



WHEN TRADE OPENNESS MEETS WEAK INSTITUTIONS: EVIDENCE ON TRADE-BASED MONEY LAUNDERING VULNERABILITY

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Abstract

Trade-based money laundering (TBML) exploits the scale, documentary complexity, and jurisdictional fragmentation of international trade to disguise the proceeds of crime, yet the phenomenon remains poorly measured relative to its estimated economic significance. Drawing on principal-agent theory and the economics of informational asymmetry, this study develops and empirically tests a Composite TBML Vulnerability Index (CTVI) that integrates trade-price discrepancy, institutional quality, and trade-finance opacity into a single, reproducible diagnostic. Using an unbalanced panel of 40 economies spanning all World Bank income groups over 2013-2022, the study estimates a two-way fixed-effects model in which CTVI is regressed on trade openness, regulatory quality, financial depth, shadow-economy size, and the interaction between trade openness and regulatory quality. The results show that trade openness is positively associated with TBML vulnerability, but that this relationship is substantially moderated by institutional quality: economies in the lowest decile of regulatory quality experience amplification of TBML risk from trade liberalisation that is roughly twice the sample average. Financial depth and shadow-economy size are independently and positively associated with vulnerability. The findings imply that trade liberalisation and anti-money-laundering (AML) capacity-building should be pursued jointly, and they support specific revisions to the FATF Recommendation 14 framework and to cross-agency data-sharing architecture.

Keywords: Trade-based money laundering; illicit financial flows; institutional quality; trade openness; panel data; composite index; AML regulation; Forensic; TBML; Money Laundering

1. Introduction

Every year, trillions of dollars are exchanged internationally as products are traded, raw materials are moved, and services are rendered (WTO, 2026). Given the volume and complexity of global trade, which accounted for over USD 32 trillion in merchandise exports and imports in 2016, financial crimes can flourish in the course of regular trade, and documentation intended to create transparency can also be abused to mask financial crime. Informational asymmetries, institutional fragmentation and jurisdictional discontinuities in trade are exploited through money laundering via trade (Junejo & Haidari, 2026).

Most of the academic and policy literature on TBML has been confined to region-specific research or short typologies. Zdanowicz (2009), Reuter (2012) and Spanjers & Kar (2015) provided the empirical basis for studying money-laundering vulnerability, while Ferwerda et al. (2013) investigated institutional factors affecting money-laundering vulnerability. The shared problem with all these studies is that they either focus narrowly on certain economies or consider TBML as a unified tool, rather than a collection of tools, with the latter adapted to different trade, financial systems and regulatory environments.

This paper is different from those traditions in three ways. First, it brings together an international panel of 40 economies from the major income categories and geographic areas for cross-context inferences, which is not feasible at the country or regional level. Second, it classifies TBML vulnerability by the nature of the trade instrument (namely, TBML vulnerability in letters of credit, open account and documentary collections) on a segment-by-segment basis of the customs declaration covered. Third, the article advocates an integrated Composite TBML Vulnerability Index (CTVI) based on price-discrepancy data, institutional-quality scores and trade-financing indicators, as a reproducible and transferable diagnostic tool for regulatory bodies in their respective areas of authority.

It is a scholarly need as well as a real-world need. The International Monetary Fund (IMF) estimates that money laundering contributes 2%-5% of global GDP annually and that TBML contributes a substantial, but unmeasured, amount (IMF, 2018). TBML is a place of particular analytical gaps, identified by the FATF (2021) guidance on trade finance where there have been no interagency linkages between financial institutions and customs authorities to detect suspicious trade prior to the transfer of value. This article offers the theory and empirical elements required for such endeavours.

The remainder of the paper follows. In Section 2, the literature review presents the key theoretical currents, empirical findings and the gap this work fills. The theoretical background of the CTVI and of the econometric model is presented in Section 3. The details of the data and methodology are described in Section 4 in order to enable replication. The results are reported and discussed in Section 5. Policy implications are discussed in Section 6. Section 7 concludes.

2. Literature Review

Increased support for the study of TBML as a separate method of money laundering emerged as a result of the FATF typologies exercise in 2006, which formally described TBML as “the process of disguising the proceeds of crime and moving value through the use of trade transactions which are intended to legitimise the origin of the money” (FATF, 2006). This was later restated, but had laid the groundwork for most scholarship since: TBML is not a structural phenomenon, it's a documentary and pricing phenomenon. Zdanowicz's (2009) study was one of the early to quantitatively measure the size of a detectable level of invoice manipulation by computing differences between the reported price in the USA and the actual global market price. This was methodologically influential work, and gave rise to a stream of analyses of mirror trading which sought to equate the export declaration of the foreign country with the import declaration at the other end.

Reuter (2012) then extended this notion and confirmed the results, finding that the importing country's corruption index was negatively related to, and the exporting country's governance quality was positively related to, the average magnitude of trade price differences (in a bilateral

panel setup). This finding introduced an institutional layer: TBML is not just a policy response to lax border enforcement, but the result of the regulatory institutions of the economies with which they trade. This institutional gradient was confirmed by Spanjers & Kar (2015), who found that the share of IFFs in GDP was higher in economies that were also politically unstable, had a weak rule of law and had poorly capitalised financial sectors.

