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A FAIR VALUE MODEL FOR EMERGING MARKET LOCAL CURRENCY BONDS

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Abstract

This study looks at how a Bayesian-based regression model for evaluating the fair value of local currency government bonds in emerging markets (EM). It uses a dataset covering 17 EM countries, including variables like central bank policy rates, real GDP growth, current account and budget balances, government debt, and the US real interest rate. Our method applies two analytical approaches, one using actual historical data and another incorporating forecasted data, such as quarterly and annual expectations. Additional forecast data for comparison were obtained from J.P. Morgan forecast, complementing the primary dataset provided by our sponsor, Neuberger-Berman. To research how our model performs to predict bond yields, we also used a rolling average technique on certain variables. The aim of this research is not to perfect yield prediction accuracy but to identify all significant parameters (alpha and beta coefficients) for building a Bayesian model. This model aims to understand the complex behavior of EM bond prices, focusing on building a detailed model instead of just aiming for the most accurate predictions. Our results show that Bloomberg forecast data yields superior outcomes in terms of p-value, and both forecast data types (Bloomberg and JP-Morgan) outperform realized data. Through this, we intend to enhance the application for financial modeling and investment strategy in emerging economies.

Keywords: emerging market, realised data, expectation data, OLS, Fixed Effect model, Bayesian regression, trading strategy

Content

1 Introduction

Emerging markets (EM) are turning more towards their domestic markets to find financing, issuing bonds in their own currencies. This shift has attracted global investors who are looking for higher returns and the chance to diversify their portfolios with EM government bonds. As a result, there's been a significant increase in the total local currency debt within these markets, underscoring the growing importance of EM debt markets. These bonds are vital for EMs as they help finance government spending and infrastructure projects. They also tend to offer higher yields than those found in developed markets, making them appealing to international investors. The rise in the issuance of local currency bonds by EMs shows how crucial these domestic markets are for their financing needs.

However, figuring out the fair value of these EM local currency bonds is challenging because of the complexities of these markets. There's a gap in understanding the key factors that drive the long-term yields of these bonds, including the term premiums. Current economic models often fall short in explaining the typical levels and fluctuations of term premiums in EMs. Additionally, there hasn't been as much research into what determines the yields of EM local currency bonds as there has been for those in more advanced economies. This lack of information makes it harder to assess the true value of these bonds, presenting a hurdle for investors interested in EM markets.

The goal of this research is to develop a Bayesian-based regression model that can assess the fair value of government bonds. We use dataset from 17 EM countries, including economic indicators: central bank policy rates, real GDP growth, current account and budget balances, government debt, and the US real interest rate. Our approach combines the analysis of historical data with future expectations data. We apply the first regression process to determine the coefficients that affect bond yields. We implemented the Ordinary Least Squares (OLS) model and the Fixed Effects (FE) model for the regression. These coefficients are then tested for their statistical significance through their p-values. To predict bond yields, we simulate future scenarios and calculate the residuals. These residuals are then reshuffled to feed into a Bayesian regression model, which helps us understand how bond yields might behave under different conditions. The end goal is to obtain alpha and beta coefficients, rather than just making exact predictions of bond yields. This way, we aim to capture the complex dynamics of EM bond prices in our model.

2 Objectives

Our research is designed to develop a Bayesian-based regression model to assess the fair value of emerging market government bonds.

2.1 Project Scope

The scope of our project includes:

1. We will be working with data that's been provided by the sponsor, which includes detailed information on bond prices.
2. Additional data on market expectations will be gathered by our team directly.
3. Our main task is to create a model that analyzes bond values, not to develop any software tools.
4. We are concentrating on data from 17 specific emerging market countries, with 6 variables/indicators: central bank policy rates, real GDP growth, current account, budget balances, government debt, and the US real interest rate.

2.2 Limitations

We address the constraints we have encountered during our research:

1. The data provided by the sponsor serves as our primary source of information.
2. Additionally, we have collected supplementary data for the expectation component, which the sponsor did not provide.
3. Our focus is on constructing and analyzing the model, rather than developing it into a software product.

For the next phase, we are planning to focus on the trading strategy section and to learn about the trading methodology for our project.

3 Initial Analysis

3.1 Methods

3.1.1 Data Processing

First of all, we dropped all missing values of RON 10Y Yields, because the 10Y Yield is the dependent variable in our models. We then did 2 month lag on Real GDP Growth, Current Account, Budget Balance, and Government Debt, because we found that with 2-month lag, the Fixed Effect Model had more significant results compared to no lagging. And 2-month lag reflects the economic meaning of actual data. We took the 12 month rolling average of Current Account, Budget Balance, and Government Debt, which was done the same way in the paper. Now we have the dataset of independent variables ready for regression models.

3.1.2 OLS & Fixed Effect model

In order to get the final Bayesian model, we first need to perform OLS regression and Fixed Effect regression respectively on our datasets. We performed OLS regression of the six fundamental variables on the 10Y yields of the 17 countries respectively, and collected 17 pairs of beta vectors and covariance matrices of each country. For the Fixed Effect model, we stacked the data of the 17 countries one following the other. And we got a reshaped dataset with over 2800 observations, which is time invariant. We then performed regression on this dataset with 17 country specific alpha added in the model. The math concept of the country specific alpha is the following:

$$y_{i,t} = \alpha_i + \beta'_{OLS,i}\, x_{i,t} + \varepsilon_{i,t}$$

y denotes the nominal yields of 10y bonds of country i at time t , and x represents the vector of fundamentals of country i at time t. From this model, we had a constant beta vector and a covariance matrix across all 17 countries.

3.1.3 Posterior Distribution of Bayesian Model

After getting the results of betas and covariance matrices from OLS and Fixed Effect models, we used the following formula to calculate the posterior distribution of our Bayesian model:

$$N(\beta_{Post,i},\, \Sigma_{Post,\, i}) \propto\; N(\beta_{OLS,i},\, \Sigma_{OLS,\, i})N(\beta_{FE},\, \Sigma_{FE})$$

where

$$\beta_{OLS}$$

$$\Sigma_{Post,\, i} = \left[\Sigma_{OLS,\, i}^{-1} \,+\, \Sigma_{FE}^{-1}\right]^{-1}$$

For each country, we had a posterior beta vector and a posterior covariance matrix.

3.1.4 Simulation & Bootstrapping

For each country we simulated 10,000 samples of beta vectors across all observations based on the posterior distribution for that country. And we applied the simulated beta to the fundamental variables to compute the fitted y values. We subtracted the y values from the realized y values and got a collection of residuals. We shuffled the residuals across different time observations and added the shuffled residuals to the fitted y values to get the pseudo y values. Our calculations followed the following formulas:

$$\epsilon = y_{obs} - y_{fitted}$$

$$y_{pseudo} = \epsilon_{reshuffled} + y_{fitted}$$

Finally we calculated the mean and confidence interval based on the series of pseudo y values. The mean is our predicted fair value based on the Bayesian model and the confidence interval is our trading signal. The following graph is one of the results we had:

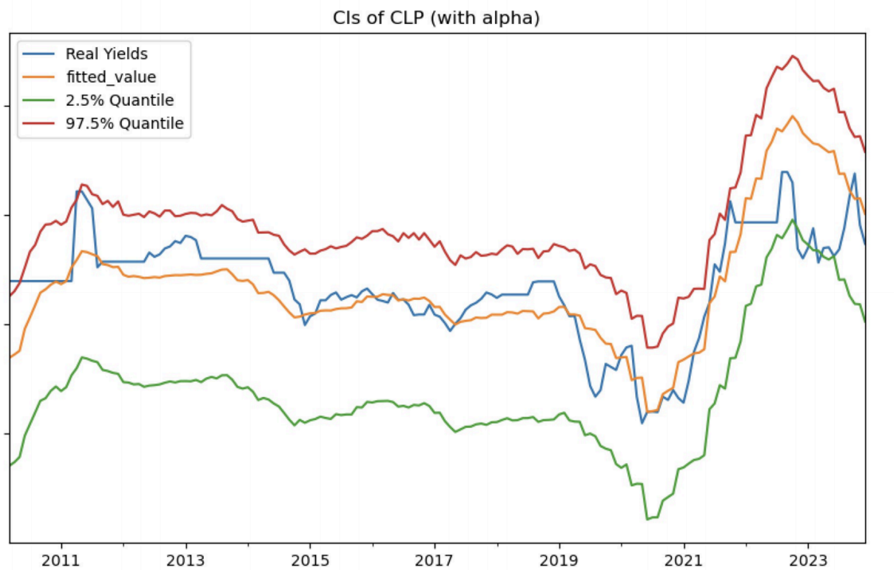


Figure 3.1.4: Results of Bayesian Regression & Bootstrapping

3.2 Realized Data Analysis

3.2.1 Data Sources

For the realized data, we use the data source provided by Neuberger Berman:

Realized Variables	Details
UST 10Y Real Rate Realized	Monthly data, (11/30/2008 - 12/31/2023)
Central Bank Policy Rate Realized	Monthly data, (11/30/2008 - 12/31/2023)
GDP Growth Realized	Monthly data, (11/30/2008 - 12/31/2023)
Current Account Realized	Monthly data, (11/30/2008 - 12/31/2023)
Budget Balance Realized	Monthly data, (11/30/2008 - 12/31/2023)
Government Debt Realized	Monthly data, (11/30/2008 - 12/31/2023)

Table 3.2.1: Realized variables

3.2.2 Data Processing Methods:

3.2.2.1 Data Preprocessing

Following Neuberger Berman's advice to mitigate the 2008 financial crisis's impacts, all data (two sets of monthly data for all countries) from 2008 will be omitted from our analysis. This step aims to ensure our financial insights reflect more stable and consistent trends, excluding the anomaly of the crisis.

Realized Variables	**Details**
UST 10Y Real Rate Realized	Monthly data, (01/31/2009 - 12/31/2023)
Central Bank Policy Rate Realized	Monthly data, (01/31/2009 - 12/31/2023)
GDP Growth Realized	Monthly data, (01/31/2009 - 12/31/2023)
Current Account Realized	Monthly data, (01/31/2009 - 12/31/2023)
Budget Balance Realized	Monthly data, (01/31/2009 - 12/31/2023)
Government Debt Realized	Monthly data, (01/31/2009 - 12/31/2023)

Table 3.2.2: Adjusted Realized variables Version 1

For the country Romania, it has been observed that data for the variable "UST 10Y Real Rate" from January 31, 2009, to May 31, 2011, are missing from the dataset. Given that these are the targeted variables, we decide to exclude all other variables for these dates for Romania from the dataset as well.

