Crypto Capture of Foreign Aid*

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Abstract

This paper investigates whether cryptocurrencies have become a new conduit for laundering diverted foreign aid. Using World Bank aid disbursement data from 2018 to 2024, linked with forensically tagged on-chain Bitcoin transactions and off-chain exchange activity, we document systematic surges in crypto transactions for anonymous wallets after disbursements, especially on exchanges located in tax haven jurisdictions. A one-standard-deviation increase in lagged aid is associated with a 0.10 log-point rise in anonymous transactions on tax haven exchanges—approximately a 11% increase—concentrated in newly created wallets and fading within two quarters. Network analysis reveals a real-time laundering pattern: funds flow through regulated platforms, then through mixers and tax haven exchanges, mirroring the classic placement, layering, and integration stages. Off-chain data confirm spikes in transactions on suspect, lightly regulated platforms. To address endogeneity in aid allocation, we use an IV strategy based on historical aid shares interacted with governance quality. Overall, our findings suggest that cryptocurrencies are increasingly used for offshore banking in concealing aid diversion. Our study shows how blockchain forensics can trace hidden financial flows and offers new tools for anti-corruption and crypto regulation.

JEL classification: G15, G18, G29, K29, K42, O16.

Keywords: Foreign aid, money laundering, tax haven, cryptocurrency, blockchain forensics.

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1 Introduction

Foreign aid is meant to support development and welfare, yet much is siphoned off by elites for private gain (e.g., Reinikka and Svensson, 2004). Recent evidence shows large sums flow to offshore accounts controlled by recipients (Andersen et al., 2022), echoing leaks like the Panama Papers, which exposed hidden wealth in shell companies and tax havens.

Increased scrutiny of traditional tax havens since the Panama Papers has raised the risks for elites in aid-dependent countries seeking to hide stolen funds (Cong et al., 2023b). This prompts the question: are corrupt elites turning to cryptocurrencies as a substitute for laundering aid? Cryptocurrencies offer fast, decentralized, and pseudonymous transfers that are difficult to trace (Cong et al., 2025b). Funds can be split across thousands of anonymous wallets and easily off-ramped through a growing network of exchanges, many based in tax havens. These jurisdictions, long associated with enabling money laundering and the concealment of assets, often host exchanges with weaker Know-Your-Customer (KYC) enforcement (see Force (2021); Cong et al. (2023b)). These features have attracted illicit actors, with early research estimating that around 46% of Bitcoin transactions (valued at approximately $76 billion annually) involve illegal trade and about one-quarter of users participate in such activity (Foley et al., 2019). However, the laundering of foreign aid through cryptocurrency remains an under-researched area.

Our contributions are threefold. First, we introduce the concept of "crypto capture" of foreign aid and provide some of the first 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 (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.

Second, we develop a novel, multi-method empirical strategy that combines blockchain network analysis, panel regressions, and jurisdictional profiling to uncover laundering behavior. Laundering typically unfolds in three stages: transferring funds abroad (placement), obscuring origins through complex transactions (layering), and storing or reinvesting proceeds under hidden ownership (integration). This paper first uses high-resolution network analysis to map how diverted aid is laundered 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 after disbursements. By clustering nodes by business type, we document that crypto not only flows to tax havens but also flows to mixers and other intermediaries. This pattern gradually reverses over the following months. The global distribution shows that the obfuscation occurs immediately after disbursement.

Third, we demonstrate the potential of blockchain-based tools to complement traditional methods of tracing illicit finance, transforming the public blockchain into a tractable and verifiable dataset for analyzing global financial flows. We document this emerging phenomenon using high-resolution blockchain forensics (Foley et al., 2019; Griffin and Shams, 2020; DeSimone et al., 2024; Gefen et al., 2024; Griffin and Mei, 2024; Cong et al., 2025a).[1] We conduct on-chain panel regressions to quantify the relationship between aid disbursements and crypto activity. We find that a 1% increase in foreign aid leads to a 0.07% increase in anonymous transactions on tax haven exchanges, but no comparable response among identified users. The same result holds for new wallet creation, consistent with laundering actors using fresh anonymous addresses to receive and cycle funds. Additionally, for identified transactions, we observe an increase in outflows and a decline in inflows. Taken together, these results point to the laundering strategy: funds first enter through identified accounts on regulated exchanges, then shift into anonymous channels in opaque jurisdictions, consistent with strategic flow reshuffling.

Our blockchain data do not allow us to identify individual actors, nor can they precisely link transaction surges to outflows from specific countries. Nevertheless, the observed spikes in crypto activity and sophisticated layering of transactions following disbursements to aid-recipient

[1]See Cong et al. (2023a); Harvey and Rabetti (2024); Griffin and Kruger (2024) for related literature.

countries, combined with the fact that low-income populations in these settings often lack even basic domestic banking access (Demirgüç-Kunt et al., 2020), are more consistent with elite capture than with broad-based household saving or remittance behavior.

Moreover, we incorporate proprietary off-chain data from centralized cryptocurrency exchanges, which record internal transactions such as user deposits, withdrawals, and trades conducted within the platform. These data help verify that the blockchain movements we observe correspond to genuine economic activity, rather than artificial transfers between wallets controlled by the same entity. We find that aid disbursements are followed by disproportionately large increases in transaction counts and volumes at exchanges located in tax havens, crypto-friendly, or unregulated jurisdictions. Exchanges in regulated environments (e.g., the U.S., EU) do not show such spikes. Using a benchmark-adjusted log-ratio approach, we isolate abnormal growth on suspect platforms relative to compliant ones. These responses are concentrated in countries with weaker institutional quality and governance scores, and fade within two quarters, suggesting short-lived laundering activity rather than structural behavioral shifts. We also present a case study of one of the largest off-chain exchanges in tax havens, Huobi's relocation to Singapore in 2021, illustrating how regulatory arbitrage and the mobility of centralized platforms amplify cross-border frictions in monitoring illicit flows.[2]

We conduct a comprehensive set of robustness checks and extensions that reinforce our baseline results. First, we mitigate concerns about endogeneity by employing two instrumental variables for foreign aid: the historical share of aid received by each country and its governance quality score. These instruments help address potential endogeneity concerns, such as the correlation between aid disbursement and domestic corruption activities, including money laundering via cryptocurrency. The IV estimates reveal a consistent and stronger impact of foreign aid on crypto transactions. Besides, we extend the analysis to geopolitical events and find suggestive evidence that foreign aid disbursements coincide with shifts in crypto activity around national elections. This suggests that diverted funds were repurposed for election-related activities.

[2]This finding supports the recent decision by the Monetary Authority of Singapore to prohibit unregulated crypto businesses from offering services to overseas clients (see https://cointelegraph.com/news/singapore-crypto-shelter-elsewhere).

Related Literature Our study bridges several strands of literature in economics and finance. In development economics, a foundational question concerns how much foreign aid benefits intended recipients. Seminal work by Reinikka and Svensson (2004) documents substantial local capture of education aid in Uganda, while Werker et al. (2009) further links aid flows to political economy distortions, especially in weak institutional contexts. Andersen et al. (2022) provides evidence of elite capture via offshore banking. More recently, attention has turned to digital channels: Cavallo et al. (2024) demonstrate 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) show 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 et al. (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 leveraging blockchain's 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. (2023a) and Cong et al. (2025b) 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 feed into ongoing policy debates on crypto regulation: while crypto enables crime, its traceability offers regulators a unique enforcement lever. Our findings support a regulatory model that combines oversight with technical capacity, echoing calls for smart regulation such as Cumming et al., 2019; Budish, 2025.

The remainder of the paper is organized as follows. Section 2 provides institutional background on foreign aid disbursement, crypto infrastructure. Section 3 shows our data sources and methods. Section 4 presents the empirical analysis: network analysis (Section 4.1), on-chain analysis (Section 4.2), off-chain analysis (Section 4.3), and robustness tests (Section 4.4). Section 5 concludes with a discussion of policy implications and future research directions.

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 et al., 2022 (the JPE paper) 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 upwards of 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, and the veil of secrecy for shell corporations was partially lifted. Consequently, corrupt actors began seeking alternative ways to move illicit money with less detection risk.