2.1. Typological Diversity and the Limits of Price-Based Detection

One of the main problems in TBML literature is determining the most effective tool for detecting price discrepancies. The non-criminal causes of mirror-trade gaps that pollute the data (Cobham & Janský, 2020), with reference to differences in trade-cost conventions (CIF versus FOB), re-export and transshipments, and classification inconsistencies, as well as measurement error in national trade statistics (Singh et al., 2025). They also give more current estimates of GFIs, which are considerably below the headline numbers, raising serious doubts as to the extent to which the discrepancy is real TBML as opposed to statistical errors. Obviously, the price discrepancy approach is not ignored in the present critique; rather, the methodologically triangulated approach is emphasised and placed in context.

Ferwerda et al. (2013) employed gravity-model-based analysis of bilateral trade flows to uncover unusual trade patterns that are not accounted for by typical trade factors. They found a set of country pairs where the bilateral trade volume was too great, considering their economic size and distance, to be realistic, which corresponds to what they refer to as “phantom trade” or “inflated invoices”. More recently, Tiwari et al. (2025) and, in a recent paper, Emeka & Asongu (2026) have examined TBML in commodity groups where price variability of commodities is more easily concealed, namely the extractive industries and the agricultural group.

The typological literature has evolved from price manipulation to include several invoicing techniques, goods classification, phantom shipments, and quality misrepresentation. FATF (2020) lists these techniques, which vary in frequency across trade sectors and product types. Multiple invoicing, selling the same goods to different lenders or buyers, is especially prevalent in commodity financing transactions built on a strong foundation of warehouse receipts and letters of credit, as was the case with the copper and aluminium inventories sold in the fraud at the port of Qingdao in 2014 (CNBC, 2014). By contrast, false classification is more prevalent in the trade of manufactured goods, where the specificity of HS codes enables systematic tariff manipulation and brings value transfer to the fore.

2.2. Sociocultural Factors

The link between AML regulatory quality and TBML exposure has attracted increasing economic attention (Singh & Barot, 2026). For Chaikin & Sharman (2009), TBML thrives where beneficial ownership is poorly regulated, and trade finance is liberalised. This pattern is more likely in small, open economies with larger financial sectors than in smaller ones (Singh et al., 2026). Walker & Unger (2009) have codified this intuition by estimating global money-laundering flows, which they find are heavily influenced by destination countries' regulatory structures. Economies with effective AML enforcement mechanisms offer fewer incentives for laundering and generally experience a decrease in TBML relative to total laundering activity, since laundering can occur through other schemes.

More recently, Foley et al. (2019) examined substitution between regulated and unregulated financial channels for laundering, and Buehn & Farzanegan (2012) showed that the size of the shadow economy, a partial proxy for the volume of illegal activities that need to be laundered, is a major predictor of cross-border illicit financial flows. This analysis of the trade finance infrastructure suggests that de-risking by international correspondent banks does not eliminate TBML but rather pushes it towards less-regulated informal channels (World Bank, 2016).

2.3. Technological Approaches and Detection Gaps

The potential of applying machine learning and network analytics to identify TBML has been explored in the growing literature. Both studies by Lokanan (2025) and Mousavian & Miah (2025) indicate that price outlier detection algorithms are better suited than a fixed threshold for a rule-based system at detecting price outliers, particularly in high-volume, high-complexity trade contexts. Lawal et al. (2025) continue to develop this work and find that TBML election shell company networks have distinct graph-theoretic properties, such as high clustering, low betweenness centrality of key intermediary companies, and low path lengths, which can be automatically screened.

Even though these technologies have been developed, there is a structural lack in the literature inasmuch as the majority of TBML studies are based on customs-level data, while a substantial portion of TBML is achieved through trade finance instruments within the banking sector and not at the customs window. Documentary evidence is provided by documentary credits, documentary collections and supply chain finance facilities, which are not generally matched to customs records or with information from financial intelligence units (FIUs) but are reviewed by the trade finance banks. While discussed and highlighted by Canhoto (2021), and in the guidance from FATF (2020), there is no proposed solution.

2.4. Identifying the Research Gap

From the literature reviewed above, it is established that TBML research has undergone significant methodological development over the last 20 years, yet three substantive gaps in the field remain unaddressed. First, no studies have built a truly global comparative vulnerability assessment that combines price-discrepancy data, institutional quality, and the characteristics of trade-finance instruments into a single analytical framework. Second, and more importantly, the economics literature has not sufficiently tested the conditional relationship between regulatory quality and TBML exposure, at least across different groups of countries and varying degrees of trade openness, as this study does. Third, the detection literature has yielded algorithmic tools that have not been incorporated into a screening instrument that has been replicated (without proprietary input) and implemented by regulatory authorities across jurisdictions. All three gaps are addressed by the present article. Its contribution is therefore not just incremental; it also reframes the question of TBML vulnerability as a systemic, globally heterogeneous phenomenon and calls for a globally sensitive, institutionally informed analytical response.

