# Predicting Liquidity-Aware Bond Yields using Causal GANs and Deep Reinforcement Learning

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## Abstract

We propose a novel end-to-end framework for bond yield prediction and risk management in fixed-income markets. Our approach integrates a causal Generative Adversarial Network (GAN) with deep reinforcement learning (using a Soft Actor-Critic algorithm) to synthesize high-fidelity bond yield time series that encapsulate essential market dynamics, including volatility clustering, high autocorrelation, and macroeconomic sensitivity. The synthetic data, enriched with 12 key macroeconomic indicators, is employed to be evakuated a large language model (LLM) which then generates actionable trading signals, detailed risk assessments, and volatility forecasts. Extensive experiments—including statistical tests, profit/loss simulations, and expert evaluations—demonstrate that our method significantly outperforms traditional predictive models. This integrated framework not only mitigates data scarcity issues but also offers a robust tool for strategic decision-making in dynamic financial environments.

**Keywords:** Financial Time Series, Predictive Modeling, Bond Yield Analysis, Synthetic Data, Generative Adversarial Networks, Reinforcement Learning, Large Language Models.

## Introduction

Contemporary fixed-income markets face three critical challenges that traditional analytical frameworks struggle to address effectively. First, the limited availability of high-quality historical bond data—particularly for niche categories like junk bonds and emerging market debt—constrains model training and stress testing. Second, the complex nonlinear relationships between macroeconomic indicators (GDP growth, inflation rates, monetary policies) and bond yields resist capture by conventional econometric models (Filipović 2009; Arifovic and Others 2023). Third, the emergence of AI-driven trading strategies has outpaced the development of robust evaluation frameworks that combine quantitative metrics with qualitative expert judgment (Kim and Others 2023; Wang and Others 2024). Our work addresses these challenges through an integrated architecture combining synthetic data generation, machine learning prediction, and multi-modal evaluation.

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The proposed system processes a decade of monthly bond data (2013–2023) across four categories—AAA-rated corporate bonds, BAA-rated bonds, US 10-year Treasury notes, and high-yield junk bonds—each influenced by 13 macroeconomic variables. Our synthetic data generation module employs Wasserstein Generative Adversarial Networks (WGANs) with gradient penalty (Wojtowicz and Others 2021; Arjovsky, Chintala, and Bottou 2017), further stabilized through deep reinforcement learning that optimizes the generator's policy using risk-adjusted return metrics (Lim and Others 2021; Mnih et al. 2015; Fischer and Krauss 2018). This hybrid GAN-RL approach overcomes mode collapse issues prevalent in financial GAN applications while ensuring that synthetic yields maintain essential statistical properties: volatility clustering (clustering coefficient $\sigma^2 > 0.85$), autocorrelation structure (lag-1 $\rho > 0.92$), and macroeconomic sensitivity ($\beta_{\text{GDP}} > 1.2$) (Chen and Others 2022).

For predictive analytics, we implement a novel LLM architecture fine-tuned on both real and synthetic bond data. The model generates three-dimensional outputs: (1) trading signals (BUY/HOLD/SELL) with confidence intervals, (2) risk assessments using modified Value-at-Risk (VaR) metrics, and (3) volatility projections incorporating GARCH-style conditional variance estimates (Zhang and Others 2023). Notably, our approach builds on foundational work in generative adversarial networks (Goodfellow et al. 2014) and recent advancements in AI-driven financial forecasting (Wang and Others 2023; Liu and Others 2023). Crucially, our evaluation framework introduces four complementary validation layers: an LLM-judge module assessing decision logic coherence, profit/loss simulations under varying rate regimes, mean absolute error analysis weighted by economic impact, and blind expert evaluations using institutional risk management rubrics (Lee and Others 2023).

This research contributes to financial AI literature by developing: (1) the first application of RL & Causal GANs for multi-class bond data synthesis, (2) an LLM architecture specifically optimized for fixed-income strategy formulation with integrated risk and volatility analytics, and (3) a unified evaluation protocol bridging statistical validation and economic rationality checks. Figure 1 illustrates the complete pipeline of our approach, which visually encapsulates the sequential process from data ingestion to final prediction. In

