

**LOCAL CURRENCY BOND RISK PREMIA IN EMERGING
MARKETS: INSIGHTS FROM
ADVANCED MACHINE LEARNING TECHNIQUES**

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LOCAL CURRENCY BOND RISK PREMIA IN EMERGING MARKETS: INSIGHTS FROM ADVANCED MACHINE LEARNING TECHNIQUES

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To my dear wife



DECLARATION OF ORIGINALITY

I hereby declare that I am the sole author of this thesis and that this is the true copy of my thesis, including the final revisions, approved by my thesis committee. All data and information have been obtained, produced, and presented in accordance with the rules of research ethics and principles of academic honesty. As required by these rules, to the best of my knowledge I have acknowledged ideas, thoughts, and any copyrighted material in accordance with the standard referencing rules. I certify that any part of this thesis has not been submitted for a degree or diploma in another educational institution.

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ABSTRACT

Understanding the determinants of local currency bond risk premia is crucial for emerging market investors and policymakers. This study investigates the determinants of local currency bond risk premia in six emerging markets—Brazil, Hungary, Poland, Thailand, South Africa, and Turkey—through the application of advanced machine learning techniques. The analysis first utilizes yield curve-based variables, including forward rates, forward-spot spreads, and term premia. Subsequently, inflation, implied foreign exchange (FX) volatility, and macroeconomic indicators are incorporated to assess their individual and combined effects on predictive accuracy. The results highlight distinct regional patterns in the drivers of excess bond returns. Findings reveal that in Brazil, Hungary, Poland, and Thailand, yield curve-based variables—especially forward rates and term premia—exhibit strong predictive power, while macroeconomic factors and FX volatility offer limited value. In contrast, Turkey and South Africa display a fundamentally different structure, where inflation, macroeconomic indicators, and implied FX volatility serve as the primary predictors, and yield curve variables fail to explain bond risk premia. A diverse set of machine learning algorithms—including linear regression, principal component analysis (PCA), partial least squares (PLS), neural networks, random forests, XGBoost, and extremely randomized trees—were employed. Country-specific analysis reveals that algorithmic performance varies significantly across emerging markets, reflecting distinct economic structures and dominant predictive factors. In Hungary and Brazil, Neural Networks yield the highest predictive accuracy. In Turkey, XGBoost delivers optimal results. Poland stands out with OLS + PCA demonstrating the utility of linear dimensionality reduction in a structured market environment. In Thailand, both Neural Networks and PCA-applied models exhibit nearly equivalent performance. For

South Africa, the most effective predictions are achieved using an Extremely Randomized Trees model. This research highlights the importance of regional differences in the drivers of local currency bond risk premia and demonstrates the value of combining diverse data sources with advanced machine learning techniques. These findings provide valuable insights for policymakers, investors, and financial institutions seeking to refine risk assessment frameworks and improve strategic decision-making in emerging bond markets.

Keywords: Local Currency Bond Risk Premia, Emerging Markets, Machine Learning, Yield Curve, Macroeconomic Indicators,

ÖZET

Yerel para cinsinden tahvil risk primlerinin belirleyicilerini anlamak, geliřmekte olan piyasa yatırımcıları ve politika yapıcıları için çok önemlidir. Bu çalışma, Brezilya, Macaristan, Polonya, Tayland, Güney Afrika ve Türkiye olmak üzere altı geliřmekte olan ülkede yerel para cinsinden tahvil risk primlerinin belirleyicilerini, ileri düzey makine öğrenmesi teknikleri kullanarak incelemektedir. Analizde ilk olarak vadeli faiz oranları, vadeli-spot faiz farkları ve vade primleri gibi getiri eğrisine dayalı değişkenler kullanılmıştır. Daha sonra, enflasyon, zımni döviz (FX) oynaklığı ve makroekonomik göstergeler, tahmin doğruluęu üzerindeki bireysel ve birleşik etkilerini değerlendirmek için dahil edilmiştir. Bulgular, bölgeler arasında önemli farklılıklar ortaya koymaktadır. Brezilya, Macaristan, Polonya ve Tayland'da, özellikle forward oranları ve vade primleri olmak üzere getiri eğrisi değişkenleri yüksek tahmin gücüne sahipken, makroekonomik faktörler ve döviz kuru oynaklığı sınırlı katkı sağlamaktadır. Buna karşın, Türkiye ve Güney Afrika'da enflasyon, makroekonomik göstergeler ve zımni döviz (FX) oynaklığı birincil belirleyiciler olurken, getiri eğrisi değişkenleri tahvil risk primlerini açıklamada yetersiz kalmaktadır. Çalışmada doğrusal regresyon, temel bileşen analizi (PCA), kısmi en küçük kareler (PLS), yapay sinir ağları, rastgele ormanlar, XGBoost ve aşırı rastgele ağaçlar (ERT) dahil olmak üzere çeşitli makine öğrenmesi algoritmaları kullanılmıştır. Ülke bazlı analizler, algoritmaların tahmin performansının ülkeler arasında önemli ölçüde değiştiğini göstermektedir. Macaristan ve Brezilya'da en yüksek doğruluk yapay sinir ağları ile elde edilirken, Türkiye'de en iyi sonuçlar XGBoost ile sağlanmıştır. Polonya'da doğrusal boyut indirgeme yöntemlerinin yapılandırılmış piyasa ortamında etkinliğini ortaya koyan OLS + PCA öne çıkmaktadır. Tayland'da ise yapay sinir ağı ve PCA uygulanan modeller neredeyse eşit başarı göstermektedir. Güney Afrika'da ise en iyi performans aşırı rastgele ağaçlar (ERT) modeliyle elde edilmiştir. Bu araştırma, yerel para cinsinden tahvil

risk primlerinin belirleyicilerinde bölgesel farklılıkların önemine dikkat çekerken, farklı veri kaynaklarının ileri düzey makine öğrenmesi teknikleriyle birleştirilmesinin değerini ortaya koymaktadır. Elde edilen bulgular, gelişmekte olan piyasalarda risk değerlendirme çerçevelerini geliştirmek ve stratejik karar alma süreçlerini iyileştirmek isteyen politika yapıcılar, yatırımcılar ve finansal kurumlar için önemli içgörüler sunmaktadır.

Anahtar Kelimeler: Yerel Para Cinsinden Tahvil Risk Primleri, Gelişmekte Olan Piyasalar, Makine Öğrenmesi, Getiri Eğrisi, Makroekonomik Göstergeler



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LIST OF ACRONYMS AND ABBREVIATIONS

ADF Augmented Dickey-Fuller

AI Artificial Intelligence

CPI Consumer Price Index

EM Emerging Markets

ERT Extremely Randomized Trees

FR Forward Rates

FSS Forward-Spot Spreads

FX Foreign Exchange

ML Machine Learning

MSE Mean Squared Error

NN Neural Networks

OECD Organization for Economic Cooperation and Development

OLS Ordinary Least Squares

PCA Principal Component Analysis

PLS Partial Least Squares

PMI Purchasing Managers' Index

RF Random Forest

TP Term Premiums

XGB XGBoost

1. INTRODUCTION

The pricing of local currency bonds in emerging markets has been a subject of increasing academic and practical interest, particularly in light of the evolving role of macroeconomic fundamentals and global financial spillovers. The estimation of local currency bond risk premia is crucial for policymakers, investors, and financial analysts, as it provides insights into the underlying risk drivers in these economies. While traditional econometric models have long been employed to predict bond risk premia, recent advancements in Machine Learning (ML) techniques have opened new avenues for enhancing prediction accuracy and capturing complex relationships in the data.

Building upon the seminal work of Bianchi, Büchner, and Tamoni [1] which demonstrated the effectiveness of machine learning in bond risk premium estimation on the United States, this study extends the analysis into an emerging market framework. The study also draws from Çepni, Selçuk, and Gül [2], who examined macroeconomic and financial variables in fourteen Emerging Markets (EM) economies, including those analyzed in this research. Çepni, Selçuk, and Gül [2] investigated the role of macroeconomic variables and financial indicators in predicting EM local currency bond risk premia.

Çepni, Selçuk, and Gül [2] employ traditional econometric techniques to examine local currency bond risk premia in emerging markets, emphasizing the role of macroeconomic factors. Their findings underscore the significance of these indicators in shaping bond risk premia; however, their approach remains confined to linear econometric models, which may not fully capture the non-linear interactions and complex dependencies inherent in financial markets. This study builds upon and extends their work by integrating Random Forest (RF), Extremely Randomized Trees (ERT), XGBoost (XGB), and Neural Networks (NN) to enhance predictive accuracy. By comparing traditional econometric models with advanced ML techniques, this research provides a more comprehensive framework for understanding the determinants of local currency bond risk premia,

uncovering potential relationships that may have been overlooked in previous studies.

1.1 Motivation and Research Questions

Several studies, including Bianchi et al. [1] and Çepni, Selçuk, and Gül [2], highlight the significance of macro-financial interactions and yield curve components in explaining bond risk premia. However, key gaps remain in the existing literature:

While Bianchi et al. [1] applies machine learning techniques to predict bond risk premia, it primarily focuses on U.S. Treasury bonds. This study extends the ML-based approach to emerging markets, where structural differences and financial volatility require a different analytical framework.

Çepni, Selçuk, and Gül [2] analyze bond risk premia in emerging markets but do not incorporate ML-based models. Their study relies on traditional econometric techniques.

Moreover, existing studies often treat predictive variables as a homogenous block without decomposing their relative contributions. There is a lack of systematic segmentation that evaluates how different combinations of macroeconomic indicators, yield curve factors, and financial risk variables (e.g., implied Foreign Exchange (FX) volatility) contribute to forecasting performance. This research addresses this gap by introducing a structured modeling strategy—comprising single-, two-, three-, and omni-factor models—to disentangle and compare the explanatory power of individual and combined factors.

To address these gaps, this research seeks to answer the following key questions:

1. How effective are traditional yield curve factors (forward rates, forward-spot spreads, and term premiums) in predicting local currency bond risk premia across emerging markets?
2. Can macroeconomic indicators (unemployment, industrial production, electricity

consumption, foreign trade, etc.), inflation and implied FX volatility improve bond risk premia forecasting?

3. Do machine learning models outperform traditional econometric methods in capturing the key determinants of bond risk premia?

1.2 Methodology and Contribution

This study analyzes local currency bond risk premia in six emerging markets using an extensive dataset that integrates:

- Yield Curve (YC) components (Forward Rates (FR), Forward-Spot Spreads (FSS), Term Premiums (TP)),
- Macroeconomic Indicators (industrial production, foreign trade, Purchasing Managers' Index (PMI), credit ratings, electricity consumption),
- Inflation and Implied FX Volatility.

The methodology follows a multi-stage approach:

- Traditional econometric models (Ordinary Least Squares (OLS), Principal Component Analysis (PCA), Partial Least Squares (PLS)) are applied to establish benchmark predictive performance.
- Machine learning models (Random Forest, Extremely Randomized Trees, XGBoost and Neural Networks) are employed to capture non-linear dependencies and complex interactions among variables.
- A comparative analysis assesses whether ML-based approaches provide higher predictive accuracy relative to traditional models.

This research makes several contributions to the literature:

- It extends the work of Bianchi et al. [1] by integrating machine learning techniques into an emerging market framework, addressing structural differences between developed and developing economies.
- It builds on Çepni, Selçuk, and Gül's [2] findings by incorporating ML models, evaluating their predictive power within different economic conditions and market structures.

1.3 Structure of the Thesis

The remainder of this thesis is organized as follows:

- Chapter 2 (Previous Work): Discusses existing research on local currency bond risk premia, macroeconomic determinants, and the role of machine learning in financial forecasting.
- Chapter 3 (Data): Describes the dataset, variable selection.
- Chapter 4 (Methodology): Describes the econometric and machine learning models used for prediction.
- Chapter 5 (Results): Presents the results of the predictive models, comparing the performance of traditional econometric and machine learning approaches.
- Chapter 6 (Conclusions): Summarizes the key findings, discusses implications for investors and policymakers, and suggests avenues for future research.

2. PREVIOUS WORK

Several studies in the finance literature have explored the predictability of excess bond returns. These studies have identified several variables that can forecast excess bond returns, including forward rates, forward-spot spreads, term premia, and macroeconomic variables. Among the most prominent early studies is the work of Fama and Bliss [3], who demonstrate that forward rates contain information about future spot rates and hence can be used to predict bond returns. Cochrane and Piazzesi [4] extend this work by constructing a single factor model that combines multiple forward rates to forecast excess bond returns, showing that this factor has substantial predictive power.

Joslin, Priebsch, and Singleton [5] examine the predictive power of forward rates and yield curve information in a dynamic term structure model framework, finding that these models can explain a significant portion of the variation in bond risk premia. Ludvigson and Ng [6] introduce macroeconomic factors into the analysis, showing that macroeconomic variables such as inflation, industrial production, and other real activity measures can enhance the forecasting ability of yield-based models.

Duffee [7] explores the role of the macroeconomy in bond pricing, suggesting that while yield curve information is important, incorporating macroeconomic data can improve the performance of predictive models. These studies collectively suggest that both yield curve factors and macroeconomic variables are important in explaining bond risk premia.

In the context of emerging markets, there has been growing interest in understanding the drivers of local currency bond risk premia. Cepni, Selcuk, and Gul [2] investigate the role of macroeconomic variables and financial indicators in predicting local currency bond risk premia across 14 emerging market economies. Using panel data techniques, they find that inflation, real activity indicators, and financial market variables significantly influence excess bond returns. Their findings highlight the relevance of country-specific

macroeconomic conditions in shaping bond risk premia in emerging markets.

While these studies provide valuable insights into the determinants of bond risk premia, they rely primarily on linear econometric models, which may not capture the complex and potentially nonlinear relationships between predictors and bond returns. Recent advances in machine learning offer new opportunities to improve prediction accuracy by capturing such nonlinearities and interactions among predictors.

Bianchi, Büchner, and Tamoni [1] apply machine learning techniques to forecast bond risk premia in the U.S. Treasury market. They compare several machine learning algorithms, including random forests, neural networks, and gradient boosting machines, against traditional linear models. Their results show that machine learning models significantly outperform linear models in terms of predictive accuracy, particularly when combining a large set of macroeconomic and financial predictors. This suggests that machine learning can uncover complex patterns in the data that traditional models may overlook.

Gu, Kelly, and Xiu [8] propose a comprehensive machine learning framework for empirical asset pricing. They show that machine learning models, particularly those that allow for flexible nonlinear relationships and variable interactions, can achieve superior predictive performance compared to conventional models. Their framework emphasizes the importance of using a broad set of predictors and advanced algorithms to capture the multifaceted nature of asset returns.

The literature on machine learning applications in emerging market bond prediction is relatively limited. Most existing studies focus on developed markets, particularly the U.S., leaving a gap in the application of these advanced techniques to emerging economies. This thesis aims to fill this gap by applying machine learning models to predict local currency bond risk premia in six emerging market countries. By comparing the performance of machine learning algorithms with traditional econometric models, this study seeks to provide new insights into the effectiveness of these methods in an emerging

market context.



3. DATA

This study employs a comprehensive dataset covering six emerging markets: Brazil, Hungary, Poland, Thailand, South Africa, and Turkey. The dataset includes information on bond yields, macroeconomic indicators, inflation, and implied foreign exchange (FX) volatility, spanning multiple years. The data are primarily sourced from Bloomberg Terminal and publicly available financial databases.

3.1 Bond Yield Data

For each country, bond yields are collected across different maturities, including 1-year, 2-year, 3-year, 4-year, 5-year, 6-year, 7-year, 8-year, 9-year and 10-year government bonds. These yields serve as a foundation for modeling the local currency bond risk premia in each market.

All bond yields used in this study are zero-coupon yields, derived from Bloomberg's BVAL (Bloomberg Valuation) Curves.

3.2 Macroeconomic Indicators

A diverse set of macroeconomic indicators is included in the dataset to examine their contribution to bond risk premia predictability. The selection of indicators follows the methodology used in Cepni, Selcuk, and Gul [2], ensuring consistency with prior literature on emerging markets. These indicators vary by country but generally include:

- Unemployment Rate
- Consumer Confidence Index
- Industrial Production Growth
- Retail Sales Growth

- Exports and Imports Volume Indices
- Business Confidence Index
- Capacity Utilization Rate
- Organization for Economic Cooperation and Development (OECD) Leading Indicators
- Car Sales Data
- Manufacturing Production Index
- Electricity Production Index
- Construction Activity

Each country's macroeconomic dataset comprises multiple economic activity variables, allowing for a robust assessment of their impact on bond return predictability. A complete list of these macroeconomic indicators and their corresponding Bloomberg tickers is provided in the appendices for each country.

3.3 Inflation

Monthly Consumer Price Index (CPI) inflation rates are included for each country. These inflation figures are essential in assessing the role of price stability in bond risk premia formation.

3.4 Implied FX Volatility

To capture foreign exchange market dynamics, 1-month implied volatility (V1M) for the local currency against the USD is incorporated. These values reflect investor expectations of future exchange rate fluctuations and provide insights into the role of currency risks in bond pricing.

3.5 Sample Period & Data Frequency

The dataset covers a varying sample period across countries, with most data spanning from May 2012 to June 2022, depending on data availability. The variables are measured at a monthly frequency, ensuring consistency across all data sources. The total number of observations per country ranges between 135 and 136 months. The specific time coverage for each country is as follows:

- Brazil: May 2012 – July 2022
- Hungary: June 2011 – July 2022
- Poland: May 2011 – July 2022
- South Africa: May 2011 – July 2022
- Thailand: June 2011 – July 2022
- Turkey: May 2011 – July 2022

4. METHODOLOGY

4.1 Definition of Excess Bond Return

Our dependent variable is defined as the one-year holding period return on a 10-year government bond, exceeding the return on a 1-year Treasury bill. This measure isolates the risk premium investors demand for holding long-term bonds relative to short-term, risk-free instruments. Our dependent variable is calculated in the following way.

We consider a zero-coupon bond with maturity $t + n$ and a payoff of one local currency unit. First, we should define the return from buying n year bond at time t and selling an $n - 1$ year bond at time $t + 1$.

Formally, the log holding period return for an n -year bond is given by:

$$r_{t+1}^{(n)} = p_{t+1}^{(n-1)} - p_t^{(n)} \quad (4.1)$$

where:

- $r_{t+1}^{(n)}$ = Log holding period return on an n year bond
- $p_{t+1}^{(n-1)}$ = Log price of an $(n-1)$ year bond at time $t + 1$
- $p_t^{(n)}$ = Log price of an n -year zero-coupon bond at time t

The log excess return to the n year bond from t to $t + 1$, when its remaining maturity is $n - 1$, is then defined as:

$$rx_{t+1}^{(n)} = p_{t+1}^{(n-1)} - p_t^{(n)} - y_t^{(1)} \quad (4.2)$$

where:

- $rx_{t+1}^{(n)}$ = Excess holding period return on an n -year bond
- $p_t^{(n)}$ = Log price of an n -year zero-coupon bond at time t

- $p_{t+1}^{(n-1)}$ = Log price of an $(n1)$ year bond at time $t + 1$
- $y_t^{(1)}$ = Log yield on a 1-year treasury bill at time t

This formulation follows Bianchi et al. [1] and serves as the dependent variable in our predictive models. The excess return captures the risk compensation required by investors for holding bonds with longer maturities and reflects key macro-financial dynamics in emerging markets.

4.2 Time Series Stationarity Analysis and Transformations

Economic and financial time series often exhibit non-stationary characteristics, meaning that their mean, variance, and autocovariance change over time. Non-stationary time series can negatively impact the accuracy and reliability of predictive models. Therefore, in this study, all time-series data were tested for stationarity, and appropriate transformations were applied when necessary.

A time series is considered stationary when its statistical properties—such as mean, variance, and autocorrelation—remain constant over time. Ensuring stationarity is essential because non-stationary data can lead to spurious correlations, where variables appear related due to shared trends or seasonality rather than a genuine relationship. This can result in misleading conclusions and invalid regression outputs. Moreover, most predictive models, including Random Forest, XGBoost, and Neural Networks, tend to perform more reliably on stationary data, as non-stationary components may introduce instability and reduce the model's predictive accuracy. To address these issues, we conducted Augmented Dickey-Fuller (ADF) tests on all time-series to determine their stationarity.

The ADF test was used to check for unit roots and determine whether a time series is stationary. The test is based on the following hypotheses:

- Null Hypothesis (H_0): The time series is non-stationary (contains a unit root).

- Alternative Hypothesis (H_1): The time series is stationary (does not contain a unit root).

If the p-value from the ADF test is below the chosen threshold (0.05), the null hypothesis is rejected, indicating that the series is stationary. However, if the p-value is greater than 0.05, the series is non-stationary, requiring transformations to achieve stationarity.

For time series that were found to be non-stationary, differencing (first-order or second-order), log transformation or percentage change calculation were applied.

4.3 Expanding Window Approach

In time series forecasting, ensuring that the model is trained on the most recent and relevant data is crucial for making accurate predictions. In this study, we employ an expanding window approach, a widely used technique in financial econometrics and machine learning for time-dependent data.

The expanding window approach progressively increases the training dataset size over time. Initially, the model is trained on a small subset of observations. As new data points become available, they are added to the training dataset, while previous data points are retained. This method allows the model to learn from past information while continuously incorporating new observations, making it particularly useful for financial predictions where market dynamics evolve over time.

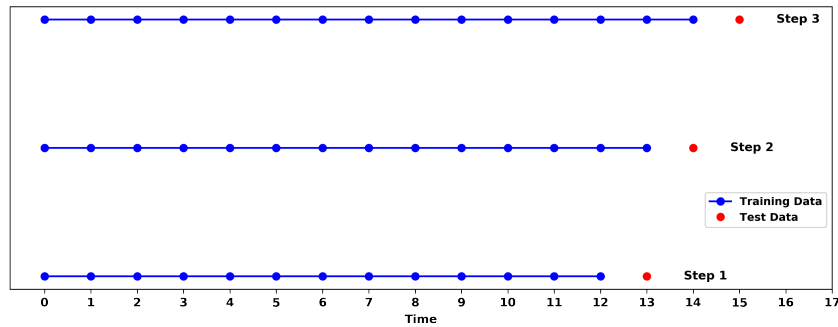
The expanding window approach was implemented as follows.

- **Initial Training Set Selection:** The first 12 months of data were used as the initial training set. This period provides the model with sufficient information to learn initial trends and relationships.
- **Incremental Expansion of the Training Window:** At each iteration t , the training set expands to include all observations from time 0 to t . The test set consists of

the next observation $X_{(t+1)}$. This ensures that the model always has more historical data available as it moves forward in time.

- **Data Standardization:** Since financial and macroeconomic variables may exhibit different scales, standardization was applied using StandardScaler from Scikit-Learn. The mean and standard deviation were computed based on the training data and then applied to both the training and test sets to ensure consistency.
- **Model Training and Prediction:** Model was trained on the expanding training set at each iteration. Predictions were made for the next time point $X_{(t+1)}$ and the model parameters were updated iteratively.
- **Inverse Transformation and Evaluation:** Since standardization was applied, the predicted values were transformed back to the original scale using the inverse transform function. The actual vs. predicted values were compared to assess the model's accuracy.

Figure 4.1: *Illustration of Expanding Window Approach.*



The expanding window approach offers notable advantages for time series prediction by enhancing both model reliability and real-world applicability. As it progressively incorporates more historical data, the model gains a deeper understanding of long-term trends and structural relationships, contributing to improved stability. Simultaneously, it

adapts to evolving market conditions by updating with each new data point, allowing it to reflect recent financial and macroeconomic dynamics. This method also mitigates look-ahead bias, as the model is trained solely on past observations and evaluated on future data—closely resembling actual forecasting environments. Additionally, by gradually increasing the training set size, it helps reduce the risk of overfitting to short-term noise or anomalies.

While the expanding window approach increases the training set size over time, an alternative method is the rolling window approach, where the training set maintains a fixed size by discarding older observations. The choice of the expanding window approach in this study was motivated by the need to preserve the full historical context, allowing the model to accumulate information continuously rather than discarding potentially useful older data points.

By employing an expanding window approach, this study ensures that the model learns from both long-term historical data and recent observations, leading to more reliable bond risk premium forecasts. This method is particularly suitable for financial markets, where historical trends, macroeconomic conditions, and investor sentiment evolve over time.

4.4 Prediction Methods

4.4.1 Dimensionality Reduction Techniques

4.4.1.1 Principal Component Analysis (PCA) – Dynamic Selection

PCA is used to transform the original dataset into a smaller set of uncorrelated variables (principal components) that capture most of the variance in the data. Instead of using a fixed number of components (e.g., 5 or 7) like Bianchi et al. [1], this study introduces a dynamic PCA selection mechanism.

The step-by-step process of the dynamic PCA selection method is as follows:

Phase 1 - Expanding Window Data Approach:

The process begins with an Expanding Window Data Approach, where the training dataset starts with an initial 12 observations and gradually increases over time as new data becomes available. At each iteration, the most recent observation is added to the training dataset, allowing the model to learn from the latest market developments while retaining past information. This adaptive approach ensures that the model dynamically adjusts to evolving features, improving its predictive power for bond risk premia.

Phase 2 - Iterative PCA Component Selection:

In this phase, the model systematically evaluates different PCA configurations. At each time step, a loop iterates over a range of possible PCA components, testing values from 1 to 10. For each tested PCA component value, the training dataset (excluding the validation observation) is projected onto the principal component space. This transformed dataset is then divided into a training subset and a validation subset. The training subset consists of all observations up to $i - 2$, while the validation subset includes only the most recent observation from the training dataset, $i - 1$. A Linear Regression model is trained on the PCA-transformed training subset and then applied to the validation subset. The validation error is computed using Mean Squared Error (MSE) to determine how well each PCA configuration explains the variance in bond risk premia. This validation approach ensures that the optimal number of PCA components is chosen based on predictive accuracy rather than arbitrary selection.

Phase 3 - Optimal PCA Component Selection and Model Application:

After iterating through all possible PCA configurations, the optimal one is selected based on the lowest validation error. The final PCA model is re-trained on the entire training dataset (including the validation observation), ensuring consistent transformation. The dataset is projected into the optimized PCA-transformed space, and a Linear Regression model is trained.

The trained model is then applied to the test observation at time i , which is projected onto the same PCA space. The predicted excess bond return is then inverse-transformed back to the original scale, ensuring financial interpretability.

This structured approach ensures that the model remains adaptive and robust, dynamically selecting only the most relevant macroeconomic indicators at each time step. The use of a validation step to fine-tune PCA components prevents overfitting, while the expanding window framework ensures that predictions are based on both historical trends and real-time market conditions.

Unlike Bianchi's fixed approach, this method adjusts dynamically to new market conditions. If new factors become important over time, the PCA selection mechanism captures this shift. This dynamic component selection ensures that, at each step, PCA representation is optimized for relevant market signals, making it a key innovation over traditional methods.

4.4.1.2 Partial Least Squares (PLS) – Dynamic Selection

Unlike PCA, which focuses on variance, PLS identifies linear combinations of variables that maximize covariance with the target variable (excess bond returns). Instead of using a fixed number of components (as in Bianchi et al. [1]), this study employs a dynamic selection mechanism.

At each time step, the model tests multiple PLS components (1 to 10) and selects the one that minimizes validation error (MSE), similar to the dynamic PCA approach. This adaptive process enhances forecast accuracy, reduces noise, and ensures the model responds to changing market conditions.

4.4.1.3 SelectKBest Feature Selection

SelectKBest is a univariate feature selection technique that scores all input variables based on their statistical significance in predicting the target variable. The k best

features are chosen based on mutual information or F-statistics, ensuring that only the most relevant variables are included in the final model.

In this study, SelectKBest is employed to identify the most statistically significant features. For each expanding window iteration, features are ranked based on their F-statistics, and multiple values of k are tested. The optimal k is selected by training a temporary model on the selected features and choosing the one that minimizes MSE.

4.4.2 Prediction Methods

4.4.2.1 PCA + OLS Model

Principal Component Analysis (PCA) combined with Ordinary Least Squares (OLS) regression framework is employed to predict excess bond returns. Once the optimal PCA-transformed features are selected as described in 4.4.1.2 Principal Component Analysis (PCA) – Dynamic Selection, an OLS regression model is applied to predict excess bond returns.

4.4.2.2 Partial Least Squares Regression

Principal Least Squares (PLS) combined with Linear Regression approach is employed to predict excess bond returns. Once the optimal PLS-transformed features are selected as described in Partial Least Squares (PLS) – Dynamic Selection, a Linear Regression model is applied.

4.4.2.3 Neural Network

A Neural Network is a machine learning algorithm inspired by the human brain. It consists of neurons (nodes) arranged in layers, where each neuron processes input information and passes the output to the next layer.

Key Components of Neural Network:

1-) Input Layer: Receives macroeconomic and financial indicators as features.

2-) Hidden Layers: Performs non-linear transformations using activation functions (e.g., ReLU). Each neuron applies weights and biases, adjusting its output through backpropagation.

3-) Output Layer: Produces predicted excess bond returns based on processed features.

First, feature selection is dynamically performed using SelectKBest ensuring that only the most relevant macroeconomic indicators are retained at each time step. The model also employs an expanding window strategy, where training data gradually increases over time, allowing the neural network to learn from evolving market conditions. Additionally, hyperparameter tuning is conducted at regular intervals to optimize the model's performance across different economic environments. To prevent overfitting, regularization techniques such as L2 penalty and dropout layers are applied, improving the model's generalization ability.

At each time step, the expanding window strategy is applied, starting with an initial 12 observations and increasing over time. This method ensures that as new data becomes available, the model continues to refine its learning without losing past information. Following this, the dataset is scaled using StandardScaler, ensuring that all variables are standardized for better numerical stability during training.

Feature selection is performed using SelectKBest, dynamically selecting the best k features from the macroeconomic dataset. Instead of fixing k , the model iteratively tests different values and selects the one that results in the lowest Mean Squared Error (MSE) during a brief test phase. To validate the k -value selection, a temporary model is trained and evaluated on train set to determine the optimal k -value, ensuring that the model only learns from the most informative features while filtering out irrelevant ones. This dynamic feature selection ensures that the model always works with the most informative variables while avoiding irrelevant or redundant factors.

The neural network itself follows a deep learning architecture with multiple layers. The input layer is configured based on the dynamically selected features. The hidden layers consist of two fully connected layers: the first with 64 neurons and the second with 32 neurons, both utilizing ReLU activation functions and L2 regularization to prevent overfitting. Between these layers, dropout layers (20%) are introduced to randomly deactivate neurons, ensuring that the model does not become overly dependent on specific patterns in the training data. The output layer consists of a single neuron with a linear activation function, as the task is a regression problem rather than classification.

To further improve predictive performance, hyperparameter optimization is performed every 10-time steps. The model tests different combinations of epochs (3, 6, 9, 12), batch sizes (6, 9, 12), and learning rates (0.001, 0.003, 0.01).

For each tested hyperparameter combination, a temporary neural network is trained on the training subset. The hyperparameter configuration that achieves the lowest Mean Squared Error (MSE) on the validation set is chosen as the optimal set. Once the best parameters are selected, the final neural network is trained on the entire training dataset and used for forecasting excess bond returns at the next time step.

This methodology ensures that the model is well-adapted to the non-linear and evolving relationships in macroeconomic and bond market data.

This neural network approach offers several advantages over traditional models. Unlike static models, it dynamically selects only the most informative macroeconomic features, ensuring that irrelevant variables do not degrade prediction quality. The expanding window strategy allows the model to continuously learn from new market conditions, making it highly adaptable to economic fluctuations. Additionally, the built-in hyperparameter optimization ensures that the model maintains peak performance by fine-tuning critical training settings such as learning rate, batch size, and training epochs.

Regularization techniques such as L2 regularization and dropout layers help prevent overfitting, allowing the model to generalize well to unseen data. Moreover, the neural network architecture is particularly well-suited for handling non-linear relationships between macroeconomic factors and bond risk premia, making it superior to linear regression models like OLS and PLS.

4.4.2.4 Random Forests

Random Forest is a supervised ensemble learning algorithm that constructs multiple decision trees and combines their outputs to generate more stable and accurate predictions. By leveraging bootstrap sampling (random sampling with replacement), each decision tree is trained on a different subset of data, allowing the model to capture diverse patterns. Additionally, each tree is trained independently using a random subset of features, which helps decorrelate the trees and reduces overfitting. For regression tasks, the final prediction is obtained by averaging the outputs of all trees, effectively smoothing variance and improving generalization.

As with all models in this study, an expanding window approach and standardized preprocessing (via `StandardScaler`) are used to ensure consistent learning over time and numerical stability.

