Using AI to Identify Relative Value Trading Opportunities in the US Credit Market

By Sai Teja Akula, Senior Director, Data Science, Broadridge and Fitim Kryeziu, VP, Data Insights, LTX, A Broadridge Company

August 2024

INTRODUCTION

In financial markets, volatility inherently presents opportunities, as fluctuating prices can result in misaligned pricing. Relative value (RV) analysis involves comparing the valuation of similar securities to identify bonds which are over- or under-valued compared to their peers based upon recent trading history. Evaluating RV opportunities can help traders generate fresh trade ideas, maximize alpha generation, and more effectively manage risk.

The increase in electronic trading has led to narrower spreads, making alpha generation more challenging. The proliferation of algorithms, capable of rapidly evaluating thousands of CUSIPs, has further complicated the landscape by swiftly identifying and neutralizing many arbitrage opportunities. Consequently, the speed at which arbitrages collapse is significantly faster than just a few years ago.

Traditionally, relative value has been assessed manually, using spreadsheets incorporating statistical methods and financial metrics. However, in today's increasingly sophisticated market, manual methods like human qualitative analysis and Excel modeling are often inadequate. While it's important to consider qualitative factors like a company's management, clients, geographic exposure, competition, corporate governance, and industry trends, it's improbable that an individual following a strictly qualitative approach can assess the entire universe of bonds with the speed and precision necessary to capitalize on trading opportunities.

With the increasing popularity of machine learning, more sophisticated anomaly detection techniques have become feasible, offering enhanced precision, speed and scalability. Many firms are developing advanced quantitative models to gain a competitive edge.

OUR APPROACH: MACHINE LEARNING POWERED RELATIVE VALUE ANALYSIS

At LTX, we've developed a relative value model, powered by machine learning, that is easily accessible via our natural language GenAI app, BondGPT. Our sophisticated approach uses an ensemble of six cutting-edge, published and publicly available linear and non-linear models to help users identify relative value trading opportunities in the US credit market.[1] Users can easily access the LTX relative value model via BondGPT, asking natural language questions to receive immediate answers that are constructed with mathematical rigor.

We have chosen to initially apply the LTX relative value model to a subset of the US investment grade corporate bond universe. Based on client feedback, we include only those bonds with more than $300 million outstanding because bonds with smaller deal sizes often lack sufficient trading activity, which may lead to poor liquidity and an inability to achieve the relative values produced by our model.

We collected historical data on bond prices and features, and clustered the bonds based on other important factors such as rating, sector and tenor as well as a number of secondary attributes. Then, we conducted feature engineering, extracting relevant features such as historical trends, bond characteristics, and market indicators to train our machine learning models. The approximately 12,000 bonds in our initial data set yielded approximately 77,000,000 pairs, which we further reduced through clustering analysis and ultimately evaluated by each of the six models to identify relative value opportunities.

DIVING INTO OUR APPROACH

To effectively harness the power of machine learning for relative value analysis, our ensemble model architecture incorporates six different models, each with its own temporal perspective and learning paradigm. This multifaceted strategy enables a more comprehensive examination of bond time series

---

[1] Local Outlier Factor Anomaly Detection Model, DBSCAN Model, Grubbs Test Anomaly Detection Model, Isolation Forest Anomaly Model, Z Score Model, Light GBM Model.

data. While the historical timeframe remains consistent across models, their temporal weighting schemes differ. Some models attribute equal significance to all data points within this timeframe, leveraging an egalitarian approach. In contrast, others utilize a decaying weight mechanism to emphasize more recent data points and current market dynamics.

Moreover, the models exhibit variation in their learning methodologies. A subset of our models engages in iterative self-learning processes, continuously refining their predictions using recursive feedback loops. This dynamic learning environment fosters adaptability, akin to the mechanisms observed in advanced machine learning systems. Alternatively, other models function as rigorous statistical engines, exhaustively parsing the entire dataset in a non-iterative manner. These models explore every possible permutation within the data, surfacing latent patterns and anomalies without iterative refinement, thereby providing a comprehensive statistical framework that complements the adaptive models.

The importance of utilizing a composite consensus approach to detect relative value trading opportunities effectively became apparent through our robust backtesting procedures. Figure 1, derived from our backtesting data, illustrates the relationship between our performance metrics (accuracy and opportunities) and the consensus thresholds of two, three, four, and five models. It reveals an inverse relationship between accuracy and the number of detected opportunities as the consensus threshold increases.