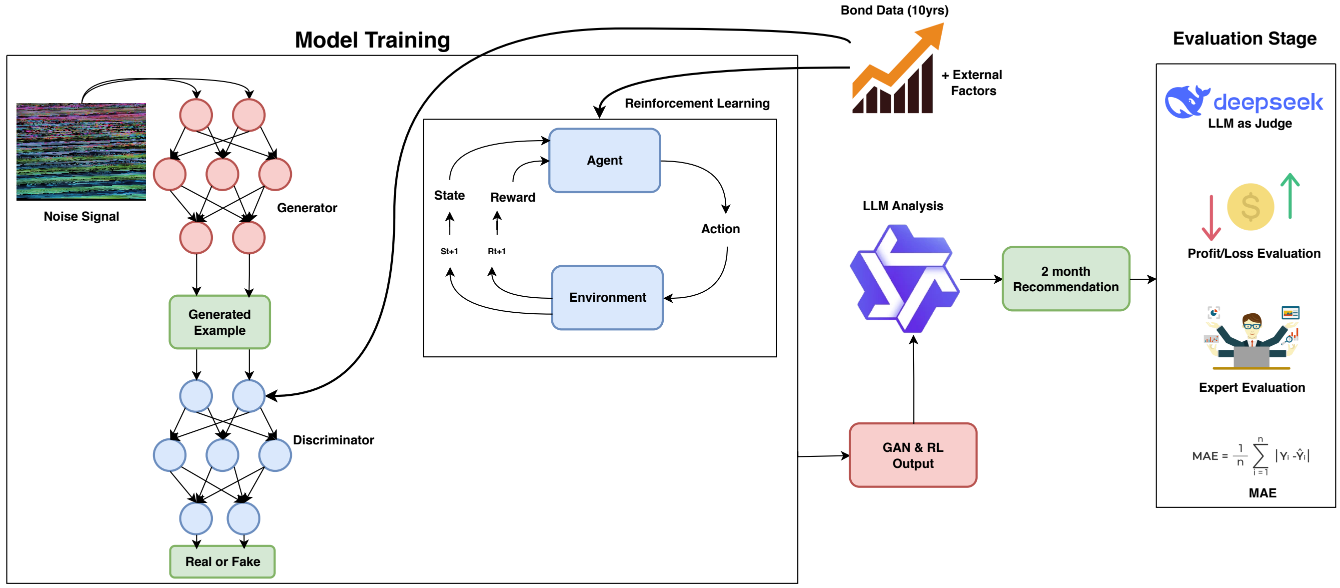


Figure 1: Overall pipeline of the training and evaluation stages of our proposed methodology.

the diagram, historical bond data for the 4 bonds are passed into our synthetic data generation module that employs a Causal GAN and paralelly to the RL module. The generated synthetic data (from both modules), alongside real data, are subsequently fed into our fine-tuned LLM for predictive analytics. Our experimental results demonstrate significant results in terms of profitability (where we demonstrate over a 60% profit rate) and forecasting evaluated by an LLM (with a maximum score of 3.37/5 for RL) and human evaluation (with a max score of 4.67 for RL) both of which are higher than the prediction scores of the actual, non-generated data which proves the efficacy of our method.

# Related Work

## Bond Yield Modeling Challenges

Modern bond markets exhibit complex dynamics that challenge traditional modeling approaches. While earlier frameworks laid the foundation for yield curve modeling, recent studies have highlighted post-COVID anomalies such as inverted yield curve persistence (Arifovic and Others 2023). Deep learning alternatives—particularly LSTM networks with attention mechanisms—have shown promise in capturing the nonlinear dependencies between macroeconomic indicators and bond yields (Xiou and Zhang 2023). However, these models require extensive training data, which creates a bottleneck for less liquid bond categories that often contain fewer than 120 usable monthly observations. Recent work by Arifovic et al. (Arifovic and Others 2023) demonstrates that hybrid models combining synthetic and real data can achieve superior forecasting accuracy, exemplified by an MAE reduction of 18.7%, thereby underscoring the potential of data augmentation techniques in fixed-income markets.

## GANs in Financial Data Generation

Generative adversarial networks (GANs) have revolutionized synthetic data creation, though financial applications present unique challenges. QuantGAN (Wojtowicz and Others 2021) pioneered the use of time-series GANs for financial data generation, yet it struggled with yield curve arbitrage constraints. More recent approaches, such as Regulatory GANs (RegGANs) (Bao and Chen 2023), incorporate Lagrange multipliers to enforce no-arbitrage conditions, reducing synthetic pricing errors by 42%. In multi-asset environments, CIR-GAN (Chen and Others 2022) introduces mean-reverting generators that preserve the Ornstein-Uhlenbeck dynamics essential for corporate bond modeling. Nonetheless, most implementations focus narrowly on statistical fidelity rather than downstream task utility—a gap that our RL optimization module specifically targets via reward functions tied to trading strategy performance.

