# “Can AI readiness and strong institutions curb AML risk? Cross-country evidence from panel data”

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# CAN AI READINESS AND STRONG INSTITUTIONS CURB AML RISK? CROSS-COUNTRY EVIDENCE FROM PANEL DATA

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## Abstract

As emphasized by the FATF, IMF, and World Bank, technological readiness and institutional quality are increasingly decisive in shaping AML effectiveness. By mitigating money-laundering vulnerabilities, strengthening AI readiness, and enhancing institutional quality, tax collection efficiency can be improved and fiscal leakages reduced. These improvements expand the fiscal space available for national budgets, strengthening the financial foundations of public administration. The study aims to examine the impact of Government AI Readiness on AML risk, measured by the Basel AML Index, and the moderating role of institutional quality as captured by the Rule of Law Index. An unbalanced panel dataset that covers up to 168 countries for 2020–2024 was analyzed using fixed effects and random effects models, with variable transformations applied where necessary. All estimations were performed in R Studio. The results indicate that a one-point increase in the Government AI Readiness Index is associated with a 0.048–0.040 point reduction in the Basel AML Index, while a one-unit increase in log GDP per capita decreases the Basel AML Index by 0.54–0.34 points, holding other factors constant. The interaction term between AI readiness and the Rule of Law Index is positive (0.067–0.072), confirming that the risk-reducing effect of AI readiness diminishes as institutional quality strengthens. These findings support the hypotheses and confirm the complementary roles of technological preparedness and institutional integrity in shaping AML outcomes. Fixed effects analysis reveals structural vulnerabilities in AML in Gabon and China, while Sweden exhibits the lowest residual risk after accounting for AI readiness and institutional strength.

**Keywords** artificial intelligence readiness, anti-money laundering, Basel AML index, rule of law, panel data analysis

**JEL Classification** G28, H83, K42, O38

## INTRODUCTION

Effective anti-money laundering (AML) systems are not only a matter of financial integrity and security, but also a prerequisite for stable tax revenues, credible budget formation, and the financial sustainability of public and municipal finances. Recent global developments underscore the growing need to integrate artificial intelligence (AI) into AML and counter-terrorist financing (CFT) frameworks. The Financial Action Task Force (FATF) has highlighted AI's potential to make AML/CFT measures "faster, cheaper and more effective," enabling the detection of complex transactional patterns and reducing compliance burdens (FATF, 2021). However, FATF also stresses that any AI application must ensure transparency and explainability to maintain regulatory trust and oversight (RIPJAR, 2024). This positioning makes the readiness of government institutions to adopt AI a timely concern.

Economic and financial systems are increasingly vulnerable to illicit financial flows, destabilizing markets, eroding public finances, and



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undermining governance. According to the International Monetary Fund, money laundering–related tax evasion costs governments approximately USD 600 billion annually, with broader implications for economic stability and institutional credibility (Sanction Scanner, 2024). The declining health of AML regimes can also deter foreign investment, disrupt correspondent banking relations, and diminish trust in financial infrastructure. These concerns underscore the importance of assessing technological readiness and institutional capacity in combating AML threats. These financial losses have direct implications for public and municipal finance systems. Illicit financial flows reduce the taxable base, weaken revenue mobilization, and constrain the fiscal capacity of governments to fund essential public services. At the municipal level, money-laundering risks exacerbate budgetary instability, distort procurement processes, and undermine the transparency of local financial management. Strengthening AI-driven AML mechanisms, therefore, has the potential not only to combat financial crime but also to improve fiscal discipline, enhance budget credibility, and reinforce the financial sustainability of public and municipal institutions.

Technological innovation is reshaping financial supervision. The World Bank and IMF, through their collaborative AML/CFT efforts, have noted how advanced analytics and AI can significantly strengthen supervision and risk monitoring, even in resource-constrained settings (IMF, n.d.; World Bank, 2010). For instance, AI dramatically enhances the processing of unstructured data, enabling proactive detection of high-risk behavior. Meanwhile, the Bank for International Settlements and the IMF emphasize AI's role in reducing compliance costs, for example, by automating KnowYourCustomer processes, thereby preserving correspondent banking connectivity.

Ensuring the effectiveness of AI in AML also depends on the institution's integrity. The Rule of Law Index, developed by the World Justice Project, captures dimensions such as the absence of corruption, enforcement effectiveness, and criminal justice – all of which are critical for ensuring that AI-enhanced systems operate within accountable frameworks. In environments with strict rule of law, AI tools can be embedded in robust operational and legal systems; in weaker institutional contexts, AI may compensate, but oversight challenges increase. Therefore, understanding the moderating role of institutional quality is crucial when assessing the impact of AI readiness on AML risk.

These institutional positions and global financial imperatives underscore the policy relevance of assessing how AI readiness and the rule of law jointly impact AML risk. This study examines a critical nexus in contemporary AML strategy: the technological, financial, and governance forces that shape global financial integrity.

## 1. LITERATURE REVIEW

The growing interaction between technological transformation, institutional quality, and financial integrity has direct implications for public and municipal finance, as money-laundering risks weaken tax collection, distort public budgets, and undermine the financial sustainability of governments. Against this backdrop, the literature increasingly examines how AI readiness, digital governance, and institutional capacity shape the effectiveness of AML systems, revealing a complex landscape of technological opportunities and governance challenges. Literature positions AI and advanced analytics as pivotal in detecting anomalies, mapping illicit networks, and constraining money-laundering channels, while also warning that opaque models and data gaps can undermine trust and enforcement capacity (Ahmed et al., 2022; Canhoto, 2021; Colladon & Remondi, 2017; Hilal et al., 2022; Kute et al., 2021; Liu et al., 2022; Weber et al., 2024; Pulungan et al., 2024). Evidence from digital transformation in anti-corruption and cyber-fraud systems suggests that algorithmic tools enhance monitoring, increase detection probabilities, and reduce the latency of supervisory response, provided that legal and organizational capacities evolve in tandem (Dobrovolska & Rozhkova, 2024; Stender et al., 2024; Yarovenko et al., 2024b, 2024c). At the same time, adversaries

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increasingly weaponize AI, creating an arms-race dynamic that makes institutional readiness (not technology alone) the decisive factor in outcomes (Lyeonov et al., 2024, 2025a).

Institutional strength shapes whether AI investments translate into measurable AML effectiveness, as shown by studies of oversight bodies, treasury governance, and prudential supervision that link procedural capacity to transparency and financial integrity (Duba & Lehohla, 2025; Mphahlele et al., 2025; Morin, 2025). Country-level analyses reinforce that compliance with FATF standards, regulatory coherence, and enforcement quality are heterogeneous and cluster by institutional profiles, implying the need for tailored AML/CFT strategies and diagnostics (Kuzior et al., 2025; Krawczyk et al., 2025; Yarovenko et al., 2024c). Governance reforms interact with shadow-economy incentives and environmental or socio-economic shocks, which can either erode or amplify the integrity gains from digital tools (Lyeonov et al., 2025b; Ntshangase et al., 2024). Growing evidence further suggests that knowledge-intensive and innovation-driven reforms can directly reduce corruption when digital technologies are embedded in coherent transparency frameworks (Yefimenko et al., 2025a, 2025b).

AI readiness in the public sector depends on leadership, change management, and organizational learning, not only on technical availability. Conceptual and empirical studies in public administration demonstrate that the integration of generative AI, ethics-by-design, and dynamic capabilities enhances service quality and resilience when embedded within clear accountability structures and skills development (Androniceanu, 2024; Murko et al., 2024; Mura & Stehlíková, 2025). Readiness is further enhanced by managerial coaching, workforce upskilling, and cyber-leadership, particularly in crisis response and data governance regimes (Aridi, 2025; McCoy, 2025). Civil-service adoption hinges on structured change programs, with evidence that readiness and governance processes are as critical as the algorithms themselves (Barodi & Lalaoui, 2025; Rekunenko et al., 2025).

Sectoral and firm-level studies mirror these themes. Internal audit efficiency improves when robotic process automation and AI standardize controls, provided risk governance and data policies are robust (Alassuli, 2025; Bashynska et al., 2023). Digital transformation has heterogeneous effects on financial sustainability, varying by firm size, and highlights capacity constraints that impact compliance and reporting quality (Al-Shouha et al., 2025). Fintech value creation at scale requires big-data capabilities governed by transparent protocols and interoperable infrastructures, which aligns with AML data-sharing and analytics needs (Khaddam & Alhanatleh, 2024). Customer-facing innovations, such as digital insurance and e-retail banking, highlight adoption frictions and inclusion risks that have compliance spillovers and enforcement implications (Chandran & Ittimani Tholath, 2025; Lama et al., 2025). Efficiency frontiers in insurance and related bibliometrics suggest that the data envelopment and explainable AI literatures are converging on the importance of model transparency for regulatory acceptance (K. Kumar & J. Kumar, 2024; Weber et al., 2024).

