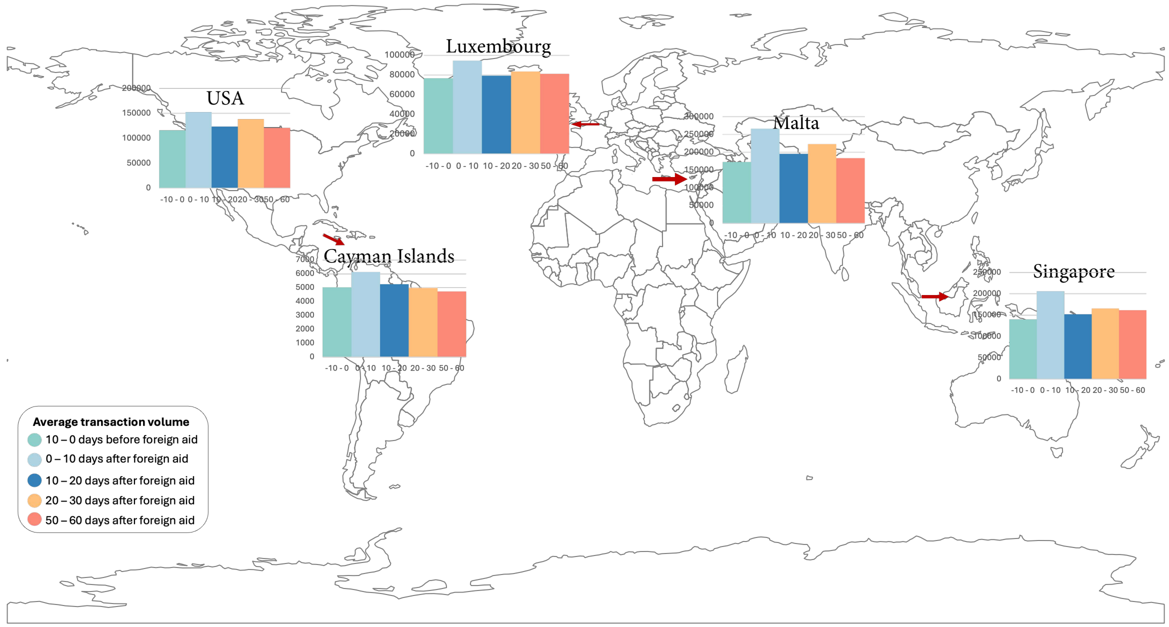
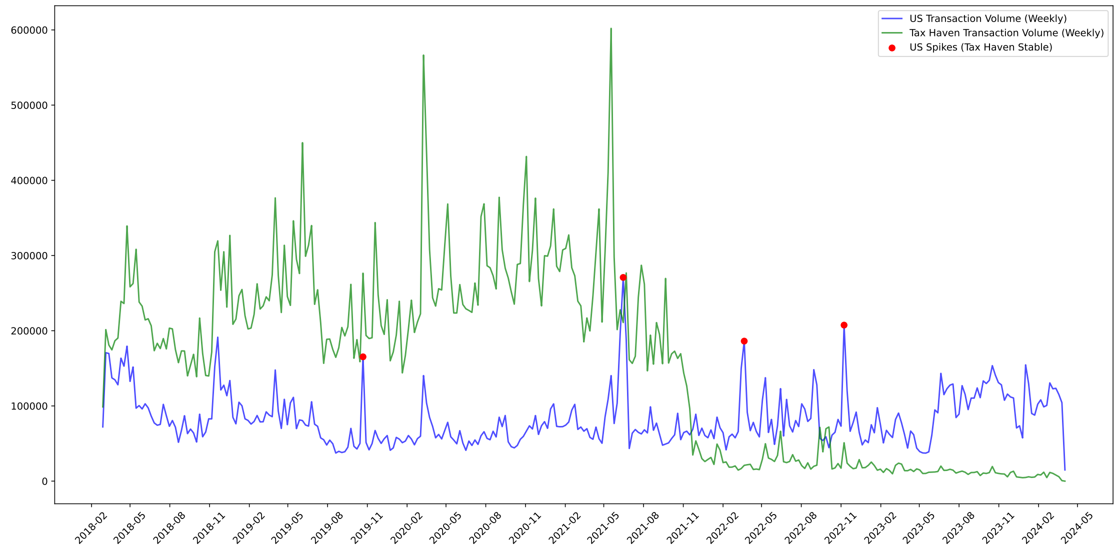


Figure A.4. U.S. vs. Tax Haven Crypto Volume Trend. This figure shows weekly cryptocurrency volumes for the United States (blue) and tax haven jurisdictions (green). Red dots indicate U.S. volume spikes without corresponding spikes in tax havens.



