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Strategic choices in money laundering: Smurfing, layering, and financial over-diversification

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ABSTRACT

Money laundering enables criminal organizations to integrate illicit funds into the legal economy while evading detection, posing significant challenges for regulators and policymakers. We develop a formal framework to examine criminal organizations' choice between two money laundering methods. Smurfing is a low-risk but high-cost strategy that disperses illicit funds through consumption and investment in the real sector, whereas asset laundering is a lower-cost yet higher-risk strategy operating through the financial system and relying on extensive transaction layering and portfolio diversification to avoid detection. Our analysis shows that anti-money laundering (AML) policies which increase the detection risk for asset laundering can unintentionally reallocate illicit funds toward smurfing. This displacement effect undermines policy goals by expanding illicit money flows in the legitimate real economy. These findings underscore the importance of anticipating criminals' adaptive behavior and accounting for the substitutability of laundering methods when designing AML policies that coordinate enforcement across both the financial and real sectors.

1. Introduction

Money laundering (ML) refers to the process of concealing the illicit origin of funds to make them appear legitimate, enabling their integration into the formal economy. As noted by Masciandaro (1998), ML is characterized by two fundamental features: illegality, as it originates in criminal activity, and concealment, as it seeks to obscure financial trails. The persistence of ML represents a critical challenge for policymakers and regulatory authorities, as it undermines financial integrity, distorts markets, and facilitates the continuation of organized crime.

Traditional studies of money laundering emphasize its sequential stages—placement, layering, and integration—yet much of the analytical literature has treated laundering channels in isolation. For example, cash-based smurfing strategies have been examined separately from financial sector strategies such as layering or portfolio diversification. This separation limits our understanding of how criminal organizations make strategic choices across alternative methods in response to regulatory pressures.

This paper addresses that gap by developing a formal framework that jointly analyzes two laundering methods: (i) smurfing, defined as a low-risk but high-cost strategy involving dispersed consumption and small-scale investments in the real sector; and (ii) asset laundering, a higher-risk but lower-cost strategy that operates through financial transactions. Within asset laundering, we focus on two mechanisms—transaction layering to obscure money trails, and portfolio diversification to reduce detection probability while preserving capital.

Our model demonstrates that laundering choices depend on both the scale of illicit funds and the enforcement environment. Smurfing is more attractive when volumes are modest and surveillance risks are high, whereas asset laundering becomes optimal for large-scale funds despite its higher exposure to detection. Importantly, we show that anti-money laundering (AML) policies designed to increase detection of asset laundering may unintentionally displace illicit activity toward smurfing, thereby expanding the circulation of illegal proceeds within the legal real economy.

The contribution of this paper is twofold. First, it rationalizes the strategic behavior of money launderers by linking real-sector and financial-sector strategies within a unified theoretical model. Second, it highlights the unintended consequences of partial enforcement: policies that disproportionately target one laundering channel risk merely reshuffling illicit activity rather than reducing it. These insights provide a foundation for future empirical testing and comparative studies across jurisdictions.

The remainder of the paper is organized as follows. Section 2 presents the theoretical framework of smurfing and asset laundering. Section 3 derives the main findings regarding optimal laundering choices and displacement effects. Section 4 discusses policy implications for AML enforcement. Section 5 concludes.

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2. Related literature

The literature on money laundering (ML) consistently emphasizes its deep connection with organized crime (COs), as both financial law and academic research recognize laundering as an essential extension of criminal operations (Albanese, 2021). While some frameworks distinguish between launderers and principals, most studies view laundering as an intrinsic component of organized crime.

Two broad strands of research can be identified. The first examines the macroeconomic consequences of laundering. Scholars such as Masciandaro (1998, 2000) and Loayza et al. (2019) highlight how illicit financial flows distort markets, undermine financial stability, and reduce economic growth. Related work shows how unchecked laundering strengthens organized crime networks (Levi, 1998, 2002; Schneider, 2004). These contributions frame ML as a systemic challenge with broad institutional and developmental implications.

The second strand adopts a microeconomic perspective, analyzing how laundering is carried out. Classic contributions include Masciandaro (1998, 2007), which model laundering agents' incentives, though often abstracting from the strategic necessity of laundering for criminal organizations. In practice, COs do not choose whether to launder, but rather how to allocate illicit funds across available methods. Within this perspective, smurfing-first formalized by Quirk (1996)-emerges as a low-scale, low-visibility method, while asset laundering channels funds into securities, real estate, or other instruments that transform illegal proceeds into apparently legitimate assets. Recent studies analyze laundering through artwork (Stoll, 2022) and real estate Teichmann (2018), while others underscore how secrecy jurisdictions and offshore structures facilitate financial layering (Masciandaro, 1999).