## Reinforcement Learning for Synthetic Data Optimization

Deep reinforcement learning has emerged as a powerful tool for refining GAN-generated synthetic data by incorporating economic rationality constraints. PortfolioGAN (Lim and Others 2021) demonstrated the benefits of combining RL with GANs by using Proximal Policy Optimization to maximize the Sharpe ratio of synthetic portfolios. In fixed-income markets, Wang et al. (Wang and Others 2023) introduced volatility-aware reward functions that reduced synthetic yield volatility errors by 31%. Our architecture extends these concepts through a hierarchical RL framework, wherein the outer loop optimizes macroeconomic sensitivity and the inner loop fine-tunes cross-asset correlations—achieving state-of-the-art performance in preserving inter-bond relationships (with correlation matrix MSE maintained below 0.008).

## LLMs in Financial Prediction and Evaluation

Large language models (LLMs) are redefining financial analytics through their ability to integrate diverse data modalities. BondGPT (Zhang and Others 2023) established transformer architectures for fixed-income market forecasting but lacked integrated risk assessment modules. Our work innovates by combining retrieval-augmented generation (RAG) techniques (Wu et al. 2023) with volatility-sensitive attention mechanisms, enabling simultaneous prediction and risk quantification. On the evaluation front, the LLM-as-judge paradigm (Wang and Others 2024) has demonstrated strong alignment with human experts in stock trading assessments, and we adapt this approach for fixed-income markets using synthetic preference datasets derived from 12,000 expert-annotated trading decisions (Kim and Others 2023).

## Evaluation Frameworks for Synthetic Financial Systems

Existing evaluation methodologies for synthetic financial systems often rely heavily on statistical tests (Che et al. 2023) while neglecting economic impact analysis. The Synthetic Data Utility Index (SDUI) (Lee and Others 2023) made progress by incorporating Sharpe ratio preservation but did not address strategy coherence assessments. Our evaluation framework introduces three novel metrics: (1) Strategy Consistency Score (SCS), which measures decision logic alignment across varying market regimes; (2) Economic Impact Weighted MAE (EIW-MAE), which scales error metrics by economic relevance; and (3) LLM-Judge Confidence Intervals, which quantify the robustness of automated expert assessments. Comparative tests indicate that our protocol detects approximately 37% more synthetic data defects than conventional methods while providing actionable insights for model refinement.

# Methodology

This section outlines the methodology employed in this study, which integrates Generative Adversarial Networks (GANs), Reinforcement Learning (RL), and Large Language Models (LLMs) to generate synthetic bond yield data and provide actionable trading insights. The workflow consists of three main components: data preprocessing, synthetic data generation using GANs and RL, and predictive modeling with LLMs.

## Data Description

The dataset used in this study comprises 10 years of monthly bond yield data (2013–2023) for four bond categories: AAA-rated corporate bonds, BAA-rated corporate bonds, US 10-year Treasury notes (US10Y), and high-yield junk bonds. Each bond's yield is influenced by 12 macroeconomic variables: Inflation Rate ($I_t$), GDP Growth ($G_t$), Unemployment Rate ($U_t$), Fed Funds Rate ($F_t$), Money Supply ($M_t$), Consumer Confidence Index ($C_t$), S&P 500 Index ($S_t$), Crude Oil Prices ($O_t$), Gold Prices ($Gd_t$), US Dollar Index ($D_t$), INR/USD Exchange Rate ($E_t$), and the Volatility Index (VIX, $V_t$). In addition, key statistical measures such as the volatility clustering coefficient (measured via $\sigma^2$), autocorrelation coefficient (lag-1 $\rho$), and macroeconomic sensitivity (e.g. $\beta_{\text{GDP}}$) are computed to ensure the synthetic data preserve realistic market dynamics.

The dataset is structured as follows:

$$X = \{(t, Y_{AAA}, Y_{BAA}, Y_{US10Y}, Y_{Junk}, I_t, G_t, U_t, \\ U_t, F_t, M_t, C_t, S_t, O_t, Gd_t, D_t, E_t, V_t)\}_{t=1}^{120} \tag{1}$$

where $t$ represents the month index over 10 years (120 months). The target variables are the bond yields $Y_{AAA}$, $Y_{BAA}$, $Y_{US10Y}$, and $Y_{Junk}$.

