Can Demonetization Defeat Grey Capital?

Evidence, a Calibrated Agent-Based Model, and a Research Agenda for Retiring Thailand's 1,000-Baht Note

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November 7, 2026

Abstract

Proposals to withdraw Thailand's 1,000-baht banknote promise to squeeze grey and black capital, vote buying and corruption. This paper evaluates that promise by combining a structured synthesis of twelve demonetization episodes, a cross-country measure of denomination size, and *DemonetSim-TH*, an agent-based model in which illicit holders choose among direct deposit, structuring through money mules, conversion into alternative stores of value, amnesty and abandonment under capacity-constrained laundering, while honest holders face a liquidity gap governed by replacement logistics. The model is calibrated to India's 2016 demonetization by approximate Bayesian computation. Four results stand out. First, at 0.38 percent of GDP per capita the 1,000-baht note is a mid-sized "large note", about a quarter of the EUR 500 at its withdrawal. Second, an India-style shock destroys or seizes a median of 7.7 percent of illicit cash while generating about one sixth of India's liquidity disruption, roughly 90 percent of which falls on vulnerable and informal holders. Third, India's 99.3 percent return rate is consistent with illicit shares between 3 and 29 percent and therefore does not identify the illicit stock. Fourth, a global sensitivity analysis shows that the bite of any design hinges on laundering capacity relative to the illicit stock, whereas disruption depends almost entirely on replacement logistics; a gradual phase-out combined with anti-money-laundering (AML) measures achieves a comparable bite (6.1 percent) at negligible liquidity cost. We formalize these regularities as a *demonetization trilemma* and propose three identification strategies to test whether the 1,000-baht note is in fact a preferred medium of illicit exchange.

Keywords demonetization · high-denomination banknotes · money laundering · shadow economy · agent-based modeling · approximate Bayesian computation · Thailand

JEL codes E41 · E42 · E58 · H26 · K42 · O17 · C63

1 Introduction

Cash remains the medium of choice for transactions that are meant to leave no trace, and large banknotes make it especially convenient: one million US dollars in USD 100 notes weighs about ten kilograms, the same value in EUR 500 notes about two (Sands et al., 2016; Rogoff, 2016). This observation underlies a series of decisions to retire large notes—the euro area stopped issuing the EUR 500 in 2019, Canada stopped

*Draft for discussion. All statistics are approximations that must be verified against primary sources, in particular Bank of Thailand banknote statistics; model parameters are assumptions, and no live data sources were consulted. References were compiled without database access and their bibliographic details must be checked. The author acknowledges AI assistance (Claude, Anthropic) in drafting, coding and figure design. Replication code: `demonet_sim_th.py` (seed 7).

issuing its CAD 1,000 in 2000 and Singapore its SGD 10,000 in 2014—and, most dramatically, India's overnight demonetization of 86 percent of its currency by value in November 2016.

In Thailand, the idea of withdrawing the 1,000-baht note resurfaces periodically as a remedy for "grey capital", "black capital", vote buying and corruption. The argument is intuitive; its empirical premise is not established. India's experience is sobering: 99.3 percent of the demonetized value returned to the banking system (Reserve Bank of India, 2018); the cash crunch lowered the growth of economic activity by at least two percentage points in the quarter of the shock (Chodorow-Reich et al., 2020); and although electronic payments expanded (Crouzet et al., 2023), the ratio of currency to GDP returned to its earlier level within a few years (Lahiri, 2020).

This paper asks three questions. What does international experience imply about the effectiveness and costs of demonetization as an instrument against illicit wealth? Under alternative designs, how would retiring the 1,000-baht note affect the stock of illicit cash, the economy and its most vulnerable participants, and the operating costs of the currency system? And if the policy were pursued, how should it be designed, and which empirical questions must be answered first?

We proceed in three steps. We synthesize twelve episodes into a typology and six stylized facts, and place the 1,000-baht note on a cross-country scale of denomination size. We then develop a stylized model in which the state cannot identify illicit holdings, audit capacity is finite and replacement currency is supplied at a bounded rate. The model yields a conditional impossibility result, the demonetization trilemma: no design simultaneously destroys a large share of illicit cash (*bite*), spares honest holders (*smoothness*) and prevents the exchange from becoming a laundering channel (*integrity*) unless audit capacity exceeds laundering throughput and replacement currency is pre-positioned in secret. Finally, we quantify the trade-offs with DemonetSim-TH, an agent-based model calibrated to India 2016 by approximate Bayesian computation (ABC), and probe it with a global sensitivity analysis.

The results are summarized in the abstract. Three deserve emphasis. First, the bite of a shock design is small even in the calibrated model (median 7.7 percent), and its distribution is right-skewed: large bites arise only when illicit holdings are large relative to the capacity of laundering networks. Second, the most widely cited statistic from India—the 99.3 percent return rate—rules out large-scale extinguishment but is nearly uninformative about the size of the illicit stock. Third, the levers that govern the bite (laundering capacity, illicit share, structuring costs) are disjoint from those that govern disruption (replacement logistics), which is why a phase-out combined with AML measures dominates a shock: it moves the stock through a tighter net without starving the economy of cash.

The paper contributes to three literatures. It adds a formal and quantitative treatment of the *stock* channel through which demonetization is supposed to work to a debate dominated by arguments about the *flow* benefits of retiring large notes (Rogoff, 1998, 2016; Sands et al., 2016) and by ex post evaluations of India's episode (Chodorow-Reich et al., 2020; Lahiri, 2020; Crouzet et al., 2023). It contributes to the economics of crime and money laundering (Becker, 1968; Unger, 2007) by modeling laundering as a capacity-constrained market, which implies that enforcement intensity matters far less than laundering capacity once the latter is abundant. And it adds to the measurement literature on the shadow economy (Tanzi, 1983; Schneider and Enste, 2000; Medina and Schneider, 2018) a non-identification result: aggregate return rates cannot discriminate between small illicit stocks and large but well-laundered ones.

The analysis also draws on several adjacent literatures. Cash in circulation has risen in many economies despite the spread of digital payments, largely because cash is held as a store of value (Bech et al., 2018; Jobst and Stix, 2017), and large notes are disproportionately hoarded or held abroad (Rogoff, 1998). Europol documents the role of high-denomination notes in organized crime (Europol, 2015), while UNODC describes a shift of laundering in East and Southeast Asia toward casinos, underground banking and stablecoins (UNODC, 2024). Work on vote buying emphasizes monitoring and reciprocity rather than denomination (Stokes, 2005; Vicente, 2014), and work on corruption stresses measurement challenges that also afflict the evaluation of demonetization (Olken and Pande, 2012).

Section 2 reviews international evidence and the Thai setting. Section 3 develops the conceptual framework. Section 4 describes the model and its calibration, and Section 5 reports results. Section 6 assesses costs, benefits and designs, and Section 7 sets out a research agenda. Section 8 discusses limitations and Section 9 concludes.

2 International evidence and the Thai setting

2.1 A typology of demonetization

We classify designs along two dimensions: whether the decision is announced in advance, and whether legal-tender status lapses at a deadline or persists. Table 1 distinguishes four designs; the fourth retains the note but restricts the use of cash.

Table 1: A typology of demonetization designs

Design	Defining features	Examples
A. Shock	Unannounced; legal tender lapses at announcement; short exchange window	India 2016; Venezuela 2016; Soviet Union 1991; Myanmar 1987
B. Announced, short window	Usable until a deadline, then exchanged; often combined with a redesign	Nigeria 2022–23; Malaysia 1998–99
C. Gradual phase-out	Issuance stops; legal tender persists for years or notes remain redeemable indefinitely	Euro area (EUR 500); Canada (CAD 1,000); Singapore (SGD 10,000); India 2023 (INR 2,000)
D. Cash restrictions	Notes retained; caps on cash payments and reporting thresholds	France, Italy, Spain; EU-wide cap of EUR 10,000 from 2027

2.2 Twelve episodes

Table 2 summarizes twelve episodes. The evidence is uneven—rigorous evaluations exist essentially only for India 2016—so the table should be read as a structured synthesis rather than a meta-analysis.

Six stylized facts emerge.

SF1. *Returns are near-complete.* Almost all demonetized value returns: 99.3 percent in India 2016 (Reserve Bank of India, 2018) and about 97–98 percent of the INR 2,000 notes withdrawn in 2023. Section 5.3 shows that high returns are consistent with small illicit stocks and with large but laundered ones.

SF2. *Logistics govern disruption.* The crises in India (2016), Venezuela (2016) and Nigeria (2023) were driven by shortfalls of replacement currency.

SF3. *Incidence is regressive.* Costs fall on cash-dependent and informal participants (Chodorow-Reich et al., 2020).

SF4. *Digital substitution is partial.* Electronic payments rise and some adoption persists (Crouzet et al., 2023), but cash demand rebounds (Lahiri, 2020).

SF5. *Gradual withdrawals are cheap but target flows, not stocks.* The euro area, Canada and Singapore reported no disruption, but also made no attempt to extinguish existing illicit holdings (European Central Bank, 2016).

