SHADOW DOLLARS: STABLECOIN RAILS, SCAM FINANCE AND THE LIMITS OF DETECTION IN THAILAND

A PREPRINT

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ABSTRACT

Thailand combines low inflation, a licensed and identity-verified crypto exchange sector, and a long border with the scam-compound economy of Myanmar, Cambodia and Laos. I ask whether Thai stablecoin behaviour is anomalous, whether USDT is a plausible channel for laundering transnational fraud proceeds, and how either claim can be tested credibly. Public on-chain data through May 2026 show that USDT on Tron is a retail dollar rail distinct from USDT on Ethereum: it carries 47% of the covered USDT supply, 74.5 million funded addresses (5.3 times Ethereum), mean balances about six times smaller and 9.3 times the transfer intensity per dollar. Ninety-five per cent of U.S. sanctions-list addresses tagged USDT, TRX or USDC are Tron addresses. Thailand itself has little macroeconomic reason to hold dollars on-chain (2019–2023 inflation of 1.7% a year, fourth lowest of 23 comparators), unlike neighbouring Laos and Myanmar. Chain-wide data cannot evaluate national enforcement: nominal 95% bands reject at 58% of 149 placebo dates, and placebo-calibrated p-values for three crackdowns range from 0.69 to 1.00. I therefore develop a pre-registered design with four estimators—a difference-in-bunching test at the 50,000-baht face-verification threshold, dwell-time mixtures, direction-aware graph exposure and synthetic control—and validate them in an agent-based simulation with planted mule accounts. The common undirected two-hop exposure rule attains 2–6% precision among top-ranked accounts; multi-signal scoring reaches 78–92%; the bunching-difference test has close-to-nominal size and 88% power at a 2% mule share. A channel-choice model explains why enforcement that displaces flows leaves chain-wide totals unchanged. Code and data are released for replication.

Keywords stablecoins · USDT · Tron · money laundering · scam centres · bunching · synthetic control · blockchain forensics · Thailand

JEL codes E42, G23, G28, K42, C63, O53

Key findings

1. **A distinct rail.** USDT on Tron is a high-turnover, small-balance dollar rail: 47% of covered USDT supply, 74.5 million funded addresses and 9.3 times the transfer intensity of USDT on Ethereum (Section 6.1).
2. **A weak macro motive.** Thai inflation and exchange-rate volatility do not explain heavy stablecoin use; the same is not true of neighbouring Laos and Myanmar, whose legitimate dollar demand can flow through Thai channels (Section 6.3).
3. **Aggregate data mislead.** Chain-level event studies over-reject at 58% of random dates; with honest, placebo-calibrated inference no crackdown is detectable, which a displacement model predicts (Sections 4.5 and 6.5).
4. **Detect differences, follow direction.** Structuring is identified by the *difference* in bunching between USDT and other assets, not by bunching itself; graph exposure must follow the direction of funds (Section 7).
5. **A ready design.** Six pre-registered hypotheses, decision rules and open code make the Thai question testable as soon as exchange or regulator data are available under the PDPA (Section 8).

1 Introduction

Stablecoins have become the settlement asset of the crypto economy and, increasingly, a dollar substitute for people outside the United States. They have also become the preferred medium of the industrialised online fraud that grew out of Southeast Asia's border casinos and special economic zones. Regional and international bodies describe a system in which victims' bank transfers are converted, through networks of rented accounts, into USDT on the Tron blockchain and moved through informal "guarantee" marketplaces and underground bankers before being integrated into real assets (United Nations Office on Drugs and Crime, 2024, 2025; Financial Action Task Force, 2023). Thailand sits at the edge of this system. It hosts a licensed, identity-verified crypto exchange industry and a large retail investor base; it shares long land borders with the compounds of Myawaddy, the casinos of Poipet and the special economic zones of the Golden Triangle; and its banks, police and regulators have spent the past four years tightening controls on so-called mule accounts.

This paper asks three questions that a Thai regulator, an exchange compliance officer or a researcher would want answered. First, is Thai stablecoin behaviour unusual—relative to other crypto-assets traded on the same platforms and relative to stablecoin use elsewhere? Second, is it plausible that criminal networks, including the "call centre" fraud gangs that target Thai victims, launder proceeds through USDT, and through Thai rails in particular? Third, and most important, how could either claim be tested in a way that separates criminal flows from the many legitimate reasons to hold and move digital dollars?

The third question disciplines the first two. Unusual behaviour is not evidence of crime. Thai investors cannot trade crypto derivatives on licensed domestic venues, so buying USDT and withdrawing it to an offshore exchange is the ordinary route to leverage. Millions of migrant workers from Myanmar, Cambodia and Laos live in Thailand and send money home, and two of those countries have recently experienced the high inflation and capital controls that make dollar stablecoins attractive. Honest peer-to-peer dealers receive baht from many counterparties and withdraw quickly, which is exactly what a mule account does. A credible study must therefore name each legitimate motive, state the fingerprint it leaves in data, and show that the residual pattern attributed to laundering survives once those fingerprints are removed.

What this paper does I make four contributions. The first is *descriptive and uses only public data*. Using the Coin Metrics community files through 23 May 2026, I document that USDT on Tron behaves as a retail payment rail that is economically distinct from USDT on Ethereum (Section 6.1). Tron carries 47% of the USDT supply on the chains covered by the data, up from 19% at the end of 2019. It hosts 74.5 million addresses with a positive balance—5.3 times as many as USDT on Ethereum—with a mean balance of about US$1,200 against roughly US$7,000, and it records 9.3 times as many transfers per dollar of supply. When Circle wound down USDC on Tron in 2024, USDC supply there fell from a peak of US$3.5 billion to under US$30 million, leaving the cheapest high-liquidity dollar rail in the region to a single issuer. In the U.S. Treasury's sanctions list, 95% of the addresses tagged USDT, TRX or USDC are Tron addresses. I also show that Thailand's macroeconomic fundamentals give its residents little reason to hold dollars on-chain—its consumer-price inflation averaged 1.7% a year over 2019–2023, the fourth lowest of 23 comparators—whereas Laos (14.9%) and Myanmar have strong legitimate demand (Section 6.3).

The second contribution is *a negative result with a methodological lesson*. Event studies on chain-wide activity are a tempting way to evaluate crackdowns because the data are free. I estimate abnormal Tron USDT activity around three dated shocks—Thailand's February 2025 power cut to border scam hubs, its June 2025 block on unlicensed offshore exchanges, and the October 2025 U.S. and U.K. sanctions on Prince Group—and calibrate inference against 149 placebo dates. Conventional bootstrap bands, which already account for serial correlation and trend uncertainty, reject the null at 58% of random dates. Calibrated against the placebo distribution, none of the three shocks is distinguishable from an ordinary week (p between 0.69 and 1.00). Section 4.5 rationalises this: in a channel-choice model in which enforcement raises the cost of one rail, flows are displaced to substitutes and the aggregate is unchanged to first order.

The third contribution is *a set of estimators matched to the economics of structuring and pass-through* (Section 4). The central one exploits the Bank of Thailand's face-verification rule, which applies to transfers of 50,000 baht or more. Honest users also dislike the scan and bunch below the threshold, so bunching by itself proves nothing. Under an assumption that hassle avoidance is the same across the assets a deposit funds, the *difference* in a slope-invariant bunching statistic between USDT-funding and other deposits identifies the volume of structured deposits (Proposition 1). I complement it with dwell-time mixtures, a direction-aware measure of graph exposure to flagged addresses, and synthetic control for policy shocks, and I prove that undirected hop counts mechanically flag exchange hubs (Proposition 2).

The fourth contribution is *validation*. Because no public dataset links Thai exchange accounts to criminal outcomes, I build an agent-based simulator of an exchange-year with five honest populations (domestic traders, offshore bridge

traders including arbitrageurs, cross-border remitters, holders and honest peer-to-peer merchants) and mule accounts whose tradecraft varies, including camouflaged mules on rented, aged accounts (Section 7). Against planted ground truth, the undirected two-hop rule attains a precision of 2–6% among its top-ranked accounts; speed alone attains 6–21%; a direction-aware exposure measure rises from 2% to 86% as prevalence grows; and multi-signal scoring reaches 78–92%. The bunching-difference test rejects in 7.5% of null simulations at a nominal 5% level and in 88% of simulations with 2% mule accounts. Synthetic control has a 2.5% false-rejection rate and 82% power for a 0.10 log-point effect. These magnitudes are properties of the simulator; the ranking of methods and their failure modes are the transferable result.

What this paper does not claim The paper does not estimate how much Thai stablecoin volume is criminal. Doing so requires account-level data that exchanges and the Anti-Money Laundering Office hold and that the Personal Data Protection Act rightly restricts. Instead, Section 8 sets out a pre-registered plan—six hypotheses, the data tier each needs, the estimator and the decision rule—so that the question can be answered as soon as such data are available, without specification search. All code is open, every figure is regenerated from raw files whose checksums are recorded, and every simulated figure is marked as such.

Roadmap Section 2 describes the Thai regime and the regional scam economy. Section 3 relates the paper to work on stablecoins, illicit crypto finance and blockchain forensics. Section 4 presents the conceptual framework, the model and the propositions. Section 5 describes the data. Section 6 reports the evidence from public data and Section 7 the simulation study. Section 8 contains the pre-registered plan, policy implications, limitations and conclusions. Proofs, simulator parameters and replication instructions are in the appendix.

2 Institutional background

This section summarises the rules that shape how stablecoins can be used in Thailand and the regional criminal economy that motivates the paper.[1]

2.1 Thailand's digital-asset regime

Crypto exchanges, brokers and dealers serving Thai residents must be licensed by the Securities and Exchange Commission under the Emergency Decree on Digital Asset Businesses of 2018. The licensed market has long been concentrated, with Bitkub holding a dominant share, and it was joined in early 2024 by a joint venture between Gulf Energy and Binance. Five features of the regime matter for stablecoin behaviour.

(i) *Baht-quoted trading.* Licensed venues have historically quoted assets against the baht; USDT and USDC were added to the list of crypto-assets that may serve as quote assets only in early 2025. Before then the USDT/THB pair was the main gate between baht and on-chain dollars.

(ii) *No domestic derivatives.* Licensed exchanges do not offer leveraged crypto derivatives. Residents who want leverage buy USDT at home and withdraw it to an offshore venue, which mechanically raises the withdrawal rate of USDT relative to other assets.

(iii) *No payments.* Since 2022 licensed businesses may not facilitate the use of crypto-assets to pay for goods and services, so payment use, where it exists, migrates to peer-to-peer and over-the-counter channels that are harder to observe.

(iv) *Tax.* In 2025 the government approved a five-year exemption from personal income tax on gains from sales through licensed Thai providers (2025–2029), raising the return to trading onshore.

(v) *Access to offshore venues.* In mid-2025 the authorities blocked access to several unlicensed foreign exchanges, a shock that should displace some activity towards peer-to-peer markets and virtual private networks.

2.2 The anti-fraud architecture

Thailand's response to online fraud has concentrated on the bank accounts through which victims' money first moves. The Emergency Decree on Measures for the Prevention and Suppression of Technology Crimes of 2023 made it an offence to open, rent out or sell accounts for others to use, and it allowed financial institutions to suspend suspicious transfers and share information. An amendment in 2025 extended these duties to digital-asset business operators and

[1] Institutional details and dates in this section were compiled from public announcements and are stated at the precision available, often the month. They should be checked against primary legal sources before being relied upon.

introduced liability for institutions whose negligence enables losses. The police established the Anti Online Scam Operation Center, reachable through the 1441 hotline, in late 2023. Since 2023 banks have also required facial biometric verification for transfers of roughly 50,000 baht or more per transaction, or 200,000 baht or more per day, and for raising transfer limits.

These measures raise the cost of the classic chain in which a victim's transfer passes through several layers of mule bank accounts before being withdrawn in cash. They create two predictions that this paper turns into tests. The verification threshold should generate structuring—deposits placed just below 50,000 baht—in the channel that launderers use (Section 4.2). And tighter bank-side controls should displace laundering towards channels in which baht leave the banking system quickly, of which converting them into USDT is the most liquid (Section 4.5).