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 done by funneling money through crypto exchanges or peer-to-peer markets, thereby transforming identifiable bank transfers into pseudonymous crypto holdings. If done skillfully, this process can obfuscate the money's origin. 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 anecdotal evidence indicated that criminals and corrupt officials were aware of these advantages. For example, investigative reports noted surges in Bitcoin usage in countries facing capital controls or sanctions, as elites sought to move wealth discreetly. Academic research also confirms that illicit actors gravitated to cryptocurrencies: Foley et al., 2019 showed that by the late 2010s, billions of dollars of illegal transactions per year were flowing through Bitcoin, and that the advent of even more opaque cryptocurrencies (such as Monero and Zcash) attracted those seeking greater anonymity. While Bitcoin's ledger is public, these alternative coins can be nearly untraceable, highlighting the evolving cat-and-mouse dynamic between launderers and law enforcement.

Crucially, though, blockchain transactions leave an immutable trail, and advances in blockchain analytics have started to pierce the veil of anonymity. Specialized firms (e.g., Chainalysis, Elliptic, TRM Labs) have developed techniques to cluster blockchain addresses and identify those controlled by the same entity. They also tag addresses associated with known exchanges, darknet markets, or other services by using data such as exchange deposit addresses or seized wallets from law enforcement actions. Such blockchain forensics have enabled remarkable breakthroughs. For instance, Amiram et al., 2022 demonstrates that on-chain Bitcoin transaction patterns can predict the timing of certain terrorist attacks, implying that terrorist networks moved funds on-chain in advance. Law enforcement has also leveraged blockchain analysis to disrupt criminal operations: a notable example was the identification and sanctioning of the SUEX exchange, which was revealed to be laundering ransomware proceeds through blockchain tracing.

In our context, these forensic tools provide a unique opportunity to observe the otherwise hidden flow of misappropriated aid. By mapping blockchain addresses to known entities (exchanges, mixers, etc.), we can effectively trace the footprints of potentially illicit actors who divert aid into crypto. If our hypothesis is correct, we expect to see telltale signs on the blockchain shortly after aid disbursements: an uptick in activity among anonymous wallets, new addresses created, and funds moving from the regulated "front door" of crypto (e.g., U.S.-based exchanges) to the shadowy "back door" (offshore exchanges and mixers).

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, focusing on aid from the World Bank. 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 utilize disbursement records that indicate when funds are actually paid out. 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, since we want to observe crypto flows in narrow windows around aid events. We restrict our sample period to 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 might not be exogenous—they are typically timed in response to economic needs or shocks in the recipient country (e.g., disaster relief following a

[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 does not count as ODA because it offers non-concessional loans, mostly to middle-income countries.

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 lags of aid 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.

3.2 On-Chain Data and Blockchain Forensics

The core of our analysis is based upon on-chain Bitcoin transaction data. Bitcoin is the dominant cryptocurrency and we can take advantage of the public availability of its full transaction ledger. We obtained the Bitcoin blockchain data for the period 2018–2024, containing information about 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., 2025 and other blockchain analytics research. It consists of two main steps:

Address Attribution: First, we link as many addresses as possible to known entities or users. We leverage public databases such as WalletExplorer, which curates revealed addresses associated with major cryptocurrency services. For example, if a deposit address for Binance (a major exchange) is known, any transactions involving that address can be attributed to Binance. We also use data from blockchain forensic firms and open-source investigations to tag addresses belonging to exchanges, mixer services, gambling sites, dark net markets, payment processors, etc. When an address is identified as belonging to a service, we effectively mark it as a non-anonymous address (since its owner or at least its affiliated service is known).

Wallet Clustering: Simply knowing individual addresses is not enough, because sophisticated users can create thousands of addresses. To aggregate addresses that likely belong to the same user or entity, we implement a union-find clustering algorithm (also known as disjoint set union) on the transaction graph. A common heuristic, first applied by Ron and Shamir, 2013, is to cluster addresses that appear as inputs in the same transaction, under the assumption that if multiple addresses are used together to fund one transaction, they are controlled by the same user. We apply this and related clustering rules to merge addresses into user-level wallets, identifying groups of addresses that function as a single unit (a user or service). Prior research (e.g., Makarov and Schoar, 2022) suggests that key patterns in exchange activity and cross-border flows remain stable even under alternative clustering assumptions.

Using these methods, we were able to map and cluster a substantial share of Bitcoin activity. In total, we identified 17 major services (clusters of addresses) that collectively account for approximately 83.3 million BTC in transaction volume over our sample period, representing around 13% of all BTC transactions during this period. These include well-known crypto exchanges (e.g., Binance, Kraken, Bitstamp, Huobi, Luno, Bittrex, HitBTC, CEX.io) which facilitate trading and conversion between crypto and fiat; payment processors (e.g., CoinPayments, Xapo) which handle cryptocurrency payments for merchants or wallets for individuals; mixers (e.g., Wasabi or JoinMarket, represented by cluster labels like "JoinMess" in our data) which pool and redistribute funds to obscure their origin; and online gambling platforms (e.g., YABTCL, 999Dice, BitZino) which accept Bitcoin for betting. We also include a category of dark markets (illicit marketplaces) if identified, although many early dark markets (like Silk Road) were already shut down before the beginning of our sample period, so this is less prominent in our data.

After identification and clustering, we classify each wallet (cluster of addresses) into one of five categories: Exchange, Mixer, Gambling, Dark Market, or Other Service/General. Wallets that we could not identify through any attribution are left unclassified; these represent anonymous users (likely individuals or entities whose identities are not tied to any known service). In our analysis, we often contrast anonymous vs. identified activity. We consider all addresses/wallets associated with known exchanges, mixers, gambling, or other services as "identified" (non-anonymous), and everything else as "anonymous". This dichotomy is crucial: a rise in transactions involving anonymous wallets post-aid is suggestive of illicit or new actors, whereas a rise in identified-wallet activity might reflect ordinary economic use of crypto.

We further enrich the on-chain data by tagging exchanges with their jurisdiction/regulatory status. In particular, we label each exchange as either "Tax Haven" exchange or "Non-Tax-Haven" exchange, based on the country in which it is legally domiciled (Landsman et al. (2025)). An exchange is considered to be in a tax haven if it is headquartered in a jurisdiction known for its offshore finance and low regulation, as listed in known tax haven lists (e.g., Cayman Islands, British Virgin Islands, Seychelles, Panama, Hong Kong, Singapore, among others). We also classify exchanges by whether they operate in a highly regulated financial market (e.g., U.S., EU, Japan, with strong crypto AML rules) or a relatively unregulated/crypto-friendly market (where regulation is minimal or not strongly enforced). These classifications allow us to test whether post-aid surges in crypto preferentially involve exchanges in lax jurisdictions, which would bolster the laundering interpretation.

3.3 Off-Chain Exchange Data

While on-chain data captures the movement of Bitcoin between addresses, they do not directly reveal trades or transactions happening 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 in these categories (for example, many tax haven jurisdictions are also crypto-friendly under 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.

From the CoinMarketCap data, we pay particular attention to off-chain transaction counts (number of trades or transfers) and volumes on exchanges around aid events. If, say, a large aid disbursement to Country X is followed by a spike in trading volume on exchanges in the Cayman Islands, that would be consistent with elites in Country X converting aid money into crypto via those exchanges. We also examine the ratio of activity between different groups of exchanges (e.g., tax haven vs. non-haven) around aid events to see if 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 been a platform of choice for certain 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 the flow of Bitcoin between nodes. The size of a node reflects a measure of 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.

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

4.1.1 Case Study—Five Major Aid Events

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 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 the Aid (Pre-event network): The largest number of nodes are non-haven exchanges (purple nodes), indicating that in the week before the aid, most Bitcoin flows were going through regulated or major-market exchanges. There are substantial inflows and outflows at these nodes, suggesting normal usage such as trading or remittances. Tax-haven exchanges and mixers are present but less connected in this pre-aid period.

Immediately After the Aid: In the week following the disbursement, we observe a surge of flows toward tax haven exchanges (dark green nodes get larger and have thicker incoming edges from various sources). Notably, new connections appear: previously inactive or small nodes become active, representing newly created wallets sending funds into these haven exchanges. We also see increased activity involving mixer nodes (light green nodes), which feed into the tax-haven exchanges. The non-haven exchanges still have volume, but comparatively, the share of flows going through them drops as the haven nodes take center stage. This indicates a re-routing of transactions: rather than going directly from user wallets to major exchanges (which are likely monitored), funds are cycling through an intermediate layering: for example, from a regulated exchange to a self-hosted wallet, then to a mixer, and finally into an offshore exchange. This pattern is consistent with a common laundering strategy: starting with a legitimate exchange to acquire crypto, which makes the initial conversion from cash to crypto harder to detect, followed by quickly moving the crypto through obfuscation channels and into storage.

