# Identifying Overvalued and Undervalued Bonds for Daily Capture through Data-Driven Analysis [a]

Author: Vincent Zhao, Group: COMP0040_3, SN: 23102278, COMP0040

## ABSTRACT

Mispricing of fixed-income assets, particularly bonds, can challenge investors seeking to determine accurate valuations. This study proposed two models for identifying potentially overvalued and undervalued bonds by employing the metrics of yield to maturity (YTM) and option-adjusted spread (OAS). The study used duration and DV01 (dollar value of an 01) to corroborate these findings. The research also explored how non-financial institutions can influence bond mispricing, especially in the oil and gas sector. While limited historical data prevented in-depth precision evaluation of the result, this study still provided a valuable framework for further exploration.

## I. INTRODUCTION

The bond market plays an essential role in global finance, offering a critical way for countries and companies to secure funding through debt issuance to investors [1]. Government-issued treasury bonds are mainly a baseline for assessing risk premiums across investment opportunities [1]. For investors, it is essential to understand bond pricing before making investment decisions. Nonetheless, the bond market could not resist differences between theoretical models and market realities, with mispricing occurring where the face value of a bond may not accurately reflect its market value [2]. This results in fundamentally healthy bonds being undervalued or risky bonds appearing overvalued.

Our study focused on the dynamics of bond valuation, employing data from a single-day capture to identify mispriced bonds. We assessed overvaluation and undervaluation using the option-adjusted spread (OAS) and yield to maturity (YTM) as primary indicators. Then, we cross-verify these findings against additional financial metrics to confirm

[a] Unless specifically mentioned, the work is produced by the author and ‘we’ refers to the author.

the result. At the end of the report, we will also cover the additional findings on how non-financial institutions affected the bond market.

## II. METHODOLOGY

This section aims to introduce the dataset and outline the analytical methods employed. First, we will introduce the data with a general understanding of the background of finance. Then, we will explain the exploratory data analysis (EDA) used to examine dataset features, specifically the influence of bond ratings on its metrics and behaviours between financial and non-financial markets. Additionally, our analysis applied techniques such as correlation analysis and network visualization. After that, we will discuss multiple methodologies for identifying undervalued and overvalued bonds, and a null model for comparative evaluation.

### A. Data Understanding

A thorough understanding of the data is crucial before tackling the problem. We worked with the iBoxx USD liquid investment with an investment-grade dataset. This dataset offers an end-of-trading day (January 25, 2016) capture of investment-grade bonds in US dollars, with ratings assigned by S&P. There are 1482 data points and 129 features in total. Before the EDA process, we would like to introduce the content of essential features in the dataset.

Each row in the dataset represents an individual bond. The **issuer** denotes the entity that has issued the bond. An issuer can have various bonds. JPMorgan Chase & Co holds the most bonds (29 total). The **coupon** rates indicate the periodic interest payment made to bondholders, which can be disbursed annually or semi-annually, depending on the bond's payment frequency. The highest coupon rate is 9.62%, with a mean of 4.26%, with the 75% percentile as 5.12% and 25% as 3.12%. The **YTM** reflects the total return an investor expects if they hold the bond until it reaches maturity [3], with the highest of 22.31% and the mean of 4.05%; with the 75% percentile as 4.77% and 25% as 2.73%. It indicates that there are diverse risk profiles among the bonds, and it is not a constant but dynamic change based on the market or issuer condition. Typically, higher YTM suggests higher risk, but undervaluation occurs where it does not hold.

The **markit iBoxx rating** measures the bond's creditworthiness, with a higher rating, such as AAA, signifying a lower probability of default [4]. In contrast, while still within the investment-grade scope, a BBB rating suggests a higher default risk than its AAA counterparts. BBB and A ratings take most of the dataset (c.42% each), and AAA holds only 2%. The **bid price** and **ask price** represent the buying and selling price of the bonds within the market [5]. A significant **bid-ask spread** indicates the market does not think the price matches; it also suggests potential mispricing within the market. The **OAS** quantifies the bond's credit risk by factoring in the variability of cash flows due to embedded options, providing a measure of the spread with adjustments for the bond's specific features [3]. There's no fixed boundary on high or low OAS scores, and the same happens for the bid-ask-spread for the price; it depends on the different ranges of the ratings. For example, AAA bonds have the highest 1.6 bid-ask spread, with the highest OAS of 198.54. However, the BBB bond has the highest bid-ask spread of 2.61 and the highest OAS at 2223.47.

The **duration** measures the bonds' sensitivity to the interest rate in percentage [3]. The higher the duration, the more potential risks when interest rates change. The 75% percentile of the dataset's duration is 12.31%, and 25% of the duration is 4.46%. The **DV01** measures the bonds' sensitivity to the interest rate in the dollar units [3]. In the dataset, the 75% percentile is \$0.12, and 25% of the duration is \$0.045.

Finally, the **daily return** reflects the bond's profit or loss percentage over a day, which is critical for investors tracking short-term performance. A risky bond (with a high OAS and lower rating) would have a higher daily return.

## B. EDA process

### 1. *Performance of the Bonds based on Ratings*

The EDA process grounded the methodology of identifying the undervalued bond. We started the EDA with a simple question: what is the performance of the different rating bonds? We used the distribution plots for further analysis, as shown in Figure 1. It has shown the coupon distribution by rating and found that the BBB held the most density at a high coupon rate of 5.0%. Additionally, we checked the OAS across the ratings and found that despite the BBB bonds having a higher OAS range, the majority range shares a similar level as the high-rating bonds. This information indicates that some lower-rating bonds share the same level of risk as high-rating bonds, indicating the existence of undervalued bonds.