At each time step, dynamic feature selection is performed using `SelectKBest`. Instead of selecting a fixed number of features, the model iteratively evaluates different k -values (6, 9, 12) and selects the configuration that produces the lowest Mean Squared Error (MSE). This ensures that only the most informative indicators are used in training while discarding noisy and redundant variables. To validate the selection of k , a temporary Random Forest model is trained and evaluated using train set to determine the optimal k -value.

Once the best k -value is selected, the hyperparameter optimization process begins.

This tuning is conducted every 10 iterations or at the start of the training process. The model evaluates multiple combinations of:

Number of trees in the forest $\rightarrow [50, 100, 150]$

Maximum depth of each decision tree $\rightarrow [3, 5, 7]$

Proportion of features used at each split $\rightarrow [0.6, 0.8, 1.0]$

For each hyperparameter combination, a temporary Random Forest model is trained using the previously selected k-value and evaluated on the train set. The combination that achieves the lowest validation MSE is chosen as the optimal set of hyperparameters.

Once the optimal k-value and hyperparameters are determined, the final Random Forest model is trained on the entire training dataset. The final model is then applied to the test data at the next time step, where the test observation is transformed using the trained feature selection method and predictions for excess bond returns are generated. The predicted values are inverse-transformed to match the original scale, ensuring proper financial interpretation.

4.4.2.5 XGBoost Regressor

XGBoost (Extreme Gradient Boosting) is a supervised machine learning algorithm that belongs to the gradient boosting family. It is designed to improve the predictive power of traditional decision trees by training weak models iteratively and combining them into a strong final prediction. Unlike Random Forest, where decision trees are trained independently, XGBoost builds trees sequentially, where each new tree corrects the errors of the previous one by minimizing residual errors. This sequential boosting technique allows XGBoost to capture complex relationships in data, making it one of the most efficient and accurate ensemble learning models for regression and classification tasks.

As with all models in this study, an expanding window approach and standardized

preprocessing (via StandardScaler) are used to ensure consistent learning over time and numerical stability.

At each time step, dynamic feature selection is performed using SelectKBest. Instead of predefining a fixed number of features (k), the model systematically evaluates different k -values (6, 9, 12) and selects the configuration that yields the lowest Mean Squared Error (MSE). This ensures that the model focuses only on the most informative macroeconomic indicators while discarding irrelevant or noisy variables. A temporary XGBoost model is trained and evaluated using train set to determine the optimal k -value.

Once the best k -value is selected, the hyperparameter optimization process begins. Every 10 iterations, or at the beginning of the training process, the model evaluates multiple combinations of key hyperparameters:

Learning rate $\rightarrow$ [0.01, 0.03, 0.1]

Maximum tree depth $\rightarrow$ [3, 4, 5]

Number of boosting rounds $\rightarrow$ [50, 100, 150]

Row sampling ratio (subsample) $\rightarrow$ [0.8, 1.0]

Column sampling ratio $\rightarrow$ [0.8, 1.0]

For each hyperparameter configuration, a temporary XGBoost model is trained using the previously selected k -value on the train set and the validation error (MSE) is recorded. The configuration that results in the lowest MSE is chosen as the optimal set of hyperparameters.

Once the best k -value and hyperparameters are determined, the final XGBoost model is trained on the entire training dataset. The trained model is then applied to the test set at the next time step. The test observation is first transformed using the trained feature selection method (SelectKBest) and then projected into the trained XGBoost model to generate a forecast of excess bond returns. The predicted value is then

inverse-transformed to match the original scale, ensuring that the predictions remain interpretable in a financial context.

4.4.2.6 Extremely Randomized Trees

Extremely Randomized Trees (ExtraTrees Regressor) is an ensemble learning algorithm that extends the Random Forest model by introducing additional randomness in the tree-building process. Unlike traditional decision trees that determine optimal split points based on feature importance, ExtraTrees selects both the feature and the split point randomly, making it more resistant to overfitting and improving generalization. This method ensures that the trees in the ensemble are highly decorrelated, leading to a more stable model that performs well across different market conditions.

As with all models in this study, an expanding window approach and standardized preprocessing (via StandardScaler) are used to ensure consistent learning over time and numerical stability.

At each iteration, dynamic feature selection is performed using SelectKBest. Instead of using a fixed number of features (k), the model systematically evaluates different k -values (6, 9, 12) and selects the configuration that produces the lowest Mean Squared Error (MSE). This step ensures that only the most relevant indicators are retained, while less informative or redundant variables are discarded. To validate the feature selection process, the last row of the training dataset is used as a validation set, while the remaining rows serve as the training set. A temporary ExtraTrees model is trained and evaluated on this validation set to determine the optimal k -value dynamically.

Once the best k -value is selected, the hyperparameter optimization process begins. This tuning is performed every 10 iterations or at the start of training. The model evaluates multiple combinations of critical hyperparameters, including:

Number of trees $\rightarrow$ [50, 100, 150]

Maximum tree depth $\rightarrow [3, 5, 7]$

Proportion of features used at each split $\rightarrow [0.6, 0.8, 1.0]$

For each hyperparameter combination, a temporary ExtraTrees model is trained using the previously selected k-value, and the MSE is recorded. The combination that results in the lowest MSE is chosen as the optimal set of hyperparameters.

Once the best k-value and hyperparameters are determined, the final ExtraTrees model is trained on the entire training dataset. The trained model is then applied to the test data at the next time step, where the test observation is first transformed using the trained feature selection method (SelectKBest) and then projected into the trained ExtraTrees model to generate a forecast for excess bond returns. The predicted values are inverse-transformed to match the original scale, ensuring that the results remain interpretable in a financial context.

The ExtraTrees model provides several advantages over traditional tree-based models by introducing higher randomness in feature selection and split points, further reducing overfitting compared to Random Forest. Additionally, ExtraTrees is computationally more efficient since it does not rely on finding the optimal split points at each node, making it well-suited for large-scale financial datasets.

4.5 Performance Evaluation

To evaluate the forecasting performance of our models, we employ the out-of-sample predictive R^2_{OOS} , a widely used metric in financial forecasting that assesses whether a predictive model improves upon a simple benchmark. Unlike traditional in-sample goodness-of-fit measures, R^2_{OOS} is specifically designed to test whether a model provides meaningful improvements in forecasting future excess bond returns compared to a naive historical mean approach. This ensures that the model's predictive ability is not merely a result of overfitting but reflects genuine economic value.

The predictive R^2 is computed as follows:

$$R_{OOS}^2 = 1 - \frac{\sum_{t_0=1}^{T-1} \left(xr_{t+1}^{(n)} - \hat{x}r_{t+1}^{(n)}(M_s) \right)^2}{\sum_{t_0=1}^{T-1} \left(xr_{t+1}^{(n)} - \bar{x}r_{t+1}^{(n)} \right)^2} \quad (4.3)$$

where:

- $xr_{t+1}^{(n)}$ denotes the realized excess bond return for a bond with maturity n at time $t + 1$,
- $\hat{x}r_{t+1}^{(n)}(M_s)$ represents the forecasted excess bond return obtained using model M_{s_t} ,
- $\bar{x}r_{t+1}^{(n)}$ is the historical mean of excess bond returns, serving as the benchmark forecast.

The numerator captures the sum of squared prediction errors from the model, while the denominator represents the sum of squared errors when using the historical mean as the predictor. A positive R_{OOS}^2 implies that the model improves upon the naive historical mean forecast, while a negative R_{OOS}^2 suggests that the model performs worse than simply assuming future excess returns will follow their historical average.

The choice of out-of-sample predictive R^2 as the primary performance measure is motivated by its ability to assess a model's practical forecasting ability, rather than just its in-sample fit. Given the dynamic nature of bond risk premia, it is essential to test whether the model adapts to changing macroeconomic and financial conditions and provides reliable out-of-sample predictions. The use of R_{OOS}^2 allows for the evaluation of the methodology based on its ability to generalize to future market conditions, establishing it as a robust and meaningful metric for forecasting excess bond returns.

5. RESULTS

5.1 Summary of Model Performance

This section provides a comparative assessment of model performance in predicting local currency bond risk premia across six emerging markets—Brazil, Hungary, Poland, Thailand, South Africa, and Turkey. Using predictive out-of-sample R^2_{OOS} as the primary evaluation metric, the effectiveness of different modeling approaches, including traditional econometric techniques (OLS, PCA, PLS) and advanced machine learning models (Random Forest, XGBoost, Neural Networks, Extremely Randomized Trees) is analyzed. The results highlight substantial variations in predictive power across countries, reflecting differences in economic structures, market liquidity, and bond yield determinants.

Table 5.1 presents the highest predictive out-of-sample R^2_{OOS} values obtained for each country, reflecting the best-performing models in forecasting local currency bond risk premia.

Table 5.1: *Best-Performing Models in Forecasting Local Currency Bond Risk Premia.*

Country	R^2_{Oos}	Model Used	Variables Used
Hungary	0.4991	Neural Network	Forward Rates
Brazil	0.3871	Neural Network	Forward Rates + Term Premiums + Implied FX Volatility
Turkey	0.3847	XGBoost	Macroeconomic Data + Inflation
Thailand	0.3391	Neural Network	Term Premiums + Forward Rates
Poland	0.2822	OLS + PCA	Term Premiums + Forward Rates
South Africa	0.0886	XGBoost	Macroeconomic Data + Inflation + Implied FX Volatility + Forward Rates + Term Premiums + Forward-Spot Spreads

Models that incorporate forward rates and term premiums exhibit strong predictive power in Brazil, Hungary, Poland, and Thailand. In contrast, yield curve-based models show limited predictive strength in Turkey and South Africa, where inflation (CPI) and implied FX volatility emerge as dominant drivers.

Advanced machine learning techniques, particularly XGBoost and Neural Networks, consistently outperform OLS and PCA-based models. Their ability to capture complex, non-linear relationships in macroeconomic and financial data makes them especially effective in more volatile markets like Turkey and South Africa.

The differences in predictive power across countries highlight the importance of region-specific modeling approaches. A standardized, one-size-fits-all methodology is not suitable for emerging markets, as the dominant risk factors vary significantly by country.

5.2 Country-Level Analysis

5.2.1 Methodology for Country-Level Bond Risk Premium Analysis

In this study, excess bond returns across six emerging market economies to identify the most effective predictors of bond risk premia is analyzed. The framework involves a two-stage evaluation for each country:

5.2.1.1 Identifying the Top 5 Performing Models

First, different predictive models are evaluated and ranked based on their out-of-sample predictive R^2_{OOS} values. This allows us to highlight the most effective models in capturing bond risk premia dynamics. Various machine learning algorithms (e.g., Neural Networks, Random Forest, XGBoost) and traditional regression-based methods are compared to assess which models offer the highest accuracy.

5.2.1.2 Decomposing the Importance of Different Factors

After identifying the best-performing models, which economic and financial factors contribute most to predicting bond risk premia is analyzed. To systematically assess this, models are segmented into four distinct categories based on the number and type of explanatory variables.

Single-Factor Models

Single-factor models include only one explanatory variable, allowing us to assess its standalone predictive power in estimating excess bond returns. These models help determine which single factor contributes most significantly to bond risk premia fluctuations. The key variables analyzed in this category are, Implied FX Volatility, Inflation (CPI), Yield Curve Factors (Forward rates, term premiums, forward-spot spreads) and Macroeconomic Variables. By evaluating these variables in isolation, we can determine

which single factor is most influential in driving bond risk premia and how its effect compares across different markets.

Two-Factor Models

Two-factor models integrate two distinct economic or financial indicators to examine their combined impact on bond risk premia. The purpose of these models is to identify how different macroeconomic and market-based factors interact and whether their joint influence enhances predictive power.

The main two-factor combinations tested include:

- **Inflation + Implied FX Volatility:** This combination assesses how inflationary pressures and exchange rate uncertainty jointly impact bond risk premia.
- **Yield Curve Factors + Implied FX Volatility:** Since yield curve movements reflect interest rate expectations, combining them with FX volatility helps determine whether interest rate and currency risks jointly drive bond risk premia.
- **Macro Variables + Inflation:** This pairing examines how broader macroeconomic fundamentals interact with inflation trends to shape bond returns.
- **Macro Variables + Implied FX Volatility:** This model investigates whether overall economic conditions moderate or amplify the impact of currency risk on bond pricing.

Three-Factor Models

Three-factor models go one step further by incorporating three distinct explanatory variables to enhance prediction accuracy. These models aim to capture more complex interactions between macroeconomic conditions, inflationary pressures, and market volatility.

Three-factor groupings include:

- **Macro Variables + Inflation + Implied FX Volatility:** This combination evaluates whether bond risk premia are shaped by broad economic fundamentals, with inflation and FX volatility acting as additional risk drivers.
- **Yield Curve Factors + Inflation + Implied FX Volatility:** This model investigates whether interest rate expectations, inflation trends, and exchange rate uncertainty collectively determine bond pricing.

By introducing a third factor, these models attempt to capture more nuanced dependencies, which may be missed in single- or two-factor models.

Omni-Factor Models

Omni-factor models integrate all major macroeconomic and financial factors to construct the most comprehensive predictive models. These models aim to provide a full-spectrum understanding of bond risk premia fluctuations by incorporating yield curve factors, macro variables, inflation and implied FX Volatility. By combining all these key variables, omni-factor models serve as a benchmark for predictive accuracy. They allow us to assess whether adding more complexity improves forecasts or if simpler models (e.g., single- or two-factor models) perform just as well.

This structured model segmentation facilitates a comprehensive assessment of the determinants of bond risk premia. Specifically, it enables the identification of the most influential factors in predicting excess bond returns. Moreover, this approach allows for an evaluation of whether incorporating multiple explanatory variables enhances or diminishes predictive accuracy. By systematically comparing different modeling approaches across multiple countries, this segmentation provides insights into the relative importance of market-based indicators, such as yield curve factors and FX volatility, versus macroeconomic variables, including inflation and economic growth. By applying this methodology across six emerging market economies, this study systematically evaluates excess bond returns and identifies the most effective predictors for each country.

5.2.1.3 Implications for Policymakers and Investors

The findings from this cross-country analysis of bond risk premia in emerging markets provide valuable insights for both policymakers and investors, equipping them with a deeper understanding of bond market risks and their determinants. These insights enable market participants to make more informed investment decisions and allow policymakers to implement strategies that enhance market stability and efficiency. This section examines the implications of these findings for bond market participants, exploring their significance for risk assessment and investment strategies. Additionally, the policy implications for monetary authorities and sovereign debt issuers are analyzed, highlighting how these results can inform monetary policy decisions and optimize government bond issuance strategies.

5.2.2 Hungary

5.2.2.1 Identifying the Top 5 Performing Models

The predictive analysis for Hungary reveals that Neural Networks (NN) consistently achieved the highest predictive R^2 values across various model configurations. Among the different models tested, those incorporating Neural Networks exhibited superior performance, demonstrating their ability to capture complex and nonlinear relationships in bond risk premia predictions.

Table 5.2: *Top 5 Predictive Models for Bond Risk Premia in Hungary.*

No.	R^2_{OOS}	Model Used	Variables Used
1	0.4991	Neural Network	Forward Rates
2	0.4657	Neural Network	Forward Rates + Term Premiums + Forward-Spot Spreads
3	0.4657	Neural Network	Implied FX Volatility + Forward Rates + Term Premiums + Forward-Spot Spreads
4	0.4370	Neural Network	Macroeconomic Data + Inflation + Implied FX Volatility + Forward Rates + Term Premiums + Forward-Spot Spreads
5	0.4282	Neural Network	Forward Rates + Term Premiums

As shown in Table 5.2, the best-performing model utilized Forward Rates as the primary predictor, achieving a predictive R^2 of 49.91%. Another highly effective model combined FX Implied Volatility, Forward Rates, Term Premiums, and Forward-Spot Spreads, reaching a predictive R^2 of 46.57%. An equal performance was observed in a model that incorporated Forward Rates, Term Premiums, and Forward-Spot Spreads, which also attained an R^2 of 46.57%. When all available data inputs were used, the model achieved a predictive R^2 of 43.70%, while a model employing Forward Rates and Term Premiums alone yielded an R^2 of 42.82%.

The findings indicate that Forward Rates consistently emerge as a key predictive variable across the highest-performing models. The dominance of Neural Networks in the top-performing models underscores their capability in modeling the intricate patterns within bond risk premia data.

These results highlight the importance of yield curve-based factors, particularly Forward Rates, in forecasting bond risk premia, while macroeconomic variables contribute only marginally to predictive performance. This suggests that bond risk premia modeling in Hungary should prioritize market-based indicators over conventional macroeconomic metrics.

5.2.2.2 Decomposing the Importance of Different Factors

Single-Factor Models for Bond Risk Premia in Hungary

To assess the relative predictive power of different factors in explaining bond risk premia in Hungary, a series of single-factor models were estimated using various econometric and machine learning techniques. Table 5.3 presents the out-of-sample performance (R^2_{OOS}) of these models, comparing the effectiveness of yield curve factors, macroeconomic variables, and standalone financial indicators across different methodologies. The results provide insights into which variables contribute most to forecasting accuracy and highlight the superiority of certain modeling approaches in capturing bond risk premia dynamics.

Table 5.3: *Single-Factor Models for Bond Risk Premia in Hungary*

No.	R^2_{OOS}	Model Used	Model Content	Details for Yield Curve
1	0.0102	OLS	Implied FX Volatility	
2	-0.0886	OLS	Inflation	
3	0.0128	OLS + PCA	Yield Curve Factors	Forward Rates
4	0.3079	OLS + PCA	Yield Curve Factors	Forward Rates + Term Premiums
5	0.2911	OLS + PCA	Yield Curve Factors	Forward Rates + Term Premiums + Forward-Spot Spreads

No.	R^2_{OOS}	Model Used	Model Content	Details for Yield Curve
6	-0.2931	PLS	Yield Curve Factors	Forward Rates
7	0.2346	PLS	Yield Curve Factors	Forward Rates + Term Premiums
8	0.1922	PLS	Yield Curve Factors	Forward Rates + Term Premiums + Forward-Spot Spreads
9	-0.1373	OLS + PCA	Yield Curve Factors	Forward-Spot Spreads
10	-0.0028	OLS + PCA	Yield Curve Factors	Term Premiums
11	-0.1486	PLS	Yield Curve Factors	Forward-Spot Spreads
12	0.0203	PLS	Yield Curve Factors	Term Premiums
13	-0.7090	PLS	Macro Variables	
14	-0.3764	OLS + PCA	Macro Variables	
15	0.4991	Neural Network	Yield Curve Factors	Forward Rates
16	0.4282	Neural Network	Yield Curve Factors	Forward Rates + Term Premiums
17	0.4657	Neural Network	Yield Curve Factors	Forward Rates + Term Premiums + Forward-Spot Spreads
18	-0.7053	Neural Network	Macro Variables	
19	0.1796	XGBoost	Yield Curve Factors	Forward Rates
20	0.2760	XGBoost	Yield Curve Factors	Forward Rates + Term Premiums
21	0.1797	XGBoost	Yield Curve Factors	Forward Rates + Term Premiums + Forward-Spot Spreads
22	-0.8402	XGBoost	Macro Variables	

No.	R^2_{OOS}	Model Used	Model Content	Details for Yield Curve
23	0.3764	Random Forest	Yield Curve Factors	Forward Rates
24	0.4065	Random Forest	Yield Curve Factors	Forward Rates + Term Premiums
25	0.3629	Random Forest	Yield Curve Factors	Forward Rates + Term Premiums + Forward-Spot Spreads
26	-0.1929	Random Forest	Macro Variables	
27	0.3896	Extra Trees	Yield Curve Factors	Forward Rates
28	0.3784	Extra Trees	Yield Curve Factors	Forward Rates + Term Premiums
29	0.3563	Extra Trees	Yield Curve Factors	Forward Rates + Term Premiums + Forward-Spot Spreads
30	-0.1970	Extra Trees	Macro Variables	

The analysis of single-factor models depicted in Table 5.3 for Hungary's bond risk premia highlights the dominant role of yield curve factors while demonstrating the limited utility of macroeconomic variables and standalone inflation or FX volatility measures. Various modeling approaches were employed to assess the relative effectiveness of different predictors, revealing that forward rates consistently outperformed all other factors. The results emphasize the superiority of neural networks in capturing non-linear relationships and the necessity of avoiding macroeconomic variables, which introduced significant noise into the models.

Among all predictive factors, forward rates emerged as the most reliable predictor of bond risk premia. The highest out-of-sample predictive accuracy was achieved using neural networks (Model 15: $R^2_{OOS} = 0.4991$), confirming their effectiveness in modeling

non-linear financial relationships. Traditional econometric techniques, such as OLS with PCA (Model 4: $R^2_{\text{OOS}} = 0.3079$) and PLS (Model 7: $R^2_{\text{OOS}} = 0.2346$), also provided reasonable predictive power but lagged behind machine learning approaches. Adding forward-spot spreads led to a decline in accuracy (Model 5: $R^2_{\text{OOS}} = 0.2911$) when compared to a simpler forward rate model, reinforcing the notion that excessive model complexity can reduce forecasting effectiveness.

A comparison of different algorithms within yield curve models further underscores the dominance of neural networks, which consistently delivered the highest predictive accuracy. Among tree-based methods, Random Forest (Model 24: $R^2_{\text{OOS}} = 0.4065$) and Extremely Randomized Trees (Model 27: $R^2_{\text{OOS}} = 0.3896$) performed well but were less effective than neural networks. Meanwhile, XGBoost underperformed relative to other machine learning models (Model 20: $R^2_{\text{OOS}} = 0.2760$), indicating potential challenges in adapting this method to the nuances of yield curve dynamics. Traditional statistical approaches, including OLS and PLS, struggled with complex interactions, particularly when incorporating forward-spot spreads (Model 8: $R^2_{\text{OOS}} = 0.1922$).

The inclusion of macroeconomic variables significantly deteriorated model performance, with all macro-based models exhibiting deeply negative R^2_{OOS} values. The worst-performing models included PLS with macroeconomic variables (Model 13: $R^2_{\text{OOS}} = -0.7090$) and XGBoost with macroeconomic variables (Model 22: $R^2_{\text{OOS}} = -0.8402$), demonstrating the inability of these variables to provide meaningful predictive insights. Across all algorithms, macroeconomic factors introduced excessive noise, leading to unreliable forecasts.

Even advanced machine learning techniques were unable to extract useful signals from macroeconomic data. Neural networks, despite their adaptability, failed when applied to macroeconomic inputs (Model 18: $R^2_{\text{OOS}} = -0.7053$), while traditional linear models collapsed entirely (Model 14: $R^2_{\text{OOS}} = -0.3764$). These findings suggest that

macroeconomic indicators should be excluded from bond risk premia prediction models unless carefully integrated with yield curve factors.

Models that relied solely on inflation or implied FX volatility provided minimal predictive value. The use of inflation as a single factor resulted in weak performance (Model 2: $R^2_{\text{OOS}} = -0.0886$), indicating that it lacks independent explanatory power for bond risk premia. Similarly, implied FX volatility exhibited almost no predictive capability (Model 1: $R^2_{\text{OOS}} = 0.0102$), further reinforcing the notion that single-variable macro-based models are ineffective.

A clear ranking of model effectiveness emerged based on the ability to predict bond risk premia. Neural networks provided the most robust results, particularly when applied to forward rates (Model 15: $R^2_{\text{OOS}} = 0.4991$). Random Forest (Model 24: $R^2_{\text{OOS}} = 0.4065$) and Extremely Randomized Trees (Model 27: $R^2_{\text{OOS}} = 0.3896$) delivered moderate accuracy but did not surpass neural networks. XGBoost lagged behind other tree-based methods (Model 20: $R^2_{\text{OOS}} = 0.2760$). Traditional methods, including OLS and PLS, demonstrated limited success, with the exception of OLS when combined with PCA (Model 4: $R^2_{\text{OOS}} = 0.3079$).

Figure 5.1: *Predictive Power of Forward Rates Across Countries.*

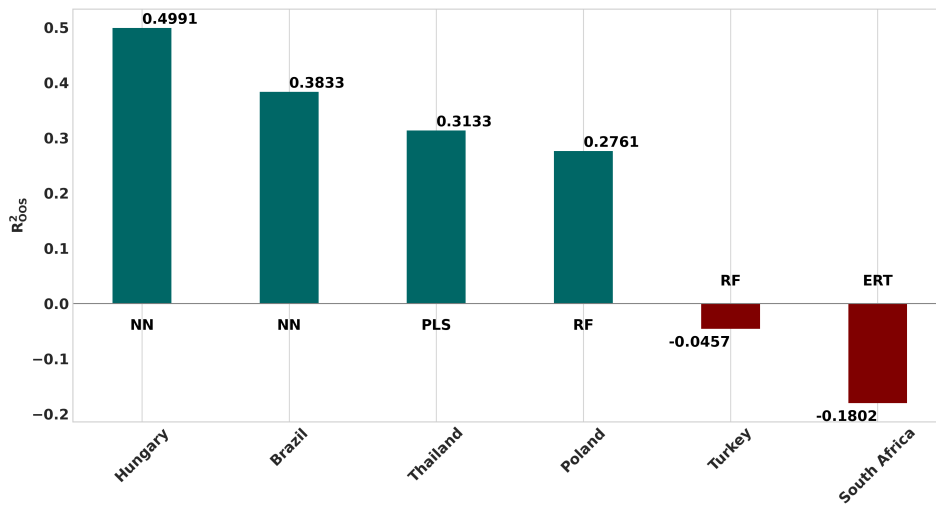


Figure 5.1 illustrates the out-of-sample predictive power of forward rates for local currency bond risk premia across six emerging markets using the best-performing models for each country. The results confirm that forward rates are the most effective predictor of bond risk premia in Hungary, reinforcing the supremacy of the yield curve in forecasting frameworks.

Among all countries examined, Hungary stands out as a benchmark, showcasing the full potential of forward rates when leveraged with non-linear algorithms. A similarly strong performance was observed for Brazil (NN, $R_{OOS}^2 = 0.3833$), suggesting the model's robustness in different market contexts. Thailand and Poland also demonstrated reasonably strong predictive performance with R_{OOS}^2 values of 0.3133 and 0.2761 respectively, utilizing PLS and Random Forest models. This reinforces the applicability of forward rates as meaningful predictors, even when paired with simpler or more interpretable machine learning methods.

In contrast, Turkey and South Africa exhibited negative R_{OOS}^2 values (-0.0457 and -0.1802 , respectively), indicating that forward rates failed to provide meaningful predictive power in these markets.

The results highlight notable cross-country heterogeneity in forecast accuracy, with Hungary and Brazil achieving the highest performance, while Turkey and South Africa exhibited negative predictive power.

The inclusion of additional factors, such as term premiums or spreads, diluted predictive power, emphasizing the importance of simplicity over complexity. Neural networks emerged as the most effective modeling approach, highlighting their superiority in capturing non-linear financial dynamics. In contrast, macroeconomic indicators consistently degraded model performance, suggesting that they should be omitted unless carefully hybridized with yield curve factors. These findings provide strong empirical support

for prioritizing forward rates, leveraging machine learning techniques, and excluding unnecessary macro variables to enhance the accuracy and efficiency of bond risk premia forecasting in Hungary.

Two-Factor Models for Bond Risk Premia in Hungary

To evaluate the predictive power of different modeling approaches in forecasting bond risk premia in Hungary, we tested a range of two-factor models incorporating various combinations of yield curve variables, implied FX volatility, inflation, and macroeconomic indicators. These models were estimated using both traditional econometric techniques (OLS, PLS, PCA) and advanced machine learning algorithms (Neural Networks, Random Forest, XGBoost, Extremely Randomized Trees). The objective was to determine which factor combinations and methodologies yield the most accurate out-of-sample predictions.

Table 5.4 summarizes the results, highlighting the relative performance of each model based on R^2_{OOS} values.

Table 5.4: *Two-Factor Models for Bond Risk Premia in Hungary*

No.	R^2_{OOS}	Model Used	Model Content	Details for Yield Curve
1	0.0255	OLS	Inflation + Implied FX Volatility	
2	0.3188	OLS + PCA	Implied FX Volatility + Yield Curve	Forward Rates + Term Premiums + Forward-Spot Spreads
3	0.2032	PLS	Implied FX Volatility + Yield Curve	Forward Rates + Term Premiums + Forward-Spot Spreads
4	-0.7663	PLS	Macro Variables + Inflation	
5	-0.3913	OLS + PCA	Macro Variables + Inflation	

No.	R^2_{OOS}	Model Used	Model Content	Details for Yield Curve
6	0.4657	Neural Network	Implied FX Volatility + Yield Curve	Forward Rates + Term Premiums + Forward-Spot Spreads
7	-0.6770	Neural Network	Macro Variables + Inflation	
8	-0.1074	Neural Network	Inflation + Implied FX Volatility	
9	0.1797	XGBoost	Implied FX Volatility + Yield Curve	Forward Rates + Term Premiums + Forward-Spot Spreads
10	-0.3531	XGBoost	Macro Variables + Inflation	
11	-0.6967	XGBoost	Inflation + Implied FX Volatility	
12	0.3629	Random Forest	Implied FX Volatility + Yield Curve	Forward Rates + Term Premiums + Forward-Spot Spreads
13	-0.1963	Random Forest	Macro Variables + Inflation	
14	-0.2139	Random Forest	Inflation + Implied FX Volatility	
15	0.3563	Extra Trees	Implied FX Volatility + Yield Curve	Forward Rates + Term Premiums + Forward-Spot Spreads
16	-0.2050	Extra Trees	Macro Variables + Inflation	
17	-0.2026	Extra Trees	Inflation + Implied FX Volatility	

The results from the two-factor models for bond risk premia in Hungary highlight

the superior predictive power of hybrid yield curve models, particularly when combined with implied FX volatility. Among the methodologies tested, Neural Networks (NN) demonstrated the highest out-of-sample predictive accuracy (Model 6: $R^2_{OOS} = 0.4657$), significantly outperforming traditional statistical approaches. Other machine learning models, such as Random Forest (RF) and Extremely Randomized Trees (ERT), also exhibited strong predictive capabilities (Model 12 and Model 15: $R^2_{OOS} \approx 0.36$), whereas traditional methods like Ordinary Least Squares (OLS) with Principal Component Analysis (PCA) achieved moderate success (Model 2: $R^2_{OOS} = 0.3188$). These findings underscore the importance of nonlinear machine learning techniques in modeling financial time series.

In contrast, macroeconomic variables consistently degraded model performance, reinforcing previous empirical evidence that these factors introduce noise rather than enhancing predictive accuracy. The poorest-performing models were Partial Least Squares (PLS) and Neural Networks when combined with macro variables, Model 4 and Model 7, with R^2_{OOS} values of -0.7663 and -0.6770, respectively. Even tree-based models, such as XGBoost, Model 10, failed to extract meaningful signals from macroeconomic inputs, further confirming their limited relevance in bond risk premia forecasting.

Additionally, the study finds limited synergy between inflation and implied FX volatility, as models incorporating these two factors yielded inconsistent results. While OLS showed minimal predictive power (Model 1: $R^2_{OOS} = 0.0255$), tree-based models such as XGBoost and RF entirely failed to generate meaningful forecasts, Model 11 and Model 14, exhibiting negative R^2_{OOS} values below -0.2 . This suggests that inflation alone does not contribute significantly to bond risk premia predictions and may only be relevant when embedded within a broader macroeconomic framework.

From a methodological perspective, machine learning models clearly outperformed

traditional techniques. Neural Networks emerged as the most effective approach, capturing complex, nonlinear relationships that conventional statistical models failed to identify. While Random Forest and ERT provided stable and reliable results, XGBoost underperformed despite its flexibility, highlighting potential limitations in handling financial data structures. Among traditional approaches, OLS and PLS were only effective when combined with PCA, demonstrating the necessity of dimensionality reduction in classical regression-based frameworks.

In conclusion, two-factor models reaffirm the dominance of yield curve factors, particularly forward rates, term premiums, and spreads, when combined with implied FX volatility. Neural Networks provide the most robust predictions, reinforcing their value in financial modeling. The inclusion of macroeconomic variables remains detrimental to model accuracy, while inflation alone adds little predictive value. These findings suggest that practitioners should prioritize hybrid yield curve models, leverage advanced machine learning techniques, and exclude macroeconomic variables to enhance the accuracy of bond risk premia forecasts in Hungary.

Three-Factor Models for Bond Risk Premia in Hungary

To further investigate the interaction between different predictive factors, three-factor models were constructed by combining inflation, implied FX volatility, and yield curve variables, as well as models incorporating macroeconomic variables alongside inflation and FX volatility.