SF6. *Abrupt designs carry legitimacy risks.* Confiscatory or abrupt designs triggered unrest in Myanmar, the Soviet Union, North Korea and Venezuela. India's Supreme Court upheld the 2016 decision by four to one, the dissent holding that it required legislation (Supreme Court of India, 2023); Nigeria's Supreme Court extended the validity of old notes.

Table 2: Demonetization episodes

Episode	Notes (share of currency)	Design	Stated aims	Main outcomes
India 2016	INR 500 and 1,000 (about 86%)	A	Black money, counterfeits, terror finance; later cashless payments	99.3% returned; growth at least 2 pp lower in the shock quarter; partly persistent digital adoption
Venezuela 2016	VES 100	A	Hoarding by cross-border mafias	New notes not ready; unrest; deadline repeatedly extended
Soviet Union 1991	RUB 50 and 100	A	Speculation, shadow economy	Three-day exchange with caps; collapse of confidence
Myanmar 1987	25, 35 and 75 kyat	A	Black market	No compensation; most money voided; contributed to the 1988 uprising
North Korea 2009	Redenomination 100:1	A	Private market activity	Savings wiped out; unrest; official reportedly executed
Nigeria 2022–23	NGN 200, 500, 1,000 (redesign)	B	Counterfeits, hoarding, vote buying, cashless policy	Severe shortages; protests; Supreme Court extended old notes to end-2023
Malaysia 1998–99	MYR 500 and 1,000	B	Offshore ringgit, laundering	Limited domestic effects (details to verify)
Euro area 2016–19	EUR 500 (about 28%)	C	Illicit use	No disruption; effect on crime not established
Canada 2000/2021	CAD 1,000	C	Laundering, organized crime	Smooth; legal tender removed in 2021; redeemable
Singapore 2014	SGD 10,000	C	Laundering risk (preventive)	Smooth
United States 1969	USD 500–10,000	C	Lack of use	Smooth; still legal tender
India 2023	INR 2,000 (about 11%)	C	Denomination management	About 97–98% returned within months; no disruption

Notes: Design letters refer to Table 1. Shares and outcomes are approximate and compiled from memory; they require verification against central-bank and court documents.

2.3 The Thai setting

Banknotes in circulation are approximately THB 1.7–2.1 trillion, about 10 percent of GDP, of which the 1,000-baht note accounts for an estimated 65–80 percent by value; our central value of 72 percent implies a stock of about THB 1.37 trillion, or 1.4 billion notes (Bank of Thailand, various years). The note is both the workhorse of ATM dispensing and a household store of value. At roughly USD 28–30 it is worth less than a third of a USD 100 note.

Figure 1 places the note on a cross-country scale. At 0.38 percent of GDP per capita—about 1.4 days of average income—it is comparable to the largest notes of the Philippines and Vietnam but between two and thirty-seven times smaller, relative to income, than the notes retired in the euro area, Canada, Singapore, Malaysia and India. The argument that large notes facilitate crime (Rogoff, 2016; Sands et al., 2016) therefore applies to the 1,000-baht note with much less force than to the EUR 500. Figure 2 shows the physical counterpart: withdrawing the note doubles the bulk of large cash payments, from 10 to 19 kilograms per THB 10 million, but leaves far more compact substitutes—US dollar notes, gold and stablecoins—untouched.

Table 3 assesses how much Thailand's main illicit channels rely on the note. The assessment is qualitative and is itself a hypothesis (H3 in Section 3); much of the modern "grey capital" economy, notably call-centre scams and online gambling, runs through mule accounts and crypto-assets rather than cash.

Instruments that target illicit finance more directly already exist: the Currency Act B.E. 2501 (1958), under which the authority to revoke legal-tender status must be examined; the Anti-Money Laundering Act B.E. 2542 (1999), which requires reporting of cash transactions above THB 2 million; the Emergency Decree

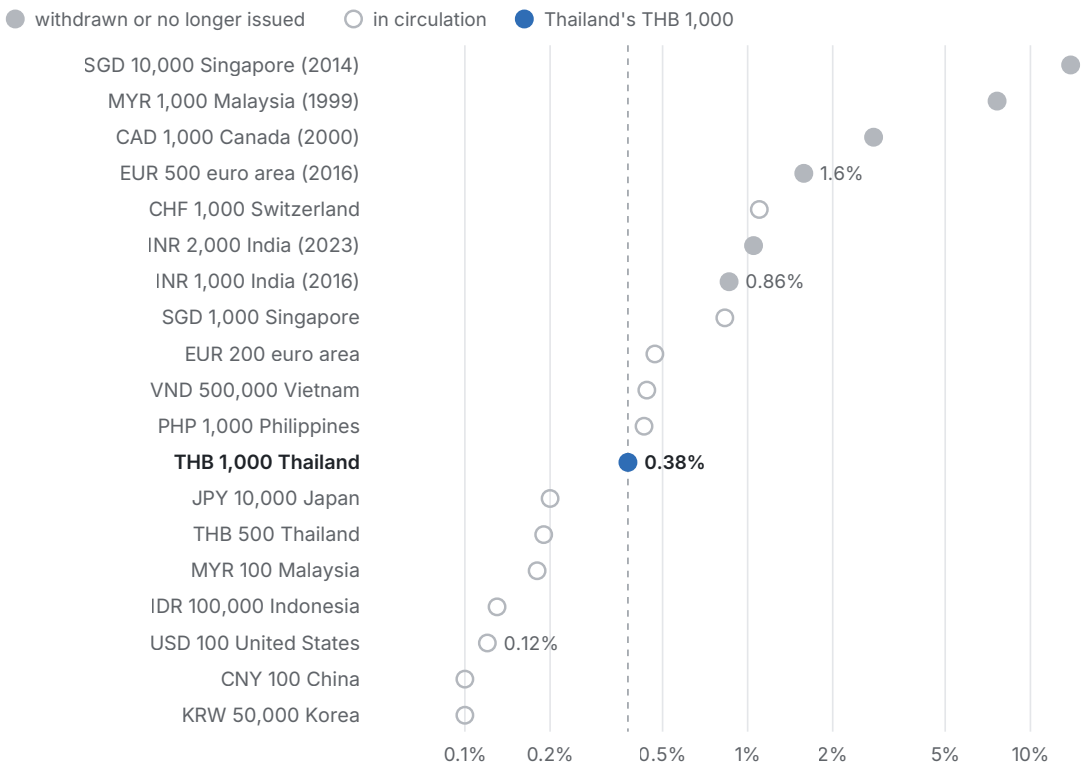


Figure 1: The 1,000-baht note is a mid-sized "large note". Face value of one note relative to nominal GDP per capita in the year indicated (log scale). At 0.38%, the THB 1,000 is about a quarter of the EUR 500 at its withdrawal. Filled grey dots mark notes withdrawn or no longer issued, hollow dots notes in circulation, and the dashed line the THB 1,000. GDP per capita and exchange rates are approximations. Source: `denomination_metrics()` in the replication code.

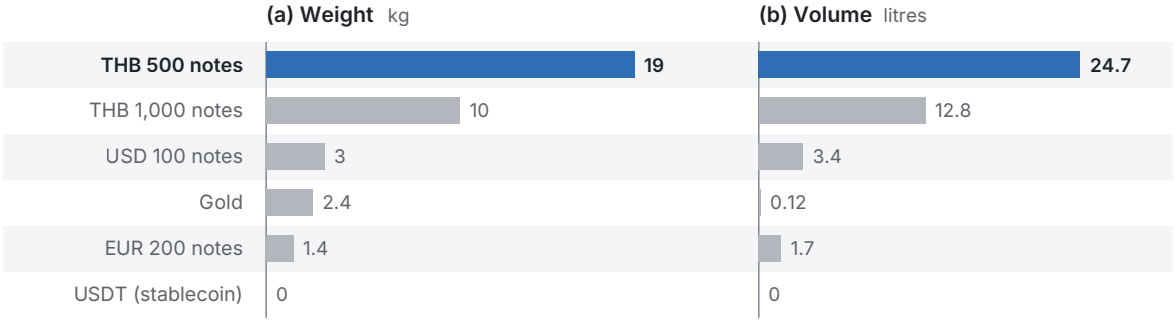


Figure 2: Withdrawing the note doubles the bulk of large cash payments but leaves compact substitutes untouched. (a) Weight and (b) volume of THB 10 million in each form; blue bars show the state after withdrawal. In 100-baht notes the same sum would weigh 90 kg and fill 119 litres. Notes weigh about one gram and are 0.11 mm thick; THB 33 per USD, USD 1.15 per EUR and USD 4,000 per troy ounce of gold. Source: `bulk_table()` in the replication code.

on Measures for the Prevention and Suppression of Technology Crimes B.E. 2566 (2023), which targets mule accounts; and a 2019 amendment of the Revenue Code that requires financial institutions to report high-frequency electronic receipts. Thailand has no general cap on cash payments, unlike several EU member states and the forthcoming EU-wide limit (European Union, 2024). On the cost side, Thailand is an aged society (roughly one in five citizens is 60 or older), about half of employment is informal, many farmers

Table 3: Reliance of illicit channels on the 1,000-baht note (author's assessment)

Channel	Reliance on 1,000-baht notes	Expected effect of withdrawal
Call-centre and online scams	Low: funds move through mule accounts into crypto-assets	Negligible
Online gambling	Low: mule accounts and e-wallets	Negligible
Narcotics	Medium: cash at retail level; crypto and informal remittance at wholesale level	Higher short-run transport costs
Bribery and corruption	Medium to high: large cash transfers, but final stores are assets and nominees	Harder delivery; converted assets untouched
Vote buying	Low to medium: per-capita payments of hundreds to a few thousand baht	Small; substitution to 500s, transfers, in-kind gifts
Tax evasion by cash businesses	High for cash-held portion	Partial; most can be structured or converted
Foreign grey capital and nominees	Low: corporate accounts and real estate	Negligible

sell output for cash, several million migrant workers have limited bank access, and baht circulates in border economies of Lao PDR, Cambodia and Myanmar. Digital payments are pervasive (PromptPay operates since 2017) but concentrated among urban, working-age users.