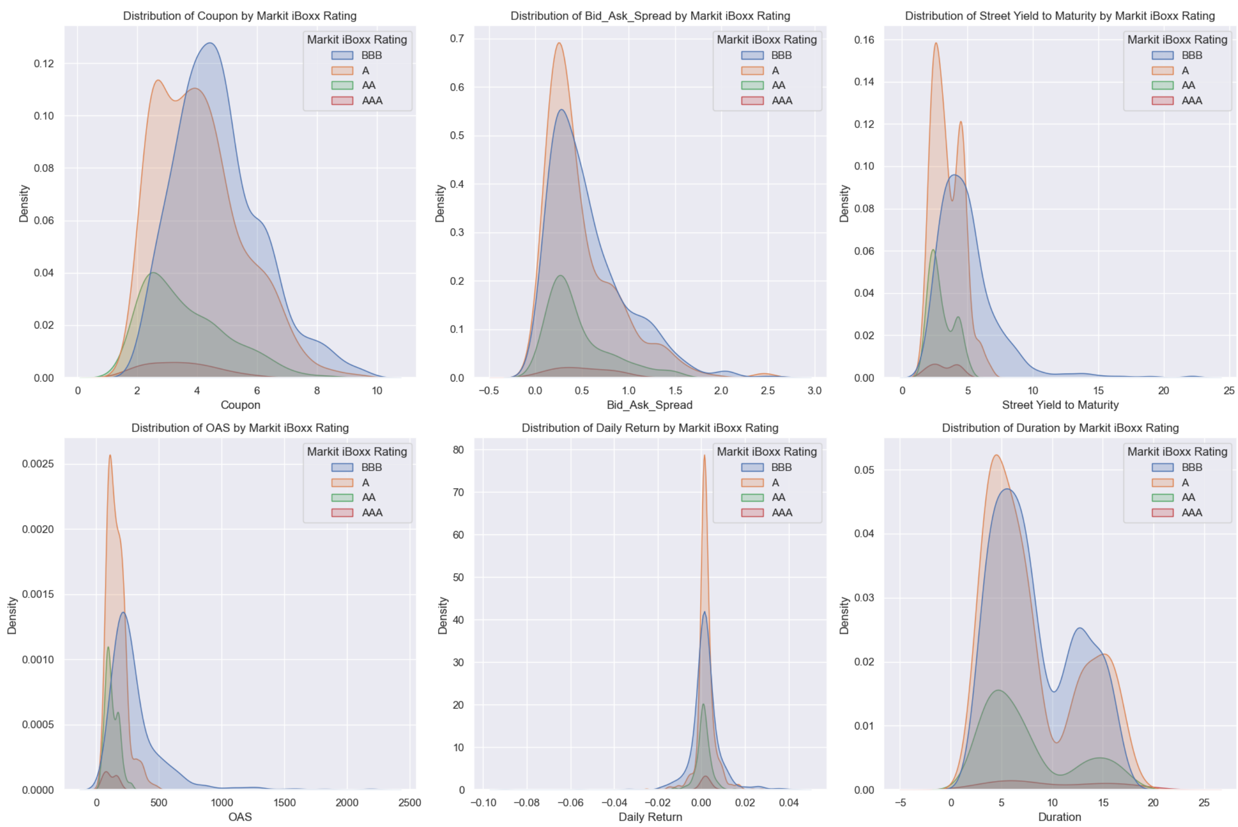


FIG. 1. Comparative Distributions of Key Financial Metrics by Bond Rating from Markit iBoxx

### 2. *Performance of two different Markets*

Following our initial investigation, we distinguished distinct behaviour patterns within financial and non-financial markets. AAA-rated bonds predominantly originated from non-financial institutions, with an impressive 97% share attributed to the technology sector. This observation naturally led us to explore further: How does the performance between these two markets differ?

Our analysis employed network visualisation, linking ratings to respective institutions, as depicted in Figure 2. It becomes apparent that, despite AAA bonds, most BBB and A-rated bonds are within non-financial institutions. In contrast, financial institutions display a majority of A-rated bonds. This contrast offers a tangible point of comparison. We assumed that the overvalued or undervalued bonds would caused by the different markets' integration.

For a deeper comparison, we employed network eigenvector centrality to determine the influence and connectivity of the various nodes within the network. Assume we have an adjacency matrix $\mathbf{A}$ of the network G with the number of nodes n, and we used $\mathbf{v}_e$ to represent the eigenvector and $\lambda$ for the largest eigenvalue of $\mathbf{A}$, then we can have the following [6]:

$$\mathbf{v}_e \cdot \mathbf{A} = \lambda \cdot \mathbf{v}_e$$

Here, $\mathbf{v}_e$ can be composed of individual components that represent the centrality scores of the nodes, described as follows [6]:

$$\mathbf{v}_e = [v_{e1}, v_{e2}, \cdots, v_{en}]$$

The eigenvector centrality score for a given node $u$ can be expressed as [6]:

