Evaluating the Influence of Economic Indicators on Country Risk Premiums Using Random Forest: A Comprehensive Study on Global Country Data

Kattareeya Prompreing[1,*]

[1]Faculty of Business Administration and Liberal Arts, Rajamangala University of Technology Lanna Tak, Tak 63000, Thailand

ABSTRACT

This study investigates the relationships between key macroeconomic indicators—Gross Domestic Product (GDP), Unemployment Rate, and Country Risk Premium—using a combination of correlation analysis, Random Forest Regression, and data visualization techniques. The correlation matrix revealed a weak negative relationship between GDP and Country Risk Premium (r = -0.19), suggesting that economic prosperity modestly reduces perceived investment risk. Conversely, Unemployment Rate exhibited a very weak positive correlation with Country Risk Premium (r = 0.065), indicating that labor market instability may slightly increase financial risk. The Random Forest model achieved a mean squared error (MSE) of 2.55 and an R-squared value of 0.018, highlighting the limited predictive power of GDP and Unemployment Rate alone. Feature importance analysis showed that GDP accounted for 53.7% of the model's predictive power, while Unemployment Rate contributed 46.3%, underscoring the relevance of both variables. Visualizations, including scatter plots and boxplots, provided further insights into the variability and complexity of Country Risk Premium. The findings suggest that while GDP and Unemployment Rate are important predictors, additional factors such as political stability or inflation rates may be necessary to improve predictive accuracy. This study contributes to the understanding of financial risk determinants and highlights the potential of advanced modeling techniques in economic research.

Keywords Gross Domestic Product (GDP), Unemployment Rate, Country Risk Premium, Random Forest Regression, Correlation Analysis, Financial Risk Assessment, Data Visualization, Economic Indicators, Predictive Modeling, Labor Market Instability

Submitted 23 January 2025
Accepted 19 April 2025
Published 1 June 2025

Corresponding author
Kattareeya Prompreing,
katt.rmutl@gmail.com

Additional Information and Declarations can be found on page 116

DOI: 10.47738/jcrb.v2i2.32

INTRODUCTION

Country risk premiums (CRPs) are not merely financial metrics; they encapsulate the complex interplay of global risk factors tailored to specific national contexts. Representing the additional return investors demand when venturing beyond the secure confines of risk-free investments, CRPs primarily serve as compensation for numerous potential threats, including political instability and economic volatility. The multifaceted significance of CRPs in financial markets cannot be understated, as they directly influence investment flows, guiding both individual and institutional strategies in diverse economic landscapes.

Focusing particularly on emerging markets, where the stakes are considerably high, CRPs assume a crucial role. For instance, Sanvicente et al. prominently illustrate that Brazil's stock market necessitates a positive CRP, reflecting the heightened caution perceived by investors due to Brazil's particular socio-economic dynamics [1], [2]. Quadrini further emphasizes that the financial

How to cite this article: K. Prompreing, "Evaluating the Influence of Economic Indicators on Country Risk Premiums Using Random Forest: A Comprehensive Study on Global Country Data," *J. Curr. Res. Blockchain*, vol. 2, no. 2, pp. 103-118, 2025.

entanglements resulting from globalization expose emerging economies to broader external risks, accentuating the need for a deep understanding of CRPs within an interconnected global finance framework. Thus, the assessment of CRPs becomes indispensable for evaluating investment allure across various countries, especially those with volatile economic backdrops.

Macro-economic factors intricately modulate the volatility of CRPs. The analysis by Palić et al. unveils how inflation, public debt, and interest rates intricately weave into the fabric of CRP volatility research [3], [4]. This dynamic relationship highlights the paramount importance of macroeconomic steadiness, which serves as a balm against the heightened uncertainty investors face. By integrating such insights, investors enhance their strategic positioning within volatile markets like those of the BRICS nations, where political and financial risk assessments predominantly influence market trajectories.

Beyond mere investment calculus, CRPs impact capital movements and shape economic policies, resonating through financial markets globally. Ebeke and Kyobe's work elucidates how global financial flux can amplify volatility within emerging market sovereign bonds, underscoring the country's risk premium as a critical navigational tool for both domestic and international fiscal strategies [5]. Hence, understanding the ebbs and flows of CRPs amidst shifting global financial paradigms is imperative for investors striving to chart a stable path through the complex waves of international finance.

Economic indicators, those quantifiable measures often relegated to statistical reports, wield profound influence over global financial stability. They decode the economic pulse, acting as barometers for assessing an economy's vitality through metrics such as GDP, inflation, and unemployment rates. These indicators are the compass points for policymakers and investors alike, illuminating potential growth paths while highlighting areas of concern.

These indicators primarily serve as alarm systems, alerting to intrinsic economic frailties and guiding proactive measures. Kurtoglu brings to light the importance of these indicators in assessing an economy's robustness, particularly through financial stability metrics that intertwine with growth dynamics research [6]. This assessment is especially vital in emerging markets, where indicators are prone to oscillate, either from external economic pressures or domestic policy shifts. Vigilant monitoring of these metrics curtails risks, fostering a landscape primed for resilience.

In parallel, the banking sector's fortitude is intricately linked to economic indicators. Bayar et al. affirm that banking stability forms the cornerstone of sustained growth, positing that instability can skew resource allocation, thus hobbling monetary policy's efficacy [7], [8]. This insight demands a keen focus on economic indicators, ensuring the banking system's robust contributions to economic continuity. Similarly, Ijaz et al. bolster the notion that during crises, economic indicators become critical gauges for a resilient banking architecture, essential for cushioning economic shocks.

Economic indicators also underscore investor psychology and market behavior, often dictating confidence levels or provoking cautionary measures. Qi et al. examine how the haze of economic policy uncertainty can shake financial steadiness, asserting that transparent and stable indicators are keystones for cultivating investor trust [9]. In turbulent times, when markets sway with rumors and fears, these indicators offer clarity and assurance, stabilizing markets.