3 Conceptual framework: the demonetization trilemma

3.1 Environment

Let K denote the value of the notes to be demonetized and $s \in (0,1)$ the share held as illicit wealth, so that the illicit stock is $S = sK$. A design specifies a notice period $L \geq 0$, an exchange window $W > 0$ and a legal-tender rule: under a shock legal tender lapses at announcement ($L = 0$); under an announced design it lapses at the deadline; under a phase-out it persists for years and the notes remain redeemable.

Laundering. Illicit holders can convert notes into alternative stores of value (gold, foreign currency, stablecoins, real assets) through intermediaries with aggregate capacity c per day at proportional cost f_c, for as long as notes are accepted; structure deposits through money mules with capacity m per day at cost f_m; deposit directly; declare under an amnesty at tax rate t; or abandon the notes. Let $\ell = c + m$ denote laundering capacity per day and T the period during which laundering channels operate ($T = L + W$).

Enforcement. Deposits arrive at rate K/W during the window. The authorities can scrutinize value A per day with quality $\kappa \in (0,1]$, so the audit probability per unit deposited is $a(W) = \min\{1, AW/K\}$, and an illicit unit passing through the banking system is detected with probability $p = \kappa q\, a(W)$, where $q \leq 1$ captures how much harder structured deposits are to flag.

Replacement. When legal tender lapses, a share R_0 of the withdrawn value has already been replaced; replacement then proceeds at rate r per day.

Objectives. The state cares about the *bite* B, the share of S extinguished or captured; the *disruption* D imposed on honest holders; and the *laundering share* Λ, the share of S that enters the financial system undetected.

Assumption 1 (Anonymity)**.** The state cannot identify illicit holdings before they are presented for exchange.

Assumption 2 (Finite capacities)**.** Audit capacity A, laundering capacity ℓ and the replacement rate r are finite.

Assumption 3 (Rational holders)**.** Each illicit holder chooses the channel that maximizes expected retained value; detection destroys a share π of the amount, with $\pi > 1$ for criminal proceeds, which carry sanctions beyond confiscation.

Lemma 1 (Liquidity gap)**.** *If legal tender lapses when a share R_0 of the withdrawn currency has been replaced and replacement proceeds linearly at rate r, the cumulative shortfall is*

$$G = \int_0^\infty (1 - R_0 - rt)^+ \, dt = \frac{(1-R_0)^2}{2r}, \tag{1}$$

and disruption is $D = \phi\, G$, where $\phi = s_{\text{dem}} \sum_h w_h d_h (1 - g_h)$ weights the shortfall by the demonetized share of currency and by the cash dependence d_h and digital readiness g_h of transactions in group h with weight w_h.

Proof. The integrand is positive on $[0, (1-R_0)/r)$ and the integral of a linear function over that interval is $(1-R_0)^2/(2r)$. □

Proposition 1 (Notice erodes the bite)**.** *Suppose laundering weakly dominates the alternatives for every holder, $(1-f)(1-p_\ell \pi) \geq \max\{1 - p\pi, 1 - t, 0\}$, where f and p_ℓ are the cost and detection probability of the laundering channel. If laundering capacity covers the illicit stock, $\ell T \geq S$, then no illicit unit is abandoned and the bite is bounded by the detection probability in laundering channels: $B \leq p_\ell$.*

Proof. Under the stated inequality every holder weakly prefers laundering; with $\ell T \geq S$ the capacity constraint never binds, so all units are laundered. Extinguishment is zero, and the captured share equals p_ℓ times the confiscated share $\min\{\pi, 1\} \leq 1$. □

Proposition 2 (Congestion)**.** *If $W < K/A$, the audit probability $a(W) = AW/K$ is strictly increasing in W. Shortening the window to deny laundering time therefore lowers the probability that a deposited unit is examined and raises the undetected share $1 - \kappa q A W/K$ of illicit value passing through the banking system.*

Proof. Immediate from $a(W) = AW/K < 1$. □

Proposition 3 (Demonetization trilemma)**.** *Fix thresholds $\bar{b} > p_\ell$, $\bar{d} > 0$ and $\bar{\lambda} \in (0,1)$, and suppose that a positive share of illicit value passes through the banking system. Under Assumptions 1–3, a design attains $B \geq \bar{b}$, $D \leq \bar{d}$ and $\Lambda \leq \bar{\lambda}$ only if*

$$\textit{(i)}\ \ \ell(L+W) < S, \qquad \textit{(ii)}\ \ \kappa q \frac{AW}{K} \geq 1 - \bar{\lambda}, \qquad \textit{(iii)}\ \ \frac{(1-R_0)^2}{2r} \leq \frac{\bar{d}}{\phi}. \tag{2}$$

Conditions (i) and (ii) are jointly feasible only if $A > (1-\bar{\lambda})\,\ell/(\kappa q s)$: audit capacity must exceed laundering throughput scaled by the inverse illicit share. Under a shock, condition (iii) requires $R_0 \geq 1 - \sqrt{2r\bar{d}/\phi}$: replacement currency must be printed and distributed before the announcement. When either requirement fails, at most two of the three objectives can be met.

Proof sketch. Condition (i) follows from Proposition 1: if $\ell(L+W) \geq S$ the bite cannot exceed $p_\ell < \bar{b}$. For illicit value passing through banks the undetected share is $1 - \kappa q\, a(W)$, so $\Lambda \leq \bar{\lambda}$ requires $a(W) \geq (1 - \bar{\lambda})/(\kappa q)$, which with $a(W) = AW/K$ yields (ii). Combining (i), with $L \geq 0$, and (ii) gives $(1-\bar{\lambda})K/(\kappa q A) \leq W < sK/\ell$, which is non-empty only under the stated bound on A. Condition (iii) follows from Lemma 1. □

Remark. The trilemma concerns designs that rely on the exchange of notes to separate illicit from licit holdings. India's 2016 design partly satisfied (i), but scrutiny of the deposit flood was necessarily ex post and partial, and replacement currency was far from sufficient; the predicted combination—low bite, high disruption, substantial legitimization—is what the episode delivered. A phase-out relaxes (ii) and (iii) at the price of (i); Figure 3 summarizes the three corners.

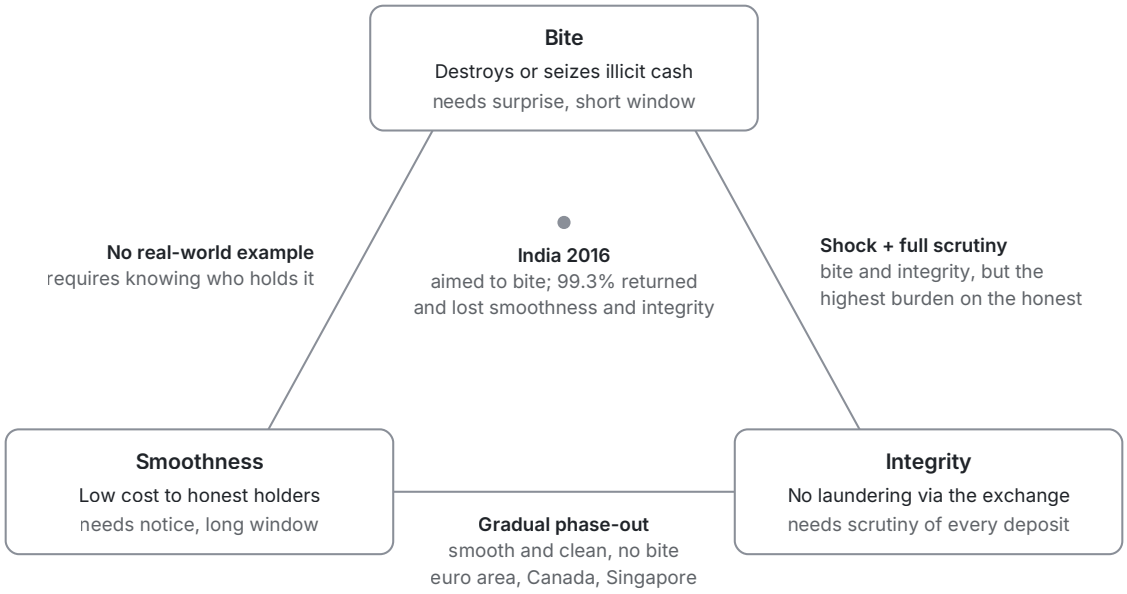


Figure 3: The demonetization trilemma: no design secures more than two of three goals. Each side of the triangle is a design that secures the goals at its two ends and sacrifices the goal at the opposite vertex (Proposition 3). India 2016 aimed at the bite but lost both smoothness and integrity.