2.3 The regional scam economy

UNODC's 2024 report on casinos, underground banking and transnational organised crime in East and Southeast Asia describes how criminal groups that grew out of junket and casino operations moved into large-scale online fraud run from compounds in Myanmar, Cambodia and Laos, staffed in part by trafficked workers, and how they settle and launder proceeds through underground banking and stablecoins, with USDT on Tron prominent among them (United Nations Office on Drugs and Crime, 2024). A 2025 follow-up documents the industry's spread to other regions (United Nations Office on Drugs and Crime, 2025). The FATF's report on cyber-enabled fraud describes the same pipeline from the perspective of financial intelligence units (Financial Action Task Force, 2023), and its 2025 update on virtual assets highlights the growing use of stablecoins by illicit actors (Financial Action Task Force, 2025). Industry analysts report that stablecoins account for a majority of the transaction volume received by addresses they classify as illicit (Chainalysis, 2025).

Enforcement against this infrastructure intensified in 2024 and 2025. Tether, the Tron Foundation and TRM Labs formed a financial crime unit to freeze USDT linked to crime. Research by blockchain analytics firms exposed Telegram-based "guarantee" marketplaces associated with the Cambodian conglomerate Huione Group, several of which Telegram removed in 2025 (Elliptic, 2024). In February 2025 Thailand cut electricity, internet and fuel supplies to areas across the Myanmar border that host scam compounds. In October 2025 the U.S. and U.K. governments sanctioned the Cambodian Prince Group and associated individuals and entities, the U.S. Department of Justice filed a forfeiture complaint against roughly 127,000 bitcoin, and FinCEN acted to sever Huione Group from the U.S. financial system (U.S. Department of the Treasury, 2025; Financial Crimes Enforcement Network, 2025). In the same month Myanmar's military raided the KK Park compound.

Figure 1 places these events on one time axis. Its message for empirical work is simple: nine of the sixteen events fall in the nine months between February and October 2025. Any design that attributes a change in Thai stablecoin flows to one of them must contend with the others, which is why the pre-registered plan relies on narrow windows, control assets and placebo inference.

3 Related literature

The paper connects four literatures.

The economics of stablecoins A first strand studies what keeps stablecoins at par and what they do to the rest of the financial system. Lyons and Viswanath-Natraj (2023) show how arbitrage capacity and the issuer's balance sheet determine deviations from the peg; Gorton and Zhang (2023) draw the analogy with free-banking-era private money; Arner et al. (2020) and the Bank for International Settlements (2025) discuss risks and regulation, and Liao and Caramichael (2022) the implications for bank funding. Work on the interaction between stablecoin issuance and crypto prices includes Griffin and Shams (2020), Ante et al. (2021) and Kristoufek (2021). This literature treats stablecoins mostly as a single asset. I show that the same token on different blockchains serves different clienteles—USDT on Tron is a small-balance, high-turnover rail, USDT on Ethereum a large-balance one—which matters for any analysis of who uses stablecoins and why.

Illicit finance in crypto-assets Foley et al. (2019) estimate the share of bitcoin activity associated with illegal goods using network clustering. Cong et al. (2023a) provide an anatomy of crypto-enabled cybercrime, and Griffin and Mei (2024) trace the flows of "pig-butchering" fraud from victims to exchanges, documenting the role of USDT and large centralised exchanges in cashing out. Policy reports by United Nations Office on Drugs and Crime (2024, 2025) and the Financial Action Task Force (2020, 2023, 2025) describe typologies and red flags. Industry reports such as Chainalysis (2025) provide aggregate estimates whose attribution methods are proprietary. Relative to this work I focus on a single

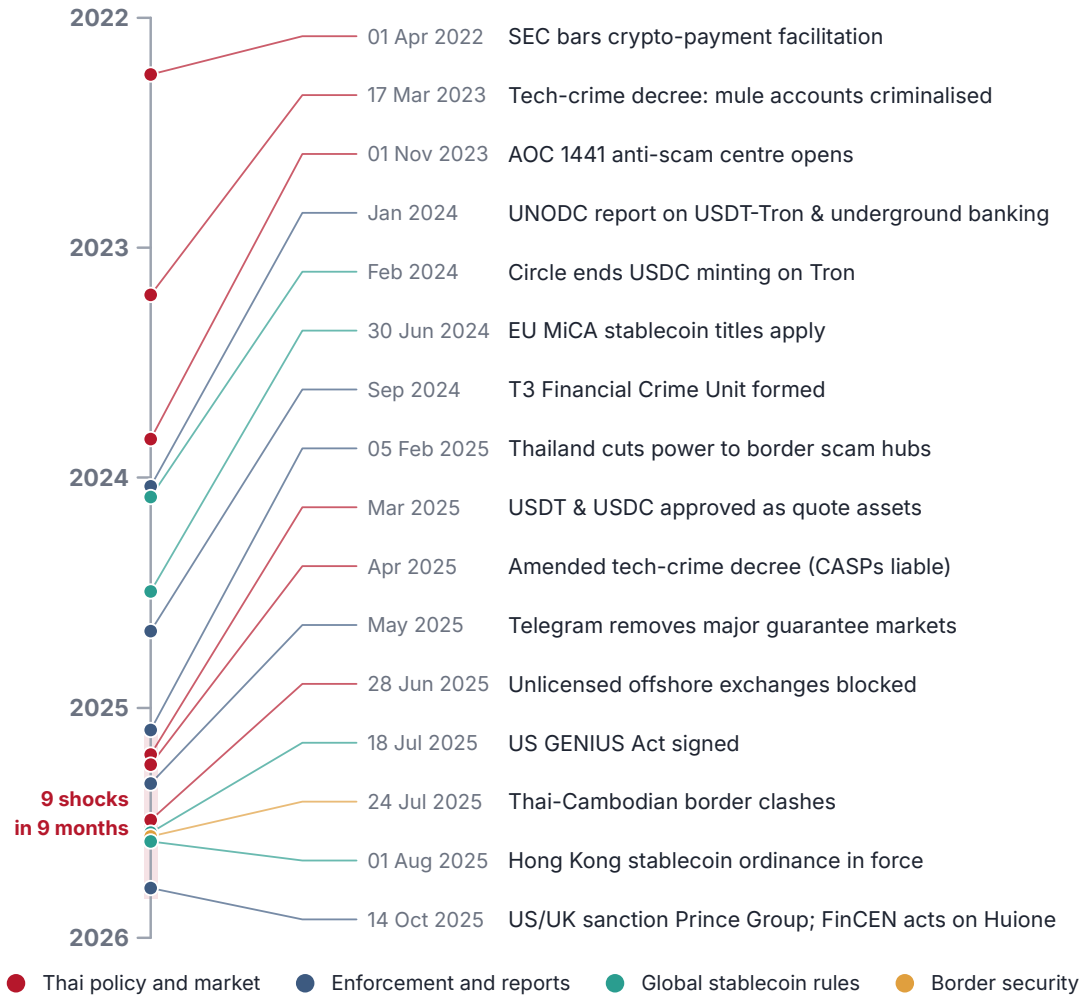


Figure 1. Policy, enforcement and market events relevant to Thai stablecoin flows, 2022–2025. Dots on the left axis sit at the true date; labels on the right are in chronological order. Colours mark the type of event. Month-level dates are shown without a day and should be verified against primary sources.

jurisdiction at the boundary between the banking system and on-chain rails, and on the identification problem: how to distinguish laundering from the legitimate motives that produce similar data.

Market structure and data quality Makarov and Schoar (2020) document persistent cross-country price premia in crypto markets, such as the Korean "kimchi premium", that reflect capital controls; I use the analogous USDT/THB premium as a fingerprint of the store-of-value motive. Cong et al. (2023b) show that reported exchange volumes are inflated by wash trading, which is why the plan relies on ratios within a platform and on adjusted volumes rather than on raw cross-exchange comparisons. Auer et al. (2022) relate retail adoption to prices using app-download data.

Blockchain forensics and anomaly detection Address clustering and labelling go back to Meiklejohn et al. (2013); supervised and graph-based approaches to anti-money-laundering on transaction graphs include Weber et al. (2019). I use unsupervised scores—the isolation forest of Liu et al. (2008) and a transparent composite of red flags—because

labels are scarce in practice, and I show formally and in simulation that the direction of fund flows must be respected when exposure to flagged addresses is measured. Community detection, used in the replication package for exploratory clustering, follows Blondel et al. (2008).

Methods The bunching estimator adapts the notch and kink designs of Saez (2010), Chetty et al. (2011) and Kleven and Waseem (2013), surveyed by Kleven (2016), to a setting in which the notch is a verification step rather than a tax, and in which a within-platform comparison across assets removes the honest response. Policy evaluation relies on synthetic control (Abadie et al., 2010; Abadie, 2021) and, as a robustness check, synthetic difference-in-differences (Arkhangelsky et al., 2021). Cross-country controls include the capital-account openness index of Chinn and Ito (2006).

4 Conceptual framework

4.1 Four motives and their fingerprints

Observed stablecoin flows on Thai rails are the sum of four motives. *Trading and offshore bridging*: residents buy USDT as collateral or as the vehicle to reach offshore derivatives. *Dollar saving*: residents hold USDT as a store of value. *Cross-border transfer*: migrant workers, traders and tourists move value across borders. *Illicit pass-through*: criminal proceeds enter as baht and leave as USDT. Each motive leaves a distinct fingerprint, summarised in Table 1, and the identification strategy is to remove the first three before interpreting the residual (Figure 2).

Table 1. Motives for holding and moving stablecoins on Thai rails, their fingerprints and how they are tested

Motive	Fingerprint in the data	Main confounder	Hypothesis
Trading and offshore bridge	USDT volume co-moves with crypto volatility and offshore funding rates; withdrawals go to labelled exchange hot wallets and return after gains	Arbitrageurs move as fast as mules	H1, H2
Dollar saving	Long holding periods; USDT/THB premium over the official rate rises when the baht weakens	Little in Thailand (low inflation)	H1
Cross-border transfer	Small, regular amounts; peaks after paydays and before festivals; destinations are P2P desks in neighbouring countries	Tainted P2P merchants	H1, H6
Illicit pass-through	Young accounts funded by many bank accounts; deposits structured below 50,000 baht; exits within minutes; forward paths to flagged addresses; responds to crackdowns, not prices	Honest P2P dealers, camouflaged mules	H3–H6

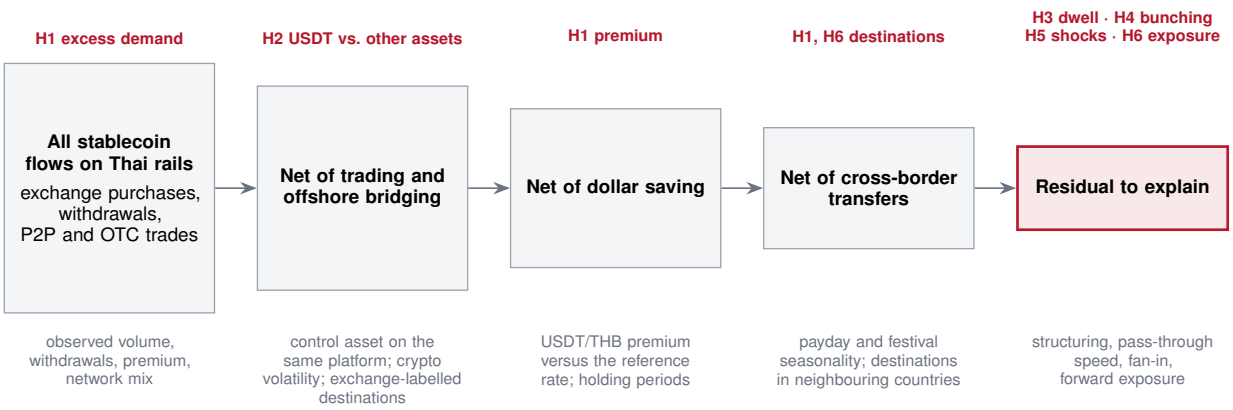


Figure 2. Identification strategy. Observed flows are the sum of four motives. Each legitimate motive is removed using its fingerprint (grey notes) before the residual is interpreted; red labels give the pre-registered hypotheses of Section 8 that test each step. Box heights are schematic, not estimates.