3.2.2.2 Start Date Selection

Given the absence of a specified start date in the relevant paper, we have opted to experiment with different start dates to accurately align with the paper's results. We will implement the Ordinary Least Squares (OLS) model and the Fixed Effects (FE) model, utilizing 12 distinct start dates from January 31, 2009, to December 31, 2009, for the 12-month moving average calculation. By comparing these results with those presented in the paper, we aim to identify the most appropriate start date.

a) OLS Model Results for 12 different start dates

OLS Model results (With 12-month Rolling Average), 102 coefficients each		
Data Start Date	Significant Coefficients (P value < 0.05)	Wrong Direction
2009/1/31	**79/102**	**19/102**
	77.45%	18.63%
2009/2/28	**79/102**	**17/102**
	77.45%	16.67%
2009/3/31	**80/102**	**17/102**
	78.43%	16.67%
2009/4/30	**77/102**	**17/102**
	75.49%	16.67%
2009/5/31	**77/102**	**18/102**
	75.49%	17.65%
2009/6/30	**78/103**	**17/103**
	76.47%	16.67%
2009/7/31	**78/104**	**17/104**
	76.47%	16.67%
2009/8/31	**76/105**	**18/105**
	74.51%	17.65%
2009/9/30	**76/106**	**19/106**
	74.51%	18.63%
2009/10/31	**75/107**	**19/107**
	73.53%	18.63%
2009/11/30	**75/108**	**19/108**
	73.53%	18.63%
2009/12/31	**75/109**	**19/109**
	73.53%	18.63%

Figure 3.2.1: OLS Model Results for 12 start dates

The analysis of the Ordinary Least Squares (OLS) model indicates that the significant coefficients and the instances of incorrect directional predictions exhibit a notable proximity when varying the start dates for the data set. Specifically, it was observed that starting from August 31, 2009, we could see a decrease in the number of significant coefficients alongside an increase in the frequency of wrong directional forecasts. Therefore, start dates subsequent to this threshold appear to be less optimal for predictive accuracy and reliability in the context of the OLS model application.

b) FE Model Results for 12 different start dates

FE Models with Realized Variables (Rolling Average)										
Data Start Date		UST 10y Real Yield	Policy Rates	Real GDP Growth	Current Account	Budget Balance	Government Debt		
2009/1/31	Parameters	0.015	0.481	0.036	-0.012	-0.123	0.0026	**R2**	**Observations**
	p-values	0.132	0.000	0.000	0.145	0.000	0.274	90.80%	2855
2009/2/28	Parameters	0.009	0.482	0.036	-0.011	-0.123	0.0034	**R2**	**Observations**
	p-values	0.390	0.000	0.000	0.160	0.000	0.035	91.00%	2839
2009/3/31	Parameters	0.012	0.483	0.036	-0.011	-0.120	0.0043	**R2**	**Observations**
	p-values	0.210	0.000	0.000	0.183	0.000	0.068	91.10%	2823
2009/4/30	Parameters	0.009	0.484	0.037	-0.011	-0.120	0.0050	**R2**	**Observations**
	p-values	0.387	0.000	0.000	0.163	0.000	0.035	91.30%	2807
2009/5/31	Parameters	0.005	0.485	0.036	-0.011	-0.117	0.0054	**R2**	**Observations**
	p-values	0.630	0.000	0.000	0.157	0.000	0.022	91.40%	2791
2009/6/30	Parameters	0.001	0.486	0.035	-0.012	-0.114	0.0060	**R2**	**Observations**
	p-values	0.898	0.000	0.000	0.149	0.000	0.015	91.50%	2775
2009/7/31	Parameters	-0.002	0.487	0.034	-0.012	-0.111	0.0062	**R2**	**Observations**
	p-values	0.827	0.000	0.000	0.141	0.000	0.009	91.60%	2759
2009/8/31	Parameters	-0.007	0.487	0.033	-0.012	-0.107	0.0064	**R2**	**Observations**
	p-values	0.464	0.000	0.000	0.135	0.000	0.007	91.70%	2743
2009/9/30	Parameters	-0.011	0.487	0.032	-0.012	-0.103	0.0070	**R2**	**Observations**
	p-values	0.255	0.000	0.000	0.126	0.000	0.006	91.70%	2727
2009/10/31	Parameters	-0.014	0.487	0.032	-0.013	-0.101	0.0065	**R2**	**Observations**
	p-values	0.156	0.000	0.000	0.122	0.000	0.006	91.80%	2711
2009/11/30	Parameters	-0.016	0.486	0.032	-0.013	-0.098	0.0065	**R2**	**Observations**
	p-values	0.098	0.000	0.000	0.118	0.000	0.006	91.80%	2695
2009/12/31	Parameters	-0.019	0.486	0.031	-0.013	-0.095	0.0066	**R2**	**Observations**
	p-values	0.531	0.000	0.000	0.110	0.000	0.006	91.80%	2679

Figure 3.2.2: FE Model Results for 12 start dates

Models with Realized Variables (*ex-post*)							
	UST 10y Real Yield	Policy Rates	Real GDP Growth	Current Account	Budget Balance	Government Debt	
Parameters	0.26	0.44	0.04	-0.03	-0.06	0.02	**R2**
p-values	0.00	0.00	0.00	0.02	0.00	0.00	0.56

Source: J.P. Morgan, Bloomberg Finance L.P., Haver Analytics. Monthly sample since 2010 (ex-Türkiye).

Figure 3.2.3: FE Model Results from paper's findings

Here are the analysis of the FE model results:

For Policy Rates, Real GDP Growth, and Budget Balance variables:

These variables are shown to be highly significant with low p-values, indicating a strong statistical significance in the model. Their effects are also mostly stable across different time periods, suggesting that they have a consistent impact on the model's dependent variable.

For the UST 10-Year Real Yield variable:

There is a noted downward trend in the UST 10-year real yield as the start date moves forward. This trend became negative after July 31, 2009. However, this observation is discarded to maintain consistency with the findings discussed in the paper. The January 31, 2009, UST Real Rate is taken as the benchmark since it aligns closely with the paper's findings and exhibits the lowest p-value, thus indicating high statistical significance.

For the Government Debt variable:

The coefficient for Government Debt increases over time, and its significance also shows a slight upward trend. This suggests that as more recent data is included in the analysis, the impact of Government Debt on the dependent variable becomes more pronounced and statistically significant.

For the Current Account variable:

The coefficient for the Current Account variable remains stable over the different time periods analyzed. However, its p-values indicate that it is not as statistically significant as the other variables. This suggests that while the effect of the Current Account may not change much over time, it is not a key driver in the model.

For R-Square:

The R-square value, which indicates the proportion of variance in the dependent variable that can be explained by the independent variables in the model, increases slightly over time. However, this increase is small, and it occurs alongside a decrease in the number of observations. This could indicate that the model fits slightly better as time progresses, but it could also be influenced by the lower number of observations.

Combining the results from both the OLS Model and the FE Model, we have decided to use 2009-01-31 as our start date for the following analysis.

3.2.3 Preliminary Results: Bayesian Regression Models

a) Results of Model Regression with Combined α and β VS. β Alone

After we integrated the code and added the intercept term to the OLS model in both methods. This brings the results of the two models even closer. The left side is the result of Model with β Alone, and the right side is the result of Model with Combined α and β. These two pictures are very similar.

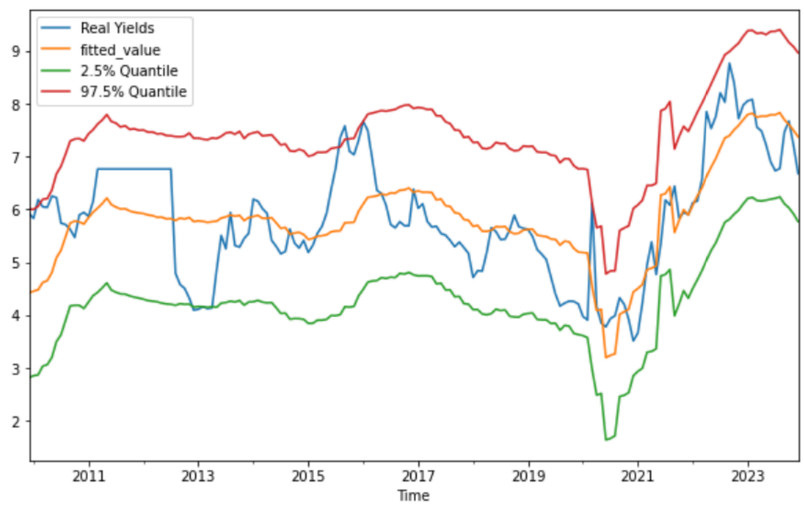


Figure 3.2.4: CIs of PEN (without alpha)

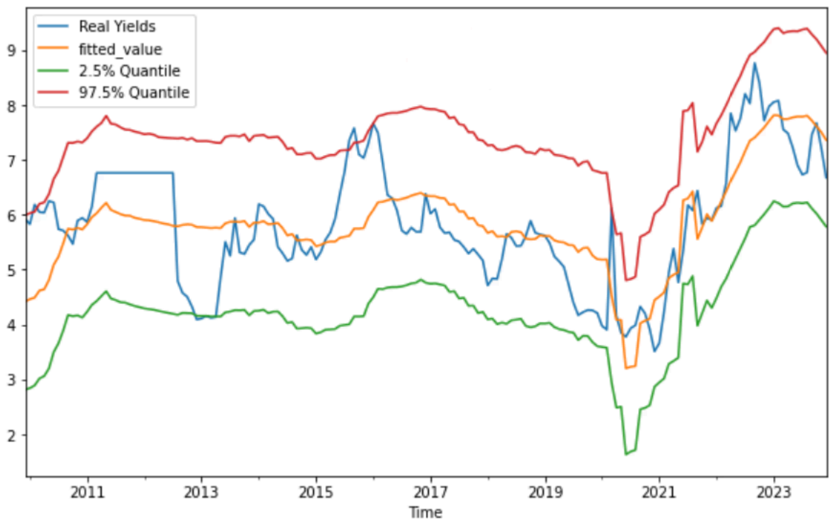


Figure 3.2.5: CIs of PEN (with alpha)

b) P-values of the two models

	ZAR	COP	BRL	MXN	PEN	THB	CNY	INR
Intercept	4.42	4.57	5.73	3.84	3.76	1.68	0.39	3.56
	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Central Bank Policy Rates (%).1	0.50	0.48	0.48	0.47	0.48	0.48	0.48	0.48
	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Real GDP Growth (%).1	0.03	0.04	0.04	0.03	0.03	0.04	0.03	0.03
	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Current Account (%GDP.1	0.04	-0.01	-0.01	-0.01	-0.02	-0.04	-0.02	-0.02
	0.00	0.14	0.07	0.14	0.04	0.00	0.02	0.01
Budget Balance (%GDP).1	-0.11	-0.13	-0.11	-0.12	-0.12	-0.12	-0.13	-0.12
	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Government Debt (%GDP).1	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	0.00	0.45	0.83	0.47	0.20	0.10	0.46	0.84
US Real Rate	0.02	0.01	0.01	0.00	0.01	0.02	0.03	0.01
	0.05	0.48	0.52	0.76	0.30	0.04	0.00	0.13

Figure 3.2.6: P-Value of the two models

When we dig into the values and p-values of the parameters, we find that except for the intercept term, the parameters obtained by the two methods are exactly the same. We think this is because in these two methods, the OLS and FE models we use are exactly the same. The only difference in the obtained prior distribution is alpha, and the beta is the same. So the posterior distribution of beta we finally get should be the same.