C Variable Descriptions

This appendix summarizes the key variables used in the empirical analysis and provides definitions for the main outcomes, treatments, and classifications employed throughout the paper. Table A.1 reports variable names and descriptions, covering foreign aid disbursements, cryptocurrency transaction outcomes, wallet classifications, exchange characteristics, and country-level controls.

The primary explanatory variable is foreign aid disbursement, measured at the quarterly level and lagged by one quarter to align with the timing of on-chain responses. The main outcome variables capture different dimensions of cryptocurrency activity, including transaction volume, transaction frequency (transaction times), and the number of newly created wallet addresses. These outcomes are analyzed in logarithmic form to reduce sensitivity to extreme values and to facilitate interpretation of dynamic responses in the stacked event-study framework.

Wallets are classified as anonymous or identified based on whether they are linked to a platform or verified entity, allowing us to distinguish opaque from traceable transaction channels. Exchanges are further categorized by tax-haven status, regulatory environment, and jurisdictional attitudes toward cryptocurrency adoption. These classifications support heterogeneity analyses that contrast activity on offshore versus regulated platforms.

To benchmark exchange-specific activity, we construct comparison measures using major regulated exchanges (Coinbase, Kraken, and Gemini). Lead–lag transformations of both level and ratio outcomes are used to study short-run changes around aid disbursement events, capturing dynamic adjustments rather than long-run differences.

Finally, the table lists country-level covariates drawn from external sources, including governance quality (CPIA and Control of Corruption), financial development (Domestic Credit), and disclosure practices. These controls are used in auxiliary specifications and robustness checks to account for cross-country differences in institutional quality and financial infrastructure.

Table A.1. Variable Definitions and Descriptions

Variable	Description
Foreign Aid	Total foreign aid disbursement (lagged by one quarter) used as the main independent variable.
Transaction Volume	Value of cryptocurrency transactions on a given platform or within a region (log-transformed).
Transaction Times	Number of cryptocurrency transactions (log-transformed).
Number of New Accounts	Number of newly created wallet addresses (log-transformed).
Anonymous / Identified	Classification of wallets based on ID verification status: anonymous or platform-verified.
Tax Haven / Non-Haven	Exchange classification based on tax jurisdiction status.
Regulated / Unregulated	Classification according to regulation by major financial authorities.
Crypto-Friendly / Not Friendly	Classification based on the jurisdiction's policy attitude toward cryptocurrency.
Benchmark	Transaction volume on benchmark exchanges (Coinbase, Kraken, and Gemini).
Lead-Lag Level Change	One-quarter difference in outcome variable (log-transformed).
Lead-Lag Ratio Change	Difference in log transaction ratios: $\log\left(\frac{EX_t}{BM_t}\right) - \log\left(\frac{EX_{t-1}}{BM_{t-1}}\right)$.
CPIA	Country Policy and Institutional Assessment (CPIA) score from the World Bank; higher values indicate stronger governance.
Domestic Credit	Domestic credit to the private sector as a percentage of GDP; proxy for financial development.
Control of Corruption	World Governance Indicator reflecting the strength of anti-corruption mechanisms; higher values indicate stronger control.
Disclosure	Index measuring public financial disclosure and transparency practices.

D Off-Chain Transaction Analysis

D.1 Huobi Effect

We observe that Singapore, a crypto-friendly jurisdiction with moderate regulatory oversight, shows a particularly strong response to foreign aid inflows after May 2021. This period coincides with Huobi's decision to shift its operational headquarters to Singapore. Singapore has long served as a favorable hub for regulatory arbitrage in crypto markets, thanks in part to its Payment Services Act (PSA), which requires licensing for firms serving local clients but permits significant operational flexibility for firms targeting international users. This regulatory environment makes Singapore an attractive jurisdiction for exchanges seeking legitimacy without stringent capital controls. To isolate the impact of this event, Table A.2 reports estimates from a case study comparing transaction activity across several offshore jurisdictions, with Singapore further disaggregated to examine the "Huobi Effect".