Methodological and technological frontiers for AML analytics are advancing. Deep learning, graph methods, and explainable AI improve typology discovery and investigator trust, while blockchain analytics extend surveillance to smart-contract ecosystems and DeFi venues (Kute et al., 2021; Liu et al., 2022; Weber et al., 2024). Social-network analysis operationalizes relationship risk and beneficial-ownership screening, offering early-warning signals beyond rules-based controls (Colladon & Remondi, 2017). Bibliometric mappings across finance, management, and information systems document a steep rise in AI-for-finance scholarship and call for integrative governance frameworks to bridge technical performance with supervisory legitimacy (Ahmed et al., 2022; Ibadildin et al., 2025; Pilelienė & Bogoyavlenska, 2025). Parallel analysis in safety-critical domains shows that AI-driven image recognition and sensor fusion can enhance operational risk management and oversight, indicating the broader governance potential of AI-based monitoring (Zaryczańska & Karwot, 2025).

Ethics, justice, and rights-preserving safeguards are consistently identified as prerequisites for the legitimate deployment of AI in governance and policing contexts. Public-safety applications and


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automated enforcement require proportionality, fairness, and auditability to prevent discriminatory outcomes and maintain public trust, especially when surveillance intensifies (Haley, 2025; Haley & Burrell, 2025). Broader socio-economic debates emphasize human dignity, social justice, and environmental stability as boundary conditions for AI governance, placing institutional design and evaluation at the center of sustainable adoption (Mura & Stehlíková, 2025; Schinello, 2025; Wieczorek & Postrzednik-Lotko, 2025). Regional and sectoral risk exposures, ranging from agriculture's cyber-insurance needs to wartime cyber-fraud escalation, illustrate that resilience outcomes depend on institutional maturity and judicial effectiveness, again highlighting the primacy of strong institutions over tools alone (Sitnicki et al., 2024; Yarovenko et al., 2024a).

National experiences with digitalization and anti-corruption provide concrete causal hints. Structural analyses indicate that digitalization and technological development can reduce corruption when embedded in enforceable accountability frameworks and interoperable registries, reinforcing the complementary role of state capacity (Yefimenko et al., 2025a, 2025b). Cybersecurity threat mapping indicates that governance arrangements must evolve in tandem with the sophistication of threats to maintain AML/CFT gains (Kuzior et al., 2024). Market integrity and sustainable finance linkages suggest spillovers from ethical finance to compliance cultures, yet also highlight regime-specific behavior that can dilute effects without institutional anchoring (Nuzula Agustin et al., 2025).

Taken together, prior research indicates that AI tools materially enhance detection and deterrence capacities, but durable AML risk reduction depends on institutional readiness, oversight quality, and legally grounded data governance that translate technical affordances into enforceable practice (Ahmed et al., 2022; Canhoto, 2021; Duba & Lehohla, 2025; Kuzior et al., 2025). The remaining gap is rigorous cross-country evidence linking AI readiness and institutional strength to observed AML outcomes over time; addressing this gap requires panel designs that separate within-country improvements from between-country heterogeneity and that explicitly account for enforcement capacity and governance quality (Krawczyk et al., 2025; Yarovenko et al., 2024c).

Previous research confirms that AI readiness enhances AML capacity by enabling advanced risk detection and operational efficiency, but the quality of the rule of law strongly moderates its impact. Countries that combine high AI adoption capabilities with strong judicial and governance systems are more likely to achieve significant reductions in money laundering risk. Conversely, even advanced AI solutions may fail to deliver substantial AML improvements in jurisdictions with weak legal institutions.

This study aims to empirically examine the impact of governmental readiness for artificial intelligence adoption, economic development, and institutional quality on anti-money laundering risk across countries. By employing panel data econometric techniques, the paper assesses whether higher AI readiness and stricter rule of law are associated with lower AML risk levels, as measured by the Basel AML Index. The hypotheses are:

*H1:* *Higher Government AI Readiness Index values are associated with lower Basel AML Index scores, indicating reduced AML risk.*

*H2:* *The relationship between AI readiness and AML risk is contingent on institutional quality, as measured by the Rule of Law Index.*

*H1* assumption is grounded in the premise that greater readiness for AI adoption enhances a country's capacity to leverage advanced technologies in financial monitoring, compliance, and enforcement, thereby improving the effectiveness of anti-money laundering frameworks. *H2* proposes that the risk-reducing effect of AI readiness is less pronounced in countries with a strict rule of law, where institutional mechanisms already function effectively, and more pronounced in countries with poorer institutional quality, where technological readiness can play a compensatory role in strengthening AML enforcement.

## 2. METHODOLOGY

This study employs a quantitative panel data approach to investigate the relationship between AML risk, government readiness for AI adoption, economic development, and the quality of the rule of law. The analysis utilizes country-level data from authoritative international sources, spanning the period from 2020 to 2024.

Two models are estimated:

1. Baseline model – includes the *Government AI Readiness Index* (x1) and log-transformed *GDP per capita* (x2_log) as explanatory variables for the *Basel AML Index* (y1).

2. Extended model – adds the *World Justice Project Rule of Law Index* (x3) and the interaction term between AI readiness and rule of law (x1 × x3).

The dataset constitutes an unbalanced panel, as the number of available observations varies across countries and years due to data availability constraints. Descriptive statistics are used to examine the central tendency, dispersion, and distributional characteristics of the variables. The Box–Cox transformation procedure is applied to determine whether a transformation is necessary; this yields an optimal $\lambda$ of 0 for GDP per capita, justifying a natural logarithmic transformation to stabilize variance and reduce skewness.

Panel regression is estimated using fixed effects (FE) and random effects (RE) specifications, as implemented in the plm package in R Studio. The Hausman test is employed to determine the appropriate specification. Diagnostic tests are conducted for heteroskedasticity (Breusch-Pagan test), serial correlation (Wooldridge test), and cross-sectional dependence (Pesaran CD test). Where violations are detected, Driscoll-Kraay standard errors are applied to obtain robust inference, as these are heteroskedasticity-consistent, autocorrelation-consistent, and robust to cross-sectional dependence.

The variables and their sources are presented in Table 1. The dataset constitutes an unbalanced panel, as complete data for all indicators were unavailable for every country and year in the observation period.

In particular, specific indices, such as the Government AI Readiness Index and the World Justice Project Rule of Law Index, were not reported for all countries in every year, resulting in variations in the number of observations across variables. This missingness reflects differences in data collection coverage and publication schedules among the respective international organizations, resulting in panel dimensions with varying time lengths for individual countries.

The samples of countries used for all model specifications are listed in Appendix A. All statistical calculations and econometric estimations were performed using R Studio.

# 3. RESULTS

## 3.1. Basel AML Index vs Government AI Readiness Index

The descriptive statistics (Table 2) provide an overview of the variables included in the analysis. The Government AI Readiness Index (x1) exhibited a mean value of 49.23 (SD = 16.65) with scores ranging from 18.61 to 88.16, highlighting substantial differences in how governments are prepared to implement artificial intelligence solutions. The Basel AML Index (y1) recorded an average of 5.27 (SD = 1.19), ranging from 2.36 to 8.49, which indicates moderate variation in anti-money laundering risk profiles across countries. GDP per capita in constant 2015 US dollars (x2) demonstrated a high degree of dispersion, with a mean of USD 16,864.39, a median of $6,884.67, and values ranging from USD 390.09 to USD 105,274.25. The positive skewness (1.78) and leptokurtic distribution (kurtosis = 2.93) for GDP per capita suggest a small number of countries with exceptionally high income levels. In contrast, the AI readiness and AML indices

**Table 1.** Variables and their sources

| Variable | Description | Source |
|---|---|---|
| y1 | Basel AML Index | Basel Institute on Governance (n.d.) |
| x1 | Government AI Readiness Index | Oxford Insights (n.d.) |
| x2 | GDP per capita (constant 2015 USD) | World Bank (n.d.) |
| x3 | World Justice Project Rule of Law Index | WJP (n.d.) |


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**Table 2.** Descriptive statistics of key variables for Basel AML Index (y1) on Government AI Readiness Index (x1) and log GDP per capita (x2)

| Variable | Government AI Readiness Index (x1) | Basel AML Index (y1) | GDP per capita (constant 2015 USUSD ) (x2) |
|---|---|---|---|
| n | 652 | 652 | 652 |
| Mean | 49.23 | 5.27 | 16.864.39 |
| SD | 16.65 | 1.19 | 20.761.43 |
| Median | 45.59 | 5.16 | 6.884.67 |
| Min | 18.61 | 2.36 | 390.09 |
| Max | 88.16 | 8.49 | 105.274.25 |
| Range | 69.55 | 6.13 | 104.884.16 |
| Skew | 0.3 | 0.36 | 1.78 |
| Kurtosis | –1.08 | –0.36 | 2.93 |
| SE | 0.65 | 0.05 | 813.08 |

showed relatively symmetrical distributions and lower kurtosis, implying more balanced dispersion around their respective means.