3.2.4 Summary

For realized data processing, we explored the impact of the data range on the results and ultimately determined that the data range from January 31, 2009, to December 31, 2023 might be the most appropriate. Upon re-examination of the impact of two parameter approaches (combining alpha and beta, and beta alone) on the results, it was found that there was no significant difference.

3.3 Forecast Data Analysis

3.3.1 Data Sources

For the forecast data, two data sources were explored, as outlined below:

a) **Bloomberg Forecast Data**

The first dataset strictly adheres to the original report's data, utilizing one year ahead Bloomberg GDP Growth forecast data, one year ahead Bloomberg Central Bank Policy Rate forecast data, one year ahead Bloomberg Budget Balance forecast data, one year ahead Bloomberg Current Account forecast data, in addition to the realized data for the UST 10Y Real Rate and Government Debt.

Expectation Variables	**Details**
UST 10Y Real Rate (Realized Data)	Monthly data, (12/31/2009 - 12/31/2022)
Bloomberg Central Bank Policy Rate Forecast	Quarterly data (12/31/2009 - 12/31/2022)
Bloomberg GDP Growth Forecast	Annual data (12/31/2009 - 12/29/2022)
Bloomberg Current Account Forecast	Annual data (12/31/2009 - 12/29/2022)
Bloomberg Budget Balance Forecast	Annual data (12/31/2009 - 12/29/2022)
Government Debt (Realized Data)	Monthly data (12/31/2009 - 12/31/2022)

Table 3.3.1: Explanatory variables using Bloomberg Forecast Data

b) **JP Morgan Forecast Data**

Furthermore, considering the original report's use of Bloomberg forecast data as annual or quarterly data, which have a lower frequency, an effort to enhance the monthly fitting precision of the model led to the incorporation of additional data sources beyond the report. This includes JP Morgan GDP Growth Forecast and JP Morgan Central Bank Policy Rate Forecasts monthly data, culminating in the second dataset for this report.

Expectation Variables	**Details**
UST 10Y Real Rate (Realized Data)	Monthly data, (12/31/2009 - 12/31/2023)
JP Morgan Central Bank Policy Rate Forecast	Monthly data (12/31/2009 - 12/31/2023)
JP Morgan GDP Growth Forecast	Monthly data (12/31/2009 - 12/29/2023)
Bloomberg Current Account Forecast	Annual data (12/31/2009 - 12/29/2023)
Bloomberg Budget Balance Forecast	Annual data (12/31/2009 - 12/29/2023)
Government Debt (Realized Data)	Monthly data (12/31/2009 - 12/31/2023)

Table 3.3.2: Explanatory variables using JP Morgan Forecast Data

3.3.2 Data Processing Methods:

a) **Bloomberg Forecast Data**

Within the Bloomberg Forecast data, there are several instances of missing data, detailed as follows and summarized in Table 3.3.3**.**

For India, the Bloomberg GDP Growth Forecast, Bloomberg Current Account Forecast, and Bloomberg Budget Balance Forecast variables lacked data for the years 2009 to 2011. Additionally, there was an absence of Bloomberg Central Bank Policy Rate Forecast data for four quarters spanning from December 31, 2009, to September 30, 2010. Israel's dataset was missing the Bloomberg GDP Growth Forecast for the year 2009. Romania was missing the Bloomberg GDP Growth Forecast data for 2009 and 2010, Bloomberg Current Account Forecast and Bloomberg Budget Balance Forecast data for three years from 2009 to 2011, and Bloomberg Central Bank Policy Rate Forecast data from December 31, 2009, to June 29, 2012. Malaysia and Thailand were lacking Bloomberg GDP Growth Forecast and Bloomberg Budget Balance Forecast data for the year 2010.

	India	Israel	Romania	Malaysia	Thailand
Bloomberg GDP Growth Forecast	12/31/2009, 12/31/2010, 12/30/2011	12/31/2009	12/31/2009, 12/31/2010	12/31/2010	12/31/2010
Bloomberg Current Account Forecast	12/31/2009, 12/31/2010, 12/30/2011		12/31/2009, 12/31/2010, 12/30/2011		
Bloomberg Budget Balance Forecast	12/31/2009, 12/31/2010, 12/30/2011		12/31/2009, 12/31/2010, 12/30/2011	12/31/2010	12/31/2010
Bloomberg Central Bank Policy Rate Forecast	12/31/2009, 3/31/2010, 6/30/2010, 9/30/2010		12/31/2009 - 6/29/2012		

Table 3.3.3: Missing Data in Bloomberg Forecast Data

Given that these data omissions occur at the beginning of the series, we have addressed these missing values by implementing a backward filling method. This approach uses the nearest available data to fill the gaps.

For annual datasets such as the Bloomberg GDP Growth Forecast, Bloomberg Current Account Forecast, and Bloomberg Budget Balance Forecast, we transformed them into monthly series through linear interpolation. In the case of quarterly datasets like the Bloomberg Central Bank Policy Rate Forecast, we utilized a forward-fill method to convert them into monthly data points.

Regarding Government Debt, we maintained the methodology for processing actual data, which involves the application of a two-month lag and a 12-month rolling average, aligning with the procedures detailed in the report. Due to the nature of the 12-month rolling average introducing a data gap in the first 11 rows, we have implemented a backward filling technique to ensure the integrity and volume of the dataset are maintained.

Expectation Variables	Details
UST 10Y Real Rate (Realized Data)	Monthly data
Bloomberg Central Bank Policy Rate Forecast	Quarterly data, forward-fill method
Bloomberg GDP Growth Forecast	Annual data, linear interpolation
Bloomberg Current Account Forecast	Annual data, linear interpolation
Bloomberg Budget Balance Forecast	Annual data, linear interpolation
Government Debt (Realized Data)	Monthly data, 2-month lag and a 12-month rolling average

Table 3.3.4: Bloomberg Forecast Data Processing

Following the aforementioned data processing techniques, we ultimately obtained a total of 157 observations per country.

b) **JP Morgan Forecast Data**

The JP Morgan dataset is complete with no missing data. The Government Debt data were treated in the same manner as the real data, with a 2-month lag and a 12-month rolling average applied. Moreover, to enhance the model's significance, we performed a 6-month rolling average on the US Real Rate, JP Morgan Forecast GDP Growth, and JP Morgan Forecast Central Bank Policy Rate. For the yearly datasets, namely the Bloomberg Current Account Forecast and Bloomberg Budget Balance Forecast, we continued to employ linear interpolation to convert them into monthly data.

Expectation Variables	Details
UST 10Y Real Rate (Realized Data)	Monthly data, 6-month rolling average
JP Morgan Central Bank Policy Rate Forecast	Monthly data, 6-month rolling average
JP Morgan GDP Growth Forecast	Monthly data, 6-month rolling average
Bloomberg Current Account Forecast	Annual data, linear interpolation
Bloomberg Budget Balance Forecast	Annual data, linear interpolation
Government Debt (Realized Data)	Monthly data, 2-month lag and a 12-month rolling average

Table 3.3.5: Bloomberg Forecast Data Processing

Following the aforementioned data processing techniques, we ultimately obtained a total of 169 observations per country.

3.3.3 Preliminary Results: Bayesian Regression Models

a) **Bloomberg Forecast Data**

In Figure 3.3.1, coefficient estimates and respective p-values for country-specific Bayesian-based models for 10y local currency bond yields using the ex-ante variables from Table 3.3.1 as explanatory variables. The column Panel FE displays the coefficient estimates from the fixed effects model results. Orange numbers indicate p-values higher than 0.05 indicating that the respective explanatory variable is not significant. As illustrated in the chart, only a few parameters are indicated as non-significant, and none of the parameters exhibit opposite signals to economic priors.

Index	ZAR	COP	BRL	MXN	PEN	THB	CNY	INR	IDR
Government Debt (%GDP)	0.04	0.02	0.02	0.02	0.02	0.02	0.01	0.02	0.02
	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
US Real Rate	0.03	0.02	0.03	0.02	0.03	0.05	0.04	0.05	0.04
	0.00	0.02	0.01	0.04	0.01	0.00	0.00	0.00	0.00
Bloomberg Forecast GDP Growth (%)	0.09	0.05	0.05	0.05	0.04	0.06	0.04	0.03	0.04
	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01
Bloomberg Forecast Current Account (%GDP)	-0.01	-0.07	-0.08	-0.08	-0.07	-0.09	-0.06	-0.13	-0.06
	0.34	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Bloomberg Forecast Budget Balance (%GDP)	-0.13	-0.12	-0.09	-0.11	-0.11	-0.10	-0.11	-0.14	-0.11
	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Bloomberg Forecast Central Bank Policy Rates (%GDP)	0.58	0.56	0.55	0.55	0.56	0.57	0.56	0.53	0.56
	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Index	CLP	PLN	CZK	ILS	KRW	MYR	HUF	RON	Panel FE
Government Debt (%GDP)	0.01	0.02	0.02	0.05	0.02	0.02	0.03	0.02	0.02
	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
US Real Rate	0.02	0.04	0.05	0.07	0.02	0.03	0.06	0.01	0.04
	0.09	0.00	0.00	0.00	0.01	0.00	0.00	0.21	0.00
Bloomberg Forecast GDP Growth (%)	0.07	0.07	0.02	0.05	0.09	0.04	0.04	0.05	0.05
	0.00	0.00	0.26	0.00	0.00	0.01	0.00	0.00	0.00
Bloomberg Forecast Current Account (%GDP)	-0.06	-0.09	-0.12	-0.13	-0.13	-0.03	-0.06	-0.10	-0.08
	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Bloomberg Forecast Budget Balance (%GDP)	-0.10	-0.14	-0.15	0.02	-0.04	-0.13	-0.11	-0.10	-0.11
	0.00	0.00	0.00	0.13	0.00	0.00	0.00	0.00	0.00
Bloomberg Forecast Central Bank Policy Rates (%GDP)	0.52	0.59	0.54	0.58	0.57	0.58	0.60	0.57	0.57
	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Figure 3.3.1: Bloomberg Forecast Data Bayesian Regression P-value Results

According to the results presented in Figure 3.3.1, it is evident that this Bayesian model works well in characterizing the behavior of 10y local market yields across EM using Bloomberg forecast data. The country-specific models with betas displayed in Figure 3.3.1 allow for a link between the level of 10y yields in EM and the value of fundamentals in a framework that has adequate sensitivities to these fundamentals without overfitting the relationship.

