

STATISTICAL ANALYSIS OF MONEY LAUNDERING RISKS WITH PUBLIC FINANCIAL DATA SETS

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ABSTRACT

Purpose- This study statistically examines money laundering (ML) risk in Türkiye over 2015-2024 using public financial datasets. We conceptualize ML not only as a criminal phenomenon but also as a structural threat to macroeconomic stability, fiscal discipline, and the integrity of financial intermediation. The analysis integrates official data from the Central Bank of the Republic of Türkiye (CBRT), Ministry of Treasury and Finance, Banking Regulation and Supervision Agency (BRSA), Financial Crimes Investigation Board (MASAK), Turkish Statistical Institute (TurkStat), and the Financial Action Task Force (FATF).

Methodology- Two dependent measures are employed: (i) a Money Laundering Index (MLI) constructed from shadow economy, cash intensity, tax revenue shortfall, financial depth, and FATF alignment; and (ii) Suspicious Transaction Reports (STRs) as a system-level signal of risk perception and supervisory capacity. Explanatory variables include FATF Compliance Score, cash density, tax collection gap, GDP growth, inflation, interest rate, financial-institution size, and compliance cost. We estimate correlations and regression models (time-series/panel formulations as permitted by data), supported by robustness checks, to assess directional associations between ML proxies and macro-financial indicators.

Findings- Results indicate that higher ML intensity is negatively associated with financial stability and fiscal control: greater cash intensity and a wider tax gap co-move with higher STR volumes and MLI values; ML pressures complicate monetary control and are consistent with heightened volatility in interest and inflation dynamics. Conversely, improvements in FATF compliance are associated with lower ML risk proxies and reduced STR intensity after controlling for business-cycle conditions-albeit with non-trivial compliance costs borne by financial institutions (e.g., KYC, reporting, internal audit). The findings highlight the strategic value of public-data analytics for early risk detection, scenario monitoring, and the calibration of risk-based supervision.

Conclusion- Policy implications are threefold: (1) strengthen data governance and routine publication of high-frequency AML-relevant indicators; (2) advance risk-based oversight using composite indices (MLI) that fuse macro-fiscal and sectoral signals; and (3) sustain FATF-aligned reforms while optimizing the distribution of compliance burdens. Limitations stem from proxy measurement (no direct ML dataset), external shocks (e.g., COVID-19), and annual granularity for select variables; hence, results support analytical rather than statistical generalization. Overall, the paper translates public finance data into actionable AML intelligence and a scalable evidence base for policy design.

Keywords: Anti-Money Laundering (AML); Illicit Financial Flows (IFFs); Shadow/Informal Economy; Suspicious Transaction Reports (STRs); Public Data Analytics

JEL Codes: O17, H26, G28

1. INTRODUCTION

The internationalization of finance, computerization of payments and high capital mobility have entwined the macroeconomic consequences of money laundering (ML) with domestic economies. ML-the concealment of illicit proceeds through formal financial systems-affects not only the internal operations of financial institutions but also macro-stability, public finance, income distribution, investment climate and overall financial soundness (Abuabdin & Shuaibu, 2024). In developing economies these effects cumulate with structural frictions such as a sizeable informal sector, tax losses, corruption and capital flight, making data-driven ML risk analysis a policy imperative. Injecting illegitimate funds complicates monetary control, destabilizes liquidity and is associated with volatility in interest, exchange and inflation indicators; on the fiscal side, it narrows the tax base and widens revenue gaps (Akkaynak, 2022). Unrecorded outflows weaken bank balance sheets and elevate systemic risk. Concurrently, algorithmic audit systems and risk-based controls have begun to improve anomaly detection and reduce false positives in financial supervision, yet they also raise compliance costs (Akkaya, 2025). FATF standards require countries to measure and monitor ML risks; FATF compliance scores thus provide a salient external benchmark.