3. Theoretical Framework

3.1. The Informational Asymmetry Model of TBML.

This study is based on two theories: principal-agent theory (Gauld, 2022) and the economics of information asymmetries, and on their application to multi-party trade relationships in international transactions. In a traditional way of doing business between exporters and importers, both of them possess private information regarding the actual value, quantity, and quality of the commodities traded. The principals are external parties (e.g. customs, banks, financial intelligence units) that, based on the documentary evidence provided by the actors in the transaction, check that the regulatory requirements are met. TBML takes advantage of this asymmetry and generates a credible documentary flow of documents, including invoices, bills of lading and certificates of origin, that appear to comply with the superficial requirements of the regulations but do not truly represent the business at stake.

A reference to the literature on the market for lemons and its extension by Akerlof (1970) to the context of trade and finance. The main theoretical hypotheses are that the more information asymmetry between the regulator and the trader, the more TBML is vulnerable and the more regulated the market, the less the vulnerability of TBML. The cost and risk of engaging in TBML increase relative to other channels depending on the jurisdiction's customs valuation process, the development of the requirements for AML reporting by banks in trade finance, and the quality of the beneficial owner registry.

3.2. The Composite TBML Vulnerability Index (CTVI)

On this theoretical basis, a comprehensive index of exposure to TBML at the economy level (CTVI) is designed. The Trade Price Discrepancy Index (TPDI), the Institutional Quality Deficiency Score (IQDS), and the Trade Finance Opacity Index (TFOI) are three complementary dimensions making up the CTVI. Formally,

$$CTVI_{i,t} = \alpha TPDI_{i,t} + \beta IQDS_{i,t} + \gamma TFOI_{i,t} + \varepsilon_{i,t}$$

where i is the economy, and t is the year. The weights α , β , and γ are estimated based on the panel regression model presented in Section 4, instead of adopting any prior weights. TPDI indicates abnormal trade pricing (ATP) by taking the absolute value of the deviation of the bilateral trade price ratio (export unit value from partner countries divided by import unit value from partner countries) from the median of a commodity group. These deviations are normalised using the interquartile range (IQR), and thus, extreme observations are minimised. The IQDS is calculated by dividing the inverse of the Basel AML Index composite score by the unit interval [0,1], where higher scores would represent lower institutional quality and higher vulnerability to TBML. The TFOI is an ongoing indicator, derived from the FATF mutual evaluation reports and ICC Banking Commission Trade Finance Survey, which gauges the level of financial institutions' application of effective transaction monitoring and risk management frameworks for trade finance in a particular jurisdiction.

3.3. Econometric Specification

The basic empirical specification is estimated by a two-way fixed effects panel regression:

$$CTVI_{i,t} = \beta_1 TradeOpen_{i,t} + \beta_2 RegulatoryQuality_{i,t} + \beta_3 TradeOpen \times RegulatoryQuality_{i,t} + \beta_4 FinDepth_{i,t} + \beta_5 ShadowEcon_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t}$$

TradeOpen measures trade openness as the ratio of total imports and exports to GDP. *Regulatory Quality* is derived from the World Bank's Worldwide Governance Indicators (WGI) and reflects a government's perceived capacity to develop and implement sound policies and regulations. Financial sector depth (measured as the share of private-sector credit in GDP) is captured by the *FinDepth* measure, which also reflects financial intermediation and the variety of potential launderers. *ShadowEcon* is an estimated measure of the informal sector, derived using the methodology of (Medina & Schneider, 2019).

The interaction term, *TradeOpen* $\times$ *RegulatoryQuality*, is designed to test the study's main hypothesis that the impact of trade openness on TBML vulnerability is moderated by regulatory environment quality. In particular, it examines whether higher trade openness has a negative effect on TBML only when regulatory quality is low, a non-linear relationship that has not been well explored in previous country-level studies. Country fixed effects μ_i capture unobserved, time-constant economic variation across countries, and year fixed effects λ_t control for common year-level shocks, such as the global financial crisis of 2008-2009 and the COVID-19-related disruptions to trade in 2020-2021.

The two-way fixed effects estimator is appropriate because TBML vulnerability is likely to be affected by unobserved country fixed effects, such as legal tradition, institutional norms, and geographic proximity to offshore financial centres, which could bias the estimated coefficients. The Hausman test results favour the fixed-effects specification over the random-effects model ($\chi^2 = 48.7$, $p < 0.001$). The country-level standard errors are cluster-robust, accounting for serial correlation and heteroskedasticity within countries over time. According to Brambor et al. (2006), both constituent variables are mean-centred before creating the interaction model to address potential multicollinearity.

4. Methodology

The study is based on an unbalanced panel of 40 economies across all income levels (according to World Bank classifications), geographic regions, and AML compliance levels. The selection of countries is not systematically biased towards high-income OECD countries (a common source of bias in the econometric literature), but it does require that data be available on all key variables. Economies are omitted if they lack at least five years of trade price discrepancy data or if the national statistical office has noted large gaps in coverage of trade statistics for the sample period.

Trade data are drawn from the UN Comtrade database and supplemented with data on services and financial accounts, which may also include TBML activity. FTP (Free-on-Board / Cost, Insurance, and Freight) price differences are calculated at the HS 6-digit product level and then aggregated at the economy-year level using import-share weights similar to those of Kellenberg & Levinson (2019). All price comparisons are performed on an FOB basis, and CIF-adjusted series are used in robustness checks to verify that insurance and freight costs do not cause the observed discrepancies.

