e-Financials

Research paper

XGB Static Model for Fixed Income Yield

Abstract

Artificial Intelligence (AI) is a powerful tool that is already widely deployed in financial services. It has great potential for positive impact if companies deploy it with sufficient diligence, prudence, and care. XGB Model applies extreme gradient boosting decision trees technique which provides clear handling of complex and non-linear relationships of individual features, which proves to be a powerful tool in estimation of non-classified issues. Our results shows that, the model's consistent outperformance against the benchmark, exceeding it on average by 0.5% on a monthly basis and cumulatively by almost 10% over a two-year horizon, underscores its robust and sustainable performance.

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1 Model overview

Characteristic	Description
Name	XGB Static Market Model
Version	1.0
Description	Gradient Boosting Decision Trees
Asset Class	Fixed Income
Sub Asset Class	
Real Time	No
Periodicity	Daily
Back test	Monthly, Long/Short, Long Only

2 Introduction

Artificial Intelligence (AI) is a powerful tool that is already widely deployed in financial services. It has great potential for positive impact if companies deploy it with sufficient diligence, prudence, and care. This paper applies Gradient boosting decision trees model to conduct relative value analysis to exploit pricing imperfection in Fixed Income Market. Particularly, we focus on financial debt including Banks, Insurance and Financial Services companies. However, model can be used for whole Global Fixed Income Market.

The main sources of mispricing come from various forms of market imperfection. Mainly, investors are usually limited to invest in specific sector/rating/maturity that affect yield/spread of securities. For example, central banks as a risk averse institution (International Monetary Fund, 2001) are active in sovereign high-grade sector. Moreover, demand and supply factors generate favorable market opportunities.

BRRD regulation (Single Resolution Board, 2020) created MREL debt that have to be issued over short period of time. Banks must attract new investors to approach desired capital level.

The model is suitable also for pricing purposes. Assuming market is efficient it allows to determine fair price of illiquid and/or high yield debt, by comparison to the relevant features of liquid and fair yield on debt.

3 Data

The model is calibrated using proprietary fixed income data covering fixed income market with focusing on financial debt. The dataset consists of Government, Quasi government, Foreign Government, Securitized, Collateralized and Corporate Sectors. Only fixed coupon securities are included. Securities with maturity bellow one year are excluded due to unstable pricing prior to final maturity data. The data consist of following features:

- Rating of issue, Currency of issue, Country of issuer, Type of issue
- Volume of the issue, Duration
- Indicators of bond properties such as:
  - Floating
  - Perpetual
  - Covered
  - Subordinated
  - Securitisation
- Lagged yield values for last three days called Lag1, Lag2 and Lag3
- The target variable is Yield

4 Model

In our terminology the model is a pipeline which has on it's input a raw data and outputs the predictions. This is a longer procedure and consists of a few steps. The first step is called data preprocessing, which prepares raw data into more suitable format and also adds new features and remove the outlying observations. The second step is fitting of suitable technique, which in our case are Gradient Boosted Decision Trees with appropriate hyperparameters. Lastly, we make our predictions using the fitted technique and then we evaluate on appropriate metrics and perform a backtest.

4.1 Data preprocessing

Firstly, we remove observations which yield is higher than 10% and lower than -3%. Secondly, we remove observations which duration is 0 and also the yield is also 0. Such an observations we will consider as false or expired observations.

We also create three new binary variables. The first variable is indicator of not being of any indicating categories, which can be expressed as:

$$Other = \begin{cases} 1, & \text{if Flt} = \text{Perp} = \text{Cov} = \text{Sub} = \text{Sec} = 0; \\ 0, & \text{otherwise.} \end{cases}$$

The second variable, which indicates a possibility of false observations, when duration is 0 and we observe non-zero yields. The third is a liquidity criterion, which distinguishes liquid issues and non-liquid issues.

For us, the liquid issues follows the following criteria:

1. Firstly, we calculate the differences between yields and lagged yield values
   - diff1 = Yield - Lag1
   - diff2 = Lag1 - Lag2
   - diff3 = Lag2 - Lag3
2. Standard deviation$(Yield, Lag1, Lag2, Lag3) < 0.00005$.
3. Mean$(\text{diff1}, \text{diff2}, \text{diff3}) < 0.001$.
4. Mean$(\text{diff1}, \text{diff2}, \text{diff3}) \neq 0$.
5. Volume of an issue is higher than 10000000.

After the procedure we split data into three subsets: ***train***, ***development*** and ***test*** datasets, where train and development datasets are issues which are marked as liquid and test data corresponds to non-liquid issues.

4.2 Techinque

In this model we utilize Extreme Gradient Boosted Decision Trees, or XGB, offer a robust and versatile machine learning technique. They excel at capturing complex relationships in data, making them ideal for high-dimensional datasets. XGB handle various data types and noise effectively, ensuring reliable performance. They strike a balance between interpretability and accuracy, making them a valuable tool for tasks like regression. The hyperparameters of XGB technique are carefully calibrated using a grid search on train data and subsequent validation on development sample.