Against this backdrop, Türkiye experienced 2015-2024 as a decade of macro-financial volatility, rapid digitalization and expanding use of e-money, mobile payments and crypto assets-factors that reshape ML typologies (Akkaynak, 2022). Quantitative studies linking ML proxies to macro-fiscal indicators for Türkiye remain scarce (Akyürek, 2022). This paper addresses that gap by constructing a Money Laundering Index

(MLI), examining Suspicious Transaction Reports (STRs) and estimating their relationships with FATF compliance, cash intensity, tax collection gap, GDP growth, inflation, interest rates, financial-institution size and compliance cost. Using official public datasets (CBRT, TurkStat, Ministry of Treasury and Finance, BRSA, MASAK, FATF), the study offers an integrated, evidence-based view of how ML pressures interact with macro-financial dynamics and derives policy-relevant implications for risk-based supervision, data governance and fiscal transparency.

2. LITERATURE REVIEW

Conceptual Framework: Illicit Proceeds and Money Laundering - Illicit proceeds arise from crimes such as narcotics, arms trafficking, tax evasion, corruption, and terrorism financing (Akyürek, 2022). “Money laundering” denotes concealing the criminal origin of funds and integrating them into the formal economy via three stages-placement, layering, and integration-aimed at disguising source, ownership, and control. Laundering distorts financial data and macro indicators, weakening fiscal policy effectiveness (Arnone & Padoan, 2008). Risk-based methods and data analytics are central to detection (Castelao-López et al., 2025).

Historical Evolution - Modern AML practice builds on cases from Prohibition-era organized crime; subsequent pillars include the U.S. BSA (1970), the 1988 Vienna Convention, FATF’s 40 Recommendations, and KYC/STR regimes. Since the 2010s, crypto-assets and darknet markets have introduced new typologies (Aytaç & Bilge, 2020).

Economic, Social, and Political Effects - Laundering misallocates resources, enlarges the shadow economy, erodes the tax base, and heightens financial instability; gray-list exposure can dampen capital inflows (Castelao-López et al., 2025; Akyürek, 2022). Socially, it undermines fairness and exacerbates inequality; politically, it fuels corruption and institutional erosion (Ercan, 2016; Çakmak, 2025; Mayernik, 2017).

Process and Stages - Placement: cash-intensive sectors, structuring/smurfing, fictitious or inflated invoicing (Çakmak, 2025). Layering: rapid multi-jurisdiction transfers, offshore shells, TBML; in crypto, mixing and chain-hopping (Doğan & Yıldız, 2021). Integration: real estate and portfolio investments, back-to-back loans, round-tripping with macro-level distortions (Egmont Group et al., 2025).

Linkages with Other Financial Crimes - Money laundering both results from and sustains corruption, tax evasion, market abuse, and payment/banking fraud schemes; high-velocity, algorithmic transactions complicate monitoring (Ekmen, 2024; Ercan, 2016).

Terrorist Financing (TF) Nexus - While objectives differ, AML and CFT share channels and risk environments; small-value, seemingly legitimate flows are operationally significant. VASPs, blockchain analytics, and the Travel Rule remain regulatory focal points (Eryılmaz & Biricikoğlu, 2011; Çakmak, 2025; IMF, 2009).

Role of Financial Intelligence - FIUs (e.g., MASAK) transform STRs into strategic and operational intelligence via anomaly detection, network analytics, and data mining; outputs inform policy and international assessments (Erdoğan, 2010; Arnone & Padoan, 2008).

Public Financial Data Sets: Definition and Value - Budget, debt, tax, SOE, local government, and financial stability indicators underpin fiscal transparency and accountability. Open-data initiatives strengthen analytical capacity and oversight (FATF & APG, 2015; Erdoğan, 2010).

Components and Principles - Revenue-expenditure, debt-assets, budget performance, audit reports, and digital reporting modules gain meaning through transparency, accountability, and open-data principles (Altun et al., 2017).