$$v_e(u) = \frac{1}{\lambda} \sum_{j=1}^{n} \mathbf{A}_{ij} v_{ej}$$

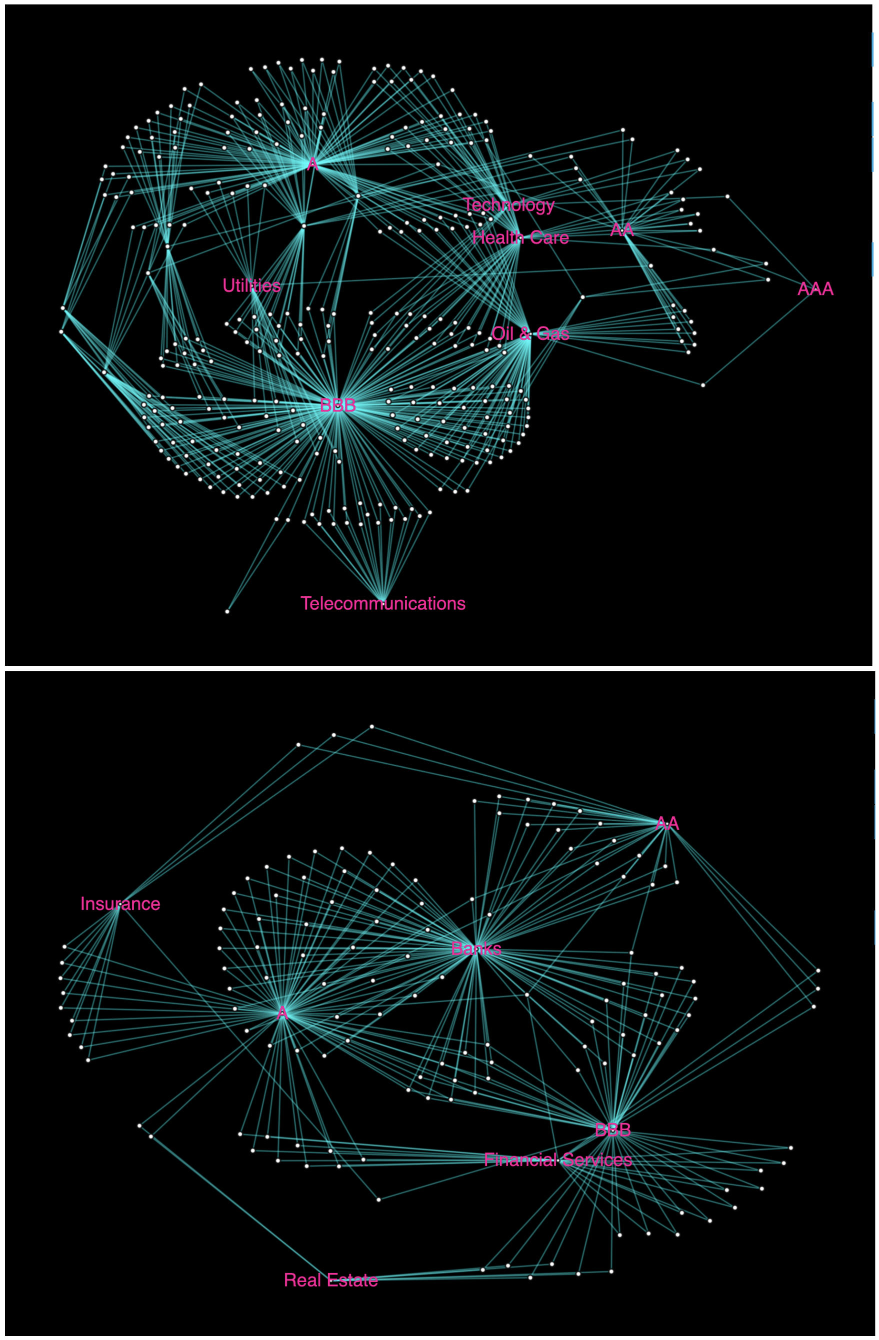


FIG. 2. Network Analysis on Markit iBoxx in Non-Financial (Top) and Financial (Down): white nodes without text labels indicated the institutions, and the white nodes with text labels indicated the Markit iBoxx rating and the institution sectors

The eigenvector centralities measure the influence based on the number and quality of links or the role of nodes as bridges in the network [6]; it also captures the power of a node with other highly connected nodes. This makes it an optimal measure for understanding the influence of the institutions and, therefore, identifying which nodes have higher connectivity to the others. As a result, we collected the top ten institutions with high eigenvector centrality for further investigation, as shown in Table I. Furthermore, it was observed that these institutions are associated with more than one bond rating.

TABLE I. Top 10 Eigenvector Centrality Scores of Financial and Non-Financial Institutions

| Financial | **Issuer** | **Eigenvector Centrality** |
|---|---|---|
| | Morgan Stanley | 0.094 |
| | Goldman Sachs Group Inc | 0.094 |
| | Citigroup Inc | 0.094 |
| | Bank of America Corp | 0.094 |
| | BNP Paribas | 0.094 |
| | Barclays Bank PLC | 0.094 |
| | Fifth Third Bancorp | 0.094 |
| | Deutsche Bank AG | 0.094 |
| | US Bancorp | 0.085 |
| | UBS AG/Stamford Branch | 0.077 |
| Non-Financial | **Issuer** | **Eigenvector Centrality** |
| | Canadian Natural Resources Limited | 0.062093 |
| | Enterprise Products Operating LLC | 0.062093 |
| | Williams Partners LP | 0.062093 |
| | Ensco PLC | 0.062093 |
| | Plains All American Pipeline L.P. | 0.062093 |
| | Williams Cos Inc | 0.062093 |
| | Williams Partners L.P. | 0.062093 |
| | Deutsche Bank AG | 0.062093 |
| | Sunoco Logistics Partners Operations LP | 0.062093 |
| | Phillips 66 | 0.062093 |

*3. Network analysis on Features*

Subsequently, we did the correlation analysis of selected variables to understand the impact of the OAS on the index price, YTM, and coupon rate. We used the Pearson correlation to identify the linear relationship between the two variables. We chose to use $x$ and $y$ to represent the variables and L to represent the number of observations; the Pearson correlation score can be represented as follows [7]:

$$r = \frac{\sum_{i=1}^{L}(x_i - \bar{x}) \cdot (y_i - \bar{y})}{\sqrt{\sum_{i=1}^{L}(x_i - \bar{x})^2} \cdot \sqrt{\sum_{i=1}^{L}(y_i - \bar{y})^2}}$$


FIG. 3. Network of Interrelationships Among Key Bond Market Metrics: each node represents the metrics, with a 0.4 Correlation Threshold

Figure 3 illustrates that our findings revealed a tangible link between the OAS and the index price and YTM, highlighting a direct relationship. Furthermore, the bid-ask spread was directly associated with the coupon rate, which correlates with YTM. In this configuration, YTM serves as a pivotal intermediary, building a connection between the index price and the coupon rate, thereby underlining its central role in the network of financial variables. To better understand the network graph, we measured the centrality according to closeness, betweenness, and eigenvectors.