The model fitted and validated on liquid issues (train and dev datasets) will produce relative values for liquid issues whereas model train on liquid data and validated on non-liquid issues will serve for predictions of non-liquid issues. The one possible problem of decision trees is the easy overfitting which is prevented by random subsampling and early stopping.

5 Model Back Test

The back test of a model is done on monthly basis calculated only on liquid issues since the yield of non-liquid bonds carries a very little information. The primary focus of this back test is on all liquid bonds across all countries and industries with both long and short positions.

Firstly, we calculate market performance of a bond which can be expressed as

$$\text{Perf}_i = (-1) * (\text{EYield}_i - \text{BYield}_i) * \text{Dur}_i, \tag{1}$$

where EYield_i is a yield of i-th bond at the end of a month, BYield_i is a yield of i-th bond at the beginning of a month and Dur_i is a duration of the i-th bond at the beginning of a month. Note, that for simplicity, we omit convexity of a bond.

As the benchmark portfolio we take equally weighted portfolio consisting of all liquid bonds. To back test the model we calculate a Relative Value for each bond which will be crucial for deciding which positions we make.

5.1 Relative Value Analysis (RVA)

The most important statistics is the relative value of a bond which serves as an indicator if the bond is over/under priced and can be mathematically expressed as

$$\mathrm{RVA}_i = \mathrm{AY}_i - \mathrm{PY}_i, \tag{2}$$

where PY_i is the predicted yield of i-th bond and AY_i is the actual yield of i-th bond. This statistics is then computed for all bonds except to non-liquid bonds since the actual yield AY_i is not accurate and such statistics would be misleading.

The important property of the relative values (RVA) is that when RVA is positive, the issue is thought to be under-priced since the actual yield is higher than the predicted yield and due to inverse relationship between yield and price we conclude that the price of the bond should be higher. On the other hand if RVA is negative the issue is thought to be over-priced and in cases of RVA being zero, the issues is priced accordingly to our model and the yield can be explained through the used data which were discussed before.

Thus in case of both long and short positions we construct our portfolio such that

- $\mathrm{RVA}_i \geq 0 \implies$ long position.
- $\mathrm{RVA}_i < 0 \implies$ short position.

If we opt for exclusively taking long positions, we will only purchase contracts with the non-negative RVA.

5.2 Results

In the following images we can observe the respective performance of benchmark portfolio (Bmk), long/short portfolio (PrtLS) and long only portfolio (PrtLO) from February 2022 until September 2023. We also provide graphs for performance for each month separately along with graphs of cumulative performance.