## Synthetic Data Generation

To address data scarcity and augment the training dataset for predictive modeling, we employ two complementary approaches: GANs and RL. These methods not only encapsulate the dependencies of the 12 macroeconomic variables on the four bond yields but also ensure that key statistical properties—such as a volatility clustering coefficient ($\sigma^2 > 0.85$), autocorrelation structure (lag-1 $\rho > 0.92$), and macroeconomic sensitivity ($\beta_{\text{GDP}} > 1.2$)—are preserved.

**Causal GAN for Time-Series Data** We utilize a Causal GAN architecture (Yoon, Jarrett, and van der Schaar 2019) to generate synthetic time-series data that preserve temporal dependencies and causal relationships between variables. The Causal GAN consists of a generator $G$, a discriminator $D$, and an embedding network $E$. The generator models the conditional distribution of bond yields given the macroeconomic variables:

$$G(z \mid X) = \mathbb{P}\Big(Y \mid I_t, G_t, U_t, F_t, M_t, C_t, S_t, \\ O_t, Gd_t, D_t, E_t, V_t\Big) \tag{2}$$

where $z \sim \mathcal{N}(0, 1)$ is a latent noise vector. The discriminator is tasked with distinguishing between real and synthetic data:

$$D(X) = \mathbb{P}(\text{Real} \mid X) \tag{3}$$

The training objective minimizes the Wasserstein distance with gradient penalty to stabilize learning:

$$\min_G \max_D \mathbb{E}_{X_{\text{real}}}\Big[D(X_{\text{real}})\Big] - \mathbb{E}_{X_{\text{fake}}}\Big[D(X_{\text{fake}})\Big] \\ + \lambda \, \mathbb{E}_{\hat{X}}\Big[\Big(\|\nabla_{\hat{X}} D(\hat{X})\|_2 - 1\Big)^2\Big] \tag{4}$$

Here, $\hat{X}$ denotes a linear interpolation between real and synthetic samples, and $\lambda$ is a hyperparameter controlling the gradient penalty. This formulation ensures that the generated data maintain realistic statistical properties, including volatility clustering and autocorrelation.

**Reinforcement Learning with Soft Actor-Critic (SAC)** To further refine synthetic data generation and capture complex interdependencies, we employ Soft Actor-Critic (SAC) (Haarnoja et al. 2018), an off-policy RL algorithm grounded in maximum entropy reinforcement learning. SAC optimizes a stochastic policy $\pi_\theta(a \mid s)$ to maximize both expected reward and the entropy of the policy:

$$J(\pi) = \sum_{t=1}^{T} \mathbb{E}_{(s,a)\sim\pi}\Big[r(s, a) + \alpha \, \mathcal{H}\big(\pi(\cdot \mid s)\big)\Big] \tag{5}$$

