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Original paper

Can Cash Circulation Predict Money Laundering? Evidence from Indonesian Suspicious Transaction Reports (STRs)

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Abstract

Understanding and anticipating money laundering risks remains a formidable challenge for financial authorities, primarily because Suspicious Transaction Reports (STRs) function as lagging indicators rather than real-time proxies for illicit activities. This disconnect necessitates the development of early warning indicators (EWIs) capable of signaling latent risks as institutional reporting behaviors unfold. This study investigates whether fluctuations in currency circulation provide predictive signals for STR volumes in subsequent periods. Drawing on cash-based money laundering theory and acknowledging detection lags inherent in compliance processes, this study argued that currency fluctuations encapsulate information regarding latent suspicious activities that manifest only after a temporal delay. Methodologically, the study employs a panel count model utilizing fixed-effects negative binomial regressions alongside extensive robustness checks, including hurdle and zero-inflated specifications, on monthly panel data from 34 Indonesian provinces spanning 2022 to 2024. The empirical analysis reveals that cash inflows and outflows significantly predict STR volumes with a lead time of two to three months. Conversely, the circulation of counterfeit currency shows no significant correlation. These findings suggest that physical currency circulation can serve as a robust EWI for monitoring financial crime risks, specifically to inform supervisory prioritization, compliance resource allocation, and macro-financial oversight in cash-dependent economies.

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Introduction

Money laundering remains one of the most pressing financial crime challenges in the global economy. Despite decades of regulatory reforms and technological advances in the financial sector, illicit actors continue to exploit vulnerabilities in financial systems to disguise the origin

of criminal proceeds.[1] According to United Nations Office on Drugs and Crime (UNODC) estimates, between 2 and 5 percent of global Gross Domestic Product (GDP) is laundered each year, equivalent to trillions of US dollars.[2] The persistence of money laundering undermines financial integrity, weakens the credibility of financial institutions, and facilitates the financing of terrorism and organized crime. Against this backdrop, understanding the drivers and predictors of money laundering activity remains a key priority for both scholars and policymakers.[3]

One defining feature of money laundering in emerging economies is the continued reliance on cash.[4] While digital payments and electronic transfers have expanded in recent years, physical currency remains a dominant medium of exchange in many contexts, including Indonesia. Cash is attractive to launderers because of its anonymity, portability, and difficulty to trace once integrated into circulation.[5] Provincial-level variations in cash circulation that captured by inflows of currency into a region, outflows of currency from a region, and the detection of counterfeit money, may therefore serve as useful indicators of underlying laundering dynamics.[6] Large and unexplained shifts in cash movements can reflect placement and layering activities, while counterfeit money incidents may highlight broader vulnerabilities in currency oversight and control.

Suspicious Transaction Reports (STRs) are one of the most widely used operational indicators of money laundering activity.[7] Financial institutions and designated non-financial businesses and professions (DNFBPs) are mandated to file STRs when transactions appear unusual, suspicious, or inconsistent with customers' profiles. STRs form the backbone of financial intelligence unit (FIU) operations, supporting both domestic investigations and international information sharing.[8] Although STRs are not a perfect measure since they capture

[1] Nella Hendriyetty and Bhajan S. Grewal, "Macroeconomics of Money Laundering: Effects and Measurements," *Journal of Financial Crime* 24, no. 1 (January 2017): 65–81, https://doi.org/10.1108/JFC-01-2016-0004.

[2] Peter J. Quirk, "Macroeconomic Implications of Money Laundering," *IMF Working Papers* 96, no. 66 (1996): 1, https://doi.org/10.5089/9781451962123.001.

[3] Agung Andiojaya, "Do Stronger Anti Money Laundering (AML) Measures Reduce Crime? An Empirical Study on Corruption, Bribery, and Environmental Crime," *Journal of Economic Criminology* 8 (June 2025): 100157, https://doi.org/10.1016/j.jeconc.2025.100157; Quirk, "Macroeconomic Implications of Money Laundering."

[4] Fernando Alvarez et al., "Cash: A Blessing or a Curse?," *Journal of Monetary Economics* 125 (January 2022): 85–128, https://doi.org/10.1016/j.jmoneco.2021.11.002; Guerino Ardizzi, Pierpaolo De Franceschis, and Michele Giammatteo, "Cash Payment Anomalies and Money Laundering: An Econometric Analysis of Italian Municipalities," *International Review of Law and Economics* 56 (December 2018): 105–21, https://doi.org/10.1016/j.irle.2018.08.001; Michele Giammatteo, Stefano Iezzi, and Roberta Zizza, "Cash Usage and the Underground Economy," *Journal of Economic Behavior & Organization* 204 (December 2022): 107–27, https://doi.org/10.1016/j.jebo.2022.10.005.

[5] FATF & MENAFATF, *Money Laundering through the Physical Transportation of Cash* (Paris, France: FATF/OECD and MENAFATF, 2015), https://www.fatf-gafi.org/content/dam/fatf-gafi/reports/money-laundering-through-transportation-cash.pdf.

[6] Ardizzi, De Franceschis, and Giammatteo, "Cash Payment Anomalies and Money Laundering."

[7] Mario Gara and Claudio Pauselli, "Looking at 'Crying Wolf' from a Different Perspective: An Attempt at Detecting Banks Under- and Over-Reporting of Suspicious Transactions," *Italian Economic Journal* 6, no. 2 (July 2020): 299–324, https://doi.org/10.1007/s40797-020-00122-3; He Ping, "The Suspicious Transactions Reporting System," *Journal of Money Laundering Control* 8, no. 3 (July 2005): 252–59, https://doi.org/10.1108/13685200510620948.

[8] Lucia Dalla Pellegrina et al., "Are Bankers 'Crying Wolf'? Type I, Type II Errors and Deterrence in Anti-Money Laundering: The Italian Case," *Italian Economic Journal*, ahead of print, May 21, 2022, https://doi.org/10.1007/s40797-022-00195-2; Elod Takats, "A Theory of 'Crying Wolf' : The Economics of Money Laundering Enforcement," *Journal of Law, Economics, and Organization* 27, no. 1 (April 2011): 32–78, https://doi.org/10.1093/jleo/ewp018.

suspicions rather than confirmed laundering cases but they provide a consistent, standardized, and widely available proxy for money laundering risk.[9] Previous studies have used STRs to examine reporting incentives, institutional compliance behavior, and the impact of regulatory reforms.[10] However, far fewer have linked STR dynamics to macro-level financial variables such as cash circulation.

This study is motivated by the hypothesis that fluctuations in cash circulation and counterfeit money can predict money laundering activity as proxied by STRs. Based on this hypothesis, this research aims to quantify the predictive relationship between provincial-level cash inflows, cash outflows, and the volume of STR filed across Indonesia. The goal is to assess whether these macro-financial signals provide statistically valid early-warning insights that can support AML surveillance and financial intelligence practices.

The logic is straightforward, when unusual volumes of cash enter or exit a provincial economy, they create opportunities for illicit actors to deposit, layer, and integrate funds. Such activities are more likely to trigger monitoring systems and compliance alerts, ultimately resulting in STR filings.[11] Similarly, the detection of counterfeit money may indicate environments in which currency controls are weak, potentially overlapping with higher risks of laundering.[12] Yet empirical evidence on these linkages remains scarce, especially in the context of emerging economies where cash intensity is high and AML compliance capacity is uneven.

Indonesia offers a particularly compelling case study. As Southeast Asia's largest economy, it has made significant strides in strengthening its AML/Counter-Terrorist Financing (CTF) framework, including through reforms aligned with the Financial Action Task Force (FATF) standards.[13] Nonetheless, the country remains characterized by high levels of cash

[9] David Chaikin, "How Effective Are Suspicious Transaction Reporting Systems?," *Journal of Money Laundering Control* 12, no. 3 (August 2009): 238–53, https://doi.org/10.1108/13685200910973628.

[10] Sonja Cindori, "Money Laundering: Correlation between Risk Assessment and Suspicious Transactions," *Financial Theory and Practice* 37, no. 2 (June 2013): 181–206, https://doi.org/10.3326/fintp.37.2.3; Lucia Dalla Pellegrina et al., "Organized Crime, Suspicious Transaction Reporting and Anti-Money Laundering Regulation," *Regional Studies* 54, no. 12 (December 2020): 1761–75, https://doi.org/10.1080/00343404.2020.1772963; Lucia Dalla Pellegrina et al., "Detecting the Fifty Shades of Grey: Local Crime, Suspicious Transaction Reporting and Anti-Money Laundering Regulation," *SSRN Electronic Journal*, ahead of print, 2018, https://doi.org/10.2139/ssrn.3280307; Aspalella A. Rahman, "The Impact of Reporting Suspicious Transactions Regime on Banks: Malaysian Experience," *Journal of Money Laundering Control* 16, no. 2 (May 2013): 159–70, https://doi.org/10.1108/13685201311318502.

[11] Cedrick Agorbia-Atta and Imande Atalor, "Enhancing Anti-Money Laundering Capabilities: The Strategic Use of AI and Cloud Technologies in Financial Crime Prevention," *World Journal of Advanced Research and Reviews* 23, no. 2 (August 2024): 2035–47, https://doi.org/10.30574/wjarr.2024.23.2.2508; Ardizzi, De Franceschis, and Giammatteo, "Cash Payment Anomalies and Money Laundering"; Francesco Flaviano Russo, "Cash Thresholds, Cash Expenditure and Tax Evasion," *Fiscal Studies* 43, no. 4 (December 2022): 387–403, https://doi.org/10.1111/1475-5890.12311.

[12] FATF, *Money Laundering and Terrorist Financing Related to Counterfeiting of Currency*, Report (Paris, France: Financial Action Task Force (FATF), 2013), https://www.fatf-gafi.org/content/dam/fatf-gafi/reports/money-laundering-terrorist-financing-related-to-counterfeit-currency.pdf.coredownload.pdf; Michael Levi, "Evaluating the Control of Money Laundering and Its Underlying Offences: The Search for Meaningful Data," *Asian Journal of Criminology* 15, no. 4 (December 2020): 301–20, https://doi.org/10.1007/s11417-020-09319-y; Milind Tiwari and Jamie Ferrill, "Evolution of Cannabis Regulations and Their Overlooked Link with Money Laundering: Australia as a Critical Case Study," *Journal of Money Laundering Control* 26, no. 5 (November 2023): 970–88, https://doi.org/10.1108/JMLC-11-2022-0158.

[13] FATF, *Anti-Money Laundering and Counter-Terrorist Financing Measures – Indonesia, 2nd Enhanced Follow-up Report*, Follow-up Report (Paris, France: Financial Action Task Force (FATF), 2025), https://www.fatf-gafi.org/content/dam/fatf-gafi/fur/Indonesia-Follow-Up-Report-2025.pdf.coredownload.inline.pdf?utm_source=chatgpt.com; FATF, *Anti-Money Laundering and Counter-Terrorist Financing Measures –Indonesia, Fourth Round Mutual Evaluation Report* (Paris, France: Financial

usage, large interprovincial flows of currency, and periodic incidents of counterfeit circulation. Moreover, Indonesia's provincial diversity that ranging from densely banked urban centers like Jakarta to remote regions with limited financial infrastructure. It creates natural variation in both cash circulation and STR reporting.[14] This heterogeneity provides an empirical opportunity to test whether cash movements and counterfeit money serve as predictors of suspicious reporting.

