Assessing Institutional Determinants of Money Laundering Risk: A Machine Learning Approach Based on Economic Freedom Indicators

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Abstract* — Money laundering remains one of the key challenges of the global financial system, and identifying its institutional determinants is a relevant task for both scholars and regulators. This paper examines the relationship between the components of the Economic Freedom of the World index (EFWI) and the Basel AML Index (BAMLI) using a cross-country sample of 156 countries. Unlike existing studies that focus on individual institutional factors or limited groups of countries, this work is the first to apply a comprehensive approach combining correlation analysis with four machine learning algorithms (Ordinary Least Squares regression (OLS), Ridge regression, Gradient Boosting, and Random Forest) with 10-fold cross-validation. The findings reveal a statistically significant negative association between the level of economic freedom and money laundering risk. The "Legal System and Property Rights" sub-index is the dominant predictor: its correlation with BAMLI is $r = -0.780$ ($p < 0.001$), and its contribution to the Random Forest model's predictive power is 67.5%. The EFWI components collectively explain approximately 52% of the variation in BAMLI ($R^2 \approx 0.53$). The consistency of results across linear and non-linear models indicates the stability and predominantly linear nature of the detected association. The findings underscore the pivotal role of legal institutional quality in preventing financial crime and may serve as a basis for developing differentiated AML strategies that account for the institutional context of individual countries.

***Keywords* — Money laundering, Basel AML Index, rule of law, Economic Freedom of the World Index, machine learning, Random Forest, institutional environment, cross-country analysis.**

I. INTRODUCTION

Money laundering remains one of the most pervasive and latent phenomena in the global financial system. According to estimates by the United Nations Office on Drugs and Crime (UNODC), between 2% and 5% of global GDP is laundered annually, which in 2024 corresponded to a range of approximately $2.22 to $5.54 trillion [1, 2]. At the same time, only around 1% of illicit funds are successfully intercepted, reflecting a critically limited efficacy of current regulatory frameworks [1].

Notwithstanding ongoing initiatives by the global community, the effectiveness of anti-money laundering measures remains critically inadequate. According to the Basel AML Index (BAMLI) 2024, the average global money laundering risk score stands at 5.28 out of 10. Meanwhile, FATF estimates indicate that the mean performance of domestic AML systems is only 28%, with the effectiveness of investigations, prosecutions, and sanctions being the lowest – at just 20% [3]. These figures point to a substantial gap between nominal adherence to international norms and actual outcomes in combating financial crime.

The substantial cross-country variation in AML risk levels has generated scholarly interest in identifying its institutional determinants [4–9]. A theoretical foundation for such inquiry is provided by institutional economics: the caliber of the legal framework, protection of property rights, and the institutional capacity of the state shape both the conditions under which financial crimes emerge and the ability to counter them [10]. The question of which specific dimensions of the regulatory landscape are most closely associated with money laundering risk levels remains open and calls for rigorous quantitative investigation.

This study aims to assess the relationship between the components of the BAMLI [3] and the Economic Freedom of the World Index (EFWI) [11] using a sample of 156 countries, applying statistical correlation techniques and machine learning approaches. The findings not only allow us to quantify the overall magnitude of the association but also to identify the relative importance of each institutional component as a predictor of AML risk, which constitutes the contribution of this work relative to existing research.

II. RELATED WORK

Research into the determinants of money laundering risk in academic literature encompasses several interrelated strands. This pertains to the role of the institutional environment and corruption. R. A. Küçükçolak et al. confirm

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in a global comparative study that corruption control is a significant factor in financial development, indirectly reducing opportunities for illicit financial operations [12]. I. W. Taylor et al., drawing on system dynamics modelling, demonstrate that institutional improvement exerts a multiplicative effect on corruption reduction over the long term, thereby affirming the central role of governance quality [13]. M. H. Lubinga and A. Mazenda find that deterioration in corruption control adversely affects the volume of financial inflows, corroborating the close link between institutional quality and the distribution of financial flows [14].

The second strand concerns the relationship between economic openness and AML risk. A. AlQudah et al. establish that corruption control consistently reduces AML risk across all country groups, whereas the effects of trade openness and foreign direct investment differ substantially depending on a country's income level [15].

The third strand covers the effectiveness of AML regulation and risk assessment methodology. C.-N. Cotoc et al. identify a substantial gap between formal compliance with FATF standards and actual anti-money laundering outcomes among EU member states [16]. W. Gaviyau and A. B. Sibindi highlight the considerable variation in national implementation of international norms contingent on institutional and economic factors [17]. B. Adamyk et al. examine emerging challenges for AML systems in the decentralized finance (DeFi) environment, where decentralization significantly complicates regulatory oversight and the enforcement of KYC/AML requirements [18].

