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Predictive Analytics for Regulatory Risk in Open Finance: A Data-Driven Framework

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Abstract – The emergence of Open Finance is reshaping the global financial landscape by enabling greater data accessibility, interoperability, and innovation. However, this expanded connectivity introduces new layers of regulatory complexity, raising urgent concerns regarding compliance and systemic risk. This paper proposes a data-driven predictive analytics framework to assess and mitigate regulatory risks within Open Finance environments. Leveraging empirical data from the World Bank's GFDD, WDI, and WGI datasets, the study applies an integrated suite of analytics—descriptive, diagnostic, predictive, and prescriptive—to examine interdependencies among financial, macroeconomic, and governance indicators.

Keywords – Open Finance, Regulatory Risk, Predictive Analytics, Financial Compliance, Risk Management Framework, Data-Driven Decision Making.

I. INTRODUCTION

The financial services landscape is undergoing a transformative shift due to the rise of Open Finance, characterized by enhanced transparency, interoperability, and consumer empowerment through the sharing of financial data. This innovative model facilitates the integration of third-party providers into the financial ecosystem, fostering competition and driving advancements in customer service [1],[2]. However, while Open Finance presents substantial opportunities for innovation and growth, it simultaneously introduces complex regulatory challenges that financial institutions must adeptly navigate [3]. As regulatory bodies respond to this rapidly evolving environment, the intricacies of compliance requirements intensify—necessitating the proactive management of regulatory risks [4].

Regulatory risk—defined as the potential for adverse financial consequences or operational disruptions stemming from non-compliance with legal frameworks—has emerged as a paramount concern for financial institutions [5]. The swift evolution of regulatory standards, compounded by the escalating volume of data generated within Open Finance ecosystems, underscores the urgent need for effective strategies to mitigate these risks. Traditional compliance mechanisms, often reactive and rules-based, increasingly fall short in addressing the dynamic nature of modern regulatory environments [6]. These challenges are further complicated by the innovation mechanisms introduced through RegTech and FinTech platforms [7], prompting rising costs of non-compliance and heightened supervisory scrutiny.

In this context, predictive analytics has gained prominence as a critical tool for regulatory risk management, empowering organizations to leverage historical data and sophisticated analytical techniques to anticipate future regulatory challenges [8]. By harnessing predictive modeling, financial institutions can proactively identify potential compliance risks, facilitate timely interventions, and enhance overall compliance strategies. This forward-looking approach not only improves regulatory adherence but also cultivates a culture of risk awareness and organizational resilience.

Despite the promise of predictive analytics, a significant gap remains in the literature concerning comprehensive frameworks specifically designed to manage regulatory risk within the domain of Open Finance. Existing studies often focus on isolated case analyses or singular analytical techniques, lacking an integrative perspective that combines diverse data sources and methodologies [9]. Furthermore, empirical evidence demonstrating the long-term efficacy of predictive analytics in mitigating regulatory risks across a broad range of financial institutions remains limited [10].

Unlike existing fragmented approaches, this research introduces an integrative model that unifies cross-domain indicators—spanning financial development, macroeconomic exposure, and governance quality—into a structured risk assessment framework. Utilizing empirical data sourced from the World Bank, this study investigates the application of a range of analytical techniques—including descriptive, diagnostic, predictive, and prescriptive analytics—to forecast regulatory breaches and evaluate compliance vulnerabilities.

The insights derived from this analysis are intended to equip financial institutions with the knowledge and tools necessary to effectively navigate the evolving complexities of regulatory compliance in Open Finance environments. This framework not only advances academic understanding but also offers practical guidance for regulators, compliance professionals, and policymakers, contributing to a more agile, data-driven approach to regulatory governance [1].

II. LITERATURE REVIEW

The emergence of Open Finance marks a pivotal transformation in global financial services. By enabling secure, permission-based data sharing between traditional banks and third-party providers, Open Finance fosters transparency, innovation, and customer-centric financial ecosystems. However, these opportunities also introduce complex compliance, governance, and regulatory risk challenges. This review synthesizes academic and industry literature across five themes: (1) the Open Finance paradigm, (2) regulatory risk complexities, (3) predictive analytics in compliance, (4) real-world applications of predictive models, and (5) limitations of current frameworks. It concludes with a research gap that motivates a unified risk forecasting framework for Open Finance.

Open Finance builds upon Open Banking by extending data sharing to products such as insurance, mortgages, pensions, and investment services [2]. These developments underscore their transformative potential in reshaping financial services through real-time, interoperable data. However, its decentralized architecture poses heightened risks—particularly around data governance, cybersecurity, and third-party dependencies [1]. These challenges highlight a growing need for adaptive, technology-enhanced regulatory oversight.