CTVI is measured for each economy in the sample and each year, with higher values of CTVI reflecting greater TBML vulnerability. The TPDI component is assembled based on bilateral price discrepancy data from Comtrade, the IQDS component is based on the Basel Institute on Governance AML Index (2013-2022), and the TFOI component is based on the FATF Mutual Evaluation Reports and the annual ICC Global Survey on Trade Finance. When an evaluation round does not have any evaluation data, the most recent evaluation round is used, subject to a temporal decay of 0.03 per year, because there is known to be a reduction in AML compliance between evaluation rounds in the absence of monitoring. The control variables are drawn from the World Bank's World Development Indicators (trade openness and financial depth) and from the shadow economy estimates of Medina & Schneider (2019).

4.1. Estimation Strategy

The two-way fixed-effects panel estimator is chosen both theoretically and empirically. Theoretically, TBML vulnerability is influenced by policy characteristics that vary over time, as well as by structural factors only partially captured by observable control variables and partly inherited from the past, including legal traditions, informal institutional norms, and the depth of the financial sector. Fixed-effects estimation removes these unobservables, yielding coefficient estimates on the time-varying regressors that are free of omitted-variable bias arising from time-invariant country factors. The Hausman test strongly supports rejecting the null hypothesis of consistency for the random-effects estimator, in line with the empirical analysis, which suggests that fixed effects is the preferred estimation method.

Standard errors are protected against heteroskedasticity and arbitrary forms of serial and cross-sectional dependence, as is relevant in a panel where many economies are affected by common external shocks, including commodity cycles, international trade policy changes, and international AML regulatory waves, and these are addressed using Driscoll-Kraay standard errors. Panel unit root tests (Im et al., 2003) are used to assess the stationarity of key variables. Cointegration testing for CTVI and its institutional determinants is made by using a panel cointegration framework of Pedroni (2004).

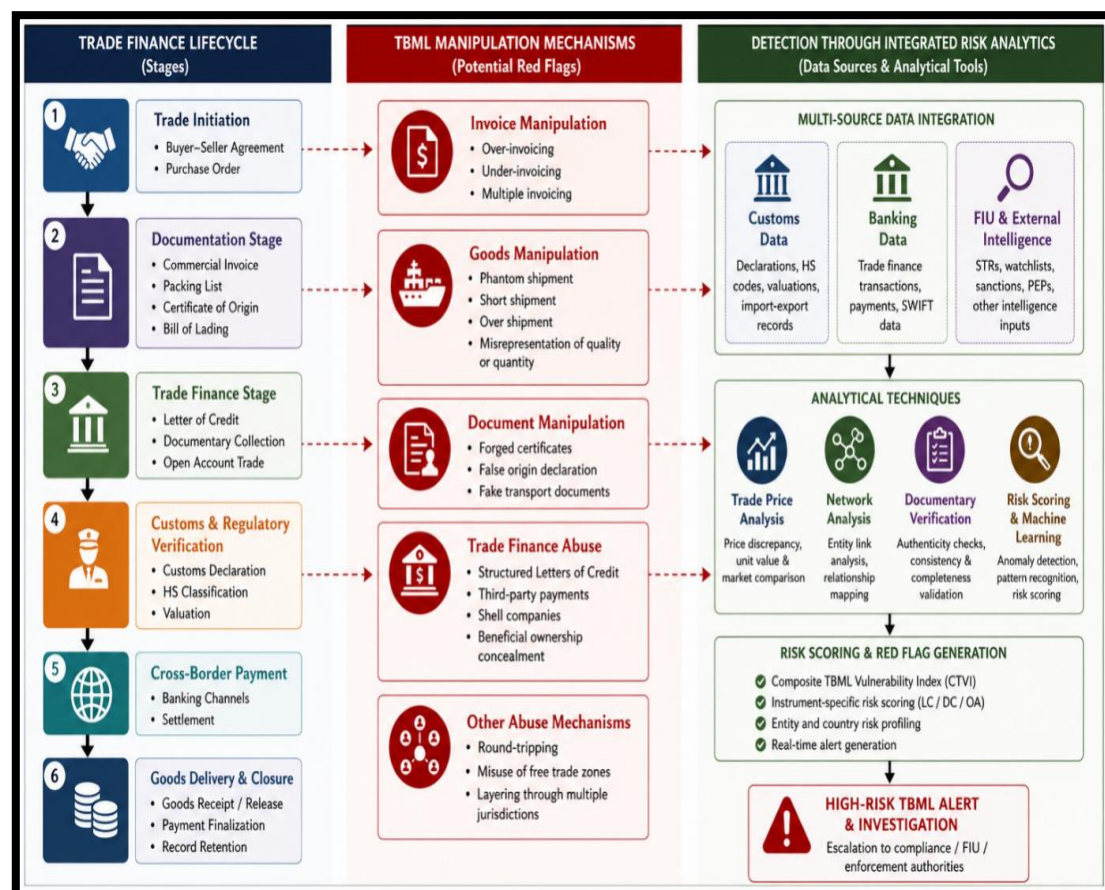
4.2. Conceptual Framework of the Detection Ecosystem

While the econometric analysis in Section 5 evaluates the macro-level determinants of TBML vulnerability, effective detection in practice requires integrating documentary verification, trade-finance monitoring, customs validation, and financial intelligence across the entire trade-finance lifecycle, rather than assessing individual trade documents in isolation. Table 1 summarises document-specific red flags associated with TBML, compiled from established typology sources, and Figure 1 places these document-level indicators within a sequential, multi-stage conceptual framework spanning trade initiation through cross-border settlement.