4.2 Structuring at a verification notch

Consider deposits of baht onto a licensed platform. Each deposit has an intended amount z and funds an asset class $a \in \{S, O\}$, where S denotes USDT and O any other crypto-asset. Banks require face verification for transfers of at least T baht. Let $h_a(z)$ be the counterfactual density of intended amounts of honest deposits funding a, and write $H_a(A) = \int_A h_a(z)\, dz$ for the counterfactual mass in a set A.

Honest depositors whose intended amount lies in a response window $[T, T + R)$ relocate to a bunching window $[T - \delta, T)$ with probability $\pi_a(z)$; they find the scan a hassle, or simply prefer to split the transfer. Launderers add a mass I_a of *structured* deposits placed in $[T - \delta, T)$ to avoid the verification step that would expose a mule's identity. The observed excess mass below the threshold and the responding share are

$$B_a = \int_T^{T+R} \pi_a(z)\, h_a(z)\, dz + I_a, \qquad \beta_a = \frac{B_a}{H_a([T, T+R))} = \bar{\pi}_a + \frac{I_a}{H_a([T, T+R))}, \tag{1}$$

where $\bar{\pi}_a$ is the average relocation probability over the response window.

Assumption A1 (Asset-invariant hassle avoidance)**.** $\bar{\pi}_S = \bar{\pi}_O$: the share of honest deposits intended for the response window that relocate below T does not depend on which asset the deposit funds.

Assumption A2 (Channel specificity)**.** $I_O = 0$: structured deposits fund the stablecoin channel, which offers immediate, liquid exit.

Assumption A3 (Smooth counterfactual)**.** h_a is smooth in $\log z$ on a neighbourhood of $[T - \delta, T + R)$, so that it is identified from the observed density outside that window, up to multiplicative round-number effects.

Proposition 1 (Difference in bunching)**.** *Under Assumptions A1 to A3,*

$$\Delta\beta \equiv \beta_S - \beta_O = \frac{I_S}{H_S([T, T+R))} \geq 0,$$

with equality if and only if $I_S = 0$. The structured stablecoin volume is identified as $I_S = \Delta\beta \cdot H_S([T, T+R))$.

The proof is immediate from Equation (1) and is given in Appendix C. Two features matter in practice. First, the normalisation: the classic statistic divides the excess by the counterfactual density just below T. When the two asset classes have amount distributions of different shapes—stablecoin deposits are larger—that statistic differs across assets even when $\bar{\pi}_S = \bar{\pi}_O$. In the simulation below, a test based on it rejected a true null in 14% of draws at a nominal 5% level; the responding share β_a in Equation (1) reduced this to 7.5%. Second, Assumption A1 can be relaxed. If deposits observed before the verification rule exist, the change in $\Delta\beta$ across the rule's introduction identifies I_S under the weaker assumption that asset-specific differences in honest bunching are stable over time.

Corollary 1 (Difference-in-difference-in-bunching)**.** *If $\bar{\pi}_S - \bar{\pi}_O$ is the same before and after the rule's introduction and no structuring occurs at T before it, then $\Delta\beta^{post} - \Delta\beta^{pre} = I_S^{post}/H_S^{post}([T, T+R))$.*

A placebo version of the test at amounts where no verification step exists (T' = 30,000 or 70,000 baht) provides a specification check: under correct specification $\Delta\beta(T')$ should be zero.

4.3 Pass-through and the limits of speed

A mule account exists to move value, so the time between a baht deposit and the withdrawal of the USDT it bought—its *dwell time*—is short. But speed is shared with honest populations: arbitrageurs exploit price gaps within minutes, and peer-to-peer dealers recycle inventory quickly. The following bound formalises why a speed-only rule cannot achieve high precision when such populations exist.

Lemma 1 (Speed is not sufficient)**.** *Let n_M mule accounts and n_F honest "fast" accounts have dwell times with distribution functions G_M and G_F, with $G_F(t) \geq G_M(t)$ for all t (honest fast accounts are at least as fast). For any rule that flags accounts with dwell time below a threshold t, the expected number of flagged mules divided by the expected number of flagged accounts is at most $n_M/(n_M + n_F)$.*

In the simulated economy of Section 7 with 2% mules, arbitrageurs and honest dealers make the bound about 0.25; the speed-only score attains a precision of 0.12. Speed is a useful input to a score, not a test.

4.4 Exposure to flagged addresses: direction matters

Compliance systems commonly flag an account if the destination of its withdrawals lies within k hops of a sanctioned or frozen address. Let $G = (V, E)$ be the directed graph of transfers, with edges pointing in the direction of funds,

and let $F \subset V$ be the flagged set. Let $d_u(v, F)$ be the undirected distance from v to F and $d_{\to}(v, F)$ the length of the shortest *forward* path from v into F. For an account i with withdrawals w of value x_w to destinations v_w, define the value-weighted exposure

$$X_i^{(k)} = \frac{\sum_w x_w \, \mathbf{1}\{d(v_w, F) \le k\}}{\sum_w x_w}, \qquad d \in \{d_u, d_{\to}\}. \tag{2}$$

Proposition 2 (Hubs and undirected distance)**.** *Let h be an exchange hot wallet that receives at least one payment from a wallet ℓ that pays a flagged address ($\ell \to f$, $f \in F$), and suppose every forward path from h into F has length at least $m > 2$, or none exists. Then $d_u(h, F) \le 2$ while $d_{\to}(h, F) \ge m$. For $2 \le k < m$, every account that withdraws only to h has $X^{(k)} = 1$ under undirected distance and $X^{(k)} = 0$ under forward distance.*

Large exchanges receive deposits from criminals cashing out, so in real data almost every exchange hot wallet satisfies the premise. Because Thai residents who bridge to offshore venues withdraw to exactly these wallets, the undirected rule generates false positives on the population that is largest and least suspicious. Forward distance removes this artefact but not *taint contagion*: an honest remitter who pays a peer-to-peer merchant that later pays a layering wallet is exposed under both definitions, which motivates value weighting and the combination with behavioural signals.

4.5 Displacement across channels

Why might a crackdown leave no trace in chain-wide data? Suppose a laundering network must move a fixed volume M of proceeds through channels $j \in J$—for example licensed-exchange mule accounts (E), peer-to-peer desks (P) and over-the-counter underground bankers (U)—with strictly convex costs $c_j(q_j)$. Enforcement raises the marginal cost of channel E by τ. The network solves

$$\min_{\{q_j \ge 0\}} \sum_{j \in J} c_j(q_j) + \tau q_E \quad \text{subject to} \quad \sum_{j \in J} q_j = M. \tag{3}$$

Proposition 3 (Displacement)**.** *At an interior optimum, $\partial q_E / \partial \tau = -(1 - \omega_E)/c_E'' < 0$ and $\partial q_j / \partial \tau = \omega_E / c_j'' > 0$ for $j \ne E$, where $\omega_E = (1/c_E'')/\sum_{l \in J}(1/c_l'') \in (0, 1)$. Total flow is unchanged: $\sum_j \partial q_j / \partial \tau = 0$.*

Corollary 2 (Invisible crackdowns)**.** *If all channels terminate in the same on-chain asset, an enforcement shock that leaves M unchanged has no first-order effect on chain-level volume. If M responds through deterrence, the effect on chain-level volume is bounded by the network's share of that volume.*

Corollary 2 is the theoretical counterpart of the event-study result in Section 6.5. It also says where to look instead: the composition of flows—the share of fast, structured deposits on licensed platforms, the peer-to-peer premium, the network mix—moves even when the total does not.

4.6 Typology and control points

Figure 3 summarises, at the level of generality used by the FATF and UNODC, the path of fraud proceeds and the points at which Thai institutions can intervene. The conversion step is the boundary: before it, funds sit in the domestic banking system where they can be frozen quickly; after it, they move on a public ledger where they can be traced indefinitely and, for USDT, frozen by the issuer.

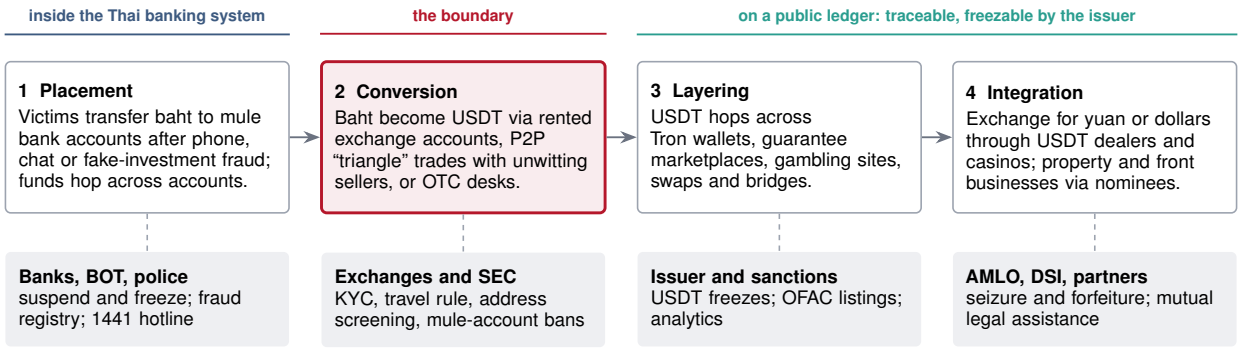


Figure 3. Laundering typology for fraud proceeds and the corresponding control points, at the level of generality of FATF and UNODC typologies. The description is deliberately non-operational. Stage 2 is where funds leave the banking system and where data held by Thai exchanges can observe them.

5 Data

The empirical sections use only data that anyone can download; the pre-registered plan specifies the additional data that would be needed. Table 2 lists the sources. All files were retrieved on 8 November 2026 through the collectors in the replication package, which record the URL, retrieval time, size and SHA-256 hash of every file in a manifest (Appendix A).

Table 2. Data sources used in this paper

Source	Content and coverage	Use
Coin Metrics Community Data (Coin Metrics, 2026)	Daily on-chain metrics by asset and chain: supply, addresses with a balance, active addresses, transfer counts. USDT on Tron (from 2019), Ethereum (2017), Omni and Avalanche; USDC on Ethereum and Tron; through 23 May 2026	Rails, clienteles, USDC exit, event studies
Federal Reserve H.10 (Board of Governors of the Federal Reserve System, 2026)	Daily noon buying rates for 22 currencies including the baht, through 30 October 2026	Exchange-rate volatility
World Bank FP.CPI.TOTL.ZG (World Bank, 2026)	Annual consumer-price inflation; Thailand to 2023	Macro motive
OFAC SDN digital-currency addresses (Office of Foreign Assets Control, 2026)	1,073 addresses under 17 currency tags; mirror updated 7 November 2026	Address formats on sanctions lists
Author's event compilation	16 dated policy and enforcement events, 2022–2025	Timeline, event windows

Coverage of on-chain data The community files cover four USDT chains whose combined supply on 23 May 2026 was US$189 billion, against US$193 billion in Coin Metrics' cross-chain USDT aggregate. Chains absent from the community files, notably TON, Solana and BNB Chain, are excluded from chain-level comparisons; shares reported for Tron are therefore shares of the covered supply. The community files do not contain transfer values, only counts, so I measure turnover as transfers per dollar of supply rather than as value velocity.

A data-quality finding The widely mirrored `datasets/inflation` package labels its two files the wrong way round: the file named for the GDP deflator contains consumer-price inflation and vice versa. I detected the transposition by checking known values—Thailand's consumer-price inflation in 2022 was 6.1%, U.S. inflation 8.0%, Türkiye's 72.3%—and use the corrected file throughout. The World Bank series omits Argentina and Venezuela, and it reports Myanmar only to 2019; the figures mark sparse series explicitly.

Sanctions data OFAC tags digital-currency addresses by currency rather than by chain. I classify each address by its encoding (Tron base58 addresses begin with "T" and have 34 characters; EVM addresses are 42-character hexadecimal strings beginning with "0x"), which identifies the chain on which a USDT address operates. The classification describes the list, not the volume of sanctioned activity.

What is not used The paper does not use proprietary attribution data, exchange account records or police case files, and it does not de-anonymise any address. The collectors for exchange order books and TronGrid transfers in the replication package were not executed in the environment in which the paper was compiled, because those services were not reachable from it; they are provided for researchers who obtain access.