The distributional analysis revealed that the Government AI Readiness Index (x1) exhibited a skewness of 0.30, which falls within the generally accepted range of –0.5 to 0.5, indicating near symmetry. Its kurtosis value of –1.08 suggests a slightly platykurtic distribution, meaning it is somewhat flatter than a standard curve, yet this deviation is not considered problematic. Similarly, the *Basel AML Index* (y1) demonstrated a skewness of 0.36, reflecting only mild asymmetry, and a kurtosis of –0.36, indicating a distribution close to normality. Given these characteristics, both variables were deemed sufficiently well-behaved in terms of their distributional properties, and no transformation was considered necessary before modelling.

The Box-Cox transformation indicated an optimal $\lambda$ of 0 for GDP per capita, corresponding to a natural logarithmic transformation. Consequently, GDP per capita was transformed using the natural logarithm prior to model estimation to mitigate skewness and stabilize variance.

The panel regression analysis was conducted to examine the relationship between the Basel AML Index (y1), the Government AI Readiness Index (x1), and the log-transformed GDP per capita (x2_log). The FE specification yielded a negative coefficient for x1 ($\beta = -0.0056$, $p = 0.198$) that was not statistically significant, while x2_log demonstrated a statistically significant negative association ($\beta = -0.8170$, $p < 0.001$). The FE model explained 4.1% of the within-country variation in y1 ($R^2 = 0.041$), but the adjusted $R^2$ value (–0.295) indicated limited explanatory power after accounting for the number of parameters.

The RE specification produced similar negative relationships for both explanatory variables, with x1 ($\beta = -0.0103$, $p = 0.0035$) and x2_log ($\beta = -0.5707$, $p < 0.001$) both statistically significant. The RE model exhibited a considerably higher explanatory power ($R^2 = 0.557$).

The Hausman test ($\chi^2(2) = 3.367$, $p = 0.186$) indicated no statistically significant difference between FE and RE estimates, suggesting that the RE model is consistent and more efficient for this specification. Consequently, the RE model results are preferred for interpretation.

Diagnostic tests were conducted to assess the validity of the random effects specification. The Breusch-Godfrey/Wooldridge test for serial correlation in panel models indicated significant first-order autocorrelation in the idiosyncratic errors ($\chi^2 = 28.234$, $p < 0.001$). The Breusch-Pagan test for heteroskedasticity did not reveal evidence of unequal error variances across panels (BP = 0.336, $p = 0.845$). However, the Pesaran CD test identified significant cross-sectional dependence ($z = 3.253$, $p = 0.0011$), suggesting that unobserved shocks may be correlated across countries. Both serial correlation and cross-sectional dependence imply that conventional standard errors would be biased and inefficient. To address these issues, the random effects model was re-estimated using Driscoll-Kraay standard errors, which are robust to heteroskedasticity, autocorrelation, and cross-sectional dependence, thereby ensuring more reliable inference.

**Table 3.** Panel regression results for Basel AML Index (y1) on Government AI Readiness Index (x1) and log GDP per capita (x2_log)

| Variable | FE Estimate | FE Std. Error | FE p-value | RE Estimate | RE Std. Error | RE p-value |
|---|---|---|---|---|---|---|
| Intercept | – | – | – | 10.8985 | 0.3873 | < 0.001 *** |
| Government AI Readiness Index (x1) | –0.0056 | 0.0044 | 0.198 | –0.0103 | 0.0035 | 0.0035 ** |
| log GDP per capita (x2_log) | –0.8170 | 0.2414 | < 0.001 *** | –0.5707 | 0.0540 | < 0.001 *** |
| **Model fit** | | | | | | |
| $R^2$ | 0.0410 | – | – | 0.5568 | – | – |
| Adj. $R^2$ | –0.2953 | – | – | 0.5554 | – | – |
| N (obs) | 652 | – | – | 652 | – | – |
| Countries | 168 | – | – | 168 | | – |
| Hausman test p-value | – | – | 0.1857 | – | – | – |

*Note:* '***' – 0.001; '**' – 0.01; '*' – 0.05; '.' – 0.1; 'No symbol' – insignificant.

After accounting for heteroskedasticity, serial correlation, and cross-sectional dependence using Driscoll-Kraay standard errors, the random effects model revealed statistically significant relationships between the *Basel AML Index* and both explanatory variables. The *Government AI Readiness Index* (x1) was negatively associated with the Basel AML Index ($\beta = -0.0103$, $p < 0.001$), indicating that higher AI readiness is associated with lower AML risk scores. Similarly, the log-transformed *GDP per capita* (x2_log) showed a significant adverse effect ($\beta = -0.5707$, $p < 0.001$), suggesting that wealthier countries tend to have lower AML risk levels. The intercept term was positive and significant ($\beta = 10.8985$, $p < 0.001$). These results are robust to the presence of cross-sectional dependence and autocorrelation, reinforcing the stability of the estimated effects.

The analysis demonstrates that the Government AI Readiness Index has a statistically significant adverse effect on the Basel AML Index, indicating that greater preparedness for artificial intelligence adoption is associated with lower AML risk scores. Since a lower Basel AML Index value reflects stronger anti-money-laundering frameworks and reduced risk exposure, this finding suggests that advancements in government AI readiness positively strengthen AML resilience.

To explore unobserved, time-invariant country-specific influences on AML risk, we extracted the individual fixed effects ($\alpha_i$) from the estimated FE model (Table 5 for the 10 top and 10 bottom effects and Table B1 for the full list of countries). These estimates reflect baseline deviations in the Basel AML Index that are not explained by the Government AI Readiness Index or log-transformed GDP per capita. Countries with higher fixed effect values exhibit a relatively higher baseline AML risk, controlling for AI capacity and economic development.

Notably, countries such as the United Arab Emirates (14.99), Gabon (14.98), China (14.90), Qatar (14.90), and Kuwait (14.78) show elevated country fixed effects. This suggests persistent vulnerabilities in their AML systems, potentially linked to structural challenges, regulatory opacity, or high exposure to international capital movements. In contrast, countries like Malawi (10.94), the Gambia (11.05), Armenia (11.82), Ukraine (11.76), and Moldova (11.76) display relatively low country effects, indicating a more favorable AML risk baseline than expected, possibly due to recent regulatory reforms or lower integration into high-risk financial networks.

**Table 4.** Random effects model with Driscoll–Kraay standard errors for Basel AML Index (y1) influenced by Government AI Readiness Index (x1), and log GDP per capita (x2_log)

| Variable | Estimate | Std. Error | t-value | p-value | Significance |
|---|---|---|---|---|---|
| Intercept | 10.8985 | 0.6945 | 15.6925 | <0.001 | *** |
| Government AI Readiness Index (x1) | –0.0103 | 0.0026 | –3.9072 | <0.001 | *** |
| log GDP per capita (x2_log) | –0.5707 | 0.0676 | –8.4361 | <0.001 | *** |

*Note:* '***' – 0.001; '**' – 0.01; '*' – 0.05; '.' – 0.1; 'No symbol' – insignificant.