Despite growing scholarly interest in the institutional determinants of financial crime, existing studies address isolated aspects of the institutional environment and have restricted geographical scope, leaving room for a more comprehensive cross-country analysis employing contemporary quantitative methods.

III. Data and Methodology

A. Data Sources and Sample

The empirical basis of the study consists of cross-country data for 156 countries as of 2024.

The dependent variable is the BAMLI – an annual indicator of money laundering and terrorist financing risk calculated by the Basel Institute on Governance. The index aggregates data from more than 17 sources, encompassing dimensions of financial transparency, legal environment quality, corruption, and public governance effectiveness. Index values range from 0 to 10, where a higher score corresponds to a higher money laundering risk [3].

The explanatory variables are the five sub-indices of the EFWI, published by the Fraser Institute and covering more than 160 countries. The index measures the level of economic freedom across five dimensions: (1) Size of Government (SG) – the level of government expenditure, taxation, and the share of state-owned enterprises; (2) Legal System & Property Rights (LSPR) – judicial independence, contract enforcement, and the rule of law; (3) Sound Money (SM) – inflation levels and monetary stability; (4) Freedom to Trade Internationally (FTI) – tariff and non-tariff barriers, and capital controls; (5) Regulation (R) – the quality of regulation in the areas of credit, labour, and business. The overall EFWI score was additionally employed as a control variable. The selection of these variables is motivated by the fact that the EFWI sub-indices capture key institutional dimensions that are theoretically associated with the conditions underlying both the proliferation and the capacity to counter it [11]. Countries with missing BAMLI values were excluded from the analysis (23 observations).

B. Methods of Analysis

The analysis was performed in Python 3.11 using the following libraries: scikit-learn 1.8.0 for building machine learning models; pandas 3.0.1 for data processing and aggregation; numpy 2.4.2 for numerical computations; matplotlib 3.10.8 and seaborn 0.13.2 for results visualization [19–23].

In the first stage, a correlation analysis (Pearson coefficient) was conducted between each explanatory variable and BAMLI. In the second stage, four machine learning models were constructed: Ordinary Least Squares regression (OLS) and Ridge regression (L2 regularization, $\alpha = 1.0$) – for estimating linear relationships, where Ridge additionally accounts for potential multicollinearity among predictors; Random Forest (100 trees, max_depth = 4, random_state = 42) and Gradient Boosting (100 iterations, max_depth = 3) – for capturing non-linear relationships and interactions among variables [24]. The value $\alpha = 1.0$ corresponds to the scikit-learn default and represents moderate regularization; given the moderate multicollinearity observed among the EFWI sub-indices (Table I), this default value was retained without further tuning. This combination of algorithms enables a comparison of the predictive accuracy of linear and ensemble approaches and allows for validation of the findings. Model performance was evaluated using 10-fold cross-validation based on R^2 and MAE metrics. The relative contribution of features was assessed using the built-in feature importance mechanism of the Random Forest algorithm [24].

IV. Results and Discussion

The results of the correlation analysis (Fig. 1) demonstrate that all EFW sub-indices, with the exception of Size of Government, exhibit a negative correlation with BAMLI.

The strongest association was recorded for the "Legal System and Property Rights" sub-index ($r = -0.780$, $p < 0.001$), followed by Regulation ($r = -0.659$), the overall EFW score ($r = -0.675$), and Freedom to Trade Internationally ($r = -0.612$), and Sound Money ($r = -0.450$). The Size of Government sub-index exhibits a weak positive correlation ($r = +0.200$), which may reflect the specific role of the public sector in financial regulation. These findings are consistent with the theoretical propositions of institutional economics: countries with well-developed legal institutions and a high-quality regulatory environment tend to exhibit lower money laundering risk levels, corroborating the conclusions of A. AlQudah et al. regarding the pivotal role of corruption control and institutional quality [15].

The scatter plots (Fig. 2) confirm the predominantly linear character of the detected relationship. The most pronounced negative linear association is observed for Legal System & Property Rights, as legal system quality declines, BAMLI values increase in a nearly monotonic fashion. For Sound Money and Size of Government, the scatter plots reveal substantial scatter around the trend line, suggesting a weaker or non-linear pattern of association. Among the outliers, Haiti stands out (AML = 8.12 with relatively average sub-index

values) and Argentina (AML = 4.44 with an exceptionally low Sound Money score of 1.25), which may be attributable to chronic monetary instability unaccompanied by a corresponding increase in AML risk through other channels.