Beyond these mechanisms, empirical research documents the linkage between specific crimes and laundering channels. Drug trafficking, fraud, and tax evasion are closely associated with asset laundering (Quirk, 1996). Financial markets are repeatedly identified as high-risk arenas due to their liquidity and global integration, with multinational banks playing a central role in layering schemes (Eulaiwi et al., 2024). Studies further reveal the vulnerabilities of financial institutions in the absence of strong oversight (Rider and Levi, 1998; Kramer et al., 2023).

A growing body of research evaluates regulatory interventions and enforcement. Reuter (2002, 2003) stress the limits of AML across jurisdictions, while Chong and Lopez-De-Silanes (2015) shows AML's role in curbing terrorism-linked laundering. International cooperation has been found essential (Ferwerda, 2009), and a risk-based approach to supervision is increasingly advocated (Arnone and Borlini, 2010). More recent work highlights challenges in compliance and reporting. Competitive pressures undermine banking compliance (Yeoh, 2020), and excessive suspicious activity reports reduce detection efficacy (Takáts, 2009; Dalla Pellegrina , 2020). Yet, robust enforcement can improve reporting quality (Gara et al., 2023). Alongside these institutional issues, customer due diligence has become central in the digital age (Gaviyau and Sibindi, 2023).

Finally, innovations in detection methodologies complement regulatory efforts. Artificial intelligence and predictive analytics are increasingly applied to identify suspicious transactions (Zhang and Trubey, 2018; Jullum et al., 2020; Lokanan, 2019, 2022). Transaction-based analyses, such as Ravenda et al. (2019), classify entities to improve the detection of laundering behaviors. These advances illustrate the growing convergence between economics, data science, and law in the AML field.

In sum, the literature has established both the systemic consequences of laundering and the variety of mechanisms through which it operates. However, most studies consider laundering channels in isolation. Few contributions analyze their substitutability and the strategic allocation of illicit funds across methods. This paper addresses that gap by presenting a unified theoretical framework that integrates smurfing, layering, and portfolio diversification, thereby offering new insights into the unintended displacement effects of AML policies.

3. Conceptual framework

The relationship between money laundering (ML) and underlying criminal activities is inherently structural, differentiating it significantly from other financial offenses such as tax evasion. To illustrate this, consider two scenarios where an investor seeks to integrate funds into the financial sector. In the first scenario, involving funds from legitimate activities, investors typically have access to official financial channels at the cost of taxation. Alternatively, they may choose to evade taxes, employing techniques overlapping with money laundering mechanisms.

In contrast, when funds originate from criminal activities, the absence of official channels to legally integrate these funds into the financial system creates a structural necessity for ML. The illicit nature of these funds inherently compromises their traceability, making asset laundering not just a strategic choice but the only feasible pathway to convert these proceeds into liquid, usable capital within the formal economy. This crucial distinction highlights how tax evasion remains on the fringe of legality, whereas money laundering explicitly involves concealing the criminal origins of proceeds.

Consider a criminal organization (CO) that possesses monetary proceeds from activities like theft, corruption, prostitution, or drug sales. Such organizations must launder their illicit funds to remain operational and integrate proceeds into the legitimate economic sector. Laundering, therefore, consists of mechanisms through which COs retain ownership of illicit proceeds without detection, facilitating either legal investment (to generate returns) or consumption in the real economy. Laundering involves two primary methods: smurf laundering and asset laundering.

Smurf laundering entails disguising illicit cash funds by dividing them into smaller amounts declared to fiscal authorities, usually below legal thresholds, minimizing detection risk. Declared but undetected funds thus become laundered and available for use in legitimate consumer transactions, while detected funds are seized by authorities. For instance, under U.S. regulations, individuals transporting over USD 10,000 must file customs reports. A CO might circumvent detection by dividing one million USD into multiple transactions of exactly USD 10,000, declared by numerous individuals as legitimate savings or income. The small transaction size drastically reduces detection risk. Another example involves purchasing multiple low-value prepaid cards with cash and physically transporting them across borders, facilitating subsequent legitimate purchases or cash exchanges.

Asset laundering, conversely, involves camouflaging illicit funds through legal investments in physical assets like real estate or financial instruments such as bonds and stocks. These transactions generally involve larger amounts and leave identifiable trails, thus carrying a higher detection risk compared to cash transactions. We explore two asset laundering mechanisms: the portfolio method, which diversifies financial risk through investments across various legitimate assets, and financial layering, which employs complex, multi-stage financial transactions to obscure the origin of funds. Both methods aim to integrate undetected illicit proceeds into the formal economy, while detected transactions result in asset seizure.

To illustrate, consider a launderer investing one million dollars of illicit funds through multiple brokers in bonds and stocks. The detection risk depends on brokers' complicity or ignorance and fiscal authority scrutiny. If funds remain undetected, investment returns facilitate complete integration into the formal economy. Alternatively, employing financial layering, a launderer might deposit illicit funds into multiple financial accounts using proxy individuals who then conduct further transactions through brokers or realtors to obscure fund origins, eventually purchasing financial securities or real estate. Undetected assets yield legitimate returns, completing the integration.