Table 5.5 presents the out-of-sample performance (R_{OOS}^2) of these models across various statistical and machine learning techniques, providing insights into how multi-factor approaches influence predictive accuracy in Hungary's bond risk premia.

Table 5.5: *Three-Factor Models for Bond Risk Premia in Hungary.*

No.	R^2_{OOS}	Model Used	Model Content	Details for Yield Curve
1	0.3073	OLS + PCA	Inflation + Implied FX Volatility + Yield Curve	Forward Rates + Term Premiums + Forward-Spot Spreads
2	0.2009	PLS	Inflation + Implied FX Volatility + Yield Curve	Forward Rates + Term Premiums + Forward-Spot Spreads
3	-0.1854	OLS + PCA	Macro Variables + Inflation + Implied FX Volatility	
4	-0.5108	PLS	Macro Variables + Inflation + Implied FX Volatility	
5	0.4207	NN	Inflation + Implied FX Volatility + Yield Curve	Forward Rates + Term Premiums + Forward-Spot Spreads
6	-0.4775	NN	Macro Variables + Inflation + Implied FX Volatility	
7	0.3533	XGB	Inflation + Implied FX Volatility + Yield Curve	Forward Rates + Term Premiums + Forward-Spot Spreads
8	-0.4395	XGB	Macro Variables + Inflation + Implied FX Volatility	
9	0.4143	RF	Inflation + Implied FX Volatility + Yield Curve	Forward Rates + Term Premiums + Forward-Spot Spreads
10	-0.1742	RF	Macro Variables + Inflation + Implied FX Volatility	

No.	R^2_{OOS}	Model Used	Model Content	Details for Yield Curve
11	0.4167	ERT	Inflation + Implied FX Volatility + Yield Curve	Forward Rates + Term Premiums + Forward-Spot Spreads
12	-0.1964	ERT	Macro Variables + Inflation + Implied FX Volatility	

Neural Networks (NN) achieved the highest performance (Model 5: $R^2_{OOS} = 0.4207$), although this was slightly lower than the best-performing two-factor NN model (Model 17: $R^2_{OOS} = 0.4657$ in Table 5.4). Among tree-based methods, Random Forest (RF) and Extremely Randomized Trees (ERT) followed closely (Models 9 and 11: $R^2_{OOS} \approx 0.41$), demonstrating robustness in handling multi-factor interactions. Traditional econometric approaches such as OLS combined with PCA (Model 1: $R^2_{OOS} = 0.3073$) exhibited moderate predictive power but lagged behind machine learning models.

The inclusion of macroeconomic variables significantly impaired predictive accuracy across all model classes. The worst-performing models included PLS with macroeconomic variables (Model 4: $R^2_{OOS} = -0.5108$) and NN incorporating macroeconomic factors (Model 6: $R^2_{OOS} = -0.4775$), demonstrating that these variables introduce noise rather than enhancing predictive capability. Even among tree-based models, RF (Model 10: $R^2_{OOS} = -0.1742$) performed better than other approaches but still failed to generate meaningful forecasts. These findings align with previous results in two-factor models, where macroeconomic indicators consistently undermined model accuracy.

The addition of inflation to hybrid yield curve models produced mixed results. While NN (Model 5) and ERT (Model 11) maintained relatively strong predictive accuracy, XGBoost underperformed in the three-factor setting (Model 7: $R^2_{OOS} = 0.3533$) compared to its two-factor counterparts. This suggests that while inflation may serve

as a supplementary factor, its standalone predictive power remains insignificant, further reinforcing its limited role in bond risk premia modeling.

Machine learning techniques continued to outperform traditional methods, though with notable variations in rankings. Neural Networks (NN) remained the most effective approach, delivering the highest accuracy despite minor declines when transitioning from two-factor to three-factor models. ERT and RF exhibited stable performance, nearly matching NN when applied to hybrid models. In contrast, XGBoost underperformed relative to other tree-based methods, indicating that it may be more sensitive to increased model complexity. Among traditional statistical approaches, OLS and PLS demonstrated limited predictive power, except when combined with PCA, highlighting the necessity of dimensionality reduction in regression-based frameworks.

Three-factor models generally underperformed relative to two-factor models. For example, the best-performing two-factor NN model (Model 17: $R_{OOS}^2 = 0.4657$ in Table 5.4) outperformed its three-factor counterpart (Model 5: $R_{OOS}^2 = 0.4207$) in Table 5.5), suggesting diminishing returns from incorporating additional factors such as inflation. These results emphasize the need for balancing model complexity with predictive gains, as excessive feature inclusion may introduce noise rather than enhance forecasting precision.

The results of the three-factor models reaffirm the critical role of yield curve factors and implied FX volatility in forecasting Hungary's bond risk premia, while inflation contributes limited incremental value. Machine learning techniques, particularly Neural Networks, remain superior in capturing complex multi-factor interactions, whereas traditional econometric methods, particularly those incorporating PCA, retain niche utility in specific settings. Macroeconomic variables persist as a liability, consistently degrading model accuracy, further validating findings from single- and two-factor models. Given these results, practitioners should prioritize streamlined models that focus on yield curve

dynamics and FX volatility, exclude macroeconomic inputs, and leverage advanced algorithms to optimize predictive accuracy. These conclusions align with earlier findings, reinforcing the importance of simplicity and algorithmic sophistication in bond risk premia modeling.

Omni-Factor Models for Bond Risk Premia in Hungary

To comprehensively evaluate the combined effects of all key macroeconomic and financial variables on bond risk premia, omni-factor models were developed. These models integrate yield curve variables (forward rates, term premiums, forward-spot spreads), macroeconomic indicators (industrial production, retail sales, business confidence), inflation (CPI), and implied FX volatility.

Table 5.6 presents the out-of-sample R^2_{OOS} values of omni-factor models applied to Hungary's bond market.

Table 5.6: *Omni-Factor Models for Bond Risk Premia in Hungary.*

No.	R^2_{OOS}	Model Used	Model Content	Details for Yield Curve
1	0.2567	OLS + PCA	Macro Variables + Yield Curve + Inflation + Implied FX Volatility	Forward Rates + Term Premiums + Forward-Spot Spreads
2	0.1147	PLS	Macro Variables + Yield Curve + Inflation + Implied FX Volatility	Forward Rates + Term Premiums + Forward-Spot Spreads
3	0.4370	NN	Macro Variables + Yield Curve + Inflation + Implied FX Volatility	Forward Rates + Term Premiums + Forward-Spot Spreads
4	0.3533	XGB	Macro Variables + Yield Curve + Inflation + Implied FX Volatility	Forward Rates + Term Premiums + Forward-Spot Spreads

No.	R^2_{OOS}	Model Used	Model Content	Details for Yield Curve
5	0.4143	RF	Macro Variables + Yield Curve + Inflation + Implied FX Volatility	Forward Rates + Term Premiums + Forward-Spot Spreads
6	0.4167	ERT	Macro Variables + Yield Curve + Inflation + Implied FX Volatility	Forward Rates + Term Premiums + Forward-Spot Spreads

The Neural Network (NN) model achieved the highest predictive accuracy (Model 3: $R^2_{OOS} = 0.4370$), demonstrating its ability to capture complex interactions among diverse variables. This aligns with earlier results, where NN consistently outperformed other methods in Hungary.

Despite incorporating all factors, macroeconomic indicators continued to introduce noise. Traditional models like OLS + PCA (Model 1: $R^2_{OOS} = 0.2567$) and PLS (Model 2: $R^2_{OOS} = 0.1147$) underperformed significantly, reinforcing the limited utility of macroeconomic data in Hungary's bond risk premia modeling.

Random Forest (RF) and Extremely Randomized Trees (ERT) delivered moderate performance (Model 5 and Model 6: $R^2_{OOS} \approx 0.41$), outperforming XGBoost. This suggests that tree-based methods, while less effective than NN, still handle multi-factor interactions better than linear models.

The inclusion of forward rates and term premiums likely stabilized predictions, even amid macroeconomic noise. This echoes findings from single- and two-factor models, where yield curve variables dominated.

Omni-factor models underperformed relative to the best two-factor NN model where implied FX volatility and yield curve factors were used (Model 6: $R^2_{OOS} = 0.4657$

in Table 5.4), indicating diminishing returns from added complexity. While NN experienced a minor drop in performance (from 0.4657 to 0.4370), traditional models deteriorated further. This highlights a critical trade-off: excessive feature inclusion risks overfitting without commensurate gains.

For Hungary, omni-factor models validate the supremacy of neural networks and the irrelevance of macroeconomic variables. Practitioners should prioritize streamlined models focusing on yield curve dynamics and leverage NN to capture nonlinearities. Macroeconomic indicators, unless carefully filtered, degrade forecasting accuracy and should be excluded in favor of market-based signals.

Figure 5.2: *Hungary – Overview.*

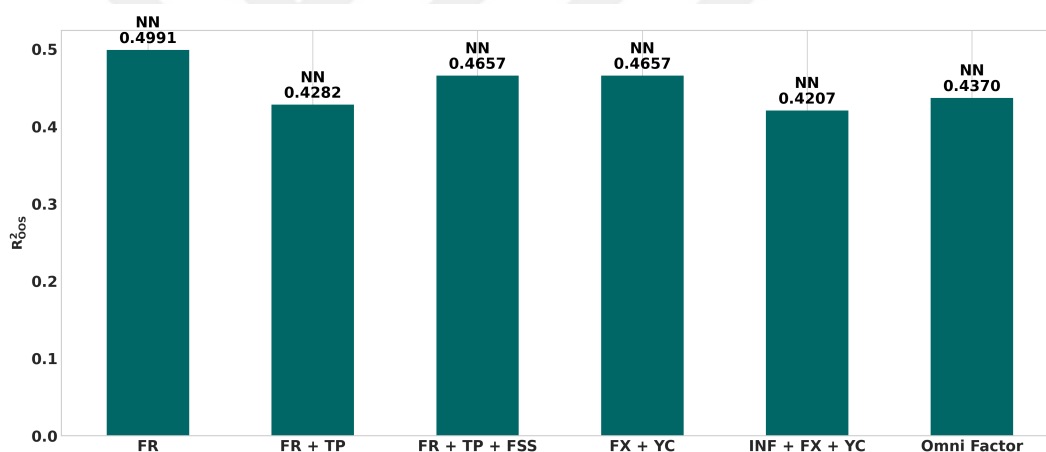


Figure 5.2 presents the out-of-sample predictive performance (R^2_{OOS}) of best-performing models as additional predictor variables are progressively incorporated into the forecasting framework for Hungary's local currency bond risk premia. The figure reveals a clear and consistent pattern: across all specifications, the Neural Network (NN) model yields the highest predictive accuracy, regardless of whether the inputs consist solely of yield curve factors or include additional financial and macroeconomic variables.

The top performance is achieved by the NN model using only forward rates (FR), with $R^2_{OOS} = 0.4991$, demonstrating the dominant role of this single yield curve variable.

When term premiums are added (FR + TP), the NN model still outperforms alternatives, although the predictive power slightly decreases to $R_{OOS}^2 = 0.4282$. Further inclusion of forward-spot spreads (FR + TP + FSS) raises R_{OOS}^2 back up to 0.4657, matching the performance of the FX + Yield Curve (FX + YC) specification, also modeled using NN.

As complexity increases with the addition of inflation (INF + FX + YC), the NN model maintains its superior predictive capacity, though the R_{OOS}^2 declines to 0.4207. Even in the most comprehensive Omni Factor specification—which includes macroeconomic indicators, inflation, FX volatility, and the full yield curve—the Neural Network remains the best-performing model, achieving $R_{OOS}^2 = 0.4370$.

These results are particularly notable because they demonstrate that Neural Networks consistently outperform all other modeling techniques—including tree-based methods, linear regressions, and regularized approaches—regardless of factor composition. This consistency highlights the flexibility and robustness of deep learning methods in capturing the nonlinear structure of bond risk premia in Hungary.

These findings form the empirical foundation for practical recommendations addressed in the next section.

5.2.2.3 Implications for Policymakers and Investors

What do these findings mean for bond market participants?

The results from Hungary's bond risk premia analysis emphasize the importance of yield curve factors, particularly forward rates, in predicting bond returns. Macroeconomic variables and inflation provide little to no predictive power. The dominant role of forward rates suggests that Hungary's bond market participants should primarily focus on market-based indicators rather than traditional macroeconomic fundamentals. This insight is crucial for bond traders, fund managers, and institutional investors, as it shifts the emphasis from conventional economic forecasting to more dynamic, yield-driven models.

Additionally, the findings underscore the efficacy of machine learning techniques, especially Neural Networks, in capturing complex financial relationships. Investors using traditional econometric models may underestimate or misprice bond risk premia, leading to potential inefficiencies in portfolio allocation. The use of Neural Networks and other Artificial Intelligence (AI)-driven models can significantly improve risk assessment and return forecasting, allowing investors to make more informed decisions in Hungary's bond market.

How can investors use predictive models for risk assessment?

The findings from Hungary's bond risk premia analysis indicate that investors can significantly enhance their risk assessment strategies by integrating advanced predictive models, particularly those leveraging machine learning techniques. Traditional econometric approaches, which rely heavily on macroeconomic indicators such as inflation and industrial production, have demonstrated limited predictive power in the Hungarian bond market. Instead, yield curve-based factors, particularly forward rates, emerge as the most reliable predictors of bond risk premia.

By incorporating machine learning models such as Neural Networks, Random Forest, and Extremely Randomized Trees (ERT), investors can achieve superior predictive accuracy compared to conventional linear models. These methodologies effectively capture the nonlinear relationships present in bond market dynamics, offering a more robust framework for forecasting excess returns. Given that forward rates have consistently exhibited the highest explanatory power, investors should develop dynamic trading strategies that prioritize these market-based indicators over macroeconomic fundamentals.

Policy Implications for Monetary Authorities and Bond Issuers

The findings of this study carry significant implications for monetary policymakers and sovereign bond issuers in Hungary. The predictive dominance of yield curve factors over macroeconomic variables suggests that traditional economic indicators, macroeconomic variables and inflation, may have limited utility in assessing bond market dynamics. Consequently, the Hungarian Central Bank (Magyar Nemzeti Bank, MNB) should focus on ensuring transparent communication regarding interest rate policies, as forward rates serve as the primary determinant of bond risk premia. Clear guidance on monetary policy expectations can reduce market uncertainty and facilitate more efficient pricing of government bonds.

Furthermore, Hungary's Debt Management Agency (ÁKK) could refine its bond issuance strategy by acknowledging that investors react predominantly to yield curve movements rather than macroeconomic conditions. Structuring long-term debt instruments with favorable term premiums may enhance the attractiveness of Hungary's local currency bonds, particularly for foreign investors seeking stable returns. This approach aligns with the empirical evidence demonstrating that term structure factors significantly outperform traditional macroeconomic indicators in forecasting bond risk premia.

In addition, financial regulators and policymakers should consider integrating artificial intelligence and machine learning techniques into their economic forecasting models. Given the superior predictive performance of Neural Networks and other machine learning approaches, central bank and financial institutions could enhance their macro-financial analysis by leveraging these advanced methodologies. Collaborative efforts between policymakers and AI researchers may improve the accuracy of debt sustainability assessments, allowing for more effective risk management in Hungary's sovereign bond market.

Ultimately, the results of this study suggest a paradigm shift in bond market analysis, emphasizing the need for data-driven, yield curve-based models in both investment

strategies and policy formulation. By adopting these insights, investors and policymakers alike can better navigate the complexities of Hungary's local currency bond market, ensuring a more stable and efficient financial environment.

5.2.3 Brazil

5.2.3.1 Identifying the Top 5 Performing Models

The predictive analysis for Brazil reveals that Neural Networks (NN) consistently achieved the highest predictive R^2 values across various model configurations.

As shown in Table 5.7, among the different models tested, those incorporating Neural Networks exhibited superior performance, demonstrating their ability to capture complex and nonlinear relationships in bond risk premia predictions.

Table 5.7: Top 5 Predictive Models for Bond Risk Premia in Brazil

No.	R^2_{OOS}	Model Used	Variables Used
1	0.3871	Neural Network	Implied FX Volatility + Forward Rates + Term Premiums + Forward-Spot Spreads
2	0.3833	Neural Network	Forward Rates
3	0.3812	Neural Network	Forward Rates + Term Premiums + Forward-Spot Spreads
4	0.3777	OLS + PCA	Implied FX Volatility + Forward Rates + Term Premiums + Forward-Spot Spreads
5	0.3750	PLS	Implied FX Volatility + Forward Rates + Term Premiums + Forward-Spot Spreads

The best-performing model utilized Implied FX Volatility, Forward Rates, Term Premiums, and Forward-Spot Spreads as the primary predictors, achieving a predictive R^2_{OOS} of 38.71%. Another highly effective model employed Forward Rates alone, reaching a predictive R^2_{OOS} of 38.33%. A similar performance was observed in a model that incorporated Forward Rates, Term Premiums, and Forward-Spot Spreads, which attained

an R^2_{OOS} of 38.12%. Additionally, PCA and PLS models incorporating similar variables also performed well, achieving predictive R^2_{OOS} values of 37.77% and 37.50%, respectively.

The findings indicate that Forward Rates consistently emerge as a key predictive variable across the highest-performing models. Additionally, the inclusion of Implied FX Volatility, Term Premiums and Forward-Spot Spreads improves predictive performance, suggesting that bond risk premia in Brazil are strongly influenced by both market-based indicators and external risk factors.

In summary, Neural Networks emerge as the most effective approach for predicting bond risk premia in Brazil, achieving up to 38.71% predictive R^2_{OOS} . These results highlight the importance of yield curve-based factors, particularly Forward Rates and Term Premiums, in forecasting bond risk premia, while macroeconomic variables contribute only marginally to predictive performance. This suggests that bond risk premia modeling in Brazil should prioritize market-driven indicators over traditional macroeconomic metrics.

5.2.3.2 Decomposing the Importance of Different Factors

Single-Factor Models for Bond Risk Premia in Brazil

The analysis of single-factor models for Brazil's bond risk premia shown in Table 5.8 reveals distinct patterns in predictive performance, emphasizing the dominance of yield curve factors while highlighting the limitations of macroeconomic variables.

Table 5.8: *Single-Factor Models for Bond Risk Premia in Brazil*

No.	R^2_{OOS}	Model Used	Model Content	Details for Yield Curve
1	-0.0914	OLS	Implied FX Volatility	
2	-0.0059	OLS	Inflation	
3	0.3367	OLS + PCA	Yield Curve Factors	Forward Rates

No.	R^2_{OOS}	Model Used	Model Content	Details for Yield Curve
4	0.3503	OLS + PCA	Yield Curve Factors	Forward Rates + Term Premiums
5	0.2964	OLS	Yield Curve Factors	Forward Rates + Term Premiums + Forward-Spot Spreads
6	0.3536	PLS	Yield Curve Factors	Forward Rates
7	0.3719	PLS	Yield Curve Factors	Forward Rates + Term Premiums
8	0.3516	PLS	Yield Curve Factors	Forward Rates + Term Premiums + Forward-Spot Spreads
9	0.0311	OLS	Yield Curve Factors	Forward-Spot Spreads
10	0.0529	OLS	Yield Curve Factors	Term Premiums
11	0.0316	PLS	Yield Curve Factors	Forward-Spot Spreads
12	0.0741	PLS	Yield Curve Factors	Term Premiums
13	-1.2163	PLS	Macro Variables	
14	-0.5451	OLS	Macro Variables	
15	0.3833	Neural Network	Yield Curve Factors	Forward Rates
16	0.3653	Neural Network	Yield Curve Factors	Forward Rates + Term Premiums
17	0.3812	Neural Network	Yield Curve Factors	Forward Rates + Term Premiums + Forward-Spot Spreads
18	-0.8243	Neural Network	Macro Variables	
19	0.1615	XGBoost	Yield Curve Factors	Forward Rates

No.	R_{OOS}^2	Model Used	Model Content	Details for Yield Curve
20	0.2024	XGBoost	Yield Curve Factors	Forward Rates + Term Premiums
21	0.1956	XGBoost	Yield Curve Factors	Forward Rates + Term Premiums + Forward-Spot Spreads
22	-0.5962	XGBoost	Macro Variables	
23	0.2878	Random Forest	Yield Curve Factors	Forward Rates
24	0.3157	Random Forest	Yield Curve Factors	Forward Rates + Term Premiums
25	0.3175	Random Forest	Yield Curve Factors	Forward Rates + Term Premiums + Forward-Spot Spreads
26	-0.2729	Random Forest	Macro Variables	
27	0.3208	Extra Trees	Yield Curve Factors	Forward Rates
28	0.3304	Extra Trees	Yield Curve Factors	Forward Rates + Term Premiums
29	0.3477	Extra Trees	Yield Curve Factors	Forward Rates + Term Premiums + Forward-Spot Spreads
30	-0.2821	Extra Trees	Macro Variables	

The results indicate that forward rates serve as the most robust predictor of bond risk premia, although the algorithmic hierarchy exhibits some differences compared to Hungary. In particular, Partial Least Squares (PLS) models demonstrated strong performance, with Model 7 (forward rates + term premiums) achieving $R_{OOS}^2 = 0.3719$, marking the highest predictive accuracy among PLS models. Neural Networks (NN) also

performed exceptionally well, with Model 15 (forward rates) reaching $R^2_{OOS} = 0.3833$, though their advantage over PLS was less pronounced in Brazil than in other markets.

The role of term premiums and forward-spot spreads varied across methodologies. While adding term premiums improved the predictive accuracy of PLS models (Model 7: $R^2_{OOS} = 0.3719$) compared to Model 6 ($R^2_{OOS} = 0.3536$), the inclusion of forward-spot spreads generally reduced performance (Model 8: $R^2_{OOS} = 0.3516$). In contrast, tree-based models such as Extremely Randomized Trees (ERT) benefited from incremental complexity, with Model 29 (forward rates + term premiums + forward-spot spreads) achieving $R^2_{OOS} = 0.3477$, outperforming simpler ERT configurations.

Among algorithmic comparisons, Neural Networks delivered the highest standalone predictive performance (Model 15: $R^2_{OOS} = 0.3833$), but the gains from adding term premiums or forward-spot spreads were marginal (Models 16–17: $R^2_{OOS} = 0.3653$ – 0.3812). PLS models outperformed traditional regression techniques such as Ordinary Least Squares (OLS) and OLS combined with Principal Component Analysis (PCA). Tree-based methods such as Random Forest (RF) and ERT showed moderate predictive accuracy (Model 24: $R^2_{OOS} = 0.3157$; Model 29: $R^2_{OOS} = 0.3477$), whereas XGBoost significantly underperformed in Brazil’s context (Model 20: $R^2_{OOS} = 0.2024$).

Consistent with findings from other emerging markets, macroeconomic variables proved to be a liability in predictive modeling. The inclusion of macroeconomic indicators led to severe declines in predictive accuracy across all models, with PLS incorporating macroeconomic variables exhibiting extreme overfitting (Model 13: $R^2_{OOS} = -1.2163$). Even flexible machine learning frameworks, such as Neural Networks, failed to extract meaningful signals from noisy macroeconomic data (Model 18: $R^2_{OOS} = -0.8243$). Traditional regression-based methods also struggled, with OLS incorporating macroeconomic variables resulting in negative predictive accuracy (Model 14: $R^2_{OOS} = -0.5451$).

These findings reinforce the conclusion that macroeconomic indicators should be excluded from single-factor models in Brazil's bond risk premia forecasting.

Inflation as a single predictor (Model 2: $R_{OOS}^2 = -0.0059$) and implied FX volatility (Model 1: $R_{OOS}^2 = -0.0914$) both generated near-zero or negative predictive accuracy, further substantiating the argument that single-variable models relying on these indicators are inadequate in Brazil's bond market context. These results mirror findings from Hungary, suggesting a broader structural pattern where yield curve-based factors significantly outperform macroeconomic indicators in bond risk premia estimation.

A clear hierarchy of predictive methodologies emerged from the analysis. Neural Networks achieved the highest accuracy when applied to yield curve factors, particularly forward rates (Model 15: $R_{OOS}^2 = 0.3833$), although PLS models demonstrated comparable effectiveness in some configurations (Model 7: $R_{OOS}^2 = 0.3719$). PLS proved remarkably robust, rivaling Neural Networks in predictive performance, which contrasts with findings from Hungary, where Neural Networks consistently outperformed all other approaches. Among tree-based methods, ERT (Model 29: $R_{OOS}^2 = 0.3477$) and RF (Model 25: $R_{OOS}^2 = 0.3175$) provided moderate utility, while XGBoost significantly underperformed (Model 20: $R_{OOS}^2 = 0.2024$). Traditional approaches, such as OLS combined with PCA, performed respectably (Model 4: $R_{OOS}^2 = 0.3503$) but lagged behind both PLS and Neural Networks.

The key conclusions from this analysis reinforce the supremacy of yield curve factors in predicting bond risk premia in Brazil, with forward rates emerging as the dominant predictive variable and term premiums adding value in select models. The performance of PLS relative to Neural Networks suggests that methodological flexibility is crucial in optimizing predictive accuracy for Brazil's bond market. The consistent underperformance of macroeconomic indicators further supports their exclusion from single-factor models.

Two-Factor Models for Bond Risk Premia in Brazil

The examination of two-factor models for Brazil's bond risk premia as presented in Table 5.9 provides crucial insights into the combined effects of yield curve variables, implied FX volatility, inflation, and macroeconomic indicators.

Table 5.9: *Two-Factor Models for Bond Risk Premia in Brazil*

No.	R^2_{OOS}	Model Used	Model Content	Details for Yield Curve
1	-0.0986	OLS	Inflation + Implied FX Volatility	
2	0.3777	OLS + PCA	Implied FX Volatility + Yield Curve	Forward Rates + Term Premiums + Forward-Spot Spreads
3	0.3750	PLS	Implied FX Volatility + Yield Curve	Forward Rates + Term Premiums + Forward-Spot Spreads
4	-1.1544	PLS	Macro Variables + Inflation	
5	-0.3115	OLS + PCA	Macro Variables + Inflation	
6	0.3871	Neural Network	Implied FX Volatility + Yield Curve	Forward Rates + Term Premiums + Forward-Spot Spreads
7	-0.8258	Neural Network	Macro Variables + Inflation	
8	-0.0762	Neural Network	Inflation + Implied FX Volatility	
9	0.1980	XGBoost	Implied FX Volatility + Yield Curve	Forward Rates + Term Premiums + Forward-Spot Spreads
10	-0.5897	XGBoost	Macro Variables + Inflation	
11	-0.8829	XGBoost	Inflation + Implied FX Volatility	

No.	R^2_{OOS}	Model Used	Model Content	Details for Yield Curve
12	0.3108	Random Forest	Implied FX Volatility + Yield Curve	Forward Rates + Term Premiums + Forward-Spot Spreads
13	-0.3238	Random Forest	Macro Variables + Inflation	
14	-0.2951	Random Forest	Inflation + Implied FX Volatility	
15	0.3609	Extra Trees	Implied FX Volatility + Yield Curve	Forward Rates + Term Premiums + Forward-Spot Spreads
16	-0.3752	Extra Trees	Macro Variables + Inflation	
17	-0.3777	Extra Trees	Inflation + Implied FX Volatility	

The findings reveal that hybrid models incorporating yield curve factors and implied FX volatility consistently outperformed all other configurations, while macroeconomic variables and inflation-based models yielded mixed results.

The most effective models were those that combined implied FX volatility with yield curve factors (forward rates, term premiums, and forward-spot spreads). Among the top-performing approaches, Neural Networks (Model 6: $R^2_{OOS} = 0.3871$) delivered the highest predictive accuracy, closely followed by OLS + PCA (Model 2: $R^2_{OOS} = 0.3777$). Extremely Randomized Trees (ERT) also performed moderately well in this category, though with lower accuracy (Model 15: $R^2_{OOS} = 0.3609$).

Macroeconomic variables and inflation failed to produce reliable forecasts, with ERT (Model 16: $R^2_{OOS} = -0.3753$) or OLS + PCA (Model 5: $R^2_{OOS} = -0.3115$) performing particularly poorly. These results reinforce the general unreliability of macroeconomic indicators in bond risk premia modeling.

Models pairing inflation with FX volatility exhibited near-zero or negative predictive accuracy, further confirming that these variables do not provide meaningful insights when combined. OLS models using inflation and FX volatility (Model 1: $R^2_{OOS} = -0.0986$) failed to generate significant predictive power, while Neural Networks incorporating the same factors performed even worse (Model 8: $R^2_{OOS} = -0.0762$). Similarly, ERT models with inflation and FX volatility (Model 17: $R^2_{OOS} = -0.3777$) showed substantial negative accuracy, reinforcing findings from Hungary that inflation lacks standalone predictive power and does not interact effectively with FX volatility. These results suggest that practitioners should avoid incorporating inflation-FX volatility pairings in bond risk premia models for Brazil, as they consistently introduce noise rather than valuable signals.

From a methodological perspective, Neural Networks demonstrated robust performance for hybrid yield curve models, particularly when combined with implied FX volatility (Model 6: $R^2_{OOS} = 0.3871$). In contrast, XGBoost performed poorly across all configurations (e.g., Model 9: $R^2_{OOS} = 0.198$), suggesting that gradient-boosted trees may not be well suited to Brazil's bond market dynamics.

The key conclusions from this analysis reinforce the importance of hybrid yield curve and FX volatility models, which consistently outperformed other factor combinations. Neural Networks emerged as the most reliable predictive frameworks, highlighting their ability to capture complex relationships in bond risk premia estimation. Moreover, inflation-FX volatility pairings should be excluded from bond risk premia models for Brazil, as they consistently reduce predictive accuracy across various methodologies.

Three-Factor Models for Bond Risk Premia in Brazil

The analysis of three-factor models for Brazil's bond risk premia as documented in Table 5.10 provides critical insights into the trade-offs between complexity and predictive accuracy. The results highlight that while hybrid yield curve models deliver the highest

predictive accuracy, the inclusion of macroeconomic variables consistently deteriorates model performance.

Table 5.10: *Three-Factor Models for Bond Risk Premia in Brazil*

No.	R^2_{OOS}	Model Used	Model Content	Details for Yield Curve
1	-2.7485	OLS + PCA	Inflation + Implied FX Volatility + Yield Curve	Forward Rates + Term Premiums + Forward-Spot Spreads
2	-2.8921	PLS	Inflation + Implied FX Volatility + Yield Curve	Forward Rates + Term Premiums + Forward-Spot Spreads
3	-0.2871	OLS + PCA	Macro Variables + Inflation + Implied FX Volatility	
4	-1.0631	PLS	Macro Variables + Inflation + Implied FX Volatility	
5	0.3504	Neural Network	Inflation + Implied FX Volatility + Yield Curve	Forward Rates + Term Premiums + Forward-Spot Spreads
6	-0.6215	Neural Network	Macro Variables + Inflation + Implied FX Volatility	
7	0.2087	XGBoost	Inflation + Implied FX Volatility + Yield Curve	Forward Rates + Term Premiums + Forward-Spot Spreads
8	-0.6583	XGBoost	Macro Variables + Inflation + Implied FX Volatility	

No.	R^2_{OOS}	Model Used	Model Content	Details for Yield Curve
9	0.3568	Random Forest	Inflation + Implied FX Volatility + Yield Curve	Forward Rates + Term Premiums + Forward-Spot Spreads
10	-0.3568	Random Forest	Macro Variables + Inflation + Implied FX Volatility	
11	0.3750	Extra Trees	Inflation + Implied FX Volatility + Yield Curve	Forward Rates + Term Premiums + Forward-Spot Spreads
12	-0.3351	Extra Trees	Macro Variables + Inflation + Implied FX Volatility	

Among the most effective models, Extremely Randomized Trees (ERT) delivered the strongest results (Table 5.10, Model 11: $R^2_{OOS} = 0.3750$), slightly outperforming Random Forest (Model 9: $R^2_{OOS} = 0.3568$) and Neural Networks (Model 5: $R^2_{OOS} = 0.3504$). These results suggest that ERT captures complex nonlinear relationships in Brazil's bond market more effectively than other machine learning methods. In contrast, traditional techniques such as PLS and OLS + PCA completely failed in this setting, producing dramatically poor results (Models 1–2: $R^2_{OOS} < -2.7$). The inability of these models to handle Brazil's three-factor complexity further reinforces the superiority of machine learning techniques in forecasting bond risk premia.