Analytical Use - Standardization, time-series construction, regression/correlation, clustering-network methods, and anomaly detection support early identification of AML risks (Georgieva, 2020; Udeh et al., 2024).

Roles and Obligations of Financial Institutions - KYC/EDD, STR filing, record-keeping, and robust compliance-internal audit systems are core; for emerging channels (fintech, crypto), real-time algorithmic monitoring is critical. Coordination among BRSA, CMB, and MASAK, and alignment with FATF/Basel/EU standards shape the framework (Hyland-Wood, 2022; Jiang, 2024).

MASAK and National FIUs - Within a prevention-analysis-coordination axis, risk-based supervision, National Risk Assessments, and Egmont-network information exchange enhance effectiveness. Electronic analytics platforms (including blockchain and network tools) expand technical capacity (Işık, 2022; Irving Fisher Committee, 2021).

International Architecture - FATF mutual evaluations and listing policies; World Bank/IMF technical assistance and FSAP; OECD transparency (CRS/BEPS); and UNODC conventions together constitute the global AML/CFT regime (Jensen & Iosifidis, 2023).

FATF Focus - Risk-based approach, beneficial ownership transparency, virtual-asset coverage (Rec. 15/Travel Rule), and cross-border cooperation are central; non-compliance can impair investment climates (Jiang, 2024; Jiao, 2023).

Egmont Group - Secure FIU-to-FIU exchange (Egmont Secure Web), standards, and capacity building enable rapid tracing of cross-border flows (Karaca, 2008).

EU Directives - AMLD1-6 establish KYC/STR, PEP, and UBO registers; extend to VASPs; require enhanced measures for high-risk countries; and, prospectively, empower the EU AMLA as a central supervisor (Kuzmenko et al., 2020; Kurban, 2023).

Turkey’s Legal Framework - Article 282 of the Turkish Penal Code criminalizes laundering; Law No. 5549 and the “Measures Regulation” set CDD/STR/record-keeping duties; MASAK’s role and administrative sanctions are defined. Law No. 6415 addresses CFT obligations (Lin, 2019; Lokanan, 2019).

Risk Analysis and Measurement- Within the Risk-Based Approach (RBA), threat-vulnerability-impact triad informs customer/product/transaction/geographic risk scoring. National and institutional assessments increasingly leverage AI-enabled early-warning systems (OECD, 2013; Rekunen et al., 2025).

Indicators and Models - Macro indicators (shadow economy size, capital flows) and micro markers (account cycles, TBML price gaps, UBO opacity, blockchain metrics) combine with time-series, clustering, network, anomaly detection, and supervised learning (OSAA, 2022; Ramanujam, 2025).

Descriptive and Econometric Toolkit - Descriptive statistics (distribution/volatility/outliers), correlation-regression, panel methods, and cointegration tests support policy evaluation and forecasting (Szołno-Koguc, 2018; Towett et al., 2019).

3. DATA AND METHODOLOGY

Method and Research Design - This study examines how the Basel risk score relates to price level, monetary composition, and expectations indicators using an annual, single-country panel (2015–2024). A multi-method quantitative design is employed, including descriptive statistics; linear (Pearson) and ordinal/monotonic (Spearman) association tests; dimensionality reduction via PCA; and predictive models-OLS, ARIMAX, and logistic classification. Internal validity is supported through diagnostics (assumption checks, residual tests), multicollinearity control via PCA/VIF, and small-sample safeguards (stationarity and causality tests). The analytic sequence proceeds from distributional summaries and confidence intervals, followed by correlation screening, then PCA-based component construction, and finally regression, time-series, and logistic modeling.

Universe and Sample - The population comprises annual country-level indicators of risk, prices, real efficiency, monetary structure, and expectations. The sample (N=10 for most series; up to N=11 for monetary ratios) includes: Basel score and ranking; MASAK STR totals and STR per capita; ln(Net Errors & Omissions) in the balance of payments; CPI inflation; real GDP growth; cash/GDP and cash/M2; and economic and consumer confidence indices.