Six Months Later: By six months post-disbursement, the network shows a somewhat normalized pattern compared to the immediate aftermath. The tax-haven exchanges remain prominent, indicating that some of the funds might still be parked or cycling there, but the frenetic spike of activity has subsided. This could imply that after an initial burst of transfers to hide the money, the launderers have settled into holding or gradually off-ramping the funds. Non-haven exchanges regain some relative prominence (perhaps reflecting unrelated activity or the tapering of the laundering flow). The key point is that the imprint of the aid event is a short-term realignment of flows: considerable movement to conceal the money happens within weeks, using the crypto ecosystem, and then activity normalizes.

Figure 2 clusters the network connectivity across business services on the chain and from one week before to one week after, and from one week before to the week six months after the largest aid disbursement. The results reveal a sharp yet short-lived reconfiguration of crypto transaction flows immediately following the aid disbursement, followed by a gradual return toward more conventional patterns.

Immediate Redistribution Activity. The upper panel of Figure 2 depicts changes in the transactional network during the week following the largest five aid disbursements. Tax haven exchanges emerge as key redistribution nodes, receiving substantial inflows from non-haven exchanges and directing outbound transfers to payment processors, mixers, and gambling-related platforms. The edge configuration suggests that tax haven exchanges are not isolated endpoints but actively integrated redistribution intermediaries. Mixers function as upstream intermediaries, channeling funds from non-haven exchanges to both tax haven exchanges and final-use services. The presence of strong reciprocal flows between mixers and tax haven exchanges suggests rapid fund cycling, consistent with coordinated obfuscation strategies immediately after the aid event.

Longer-Term Realignment. The lower panel of Figure 2 presents the network difference one week before to the week six months after the largest aid disbursement. Non-haven exchanges reappear with more pronounced linkages, indicating a partial reversion to conventional or regulated pathways. Tax haven exchanges and payment processors continue to supply substantial inflows to non-haven platforms, suggesting a gradual reintegration of previously segmented funds.

We replicate similar network analyses for one of the largest foreign aid disbursements in our data, a World Bank disbursement of approximately $24.4 billion to Nigeria on 2019-05-27, shown in Figure A.1. The network patterns are qualitatively similar. The difference graphs highlight how certain channels "light up" post-aid (edges from mixers to haven exchanges strengthen, new nodes appear) and then some dim by six months, though not completely returning to baseline.

In summary, the network analysis provides qualitative but compelling evidence of "crypto capture" of aid: after aid inflows, the crypto transaction network temporarily reorients to facilitate the hiding of those funds. It is essentially a real-time visualization of a laundering operation: initial conversion through legitimate means, followed by quick relocation to obscure havens. This layered flow of funds—from transparent to opaque venues—mirrors patterns noted in law enforcement cases and expert reports. While network graphs illustrate these patterns, we next turn to formal statistical analysis to confirm and quantify the effects across the whole sample of aid disbursements.

4.1.2 Global Redistribution Patterns

Figure 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 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.

4.2 Part II: On-Chain Transaction Analysis

To systematically analyze the abnormal crypto transactions surrounding aid disbursements, we combine network visualization with formal panel regressions to capture more detailed structural patterns and statistical relationships. We use panel regressions to estimate the impact of foreign aid disbursements on various measures of on-chain crypto activity. The regression specification is a fixed-effects model of the form:

$$\log(Y_t) = \alpha + \lambda \cdot \log(\text{Aid}_{c,t-\text{lag}}) + \mathbf{X}_t'\theta + \delta_c + \delta_t + \epsilon_{it},$$

where Y_t is an outcome capturing crypto activities in quarter t, δ_c is the aid recipient country fixed effect, δ_t is the time fixed effect (to absorb global time trends), $\text{Aid}_{t-\text{lag}}$ is the aggregated aid disbursed on date t (in logarithms) in the previous quarter (or specified lag), and $\mathbf{X}_t$ includes control variables such as lagged Bitcoin market volume (to account for overall crypto market fluctuations). Standard errors are clustered at the level of aid recipient countries.

4.2.1 Anonymous vs. Identified Transaction

Our first set of results examines Bitcoin transactions flowing through anonymous versus identified addresses following aid shocks. Figure 5 illustrates the dynamic effects of foreign aid disbursements on cryptocurrency platform activity, using data from two quarters before to three quarters after each disbursement. Panels A and B show changes in volumes, while Panels C and D depict the percentage change in the number of newly created accounts. We include two quarters of leads and three quarters of lags of the aid variable in these dynamic regressions to check for pre-trends and duration of effects. The point estimates (dots) and 95% confidence intervals (whiskers) clearly show a divergent pattern: for anonymous accounts, the coefficients on aid are near zero in the lead (pre-aid) quarters, but increase significantly and become positive in the first and second quarters after an aid disbursement. In contrast, for identified accounts, the coefficients remain around zero or negative, with no significant post-aid increases. This indicates no anticipatory rise in anonymous activity before aid (no pre-trend), followed by a substantial surge after aid, which then decays. The timing aligns with the idea that once aid is received (often within a quarter, as we measure disbursement on a quarterly rolling basis), illicit actors move swiftly to crypto.

To quantify this effect, Table 4 presents regression estimates where both the outcome variable, crypto transaction frequency, and the key explanatory variable, quarterly foreign aid, are in natural logarithms. We begin with tax haven exchanges. For all transactions, the coefficient on lagged aid is significantly positive for anonymous addresses, while the corresponding estimate for identified addresses is smaller and statistically insignificant. The effects on identified addresses are statistically insignificant and exhibit no consistent direction. These results suggest that the increase in aid-related crypto activity on tax haven exchanges is primarily driven by anonymous users, consistent with the interpretation that these actors engage in strategic behavior to obfuscate fund flows through fragmented transfers and intermediate wallets.

We then extend the analysis to non–tax-haven exchanges. The results indicate that increases in foreign aid are associated with a contraction in overall transaction frequency, suggesting possible fragmentation or consolidation of trading activity. This pattern may reflect attempts to reduce visibility or avoid detection on more heavily regulated platforms. At the same time, aid inflows are linked to higher volumes of anonymous transactions and lower volumes of identified transactions, consistent with a reallocation of activity toward less traceable channels. There is no significant change in transaction outflows in non tax-haven exchanges. These results suggest that following aid disbursements, there is a reallocation of crypto activities within non-tax haven exchanges towards more opaque channels. Specifically, the increase in anonymous inflows alongside a decrease in identified inflows indicates that new funds are increasingly routed through channels that obscure the origin or identity of users, consistent with attempts to conceal illicit activities.

4.2.2 New Wallets Creation

Creating a substantial number of wallets is commonly associated with money laundering activities. To investigate whether these wallets ultimately end up on offshore exchanges, as hypothesized, we examine the relationship between aid disbursements and the creation of new accounts linked to tax haven exchanges. Table 5 confirms that quarters with large aid disbursements are followed by a significant increase in the number of new accounts associated with tax haven exchanges. In contrast, the creation of new identified accounts responds negatively, though the effect is statistically insignificant. In other words, the post-aid surge in crypto activity is disproportionately concentrated on offshore platforms, reinforcing the patterns observed in our earlier network visualizations.

When disaggregating the data into inflows and outflows, we find that anonymous outflows increase and inflows decrease, though insignificantly. This suggests a pattern where, after aid disbursements, funds may be gradually withdrawn from the crypto ecosystem through less traceable, anonymous channels. Once these new accounts are created, they are not heavily used to receive additional funds but rather to facilitate the onward movement of assets.

Shifting focus to non-tax haven crypto exchanges, we observe a stark contrast: a 1% increase in lagged foreign aid is associated with a 0.04% decline in newly identified accounts, while the number of anonymous accounts remains largely unchanged.

The observed increase in new anonymous wallets, addresses not linked to any known exchange or regulated service, suggests a strategic behavioral response. Specifically, it indicates that actors, possibly including corrupt intermediaries, may be creating fresh, untraceable addresses on less-regulated platforms to manage aid-related flows. This behavior likely serves to obscure transaction histories and reduce traceability. The absence of a comparable rise in newly identified accounts, coupled with the negative coefficients on their creation, points to a shift away from traceable, regulated platforms. Taken together, these patterns suggest intentional reshuffling behavior: instead of channeling funds through existing wallets, actors appear to enter the crypto system using newly created, anonymous identities following foreign aid disbursements. This aligns with attempts to evade detection and facilitate laundering through greater anonymity.