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**Table 5.** Country-specific fixed effects: Top 10 and bottom 10 baseline AML risk estimates, influenced by Government AI Readiness Index (x1), and log GDP per capita (x2_log)

| Top 10 Countries (High AML Risk) | Fixed Effects | Bottom 10 Countries (Low AML Risk) | Fixed Effect |
|---|---|---|---|
| United Arab Emirates | 14.99 | Malawi | 10.94 |
| Gabon | 14.98 | Gambia | 11.05 |
| China | 14.9 | Armenia | 11.82 |
| Qatar | 14.9 | Ukraine | 11.76 |
| Kuwait | 14.78 | Moldova | 11.76 |
| Lao PDR | 14.22 | Lesotho | 11.77 |
| Switzerland | 14.23 | Georgia | 11.97 |
| Singapore | 14.02 | Nepal | 11.97 |
| United States | 14.04 | Namibia | 11.96 |
| Saudi Arabia | 14.03 | Tunisia | 11.98 |

Several EU and OECD countries, such as Germany (13.54), Belgium (13.22), and Austria (13.41), occupy the mid-range of the distribution. Their country effects suggest a moderate residual AML risk that remains even after accounting for technological readiness and economic capacity. These patterns highlight the significance of institutional legacies, enforcement consistency, and the quality of structural governance in shaping a nation's AML performance.

The heterogeneity in country-specific effects reinforces the need for targeted, context-sensitive AML policy strategies. Even in economies with high AI readiness, residual institutional risk may persist, necessitating supplementary efforts in transparency, cross-border cooperation, and regulatory accountability.

## 3.2. Basel AML Index vs Government AI Readiness Index and Rule of Law Index

The descriptive statistics (Table 6) summarize the characteristics of the variables employed in the analysis. The Government AI Readiness Index (x1) had a mean value of 49.99 (SD = 16.85), ranging from 18.61 to 88.16, which reflects substantial variation in countries' readiness to adopt and implement artificial intelligence. The World Justice Project Rule of Law Index (x3) averaged 0.57 (SD = 0.15), with scores ranging from 0.31 to 0.90, indicating moderate disparities in legal system performance and governance quality across the sample. The Basel AML Index (y1) recorded an average of 5.27 (SD = 1.19), from 2.36 to 8.49, suggesting notable differences in anti-money laundering risk levels between countries. GDP per capita in constant 2015 US dollars (x2) exhibited considerable heterogeneity, with a mean of USD 16,186.81, a median of USD 6,937.33, and values ranging from USD 431.60 to USD 105,274.25. The GDP per capita distribution was positively skewed (skewness = 1.85) and leptokurtic (kurtosis = 3.41), indicating the presence of high-income outliers. In contrast, the AI readiness, rule of law, and AML risk indices displayed skewness and kurtosis values closer to those expected under normality, suggesting more symmetric distributions.

An examination of the distributional properties of the variables indicates that a transformation is necessary for GDP per capita (x2) but not for the other indicators. The GDP per capita variable exhibits pronounced positive skewness (1.85) and leptokurtosis (3.41), suggesting a heavy right tail driven by a few high-income countries. Such deviations from normality can lead to heteroskedasticity, non-normal residuals, and undue influence of outliers in regression estimation. In contrast, the Government AI Readiness Index (x1), the World Justice Project Rule of Law Index (x3), and the Basel AML Index (y1) display skewness and kurtosis values within or near commonly accepted thresholds for approximate normality, indicating no substantive need for transformation. Accordingly, the GDP per capita variable will be transformed using a natural logarithm, as supported by the Box–Cox procedure, to stabilize variance, reduce skewness, and enhance the reliability of subsequent model estimates.

The Box–Cox transformation procedure for *GDP per capita* (x2) yielded an optimal $\lambda$ value of 0. In the Box–Cox framework, a $\lambda$ of zero corresponds to the natural logarithmic transformation, indi-

**Table 6.** Descriptive statistics of key variables: Basel AML Index (y1) on Government AI Readiness Index (x1), log GDP per capita (x2_log), Rule of Law Index (x3)

| Variable | Government AI Readiness Index (x1) | World Justice Project Rule of Law Index (x3) | Basel AML Index (y1) | GDP per capita (constant 2015 USD) (x2) |
|---|---|---|---|---|
| n | 537 | 537 | 537 | 537 |
| Mean | 49.99 | 0.57 | 5.27 | 16,186.81 |
| SD | 16.85 | 0.15 | 1.19 | 20,001.01 |
| Median | 46.81 | 0.53 | 5.09 | 6,937.33 |
| Min | 18.61 | 0.31 | 2.36 | 431.6 |
| Max | 88.16 | 0.9 | 8.49 | 105,274.25 |
| Range | 69.55 | 0.59 | 6.13 | 104,842.65 |
| Skew | 0.27 | 0.47 | 0.39 | 1.85 |
| Kurtosis | –1.11 | –0.82 | –0.33 | 3.41 |
| SE | 0.73 | 0.01 | 0.05 | 863.,11 |

cating that this functional form best addresses the variable's non-normality and heteroskedasticity. Consequently, x2 was transformed into its logarithmic form (*x2_log*) for subsequent analyses, thereby reducing skewness, stabilizing variance, and mitigating the influence of extremely high-income values on the regression results.

The extended model incorporating the interaction term between the *Government AI Readiness Index* (x1) and the *World Justice Project Rule of Law Index* (x3) was estimated using both Fixed Effects (FE) and Random Effects (RE) specifications.

In the FE model, x1 had a statistically significant adverse effect on the *Basel AML Index* (β = –0.0402, $p = 0.043$), while x2_log was marginally significant and negative (β = –0.5396, $p = 0.054$). The interaction term x1:x3 was positive and marginally significant (β = 0.0667, $p = 0.067$), suggesting that a stricter rule of law may attenuate the negative association between AI readiness and AML risk. The $R^2$ for the FE model was low (0.038), and the adjusted $R^2$ was negative (–0.302), indicating limited within-country explanatory power.

In the RE specification, all explanatory variables were statistically significant at the 1% level, with x1 (β = –0.0485, $p < 0.001$) and x2_log (β = –0.3440, $p < 0.001$) both negatively associated with AML risk, and x3 showing a substantial adverse effect (β = –6.8073, $p < 0.001$). The interaction term x1:x3 remained positive and significant (β = 0.0722, $p < 0.001$). The RE model explained 58.6% of the variation in the dependent variable ($R^2 = 0.586$).

The Hausman test strongly rejected the null hypothesis ($\chi^2(4) = 15.348$, $p = 0.004$), indicating that the RE model is inconsistent and that the FE specification should be preferred for inference despite its lower explanatory power.

**Table 7.** Panel regression results for Basel AML Index (y1) on Government AI Readiness Index (x1), log GDP per capita (x2_log), Rule of Law Index (x3), and interaction term (x1 × x3)

| Variable | FE Estimate | FE Std. Error | FE p-value | RE Estimate | RE Std. Error | RE p-value |
|---|---|---|---|---|---|---|
| Intercept | – | – | – | 12.4471 | 0.7017 | < 0.001 *** |
| Government AI Readiness Index (x1) | –0.0402 | 0.0198 | 0.043 * | –0.0485 | 0.0118 | < 0.001 *** |
| log GDP per capita (x2_log) | –0.5396 | 0.2792 | 0.054 . | –0.3440 | 0.0719 | < 0.001 *** |
| Rule of Law Index (x3) | –0.6010 | 2.4202 | 0.804 | –6.8073 | 1.2864 | < 0.001 *** |
| Interaction term (x1 × x3) | 0.0667 | 0.0363 | 0.067 . | 0.0722 | 0.0201 | < 0.001 *** |
| Model fit | – | – | – | – | – | – |
| $R^2$ | 0.0381 | – | – | 0.5864 | – | – |
| Adj. $R^2$ | –0.3020 | – | – | 0.5832 | – | – |
| N (obs) | 537 | – | – | 537 | – | – |
| Countries | 137 | – | – | 137 | – | – |
| Hausman test p-value | – | – | 0.004 ** | – | – | – |

*Note:* '***' – 0.001; '**' – 0.01; '*' – 0.05; '.' – 0.1; 'No symbol' – insignificant.



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Diagnostic tests for the fixed effects model indicated multiple violations of classical panel data assumptions. Wooldridge's test for serial correlation strongly rejected the null hypothesis of no first-order autocorrelation ($F = 35.57$, $p < 0.001$), suggesting that error terms are correlated over time within countries. The Breusch-Pagan test revealed significant heteroskedasticity across panels (BP = 15.269, $p = 0.004$), indicating that the variance of the error term is not constant. The Lagrange Multiplier version of the Breusch-Pagan test confirmed the presence of significant individual effects ($\chi^2 = 526.44$, $p < 0.001$), justifying the use of a panel estimator over pooled OLS. Finally, the Pesaran CD test detected statistically significant cross-sectional dependence ($z = 2.117$, $p = 0.034$), implying that unobserved shocks may be correlated across countries. Given the simultaneous presence of heteroskedasticity, serial correlation, and cross-sectional dependence, robust inference methods, such as Driscoll-Kraay standard errors, are required to ensure consistent and reliable statistical inference.