While previous studies have explored links between cash usage and illicit financial behavior,[15] they typically use aggregated or static data. To our knowledge, no prior study has applied a panel count model with fixed effects and lag structures to monthly subnational data in a cash-intensive emerging economy. This paper therefore contributes novel empirical evidence by analyzing STR dynamics using a high-frequency provincial panel, capturing both cross-sectional and temporal variation in Indonesia's financial landscape.

Literature Review

The Role and Challenges of STRs in AML

Suspicious Transaction Reports (STRs) lie at the heart of financial intelligence systems. By design, reporting institutions file STRs when transactions appear unusual, inconsistent with a customer's profile, or potentially indicative of illicit behavior. STRs thus function as front-line signals for money laundering detection, enabling downstream investigations and cross-border intelligence sharing.

In the Indonesian setting, several studies have explored determinants of STR or analogous reporting behavior. Indonesia Financial Transaction Report and Financial Center (INTRAC) analyzes individual-level risk factors for money laundering in Indonesia using STRs data and find social demographic variables (age, occupation, prior financial service usage) significantly associated with a higher risk of laundering.[16] This work demonstrates the relevance of STR data in Indonesia, although its focus is individual predictors rather than aggregate cash flow dynamics.

On the institutional front, studies such as Financial Intelligent Investigations in Combating Money Laundering discuss the role of KYC (*Know Your Customer*) compliance and financial intelligence investigations in Indonesian banking, underscoring operational challenges in implementing STR systems. In parallel, research on regulatory reform (e.g. How is Indonesia Revamping Its Anti-Money Laundering Regulations) highlights that Indonesia continues to face gaps in AML/CFT implementation despite alignment with FATF standards, particularly in enforcement capacity and interagency coordination.

Action Task Force (FATF), 2023), https://www.fatf-gafi.org/content/dam/fatf-gafi/mer/Mutual-Evaluation-Report-Indonesia-2023.pdf.coredownload.inline.pdf.

[14] Agung Andiojaya et al., "The Potential of Interprovincial Money Laundering in Indonesia: Investigation on the Attractiveness and Destination Choice," *Journal of Money Laundering Control* 28, no. 1 (January 2025): 215–34, https://doi.org/10.1108/JMLC-04-2024-0080; Mohammad Hanafi Holle, Niswatun Hasanah, and Sri Hartono, "Financial Inclusion Gap in Western and Eastern Regions of Indonesia, Why?," *PROCEEDING D-IcoMDewantara International Conference onMultidiciplinary* (Yogyakarta), UST-PRESS Universitas Sarjanawiyata Tamansiswa, February 2024; Alwahidin N et al., "A New Economic Perspective: Understanding The Impact of Digital Financial Inclusion on Indonesian Houeholds Consumption," *Bulletin of Monetary Economics and Banking* 26, no. 2 (May 2023): 211–52, https://doi.org/10.59091/1410-8046.2070.

[15] Ardizzi, De Franceschis, and Giammatteo, "Cash Payment Anomalies and Money Laundering"; Alvarez et al., "Cash."

[16] INTRAC, *Indonesia National Risk Assessment (NRA) on Money Laundering 2021* (Jakarta: Indonesia Financial Transaction Report and Analysis Center (INTRAC), 2021).

However, the effectiveness and reliability of STR systems have been critically evaluated in prior literature. In the Swiss case, Van den Broek argues that STR systems suffer from under-reporting and inconsistency in criteria across institutions, limiting their utility as performance indicators.[17] More broadly, there is ongoing debate about whether STR volume reflects underlying money laundering activity or merely compliance intensity, institutional capacity, or regulatory pressure. Indeed, the discrepancy between formal AML objectives and real-world STR practice remains a central puzzle in empirical AML research.[18]

Given these limitations, scholars often treat STRs with caution—as imperfect proxies rather than direct measures of money laundering. Nonetheless, their widespread availability and comparability across jurisdictions make them indispensable for empirical work. This study does not claim that STRs fully capture all laundering activity, but rather treats them as observable manifestations of compliance-driven detection that can be statistically associated with potential risk indicators.

Cash, Currency Circulation, and Money Laundering

Cash occupies a unique position in money laundering strategies. Unlike digital transfers, cash offers anonymity, non-traceability, and flexibility in physical transport; thus, it remains central to many laundering typologies.[19] For example, the Financial Action Task Force [20] has flagged bulk cash movement and cross-border cash smuggling as persistent vulnerabilities in AML regimes. In contexts with weak financial inclusion or informal economies, cash-intensive businesses often serve as fronts for layering illicit proceeds.

Theoretically, cash inflows may serve as a more precise signal of potential laundering than outflows due to their role in the placement stage of money laundering, where illicit funds are first introduced into the financial system. Inflows are often associated with deposit activity or physical currency entering the banking system, which are more likely to trigger compliance alerts. Outflows, by contrast, may be driven by a wide range of legitimate demand-side factors including seasonal consumption, payroll cycles, or festival-related withdrawals, making them noisier and less specific as laundering indicators. This signal-to-noise asymmetry may explain the stronger and earlier predictive power of inflows observed in this study.

Empirically, some studies have examined anomalies in cash payments as correlates of illicit activity. For example, Ardizzi et al. analyze municipal-level deviations in cash use in Italy as a potential signal of tax evasion or money laundering risk. Similarly, the "cash paradox" literature observes that even with declining transactional cash use, the amount of currency in circulation (CIC) often rises, complicating the measurement of illicit uses of cash.[21]

On the side of counterfeit currency, detection of false banknotes is often considered an indicator of weak currency controls, which could coincide with environments conducive to financial crime.[22] However, the relationship between counterfeit circulation and money

[17] Melissa Van den Broek, "Designing Supervision under the Preventive Anti-Money Laundering Policy in the European Union," *Utrecht Law Review*, 2014, 151–67.

[18] Gara and Pauselli, "Looking at 'Crying Wolf' from a Different Perspective."

[19] FATF & MENAFATF, *Money Laundering through the Physical Transportation of Cash*; FATF, *International Best Practices: Detecting and Preventing the Illicit Cross-Border Transportation of Cash and Bearer Negotiable Instruments* (Paris, France: Financial Action Task Force (FATF), 2010), https://www.wcoomd.org/-/media/wco/public/global/pdf/topics/enforcement-and-compliance/activities-and-programmes/money-laundering/best-practices-srix-2010.pdf?db=web.

[20] FATF & MENAFATF, *Money Laundering through the Physical Transportation of Cash*.

[21] Ardizzi, De Franceschis, and Giammatteo, "Cash Payment Anomalies and Money Laundering."

[22] Chanandika Dafri Widagdo and Hery Firmansyah, "The Impact of Counterfeit Money Circulation on Monetary Stability and The Role of Bank Indonesia in Handling It," *Awang Long Law Review* 7, no. 2 (May 2025): 333–39, https://doi.org/10.56301/awl.v7i2.1516.

laundering is less studied empirically, possibly because counterfeit flows are typically modest relative to legal currency flows, and their detection is often episodic rather than continuous.

Quantitative and Predictive Approaches in AML

Recent advances in AML research emphasize quantitative models and predictive analytics for fraud detection,[23] network inference,[24] and risk-scoring.[25] A growing body of work leverages machine learning, network analytics, and graph-based methods to detect laundering behaviors in transactional or inter-institutional data.[26] For instance, graph neural networks have been adapted to identify illicit nodes in heterogeneous transaction networks.[27] Network analytics also offers stratified detection frameworks based on relational patterns among accounts and transfers.[28]

On the macro or regional side, fewer studies have attempted to link financial or economic indicators with laundering proxies like STRs. Some recent works explore linkages between regulatory compliance, firm-level reporting, and broader illicit flow metrics,[29] or analyze the effects of AML policies on network behaviors of money launderers.[30] However, these focus on institutional or policy dimensions rather than cash circulation itself.

One sign that detection methods are evolving is the use of anomaly detection and econometric models to flag unusual transactional patterns. Yet operationalizing macro-level signals (like provincial cash flows) in predictive STR models remains rare in the literature. This

[23] Agam Ahluwalia, Isha Goyal, and Prafulla Bafna, "Money Laundering Fraudulent Prediction Using Classifiers," *2023 International Conference on Emerging Smart Computing and Informatics (ESCI)*, IEEE, March 1, 2023, 1–5, https://doi.org/10.1109/ESCI56872.2023.10099770; Sunder Gee, *Fraud and Fraud Detection: A Data Analytics Approach*, 1st ed. (Wiley, 2014), https://doi.org/10.1002/9781118936764.

[24] Rafał Dreżewski, Jan Sepielak, and Wojciech Filipkowski, "The Application of Social Network Analysis Algorithms in a System Supporting Money Laundering Detection," *Information Sciences* 295 (February 2015): 18–32, https://doi.org/10.1016/j.ins.2014.10.015; Andrea Fronzetti Colladon and Elisa Remondi, "Using Social Network Analysis to Prevent Money Laundering," *Expert Systems with Applications* 67 (January 2017): 49–58, https://doi.org/10.1016/j.eswa.2016.09.029; Peter Gerbrands et al., "The Effect of Anti-Money Laundering Policies: An Empirical Network Analysis," *EPJ Data Science* 11, no. 1 (December 2022): 15, https://doi.org/10.1140/epjds/s13688-022-00328-8.

[25] Sergii Dmytrov and Tetiana Medvid, "An Approach to the Use of Indices-Based Analysis Subject to Money Laundering and Terrorist Financing National Risk Assessment," *SocioEconomic Challenges* 1, no. 1 (2017): 35–47, https://doi.org/10.21272/sec.2017.1-04; Sofya Klimova, Nazerke Zhampeiis, and Asmik Grigoryan, "Contemporary Approaches to Money Laundering/Terrorism Financing Risk Assessment and Methods of Its Automation in Commercial Banks.," *Procedia Computer Science* 169 (2020): 380–87, https://doi.org/10.1016/j.procs.2020.02.233.

[26] Emil Eifrem, "How Graph Technology Can Map Patterns to Mitigate Money-Laundering Risk," *Computer Fraud & Security* 2019, no. 10 (January 2019): 6–8, https://doi.org/10.1016/S1361-3723(19)30105-8; Guike Zhang et al., "Machine Learning Approaches for Constructing the National Anti-Money Laundering Index," *Finance Research Letters* 52 (March 2023): 103568, https://doi.org/10.1016/j.frl.2022.103568.