4.2.3 Time Pattern and Persistence

Our dynamic specifications in Figure 5 indicate that the response is most pronounced in the first quarter following an aid disbursement and tends to fade thereafter. By two quarters out, the coefficients on lagged aid become smaller and often statistically insignificant. This temporal pattern suggests that crypto-linked laundering behavior is relatively immediate, likely reflecting the urgency to obscure aid-linked funds soon after receipt. This fact suggests that diversion is the main channel at work. If, instead, the link between aid and foreign deposits simply captured rising incomes and aggregate demand, we would expect a slower, more persistent effect consistent with typical business cycle dynamics.

4.2.4 Interpreting the Laundering Patterns

The on-chain analysis supports the notion of layered laundering via crypto. We can interpret the flows in three stages, akin to classical money laundering stages (placement, layering, integration):

Placement (Entry into Crypto): Aid funds (originating as fiat money, such as in a government account) are first converted into cryptocurrency. Fiat-to-crypto refers to the process of exchanging currency for cryptocurrency (e.g., Bitcoin, Ethereum) through an exchange platform. This likely occurs through a compliant, high-liquidity exchange, often in a major jurisdiction (e.g., using a U.S. or EU exchange), because they offer the easiest and most accessible fiat-to-crypto on-ramps. Panel B of Table 4 shows statistically significant increases in inflows to non-tax haven exchanges following aid disbursements. This evidence supports the interpretation that aid funds first enter the crypto ecosystem through regulated exchanges, consistent with the placement stage.

Layering (Obfuscation via Transfers): Once in crypto, the funds are rapidly moved off the regulated exchange to avoid detection. Typically, the funds might be withdrawn to a self-hosted wallet (an address controlled by the launderer), then sent to a mixer or series of addresses to break the trail, and then forwarded to one or multiple offshore (tax haven) exchanges. Crucially, Panels B and C of Table 4 show much larger and highly significant inflows and outflows at tax haven exchanges (anonymous addresses). These results corroborate the network evidence of funds moving swiftly into and through offshore jurisdictions. The magnitude and significance of these flows are consistent with the layering process, where crypto assets are cycled through less transparent venues to obscure their origin. This pattern matches forensic reports of illicit flows exiting regulated platforms and entering jurisdictions with weaker oversight.

Integration (Extraction or Storage): The final stage involves extracting or storing laundered funds in a usable form. While our data do not directly capture conversion back to fiat, Panel C shows significant outflows from tax haven exchanges, suggesting structured movement towards potential integration endpoints. These outflows are consistent with funds either being stored long-term within the crypto ecosystem or moved towards channels facilitating re-entry into the real economy, such as crypto payment processors or stablecoins.

Summary: Together, the formal evidence aligns closely with the qualitative network patterns. Aid inflows initially drive crypto inflows on regulated exchanges (placement), followed by rapid transfers to offshore venues (layering), and eventual movements suggestive of further obfuscation or extraction (integration). These transaction patterns provide quantitative support for the hypothesis that foreign aid disbursements are, in part, captured through crypto-based laundering mechanisms.

4.3 Part III: 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 6 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 6, 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 6, 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.2.

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.

4.3.4 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 7 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 7 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.

4.4 Robustness and Extensions

We perform several additional analyses to assess the robustness of our core findings and to explore underlying mechanisms.

4.4.1 IV Analysis

A central challenge in estimating the effect of foreign aid on cryptocurrency activity is the potential endogeneity of aid allocation. Aid disbursements may be systematically targeted toward countries with weaker institutions, higher corruption risk, or limited financial oversight-precisely the conditions under which aid is more likely to be diverted into illicit crypto flows. This creates a concern that observed correlations between aid and crypto activity may reflect underlying governance failures rather than a causal effect. For example, as shown in Table 8, the aid-to-crypto relationship is significantly stronger in countries with below-median governance indicators, such as low control of corruption or weak financial depth. In contrast, in countries with stronger institutions, the relationship is weaker or insignificant, suggesting institutional quality plays a mediating role. To disentangle these effects and isolate exogenous variation in aid, we construct an instrumental variable that interacts the historical distribution of aid with time-invariant measures of institutional quality.

To address this identification concern, we construct a governance-adjusted shift-share instrumental variable. Specifically, we examine the historical distribution of foreign aid across countries with time-invariant measures of institutional quality. This strategy builds on the logic of shift-share designs in the aid effectiveness literature and exploits cross-country differences in historical aid exposure and baseline governance to generate plausibly exogenous variation in predicted aid flows. The instrument is designed to be orthogonal to contemporaneous shocks or unobserved policy responses that may simultaneously affect both aid disbursements and crypto-based laundering activity.

Formally, our instruments are defined as:

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

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,

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

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 fixed effects, respectively. In the second stage, we estimate:

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

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 the OLS regressions, our IV estimates indicate that aid shocks cause meaningful increases in crypto activity on platforms associated with illicit use (see Table 9). 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 0.10 log-point rise in anonymous transactions on tax-haven exchanges (approximately a 10.75% 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). 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.

Taken together, these 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 examine how blockchain-based forensic methods can shed light on political cycles, particularly elections. As a case study, we focus on Brazil, one of the largest recipients of foreign aid. In recent years, Brazil has experienced heightened political turmoil and challenges to democratic institutions. In 2018, general elections were held on October 7, followed by a runoff on October 28 after no candidate secured more than 50% of the vote. Jair Bolsonaro won the runoff and was subsequently elected president. Theoretically, the period leading up to major elections in aid-recipient countries may incentivize elites not simply to accumulate and conceal funds, but to actively deploy them for purposes such as vote-buying, political donations, or securing the support of key actors in exchange for future favors. Rather than serving merely as a hedge against instability, these financial flows may be used strategically to influence political outcomes. We hypothesize that the political turmoil and institutional uncertainty in Brazil may have contributed to increased use of blockchain networks to facilitate such covert financial transfers during election periods.

As shown in Table A.3, we document significant pre-election spikes in crypto transactions in Brazil, concentrated among anonymous wallets, with no comparable surge post-election. This pattern, especially the increase in unidentified accounts, suggests that foreign aid disbursements are associated with shifts in crypto activity around elections, though the magnitude and direction vary across countries. Diverted money was used for different purposes during election time, influencing elections.

These results suggest that diverted funds are repurposed for various activities during election periods, with crypto-based financial transactions serving as a channel to influence electoral outcomes. While this analysis is exploratory and outside the core identification strategy of the paper, it underscores the broader applicability of blockchain-based forensic methods to political economy questions involving illicit financial flows.

5 Conclusion

This study provides systematic evidence that foreign aid disbursements lead to short-lived but substantial money laundering behavior in the cryptocurrency market. Leveraging detailed on-chain and off-chain transaction data from 2018 to 2024, we document that aid flows to developing countries—particularly those with weak institutions—trigger significant post-disbursement surges in Bitcoin transactions involving anonymous wallets on exchanges located in tax haven jurisdictions.

Our forensic analyses reveal a distinct laundering mechanism: aid-linked funds initially enter the crypto ecosystem via regulated exchanges, then quickly shift into anonymous wallets and are routed through mixers and offshore exchanges. These flows mirror the classic money laundering sequence—placement, layering, and integration—executed rapidly and with high frequency across blockchain rails. A one-standard-deviation increase in lagged aid corresponds to a 0.10 log-point rise in anonymous volume on tax haven exchanges, driven by both new wallet creation and high transaction frequency, but not mirrored among identified users or regulated platforms.

Complementing our on-chain results, off-chain transaction analysis confirms disproportionate transaction growth on unregulated, crypto-friendly platforms post-aid disbursement, with no comparable effect observed in regulated jurisdictions. Heterogeneity analysis shows these patterns are most pronounced in countries with low governance quality, limited financial transparency, and poor corruption control, suggesting that elites in such environments strategically exploit crypto markets to conceal diverted aid.