The closeness centrality measures how the nodes interact with the other nodes; imagine we have a node $u_i$ and $d(u_i, u_k)$ represents the shortest path distance between $u_i$ to $u_k$, then we have [6]:

$$v_c(u) = \frac{n-1}{\sum_{\substack{i=1 \\ k=1 \\ i \neq k}}^{n-1} d(u_i, u_k)}$$

The betweenness centrality measures the frequency of a node on the shortest path between the other nodes. The higher the betweenness, the higher the frequency with which the node acts as a bridge. We used the $N(u_i, u_k)$ to represent the number of the shortest paths from $u_i$ to $u_k$, and $N(u_i, u_k|uj)$ to represent the number of the shortest path from $u_i$ to $u_k$ by crossing through the node $u_j$. Therefore, we can calculate the betweenness as follows [6]:

$$v_b(u) = \sum_{\substack{i=1 \\ j=1 \\ i \neq j}}^{n} \sum_{\substack{k=1 \\ k \neq i \\ k \neq j}}^{n} \frac{N(u_i, u_k|uj)}{N(u_i, u_k)}$$

As shown in Table II, we could see that the YTM has the highest betweenness centrality, which verifies the assumption and observation we made previously. We also identified the high value in Closeness Centrality for YTM and Coupon, indicating they play a central role in the network. We then found that duration and OAS have an exceptionally high value in Eigenvector Centrality and Degree Centrality, indicating critical factors in bond pricing.

TABLE II. Centrality Measures of Financial Metrics in a Bond Market Network

| **Metrics** | **Eigenvector** | **Closeness** | **Betweenness** |
|---|---|---|---|
| Coupon | **0.49** | **0.50** | 0.11 |
| Bid-Ask spread | 0.40 | 0.37 | 0.00 |
| YTM | 0.38 | **0.50** | **0.28** |
| Duration | **0.49** | **0.50** | 0.11 |
| DV01 | 0.40 | 0.37 | 0.00 |
| Index Price | 0.15 | 0.25 | 0.00 |
| OAS | 0.15 | 0.25 | 0.00 |

Upon completing the EDA, we found several insights from the dataset. The analysis emphasises that the OAS exercises an intelligible influence on the index price, exhibiting a robust correlation with the YTM. The network also suggests an indirect connection between the Coupon rate and the OAS. These indicate that YTM and OAS hold the potential to be critical determinants in identifying bonds as either undervalued or overvalued.

### C. General Model (Model-G) Description

As the EDA discovered, we identified the performance difference between the different markets and different ratings. We were also able to find the correlation between the different features. This section will propose a methodology for identifying undervalued and overvalued bonds. Then, we will also bring a methodology to test the result and measure how valuable and trustworthy our proposed method is. The structure of the method has been shown in Figure 4.

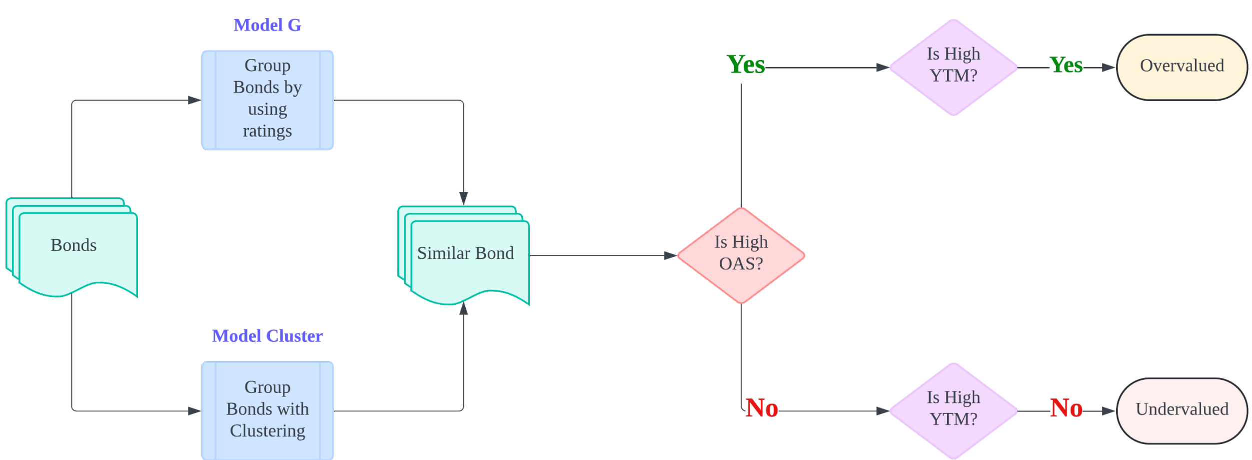


FIG. 4. Architecture of both models

The two models were based on one general idea: analysing similar bonds to identify overvalued and undervalued bonds by analysing the OAS and YTM. The difference between the two models is how to identify similar bonds.

### 1. *Method on determinating Undervalued Bonds*

Firstly, we defined the undervalued bonds we were looking for. An undervalued bond should demonstrate a relatively 'high' OAS score within its rating category, indicating that it offers a higher yield than similar rating bonds, suggesting being undervalued. Typically, from the EDA result, higher yields could imply higher risk, leading investors to demand higher compensation. The low expected yield (low YTM) despite the higher risk (high OAS) presents a potential abnormality. This combination suggests that the bond might be undervalued, as it offers higher returns than its equivalents without a corresponding decrease in marketability.

The next question is, how do we identify a 'high' OAS score? As we discussed, the different ratings have different levels of 'high' OAS scores, and no fixed 'high' or 'low' OAS scores. The most intuitive way would be to find the medium value of the OAS in a rating group and then take a score higher than the medium value as the high OAS score. However, Figure 5 shows the distribution of OAS and YTM from a percentile perspective. We can observe that the medium value of OAS shows different value ranges across the ratings, and in contrast, the medium in YTM provides similar values.