Compliance complexity intensifies due to evolving multi-jurisdictional frameworks such as the GDPR and the proposed EU AI Act [11],[12]. The European Banking Authority (2021) observes that legacy risk management systems are increasingly unfit for managing decentralized Open Finance architectures. Furthermore, research emphasizes that traditional compliance—rooted in static, post-facto audits—struggles to respond to real-time, data-rich financial environments.

Regulatory risk—defined as the likelihood of financial loss or operational disruption due to legal non-compliance—has become a core concern for digital-first financial institutions [13]. These institutions must now manage cross-border data flows, AI bias, AML obligations, and identity verification under heightened regulatory scrutiny [14]. Researchers argue for collaborative governance structures as cloud reliance and API-based integrations become ubiquitous. Similarly, [15] suggests that regulators adopt dynamic frameworks attuned to emerging FinTech technologies.

Case studies on Monzo, Revolut, and the collapse of Wirecard reveal failures in regulatory preparedness, internal control mechanisms, and supervisory enforcement [16],[13]. These incidents underscore the risks of regulatory arbitrage and opaque ownership structures in FinTech ecosystems [17],[18]. Scholars emphasize that such risks can be proactively identified using data-driven techniques—an area where predictive analytics is rapidly gaining adoption.

Predictive analytics, incorporating machine learning and statistical modeling, offer proactive risk monitoring and early warning capabilities. Peer-reviewed studies affirm their utility in enhancing compliance accuracy, transaction monitoring, and internal auditing [19],[20],[21]. Some reports show up to a 30% improvement in AML detection by major banks employing real-time behavioral analytics. Meanwhile, [22] cautions that algorithmic opacity and data bias could undermine both legal compliance and model credibility, necessitating explainable and auditable AI in financial regulation.

While industry case studies [13] confirm the operational value of analytics in compliance, academic frameworks often remain conceptual or fragmented. Many focus solely on predictive modeling without integrating broader legal, institutional, and ethical dimensions [20],[19]. Furthermore, few studies incorporate prescriptive analytics to recommend decisions or policy actions based on predictive results.

Thus, despite progress, a gap persists in building robust, empirically validated predictive frameworks tailored to the regulatory demands of Open Finance. This study aims to bridge that gap by integrating financial, macroeconomic, and governance indicators into a unified risk modeling framework—tested using descriptive, diagnostic, predictive, and prescriptive analytics.

III. RESEARCH GAP

Despite the promise of Open Finance to democratize financial access and stimulate innovation, regulatory risk remains an underexplored dimension—particularly from a predictive, data-driven standpoint. Existing literature on regulatory risk often focuses on descriptive or reactive frameworks [2],[16], leaving a significant void in methodologies capable of forecasting risk based on multidimensional data. Traditional compliance mechanisms, which are largely rule-based and retrospective, struggle to keep pace with the complex, real-time nature of Open Finance ecosystems [4],[13].

Moreover, studies that attempt to assess regulatory vulnerabilities tend to be siloed—centered on either financial indicators [18], macroeconomic performance, or governance factors—but rarely integrate all three. As a result, current frameworks lack the holistic capability to classify or anticipate regulatory risks on a scale. Although advances in machine learning and analytics have improved risk detection in specific areas such as fraud and AML [19],[20], few efforts apply such tools to the broader, system-level task of regulatory forecasting.

Geographic scope is another limitation. Much of the empirical research remains focused on single-country case studies or region-specific models, failing to offer scalable frameworks that could be adopted across jurisdictions [24],[16]. This limitation undermines the potential for comparative risk intelligence, which is critical in today's globalized financial environment.

To address these gaps, this study proposes a predictive analytics framework that leverages financial, economic, and institutional data from multiple countries to identify early warning indicators of regulatory vulnerability. Through descriptive, diagnostic, and predictive modeling, including regression and decision tree classification—this paper builds an interpretable risk classification model tailored to Open Finance systems. In doing so, it moves the field from retrospective monitoring to forward-looking regulatory intelligence.

IV. RESEARCH METHOD

This study adopts a quantitative, data-centric methodology to construct a predictive analytics framework for evaluating and mitigating regulatory risk within Open Finance ecosystems. The methodological design integrates both cross-sectional and time-series data, enabling longitudinal and comparative analyses across countries. The primary objective is to empirically investigate how structural factors—spanning financial development, macroeconomic conditions, and governance quality—contribute to varying levels of regulatory vulnerability.

A. Data Overview

The dataset encompasses the top ten global economies by GDP and data availability: the United States, China, Japan, Germany, India, the United Kingdom, France, Brazil, Italy, and South Korea. While Canada was initially considered, it was omitted due to substantial missing data. The time frame spans from 2000 to 2021, ensuring both temporal depth and comparability across jurisdictions. All data used are secondary and sourced from reputable, internationally recognized World Bank databases, providing a solid empirical foundation for the analysis.