Despite the inclusion of inflation in some of the top-performing models, macroeconomic variables remained detrimental to predictive accuracy across all tested configurations. The worst results were observed in models that incorporated macroeconomic indicators, with PLS producing extremely poor performance (Model 4: $R^2_{OOS} = -1.0631$) and XGBoost suffering similar accuracy degradation (Model 8: $R^2_{OOS} = -0.6583$). Even within more flexible machine learning frameworks, Neural Networks incorporating

macroeconomic variables (Model 6: $R^2_{OOS} = -0.6215$) and ERT (Model 12: $R^2_{OOS} = -0.3351$) failed to extract meaningful predictive signals, reinforcing the argument that macroeconomic indicators introduce excessive noise rather than enhancing forecast accuracy.

The role of inflation in three-factor models was also found to be highly dependent on the modeling approach. While inflation contributed positively when combined with yield curve factors in ERT models (Model 11: $R^2_{OOS} = 0.3750$), its standalone predictive power remained negligible. For instance, XGBoost incorporating inflation showed only modest gains (Model 7: $R^2_{OOS} = 0.2087$), significantly underperforming relative to ERT and RF. Additionally, traditional statistical frameworks such as OLS + PCA and PLS collapsed entirely when inflation was included (Models 1–2: $R^2_{OOS} < -2.7$), emphasizing that inflation’s volatility renders it ineffective in linear modeling settings.

From a methodological standpoint, machine learning algorithms outperformed traditional approaches, with ERT, RF, and NN delivering the most robust predictions. The superior performance of ERT (Model 11: $R^2_{OOS} = 0.3750$) over other methodologies contrasts with Hungary, where Neural Networks dominated, suggesting that optimal algorithm selection is highly country-specific. Conversely, XGBoost struggled to adapt to Brazil’s bond market, lagging behind other machine learning techniques (Model 7: $R^2_{OOS} = 0.2087$). This result is likely due to overfitting or incompatibility with the structure of Brazil’s yield curve, reinforcing the need for algorithmic adaptability across different markets.

Traditional econometric models performed the worst in three-factor settings, as evidenced by PLS and OLS + PCA generating substantially negative results (Models 1–2: $R^2_{OOS} < -2.7$). The failure of these methods underscores their inability to handle Brazil’s multi-factor complexity without appropriate dimensionality reduction techniques.

While three-factor models provided some improvement over single-factor frameworks, their advantage over two-factor models was inconsistent. For example, ERT's three-factor model (Table 5.10, Model 11: $R^2_{OOS} = 0.3750$; content: Inflation + Implied FX Volatility + Yield Curve [Forward Rates + Term Premiums + Forward-Spot Spreads]) outperformed its single-factor counterpart (Table 5.8, Model 29: $R^2_{OOS} = 0.3477$; content: Yield Curve [Forward Rates + Term Premiums + Forward-Spot Spreads]), suggesting incremental gains from incorporating inflation.

However, this trend was not universal, as Neural Networks exhibited diminishing returns when moving from two-factor (Table 5.9, Model 6: $R^2_{OOS} = 0.3871$; content: Implied FX Volatility + Yield Curve [Forward Rates + Term Premiums + Forward-Spot Spreads]) to three-factor settings (Table 5.10, Model 5: $R^2_{OOS} = 0.3504$; content: Inflation + Implied FX Volatility + Yield Curve [Forward Rates + Term Premiums + Forward-Spot Spreads]).

These findings indicate that while increased model complexity can enhance predictive accuracy in certain cases, it does not always translate into meaningful improvements and may instead introduce overfitting risks.

The key conclusions from this analysis emphasize that hybrid models integrating yield curve factors, FX volatility, and inflation provide the best results, particularly when ERT or RF are used as the modeling framework. However, the marginal improvements from inflation suggest that simpler two-factor models may be preferable in certain cases. Additionally, macroeconomic variables should be excluded from bond risk premia models in Brazil, as they consistently degrade accuracy across multiple methodologies. The importance of selecting the appropriate machine learning algorithm is also evident, with ERT and RF proving optimal for Brazil's bond market, while XGBoost and traditional methods should be avoided.

Ultimately, these findings advocate for a balanced approach to complexity in bond

risk premia forecasting. While three-factor models offer some advantages over single-factor frameworks, they do not consistently outperform two-factor models and may introduce additional risks.

Omni-Factor Models for Bond Risk Premia in Brazil

Unlike previous findings from Hungary, where Neural Networks dominated, the results for Brazil indicate that traditional econometric methods unexpectedly outperformed machine learning frameworks in some cases. As shown in Table 5.11, the omni-factor models for Brazil highlight this pattern, where traditional econometric approaches occasionally outperform machine learning methods.

Table 5.11: *Omni-Factor Models for Bond Risk Premia in Brazil.*

No.	R^2_{OOS}	Model Used	Model Content	Details for Yield Curve
1	0.3622	OLS + PCA	Macro Variables + Yield Curve + Inflation + Implied FX Volatility	Forward Rates + Term Premiums + Forward-Spot Spreads
2	0.2091	PLS	Macro Variables + Yield Curve + Inflation + Implied FX Volatility	Forward Rates + Term Premiums + Forward-Spot Spreads
3	0.3548	Neural Network	Macro Variables + Yield Curve + Inflation + Implied FX Volatility	Forward Rates + Term Premiums + Forward-Spot Spreads
4	0.1269	XGBoost	Macro Variables + Yield Curve + Inflation + Implied FX Volatility	Forward Rates + Term Premiums + Forward-Spot Spreads
5	0.3256	Random Forest	Macro Variables + Yield Curve + Inflation + Implied FX Volatility	Forward Rates + Term Premiums + Forward-Spot Spreads

No.	R^2_{OOS}	Model Used	Model Content	Details for Yield Curve
6	0.3032	Extra Trees	Macro Variables + Yield Curve + Inflation + Implied FX Volatility	Forward Rates + Term Premiums + Forward-Spot Spreads

The highest predictive accuracy was achieved by OLS with PCA (Model 1 in Table 5.11: $R^2_{OOS} = 0.3622$), slightly surpassing Neural Networks (Model 3: $R^2_{OOS} = 0.3548$). This suggests that dimensionality reduction techniques such as PCA effectively mitigate the noise introduced by macroeconomic variables, enabling simpler models to extract stable predictive signals in Brazil's complex bond market.

Some models, such as PLS (Model 2: $R^2_{OOS} = 0.2091$) and XGBoost (Model 4: $R^2_{OOS} = 0.1269$), delivered weak but moderately acceptable results.

The stability observed in omni-factor models can be attributed to the anchoring role of yield curve factors, which have consistently been identified as the most reliable predictors of bond risk premia across different configurations. As seen in previous analyses, forward rates, term premiums, and forward-spot spreads play a crucial role in offsetting the noise introduced by macroeconomic data, reinforcing findings from single-factor (Table 5.8) and two-factor models (Table 5.9).

Machine learning approaches, which had previously demonstrated strong performance in Brazil's bond market, did not meet expectations in the omni-factor setting. While Neural Networks remained a top performer (Model 3: $R^2_{OOS} = 0.3548$), it lagged behind OLS+PCA, contrary to the trends observed in Hungary. Among tree-based models, Random Forest (Model 5: $R^2_{OOS} = 0.3256$) and Extremely Randomized Trees (Model 6: $R^2_{OOS} = 0.3032$) delivered moderate accuracy, yet neither surpassed simpler econometric models such as OLS+PCA. XGBoost continued to struggle (Model

4: $R^2_{OOS} = 0.1269$), further reinforcing its incompatibility with Brazil's bond market dynamics. These findings suggest that Brazil's market structure favors simpler, regularized models over highly complex machine learning frameworks, a trend that contrasts with the Hungarian results.

Comparisons with simpler models reveal that omni-factor frameworks failed to surpass the best-performing two-factor models. For example, Neural Network's two-factor model (Model 6 in Table 5.9: $R^2_{OOS} = 0.3871$) outperformed all omni-factor models, highlighting the diminishing returns of increased model complexity. However, omni-factor models still outperformed most three-factor models, such as ERT's best three-factor model (Model 11 in Table 5.10: $R^2_{OOS} = 0.3750$).

The dramatic improvement observed in OLS+PCA's omni-factor model (Table 5.11, Model 1: $R^2_{OOS} = 0.3622$; content: Macro Variables + Yield Curve + Inflation + Implied FX Volatility [Forward Rates + Term Premiums + Forward-Spot Spreads]) over its three-factor counterpart (Table 5.10, Model 1: $R^2_{OOS} = -2.7485$; content: Inflation + Implied FX Volatility + Yield Curve [Forward Rates + Term Premiums + Forward-Spot Spreads]) underscores the critical role of expanding the factor universe to include macroeconomic variables and refining dimensionality reduction techniques. By integrating broader macroeconomic indicators and restructuring the PCA to holistically capture interactions between forward rates, term premiums, and forward-spot spreads, the omni-factor model mitigates the severe misspecification and overfitting evident in the three-factor framework. This shift not only resolves the paradoxical negative R^2 but also enhances the model's capacity to explain cross-sectional variance, reflecting the necessity of balancing parsimony with comprehensive factor representation in financial forecasting.

In contrast, Neural Networks exhibited a slight decline in the omni-factor setting (Table 5.11, Model 3: $R^2_{OOS} = 0.3548$) compared to their two-factor performance (Table 5.9, Model 6: $R^2_{OOS} = 0.3871$; content: Implied FX Volatility + Yield Curve

[Forward Rates + Term Premiums + Forward-Spot Spreads]), suggesting overfitting risks from added complexity.

The methodological insights derived from these findings emphasize the importance of dimensionality reduction in handling Brazil's macroeconomic noise. The success of OLS+PCA (Model 1) underscores the necessity of applying PCA or similar regularization techniques when incorporating a large number of variables, ensuring that redundant or unstable features do not distort predictions. These results also demonstrate the heterogeneity in algorithmic preferences across different markets, as Brazil's bond market appears to favor simpler, structured models, while Hungary's results indicated that Neural Networks were the dominant predictive framework.

Another key insight is the conditional utility of macroeconomic variables. While their inclusion in single-, two-, and three-factor models significantly degraded performance, omni-factor frameworks demonstrate that macroeconomic indicators do not universally harm predictions when balanced against yield curve and FX variables. This suggests that while macroeconomic data should generally be excluded from simple bond risk premia models, it may still be useful when paired with robust dimensionality reduction techniques and yield curve anchoring.

The overall conclusions from this analysis reinforce several key takeaways for Brazil's bond risk premia forecasting. OLS+PCA and Neural Networks emerged as the most effective frameworks in omni-factor models, offering a balance between complexity and accuracy. XGBoost performed poorly across all configurations and should be avoided, as its struggles persisted across different model types. Yield curve factors remain the foundation of predictive accuracy, as models that included forward rates, term premiums, and spreads consistently outperformed those that did not. Finally, the trade-off between complexity and practicality must be carefully considered, as omni-factor models do not provide a decisive advantage over streamlined two-factor approaches.

These findings advocate for a cautious approach to comprehensive modeling in Brazil's bond market, emphasizing the importance of yield curve factors, leveraging PCA for handling macroeconomic noise, and prioritizing methodological flexibility over algorithmic complexity.

Figure 5.3: *Brazil – Overview.*

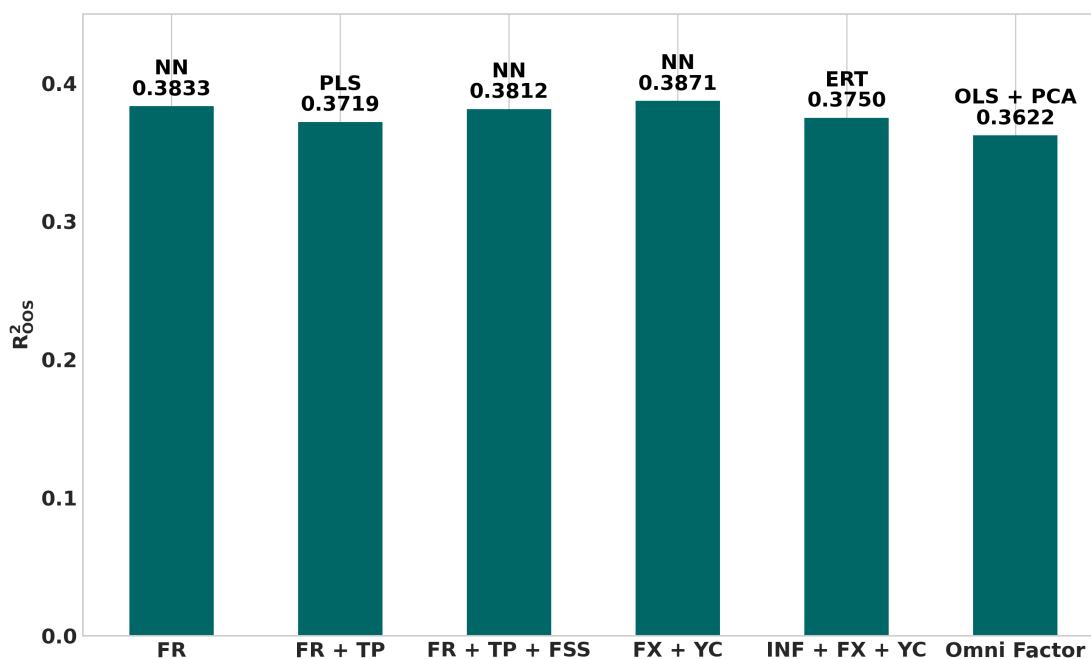


Figure 5.3 illustrates how the out-of-sample predictive accuracy (R^2_{OOS}) evolves as additional predictor variables are sequentially integrated into the forecasting models for Brazil's local currency bond risk premia. Unlike Hungary, where Neural Networks (NN) dominated across all configurations, the Brazilian context exhibits a more nuanced hierarchy in which model performance varies depending on factor complexity.

The highest R^2_{OOS} value (0.3833) is achieved by a Neural Network model using only forward rates (FR), reaffirming the critical role of forward rates as the most reliable standalone predictor. However, when term premiums are added (FR + TP), Partial Least

Squares (PLS) outperforms all other approaches with $R^2_{OOS} = 0.3719$, suggesting that linear techniques based on dimensionality reduction can perform competitively in Brazil when yield curve inputs are moderately expanded.

Upon including forward-spot spreads (FR + TP + FSS), Neural Networks regain the lead with $R^2_{OOS} = 0.3812$, showcasing their ability to model more complex, nonlinear structures effectively. This demonstrates that, in Brazil, the predictive advantage of Neural Networks becomes more apparent as model complexity increases, particularly when all key yield curve components are jointly considered.

The combination of FX volatility and yield curve factors (FX + YC) also yields strong results under the NN framework ($R^2_{OOS} = 0.3871$), exceeding the simpler FR-only model. This suggests that in Brazil, unlike in some other markets, implied FX volatility contains useful forward-looking information about risk premia when incorporated into flexible algorithms like neural networks.

However, once inflation is added to the model (INF + FX + YC), the best results are achieved by Extremely Randomized Trees (ERT), with a slightly lower $R^2_{OOS} = 0.3750$. The fact that a tree-based method outperforms NN in this setting implies that nonlinear interactions involving inflation may be better captured through ensemble models with randomized splits, which are less sensitive to noise.

Finally, the Omni Factor model—combining all available variables, including macroeconomic indicators—performs best under OLS with Principal Component Analysis (PCA), producing $R^2_{OOS} = 0.3622$. Although this is below the top-performing NN configurations, it illustrates the stabilizing effect of dimensionality reduction in highly saturated variable environments. Notably, NN does not outperform OLS + PCA in the Omni setup, suggesting that the benefit of deep learning declines when faced with noisy, high-dimensional macroeconomic data in Brazil's context.

5.2.3.3 Implications for Policymakers and Investors

What do these findings mean for bond market participants?

The analysis of Brazil's bond risk premia underscores the critical role of yield curve factors and implied FX volatility as primary drivers of excess bond returns. Brazil's bond market participants should recalibrate their strategies to focus on real-time yield curve movements and currency risk indicators, which offer more reliable signals for pricing and risk assessment.

The superior performance of machine learning models (e.g., Neural Networks) further suggests that investors relying on linear econometric models may misprice risk or overlook nonlinear interactions between yield curve components and FX volatility. Adopting AI-driven frameworks can enhance decision-making, particularly in Brazil's volatile emerging market context, where abrupt shifts in investor sentiment and currency risks are common.

How can investors use predictive models for risk assessment?

Investors in Brazil's local currency bond market can leverage machine learning models to refine risk assessment and return forecasting. The study demonstrates that models incorporating forward rates, term premiums and implied FX volatility processed through techniques like Neural Networks—deliver robust predictive accuracy. These models excel at capturing nonlinear relationships, such as how sudden FX depreciation amplifies bond risk premia or how term premiums adjust to shifts in monetary policy expectations.

To optimize risk management, investors should:

1. Integrate yield curve dynamics: Develop trading strategies that respond to forward rate trends and term premium fluctuations, which are pivotal in Brazil's bond market.

2. Monitor FX volatility: Incorporate implied FX volatility metrics to hedge currency risks, given Brazil's sensitivity to global risk sentiment and commodity price cycles.
3. Deploy ensemble models: Combine tree-based methods (e.g., XGBoost, Random Forest) with Neural Networks to balance interpretability and predictive power, ensuring adaptability to Brazil's evolving market conditions.

Policy Implications for Monetary Authorities and Bond Issuers

For Brazil's central bank (Banco Central do Brazil, BCB) and debt management agency (Tesouro Nacional), the findings underscore the importance of prioritizing yield curve stability and mitigating foreign exchange (FX) risk in policy formulation. The limited predictive power of macroeconomic variables in explaining bond risk premia suggests that traditional indicators, such as inflation or industrial production, may not be sufficient for assessing market sentiment. Instead, policymakers should focus on market-based indicators, particularly those derived from the yield curve and currency volatility, to enhance financial stability and improve debt management strategies.

One of the most critical policy recommendations derived from the analysis is the need for enhanced transparency in monetary policy communication. Since forward rates play a dominant role in shaping bond risk premia, providing clear guidance on future interest rate trajectories can help anchor market expectations and reduce bond market volatility. By ensuring consistent and transparent communication of monetary policy decisions, the central bank can facilitate a more predictable bond pricing environment, thereby improving investor confidence and market efficiency.

In addition, the results highlight the necessity of strengthening FX risk management frameworks to mitigate the impact of currency fluctuations on bond pricing. The volatility of the Brazilian real (BRL) poses a significant risk to local currency bond investors, making it imperative for policymakers to implement measures aimed at stabilizing exchange rate dynamics. These measures could include strategic foreign reserve

management, enhancing market liquidity through well-structured derivatives markets, or providing hedging mechanisms to offset FX risks. By adopting a more proactive approach to FX risk mitigation, policymakers can reduce the uncertainty surrounding Brazil's sovereign bond market, thereby enhancing its attractiveness to both domestic and international investors.

Furthermore, the findings suggest that integrating artificial intelligence (AI) and machine learning techniques into Brazil's economic forecasting models could significantly improve debt sustainability assessments and market risk evaluations. Given the superior predictive accuracy of machine learning models over traditional econometric methods, incorporating AI-driven methodologies into monetary and fiscal policy analyses can enhance the ability of policymakers to anticipate market stress points and respond effectively to evolving financial conditions. By leveraging data-driven models for sovereign risk assessment, Brazil's financial authorities can develop more precise and forward-looking macroeconomic policies, thereby strengthening the resilience of its bond market.

For sovereign bond issuers, the findings indicate that structuring debt instruments in alignment with yield curve dynamics can optimize borrowing costs and improve debt sustainability. Since term structure factors, particularly forward rates and term premiums, are the primary drivers of bond risk premia, adjusting debt issuance strategies to reflect yield curve conditions can enhance Brazil's appeal to foreign investors. Issuing longer-dated bonds during periods of compressed term premiums may help extend debt maturities at lower financing costs, while offering FX-hedged bond options could further attract international capital flows. By designing debt instruments that align with market-based indicators, Brazil's debt management agency can improve liquidity conditions, enhance investor participation, and create a more resilient sovereign bond market.

Ultimately, by prioritizing yield curve stability, enhancing FX risk mitigation measures, and leveraging AI-powered forecasting models, both the Banco Central do Brasil and Tesouro Nacional can foster a more efficient and stable financial environment, ensuring the long-term sustainability of Brazil's sovereign bond market.

5.2.4 Thailand

5.2.4.1 Identifying the Top 5 Performing Models

The process of predicting local currency bond risk premia in Thailand reveals that Neural Network (NN) models and PCA-applied models exhibit the highest predictive power.

As shown in Table 5.12, NN-based models achieved the highest predictive R^2 of 33.91%, demonstrating their effectiveness in capturing the nonlinear nature of bond returns. Similarly, PCA-applied models, particularly those based on forward rates and term premiums, performed strongly ($R^2 = 33.30\%$).

Table 5.12: Top 5 Predictive Models for Bond Risk Premia in Thailand.

No.	R^2_{OOS}	Model Used	Variables Used
1	0.3391	Neural Network	Forward Rates + Term Premiums
2	0.3330	OLS + PCA	Forward Rates + Term Premiums
3	0.3208	Neural Network	Forward Rates + Term Premiums + Forward-Spot Spreads
4	0.3133	PLS	Forward Rates
5	0.3125	OLS + PCA	Forward Rates + Term Premiums + Forward-Spot Spreads

Another Neural Network model closely followed with an R^2 of 32.08%. Partial Least Squares (PLS) and PCA-applied OLS models also ranked among the top-performing approaches, though with slightly lower predictive power.

These results for Thailand emphasize the significance of yield curve-based factors, particularly forward rates and term premiums, in forecasting bond risk premia. Forward Rates and Term Premiums are critical predictors, mirroring findings from Hungary and Brazil. Their combination consistently drives higher predictive accuracy.

5.2.4.2 Decomposing the Importance of Different Factors

Single-Factor Models for Bond Risk Premia in Thailand.

Thailand's single-factor models presented in Table 5.13 reveal distinct patterns in bond risk premia drivers, with yield curve factors dominating predictive accuracy, similar to Hungary and Brazil.

Table 5.13: *Single-Factor Models for Bond Risk Premia in Thailand.*

No.	R^2_{OOS}	Model Used	Model Content	Details for Yield Curve
1	-0.0430	OLS	Implied FX Volatility	
2	-0.0450	OLS	Inflation	
3	0.3108	OLS + PCA	Yield Curve Factors	Forward Rates
4	0.3330	OLS + PCA	Yield Curve Factors	Forward Rates + Term Premiums
5	0.3125	OLS + PCA	Yield Curve Factors	Forward Rates + Term Premiums + Forward-Spot Spreads
6	0.3133	PLS	Yield Curve Factors	Forward Rates
7	0.3119	PLS	Yield Curve Factors	Forward Rates + Term Premiums
8	0.3029	PLS	Yield Curve Factors	Forward Rates + Term Premiums + Forward-Spot Spreads

No.	R^2_{OOS}	Model Used	Model Content	Details for Yield Curve
9	0.1427	OLS + PCA	Yield Curve Factors	Forward-Spot Spreads
10	0.1739	OLS + PCA	Yield Curve Factors	Term Premiums
11	0.1829	PLS	Yield Curve Factors	Forward-Spot Spreads
12	-1.8021	PLS	Yield Curve Factors	Term Premiums
13	-0.4687	PLS	Macro Variables	
14	-0.2147	OLS + PCA	Macro Variables	
15	0.2983	Neural Network	Yield Curve Factors	Forward Rates
16	0.3391	Neural Network	Yield Curve Factors	Forward Rates + Term Premiums
17	0.3208	Neural Network	Yield Curve Factors	Forward Rates + Term Premiums + Forward-Spot Spreads
18	-0.6231	Neural Network	Macro Variables	
19	-0.0051	XGBoost	Yield Curve Factors	Forward Rates
20	-0.0159	XGBoost	Yield Curve Factors	Forward Rates + Term Premiums
21	-0.0787	XGBoost	Yield Curve Factors	Forward Rates + Term Premiums + Forward-Spot Spreads
22	-0.4440	XGBoost	Macro Variables	
23	0.2286	Random Forest	Yield Curve Factors	Forward Rates
24	0.2242	Random Forest	Yield Curve Factors	Forward Rates + Term Premiums
25	0.2227	Random Forest	Yield Curve Factors	Forward Rates + Term Premiums + Forward-Spot Spreads

No.	R^2_{OOS}	Model Used	Model Content	Details for Yield Curve
26	-0.2152	Random Forest	Macro Variables	
27	0.2253	Extra Trees	Yield Curve Factors	Forward Rates
28	0.1928	Extra Trees	Yield Curve Factors	Forward Rates + Term Premiums
29	0.2031	Extra Trees	Yield Curve Factors	Forward Rates + Term Premiums + Forward-Spot Spreads
30	-0.2038	Extra Trees	Macro Variables	

Model 3 (OLS + PCA, Yield Curve Factors: Forward Rates, $R^2_{OOS} = 0.3108$) demonstrates moderate predictive ability using linear combinations of forward rates and term premiums. However, the best performance among yield curve-based models with OLS + PCA is achieved by Model 4 (OLS + PCA, Yield Curve Factors: Forward Rates + Term Premiums, $R^2_{OOS} = 0.3330$), indicating that the inclusion of term premiums offers a slight improvement in forecast accuracy.

Neural Networks (NN) do not substantially outperform traditional models. Model 17 (NN, Yield Curve Factors: Forward Rates + Term Premiums + Forward-Spot Spreads) yields the highest predictive accuracy with an R^2_{OOS} of 0.3391—only marginally better than its OLS + PCA counterpart (Model 4). This suggests that while deep learning models can capture slightly more complex patterns, their advantage over linear methods remains limited in this context.

Macroeconomic variables, as in Hungary and Brazil, generally degrade predictive accuracy. Model 14 (OLS, Macro Variables, $R^2_{OOS} = -0.4687$) exhibits severe overfitting or irrelevance. Even when processed through advanced techniques, such as Model 18 (NN, Macro Variables, $R^2_{OOS} = 0.3208$), predictive accuracy remains inferior

to yield curve-focused models, reinforcing the limited utility of macroeconomic indicators in Thailand's bond market.

Tree-based methods exhibit mixed results. Model 24 (RF, Yield Curve Factors: Forward Rates + Term Premiums, $R^2_{OOS} = 0.2286$) and Model 28 (ERT, Yield Curve Factors: Forward Rates + Term Premiums, $R^2_{OOS} = 0.2253$) both lag behind NN's performance, similar to Brazil, where tree-based models underperformed relative to NN and XGBoost. Notably, XGBoost struggles in Thailand, as Model 20 (XGB, Yield Curve Factors: Forward Rates + Term Premiums, $R^2_{OOS} = -0.0051$) suggests incompatibility with Thailand's market structure.

The role of inflation and FX volatility is minimal in single-factor frameworks. Model 2 (OLS, Inflation, $R^2_{OOS} = -0.0430$) and Model 1 (OLS, Implied FX Volatility, $R^2_{OOS} = 0.0102$) both produce statistically insignificant results.

In summary, Thailand's bond risk premia are primarily driven by yield curve factors, particularly forward rates and term premiums, with Neural Networks offering the most robust predictive framework. Macroeconomic variables remain a liability, aligning with Hungary and Brazil, while tree-based models show limited adaptability. These findings underscore the importance of region-specific modeling, as Thailand's market dynamics diverge from both European (Hungary) and Latin American (Brazil) emerging economies.

Two-Factor Models for Bond Risk Premia in Thailand

Thailand's two-factor models presented in Table 5.14 underscore the continued dominance of yield curve factors when paired with implied FX volatility, though gains over single-factor models are marginal.

Table 5.14: *Two-Factor Models for Bond Risk Premia in Thailand.*

No.	R^2_{OOS}	Model Used	Model Content	Details for Yield Curve
1	-0.0889	OLS	Inflation + Implied FX Volatility	
2	0.3061	OLS + PCA	Implied FX Volatility + Yield Curve	Forward Rates + Term Premiums + Forward-Spot Spreads
3	0.2673	PLS	Implied FX Volatility + Yield Curve	Forward Rates + Term Premiums + Forward-Spot Spreads
4	-0.4349	PLS	Macro Variables + Inflation	
5	-0.1848	OLS + PCA	Macro Variables + Inflation	
6	0.3079	Neural Network	Implied FX Volatility + Yield Curve	Forward Rates + Term Premiums + Forward-Spot Spreads
7	-0.2890	Neural Network	Macro Variables + Inflation	
8	-0.1256	Neural Network	Inflation + Implied FX Volatility	
9	-0.0787	XGBoost	Implied FX Volatility + Yield Curve	Forward Rates + Term Premiums + Forward-Spot Spreads
10	-0.4242	XGBoost	Macro Variables + Inflation	
11	-0.4854	XGBoost	Inflation + Implied FX Volatility	
12	0.2227	Random Forest	Implied FX Volatility + Yield Curve	Forward Rates + Term Premiums + Forward-Spot Spreads

No.	R^2_{OOS}	Model Used	Model Content	Details for Yield Curve
13	-0.2150	Random Forest	Macro Variables + Inflation	
14	-0.2051	Random Forest	Inflation + Implied FX Volatility	
15	0.2031	Extra Trees	Implied FX Volatility + Yield Curve	Forward Rates + Term Premiums + Forward-Spot Spreads
16	-0.1618	Extra Trees	Macro Variables + Inflation	
17	-0.1487	Extra Trees	Inflation + Implied FX Volatility	

Model 6 (Neural Network, Implied FX Volatility + Yield Curve [Forward Rates + Term Premiums + Forward-Spot Spreads], $R^2_{OOS} = 0.3079$) achieves the highest predictive accuracy among Thailand's two-factor models, slightly below Thailand's top single-factor model (Table 5.13, Model 16, $R^2_{OOS} = 0.3391$). This contrasts with Brazil, where hybrid models combining yield curve factors and FX volatility outperformed single-factor approaches, highlighting Thailand's relatively weaker synergy between FX and yield curve dynamics.

Traditional methods, such as Model 2 (OLS + PCA, Implied FX Volatility + Yield Curve, $R^2_{OOS} = 0.3061$), yield predictive accuracy comparable to Neural Networks, a pattern also observed in Hungary's PCA-driven models. However, unlike Hungary, where Neural Networks significantly outperformed linear models, Thailand's NN gains are modest, suggesting less complex nonlinear interactions in its bond market.

Macroeconomic variables remain detrimental to predictive accuracy. Model 7 (Neural Network, Macro Variables + Inflation, $R^2_{OOS} = -0.289$) collapses, mirroring trends in Hungary (Table 5.4, Model 7, $R^2_{OOS} = -0.6770$) and Brazil (Table 5.9, Model 10, $R^2_{OOS} = -1.1544$). Even advanced machine learning algorithms fail to extract meaningful signals

from Thailand's macroeconomic data, reinforcing the irrelevance of traditional indicators in yield curve-driven markets.

The combination of inflation and implied FX volatility proves ineffective in Thailand. Model 8 (Neural Network, Inflation + Implied FX Volatility, $R^2_{OOS} = -0.1256$) demonstrates that these factors do not contribute meaningful signals to bond risk premia forecasting.

Tree-based models underperform across the board. Model 12 (Random Forest, Implied FX Volatility + Yield Curve, $R^2_{OOS} = 0.2227$) achieves only moderate predictive accuracy, while Model 15 (Extremely Randomized Trees, Implied FX Volatility + Yield Curve, $R^2_{OOS} = 0.2031$) lags further behind. These results fail to surpass both Neural Networks and traditional PCA/OLS approaches, similar to Brazil, where XGBoost struggled (Table 5.9, $R^2_{OOS} = 0.2760$) relative to Neural Networks.

In summary, Thailand's two-factor models reaffirm the primacy of yield curve factors and the futility of macroeconomic variables, aligning with Hungary and Brazil. However, the lack of significant improvement over single-factor models—unlike in Brazil, where multi-factor frameworks added predictive value—suggests that Thailand's bond risk premia are predominantly driven by linear yield curve dynamics, with limited incremental signal from FX or inflation. This positions Thailand closer to Hungary's yield curve-centric market structure, distinct from Brazil's hybrid (yield curve + FX) regime.

Three-Factor Models for Bond Risk Premia in Thailand

Thailand's three-factor models reported in Table 5.15 reveal modest improvements over single- and two-factor frameworks but underscore persistent limitations compared to Hungary and Brazil.