From a policy perspective, our findings underscore an urgent need to update anti-corruption frameworks for the blockchain era. The increasing transparency and enforcement in traditional offshore finance (post-Panama Papers) may have inadvertently displaced illicit flows into less visible crypto channels. However, the traceability of blockchains offers regulators and researchers an opportunity: by combining public ledger data with forensic attribution, we demonstrate that illicit behavior can be detected in near real-time, even when actors operate pseudonymously.

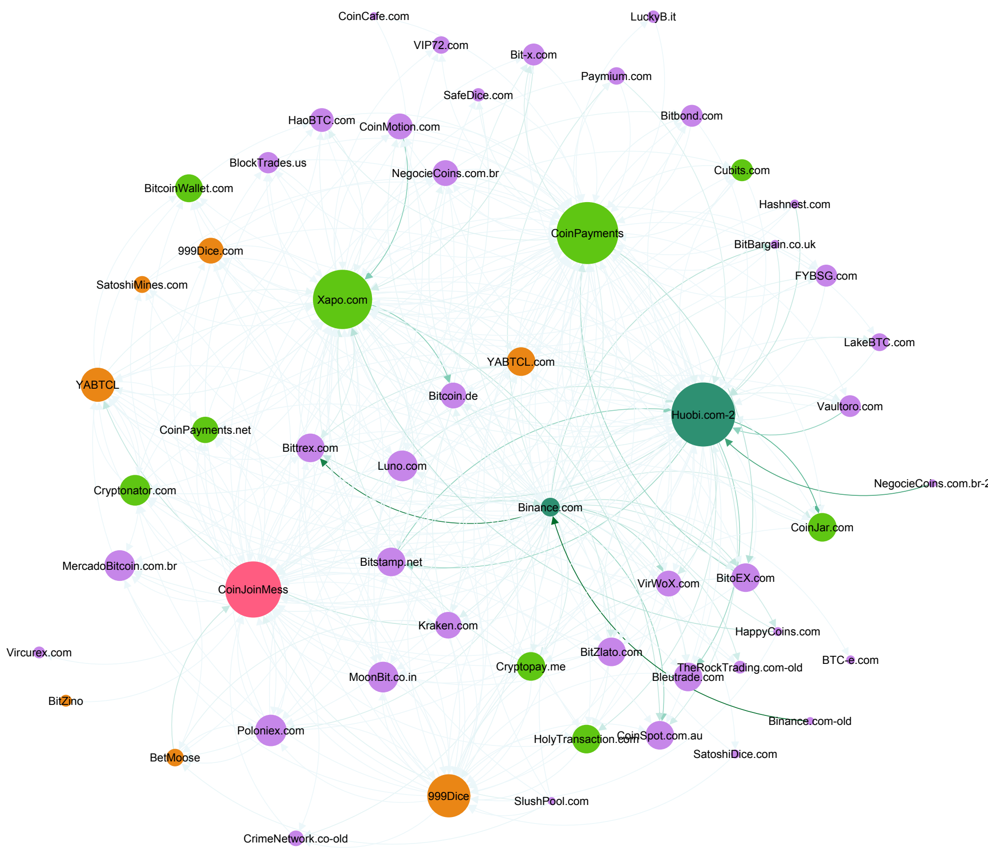
Our contributions are threefold. First, we introduce the concept of "crypto capture" of foreign aid and provide empirical evidence of its occurrence. Second, we develop a novel, multi-method empirical strategy that combines blockchain network analysis, panel regressions, and jurisdictional profiling to uncover laundering behavior. Third, we highlight how blockchain-based tools can complement traditional methods of tracing illicit finance, pointing toward a new direction in empirical research on corruption, capital flight, and financial secrecy.

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.

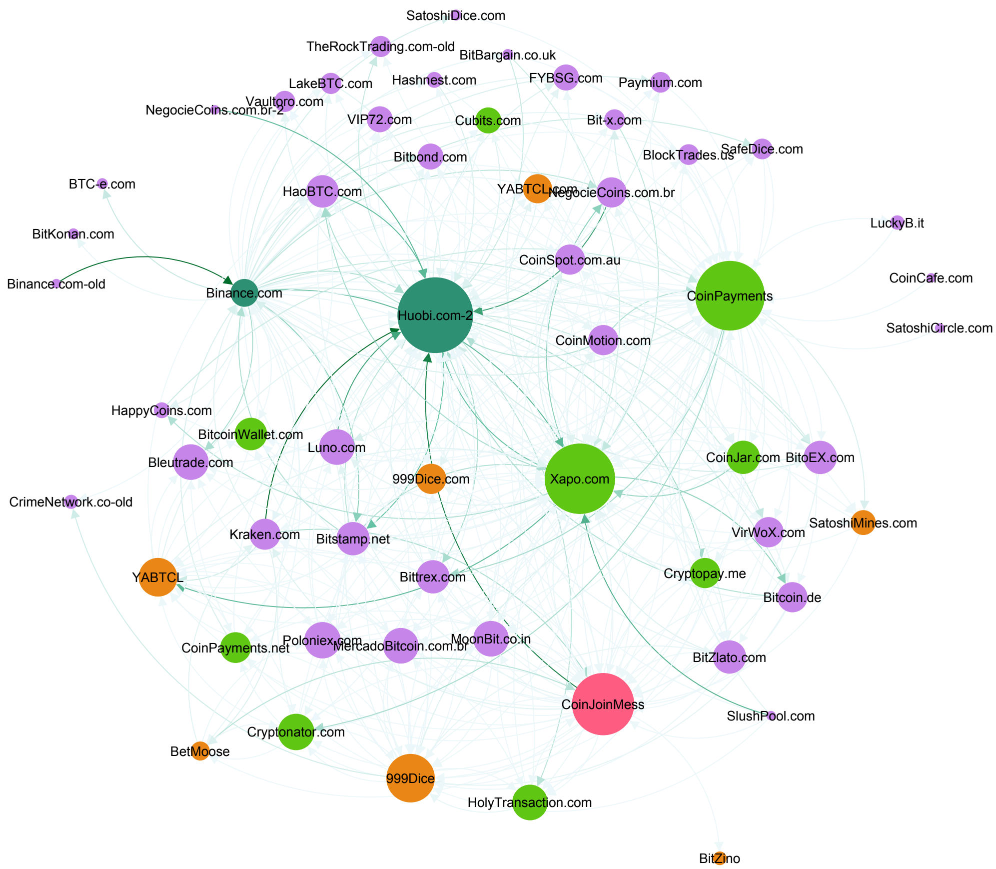
In sum, while the blockchain was once hailed as a tool for financial transparency, it has also become a new frontier for concealment. Yet that concealment is not perfect. With the right tools, patterns of misuse, including the diversion of aid meant for the world's poorest, can be traced, quantified, and, ultimately, addressed.

Figures

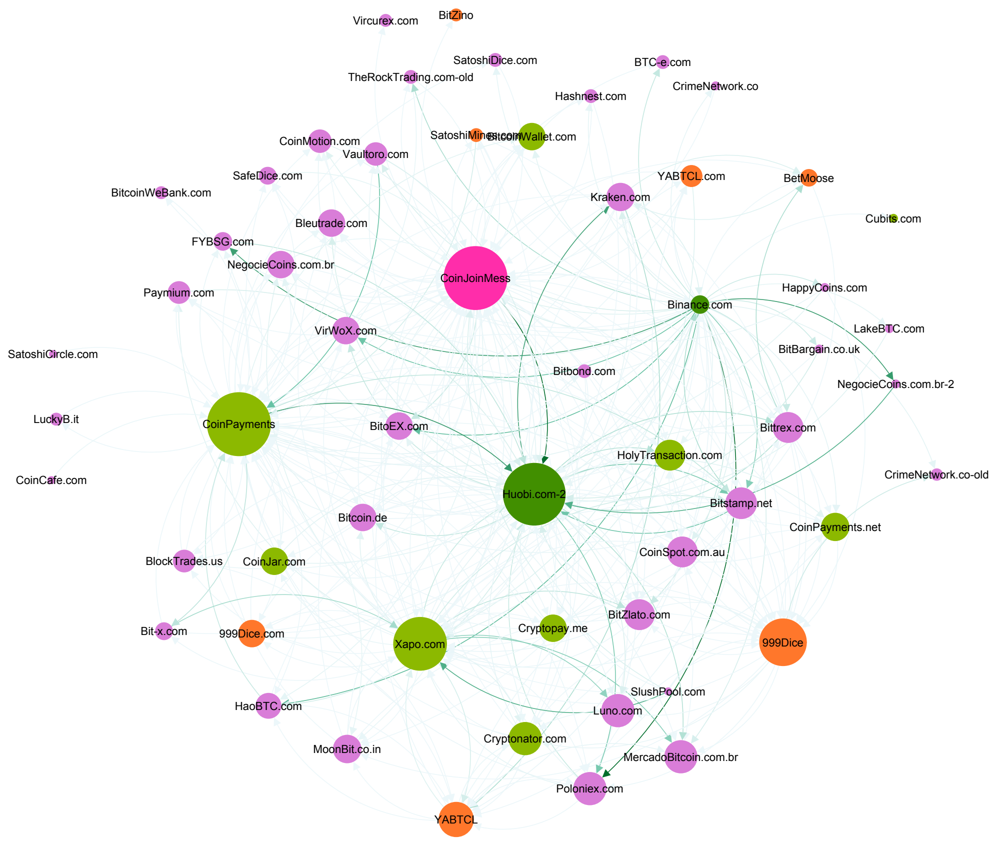
Figure 1. Network Analysis Around Top Five Aid Disbursements. Larger nodes represent higher centrality; darker edges indicate greater volumes. The panels show the networks one month before, one month after, and six months after the major aid disbursements. Colors distinguish service categories: non-tax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