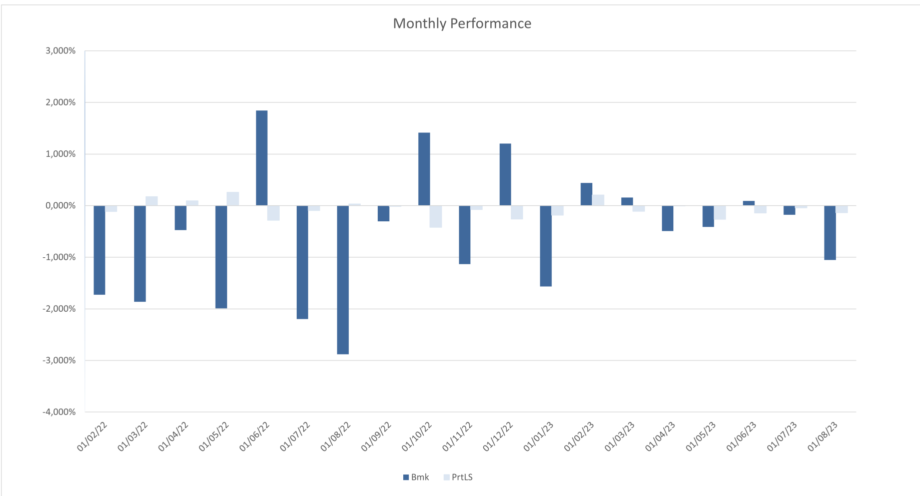

Figure 1: Monthly Performance / All bonds / Long-Short

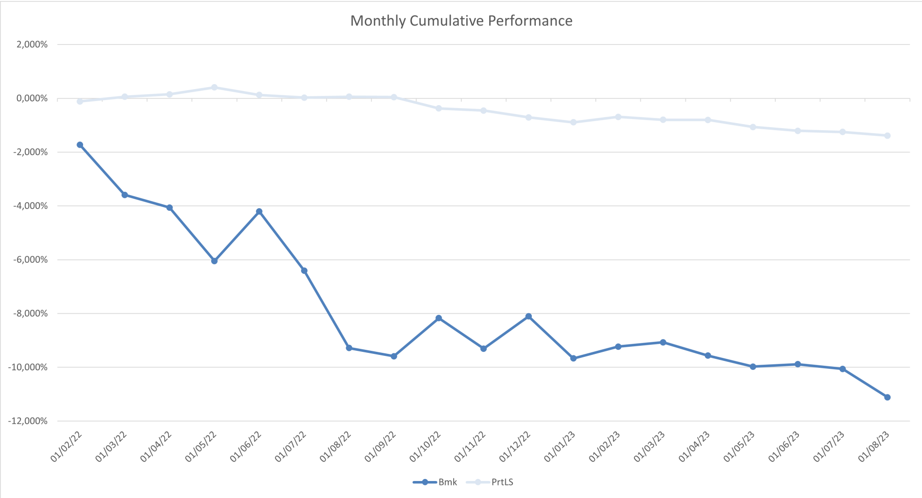

Figure 2: Cumulative Performance / All bonds / Long-Short

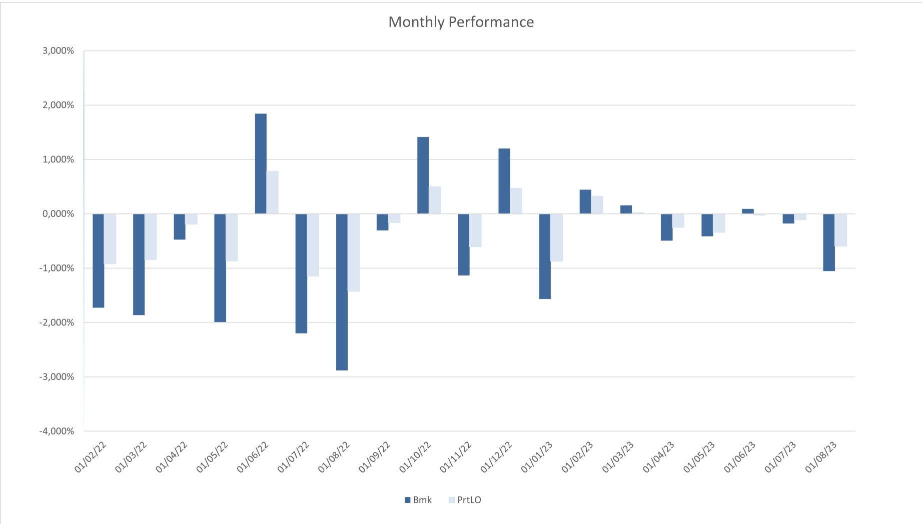

Figure 3: Monthly Performance / All bonds / Long-Only

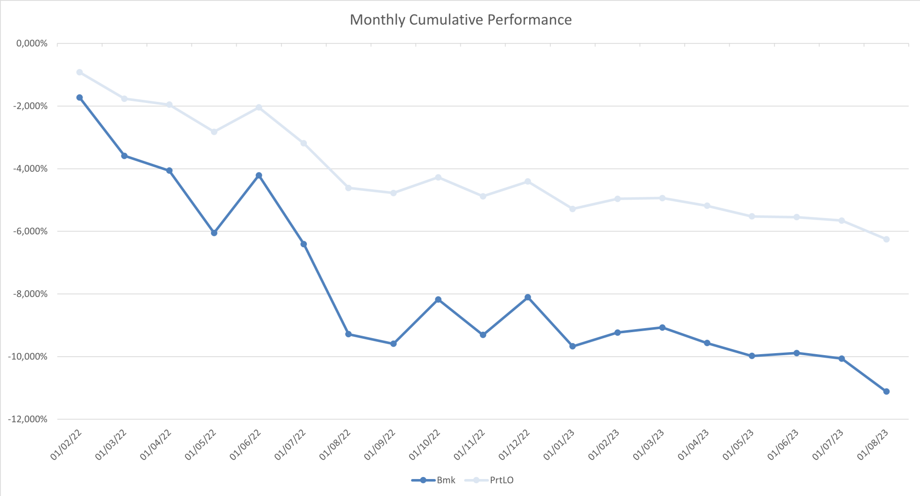

Figure 4: Cumulative Performance / All bonds / Long-Only

To understand the results of the backtest it is crucial to notice that we do not use prices of bonds but instead we use yields. Thus we had to multiply by minus one to ensure that positive performance of a bond means that the price of a given bond grew, which could only happen if the yield dropped. We also gave a similar explanation of the sign of RVA of the bond.

6 Conclusion

In conclusion, we gave a brief description of a model where we explained step by step the underlying data, the procedures to transform the raw data into data used for model. In the next step we described the model and what it means in our terminology and described the technique used for evaluation/prediction. Finally, we presented a comprehensive backtesting framework for liquid data, accompanied by illustrative figures showcasing the backtest results.

From practical standpoint, in case of Long-Short portfolio we observe outperformance against the benchmark, exceeding it on average by 0.5% on a monthly basis and cumulatively by almost 10% over a two-year horizon. In case of Long-Only portfolio we observe outperformance against benchmark by 0.25% on a monthly basis and cumulatively by almost 5% over two year horizon. This level of consistent superiority demonstrates the model's ability to deliver superior results, providing valuable insights and potential opportunities for long-term investment strategies. Its track record of achieving and maintaining such impressive gains reinforces its credibility as a reliable tool for investors and decision-makers in the financial industry.

We also recognize that the market was falling in the backtest sample which might have affected the results and possibly skew the view on performance of the model.