6 Evidence from public data

6.1 USDT on Tron is a retail dollar rail

Figure 4 shows the migration of USDT onto Tron. At the end of 2019 Tron carried 19% of the USDT supply on the covered chains; by mid-2021 it carried half, and on 23 May 2026 it carried 47% (US$89 billion) against 51% on

Ethereum (US$97 billion). The share has oscillated around one half since 2021, so "Tron versus Ethereum" is not a story of one chain displacing the other but of two rails of similar size.

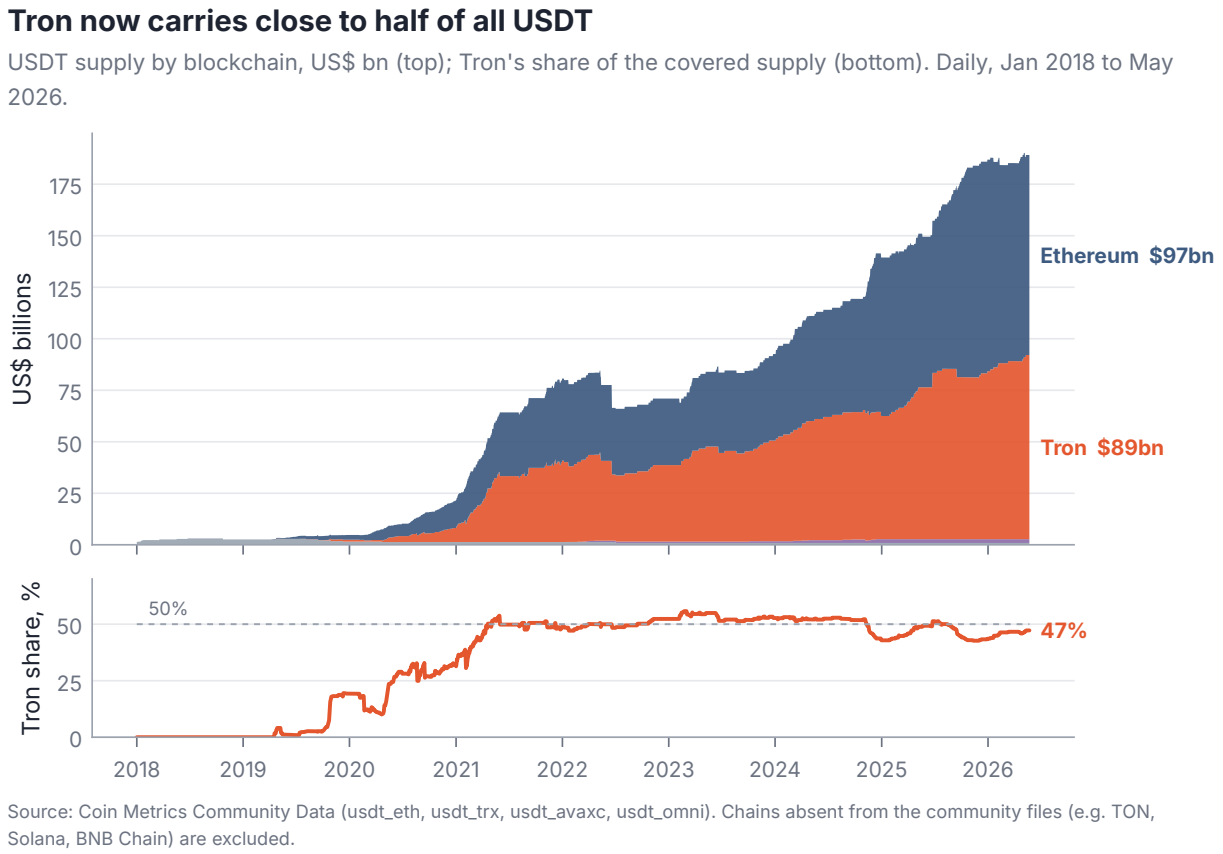


Figure 4. USDT supply by blockchain. Top: US$ billions, stacked. Bottom: Tron's share of the covered supply.

The two rails serve different clienteles. Table 3 reports a snapshot and Figure 5 the history. On 23 May 2026, 74.5 million addresses held USDT on Tron, 5.3 times the 14.0 million on Ethereum, and the mean balance per holding address was about US$1,200 against about US$6,900. Tron recorded 2.1 million USDT transfers that day, 3.1 times Ethereum's 0.67 million, with less supply. Measured as transfers per US$1 million of supply—a count-based turnover rate—Tron's median since January 2024 is 32 a day, 9.3 times that of USDT on Ethereum (3.4) and 6.7 times that of USDC on Ethereum (4.8). Small balances turned over often are the signature of a payments rail; large balances turned over rarely are the signature of a settlement and treasury rail.

Table 3. On-chain snapshot of the main dollar-stablecoin rails, 23 May 2026

	Supply US$bn	1-yr %	Holders m	1-yr %	Active k/day	Transfers k/day	Mean balance US$
USDT on Tron	89.36	+21	74.49	+13	941	2,071	1,200
USDT on Ethereum	97.07	+33	14.01	+83	212	667	6,926
USDC on Ethereum	52.72	+31	6.99	+118	118	505	7,543
USDC on Tron	0.03	-30	0.38	+0	0	0	74

Notes: Supply in US$ billions; holders are addresses with a positive balance (millions); active addresses and transfers are daily counts (thousands); 1-yr columns give percentage changes over 365 days. Mean balance is supply divided by holders. Source: Coin Metrics Community Data; author's calculations.

Two caveats apply. An address is not a person: exchanges hold customer funds in omnibus wallets, and individuals hold many addresses. Both biases are, if anything, larger on Tron, where exchanges custody much of the retail float

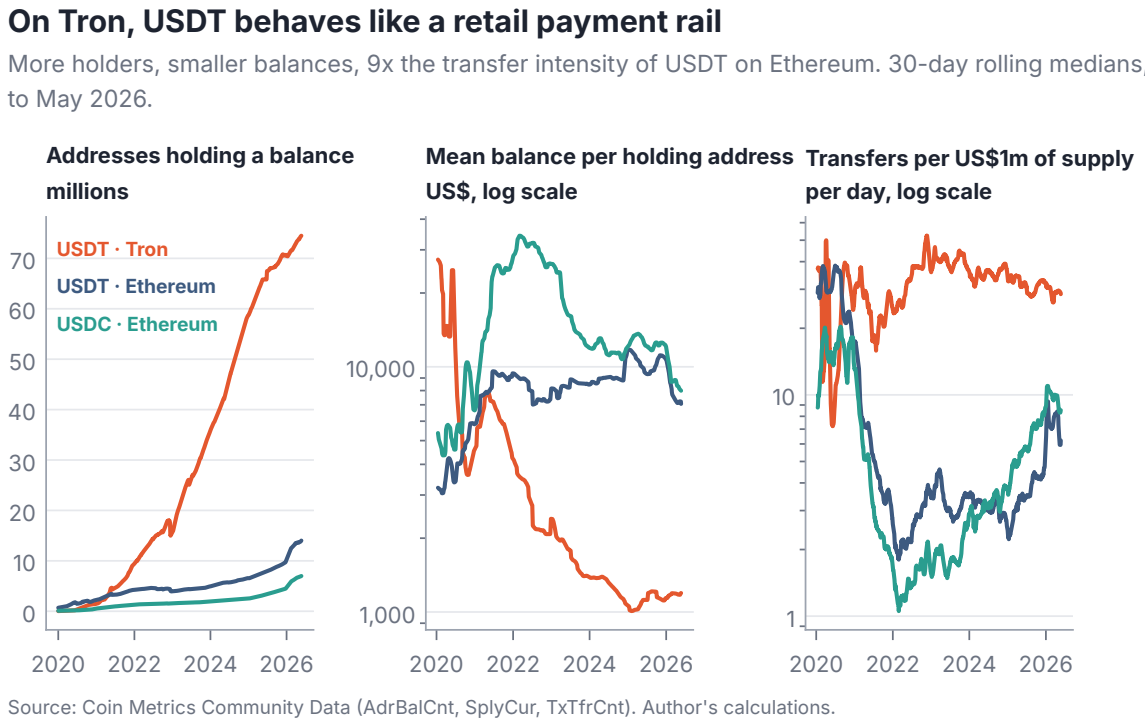


Figure 5. Holders, mean balances and turnover of USDT on Tron and Ethereum and of USDC on Ethereum. 30-day rolling medians; the middle and right panels use logarithmic scales.

and address creation is cheap, so the comparison of balances per address is indicative rather than exact. The turnover comparison does not depend on address counts and is the more robust of the two.

6.2 Circle's exit left the cheapest rail to a single issuer

USDC on Tron grew to US$3.5 billion in August 2022 and then shrank. After Circle announced that it would stop minting USDC on Tron in early 2024, supply fell below US$30 million (Figure 6). For users in Southeast Asia who need a cheap, liquid dollar token, USDT on Tron is now, in practice, the only option at scale. This concentration cuts both ways for enforcement: one issuer with the technical ability to freeze tokens sits on the main rail, but regulatory regimes that would restrict USDT, such as the European Union's, have no regional substitute to push users towards.

6.3 Thailand has little macroeconomic reason to hold dollars on-chain

Where inflation is high, currencies are volatile or capital is controlled, people hold dollar stablecoins for reasons that have nothing to do with crime. Figure 7 shows that Thailand is not such a place. Its consumer-price inflation averaged 1.7% a year over 2019–2023, the fourth lowest of 23 economies after Japan, China and Malaysia. The baht's volatility against the dollar since January 2021, 7.8% a year, is in the middle of the 21 currencies in the Federal Reserve's H.10 release—below the yen, the won and the Australian dollar.

The neighbourhood is different. Inflation averaged 14.9% in Laos over 2019–2024 and was 8.8% in Myanmar in 2019, the last year the World Bank reports, before a period of currency collapse and capital controls. Cambodia is largely dollarised already. Legitimate dollar demand on the other side of Thailand's borders can and plausibly does flow through Thai platforms and peer-to-peer markets, especially given the millions of migrant workers from these countries in Thailand. This is the most important legitimate confounder for any claim that Thai stablecoin flows are "excessive", and the pre-registered plan treats it as such (H1 and H6 in Table 8).

6.4 Sanctions lists point to Tron

Table 4 classifies the 1,073 digital-currency addresses on the OFAC list by the currency tag OFAC assigns and by address encoding. Of the 368 addresses tagged USDT, TRX or USDC, 351 (95%) are Tron addresses; among the 94

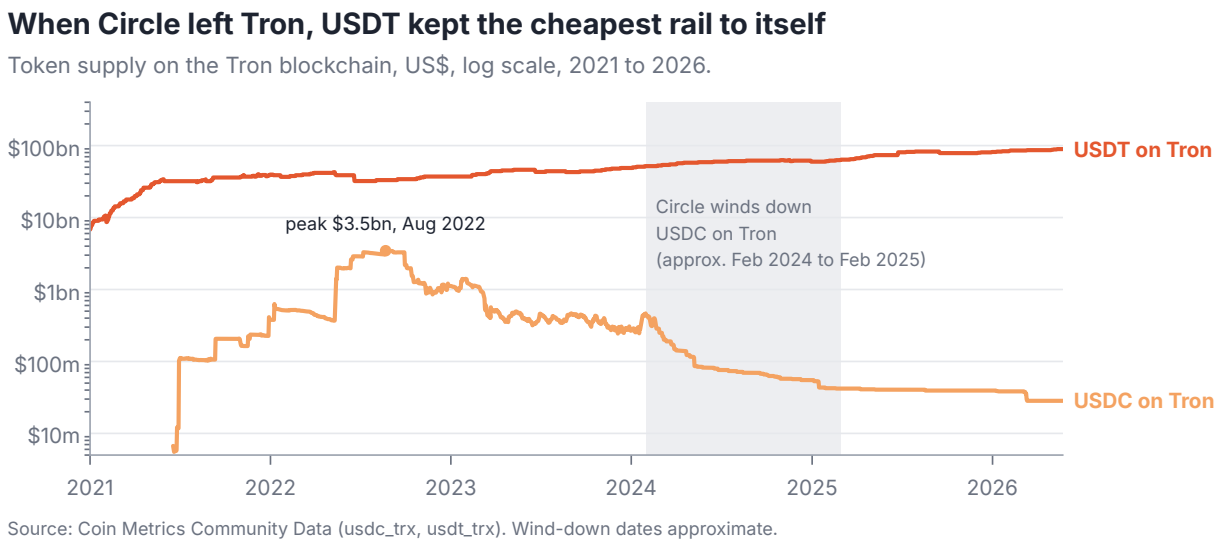


Figure 6. USDC and USDT supply on the Tron blockchain, logarithmic scale. The shaded band marks the approximate wind-down period.

tagged USDT, 79 are Tron addresses, eight are Ethereum-style addresses and seven are Bitcoin-style addresses that operated on the legacy Omni layer. Counts of listed addresses are a crude measure: one listing can cover a single wallet or the hub of a large network, and listings reflect enforcement priorities. They nonetheless confirm that, for the authority with the most active crypto-sanctions programme, the stablecoin activity worth sanctioning happens mainly on Tron.