Table 5.15: *Three-Factor Models for Bond Risk Premia in Thailand.*

No.	R^2_{OOS}	Model Used	Model Content	Details for Yield Curve
1	0.2784	OLS + PCA	Inflation + Implied FX Volatility + Yield Curve	Forward Rates + Term Premiums + Forward-Spot Spreads
2	0.2413	PLS	Inflation + Implied FX Volatility + Yield Curve	Forward Rates + Term Premiums + Forward-Spot Spreads
3	-0.1630	OLS + PCA	Macro Variables + Inflation + Implied FX Volatility	
4	-0.6354	PLS	Macro Variables + Inflation + Implied FX Volatility	
5	0.2887	Neural Network	Inflation + Implied FX Volatility + Yield Curve	Forward Rates + Term Premiums + Forward-Spot Spreads
6	-0.3003	Neural Network	Macro Variables + Inflation + Implied FX Volatility	
7	-0.0812	XGBoost	Inflation + Implied FX Volatility + Yield Curve	Forward Rates + Term Premiums + Forward-Spot Spreads
8	-0.4146	XGBoost	Macro Variables + Inflation + Implied FX Volatility	
9	0.2150	Random Forest	Inflation + Implied FX Volatility + Yield Curve	Forward Rates + Term Premiums + Forward-Spot Spreads
10	-0.2205	Random Forest	Macro Variables + Inflation + Implied FX Volatility	

No.	R^2_{OOS}	Model Used	Model Content	Details for Yield Curve
11	0.1836	Extra Trees	Inflation + Implied FX Volatility + Yield Curve	Forward Rates + Term Premiums + Forward-Spot Spreads
12	-0.1725	Extra Trees	Macro Variables + Inflation + Implied FX Volatility	

Model 5 (Neural Network, Inflation + Implied FX Volatility + Yield Curve [Forward Rates + Term Premiums + Forward-Spot Spreads], $R^2_{OOS} = 0.2887$) achieves the highest predictive accuracy among Thailand's three-factor models, slightly underperforming Thailand's two-factor Neural Network model (Table 5.14, Model 6, Implied FX Volatility + Yield Curve, $R^2_{OOS} = 0.3079$) and falling short of Hungary's three-factor NN performance (Table 5.5, Model 5, $R^2_{OOS} = 0.4207$) and Brazil's top hybrid models (Table 5.10, Model 9, $R^2_{OOS} = 0.3568$). This suggests that adding inflation as a third factor reduces predictive accuracy in Thailand. This reflects Thailand's stable inflation regime.

Traditional linear models remain competitive with machine learning approaches. Model 1 (OLS + PCA, Inflation + Implied FX Volatility + Yield Curve, $R^2_{OOS} = 0.2784$) nearly matches Neural Networks, aligning with Brazil's trend, where PCA-driven models performed competitively.

Macroeconomic variables again prove detrimental. Models incorporating macro factors, such as Model 6 (NN, Macro Variables + Inflation + FX Volatility, $R^2_{OOS} = -0.3003$) and Model 8 (XGBoost, Macro Variables + Inflation + FX Volatility, $R^2_{OOS} = -0.4146$) produce dramatically poor results, mirroring results in Hungary (Table 5.5, Model 6, $R^2_{OOS} = -0.4775$) and Brazil (Table 5.10, Model 8, $R^2_{OOS} = -0.6583$). This reinforces the irrelevance of macroeconomic indicators in yield curve-driven markets like Thailand.

Tree-based models underperform across the board. Model 9 (Random Forest, Inflation + Implied FX Volatility + Yield Curve, $R^2_{OOS} = 0.2150$) achieves only moderate predictive accuracy, while Model 11 (ERT, same factors, $R^2_{OOS} = 0.1836$) performs even worse. These results fail to surpass both NN and traditional PCA/OLS methods, similar to Brazil and Hungary, where tree-based approaches struggled to match NN's flexibility.

XGBoost's poor performance stands out. Model 7 (XGBoost, Inflation + Implied FX Volatility + Yield Curve, $R^2_{OOS} = -0.0812$) underperforms, contrasting with Brazil's XGBoost success (Table 5.10, Model 7, same factors, $R^2_{OOS} = 0.2087$). This suggests that Thailand's bond market structure—possibly due to lower volatility or simpler relationships—does not align well with gradient-boosting frameworks optimized for complex nonlinearities.

Thailand's three-factor models confirm the supremacy of yield curve dynamics and the futility of macroeconomic variables, aligning with Hungary and Brazil. However, success of traditional linear models positions Thailand closer to Hungary.

Omni-Factor Models for Bond Risk Premia in Thailand

Thailand's omni-factor models presented in Table 5.16, which integrate macroeconomic variables, yield curve factors, inflation, and implied FX volatility, exhibit weaker performance compared to both Hungary and Brazil while also showing limited improvement over Thailand's own three-factor models.

Table 5.16: *Omni-Factor Models for Bond Risk Premia in Thailand*

No.	R^2_{OOS}	Model Used	Model Content	Details for Yield Curve
1	0.3054	OLS + PCA	Macro Variables + Yield Curve + Inflation + Implied FX Volatility	Forward Rates + Term Premiums + Forward-Spot Spreads

No.	R^2_{OOS}	Model Used	Model Content	Details for Yield Curve
2	0.1163	PLS	Macro Variables + Yield Curve + Inflation + Implied FX Volatility	Forward Rates + Term Premiums + Forward-Spot Spreads
3	0.2780	Neural Network	Macro Variables + Yield Curve + Inflation + Implied FX Volatility	Forward Rates + Term Premiums + Forward-Spot Spreads
4	-0.0812	XGBoost	Macro Variables + Yield Curve + Inflation + Implied FX Volatility	Forward Rates + Term Premiums + Forward-Spot Spreads
5	0.2150	Random Forest	Macro Variables + Yield Curve + Inflation + Implied FX Volatility	Forward Rates + Term Premiums + Forward-Spot Spreads
6	0.1836	Extra Trees	Macro Variables + Yield Curve + Inflation + Implied FX Volatility	Forward Rates + Term Premiums + Forward-Spot Spreads

The highest accuracy among Thailand's omni-factor models is achieved by Model 1 (OLS + PCA, $R^2_{OOS} = 0.3054$), yet it remains lower than Hungary's best-performing omni-factor model, Table 5.6, Model 3 (Neural Network, $R^2_{OOS} = 0.4370$), and Brazil's strongest omni model, Table 5.11, Model 1 (OLS + PCA, $R^2_{OOS} = 0.3622$).

The predictive performance of Neural Networks in Thailand lags behind its counterparts in other countries. Model 3 (Neural Network, $R^2_{OOS} = 0.2780$) performs significantly worse than Hungary's Model 3 (Table 5.6, $R^2_{OOS} = 0.4370$) and Brazil's Model 3 (Table 5.11, $R^2_{OOS} = 0.3548$). This suggests that Thailand's bond market dynamics are either less complex or less conducive to the nonlinear capabilities of Neural Networks, possibly due to more stable inflation and lower FX volatility.

Tree-based models in Thailand also fail to achieve substantial gains in predictive accuracy. Model 5 (Random Forest, $R^2_{\text{OOS}} = 0.2150$) and Model 6 (Extremely Randomized Trees, $R^2_{\text{OOS}} = 0.1836$) perform significantly worse than Brazil's omni-factor Random Forest model (Table 5.11, Model 5, $R^2_{\text{OOS}} = 0.3256$) and Hungary's omni-factor Extremely Randomized Trees model (Table 5.6, Model 6, $R^2_{\text{OOS}} = 0.4167$). This cross-country comparison of omni-factor specifications underscores the considerable variation in tree-based model performance, revealing that their predictive utility is highly dependent on country-specific economic structures and data dynamics. This suggests that Thailand's simpler bond market structure limits the ability of tree-based methods to capture meaningful patterns beyond yield curve factors. Additionally, XGBoost collapses entirely in Thailand, with Model 4 ($R^2_{\text{OOS}} = -0.0812$), in stark contrast to its moderate success in Brazil (Table 5.11, Model 4, $R^2_{\text{OOS}} = 0.1269$) and Hungary (Table 5.6, Model 4, $R^2_{\text{OOS}} = 0.3533$). This reflects the incompatibility of Thailand's bond market data structure with gradient-boosting techniques.

A closer comparison between Thailand's omni-factor models and its three-factor frameworks reveals that incorporating macroeconomic data often reduces predictive accuracy. For example, the Neural Network omni-factor model ($R^2_{\text{OOS}} = 0.2780$) underperforms its three-factor counterpart (Table 5.15, Model 5: Inflation + Implied FX Volatility + Yield Curve, $R^2_{\text{OOS}} = 0.2887$), suggesting that the addition of macroeconomic variables may introduce noise rather than improving forecast performance. Similarly, the Random Forest model achieves identical results in both omni-factor and three-factor settings ($R^2_{\text{OOS}} = 0.2150$), indicating that macroeconomic variables do not add incremental predictive power beyond the already strong combination of yield curve factors and FX volatility.

However, there are notable exceptions. Thailand's OLS + PCA omni-factor model ($R^2_{\text{OOS}} = 0.3054$) outperforms its corresponding three-factor model (Table 5.15, Model

1, $R^2_{OOS} = 0.2784$), suggesting that macroeconomic variables can enhance predictive accuracy when integrated with other relevant factors through dimensionality reduction. A similar pattern is observed in Brazil, where omni-factor models such as Random Forest ($R^2_{OOS} = 0.3256$) outperform their three-factor counterparts ($R^2_{OOS} = 0.2728$), implying that in certain contexts, macroeconomic variables may complement rather than hinder yield curve-based forecasts. The overall findings from Thailand's omni-factor models confirm the dominance of yield curve dynamics and the ineffectiveness of macroeconomic variables, which aligns with results observed in Hungary and Brazil. However, Thailand's lower overall performance, particularly in machine learning models, suggests that its bond market structure is simpler, with fewer nonlinear interactions similar to Hungary.

Thailand's bond market ultimately exhibits a yield curve-centric regime. Moreover, the effectiveness of advanced machine learning techniques appears more limited in Thailand compared to markets like Hungary and Brazil.

Figure 5.4: *Thailand – Overview.*

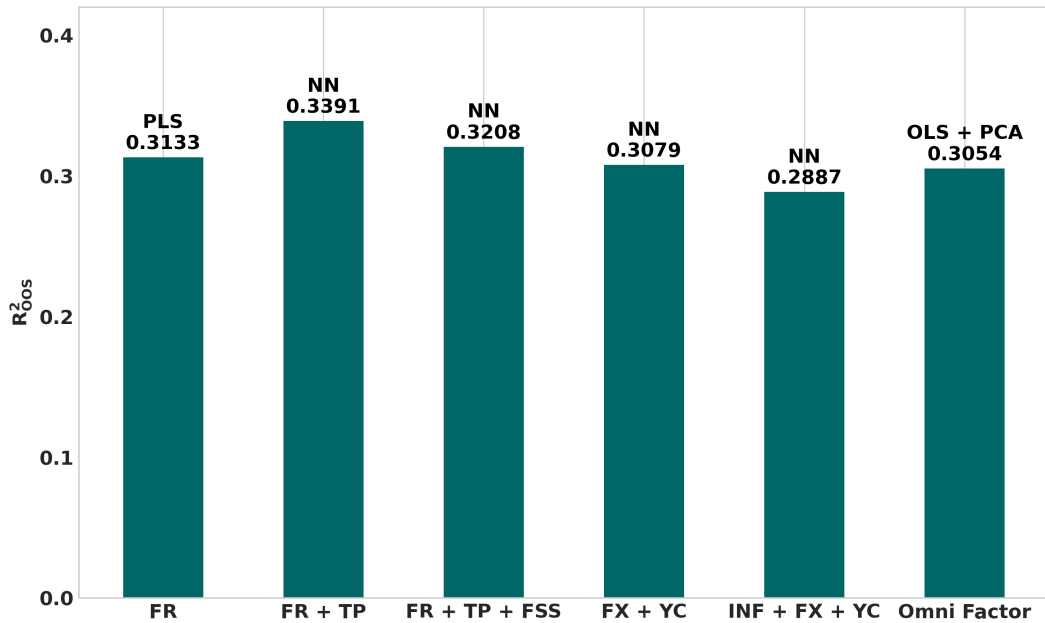


Figure 5.4 shows the progression of out-of-sample predictive accuracy (R^2_{OOS})

of the best-performing models as successive predictor variables are incorporated into the models estimating Thailand's local currency bond risk premia. The results confirm the primacy of yield curve-based variables, while also revealing that the relative advantage of advanced machine learning techniques—particularly Neural Networks—is less pronounced in Thailand compared to Hungary and Brazil.

The strongest performance is observed in the model combining forward rates and term premiums (FR + TP), estimated using a Neural Network (NN), with $R^2_{\text{OOS}} = 0.3391$. This indicates that adding a second yield curve factor modestly enhances forecast accuracy relative to single-factor models, suggesting that Thailand's term premiums contribute unique, albeit limited, predictive information beyond forward rates.

Interestingly, when forward rates are used alone, the best-performing model is based on Partial Least Squares (PLS), with $R^2_{\text{OOS}} = 0.3133$, outperforming the Neural Network model for the same factor. This contrasts with patterns observed in Hungary and Brazil, where Neural Networks clearly dominated all configurations. In Thailand, traditional linear techniques like PLS remain highly competitive, especially in simpler modeling contexts.

Further expansion of the yield curve specification to include forward-spot spreads (FR + TP + FSS) yields $R^2_{\text{OOS}} = 0.3208$ under a Neural Network, a small improvement over the PLS and OLS + PCA models, but still lower than the simpler FR + TP combination. This suggests diminishing marginal returns from adding more complexity to the yield curve structure—especially in a market like Thailand, where relationships may be more linear and stable.

When FX volatility is incorporated alongside yield curve factors (FX + YC), the NN model achieves $R^2_{\text{OOS}} = 0.3079$, showing that implied FX volatility provides only marginal incremental information. A similar decline occurs with the inclusion of inflation (INF + FX + YC), where NN performance drops to $R^2_{\text{OOS}} = 0.2887$, confirming inflation's

limited role in Thailand's predictive environment.

The Omni Factor model, which integrates all available financial and macroeconomic variables, performs best under OLS + PCA, with $R^2_{\text{OOS}} = 0.3054$. This signals that the inclusion of macroeconomic indicators does not substantially improve predictive performance. In fact, it often results in performance degradation when not carefully filtered or structured.

These findings suggest that Thailand's bond market exhibits a simpler, more linear structure where traditional models can compete with or even surpass machine learning techniques in certain configurations. The relatively modest gains from model complexity and additional features point to a need for tailored, parsimonious approaches that focus on core market-based signals.

This analysis sets the stage for the next section, which considers the broader implications of these results for investors and policymakers in Thailand. The following discussion explores how the empirical insights derived from model performance can inform strategy, communication, and policy design in local bond markets.

5.2.4.3 Implications for Policymakers and Investors

What do these findings mean for bond market participants?

Thailand's bond risk premia are primarily driven by yield curve factors, particularly forward rates and term premiums, aligning with findings from Hungary and Brazil. However, Thailand's market exhibits simpler dynamics. Linear models, such as OLS + PCA, perform nearly as well as machine learning approaches, indicating that Thailand's bond market is less susceptible to abrupt nonlinear shifts. This reduces the complexity required in predictive frameworks.

For investors, this suggests a strong emphasis on yield curve analytics while deprioritizing macroeconomic indicators, which consistently degrade predictive accuracy. Investors should focus on real-time yield curve movements, particularly forward rate trends and term premium fluctuations, while cautiously integrating FX volatility metrics, given Thailand's lower currency risk compared to Brazil.

How can investors use predictive models for risk assessment?

Thailand's bond market participants should adopt hybrid models that combine yield curve factors with selective use of machine learning. For instance, Table 5.14, Model 6 (Neural Network, Implied FX Volatility + Yield Curve, $R^2_{OOS} = 0.3079$) demonstrates that even limited nonlinearity can be captured, though the incremental gains over linear models remain smaller than those observed in Brazil or Hungary. Table 5.16, Model 1 (OLS + PCA, Macro Variables + Yield Curve + Inflation + Implied FX Volatility, $R^2_{OOS} = 0.3054$) offers a simpler, interpretable alternative for investors wary of AI's "black box" nature.

Policy Implications for Monetary Authorities and Bond Issuers

For Thailand's central bank (Bank of Thailand, BOT) and the debt management office (Public Debt Management Office, PDMO), the findings highlight three key policy priorities. First, enhancing yield curve transparency is crucial. Similar to Hungary's central bank (MNB), BOT should provide clear guidance on interest rate policies to anchor forward rate expectations. Transparent communication can help reduce market volatility, as forward rates remain the primary driver of bond risk premia.

Second, the reliance on macroeconomic indicators should be reconsidered. Traditional macroeconomic indicators, such as inflation and industrial production, provide no meaningful predictive value in Thailand's bond market. For instance, Table 5.16, Model 3 (Neural Network, Macro Variables + Yield Curve + Inflation + Implied FX Volatility, $R^2_{OOS} = 0.2780$) underperforms models based solely on yield curve factors, reinforcing

the limited usefulness of macroeconomic variables in bond pricing.

Finally, a cautious approach to AI integration in forecasting should be adopted. While Neural Networks provide some forecasting improvements, Thailand's bond market does not demand the high level of AI sophistication seen in Brazil or Hungary. Instead, BOT could pilot AI-driven tools for stress-testing scenarios, such as sudden FX shocks, while continuing to rely on simpler PCA/OLS frameworks for routine analysis.

For bond issuers, structuring debt around term premiums and forward rate trends, similar to Hungary's approach, can help optimize borrowing costs and extend maturities.

Thailand's bond market demands a streamlined, yield curve-centric strategy, distinct from the hybrid frameworks of Brazil and the AI-driven models of Hungary. Investors should prioritize forward rates and term premiums while avoiding macroeconomic noise. Policymakers must enhance yield curve transparency and integrate AI cautiously, while issuers should align debt instruments with term structure dynamics. By adopting these tailored strategies, Thailand can maintain market stability while navigating regional economic uncertainties.

Thailand's bond market exemplifies a middle ground between Brazil's volatility-driven complexity and Hungary's nonlinear sophistication, offering stability at the cost of fewer predictive challenges for advanced models.

5.2.5 Poland

5.2.5.1 Identifying the Top 5 Performing Models

The predictive analysis for Poland demonstrates that PCA-applied models and Random Forest (RF) models achieved the highest predictive R^2 values across various configurations. As shown in Table 5.17, PCA-based models leveraging forward rates and

term premiums performed best, achieving a predictive R^2 of 28.22%. Additionally, Random Forest models consistently ranked among the top-performing approaches, demonstrating their capability to capture complex, nonlinear relationships in bond risk premia predictions.

Table 5.17: *Top 5 Predictive Models for Bond Risk Premia in Poland*

No.	R^2_{OOS}	Model Used	Variables Used
1	0.2822	OLS + PCA	Forward Rates + Term Premiums
2	0.2761	Random Forest	Forward Rates
3	0.2728	Random Forest	Implied FX Volatility + Inflation + Forward Rates + Term Premiums + Forward-Spot Spreads
4	0.2638	PLS	Forward Rates + Term Premiums
5	0.2627	Random Forest	Forward Rates + Term Premiums + Forward-Spot Spreads

As seen in Table 5.17, the best-performing model was a PCA-applied approach, which incorporated forward rates and term premiums, reaching a predictive R^2 of 28.22%. Following closely, Random Forest models ranked second, third, and fifth, showcasing their robustness in bond risk premia prediction, with predictive R^2 values ranging between 27.61% and 26.27%. Additionally, PLS Regression performed reasonably well, attaining a predictive R^2 of 26.38%.

These results emphasize the role of yield curve-based factors, particularly forward rates and term premiums, in driving bond risk premia dynamics. The top two models (No. 1 and No. 2) use only Forward Rates or Forward Rates + Term Premiums. Despite adding FX Implied Volatility and F Spreads, it underperforms the simpler PCA/RF models.

Moreover, in Poland, PCA-based models and Random Forest dominate the top-performing models, in stark contrast to Hungary, where all of the top five models are

Neural Networks. Similarly, in Brazil and Thailand, Neural Networks appear prominently, accounting for two or three of the top five models in each country. This suggests that while Neural Networks are generally effective in capturing bond return dynamics in most countries, Poland stands out as a case where simpler linear methods and tree-based algorithms outperform deep learning approaches.

Poland's peak R^2 (28.22%) is lower than Hungary's (49.91%), Brazil's (38.71%) and Thailand's (33.91%) indicating potential structural differences in bond market dynamics. Future work should explore hybrid PCA-Random Forest frameworks and deeper integration of yield curve dynamics to bridge the performance gap observed relative to Hungary, Brazil and Thailand.

5.2.5.2 Decomposing the Importance of Different Factors

Single-Factor Models for Bond Risk Premia in Poland

Poland's single-factor models shown in Table 5.18 exhibit similarities with other emerging markets, such as Hungary, Brazil, and Thailand, in determining local currency bond risk premia. However, they also display distinct differences, with lower predictive performance compared to their counterparts.

Table 5.18: *Single-Factor Models for Bond Risk Premia in Poland.*

No.	R^2_{OOS}	Model Used	Model Content	Details for Yield Curve
1	-0.0564	OLS	Implied FX Volatility	
2	-0.0336	OLS	Inflation	
3	0.2621	OLS + PCA	Yield Curve Factors	Forward Rates
4	0.2822	OLS + PCA	Yield Curve Factors	Forward Rates + Term Premiums

No.	R^2_{OOS}	Model Used	Model Content	Details for Yield Curve
5	0.2046	OLS	Yield Curve Factors	Forward Rates + Term Premiums + Forward-Spot Spreads
6	0.2524	PLS	Yield Curve Factors	Forward Rates
7	0.2638	PLS	Yield Curve Factors	Forward Rates + Term Premiums
8	0.2336	PLS	Yield Curve Factors	Forward Rates + Term Premiums + Forward-Spot Spreads
9	-0.0208	OLS	Yield Curve Factors	Forward-Spot Spreads
10	-1.7379	OLS	Yield Curve Factors	Term Premiums
11	-1.7652	PLS	Yield Curve Factors	Forward-Spot Spreads
12	-1.8021	PLS	Yield Curve Factors	Term Premiums
13	-0.7271	PLS	Macro Variables	
14	-0.2580	OLS	Macro Variables	
15	0.2588	NN	Yield Curve Factors	Forward Rates
16	0.1738	NN	Yield Curve Factors	Forward Rates + Term Premiums
17	0.1064	NN	Yield Curve Factors	Forward Rates + Term Premiums + Forward-Spot Spreads
18	-0.5378	NN	Macro Variables	
19	0.1572	XGB	Yield Curve Factors	Forward Rates
20	0.1334	XGB	Yield Curve Factors	Forward Rates + Term Premiums

No.	R^2_{OOS}	Model Used	Model Content	Details for Yield Curve
21	0.1629	XGB	Yield Curve Factors	Forward Rates + Term Premiums + Forward-Spot Spreads
22	-0.4822	XGB	Macro Variables	
23	0.2761	RF	Yield Curve Factors	Forward Rates
24	0.2621	RF	Yield Curve Factors	Forward Rates + Term Premiums
25	0.2627	RF	Yield Curve Factors	Forward Rates + Term Premiums + Forward-Spot Spreads
26	-0.2342	RF	Macro Variables	
27	0.2568	ERT	Yield Curve Factors	Forward Rates
28	0.2338	ERT	Yield Curve Factors	Forward Rates + Term Premiums
29	0.2220	ERT	Yield Curve Factors	Forward Rates + Term Premiums + Forward-Spot Spreads
30	-0.2413	ERT	Macro Variables	

Model 4 (OLS + PCA, Yield Curve Factors: Forward Rates + Term Premiums) achieves the highest predictive accuracy in Poland, with $R^2_{OOS} = 0.2822$. This performance lags behind Hungary's Table 5.3, Model 15 (Neural Network, Yield Curve Factors: Forward Rates, $R^2_{OOS} = 0.4991$) and Brazil's Table 5.8, Model 15 (Neural Network, Yield Curve Factors: Forward Rates, $R^2_{OOS} = 0.3833$), suggesting that Poland's bond market exhibits lower predictability or unique risk dynamics compared to these markets.

Yield curve factors play a dominant role in Poland, as in other countries. Model

5 (OLS, Yield Curve Factors: Forward Rates + Term Premiums + Forward-Spot Spreads) achieves $R_{OOS}^2 = 0.2046$, underperforming the simpler Model 4 with Forward Rates + Term Premiums. This contrasts with Thailand's Table 5.13, Model 5 (OLS, Yield Curve Factors: Forward Rates + Term Premiums + Forward-Spot Spreads, $R_{OOS}^2 = 0.3330$), where additional yield curve components improve model accuracy. The findings suggest that Poland's yield curve exhibits a more linear structure with fewer complex relationships, limiting the added value of additional curve-related factors.

Macroeconomic variables, as in other countries, substantially reduce predictive accuracy. Model 14 (OLS, Macro Variables) produces a negative accuracy of $R_{OOS}^2 = -0.258$, while Model 18 (Neural Network, Macro Variables) collapses further with $R_{OOS}^2 = -0.5378$. These results confirm that Poland's market structure, similar to other emerging economies, does not support the use of macroeconomic indicators in forecasting bond risk premia.

Machine learning models provide only limited advantages over traditional approaches. Model 23 (Random Forest, Yield Curve Factors: Forward Rates) achieves $R_{OOS}^2 = 0.2761$, making it the best-performing tree-based model. However, it lags behind Hungary's Table 5.3, Model 23 (Random Forest, Yield Curve Factors: Forward Rates, $R_{OOS}^2 = 0.3764$) and Brazil's Table 5.8, Model 24 (Random Forest, Yield Curve Factors: Forward Rates + Term Premiums, $R_{OOS}^2 = 0.3157$). Similarly, Model 15 (Neural Network, Yield Curve Factors: Forward Rates) achieves $R_{OOS}^2 = 0.2588$, highlighting the limited impact of neural networks in Poland. This suggests that Poland's bond market dynamics may be less complex or contain structural differences that machine learning models fail to capture.

Furthermore, while FX volatility plays a crucial role in Brazil, Model 1 (OLS, Implied FX Volatility) in Poland delivers $R_{OOS}^2 = -0.0564$, suggesting that currency fluctuations do not contribute meaningfully to Poland's bond risk premia.

Poland's bond risk premia are predominantly driven by yield curve factors, particularly forward rates and term premiums. However, compared to Hungary and Brazil, Poland exhibits lower predictability, highlighting its distinct bond market structure and potential limitations for machine learning models in improving forecasting accuracy.

Two-Factor Models for Bond Risk Premia in Poland.

The analysis of two-factor models for Poland's bond risk premia reveals limited improvements over single-factor frameworks, with yield curve factors remaining the dominant predictors. Macroeconomic variables and inflation continue to degrade performance, reinforcing Poland's alignment with other yield curve-driven markets like Hungary and Thailand.

Table 5.19: *Two-Factor Models for Bond Risk Premia in Poland*

No.	R^2_{OOS}	Model Used	Model Content	Details for Yield Curve
1	0.0530	OLS	Inflation + Implied FX Volatility	
2	0.2143	OLS + PCA	Implied FX Volatility + Yield Curve	Forward Rates + Term Premiums + Forward-Spot Spreads
3	0.2318	PLS	Implied FX Volatility + Yield Curve	Forward Rates + Term Premiums + Forward-Spot Spreads
4	-0.7552	PLS	Macro Variables + Inflation	
5	-0.2833	OLS + PCA	Macro Variables + Inflation	
6	0.1064	NN	Implied FX Volatility + Yield Curve	Forward Rates + Term Premiums + Forward-Spot Spreads
7	-0.1137	NN	Macro Variables + Inflation	

No.	R^2_{OOS}	Model Used	Model Content	Details for Yield Curve
8	-0.1228	NN	Inflation + Implied FX Volatility	
9	0.1629	XGB	Implied FX Volatility + Yield Curve	Forward Rates + Term Premiums + Forward-Spot Spreads
10	-0.2344	XGB	Macro Variables + Inflation	
11	-0.4402	XGB	Inflation + Implied FX Volatility	
12	0.2627	RF	Implied FX Volatility + Yield Curve	Forward Rates + Term Premiums + Forward-Spot Spreads
13	-0.2399	RF	Macro Variables + Inflation	
14	-0.2950	RF	Inflation + Implied FX Volatility	
15	0.2220	ERT	Implied FX Volatility + Yield Curve	Forward Rates + Term Premiums + Forward-Spot Spreads
16	-0.2859	ERT	Macro Variables + Inflation	
17	-0.2352	ERT	Inflation + Implied FX Volatility	

The limited synergy between factors is evident in the performance of Poland's two-factor models. The best-performing model, as observed in Table 5.19, Model 12 (Random Forest, Implied FX Volatility + Yield Curve [Forward Rates + Term Premiums + F-S Spreads], $R^2_{OOS} = 0.2627$), underperforms Poland's top single-factor model. Specifically, Table 5.18, Model 4 (OLS + PCA, Yield Curve [Forward Rates + Term

Premiums], $R^2_{OOS} = 0.2822$) yields better results, suggesting that the inclusion of FX volatility introduces noise rather than enhancing accuracy.

The incorporation of macroeconomic variables significantly deteriorates model performance. For instance, Poland's Table 5.19, Model 13 (RF, Macro Variables + Inflation, $R^2_{OOS} = -0.2399$) exhibits a complete collapse, a trend mirrored in Hungary's Table 5.4, Model 7 (NN, Macro Variables + Inflation, $R^2_{OOS} = -0.6770$) and Brazil's Table 5.9, Model 10 (XGBoost, Macro Variables + Inflation, $R^2_{OOS} = -1.1544$). This widespread failure underscores the inefficacy of macroeconomic factors in predicting bond risk premia across different emerging markets.

The contribution of FX volatility remains weak in Poland, particularly when compared to Brazil. While Brazil's hybrid models demonstrate notable gains, as exemplified by Table 5.9, Model 12 (RF, Implied FX Volatility + Yield Curve [Forward Rates + Term Premiums + F-S Spreads], $R^2_{OOS} = 0.3871$), Poland's hybrid models exhibit minimal improvements. For instance, Model 6 (NN, Implied FX Volatility + Yield Curve, $R^2_{OOS} = 0.1064$) illustrates Poland's lower sensitivity to currency risk in contrast to economies like Brazil.

The findings suggest that Poland's bond risk premia remain predominantly anchored to forward rates and term premiums, with little incremental value derived from FX volatility or macroeconomic variables.

Three-Factor Models for Bond Risk Premia in Poland

The analysis of three-factor models for Poland's bond risk premia highlights marginal improvements over two-factor frameworks but reaffirms the dominance of yield curve factors.

Table 5.20: *Three-Factor Models for Bond Risk Premia in Poland.*

No.	R^2_{OOS}	Model Used	Model Content	Details for Yield Curve
1	0.2522	OLS + PCA	Inflation + Implied FX Volatility + Yield Curve	Forward Rates + Term Premiums + Forward-Spot Spreads
2	0.1772	PLS	Inflation + Implied FX Volatility + Yield Curve	Forward Rates + Term Premiums + Forward-Spot Spreads
3	-0.2334	OLS + PCA	Macro Variables + Inflation + Implied FX Volatility	
4	-0.7511	PLS	Macro Variables + Inflation + Implied FX Volatility	
5	0.1205	NN	Inflation + Implied FX Volatility + Yield Curve	Forward Rates + Term Premiums + Forward-Spot Spreads
6	-0.6920	NN	Macro Variables + Inflation + Implied FX Volatility	
7	0.1704	XGB	Inflation + Implied FX Volatility + Yield Curve	Forward Rates + Term Premiums + Forward-Spot Spreads
8	-0.3219	XGB	Macro Variables + Inflation + Implied FX Volatility	
9	0.2728	RF	Inflation + Implied FX Volatility + Yield Curve	Forward Rates + Term Premiums + Forward-Spot Spreads
10	-0.2588	RF	Macro Variables + Inflation + Implied FX Volatility	

No.	R^2_{OOS}	Model Used	Model Content	Details for Yield Curve
11	0.2453	ERT	Inflation + Implied FX Volatility + Yield Curve	Forward Rates + Term Premiums + Forward-Spot Spreads
12	-0.2906	ERT	Macro Variables + Inflation + Implied FX Volatility	

The top-performing model in three-factor models, Model 9 (RF, Inflation + Implied FX Volatility + Yield Curve [Forward Rates + Term Premiums + F-S Spreads], $R^2_{OOS} = 0.2728$), slightly outperforms best two-factor model, Table 5.19, Model 1 (Random Forest, Implied FX Volatility + Yield Curve [Forward Rates + Term Premiums + F-S Spreads], $R^2_{OOS} = 0.2627$). However, this improvement is marginal, suggesting limited value from adding inflation as a third factor.