Fig. 1 illustrates the ML stages with both placement mechanisms, emphasizing the transition of illicit funds into the legal economy through consumption or investment activities once undetected.

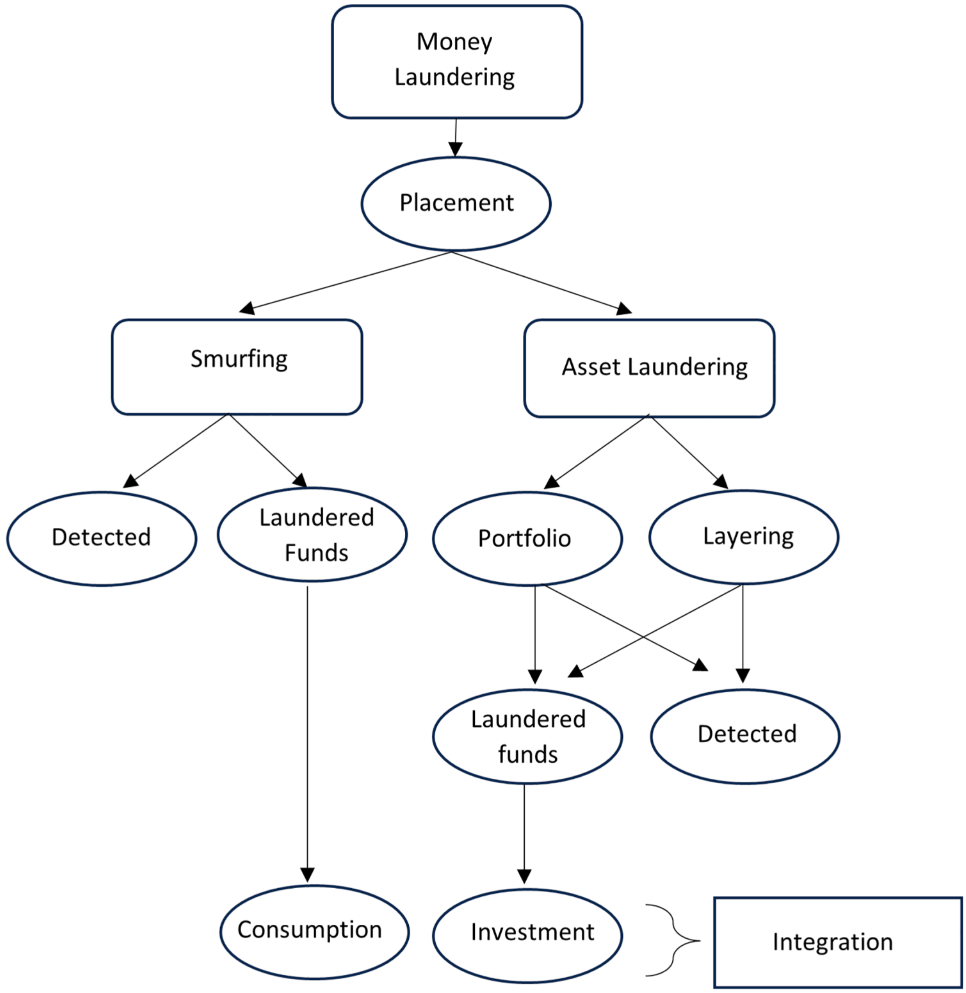

Fig. 1. Stages of Money Laundering.

A notable example illustrating these mechanisms is the Franklin Jurado case (Information, 1998). Jurado, sentenced in 1996, laundered USD 36 million for the Colombian Cali cartel, initially placing funds into European banks from Panama. The layering stage involved dispersing these funds across multiple European accounts, each below €10,000, to avoid regulatory scrutiny. Integration occurred as front companies legally reinvested laundered money into legitimate enterprises controlled by the cartel.

A distinctive element of our conceptual framework is the recognition of ML as an essential operational component for pecuniary criminal enterprises rather than a discretionary activity. Consider a small-scale CO comprising four thieves who collectively steal USD 1,000, subsequently dividing the proceeds equally. When each member spends their share on legitimate goods or services, they engage inevitably in ML by integrating illicit proceeds into the formal economy through consumption, fulfilling their criminal enterprise's ultimate goal.

Alternatively, if a CO member chooses to save their share without immediate spending, ML is merely postponed until those funds are eventually used for legitimate purchases. Even reinvesting proceeds into criminal operations, such as acquiring weapons legally, constitutes ML by converting illicit funds into legitimate durable goods. Conversely, if weapons are purchased illicitly, the seller becomes an inadvertent intermediary, eventually integrating the proceeds into the legal economy.

This framework underscores ML as a fundamental economic function within COs. Without laundering, criminal proceeds lack practical utility, emphasizing ML's integral role in the operational success of criminal enterprises.

The subsequent section introduces a theoretical model that formalizes these placement mechanisms detailed in Fig. 1.