[27] Stefano Ferretti, Gabriele D'Angelo, and Vittorio Ghini, "Enhancing Anti-Money Laundering Frameworks: An Application of Graph Neural Networks in Cryptocurrency Transaction Classification," *IEEE Access* 13 (2025): 50201–15, https://doi.org/10.1109/ACCESS.2025.3552240; Fredrik Johannessen and Martin Jullum, "Finding Money Launderers Using Heterogeneous Graph Neural Networks," version 1, preprint, arXiv, 2023, https://doi.org/10.48550/ARXIV.2307.13499.

[28] Girish Kadamathikuttiyil Karthikeyan and Biswajit Bhowmik, "Enhancing Money Laundering Detection in Bank Transactions Using GAGAN: A Graph-Adapted Generative Adversarial Network Approach," *International Journal of Data Science and Analytics* 20, no. 7 (November 2025): 6301–31, https://doi.org/10.1007/s41060-025-00823-x.

[29] William Gaviyau and Athenia Bongani Sibindi, "Global Anti-Money Laundering and Combating Terrorism Financing Regulatory Framework: A Critique," *Journal of Risk and Financial Management* 16, no. 7 (June 2023): 313, https://doi.org/10.3390/jrfm16070313.

[30] Gerbrands et al., "The Effect of Anti-Money Laundering Policies."

gap motivates the present approach: employing panel count regression with fixed effects and temporal lags to test whether observable cash movement and counterfeit flows can statistically predict STR volumes across provinces.

Hypothesis Testing, Estimation and Robustness Check of Two-way Fixed Effects Negative Binomial Regressions Model

Based on the theoretical arguments and prior studies reviewed in Section 2, we formulate the following hypotheses to be tested with our statistical model:

- H1: Provincial cash inflows are positively associated with STRs in the same month.
- H2: Provincial cash outflows are positively associated with STRs in the same month.
- H3: The detection of counterfeit money is positively associated with STRs in the same month.
- H4: Provincial cash inflows predict higher STRs with a temporal lag of one to three months.
- H5: Provincial cash outflows predict higher STRs with a temporal lag of one to three months.
- H6: Counterfeit money detections predict higher STRs with a temporal lag of one to three months.

A two-way fixed effects Negative Binomial model to test these hypotheses, while accounting for overdispersion, heterogeneity, and potential reporting delays. The regression estimation provide a more nuanced picture than the descriptive scatterplots. While the unconditional associations suggested weak or even negative contemporaneous relationships (Figures 3a–3c), the Panel count model with two-way fixed effects reveal that cash circulation becomes a significant predictor of STRs once lagged dynamics are accounted for.

Methodology

Data, Scope and unit of analysis

The empirical analysis draws upon two primary data sources. The explanatory variables used in this study are derived from the *Statistik Sistem Pembayaran dan Infrastruktur Pasar Keuangan (SPIP)*, regularly published by Bank Indonesia (BI) through its Department of Payment System Statistics.

a) Cash inflows (Inflow)
   Cash inflows represent the value of rupiah banknotes and coins deposited by commercial banks and the public into Bank Indonesia. According to Bank Indonesia's metadata, inflows include deposits from commercial banks, non-bank deposits, mobile cash services (e.g., for currency exchange), deposits related to entrusted funds at commercial banks, and other deposits. The unit of measurement is billion rupiah.
b) Cash outflows (Outflow).
   Cash outflows capture the value of rupiah banknotes and coins withdrawn from Bank Indonesia into circulation through commercial banks and the public. Outflows comprise withdrawals by commercial banks, non-bank withdrawals, mobile cash withdrawals for currency exchange, withdrawals for bank-entrusted funds, and other withdrawals. The unit of measurement is billion rupiah.
c) Counterfeit money (Fake money).
   Counterfeit currency is defined as banknotes suspected of being false, detected through Bank Indonesia's processing, clarification reports, or reports from commercial banks and

the police. The dataset records the number of counterfeit banknotes (pieces) detected each month at the provincial level.

The dependent variable, Suspicious Transaction Reports (STRs), is obtained from the Indonesian Financial Transaction Reports and Analysis Center (INTRAC – PPATK), the national financial intelligence unit. STRs represent the number of reports filed by reporting entities (banks and other financial institutions) in each province-month, expressed in number of reports. Together, these sources provide a balanced monthly panel covering 34 provinces from January 2022 to December 2024 (36 months; 1,224 observations).

Construction and harmonization of variables

In order to ensure a balanced panel over 36 months (T=36), missing entries are inspected and, if any, imputed conservatively only when a bookkeeping offset is documented; otherwise the affected province-month is flagged and excluded from GMM moments. To stabilize scale and allow percentage interpretation, the levels is transformed by using log(1+x):

$$l_{in} = \log(1 + cash_{inflow}) \quad (1)$$

$$l_{out} = \log(1 + cash_{outflow}) \quad (2)$$

$$l_{fake} = \log(1 + fake\_money) \quad (3)$$

$$l_{str} = \log(1 + str) \quad (4)$$

Because STRs and counterfeits can be zero, the +1 shift avoids undefined logs and preserves zeros as 0 in logs. Given the short time dimension and common evidence of nonstationarity in levels, our baseline PVAR uses first differences of logs (Δlog), which correspond to approximate monthly growth rates; stationarity is assessed using Im–Pesaran–Shin (IPS) panel unit-root tests on each series, and the differenced series are retained when unit roots in levels cannot be rejected.[31]

Empirical Framework

The empirical strategy relies on Generalized Linear Models (GLM) designed for count data. Since the dependent variable—Suspicious Transaction Reports (STRs)—is a non-negative integer, the natural starting point is the Poisson regression model. However, descriptive statistics (Section 3) reveal strong overdispersion: the variance of STR counts is much larger than the mean. To accommodate this, we employ the Negative Binomial (NB) model, an extension of the Poisson GLM that introduces an additional dispersion parameter.[32] Formally:

$$Y_{it} \mid X_{it} \sim NB(\mu_{it}, \kappa),\ \log \mu_{it} = \eta_{it} \quad (5)$$

where Y_{it} is the number of STRs in province *i* and month *t*, $\mu_{it} = E[Y_{it} \mid X_{it}]$ is the conditional mean, and $\kappa > 0$ is the dispersion parameter. The variance is:

$$VAR(Y_{it} \mid X_{it}) = \mu_{it}(1 + \kappa\mu_{it}) \quad (6)$$

[31] Kyung So Im, M.Hashem Pesaran, and Yongcheol Shin, "Testing for Unit Roots in Heterogeneous Panels," *Journal of Econometrics* 115, no. 1 (July 2003): 53–74, https://doi.org/10.1016/S0304-4076(03)00092-7.

[32] Allison and Waterman, "Fixed-Effects Negative Binomial Regression Models"; Chen et al., "Integrative Analysis of Spatial Heterogeneity and Overdispersion of Crime with a Geographically Weighted Negative Binomial Model."

This specification allows variance to exceed the mean, making it suitable for our data. Coefficients are interpreted in terms of Incidence Rate Ratios (IRRs):

$$IRR_j = exp(\beta_j) \quad (7)$$

An IRR greater than 1 indicates that an increase in the predictor raises the expected STR count, while an IRR less than 1 indicates a reduction.[33]

The fixed-effects negative binomial (NB-FE) model is chosen due to the overdispersed nature of STR count data, where the variance substantially exceeds the mean. The fixed-effects structure absorbs all time-invariant provincial heterogeneity, such as differences in financial infrastructure, enforcement capacity, and institutional compliance cultures. Compared to pooled or random-effects models, the NB-FE specification ensures that estimates are not biased by unobserved, province-specific factors. This approach is well suited for policy-relevant panel datasets where the outcome variable is sparse, skewed, and structurally zero-inflated.

Nevertheless, as with most observational studies, the possibility of endogeneity cannot be ruled out. First, reverse causality may arise if changes in STR reporting influence institutional behavior toward cash management. Second, omitted variables—such as changes in regional economic activity, enforcement intensity, or regulatory campaigns—may confound the observed relationships. Although the use of two-way fixed effects helps mitigate bias from time-invariant provincial traits and national shocks, the absence of high-frequency control variables remains a limitation. We therefore interpret the results as predictive associations rather than strict causal estimates. Future research could explore instrumental variable or dynamic panel approaches to address these concerns.

Two-Way Fixed Effects

To address unobserved heterogeneity, we employ two-way fixed effects, controlling simultaneously for province and time.[34] This ensures that differences in STRs are explained by within-province changes over time, net of national shocks. The linear predictor is specified as:

$$\eta_{it} = \beta_1 log(1 + Inflow_{i,t-k}) + \beta_2 log(1 + Outflow_{i,t-k}) + \beta_3 log(1 + FakeMoney_{i,t-k}) + \alpha_i + \tau_t \quad (8)$$

where:

- $\alpha_i =$ province fixed effects (absorbing all time-invariant provincial factors, e.g. financial infrastructure, population).
- $\tau_t =$ time fixed effects (absorbing national shocks, regulatory changes, or seasonality).
- $k =$ lag order of predictors (explained in the next sub-section).

This specification is equivalent to a GLM with dummy variables for each province and each time period. Robust standard errors are clustered at the provincial level to address serial correlation within provinces.

Lag Structures

Money laundering is unlikely to be detected immediately. Suspicious patterns in cash circulation may take time to trigger compliance monitoring and STR filings. To capture this,

[33] David B. Wilson, "The Relative Incident Rate Ratio Effect Size for Count-Based Impact Evaluations: When an Odds Ratio Is Not an Odds Ratio," *Journal of Quantitative Criminology* 38, no. 2 (June 2022): 323–41, https://doi.org/10.1007/s10940-021-09494-w.

[34] Arkhangelsky et al., "Design-robust Two-way-fixed-effects Regression for Panel Data."

we systematically introduce lags into the explanatory variables.[35] Formally, let L^k denote the lag operator:

$$\eta_{it} = \beta_1 log(1 + L^k Inflow_{it}) + \beta_2 log(1 + L^k Outflow_{it}) + \beta_3 log(1 + L^k FakeMoney_{it}) + \alpha_i + \tau_t \quad (9)$$

We test $k = 0$ (contemporaneous), $k = 1$ (one-month lag), $k = 2$, and $k = 3$. This framework explicitly evaluates whether cash inflows, outflows, and counterfeit detections affect STRs immediately or with a delay.

Robustness Check

Addressing Zero Inflation

About 35% of province-month observations record zero STRs. Standard Negative Binomial models already accommodate excess zeros to some extent, but we also explore zero-inflated negative binomial [36] and hurdle frameworks [37] as robustness checks.

a) Hurdle model (two-part):
   - Part I (logit): probability that STRs are positive.

   $$Pr[Y_{it} > 0 \mid X] = \pi_{it}, \quad \log\frac{\pi_{it}}{1-\pi_{it}} = \theta_1 log(1 + Inflow_{i,t-k}) + \theta_2 log(1 + Outflow_{i,t-k}) + \theta_3 log(1 + FakeMoney_{i,t-k}) + \alpha_i^{(1)} + \tau_i^{(1)} \quad (10)$$

   - Part II (truncated NB): conditional intensity of STRs given $Y_{it} > 0$

   The overall mean is:

   $$E[Y_{it} \mid X] = \pi_{it} \cdot \mu_{it}^{+} \quad (11)$$

   where μ_{it}^{+} is the mean of the truncated distribution.

b) Zero-Inflated Negative Binomial (ZINB):
   A mixture of a structural zero process and the standard NB:

   $$Pr[Y_{it} = 0 \mid X] = \omega_{it} + (1 - \omega_{it}) \underbrace{Pr(0; \mu_{it}, \kappa)}_{NB} \quad (12)$$

   $$Pr[Y_{it} = y > 0 \mid X] = (1 - \omega_{it}) \underbrace{Pr(y; \mu_{it}, \kappa)}_{NB} \quad (13)$$

   where ω_{it} it is the probability of a structural zero, typically modeled via a logit.