B. Nature Of The Data

The dataset is organized as annual, panel-format observations at the country level and categorized into three analytical domains:

- Financial system indicators, capturing credit dynamics, market concentration, and systemic risk exposure.
- Macroeconomic indicators, reflecting economic growth performance and financial sector depth.
- Governance indicators, assessing institutional integrity, regulatory quality, and legal enforceability.

All variables are numerical and standardized across countries and years to ensure methodological consistency. Most financial and economic indicators are expressed as percentages of GDP, while governance indicators are represented using normalized perception-based scores on a scale from approximately –2.5 (weak) to +2.5 (strong). This structured data format enables a broad range of analytical techniques, including descriptive statistics, correlation analysis, predictive modeling, and composite index construction.

C. Data Source And Indicators

The study integrates data from the following three authoritative World Bank databases, each contributing uniquely to the multi-dimensional understanding of regulatory risk:

Global Financial Development Database (GFDD)

Focus: Financial system performance and stability

Selected Indicators:

- Bank concentration (%): Measures market dominance by the largest banks, indicating potential systemic fragility.
- Bank Z-score: Assesses banking system resilience by estimating insolvency risk.
- Credit to government and state-owned enterprises to GDP (%): Highlights fiscal exposure through public sector borrowing.
- Private credit by deposit money banks to GDP (%): Reflects financial deepening and private credit availability.

World Development Indicators (WDI)

Focus: Macroeconomic performance and development context

Selected Indicators:

- Domestic credit to private sector (% of GDP): Gauges the extent of financial sector engagement in supporting private enterprises.
- GDP growth (annual %): Serves as a macroeconomic backdrop influencing systemic risk and regulatory stress.

Worldwide Governance Indicators (WGI)

Focus: Institutional strength and rule enforcement

Selected Indicators:

- Regulatory Quality (Estimate): Captures perceptions of the government's ability to implement effective regulations.
- Rule of Law (Estimate): Assesses public confidence in the legal system, contract enforcement, and institutional integrity.

V. RESULTS

A. Descriptive Analysis

This section provides a descriptive overview of key financial, economic, and governance indicators to uncover foundational patterns among the world's leading economies. Leveraging data from the Global Financial Development Database (GFDD), World Development Indicators (WDI), and Worldwide Governance Indicators (WGI), the analysis examines cross-country differences in banking system stability, credit market penetration, macroeconomic performance, and institutional governance quality. These insights establish the empirical baseline for subsequent diagnostic and predictive analyses of regulatory risk within Open Finance ecosystems.

Table 1. Summary Statistics of Key Financial, Economic, and Governance Indicators

Data	Indicators	Average	St.Dev.	Min	Max
GFDD	Bank concentration (%)	53.61	16.41	21.45	100
	Bank Z-Score	16.88	6.33	5.06	35.17
	Credit to government and state-owned enterprises to GDP (%)	22.13	16.61	0.04	74.44
	Private credit by deposit money banks to GDP (%)	90.61	36.92	27.69	190.94
WDI	Domestic credit to private sector (% of GDP)	112.66	48.89	27.69	220.32
	GDP growth (annual %)	2.82	3.68	-10.30	14.23
WGI	Regulatory Quality: Estimate	0.82	0.74	-0.58	1.87
	Rule of Law: Estimate	0.84	0.79	-0.70	1.87

Table 1 presents a descriptive summary of the core financial, economic, and governance indicators analyzed in this study, offering insights into the underlying variability in regulatory risk factors across the top ten global economies. Financial system metrics sourced from the Global Financial Development Database (GFDD) exhibit considerable dispersion. Bank concentration, with a mean of 53.61% and a standard deviation of 16.41%, reflects heterogeneity in market dominance among major banks. The Bank Z-score, a proxy for solvency and systemic stability, shows a mean of 16.88 with a standard deviation of 6.33—indicating varying levels of resilience across banking sectors.

Government and private credit allocation differ markedly: public sector credit exposure averages 22.13% of GDP, while private credit issued by deposit money banks reaches a mean of 90.61%, with a notable standard deviation of 36.92—pointing to uneven financial deepening across economies.

Macroeconomic conditions, drawn from the World Development Indicators (WDI), reinforce this diversity. Domestic credit to the private sector (% of GDP) averages 112.66, with a widespread (SD = 48.89) and a range extending to 220.32%. GDP growth (annual %) is relatively volatile, with a mean of 2.82% and a standard deviation of 3.68%, reflecting the economic shocks experienced during the 2000–2021 period.