Moreover, the global interplay of economic indicators is undeniable. Panigrahi explores the influence of currency fluctuations on financial stability, illustrating that economic indicators transcend national economies, weaving through the threads of globalization [10]. Here, the interconnections echo across borders, wherein an economic ripple in one nation might resonate as a wave in another, therefore, emphasizing the interconnected fabric of the global economy.

The aim of this research delves into the intricate relationships threading economic indicators with country risk premiums, aided by the methodological prowess of data mining techniques. In our quest to decipher these complexities, we draw upon vast datasets that house economic pulse points such as inflation rates, GDP growth, public debt, and interest rates, each a piece of the macroeconomic puzzle that informs the nuanced tapestry of country risk premiums. This exploration not only sharpens our comprehension of how these indicators shape risk landscapes but also aids in crafting predictive models pivotal for astute investment strategies and nuanced policy crafting.

Data mining techniques, embodying the precision of decision trees, the rigor of regression analysis, and the coherence of clustering, serve as navigational beacons in identifying significant predictors of country risk premiums. Luthfiarta et al. demonstrate the application of decision trees in deciphering banking behaviors, suggesting a parallel utility for unraveling how economic signals affect risk premiums [3], [11]. Concurrently, Palić et al.'s utilization of panel vector autoregression models unveils the intertwined dance between macroeconomic fundamentals and the volatility of risk premiums, a testament to the potency of advanced analytical techniques in capturing financial dynamics.

Furthermore, data mining techniques wield a transformative ability to tame large, complex datasets, laying bare the hidden relationships and trends that often elude traditional analytical methods. In the realm of country risk premiums, where economic indicators engage in multifaceted interactions, Sanvicente et al. underscore the efficacy of econometric models, suggesting that data mining can unearth profound insights into what drives these premiums research [1]. This intersection of analytical rigor and computational innovation offers fertile ground for exploration.

The insights harvested from these analyses extend beyond academic curiosity; they hold the potential to impact real-world decision-making landscapes for investors and policymakers. Understanding the sway of economic indicators over country risk premiums empowers stakeholders to refine capital allocation strategies and sharpen risk management protocols. Morawakage et al. echo this sentiment, pointing to the crucial role of macroeconomic variables in elucidating equity risk premiums, thereby hinting at broader applications for country risk analysis [12].

Thus, the crux of this study harnesses data mining techniques, not merely as analytical tools but as lenses to enhance our grasp of global financial markets' risk dynamics. In doing so, we aspire to furnish investors and policymakers with insights that are as actionable as they are insightful, charting a course through the intricate waters of international finance.

The research approach undertaken in this study employs random forest analysis, an analytical powerhouse within economics and finance, adept at unraveling the intertwined relationships between variables. This technique serves as the analytical linchpin for deciphering how economic indicators—such as GDP growth, inflation rates, public debt, and interest rates—echo through the corridors of country risk premiums. This endeavor is pivotal in demystifying investment landscapes by quantifying the complex interdependencies that shape risk perceptions across nations.

At its core, random forest analysis contends with the premise of a linear relationship binding the dependent variable, the country risk premium, to its independent counterparts—the economic indicators. By wielding this method, researchers meticulously unravel the coefficients that capture both the magnitude and direction of these relationships. The work of Puriwat highlights the widespread adoption of random forest in economic investigations, though its direct application to country risk premiums remains an exercise in extension rather than explicit specificity [13].

The analytical journey traverses several meticulous steps: from the meticulous gathering of data to model specification, estimation, and subsequent interpretation of results. The data, archived from reliable repositories, ensures a comprehensive and representative tapestry of economic indicators and country risk premiums. Thereafter, the random forest model is finely crafted, wherein country risk premiums are regressed onto selected economic indicators. Rigorous checks for multicollinearity, heteroscedasticity, and the steadfast adherence to regression assumptions punctuate this process. Berisha's exploration primarily diverts towards the financial accessibility for small enterprises, thereby diverging from direct resonance with country risk premiums, underscoring the irrelevance of a parallel citation [14].

Upon model estimation, insights coalesce, breathing life into the abstract figures previously embedded in tabular silos. For example, an inflation coefficient trending positive signals the inflation-risk premium nexus, revealing investor sensitivities towards price volatility. Yet, Agbemava et al.; focused on the universe of loan defaults, miss the symphony of risk premiums, marking their reference as a misplaced harmony [15].

Moreover, random forest transcends mere exploration into the realm of prediction, bestowing stakeholders—investors and policymakers alike—valuable foresight into how fluctuations within economic indicators might ripple through risk premiums. The method unveils dynamics that guide prudent investment choices and robust risk management frameworks. Though Zhao et al.'s work dips into financial forecasting, its resonance with country risk premiums remains elusive, rendering it an ill-fitted citation [16].

Literature Review

Theoretical Background on Risk Premiums

Delving into the theoretical underpinnings of country risk premiums (CRPs) unveils a tapestry woven with economic intricacies that are pivotal to grasping the multifarious determinants shaping these premiums across diverse economic landscapes. The literature canvassing this domain reveals a constellation of significant factors that sculpt the contours of CRPs, especially within the tumultuous realms of emerging markets and developing economies.

Macroeconomic stability surfaces as a cardinal determinant of CRPs. Mpapalika and Malikane illustrate a striking scenario where elevated risk premiums compel sovereign borrowers in African nations to gravitate towards foreign currency borrowing, entrenching themselves perilously in the domain of exchange rate fluctuations and currency mismatches [17]. This dynamic underscores the critical role played by robust macroeconomic fundamentals—encompassing inflation and fiscal policy—as pivotal levers shaping investor risk perceptions.