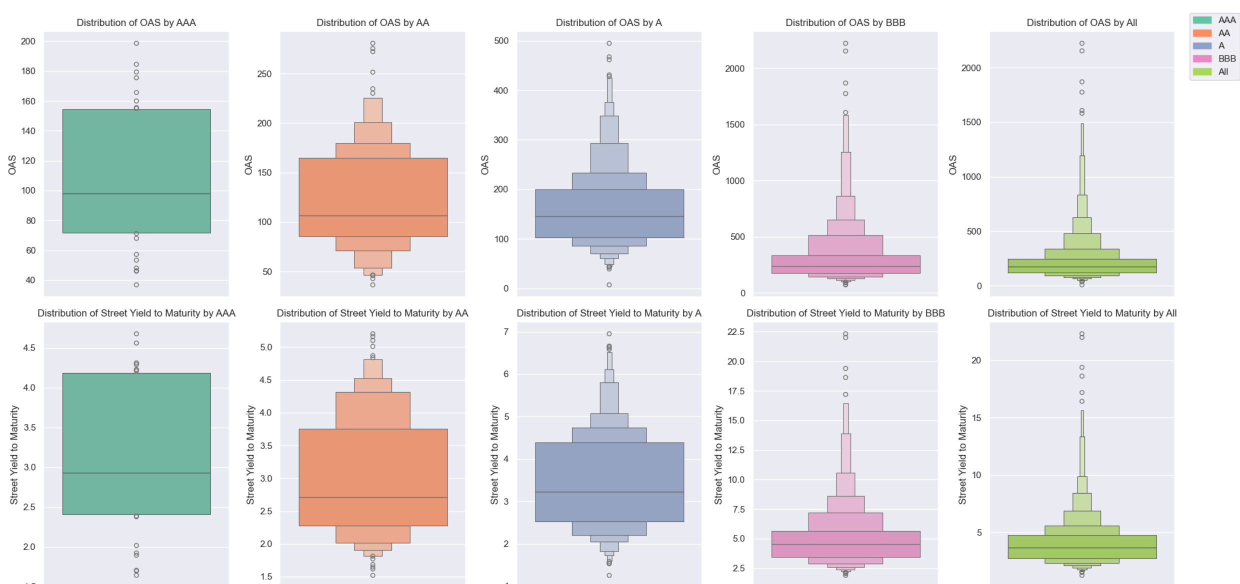


FIG. 5. Comparative Distribution of OAS and YTM Across Bond Ratings

Consequently, we found that the 75th percentile is a separation line dividing the upper quartile, which represents the top 25% of OAS scores. Furthermore, the median, or 50th percentile, could be applied to show the central tendency of the YTM. Therefore, we can define the 'high' OAS as above the 75th percentile and the 'low' OAS as the below 25th percentile; similarly, above the 50th percentile is the 'high' YTM, and below as the 'low' YTM.

### *2. Method on determinating Overvalued Bonds*

Similar to identifying undervalued bonds, defining overvalued bonds is crucial. Considering its risk profile, an overvalued bond is priced higher than its intrinsic value. This discrepancy may arise when a bond's expected yield (YTM) does not adequately reflect its actual risk, as assessed through detailed analysis, including its credit rating, interest rate sensitivity (duration), YTM, and OAS. If a high rating bonds with a relatively low OAS, indicating a relatively lower risk, but with a relatively higher YTM, we considered the bond overvalued. Similar in the previous section, we identified lower OAS (75th quantile), and then we found the bonds with the higher YTM, which is over the 50th quantile of the whole dataset.

## D. Alternative Model (Model-Cluster) Description

In our standard approach, bond ratings served as the criterion for distinguishing similar bonds, enabling the identification of those overvalued or undervalued. This section will introduce an alternative methodology for classifying bonds by employing clustering techniques. The adoption of clustering is justified by its ability to manage unlabeled data and its efficacy in categorising items with similar characteristics into groups that directly align with our objectives [8].

We chose to use Agglomerative Clustering, a hierarchical method that considers each data point as an individual cluster and merges them until a single comprehensive cluster remains [8]. The pseudocode has been provided as follows:

**Algorithm 1** Agglomerative Clustering

$clusters \leftarrow$ create a cluster for each data point

$distance\_matrix \leftarrow$ compute distances between all clusters

**while** Length(clusters) $> 0$ **do**

  $(cluster_i, cluster_j) \leftarrow$ find the pair of clusters with the smallest distance

  $new\_cluster \leftarrow$ merge $cluster_i, cluster_j$ into a new cluster

  remove $cluster_i, cluster_j$ from $clusters$

  add $new\_cluster$ to $clusters$

  update $distance\_matrix$ from the new cluster

**end while**

**return** $clusters$ =0

This method is favoured over others, such as K-Means, for several reasons. Firstly, it clusters from the bottom-up and does not depend on the number of pre-defined clusters, which provides convenience [8]. Secondly, it offered a visible, hierarchical structure of clusters and, therefore, enhanced the explainability of the model. As shown in Figure 6, the dendrogram of cluster 5 shows the better similarity within clusters.

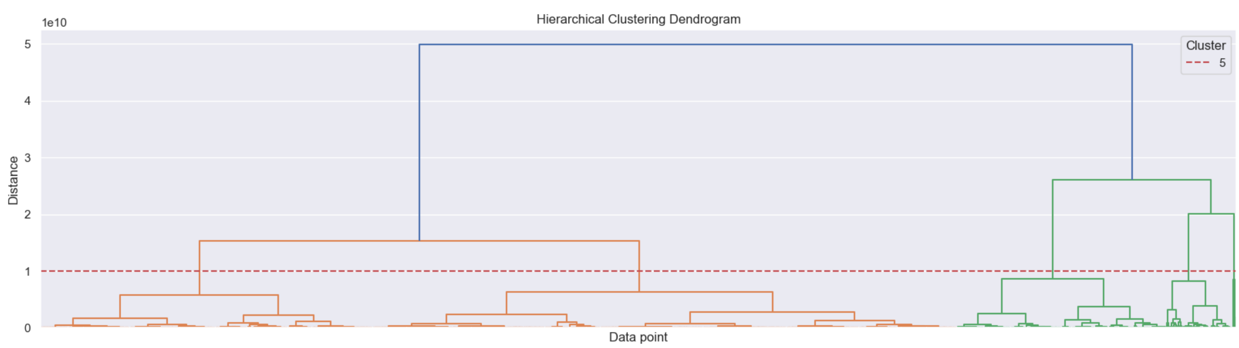


FIG. 6. Dendrogram Highlighting Cluster 5 as the Basis for Identifying Similar Bonds