Models incorporating macroeconomic indicators collapse entirely. For example, Table 5.20, Model 10 (RF, Macro Variables + Inflation + Implied FX Volatility, $R^2_{OOS} = -0.2588$) mirrors trends in Hungary, Table 5.5, Model 6 (NN, Macro Variables + Inflation + FX Volatility, $R^2_{OOS} = -0.4775$) and Brazil, Table 5.10, Model 8 (XGBoost, Macro Variables + Inflation + FX Volatility, $R^2_{OOS} = -0.6583$).

Despite its inclusion, inflation fails to enhance predictions. For instance, Table 5.20, Model 5 (NN, Inflation + Implied FX Volatility + Yield Curve, $R^2_{OOS} = 0.0904$) underperforms Poland's simpler yield curve models, such as Table 5.18, Model 4 (OLS + PCA, Yield Curve [Forward Rates + Term Premiums], $R^2_{OOS} = 0.2822$).

Random Forest remains the most robust method, as seen in Model 9 ($R^2_{OOS} = 0.2728$), while Neural Networks struggle, as evident in Model 5 ($R^2_{OOS} = 0.0904$). This contrasts with Hungary, Table 5.5, Model 5 (NN, Inflation + FX Volatility + Yield Curve, $R^2_{OOS} = 0.4207$), where Neural Networks dominate. While Random Forest (Table 5.20,

Model 9, $R_{OOS}^2 = 0.2728$) offers slight improvements over simpler models, traditional methods like OLS + PCA (Table 5.20, Model 1, $R_{OOS}^2 = 0.2522$) remain competitive.

Poland's three-factor models reaffirm the primacy of forward rates and term premiums, with inflation and FX volatility contributing minimal incremental value.

Omni-Factor Models for Bond Risk Premia in Poland

The analysis of omni-factor models for Poland's bond risk premia underscores the persistent dominance of yield curve factors and the irrelevance of macroeconomic variables. Despite incorporating all available predictors, these models fail to surpass simpler frameworks, aligning Poland with yield curve-centric markets like Hungary and Thailand.

Table 5.21: *Omni-Factor Models for Bond Risk Premia in Poland.*

No.	R_{OOS}^2	Model Used	Model Content	Details for Yield Curve
1	0.1679	OLS + PCA	Macro Variables + Yield Curve + Inflation + Implied FX Volatility	Forward Rates + Term Premiums + Forward-Spot Spreads
2	0.1612	PLS	Macro Variables + Yield Curve + Inflation + Implied FX Volatility	Forward Rates + Term Premiums + Forward-Spot Spreads
3	0.0845	NN	Macro Variables + Yield Curve + Inflation + Implied FX Volatility	Forward Rates + Term Premiums + Forward-Spot Spreads
4	0.1716	XGB	Macro Variables + Yield Curve + Inflation + Implied FX Volatility	Forward Rates + Term Premiums + Forward-Spot Spreads
5	0.2612	RF	Macro Variables + Yield Curve + Inflation + Implied FX Volatility	Forward Rates + Term Premiums + Forward-Spot Spreads

No.	R_{OOS}^2	Model Used	Model Content	Details for Yield Curve
6	0.2540	ERT	Macro Variables + Yield Curve + Inflation + Implied FX Volatility	Forward Rates + Term Premiums + Forward-Spot Spreads

The best-performing omni-factor model, Model 5 (RF, Macro Variables + Yield Curve + Inflation + FX Volatility, $R_{OOS}^2 = 0.2612$), underperforms Poland's top three-factor model, Table 5.20, Model 9 (RF, Inflation + FX Volatility + Yield Curve, $R_{OOS}^2 = 0.2728$). This confirms that adding macroeconomic variables degrades predictive accuracy.

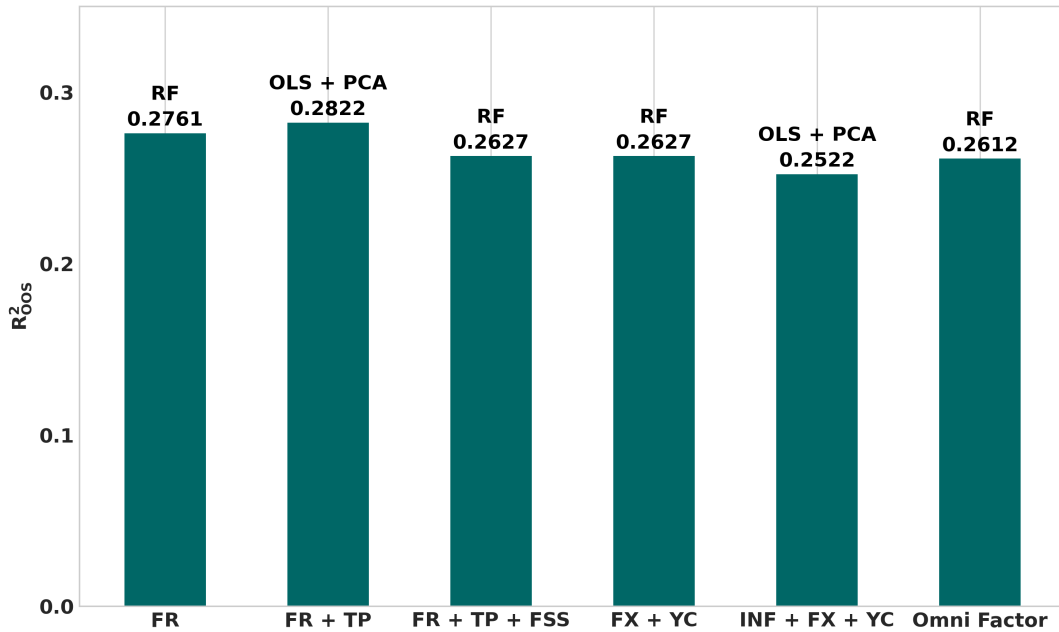
Random Forest remains the most reliable method, as seen in Model 5 ($R_{OOS}^2 = 0.2612$), while Neural Networks collapse, as evidenced by Model 3 ($R_{OOS}^2 = 0.0845$). However, although Random Forest (Table 5.21, Model 5) delivers the best performance among omni-factor models, traditional yield curve-focused approaches such as OLS + PCA in the single-factor setting (Table 5.18, Model 4, OLS + PCA, Forward Rates + Term Premiums, $R_{OOS}^2 = 0.2822$) remain superior. This is consistent with Poland's simpler market structure.

Poland's omni-factor models reaffirm that forward rates and term premiums are the sole reliable predictors of bond risk premia. Macroeconomic variables, inflation, and FX volatility add no value and should be excluded.

Figure 5.5 summarizes the out-of-sample predictive performance (R_{OOS}^2) of the best-performing models as additional predictor variables are progressively incorporated into the forecasting framework for Poland's local currency bond risk premia.

The highest predictive performance is achieved by an OLS+PCA model using only forward rates (FR) and term premiums (TP), yielding $R_{OOS}^2 = 0.2822$. Notably, this result remains significantly below the top-performing models in Hungary (NN, $R_{OOS}^2 = 0.4991$;

Figure 5.5: Poland – Overview.



see Figure 5.2) and Brazil (NN, $R^2_{OOS} = 0.3871$; see Figure 5.3), reflecting the inherently lower predictability or more linear risk structure in Poland's bond market.

Expanding further to include forward-spot spreads (FR + TP + FSS) does not yield substantial improvement ($R^2_{OOS} = 0.2627$). These findings highlight a recurring theme: in Poland's bond market, simpler yield curve models are often more effective, and additional structural components (like FSS) may introduce noise or redundancy.

Incorporating FX volatility alongside yield curve variables (FX + YC) results in a performance level nearly identical to that of FR + TP + FSS models ($R^2_{OOS} = 0.2627$, RF). This marginal gain suggests that FX risk plays a limited role in shaping Poland's bond risk premia—an outcome that contrasts with Brazil's FX-sensitive structure.

The inclusion of inflation alongside FX and yield curve factors (INF + FX + YC) slightly degrades predictive accuracy, with OLS + PCA producing $R^2_{OOS} = 0.2522$.

Finally, the Omni Factor model—which integrates all available macroeconomic,

FX, and financial variables—delivers $R_{OOS}^2 = 0.2612$ via a Random Forest model. Despite its comprehensiveness, the model fails to outperform the simpler RF and OLS + PCA specifications based solely on yield curve variables. This reiterates the notion that in Poland's bond market, model parsimony and variable selection are more critical than sheer informational breadth.

Another important insight from Figure 5.5 is that Random Forest appears as the most consistently effective modeling technique across nearly all configurations in Poland. Unlike Hungary, where Neural Networks dominated, Poland's yield curve dynamics appear more linear and stable, lending themselves well to ensemble tree-based methods rather than complex nonlinear models.

These empirical patterns emphasize the importance of yield curve-driven models tailored to Poland's relatively linear financial environment. They also provide a methodological foundation for translating these results into actionable insights. The following section explores how these findings inform strategic considerations for investors and policymakers engaged in Poland's local currency bond markets.

5.2.5.3 Implications for Policymakers and Investors

What do these findings mean for bond market participants?

Poland's bond risk premia are predominantly driven by yield curve dynamics, particularly forward rates and term premiums, with macroeconomic variables and inflation offering negligible predictive value. This contrasts sharply with hybrid regimes like Brazil, where FX volatility plays a critical role. For investors, this underscores the importance of prioritizing market-based yield curve indicators over traditional macroeconomic metrics such as industrial production or unemployment rates.

The superior performance of Random Forest (RF) and OLS + PCA models highlights Poland's relatively stable and linear bond market structure. Unlike Hungary, where

Neural Networks dominate, or Brazil, where FX volatility adds complexity, Poland's predictability hinges on streamlined yield curve analytics. Investors relying on macroeconomic models risk mispricing bonds, as these variables introduce noise rather than actionable signals.

How can investors use predictive models for risk assessment?

Investors should develop strategies centered on forward rate trends and term premium fluctuations, which consistently explain Poland's bond risk premia. For example, top performing model, Table 5.18, Model 4 (OLS + PCA, Yield Curve [Forward Rates + Term Premiums], $R^2_{OOS} = 0.2822$) provide reliable forecasts without overcomplication. While Random Forest, such as, Table 5.20, Model 9 ($R^2_{OOS} = 0.2728$), deliver slightly lower performance, it reinforces the finding that added model complexity or redundant variables do not necessarily enhance predictive accuracy. Investors should adopt Random Forest or OLS + PCA models for risk assessment, avoiding overengineered frameworks. Hybrid frameworks combining RF with PCA-filtered yield curve data may balance accuracy and interpretability. Macro indicators degrade performance across all model types, as seen in Table 5.21, Model 3 (NN, $R^2_{OOS} = 0.0845$). Investors should treat macroeconomic data as secondary to yield curve signals.

Policy Implications for Monetary Authorities and Bond Issuers

Poland's bond market is less sensitive to external shocks compared to Brazil. However, shifts in EU monetary policy or regional economic sentiment could indirectly impact yield curve dynamics. Central bank policies should enhance yield curve transparency, as clear communication on interest rate policies and term structure expectations can reduce market volatility. Given the irrelevance of macroeconomic variables in predictive models, the focus should be on yield curve stability.

From a debt management perspective, Poland's authorities should structure debt around yield curve signals. Issuing long-term bonds during periods of compressed term

premiums, as identified by models like OLS + PCA, can optimize borrowing costs. Since Poland's bond market exhibits low sensitivity to currency risks, unlike Brazil, there is little need for FX-hedged debt, simplifying issuance strategies. While Random Forest models show promise, Poland's bond market does not demand the algorithmic sophistication required in Hungary or Brazil. Pilot projects using RF for stress-testing, such as simulating rate hikes or liquidity shocks, could enhance risk management without overcomplicating operations.

Poland's yield curve-driven dynamics align more closely with Hungary. Collaborative research with EU partners on yield curve modeling could harmonize risk assessment frameworks across Central and Eastern Europe. In Hungary, Neural Networks dominate due to complex yield curve-FX interactions whereas Poland's simplicity favors RF and traditional methods.

5.2.6 Turkey

5.2.6.1 Identifying the Top 5 Performing Models

The predictive analysis for Turkey demonstrates that XGBoost and Neural Networks (NN) achieved the highest predictive R^2 values across various configurations. As shown in Table 5.22, XGBoost-based models performed best, achieving a predictive R^2 of 38.47%, followed closely by another XGBoost model with an R^2 of 38.23%. Additionally, Neural Network models also ranked among the top-performing approaches, demonstrating their ability to capture nonlinear relationships in bond risk premia predictions.

Table 5.22: *Top 5 Predictive Models for Bond Risk Premia in Turkey.*

No.	R^2_{OOS}	Model Used	Variables Used
1	0.3847	XGB	Macroeconomic Data + Inflation

No.	R^2_{OOS}	Model Used	Variables Used
2	0.3823	XGB	Macroeconomic Data + Inflation + Implied FX Volatility
3	0.3302	NN	Macroeconomic Data + Inflation + Implied FX Volatility
4	0.3062	NN	Macroeconomic Data + Inflation
5	0.3058	ERT	Macroeconomic Data + Inflation

As seen in Table 5.22, Neural Networks also performed well, attaining predictive R^2_{OOS} values of 33.02% and 30.62%, showcasing their capacity to model complex dependencies. Additionally, Extremely Randomized Trees (ERT) ranked among the top models, with a predictive R^2_{OOS} of 30.58%.

These findings indicate that ensemble learning techniques such as XGBoost (BRT) and ERT, along with Neural Networks, are particularly effective for bond risk premia predictions in Turkey. Turkey exhibits a preference for boosted tree-based models and deep learning approaches.

Macro Data and Inflation are pivotal in all top-performing models, contrasting with Hungary, Brazil, Thailand and Poland where yield curve metrics (e.g., Forward Rates) dominated. Models using implied FX volatility alongside macro variables (e.g., Rank 2: $R^2_{OOS} = 38.23\%$) show minimal improvement over macro-inflation-only models, indicating limited incremental value from FX volatility.

5.2.6.2 Decomposing the Importance of Different Factors

Single-Factor Models for Bond Risk Premia in Turkey

The analysis of single-factor models presented in Table 5.23 for Turkey's local currency bond risk premia reveals distinct patterns that diverge significantly from other

emerging markets in the study. Unlike countries where yield curve factors dominate predictive accuracy, Turkey's bond risk premia are primarily driven by macroeconomic variables and inflation, while yield curve-based factors exhibit negligible or even counterproductive explanatory power.

Table 5.23: *Single-Factor Models for Bond Risk Premia in Turkey.*

No.	R^2_{OOS}	Model Used	Model Content	Details for Yield Curve
1	-0.1174	OLS	Implied FX Volatility	
2	0.1388	OLS	Inflation	
3	-0.1676	OLS + PCA	Yield Curve Factors	Forward Rates
4	-0.3108	OLS + PCA	Yield Curve Factors	Forward Rates + Term Premiums
5	-0.3301	OLS	Yield Curve Factors	Forward Rates + Term Premiums + Forward-Spot Spreads
6	-0.2510	PLS	Yield Curve Factors	Forward Rates
7	-0.3488	PLS	Yield Curve Factors	Forward Rates + Term Premiums
8	-0.3355	PLS	Yield Curve Factors	Forward Rates + Term Premiums + Forward-Spot Spreads
9	-0.3340	OLS	Yield Curve Factors	Forward-Spot Spreads
10	-0.1885	OLS	Yield Curve Factors	Term Premiums
11	-0.2879	PLS	Yield Curve Factors	Forward-Spot Spreads
12	-0.2506	PLS	Yield Curve Factors	Term Premiums
13	< -1	PLS	Macro Variables	
14	< -1	OLS	Macro Variables	

No.	R^2_{OOS}	Model Used	Model Content	Details for Yield Curve
15	-0.0883	NN	Yield Curve Factors	Forward Rates
16	-0.1075	NN	Yield Curve Factors	Forward Rates + Term Premiums
17	-0.1203	NN	Yield Curve Factors	Forward Rates + Term Premiums + Forward-Spot Spreads
18	0.1444	NN	Macro Variables	
19	-0.0481	XGB	Yield Curve Factors	Forward Rates
20	-0.1291	XGB	Yield Curve Factors	Forward Rates + Term Premiums
21	-0.0417	XGB	Yield Curve Factors	Forward Rates + Term Premiums + Forward-Spot Spreads
22	0.2694	XGB	Macro Variables	
23	-0.0457	RF	Yield Curve Factors	Forward Rates
24	-0.0965	RF	Yield Curve Factors	Forward Rates + Term Premiums
25	-0.1191	RF	Yield Curve Factors	Forward Rates + Term Premiums + Forward-Spot Spreads
26	0.2901	RF	Macro Variables	
27	-0.0815	ERT	Yield Curve Factors	Forward Rates
28	-0.0601	ERT	Yield Curve Factors	Forward Rates + Term Premiums

No.	R^2_{OOS}	Model Used	Model Content	Details for Yield Curve
29	-0.0858	ERT	Yield Curve Factors	Forward Rates + Term Premiums + Forward-Spot Spreads
30	0.2395	ERT	Macro Variables	

Among the variables tested, macroeconomic indicators and inflation emerge as the most reliable predictors. For instance, Model 22 (XGB, Macro Variables, $R^2_{OOS} = 0.2694$) and Model 26 (RF, Macro Variables, $R^2_{OOS} = 0.2901$) demonstrate that macroeconomic data, when processed through advanced machine learning algorithms, capture meaningful signals in Turkey's bond market.

Figure 5.6: *Predictive Power of Macroeconomic Variables Across Countries.*

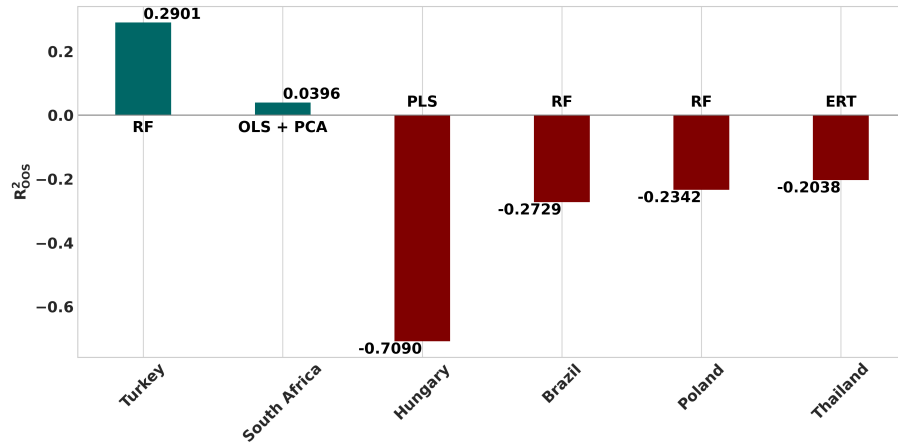


Figure 5.6 presents the best-performing single-factor model that uses macroeconomic variables for each country, thereby enabling a consistent cross-country comparison of the standalone explanatory power of macro-based predictors. Among all six countries, Turkey stands out as the only market where macroeconomic indicators—when processed through Random Forest—achieve positive out-of-sample predictive performance ($R^2_{OOS} = 0.2901$).

In contrast, macro-based models fail to extract meaningful signals elsewhere. Hungary's Partial Least Squares model collapses with $R^2_{OOS} = -0.7090$, while Brazil ($R^2_{OOS} = -0.2729$), Poland ($R^2_{OOS} = -0.2342$), and Thailand ($R^2_{OOS} = -0.2038$) also exhibit significantly negative performance, regardless of the algorithm used. Even in South Africa, where macroeconomic volatility could be expected to carry informational value, the OLS + PCA model produces only a marginal gain ($R^2_{OOS} = 0.0396$), underscoring the weak standalone forecasting potential of macro variables in these contexts.

These findings highlight Turkey's unique macro-financial structure, where bond risk premia are more sensitive to macroeconomic fundamentals and policy signals than in peer economies. The relatively strong results from macro-based models in Turkey suggest that inflation, in particular, plays a critical role in shaping investor expectations. This hypothesis is explored further in the next paragraph.

Inflation also shows predictive capacity, as seen in Table 5.23, Model 2 (OLS, Inflation, $R^2_{OOS} = 0.1388$).

Figure 5.7: *Predictive Power of Inflation Across Countries.*

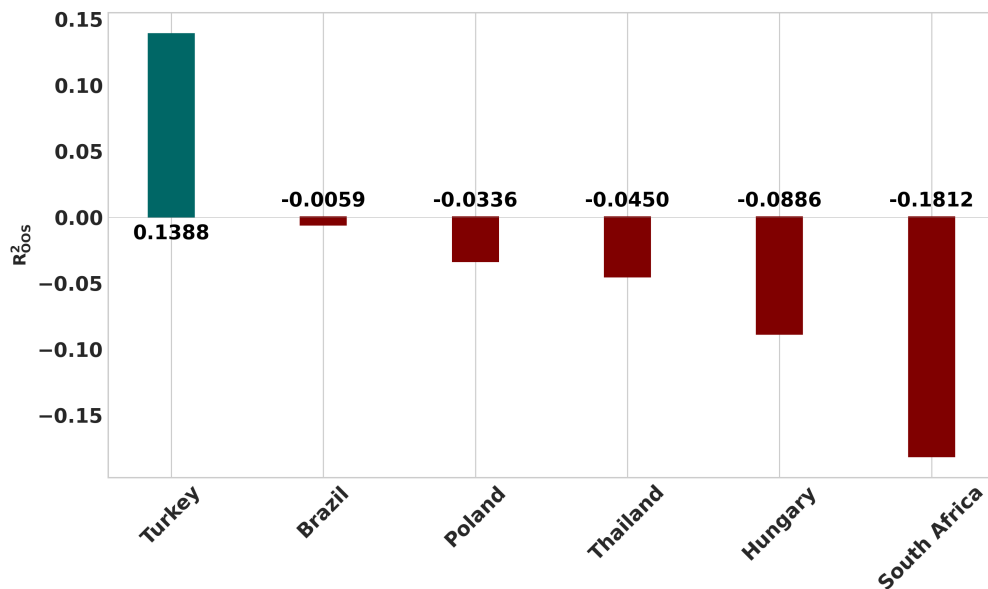


Figure 5.7 compares the out-of-sample R^2_{OOS} values of single-factor models that use inflation as the sole predictor and apply Ordinary Least Squares (OLS) to estimate bond risk premia across all countries in the sample.

As illustrated in Figure 5.7, Turkey stands out as the only country in the sample where inflation yields a positive out-of-sample R^2_{OOS} , highlighting its unique explanatory relevance in bond risk premia forecasting. In sharp contrast, inflation-based models in Brazil ($R^2_{OOS} = -0.0059$), Poland ($R^2_{OOS} = -0.0336$), Thailand ($R^2_{OOS} = -0.0450$), Hungary ($R^2_{OOS} = -0.0886$), and South Africa ($R^2_{OOS} = -0.1812$) exhibit consistently negative performance, indicating that inflation fails to capture meaningful signals in those markets.

Turkey's inflation dynamics—characterized by heightened volatility—likely contribute to this divergence. In such an environment, bond investors may place disproportionate weight on inflation expectations, making inflation a more potent pricing factor. Thus, Figure 5.7 not only confirms Turkey's idiosyncratic position within the emerging market landscape but also reinforces the broader conclusion that macroeconomic conditions must be interpreted within local context rather than assumed to have universal explanatory power.

In Turkey, yield curve factors consistently underperform. As presented in Table 5.23, models incorporating forward rates, term premiums, or forward-spot spreads such as Model 3 (OLS + PCA, Yield Curve Factors: Forward Rates, $R^2_{OOS} = -0.1676$) and Model 5 (OLS, Yield Curve Factors: Forward Rates + Term Premiums + Forward-Spot Spreads, $R^2_{OOS} = -0.3301$)—produce negative R^2_{OOS} values, indicating that these variables introduce noise rather than predictive insights. Even machine learning approaches applied to yield curve data, such as Model 15 (NN, Yield Curve Factors: Forward Rates, $R^2_{OOS} = -0.0883$), fail to generate positive results, underscoring the limited relevance of yield curve dynamics in Turkey's context.

Two-Factor Models for Bond Risk Premia in Turkey

The two-factor models for Turkey's bond risk premia further underscore the dominance of macroeconomic variables and inflation, while yield curve-based combinations continue to underperform, as evidenced by Table 5.24. Among the tested configurations, models integrating macroeconomic indicators with inflation achieve the highest predictive accuracy, whereas those incorporating yield curve factors or foreign exchange (FX) volatility exhibit instability or negative explanatory power.

Table 5.24: *Two-Factor Models for Bond Risk Premia in Turkey.*

No.	R^2_{OOS}	Model Used	Model Content	Details for Yield Curve
1	0.1452	OLS	Inflation + Implied FX Volatility	
2	-0.2047	OLS + PCA	Implied FX Volatility + Yield Curve	Forward Rates + Term Premiums + Forward-Spot Spreads
3	-0.2513	PLS	Implied FX Volatility + Yield Curve	Forward Rates + Term Premiums + Forward-Spot Spreads
4	< -1	PLS	Macro Variables + Inflation	
5	< -1	OLS + PCA	Macro Variables + Inflation	
6	-0.1543	NN	Implied FX Volatility + Yield Curve	Forward Rates + Term Premiums + Forward-Spot Spreads
7	0.3062	NN	Macro Variables + Inflation	
8	0.1713	NN	Inflation + Implied FX Volatility	

No.	R^2_{OOS}	Model Used	Model Content	Details for Yield Curve
9	-0.0385	XGB	Implied FX Volatility + Yield Curve	Forward Rates + Term Premiums + Forward-Spot Spreads
10	0.3847	XGB	Macro Variables + Inflation	
11	0.0919	XGB	Inflation + Implied FX Volatility	
12	-0.1032	RF	Implied FX Volatility + Yield Curve	Forward Rates + Term Premiums + Forward-Spot Spreads
13	0.1308	RF	Macro Variables + Inflation	
14	0.1464	RF	Inflation + Implied FX Volatility	
15	-0.0844	ERT	Implied FX Volatility + Yield Curve	Forward Rates + Term Premiums + Forward-Spot Spreads
16	0.3058	ERT	Macro Variables + Inflation	
17	-0.1260	ERT	Inflation + Implied FX Volatility	

Among Turkey's two-factor configurations, models combining macroeconomic variables with inflation achieve the highest predictive accuracy. For instance, Table 5.24, Model 10 (XGB, Macro Variables + Inflation, $R^2_{OOS} = 0.3847$) outperforms other combinations, reflecting the compounded explanatory power of macroeconomic fundamentals and price stability. In contrast, models incorporating yield curve factors or FX volatility such as Table 5.24, Model 6 (NN, Implied FX Volatility + Yield Curve, $R^2_{OOS} = -0.1543$) and Table 5.24, Model 9 (XGB, Implied FX Volatility + Yield Curve, $R^2_{OOS} = -0.0385$)

exhibit negative or negligible predictive power. Even neural networks, which excel in capturing non-linear relationships, fail to extract meaningful signals from yield curve data in Turkey.

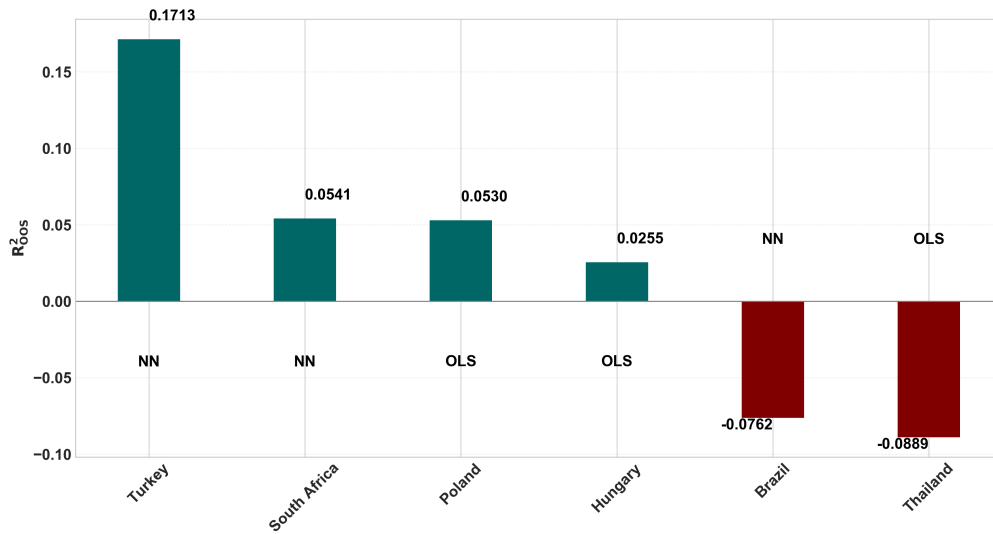
Two-factor models generally outperform single-factor counterparts when combining complementary variables. For example, Model 10 (XGB, Macro Variables + Inflation, $R^2_{\text{OOS}} = 0.3847$) surpasses the standalone performance of macroeconomic variables (Table 5.23, Model 22: XGB, Macro Variables, $R^2_{\text{OOS}} = 0.2694$) and inflation (Table 5.23, Model 2: OLS, Inflation, $R^2_{\text{OOS}} = 0.1388$). However, integrating yield curve factors deteriorates predictions. Model 3 (PLS, Implied FX Volatility + Yield Curve, $R^2_{\text{OOS}} = -0.2513$) confirms the structural incompatibility of yield curve data with Turkey's risk premia dynamics.

Combined inclusion of implied FX volatility and inflation yields modest but consistent predictive power across several model types. For example, Table 5.24, Model 1 (OLS, $R^2_{\text{OOS}} = 0.1452$), Model 8 (NN, $R^2_{\text{OOS}} = 0.1713$), Model 11 (XGB, $R^2_{\text{OOS}} = 0.0919$), and Model 14 (RF, $R^2_{\text{OOS}} = 0.1464$) all show positive out-of-sample R^2 values when using Inflation + Implied FX Volatility. This suggests that their joint dynamics—possibly reflecting inflation expectations and exchange rate risk—offer a more stable signal, especially for non-linear methods like NN and RF. However, Extremely Randomized Trees (ERT, Model 17, $R^2_{\text{OOS}} = -0.1260$) fail to capture these effects, underlining the sensitivity of model choice.

The nuanced role of inflation and implied FX volatility in bond risk premia forecasting is further illustrated in Figure 5.8, which displays the best-performing two-factor models that jointly incorporate inflation and implied FX volatility for each country. This cross-country comparison reveals marked heterogeneity in the predictive utility of these variables.

Turkey distinguishes itself, with a Neural Network model achieving the highest

Figure 5.8: *Best-Performing Two-Factor Models Using Inflation and Implied FX Volatility Across Countries.*



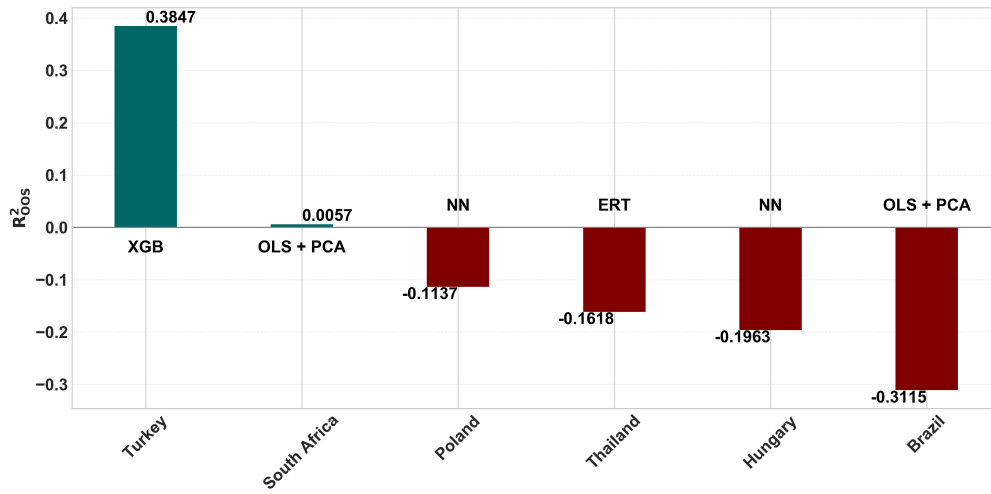
accuracy among all countries ($R^2_{OOS} = 0.1713$), highlighting the relevance of non-linear relationships between inflation dynamics and exchange rate uncertainty in its bond market. South Africa ($R^2_{OOS} = 0.0541$) and Poland ($R^2_{OOS} = 0.0530$) also exhibit modest predictive success, albeit through different modeling frameworks—Neural Networks and OLS, respectively—suggesting the broader applicability of inflation–FX pairings in certain macro-financial environments.