(a) Network One Month Before Aid

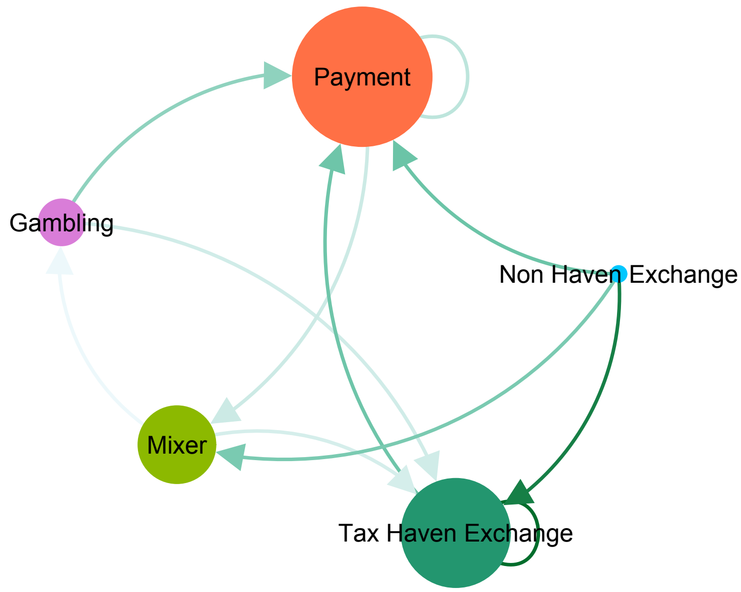


(b) Network One Month After Aid

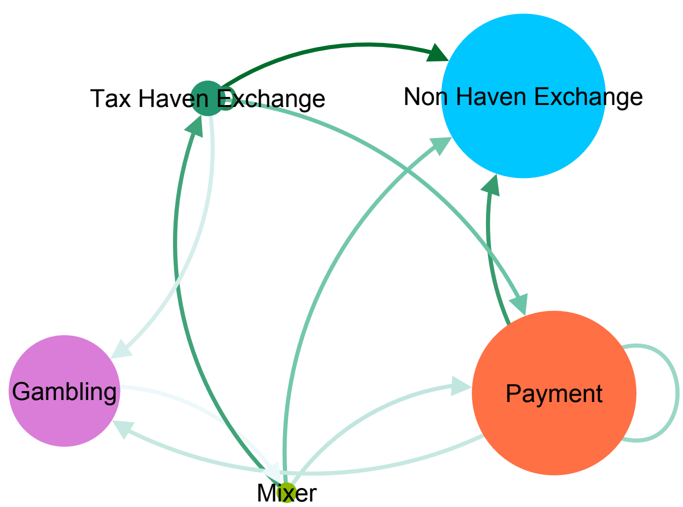


(c) Network Six Months After Aid

Figure 2. Clustered Network Analysis Around Top Five Aid Disbursements. Larger nodes represent higher centrality; darker edges indicate greater volumes. 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. 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.

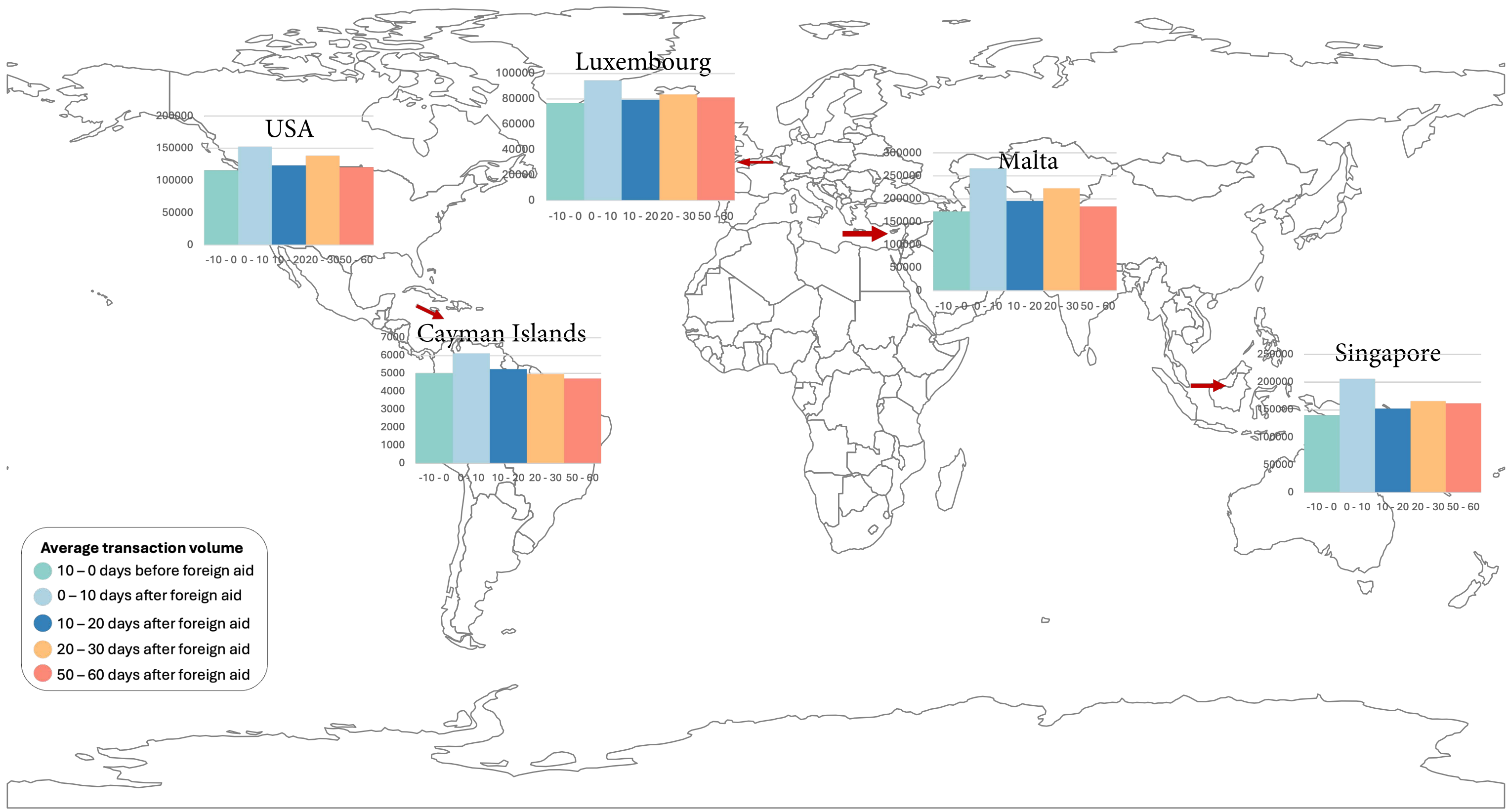


Figure 4. U.S. vs. Tax Haven Crypto Volume Trend. This figure shows weekly cryptocurrency volumes for the United States (blue) and tax haven jurisdictions (green). Red dots indicate U.S. volume spikes without corresponding spikes in tax havens.