We then employed silhouette score evaluations to verify the optimal number of clusters. The silhouette score measures the similarity from each data point to each cluster. We denoted individual silhouette score as $s_i$, $avg_i$ to represent the average distance from $i$ th datapoint to others under the same cluster, and $low_i$ to represent the lowest average distance from $i$ th datapoint to others under the different cluster, then we have the following equation

[9]:

$$s_i = \frac{low_i - avg_i}{max(avg_i, low_i)}$$

After calculating the silhouette score in each data point, we assumed there were $p$ data points and calculated the mean value of the silhouette scores. Therefore, we have the following equation [9]:

$$s = \frac{1}{p} \sum_{i=1}^{p} s_i$$

We calculated the silhouette score of 5 clusters, as **0.56**, which suggests the data points have well balanced matched to its clusters and the other clusters. After that, we applied the same methodology as described previously to determine the overvalued and undervalued bonds. Finally, we found three overvalued bonds and five undervalued bonds.

### E. Null Model Description

In our baseline model, we randomly selected an equivalent number of bonds to match the sample size yielded by the preceding methodology. If our model provides the same distribution as shown in the null model, we would not consider the valuation of our version of the model. Conversely, if our model does not have the same distribution as the null model, it also does not indicate a successful model. Instead, the objective of using the null model is to discard the non-valuable model.

### F. Justification Methodology

We then proposed a justification method to verify whether our methodology successfully identified the undervalued and overvalued bonds. First, we measured the DV01 and duration, two risk metrics, to verify whether the result makes logical sense. After that, we checked if the model prediction had a similar distribution to the null model, and therefore, we could discard the non-valuable model. However, this method did not check the precision of the results, and we will explain the reason in a later section.

## III. RESULTS

This section will first analyse the overvalued and undervalued bonds under both methodologies by checking different metrics like duration and DV01 to verify whether they are undervalued or overvalued.

In the Model-Cluster, we identified 5 undervalued bonds (80% Non-Financial, 20% Financial) and 3 overvalued bonds (66.7% Non-Financial, 33.3% Financial). In the Model-G, we identified 16 undervalued bonds (94% Non-Financial, 4% Financial) and 5 overvalued bonds (80% Non-Financial, 20% Financial). There are 3 overlapping bonds in the overvalued category and 1 in the undervalued category. We also found that none of them were rated AAA.

Figure 7 compared overvalued and undervalued bonds, the result generated by both models. Generally, the overvalued bonds hold a higher duration than the undervalued ones. Meanwhile, we also observed that overvalued bonds hold a higher DV01 than undervalued ones. It indicates that overvalued bonds may imply a higher risk profile regarding interest rate sensitivity and price volatility when compared to undervalued bonds.

We then used the null model to generate the overvalued and undervalued bonds randomly. We generated 21 bonds to match the total number of the bonds in the Model-G. Then, we did the same metric analysis as above, as shown in Figure 8. We can see that the randomly selected overvalued and undervalued bonds follow the different distributions in DV01 and duration, which indicates our model's result is not randomly selected.

We tried to find historical data to verify whether the bonds are overvalued or undervalued in the real world. However, most of the bonds had already been redeemed, and we could not find valuable data to verify the truth or precision of the result. We put the results in the Appendix but could not able to run a more profound analysis as we did not find the ground truth.