Data Collection Process - Data are compiled from official statistics, regulator reports, and public index databases on a calendar-year basis. Definitions and scope are validated against metadata; primary sources are tracked end-to-end. Price/growth/confidence indicators come from official statistical tables; monetary ratios from central bank balance sheets/statistics; STR series from FIU publications; Basel indicators from annual index releases. When methodology updates occur, retrospective revisions are reviewed and harmonized.

Data Collection Tools - Spreadsheets and scripted workflows are used for ingestion, alignment, missing-value screening, and outlier checks. A data dictionary records each variable's definition, unit, transformations, source, and revision history. PCA, regression, time-series, and classification routines run in the same scripted environment with versioned, reproducible outputs.

Data Analysis

1. Descriptives: mean, SD, min-max, and 95% CIs; distributional features assessed.
2. Associations: Pearson (linear) and Spearman (monotonic), including blockwise comovement across price, monetary composition, and confidence sets.
3. PCA: two high-eigenvalue components interpreted as “price-monetary composition” and “real efficiency-sentiment.”
4. OLS: Basel score on PCA scores; report coefficients, CIs, p-values; monitor multicollinearity (VIF) and test residual normality, autocorrelation, and heteroskedasticity.
5. ARIMAX: short-horizon dynamics for Basel with differencing, autoregressive terms, and exogenous PCA components; select by information criteria; verify white-noise residuals.
6. Logistic classification: binary “high-risk year” outcome; evaluate with ROC-AUC and accuracy; assess sensitivity-specificity via confusion matrix; add a shallow decision tree for interpretability and policy-oriented thresholds.

4. FINDINGS

The Basel risk score averages 5.922 with a narrow 95% CI (5.706-6.138), indicating strong clustering; Basel rank is dispersed (33k-71k), implying material year-to-year shifts. MASAK per-capita STR averages 0.603 (0.423-0.988) and is volatile yet more stable than total STR volume (avg 313.8M; high heterogeneity). ln(BOP net errors & omissions) centers at 23.015 (SD 0.594), signaling imbalances without dominance of extremes. CPI inflation averages 28.5% (95% CI: 14.7-42.4%) with a post-2020 upward drift; real GDP growth averages 4.81% (0.9-11.4%). Monetary composition varies strongly (cash/M2 3.00-7.94; mean 5.71), consistent with liquidity preference/substitution, while economic (≈ 98) and consumer (≈ 82.8) confidence move largely in sync.

Correlation evidence shows the Basel score is positively associated with per-capita STR (≈ 0.45) and inversely with confidence (economic $\approx -0.46/-0.49$; consumer ≈ -0.37). Inflation co-moves tightly with liquidity measures (cash/M2 $\approx 0.71-0.75$; cash/GDP $\approx 0.60-0.63$), economic vs consumer confidence are near-collinear (≈ 0.91), and growth has a near-zero link to Basel. PCA reveals a dominant “price-money composition” axis (PC1; 60.25% variance) loading positively on inflation, cash/GDP and cash/M2 and negatively on confidence, and a “real activity-sentiment” axis (PC2; 26.90%) loading positively on growth and negatively on confidence. PC1 rises from -1.231 (2015) to $+1.418$ (2023), turning positive after 2020-evidence of a regime shift toward stronger price-liquidity pressures-while PC2 turns positive from 2019, indicating intermittent sentiment/activity rebounds. In OLS (basel_score $\sim$ PC1 + PC2 + year_trend), PC1 has a significant positive effect ($\beta=0.110$, $p=0.024$) whereas PC2 and trend are insignificant; diagnostics support specification quality ($R^2=0.566$; DW ≈ 2.34 ; no

autocorrelation/heteroskedasticity; low VIFs). Short-run ARIMAX on differenced Basel (best (1,1,0)) yields white-noise residuals but insignificant AR and PC terms, consistent with limited short-horizon power in a small annual sample. A high-risk-year classifier shows insignificant coefficients yet solid discrimination (AUC=0.833; accuracy=0.70; sensitivity=67%, specificity=75%), suggesting threshold tuning or cost-sensitive calibration for operational use; decision-tree rules (depth ≤ 3) highlight low confidence and weak cash/GDP (or high inflation with low liquidity share) as high-risk leaves, with economic confidence (~ 89.5) the most discriminatory splitter.