Table 4. OFAC-listed digital-currency addresses by currency tag and address encoding

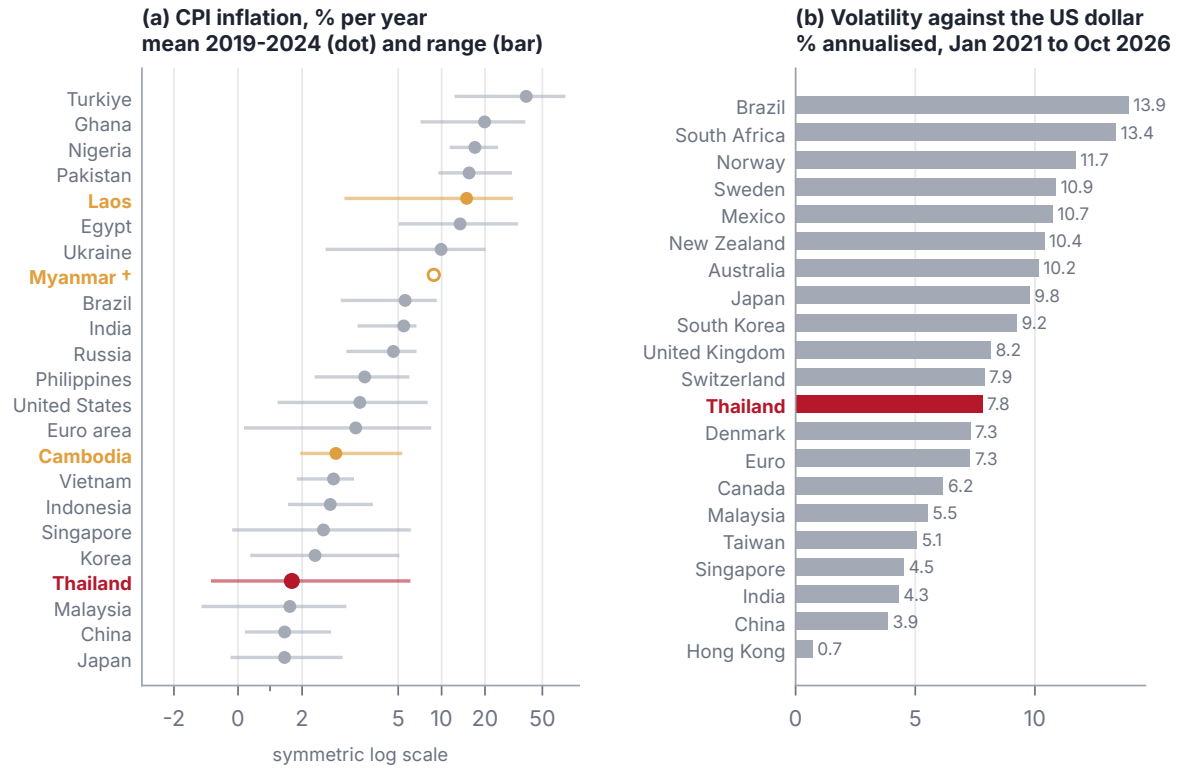
Listed under	Bitcoin	EVM (0x…)	Other	Tron (T…)	Total
XBT	531	0	0	1	532
TRX	0	0	0	272	272
ETH	0	123	0	0	123
USDT	7	8	0	79	94
LTC	0	0	13	0	13
XMR	0	0	11	0	11
BCH	1	0	6	0	7
DASH	0	0	5	0	5

Notes: The eight currency tags with the most listed addresses; the remaining nine tags hold 34 addresses. Encoding is inferred from address syntax. Source: OFAC SDN list via the `0xB10C` mirror, updated 7 November 2026; author's classification.

6.5 What chain-wide data cannot do

It is tempting to evaluate crackdowns with the free data used above. For each of three shocks dated to the day—the power cut to border scam hubs on 5 February 2025, the block on unlicensed offshore exchanges on 28 June 2025 and the Prince Group sanctions on 14 October 2025—I estimate a counterfactual for the log of daily Tron USDT transfers from a linear trend with day-of-week effects fitted over days -150 to -31, and cumulate abnormal activity over days 0 to 30. Bands come from a moving-block bootstrap (14-day blocks) that redraws both the estimation residuals, so that the uncertainty of the extrapolated trend is included, and the future shocks.

Figure 8 reports the result. Two of the three shocks appear "significant" with opposite signs: after the offshore block, activity falls below the band (cumulative abnormal value -2.83 log points by day 30); after the sanctions it rises above it ($+2.54$). The bottom panel shows why neither should be believed. Repeating the exercise at 149 placebo dates spaced a week apart, the nominal bands exclude zero at 58% of them. Chain-wide activity is driven by global market events—the sanctions date, for instance, falls days after one of the largest liquidation episodes in crypto history—and by structural breaks that no trend model anticipates. Calibrated against the placebo distribution, the shocks have p-values of 1.00,



Sources: World Bank FP.CPI.TOTL.ZG (via datasets/inflation, file labels corrected); Federal Reserve H.10 noon rates (via datasets/exchange-rates). † Hollow marker: fewer than three annual observations (Myanmar: 2019 only). Argentina and Venezuela are not reported in this World Bank series. Author's calculations.

Figure 7. (a) Consumer-price inflation, mean of available years 2019–2024 (dot) and range (bar); hollow markers denote fewer than three observations. (b) Annualised volatility of daily log changes in each currency's exchange rate against the US dollar, January 2021 to October 2026.

0.69 and 0.73. The 95th percentile of the absolute placebo values is 11.1 log points, so a shock would have to move global Tron USDT activity by about 36 log points a day, sustained for a month, to stand out. A national crackdown cannot plausibly do that, and by Proposition 3 it need not change the total at all.

The lesson is general. Evaluations of anti-laundering policy that rely on chain-wide aggregates, or on any series dominated by global activity, should report placebo-calibrated inference, and null results from such data say little about whether a policy worked. Credible evaluation needs data on the composition of flows through the channel that the policy targets.

7 Detection design and simulation evidence

No public dataset links Thai exchange accounts to criminal outcomes, and the data that do exist cannot be shared. To learn how the estimators of Section 4 behave before such data are available, I simulate exchange-years in which the truth is known. The simulator is a method-validation device: it is built to make detection *hard*, its parameters are stylised rather than calibrated to any proprietary dataset, and none of its outputs is evidence about real markets.

7.1 The simulated economy

Each draw simulates 8,000 accounts on one licensed platform over 365 days. An account generates *cycles*: a baht deposit, the purchase it funds and, possibly, an on-chain withdrawal. Honest accounts belong to five populations that

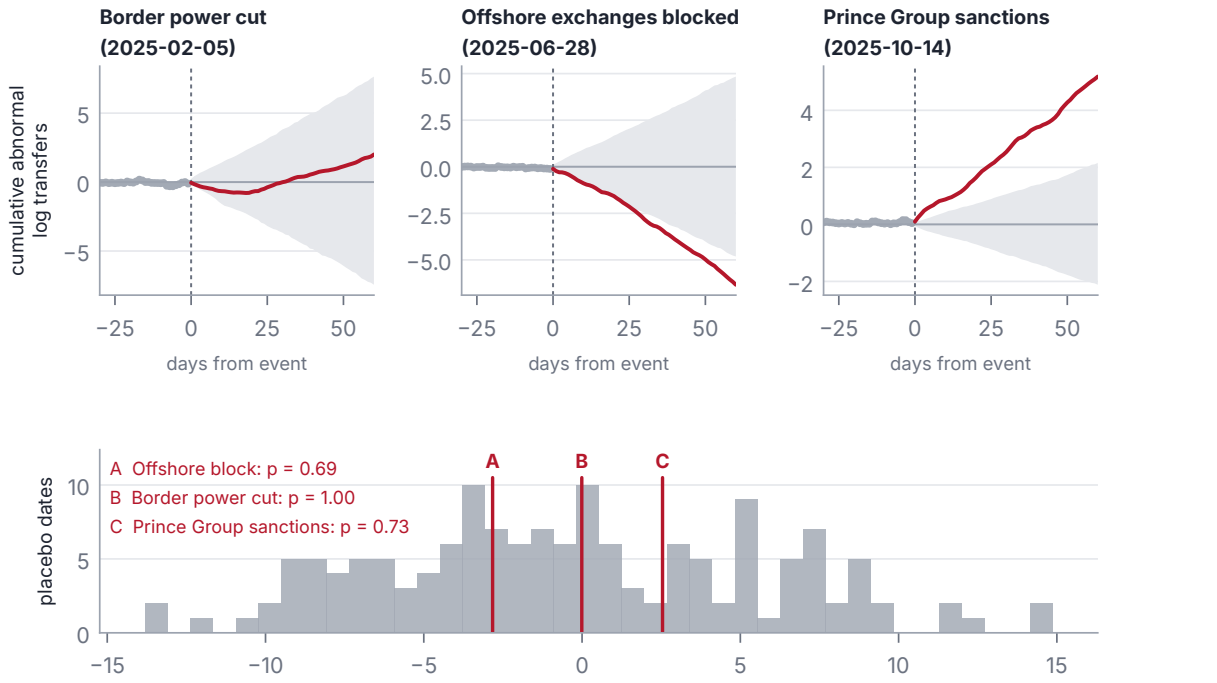


Figure 8. Top: cumulative abnormal log transfers of USDT on Tron after three enforcement shocks, with moving-block bootstrap 95% bands; grey dots are daily abnormal values before the event. Bottom: distribution of the 30-day cumulative abnormal value at 149 placebo dates at least 45 days from any of the three shocks.

embody the legitimate motives of Section 4.1; Table 5 summarises them and Appendix B lists every parameter.

Table 5. Populations in the simulated exchange-year

Population	Share	Median deposit (THB)	Median exit	Distinguishing behaviour
Domestic traders	53%	4,000	3 days	Mostly non-stablecoin purchases; rarely withdraw
Offshore bridge traders	21%	20,000	20 min	90% USDT; withdraw to exchange hot wallets; 15% are arbitrageurs exiting in about 5 min
Cross-border remitters	10%	6,000	6 hours	Small regular USDT purchases forwarded to P2P merchants abroad, 10% of whom are tainted
Holders	13%	15,000	30 days	Buy USDT and keep it on the platform
Honest P2P merchants	3%	30,000	15 min	Many counterparties (70% of deposits from new bank accounts); fast exits
Mules	0.25–4%	structured	3–90 min	Draw their own tradecraft; 40% camouflaged on rented aged accounts with pre-layered funding

Notes: Shares of honest accounts are normalised to sum to one; mules are added at the stated share of all accounts. 35% of honest deposits intended for 50,000–62,500 baht relocate just below 50,000 baht in every population (Assumption A1). Amounts heap at multiples of 1,000 (30% of deposits) and 5,000 baht (12%).

Mules differ from honest accounts on several dimensions at once, but never on all of them. Each mule draws its own exit speed (log-uniform between 3 and 90 minutes), its propensity to structure deposits into the 40,000–50,000-baht

band (20–90%) and its share of deposits from fresh bank accounts (40–95%). Forty per cent are *camouflaged*: they operate rented accounts opened up to three years earlier, receive pre-layered funds from one or two bank accounts, structure little, exit no faster than 30 minutes and route half their withdrawals through exchange hot wallets.