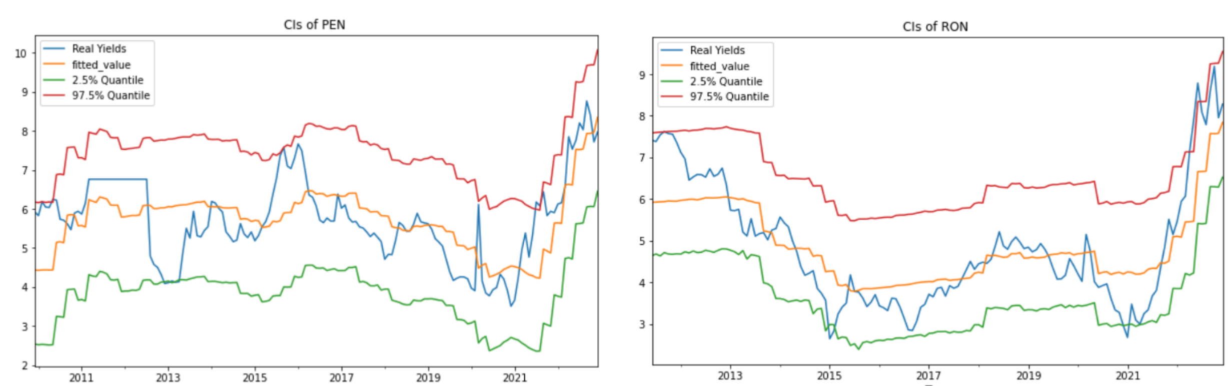


Figure 3.3.2: Bloomberg Forecast Data Bayesian Regression Model fit with respective simulated confidence intervals

Because the model uses mostly macroeconomic fundamentals (all except UST 10y Real Rates) to explain the movement in 10y EM local bond yields, it doesn't have the same high frequency variation of the yields themselves, but it is able to capture most of the medium-to-long term dynamics, as demonstrated in Figure 3.3.2.

b) JP Morgan Forecast Data

In Figure 3.3.3, coefficient estimates and respective p-values for country-specific Bayesian-based models for 10y local currency bond yields using the ex-ante variables from Table 3.3.2 as explanatory variables. The column Panel FE displays the coefficient estimates from the fixed effects model results. Red numbers indicate coefficients that have signs opposite to the expected economic priors. Orange numbers indicate p-values higher than 0.05 indicating that the respective explanatory variable is not significant.

Index	ZAR	COP	BRL	MXN	PEN	THB	CNY	INR	IDR
Government Debt (%GDP)	0.04	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.03
	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
US Real Rate	0.04	0.03	0.03	0.03	0.03	0.04	0.04	0.04	0.04
	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Bloomberg Forecast Current Account (%GDP)	0.02	-0.04	-0.05	-0.05	-0.04	-0.07	-0.06	-0.06	-0.04
	0.09	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Bloomberg Forecast Budget Balance (%GDP)	-0.12	-0.11	-0.09	-0.10	-0.10	-0.10	-0.10	-0.08	-0.10
	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
JPM Forecast GDP	0.04	0.05	0.05	0.05	0.04	0.05	0.04	0.03	0.05
	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
JPM Forecast Central Bank Policy Rate	0.60	0.60	0.59	0.57	0.59	0.59	0.58	0.58	0.59
	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Index	CLP	PLN	CZK	ILS	KRW	MYR	HUF	RON	Panel FE
Government Debt (%GDP)	0.02	0.03	0.02	0.05	0.02	0.02	0.03	0.02	0.03
	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
US Real Rate	0.03	0.05	0.06	0.08	0.03	0.05	0.05	0.00	0.04
	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.68	0.00
Bloomberg Forecast Current Account (%GDP)	-0.03	-0.06	-0.10	-0.09	-0.08	-0.02	-0.03	-0.05	-0.05
	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00
Bloomberg Forecast Budget Balance (%GDP)	-0.10	-0.11	-0.16	-0.01	-0.06	-0.10	-0.09	-0.09	-0.10
	0.00	0.00	0.00	0.57	0.00	0.00	0.00	0.00	0.00
JPM Forecast GDP	0.07	0.06	0.04	0.06	0.06	0.05	0.04	0.03	0.05
	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
JPM Forecast Central Bank Policy Rate	0.57	0.60	0.57	0.61	0.59	0.60	0.59	0.60	0.59
	0.00	0.06	0.87	0.00	0.00	0.45	0.29	0.00	0.00

Figure 3.3.3: JP Morgan Forecast Data Bayesian Regression P-value Results

According to the results presented in Figure 3.3.3, the performance of the Bayesian model constructed using JP Morgan data does not match that of the model using Bloomberg forecast data, with a greater number of coefficients being statistically insignificant. However, overall, there is only one coefficient with opposite signals, indicating that the model generally outperforms those using realized data.

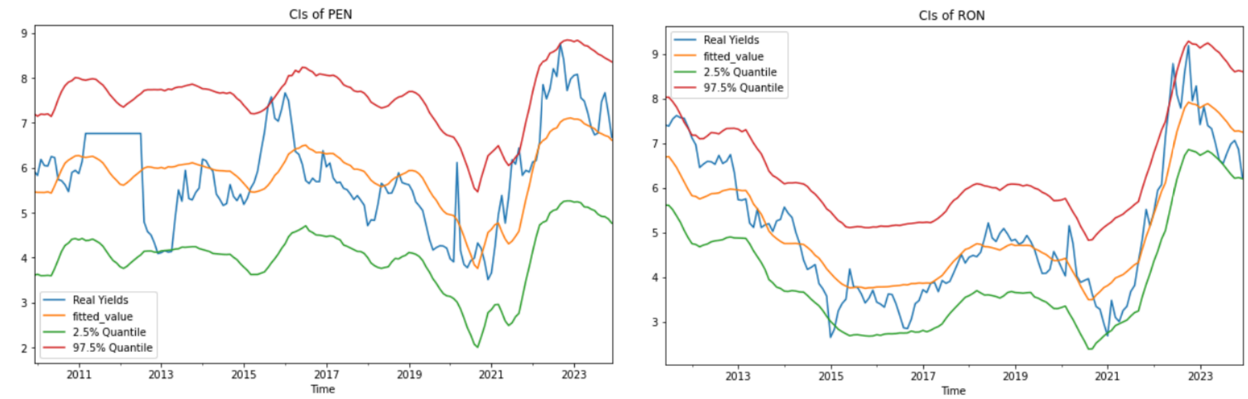


Figure 3.3.4: JP Morgan Forecast Data Bayesian Regression Model fit with respective simulated confidence intervals

The utilization of a 6-month rolling average on JP Morgan data results in a fitted curve that exhibits reduced volatility and a more pronounced smoothing effect. This method effectively captures the macro-level trends in yields, yet it attenuates the high-frequency fluctuations, leading to a representation that is smoother and less sensitive to short-term variations.

3.3.4 Summary

From the modeling results of the two types of forecast data, it is observed that the outcomes using Bloomberg forecast data are superior in terms of p-value. However, the results from both types of forecast data outperform those using realized data, which is consistent with the findings reported in the original paper.

4. Trading Strategy and Backtesting Results

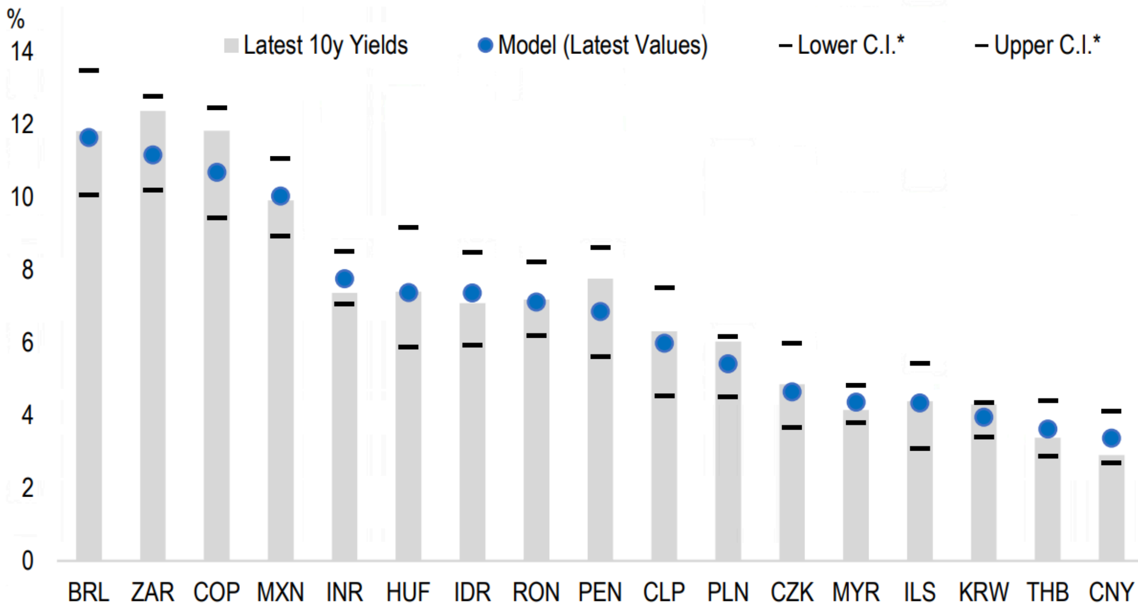
4.1 Signal for 10-Year Yields

After constructing the Bayesian model, we first implemented the model to predict the 10-year yields of various national markets for the next period and analyze the prediction results. We checked whether the actual value for the next period falls within the 95% confidence interval and compared the Z-quantiles of the actual 10-year yield values of various countries in the forecast distribution, and then investigated which countries' yields are 'cheap' and which countries' yields are 'expensive' in comparison to the paper’s results.