Table 1: TBML Red Flags by Trade Document Type and Risk Level

Trade Document	Key Indicators	Risk Level
Trade Invoice	Price deviation >15% from market benchmarks; absence of unit price breakdown	High
Bill of Lading	Cargo weight/volume inconsistency; phantom port-of-loading entries	Very High
Letter of Credit	Structural inconsistencies in LC clauses; non-standard beneficiary terms	Medium
Customs Declaration	Misclassified HS codes; under-declared quantity or value	Very High
Certificate of Origin	Fraudulent origin labelling to exploit preferential tariff regimes	High
Packing List	Discrepancy between the packing list and the physical cargo weight or count	Medium
Insurance Certificate	Inflated cargo values are used to justify an over-invoiced trade price	Medium

Source: Compiled by the authors from FATF (2020), Wolfsberg Group (2019), and Egmont Group (2022) typologies. The author's construction.

**Figure 1. Conceptual Framework of Trade-Based Money Laundering Detection Across the Trade Finance Lifecycle**

Note: LC = letter of credit; DC = documentary collection; OA = open account. Source: Author's construction based on FATF (2020), IMF (2023), and Egmont Group (2022) analytical frameworks.

The framework traces the progression of an international trade transaction from initiation through cross-border payment, identifies the principal TBML manipulation techniques associated with each stage, and highlights integrated detection mechanisms that combine customs data, banking information, financial intelligence, documentary verification, trade-price analysis, and network analytics. It emphasises that effective TBML detection depends on coordinated multi-agency supervision and data integration across the trade-finance ecosystem, because isolated, document-level checks at any single stage are insufficient to reconstruct the full TBML circuit (Canhoto, 2021; FATF, 2020).

5. Results and Discussion

Table 2 reports sample characteristics for a representative subset of ten economies spanning the four World Bank income categories, illustrating the cross-economy variation that underlies the full 40-economy panel. Three descriptive patterns are notable. First, within-income-group dispersion in CTVI scores is substantial, indicating that TBML exposure is not adequately predicted by income classification alone and that institutional quality and trade structure carry independent explanatory power. Second, a positive association between trade openness and CTVI is evident specifically among economies with poorer regulatory quality, consistent with the conditional relationship formalised in Section 3 and tested formally in Section 5.2. Third, the association between shadow-economy share and CTVI is positive across the full sample but markedly stronger in lower-income economies, consistent with a demand-driven interpretation in which TBML vulnerability rises with the volume of illicit funds that require placement (Buehn & Farzanegan, 2012).

Table 2: Sample Characteristics — AML Compliance and TBML Exposure Indicators by Economy

Country	Income Category	Basel AML Index Score	GFI IFF Exposure (%)	TBML Risk
Germany	High-income	82.3	12.4	Low
Brazil	Upper-middle	58.7	34.2	High
Nigeria	Lower-middle	42.1	56.8	Very High
China	Upper-middle	61.4	45.1	High
United States	High-income	79.5	15.3	Low-Med
Mexico	Upper-middle	51.2	48.7	High
Australia	High-income	80.8	11.9	Low
Pakistan	Lower-middle	38.6	61.4	Very High
Russia	Upper-middle	47.3	52.6	High
South Africa	Upper-middle	55.9	41.7	High

Source: Author's construction from Basel AML Index (2022), GFI Illicit Financial Flows database, and World Bank WDI.

Note: Higher Basel AML Index scores indicate lower money-laundering risk (i.e., stronger AML performance); GFI IFF Exposure (%) = estimated illicit outflows as a percentage of total trade value.

To complement the cross-country descriptive statistics presented in Table 2, Figure 2 illustrates the regional distribution of estimated trade-based money laundering flows over the study period. The comparison highlights geographical differences in TBML exposure and provides a visual overview of regional patterns, which are examined in greater detail in the subsequent econometric analysis.