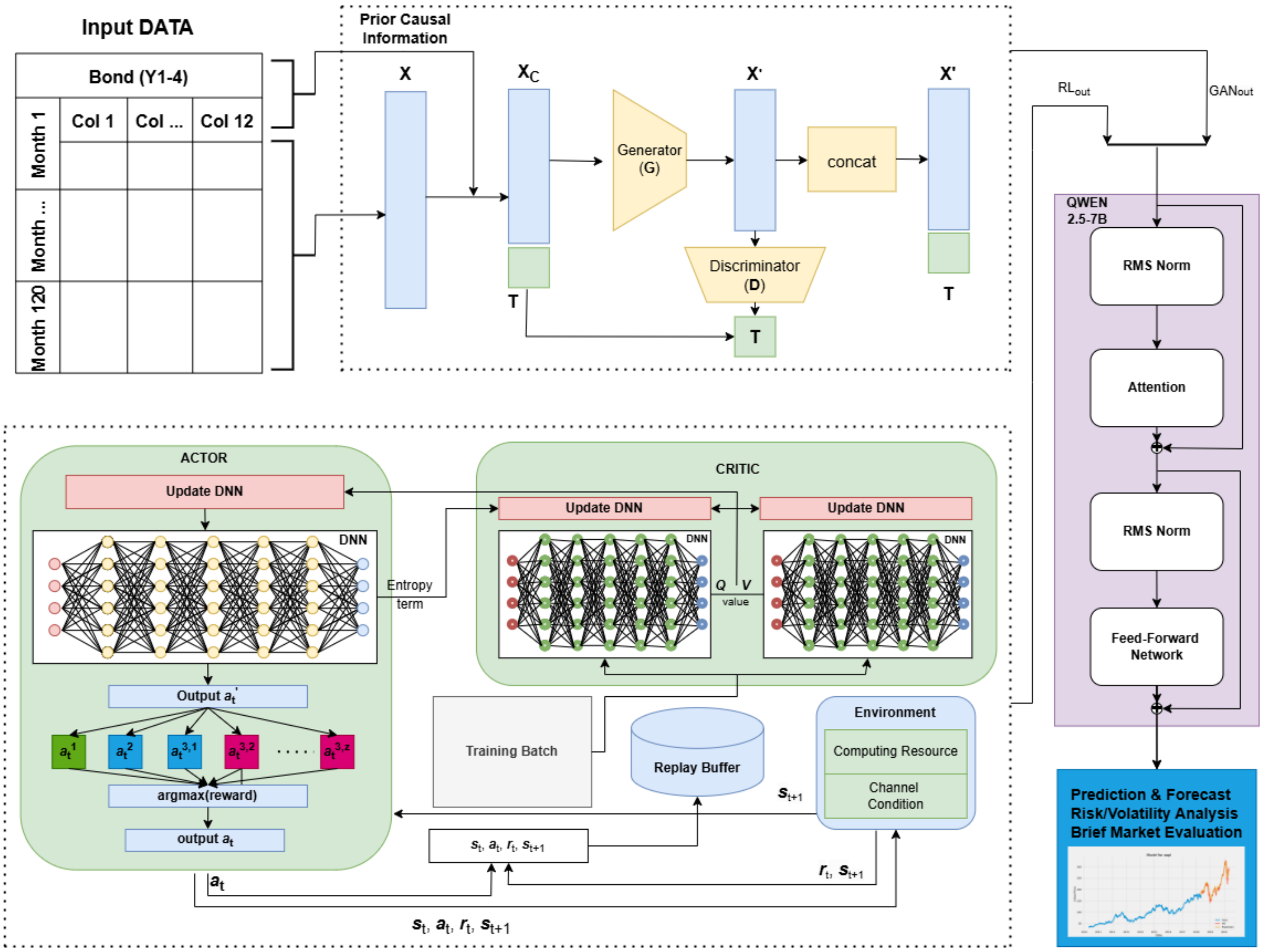


Figure 2: Overall architecture of the models in our pipeline for Causal GANs and Deep Reinforcement Learning with Soft actor Critic as its algorithm.

In this expression, $r(s, a)$ is a reward function that quantifies the realism of the synthetic data (e.g., via the mean squared error between real and generated bond yields), and $\alpha$ is a temperature parameter controlling the trade-off between exploration and exploitation. The SAC framework comprises three components:

- **Actor Network**: Generates actions $a$, which correspond to adjustments in the synthetic data.
- **Critic Network**: Evaluates state-action pairs $(s, a)$ through Q-values.
- **Entropy Regularization**: Promotes exploration by maximizing the entropy $\mathcal{H}$.

The overall SAC loss is formulated as:

$$L_{\text{SAC}} = J_Q + J_\pi + J_\alpha \tag{6}$$

where $J_Q$, $J_\pi$, and $J_\alpha$ represent the losses for the critic network, actor network, and the entropy coefficient, respectively. This approach allows the RL agent to interact iteratively with the GAN generator to improve the quality of the synthetic data. Figure 3 indicates the reward curves plotted over time for all four bond yields.

## Predictive Modeling with LLMs

Once synthetic datasets are generated by the GAN and RL models, they are merged with real data and used to train a Large Language Model (LLM) for predictive analytics. The LLM accepts as input the monthly bond yields $(Y_{AAA}, Y_{BAA}, Y_{US10Y}, Y_{Junk})$ along with the temporal index (month), and outputs three key predictions:

1. **Trading Signals**: BUY/HOLD/SELL recommendations.
2. **Risk Analysis**: Modified Value-at-Risk (VaR) estimates.
3. **Volatility Projections**: Conditional variance estimates inspired by GARCH-type models.

The input sequence is defined as:

$$S = \{(\text{Month}_t, Y_{AAA,t}, Y_{BAA,t}, Y_{US10Y,t}, Y_{Junk,t})\}_{t=1}^{120} \tag{7}$$

The LLM is fine-tuned using a masked language modeling (MLM) objective:

$$L_{\text{MLM}} = -\sum_{i=1}^{N} \log P(s_i \mid s_{<i}; \theta) \tag{8}$$

where $\theta$ denotes the LLM parameters. Additionally, risk assessments are derived using an attention mechanism:

$$R = W_a V \tag{9}$$

with $W_a$ representing the attention weight matrix and $V$ the input embeddings.