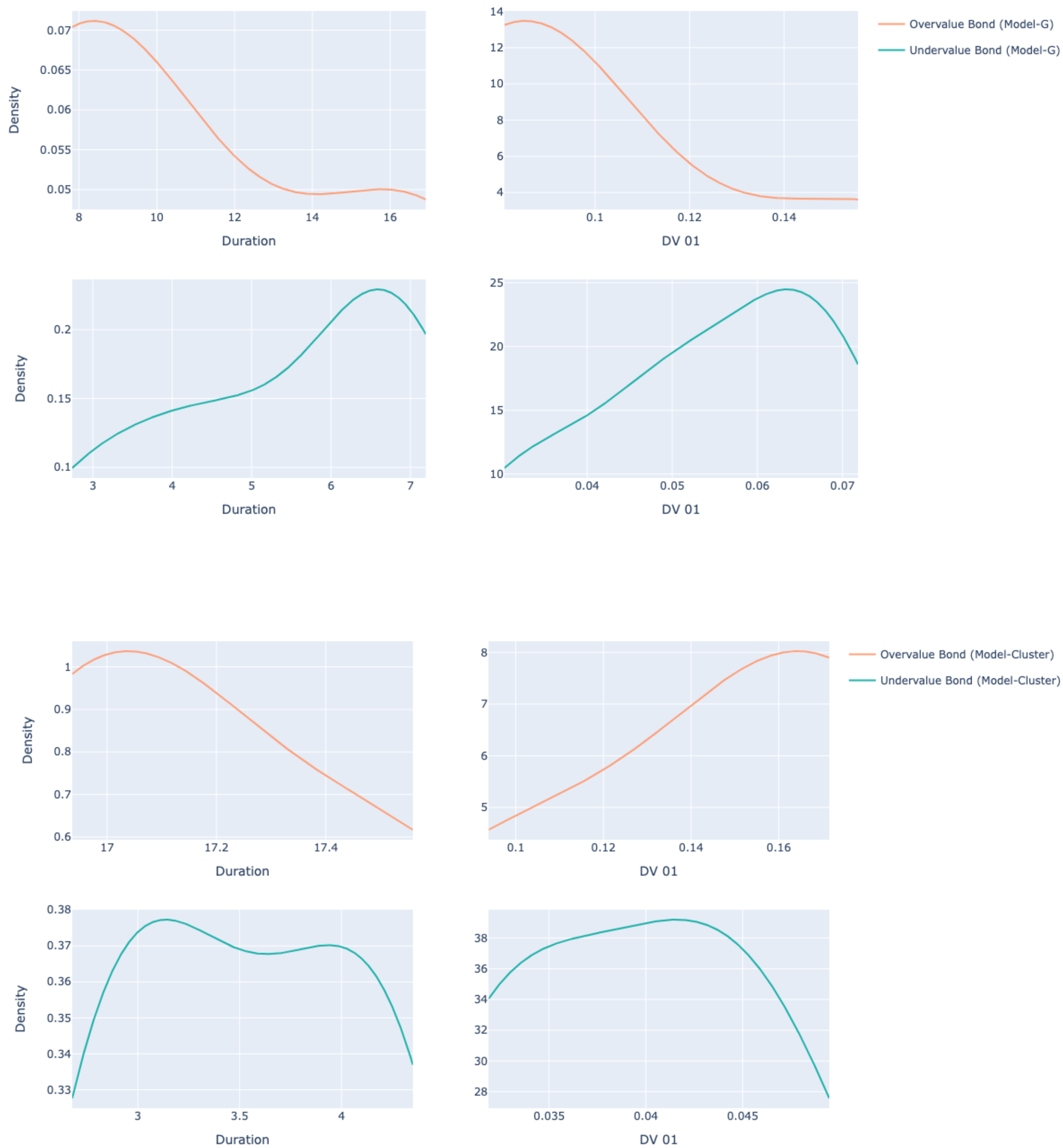


FIG. 7. Comparative Distribution Analysis of Overvalued and Undervalued Bond Metrics Using Model-G (Top) and Model-Cluster (Down)

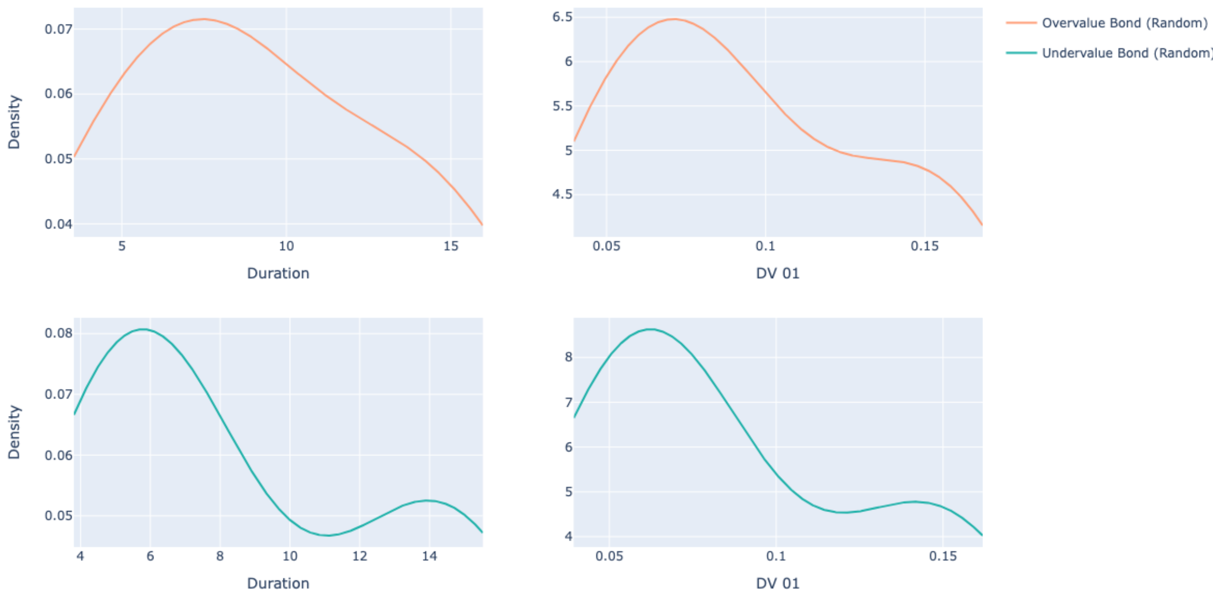


FIG. 8. Comparative Distribution Analysis of Overvalued and Undervalued Bond Metrics Using Null Model

## IV. DISCUSSION

In this section, we will compare the two proposed methods on the DV01 and duration and then comment on other interesting findings.

When comparing the two models (Figure 7), it becomes apparent that the Model-Cluster traces overvalued bonds with a broader duration distribution than the general method. This suggests that the clustering method better identifies potentially riskier overvalued bonds. Similarly, undervalued bonds identified through clustering indicate a shorter duration than those flagged by the general method, indicating lower interest rate risk. The DV01 metric corroborates these findings; the clustering method separates undervalued bonds with lower DV01 values, indicating less price sensitivity to yield changes. Conversely, the DV01 for overvalued bonds is higher when identified through clustering, signalling a heightened financial risk for small movements in yields.

We can also see that Model-Cluster only can identify the 8 bonds and Model-G can determine the 22 bonds, which we consider the Model-G can provide a broader range of potentially overvalued and undervalued bonds than the Model-Cluster. Furthermore, an intriguing pattern occurs within the mispriced bonds primarily classified as non-financial, with a significant portion from the Oil & Gas sector.

## V. CONCLUSION

In this study, we proposed two models to identify the overvalued and undervalued bonds on a day capture with the OAS and YTM. Then, we verified the result with the DV01 and duration and the comparison to the null model to ensure the result was not random. Although Model-Cluster can provide a risk in overvalued bonds, it can not provide a wide range of potential overvalued and undervalued bonds. We then identified that the Non-financial institutions were quickly overvalued and undervalued bonds, and most non-financial institutions were Oil & Gas.