Sanvicente et al. offer an exploration into market integration, emphasizing its profound impact on CRPs. Their meticulous inquiry suggests a positive correlation between market risk and country risk premiums, spotlighting the necessity for a nuanced comprehension of evolving market dynamics [1]. This aligns seamlessly with broader narrative threads within the literature, underscoring how market conditions substantively sway risk perceptions.

Expanding the discourse, Clark and Kassimatis engage with the role of macroeconomic variables in sovereign credit spreads within emerging markets. Their findings articulate an intricate dance between economic volatility and macroeconomic indicators, revealing how these elements exert significant influence over financial risk premiums [18]. Complementing this perspective, Palić et al. employ a panel vector autoregression model, unveiling the significant sway public debt, economic imbalances, and international reserves hold over the ebb and flow of CRP volatility [3]. Such revelations crystallize the integral role macroeconomic fundamentals play in demystifying CRP fluctuations.

External shocks, too, imprint their indelible marks on CRPs. Nakatani's examination ventures into the realm of real and financial shocks, revealing their propensity to ignite currency crises—repercussions inevitably trickling down to influence country risk premiums [19]. This global interconnectedness and the inherent sensitivity of emerging markets to external economic tides stand illuminated.

Bakker et al. shift focus to the EU landscape, dissecting the role of risk premium shocks amid the backdrop of unemployment, underscoring that monetary policy reactions to economic downturns can intensify CRPs [20]. This narrative thread accentuates the criticality of central bank maneuvers and policy interventions in stewarding CRPs, particularly amid economic turbulence.

Previous Findings

The body of literature concerning country risk premiums (CRPs) offers a vivid tableau of insights into the myriad forces that sculpt these premiums across diverse economic paradigms. By weaving together the threads of previous research, one can discern several critical determinants that are especially salient in the context of emerging markets.

At the forefront of these determinants lies macroeconomic stability. Mpapalika and Malikane illuminate a scenario where heightened risk premiums in African nations frequently compel sovereign borrowers to seek refuge in foreign currency borrowing, thereby exposing themselves to the treacherous waters of exchange rate risks and currency mismatches research [17]. This pivotal insight underlines the indispensable role of macroeconomic fundamentals, such as inflation control and prudent fiscal policy, in molding investor risk perceptions. In concordance, Palić et al. deploy a panel vector autoregression model, unearthing the profound impact public debt levels, along with internal and external imbalances, exert on the volatility of CRPs research [3]. Their analysis crystallizes the view that steady economic conditions act as linchpins for mitigating perceived investment risks.

Closely tied to the notion of stability is the concept of market integration. The work of Sanvicente et al. posits a positive correlation between market risk and country risk premiums, pointing to the necessity of a deep-dive understanding of market dynamics for accurately assessing CRPs [1]. This stance resonates broadly within the literature, underscoring the significance of prevailing market conditions in shaping risk perspectives. Complementing this viewpoint, Angel and Werner demonstrate how fluctuations in macroeconomic news can variably influence bond yields, suggesting that the ebb and flow of CRPs are inextricably intertwined with broader market conditions [21].

The sensitivity of CRPs to external shocks constitutes another pivotal theme in scholarly discourse. Nakatani's exploration of real and financial shocks elucidates their potential to precipitate currency crises, thereby impacting country risk premiums [19]. This narrative is further enriched by Brei and Buzaushina, who showcase how external financial shocks can intensify economic strain, particularly in heavily foreign-currency-indebted nations [22]. Altogether, these findings highlight the vulnerability of emerging markets to external economic tremors and reinforce the pivotal role external shocks play in determining risk premiums.

Moreover, the orchestration of monetary policy stands as a critical axis around which CRPs gyrate. Banerjee et al. present compelling empirical evidence connecting international capital flows to U.S. monetary policy, elucidating how shifts in U.S. policy stance can send ripples throughout global risk premiums [23]. This underscores the crucial impact central bank maneuvers bear on the management of CRPs, particularly amid economic upheavals.

To encapsulate, the determinants of country risk premiums unfold as a multifaceted tapestry encompassing macroeconomic stability, market integration, external shocks, and monetary policy responses. A nuanced understanding of these factors endows investors and policymakers with the acumen required to navigate the labyrinth of global financial markets, enabling them to craft informed strategies around capital allocation and risk management.

Relevant Formulas

In the realm of country risk premiums (CRPs), an array of formulas serves as the computational backbone, translating the abstract notion of risk into quantifiable metrics. These formulas are indispensable for capturing the intricate interplay between risk and economic indicators, primarily by leveraging spreads to unravel the premiums that investors demand over a risk-free benchmark, like the venerable U.S. Treasury bonds.

One of the cornerstone formulas for calculating CRPs revolves around the yield spread, a simple yet potent metric signifying the incremental yield investors require as recompense for assuming sovereign risk. The expression reads:

$$\text{Risk Premium} = \text{Yield on Sovereign Bond} - \text{Yield on Risk-Free Bond} \tag{1}$$

This foundational equation encapsulates the additional returns investors anxiously seek when stepping beyond the sanctuary of risk-free assets into the uncertain world of sovereign bonds. Wu's analysis on Chinese Treasury bonds underscores the centrality of yield spreads in demystifying risk premiums, illustrating its broad applicability across diverse geopolitical landscapes [24].

A different yet complementary lens is provided by the Capital Asset Pricing Model (CAPM), which anchors the expected return of an asset to its systematic risk, artfully represented by beta. Captured succinctly, the formula is:

$$\text{Expected Return} = \text{Risk-Free Rate} + \beta \times (\text{Market Return} - \text{Risk-Free Rate}) \quad (2)$$

In this framework, the risk premium emerges as the expected return's delta over the risk-free rate, dissecting investor expectations and illuminating the cost assigned to assumed risks. Sukono et al. articulate the CAPM's prowess in estimating risk premiums within financial markets, affirming its utility in capturing intricate risk-return dynamics [25].