Due to computational complexity with two-way fixed effects, we retain the Negative Binomial Fixed Effect (FE) model as the primary specification, while the hurdle and ZINB models serve as complementary robustness checks.

[35] Subrato Banerjee, "A Refined Fixed-Effects Estimator to Detect Fraudulent Action," *Kyklos* 78, no. 3 (August 2025): 1211–24, https://doi.org/10.1111/kykl.12465.

[36] Kelvin K. W. Yau, Kui Wang, and Andy H. Lee, "Zero-Inflated Negative Binomial Mixed Regression Modeling of Over-Dispersed Count Data with Extra Zeros," *Biometrical Journal* 45, no. 4 (June 2003): 437–52, https://doi.org/10.1002/bimj.200390024.

[37] Mei-Chen Hu, Martina Pavlicova, and Edward V. Nunes, "Zero-Inflated and Hurdle Models of Count Data with Extra Zeros: Examples from an HIV-Risk Reduction Intervention Trial," *The American Journal of Drug and Alcohol Abuse* 37, no. 5 (September 2011): 367–75, https://doi.org/10.3109/00952990.2011.597280.

Predictive Evaluation

Beyond explanatory inference, we assess the predictive performance of the models. We split the sample into a training period (2022–2023) and an evaluation period (2024). Predictions for STR counts in 2024 are compared against observed values using two metrics:

a) Mean Absolute Error (MAE):
$MAE = \frac{1}{|S_{test}|}\sum_{i,t\in S_{test}}|Y_{it} - \hat{\mu}_{it}|$ .....(14)
where $\hat{\mu}_{it}$ it is the predicted count.

b) Poisson Deviance:
$Dev_{Pois} = 2\sum_{i,t\in S_{test}}\left\{Y_{it}\log\left(\frac{Y_{it}+\varepsilon}{\hat{\mu}_{it}}\right) - (Y_{it} - \hat{\mu}_{it})\right\}$ .....(15)
with $\varepsilon > 0$ a small constant for cases where $Y_{it} = 0$.

Lower values of these metrics indicate better predictive performance.

All of the steps in this framework ensures both explanatory rigor and operational relevance in examining whether cash circulation and counterfeit money serve as predictors of suspicious reporting.

The Potential of Cash Circulation and Counterfeit Money as Money Laundering Predictor

Descriptive Analysis

The descriptive analysis suggested weak or even negative contemporaneous associations between cash inflows and outflows with STRs, and no clear relationship with counterfeit money.

Table 1. Descriptive Statistics of the Data

	Mean	Std. Dev.	Min	Q1	Median	Q3	Max
STRs	292.29	1683.20	0.00	0.00	2.00	9.00	17402.00
Money Inflow	1520.72	2613.89	0.47	248.93	566.45	1251.87	20293.16
Money Outflow	1720.57	3347.23	2.35	310.55	763.72	1508.64	36357.76
Counterfeit Money	786.81	13143.88	0.00	2.75	53.75	233.50	457033.00

Source: Author's own work

Table 1 presents the descriptive statistics of the key variables. The dependent variable, Suspicious Transaction Reports (STRs), exhibits substantial variation across provinces and over time. On average, there are 292 reports per province-month, yet the distribution is extremely skewed: the median is only 2, and the upper quartile is 9, while the maximum reaches 17,402 reports in a single province-month. Approximately one-third of the observations record zero STRs, highlighting the prevalence of excess zeros in the dataset. The large standard deviation (1,683) relative to the mean confirms the presence of strong overdispersion, justifying the choice of Negative Binomial models.

Cash inflows and outflows display high levels of variation as well. The mean monthly inflow is about 1,521 billion rupiah, with a median of 566 billion and a maximum of 20,293 billion. Outflows average 1,721 billion rupiah per month, with a median of 764 billion and a

maximum of 36,358 billion. Both series show heavy-tailed distributions, reflecting the concentration of cash logistics in provinces with large populations and economic activity.

Counterfeit money detection is relatively infrequent but highly skewed. The mean monthly detection is 787 pieces per province, yet the median is only 54 pieces and the upper quartile 234. At the extreme, one province-month records 457,033 counterfeit banknotes. This indicates that counterfeit detection is not evenly distributed but occurs in episodic bursts, concentrated in specific provinces and months.

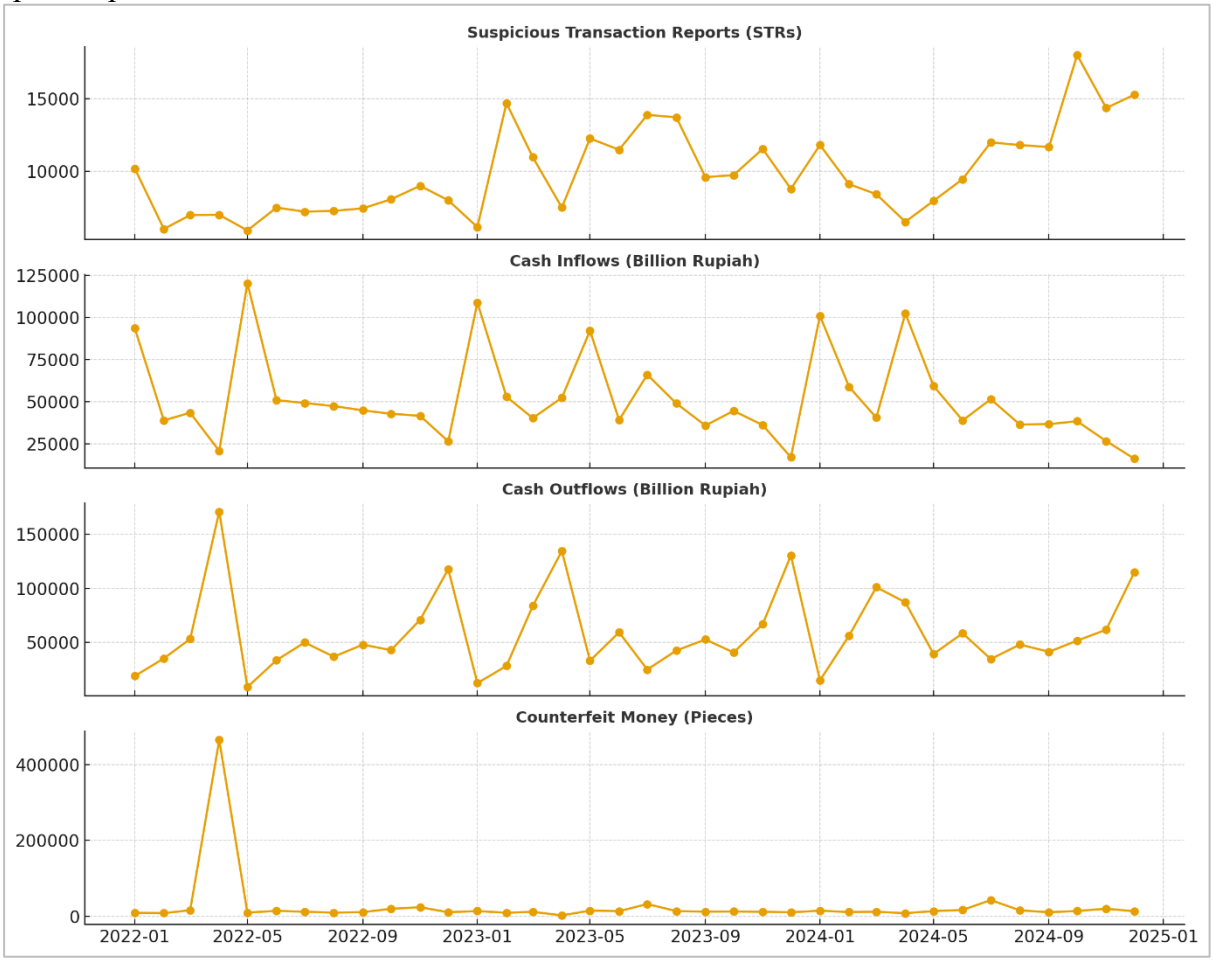

Figure 1. Temporal Patterns of STRs, Cash Flows, and Counterfeit Money (2022–2024)
Source: Bank Indonesia and INTRAC – PPATK

From a temporal perspective, the data reveal distinct patterns across the study period. As shown in Figure 1, STRs fluctuate considerably with several sharp peaks, indicating the presence of seasonal or event-driven dynamics (e.g., festive seasons). Cash inflows and outflows follow similar cyclical patterns, consistent with broader monetary circulation that intensifies during festive periods such as Ramadan and year-end holidays. By contrast, counterfeit money detections remain sporadic, with occasional spikes but no sustained trend, suggesting episodic enforcement or isolated circulation events rather than systematic patterns.