The transaction graph contains 60 flagged addresses, 400 layering wallets, 20 exchange hot wallets and 200 peer-to-peer merchants, plus a personal wallet per account and consolidation wallets for mules. Blacklists are incomplete by design: half of the layering wallets pay a flagged address directly, a fifth do so through another layering wallet and the rest belong to infrastructure nobody has flagged. Forty per cent of layering wallets cash out through exchange hot wallets, which therefore sit two undirected hops from a flagged address—the premise of Proposition 2.

7.2 Estimators and evaluation

The bunching-difference test uses 1,000-baht bins between 10,000 and 110,000 baht, an exclusion window from 45,000 to 65,000 baht, a Poisson counterfactual that is cubic in $\log(z/T)$ with multiplicative round-number effects, and a Poisson bootstrap with 200 replications. The dwell score is an account's mean posterior probability of belonging to the fastest component of a BIC-selected Gaussian mixture on log dwell times. Exposure is Equation (2) with $k = 2$ on the undirected graph and $k = 3$ on the directed graph. The red-flag composite averages the percentile ranks of eight indicators adapted from the FATF's red flags (Financial Action Task Force, 2020): account youth, funding fan-in, stablecoin share, fast exits, deposits near the threshold, unlabelled destinations, daytime activity and directed exposure. The isolation forest uses the same indicators. "Behaviour" variants drop the exposure indicator, mimicking an exchange without blockchain-analytics data.

Because mules are rare, I report the area under the ROC curve (AUC) and *precision at* k, the share of mules among the k highest-scored accounts when k equals the number of mules. Precision at k is what a compliance team with capacity to review k accounts experiences; AUC averages over thresholds nobody uses. For tests, I report size (the rejection rate when no mules exist) and power.

7.3 Results

Structuring is visible as a difference Figure 9 shows one simulated exchange-year with 2% mules. Both channels bunch below the threshold because every population avoids the scan: the responding share is 0.34 for deposits funding other assets, close to the true honest response of 0.35, and 0.51 for deposits funding USDT. The difference, 0.17 (s.e. 0.06), rejects the null of no structuring with a one-sided p-value of 0.001. Across the Monte Carlo (Table 6, Panel C), the test rejects in 7.5% of 200 null draws at a nominal 5% level and in 10%, 30%, 38%, 88% and 100% of draws as the mule share rises from 0.25% to 4%. The mild over-rejection reflects a bootstrap standard error about 12% smaller than the Monte Carlo standard deviation; the plan therefore pairs the test with placebo thresholds. Because the standard error scales with the square root of the number of deposits near the threshold, a platform with a hundred times the simulated activity would detect a structuring share an order of magnitude smaller.

Speed cannot separate mules from honest fast traders Figure 10(a) shows why. Arbitrageurs exit faster than most mules, and honest peer-to-peer merchants exit as fast as camouflaged ones. A speed-only score reaches an AUC of 0.83 but a precision at k of only 0.06–0.21 (Table 6), consistent with the bound of Lemma 1. Panel (b) shows the trade-off at the low false-positive rates that matter in practice.

Direction matters The undirected two-hop rule flags every bridge trader and honest merchant, because their withdrawals go to exchange hot wallets that sit, on average, 2.05 undirected hops from a flagged address (Figure 11). Its precision at k is 0.02–0.06 at every prevalence—the worst of all detectors—even though its AUC of 0.77 looks respectable. Following funds forward removes this artefact: directed exposure reaches an AUC of 0.98. Its precision at k, however, rises only from 0.02 to 0.86 as prevalence grows, because honest remitters who use one of the tainted merchants are fully exposed and tie with mules at the top of the ranking. This is taint contagion, and it is the reason exposure should be one input to a score rather than a verdict.

Layered evidence holds up Scores that combine behaviour and exposure dominate (Figure 12 and Table 6). The isolation forest on all indicators attains a precision at k of 0.78 at the lowest prevalence and 0.90–0.92 from 1% upwards; without the exposure indicator it attains 0.70–0.83, so blockchain intelligence adds roughly eight to ten points of precision. The transparent red-flag composite is less precise (about 0.60 at every prevalence) but each of its components can be explained to an account holder or a court, a property that matters when accounts are frozen.

Synthetic control is well sized For policy shocks I simulate weekly flow indices for a treated country and 19 donors driven by two persistent common factors, plant an effect after week 104, and apply synthetic control with rank-based

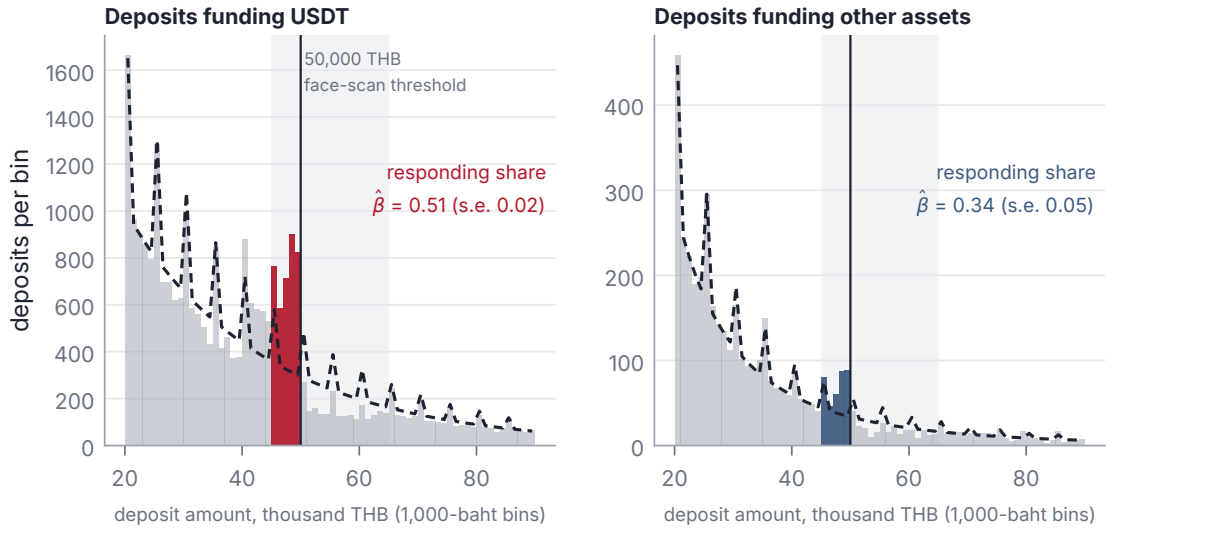


Figure 9. Deposit amounts near the 50,000-baht face-verification threshold in one simulated exchange-year with 2% mule accounts, by the asset the deposit funds. Dashed lines are counterfactual densities fitted outside the shaded window; coloured bars are the excess mass. *Simulated data.*

placebo inference. In the example of Figure 13, the method recovers a planted effect of -0.150 log points as -0.155 with seven donors receiving weight, and the treated unit ranks first among 20 ($p = 0.05$). Across 200 panels per effect size (Table 7), the false-rejection rate is 2.5%, power is 38% for a 0.05 log-point effect and 82% for 0.10, and the mean estimate is unbiased.

7.4 What transfers to real data

The absolute levels in Table 6 depend on choices about populations and tradecraft that real data will revise. Four conclusions do not depend on them. First, a statistic that compares the stablecoin channel with another channel on the same platform is far more robust than one that measures the stablecoin channel alone, and its normalisation must not depend on the shape of the amount distribution. Second, speed and undirected proximity, the two heuristics most often described in compliance practice, fail by construction whenever honest fast traders and exchange hubs exist. Third, at low prevalence AUC flatters detectors and precision at k should be reported. Fourth, combining behaviour with direction-aware blockchain intelligence is what makes detection precise; neither suffices alone.

8 A pre-registered plan for Thailand

The evidence so far establishes the rail, the weak macroeconomic motive, the regional threat and the limits of aggregate data. Whether Thai stablecoin flows actually carry fraud proceeds, and how much, is an empirical question that requires data held by exchanges, the Securities and Exchange Commission and the Anti-Money Laundering Office. To prevent the specification search that such sensitive questions invite, Table 8 commits in advance to six hypotheses, the data each needs, the estimator, the primary statistic and the decision rule.

Interpretation The hypotheses are ordered to separate structure from crime. If H1 and H2 hold but H3–H6 do not, Thai stablecoin behaviour is unusual because of market structure: the absence of domestic derivatives, the

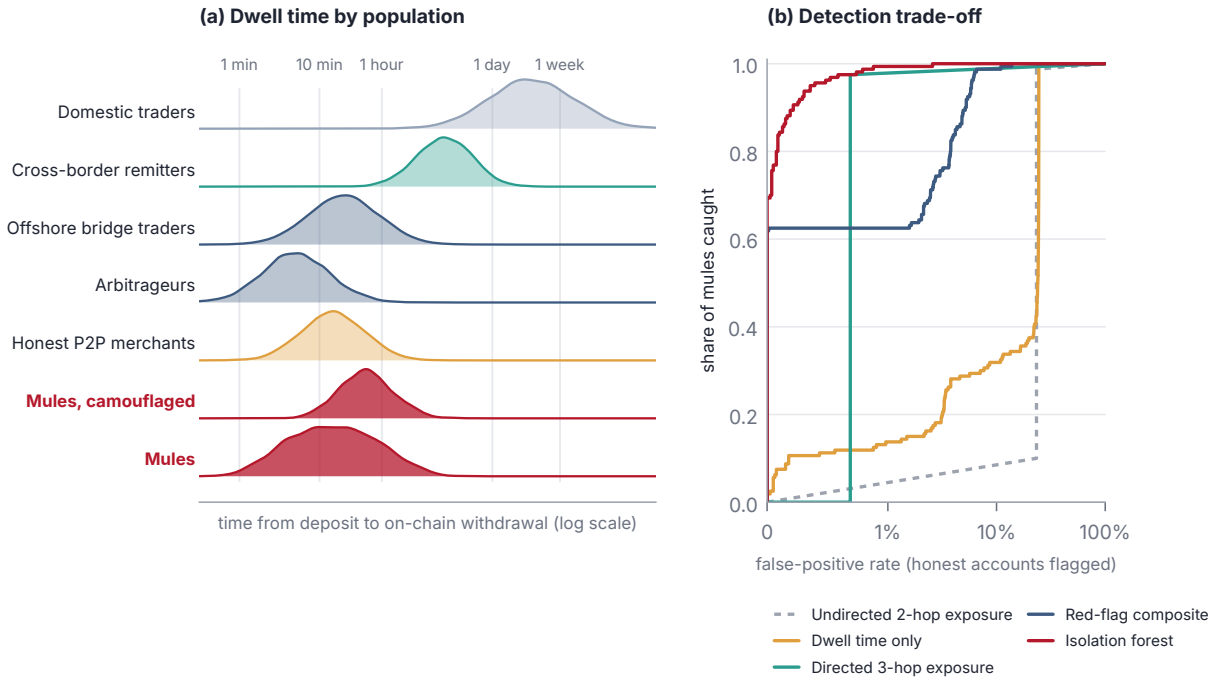


Figure 10. (a) Kernel densities of the time from deposit to on-chain withdrawal by population, logarithmic scale. (b) ROC curves of five detectors in the same simulated exchange-year; the horizontal axis is logarithmic above 1%. *Simulated data.*

baht-quoted market and cross-border demand. If H3–H6 also hold, the residual pattern carries the fingerprints of pass-through laundering, and Proposition 1 converts the bunching estimate into a lower bound on structured volume, since unstructured illicit deposits are not counted.

Data access and privacy Tier-3 analyses should follow a "code goes to the data" model: the replication package runs on the simulator's synthetic ledger, which has the same schema as the exchange data required, so code can be reviewed, tested and approved before it touches personal data inside a regulator's or exchange's secure environment. Only aggregate, disclosure-controlled outputs leave that environment. No address of a person who has not been charged is published.

9 Policy implications

Six implications follow, each conditional on the evidence that the plan would produce.