3.2 Testable implications

Hypothesis 1 (Non-identification)**.** Aggregate return rates do not identify s when ℓT is large relative to S.

Hypothesis 2 (Capacity)**.** The bite is decreasing in laundering capacity; scrutiny has first-order effects on the bite only when $\ell T < S$.

Hypothesis 3 (Denomination premium)**.** If the 1,000-baht note is a preferred illicit medium, its share in seized cash exceeds its share in circulation.

Hypothesis 4 (Political money cycle)**.** If vote buying relies on large notes, demand for 1,000-baht notes rises disproportionately before elections.

Hypotheses 1 and 2 are examined with the model in Section 5; Hypotheses 3 and 4 require new data and motivate the designs in Section 7.

4 DemonetSim-TH: model and calibration

4.1 Structure

DemonetSim-TH is a partial-equilibrium Monte Carlo model with two modules. Uncertain parameters are drawn 600 times per scenario; each draw simulates six groups of honest holders and 1,500 illicit agents. Parameter ranges are reported in Appendix A.

Honest holders. Group h holds share σ_h of the demonetized stock and has bank access a_h, digital readiness g_h, cash dependence d_h and transaction weight w_h (Table A1). The share converted before the window closes is

$$c_h = 1 - \exp\left(-\frac{a_h^{\text{eff}} W}{\tau_0}\right), \qquad a_h^{\text{eff}} = a_h\left[1 - \tfrac{1}{2}\kappa_b(1-a_h)\right], \tag{3}$$

with $\tau_0 = 4$ days, so stricter documentation slows down holders with poor bank access. The disruption index applies Lemma 1,

$$I = 100 \times \frac{s_{\text{dem}} \sum_h w_h d_h (1 - g_h) G}{\bar{L}_{\text{IN16}}}, \tag{4}$$

where $R_0 = \min\{1, \bar{R}_0 + rW\}$ if legal tender persists to the deadline, $G = 0$ under a phase-out, and $\bar{L}_{\text{IN16}}$ is the mean disruption of the India prior draws.

Illicit holders. Holdings x_i, measured in units of the scrutiny threshold, are log-normal with parameters $\ln 0.3$ and 1.8, so that a small number of large holders own most illicit value. A holder is "black" (criminal proceeds) with probability β, in which case detection costs $\pi_i \sim U(1.5, 3)$ times the amount, or "grey" (undeclared legal income) with $\pi_i \sim U(0.6, 0.9)$; the state recovers $\min\{\pi_i, 1\}$. Perceived risk is scaled by $\rho_i \sim \text{LogNormal}(0, 0.4)$. The values of the five channels are

$$\begin{aligned}
V_i^{\text{dep}} &= 1 - p_i^{\text{dep}} \pi_i, & p_i^{\text{dep}} &= \kappa_b \left(1 - e^{-x_i}\right) \rho_i, \\
V_i^{\text{str}} &= (1 - f_i^s)\left(1 - p_i^{\text{str}} \pi_i\right), & p_i^{\text{str}} &= \kappa_b \, q_s \, \rho_i, \\
V_i^{\text{cnv}} &= (1 - f_i^c)\left(1 - p_i^{\text{cnv}} \pi_i\right), & p_i^{\text{cnv}} &= \kappa_d \, q_c \, \rho_i, \\
V_i^{\text{amn}} &= 1 - t \;\; \text{(grey holders only)}, & V_i^{\text{abn}} &= 0,
\end{aligned} \tag{5}$$

and holder i chooses $k_i^* = \arg\max_{k \in \mathscr{A}_i} \left(V_i^k + \varepsilon_{ik}\right)$ with $\varepsilon_{ik} \sim \text{Gumbel}(0, 0.02)$ (McFadden, 1974). Structuring and conversion are capacity-constrained: their capacities, expressed as shares of all demonetized cash over the operating period, are divided by s to obtain capacities relative to illicit holdings. Agents are processed in random order, and those who find their preferred channel full fall back to their next-best option (Appendix Table A3). Detected deposits are captured or regularized after penalty; undetected deposits and structured deposits net of fees are *laundered*; conversions and fees are *displaced*; abandoned notes are *extinguished*. The bite is extinguished plus captured value, and the return rate is $1 - s \times$ extinguished $-$ honest value not converted.

4.2 Scenarios

Table 4 defines four Thai scenarios and the India calibration scenario. S2 captures the main Nigerian risk—insufficient replacement currency at the deadline—through a wide range for $\bar{R}_0$ and r; S4 adds a package of cash-payment caps, enhanced due diligence on gold, crypto and property purchases and a crackdown on mule accounts, modeled as higher detection and lower laundering capacity.

Table 4: Scenarios

Code	Scenario	Key features
S1	Shock (India-style)	Legal tender lapses at once; 50-day window; amnesty at 50–60% tax
S2	Announced, 90-day deadline	Usable until the deadline; no amnesty; outcome depends on printing enough 500-baht notes
S3	Phase-out, 5 years	Issuance stops; legal tender for five years; redeemable at the central bank indefinitely
S4	Phase-out + AML package	S3 plus cash-payment cap, enhanced due diligence on dealers, mule-account crackdown
IN16	India 2016 (calibration)	Indian parameters; draws retained by ABC if the simulated return rate is $99.3 \pm 0.3\%$

4.3 Calibration and sensitivity analysis

We treat India 2016 as the calibration target. We draw 4,000 parameter vectors from the IN16 priors, simulate the return rate, and retain draws with $|\hat{R} - 0.993| \leq 0.003$ (Beaumont et al., 2002). Of the 4,000 draws, 1,214 (30.3 percent) are accepted. To understand which inputs drive the outcomes, we compute partial rank

correlation coefficients (PRCC) between each of 13 sampled parameters and three outcomes across the 600 S1 draws (Marino et al., 2008). PRCCs measure the monotone association between an input and an outcome after removing the linear effects of all other inputs on the ranks; with 39 coefficients estimated from 600 draws, values below about 0.15 in absolute value are within sampling noise.

5 Results

5.1 Bite versus disruption

Table 5 and Figure 4 report the central results. A Thai shock (S1) produces a disruption index of 17 against 97 for calibrated India—about one sixth—because the 1,000-baht note is a smaller share of currency and digital readiness is far higher. Incidence is nonetheless highly regressive: about 91 percent of the disruption falls on vulnerable households and informal businesses (81 percent in India). Honest holders fail to convert about 0.28 percent of the stock, roughly THB 3.9 billion, three quarters of it held across the border. S2 is benign at the median but reaches an index of about 10 in the worst decile of replacement outcomes, which is precisely the Nigerian failure mode.

Table 5: Main simulation results

	Disruption index	Bite (%)	Laundered (%)	Displaced (%)	Return rate (%)
IN16 (calibrated)	96.8 [85.4, 113.2]	8.5 [6.2, 12.0]	60.2	27.8	99.50
S1 Shock	17.2 [13.2, 23.9]	7.7 [5.5, 15.4]	60.9	25.2	99.63
S2 Announced, 90 days	0.4 [0.0, 3.8]	3.4 [2.7, 4.1]	30.0	65.5	99.98
S3 Phase-out	0.0 [0.0, 0.0]	1.0 [0.9, 1.2]	52.9	45.8	100.00
S4 Phase-out + AML	0.0 [0.0, 0.0]	6.1 [4.8, 7.5]	67.4	24.7	100.00

Notes: Medians with interquartile ranges in brackets over 600 draws per scenario (IN16: ABC-accepted draws). Laundered and displaced are means, in percent of the illicit stock. Bootstrap standard errors of the medians (1,000 resamples) are 0.25 pp for the S1 and IN16 bites, 0.09 pp for S4, and 0.42 for the S1 disruption index.

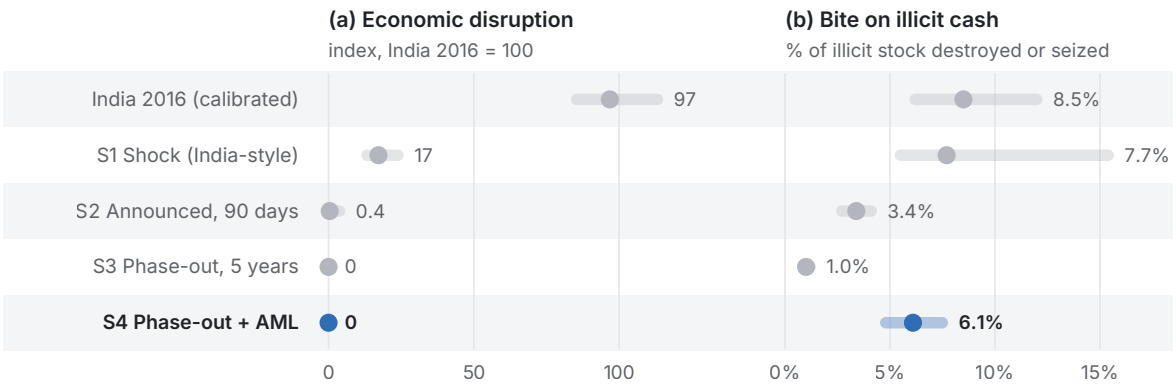


Figure 4: A phase-out with AML measures bites nearly as hard as a shock at no liquidity cost. (a) Economic disruption, indexed to the mean India 2016 prior draw (= 100). (b) Share of illicit cash destroyed or seized. Dots are medians and bars interquartile ranges over 600 Monte Carlo draws per scenario; S4 is highlighted. Source: DemonetSim-TH, `scenario_summary.csv`.