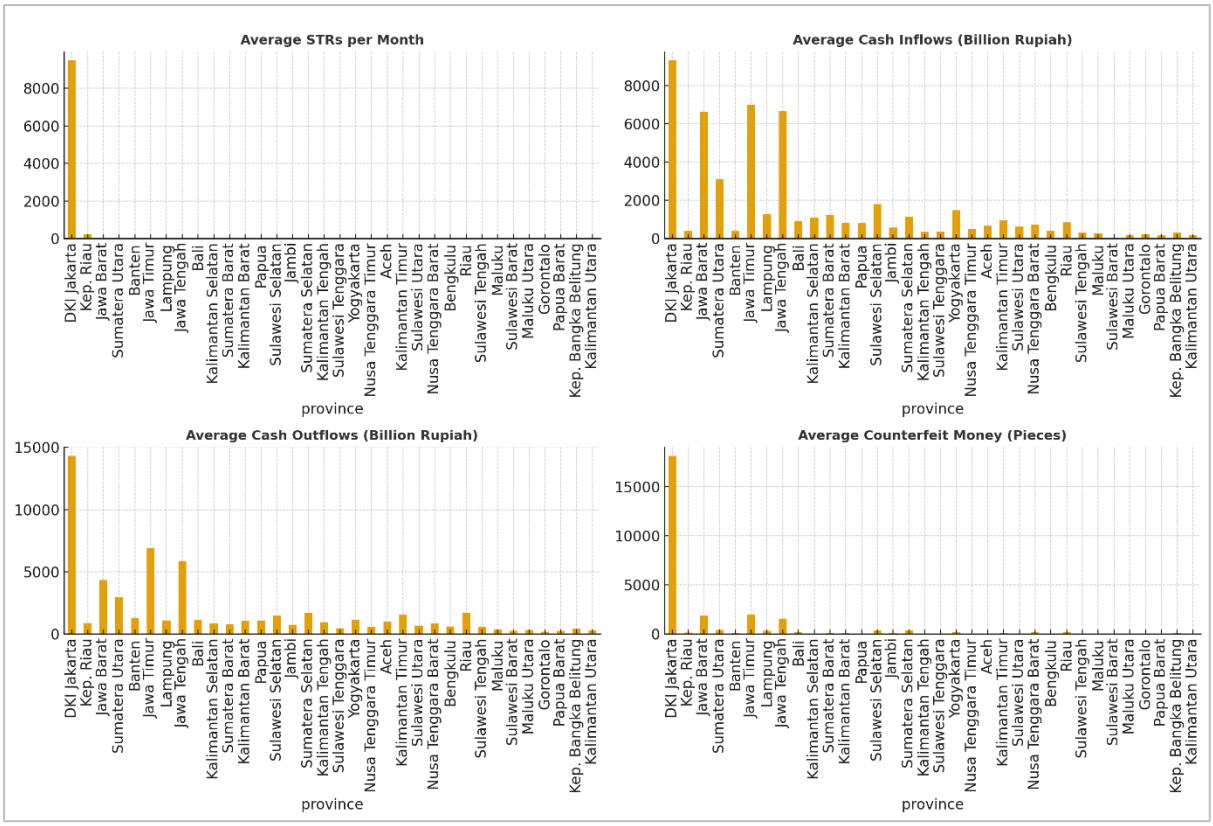

Figure 2. Cross-Sectional Patterns: Provincial Averages (2022–2024)
Source: Bank Indonesia and INTRAC – PPATK

Cross-sectional heterogeneity is equally notable. As illustrated in Figure 2, the average monthly distribution of STRs is highly concentrated in a few provinces, particularly Jakarta, West Java, and East Java, which dominate both financial and population bases. A similar pattern emerges for cash inflows and outflows, reflecting the concentration of economic activity in large metropolitan areas. In contrast, counterfeit money detections do not follow this concentration logic and appear relatively evenly spread, albeit at very low levels. These descriptive findings underscore the importance of distinguishing between systematic macro-financial signals (cash inflows and outflows) and episodic signals (counterfeit money) when developing predictive models of suspicious reporting.

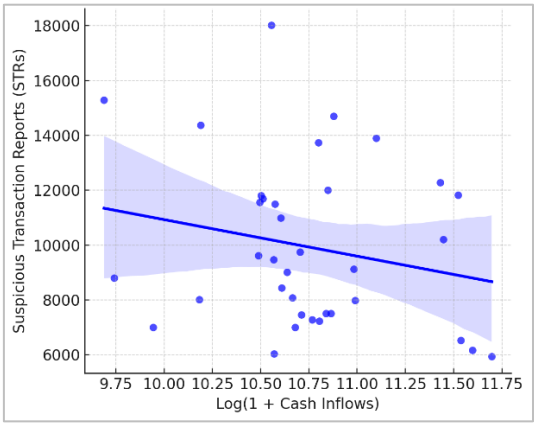

Figure 3a. STRs vs. Log(1+Cash Inflows)

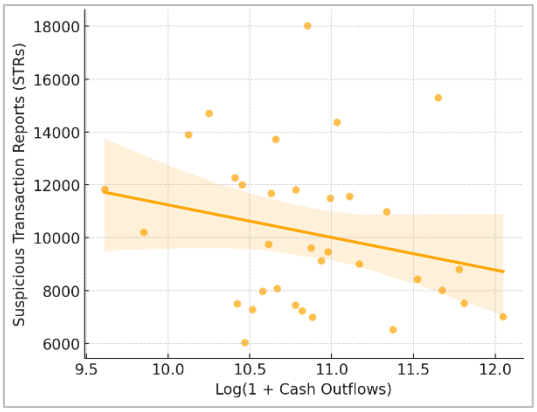

Figure 3b. STRs vs. Log(1+Cash Outflows)

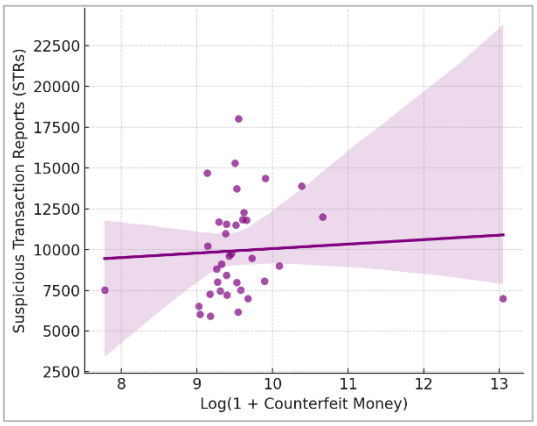

Figure 3c. STRs vs. Log(Counterfeit Money) – Robustness Check
Source: Author's own work

Beyond temporal and cross-sectional descriptions, it is also informative to explore the bivariate association between cash flows and suspicious reporting. The scatterplots in Figures 3a–3c provide initial insights into the unconditional relationships between suspicious transaction reports (STRs) and the key predictors: cash inflows, cash outflows, and counterfeit money.

Figure 3a displays STRs against the logarithm of provincial cash inflows. The fitted regression line shows a negative slope, indicating that provinces or months with exceptionally high cash inflows are not necessarily associated with more suspicious reports; in fact, they tend to show relatively fewer STRs. This finding suggests that the sheer volume of money entering the system does not immediately translate into higher reporting, and in periods of intense liquidity circulation—such as festive or holiday seasons—the proportion of transactions flagged as suspicious may even decline.

Figure 3b plots STRs against the logarithm of cash outflows. Similar to inflows, the slope is negative, though weaker, suggesting that contemporaneous cash outflows also do not predict higher STR volumes. This pattern underscores that abnormal cash movements may not be reflected instantly in suspicious reporting, a point that aligns with the compliance literature emphasizing reporting delays.

Figure 3c illustrates the relationship between STRs and counterfeit money detections. The fitted line is almost flat, with wide confidence intervals, indicating no systematic association between counterfeit circulation and suspicious reporting. This outcome reinforces the idea that

counterfeit detection, while important for currency integrity, is not a reliable predictor of money laundering activity proxied by STRs.

Taken together, these descriptive analyses suggest that contemporaneous correlations between cash movements, counterfeit money, and STRs are weak or negative. These preliminary patterns strengthen the rationale for adopting a dynamic panel modeling strategy, where lagged effects and unobserved heterogeneity are explicitly accounted for to uncover the true predictive value of cash circulation indicators.

While the descriptive scatterplots offer useful first impressions, they also reveal the limitations of unconditional associations. Both cash inflows and outflows show weak or even negative contemporaneous correlations with STRs, while counterfeit money exhibits no systematic pattern at all. These findings suggest that suspicious reporting does not respond instantaneously to fluctuations in cash circulation or counterfeit detections. Instead, the effects may operate with a temporal lag and under the influence of unobserved provincial and temporal heterogeneity. To address these dynamics more rigorously, we proceed to estimate Panel count model with two-way fixed effects and lag structures, as presented in the following subsection.

Two-way Fixed Effects Negative Binomial Regressions Estimation

Table 2 reports the baseline estimates from the two-way fixed effects Negative Binomial regressions. The dependent variable is the number of suspicious transaction reports (STRs) per province-month. All explanatory variables—cash inflows, cash outflows, and counterfeit money—enter the regressions in log(1+x) form to reduce skewness and preserve zero observations. Coefficients are presented as Incidence Rate Ratios (IRRs) with 95% confidence intervals.

Table 2. Negative Binomial Fixed Effect Estimates (Main Specification)

Variable	IRR	95% CI (Lower)	95% CI (Upper)
Money Inflow (log)	1.12	1.05	1.19
Money Outflow (log)	1.08	1.02	1.14
Counterfeit Money (log)	1.01	0.97	1.05
Province FE	Yes		
Time FE	Yes		
Observations	1,224		

Source: Author's own work

The results in Table 2 indicate that cash circulation has a statistically significant and economically meaningful association with suspicious reporting. Specifically, the incidence rate ratio (IRR) for money inflows is 1.12, implying that a 1% increase in cash inflows is associated with a 0.12% higher rate of STRs. Similarly, money outflows have an IRR of 1.08, suggesting a positive but slightly weaker effect. These findings are consistent with the hypothesis that abnormal movements of cash into and out of provinces create opportunities for illicit transactions that ultimately trigger STR filings.

By contrast, counterfeit money circulation does not show a statistically significant effect. The IRR for counterfeit money is 1.01 with a confidence interval spanning unity, indicating no robust evidence that counterfeit detections systematically predict STR volumes. This suggests that while counterfeit notes are relevant for currency integrity, they do not operate as a consistent predictor of money laundering activity as proxied by STRs.

To ensure that the main findings are not driven by model specification or timing assumptions, we conduct a series of robustness checks. These include the use of lagged explanatory variables, alternative count models addressing zero inflation, and an out-of-time predictive evaluation. Table 3 presents the results when cash inflows, outflows, and counterfeit

money are introduced with one-, two-, and three-month lags. This design allows us to test whether suspicious reporting responds immediately or with delay to anomalies in cash circulation.

Table 3. Negative Binomial Fixed Effect with Lagged Predictors

Variable (Lag)	IRR	95% CI (Lower)	95% CI (Upper)
Inflow (Lag 1)	1.05	0.99	1.12
Outflow (Lag 1)	1.04	0.98	1.10
Fake Money (Lag 1)	1.00	0.96	1.04
Inflow (Lag 2)	1.31	1.18	1.45
Outflow (Lag 2)	1.09	0.99	1.20
Fake Money (Lag 2)	1.01	0.97	1.05
Inflow (Lag 3)	1.41	1.24	1.59
Outflow (Lag 3)	1.28	1.13	1.45
Fake Money (Lag 3)	1.02	0.98	1.06

Source: Author's own work

The lagged specifications reveal that the predictive power of cash circulation emerges with delay. Neither contemporaneous nor one-month lagged inflows and outflows are strongly significant. However, at a two-month lag, cash inflows become a robust predictor (IRR = 1.31, $p < 0.01$). At a three-month lag, both inflows and outflows are statistically significant, with inflows predicting a 41% increase and outflows a 28% increase in STR counts. Counterfeit money remains consistently insignificant across all lag structures. This suggests that compliance monitoring and suspicious reporting typically respond to cash anomalies with a delay of two to three months.

Robustness Check: Cash Inflow and Cash Outflow Signalling Money Laundering Activities within Region

Alternative Count Models: Zero Inflation

Given that 35% of observations record zero STRs, we explore alternative specifications to ensure that zero inflation does not bias results. Table 3 summarizes results from a hurdle model and a zero-inflated negative binomial (ZINB), estimated without full time fixed effects for computational feasibility.