1. **Monitor differences, not levels.** Supervisors and exchanges should track structuring and pass-through as contrasts between the stablecoin channel and other channels on the same platform, with normalisations that do not depend on the shape of the amount distribution. Levels confound crime with hassle avoidance and market structure.
2. **Make exposure screening direction-aware.** Screening that counts undirected hops to flagged addresses mechanically flags the exchange hubs to which ordinary investors withdraw. Exposure should follow funds forward, weight by value and decay with distance.
3. **Protect honest peer-to-peer dealers.** Honest dealers are the population most easily mistaken for mules and the usual victims of "triangle" fraud, in which a criminal has a victim pay the dealer directly. Requiring that baht

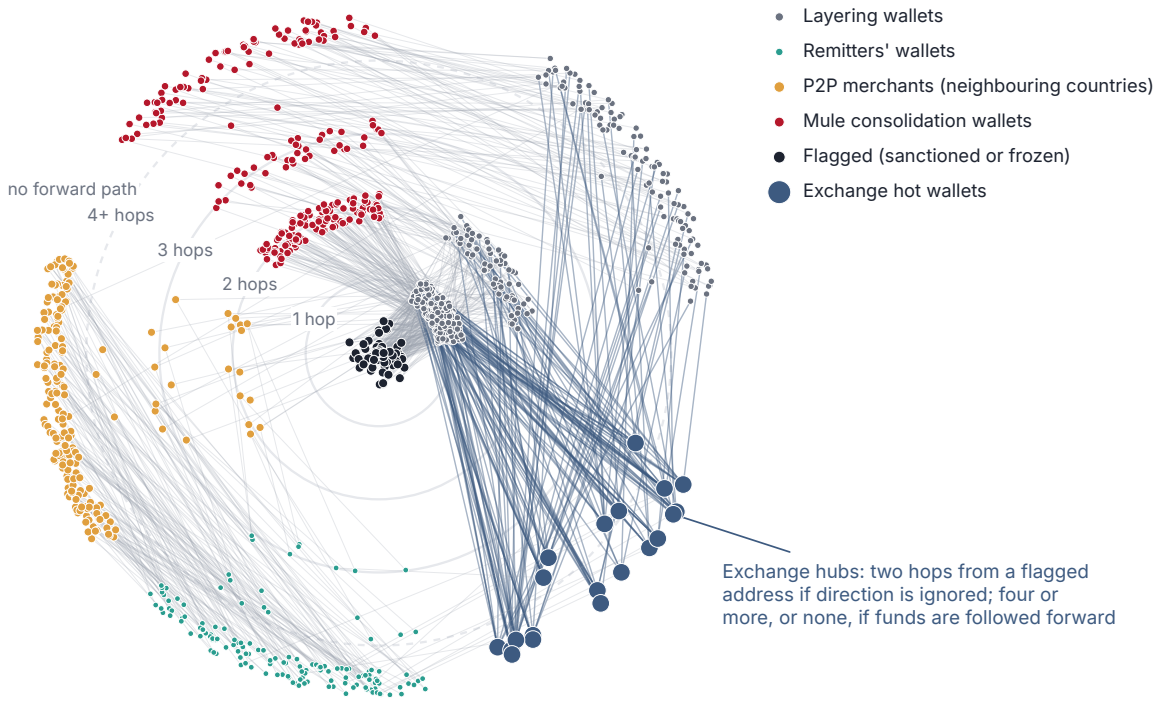


Figure 11. A sample of the simulated transaction graph. Nodes are placed on rings by their forward distance to the nearest flagged address and grouped by type; blue lines are payments into exchange hot wallets. *Simulated data.*

payments for peer-to-peer trades come from a bank account in the buyer's verified name, and creating a fast channel to review frozen dealer accounts, would reduce both the fraud and its collateral damage.

4. **Evaluate crackdowns with composition data and honest inference.** Chain-wide aggregates cannot show whether a crackdown worked (Section 6.5). Publishing weekly, anonymised composition indicators—the share of deposits just below verification thresholds, the share of fast exits, the peer-to-peer premium—would make evaluation possible without disclosing personal data.
5. **Anticipate displacement.** Fixed, publicly known thresholds create the notch that structuring exploits, and pressure on one channel moves flows to others (Proposition 3). Risk-based verification and coordinated action across banks, licensed exchanges and peer-to-peer markets limit the gain from switching.
6. **Use the issuer and the ledger.** Because the region's main dollar rail has a single issuer able to freeze tokens and a public ledger, regional cooperation with the issuer and with neighbouring authorities can act after the conversion boundary, where Thai banks no longer can.

10 Limitations and ethics

The descriptive evidence covers the chains in the Coin Metrics community files and measures turnover by transfer counts, not values. Address-based statistics are affected by custodial omnibus wallets. Event dates and institutional details were compiled without access to primary legal databases and must be verified. The simulation's absolute results

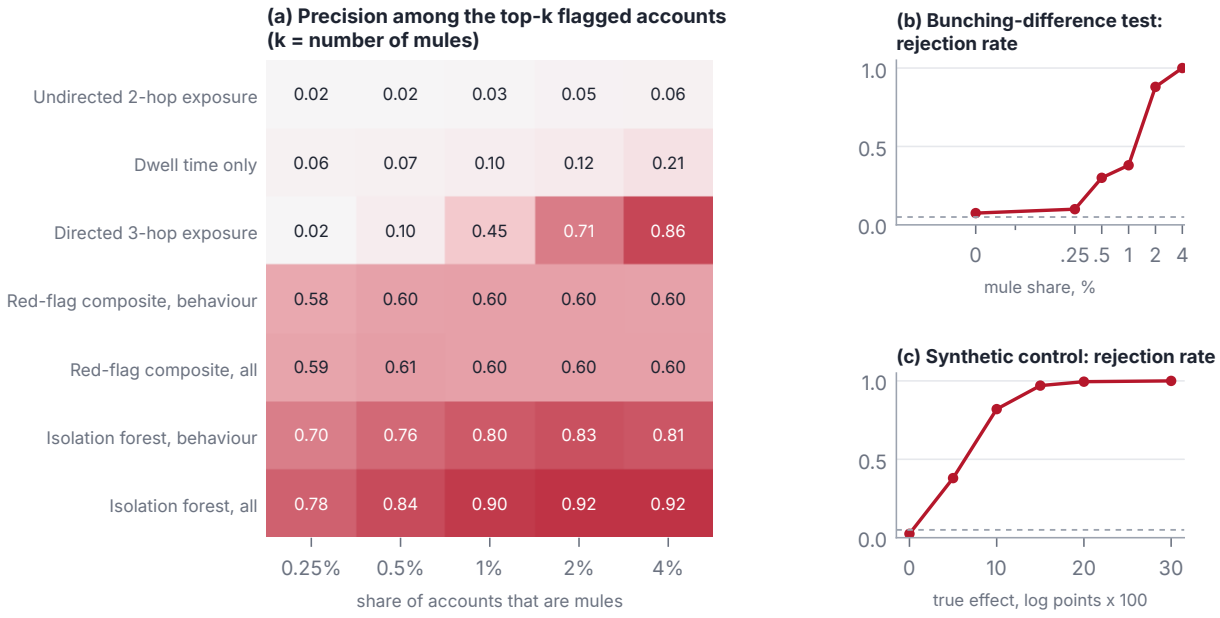


Figure 12. Monte Carlo summary. (a) Precision at k by detector and mule share (50 exchange-years per cell). (b) Rejection rate of the bunching-difference test (200 draws under the null). (c) Rejection rate of synthetic control by true effect size (200 country panels per effect). *Simulated data.*

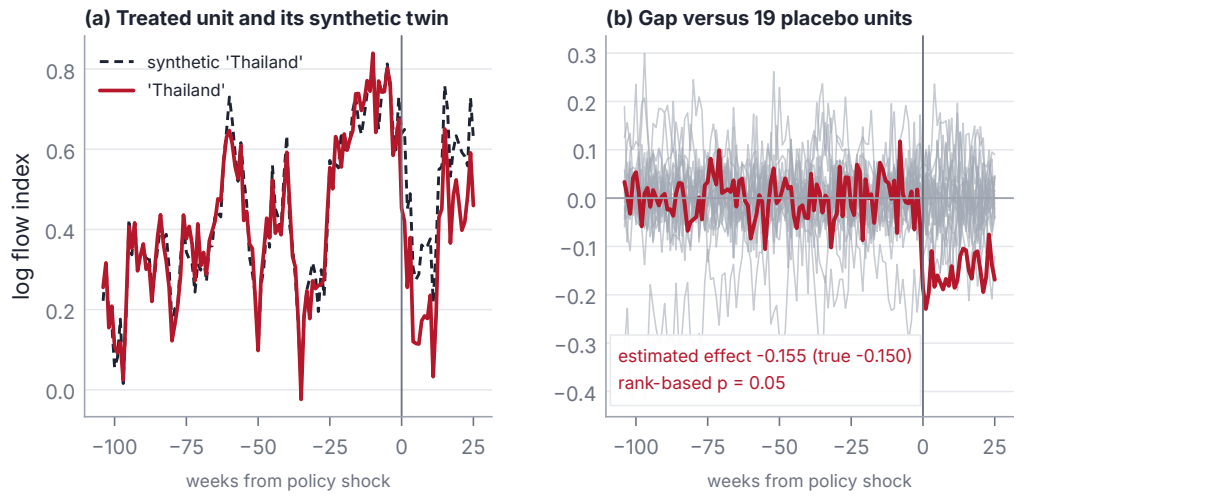


Figure 13. Synthetic control on a simulated country panel with a planted effect of -0.15 log points. (a) Treated unit and its synthetic counterpart. (b) The treated gap (red) against the gaps of 19 placebo units. *Simulated data.*

Table 6. Monte Carlo performance of detectors and of the bunching-difference test

	Share of accounts that are mules				
Detector	0.25%	0.5%	1%	2%	4%
Panel A. Area under the ROC curve					
Undirected 2-hop exposure	0.774	0.775	0.775	0.773	0.775
Dwell time only	0.826	0.827	0.828	0.829	0.827
Directed 3-hop exposure	0.981	0.981	0.980	0.981	0.982
Red-flag composite, behaviour	0.958	0.960	0.959	0.960	0.959
Red-flag composite, all	0.982	0.982	0.982	0.983	0.982
Isolation forest, behaviour	0.996	0.997	0.997	0.997	0.995
Isolation forest, all	0.999	0.999	0.999	0.999	0.999
Panel B. Precision at k					
Undirected 2-hop exposure	0.02	0.02	0.03	0.05	0.06
Dwell time only	0.06	0.07	0.10	0.12	0.21
Directed 3-hop exposure	0.02	0.10	0.45	0.71	0.86
Red-flag composite, behaviour	0.58	0.60	0.60	0.60	0.60
Red-flag composite, all	0.59	0.61	0.60	0.60	0.60
Isolation forest, behaviour	0.70	0.76	0.80	0.83	0.81
Isolation forest, all	0.78	0.84	0.90	0.92	0.92
Panel C. Bunching-difference test					
Rejection rate at 5%	0.10	0.30	0.38	0.88	1.00
Mean $\hat{\beta}_{\mathrm{USDT}} - \hat{\beta}_{\mathrm{other}}$	0.014	0.056	0.088	0.180	0.281

Notes: Means over 50 simulated exchange-years of 8,000 accounts per column. Precision at k is the share of mules among the k highest-scored accounts, with k equal to the number of mules. Under the null of no mules, the bunching-difference test rejects in 7.5% of 200 draws (mean difference -0.007). *Simulated data.*

Table 7. Size and power of synthetic control in simulated country panels

True effect (log points $\times$ 100)	0	5	10	15	20	30
Rejection rate ($p \leq 0.05$)	0.025	0.380	0.820	0.970	0.995	1.000
Mean estimated effect	-0.001	-0.051	-0.101	-0.151	-0.201	-0.301

Notes: 200 panels per column, 20 units, 104 pre-treatment and 26 post-treatment weeks; rejection if the treated unit has the largest post/pre RMSPE ratio ($p \leq 0.05$). *Simulated data.*

depend on stylised parameters; its purpose is to rank methods and reveal failure modes, not to estimate prevalence. Statistical anomalies are not evidence of wrongdoing by any person, dealer or exchange, and the paper names entities only where public authorities have acted. The laundering typology is described at the level of published FATF and UNODC material and omits operational detail.