The median bite of a shock is 7.7 percent; a phase-out combined with AML measures attains 6.1 percent at no liquidity cost. The comparison should not be over-read: S4's bite stems from assumed improvements in detection that could be pursued without withdrawing the note. What the phase-out adds is to force the stock through that tighter net within a known horizon.

5.2 Where illicit cash goes

Figure 5 decomposes the fate of illicit cash. In every scenario most of it survives: between 30 and 67 percent enters the banking system undetected and between 25 and 65 percent is displaced into gold, foreign currency and crypto-assets or absorbed as fees by laundering intermediaries. Advance notice (S2) maximizes displacement, because notes remain spendable while holders buy alternative assets. Amnesty is almost never used (about 1 percent of illicit value): at 50–60 percent it is more expensive than laundering, which matches the weak take-up of India's 2016 scheme. The distribution of the bite is right-skewed; in the best decile of draws a shock destroys or seizes more than 24 percent, which happens only when the illicit stock is large and laundering capacity scarce.

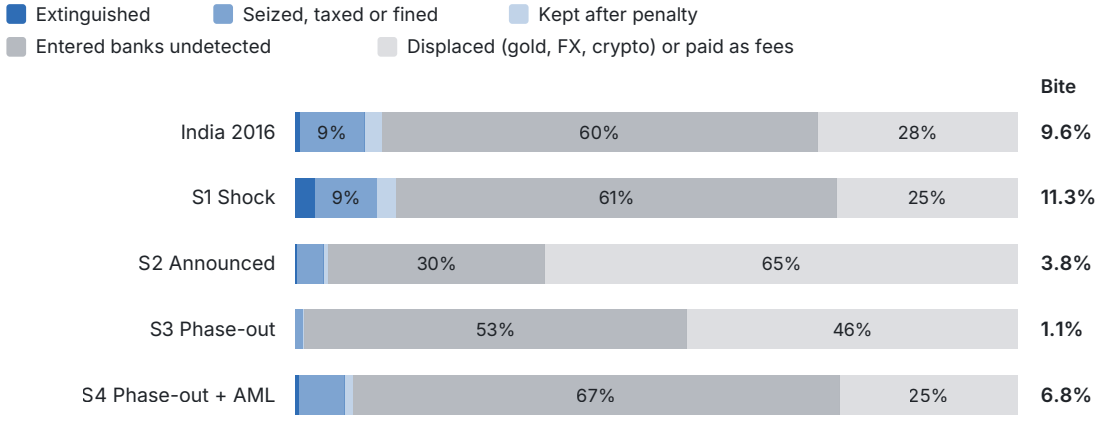


Figure 5: Most illicit cash survives: only 1–11% is destroyed or seized in any scenario. Value-weighted means across draws, hence above the medians in Figure 4. Blue segments are gains to the state; grey segments are illicit value that survives. The bite is the sum of extinguished and seized value. Source: DemonetSim-TH, `mc_results.csv`.

5.3 What India's return rate can and cannot tell us

Figure 6 plots the simulated return rate against the assumed illicit share for the India prior draws. The acceptance region overlaps the simulated distribution at every illicit share between 3 and 29 percent. Table 6 compares prior and posterior distributions: the posterior median of the illicit share (13.0 percent) barely differs from the prior (15.7 percent), and the 10–90 percent interval shrinks only from 4.8–27.1 to 4.2–25.9 percent. The return rate does trim the upper tail of the bite, from 23.8 to 15.9 percent at the 90th percentile. In short, the 99.3 percent statistic rules out large-scale extinguishment, but it is nearly uninformative about the illicit stock (Hypothesis 1).

Table 6: Approximate Bayesian computation: prior versus posterior

Quantity (%)	Prior: median [p10, p90]	Posterior: median [p10, p90]
Illicit share of demonetized cash, s	15.7 [4.8, 27.1]	13.0 [4.2, 25.9]
Bite	9.3 [5.0, 23.8]	8.5 [4.7, 15.9]
Laundered undetected	61.8 [46.9, 73.9]	62.0 [46.1, 72.8]
Displaced	22.0 [12.6, 39.6]	25.0 [14.3, 44.2]

Notes: 4,000 prior draws; 1,214 accepted with $|\hat{R} - 0.993| \leq 0.003$.

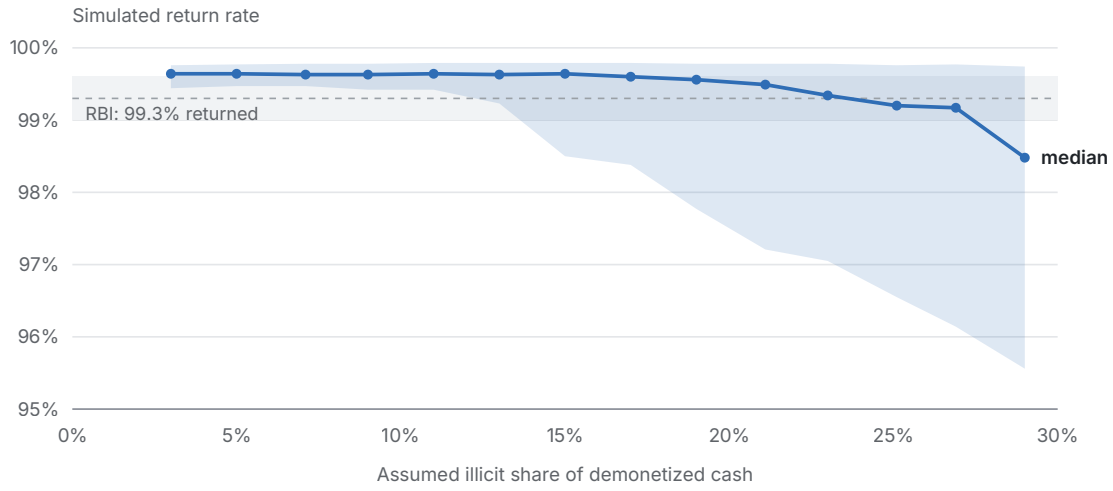


Figure 6: India's 99.3% return rate fits any illicit share between 3% and 29%. Simulated return rates from 4,000 draws of the India priors, grouped by the assumed illicit share; the line is the median, the blue band the 10th–90th percentile range and the grey band the ABC acceptance region ($99.3 \pm 0.3\%$). Sources: DemonetSim-TH, `india_calibration_curve.csv`; the target is from Reserve Bank of India (2018).

5.4 The binding constraint: laundering capacity

Figure 7 fixes the illicit share at 10 percent and varies laundering capacity. When the laundering network can absorb only 1 percent of demonetized cash during the window, stricter scrutiny raises the bite from 18 to 41 percent. Once capacity exceeds about 7.5 percent—roughly the illicit stock net of conversion capacity—the bite falls to 5–7 percent irrespective of scrutiny, as Proposition 1 predicts (Hypothesis 2). Disrupting mule networks, cash purchases of gold and peer-to-peer crypto markets is therefore a precondition for, not a complement to, any design that aims at the stock.

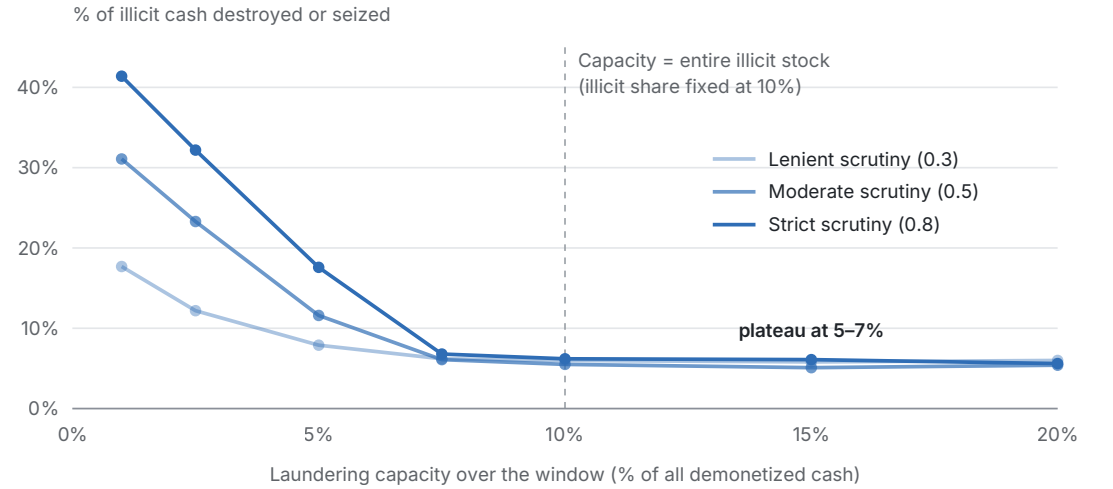


Figure 7: Once laundering capacity exceeds the illicit stock, scrutiny barely matters. Bite in scenario S1 as a function of laundering capacity over the exchange window, for three levels of bank scrutiny, with the illicit share fixed at 10%; medians of 80 draws per point. The dashed line marks capacity equal to the illicit stock. Source: DemonetSim-TH, `sensitivity_s1.csv`.