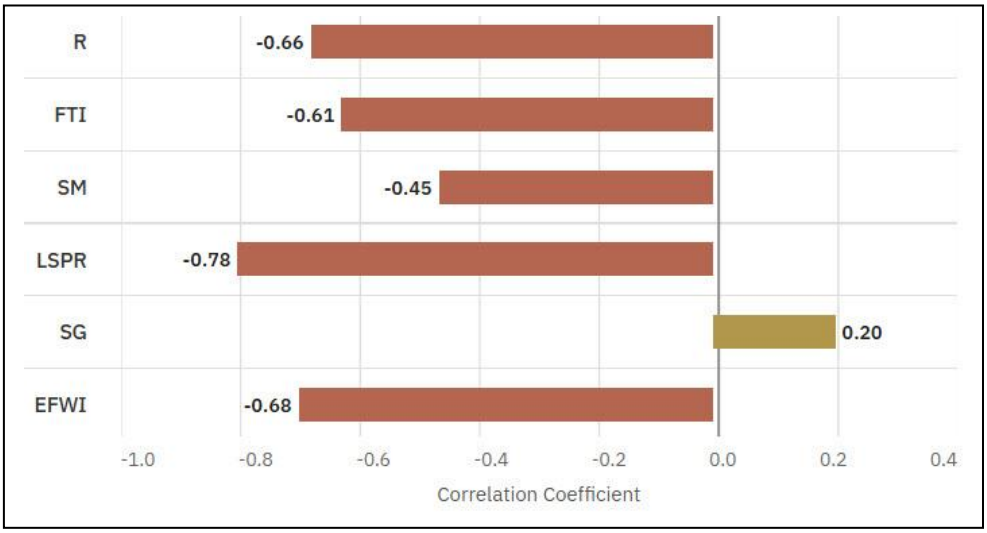


Fig. 1. Pearson Correlation with BAMLI (authors' own work)