### A. Limitations

There are also some limitations in this study. Firstly, the analysis lacks a strict precision test to verify the overvaluation or undervaluation of bonds, primarily due to a limited historical dataset. Additionally, our evaluation rests upon the assumptions regarding overvalued and undervalued bonds, which may not contain the full scope of the bonds' characteristics. Furthermore, the dataset is derived from a single-day snapshot, which prevents an in-depth exploration of variables such as spot price growth or YTM fluctuations. As a result, the insights garnered indicate immediate investment potential rather than long-term trends.

### B. Future Work

Regarding future work, we would like to collect more historical data on the bonds, run the same methodology, and verify the models' goodness. Secondly, we will combine more features to analyse the overvalued or undervalued bonds, which are not just based on the YTM and OAS. Furthermore, we would like to analyse further how non-financial institutions affect the bonds in general and focus more on how Gas & Oil are positively or negatively correlated with the other bond prices. Additionally, we would like to obtain time-series data of bonds from S&P to make a more precise analysis of the overvalued and undervalued bonds and, therefore, able to provide long-term investment suggestions.

---


[1] Vanguard, What is a bond?, https://investor.vanguard.com/investor-resources-education/understanding-investment-types/what-is-a-bond (2023), accessed: 2023-04-05.

[2] K. Bluwstein and J. Yung, Back to the real economy: The effects of risk mispricing on the term premium and bank lending, (2022).

[3] B. Tuckman and A. Serrat, *Fixed income securities: tools for today's markets* (John Wiley & Sons, 2022).

[4] P. Barclay, What is a aaa credit rating? (2023), accessed: 2023-04-06.

[5] G. Akhilesh, What is a bid-ask spread, and how does it work in trading? (2023), accessed: 2023-04-04.

[6] S. Bhattacharya, S. Sinha, P. Dey, A. Saha, C. Chowdhury, and S. Roy, Online social-network sensing models, in *Computational Intelligence Applications for Text and Sentiment Data Analysis* (Elsevier, 2023) pp. 113–140.

[7] J. J. Berman, Indispensable tips for fast and simple big data analysis, Principles and practice of big data , 231 (2018).

[8] A. Subasi, *Practical machine learning for data analysis using python* (Academic Press, 2020).

[9] P. J. Rousseeuw, Silhouettes: a graphical aid to the interpretation and validation of cluster analysis, Journal of computational and applied mathematics **20**, 53 (1987).

## Appendix A: Overvalued Bonds by Model-G

TABLE III. Overvalued Bonds Identified by Model-G

| Issuer | ISIN | Level 4 | Level 6 |
|---|---|---|---|
| Toyota Motor Credit Corp | XS1283509427 | Non-Financials | Automobiles & Parts |
| Kraft Heinz Foods Co | US423074AX14 | Non-Financials | Food & Beverage |
| McDonald's Corp | US58013MEY66 | Non-Financials | Travel & Leisure |
| Waste Management Inc | US94106LBC28 | Non-Financials | Industrial & Goods Services |
| ProLogis LP | US74340XBE04 | Financials | Real Estate |

## Appendix B: Undervalued Bonds by Model-G

TABLE IV. Undervalued Bonds Identified by Model-G

| Issuer | ISIN | Level 4 | Level 6 |
|---|---|---|---|
| Total Capital Canada Ltd | US89153UAF84 | Non-Financials | Oil & Gas |
| Statoil ASA | US85771PAK84 | Non-Financials | Oil & Gas |
| Statoil ASA | US85771PAG72 | Non-Financials | Oil & Gas |
| Total Capital International SA | US89153VAG41 | Non-Financials | Oil & Gas |
| Schlumberger Investment SA | US806854AH81 | Non-Financials | Oil & Gas |
| Shell International Finance BV | US822582AV48 | Non-Financials | Oil & Gas |
| Shell International Finance BV | US822582AX04 | Non-Financials | Oil & Gas |
| Statoil ASA | US85771PAF99 | Non-Financials | Oil & Gas |
| TOTAL CAPITAL INTERNATIONAL | US89153VAL36 | Non-Financials | Oil & Gas |
| BHP Billiton Finance USA Ltd | US055451AH17 | Non-Financials | Basic Resources |
| Occidental Petroleum Corp | US674599BY08 | Non-Financials | Oil & Gas |
| EOG Resources Inc. | US26875PAD33 | Non-Financials | Oil & Gas |
| HSBC Finance Corp | US40429CGD83 | Financials | Banks |
| TransCanada PipeLines Ltd | US893526DK63 | Non-Financials | Oil & Gas |
| Baker Hughes Inc | US057224BC05 | Non-Financials | Oil & Gas |
| TransCanada Corp | US8935268Y20 | Non-Financials | Oil & Gas |

## Appendix C: Overvalued Bonds by Model-Cluster

TABLE V. Overvalued Bonds Identified by Model-Cluster

| **Issuer** | **ISIN** | **Level 4** | **Level 6** |
|---|---|---|---|
| Eli Lilly & Co | US532457BJ65 | Non-Financials | Health Care |
| Toyota Motor Credit Corp | XS1283509427 | Non-Financials | Automobiles & Parts |
| Visa Inc | US92826CAF95 | Financials | Financial Services |

## Appendix D: Undervalued Bonds by Model-Cluster

TABLE VI. Undervalued Bonds Identified by Model-Cluster

| **Issuer** | **ISIN** | **Level 4** | **Level 6** |
|---|---|---|---|
| BHP Billiton Finance USA Ltd | US055451AH17 | Non-Financials | Basic Resources |
| HSBC Finance Corp | US40429CGD83 | Financials | Banks |
| Hewlett Packard Enterprise Co | US42824CAE93 | Non-Financials | Technology |
| Time Warner Cable Inc. | US88732JAP30 | Non-Financials | Media |
| Ford Motor Credit Co LLC | US345397VM25 | Non-Financials | Automobiles & Parts |