4. Model

We develop a theoretical model describing how a CO strategically launders illicit funds through two primary mechanisms: smurf laundering, involving the transformation of illicit proceeds into liquid, consumable resources, and asset laundering, involving investment in legal assets that yield financial returns. The former is considered less risky but more costly than the latter.

Our approach diverges from Masciandaro (2007), who analyzes ML from the perspective of an agent (such as Jurado in the Cali cartel case), treating ML itself as the primary offense. In contrast, our analysis examines ML directly from the principal's viewpoint, the CO (e.g., the Colombian cartel led by Santacruz-Londono). We explicitly model the ML cycle (placement, layering, and integration) as integral to the rational operational decisions of the CO itself. Consequently, figures like Jurado are conceptualized not as independent agents but rather as integral parts of the CO's internal structure. This assumption is supported by evidence from Van Duyne (2003) and Truman and Reuter (2004), who find that criminals typically prefer to launder their funds directly rather than outsourcing these activities.

4.1. Money laundering as smurfing

Consider a threshold, $\tilde{x}$, established by fiscal authorities, defining the maximum transaction amount that can be reported without triggering detection risk. A CO with an amount x of illicit funds can perfectly eliminate detection risk by dividing this sum across N smaller transactions, each transaction $x_n \leq \tilde{x}$, where $n = 1, \ldots, N$. Consequently, the minimum number of transactions required to launder the total amount x via smurfing is $N \geq \frac{x}{\tilde{x}}$.

The detection threshold $\tilde{x}$ thus acts as a fixed transaction cost, making smurf laundering virtually risk-free, provided individual transactions remain below this threshold. Smurf laundering increases the number of transactions, each incurring a fixed cost a, leading to a stepwise cost function:

$$c(x) = \begin{cases} a & \text{if } 0 \leq x \leq \tilde{x} \\ 2a & \text{if } \tilde{x} < x \leq 2\tilde{x} \\ \vdots & \\ na & \text{if } (n-1)\tilde{x} < x \leq n\tilde{x} \\ \vdots & \end{cases}.$$

Given the proportionality, the cost function can be approximated linearly as $\zeta(x) = \nu x$. Therefore, the profit from smurf laundering (denoted s) for the CO is $\pi_s = N\tilde{x}(1-\nu)$. Alternatively, suppose any transaction exceeding the threshold $\tilde{x}$ carries a detection probability q. If detected, illicit funds are fully confiscated, and the CO incurs an additional penalty T. Assuming a fixed transaction cost c_1, the expected profit for a single transaction (denoted l for lottery) is $\mathbf{E}[\pi_l] = (1-q)x - qT - c_1$.

A risk-neutral CO prefers smurf laundering to a single risky transaction if $\mathbf{E}[\pi_l] \leq \pi_s$, implying the threshold condition $x \leq \frac{qT+c_1}{\nu-q}$. Intuitively, this threshold indicates that smurfing is preferable for laundering relatively small amounts of illicit funds. The threshold value decreases with higher costs of smurfing (ν) and increases with higher detection probability (q) and penalty severity (T). Consequently, jurisdictions with stringent anti-money laundering enforcement indirectly incentivize greater reliance on smurfing.

To illustrate, suppose a CO possesses \$1 million USD in illicit proceeds from drug trafficking. Assume $\nu = 0.2$, threshold $\tilde{x} = 10,000$ USD, resulting in $N = 100$. If detection probability $q = 0.15$, penalty $T = 1.5$ million USD, and transaction cost $c_1 = 0.001$, the derived threshold from the above condition equals approximately \$4.52 million USD. Thus, the CO clearly prefers smurf laundering for \$1 million. However, if $q = 0.05$, the threshold reduces to about \$0.51 million USD, making the risky single transaction approach preferable in this latter scenario.

4.2. Asset laundering

As highlighted in our conceptual framework, COs often integrate illicit funds through the financial system. Malm and Bichler (2013) emphasize the significant role of financial professionals, such as accountants or financial agents, in facilitating ML, particularly in illicit markets like drug trafficking. We analyze two asset-laundering mechanisms prevalent in financial markets: multi-layering transactions for purchasing assets, and portfolio diversification with simpler transactional structures. We first address multi-layering.

4.2.1. Placement: Multi-layering

Consider a launderer with an initial monetary endowment of illicit funds x, intending to transform these into legally consumable capital. Under conditions of perfect monitoring and zero surveillance cost, layering transactions would provide no benefit, as fiscal authorities could easily detect illicit activity. However, when monitoring involves positive costs, additional transaction layers help conceal illicit origins. Thus, modeling layering effectively requires departing from costless monitoring assumptions.

Table 1
Probability of non-detection for different layers and surveillance capacities ($p_0 = 0.5$).

	$\gamma = 1$	$\gamma = 2$
$L = 1$	0.5	0.5
$L = 2$	0.75	0.875

Table 2
Optimal number of layers (L^*) under varying enforcement and surveillance capacities.