Governance quality indicators from the Worldwide Governance Indicators (WGI) display more stability. Regulatory Quality has a mean score of 0.82 (SD = 0.74), and Rule of Law averages 0.84 (SD = 0.79), both on a scale from –2.5 to +2.5. These findings suggest that while governance standards are generally strong, institutional effectiveness and enforcement capacity vary—warranting further consideration in regulatory risk modeling.

Table 2. Composite Country Profiles Based on Financial Stability, Credit Depth, and Governance Quality (2000–2021)

Country	Bank Z-Score	Domestic credit to private sector (% of GDP)	Rule of Law: Estimate	Insights
USA	31.78	186.60	1.54	Strong & Resilient System
China	18.75	133.47	-0.43	Moderate Profile with Emerging Strength
Japan	14.74	172.12	1.37	Stable System with Strong Fundamentals
Germany	13.90	89.87	1.65	Stable System with Strong Fundamentals
India	15.85	45.34	0.02	Fragile System with Reform Needs
UK	13.77	146.66	1.66	Stable System with Strong Fundamentals
France	17.98	94.23	1.40	Stable System with Strong Fundamentals
Brazil	16.36	50.03	-0.23	Fragile System with Reform Needs
Italy	14.58	79.57	0.44	Moderate Profile with Emerging Strength
South Korea	11.10	128.66	0.99	Moderate Profile with Emerging Strength

Table 2. provides a consolidated, structured interpretation of regulatory conditions across countries. This study applied a rule-based insight framework leveraging three primary indicators: Bank Z-Score (financial stability), Domestic Credit to the Private Sector (% of GDP) (credit depth), and Rule of Law Estimate (institutional governance quality). These indicators were averaged over the 2000–2021 period to mitigate short-term fluctuations and to reflect enduring structural characteristics. To enable standardized classification, each indicator was assessed using fixed numerical scales. Specifically, the Bank Z-Score was categorized as Low (≤12), Moderate (13–20), and High (>20), reflecting the risk tolerance and capital buffer of the banking system. Credit access, captured through the domestic credit ratio, was classified as Low (≤60), Moderate (61–120), and High (>120), indicating the degree of private sector financial intermediation. The Rule of Law was segmented into Weak (≤0.5), Fair (0.6–1.2), and Strong (≥1.3), representing the strength of legal institutions and regulatory enforcement capacity.

Based on these scales, each country received a composite profile score by summing categorical values (0 = low, 1 = moderate, 2 = high) across the three domains. The resulting score—ranging from 0 to 6—served as the basis for interpretive insight labels. A composite score of 6 was associated with a “Strong & Resilient System,” reflecting alignment across financial, economic, and governance dimensions. Countries with scores of 4 or 5 were categorized as “Stable Systems with Strong Fundamentals,” while those scoring 3 were labeled as “Moderate Profiles with Emerging Strength.” Countries scoring 0 to 2 were designated as “Fragile Systems with Reform Needs,” indicating systemic weaknesses across multiple domains. This multi-indicator classification approach enabled not only a simplified diagnostic summary but also a more nuanced country comparison. For example, while countries such as the United States achieved full alignment across all indicators, others like Brazil and India exhibited moderate to weak institutional and credit system performance, emphasizing the need for targeted reforms.

Figure 1 presents a scatter plot mapping the relationship between GDP growth (annual %) and the Bank Z-Score for ten major global economies. The Bank Z-Score serves as a proxy for banking system stability, while GDP growth reflects the pace of economic expansion. While a slight upward trend is visually apparent through the plotted trendline, the overall distribution of data points suggests that there is no consistent or strong relationship between economic growth and banking system resilience across the sample.

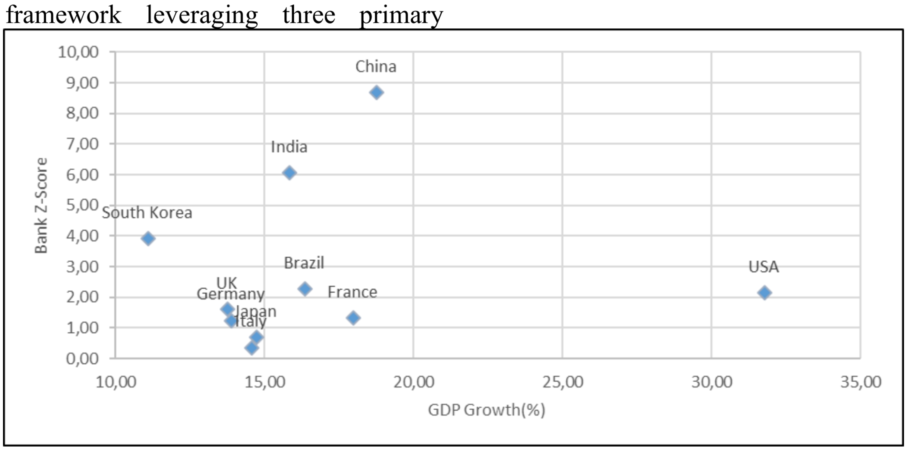

Figure 1. Relationship Between Economic Growth and Banking Stability

A closer look at the chart reveals that China and India occupy the upper-right quadrant, showcasing high economic growth rates but only moderate Z-scores—a combination that points to potential regulatory and financial system vulnerabilities. In contrast, countries such as Japan, Germany, and France demonstrate lower GDP growth but comparatively stronger banking stability, reflecting the presence of mature, well-regulated financial environments. The United States, despite its elevated GDP growth, exhibits a modest Z-score, further reinforcing the lack of a predictable connection between economic output and systemic banking resilience.