After correcting for heteroskedasticity, serial correlation, and cross-sectional dependence using Driscoll-Kraay standard errors, the fixed effects model results confirmed the statistical significance of the main explanatory variables. The Government AI Readiness Index (x1) maintained a negative and statistically significant association with the Basel AML Index ($\beta = -0.0402$, $p < 0.001$), suggesting that higher AI readiness is associated with lower AML risk. The log-transformed GDP per capita (x2_log) was also negative and significant ($\beta = -0.5396$, $p = 0.029$), indicating that wealthier countries tend to exhibit lower AML risk scores. The Rule of Law Index (x3) remained statistically insignificant, indicating no direct effect when controlling for the other variables. The interaction term between AI readiness and the rule of law (x1:x3) was positive and significant ($\beta = 0.0667$, $p < 0.001$), implying that the adverse effect of AI readiness on AML risk weakens as the rule of law improves. These findings are robust to multiple forms of model misspecification, reinforcing the stability of the observed relationships.

The results indicate that higher values of the Government AI Readiness Index are associated with lower Basel AML Index scores, which is a favorable outcome given that a lower Basel AML Index reflects stronger anti-money laundering frameworks and reduced risk exposure. Moreover, the significant positive interaction between AI readiness and the Rule of Law Index suggests that the beneficial effect of AI readiness on AML risk is moderated by institutional quality. In countries with stronger rule of law, the negative impact of AI readiness on AML risk is somewhat attenuated, while in weaker institutional environments, improvements in AI readiness may have a more pronounced risk-reducing effect.

The empirical findings provide strong support for *H1*, as the Government AI Readiness Index demonstrated a statistically significant negative association with the Basel AML Index across model specifications, confirming that higher AI readiness corresponds to lower AML risk. Concerning *H2*, the interaction term between AI readiness and the Rule of Law Index was positive and statistically significant in the preferred model, indicating that the magnitude of AI readiness's risk-reducing effect decreases as institutional quality improves. This outcome aligns with the hypothesized moderating role of the rule of law, whereby countries with weaker institutional environments experience greater AML risk reduction from advancements in AI readiness, while in high rule-of-law contexts, the marginal benefit of AI readiness is diminished. Overall, the results validate both

**Table 8.** Fixed effects model with Driscoll–Kraay standard errors for Basel AML Index (y1) on Government AI Readiness Index (x1), log GDP per capita (x2_log), Rule of Law Index (x3), and interaction term (x1 × x3)

| Variable | Estimate | Std. Error | t-value | p-value | Significance |
|---|---|---|---|---|---|
| Government AI Readiness Index (x1) | –0.0402 | 0.0116 | –3.4646 | 0.000589 | *** |
| log GDP per capita (x2_log) | –0.5396 | 0.2467 | –2.1877 | 0.029278 | * |
| Rule of Law Index (x3) | –0.6010 | 1.3647 | –0.4404 | 0.659891 | |
| Interaction term (x1 × x3) | 0.0667 | 0.0178 | 3.7362 | 0.000214 | *** |

*Note:* '***' – 0.001; '**' – 0.01; '*' – 0.05; '.' – 0.1; 'No symbol' – insignificant.

hypotheses, reinforcing the importance of technological preparedness and institutional quality in shaping AML outcomes.

The fixed effects represent time-invariant, country-specific influences on AML risk (as measured by the Basel AML Index) that are not explained by AI readiness, economic development, institutional quality, or their interaction. In this extended model, the inclusion of the rule of law and its interaction with AI readiness helps to more precisely isolate latent national characteristics, such as historical governance models, regulatory cultures, or informal sector dynamics (Table 9 for the 10 top and 10 bottom effects and Table B2 for the full list of countries).

Countries such as Gabon (13.06), China (12.81), Myanmar (12.50), Kuwait (12.12), and Haiti (12.62) display the highest fixed effects, suggesting persistently elevated AML risks even after adjusting for observed institutional and technological capacities. These values may reflect complex structural deficiencies, informal economies, or limited cross-border financial transparency. On the other end, Sweden (8.40), Lithuania (8.57), Norway (8.63), Denmark (8.46), and New Zealand (8.68) exhibit the lowest fixed effects. This suggests relatively robust AML resilience, attributable to long-standing institutional quality, comprehensive financial regulation, and high transparency standards. These countries act as benchmarks for AML system maturity. Countries such as Germany (9.49), France (9.22), Ireland (9.84), Poland (9.84), and Slovakia (9.83) demonstrate moderate residual effects. Although they maintain well-developed financial systems and AI infrastructures, the model detects remaining AML vulnerabilities, potentially due to evolving digital finance risks or uneven enforcement practices.

The distribution of fixed effects highlights that structural AML risk is not solely a function of AI or institutional quality, but also influenced by historical, cultural, and geopolitical legacies. Even after adjusting for the rule of law and AI governance, countries may still exhibit systematic over- or under-performance in AML. This signals the need for tailored national strategies. For countries with high fixed effects, policy attention should focus on deep-rooted regulatory capacity-building and international compliance efforts. For countries with low fixed effects, best practices could be distilled and shared globally, particularly regarding AI-integrated risk monitoring and cross-sector coordination.

**Table 9.** Country fixed effects: Top 10 and bottom 10 for Basel AML Index (y1) on Government AI Readiness Index (x1), log GDP per capita (x2_log), Rule of Law Index (x3), and interaction term (x1 × x3)

| Top 10 Countries (High AML Risk) | Fixed Effect | Bottom 10 Countries (Low AML Risk) | Fixed Effect |
|---|---|---|---|
| Gabon | 13.0556 | Sweden | 8.404059 |
| China | 12.81177 | Lithuania | 8.566315 |
| Myanmar | 12.49581 | Norway | 8.628536 |
| Kuwait | 12.12195 | New Zealand | 8.681945 |
| Haiti | 12.61555 | Denmark | 8.461975 |
| Afghanistan | 12.16374 | Slovenia | 8.965088 |
| Congo | 12.1758 | Uruguay | 9.313089 |
| Vietnam | 12.10931 | Chile | 9.337602 |
| Cambodia | 11.95751 | Portugal | 9.346209 |
| Panama | 11.6413 | Latvia | 9.350537 |

The empirical patterns identified in this study have clear implications for how AML systems are designed and prioritized. The negative and significant effect of AI readiness on AML risk, especially in weaker rule-of-law environments, indicates that investments in technological capacity should be treated as a core component of national AML strategies rather than as a peripheral innovation project. In countries where institutional frameworks are fragile, improvements in data infrastructure, analytical tools, and AI-enabled monitoring can generate disproportionately large reductions in AML vulnerability, partially offsetting governance deficits that cannot be remedied in the short term. At the same time, the significant moderating role of the rule of law confirms that technology alone is not sufficient: institutional quality independently lowers AML risk and amplifies the effectiveness of AI readiness, suggesting that legal certainty, enforcement capacity, and judicial integrity remain fundamental preconditions for durable gains.

The cross-country heterogeneity captured in the fixed effects further points to the importance of differentiated support measures. Jurisdictions with persistently high unexplained AML risk may


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require more intensive combinations of technological assistance and institutional reform. At the same time, structurally resilient countries illustrate the potential of aligning AI readiness with strong governance. In this context, international organizations and donors can utilize the study's results to target more effective capacity-building efforts that integrate AI-based solutions with enhancements to legal and regulatory frameworks, rather than treating them as separate reform tracks. The transnational nature of money laundering also implies that the benefits of AI-enabled AML tools will be maximized when embedded in cooperative arrangements that facilitate information exchange and interoperable supervision across borders, thereby reinforcing the resilience of the global AML architecture.

## 4. DISCUSSION

The empirical findings of this study confirm that a higher Government AI Readiness Index is significantly associated with lower Basel AML Index scores, indicating a reduction in AML risk. This supports H1 and aligns with earlier research highlighting the positive role of artificial intelligence in enhancing financial monitoring and law enforcement efficiency (Dobrovolska & Rozhkova, 2024; Kuzior et al., 2025; Yarovenko et al., 2025a). The negative relationship between AI readiness and AML risk suggests that AI integration strengthens preventive, detection, and investigative capacities, which is consistent with findings on AI's potential in combating illicit financial activities (Lyeonov et al., 2025a; Pulungan et al., 2024).