4.1.1 10-Year Yields Signal Results

4.1.1.1 Results of the paper

As a reference, the paper's study findings indicate that the assessment of market pricing using prediction confidence intervals reveals that all yields fall within the 95% confidence intervals.



Source: J.P. Morgan, Bloomberg Finance L.P., Haver Analytics.* 95% prediction confidence intervals. As of 23-Oct-23.

Figure 4.1.1.1 10y Yields results of the paper

4.1.1.2 Results of the Bloomberg Forecast

Consistent with the findings of the referenced paper, our analysis confirms that the current yields for all countries remain within the 95% confidence intervals. Notably, all predicted values exceed the latest 10-year yields, with the exception of South Africa.

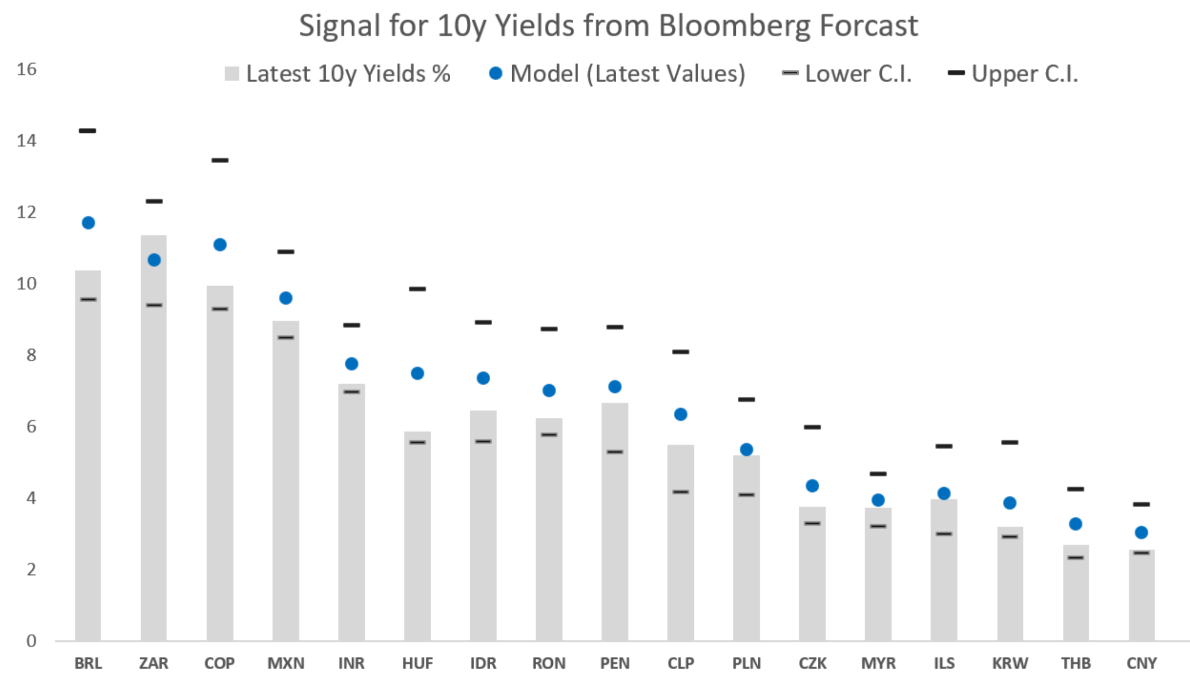


Figure 4.1.1.2 10y Yields results of the Bloomberg Forecast

4.1.1.3 Results of the JPM Forecast

Our analysis diverges from the referenced study in one significant aspect: Thailand's current yield falls outside the 95% confidence interval. Additionally, all predicted values surpass the latest 10-year yields, except for South Africa and Peru.

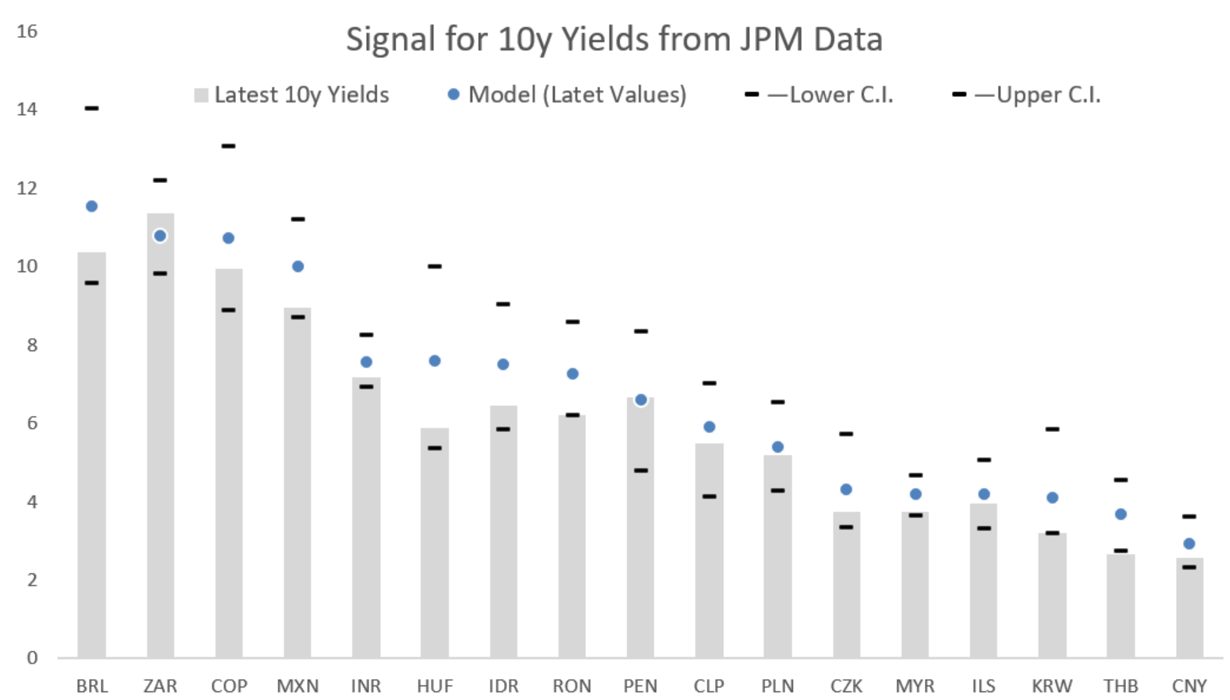


Figure 4.1.1.3 10y Yields results of the JPM Forecast

4.1.2 Z-Scores Results

4.1.2.1 Z-Scores results of the paper

Using Z-Scores, the paper finds that values above zero on the Blackline indicate the latest 10-year yields surpass the estimated values, suggesting potential undervaluation or "cheapness." The analysis further reveals that, with the exception of Korea, most Asian countries are considered expensive. In contrast, yields in Poland, Colombia, Korea, South Africa, and Peru are identified as being attractively priced.

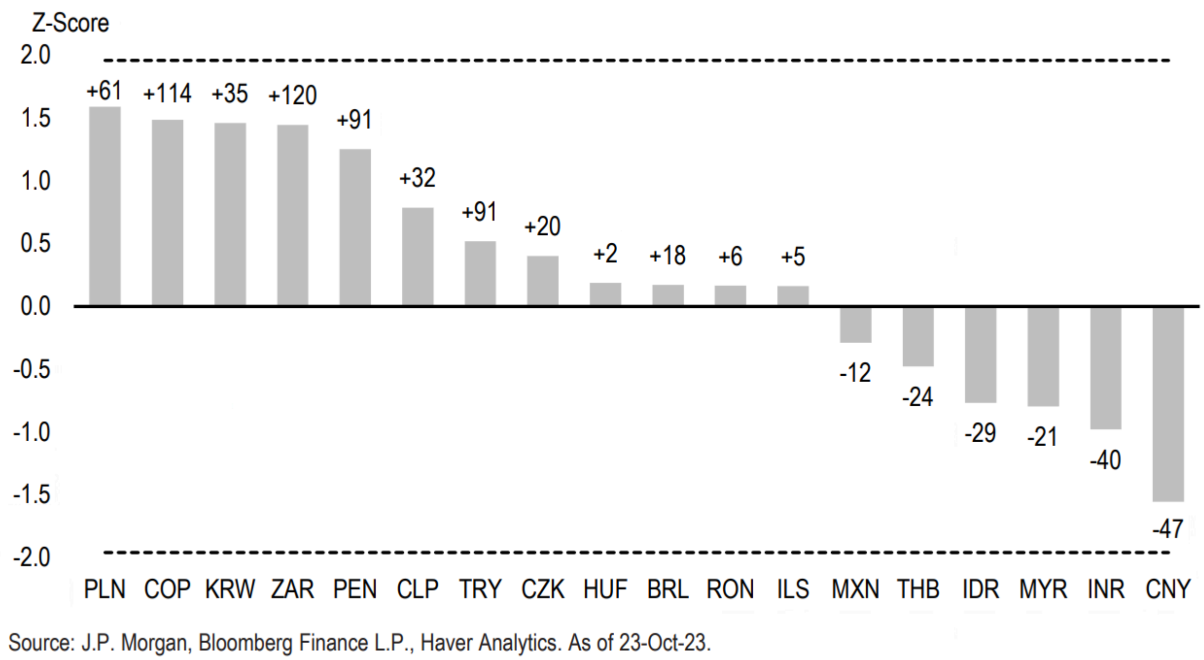


Figure 4.1.2.1 Z-Scores Results of the Paper

4.1.2.2 Z- Scores Results of the Bloomberg Forecast

Our results suggest that, in general, the latest 10-year yields are lower than estimated, categorizing most as "expensive," except for South Africa. In contrast to the findings in the paper, the countries providing the least attractive yields are Hungary, China, Thailand, India, and Brazil.