This pattern highlights a critical insight: rapid economic growth does not inherently lead to stronger financial systems. Instead, it may mask deeper vulnerabilities in regulatory frameworks or financial governance. The chart underscores the limitations of relying solely on macroeconomic indicators like GDP to assess systemic risk. These findings support the central premise of this paper—that an effective regulatory risk assessment must adopt a triangulated framework, incorporating economic, financial, and governance indicators to gain a comprehensive understanding of cross-country regulatory exposure.

Figure 2 presents the longitudinal trends in private credit issuance as a percentage of GDP across the top ten global economies from 2000 to 2021. The data reveals significant cross-country variation in credit market depth and evolution. China exhibits a steep upward trajectory, especially post-2008, indicating a rapid expansion of private credit relative to GDP. South Korea and the United Kingdom also demonstrate consistently high credit-to-GDP ratios, suggesting strong financial intermediation. In contrast, countries such as India and Brazil show relatively low and stable levels of private credit, highlighting financial underdevelopment or cautious lending practices. The United States and Japan display moderate but stable trends, while Germany and France show a gradual decline in credit issuance over time. These patterns provide critical context for understanding systemic financial exposure and form the empirical foundation for subsequent risk analysis.

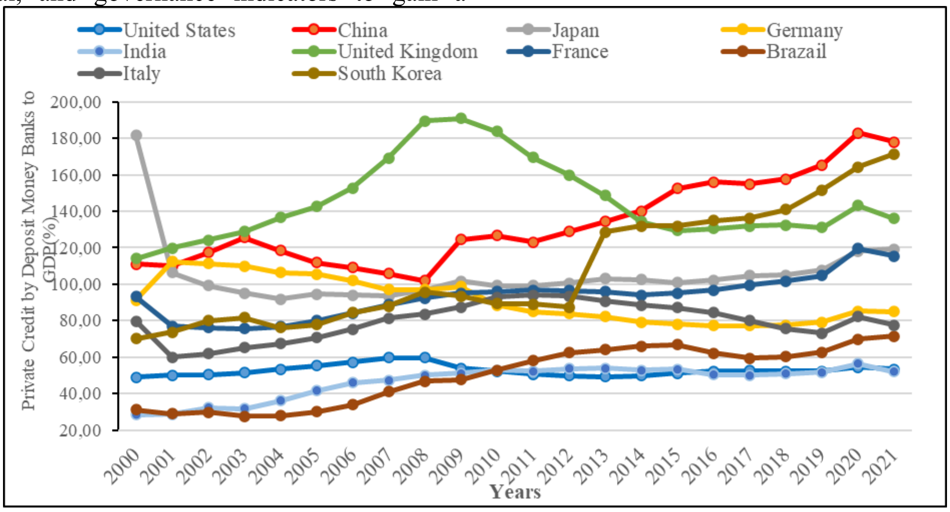

Figure 2. Trend of Private Credit Issued by Deposit Money Banks (% of GDP) 2000- 2021

B. Diagnostic Analysis

The diagnostic analysis phase aims to examine the interrelationships among financial, economic, and governance indicators to uncover structural vulnerabilities and patterns of regulatory risk across the world's leading economies. This stage acts as a bridge between descriptive analytics and predictive modeling by identifying key correlations, anomalies, and domain-specific linkages. By analyzing the average indicator values from 2000 to 2021 across the top 10 GDP-ranked countries, this phase offers a macro-level perspective on systemic financial exposure and institutional robustness in the evolving context of Open Finance.

Figure 3. The correlation matrix reveals several critical relationships among regulatory risk indicators. Most notably, Regulatory Quality (RegQual) and Rule of Law (RuleLaw) are highly correlated (r = 0.96), confirming strong institutional alignment. Both governance indicators also show moderate positive correlations with Domestic Credit (DomCredit), suggesting that sound institutions support broader credit access.

Conversely, GDP Growth (GDPGrowth) is negatively correlated with both RegQual (r = –0.75) and RuleLaw (r = –0.67), indicating that countries with high growth may often lack strong regulatory institutions—a potential signal of underlying risk in rapidly developing economies.