	$\gamma = 1$	$\gamma = 2$
$p_0 = 0.5$	35	13
$p_0 = 0.4$	39	14

To avoid trivial infinite layering solutions, we introduce either explicit surveillance costs or a fixed monitoring capacity constraint. Suppose the probability of non-detection, given $L \geq 1$ transaction layers, is proportional to enforcement and surveillance capacities. Specifically, we model the probability as $p_L = p_0 + (1-p_0)\left[1 - \left(\frac{1}{L}\right)^{\gamma}\right]$ where p_0 is the baseline probability of non-detection with a single layer, and $\gamma > 0$ governs the convergence rate, inversely related to surveillance resources. Table 1 illustrates how probabilities vary with surveillance capacities and layering depth. For instance, with low surveillance capacity ($\gamma = 2$), the probability of non-detection significantly increases from 0.5 at one layer ($L = 1$) to 0.875 at two layers ($L = 2$). Conversely, higher surveillance capacity ($\gamma = 1$) yields a lower probability of non-detection at two layers (0.75).

Assuming detected funds incur a penalty T (including confiscation and associated opportunity costs), the expected profit for a risk-neutral CO engaging in $L > 1$ layers is defined to be $\mathbf{E}[\pi_L] = p_L x - (1-p_L)T - c(L)$ where $c(L) = cL$ represents the linear cost of layering. The optimal layering level is derived by solving:

$$L^*(x, c, \gamma, p_0) = \arg\max_L \left[\left(p_0 + (1-p_0)\left[1 - \left(\frac{1}{L}\right)^{\gamma}\right]\right)(x+T) - cL - T\right].$$

Given strict concavity, the optimal solution is explicitly:

$$L^*(x, c, \gamma, T, p_0) = \left[\frac{\gamma(1-p_0)(x+T)}{c}\right]^{\frac{1}{\gamma+1}}.$$

Intuitively, higher illicit fund levels x or penalties T increase optimal layering, though with diminishing returns. Conversely, enhanced enforcement (lower p_0 or γ) or reduced transaction costs (c) also encourage increased layering to reduce detection probability.

Table 2 provides illustrative optimal layering results. For instance, with $p_0 = 0.5$, $\gamma = 2$, $c = 0.001$, $x = 1$, and $T = 1.5$ (in millions of USD), optimal layering is approximately 13. Improved enforcement capacity ($p_0 = 0.4$) increases optimal layering slightly, as depicted.

Substituting L^* into expected profit yields $\pi_L^* = \left[p_0 + (1-p_0)\left(1 - \left(\frac{1}{L^*}\right)^{\gamma}\right)\right](x+T) - cL^* - T$. As L^* is concave and increasing in x, expected profits also rise with illicit fund amounts x. Layering becomes preferable to smurfing when $\pi_L^* \geq \pi_s = x(1-\nu)$. With very low smurfing costs ($\nu \approx 0$), smurfing always dominates due to its riskless nature. Conversely, for sufficiently large smurfing costs ($\nu > 0$), layering is preferred at high fund levels. For instance, with minimal funds ($x = 0$), smurfing dominates since $\pi_s = 0$ and $\pi_L^*(0) < 0$. However, if ν is large enough, there exists a threshold $x_L > 0$ beyond which layering consistently yields higher expected profits.

Fig. 2 illustrates this relationship, comparing smurfing (π_s, dashed line) and layering (π_L^*, solid line) for parameters $\nu = 0.2$, $p_0 = 0.5$, $\gamma = 1$, $T = 1.5$, and $c = 0.001$ (all in millions of USD). Initially, smurfing is preferable, but beyond a threshold illicit fund amount, layering dominates.

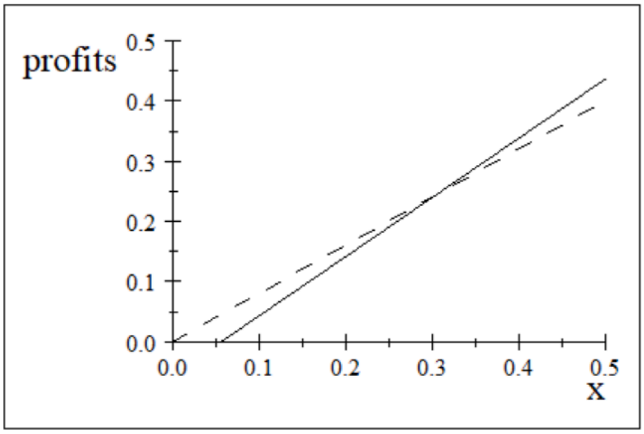

Fig. 2. Choice between Smurfing and Layering.

This analysis explains why highly profitable criminal enterprises (e.g., drug trafficking) predominantly engage in asset laundering as in layering, whereas smaller-scale crimes (e.g., theft or extortion) prefer smurfing. Moreover, enhanced enforcement against asset laundering primarily displaces illicit activity toward smurfing, thus limiting rather than eliminating laundering activities.