By contrast, Hungary ($R^2_{OOS} = 0.0255$) shows minimal gain, while Brazil ($R^2_{OOS} = -0.0762$) and Thailand ($R^2_{OOS} = -0.0889$) suffer negative out-of-sample performance, indicating that these variables are either weakly linked to bond risk premia or introduce excess noise in these contexts.

These findings imply that while inflation and FX volatility can offer forecasting potential when carefully modeled, their joint value is highly country- and method-dependent. Turkey’s leading performance underscores the importance of both variable selection and algorithmic flexibility.

Figure 5.9 provides a comparative overview of the best-performing two-factor

Figure 5.9: *Predictive Power of Two-Factor Models Combining Macroeconomic Variables and CPI Across Countries.*



models combining macroeconomic variables and inflation across six emerging market economies. This visual encapsulation illustrates pronounced cross-country divergence in predictive performance, reinforcing the notion that the relevance and interplay of macroeconomic indicators and inflation vary substantially by context.

Turkey once again emerges as the standout case, with the XGBoost model achieving a notably high out-of-sample $R^2_{OOS} = 0.3847$. This suggests that the interaction between macroeconomic fundamentals and inflationary dynamics is particularly potent in capturing bond risk premia variations within Turkey's financial environment. The strength of this result may stem from the country's heightened macro-financial sensitivity and frequent policy shifts, which make nonlinear, high-capacity models like XGB well-suited to uncovering complex patterns.

In contrast, South Africa exhibits minimal predictive success ($R^2_{OOS} = 0.0057$) using an OLS + PCA framework. While the sign is positive, the near-zero coefficient indicates that macroeconomic variables and inflation lack explanatory coherence or that PCA transformation may dilute key signal structures. This underlines the need for methodological caution when dimensionality reduction techniques are applied to relatively weak

predictors.

Poland, Thailand, Hungary, and Brazil all experience negative out-of-sample performance, signaling that the joint inclusion of macroeconomic variables and inflation introduces more noise than signal in these contexts. Notably, Brazil ($R^2_{OOS} = -0.3115$) and Hungary ($R^2_{OOS} = -0.1963$) record the worst performance, despite employing advanced techniques such as OLS + PCA and Neural Networks, respectively. This suggests that either the macro-inflation nexus is inherently weak in these economies or that critical features are omitted or misrepresented in the modeling process.

Interestingly, Neural Networks, though powerful, fail to deliver in Poland and Hungary, implying that nonlinearity alone does not compensate for inadequate variable relevance or unstable factor relationships. Similarly, Extremely Randomized Trees in Thailand ($R^2_{OOS} = -0.1618$) fall short, hinting at overfitting or lack of robust patterns in the input space.

Overall, Figure 5.9 underscores that Turkey's reliance on macroeconomic-inflation hybrids starkly contrasts with patterns in other emerging markets.

Three-Factor Models for Bond Risk Premia in Turkey

The analysis of three-factor models for Turkey's bond risk premia reinforces the dominance of macroeconomic variables and inflation, while combinations incorporating yield curve factors or foreign exchange (FX) volatility exhibit limited predictive utility, as evidenced by Table 5.25.

Table 5.25: *Three-Factor Models for Bond Risk Premia in Turkey.*

No.	R^2_{OOS}	Model Used	Model Content	Details for Yield Curve
1	0.0671	OLS + PCA	Inflation + Implied FX Volatility + Yield Curve	Forward Rates + Term Premiums + Forward-Spot Spreads

No.	R^2_{OOS}	Model Used	Model Content	Details for Yield Curve
2	0.0249	PLS	Inflation + Implied FX Volatility + Yield Curve	Forward Rates + Term Premiums + Forward-Spot Spreads
3	< -1	OLS + PCA	Macro Variables + Inflation + Implied FX Volatility	
4	< -1	PLS	Macro Variables + Inflation + Implied FX Volatility	
5	0.0904	NN	Inflation + Implied FX Volatility + Yield Curve	Forward Rates + Term Premiums + Forward-Spot Spreads
6	0.3302	NN	Macro Variables + Inflation + Implied FX Volatility	
7	0.0572	XGB	Inflation + Implied FX Volatility + Yield Curve	Forward Rates + Term Premiums + Forward-Spot Spreads
8	0.3823	XGB	Macro Variables + Inflation + Implied FX Volatility	
9	0.0694	RF	Inflation + Implied FX Volatility + Yield Curve	Forward Rates + Term Premiums + Forward-Spot Spreads
10	0.2759	RF	Macro Variables + Inflation + Implied FX Volatility	
11	0.0981	ERT	Inflation + Implied FX Volatility + Yield Curve	Forward Rates + Term Premiums + Forward-Spot Spreads

No.	R^2_{OOS}	Model Used	Model Content	Details for Yield Curve
12	0.2872	ERT	Macro Variables + Inflation + Implied FX Volatility	

Models integrating macroeconomic variables, inflation, and FX volatility achieve the highest predictive accuracy in Turkey. For instance, Table 5.25, Model 8 (XGB, Macro Variables + Inflation + Implied FX Volatility, $R^2_{OOS} = 0.3823$) and Table 5.25, Model 6 (NN, Macro Variables + Inflation + Implied FX Volatility, $R^2_{OOS} = 0.3302$) outperform other configurations, reflecting the compounded explanatory power of macroeconomic fundamentals.

In contrast, models incorporating yield curve factors—such as Table 5.25, Model 5 (NN, Inflation + Implied FX Volatility + Yield Curve, $R^2_{OOS} = 0.0904$) and Table 5.25, Model 7 (XGB, Inflation + Implied FX Volatility + Yield Curve, $R^2_{OOS} = 0.0572$) demonstrate minimal predictive power. This further underscores the structural irrelevance of yield curve dynamics in Turkey’s bond market.

The three-factor models generally underperform their two-factor counterparts when Implied FX Volatility is introduced. For example, Table 5.25, Model 8 (XGB, Macro Variables + Inflation + Implied FX Volatility, $R^2_{OOS} = 0.3823$) slightly lags behind Turkey’s top two-factor model (Table 5.24, Model 10 (XGB, Macro Variables + Inflation, $R^2_{OOS} = 0.3847$)), suggesting that adding FX volatility does not enhance predictions. Similarly, Table 5.25, Model 6 (NN, Macro Variables + Inflation + Implied FX Volatility, $R^2_{OOS} = 0.3302$) underperforms relative to two-factor macroeconomic-inflation hybrids (e.g., Table 5.24, Model 16 (ERT, Macro Variables + Inflation, $R^2_{OOS} = 0.3058$)). This implies diminishing returns from increasing model complexity in Turkey’s context.

Models incorporating yield curve factors—such as Table 5.25, Model 5 (NN, Inflation + Implied FX Volatility + Yield Curve, $R^2_{OOS} = 0.0904$)—perform worse than their

two-factor equivalents (e.g., Table 5.24, Model 8 (NN, Inflation + Implied FX Volatility, $R_{OOS}^2 = 0.1713$)), reinforcing the noise introduced by yield curve data.

Turkey's three-factor results starkly contrast with patterns in other emerging markets. In Hungary, Table 5.5, Model 6 (NN, Macro Variables + Inflation + FX Volatility, $R_{OOS}^2 = -0.4775$), combining macroeconomic variables with inflation and FX volatility severely degrades predictions, whereas yield curve-centric models dominate. Similarly, Table 5.20, Model 9 (RF, Inflation + Implied FX Volatility + Yield Curve, $R_{OOS}^2 = 0.2728$) in Poland and Table 5.15, Model 5 (NN, Inflation + Implied FX Volatility + Yield Curve, $R_{OOS}^2 = 0.2887$) in Thailand demonstrate constructive interactions between yield curve factors and macroeconomic variables, unlike Turkey's yield curve-driven failures. Table 5.10, Model 9 (RF, Inflation + Implied FX Volatility + Yield Curve, $R_{OOS}^2 = 0.3568$) in Brazil further highlights how yield curve integration enhances accuracy in structurally stable markets.

Turkey's three-factor models underscore the dominance of macroeconomic instability in shaping bond risk premia. This contrasts with countries like Hungary, Brazil, Thailand and Poland where yield curves reflect risk premia accurately.

Omni-Factor Models for Bond Risk Premia in Turkey

The omni-factor models for Turkey highlight the persistent dominance of macroeconomic variables and inflation in driving bond risk premia, while yield curve factors continue to degrade predictive accuracy, as evidenced by Table 5.26.

Table 5.26: *Omni-Factor Models for Bond Risk Premia in Turkey.*

No.	R_{OOS}^2	Model Used	Model Content	Details for Yield Curve
1	< -1	OLS + PCA	Macro Variables + Yield Curve + Inflation + Implied FX Volatility	Forward Rates + Term Premiums + Forward-Spot Spreads

No.	R^2_{OOS}	Model Used	Model Content	Details for Yield Curve
2	< -1	PLS	Macro Variables + Yield Curve + Inflation + Implied FX Volatility	Forward Rates + Term Premiums + Forward-Spot Spreads
3	0.1808	NN	Macro Variables + Yield Curve + Inflation + Implied FX Volatility	Forward Rates + Term Premiums + Forward-Spot Spreads
4	0.3013	XGB	Macro Variables + Yield Curve + Inflation + Implied FX Volatility	Forward Rates + Term Premiums + Forward-Spot Spreads
5	0.2758	RF	Macro Variables + Yield Curve + Inflation + Implied FX Volatility	Forward Rates + Term Premiums + Forward-Spot Spreads
6	0.2854	ERT	Macro Variables + Yield Curve + Inflation + Implied FX Volatility	Forward Rates + Term Premiums + Forward-Spot Spreads

Among the omni-factor configurations, XGBoost (Model 4: XGB, Macro Variables + Yield Curve + Inflation + Implied FX Volatility, $R^2_{OOS} = 0.3013$) and Extremely Randomized Trees (Model 6: ERT, Macro Variables + Yield Curve + Inflation + Implied FX Volatility, $R^2_{OOS} = 0.2854$) deliver the highest predictive performance. These results underscore the ability of tree-based methods to prioritize macroeconomic fundamentals over yield curve noise. In contrast, traditional econometric approaches such as OLS + PCA (Model 1: $R^2_{OOS} < -1$) and PLS (Model 2: $R^2_{OOS} < -1$) collapse entirely, reflecting their incompatibility with Turkey's complex macroeconomic-driven risk premia. Neural Networks (Model 3: NN, $R^2_{OOS} = 0.1808$) underperform relative to tree-based models.

When compared to Turkey's three-factor models, the omni-factor frameworks exhibit mixed performance. For instance, the top three-factor model (Table 5.25, Model 8: XGB, Macro Variables + Inflation + Implied FX Volatility, $R^2_{\text{OOS}} = 0.3823$) outperforms the best omni-factor model (Table 5.26, Model 4: XGB, $R^2_{\text{OOS}} = 0.3013$), indicating that adding yield curve factors introduces noise rather than enhancing forecasts. Similarly, the three-factor Neural Network model (Table 5.25, Model 6: NN, Macro Variables + Inflation + Implied FX Volatility, $R^2_{\text{OOS}} = 0.3302$) surpasses its omni-factor counterpart (Table 5.26, Model 3: NN, $R^2_{\text{OOS}} = 0.1808$), reinforcing the detrimental impact of yield curve variables.

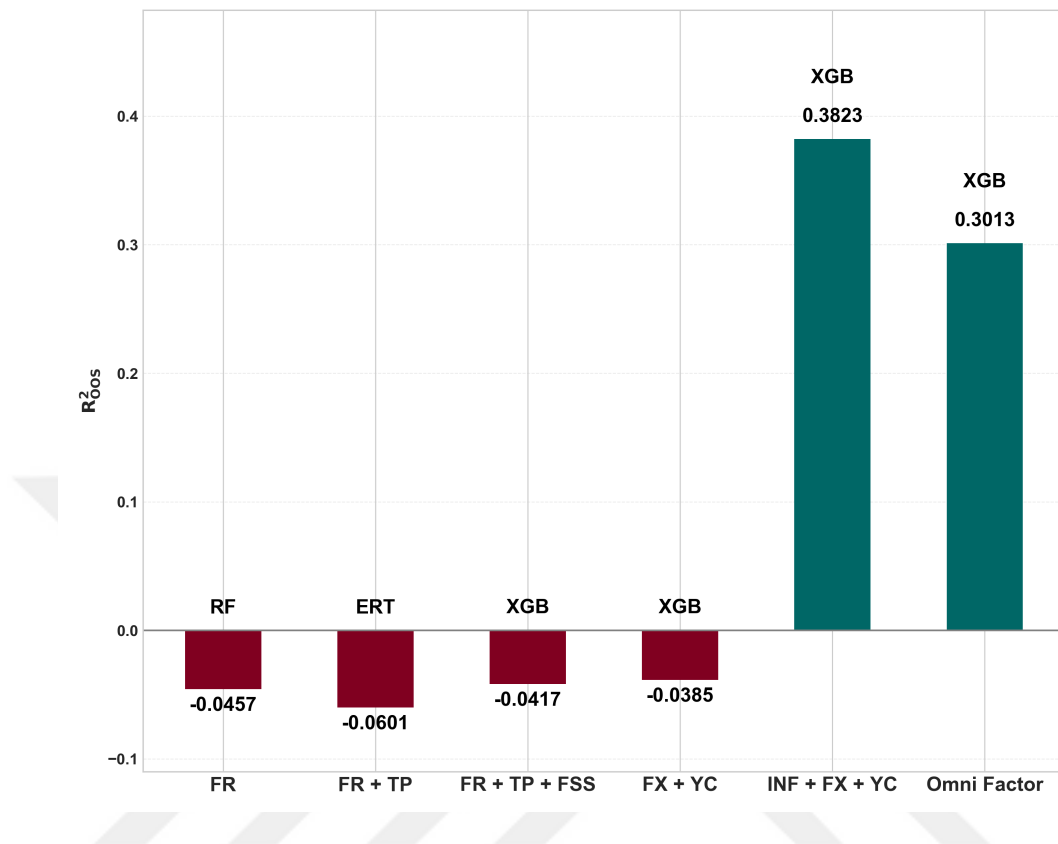
These findings contrast sharply with three-factor models in other emerging markets, such as Poland (Table 5.20, Model 9: RF, Inflation + Implied FX Volatility + Yield Curve, $R^2_{\text{OOS}} = 0.2728$) and Thailand (Table 5.15, Model 5: NN, Inflation + Implied FX Volatility + Yield Curve, $R^2_{\text{OOS}} = 0.2887$), where yield curve factors contribute positively to predictive accuracy.

In summary, Turkey's omni-factor models reaffirm the primacy of macroeconomic fundamentals and inflation, while yield curve factors remain structurally irrelevant. The superior performance of XGBoost and ERT models underscores the adaptability of tree-based methods in filtering noisy yield curve data. These findings align with Turkey's unique economic context, where macroeconomic volatility dominates bond risk premia, setting it apart from yield curve-centric markets like Hungary or hybrid regimes like Brazil.

Figure 5.10 summarizes the out-of-sample predictive performance (R^2_{OOS}) of the best-performing models as additional predictor variables are progressively incorporated into the forecasting framework for Turkey's local currency bond risk premia.

Each subsequent augmentation of the predictor set with market-based variables produces varied outcomes, but still without yielding positive R^2_{OOS} until macroeconomic

Figure 5.10: Turkey – Overview.



indicators are introduced. The models with all yield-curve (YC) and FX variables cannot beat the simplistic benchmark out-of-sample.

A dramatic improvement in predictive performance occurs only when inflation enters the model. Once inflation (INF) is added to the predictor set (along with the FX and yield curve variables), the XGBoost model's R^2_{OOS} jumps into positive territory. The bar for the INF + FX + YC model shows a substantial positive R^2_{OOS} of 0.3823. This positive R^2_{OOS} is a striking contrast to the consistently negative values seen for models lacking inflation, and it highlights inflation's critical role in predicting risk premia in Turkey.

Interestingly, however, the subsequent inclusion of broader macroeconomic variables results in a deterioration of performance, with the R^2_{OOS} declining to 0.3013. This suggests that while inflation captures a substantial portion of the relevant macro-financial dynamics in Turkey, adding a larger set of macroeconomic indicators may introduce noise

or multicollinearity, reducing the overall signal quality.

Compared to other countries in the study, Turkey stands out in two ways: first, yield curve-based predictors offer virtually no value, contrary to Hungary, Brazil, Thailand, and Poland. Second, XGBoost consistently outperforms traditional and other machine learning models, underlining its ability to isolate meaningful patterns in a high-noise macroeconomic environment.

These insights are pivotal for informing both economic policy and investment decisions, reinforcing the broader conclusions of the study.

5.2.6.3 Implications for Policymakers and Investors

What do these findings mean for bond market participants?

The findings underscore that Turkey's local currency bond risk premia are fundamentally shaped by macroeconomic variables with yield curve factors offering negligible predictive power. For bond market participants, this implies a critical need to prioritize macroeconomic indicators over market-based signals like forward rates or term premiums. Unlike in Hungary or Brazil, where yield curve dynamics dominate, Turkey's bond risk premia reflect a macroeconomic-first approach to risk assessment. Investors must also recognize the limitations of conventional econometric models in Turkey's context, as linear frameworks fail to capture the nonlinear interactions between inflation shocks, currency depreciation, and sovereign risk perceptions. Advanced machine learning models, particularly XGBoost and Extremely Randomized Trees (ERT), emerge as essential tools for navigating Turkey's volatile bond market, as they dynamically adapt to rapid shifts in macroeconomic conditions while filtering out yield curve noise.

How can investors use predictive models for risk assessment?

Investors in Turkey's local currency bond market should deploy predictive models that explicitly focus on macroeconomic variables and inflation while excluding yield

curve factors. For instance, XGBoost models (Table 5.26, Model 4: XGB, Macro Variables + Yield Curve + Inflation + Implied FX Volatility, $R^2_{\text{OOS}} = 0.3013$) and ERT models (Table 5.26, Model 6: ERT, $R^2_{\text{OOS}} = 0.2854$) demonstrate robustness in isolating macroeconomic-driven risks, even when yield curve data is included. However, simpler frameworks that exclude yield curve variables entirely—such as the top three-factor XGBoost model (Table 5.25, Model 8: XGB, Macro Variables + Inflation + Implied FX Volatility, $R^2_{\text{OOS}} = 0.3823$)—deliver superior accuracy, suggesting that parsimonious models may be more effective. Investors should also incorporate real-time macroeconomic data feeds to capture sudden policy shifts or inflation surprises, which are critical in Turkey’s environment.

Policy Implications for Monetary Authorities and Bond Issuers

For Turkey’s central bank and debt management office, the findings highlight the urgency of stabilizing macroeconomic fundamentals to reduce bond risk premia and borrowing costs. Policymakers should prioritize credible inflation-targeting frameworks and transparent communication to anchor expectations, as unanticipated policy shifts exacerbate risk premia. The structural irrelevance of yield curve factors further suggests that conventional monetary tools, such as interest rate adjustments, may have limited transmission to bond markets unless accompanied by macroeconomic stabilization.

Finally, integrating machine learning into fiscal and monetary policy analysis—for instance, using XGBoost to simulate the impact of inflation shocks on debt sustainability—could enhance policymaking agility in Turkey’s unpredictable economic landscape. Collaborative efforts between regulators, academia, and financial institutions to develop localized AI-driven tools would further strengthen Turkey’s capacity to manage bond market risks in alignment with its unique macroeconomic challenges.

These implications collectively emphasize that Turkey’s bond market requires a distinct strategy, diverging from yield curve-centric approaches used in Hungary or Brazil.

Success hinges on stabilizing macroeconomic fundamentals, leveraging advanced predictive models, and fostering institutional credibility to align investor expectations with policy outcomes.

5.2.7 South Africa

5.2.7.1 Identifying the Top 5 Performing Models

The analysis of local currency bond risk premia in South Africa reveals distinct challenges and predictive dynamics compared to other emerging markets in the study, as shown in Table 5.27.

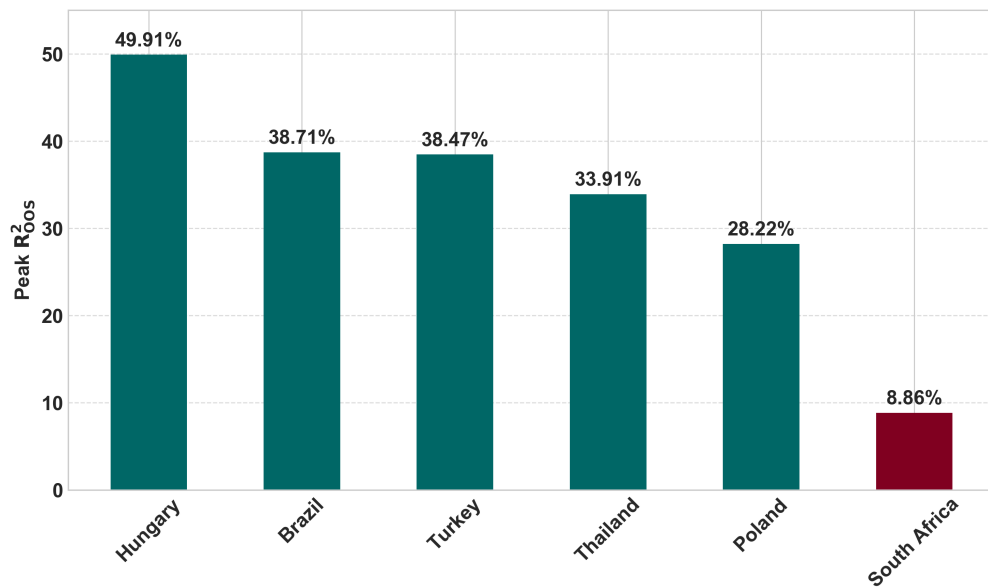
Table 5.27: *Top 5 Predictive Models for Bond Risk Premia in South Africa.*

No.	R^2_{OOS}	Model Used	Variables Used
1	0.0886	ERT	Macroeconomic Data + Inflation + Implied FX Volatility + Forward Rates + Term Premiums + Forward-Spot Spreads
2	0.0868	RF	Macroeconomic Data + Inflation + Implied FX Volatility
3	0.0821	RF	Macroeconomic Data + Inflation + Implied FX Volatility + Forward Rates + Term Premiums + Forward-Spot Spreads
4	0.0771	RF	Macroeconomic Data + Inflation + Implied FX Volatility
5	0.0554	OLS	Implied FX Volatility

Even the top performing model only achieves $R^2_{OOS} = 0.0886$. The similarity in R^2 values across top four models (Models 1–4) suggests that adding more predictors in South Africa yields diminishing returns.

Figure 5.11 displays the highest out-of-sample R^2_{OOS} values achieved across the

Figure 5.11: *Peak R^2_{OOS} Across Countries.*



six emerging markets, highlighting South Africa’s significantly weaker predictive performance relative to its peers.

Figure 5.11 and Table 5.27 above jointly reveal a striking result: despite employing comprehensive sets of predictors—including macroeconomic variables, inflation, implied FX volatility, and full yield curve dynamics—South Africa consistently yields the lowest predictive accuracy among all six emerging markets studied.

In the bar chart, South Africa’s peak out-of-sample $R^2_{OOS} = 8.86\%$ sharply contrasts with countries like Hungary (49.91%), Brazil (38.71%), or even Poland (28.22%).

The study’s dataset, while comprehensive, may not fully capture structural shifts in South Africa’s economy post-2020 (e.g., pandemic impacts, energy crises). Future research should test deep learning architectures (e.g., LSTMs) to model temporal dependencies in FX volatility and explore panel data frameworks integrating regional risk factors. Lastly, addressing data gaps—such as granular sectoral performance metrics—could refine predictive accuracy.

In summary, South Africa's bond risk premia remain a frontier for financial forecasting, demanding innovative approaches to navigate its unique interplay of volatility, external dependencies, and macroeconomic fragility.

5.2.7.2 Decomposing the Importance of Different Factors

Single-Factor Models for Bond Risk Premia in South Africa

The single-factor models for bond risk premia in South Africa reveal distinct patterns in predictive performance, characterized by the general ineffectiveness of yield curve-based variables and the limited utility of macroeconomic indicators, as evidenced by Table 5.28.

Table 5.28: *Single-Factor Models for Bond Risk Premia in South Africa.*

No.	R^2_{OOS}	Model Used	Model Content	Details for Yield Curve
1	0.0554	OLS	Implied FX Volatility	
2	-0.1812	OLS	Inflation	
3	-0.5649	OLS + PCA	Yield Curve Factors	Forward Rates
4	-0.5457	OLS + PCA	Yield Curve Factors	Forward Rates + Term Premiums
5	-0.5313	OLS	Yield Curve Factors	Forward Rates + Term Premiums + Forward-Spot Spreads
6	-0.5608	PLS	Yield Curve Factors	Forward Rates
7	-0.5742	PLS	Yield Curve Factors	Forward Rates + Term Premiums
8	-0.8370	PLS	Yield Curve Factors	Forward Rates + Term Premiums + Forward-Spot Spreads

No.	R^2_{OOS}	Model Used	Model Content	Details for Yield Curve
9	-0.6076	OLS	Yield Curve Factors	Forward-Spot Spreads
10	-0.4785	OLS	Yield Curve Factors	Term Premiums
11	-0.5971	PLS	Yield Curve Factors	Forward-Spot Spreads
12	-0.6191	PLS	Yield Curve Factors	Term Premiums
13	< -1	PLS	Macro Variables	
14	0.0396	OLS	Macro Variables	
15	-0.3408	NN	Yield Curve Factors	Forward Rates
16	-0.2432	NN	Yield Curve Factors	Forward Rates + Term Premiums
17	-0.2938	NN	Yield Curve Factors	Forward Rates + Term Premiums + Forward-Spot Spreads
18	< -1	NN	Macro Variables	
19	-0.5790	XGB	Yield Curve Factors	Forward Rates
20	-0.6881	XGB	Yield Curve Factors	Forward Rates + Term Premiums
21	-0.7236	XGB	Yield Curve Factors	Forward Rates + Term Premiums + Forward-Spot Spreads
22	-0.3306	XGB	Macro Variables	
23	-0.1888	RF	Yield Curve Factors	Forward Rates
24	-0.2844	RF	Yield Curve Factors	Forward Rates + Term Premiums
25	-0.3593	RF	Yield Curve Factors	Forward Rates + Term Premiums + Forward-Spot Spreads

No.	R^2_{OOS}	Model Used	Model Content	Details for Yield Curve
26	-0.0807	RF	Macro Variables	
27	-0.1802	ERT	Yield Curve Factors	Forward Rates
28	-0.2983	ERT	Yield Curve Factors	Forward Rates + Term Premiums
29	-0.2680	ERT	Yield Curve Factors	Forward Rates + Term Premiums + Forward-Spot Spreads
30	-0.1148	ERT	Macro Variables	

Implied FX volatility emerges as the strongest standalone predictor, with Model 1 (OLS, Implied FX Volatility, $R^2_{OOS} = 0.0554$) demonstrating modest positive predictive power.

Figure 5.12: *Predictive Power of Implied FX Volatility Across Countries.*

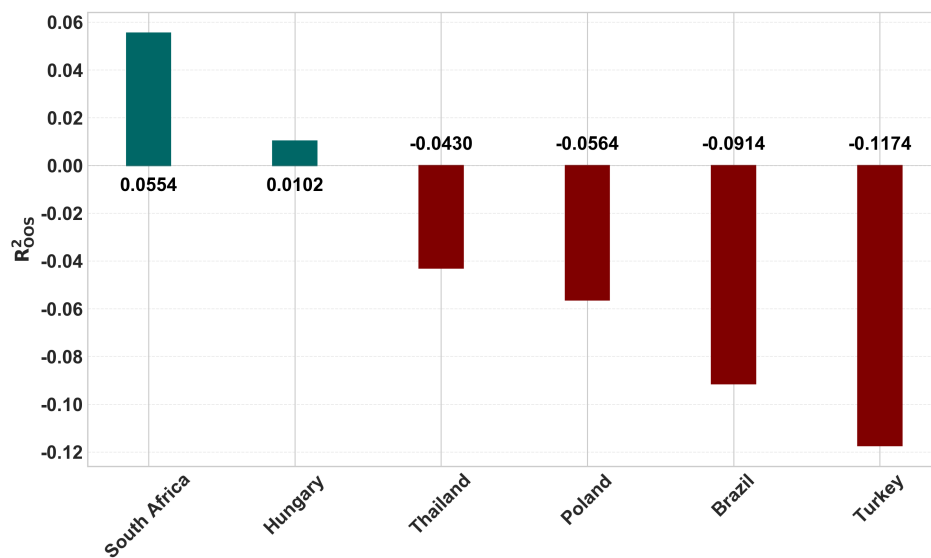


Figure 5.12 displays the out-of-sample predictive power (R^2_{OOS}) of single-factor models that incorporate only implied FX volatility as a predictor of excess bond returns in six emerging markets.

South Africa emerges as the only country with a notably positive R^2_{OOS} value (0.0554), indicating that exchange rate uncertainty plays a modest but meaningful role in explaining bond risk premia. This finding suggests that FX volatility in South Africa may be more systematically priced into bond returns, potentially reflecting greater sensitivity to global risk factors or investor positioning.

In contrast to the modest positive performance observed in Figure 5.12, yield curve-based variables such as forward rates, term premiums, and forward-spot spreads consistently underperform in South Africa, exhibiting negative out-of-sample R^2_{OOS} values across all modeling approaches. As evidenced by Table 5.28, this pattern holds regardless of the method employed.

For example, Model 3 (OLS + PCA, Yield Curve Factors: Forward Rates, $R^2_{\text{OOS}} = -0.5649$), Model 7 (PLS, Yield Curve Factors: Forward Rates + Term Premiums, $R^2_{\text{OOS}} = -0.5742$), Model 15 (NN, Yield Curve Factors: Forward Rates, $R^2_{\text{OOS}} = -0.3408$), and Model 19 (XGB, Yield Curve Factors: Forward Rates, $R^2_{\text{OOS}} = -0.5790$) illustrate the ineffectiveness of traditional yield curve components in predicting bond risk premia in South Africa.

Macroeconomic variables demonstrate limited predictive capability, exhibiting mixed performance across different modeling techniques. While Model 14 (OLS, Macro Variables, $R^2_{\text{OOS}} = 0.0396$) provides a slight improvement relative to yield curve factors, the overall predictive power remains weak, as further indicated by Model 26 (RF, Macro Variables, $R^2_{\text{OOS}} = -0.0807$) and Model 22 (XGB, Macro Variables, $R^2_{\text{OOS}} = -0.3306$). Additionally, inflation alone (Model 2: OLS, Inflation, $R^2_{\text{OOS}} = -0.1812$) does not offer reliable predictive power.

Overall, the underperformance of traditional yield curve and macroeconomic variables in South Africa underscores the need for alternative modeling approaches. The relatively stronger performance of implied FX volatility as a single predictor suggests its

potential importance.

Two-Factor Models for Bond Risk Premia in South Africa

The analysis of two-factor models for bond risk premia in South Africa reveals varying degrees of predictive accuracy depending on the variables and methodologies employed, as shown in Table 5.29.

Table 5.29: *Two-Factor Models for Bond Risk Premia in South Africa.*

No.	R^2_{OOS}	Model Used	Model Content	Details for Yield Curve
1	-0.0086	OLS	Inflation + Implied FX Volatility	
2	-0.3009	OLS + PCA	Implied FX Volatility + Yield Curve	Forward Rates + Term Premiums + Forward-Spot Spreads
3	-0.4689	PLS	Implied FX Volatility + Yield Curve	Forward Rates + Term Premiums + Forward-Spot Spreads
4	< -1	PLS	Macro Variables + Inflation	
5	0.0057	OLS + PCA	Macro Variables + Inflation	
6	-0.1620	NN	Implied FX Volatility + Yield Curve	Forward Rates + Term Premiums + Forward-Spot Spreads
7	-0.4873	NN	Macro Variables + Inflation	
8	0.0541	NN	Inflation + Implied FX Volatility	
9	-0.2385	XGB	Implied FX Volatility + Yield Curve	Forward Rates + Term Premiums + Forward-Spot Spreads

No.	R^2_{OOS}	Model Used	Model Content	Details for Yield Curve
10	-0.3348	XGB	Macro Variables + Inflation	
11	-0.3082	XGB	Inflation + Implied FX Volatility	
12	-0.0791	RF	Implied FX Volatility + Yield Curve	Forward Rates + Term Premiums + Forward-Spot Spreads
13	-0.0807	RF	Macro Variables + Inflation	
14	-0.1406	RF	Inflation + Implied FX Volatility	
15	-0.0184	ERT	Implied FX Volatility + Yield Curve	Forward Rates + Term Premiums + Forward-Spot Spreads
16	-0.1146	ERT	Macro Variables + Inflation	
17	-0.0824	ERT	Inflation + Implied FX Volatility	

Among the models tested, the combination of inflation and implied FX volatility using a Neural Network approach (Model 8: NN, Inflation + Implied FX Volatility, $R^2_{OOS} = 0.0541$) exhibited the highest predictive performance, albeit modest. Similarly, the single-factor model using implied FX volatility alone (Model 1: OLS, Implied FX Volatility, $R^2_{OOS} = 0.0554$) demonstrated slightly superior performance, suggesting no incremental predictive benefit from adding inflation. Conversely, models incorporating yield curve factors with implied FX volatility consistently underperformed, as exemplified by Model 6 (NN, Implied FX Volatility + Yield Curve: Forward Rates + Term Premiums + Forward-Spot Spreads, $R^2_{OOS} = -0.1620$) and Model 2 (OLS + PCA, Implied FX Volatility + Yield Curve, $R^2_{OOS} = -0.3009$), indicating the ineffectiveness of yield curve

variables even when combined with FX volatility.