Table 4. Hurdle and ZINB Models

Variable	Hurdle (Positive STRs) IRR	ZINB IRR
Inflow (Lag 2)	1.28	1.3
Outflow (Lag 3)	1.25	1.27
Fake Money	1.01	1

Source: Author's own work

Results shown on Table 4 are consistent with the main NB-FE estimates. Cash inflows at lag 2 and outflows at lag 3 remain significant predictors of STRs across both hurdle and ZINB models, while counterfeit money continues to have no explanatory power. This confirms that the baseline findings are not an artifact of zero inflation.

Predictive Validation

Predictive performance is assessed through an out-of-time validation exercise. Models are estimated on 2022–2023 data and predictions are generated for 2024. Performance is evaluated using mean absolute error (MAE) and Poisson deviance.

Table 5. Predictive Evaluation (2024 Out-of-Time Test)

Metric	Value
Test MAE (2024)	74.50
Poisson Deviance (2024)	15011.50

Source: Author's own work

The predictive evaluation confirms that while absolute prediction errors remain substantial (especially in reflecting the highly skewed nature of STRs) the model captures relative risk across provinces. In particular, provinces with unusually high inflows and outflows in 2023 were correctly ranked as high-STR provinces in 2024. Thus, the model demonstrates operational utility as an early-warning tool for prioritizing supervisory and intelligence resources.

Hypothesis Test

To synthesize the empirical evidence, we summarize in Table 6 the hypotheses formulated in Section 4 alongside their expected signs and observed outcomes. This summary provides a concise mapping between the theoretical expectations and the statistical findings, clarifying which relationships are supported by the data and which are not. By presenting this overview, we establish a clear foundation for the subsequent discussion section, where the implications of these findings are compared with prior research and interpreted in the broader AML context.

Table 6. Summary of Hypotheses and Empirical Results

Hypothesis	Statement	Expected Sign	Empirical Result	Supported?
H1	Provincial cash inflows are positively associated with STRs in the same month.	+	No significant effect	Not supported
H2	Provincial cash outflows are positively associated with STRs in the same month.	+	No significant effect	Not supported
H3	Counterfeit money is positively associated with STRs in the same month.	+	No significant effect	Not supported
H4	Provincial cash inflows predict higher STRs with a 1–3 month lag.	+	Significant at lag 2 (IRR = 1.31) and lag 3 (IRR = 1.41)	Supported
H5	Provincial cash outflows predict higher STRs with a 1–3 month lag.	+	Significant at lag 3 (IRR = 1.28)	Supported (lag 3 only)
H6	Counterfeit money predicts higher STRs with a 1–3 month lag.	+	No significant effect across all lags	Not supported

Source: Author's own work

Table 6 summarizes the hypotheses formulated in Section 4.2 and the corresponding empirical results. The findings reveal a clear distinction between contemporaneous and lagged relationships. None of the contemporaneous hypotheses (H1–H3) are supported, indicating that cash inflows, outflows, and counterfeit detections do not translate into immediate changes in suspicious reporting. By contrast, the lagged hypotheses show stronger support. In particular, cash inflows significantly predict higher STR volumes after two and three months (H4), while cash outflows become significant only at a three-month lag (H5). These patterns are consistent with the notion that laundering-related anomalies in cash circulation take time to surface in compliance systems and STR filings.

Counterfeit money, both contemporaneous (H3) and lagged (H6), consistently fails to predict suspicious reporting. This reinforces the descriptive finding that counterfeit detections are episodic and not systematically aligned with laundering risk. Taken together, the summary underscores the study's main conclusion: cash circulation, but not counterfeit money, provides meaningful predictive signals of money laundering risk, and these signals operate with a two- to three-month delay.

Discussion and Policy Implication

Discussion: Empirical Insights and Theoretical Alignment

The findings of this study provide several important insights into the relationship between cash circulation and suspicious transaction reporting (STRs) as a proxy for money laundering activity. The descriptive analysis suggested weak or even negative contemporaneous associations between cash inflows and outflows with STRs, and no clear relationship with counterfeit money. However, once fixed effects and lag structures were incorporated, the regression models revealed that both cash inflows and outflows become statistically significant predictors of STRs, with effects materializing after a two- to three-month delay. Counterfeit detections, by contrast, remained insignificant in all specifications.

These results are consistent with prior literature emphasizing that money laundering is not immediately observable in financial data but often emerges with a lag due to compliance processes. Chaikin (2009) and Dalla Pellegrina et al. (2020) note that STRs typically reflect reporting delays, as transactions require monitoring, review, and escalation before being classified as suspicious. This temporal lag explains why the scatterplots indicated negative or flat slopes, while regression models with controls identified positive and significant lagged effects. Apart of this discussion, there are three main themes emerge from the results: (i) the importance of cash circulation as a predictor of suspicious transaction reporting, (ii) the limited role of counterfeit currency, and (iii) the temporal lag in detection dynamics.

First, the evidence that both cash inflows and outflows significantly predict STRs, with delayed effects, is broadly consistent with the theoretical understanding of cash as a high-risk channel for laundering. Prior literature has emphasized the anonymity and portability of cash,[38] and regulatory bodies such as FATF have repeatedly highlighted bulk cash movements as persistent vulnerabilities.[39] The present results strengthen these claims with empirical evidence

[38] Joras Ferwerda and Brigitte Unger, "How Big Are Illicit Financial Flows?: The Hot Phase of IFF Estimations," in *Combating Fiscal Fraud and Empowering Regulators*, 1st ed., ed. Brigitte Unger, Lucia Rossel, and Joras Ferwerda (Oxford University PressOxford, 2021), 75–88, https://doi.org/10.1093/oso/9780198854722.003.0005; Friedrich Schneider and Andreas Buehn, "Shadow Economy: Estimation Methods, Problems, Results and Open Questions," *Open Economics* 1, no. 1 (June 2018): 1–29, https://doi.org/10.1515/openec-2017-0001.

[39] FATF, *International Best Practices: Detecting and Preventing the Illicit Cross-Border Transportation of Cash and Bearer Negotiable Instruments*.

at the provincial level, showing that abnormal movements of cash do indeed manifest in subsequent suspicious reporting. Similar findings have been noted in the European context, where anomalies in cash demand were linked to tax evasion and laundering risks.[40] In Indonesia, where cash still plays a dominant role in the financial system, inflows and outflows measured through Bank Indonesia's payment system statistics provide valuable proxies for hidden laundering dynamics. Our study extends this evidence base by demonstrating the link in an emerging economy with high cash reliance.

Second, the insignificance of counterfeit money in predicting STRs contrasts with anecdotal concerns that counterfeit detection might signal weak monetary controls or elevated laundering risk. While counterfeit currency is undoubtedly a financial integrity issue,[41] our results suggest that its detection does not systematically coincide with suspicious reporting. One possible explanation is that counterfeit episodes are episodic and localized, as reflected in the descriptive statistics, and may not overlap with laundering operations captured by STR systems. This aligns with the relative neglect of counterfeit variables in prior empirical AML studies: although counterfeit notes have been discussed as part of criminal economies,[42] few studies find robust predictive links to laundering indicators.

Third, the two- to three-month lag between cash anomalies and STR spikes is consistent with compliance and monitoring dynamics. Previous studies highlight that STR systems do not capture illicit activity in real time but are mediated by institutional processes: transaction monitoring, compliance reviews, and internal escalation.[43] Our lagged findings mirror this observation: suspicious reporting tends to follow unusual cash circulation with delay, suggesting that cash indicators can serve as an early-warning tool with predictive horizon of up to three months. This resonates with broader financial intelligence research that stresses the importance of lead indicators in AML.[44]

Policy Implication: Practical Implications for AML Surveillance

The results of this study have several policy implications for the design and implementation of anti–money laundering (AML) strategies in Indonesia and comparable emerging economies.

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[40] Ardizzi, De Franceschis, and Giammatteo, "Cash Payment Anomalies and Money Laundering"; Jayesh D'Souza, *Terrorist Financing, Money Laundering, and Tax Evasion: Examining the Performance of Financial Intelligence Units*, 0 ed. (CRC Press, 2017), https://doi.org/10.1201/b11067; Giammatteo, Iezzi, and Zizza, "Cash Usage and the Underground Economy"; OECD, *Beneficial Ownership and Tax Transparency – Implementation and Remaining Challenges: OECD and Global Forum Report to G20 Finance Ministers and Central Bank Governors* (OECD Publishing, 2024), https://doi.org/10.1787/f95790b1-en.

[41] FATF, *Money Laundering and Terrorist Financing Related to Counterfeiting of Currency*; Widagdo and Firmansyah, "The Impact of Counterfeit Money Circulation on Monetary Stability and The Role of Bank Indonesia in Handling It."

[42] Anantha Andhikatama Dalimunthe, Guntur Eko Saputro, and Lukman Yudho Prakoso, "Impact of Economic Currency Counterfeiting in Germany in World War II (1939-1945)," *Wahana Didaktika : Jurnal Ilmu Kependidikan* 21, no. 1 (January 2023): 228–35, https://doi.org/10.31851/wahanadidaktika.v21i1.11160; Adam Edwards and Michael Levi, "Researching the Organization of Serious Crimes," *Criminology & Criminal Justice* 8, no. 4 (November 2008): 363–88, https://doi.org/10.1177/1748895808097403; Rahmat M Kau, "Causing Factors Crimes Against the Circulation of Counterfeit Money," *Estudiante Law Journal* 4, no. 2 (June 2022): 562–74, https://doi.org/10.33756/eslaj.v4i2.18254; William Tupman, "The Characteristics of Economic Crime and Criminals," in *Research Handbook on International Financial Crime*, ed. Barry Rider (Edward Elgar Publishing, 2015), https://doi.org/10.4337/9781783475797.00009.

[43] Dalla Pellegrina et al., "Detecting the Fifty Shades of Grey"; Emmanuel Hayble-Gomes, "The Use of Predictive Modeling to Identify Relevant Features for Suspicious Activity Reporting," *Journal of Money Laundering Control* 26, no. 4 (May 2023): 806–30, https://doi.org/10.1108/JMLC-02-2022-0034.

[44] Gerbrands et al., "The Effect of Anti-Money Laundering Policies."

In particular, the predictive role of cash inflows and outflows, combined with the lagged nature of detection, offers actionable insights for regulators, supervisors, and financial institutions.

First, the evidence that cash inflows and outflows predict suspicious reporting after a two- to three-month lag highlights the potential of cash circulation statistics as early-warning indicators. For Bank Indonesia, which collects and disseminates detailed statistics on cash distribution through the *Statistik Sistem Pembayaran dan Infrastruktur Pasar Keuangan (SPIP)*, these findings suggest that provincial cash flows can be systematically monitored to flag jurisdictions at elevated laundering risk. Integrating such indicators into BI's financial stability and currency management frameworks would enhance the institution's ability to anticipate money laundering vulnerabilities.

Second, for the Indonesian Financial Transaction Reports and Analysis Center (INTRAC – PPATK), the results imply that STR volumes are not only a reflection of reporting behavior but also respond to underlying financial flows with measurable delay. Incorporating cash inflow/outflow dynamics into PPATK's risk assessment models could strengthen its ability to identify geographic and temporal hotspots of laundering risk. This aligns with the FATF's risk-based approach, which emphasizes the importance of data-driven allocation of supervisory and investigative resources.