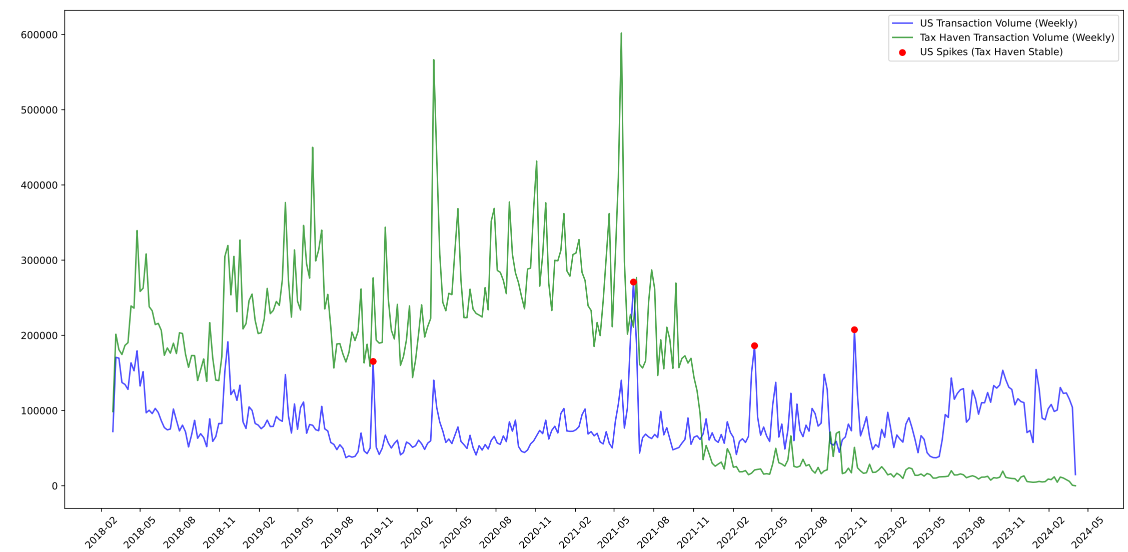
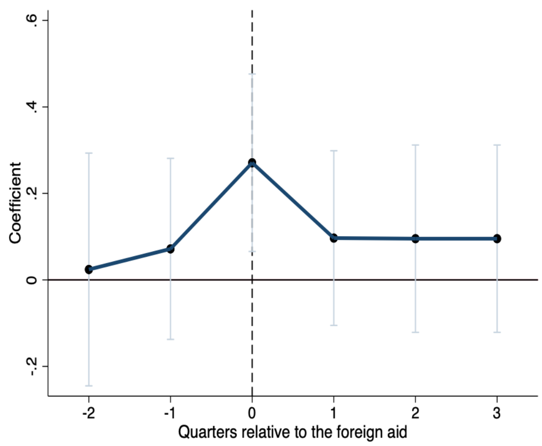
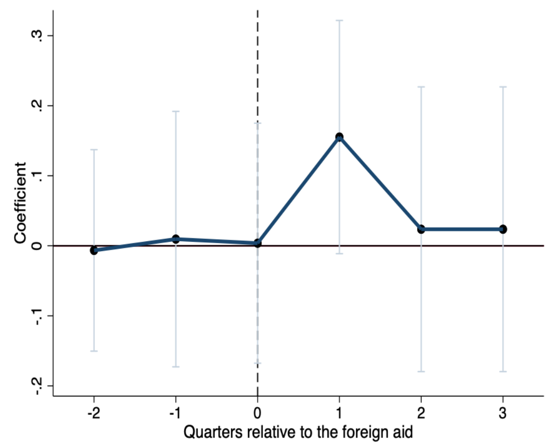


Figure 5. The volume and the number of new accounts dynamic results. The figure shows the results from the baseline specification, with two leads and three lags of the disbursement variable. In Panels A and B: The dependent variable is the percentage change in volume in crypto exchange platforms and the explanatory variable of interest is quarterly disbursements. In Panes C and D: The dependent variable is the percentage change in the number of new accounts created in crypto exchange platforms. The regression controls for the two-quarter lagged disbursement amount and one-quarter lagged BTC volume and include time fixed effect. Both dependent and independent variables are expressed in log-levels. The dark blue dots indicate the point estimates on the aid disbursement variables and the light blue lines indicate 95%-level confidence intervals.

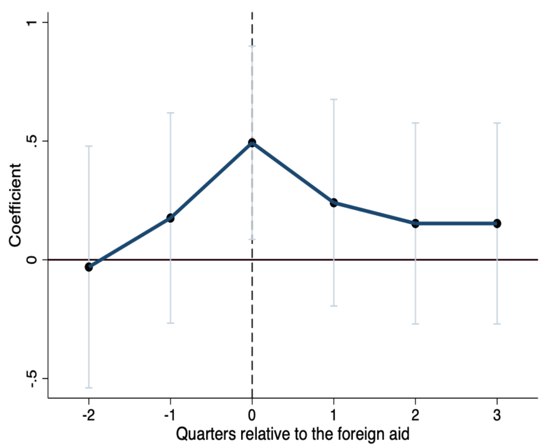
Panel A: Volume of anonymous accounts



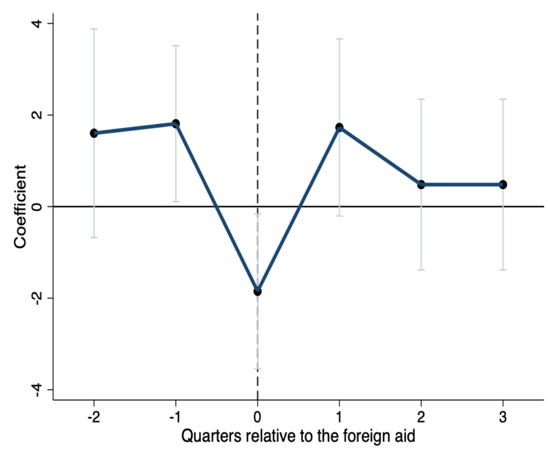
Panel B: Volume of identified accounts



Panel C: Number of new anonymous accounts created



Panel D: Number of new identified accounts created



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

Region	Europe Islands	North America	Central America	South America	Oceania
Proportion	0.12	0.14	0.02	0.00	0.01

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 billions)	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. 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. Coefficients are multiplied by 100. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Crypto Exchanges in Tax Haven			Crypto Exchanges in Non-Tax Haven		
	All	Anonymous	Identified	All	Anonymous	Identified
Panel A: All Transactions						
Foreign Aid $_{lagged}$	0.33***	0.35***	0.02	0.09	0.11	-0.15*
	(0.12)	(0.12)	(0.09)	(0.08)	(0.08)	(0.09)
Controls	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓
Obs.	5,052	5,052	5,052	5,052	5,052	5,052
Adj. R^2	0.92	0.92	0.96	0.90	0.90	0.95
Panel B: Inflows						
Foreign Aid $_{lagged}$	0.22**	0.26**	-0.14	0.12*	0.14**	-0.16*
	(0.10)	(0.10)	(0.10)	(0.07)	(0.07)	(0.09)
Controls	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓
Obs.	5,052	5,052	5,052	5,052	5,052	5,052
Adj. R^2	0.90	0.89	0.96	0.82	0.80	0.95
Panel C: Outflows						
Foreign Aid $_{lagged}$	0.45***	0.45***	0.33***	0.04	0.05	-0.14
	(0.14)	(0.14)	(0.12)	(0.09)	(0.09)	(0.09)
Controls	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓
Obs.	5,052	5,052	5,052	5,052	5,052	5,052
Adj. R^2	0.93	0.93	0.90	0.93	0.93	0.94

Table 5. 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 one-quarter lagged total number of new accounts (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. Coefficients are multiplied by 100. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Crypto Exchanges in Tax Haven			Crypto Exchanges in Non-Tax Haven		
	All	Anonymous	Identified	All	Anonymous	Identified
Panel A: All Transactions						
Foreign Aid $_{lagged}$	0.45*	0.45*	-0.83	0.09	0.09	-4.48***
	(0.24)	(0.24)	(1.02)	(0.15)	(0.15)	(1.19)
Controls	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓
Obs.	5,052	5,052	5,052	5,052	5,052	4,031
Adj. R^2	0.92	0.92	0.58	0.90	0.90	0.63
Panel B: Inflows						
Foreign Aid $_{lagged}$	0.22	0.22	-0.45	0.07	0.07	-2.56**
	(0.13)	(0.13)	(1.19)	(0.20)	(0.20)	(1.11)
Controls	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓
Obs.	5,052	5,052	5,052	5,052	5,052	4,031
Adj. R^2	0.91	0.91	0.44	0.88	0.88	0.41
Panel C: Outflows						
Foreign Aid $_{lagged}$	0.67**	0.67**	0.09	0.07	0.07	-2.29**
	(0.28)	(0.28)	(0.98)	(0.18)	(0.18)	(1.08)
Controls	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓
Obs.	5,052	5,052	5,052	5,052	5,052	4,031
Adj. R^2	0.92	0.92	0.60	0.91	0.91	0.54