This result aligns with criticisms from law enforcement experts regarding the effectiveness of current anti-money laundering strategies. For instance, Cassara (2020) highlights IMF estimates indicating around $4 trillion USD in global money laundering activity in 2010, with only about 1 % seized by authorities. Even the United States, with advanced AML enforcement, confiscates only approximately 2 % of an estimated $300 billion annually laundered. Our findings suggest these low seizure rates result from displacement rather than the eradication of money laundering activities.

4.2.2. Placement: One-layer laundering portfolio selection

Beyond multi-layering, asset laundering can also involve simpler, one-layer portfolio placements into legal financial assets. Here, we study the optimal allocation of illicit resources between smurfing and a two-asset portfolio.

Consider a CO possessing an initial endowment m of illicit monetary funds. The CO chooses a portion x for smurf laundering, yielding net profits αx, with $\alpha = 1 - \nu$. The remaining amount, $m - x$, is invested across two legal financial assets. Asset laundering faces a detection probability q, leading to confiscation of the invested funds upon detection. Thus, the launderer encounters the compound lottery $\tilde{w} = q \circ ((1-\alpha)x) \oplus (1-q) \circ ((1-\alpha)x + \tilde{l})$, where $\tilde{l}$ represents portfolio payoffs from asset laundering. If undetected (with probability $p = 1 - q$), the CO retains both smurfed funds and returns from asset investments.

The portfolio payoff is given by $\boldsymbol{\omega}'\tilde{R}$, where $\boldsymbol{\omega}$ is the vector of asset weights, and $\tilde{R}$ is a random vector representing asset returns. The CO's risk preferences are modeled by a CARA utility function $\mathbf{E}[U(\tilde{\pi})] = -\mathbf{E}[\exp(-\rho\tilde{\pi})]$ with absolute risk aversion parameter ρ and total payoff $\tilde{\pi} = \alpha x + p\boldsymbol{\omega}'\tilde{R}(m - x)$. An optimal asset laundering portfolio consists of allocations (x^*, ω^*), maximizing expected profits, where x^* is the optimal amount allocated to smurfing, and ω^* is the portfolio weight distribution in asset investments.

Assume a two-asset portfolio, such that $\boldsymbol{\omega}'\tilde{R} = \omega\tilde{R}_1 + (1-\omega)\tilde{R}_2$ with returns following a multivariate normal distribution:

$$\tilde{R} \sim MN\left(\begin{bmatrix}\bar{R}_1 \\ \bar{R}_2\end{bmatrix}, \begin{bmatrix}\sigma_1^2 & 0 \\ 0 & \sigma_2^2\end{bmatrix}\right),$$

where $\bar{R}_i$ and σ_i^2 are the mean return and variance of asset i, respectively. The portfolio selection problem is thus:

$$\max_{(x,\omega)} \mathbf{E}[\pi(x,\omega)] + \frac{\rho}{2}\mathbf{V}[\pi(x,\omega)],$$

with expected payoff $\mathbf{E}[\pi(x,\omega)] = \alpha x + p(m-x)(\omega\bar{R}_1 + (1-\omega)\bar{R}_2)$ and variance $\mathbf{V}[\pi(x,\omega)] = [p(m-x)]^2(\omega^2\sigma_1^2 + (1-\omega)^2\sigma_2^2)$.

Given concavity, the internal solution for optimal weights and smurfing allocation is:

$$\omega(x) = \frac{1}{\sigma_1^2 + \sigma_2^2}\left[\frac{\bar{R}_1 - \bar{R}_2}{\rho(1-p)(m-x)} + \sigma_2^2\right],$$

$$x(\omega) = m - \frac{(1-p)[\omega(\bar{R}_1 - \bar{R}_2) + \bar{R}_2] - \alpha}{(1-p)^2\rho[\omega^2\sigma_1^2 + (1-\omega)^2\sigma_2^2]}.$$

The optimal weight $\omega(x)$ for asset 1 increases with illicit funds allocated to smurfing x if and only if $\bar{R}_1 > \bar{R}_2$. It also increases with higher differences in asset returns $(\bar{R}_1 - \bar{R}_2)$, higher probabilities of non-detection p, and greater absolute risk aversion ρ. Furthermore, $\omega(x)$ rises with the variance σ_2^2, assuming asset returns are not excessively divergent.

Conversely, the optimal amount $x(\omega)$ allocated to smurfing rises with $\alpha = 1 - \nu$, reflecting smurfing profitability. It declines with greater differences in asset returns $(\bar{R}_1 - \bar{R}_2)$, higher risk aversion ρ, and greater probabilities of successful laundering p, indicating increased asset laundering profitability. Notably, when asset returns are equal $(\bar{R}_1 = \bar{R}_2 > (1-p)\alpha)$, the optimal portfolio simplifies to $\omega^* = \frac{\sigma_2^2}{\sigma_1^2 + \sigma_2^2}$, which lies within the unit interval independently of x. In this scenario, smurfing allocation remains positive. Slight variations in returns shift optimal weights accordingly, reflecting continuous adjustments.