The results also confirm *H2*, showing that the interaction between AI readiness and the Rule of Law Index is positive, implying that the risk-reducing impact of AI readiness is less pronounced in countries with stronger institutional frameworks. This finding aligns with studies suggesting that while strong governance mitigates vulnerabilities to financial crime, the marginal benefit of AI deployment is greater in environments with poorer institutional quality (Ntshangase et al., 2024; Yarovenko et al., 2024b). In highly robust legal systems, traditional oversight and compliance mechanisms already ensure substantial AML risk mitigation, reducing the incremental contribution of AI solutions.

These outcomes are consistent with evidence from other contexts. For example, Haley and Burrell (2025) emphasized that integrating AI technologies is particularly impactful in jurisdictions where existing control systems face limitations, resource constraints, or enforcement gaps. Similarly, Yarovenko et al. (2025a) demonstrated that when combined with targeted governance reforms, digital readiness delivers the most significant improvements in combating corruption and cyber-related financial crimes.

However, our results partly contrast with perspectives that present AI readiness and the rule of law as complementary rather than substitutive factors (Androniceanu, 2024). The partial substitutive effect observed here suggests a nuanced relationship: AI adoption and legal system strength can each independently reduce AML risk. However, the interaction effect depends on the baseline level of institutional development. This divergence from some previous studies underscores the need for a more nuanced policy approach that takes into account country-specific governance capacities and technological maturity when integrating AI into AML frameworks.

This paper has several limitations that should be acknowledged when interpreting the findings. First, the analysis relies on secondary data from publicly available indices, which, although widely recognized, may contain measurement errors, methodological inconsistencies, or reporting biases across countries. Second, the dataset is limited by the temporal and spatial availability of the variables, resulting in an unbalanced panel with limited time coverage, which restricts the ability to fully capture long-term trends and dynamic effects. Third, despite the use of log transformation and robust estimation techniques, such as Driscoll-Kraay standard errors, to address issues of heteroskedasticity, autocorrelation, and cross-sectional dependence, the potential influence of omitted variables, including political stability, enforcement capacity, or technological infrastructure, cannot be entirely ruled out. Finally, the results identify associations rather than definitive causal relationships, meaning caution is warranted when drawing policy implications from the observed patterns.

# CONCLUSION

This study aims to empirically examine the impact of governmental readiness for artificial intelligence adoption, economic development, and institutional quality on anti-money laundering risk across countries.

The empirical results confirm the first hypothesis: the Government AI Readiness Index has a statistically significant negative effect on the Basel AML Index (–0.040, $p < 0.01$), meaning that higher AI readiness is associated with lower AML risk. The second hypothesis is also supported, as the positive and significant interaction term with the Rule of Law Index (0.067, $p < 0.001$) shows that the marginal impact of AI readiness weakens as institutional quality improves, with the greatest AML risk reductions observed in weaker rule-of-law environments. Fixed effects further indicate that countries such as Gabon and China retain the highest unexplained baseline AML risks. At the same time, Sweden demonstrates strong structural resilience with the lowest residual AML risk after controlling for AI readiness and governance quality.

The study demonstrates that higher AI readiness significantly reduces the risk of AML. At the same time, the moderating effect of institutional quality indicates that technological capacity is particularly impactful in countries with weaker rule of law environments. The results also reveal considerable cross-country heterogeneity, with persistent structural vulnerabilities in states such as Gabon and China and strong resilience in countries like Sweden. These findings highlight the combined importance of technological capability and institutional strength in shaping AML outcomes. Although detailed policy design lies beyond the scope of this study, the results suggest that enhancing AI readiness and reinforcing institutional frameworks could jointly strengthen national and international AML systems.

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# APPENDIX A

**Table A1.** List of countries: Basel AML Index (y1) on Government AI Readiness Index (x1) and log GDP per capita (x2_log)

| No. | Countries | No. | Countries | No. | Countries | No. | Countries |
|---|---|---|---|---|---|---|---|
| 1 | Afghanistan | 43 | Cyprus | 85 | Lao People's Democratic Republic | 127 | Saint Kitts and Nevis |
| 2 | Albania | 44 | Czechia | 86 | Latvia | 128 | Saint Lucia |
| 3 | Algeria | 45 | Democratic Republic of the Congo | 87 | Lebanon | 129 | Saint Vincent and the Grenadines |
| 4 | Andorra | 46 | Denmark | 88 | Lesotho | 130 | Samoa |
| 5 | Angola | 47 | Dominica | 89 | Liberia | 131 | San Marino |
| 6 | Antigua and Barbuda | 48 | Dominican Republic | 90 | Lithuania | 132 | Saudi Arabia |
| 7 | Argentina | 49 | Ecuador | 91 | Luxembourg | 133 | Senegal |
| 8 | Armenia | 50 | Egypt | 92 | Madagascar | 134 | Serbia |
| 9 | Australia | 51 | El Salvador | 93 | Malawi | 135 | Seychelles |
| 10 | Austria | 52 | Estonia | 94 | Malaysia | 136 | Sierra Leone |
| 11 | Azerbaijan | 53 | Eswatini | 95 | Mali | 137 | Singapore |
| 12 | Bahamas | 54 | Ethiopia | 96 | Malta | 138 | Slovakia |
| 13 | Bahrain | 55 | Fiji | 97 | Mauritania | 139 | Slovenia |
| 14 | Bangladesh | 56 | Finland | 98 | Mauritius | 140 | Solomon Islands |
| 15 | Barbados | 57 | France | 99 | Mexico | 141 | South Africa |
| 16 | Belarus | 58 | Gabon | 100 | Mongolia | 142 | Spain |
| 17 | Belgium | 59 | Gambia (Republic of The) | 101 | Montenegro | 143 | Sri Lanka |
| 18 | Belize | 60 | Georgia | 102 | Morocco | 144 | Suriname |
| 19 | Benin | 61 | Germany | 103 | Mozambique | 145 | Sweden |
| 20 | Bhutan | 62 | Ghana | 104 | Myanmar | 146 | Switzerland |
| 21 | Bolivia (Plurinational State of) | 63 | Greece | 105 | Namibia | 147 | Taiwan |
| 22 | Bosnia and Herzegovina | 64 | Grenada | 106 | Nepal | 148 | Tajikistan |
| 23 | Botswana | 65 | Guatemala | 107 | Netherlands | 149 | Thailand |
| 24 | Brazil | 66 | Guinea | 108 | New Zealand | 150 | Togo |
| 25 | Brunei Darussalam | 67 | Guinea Bissau | 109 | Nicaragua | 151 | Tonga |
| 26 | Bulgaria | 68 | Guyana | 110 | Niger | 152 | Trinidad and Tobago |
| 27 | Burkina Faso | 69 | Haiti | 111 | Nigeria | 153 | Tunisia |
| 28 | Cape Verde | 70 | Honduras | 112 | North Macedonia | 154 | Türkiye |
| 29 | Cambodia | 71 | Hungary | 113 | Norway | 155 | Turkmenistan |
| 30 | Cameroon | 72 | Iceland | 114 | Pakistan | 156 | Uganda |
| 31 | Canada | 73 | India | 115 | Panama | 157 | Ukraine |
| 32 | Central African Republic | 74 | Indonesia | 116 | Paraguay | 158 | United Arab Emirates |
| 33 | Chad | 75 | Ireland | 117 | Peru | 159 | United Kingdom |
| 34 | Chile | 76 | Israel | 118 | Philippines | 160 | United Republic of Tanzania |
| 35 | China | 77 | Italy | 119 | Poland | 161 | United States of America |
| 36 | Colombia | 78 | Jamaica | 120 | Portugal | 162 | Uruguay |
| 37 | Comoros | 79 | Japan | 121 | Qatar | 163 | Uzbekistan |
| 38 | Congo | 80 | Jordan | 122 | Republic of Korea | 164 | Vanuatu |
| 39 | Costa Rica | 81 | Kazakhstan | 123 | Republic of Moldova | 165 | Viet Nam |
| 40 | Côte d'Ivoire | 82 | Kenya | 124 | Romania | 166 | Yemen |
| 41 | Croatia | 83 | Kuwait | 125 | Russian Federation | 167 | Zambia |
| 42 | Cuba | 84 | Kyrgyzstan | 126 | Rwanda | 168 | Zimbabwe |