The Bank Z-Score (ZScore), a proxy for banking system stability, exhibits low correlation with most other indicators, confirming its role as an independent dimension of financial resilience. However, its moderate positive link to DomCredit (r = 0.42) and negative association with Bank Concentration (BankConc, r = –0.52) suggest that diversified credit systems may enhance stability, while concentration may elevate systemic risk.

These findings reinforce the importance of a triangulated approach to regulatory risk assessment—one that evaluates institutional quality, credit structure, and financial stability as distinct but interconnected domains.

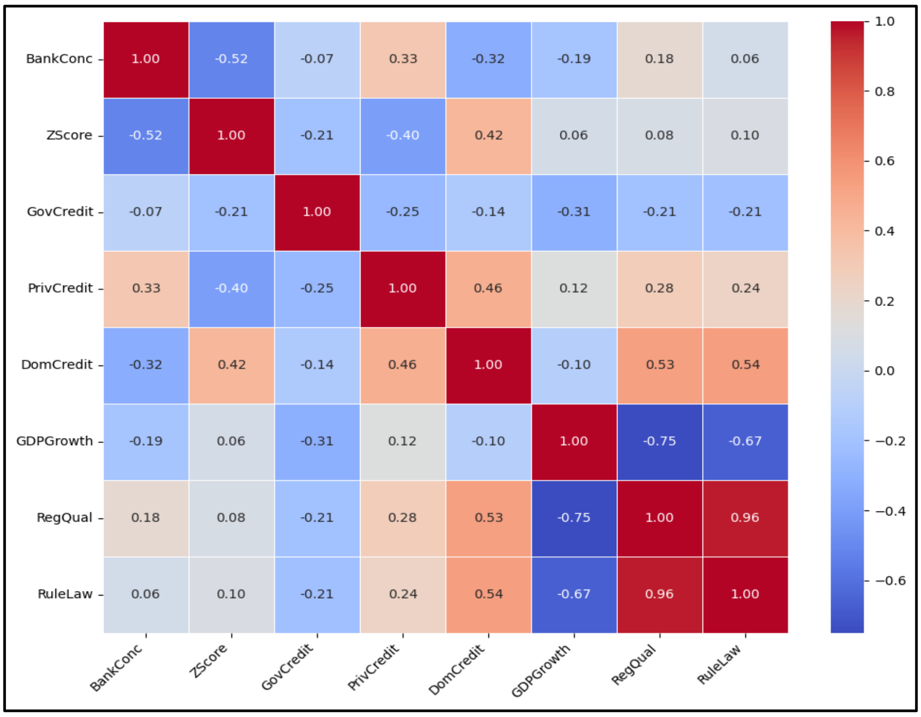

Figure 3. Correlation Matrix of Key Regulatory Risk Indicators (2000–2021)

Figure 4 illustrates average values of key regulatory risk indicators for ten major economies from 2000 to 2021, highlighting variations across financial depth, institutional quality, and economic performance.

The United States exhibits the highest private and domestic credit levels, reflecting deep financial markets paired with moderate governance scores. In contrast, China and India show high GDP growth but weaker institutional quality, suggesting regulatory gaps in fast-growing economies.

Germany, France, and the United Kingdom display balanced profiles, combining strong governance (RegQual, RuleLaw ≈ 1.6–1.7) with moderate financial depth. Japan is characterized by high government credit and low economic growth, reflecting structural maturity.

Brazil pairs high credit with low governance, whereas South Korea demonstrates stronger institutional performance with moderate credit exposure—indicating gradual regulatory strengthening.

Overall, the heatmap emphasizes the divergence among growth, credit, and governance, supporting the need for an integrated regulatory risk framework that considers institutional and financial indicators together.