Stationarity tests indicate non-stationarity for Basel, $\ln(\text{BOP NEO})$, inflation and growth in levels, encouraging differencing/cointegration or structural-break treatments; an alternative ADF panel finds STR total stationary ($p=0.002$) while Basel remains non-stationary, implying persistence or breaks. A partial correlation of Basel with CPI (controlling for others) is 0.294, consistent with price effects mediated by confidence and liquidity. Comparing 2015-19 to 2020-24, the Basel score declines from 6.213 to 5.632 (-0.581), STR surges by $\sim 303.7\text{M}$, inflation rises ($+0.325$) and economic confidence falls (-3.934), aligning with the PCA/correlation narrative. Granger tests (lags ≤ 2) show no directional predictability between $\ln(\text{BOP NEO})$ and Basel. Overall, the price-liquidity complex (inflation + cash share) emerges as the dominant linear driver of Basel risk, confidence moves inversely and provides the most policy-readable threshold splits, short-run dynamics are weak at annual frequency, and the post-2020 regime shift on PC1 coincides with higher inflation, stronger cash preference and lower confidence alongside the observed decline in the Basel score.

5. CONCLUSION

This study examined how the Basel AML/CFT risk score co-moves with the price level, monetary composition, and expectations indicators within a compact multivariate design. Even with a short annual sample, a coherent narrative emerges. Descriptives show the Basel score tightly clustered around its mean (5.922; 95% CI: 5.706-6.138), while inflation and cash ratios display wide swings-evidence of regime rupture after 2020. Cash/M2 varies strongly (3.003-7.944; SD 1.835), consistent with shifts in liquidity preference and currency substitution as prices accelerate.

Correlation patterns reinforce a “price-money” block. Inflation correlates strongly with cash/M2 (≈ 0.71) and cash/GDP (≈ 0.60), indicating that higher prices tilt portfolios toward cash and reshape monetary composition. Economic and consumer confidence are near-collinear (≈ 0.91), implying a shared information set. Basel’s positive association with per-capita STR (Pearson 0.449; Spearman 0.418) suggests that oversight/compliance intensity and the pressure to surface informality rise with perceived risk-consistent with AML/CFT work on capacity, openness, and supervision (Arnone & Padoan, 2008; Ferwerda & Reuter, 2024; Egmont Group et al., 2025; Doğan & Yıldız, 2021).

Dimensionality reduction shows that co-volatility is well summarized on two axes. PC1 loads positively on inflation, cash/GDP, and cash/M2 and negatively on confidence, capturing a “price-money composition” force; PC2 loads positively on growth and negatively on confidence, reflecting a “real activity-sentiment” dimension. Together they explain 87.147% of variance. PC1’s score turns decisively positive after 2020, evidencing a post-shock regime dominated by price-liquidity pressures, in line with policy-surveillance studies on the coordination of money-credit and price regimes (FATF & APG, 2015; Irving Fisher Committee, 2021; Usta & Akinci, 2020).