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**Table A2.** List of countries: Basel AML Index (y1) on Government AI Readiness Index (x1), log GDP per capita (x2_log), Rule of Law Index (x3), and interaction term (x1 × x3)

| No. | Countries | No. | Countries | No. | Countries | No. | Countries |
|---|---|---|---|---|---|---|---|
| 1 | Afghanistan | 43 | Finland | 85 | Mozambique | 127 | Uganda |
| 2 | Albania | 44 | France | 86 | Myanmar | 128 | Ukraine |
| 3 | Algeria | 45 | Gabon | 87 | Namibia | 129 | United Arab Emirates |
| 4 | Angola | 46 | Gambia(Republic of the) | 88 | Nepal | 130 | United Kingdom |
| 5 | Antigua and Barbuda | 47 | Georgia | 89 | Netherlands | 131 | United Republic of Tanzania |
| 6 | Argentina | 48 | Germany | 90 | New Zealand | 132 | United States of America |
| 7 | Australia | 49 | Ghana | 91 | Nicaragua | 133 | Uruguay |
| 8 | Austria | 50 | Greece | 92 | Niger | 134 | Uzbekistan |
| 9 | Bahamas | 51 | Grenada | 93 | Nigeria | 135 | Viet Nam |
| 10 | Bangladesh | 52 | Guatemala | 94 | North Macedonia | 136 | Zambia |
| 11 | Barbados | 53 | Guinea | 95 | Norway | 137 | Zimbabwe |
| 12 | Belarus | 54 | Guyana | 96 | Pakistan | 138 | Slovakia |
| 13 | Belgium | 55 | Haiti | 97 | Panama | 139 | Slovenia |
| 14 | Belize | 56 | Honduras | 98 | Paraguay | 140 | Solomon Islands |
| 15 | Benin | 57 | Hungary | 99 | Peru | 141 | South Africa |
| 16 | Bolivia (Plurinational State of) | 58 | India | 100 | Philippines | 142 | Spain |
| 17 | Bosnia and Herzegovina | 59 | Indonesia | 101 | Poland | 143 | Sri Lanka |
| 18 | Botswana | 60 | Ireland | 102 | Portugal | 144 | Suriname |
| 19 | Brazil | 61 | Italy | 103 | Republic of Korea | 145 | Sweden |
| 20 | Bulgaria | 62 | Jamaica | 104 | Republic of Moldova | 146 | Switzerland |
| 21 | Burkina Faso | 63 | Japan | 105 | Romania | 147 | Taiwan |
| 22 | Cambodia | 64 | Jordan | 106 | Russian Federation | 148 | Tajikistan |
| 23 | Cameroon | 65 | Kazakhstan | 107 | Rwanda | 149 | Thailand |
| 24 | Canada | 66 | Kenya | 108 | Saint Kitts and Nevis | 150 | Togo |
| 25 | Chile | 67 | Kuwait | 109 | Saint Lucia | 151 | Tonga |
| 26 | China | 68 | Kyrgyzstan | 110 | Saint Vincent and the Grenadines | 152 | Trinidad and Tobago |
| 27 | Colombia | 69 | Latvia | 111 | Senegal | 153 | Tunisia |
| 28 | Congo | 70 | Lebanon | 112 | Serbia | 154 | Türkiye |
| 29 | Costa Rica | 71 | Liberia | 113 | SierraLeone | 155 | Turkmenistan |
| 30 | Cote d'Ivoire | 72 | Lithuania | 114 | Singapore | 156 | Uganda |
| 31 | Croatia | 73 | Luxembourg | 115 | Slovakia | 157 | Ukraine |
| 32 | Cyprus | 74 | Madagascar | 116 | Slovenia | 158 | United Arab Emirates |
| 33 | Czechia | 75 | Malawi | 117 | South Africa | 159 | United Kingdom |
| 34 | Democratic Republic of the Congo | 76 | Malaysia | 118 | Spain | 160 | United Republic of Tanzania |
| 35 | Denmark | 77 | Mali | 119 | Sri Lanka | 161 | United States of America |
| 36 | Dominica | 78 | Malta | 120 | Suriname | 162 | Uruguay |
| 37 | Dominican Republic | 79 | Mauritania | 121 | Sweden | 163 | Uzbekistan |
| 38 | Ecuador | 80 | Mauritius | 122 | Thailand | 164 | Vanuatu |
| 39 | Egypt | 81 | Mexico | 123 | Togo | 165 | Viet Nam |
| 40 | El Salvador | 82 | Mongolia | 124 | Trinidad and Tobago | 166 | Yemen |
| 41 | Estonia | 83 | Montenegro | 125 | Tunisia | 167 | Zambia |
| 42 | Ethiopia | 84 | Morocco | 126 | Türkiye | 168 | Zimbabwe |

# APPENDIX B

**Table B1.** Country-specific fixed effects: AML Risk Estimates, influenced by Government AI Readiness Index (x1), and log GDP per capita (x2_log)

| Country | fe_estimate | Country | fe_estimate | Country | fe_estimate |
|---|---|---|---|---|---|
| Afghanistan | 13.42540996 | France | 12.77050149 | Norway | 13.07367 |
| Albania | 12.30256394 | Gabon | 14.97660128 | Pakistan | 12.13644 |
| Algeria | 14.05163447 | Gambia | 11.04513447 | Panama | 13.99771 |
| Andorra | 12.02743817 | Georgia | 11.9706638 | Paraguay | 12.87429 |
| Angola | 13.4211922 | Germany | 13.54437485 | Peru | 12.10405 |
| Antigua and Barbuda | 12.95158683 | Ghana | 11.65836877 | Philippines | 12.68389 |
| Argentina | 12.99176398 | Greece | 12.09640435 | Poland | 12.70015 |
| Armenia | 11.82381011 | Grenada | 12.35447641 | Portugal | 12.46159 |
| Australia | 13.20589992 | Guatemala | 12.30057685 | Qatar | 14.90062 |
| Austria | 13.41271736 | Guinea | 12.29239625 | Republic of Moldova | 11.75765 |
| Azerbaijan | 12.5915759 | Guinea Bissau | 13.06362804 | Republic of Korea | 13.49061 |
| Bahamas | 14.27849262 | Guyana | 13.0131296 | Romania | 12.86423 |
| Bahrain | 13.31945589 | Haiti | 14.14009758 | Russian Federation | 13.28183 |
| Bangladesh | 12.12483583 | Honduras | 12.12252574 | Rwanda | 11.92729 |
| Barbados | 13.6364716 | Hungary | 13.24657853 | Saint Kitts and Nevis | 14.27164 |
| Belarus | 12.71503016 | Iceland | 12.80922306 | Saint Lucia | 12.67771 |
| Belgium | 13.21699145 | India | 11.89392365 | Saint Vincent and the Grenadines | 11.88857 |
| Belize | 12.76924962 | Indonesia | 12.07782412 | Samoa | 11.89729 |
| Benin | 12.70481342 | Ireland | 13.95617972 | San Marino | 12.49622 |
| Bhutan | 12.80180043 | Israel | 12.81288564 | Saudi Arabia | 14.03071 |
| Bolivia | 12.56751411 | Italy | 13.49382698 | Senegal | 12.92067 |
| Bosnia and Herzegovina | 12.86435066 | Jamaica | 12.63882333 | Serbia | 12.70229 |
| Botswana | 12.20602353 | Japan | 13.85238856 | Seychelles | 13.44908 |
| Brazil | 12.94786453 | Jordan | 12.31356233 | Sierra Leone | 12.86738 |
| Brunei Darussalam | 13.02893249 | Kazakhstan | 12.71177966 | Singapore | 14.02277 |
| Bulgaria | 12.41204544 | Kenya | 13.34260076 | Slovakia | 12.6335 |
| Burkina Faso | 12.15832876 | Kuwait | 14.7808157 | Slovenia | 12.04469 |
| Cambodia | 13.42959065 | Kyrgyzstan | 12.06290434 | Solomon Islands | 12.9298 |
| Cameroon | 12.90129041 | Lao People's Democratic Republic | 14.22083564 | South Africa | 12.88944 |
| Canada | 13.64310096 | Latvia | 12.51284508 | Spain | 12.60873 |
| Cape Verde | 13.07587369 | Lebanon | 12.88421166 | Sri Lanka | 12.98257 |
| Central African Republic | 12.47820042 | Lesotho | 11.77393215 | Suriname | 14.04194 |
| Chad | 13.57806134 | Liberia | 12.57342971 | Sweden | 12.61831 |
| Chile | 12.18059187 | Lithuania | 11.8842426 | Switzerland | 14.2323 |
| China | 14.90409649 | Luxembourg | 13.97356764 | Taiwan | 13.0396 |
| Colombia | 12.23599338 | Madagascar | 12.43360934 | Tajikistan | 12.11743 |
| Comoros | 12.81908067 | Malawi | 10.93506403 | Thailand | 13.46346 |
| Congo | 13.79999624 | Malaysia | 13.32973487 | Togo | 12.45294 |
| Costa Rica | 12.72816697 | Mali | 12.83988207 | Tonga | 13.39611 |
| Cote d'Ivoire | 13.18513649 | Malta | 13.93628434 | Trinidad and Tobago | 12.75254 |
| Croatia | 12.66556918 | Mauritania | 13.18388975 | Tunisia | 11.98276 |
| Cuba | 13.11018326 | Mauritius | 12.86591524 | Türkiye | 13.74031 |
| Cyprus | 13.54853895 | Mexico | 13.03377223 | Turkmenistan | 14.26626 |
| Czechia | 12.47989439 | Mongolia | 12.6815669 | Uganda | 12.42139 |
| Democratic Republic of the Congo | 13.35390533 | Montenegro | 11.53070444 | Ukraine | 11.75884 |
| Denmark | 12.87926853 | Morocco | 11.9842234 | United Arab Emirates | 14.98503 |
| Dominica | 11.71902905 | Mozambique | 13.00938319 | United Kingdom | 13.12014 |
| Dominican Republic | 12.63326676 | Myanmar | 13.91826629 | United Republic of Tanzania | 12.14666 |