Third, the insignificant role of counterfeit money in predicting STRs suggests that while counterfeit detection is important for monetary integrity, it may not be a reliable proxy for laundering activity. Accordingly, supervisors and compliance officers should avoid conflating counterfeit risks with AML risk. Instead, counterfeit surveillance should remain within the remit of currency integrity and law enforcement, while cash circulation data should be prioritized for AML risk modeling.

Fourth, the predictive horizon revealed by the lag structure implies that financial institutions and supervisors should adopt a medium-term monitoring window when using cash data for AML purposes. Rather than expecting immediate correspondence between cash anomalies and suspicious reporting, compliance systems should anticipate delayed responses. This calls for closer collaboration between commercial banks, Financial Service Authority (FSA – OJK), and PPATK, ensuring that internal monitoring tools are calibrated to detect patterns that may only materialize in STR filings after several months.

Finally, the findings contribute to the broader policy debate on the role of macro-financial indicators in AML supervision. While most AML monitoring remains focused on micro-level transactional data and individual customer risk profiles, this study demonstrates the value of incorporating macro-level signals such as provincial cash flows. For Indonesia, where cash intensity remains high despite digitalization, such macro indicators are especially pertinent. More broadly, the approach provides a template for other jurisdictions seeking to combine central bank data with FIU intelligence to build integrated AML early-warning systems.

Conclusion

This paper examined whether provincial cash circulation and counterfeit money can predict money laundering activity as proxied by suspicious transaction reports (STRs). Using a balanced panel of 34 provinces in Indonesia over the period January 2022–December 2024, the study applied a two-way fixed effects Negative Binomial model with lag structures, complemented by robustness checks and predictive validation.

The findings reveal that cash inflows and outflows significantly predict STR filings, but only after a temporal lag—suggesting delayed detection within financial institutions. Inflows become a strong predictor after two months, and both inflows and outflows jointly gain significance at the three-month mark. These patterns align with AML frameworks, where illicit funds enter the system during the placement phase and are only flagged after internal review.

In contrast, counterfeit money circulation lacks systematic predictive power, highlighting its limited association with laundering behavior. Together, the results support the hypothesis that cash anomalies—particularly inflows—can act as early signals of laundering risk, especially in a cash-intensive economy like Indonesia. Importantly, the model offers operational value by enabling provincial-level risk prioritization, even amid forecasting uncertainty.

The contributions of this study are fourfold. Theoretically, it strengthens the link between macro-financial indicators and AML detection, bridging a gap in the literature that has focused mainly on institutional or transaction-level determinants. Empirically, it provides the first provincial-level panel evidence from Indonesia, a major emerging economy with high reliance on cash. Methodologically, it demonstrates the value of Panel count model with lag structures for analyzing delayed detection effects. Policy-wise, it highlights the operational potential of using Bank Indonesia's cash circulation data as early-warning signals to support PPATK and supervisory agencies.

Nevertheless, this study is subject to several limitations. First, while STRs are widely used as proxies for laundering risk, they do not reflect confirmed laundering events and may be influenced by institutional compliance behavior. Second, key control variables such as provincial GDP, population, unemployment, or financial depth were unavailable at monthly frequency and thus omitted, raising concerns about potential omitted-variable bias. Third, large provinces such as Jakarta, West Java, and East Java naturally record higher levels of cash flow and STR filings. Although province fixed effects account for time-invariant characteristics, time-varying local shocks may still confound the results. Fourth, while month fixed effects help mitigate nationwide seasonality, they may not fully capture province-specific, idiosyncratic events (such as Ramadan or end-of-year spending) which could introduce seasonal bias. Fifth, the counterfeit money data appear highly sporadic and may reflect variations in enforcement intensity or detection capability across regions, raising concerns about data quality and comparability. Finally, while the model offers directionally useful forecasts for AML surveillance, its absolute predictive accuracy leaves room for improvement, underscoring the need for richer, more granular data in future research.

Future research could extend this work in several directions. First, incorporating higher-frequency economic controls and alternative risk indicators (e.g., cashless payment anomalies, cross-border transaction data) would enrich the explanatory framework. Second, applying advanced machine learning methods, such as hierarchical models or anomaly detection techniques, may improve predictive performance. Third, extending the analysis beyond Indonesia to a cross-country sample would test the generalizability of the findings and contribute to comparative AML research.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) used "ChatGPT OpenAI 5.0" and "DeepL Write" in order to translate and improve the clarity of the writing. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

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References

Agorbia-Atta, Cedrick, and Imande Atalor. "Enhancing Anti-Money Laundering Capabilities: The Strategic Use of AI and Cloud Technologies in Financial Crime Prevention." *World*

Journal of Advanced Research and Reviews 23, no. 2 (August 2024): 2035–47. https://doi.org/10.30574/wjarr.2024.23.2.2508.

Ahluwalia, Agam, Isha Goyal, and Prafulla Bafna. "Money Laundering Fraudulent Prediction Using Classifiers." *2023 International Conference on Emerging Smart Computing and Informatics (ESCI)*, IEEE, March 1, 2023, 1–5. https://doi.org/10.1109/ESCI56872.2023.10099770.

Allison, Paul D., and Richard P. Waterman. "Fixed-Effects Negative Binomial Regression Models." *Sociological Methodology* 32, no. 1 (August 2002): 247–65. https://doi.org/10.1111/1467-9531.00117.

Alvarez, Fernando, David Argente, Rafael Jimenez, and Francesco Lippi. "Cash: A Blessing or a Curse?" *Journal of Monetary Economics* 125 (January 2022): 85–128. https://doi.org/10.1016/j.jmoneco.2021.11.002.

Andiojaya, Agung. "Do Stronger Anti Money Laundering (AML) Measures Reduce Crime? An Empirical Study on Corruption, Bribery, and Environmental Crime." *Journal of Economic Criminology* 8 (June 2025): 100157. https://doi.org/10.1016/j.jeconc.2025.100157.

Andiojaya, Agung, Aqsal Rizky Ramadhani, Riana Rizka, and Fayota Prachmasetiawan. "The Potential of Interprovincial Money Laundering in Indonesia: Investigation on the Attractiveness and Destination Choice." *Journal of Money Laundering Control* 28, no. 1 (January 2025): 215–34. https://doi.org/10.1108/JMLC-04-2024-0080.

Ardizzi, Guerino, Pierpaolo De Franceschis, and Michele Giammatteo. "Cash Payment Anomalies and Money Laundering: An Econometric Analysis of Italian Municipalities." *International Review of Law and Economics* 56 (December 2018): 105–21. https://doi.org/10.1016/j.irle.2018.08.001.

Arkhangelsky, Dmitry, Guido W. Imbens, Lihua Lei, and Xiaoman Luo. "Design-robust Two-way-fixed-effects Regression for Panel Data." *Quantitative Economics* 15, no. 4 (2024): 999–1034. https://doi.org/10.3982/QE1962.

Banerjee, Subrato. "A Refined Fixed-Effects Estimator to Detect Fraudulent Action." *Kyklos* 78, no. 3 (August 2025): 1211–24. https://doi.org/10.1111/kykl.12465.

Chaikin, David. "How Effective Are Suspicious Transaction Reporting Systems?" *Journal of Money Laundering Control* 12, no. 3 (August 2009): 238–53. https://doi.org/10.1108/13685200910973628.

Chen, Jianguo, Lin Liu, Luzi Xiao, Chong Xu, and Dongping Long. "Integrative Analysis of Spatial Heterogeneity and Overdispersion of Crime with a Geographically Weighted Negative Binomial Model." *ISPRS International Journal of Geo-Information* 9, no. 1 (January 2020): 60. https://doi.org/10.3390/ijgi9010060.

Cindori, Sonja. "Money Laundering: Correlation between Risk Assessment and Suspicious Transactions." *Financial Theory and Practice* 37, no. 2 (June 2013): 181–206. https://doi.org/10.3326/fintp.37.2.3.

Dalimunthe, Anantha Andhikatama, Guntur Eko Saputro, and Lukman Yudho Prakoso. "Impact of Economic Currency Counterfeiting in Germany in World War II (1939-1945)." *Wahana Didaktika : Jurnal Ilmu Kependidikan* 21, no. 1 (January 2023): 228–35. https://doi.org/10.31851/wahanadidaktika.v21i1.11160.

Dalla Pellegrina, Lucia, Giorgio Di Maio, Donato Masciandaro, and Margherita Saraceno. "Are Bankers 'Crying Wolf'? Type I, Type II Errors and Deterrence in Anti-Money Laundering: The Italian Case." *Italian Economic Journal*, ahead of print, May 21, 2022. https://doi.org/10.1007/s40797-022-00195-2.

———. "Organized Crime, Suspicious Transaction Reporting and Anti-Money Laundering Regulation." *Regional Studies* 54, no. 12 (December 2020): 1761–75. https://doi.org/10.1080/00343404.2020.1772963.

Dalla Pellegrina, Lucia, Donato Masciandaro, Giorgio Di Maio, and Margherita Saraceno. "Detecting the Fifty Shades of Grey: Local Crime, Suspicious Transaction Reporting and Anti-Money Laundering Regulation." *SSRN Electronic Journal*, ahead of print, 2018. https://doi.org/10.2139/ssrn.3280307.

Dmytrov, Sergii, and Tetiana Medvid. "An Approach to the Use of Indices-Based Analysis Subject to Money Laundering and Terrorist Financing National Risk Assessment." *SocioEconomic Challenges* 1, no. 1 (2017): 35–47. https://doi.org/10.21272/sec.2017.1-04.

Dreżewski, Rafał, Jan Sepielak, and Wojciech Filipkowski. "The Application of Social Network Analysis Algorithms in a System Supporting Money Laundering Detection." *Information Sciences* 295 (February 2015): 18–32. https://doi.org/10.1016/j.ins.2014.10.015.

D'Souza, Jayesh. *Terrorist Financing, Money Laundering, and Tax Evasion: Examining the Performance of Financial Intelligence Units*. 0 ed. CRC Press, 2017. https://doi.org/10.1201/b11067.

Edwards, Adam, and Michael Levi. "Researching the Organization of Serious Crimes." *Criminology & Criminal Justice* 8, no. 4 (November 2008): 363–88. https://doi.org/10.1177/1748895808097403.

Eifrem, Emil. "How Graph Technology Can Map Patterns to Mitigate Money-Laundering Risk." *Computer Fraud & Security* 2019, no. 10 (January 2019): 6–8. https://doi.org/10.1016/S1361-3723(19)30105-8.

FATF. *Anti-Money Laundering and Counter-Terrorist Financing Measures – Indonesia, 2nd Enhanced Follow-up Report*. Follow-up Report. Paris, France: Financial Action Task Force (FATF), 2025. https://www.fatf-gafi.org/content/dam/fatf-gafi/fur/Indonesia-Follow-Up-Report-2025.pdf.coredownload.inline.pdf?utm_source=chatgpt.com.