5.5 Global sensitivity

Figure 8 reports PRCCs for the shock scenario. The bite is governed by the ratio of the illicit stock to laundering capacity: the illicit share and structuring capacity have PRCCs of $+0.73$ and -0.73; the detectability of structured deposits ($+0.33$) and the costs of structuring and conversion ($+0.22$, $+0.20$) follow, while bank scrutiny intensity has a coefficient of only $+0.13$. The laundering share responds to capacity ($+0.71$), fees (-0.54) and scrutiny (-0.44): scrutiny matters for integrity far more than for bite. Disruption depends almost exclusively on the replacement rate (-0.97) and on currency ready on day zero (-0.87). The levers of bite and disruption are thus disjoint, consistent with Lemma 1 and Proposition 3.

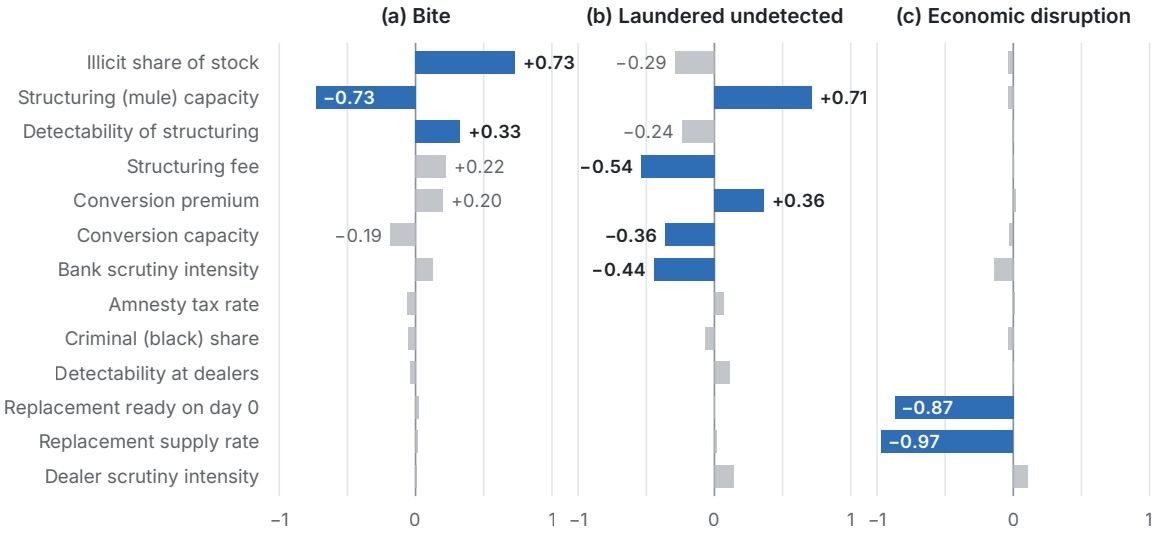


Figure 8: Bite hinges on laundering capacity; disruption hinges on replacement logistics. Partial rank correlation coefficients between each sampled parameter and (a) the bite, (b) the share laundered undetected and (c) the disruption index, across 600 draws of scenario S1 (Marino et al., 2008). Blue bars mark $|\text{PRCC}| \geq 0.3$; values below about 0.15 in absolute value are within sampling noise. Source: DemonetSim-TH, `prcc_s1.json`.

5.6 Operating costs

Table 7 reports the operating costs of replacing the note. Together they amount to less than 0.1 percent of GDP. The real costs of the policy are the disruption, its incidence and the risk to confidence in the baht, not printing.

Table 7: Operating costs of replacing the 1,000-baht note

Item	Median	5th–95th percentile
1,000-baht notes withdrawn (billion)	1.37	1.19–1.58
500- and 100-baht notes printed (billion)	2.27	1.76–2.83
Initial printing cost (THB billion)	5.7	3.6–8.2
Additional annual printing cost (THB billion)	0.8	0.2–1.7
Seigniorage shifted per year (THB billion)	9.1	5.3–14.6
One-off ATM reconfiguration (THB billion)	0.3	0.1–0.5

Notes: 5,000 Monte Carlo draws over assumed ranges of currency in circulation, the 1,000-baht share, demand migration, unit printing costs, note lifetimes and interest rates.

6 Assessment and policy design

6.1 Costs and benefits

Figure 9 and Table 8 position each claimed benefit and cost by impact and strength of evidence. The largest costs—disruption of the informal economy and its regressive incidence—rest on strong evidence; every benefit is either small or weakly evidenced. The strongest argument in favor of withdrawal is dynamic: without large notes, bribery and hoarding become costlier every year, and societies may grow accustomed to traceable payments (Rogoff, 2016; Sands et al., 2016). These flow effects lie outside the model and are a priority for research.

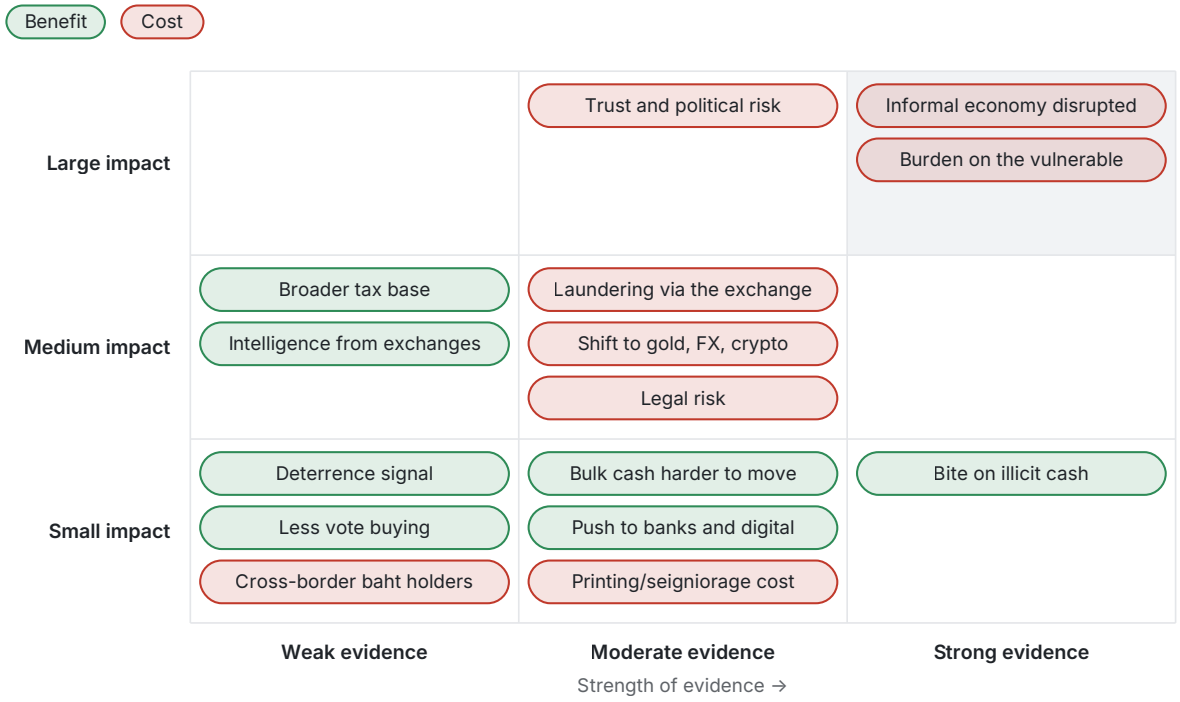


Figure 9: The largest costs are well evidenced; every benefit is small or weakly evidenced. Benefits (green) and costs (red) positioned by impact and strength of evidence; the shaded cell is the most worrying corner. Author's qualitative assessment, detailed in Table 8.

6.2 Comparative evaluation

Figure 10 scores five options against seven criteria. With equal weights the shock design scores lowest (1.7 of 5) and the AML-based options highest (3.7–3.9). Doubling the weight on the bite makes the phase-out with AML (C+) the top option; even with a fivefold weight on the bite, the shock design remains last. Because the scores are judgments, the ranking should be read as a structured summary of the preceding evidence rather than as an independent result.