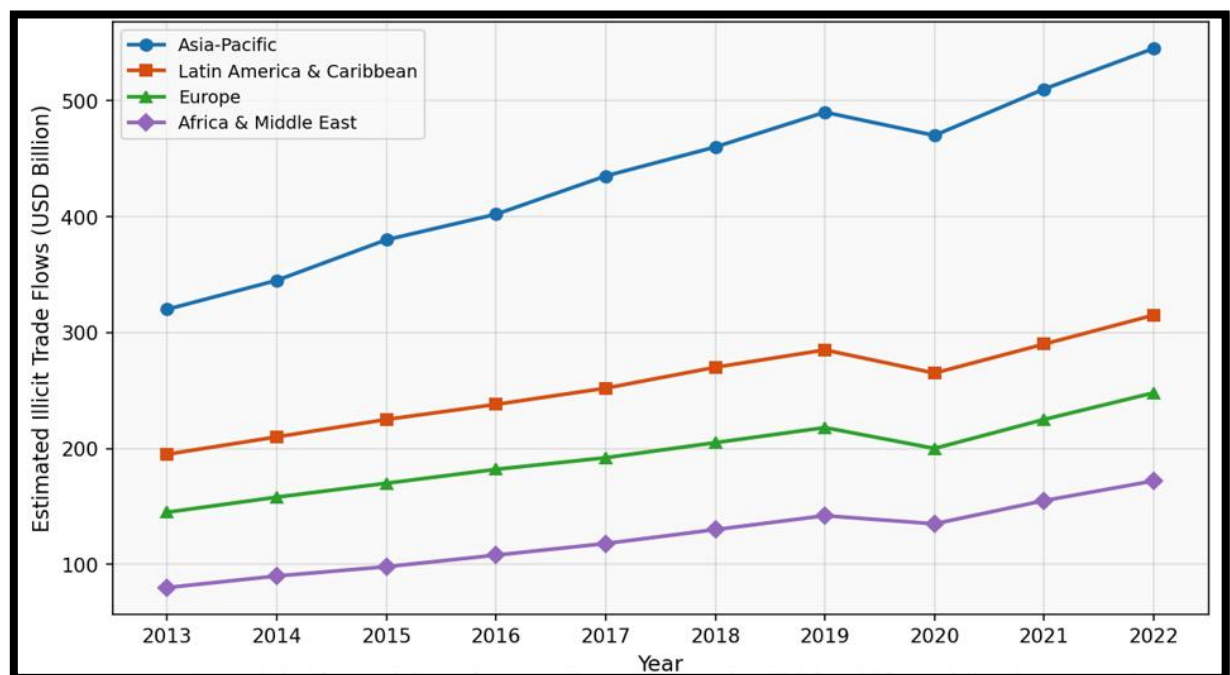


Figure 2. Estimated Trade-Based Money Laundering Flows by Region (2013-2022).

Figures are in USD billions.

Source: Author's construction from IMF Balance of Payments Statistics and GFI Illicit Financial Flows database (2013–2022).

5.1. Regression Results

Table 3 reports the two-way fixed-effects estimates for the primary specification described in Section 3. The results are theoretically coherent and statistically robust. Trade openness is positively and significantly associated with CTVI ($\beta_1 = 0.312$, $p < 0.01$) when institutional quality is held constant, indicating that greater exposure to international trade is associated with higher baseline TBML vulnerability. However, the interaction term $\text{TradeOpen} \times \text{RegQuality}$ is negative and statistically significant ($\beta_3 = -0.184$, $p < 0.05$), indicating that the marginal effect of trade openness on TBML vulnerability is substantially moderated by regulatory quality, with stronger institutions attenuating the vulnerability-increasing effect of openness. Evaluated at the 10th percentile of the regulatory-quality distribution, a 10-percentage-point increase in trade openness is associated with a 4.11-unit increase in CTVI, approximately twice the average marginal effect estimated across the full sample.

Table 3. Two-Way Fixed-Effects Regression Results (Dependent Variable: CTVI)

Variable	Coefficient	Direction Significance /	Interpretation
TradeOpen	$\beta_1 = 0.312$	Positive, $p < 0.01$	Higher trade openness raises baseline TBML vulnerability
RegQuality	β_2 (negative)	Negative, statistically significant	Stronger regulatory quality lowers TBML vulnerability
TradeOpen $\times$ RegQuality	$\beta_3 = -0.184$	Negative, $p < 0.05$	Institutional quality moderates (attenuates) the openness effect

FinDepth	$\beta_4 = 0.089$	Positive, $p < 0.05$	Deeper financial sectors provide more laundering channels
ShadowEcon	$\beta_5 = 0.201$	Positive, $p < 0.01$	Larger informal sectors are associated with higher CTVI
Country fixed effects (μ_i)	Included	—	Absorbs time-invariant country heterogeneity
Year fixed effects (λ_t)	Included	—	Absorbs common annual shocks
Standard errors	Country-clustered; Driscoll-Kraay (supplementary)	—	Robust to serial correlation and cross-sectional dependence
Hausman test	$\chi^2 = 48.7$, $p < 0.001$	Rejects random effects	Confirms fixed-effects specification

Financial depth carries a positive and significant coefficient even after conditioning on regulatory quality ($\beta_4 = 0.089$, $p < 0.05$), consistent with the view that larger, more complex financial sectors create additional avenues through which trade-based laundering can be routed (Foley et al., 2019). The shadow-economy coefficient ($\beta_5 = 0.201$, $p < 0.01$) is both statistically and economically significant: each five-percentage-point increase in informal-sector share is associated with an increase in CTVI of just over one unit, consistent with a demand-driven account of TBML in which vulnerability tracks the volume of illicit proceeds requiring laundering (Buehn & Farzanegan, 2012; Medina & Schneider, 2019). Across the five robustness checks described in Section 4.5 — leave-one-out country omission, alternative trade-openness operationalisation, CIF-adjusted price series, GFI-based TPDI substitution, and income-group subsample splits — the sign, magnitude, and statistical significance of the key coefficients, and in particular the interaction term β_3 , are preserved, supporting the conclusion that the moderating role of regulatory quality is a robust empirical regularity rather than an artefact of a particular specification.