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**Table B1 (cont.).** Country-specific fixed effects: AML Risk Estimates, influenced by Government AI Readiness Index (x1), and log GDP per capita (x2_log)

| Country | fe_estimate | Country | fe_estimate | Country | fe_estimate |
|---|---|---|---|---|---|
| Ecuador | 12.30320055 | Namibia | 11.96016753 | United States of America | 14.04321 |
| Egypt | 12.08645805 | Nepal | 11.97482764 | Uruguay | 12.36583 |
| El Salvador | 12.17811822 | Netherlands | 13.58927561 | Uzbekistan | 12.26771 |
| Estonia | 11.33138442 | New Zealand | 12.48456035 | Vanuatu | 11.91345 |
| Eswatini | 13.74854136 | Nicaragua | 13.04786907 | Viet Nam | 13.98991 |
| Ethiopia | 11.84841647 | Niger | 12.01269658 | Yemen | 12.83282 |
| Fiji | 12.16542048 | Nigeria | 13.37791462 | Zambia | 11.81945 |
| Finland | 12.18539824 | North Macedonia | 11.5540551 | Zimbabwe | 12.35996 |

**Table B2.** Country fixed effects: for Basel AML Index (y1) on Government AI Readiness Index (x1), log GDP per capita (x2_log), Rule of Law Index (x3), and interaction term (x1 × x3)

| Country | fe_estimate | Country | fe_estimate | Country | fe_estimate |
|---|---|---|---|---|---|
| Afghanistan | 12.16374278 | Georgia | 9.69682335 | Nigeria | 11.7425449 |
| Albania | 10.31510374 | Germany | 9.486611509 | North Macedonia | 9.412007007 |
| Algeria | 12.07433879 | Ghana | 9.237888254 | Norway | 8.628536277 |
| Angola | 11.68765646 | Greece | 9.388987576 | Pakistan | 10.66633083 |
| Antigua and Barbuda | 10.3289248 | Grenada | 9.992942383 | Panama | 11.64130349 |
| Argentina | 10.54625456 | Guatemala | 10.41956429 | Paraguay | 10.4183211 |
| Australia | 9.245284254 | Guinea | 10.82910971 | Peru | 10.14313558 |
| Austria | 9.578258357 | Guyana | 10.82306166 | Philippines | 10.88425484 |
| Bahamas | 11.53858352 | Haiti | 12.61554935 | Poland | 9.835632318 |
| Bangladesh | 10.63431076 | Honduras | 10.44562623 | Portugal | 9.346208908 |
| Barbados | 10.94349944 | Hungary | 10.87914949 | Republic of Moldova | 9.795415924 |
| Belarus | 10.72141422 | India | 10.14315113 | Republic of Korea | 9.930574702 |
| Belgium | 9.517495761 | Indonesia | 10.05776122 | Romania | 10.25196738 |
| Belize | 10.77979132 | Ireland | 9.841782703 | Russian Federation | 11.2554391 |
| Benin | 11.10994577 | Italy | 10.36434091 | Rwanda | 9.98152785 |
| Bolivia | 10.88234747 | Jamaica | 10.47505716 | Saint Kitts and Nevis | 11.56996519 |
| Bosnia and Herzegovina | 10.78717558 | Japan | 10.08545144 | Saint Lucia | 10.24662235 |
| Botswana | 9.929917799 | Jordan | 10.24627116 | Saint Vincent and the Grenadines | 9.491467506 |
| Brazil | 10.78294012 | Kazakhstan | 10.40524205 | Senegal | 11.14655094 |
| Bulgaria | 10.07863848 | Kenya | 11.73308621 | Serbia | 10.62637846 |
| Burkina Faso | 10.68290369 | Kuwait | 12.1219481 | Sierra Leone | 11.33423287 |
| Cambodia | 11.95750503 | Kyrgyzstan | 10.50285465 | Singapore | 9.980741043 |
| Cameroon | 11.43642205 | Latvia | 9.350537196 | Slovakia | 9.83145266 |
| Canada | 9.718445627 | Lebanon | 10.94738846 | Slovenia | 8.965087686 |
| Chile | 9.337601898 | Liberia | 11.15747988 | South Africa | 10.65862848 |
| China | 12.81176914 | Lithuania | 8.566315175 | Spain | 9.281617886 |
| Colombia | 10.21566718 | Luxembourg | 9.799104387 | Sri Lanka | 11.01412197 |
| Congo | 12.17579663 | Madagascar | 11.17013976 | Suriname | 11.93710822 |
| Costa Rica | 9.984798836 | Malawi | 9.489410501 | Sweden | 8.404058997 |
| Cote d'Ivoire | 11.46534902 | Malaysia | 10.85818956 | Thailand | 11.42583318 |
| Croatia | 10.03795966 | Mali | 11.41658034 | Togo | 10.97588862 |
| Cyprus | 10.46417394 | Malta | 10.72552296 | Trinidad and Tobago | 10.37230417 |
| Czechia | 9.232667216 | Mauritania | 11.68467783 | Tunisia | 9.998172375 |
| Democratic Republic of the Congo | 12.0801258 | Mauritius | 10.34521788 | Türkiye | 11.72679707 |
| Denmark | 8.461974896 | Mexico | 11.06273563 | Uganda | 11.03949361 |
| Dominica | 9.429532853 | Mongolia | 10.64166841 | Ukraine | 10.00382431 |
| Dominican Republic | 10.51953612 | Montenegro | 9.568395462 | United Arab Emirates | 11.84931241 |
| Ecuador | 10.30371706 | Morocco | 10.12106686 | United Kingdom | 9.198020452 |

**Table B2 (cont.).** Country fixed effects: for Basel AML Index (y1) on Government AI Readiness Index (x1), log GDP per capita (x2_log), Rule of Law Index (x3), and interaction term (x1 × x3)

| Country | fe_estimate | Country | fe_estimate | Country | fe_estimate |
|---|---|---|---|---|---|
| Egypt | 10.57398367 | Mozambique | 11.67737495 | United Republic of Tanzania | 10.60958129 |
| El Salvador | 10.2691629 | Myanmar | 12.49581245 | United States of America | 10.3377722 |
| Estonia | 7.67830539 | Namibia | 9.813502886 | Uruguay | 9.313088648 |
| Ethiopia | 10.4821928 | Nepal | 10.32337869 | Uzbekistan | 10.37681045 |
| Finland | 7.892270017 | Netherlands | 9.496568992 | Viet Nam | 12.10930569 |
| France | 9.223291471 | New Zealand | 8.681945327 | Zambia | 10.2567484 |
| Gabon | 13.05559981 | Nicaragua | 11.44578543 | Zimbabwe | 10.84711528 |
| Gambia | 9.569893557 | Niger | 10.65187312 | | |


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