6.3 A gated phase-out

If the note is to be withdrawn, Figure 11 outlines a five-year phase-out with three decision gates at which the process can be paused or reversed; reversal remains possible because the note stays legal tender until the final phase. Five preconditions should be met before the first gate: (1) evidence that the note carries a premium in illicit use (Section 7); (2) a demonstrable reduction in laundering capacity—mule accounts, cash purchases of gold, peer-to-peer crypto markets and nominee structures; (3) adequate stocks of 500-baht

Table 8: Benefits and costs of withdrawal (author's assessment)

Item	Impact	Evidence	Basis
Costs			
Informal economy disrupted (shock)	Large	Strong	Chodorow-Reich et al. (2020)
Burden on vulnerable groups	Large	Strong	India evidence; about 90% of simulated disruption
Trust and political risk	Large	Moderate	Myanmar 1987, Soviet Union 1991, Venezuela 2016, Nigeria 2023
Laundering via the exchange	Medium	Moderate	30–67% of illicit cash enters banks undetected (model)
Displacement to gold, FX, crypto	Medium	Moderate	25–65% displaced (model)
Legal risk	Medium	Moderate	Indian (4–1) and Nigerian Supreme Court rulings
Printing and seigniorage	Small	Moderate	About THB 6 billion once and THB 10 billion a year
Cross-border baht holders	Small	Weak	No data
Benefits			
Broader tax base	Medium	Weak	Indian filings rose, confounded by the GST
Intelligence from exchanges	Medium	Weak	Depends on analytical capacity
Bite on illicit cash	Small	Strong	99.3% returned in India; 1–11% in the model
Bulk cash harder to move	Small	Moderate	10 to 19 kg per THB 10 million
Push to banks and digital payments	Small	Moderate	Crouzet et al. (2023); Thailand already highly digital
Deterrence signal	Small	Weak	No systematic evidence
Less vote buying	Small	Weak	Payments small; substitution to 500s and in-kind gifts

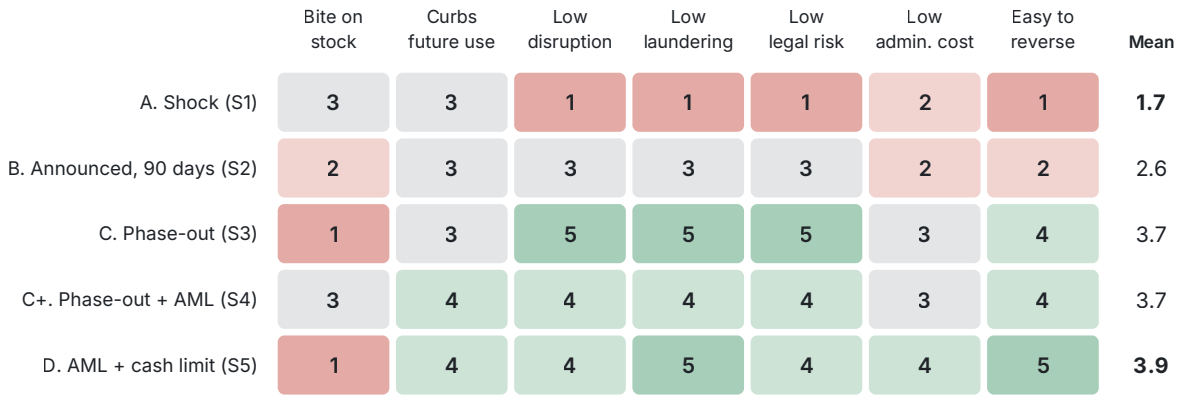


Figure 10: The shock design scores lowest; AML-based options score highest. Author's scores from 1 (poor, red) to 5 (good, green) for five options against seven criteria; legal risk includes political risk, and the mean weights criteria equally. Options C and C+ phase out the 1,000-baht note; option D retains it.

notes and reconfigured ATMs; (4) a statutory basis and exchange channels for the elderly, rural residents and holders in neighboring countries; and (5) an independent evaluation plan with monthly open data by denomination. Four designs should be avoided: surprise announcements; per-person exchange caps low enough to strand honest holders; simultaneous redesigns that create shortages; and amnesties priced above market laundering fees, which attract almost no declarations.

7 A research agenda

Fifteen research topics follow from the analysis (Table 9 and Figure 12). Three flagship studies address the premise of the policy directly and are described in detail below.

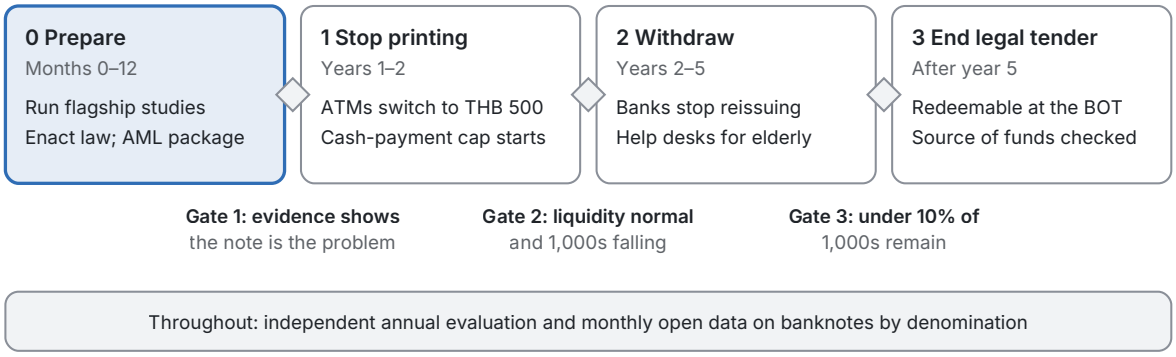


Figure 11: A gated five-year phase-out. Phases are not drawn to scale. The blue frame marks what can start immediately; diamonds mark decision gates at which the process is paused or reversed if the criterion is not met. Author's proposal.

Table 9: Research agenda

ID	Topic	Question	Design and data
A1	Who holds 1,000s	How much demand reflects transactions, hoarding or the informal economy?	Cash-demand models (ARDL), note return frequencies; BOT data
A2	Shadow economy	How has the shadow economy changed with digital payments?	MIMIC and currency-demand approaches (Tanzi, 1983; Medina and Schneider, 2018)
A3⋆	Pre-election cash	Does demand for 1,000s and 500s rise before elections?	Local projections, placebo dates; monthly data by denomination
B1	Cross-country	Which conditions make demonetization succeed or fail?	fsQCA (Ragin, 2008); synthetic control (Abadie et al., 2010)
B2	Symbolic politics	Why choose low-yield, high-salience instruments?	Discourse and voting analysis
C1	Distributional costs	Who bears the costs, and how much?	Microsimulation; household surveys
C2	Public acceptance	Which designs do citizens accept?	Conjoint experiment (Hainmueller et al., 2014)
C3	Cross-border baht	How much baht is held in Lao PDR, Cambodia, Myanmar?	Border-market surveys
D1⋆	Seized-cash premium	Is the 1,000's share in seized cash above its circulation share?	Content analysis of judgments and seizure reports
D2	Vote-buying modes	Which notes, transfers or goods buy votes?	List experiment (Blair and Imai, 2012)
D3	Displacement and mules	What is the laundering capacity of mule networks?	Network and on-chain analysis; partnership data
E1	Legal authority	Secondary legislation or an Act of Parliament?	Comparative law; proportionality
E2	Cash caps	Do cash-payment caps shrink the shadow economy?	Natural experiments from Italian caps
F1⋆	E-payment bunching	Do merchants stay below reporting thresholds and revert to cash?	Bunching estimation (Saez, 2010; Kleven, 2016)
F2	Model extensions	Does the trilemma survive richer models?	ABM, heterogeneous-agent and game-theoretic models

7.1 D1: an illicit denomination premium

Let y_c be the value share of 1,000-baht notes in the cash seized in case c, and π_t^{circ} the share of the note in circulation at the seizure date $t(c)$. The estimand is the premium by crime type, $\theta_k = E[y_c \mid k(c) = k] - \pi_{t(c)}^{\text{circ}}$. We propose a fractional logit (Papke and Wooldridge, 1996),

$$E[y_c \mid X_c] = \Lambda\big(\alpha + \textstyle\sum_k \beta_k \mathbf{1}\{k(c) = k\} + \gamma_{t(c)} + \delta' Z_c\big)\,, \tag{6}$$

estimated on a sample of 300 to 1,000 judgments and seizure reports that record denominations, with region and enforcement-channel controls Z_c. Hypothesis 3 predicts $\theta_k > 0$ for bribery and wholesale narcotics. The main threat is selection into detection; reporting estimates separately by detection channel and bounding the premium under alternative selection assumptions mitigates it. A premium indistinguishable from zero would remove the empirical premise of the policy.