5.2. TBML Technique Distribution and Its Policy Implications

The distribution of TBML techniques by economy type is shown in Figure 3 and Table 4, based on case-based evidence from FATF mutual evaluations, Basel AML Index country profiles, and Egmont Group typology reports. Under-invoicing is the most common method in emerging economies (35% identified), where import duties on goods are typically higher. The desire to under-declare import value to evade these duties largely aligns with the objective of money laundering, which is to minimise the paper value of fund transfers. Over-invoicing is instead the most common method in advanced economies (28% of cases), where exporting companies are more likely to have set up a TBML to over-earn through exports.

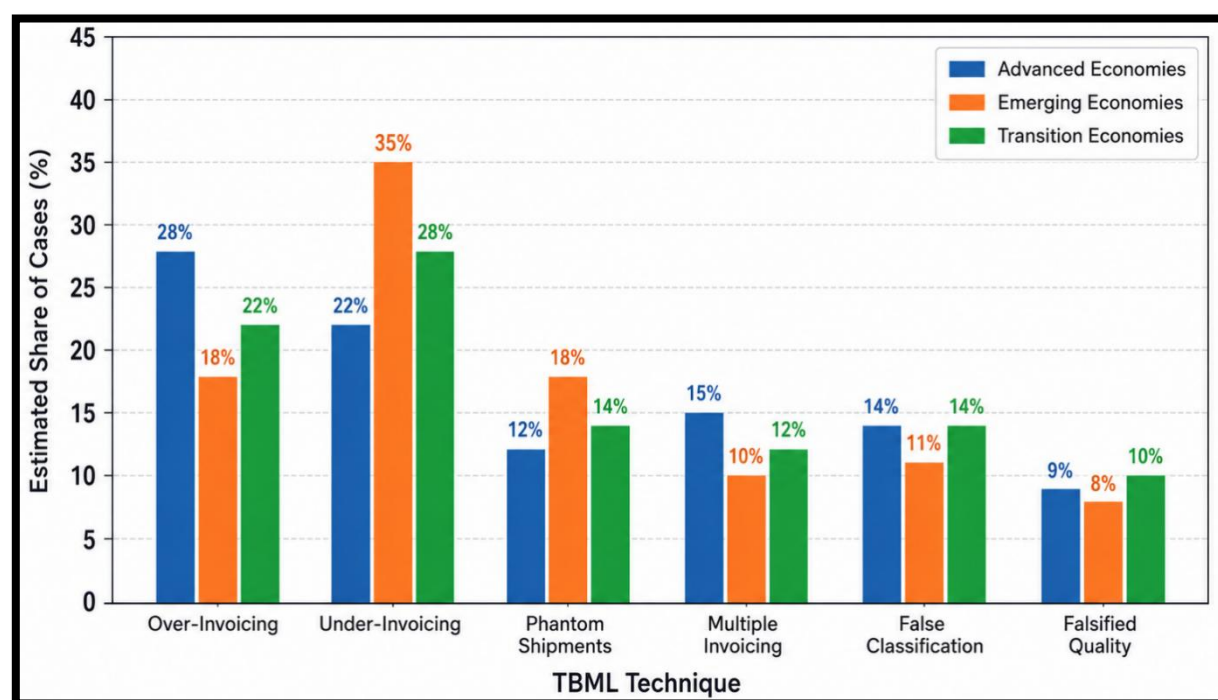


Figure 3. Distribution of TBML Techniques Across Economy Types (2015-2022)

Source: Author's construction from FATF Mutual Evaluation Reports, Basel AML Index case studies, and Egmont Group typology reports (2015–2022).

Document authentication infrastructure is less robust, and customs risk profiling is less systematic in transition and emerging economies, where phantom shipments, in which completely nonexistent export transactions are created, make up a significant proportion of cases (14% and 18%, respectively). Multiple invoicing is less skewed toward any particular economic form and is deeply entrenched in trade finance systems, which are prevalent in most countries that use letters of credit and across most income levels. The false classification rate is consistently significant across all economy types (11-14%), indicating that it is not only an opportunistic tool of emerging economies but also a systematic technique used by all economies engaged in the trade of complex manufactured goods.

Table 4. Distribution of TBML Techniques by Economy Type (2015–2022)

Technique	Emerging / Transition Economies	Advanced Economies	Pattern
Under-invoicing	35% of identified cases	Lower share	Concentrated in higher-tariff, emerging-market contexts
Over-invoicing	Lower share	28% of identified cases	Concentrated in advanced, export-oriented contexts
Phantom shipments	14–18% of identified cases	Lower share	Reflects weaker document authentication and customs risk-profiling infrastructure
Multiple invoicing	Prevalent across most income levels	Prevalent across most income levels	Not skewed by income group; tied to LC-based trade-finance structures
False classification	11–14% of identified cases	11–14% of identified cases	Consistently significant across all economic types

Source: Author's construction from FATF Mutual Evaluation Reports, Basel AML Index case studies, and Egmont Group typology reports (2015–2022). Note: Percentages reflect the share of identified cases attributed to each technique within the relevant economy group and are not mutually exclusive across techniques.