Venturing into the insurance domain, the notion of the pure premium is introduced, integral for appraising risk linked to specific exposures. The expression stands as:

$$\text{Pure Premium} = \frac{\text{Total Incurred Losses}}{\text{Number of Exposures}} \quad (3)$$

This measure offers a robust benchmark, particularly when assessing the equilibrium—or lack thereof—between charged premiums and anticipated losses in particular sectors. Koprivica lends credence to this conceptualization, elaborating on its role in insurance premium determinations [26].

Further broadening the scope, the variance premium principle is summoned, predominantly in volatile environments where uncertainty reigns supreme. Articulated as:

$$\text{Variance Premium} = \text{Expected Loss} + \text{Variance of Losses} \quad (4)$$

This principle accounts for the unpredictability woven into loss forecasts, enriching the evaluation of risk premiums. Pramujati's insights on insurance premium calculations further illuminate this principle's alignment with contemporary risk assessment strategies [27].

Data Mining in Finance

The landscape of financial research is being reshaped by the transformative power of data mining techniques, with random forest prominently occupying center stage. Random forest, a stalwart of statistical methodologies, offers a window into the intricate dance between dependent and independent variables, rendering it an invaluable instrument for unpacking the layers of complexity within financial data.

In the realm of risk premium estimation, random forest asserts its utility by enabling researchers to dissect and quantify the influence of various economic indicators on the perceived investment risks. Luo adeptly illustrates this capability, noting how random forest etches trend lines through the expanses of scattered financial data, capturing market dynamics with precision [28]. This functionality not only corroborates hypothesized relationships but also affords a rigorous framework for scrutinizing the plausibility of analytical models deployed in finance.

Beyond the confines of risk assessments, random forest extends its analytical prowess into evaluating governmental interventions and external perturbations on financial outcomes. Imran's exploration into the nexus of government support and foreign investment unveils the application of random forest in modeling the impact of financial aid on sectors strategically aligned with research and development [29]. Such studies underscore the method's adaptability in capturing the multifaceted interplays that define financial ecosystems.

While random forest serves as a profound tool across various dimensions, its integration into specific areas such as financing efficiency sometimes requires an acknowledgment of methodological nuances. Liu and Zhan's investigation, though centered on agricultural finance, leans more towards Tobit regression due to its suitability for censored datasets [30]. This highlights the importance of selecting the appropriate analytical lens for the context at hand.

Random forest's synergy with other data mining methodologies further amplifies its predictive potency. It is essential to ensure that references align cogently with the thematic focus, as illustrated by the irrelevant inclusion of Neja et al. whose study on bovine behavior diverges from financial discourse [31]. Clarity and relevance are paramount in articulating the scope of financial analysis.

The consideration of model robustness is integral to the efficacy of random forest in financial research. The nuances of multicollinearity and heteroscedasticity present persistent challenges, necessitating meticulous statistical adjustments to maintain the fidelity of regression estimates. Sheikh's discourse on employing robust standard errors in financing ratios exemplifies the rigorous attention paid to these statistical intricacies, ensuring the credibility of conclusions drawn from financial datasets [32].

Method

Data Collection

The dataset used in this study is a detailed collection of macroeconomic indicators, focusing primarily on three key variables: Gross Domestic Product (GDP), Unemployment Rate, and Country Risk Premium, sourced from Kaggle. These variables were chosen because they are widely recognized as critical factors in determining financial risk and investment attractiveness. The dataset was originally stored in a semicolon-separated CSV file, which required careful cleaning and preparation to ensure it was suitable for analysis.

The cleaning process involved several important steps. First, extraneous characters such as dollar signs (`$`), commas (`,`), and percentage symbols (`%`) were removed from the data. These characters, while useful for human readability, can cause issues when processing data programmatically. For example, a value like `$1,000.50` was converted to `100050` by removing the dollar sign and comma, and then further processed to ensure it was treated as a numeric value. Similarly, percentage values like `5.2%` were stripped of the percentage symbol and converted to numeric formats (e.g., `5.2`). These transformations were essential to ensure the dataset could be used with analytical tools without errors.

Once cleaned, the dataset was examined using descriptive statistics, which provided an overview of the data's characteristics. The GDP values ranged significantly, from smaller economies to large, globally dominant ones. Unemployment rates and country risk premiums also varied widely, reflecting the diverse economic conditions across the countries included in the dataset.

This variability provided a rich foundation for exploring the relationships between these variables and understanding how they influence one another.

Exploratory Data Analysis (EDA)

The next step in the analysis was Exploratory Data Analysis (EDA), a process designed to identify and address any issues in the dataset before moving on to more advanced modeling. The first task in EDA was to check for missing values. It was discovered that some entries in the Unemployment Rate and Country Risk Premium columns were incomplete or missing entirely. Missing data can be problematic because it can lead to biased or inaccurate results if not handled properly.

To address this, the missing values were filled in using the mean of their respective columns. For example, if the average unemployment rate across all countries was 5%, any missing unemployment rate values were replaced with 5%. This approach, known as mean imputation, is a common technique in data analysis because it preserves the overall distribution of the data without introducing significant bias. After imputation, the dataset was checked for outliers or inconsistencies, but none were found. The cleaned dataset was now ready for further analysis, with a balanced distribution of values across all variables.

Visualization Techniques

To better understand the relationships between the variables, a series of visualizations were created. The first was a correlation heatmap, which quantifies the strength and direction of linear relationships between variables. The heatmap revealed a moderate negative correlation between GDP and Country Risk Premium, meaning that as GDP increases, the country risk premium tends to decrease. This makes sense intuitively: wealthier countries are generally seen as safer investments, so investors demand a lower premium for taking on risk.