Regression and diagnostics indicate that PC1 is the main linear driver of Basel risk. In OLS ($\text{basel_score} \sim \text{PC1} + \text{PC2} + \text{trend}$), PC1 is positive and significant ($\beta=0.110$, $p=0.024$), while PC2 and trend are insignificant. Model quality is supported by $R^2=0.566$ (Adj. 0.362), DW=2.34, normal residuals, homoskedasticity, no autocorrelation, and low VIFs. On the time-series side, a parsimonious ARIMAX(1,1,0) yields white-noise residuals but no short-run significance for exogenous PCs-unsurprising at annual frequency and small N. Classification results echo this: coefficients are imprecise, yet the model separates classes well (AUC=0.833; accuracy=0.70). The complexity matrix ($\approx 67\%$ sensitivity) argues for threshold recalibration to manage false-negative risk, and shallow decision-tree rules provide policy-readable splits where low confidence and weak cash/GDP (or high inflation at low liquidity share) define high-risk leaves-evidence that simple, explainable early-warning rules can aid supervision (Fronzetti Colladon & Remondi, 2017; Jensen et al., 2023; Jacsó & Vámosi, 2023).

Methodological checks highlight the limits of short samples. ADF tests show level non-stationarity for Basel, inflation, growth, and $\ln(\text{NEO})$; STR total appears stationary. Granger tests do not reveal directional predictability between $\ln(\text{NEO})$ and Basel at short lags, pointing to the need for longer horizons, richer frequencies, and structural-break analysis. A period comparison (2015-19 vs 2020-24) confirms a regime shift: the Basel score declines (6.213 - 5.632), inflation rises (0.123 - 0.448), and aggregate STR surges, consistent with intensified surveillance/reporting and greater transactional volatility. This composite picture aligns with recommendations on institutional harmonization, data sharing, and stronger financial-control mechanisms (IMF, 2009; FATF & APG, 2015; OECD, 2013; United Nations OSAA, 2022; Akyürek, 2022) and with evidence that openness, accountability, and audit capacity reduce AML risk when supported by robust data architectures (Karaca & Özsalmanlı, 2022; Eryılmaz & Biricikoğlu, 2011; Szołno-Koguc, 2018).

The main limitations are the small number of observations and integrity issues in some variables. PCA-based summaries help mitigate multicollinearity and overfitting, but short horizons widen coefficient CIs and complicate stationarity assessment; reporting-regime shifts blur distinctions between true intensity and disclosure behavior in STR metrics; survey-based confidence indicators may introduce measurement error; PC interpretations assume stable loadings, which can drift across regimes; differencing in ARIMAX can mask short-run exogenous effects; and class imbalance in binary models inflates AUC-accuracy tensions. Excluding granular institutional indicators (e.g., sanction intensity, cross-border information-sharing depth, financial openness) risks omitted-variable bias. Single-country, narrow-period focus also constrains external validity.

Future work should expand coverage horizontally and vertically. Longer spans and higher-frequency series would support stationarity transformations and cointegration (Johansen/ARDL), while regime-shift tools (Bai-Perron, Markov switching) can detect breaks. Cross-country or regional panels with the same variable set would strengthen causal claims via fixed effects/IV and isolate institutional heterogeneity. PCA summaries should be stress-tested with factor-number cross-validation, rotations, and rolling windows to track regime-sensitive meanings. For early warning, cost-sensitive learning, resampling, and calibration-evaluated with AUC, Brier scores, and retention

curves-should be paired with explainable methods (e.g., SHAP over gradient-boosted trees) for accountable decisioning. From a time-series angle, state-space/Kalman models, nonlinear TAR/STAR, and Bayesian VARs can better represent shock transmission and uncertainty. Strengthening data governance-source cross-validation (e.g., cash/GDP), metadata standards, and version control-will reduce measurement error and improve reproducibility. Decomposing STR into sub-channels (e.g., letter-money, POS, trade-based patterns) will clarify the roles of shadow-banking and trade-based mechanisms and align metrics to policy targets. Open-science sharing of versioned data/code/reporting will enhance auditability and foster comparative analysis.

Policy implications-Monitoring the price-liquidity complex (inflation plus cash share) alongside confidence erosion offers the most informative early-warning bundle for Basel risk in this horizon. Calibrated thresholds-grounded in explainable splits and adjusted for class imbalance-can turn these statistical signals into actionable supervisory triggers.

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