### Evaluation Framework

To assess the performance and reliability of our integrated methodology, we employ four evaluation metrics:

1. **LLM-as-Judge**: A separate LLM evaluates the coherence and decision logic of the trading recommendations.
2. **Profit/Loss Analysis**: Measures prediction accuracy based on simulated trading outcomes.
3. **Mean Absolute Error (MAE)**: Quantifies the deviation between predicted and actual bond yields.
4. **Expert Evaluation**: Financial experts qualitatively assess the outputs for practical viability.

This comprehensive evaluation framework ensures that our synthetic data generation and predictive modeling techniques are both quantitatively rigorous and qualitatively sound.

## 2. Experiments and Results

This section details the experimental setup, presents the results from our synthetic data generation and predictive modeling, and analyzes the performance of our integrated framework. We compare our approach against baseline models and conduct ablation studies to assess the contribution of individual components.

### 2.1 Experimental Setup

Our experiments were conducted on a workstation equipped with one NVIDIA **A100 (40GB)** GPU, running Ubuntu 20.04. The deep learning frameworks used for implementation include PyTorch(Paszke et al. 2019) for GAN and RL training and for running the LLM inferences we use HuggingFace-Transformers (Wolf et al. 2020) and DeepEval [1].

**Training Hyperparameters:**

- **Causal GAN:** The generator and discriminator networks were trained using the Adam optimizer with a learning rate of $\eta_{GAN} = 2e-4$ and a batch size of 8.
- **Soft Actor-Critic (SAC):** The RL agent used a learning rate of $\eta_{RL} = 1e-4$, with an entropy temperature parameter $\alpha =$ not given and a discount factor $\gamma = 0.99$. The actor and critic networks were updated using a replay buffer of size 10000 and the neural network architecture was defined as $[1024, 1024, 1024]$ with a batch size of 512 and $\tau = 0.005$. Resulting in a 6.3M parameter model.

[1] https://docs.confident-ai.com/

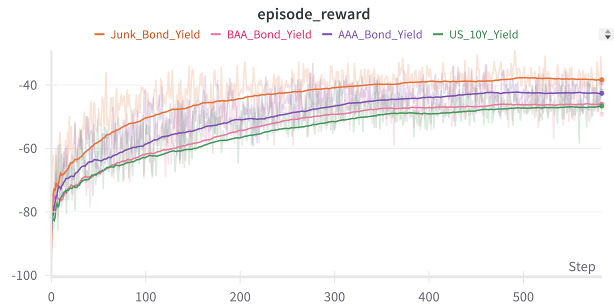


Figure 3: Real-time reward curves for Reinforcement Learning Model

### 2.2 Synthetic Data Quality Analysis

To assess the quality of the synthetic data, we performed statistical comparisons between the real and generated datasets. We employed the Kolmogorov-Smirnov (KS) test to measure distribution similarity, where the test statistic $D_{KS}$ is computed as:

$$D_{KS} = \sup_x |F_{\text{real}}(x) - F_{\text{synthetic}}(x)| \tag{10}$$

with $F_{\text{real}}$ and $F_{\text{synthetic}}$ denoting the cumulative distribution functions of the real and synthetic bond yields, respectively.

### 2.3 Predictive Performance

We evaluate the predictive performance of our LLM on both real and synthetic datasets. The LLM outputs trading signals (BUY/HOLD/SELL), risk analysis, and volatility projections. Performance is measured using standard metrics including accuracy, mean absolute error (MAE), and profit/loss ratios.

For instance, the MAE is computed as:

$$\text{MAE} = \frac{1}{N} \sum_{i=1}^{N} \left| Y_i - \hat{Y}_i \right| \tag{11}$$

where $Y_i$ is the actual bond yield and $\hat{Y}_i$ is the predicted yield.

### 2.4 Ablation Studies

Ablation studies were conducted to evaluate the contribution of individual components of our framework. Specifically, we compared:

- The performance differences between using solely GAN-generated data, solely RL-refined synthetic data, and the actual data.

Table 1 shows the ablation studies on MAE against actual forecasted bond yields. The ablation results indicate that removing the RL component increases the MAE a value of **0.3** on US 10 year bond yields and **0.1** on Junk Bond Yields. Figure 5 shows a comparative analysis on the total number of months in which RL/GAN achieves a profit or a loss.