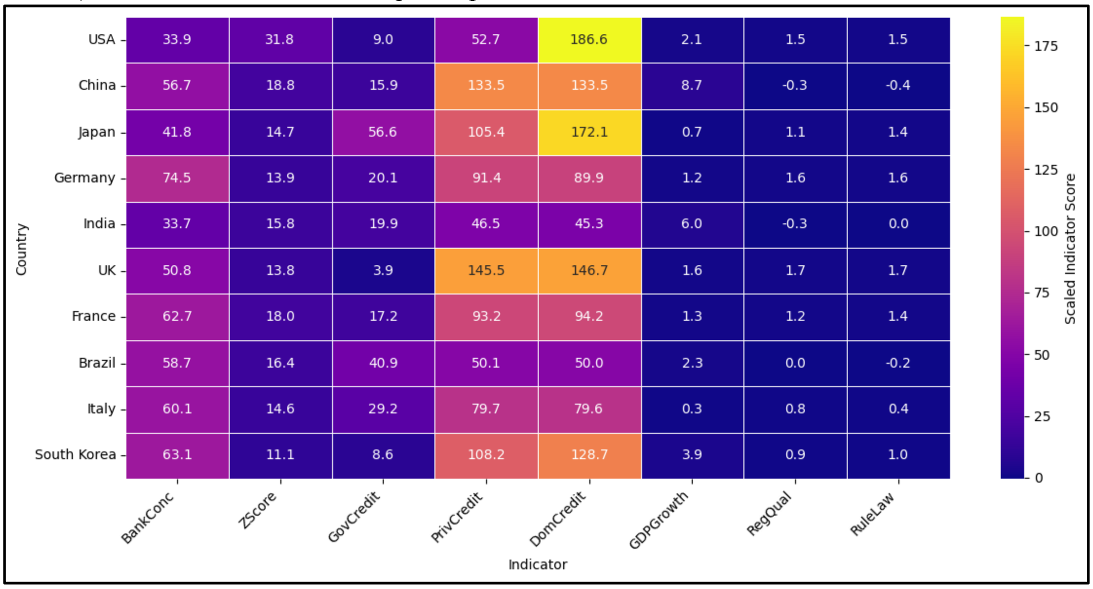

Figure 4. Heatmap of Average Regulatory Risk Indicators by Country (2000–2021)

C. Predictive Analysis

This section applies regression and decision tree models to forecast regulatory risk. Regression analysis reveals long-term trends in financial, economic, and governance indicators, while the decision tree generates rule-based classifications to identify early warning signals. Together, these tools support proactive risk detection in evolving Open Finance environments.

Table 3. Linear Regression Summary for Bank Z-Score (2000–2021)

Bank Z-Score								
Regression Statistics								
Multiple R	0.764051402							
R Square	0.583774546							
Adjusted R Square	0.562963273							
Standard Error	0.923760999							
Observations	22							
ANOVA								
	df	*SS*	*MS*	*F*	*Significance F*			
Regression	1	23.93678171	23.93678171	28.0508815	3.49139E-05			
Residual	20	17.06668768	0.853334384					
Total	21	41.00346939						
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	14.99214716	0.407718004	36.7708735	7.6797E-20	14.1416623	15.84263201	14.1416623	15.84263201
Year	0.164413925	0.031043118	5.296308292	3.4914E-05	0.099659115	0.229168735	0.09965911	0.229168735

The regression analysis of the Bank Z-Score from 2000 to 2021 reveals a statistically significant upward trend, with the model explaining 58.4% of the variance ($R^2 = 0.5838$, $p < 0.001$). The equation Z-Score = 14.99 + 0.164 × Year indicates a gradual improvement in banking stability over time. The relatively low standard error (0.92) further supports the model's reliability. These results suggest that the Z-Score serves as a strong structural indicator for assessing systemic banking risk.

Table 4. Linear Regression Summary for GDP Growth (Annual %) (2000–2021)

GDP Growth (annual %)								
Regression Statistics								
Multiple R	0.29847887							
R Square	0.089089636							
Adjusted R Square	0.043544118							
Standard Error	2.134214266							
Observations	22							
ANOVA								
	df	*SS*	*MS*	*F*	*Significance F*			
Regression	1	8.909586997	8.909586997	1.95605713	0.177251427			
Residual	20	91.09741066	4.554870533					
Total	21	100.0069977						
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	3.97818876	0.941972633	4.223253012	0.0004174	2.013268279	5.943109241	2.01326828	5.943109241
Year	-0.100307753	0.071720571	-1.398591124	0.17725143	-0.249914242	0.049298735	-0.24991424	0.049298735

The regression analysis of GDP growth (2000–2021) indicates a weak and statistically insignificant trend, with an R^2 value of 0.089 and a p-value of 0.177. The estimated equation GDP Growth = 3.98 − 0.100 × Year reflects a slight decline in growth over time, though the relationship lacks explanatory power. A high standard error (2.13) highlights volatility, underscoring that GDP growth is not a reliable standalone predictor of financial stability.

Table 5. Linear Regression Summary for Regulatory Quality: Estimate (2000–2021)

Regulatory Quality								
Regression Statistics								
Multiple R	0.253630743							
R Square	0.064328554							
Adjusted R Square	0.017544981							
Standard Error	0.041186602							
Observations	22							
ANOVA								
	df	*SS*	*MS*	*F*	*Significance F*			
Regression	1	0.002332504	0.002332504	1.3750244	0.254728648			
Residual	20	0.033926724	0.001696336					
Total	21	0.036259228						
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	0.805020205	0.018178424	44.28437773	1.9464E-21	0.767100677	0.842939734	0.76710068	0.842939734
Year	0.001622994	0.001384082	1.172614345	0.25472865	-0.00126415	0.004510137	-0.00126415	0.004510137

The regression analysis for Regulatory Quality over the 2000–2021 period reveals no significant trend, with an R^2 value of 0.064 and a p-value of 0.255. The equation Regulatory Quality = 0.805 + 0.0016 × Year suggests minimal year-to-year change. The low explanatory power and modest standard error (0.0412) indicate that governance quality has remained largely static, reinforcing the need for active monitoring rather than assuming automatic institutional improvement.