An increase in asset volatility (σ_i^2) reduces asset laundering attractiveness, favoring smurfing. For instance, if $\bar{R}_1 = \bar{R}_2$, higher σ_1^2 enhances smurf laundering allocations. Crucially, higher probabilities of successful asset laundering (p) significantly reduce smurfing allocations in favor of asset laundering. This insight rationalizes the prevalence of asset laundering portfolios in highly profitable illicit activities like drug trafficking, contrasting with the preference for smurfing in lower-profit crimes such as theft, extortion, and kidnapping.

4.3. Integration of laundered funds

The final stage of ML involves integrating illicit funds into the legitimate economy. As previously emphasized, all pecuniary criminal activities inevitably require ML for their operational success. Laundered funds cannot remain indefinitely within the illicit economy; therefore, this section explores various integration channels based on the specific laundering mechanism employed.

Integration via Smurfing

As established earlier, smurfing efficiently launders relatively small amounts of illicit funds. Typically, these funds re-enter the legal economy through consumption or physical investment goods, as the low transaction thresholds-intended to minimize fiscal authorities' auditing costs-make large-scale capital accumulation through financial markets impractical. Consequently, smurfing primarily funds consumption goods, frequently supporting the extravagant lifestyles of CO members and their associates.

Smurfing notably distorts consumption patterns, particularly toward semi-durable and durable goods. Certain durable items, such as jewelry, artworks, and luxury products, retain substantial value over time, despite offering low or even negative financial returns. Their attractiveness arises from their low detection risk, despite higher laundering costs compared to financial market-based asset laundering.

Housing exemplifies a durable consumption good frequently implicated in ML, functioning both as a physical asset and a financial investment. The literature consistently identifies positive relationships between ML activities and inflated durable goods prices, particularly real estate (Novaro et al., 2022; Teichmann, 2018; Schneider, 2004; Remeur, 2019). Similarly, portable durable goods, such as paintings, serve as efficient vehicles for smurf laundering due to their ease of transfer and value retention, as evidenced by Stoll (2022).

Integration via Layering and Portfolio Diversification

In contrast, asset laundering mechanisms, such as layering and portfolio diversification, enable illicit funds to enter high-return financial markets. Through sophisticated transactions involving financial instruments, illicit funds infiltrate short-term money markets and equity markets, where financial securities become the primary vehicles for laundering (Teichmann, 2020). These transactions not only legitimize illicit gains but also produce tangible financial returns, solidifying their integration into the formal economy. This practice is particularly pronounced in jurisdictions that function as tax havens (Schwarz, 2011).

Such asset laundering activities frequently involve complex coordination among CO members and financial sector professionals, including accountants and investment managers, who may operate within or outside the criminal enterprise (Malm and Bichler, 2013; Truman and Reuter, 2004). For instance, Mitchell et al. (1998) highlights case studies in the United Kingdom illustrating how accountants and financial advisors create sophisticated transaction networks to obscure illicit funds. These professionals simultaneously face obligations from regulators, such as Financial Intelligence Units, to report suspicious transactions. The resulting dual responsibilities often generate conflicts of interest, further exacerbated by regulatory hesitance to address these issues publicly.

Due to the substantial coordination, complexity, and associated costs involved, asset laundering is typically viable only when laundering substantial sums of money. The complexity inherent in layering and portfolio diversification activities can significantly distort asset prices, creating congestion and irrational exuberance in financial markets. Portfolio diversification driven by laundering activities also risks fueling asset bubbles, subsequently affecting legitimate investors' returns and increasing market volatility. Undetected asset laundering, therefore, not only disrupts market integrity but also potentially amplifies economic fluctuations, as discussed by Barone et al. (2018).

Implications for the Economy

ML affects the legitimate economy differently, depending on whether it occurs through smurfing or asset laundering. The channels through which these distinct laundering methods impact economic activity are outlined below.

Asset laundering, particularly through layering and portfolio diversification, can generate positive short-term externalities for the formal economy, provided the laundered funds remain undetected. Increased transactional volumes arising from asset laundering can stimulate financial institutions, enhance their revenue streams, and potentially contribute to overall financial stability by bolstering the circulation of financial capital. Paradoxically, this may incentivize financial regulators to suppress information regarding the detection of illicit funds, as public disclosures could undermine market confidence and trigger financial instability.

Conversely, smurfing typically yields fewer direct financial benefits for the formal economy, as it tends to circulate funds outside the regulated financial sector, thus limiting capital accumulation potential. However, smurfing-driven consumption of semi-durable and durable goods can indirectly promote economic activity and support capital accumulation over the medium to long term. Nevertheless, such consumption-driven growth may be unsustainable, with its positive effects dissipating rapidly once laundering activities cease.