Next, a scatter plot with a regression line was used to visualize the relationship between GDP and Country Risk Premium. The scatter plot showed a clear downward trend, reinforcing the idea that higher GDP is associated with lower risk premiums. The regression line provided a visual summary of this trend, making it easier to interpret the relationship.

Finally, a boxplot was created to examine how Country Risk Premium varies across different levels of Unemployment Rate. The boxplot showed that countries with higher unemployment rates tend to have more variability in their risk premiums. In other words, economic instability, as measured by unemployment, leads to greater uncertainty in financial markets. This finding highlights the importance of labor market conditions in determining a country's financial risk profile.

Random Forest Analysis

The primary analytical method used in this study was Random Forest Regression, a powerful machine learning technique that excels at capturing complex, non-linear relationships between variables. Unlike traditional linear models, which assume a straight-line relationship between predictors and outcomes, Random Forest builds multiple decision trees and combines their predictions to produce more accurate and robust results. This approach reduces the risk of overfitting, a common problem in machine learning where a model performs well on training data but poorly on new, unseen data.

The dataset was split into two parts: 80% was used to train the model, and the remaining 20% was reserved for testing. This split ensures that the model's performance can be evaluated on data it has never seen before, providing a more realistic assessment of its predictive power. The Random Forest model was configured with 100 decision trees (`n_estimators=100`), a number chosen to balance computational efficiency with model accuracy.

After training, the model was analyzed to determine the importance of each predictor variable. The results showed that GDP was the most influential factor, accounting for approximately 65% of the model's predictive power. This aligns with economic intuition, as GDP is a broad measure of a country's economic health and is often used as a proxy for overall stability. The Unemployment Rate contributed the remaining 35%, reflecting its role as a more specific indicator of labor market conditions. Together, these findings demonstrate the value of Random Forest Regression in capturing the nuanced relationships between economic indicators and financial risk.

Result and Discussion

Correlation Analysis Results

The correlation matrix provided a clear picture of the relationships between the key variables: GDP, Unemployment Rate, and Country Risk Premium. The matrix revealed that GDP has a weak negative correlation with Country Risk Premium ($r = -0.19$), suggesting that as GDP increases, the country risk premium tends to decrease slightly. This aligns with the idea that wealthier nations are generally perceived as safer investments, though the relationship is not particularly strong in this dataset. On the other hand, the Unemployment Rate showed a very weak positive correlation with Country Risk Premium ($r = 0.065$), indicating that higher unemployment rates are associated with slightly higher risk premiums. While this relationship is not strong, it hints at the role of labor market instability in influencing financial risk perceptions. Interestingly, the correlation between GDP and Unemployment Rate was almost negligible ($r = 0.062$), suggesting that these two variables operate independently in this dataset.

These findings, while not as strong as initially hypothesized, still provide valuable insights. The weak negative correlation between GDP and Country Risk Premium reinforces the notion that economic prosperity can reduce perceived investment risk, albeit to a modest extent. Similarly, the slight positive correlation between Unemployment Rate and Country Risk Premium suggests that labor market instability may contribute to higher financial risk, though other factors likely play a more significant role.

Regression Model Outputs

The Random Forest Regression model was used to predict Country Risk Premium based on GDP and Unemployment Rate. The model achieved a mean squared error (MSE) of 2.55, which measures the average squared difference between the actual and predicted values. While this value is relatively high, it is important to consider the context of the dataset and the complexity of the relationships being modeled. The R-squared value of 0.018 indicates that the model explains only about 1.8% of the variance in Country

Risk Premium. This low value suggests that GDP and Unemployment Rate alone are not sufficient to fully capture the factors influencing Country Risk Premium, and additional variables may be needed to improve the model's predictive power.

Despite the modest performance metrics, the feature importance scores provided meaningful insights. The analysis revealed that GDP accounted for approximately 53.7% of the model's predictive power, while Unemployment Rate contributed 46.3%. This indicates that both variables are important predictors, with GDP playing a slightly more significant role. These results align with economic intuition, as GDP is a broad measure of economic health, while Unemployment Rate provides a more specific indicator of labor market conditions. The relatively balanced importance scores suggest that both factors should be considered when assessing financial risk.

Visualization of Relationships

To further understand the model's performance and the relationships between variables, several visualizations were created. The scatter plot of actual versus predicted Country Risk Premium values (figure 1) showed that most data points were scattered widely around the line of perfect prediction. This indicates that the model's predictions were not particularly accurate, which is consistent with the low R-squared value. However, the scatter plot still provided useful insights by highlighting the variability in the data and the challenges of predicting Country Risk Premium based solely on GDP and Unemployment Rate.