Figure 4.1.2.2 Z-Scores Results of the Bloomberg Forecast

4.1.2.3 Z-Scores Results of the JPM Forecast

Using J.P. Morgan's forecast for our scenario analysis, the paper discovers that Poland is identified as significantly "cheap," while Turkey is deemed the most "expensive."

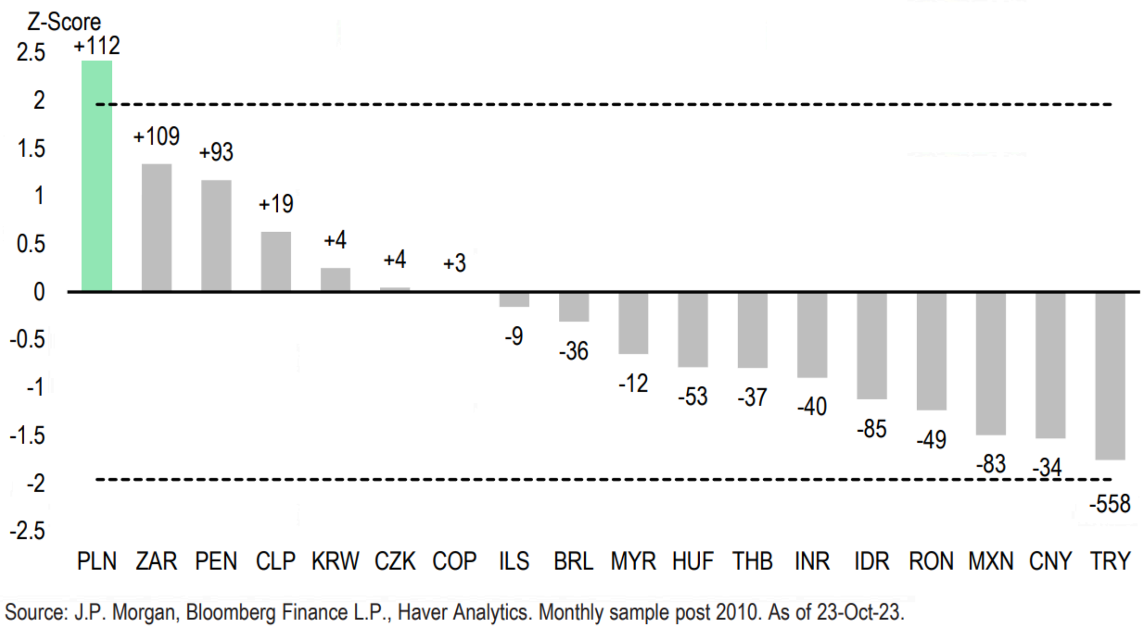


Figure 4.1.2.3 Z-Scores Results of the JPM Forecast

4.1.2.4 Z- Scores from our JPM Forecast results

Our results suggest that the latest 10-year yields are generally lower than estimated, except in South Africa and Peru, indicating that most are "expensive." The countries Hungary, China, Thailand, Mexico, and Romania offer the least attractive yields, differing from the paper's conclusions. Thailand is the most "expensive," with the only significant z-value below -1.96.

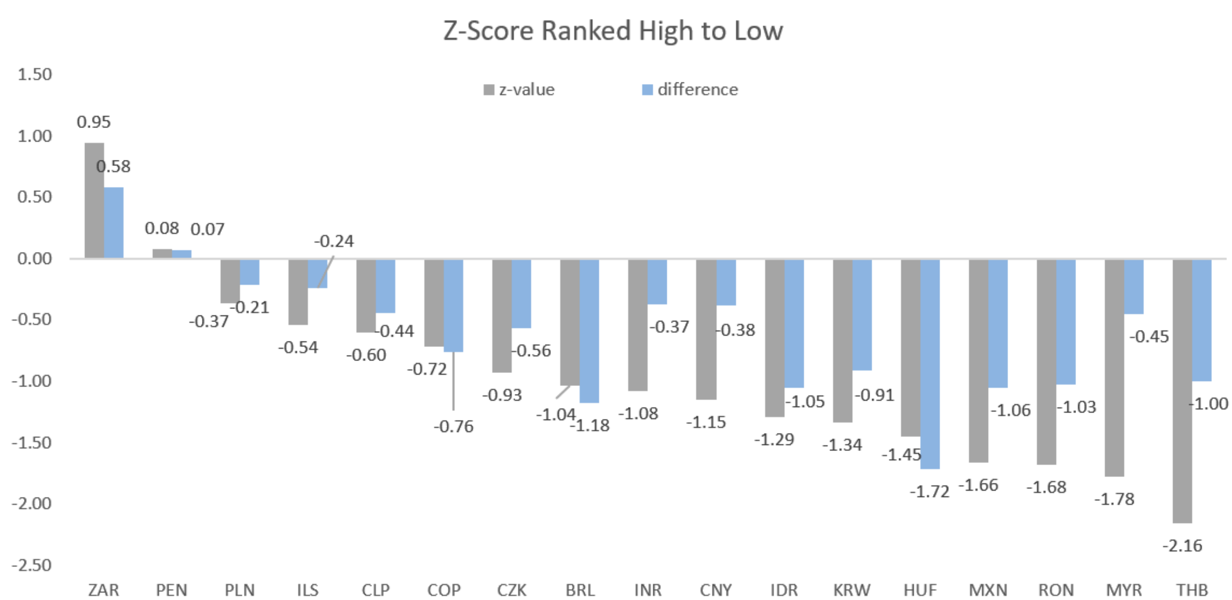


Figure 4.1.2.4 Z-Scores Results of the JPM Forecast ranked high to low

4.2 Trading Strategies and Backtesting Results

This section measures the performance of our trading strategies by applying them to past data, using the predictive confidence intervals as triggers for trade execution. We explore the mechanisms of our strategies, which are designed to open and close trades based on the yields from the Bayesian model's fair value confidence intervals, and we detail the use of Fixed Train-Test Split, Expanding Window, and Rolling Window approaches as our primary backtesting methods. To measure how well these strategies did, we analyzed the results upon the Monthly Average Return to see how much the average of return each month (in percentage) and the Sharpe Ratio to analyze the return obtained of every volatility.

4.2.1 Trading Strategy Overview

We experimented with different methods to trade. For some, we changed the chances of when to start or stop a trade, the second one we only looked at what happens if we start a trade and keep holding the position. We also looked at how long we hold onto a trade and how that affects our results. Plus, we used a Z-score trading strategy to see when yields were way off from what we expected, which might mean it's time to make a trade.

Based on our experiment, we obtained the fair value based on the results of the Bayesian regression. From this, we can derive the confidence interval of this fair value. Our trading strategy is constructed from the real value of the bond yield and these confidence intervals.

Below is the general trading strategy based on the confidence interval:

- If the actual bond yield is higher than the upper bound of the confidence interval, it indicates that the bond is overpriced (yield is too low compared to the model's fair value). In this case, the trading strategy might be to short the bond, betting on the yield to increase (and the bond price to decrease) and move back towards the model's predicted value.
- If the actual yield is lower than the lower bound of the confidence interval, the bond might be underpriced (yield is too high compared to the model's fair value). The strategy would then be to go long on the bond, expecting the yield to decrease (and the bond price to increase) as the market corrects itself.

The next part will discuss further details on how to implement the trading strategy based on different backtesting methods.

4.2.2 Method 1: Fixed Train-test Split

In machine learning and statistical modeling, splitting datasets is crucial for evaluating model performance. In this section, we focus on a training method which is known as Fixed Train-test Split Method. The Fixed Train-test Split Method is a commonly used data partitioning technique, which involves dividing the dataset into a training set and a test set beforehand. This method is simple, straightforward, and often employed in academic research and papers to ensure consistency and reproducibility in model evaluation.

The Fixed Train-test Split Method is a data partitioning technique where the dataset is divided into two non-overlapping subsets: the training set and the test set. The training set is used to train the model, i.e., to adjust the model's parameters; the test set is used to evaluate the performance of these trained models, providing an unbiased estimate of the model's performance on new, unseen data. The Fixed Split Method is straightforward to implement, especially when data volume is small or experimental conditions are limited. Besides, since the dataset split is fixed, other researchers can repeat the experiment and verify the results, enhancing the transparency and credibility of the research.

In implementing the Fixed Train-test Split Method, the dataset is initially randomly partitioned into a training set and a test set, with the ratio of division typically tailored to the specific research requirements. In our research, we set the ratio as 1:1 which is the same as that in the reference paper. In other words, we use the year 2017 as the dividing point for train-test split, with data prior to this year used as the training set and data following it as the test set.

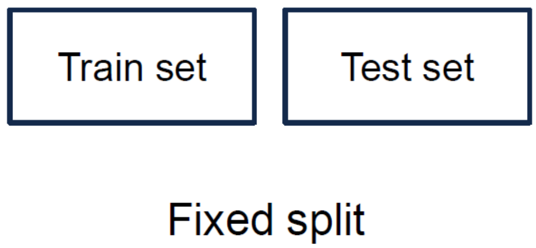


Figure 4.2.2.1: Diagram of the Fixed Train-Test Split Method

After completing the split between the training set and the test set, we began model training and backtesting. In the backtesting, we used different trading strategies with the aim of finding the strategy that yields the highest return and Sharpe ratio, along with its parameters and hyperparameters. In this section, we mainly used **Original CI Strategy** and **New CI Strategy** to backtest the model.

In the Original CI Strategy, two parameters are required: the probability of opening trades and the probability of closing trades. In our research, the probabilities for opening trades were selected from the set {0.975, 0.95, 0.925, 0.90}, while those for closing trades were chosen from {0.90, 0.85, 0.80, 0.70}. Consequently, we derived a series of cumulative return index curves.