The extent and nature of ML's prevalence in an economy also depend significantly on the country's level of financial development and regulatory robustness. In more developed economies characterized by stringent financial regulation and surveillance, asset laundering becomes less attractive due to higher detection risks, resulting in a relatively higher incidence of smurfing activities. In contrast, less developed economies with weaker financial oversight and lower detection probabilities tend to experience greater prevalence and profitability of asset laundering. Consequently, asset laundering often predominates in these economies relative to smurfing, facilitating larger-scale integration of illicit funds into formal financial markets.

5. Policy recommendation

Our conceptual framework highlights that ML is an indispensable component of criminal enterprises. From this perspective, conventional deterrence strategies focused solely on detection and punishment are unlikely to succeed, since criminal organizations are not deciding whether to launder but rather how to do so. Smurfing, in particular, allows illicit proceeds to enter the real economy with minimal detection risks. As a result, AML measures that concentrate narrowly on financial markets may unintentionally displace illicit activity toward smurfing, thereby undermining their own objectives.

This insight generates a policy dilemma for small open economies. On the one hand, such economies may experience temporary financial benefits from inflows of illicit funds, especially through asset laundering, while not fully internalizing the broader social costs of the underlying criminal activity. As argued by Gnutzmann et al. (2010), closed economies bear the full burden of crime's economic and social costs and thus have stronger incentives to adopt strict AML enforcement. In contrast, smaller open economies-insulated from many of these costs-may rationally tolerate laundering to capture short-term financial gains. This economic calculus offers an alternative explanation to the traditional view that weak enforcement is driven only by institutional capture or regulatory corruption.

At the global level, however, AML initiatives consistently stress the severe social harms linked to laundering, regardless of any temporary financial benefits for individual jurisdictions. Reports such as Information (1998) and indicators like the Basel AML Index highlight the risks ML poses to financial integrity, governance, and social stability. Yet an endogenous challenge emerges: the countries most exposed to ML-typically small open economies that benefit from illicit inflows-often have the weakest domestic incentives to enforce stringent regulation. Conversely, larger and more financially regulated economies, though less directly exposed, have stronger motivations and capacities to implement robust AML measures, particularly against smurfing.

The implication is clear: effective AML policy cannot rely on unilateral or fragmented enforcement. Coordinated international strategies are essential to reduce laundering opportunities across both financial and real sectors simultaneously. Without such coordination, partial interventions risk redistributing rather than reducing illicit financial activity. Our framework thus reinforces the need for globally aligned policies that internalize cross-border spillovers and address the substitutability of laundering methods.

6. Concluding remarks

This article develops a conceptual framework that aligns with the well-established money laundering (ML) cycle-placement, layering, and integration-commonly used by law enforcement agencies and policymakers. We examine two strategic mechanisms through which criminal organizations (COs) implement this cycle: smurfing, which involves breaking down illicit funds into smaller transactions; and asset laundering, which channels illicit proceeds through financial markets using complex layering strategies or diversified portfolios.

Our central argument is that ML is not a discretionary or easily deterrable activity. Rather, it is a functional necessity for pecuniary criminal enterprises. COs rely on ML to operationalize and legitimize the profits generated from illicit activities. Consequently, understanding the mechanisms of ML is critical for designing effective anti-money laundering (AML) interventions.

We characterize smurfing as a low-detection-risk strategy involving real sector cash transactions often tied to durable and semi-durable goods such as jewelry, luxury items, artworks, and real estate. These goods serve as physical assets that help obscure the origin of illicit funds minimizing detection risks. Given its decentralized and small-scale nature, smurfing is typically used for laundering relatively modest sums and remains largely invisible to enforcement due to its cash-based, low-threshold transaction structure.

In contrast, asset laundering relies on financial sector strategies that are better suited for laundering large volumes of illicit funds. These strategies carry a higher risk of detection but benefit from economies of scale. We model two variants of asset laundering: (i) multi-layering, in which funds pass through a network of nested financial transactions to reduce traceability; and (ii) one-layer portfolio diversification, where funds are strategically allocated across financial assets to reduce detection probability while preserving capital.

Our findings demonstrate that COs choose strategically between these mechanisms based on the volume of illicit funds and the risk-return tradeoffs. Smurfing is preferred when the laundering volume is low and detection costs are high. Asset laundering becomes optimal for large volumes, despite greater exposure to surveillance and legal risk.

From a policy standpoint, these insights underscore the importance of coordinated international AML efforts. Enforcement strategies that disproportionately target asset laundering, such as financial reporting requirements or transaction surveillance, may inadvertently push criminal activity toward smurfing, displacing rather than reducing laundering. Effective AML policy must, therefore, address both mechanisms in tandem. Without such comprehensive coordination, regulatory actions risk merely reshuffling laundering activities across sectors and jurisdictions, rather than eliminating them.

Declaration of generative AI and AI-assisted technologies in the manuscript preparation process

During the preparation of this work, the authors used ChatGPT in order to check spelling and grammar corrections. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

CRediT authorship contribution statement

Alfredo Contreras: Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Conceptualization; **Edgar Villa Pérez:** Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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