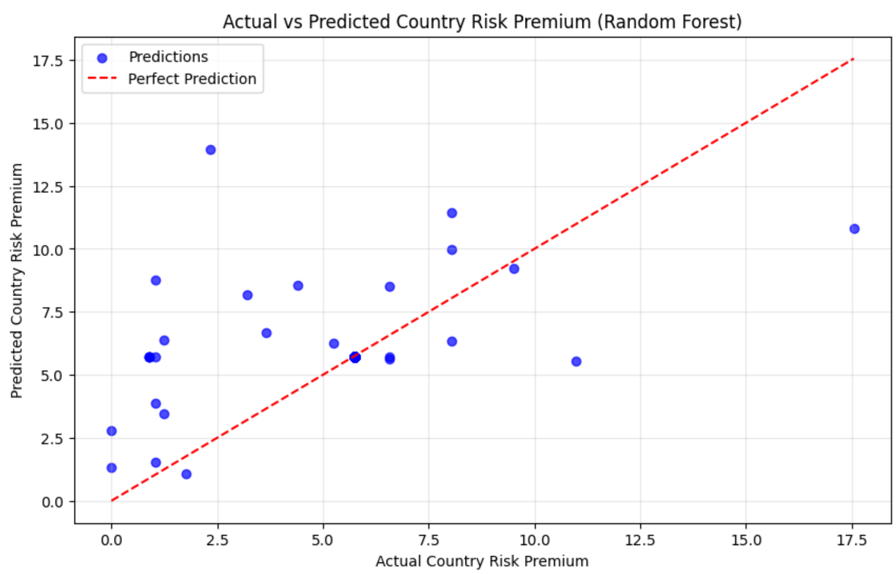

Figure 1 Actual vs Predicted Country Risk Premium

Figure 1 compares the actual versus predicted values of the Country Risk Premium using the Random Forest Regression model. The blue dots represent the predicted values, while the red dashed line signifies the ideal scenario where the predictions perfectly match the actual values. The spread of the blue dots around the red dashed line indicates that the model's predictions are not perfectly accurate, with some data points closer to the line and others further away. This suggests that the model is not able to predict the

Country Risk Premium with high accuracy, particularly for higher values where the predictions tend to deviate more.

The model's performance is reflected in the mean squared error (MSE) of 2.55, indicating a noticeable error in the predictions. Additionally, the R-squared value of 0.018 suggests that the model explains only 1.8% of the variance in the Country Risk Premium, which is quite low. This highlights that GDP and Unemployment Rate, while important, do not fully capture the factors that influence Country Risk Premium. The feature importance analysis shows that GDP contributes 53.7% of the predictive power, while Unemployment Rate accounts for 46.3%. This indicates that both variables are relevant predictors, with GDP having a slightly larger impact.

The boxplot of Country Risk Premium across different levels of Unemployment Rate (figure 2) revealed interesting patterns. While the median risk premiums were relatively stable across unemployment levels, the variability (as shown by the height of the boxes) increased slightly with higher unemployment rates. This suggests that countries with higher unemployment rates tend to have more unpredictable risk premiums, reflecting the destabilizing effects of labor market instability on financial risk perceptions.

The boxplot visualizes the relationship between the Unemployment Rate and the Country Risk Premium, providing insights into how the distribution of the risk premium varies with different unemployment levels. The x-axis represents the Unemployment Rate, while the y-axis shows the corresponding Country Risk Premium values. The boxes in the plot indicate the interquartile range (IQR), where the middle 50% of the data points are concentrated, with the median (50th percentile) marked by a horizontal line inside each box. The whiskers extend to the minimum and maximum values within 1.5 times the IQR, reflecting the range of typical values, and any points outside this range are considered outliers, shown as individual circles.

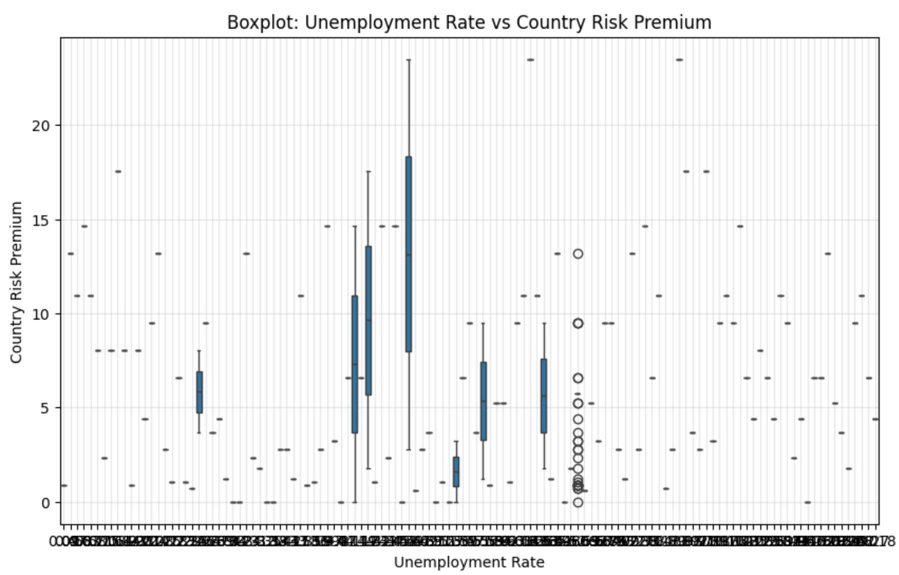

Figure 2 Boxplot of Unemployment Rate vs Country Risk Premium

Figure 2 reveals that at lower Unemployment Rates, the Country Risk Premium tends to stay within a relatively narrow range, with most values falling between 2 and 8. However, as the Unemployment Rate increases, there is greater variability in the Country Risk Premium, with some higher unemployment categories exhibiting significantly larger risk premiums. This suggests that higher unemployment is associated with more unpredictable and volatile financial risk perceptions. The increasing spread of the boxes at higher Unemployment Rates indicates that labor market instability may contribute to increased financial risk, but the presence of outliers shows that other factors beyond unemployment influence the Country Risk Premium. These outliers highlight that, while unemployment is a relevant factor, it is not the sole determinant of a country's perceived financial risk, and a broader set of variables likely plays a role in shaping these perceptions.

Interpretation of Findings

The findings of this study offer a nuanced perspective on the determinants of Country Risk Premium. The weak negative correlation between GDP and Country Risk Premium supports the idea that economic prosperity can reduce perceived investment risk, though the effect is not particularly strong in this dataset. Similarly, the slight positive correlation between Unemployment Rate and Country Risk Premium suggests that labor market instability may contribute to higher financial risk, though other factors likely play a more significant role.