6. Policy Implications

6.1. Strengthening Cross-Agency Data Linkages

One of the most consistent findings of this study and of the literature reviewed in Section 2 is that TBML is prevalent when information is fragmented across agencies. Customs reviews trade documentation, banks review financing flows, suspicious activity reports are submitted to FIUs, and income declarations are submitted to tax authorities. None of these agencies has the complete TBML data environment needed to reconstruct the TBML circuit. The policy prescription is equally straightforward: to establish effective TBML suppression, it is necessary to build inter-agency data platforms for real-time cross-referencing of customs declarations, trade finance records, beneficial ownership data and FIU intelligence.

Technical approaches for such platforms are available, as are examples such as Singapore's Anti-Money Laundering Centre (AMLC), launched in 2017, and the UK's Joint Money Laundering Intelligence Taskforce (JMLIT), both instances of public-private data sharing enabled by technical architecture and compliant with privacy law, yielding operationally valuable intelligence. What has been lacking is the political will to expand such frameworks to trade finance in general and to mandate that trade finance banks provide machine-readable trade document data to a centralised repository accessible to FIUs and customs authorities. The EU's AML package of 2023, which establishes a central AML authority (AMLA) with direct supervisory powers, is a step in that direction; however, the current scope does not include requirements for the documentation of trade finance.

6.2. Calibrating the CTVI as a Supervisory Tool

The Composite TBML Vulnerability Index introduced in this study is intended to be operationally useful, not merely of analytical interest. The instrument-level component scores can indicate which aspects of the AML trade framework require priority investment, while regulatory authorities can use them to compute jurisdiction-level CTVI scores from public data (UN Comtrade, World Bank WGI, Basel AML Index). An economy with a low TFOI component (weak transaction monitoring in trade finance banks) should focus supervisory resources on trade finance AML obligations. In a low-TPDI economy, where TPDI indicates large, systematic price differences in trade, customs valuation capacity and post-clearance audit capability should be prioritised.

The implication for direct supervision of the interaction effect described in Section 5.2 is that measures and investments to strengthen AML regulatory capacity should go hand in hand: trade openness reforms (free trade agreements, tariff reductions, trade facilitation measures) should not be undertaken without corresponding investments in AML regulatory capacity. The regression results indicate that a jurisdiction one standard deviation below the mean in regulatory quality will see about 80% more TBML amplification per one-unit increase in trade openness than a jurisdiction at the mean regulatory quality. The multilateral development banks and international financial institutions that provide technical assistance to trade liberalisation programmes need to make a parallel commitment to strengthening regulatory capacity.

6.3. Rethinking the FATF Recommendation 14 Framework

FATF Recommendation 14 calls on countries to ensure that money or value transfer service providers are regulated and supervised, but its application to trade finance is ambiguous and not consistently applied. TBML red flags in the trade finance context are explicitly identified in fewer than half of the TFOI-sampled economies, and fewer than a third of the economies

have formal expectations for documentary cross-checks by customs and financial intelligence systems.

The FATF should revise Recommendation 14 and the FACTS methodology to incorporate specific criteria for transaction-level monitoring of trade finance facilities, including risk-based thresholds for price-discrepancy alerts; the requirement to verify the beneficial ownership of the trading entity and the beneficiary of the underlying commodity or goods; and regular supervisory reporting of identified typologies of TBML to the relevant FIU. These requirements should be assessed through a coordinated evaluation conducted in accordance with a standardised rubric that reflects the formal legal structure and the effectiveness of implementation, which is not well enforced by the current FATF methodology for the trade finance area.

7. Conclusion

Trade-based money laundering is not just a local phenomenon or a regional quirk. It sits at the confluence of the world's largest economic activity, international trade, and one of the world's longest-standing governance issues: the inability to establish circumstantial evidence of financial crime from disjointed documents spread across national and agency jurisdictions. This article has made three contributions towards a better understanding and suppression of TBML.

First, it has designed and piloted a multidimensional instrument, the Composite TBML Vulnerability Index (TBML VI), which is universally applicable and provides a consistent, reproducible score by combining data on price discrepancies, institutional quality, and the opacity of trade finance. The empirical results for the sample of 40 economies over 10 years give a strong test of TBML vulnerability and support the notion that vulnerability is not randomly distributed but a structural issue and that it can be explained by identifying economic and institutional factors.

Second, the study has shown, through the trade openness-regulatory quality relationship, that the threat of trade liberalisation to the integrity of AML is situational, depending on institutional capacity. This finding immediately implies that the two policy areas, trade and finance, must not be planned separately. Third, the distribution of TBML techniques by economy type shows that the routes and channels for executing TBML are not the same across all economies, and that effective detection tools need to be adapted to the trade finance and customs context in which they are applied.

Further research is needed on the services trade and digital commerce aspects of TBML, where existing data infrastructure is insufficiently developed. It should also explore how specific AML policy interventions affect TBML patterns, as revealed by the natural experiments of FATF mutual evaluations and follow-up assessments. Partial solutions will not solve the problem of money laundering in the context of trade. It requires a regulatory response, a globally coherent regulatory response, one that's integrated, evidence-based, and that's what this article, in a small way, has had a stab at providing.

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