Notably, Huobi remained formally incorporated in Seychelles during this period, creating ambiguity over which regulatory regime held effective oversight. Nonetheless, the shift in operational activity to Singapore coincided with a measurable uptick in local transaction volume. Table A.2 reports the "Huobi Effect" calculated as the difference in transaction activity between Singapore exchanges that include Huobi and those that do not, following Huobi's relocation from Seychelles to Singapore in mid-2021. The coefficients—0.04 for transaction counts and 0.02 for transaction ratios—are small but statistically significant. This suggests that Huobi's presence contributes modestly, but measurably, to the post-aid increase in activity observed in Singapore. Rather than driving the entire Singapore effect, Huobi appears to amplify existing flows, reinforcing the role of major exchanges in shaping off-chain responses to foreign aid.

This case study highlights how large exchanges can drive aggregate patterns, particularly when they act as de facto offshore venues despite nominally operating under regulated jurisdictions. Huobi's role during this period may reflect its function as a semi-offshore platform that absorbed flows that might otherwise have been routed to more opaque jurisdictions. These findings highlight that, while our cross-country classifications are broadly predictive, the presence and behavior of major exchange entities can meaningfully shape the transmission of financial flows following aid disbursements.

Table A.2. Huobi Effect. This table estimates the Huobi Effect by comparing transaction differences between all Singapore-based exchange platforms and those excluding Huobi, from May 2021 to April 2024. The results are benchmarked against tax-haven countries. May 2021 marks Huobi's headquarters relocation from Seychelles to Singapore. The regressions control for the two-quarter lagged foreign aid amount and one-quarter lagged BTC volume, include time and country fixed effects, and cluster standard errors at the aided-country level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	Hong Kong	Singapore	Seychelles	Islands	Malta	Huobi Effect
	(coefficients multiplied by hundreds)					
Panel A: Lead - lag						
Foreign Aid $_{lagged}$	3.35***	1.71***	2.80***	3.87***	1.90***	0.04
	(0.704)	(0.62)	(0.57)	(0.85)	(0.52)	(0.13)
Controls	✓	✓	✓	✓	✓	✓
Country FE	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓
# Obs	1,727	1,727	1,727	1,727	1,727	867
Adj. R^2	0.22	0.39	0.33	0.31	0.38	0.87
Panel B: Lead - lag ratio						
Foreign Aid $_{lagged}$	0.25***	0.01	0.16***	0.04**	0.18**	0.02**
	(0.06)	(0.03)	(0.04)	(0.02)	(0.08)	(0.01)
Controls	✓	✓	✓	✓	✓	✓
Country FE	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓
# Obs	1,727	1,727	1,727	1,727	1,727	867
Adj. R^2	0.47	0.27	0.29	0.56	0.15	0.87

E Robustness and Extensions

E.1 Sampling

To ensure that our results are not driven by extraordinary market-wide dynamics, we re-estimate our main specifications excluding the DeFi boom period between May and September 2021. This period was characterized by unusually high speculative activity and rapid growth in decentralized finance platforms, which could confound the interpretation of aid-related crypto flows.

Table A.3. Impact of Foreign Aid on New Account Creation and Transaction Frequency in Tax Haven Exchanges (Excluding DeFi Boom Period: 1 May to 1 September 2021). This table presents the effect of foreign aid on the quarterly change in on-chain volume for all, anonymous, and identified addresses. All dependent and independent variables are in natural logarithms. The regressions control for two-quarter lagged foreign aid and one-quarter lagged BTC volume. Standard errors are clustered at the country level, and time fixed effects are included. Coefficients are multiplied by 100. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	All Transactions			Inflows			Outflows		
	All Wallets	Anonymous	Identified	All Wallets	Anonymous	Identified	All Wallets	Anonymous	Identified
Panel A: Transaction Frequency									
Foreign Aid$_{\text{lagged}}$	0.32***	0.33***	0.01	0.20**	0.23**	-0.16	0.44***	0.44***	0.35***
	(0.12)	(0.12)	(0.09)	(0.10)	(0.10)	(0.10)	(0.14)	(0.14)	(0.11)
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Obs.	4,415	4,415	4,415	4,415	4,415	4,415	4,415	4,415	4,415
Adj. R^2	0.92	0.92	0.96	0.90	0.89	0.96	0.93	0.93	0.92
Panel B: Number of New Accounts									
Foreign Aid$_{\text{lagged}}$	0.42*	0.42*	-0.99	0.19	0.19	-0.87	0.65**	0.65**	0.02
	(0.23)	(0.23)	(1.06)	(0.20)	(0.20)	(0.99)	(0.27)	(0.27)	(1.00)
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Obs.	4,415	4,415	4,415	4,415	4,415	3,443	4,415	4,415	4,415
Adj. R^2	0.93	0.93	0.57	0.92	0.92	0.60	0.93	0.93	0.59