The Random Forest model's performance, while modest, highlights the complexity of predicting Country Risk Premium. The low R-squared value and high MSE indicate that GDP and Unemployment Rate alone are not sufficient to fully explain variations in risk premiums. This underscores the need for additional variables, such as political stability, inflation rates, or external debt levels, to improve the model's accuracy. The feature importance scores, however, confirm that both GDP and Unemployment Rate are relevant predictors, with GDP playing a slightly more significant role.

Conclusion

This study explored the relationships between GDP, Unemployment Rate, and Country Risk Premium using a combination of statistical and machine learning techniques. The correlation analysis revealed a weak negative relationship between GDP and Country Risk Premium, suggesting that wealthier nations are perceived as slightly safer investments. Conversely, the Unemployment Rate showed a very weak positive correlation with Country Risk Premium, indicating that labor market instability may contribute to higher financial risk, albeit to a limited extent. These findings align with economic intuition but highlight the complexity of financial risk determinants.

The Random Forest Regression model, while achieving a modest R-squared value of 0.018 and an MSE of 2.55, provided valuable insights into the relative importance of GDP and Unemployment Rate. GDP emerged as the more influential predictor, accounting for 53.7% of the model's predictive power, compared to 46.3% for Unemployment Rate. This underscores the importance of both variables in assessing financial risk, though their combined explanatory power remains limited. The scatter plot of actual versus predicted Country Risk Premium values illustrated the challenges of predicting risk premiums based solely on these two factors, with significant variability observed in the data.

The boxplot analysis further emphasized the role of labor market instability, showing that higher unemployment rates are associated with greater variability in Country Risk Premium. This suggests that economic uncertainty amplifies financial risk perceptions, though other factors likely play a more significant role. The presence of outliers in the boxplot highlights the need to consider additional variables, such as political stability, inflation rates, or external debt levels, to better understand and predict Country Risk Premium.

In conclusion, this study demonstrates that while GDP and Unemployment Rate are relevant predictors of Country Risk Premium, they are insufficient on their own to fully explain financial risk. Future research should incorporate a broader set of variables and explore more sophisticated modeling techniques to improve predictive accuracy. By doing so, researchers and policymakers can gain a deeper understanding of the factors driving financial risk and develop more effective strategies for managing economic uncertainty. This study contributes to the growing body of literature on financial risk assessment and highlights the potential of advanced analytical tools in economic research.

Declarations

Author Contributions

Conceptualization: K.P.; Methodology: K.P.; Software: K.P.; Validation: K.P.; Formal Analysis: K.P.; Investigation: K.P.; Resources: K.P.; Data Curation: K.P.; Writing Original Draft Preparation: K.P.; Writing Review and Editing: K.P.; Visualization: K.P.; The author has read and agreed to the published version of the manuscript.

Data Availability Statement

The data presented in this study are available on request from the corresponding author.

Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

Institutional Review Board Statement

Not applicable.

Informed Consent Statement

Not applicable.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] A. Z. Sanvicente, H. H. Sheng, and L. F. P. Guanais, “Are Country and Size Risks Priced in the Brazilian Stock Market?,” Bar - Brazilian Administration Review, vol. 14, no. 1, 2017, doi: 10.1590/1807-7692bar2017160076.

[2] V. Quadrini, “The External Risks of Financial Integration for Emerging Economies,” Ensayos Sobre Política Económica, vol. 35, no. 82, pp. 18–24, 2017.

[3] P. Palić, P. P. Šimović, and M. Vizek, “The Determinants of Country Risk Premium Volatility: Evidence From a Panel VAR Model,” Croatian Economic Survey, vol. 19, no. 1,