Table 6. 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 7. 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

Table 8. 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 9. 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. 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

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Appendix: Crypto Capture of Foreign Aid

Agarwal, Jin, Prasad, and Rabetti – October 2025

Appendix — Tables

A Descriptive Statistics

B Robustness and Complementary Analyses

B.1 Sampling

Table A.2. 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

B.2 Election

Table A.3. 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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

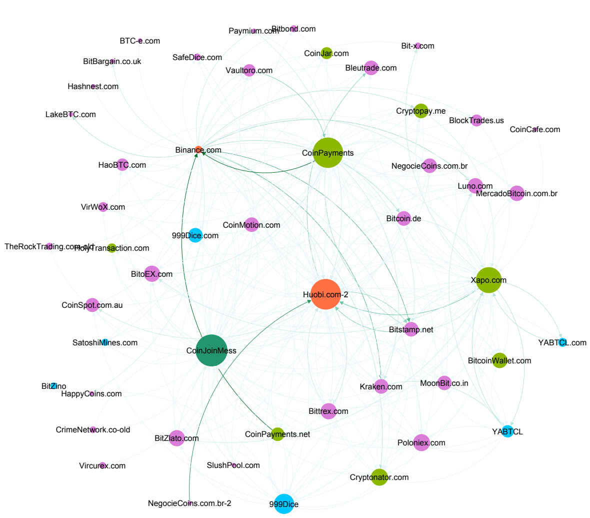
	10-Month Period Before Election			10-Month Period After Election		
	All Wallets	Anonymous	Identified	All Wallets	Anonymous	Identified
Panel A: Transaction Frequency						
Foreign Aid $_{lagged}$	3.90***	4.03***	1.59***	-0.07	-0.07	-0.15
	(0.30)	(0.30)	(0.20)	(0.37)	(0.37)	(0.22)
Controls	✓	✓	✓	✓	✓	✓
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

Table A.1. Variable Definitions and Descriptions

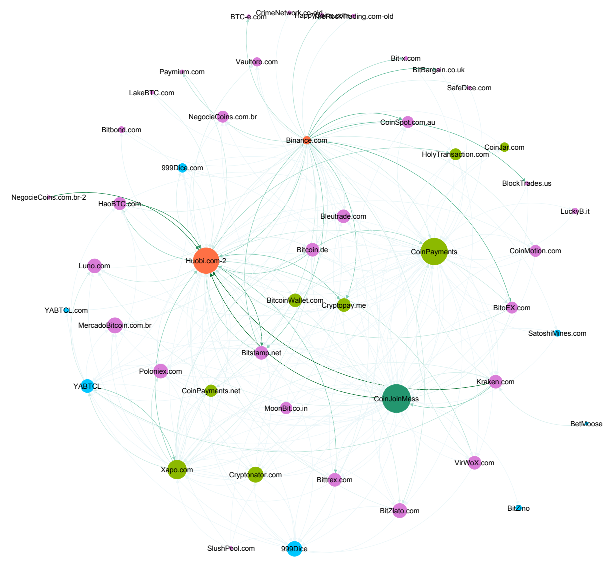
Variable	Description
Foreign Aid	Total foreign aid disbursement (lagged by one quarter) used as the main independent variable.
Transaction Volume	Value of cryptocurrency transactions on a given platform or within a region (log-transformed).
Transaction Times	Number of cryptocurrency transactions (log-transformed).
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.

C Network Analysis

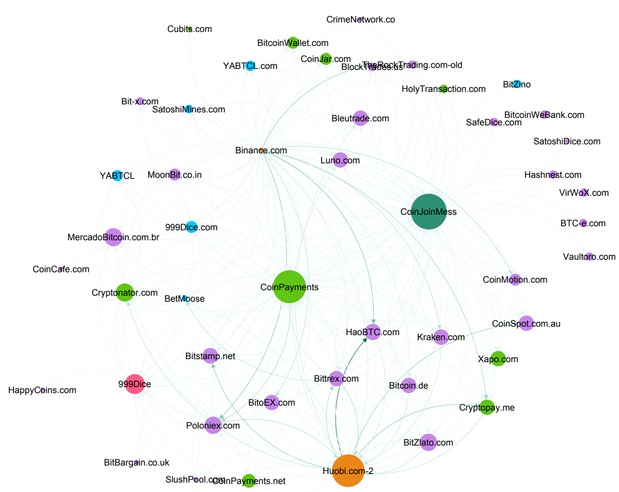
Figure A.1. Network Analysis: Largest Aid (Nigeria). The figures show the average network one month before, one month after, and six months after the top five disbursement dates. The width of arrows represents transfer magnitudes; node sizes represent platform centrality. Non-tax haven exchanges are 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.



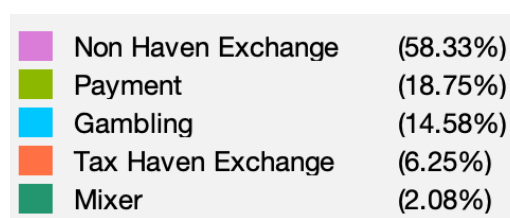
(a) One month before the aid



(b) One month after the aid

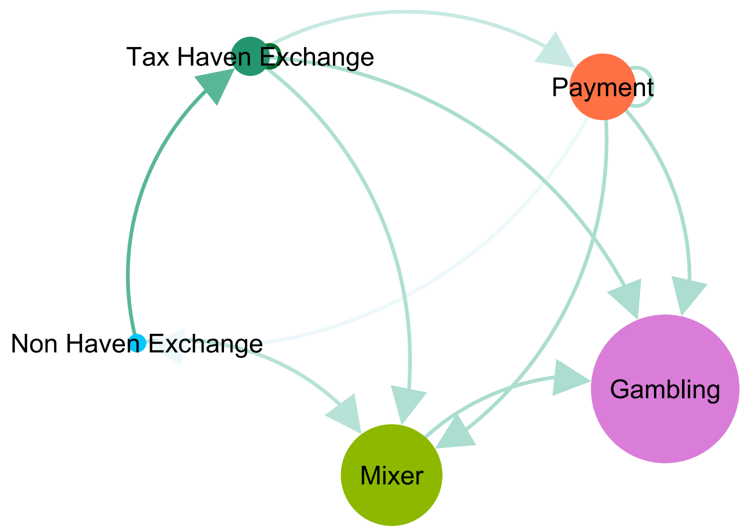


(c) Six months after the aid

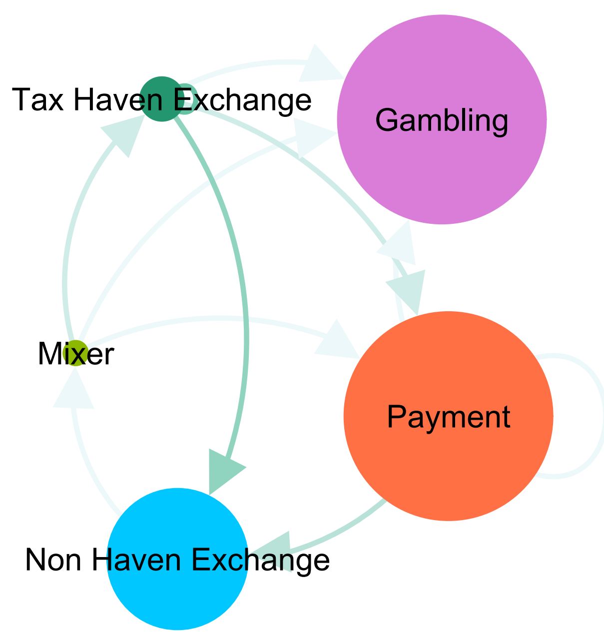


Service Category Color Legend

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