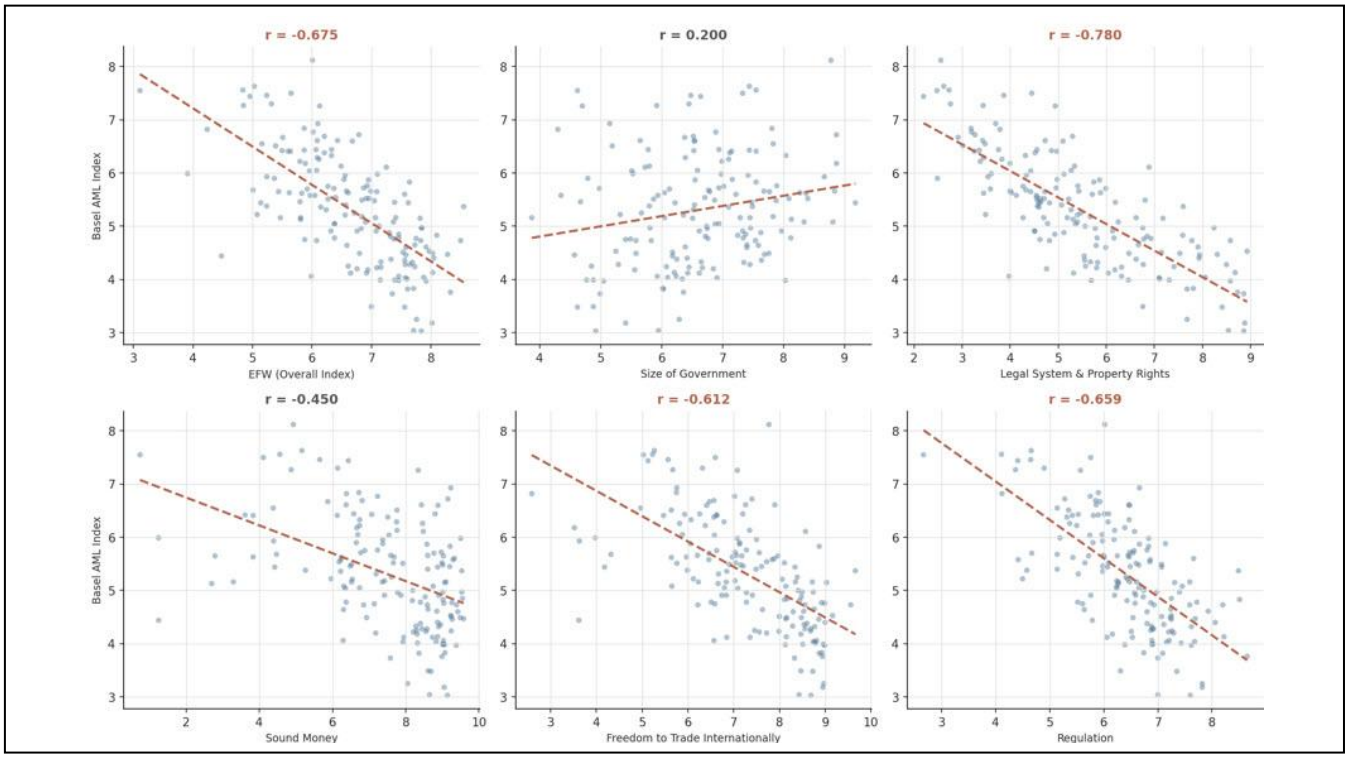


Fig. 2. Pearson Scatter plots: EFWI sub-indices vs BAMLI with OLS trend lines (authors' own work)

The correlation matrix (Table I) reveals moderate multicollinearity among certain sub-indices.

TABLE I. PEARSON CORRELATION MATRIX: BAMLI AND EFWI SUB-INDICES, N = 156 COUNTRIES

	EFWI	***LSPR***	***SG***	***SM***	***FTI***	***R***	***BAMLI***
EFWI	1.00	0.11	0.81	0.83	0.87	0.85	-0.68
LSPR	0.11	1.00	-0.23	-0.03	-0.11	0.69	0.20
SG	0.81	-0.23	1.00	0.51	0.71	0.75	-0.78
SM	0.83	-0.03	0.51	1.00	0.67	0.58	-0.45
FTI	0.87	-0.11	0.71	0.67	1.00	0.69	-0.61
R	0.85	0.69	0.75	0.58	0.69	1.00	-0.66
BAMLI	-0.68	0.20	-0.78	-0.45	-0.61	-0.66	1.00

Source: authors' own work

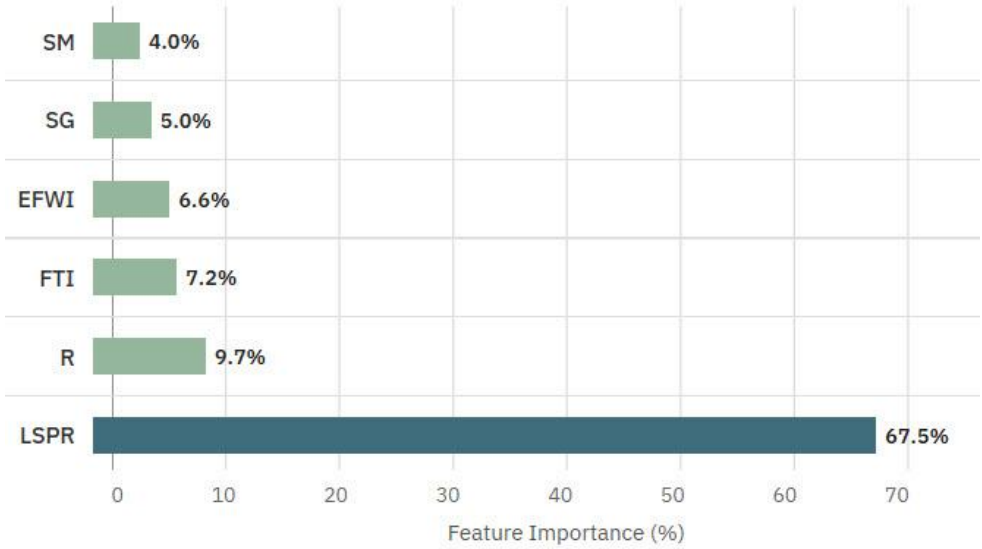


Fig. 3. Feature importance scores: Random Forest algorithm (authors' own work)

In particular, LegalProp and Regulation exhibit a notable positive correlation with each other ($r \approx 0.69$): countries with well-developed legal institutions tend to also have a high-quality regulatory environment. The overall EFWI score naturally correlates strongly with all sub-indices as their aggregate. The presence of multicollinearity provides a justification for Ridge regression and ensemble methods over conventional OLS.

The feature importance analysis of the Random Forest algorithm confirms the dominant role of the "Legal System and Property Rights" sub-index (Fig. 3).

Its contribution amounts to 67.5%, which is more than six times that of the second most important predictor – Regulation (9.7%). Freedom to Trade Internationally (7.2%), the overall EFW score (6.6%), Size of Government (5.0%), and Sound Money (4.0%) exhibit relatively modest independent contributions. The dominance of LegalProp is consistent with the findings of W. Gaviyau and A. B. Sibindi, who contend that the effectiveness of AML systems is substantially determined by the quality of national implementation of regulatory standards [17].