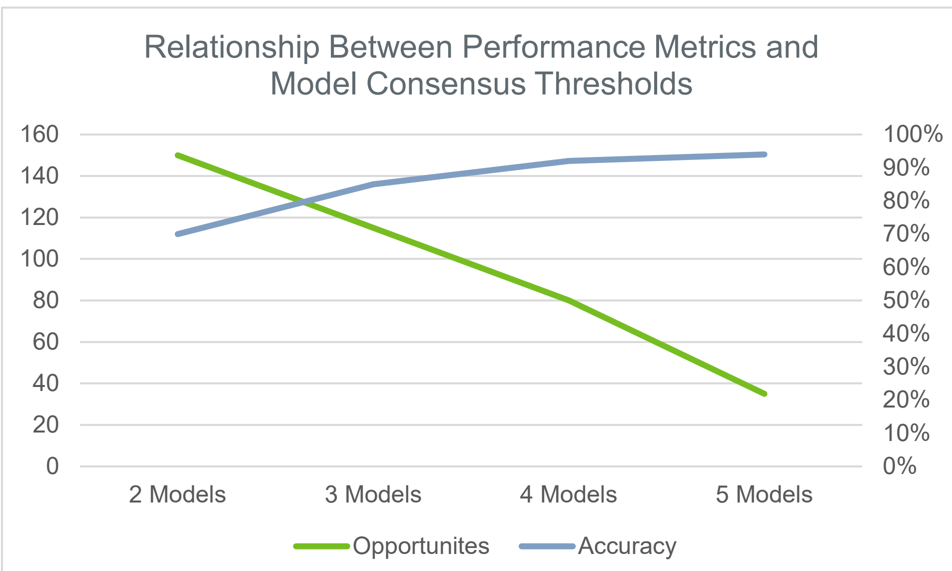

Figure 1.

When opportunities were flagged by only one or two models, a high incidence of false positives occurred: 30% of the 150 opportunities detected by the two-model consensus failed subsequent qualitative assessments, highlighting clear reasons why they were not viable trading opportunities.

Interestingly, detecting opportunities through a consensus of three models showed some improvement but still resulted in a high level of false positives, demonstrating insufficient robustness for reliable relative value identification. Extensive backtesting and pilot testing with users revealed that a three-model consensus still lacked the necessary rigor.

Consequently, we determined that a consensus of four models is optimal for robust relative value detection. Requiring agreement among four models significantly reduces false positives, ensuring flagged opportunities are both actionable and reliable. For instance, from the 77M pairs derived from the set of 12,000 bonds, a four-model consensus detected 80 opportunities which were 92% accurate, effectively balancing the need for precision and a manageable number of trading signals. This consensus strikes a balance by leveraging each model's unique strengths while mitigating their weaknesses.

When increasing the consensus requirement to five models, the approach became overly restrictive. Although accuracy exceeded 94%, it substantially increased sensitivity, excluding many potential trading opportunities. The five-model consensus detected 40 opportunities, a 50% decrease from the four-model consensus, emphasizing our finding that the four-model consensus achieves an ideal equilibrium by optimizing for both precision and detection.

As seen in Figure 1, there are intrinsic trade-offs in our ensemble model approach. Specifically, accuracy improves significantly from 70% with a two-model consensus to 94% with a five-model consensus. However, the number of detected opportunities decreases sharply from 150 with a two-model consensus to just 40 with a five-model consensus. As such, while a five-model consensus achieves the highest accuracy, it may exclude viable trading opportunities. Conversely, a two-model consensus detects the most opportunities but suffers from lower accuracy and higher false positives. Ultimately, the choice between maximal accuracy and broader detection depends on user preference. Some users may prioritize minimizing false positives, while others may prefer detecting more opportunities which they will subject to qualitative analysis. Our relative value model is designed to be flexible and adaptable, and BondGPT+ enterprise users can enable fine-tuning to meet their specific requirements.

UNPARALLELED ACCESS

LTX makes this sophisticated, machine-learning relative value model easily and quickly accessible through our award-winning GenAI-powered BondGPT application, launched in June 2023, which answers complex bond-related questions in seconds. BondGPT provides timely, accurate responses generated from the blending of multiple curated datasets and models simultaneously.

Within BondGPT, users can ask natural language questions to invoke the LTX relative value model. Unlike traditional methods that require a user to assess multiple spreadsheets or other data sources, it’s as simple as typing in a question like “Show me relative value opportunities in the 10 Year Tenor and Technology sector.”

Example Relative Value Questions

- Show me relative value opportunities in the 10 Year and Technology
- Show me relative value opportunities for bonds that have traded more than $50 million in TRACE yesterday
- Show me relative value opportunities for CUSIP X, CUSIP Y, CUSIP Z
- Show me RV opportunities in bonds that traded last month from issuers with revenue growth in 2023 greater than 5%

CONCLUSION

While automation and quantitative models provide calculations to assist financial professionals, the human element remains crucial for decisive action. In the present landscape where market participants are grappling with how to capitalize on new AI tools, platforms like LTX empower traders to more easily conduct a quantitative evaluation of RV opportunities, overlay their own qualitative assessment, and decide how to act, striking a balance between sophisticated machine learning and critical human judgment.

Our approach leverages the power of machine learning to enhance traditional, manual relative value analysis in bond markets. By using a diverse ensemble of six anomaly detection models, and requiring a consensus of at least four of the six models, users can quickly identify relative value opportunities in the vast universe of bonds based on their criteria. This methodology not only improves the accuracy of anomaly detection but also provides actionable insights for trading and risk management strategies in the US credit market.