Macroeconomic variables paired with inflation showed mixed results, with Model 8 (NN, Inflation + Implied FX Volatility, $R^2_{OOS} = 0.0541$) achieving modest predictive success, yet generally macroeconomic variables continued to add noise rather than valuable signals, exemplified by Model 7 (NN, Macro Variables + Inflation, $R^2_{OOS} = -0.4873$).

The consistent underperformance across both single-factor and two-factor models highlights the need for alternative predictive approaches specific to South Africa's market characteristics.

Three-Factor Models for Bond Risk Premia in South Africa

The analysis of three-factor models for bond risk premia in South Africa reveals notable differences in predictive performance depending on the combination of factors and methodologies employed, as shown in Table 5.30.

Table 5.30: *Three-Factor Models for Bond Risk Premia in South Africa.*

No.	R^2_{OOS}	Model Used	Model Content	Details for Yield Curve
1	-0.3875	OLS + PCA	Inflation + Implied FX Volatility + Yield Curve	Forward Rates + Term Premiums + Forward-Spot Spreads
2	-0.3756	PLS	Inflation + Implied FX Volatility + Yield Curve	Forward Rates + Term Premiums + Forward-Spot Spreads
3	-0.1252	OLS + PCA	Macro Variables + Inflation + Implied FX Volatility	
4	< -1	PLS	Macro Variables + Inflation + Implied FX Volatility	

No.	R^2_{OOS}	Model Used	Model Content	Details for Yield Curve
5	-0.1271	NN	Inflation + Implied FX Volatility + Yield Curve	Forward Rates + Term Premiums + Forward-Spot Spreads
6	< -1	NN	Macro Variables + Inflation + Implied FX Volatility	
7	-0.2422	XGB	Inflation + Implied FX Volatility + Yield Curve	Forward Rates + Term Premiums + Forward-Spot Spreads
8	-0.0512	XGB	Macro Variables + Inflation + Implied FX Volatility	
9	-0.1343	RF	Inflation + Implied FX Volatility + Yield Curve	Forward Rates + Term Premiums + Forward-Spot Spreads
10	0.0868	RF	Macro Variables + Inflation + Implied FX Volatility	
11	-0.0689	ERT	Inflation + Implied FX Volatility + Yield Curve	Forward Rates + Term Premiums + Forward-Spot Spreads
12	0.0771	ERT	Macro Variables + Inflation + Implied FX Volatility	

Among three-factor models, Random Forest (RF) using macroeconomic variables combined with inflation and implied FX volatility (Model 10: RF, Macro Variables + Inflation + Implied FX Volatility, $R^2_{OOS} = 0.0868$) delivered the highest predictive accuracy, albeit modestly. Conversely, the poorest performance was observed in the PLS model using the same variable combination (Model 4: PLS, Macro Variables + Inflation

+ Implied FX Volatility, $R_{\text{OOS}}^2 < -1$), suggesting that the choice of modeling technique significantly influences predictive outcomes when dealing with macroeconomic inputs.

Models incorporating yield curve factors, inflation, and implied FX volatility consistently perform poorly, exemplified by Model 1 (OLS + PCA, Inflation + Implied FX Volatility + Yield Curve, $R_{\text{OOS}}^2 = -0.3875$) and Model 9 (RF, Inflation + Implied FX Volatility + Yield Curve, $R_{\text{OOS}}^2 = -0.1343$), further confirming the limited relevance of yield curve variables in South Africa.

When compared to single-factor (Table 5.28) and two-factor (Table 5.29) models for South Africa, three-factor models offer limited improvement, and in some instances, performance deteriorates notably due to additional noise from incorporating ineffective predictors.

Notably, the single-factor implied FX volatility model (Table 5.28, Model 1: OLS, Implied FX Volatility, $R_{\text{OOS}}^2 = 0.0554$) and two-factor NN model combining inflation with implied FX volatility (Table 5.29, Model 8: NN, Inflation + Implied FX Volatility, $R_{\text{OOS}}^2 = 0.0541$) achieve comparable performance to the best three-factor RF model (Table 5.30, Model 10: RF, Macro Variables + Inflation + Implied FX Volatility, $R_{\text{OOS}}^2 = 0.0868$), emphasizing the minimal incremental predictive benefit from introducing additional complexity.

Compared to the predictive accuracy of three-factor models in other emerging markets, South Africa again demonstrates distinct performance. For instance, in Turkey, macroeconomic variables combined with inflation and implied FX volatility achieve robust predictive results (Table 5.25, Model 6: NN, Macro Variables + Inflation + Implied FX Volatility, $R_{\text{OOS}}^2 = 0.3302$), whereas the same variable combination in South Africa delivers marginal improvements at best. Similarly, yield curve factors show significant predictive relevance in Hungary (Table 5.3, Model 15: NN, Yield Curve Factors: Forward Rates, $R_{\text{OOS}}^2 = 0.4991$), highlighting stark regional differences.

Overall, these findings highlight the challenges of employing conventional predictive methodologies in South Africa's bond market, emphasizing the limited utility of traditional yield curve and macroeconomic indicators. Effective forecasting in this context likely requires innovative approaches that incorporate structural risk factors specific to the South African market environment, rather than relying solely on standard macroeconomic or yield curve predictors.

Omni-Factor Models for Bond Risk Premia in South Africa

The results from omni-factor models for bond risk premia in South Africa reinforce the limited explanatory power of traditional bond risk premia predictors in the South African context, as shown in Table 5.31.

Table 5.31: *Omni-Factor Models for Bond Risk Premia in South Africa.*

No.	R^2_{OOS}	Model Used	Model Content	Details for Yield Curve
1	0.0011	OLS + PCA	Macro Variables + Yield Curve + Inflation + Implied FX Volatility	Forward Rates + Term Premiums + Forward-Spot Spreads
2	-0.9612	PLS	Macro Variables + Yield Curve + Inflation + Implied FX Volatility	Forward Rates + Term Premiums + Forward-Spot Spreads
3	-0.1776	NN	Macro Variables + Yield Curve + Inflation + Implied FX Volatility	Forward Rates + Term Premiums + Forward-Spot Spreads
4	-0.0535	XGB	Macro Variables + Yield Curve + Inflation + Implied FX Volatility	Forward Rates + Term Premiums + Forward-Spot Spreads

No.	R^2_{OOS}	Model Used	Model Content	Details for Yield Curve
5	0.0821	RF	Macro Variables + Yield Curve + Inflation + Implied FX Volatility	Forward Rates + Term Premiums + Forward-Spot Spreads
6	0.0886	ERT	Macro Variables + Yield Curve + Inflation + Implied FX Volatility	Forward Rates + Term Premiums + Forward-Spot Spreads

The best-performing model is the Extremely Randomized Trees (ERT) model (Model 6: ERT, Macro Variables + Yield Curve + Inflation + Implied FX Volatility, $R^2_{OOS} = 0.0886$), showing a slight improvement over simpler models. This suggests that ERT's ability to handle noise and capture non-linear interactions makes it relatively more effective in extracting signal from the full factor set. Similarly, Random Forest (RF) (Model 5: RF, Macro Variables + Yield Curve + Inflation + Implied FX Volatility, $R^2_{OOS} = 0.0821$) also demonstrates a marginally positive predictive power, reinforcing the trend that ensemble tree-based methods outperform traditional regression and neural network models.

Conversely, Partial Least Squares (PLS) (Model 2: PLS, Macro Variables + Yield Curve + Inflation + Implied FX Volatility, $R^2_{OOS} = -0.9612$) performs the worst among all models, showing significant overfitting and a failure to generalize out-of-sample. Similarly, Neural Networks (NN) (Model 3: NN, Macro Variables + Yield Curve + Inflation + Implied FX Volatility, $R^2_{OOS} = -0.1776$) underperforms. The XGBoost model (Model 4: XGB, $R^2_{OOS} = -0.0535$) also struggles.

When comparing these results to South Africa's three-factor models in Table 5.30, it is clear that including all available factors does not necessarily improve predictive accuracy. The best three-factor model (Table 5.30, Model 10: RF, Macro Variables + Inflation + Implied FX Volatility, $R^2_{OOS} = 0.0868$) achieves nearly the same level of performance

as the best omni-factor model (ERT, $R_{\text{OOS}}^2 = 0.0886$), suggesting that adding yield curve variables does not contribute meaningful predictive value in South Africa. This aligns with previous findings indicating that yield curve factors are generally ineffective in predicting bond risk premia in South Africa, unlike in other emerging markets.

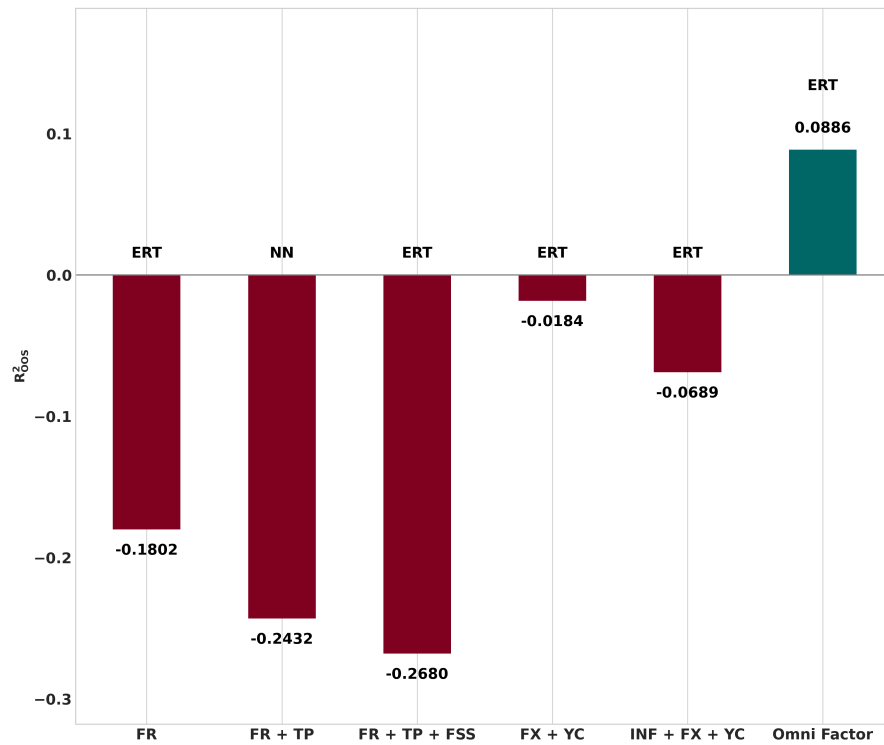
Moreover, the three-factor model using Neural Networks (Table 5.30, Model 6: NN, Macro Variables + Inflation + Implied FX Volatility, $R_{\text{OOS}}^2 < -1$) performed significantly worse than expected, and its performance does not improve in the omni-factor setting. This suggests that non-linear methods may struggle with South Africa's data, possibly due to structural breaks or inherent noise in the macroeconomic and financial variables.

South Africa's omni-factor models significantly underperform compared to those of other emerging markets, where integrating multiple factors often leads to higher predictive power. South Africa's best omni-factor models (ERT and RF, with $R_{\text{OOS}}^2 \approx 0.08$ – 0.09) are far weaker than those in Hungary, Brazil, or Poland, where yield curve factors play a dominant role. For example, in Brazil, an OLS + PCA model incorporating macroeconomic, yield curve, inflation, and FX volatility factors (Table 5.10, Model 1, $R_{\text{OOS}}^2 = 0.3622$) achieves four times the predictive accuracy of South Africa's best-performing model.

Figure 5.13 illustrates the out-of-sample predictive performance (R_{OOS}^2) of the best-performing models as additional predictor variables are progressively incorporated, beginning with forward rates and expanding to include term premiums, forward-spot spreads, inflation, implied FX volatility, and macroeconomic indicators.

The analysis begins with forward rates as the sole predictor, yielding a negative R_{OOS}^2 of -0.1802 under an Extremely Randomized Trees framework, indicating that yield curve factors alone fail to explain bond risk premia in South Africa—a stark contrast to markets like Hungary or Brazil, where forward rates dominate predictions ($R_{\text{OOS}}^2 =$

Figure 5.13: South Africa Overview.



0.4991 and 0.3833, respectively).

The inclusion of term premiums and forward-spot spreads further deteriorates model performance, with R^2_{OOS} values remaining firmly negative. This outcome suggests that, in the context of South Africa, the term structure of interest rates—typically informative in more developed or structurally stable emerging markets—fails to capture the key dynamics underlying excess bond returns.

As inflation is introduced into the modeling framework, a marginal improvement is observed; however, R^2_{OOS} continues to fall short of statistical significance, implying that inflationary pressures, while important for monetary policy transmission, do not independently drive variations in bond risk premia in this market.

The final expansion of the model to include macroeconomic indicators delivers a modest enhancement in predictive accuracy. While the overall R^2_{OOS} remains relatively low (0.0886 in the best-performing omni-factor model), the inclusion of these variables

contributes to a more comprehensive risk assessment, suggesting that bond premia in South Africa are influenced by a confluence of external (currency volatility) and internal (macroeconomic) factors. Notably, this multifactor structure contrasts sharply with the more parsimonious, yield curve-driven predictive frameworks that succeed in countries such as Hungary, Brazil, Poland and Thailand.

From a comparative standpoint, South Africa resembles Turkey in its reliance on non-yield curve variables, albeit with a different configuration of predictive strength. Whereas Turkey's bond premia are predominantly shaped by inflation and macro variables, South Africa's profile is more heavily skewed toward FX volatility.

For South Africa, the Extremely Randomized Trees (ERT) algorithm consistently outperforms other modeling techniques. This also resembles the case of Turkey, where XGBoost outperforms alternative methods.

5.2.7.3 Implications for Policymakers and Investors

What do these findings mean for bond market participants?

The findings underscore the distinct determinants of local currency bond risk premia in South Africa, where implied foreign exchange (FX) volatility emerges as the predominant driver, complemented by macroeconomic indicators and inflationary pressures. Unlike other emerging markets such as Brazil or Hungary, yield curve-based factors—including forward rates and term premiums—exhibit negligible predictive power, highlighting the outsized influence of currency risks and macroeconomic instability on bond pricing.

For bond market participants, this necessitates a strategic emphasis on monitoring FX volatility trends, inflationary dynamics, and macroeconomic fundamentals such as fiscal balances and trade conditions. The sensitivity of South Africa's bond market to global risk sentiment and capital flow reversals further underscores the imperative for

robust currency risk management frameworks, as abrupt currency depreciations or shifts in investor confidence can amplify risk premia and destabilize returns.

How can investors use predictive models for risk assessment?

Investors operating in this environment may enhance risk assessment by integrating advanced predictive models, such as Extremely Randomized Trees, which demonstrated superior performance in capturing nonlinear interactions between yield curve, FX volatility, inflation, and macroeconomic variables.

By incorporating real-time data on metrics like 1-month USD/ZAR implied volatility and macroeconomic stability indices, investors can refine portfolio allocations, hedge currency exposures dynamically, and optimize entry or exit timing. While the modest predictive accuracy ($R^2_{\text{OOS}} = 0.0886$) relative to other markets reflects structural complexities, these tools remain valuable for navigating South Africa's idiosyncratic risks, particularly when paired with scenario analysis that accounts for political or fiscal shocks.

Policy Implications for Monetary Authorities and Bond Issuers

For monetary authorities and sovereign debt issuers, the results advocate for a multipronged policy approach to mitigate risk premia and enhance market resilience. The South African Reserve Bank (SARB) could prioritize interventions aimed at stabilizing the currency, such as strategic accumulation of foreign exchange reserves or enhanced liquidity provision in derivatives markets, to reduce speculative pressures.

Concurrently, structural reforms addressing fiscal sustainability would bolster macroeconomic credibility, thereby attenuating the risk premia associated with sovereign debt. The National Treasury might further consider diversifying debt instruments—such as issuing USD-linked or inflation-indexed bonds—to align investor risk preferences with funding needs during periods of volatility.

Finally, improving the granularity and accessibility of high-frequency economic data would empower both policymakers and market participants to anticipate systemic

risks, fostering a more transparent and adaptive financial ecosystem. Collectively, these measures could reduce borrowing costs, attract stable capital inflows, and strengthen South Africa's position within global fixed-income markets, underscoring the critical interplay between macroeconomic stewardship, currency stability, and investor confidence in shaping bond risk premia.



6. CONCLUSIONS

This study investigates the determinants of local currency bond risk premia in six emerging markets—Brazil, Hungary, Poland, Thailand, South Africa, and Turkey—using advanced machine learning techniques. By integrating yield curve dynamics, macroeconomic indicators, inflation, and implied FX volatility, the research provides critical insights into the drivers of excess bond returns and evaluates the predictive power of both traditional econometric and machine learning models.

6.1 Summary of Findings

The results reveal significant regional heterogeneity in predictive factors. In Brazil, Hungary, Poland, and Thailand, yield curve factors—particularly forward rates and term premiums—dominate bond risk premia predictions. Machine learning models such as Neural Networks and Random Forest outperform linear models by capturing nonlinear yield curve interactions. Conversely, in Turkey and South Africa, macroeconomic variables, CPI, and implied FX volatility emerge as primary drivers, while yield curve factors offer no predictive power. In these markets, XGBoost and Extremely Randomized Trees deliver superior results, reflecting the importance of nonlinear relationships.

Algorithmic performance varies significantly across countries and methodologies. Neural Networks deliver the highest predictive accuracy in Hungary ($R^2_{\text{OOS}} = 0.4991$) and Brazil ($R^2_{\text{OOS}} = 0.3871$), primarily driven by yield curve variables. XGBoost performs best in Turkey ($R^2_{\text{OOS}} = 0.3847$) and Extremely Randomized Trees in South Africa ($R^2_{\text{OOS}} = 0.0886$), leveraging macroeconomic indicators, inflation, and implied FX volatility. In Poland, however, the highest accuracy is achieved by OLS + PCA with an R^2_{OOS} of 0.2822, highlighting the contextual effectiveness of linear dimensionality reduction techniques. In Thailand, both Neural Network and PCA-applied OLS models stand out, with R^2_{OOS} values of 0.3391 and 0.3330 respectively, underscoring the predictive value of

forward rates and term premiums within yield curve-based frameworks.

Macroeconomic variables play different roles depending on the market structure. While macro indicators degrade predictive accuracy in yield curve-centric markets such as Hungary, Brazil, Thailand and Poland they are indispensable in Turkey and South Africa. Inflation proves to be a critical standalone predictor in Turkey, whereas implied FX volatility complements macroeconomic factors in South Africa. Both variables exhibit limited utility in yield curve-driven markets.

6.2 Key Contributions

This thesis offers several methodological and empirical contributions to the literature on bond risk premia in emerging markets, which are summarized as follows:

- Introduces a novel application of machine learning methods—including Neural Networks, XGBoost, Random Forest, and Extremely Randomized Trees—to the prediction of bond risk premia in emerging markets.
- Implements a dynamic PCA/PLS selection mechanism combined with an expanding window approach.
- Establishes a comprehensive model classification framework: single-factor, two-factor, three-factor, and omni-factor models.
- Demonstrates country-specific heterogeneity in bond risk premia drivers and algorithmic performance.
- Highlights the contextual limitations of yield curve predictors in markets with macroeconomic volatility.

6.3 Policy and Investment Implications

The findings have important implications. In yield curve-centric markets such as Hungary, Poland, Brazil, and Thailand, central banks should emphasize transparent communication to anchor interest rate expectations. In inflation-driven economies such as Turkey, efforts should focus on stabilizing inflation and macroeconomic fundamentals. For South Africa, FX risk mitigation is essential given the influence of currency volatility on bond pricing.

For investors, yield curve-driven markets require forward rate-based trading strategies supported by machine learning models like Neural Networks. In macro-driven markets, forecasting should rely on macroeconomic indicators and inflation processed through ensemble methods such as XGBoost and Extremely Randomized Trees. Investors should avoid overreliance on macroeconomic data in yield curve-dominant markets where it introduces noise.

6.4 Limitations and Future Outlook

Despite its contributions, this study faces limitations. Variations in data availability and quality may affect generalizability. Model interpretability remains limited, particularly in machine learning techniques. Additionally, the effects of external shocks—such as financial crises or pandemics—are not explicitly modeled.

Given the relatively weak predictive performance observed for South Africa ($R^2_{\text{OOS}} = 0.0886$), future research should explore more tailored approaches to capture the country's unique risk structure. In particular, the incorporation of deep learning architectures—such as Long Short-Term Memory (LSTM) networks—could enhance the modeling of temporal dependencies in FX volatility. Addressing structural data gaps by incorporating high-frequency macroeconomic releases, energy market indicators, and sectoral performance data could also significantly refine predictive power in the South African context.

Future research can expand country coverage and integrate alternative data sources such as geopolitical risk indices, ESG metrics, and high-frequency data. Hybrid models combining machine learning with interpretable AI tools (e.g., SHAP) could bridge the gap between predictive power and transparency. Finally, analyzing model behavior during periods of systemic stress would provide further insights into bond market resilience.

6.5 Final Remarks

This study underscores the transformative potential of machine learning in understanding local currency bond risk premia. By recognizing regional disparities and leveraging algorithmic flexibility, investors and policymakers can make more informed decisions in an increasingly complex financial environment. Future advancements in data availability and interpretability will further unlock the value of AI-driven approaches in sovereign debt markets.

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APPENDICES

APPENDIX A. MACRO VARIABLES – HUNGARY

No.	Ticker	Description
1	HUGWLYOY Index	Hungary Avg Gross Wages YoY
2	HUPMISA Index	Hungary PMI SA
3	HUEMUNR Index	Hungary Unemployment Rate
4	HUIPIYOY Index	Hungary Industrial Production SWDA YoY
5	GKIESNDX Index	GKI Hungary Economic Sentiment
6	HUCCINDX Index	GKI Hungary Consumer Confidence
7	HUBCINDX Index	GKI Hungary Business Confidence Index
8	EUESHU Index	European Commission Economic Sentiment Indicator Hungary
9	HUTREXP Index	Hungary Foreign Trade Exports EUR
10	HUTRIMP Index	Hungary Foreign Trade Imports EUR
11	OEHUKLAP Index	Hungary OECD Leading Indicators CLI Trend Restored YoY SA
12	EUBPHU Index	EU Residential Permits Excluding Residences for Communities Hungary SWDA
13	HURTAYOY Index	Hungary Retail Trade Yearly
14	HURTYFDT Index	Hungary Retail Trade Food, Drinks, Tobacco Yearly
15	WCARHUY Index	Europe Hungary New Passenger Car Registrations YoY
16	EUUCHU Index	European Commission Capacity Utilization Hungary SA
17	HUHHHHTO Index	Hungary Loans to Households Total

APPENDIX B. MACRO VARIABLES – BRAZIL

No.	Ticker	Description
1	2236689 Index	IMF Brazil Unemployment Rate
2	BZJCYTOT Index	Brazil Government Registered Job Creation Total NSA YTD
3	BZREPERD Index	Secovi Brazil Real Estate Units Average Sale Time Period
4	BZRESOLD Index	Brazil Sao Paulo Secovi Real Estate Units Sold
5	IBREINCM Index	FGV Brazil IGP-M Construction Prices INCC-M
6	BZLNTOTA Index	Brazil Financial System Loans
7	BZICINDX Index	CNI Brazil Industrial Confidence General
8	BZCCI Index	CNI Brazil Consumer Confidence
9	OLED BRAZ Index	OECD Brazil Composite Leading Ind. Total Trend Restored Stock
10	BZTBEXPM Index	Brazil Trade Balance FOB Exports
11	BZTBIMPM Index	Brazil Trade Balance FOB Imports NSA
12	BZIPTLSA Index	Brazil Real Industrial Production SA 2012=100
13	BZIXEXTR Index	Brazil Industrial Production Activity Extractive Industry 2012
14	BZASSUBT Index	Brazil Auto Sales Subtotal
15	BZCNCNIS Index	CNI Brazil Manufacture Industry Capacity Utilization SA
16	BZCNSALS Index	CNI Brazil Manufacture Industry Real Sales SA 2006=100
17	BZCNEMPS Index	CNI Brazil Manufacture Industry Employment SA 2006=100
18	BZVPTLVH Index	Anfavea Brazil Vehicle Production
19	BZRTRTSA Index	Brazil Retail Sales Volume SA
20	BZRTCOSA Index	Brazil Retail Sales Volume Construction Materials Index SA
21	BZRTFDSA Index	Brazil Retail Sales Volume Supermarket Food Beverages & Tobacco SA
22	OEBRV008 Index	OECD Brazil Prod. Manufacturing Total Manufacturing SA 2010=100
23	BZEASA Index	Economic Activity GDP SA IBC-BR

APPENDIX C. MACRO VARIABLES – THAILAND

No.	Ticker	Description
1	THCTEXPY Index	Thailand Customs Department Foreign Trade Exports YoY
2	THCTIMPY Index	Thailand Customs Department Foreign Trade Imports YoY
3	THCCI Index	Thailand Consumer Confidence
4	THNFEXPY Index	Thailand Foreign Trade Merchandise Exports YoY
5	THBSI Index	Thailand Business Sentiment Index
6	THVHSCAR Index	Thailand Car Sales
7	THNFIMPY Index	Thailand Foreign Trade Merchandise Imports YoY
8	THLMUERT Index	Thailand Unemployment Rate
9	THRSY Index	Thailand Retail Sales YoY
10	THCCECON Index	Thailand Consumer Confidence Economic
11	THPIIYOY Index	Thailand Private Investment YoY 2010=100
12	THNHTOTL Index	Thailand New Housing
13	THBSORD Index	Thailand Business Sentiment Index Order Book
14	THBSEMP Index	Thailand Business Sentiment Index Employment
15	THBSINV Index	Thailand Business Sentiment Index Investment
16	THPIPDNF Index	Thailand Private Investment – Permitted by Department Industrial Work – No of Factories
17	THACEI Index	Thailand Coincident Economic Index 2000=100
18	THCRTTCR Index	Thailand Outstanding Credit Amount
19	THEMIRTL Index	Thailand Labor Home Inward Remittance

APPENDIX D. MACRO VARIABLES – POLAND

No.	Ticker	Description
1	POUER Index	Poland Unemployment Rate
2	POWGYOY Index	Poland Average Monthly Gross Wage YoY %
3	PORSYOY Index	Poland Retail Sales YoY
4	POISCYOY Index	Poland Sold Industrial Output of Goods & Services at Constant Prices YoY
5	POOSCYOY Index	Poland - Sales of Construction and Assembly Production YoY
6	EUESPL Index	European Commission Economic Sentiment Indicator Poland
7	EUCCPL Index	European Commission Consumer Confidence Indicator Poland
8	POPENGAB Index	Poland Synthetic Banking Climate Indicator Pengab
9	OEPLKLAP Index	Poland OECD Leading Indicators CLI Trend Restored YoY SA
10	WCARPOY Index	Europe Poland New Passenger Car Registrations YoY
11	E6BDFPLY Index	EU Industrial Production Mining and Quarrying, Manufacturing, Energy & Construction Poland WDA
12	EUILPOY Index	Eurostat Industrial Production Poland Industry Excluding Construction YoY WDA
13	EUUCPL Index	European Commission Capacity Utilization Poland SA
14	OEPLKLAC Index	Poland OECD Leading Indicators CLI Amplitude Adjusted SA
15	POFTTX Index	Poland Foreign Trade Exports at Current Prices
16	POFTTM Index	Poland Foreign Trade Imports at Current Prices

APPENDIX E. MACRO VARIABLES - TURKEY

No.	Ticker	Description
1	TULSUR Index	Turkey Labor Statistics Unemployment Rate SA
2	TBRDELTA Index	Export Loans - Total
3	TBRDWCLT Index	Working Capital Loans - Total
4	TBRDLOAN Index	Turkey SME Loans Total
5	TURWL Index	Turkey Gross Foreign Exchange Reserves (Weekly)
6	TUCOGY2S Index	Turkey Real Sector Confidence Index Volume of Orders (Current Situation) SA
7	TUCOGY3S Index	Turkey Real Sector Confidence Stocks of Finished Goods (Current Situation) SA
8	TUCOGY7S Index	Turkey Real Sector Confidence Index Export Orders (Next 3 Months) SA
9	TUCOREAL Index	Turkey Confidence Index Real Sector
10	TUCDCONF Index	Consumer Confidence
11	TUCOGY1S Index	Turkey Real Sector Confidence SA
12	TUCOGY9S Index	Turkey Business Situation SA
13	ECOCTRAN Index	Turkey Current Account Balance (Billion USD) NSA
14	ECOYMTRN Index	Turkey Imports (Billion USD) NSA
15	TUCSET Index	Turkey Current Account Balance (Billion USD) NSA
16	E50DGTR Index	Turkey Motor Vehicle Industry Export Total
17	E50KGTR Index	EU Industrial Production Durable Consumer Goods Turkey SWDA
18	TUIOMT Index	EU Industrial Production Intermediate Goods Turkey SWDA
19	TUINTURN Index	EU Industrial Production Capital Goods Turkey SWDA
20	TUIOSA Index	Turkey Industrial Production Manufacturing 2010=100
21	TUIOST Index	Turkey Industry Turnover 2010=100
22	TUIOET Index	Turkey Industrial Production SWDA 2010=100
23	TYCOLEVS Index	Turkey Industrial Production Mining 2010=100
24	TUCSPT Index	Turkey Industrial Production Electricity 2010=100

No.	Ticker	Description
25	TUCSMT Index	Turkey Capacity Utilization SA
26	TUCSMP Index	Turkey Motor Vehicle Industry Production Total



APPENDIX F. MACRO VARIABLES – SOUTH AFRICA

No.	Ticker	Description
1	EHUPZA Index	South Africa Unemployment Rate (%)
2	SACWC Index	South Africa Consumer Confidence
3	SACUI Index	South Africa Utilization of Production Capacity
4	SASGAGR Index	South Africa Agriculture SA Constant Prices
5	SASGMINE Index	South Africa Mining SA Constant Prices
6	SASGMANU Index	South Africa Manufacturing SA Constant Prices
7	SASGCON Index	South Africa Construction SA Constant 2000 Prices
8	SASGWRH Index	South Africa Wholesale Retail Hotels SA Constant Prices
9	SATCTREM Index	Trade Activity Index Employment
10	SAPME Index	South Africa Barclays PMI Employment SA
11	SATCTRNO Index	Trade Activity Index New Orders
12	SACSPSTO Index	SA Recorded Building Plans Total SA
13	SACSPSNR Index	SA Recorded Building Plans Non-Residential Buildings SA
14	SACBLI Index	Composite Business Cycle Indicator - Leading Indicator
15	SACBLG Index	Composite Business Cycle Indicator - Lagging Indicator
16	SACBCI Index	Composite Business Cycle Indicator - Coincident Indicator
17	SATBEX Index	South Africa Trade Balance Exports Incl. Oil, Arms & Bullion
18	SATBIM Index	South Africa Trade Balance Imports Incl. Oil, Arms & Bullion
19	NAAMTTMS Index	NAAMSA South Africa Total Market Sales Level
20	SARSTCSA Index	South Africa Retail Sales Total Sales Constant Prices SA 2012=100
21	SFMPPET Index	South Africa Manufacturing Production SA 2005=100 Petroleum Chemical Prod
22	SFPMI Index	South Africa Manufacturing Production SA 2010=100
23	SAMPTTSY Index	South Africa Mining Production Volume Total Incl. Gold SA YoY
24	SAPW09Y Index	South Africa Electricity Production Index Year-on-Year %

No.	Ticker	Description
25	SAPW08Y Index	South Africa Electricity Consumption Year-on-Year %