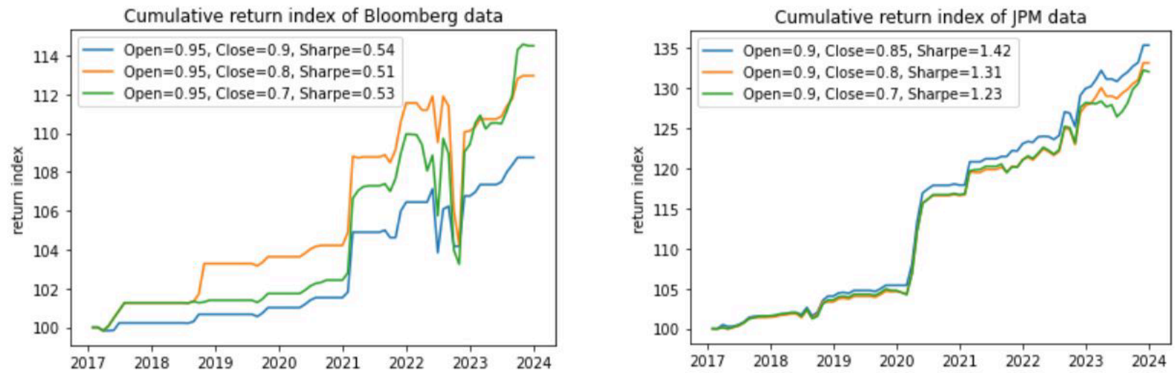


Figure 4.2.2.2: Cumulative return of Bloomberg and JPM data by **Original CI Strategy**

Backtesting results on Bloomberg data reveal that setting open=0.95 and close=0.70 resulted in the highest returns and a comparatively high annual Sharpe ratio, achieving a cumulative return of 14% and an annual Sharpe of 0.53; however, the overall performance was not particularly impressive. In contrast, an open=0.90 and close=0.85 configuration on JPM data yielded the highest returns and annual Sharpe ratio, with a cumulative return of approximately 35% and an annual Sharpe of 1.42. Overall, backtesting results using JPM data significantly outperformed those from Bloomberg data, aligning closely with the findings presented in the reference paper.

In addition, in the New CI Strategy, only one parameter is required: the probability of opening trades (trades will be closed automatically after one month). In our research, the probabilities for opening trades were selected from the set {0.95, 0.90, 0.85, 0.80, 0.70, 0.60}. Consequently, we derived a series of cumulative return index curves.

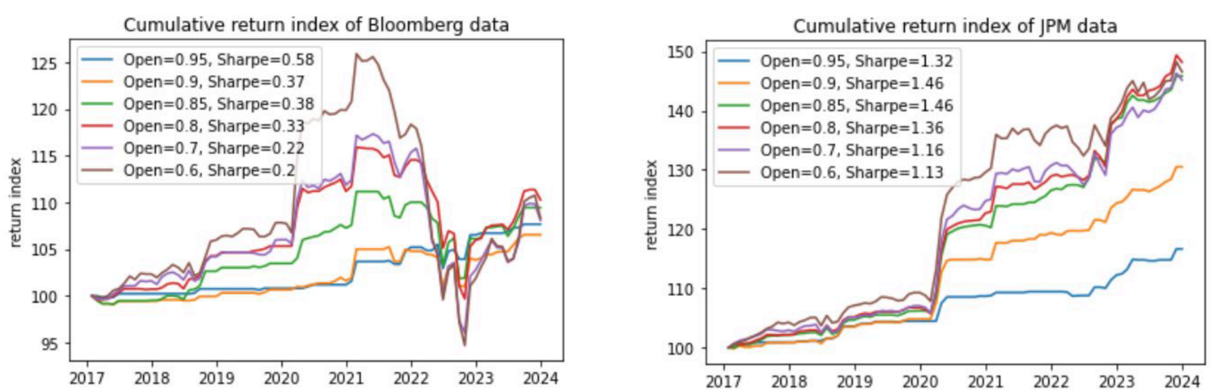


Figure 4.2.2.3: Cumulative return of Bloomberg and JPM data by **New CI Strategy**

Backtesting results on Bloomberg data indicate that the **New CI Strategy** did not produce significant improvements, as evidenced by a reduction in the return index. In contrast, the **New CI Strategy** performs effectively on JPM data, leading to an increase in the return index, which reaches a peak value of approximately 150. An open=0.85 configuration on JPM data yielded the highest returns and annual Sharpe ratio, with a cumulative return of approximately 45% and an annual Sharpe of 1.46. Overall, the New CI Strategy did not significantly enhance the cumulative return in backtesting on Bloomberg data. However, on JPM data, it achieved an approximate 10 percentage point increase in cumulative return compared to the Original CI Strategy, with a slight improvement in the annual Sharpe ratio as well.

In summary, employing the Fixed Train-test Split, our backtesting on the JPM data dataset yielded a maximum cumulative return of approximately 45%, with an annual Sharpe ratio of 1.46, which is close to the results of the reference paper. Such backtesting outcomes demonstrate the effectiveness of our constructed fair value model. Moreover, our newly developed trading strategy exhibits lower volatility compared to the results in the literature, enhancing the backtesting performance.

4.2.3 Method 2: Expanding Window

We adopted a back-testing method called expanding window to test our trading strategy. Expanding window backtesting, often referred to as a "rolling" or "walk-forward" testing method, is a technique used in finance and other fields involving time series data to assess the performance of trading strategies or predictive models over time. This method is designed to simulate real-world operations and help in understanding how a strategy or model would have performed historically.

We first take an initial window. The test begins with a fixed initial data set. This is the minimum amount of data needed to start making predictions or executing trades. We then expand the Window as the test progresses. The window of historical data used for making decisions expands. After each period, new data is added to the window. This means that the model or strategy is re-evaluated and adjusted based on an ever-increasing dataset. The key to this method is that the strategy or model makes decisions based on historical data up to a certain point, and these decisions are then tested on the following data period, which has not been used to make those decisions. This continues throughout the dataset. Performance metrics are collected continuously as the window expands and decisions are tested.

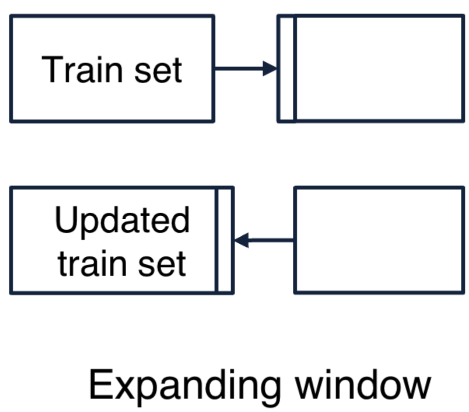


Figure 4.2.3.1: Diagram of the Expanding Window Method

After back-testing we found out that using open position at 90% confidence interval and close position at 80% confidence interval will generate the best returns. The cumulative returns are on the following graph.

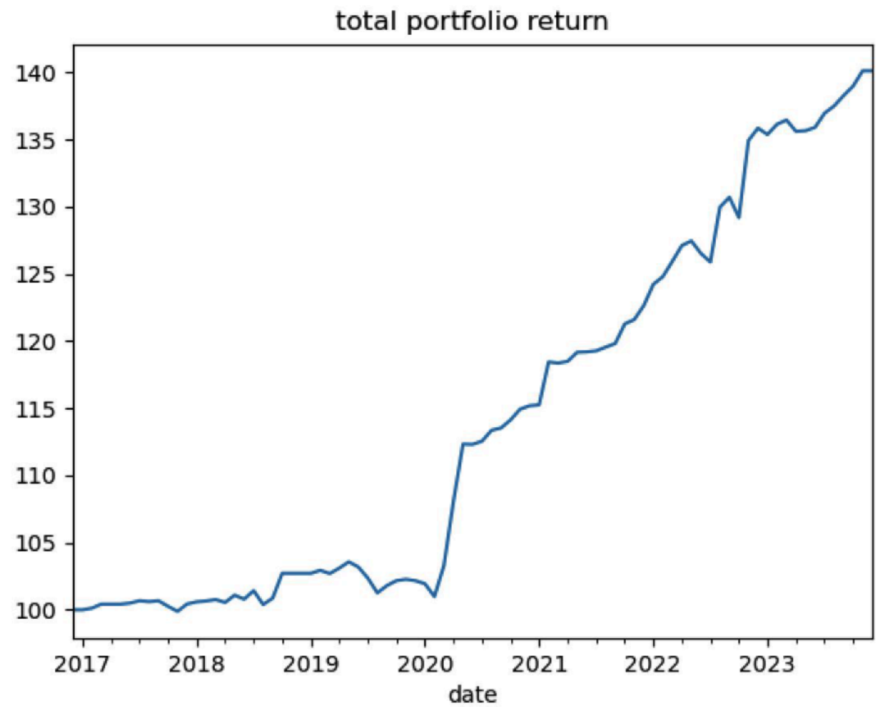


Figure 4.2.3.2: Diagram of the Expanding Window Total Return

We also tested individual country's returns on the following graph.

	ZAR	COP	BRL	MXN	PEN	THB	CNY	INR	IDR	CLP	PLN	CZK	ILS	KRW	MYR	HUF	RON	Strategy2
Monthly_return_mean	0.13%	0.20%	0.21%	0.09%	0.50%	0.04%	0.01%	-0.02%	0.27%	-0.05%	0.27%	0.20%	-0.01%	0.05%	0.02%	0.16%	0.30%	0.40%
Monthly_volatility	0.40%	0.95%	0.58%	0.32%	0.73%	0.19%	0.13%	0.19%	0.23%	0.45%	0.47%	0.34%	0.22%	0.21%	0.20%	0.44%	0.54%	1.03%
Sharpe_ratio	1.16	0.72	1.22	0.95	2.39	0.82	0.24	-0.40	3.91	-0.38	1.94	1.97	-0.11	0.81	0.36	1.25	1.92	1.35
Months Traded	33	11	16	13	7	26	13	23	4	25	15	20	24	21	24	43	12	330
No. of Trades	10	2	6	4	4	6	3	5	1	3	7	5	3	3	7	7	7	83

Figure 4.2.3.3: Diagram of the Expanding Window Countries Return

Besides trading based on confidence interval signals. We also tested the buy and hold strategy. We opened the position at 90% confidence interval and closed the position after holding for one month. And we found that this strategy generated negative returns.

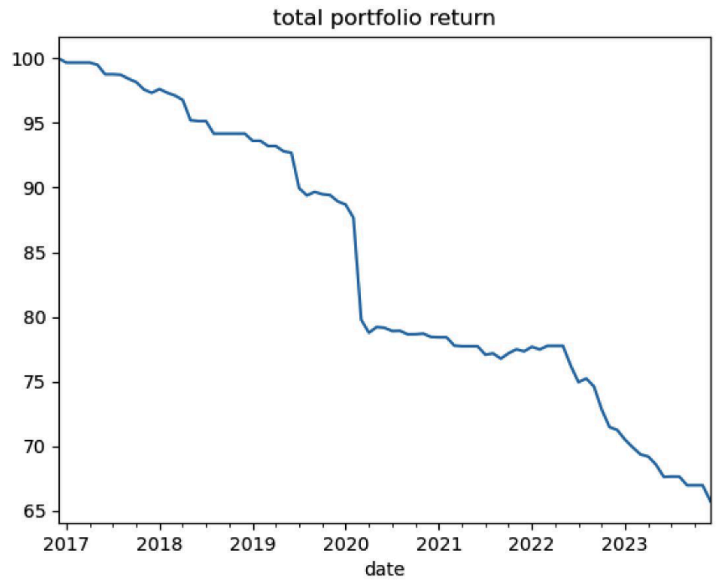


Figure 4.2.3.4: Diagram of the Buy and Hold Returns

We concluded that the expanding window strategy when using confidence intervals as the trading signals generated returns that are similar to other trading strategies. And the buy and hold strategy does not work for our data.