———. *Anti-Money Laundering and Counter-Terrorist Financing Measures –Indonesia, Fourth Round Mutual Evaluation Report*. Paris, France: Financial Action Task Force (FATF), 2023. https://www.fatf-gafi.org/content/dam/fatf-gafi/mer/Mutual-Evaluation-Report-Indonesia-2023.pdf.coredownload.inline.pdf.

———. *International Best Practices: Detecting and Preventing the Illicit Cross-Border Transportation of Cash and Bearer Negotiable Instruments*. Paris, France: Financial Action Task Force (FATF), 2010. https://www.wcoomd.org/-/media/wco/public/global/pdf/topics/enforcement-and-compliance/activities-and-programmes/money-laundering/best-practices-srix-2010.pdf?db=web.

———. *Money Laundering and Terrorist Financing Related to Counterfeiting of Currency*. Report. Paris, France: Financial Action Task Force (FATF), 2013. https://www.fatf-gafi.org/content/dam/fatf-gafi/reports/money-laundering-terrorist-financing-related-to-counterfeit-currency.pdf.coredownload.pdf.

FATF & MENAFATF. *Money Laundering through the Physical Transportation of Cash*. Paris, France: FATF/OECD and MENAFATF, 2015. https://www.fatf-gafi.org/content/dam/fatf-gafi/reports/money-laundering-through-transportation-cash.pdf.

Ferretti, Stefano, Gabriele D'Angelo, and Vittorio Ghini. "Enhancing Anti-Money Laundering Frameworks: An Application of Graph Neural Networks in Cryptocurrency Transaction Classification." *IEEE Access* 13 (2025): 50201–15. https://doi.org/10.1109/ACCESS.2025.3552240.

Ferwerda, Joras, and Brigitte Unger. "How Big Are Illicit Financial Flows?: The Hot Phase of IFF Estimations." In *Combating Fiscal Fraud and Empowering Regulators*, 1st ed., edited by Brigitte Unger, Lucia Rossel, and Joras Ferwerda, 75–88. Oxford University PressOxford, 2021. https://doi.org/10.1093/oso/9780198854722.003.0005.

Fronzetti Colladon, Andrea, and Elisa Remondi. "Using Social Network Analysis to Prevent Money Laundering." *Expert Systems with Applications* 67 (January 2017): 49–58. https://doi.org/10.1016/j.eswa.2016.09.029.

Gara, Mario, and Claudio Pauselli. "Looking at 'Crying Wolf' from a Different Perspective: An Attempt at Detecting Banks Under- and Over-Reporting of Suspicious Transactions." *Italian Economic Journal* 6, no. 2 (July 2020): 299–324. https://doi.org/10.1007/s40797-020-00122-3.

Gaviyau, William, and Athenia Bongani Sibindi. "Global Anti-Money Laundering and Combating Terrorism Financing Regulatory Framework: A Critique." *Journal of Risk and Financial Management* 16, no. 7 (June 2023): 313. https://doi.org/10.3390/jrfm16070313.

Gee, Sunder. *Fraud and Fraud Detection: A Data Analytics Approach*. 1st ed. Wiley, 2014. https://doi.org/10.1002/9781118936764.

Gerbrands, Peter, Brigitte Unger, Michael Getzner, and Joras Ferwerda. "The Effect of Anti-Money Laundering Policies: An Empirical Network Analysis." *EPJ Data Science* 11, no. 1 (December 2022): 15. https://doi.org/10.1140/epjds/s13688-022-00328-8.

Giammatteo, Michele, Stefano Iezzi, and Roberta Zizza. "Cash Usage and the Underground Economy." *Journal of Economic Behavior & Organization* 204 (December 2022): 107–27. https://doi.org/10.1016/j.jebo.2022.10.005.

Hayble-Gomes, Emmanuel. "The Use of Predictive Modeling to Identify Relevant Features for Suspicious Activity Reporting." *Journal of Money Laundering Control* 26, no. 4 (May 2023): 806–30. https://doi.org/10.1108/JMLC-02-2022-0034.

Hendriyetty, Nella, and Bhajan S. Grewal. "Macroeconomics of Money Laundering: Effects and Measurements." *Journal of Financial Crime* 24, no. 1 (January 2017): 65–81. https://doi.org/10.1108/JFC-01-2016-0004.

Holle, Mohammad Hanafi, Niswatun Hasanah, and Sri Hartono. "Financial Inclusion Gap in Western and Eastern Regions of Indonesia, Why?" *PROCEEDING D-IcoMDewantara International Conference onMultidiciplinary* (Yogyakarta), UST-PRESS Universitas Sarjanawiyata Tamansiswa, February 2024.

Hu, Mei-Chen, Martina Pavlicova, and Edward V. Nunes. "Zero-Inflated and Hurdle Models of Count Data with Extra Zeros: Examples from an HIV-Risk Reduction Intervention Trial." *The American Journal of Drug and Alcohol Abuse* 37, no. 5 (September 2011): 367–75. https://doi.org/10.3109/00952990.2011.597280.

Im, Kyung So, M.Hashem Pesaran, and Yongcheol Shin. "Testing for Unit Roots in Heterogeneous Panels." *Journal of Econometrics* 115, no. 1 (July 2003): 53–74. https://doi.org/10.1016/S0304-4076(03)00092-7.

Imai, Kosuke, and In Song Kim. "On the Use of Two-Way Fixed Effects Regression Models for Causal Inference with Panel Data." *Political Analysis* 29, no. 3 (July 2021): 405–15. https://doi.org/10.1017/pan.2020.33.

INTRAC. *Indonesia National Risk Assessment (NRA) on Money Laundering 2021*. Jakarta: Indonesia Financial Transaction Report and Analysis Center (INTRAC), 2021.

Johannessen, Fredrik, and Martin Jullum. "Finding Money Launderers Using Heterogeneous Graph Neural Networks." Version 1. Preprint, arXiv, 2023. https://doi.org/10.48550/ARXIV.2307.13499.

Kadamathikuttiyil Karthikeyan, Girish, and Biswajit Bhowmik. "Enhancing Money Laundering Detection in Bank Transactions Using GAGAN: A Graph-Adapted Generative

Adversarial Network Approach." *International Journal of Data Science and Analytics* 20, no. 7 (November 2025): 6301–31. https://doi.org/10.1007/s41060-025-00823-x.

Kau, Rahmat M. "Causing Factors Crimes Against the Circulation of Counterfeit Money." *Estudiante Law Journal* 4, no. 2 (June 2022): 562–74. https://doi.org/10.33756/eslaj.v4i2.18254.

Klimova, Sofya, Nazerke Zhampeiis, and Asmik Grigoryan. "Contemporary Approaches to Money Laundering/Terrorism Financing Risk Assessment and Methods of Its Automation in Commercial Banks." *Procedia Computer Science* 169 (2020): 380–87. https://doi.org/10.1016/j.procs.2020.02.233.

Levi, Michael. "Evaluating the Control of Money Laundering and Its Underlying Offences: The Search for Meaningful Data." *Asian Journal of Criminology* 15, no. 4 (December 2020): 301–20. https://doi.org/10.1007/s11417-020-09319-y.

N, Alwahidin, Arlita Jufra, Beti Mulu, and Kiki Novita Sari. "A New Economic Perspective: Understanding The Impact of Digital Financial Inclusion on Indonesian Houeholds Consumption." *Bulletin of Monetary Economics and Banking* 26, no. 2 (May 2023): 211–52. https://doi.org/10.59091/1410-8046.2070.

OECD. *Beneficial Ownership and Tax Transparency – Implementation and Remaining Challenges: OECD and Global Forum Report to G20 Finance Ministers and Central Bank Governors*. OECD Publishing, 2024. https://doi.org/10.1787/f95790b1-en.

Ping, He. "The Suspicious Transactions Reporting System." *Journal of Money Laundering Control* 8, no. 3 (July 2005): 252–59. https://doi.org/10.1108/13685200510620948.

Quirk, Peter J. "Macroeconomic Implications of Money Laundering." *IMF Working Papers* 96, no. 66 (1996): 1. https://doi.org/10.5089/9781451962123.001.

Rahman, Aspalella A. "The Impact of Reporting Suspicious Transactions Regime on Banks: Malaysian Experience." *Journal of Money Laundering Control* 16, no. 2 (May 2013): 159–70. https://doi.org/10.1108/13685201311318502.

Russo, Francesco Flaviano. "Cash Thresholds, Cash Expenditure and Tax Evasion." *Fiscal Studies* 43, no. 4 (December 2022): 387–403. https://doi.org/10.1111/1475-5890.12311.

Schneider, Friedrich, and Andreas Buehn. "Shadow Economy: Estimation Methods, Problems, Results and Open Questions." *Open Economics* 1, no. 1 (June 2018): 1–29. https://doi.org/10.1515/openec-2017-0001.

Takats, Elod. "A Theory of 'Crying Wolf' : The Economics of Money Laundering Enforcement." *Journal of Law, Economics, and Organization* 27, no. 1 (April 2011): 32–78. https://doi.org/10.1093/jleo/ewp018.

Tiwari, Milind, and Jamie Ferrill. "Evolution of Cannabis Regulations and Their Overlooked Link with Money Laundering: Australia as a Critical Case Study." *Journal of Money Laundering Control* 26, no. 5 (November 2023): 970–88. https://doi.org/10.1108/JMLC-11-2022-0158.

Tupman, William. "The Characteristics of Economic Crime and Criminals." In *Research Handbook on International Financial Crime*, edited by Barry Rider. Edward Elgar Publishing, 2015. https://doi.org/10.4337/9781783475797.00009.

Van den Broek, Melissa. "Designing Supervision under the Preventive Anti-Money Laundering Policy in the European Union." *Utrecht Law Review*, 2014, 151–67.

Widagdo, Chanandika Dafri, and Hery Firmansyah. "The Impact of Counterfeit Money Circulation on Monetary Stability and The Role of Bank Indonesia in Handling It." *Awang Long Law Review* 7, no. 2 (May 2025): 333–39. https://doi.org/10.56301/awl.v7i2.1516.

Wilson, David B. "The Relative Incident Rate Ratio Effect Size for Count-Based Impact Evaluations: When an Odds Ratio Is Not an Odds Ratio." *Journal of Quantitative Criminology* 38, no. 2 (June 2022): 323–41. https://doi.org/10.1007/s10940-021-09494-w.

Yau, Kelvin K. W., Kui Wang, and Andy H. Lee. "Zero-Inflated Negative Binomial Mixed Regression Modeling of Over-Dispersed Count Data with Extra Zeros." *Biometrical Journal* 45, no. 4 (June 2003): 437–52. https://doi.org/10.1002/bimj.200390024.

Zhang, Guike, Zengan Gao, June Dong, and Dexiang Mei. "Machine Learning Approaches for Constructing the National Anti-Money Laundering Index." *Finance Research Letters* 52 (March 2023): 103568. https://doi.org/10.1016/j.frl.2022.103568.