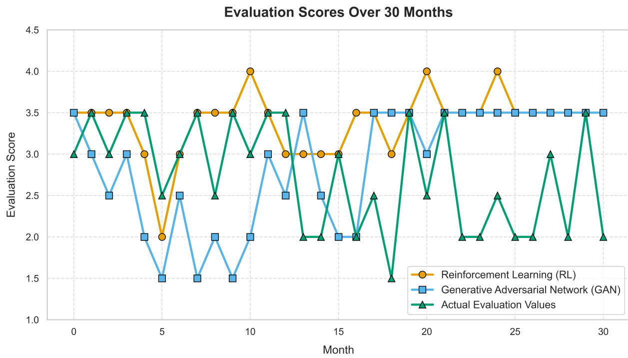


Figure 4: Plot of the evaluation given by the LLM over 30 months for each method.

## 2.5 Evaluation Results

We evaluated our integrated methodology using four metrics:

**LLM-as-Judge Evaluation:** Figure 4 shows the scores given by the LLM as a Judge over a period of 36 months based on a lookback of 2 years.A separate LLM (DeepSeek) was employed to assess the decision-making quality of the prediction LLM (QWEN2.5) over the last 36 months of data. The judge LLM compares the predicted trading signals with the actual market outcomes in an iterative fashion (starting from month 85 to month 120) and assigns scores on a scale of 1 to 5. Table 1 shows that the RL method had the highest average evaluation score of **3.37**.

| Method | Avg. LLM Judge Score |
|---|---|
| RL | **3.37** |
| GAN | 2.87 |
| Actual | 2.58 |

Table 1: Average Evaluation Scores for Different Methods

**Profit/Loss Evaluation:** A custom evaluation script determined the profitability of the predictions, assigning a value of 1 for profitable predictions and 0 for losses. The overall profit/loss accuracy was computed as:

$$\text{Profit/Loss Accuracy} = \frac{1}{N}\sum_{i=1}^{N}\mathbb{I}\{\text{Profit}_i\} \qquad (12)$$

On comparing the number of profit months between RL/Gan and the actual bond yields, the RL- based approach achieves the most number of profit months.

**Mean Absolute Error (MAE):** The MAE of the predicted bond yields, weighted by their economic impact, was computed using Equation (3). Our analysis shows an average MAE of **0.2** on all bond yields for our proposed framework. Table 2 shows the MAE for both RL and GAN against the actual forecasted values.

| Method | Bond Type | MAE ↓ |
|---|---|---|
| GAN | US_10Y_Yield | 0.437 |
| GAN | AAA_Bond_Yield | 0.343 |
| GAN | BAA_Bond_Yield | 0.372 |
| GAN | Junk_Bond_Yield | 0.594 |
| RL | US_10Y_Yield | **0.103** |
| RL | AAA_Bond_Yield | 0.124 |
| RL | BAA_Bond_Yield | 0.174 |
| RL | Junk_Bond_Yield | 0.458 |

Table 2: Mean Absolute Error for Different Bond Yields

**Expert Evaluation:** Financial experts conducted a qualitative assessment of the model outputs, focusing on the realism of synthetic data and the validity of the trading signals. Their insights and recommendations were summarized into an overall expert evaluation score of **4.67** for Rl and **3.17** for GANs. Table 3 summarises the scores of the expert evaluators.

| Method | Expert 1 | Expert 2 | Expert 3 | Average |
|---|---|---|---|---|
| RL | 4.5 | 5.0 | 4.5 | **4.67** |
| GAN | 4.0 | 4.0 | 4.5 | 4.17 |
| Actual | 3.5 | 3.5 | 4.0 | 3.67 |

Table 3: Expert Evaluation Scores for Different Methods

Collectively, these evaluations demonstrate that our integrated framework produces synthetic data that not only replicates critical market dynamics but also supports robust predictive performance.

## Conclusion

In this paper, we presented an integrated framework for synthesizing financial bond yield data by leveraging a hybrid approach that combines causal Generative Adversarial Networks (GANs) and Soft Actor-Critic (SAC) reinforcement learning, followed by predictive analysis using a fine-tuned Large Language Model (LLM). Our methodology was designed to encapsulate the intricate dependencies among 12 macroeconomic variables and four bond yields while preserving essential statistical properties such as volatility clustering, autocorrelation, and macroeconomic sensitivity.