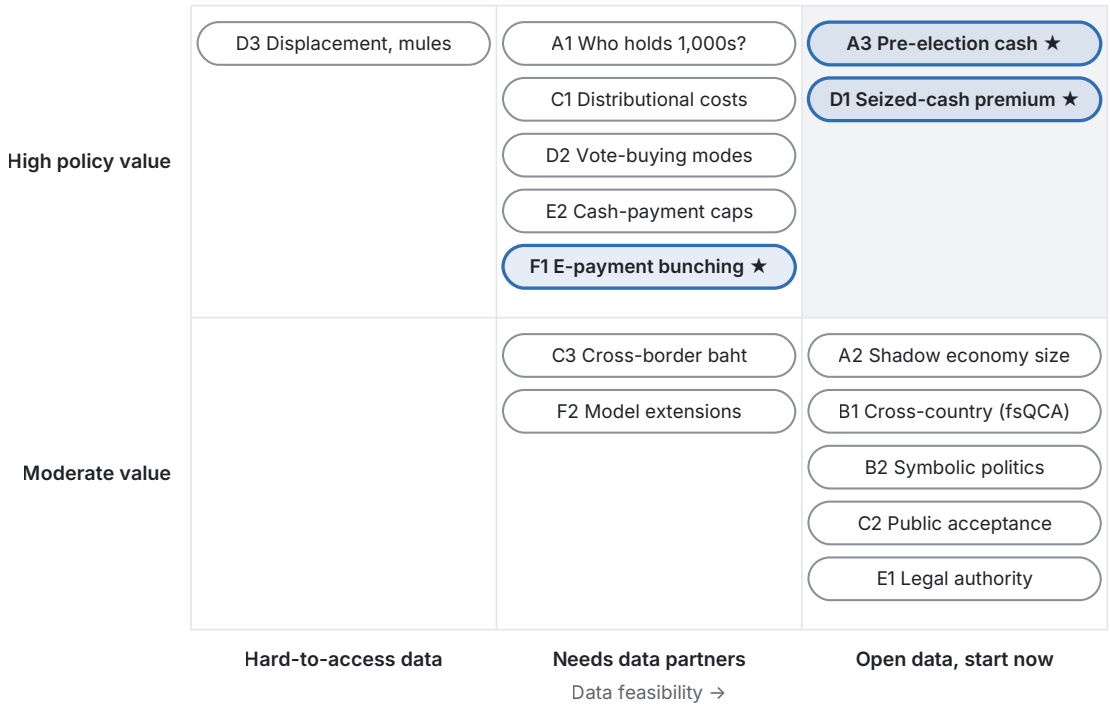


Figure 12: Three flagship studies offer high policy value, and two can start with open data. Fifteen research topics positioned by policy value and data feasibility; stars mark flagship studies and the shaded cell the topics to start with. Author's assessment; see Table 9.

7.2 A3: a political money cycle

Let C_t^d be notes in circulation of denomination $d \in \{100, 500, 1000\}$ in month t. Local projections (Jordà, 2005),

$$\ln C_{t+h}^d - \ln C_{t-1}^d = \alpha_h^d + \beta_h^d E_t + \Gamma_h^{d\prime} X_t + \varepsilon_{t+h}^d, \qquad h = 0, \ldots, H, \tag{7}$$

trace the response to the pre-election period E_t, controlling for New Year, Chinese New Year and Songkran, the policy rate and lags, and checked against placebo dates. With regional data, a difference-in-differences design interacts the pre-election period with electoral competitiveness. If $\beta_h^{500} > 0$ while $\beta_h^{1000} \approx 0$, vote buying runs on smaller notes and withdrawing the 1,000-baht note is mis-targeted (Hypothesis 4).

7.3 F1: bunching at e-payment reporting thresholds

Financial institutions report accounts that receive at least 3,000 electronic transfers a year, or at least 400 transfers totaling THB 2 million (thresholds to be verified). If merchants avoid reporting by steering customers to cash, the distribution of annual transfer counts will exhibit excess mass below the thresholds. Following Saez (2010), Kleven and Waseem (2013) and Kleven (2016), the normalized excess mass is

$$\hat{b} = \frac{\sum_{j=z_L}^{z} (n_j - \hat{n}_j)}{\hat{n}(z)}, \tag{8}$$

where n_j is the number of accounts in bin j, $\hat{n}_j$ the counterfactual from a polynomial fitted outside the excluded window $[z_L, z_U]$ and $\hat{n}(z)$ the counterfactual density at the threshold z. Evidence of bunching would indicate that tax-reporting rules push merchants back to cash, so currency and tax policy must be designed jointly.

8 Limitations

Five limitations qualify the results. First, the Thai statistics are approximations that have not been verified against primary sources. Second, the model is partial-equilibrium: it omits general-equilibrium feedbacks, dynamic responses of the central bank and the long-run flow effects of retiring large notes, which are the strongest argument in favor of withdrawal. Third, the illicit share is unknown; we therefore report results as distributions over wide priors, and the India calibration shows that available aggregate data cannot narrow it. Fourth, detection is modeled in reduced form; in particular, the compliance costs of the AML package in S4 for honest users are not quantified. Fifth, the scorecard and the evidence map are qualitative judgments, and external validity of a calibration to India rests on the assumption that laundering technologies are broadly similar.

9 Conclusion

A shock withdrawal of the 1,000-baht note would likely do more harm than good: in the calibrated model it destroys or seizes about 8 percent of illicit cash, concentrates about 90 percent of the disruption on vulnerable groups and turns the exchange into a large-scale laundering channel. The note is not a large denomination by international standards, and Thailand's grey capital increasingly moves through digital channels. The binding constraint on any design is the capacity of laundering networks, which points to mule accounts, cash purchases of gold, peer-to-peer crypto markets and nominee structures as the more promising targets, together with caps on cash payments. If withdrawal is nonetheless pursued, a gated five-year phase-out preceded by the three flagship studies would test the premise before the costs are incurred.

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A Model details

Table A1: Holder groups: shares and behavioral parameters

	Thailand					India 2016				
Group	σ_h	w_h	a_h	g_h	d_h	σ_h	w_h	a_h	g_h	d_h
Formal households	0.32	0.30	0.95	0.85	0.35	0.20	0.20	0.80	0.30	0.60
Vulnerable households	0.17	0.20	0.55	0.35	0.80	0.27	0.30	0.45	0.05	0.95
Formal firms	0.08	0.25	1.00	0.90	0.25	0.08	0.20	1.00	0.50	0.40
Informal businesses	0.20	0.25	0.60	0.50	0.85	0.30	0.30	0.55	0.05	0.95
Cross-border holders	0.05	0.00	0.30	0.20	0.70	0.02	0.00	0.30	0.10	0.80
Banks and ATMs	0.08	0.00	1.00	1.00	0.00	0.03	0.00	1.00	1.00	0.00

Notes: σ_h: share of the demonetized stock (summing to 0.90 at an illicit share of 0.10 and rescaled otherwise); w_h: transaction weight; a_h: bank access; g_h: digital readiness; d_h: cash dependence. Access, readiness and dependence receive $\pm 15\%$ multiplicative noise in each draw.

Table A2: Parameter ranges (uniform priors)

Parameter	S1	S2	S3	S4	IN16
Window or legal-tender period (days)	50	90	1,825	1,825	50
Demonetized share of currency	0.72	0.72	0.72	0.72	0.86
Bank scrutiny κ_b	0.35–0.65	0.30–0.60	0.20–0.40	0.50–0.80	0.25–0.55
Dealer scrutiny κ_d	0.20–0.40	0.20–0.40	0.10–0.30	0.50–0.80	0.10–0.30
Structuring fee f^s	10–30%	5–20%	0–3%	3–10%	15–35%
Structuring capacity (% of stock per day)	0.05–0.30	0.05–0.25	0.008–0.022	0.003–0.008	0.05–0.40
Conversion premium f^c	15–40%	3–10%	1–4%	5–15%	15–40%
Amnesty tax t	50–60%	none	none	none	50–60%
Illicit share s	4–20%	4–20%	4–20%	4–20%	2–30%
Replacement rate r (% per day)	0.4–1.5	0.3–1.2	–	–	0.4–0.7

Notes: Common to all scenarios: black share $\beta \sim U(0.25, 0.60)$; detectability of structuring $q_s \sim U(0.05, 0.15)$ and of conversion $q_c \sim U(0.05, 0.15)$ unless stated in the code; holdings LogNormal$(\ln 0.3, 1.8)$; $\tau_0 = 4$ days; Gumbel scale 0.02.

Table A3: Capacity-constrained allocation

1. Draw holdings x_i, types, loss parameters π_i, risk multipliers ρ_i and fees; compute V_i^k from (5) and add Gumbel noise.
2. Set structuring and conversion capacities as shares of illicit holdings; draw a random processing order.
3. For up to five rounds: each unassigned agent selects its best available channel. Unconstrained channels (deposit, amnesty, abandonment) accept immediately; for each constrained channel, accept agents in processing order while cumulative holdings do not exceed remaining capacity, and remove the channel from the choice set of rejected agents.
4. Compute value-weighted shares of extinguished, captured, regularized, laundered and displaced value.

B Replication

The model is implemented in `demonet_sim_th.py` (Python 3 with NumPy, pandas and Matplotlib). The command `python demonet_sim_th.py -draws 600 -seed 7 -out out` reproduces all simulation results, writing ten CSV files and six PNG figures; the PRCC coefficients are computed from `mc_results.csv`. Before any policy use, the denomination data, holder parameters, logistics ranges and scenario priors must be replaced with verified values; the items most in need of verification are the stock of banknotes by denomination, the reporting thresholds under Thai AML and tax law, and the episode-level figures in Table 2.