The actual versus predicted values plot (Fig. 4) demonstrates a high goodness-of-fit for the Random Forest model on the training sample ($R^2 = 0.81$). Countries with the lowest AML risk levels (Denmark, Finland, New Zealand) and the highest (Haiti, Venezuela, Chad) are classified with considerable accuracy. The largest deviations are evident for countries with atypical combinations of institutional characteristics, which underscores the inherent difficulty of prediction for transitional and unstable economies.

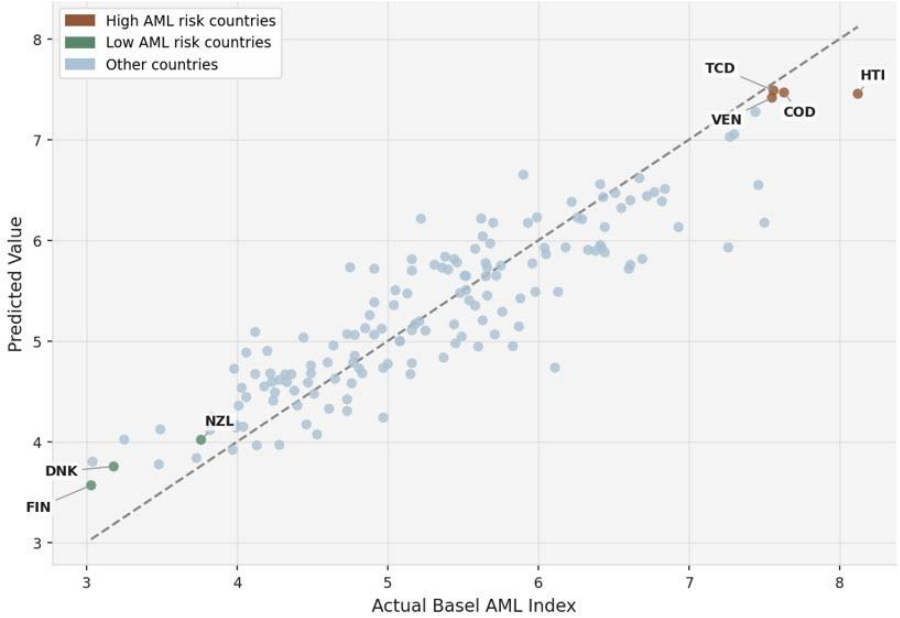


Fig. 4. Actual vs predicted Basel AML Index values: Random Forest, training sample $R^2 = 0.81$ (authors' own work)

The body of findings points to a robust and statistically significant inverse relationship between the EFWI components and BAMLI. The dominant role of the "Legal System and Property Rights" sub-index is confirmed by both the correlation-based analysis and the Random Forest algorithm, ensuring consistency of conclusions across parametric and non-parametric methods. The comparable predictive accuracy of all four models indicates the

predominantly linear nature of the relationship and the stability of the identified patterns.

V. CONCLUSION

The empirical study performed corroborates the existence of a statistically significant inverse relationship between the level of economic freedom and money laundering risk across a sample of 156 countries.

The "Legal System and Property Rights" sub-index proved to be the strongest predictor of BAMLI both in terms of the linear association ($r = -0.780$, $p < 0.001$) and variable importance within the Random Forest algorithm (67.5%). This suggests that the rule of law and protection of property rights constitute a fundamental institutional foundation for effective anti-money laundering efforts, regardless of other country-specific characteristics. The Size of Government sub-index constitutes the only exception to the overall pattern: its weak positive correlation ($r = +0.200$) may reflect the specific role of the public sector in financial regulation.

The EFWI components jointly explain approximately 52% of the variation in BAMLI ($R^2 \approx 0.53$ under 10-fold cross-validation), which represents a meaningful result for cross-country analysis. The similar predictive performance across all four tested algorithms (OLS, Ridge, Random Forest, and Gradient Boosting) confirms the robustness of the detected relationship and its predominantly linear character.

The research has certain limitations. First, the cross-sectional nature of the data precludes causal inferences to be drawn between the variables. Second, 48% of the variation in BAMLI remains unexplained within the model, pointing to the presence of relevant factors beyond the scope of EFWI. Third, the exclusion of 23 countries due to missing data may influence the representativeness of the sample. Directions for further research involve expanding the set of predictors to incorporate the Corruption Perceptions Index, World Bank Rule of Law indicators, and shadow economy measures, as well as employing panel data to examine the dynamics of the identified relationships over time. In particular, a panel data analysis covering multiple years would allow us to assess whether improvements in institutional quality lead to measurable reductions in AML risk over time, thereby enabling causal inference beyond the cross-sectional associations identified in this study.

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