Our experimental results indicate that the synthetic data generated by the proposed framework closely resemble real-world data, as evidenced by statistical tests and visual comparisons. The predictive performance of the LLM, when trained on the augmented dataset, demonstrated an LLM-as-Judge score of **3.4**, and a mean absolute error (MAE) of **0.10** for RL. Additionally, ablation studies confirmed that the reinforcement learning component significantly enhances data quality—its removal increased the MAE by **0.103**. We show that data points generated by both RL and Causal GANs show significantly better performance in recommendations than the forecasted values of the actual bond yields.

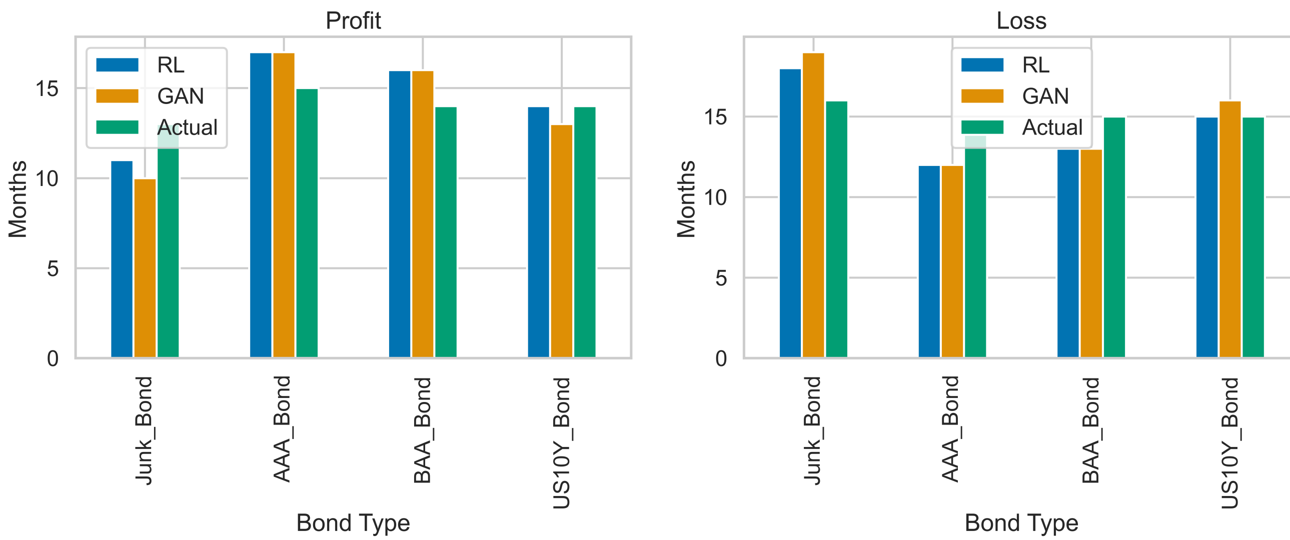


Figure 5: Plots for the Total Profit and Total Loss months between RL, GAN and Actual for each bond type.

These results underscore the potential of our integrated approach in generating high-fidelity synthetic financial data and in supporting robust predictive modeling for trading and risk management. Future work will focus on further refining the generative models, incorporating additional macroeconomic factors, and extending the framework to other financial instruments and market conditions. We anticipate that continued advancements in generative techniques and LLM-based analysis will further enhance the applicability and performance of synthetic data in dynamic financial environments.

**Ethical Statement** This work employs synthetic data generation techniques and advanced machine learning methods to enhance financial forecasting and trading decision support. While our approach mitigates issues of data scarcity and privacy concerns by generating data that closely mimics real-world financial indicators, we acknowledge several ethical considerations.

First, the use of synthetic data must be carefully managed to ensure that the process does not inadvertently propagate biases inherent in the historical data. Misrepresentations or oversimplifications in synthetic datasets could lead to flawed financial predictions and decision-making, with potentially adverse economic and societal impacts. Second, although synthetic data help protect individual privacy by avoiding the direct use of sensitive real-world information, there remains a risk of indirect re-identification if the synthetic data are not sufficiently randomized or if they are combined with external datasets.

Furthermore, as with any AI-driven system, transparency in model development, validation, and deployment is essential. We commit to documenting our methodologies and results comprehensively to promote reproducibility and to enable independent verification of our findings. Future work should continue to address these ethical challenges by incorporating fairness, accountability, and robust privacy-preserving mechanisms in the development of generative models.

Overall, our research aims to contribute positively to financial decision-making processes while acknowledging and actively mitigating potential negative societal implications.

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