4.2.4 Method 3: Rolling Window

In our study, we implemented a third trading method known as the rolling window method. This involves setting a fixed rolling window to model only the data within this interval, forecasting the fair value range for the following month.

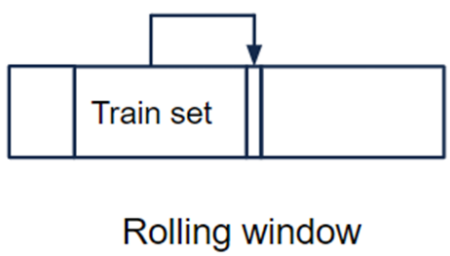


Figure 4.2.4.1: Diagram of the Rolling Window Method

Building on this modeling approach, we explored two types of trading strategies.

The first strategy relates to confidence intervals. We established a range for opening positions (open position confidence interval) and for closing positions (close position confidence interval). Specifically, if the actual monthly return exceeds the boundary of our opening confidence interval, we opt to open a position. Conversely, if it reenters the range of the closing confidence interval, we proceed to close the position.

This method involves parameters such as the size of the rolling window, the range of the open position confidence interval, and the range of the close position confidence interval. During our experiments, we tested various window sizes and settings for both opening and closing positions.

Furthermore, we experimented with a new confidence interval (CI) trading strategy based solely on the opening confidence interval, where positions are mandatorily closed in the subsequent month, irrespective of specific closing intervals.

The following figure demonstrates the overall performance of these strategies on the JP Morgan dataset. In summary, for the original CI trading strategy, the best performance was achieved with an open position at 0.93, close position at 0.8, and a window size of 84, resulting in an average annual return of 0.32% and a Sharpe ratio of 1.24. For the new CI trading strategy, the best performance occurred with an open position at 0.85, yielding an average annual return of 0.31% and a Sharpe ratio of 1.09.

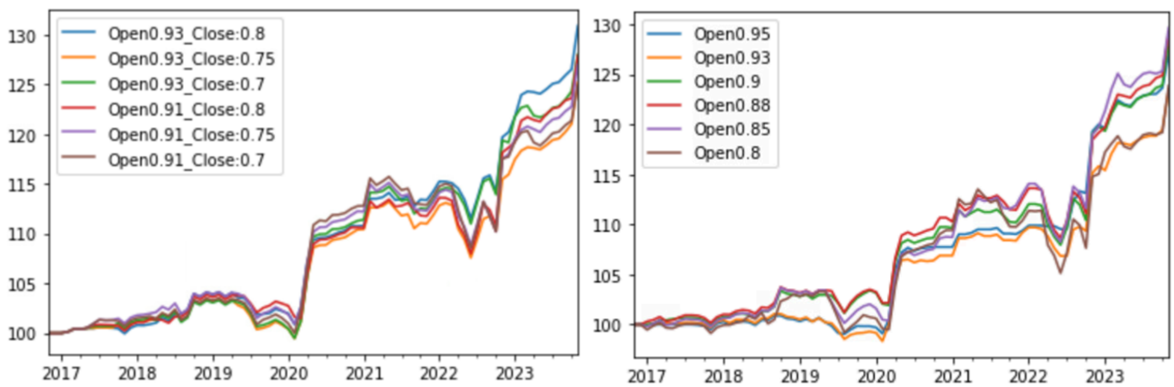


Figure 4.2.4.2: Cumulative Returns of JPM Data: CI Strategy (Left), New CI Strategy (Right)

Additionally, we tested another trading strategy based on z-scores. This strategy performed exceptionally well on datasets from Bloomberg and JP Morgan. The z-score strategy involves calculating the z-score for each country monthly and short-selling the countries with the highest z-scores (indicating relatively high returns) while buying into those with the lowest z-scores (indicating relatively low returns). The parameters of this strategy include the trading frequency, the number of countries involved in each transaction (N), and the window size of the model.

For the Bloomberg dataset, we found the optimal results with a trading frequency of once per month and N = 4, achieving an average monthly return of 0.21% and a Sharpe ratio of 0.631.

For the JP Morgan dataset, optimal performance was noted with a trading frequency of once per month and N = 6, resulting in an average monthly return of 0.41% and a Sharpe ratio of 1.121.

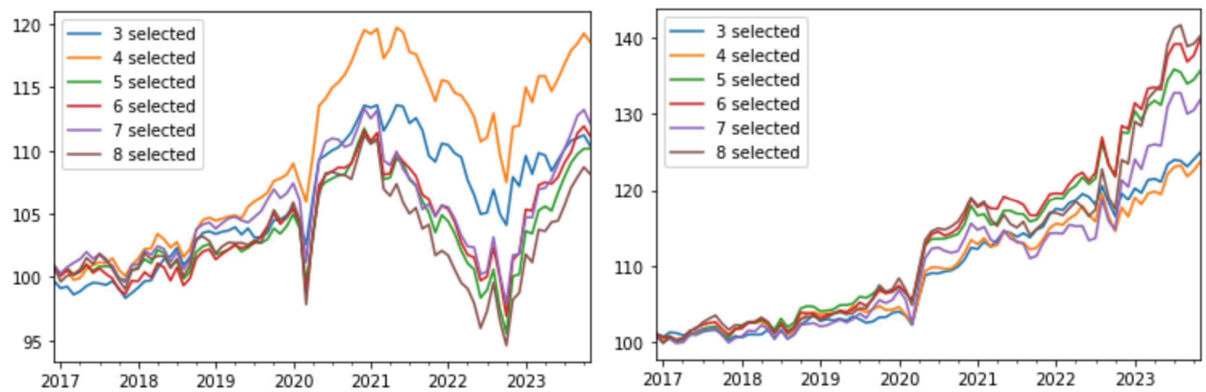


Figure 4.2.4.3: Cumulative Returns of Z-score Strategy: Bloomberg(Left), JP Morgan(Right)

4.2.5 Best Trading Strategy and Result

The results on Table 4.2.1 provides a comparative analysis of the trading strategies backtested on data from JP Morgan and Bloomberg.

	JP Morgan		**Bloomberg**	
Methods	Monthly Average Return	Sharpe Ratio	Monthly Average Return	Sharpe Ratio
Fixed Train-test Split	0.42%	1.49	0.15%	0.46
Expanding Window	0.40%	1.35	0.12%	0.46
Rolling Window	0.41%	1.21	0.21%	0.631

Table 4.2.1: Trading Result Comparison

The Fixed Train-Test Split method, applied to the JP Morgan dataset, stands out with a monthly average return of 0.42% and a Sharpe Ratio of 1.49. This strategy, which uses a 90% confidence interval for opening positions and an 80% confidence interval for closing them, not only yielded the highest monthly profitability but also the most favorable risk-adjusted returns among the strategies tested with the JP Morgan data.

Conversely, the Bloomberg dataset showed optimal performance with the Rolling Window method, delivering a monthly average return of 0.21% and a Sharpe Ratio of 0.631. The Fixed Train-Test Split approach, which involved training on 2010-2016 data and testing on 2017-2023 data, proved to be the most effective, particularly with the JP Morgan forecast dataset, due to its strategic use of defined confidence intervals for trading decisions.

In conclusion, the Fixed Train-Test Split method, with 90% confidence interval for opening positions and an 80% confidence interval for closing, with its clear conditions for trade execution and strong performance metrics, is the top trading strategy for the JP Morgan dataset, affirming its effectiveness and reliability.

5. Summary

In our research, we aimed to develop and evaluate a Bayesian-based regression model for determining the fair value of local currency government bonds in emerging markets (EM). The study drew on a dataset spanning 17 EM countries and incorporated key economic indicators such as central bank policy rates, real GDP growth, current account and budget balances, government debt, and the US real interest rate.

We utilized a blend of historical (realized) data and forecasted data from Bloomberg and J.P. Morgan, employing methodologies including Ordinary Least Squares (OLS), Fixed Effects models, and Bayesian regression to isolate significant parameters that affect bond yields.

Key insights from our study include:

1. **Model Development:** We built a Bayesian model that predicts bond yields by integrating historical and forecast data, aiming to uncover a more nuanced understanding of the factors influencing EM bond yields.
2. **Data Analysis:** Comprehensive data processing was conducted, which included addressing missing data, applying data lags, and converting annual and quarterly data into monthly series to enhance the model's applicability.
3. **Results:** Our findings showed that models using forecast data generally outperformed those based on historical data alone. Specifically, Bloomberg forecast data yielded better statistical significance than J.P. Morgan data.

Regarding trading strategies and backtesting, we evaluated several approaches that utilize the predictions from our Bayesian model. The strategies created signals based on the model’s confidence intervals for 10-year bond yields.

Best Trading Strategy Results:

- **J.P. Morgan Data:** The best results were achieved using the Fixed Train-Test Split method with the Confidence Interval (CI) trading strategy. We used data from 2010-2016 as the training set and 2017-2023 as the test set, applying a trading strategy that opens positions at the 90% confidence interval and closes them at the 80% confidence interval.

This strategy yielded significantly higher returns and a better Sharpe ratio compared to strategies applied on Bloomberg data.

- **Bloomberg Data:** The most effective strategy was the Rolling Window method combined with a Z-score trading strategy. This approach involves shorting the six countries with the highest Z-scores and going long on the six with the lowest Z-scores, adjusting the trades each month based on new data. The Z-score is calculated as the difference between the real yields and predicted yields, normalized by the prediction error (σ_predict).

Our conclusion highlights the efficacy of the Bayesian model in capturing the complexities of EM bond prices and provides a robust framework for financial modeling and investment strategy in emerging economies. Our findings significantly enhance the tools available for assessing the fair value of EM local currency bonds, thus aiding more informed investment decisions within these markets.

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