11 Conclusion

Thailand's stablecoin question is easy to pose and hard to answer. Public data establish that the region's dominant digital dollar, USDT on Tron, is a high-turnover retail rail on which sanctioned activity concentrates; that Thailand, unlike its neighbours, has little macroeconomic reason to use it heavily; and that chain-wide data cannot tell whether crackdowns work. The answer to whether Thai rails carry scam proceeds lies in the composition of flows at the boundary where baht become tokens. This paper supplies the estimators for that boundary—a slope-invariant difference in bunching at the face-verification threshold, dwell-time mixtures, direction-aware exposure and synthetic control—shows in simulation which of them work and why the common heuristics fail, and commits in advance to how the answer will be read once the data are in hand.

Data and code availability

All data are public. Replication code—the Python package `shadowdollars`, the scripts that produce every figure and table, unit tests and the data manifest—is provided as ancillary files with this submission. The manifest records the

Table 8. Pre-registered hypotheses, data, estimators and decision rules

Hypothesis	Data (tier)	Estimator	Decision rule
H1 Excess stablecoin demand	Exchange volumes by quote asset across 20+ countries; inflation, FX volatility, remittances, migrant stock, capital-account openness, derivatives access (1–2)	Panel regression of the stablecoin share of volume on fundamentals; Thailand's standardised residual	Residual positive and in the top decile of a leave-one-country-out distribution
H2 USDT exits more than other assets	Daily purchases and on-chain withdrawals by asset on Thai platforms (2–3)	Difference between USDT and BTC withdrawal-to-purchase ratios, controlling for volatility and offshore funding rates	One-sided test of a positive difference at 5%; reported net of exchange-labelled destinations
H3 Fast pass-through concentrated in young, fan-in accounts	Account-level deposit–purchase–withdrawal cycles (3)	Gaussian mixture on log dwell; fast-component share by account age and fan-in	Difference positive with a bootstrap interval excluding zero, after removing withdrawals to labelled exchanges
H4 Structuring below 50,000 baht	Deposit amounts by funded asset, ideally before and after the verification rule (3)	Difference in responding shares (Proposition 1); difference-in-difference if pre-rule data exist (Corollary 1)	One-sided $p < 0.05$ at 50,000 baht and no significant difference at placebo thresholds of 30,000 and 70,000 baht
H5 Crackdowns change the composition of flows	Weekly composition series (share of fast structured deposits, peer-to-peer premium, network mix) for Thailand and donor countries (2–3)	Synthetic control and synthetic difference-in-differences; triple difference USDT versus BTC	Rank-based placebo $p \leq 0.05$ with pre-period fit no worse than the median donor's
H6 Thai withdrawals are more exposed than peers'	Tron transfers from labelled Thai and peer-country exchange hot wallets; issuer freezes; OFAC list (1–3)	Directed, value-weighted three-hop exposure (Equation (2))	Thai exposure above the 75th percentile of peer exchanges with a bootstrap interval excluding the peer median

Data tiers: 1 public; 2 commercial or academic licence; 3 partnership under the PDPA. H3–H6 form the primary family and are adjusted with the Holm–Bonferroni procedure; H1–H2 are secondary.

URL, retrieval time and SHA-256 hash of each raw file in the vintage used here; some sources are updated daily, so a fresh download yields a later vintage.

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The author used Claude (Anthropic), an AI assistant, to help draft the text, write the replication code and produce the figures. All quantitative results are computed by the code in the replication package from the data it documents. Simulated results validate methods against planted ground truth and are not evidence about real markets. No individual is accused of wrongdoing; entities are named only where public authorities have acted. Responsibility for any errors remains with the author.

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A Data appendix

Table 9 lists the raw files behind every number in Section 6, with the first characters of their SHA-256 hashes. The full manifest, including retrieval timestamps and complete hashes, is `data/raw/MANIFEST.json` in the replication package.

Table 9. Raw data files used in the paper

Series	File	Rows	From	To	SHA-256 (prefix)
USDT on Tron	cm_usdt_trx.csv	2,595	2019-04-16	2026-05-23	3d4b5f8ad882
USDT on Ethereum	cm_usdt_eth.csv	3,099	2017-11-28	2026-05-23	700d5db4d59a
USDT on Omni	cm_usdt_omni.csv	4,248	2014-10-06	2026-05-23	298d09512e19
USDT on Avalanche	cm_usdt_avaxc.csv	1,706	2021-09-21	2026-05-23	cadec2e1a8ba
USDC on Ethereum	cm_usdc_eth.csv	2,851	2018-08-03	2026-05-23	e08a8607cd78
USDC on Tron	cm_usdc_trx.csv	1,810	2021-06-09	2026-05-23	b96e0d1a28e2
USDT, all chains	cm_usdt.csv	4,531	2013-12-28	2026-05-24	bc6cec81ee59
FX rates, H.10	fx_daily.csv	274,031	1971-01-04	2026-10-30	013e19fbdcae
CPI inflation	wb_cpi.csv	11,182	1960	2024	346d29c904c1
OFAC addresses	ofac/*.txt (17)	1,073	—	—	see manifest

Notes: Retrieved on 8 November 2026. Rows are data rows; for the OFAC lists, addresses.

Validating the inflation files Table 10 compares the two files of the `datasets/inflation` mirror with consumer-price inflation figures that are well known. The file labelled as the GDP deflator matches them; the file labelled as consumer prices does not. The analysis uses the former.

Table 10. The inflation files are mislabelled: values for 2022, per cent

	File labelled "GDP deflator"	File labelled "consumer prices"	Known CPI inflation
Thailand	6.08	4.8	6.1
United States	8.00	7.1	8.0
Türkiye	72.3	96.0	72.3

B Simulator parameters

C Proofs

Proof of Proposition 1. By Assumption A3, the counterfactual densities h_S and h_O, and hence $H_a([T, T+R))$ and the excess masses B_a, are identified from the observed densities outside the exclusion window. By Equation (1), $\beta_a = \bar{\pi}_a + I_a / H_a([T, T+R))$ for $a \in \{S, O\}$. Assumption A2 gives $\beta_O = \bar{\pi}_O$, and Assumption A1 gives $\bar{\pi}_S = \bar{\pi}_O$. Subtracting, $\Delta\beta = I_S / H_S([T, T+R))$. Because $I_S \geq 0$ and $H_S([T, T+R)) > 0$, $\Delta\beta \geq 0$ with equality if and only if $I_S = 0$, and $I_S = \Delta\beta \cdot H_S([T, T+R))$. □

Proof of Corollary 1. Before the rule there is no verification step at T and, by assumption, no structuring at T, so $\Delta\beta^{\text{pre}} = \bar{\pi}_S^{\text{pre}} - \bar{\pi}_O^{\text{pre}}$. After it, $\Delta\beta^{\text{post}} = \bar{\pi}_S^{\text{post}} - \bar{\pi}_O^{\text{post}} + I_S^{\text{post}} / H_S^{\text{post}}$. If the asset gap in honest relocation is stable, the first terms cancel in the difference. □

Table 11. Parameters of the agent-based exchange simulator

Population	Share of honest	Cycles per year	Median deposit	σ of log deposit	P(USDT)	P(exit | USDT)	Median exit (min)	Peak hour
Domestic traders	0.534	11	4,000	1.0	0.15	0.15	4,320	20
Bridge traders	0.214	21	20,000	0.9	0.90	0.95	20 (5)[a]	21
Remitters	0.097	11	6,000	0.6	0.95	0.95	360	19
Holders	0.126	6	15,000	1.0	0.80	0.03	43,200	20
P2P merchants	0.029	41	30,000	0.8	1.00	0.95	15	15
Mules	—	36[b]	structured[c]	0.9	1.00	0.98	3–90[d]	13

[a] 15% of bridge accounts are arbitrageurs with a median exit of 5 minutes.
[b] Within a 45-day active life. Cycles per year are Poisson means plus one.
[c] Each mule structures a share of its deposits drawn from $U(0.2, 0.9)$ (camouflaged: $U(0, 0.4)$) into $U(0.8T, T)$; other deposits are log-normal with median 20,000 baht.
[d] Log-uniform per mule; camouflaged mules no faster than 30 minutes.
Other parameters: 8,000 accounts; 365 days; threshold T = 50,000 baht; honest relocation probability 0.35 for intended amounts in $[T, 1.25T)$; heaping at 1,000 (30%) and 5,000 baht (12%); exit-speed dispersion σ between 0.7 and 1.2 by population; fresh funding sources for 70% of merchant deposits and 40–95% of non-camouflaged mule deposits; graph of 60 flagged, 400 layering, 20 exchange and 200 P2P-merchant wallets as described in Section 7.1.

Proof of Lemma 1. For a threshold t with $G_M(t) > 0$, the expected number of flagged mules is $n_M G_M(t)$ and the expected number of flagged honest fast accounts is $n_F G_F(t) \geq n_F G_M(t)$. Other honest accounts can only add to the denominator. Hence the ratio of expected flagged mules to expected flagged accounts is at most $n_M G_M(t) / (n_M G_M(t) + n_F G_M(t)) = n_M/(n_M + n_F)$. □

Proof of Proposition 2. The path $h \leftarrow \ell \rightarrow f$ has two edges, so $d_u(h, F) \leq 2$. By assumption every forward path from h into F has at least m edges, or none exists, so $d_{\rightarrow}(h, F) \geq m$. For $2 \leq k < m$ the indicator in Equation (2) equals one under d_u and zero under $d_{\rightarrow}$ for every withdrawal to h, so an account that withdraws only to h has $X^{(k)} = 1$ and $X^{(k)} = 0$ respectively. □

Proof of Proposition 3. The Lagrangian of Equation (3) is $\mathcal{L} = \sum_j c_j(q_j) + \tau q_E - \lambda \left(\sum_j q_j - M \right)$. At an interior optimum, $c_j'(q_j) + \tau \mathbf{1}\{j = E\} = \lambda$ for all j. Differentiating with respect to τ and imposing $\sum_j \partial q_j / \partial \tau = 0$ (because $\sum_j q_j = M$),

$$c_j'' \frac{\partial q_j}{\partial \tau} = \frac{\partial \lambda}{\partial \tau} - \mathbf{1}\{j = E\}, \qquad \frac{\partial \lambda}{\partial \tau} \sum_{l \in J} \frac{1}{c_l''} - \frac{1}{c_E''} = 0 \implies \frac{\partial \lambda}{\partial \tau} = \omega_E.$$

Substituting back, $\partial q_E / \partial \tau = -(1 - \omega_E)/c_E'' < 0$ and $\partial q_j / \partial \tau = \omega_E / c_j'' > 0$ for $j \neq E$; the derivatives sum to zero by construction. □

Proof of Corollary 2. Let chain-level volume be $V = \sum_j q_j + V_0$, where V_0 is unrelated activity. If every channel terminates in the same token, $\partial V / \partial \tau = \sum_j \partial q_j / \partial \tau = 0$ by Proposition 3. If instead M falls with τ, $\partial V / \partial \tau = \partial M / \partial \tau$ and the proportional change in V is at most $|\partial M / \partial \tau| / V \leq |\partial \log M / \partial \tau| \cdot M/V$, which is bounded by the network's share of chain-level volume, M/V. □

D Replication

The replication package, provided as ancillary files (folder `anc/`) with this arXiv submission, contains the Python package `shadowdollars` (collectors, metrics, detectors, simulator, Monte Carlo), the scripts that produce every figure and table, the raw data with their manifest, and the LaTeX source of this paper. From the package root:

Command	Purpose
`pip install -e .`	install the package
`python -m shadowdollars.collectors.public`	download raw data and write the manifest
`python scripts/figures_real.py`	figures and tables of Sections 2 and 6
`bash run_mc.sh`	Monte Carlo (about 10 minutes on one core)
`python scripts/figures_sim.py`	figures and tables of Section 7
`pytest -q`	unit tests for the estimators
`latexmk -pdf main`	compile this paper (pdfLaTeX)

Exchange and TronGrid collectors (`collectors/local.py`) and the account-level schema used by the plan in Section 8 are included but were not executed in the compilation environment. Random seeds are fixed, so the simulation results reproduce exactly.