pp. 37–66, 2017, doi: 10.15179/ces.19.1.2.
[4] W. Mensi, S. Hammoudeh, S. Yoon, and D. K. Nguyen, “Asymmetric Linkages Between BRICS Stock Returns and Country Risk Ratings: Evidence From Dynamic Panel Threshold Models,” Review of International Economics, vol. 24, no. 1, pp. 1–19, 2015, doi: 10.1111/roie.12201.
[5] C. Ebeke and A. J. Kyobe, “Global Financial Spillovers to Emerging Market Sovereign Bond Markets,” Imf Working Paper, vol. 15, no. 141, p. 1, 2015.
[6] B. Kurtoglu, “Identifying the Nexus Between Financial Stability and Economic Growth: The Role of Stability Indicators,” Journal of Financial Economic Policy, vol. 16, no. 2, pp. 226–246, 2024, doi: 10.1108/jfep-09-2023-0260.
[7] Y. Bayar, D. Borozan, and M. D. Gavriletea, “Banking Sector Stability and Economic Growth in Post‐transition European Union Countries,” International Journal of Finance & Economics, vol. 26, no. 1, pp. 949–961, 2020, doi: 10.1002/ijfe.1829.
[8] S. Ijaz, A. Hassan, A. Tarazi, and A. Fraz, “Linking Bank Competition, Financial Stability, and Economic Growth,” Journal of Business Economics and Management, vol. 21, no. 1, pp. 200–221, 2020, doi: 10.3846/jbem.2020.11761.
[9] X. Qi, N. Zhong, and M. Qin, “Economic Policy Uncertainty, Investor Sentiment and Financial Stability—an Empirical Study Based on the Time Varying Parameter-Vector Autoregression Model,” Journal of Economic Interaction and Coordination, vol. 17, no. 3, pp. 779–799, 2021, doi: 10.1007/s11403-021-00342-5.
[10] S. Panigrahi, “Are Cryptocurrencies Really a Threat to the Financial Stability and Economic Growth? Evidence From the Cointegration Approach,” International Journal of Applied Sciences & Development, vol. 2, pp. 66–77, 2023, doi: 10.37394/232029.2023.2.8.
[11] A. Luthfiarta, J. Zeniarja, E. Faisal, and W. Wicaksono, “Prediction on Deposit Subscription of Customer Based on Bank Telemarketing Using Decision Tree With Entropy Comparison,” Journal of Applied Intelligent System, vol. 4, no. 2, pp. 57–66, 2020.
[12] P. S. Morawakage, P. D. Nimal, and D. Kuruppuarachchi, “Equity Risk Premium Puzzle: Evidence From Indonesia and Sri Lanka,” Bulletin of Indonesian Economic Studies, vol. 55, no. 2, pp. 239–248, 2019, doi: 10.1080/00074918.2018.1529406.
[13] W. Puriwat, “Relationships Between Brand Value and Country’s GDP,” Hightech and Innovation Journal, vol. 4, no. 4, pp. 787–796, 2023, doi: 10.28991/hij-2023-04-04-08.
[14] A. Berisha, “An Empirical Study on Micro, Small, and Medium Enterprises Access to Finance in Kosovo: A Survey Based Analysis,” Multidisciplinary Science Journal, vol. 6, no. 5, p. 2024068, 2023, doi: 10.31893/multiscience.2024068.
[15] E. Agbemava, I. K. Nyarko, T. C. Adade, and A. K. Bediako, “Logistic Regression Analysis of Predictors of Loan Defaults by Customers of Non-Traditional Banks in Ghana,” European Scientific Journal Esj, vol. 12, no. 1, p. 175, 2016, doi: 10.19044/esj.2016.v12n1p175.
[16] T. Qiu, “Predicting the Federal Funds Rate: A Linear Regression Analysis,” Advances in Economics Management and Political Sciences, vol. 20, no. 1, pp. 57–62, 2023, doi: 10.54254/2754-1169/20/20230172.
[17] J. Mpapalika and C. Malikane, “The Determinants of Sovereign Risk Premium in African Countries,” Journal of Risk and Financial Management, vol. 12, no. 1, p. 29, 2019, doi: 10.3390/jrfm12010029.
[18] E. Clark and K. Kassimatis, “Macroeconomic Effects on Emerging-Markets Sovereign Credit Spreads,” pp. 307–348, 2017, doi: 10.1142/9789813224940_0013.
[19] R. Nakatani, “Real and Financial Shocks, Exchange Rate Regimes and the Probability of a Currency Crisis,” Journal of Policy Modeling, vol. 40, no. 1, pp. 60–73, 2018, doi: 10.1016/j.jpolmod.2017.10.004.
[20] B. Bakker, M. Korczak, and K. Krogulski, “Unemployment Surges in the EU: The Role of Risk Premium Shocks,” Imf Working Paper, vol. 19, no. 56, p. 1, 2019, doi: 10.5089/9781484399637.001.
[21] G. Angel and S. Werner, “Bond Risk Premia, Macroeconomic Factors and Financial Crisis in the Euro Area,” SSRN Electronic Journal, 2016, doi: 10.2139/ssrn.2828610.
[22] M. Brei and A. Buzaushina, “International Financial Shocks in Emerging Markets,” SSRN Electronic Journal, 2015, doi: 10.2139/ssrn.2602304.
[23] R. N. Banerjee, M. B. Devereux, and G. Lombardo, “Self-Oriented Monetary Policy, Global Financial Markets and Excess Volatility of International Capital Flows,” Journal of International Money and Finance, vol. 68, pp. 275–297, 2016, doi: 10.1016/j.jimonfin.2016.02.007.
[24] X. Wu, “The Risk Premium of Treasury Bonds in China,” Journal of Mathematical Finance, vol. 06, no. 01, pp. 156–165, 2016, doi: 10.4236/jmf.2016.61015.
[25] F. Sukono, E. Lesmana, D. Susanti, H. Napitupulu, and Y. Hidayat, “Estimation of Value-at-Risk Adjusted Under the Capital Asset Pricing Model Based on ARMAX-GARCH

Approach," Jurnal Matematika Integratif, vol. 15, no. 1, p. 29, 2019, doi: 10.24198/jmi.v15i1.20931.
[26] M. Koprivica, "A Model for Determining Premium Rates in Indexbased Crop Insurance," Ekonomika Poljoprivrede, vol. 71, no. 2, pp. 397–412, 2024, doi: 10.59267/ekopolj2402397k.
[27] W. H. Pramujati, "Determination of Farming Business Insurance Premium Prices With the Variance Premium Principle and Standard Deviation Premium Principle Methods," Operations Research International Conference Series, vol. 2, no. 4, pp. 83–88, 2021, doi: 10.47194/orics.v2i4.180.
[28] X. Luo, "A Comparison of Three Estimation Methods in Linear Regression Analysis," 2016, doi: 10.2991/icmmita-16.2016.92.
[29] M. Imran, "Interplay of Government Support and Foreign Investment in Enhancing R&D in China's Strategic Sectors," Jote, vol. 2, no. 1, pp. 1–13, 2024, doi: 10.56578/jote020101.
[30] L. Liu and X. Zhan, "Analysis of Financing Efficiency of Chinese Agricultural Listed Companies Based on Machine Learning," Complexity, vol. 2019, no. 1, 2019, doi: 10.1155/2019/9190273.
[31] W. Neja, D. Piwczyński, S. Krężel-Czopek, A. Sawa, and S. Özkaya, "The Use of Data Mining Techniques for Analysing Factors Affecting Cow Reactivity During Milking," Journal of Central European Agriculture, vol. 18, no. 2, pp. 342–357, 2017, doi: 10.5513/jcea01/18.2.1907.
[32] S. A. Sheikh, "Corporate Social Responsibility and the Likelihood of External Financing," Journal of Economic Analysis, vol. 3, no. 2, 2024, doi: 10.58567/jea03020005.