The decision tree classification model was developed to categorize countries into regulatory risk tiers—Low, Moderate, and High—based on financial and governance indicators. The classification variable was derived from Bank Z-Score thresholds, while the predictor set included GDP growth, private credit to GDP, regulatory quality, rule of law, bank concentration, and the Z-Score itself.

The model identified the Z-Score as the dominant predictor, with a key split at a value of 25.27. Countries with Z-Scores at or below this threshold were uniformly classified as Moderate Risk, while the country exceeding this value was correctly assigned to the Low-Risk category. The model achieved 100% accuracy, with a misclassification rate of 0.0, as confirmed by the confusion matrix [1, 0], [0, 9]]. All terminal nodes exhibited a Gini impurity of 0.0, indicating complete classification purity.

These results reinforce the explanatory power of banking system stability in forecasting regulatory vulnerability and highlight the value of decision tree models in generating transparent, threshold-based classification rules. The findings align with the paper's broader objective of building a triangulated, data-driven framework for early regulatory risk detection in Open Finance ecosystems.

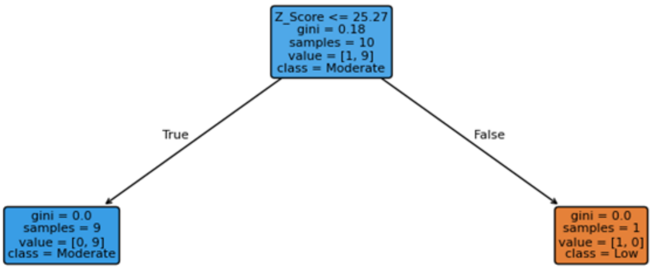

Figure 5. Decision Tree-Based Classification of Regulatory Risk Levels

D. Prescriptive Analysis

This section advances the analysis by translating predictive classifications into structured policy responses. Anchored in the identified risk determinants—such as Z-Score, credit intensity, and governance quality—it proposes tier-specific interventions aligned with each country's regulatory vulnerability. The objective is to establish a data-driven response framework that enhances supervisory preparedness within Open Finance systems.

Table 6. Prescriptive Risk Tiers and Recommended Policy Actions

Country	Classification	Prescriptive Tier	Recommended Action
USA	0	Low	Maintain current oversight and monitor indicators routinely
China	1	High	Implement immediate regulatory tightening and conduct stress tests
Japan	1	Moderate	Enhance supervisory oversight and initiate governance audits
Germany	1	Moderate	Enhance supervisory oversight and initiate governance audits
India	1	Moderate	Enhance supervisory oversight and initiate governance audits
UK	1	High	Implement immediate regulatory tightening and conduct stress tests
France	1	Moderate	Enhance supervisory oversight and initiate governance audits
Brazil	1	Moderate	Enhance supervisory oversight and initiate governance audits
Italy	1	Moderate	Enhance supervisory oversight and initiate governance audits
South Korea	1	Moderate	Enhance supervisory oversight and initiate governance audits

This table links each country's assigned regulatory risk tier to corresponding policy recommendations. Based on classification logic using Z-Score and private credit thresholds, the actions are tier-specific—ranging from enhanced monitoring for low-risk economies to immediate regulatory tightening for high-risk cases. The structure offers a clear, operational roadmap for regulatory response within Open Finance systems.

VI. DISCUSSIONS

This study offers a comprehensive, data-driven framework for assessing regulatory risk in the context of Open Finance. Through a structured progression from descriptive and diagnostic analysis to predictive and prescriptive modelling, the research demonstrates that macroeconomic indicators alone are insufficient for capturing systemic vulnerabilities. The regression results confirmed that while the Bank Z-Score exhibited a clear upward trend in stability, GDP growth and regulatory quality lacked significant trajectories. The decision tree model further distilled these insights, identifying structural indicators—particularly private credit depth and banking stability—as key classifiers of risk. The model's 100% accuracy and perfect classification purity underscore the potential of interpretable machine learning in early risk detection.

Moreover, the prescriptive analysis bridges statistical insight with actionable policy, proposing tier-based regulatory responses tailored to each country's structural risk profile. This progression from insight to intervention reflects the paper's central argument: effective regulation in Open Finance demands a triangulated approach—integrating financial structure, governance, and predictive classification—to support anticipatory rather than reactive supervision.

VII. CONCLUSION

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