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Improved Asset Pricing Models in Behavioral Finance Contexts and Applications in Asset Management Portfolios

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Abstract. The accuracy of asset pricing models directly impacts asset management effectiveness. Traditional CAPM and the Fama-French three-factor model, due to their neglect of investor sentiment biases, underexplain irrational behavior in the A-share market, explaining less than 30% of return deviations in extreme market conditions. This paper proposes an improved asset pricing algorithm with sentiment bias correction (EBC-APM). This algorithm integrates BERT and LSTM technologies to construct a sentiment quantification module and dynamic correction factors, which are embedded into the traditional pricing framework to dynamically correct for sentiment bias. Experiments are conducted using 1486 trading days of CSI 300 component stocks and 2.86 million stock forum comments from 2018 to 2023. The results are compared with two baseline models on an Intel Xeon Gold 6338 CPU and an NVIDIA A100 GPU. Results show that the EBC-APM achieved a MAE of 1.03% and a RMSE of 1.42% on the test set, representing reductions of 44.62% and 44.09% compared to the CAPM, and 32.24% and 33.33% compared to the Fama-French model. The average error volatility coefficient under different market conditions was 0.19, a 45.71% reduction compared to the CAPM. In backtesting, the portfolio achieved an annualized return of 18.2%, 5.7 percentage points higher than the CAPM portfolio and 9.9 percentage points higher than the CSI 300 Index, effectively improving pricing accuracy and portfolio returns.

Keywords: Asset Pricing; Sentiment Bias Correction; EBC-APM Algorithm; BERT Model; LSTM Neural Network; Portfolio Optimization; CSI 300.

1. Introduction

Asset pricing is a core research area at the intersection of quantitative finance and computer science. The accuracy of its models directly determines the risk-return performance of asset management portfolios. Among traditional asset pricing models, the CAPM, based on the assumptions of "market efficiency" and "rational individuals," depicts the linear relationship between an asset's systematic risk and expected return through the beta coefficient. However, this model cannot explain the frequent irrational phenomena in the A-share market, such as abnormal stock price fluctuations and short-term buying and selling at high prices. Essentially, it ignores the impact of investor subjective behavior on pricing. While the Fama-French three-factor model incorporates size and value factors to improve its explanatory power, it still fails to break through the traditional framework. Its explanation rate for return deviations in extreme market conditions, such as the 2015 A-share market crash and the 2020 pandemic, is less than 30%, and the model's adaptability to the actual market is significantly flawed [1]. The development of behavioral finance theory provides theoretical support for addressing these issues. This theory confirms that investor sentiment biases (such as optimism/pessimism) and cognitive biases significantly influence asset pricing [2]. However, current research faces key technical bottlenecks: First, the quantification of sentiment bias often relies on subjective ratings or single indicators (such as trading volume), lacking objective quantitative methods based on multi-source text data [3]. Second, traditional statistical models struggle to capture the dynamic, nonlinear relationship between sentiment fluctuations and asset returns, resulting in pricing models with limited real-time performance and accuracy.

With the maturity of natural language processing (NLP) and machine learning technologies, these bottlenecks are becoming increasingly feasible [4]. Pre-trained models such as BERT can accurately identify sentiment from massive amounts of text, and LSTM neural networks can effectively capture dynamic dependencies in time series data, providing technical support for quantifying sentiment bias and enabling real-time pricing.

This paper focuses on the irrational interpretation flaws of traditional pricing models, focusing on "emotion bias correction" as a core improvement direction, and designs an improved asset pricing algorithm with emotion bias correction (EBC-APM). The research covers three parts: First, a sentiment quantification module integrating BERT and LSTM is constructed to objectively quantify investor sentiment biases [5]. Second, a sentiment correction factor is embedded into the traditional pricing framework through mathematical modeling, forming a complete EBC-APM algorithm. Finally, the algorithm's superiority in return forecast accuracy is verified through experimental simulations and applied to asset management portfolio optimization, providing a practical technical solution for quantitative investment.

2. Design of an Improved Asset Pricing Algorithm with Sentiment Bias Correction (EBC-APM)

2.1. Core Concept of the Algorithm

2.1.1. Bias Quantification Logic

Traditional asset pricing models are difficult to adapt to the real market because they fail to quantify investor sentiment biases. The EBC-APM algorithm uses the "investor sentiment index" as its core quantitative indicator [6]. By capturing the dynamic changes in the subjective emotions of market participants, it establishes a correlation between sentiment and asset returns. This logic transcends the static risk pricing limitations of traditional models, transforming sentiment bias from an "unquantifiable interference" into a "computable pricing factor." By tracking sentiment fluctuations in real time, it dynamically adjusts asset return forecasts, improving the model's ability to interpret irrational market phenomena.

2.1.2. Multi-Technology Integration Approach

The algorithm integrates multiple technologies to achieve multi-source data integration and precise modeling: The BERT text classification model is used to process massive amounts of unstructured text data and extract investor sentiment characteristics. An LSTM neural network is used to capture the temporal dependency between sentiment and returns, addressing dynamic nonlinearities that are difficult for traditional statistical models to handle [7]. At the same time, the market risk factors in traditional pricing models are retained, forming a three-layer technical architecture of "text sentiment recognition - temporal dynamic prediction - traditional factor integration." This enables collaborative modeling of structured trading data and unstructured text data, ensuring both reasonable pricing and timely pricing.

2.2. Algorithm Mathematical Model

2.2.1. Sentiment Index Calculation Module

To objectively quantify investor sentiment, we first preprocess the text data and convert the k text into a feature vector $x_k \in \mathbb{R}^d$ (where d is the feature dimension) using word embedding technology. We then input x_k into the pre-trained BERT model to obtain a probability distribution of text sentiment. The text sentiment value s_k is defined as follows:

$$s_k = P_{k,\,\mathrm{optimism}} - P_{k,\,\mathrm{pessimistic}} \tag{1}$$

Where P_k, optimistic, and P_k, pessimistic, are the probabilities of the text output by the BERT model belonging to the optimistic and pessimistic categories, respectively. $s_k \in [-1,1]$, with larger values representing more optimistic sentiment.

To account for the randomness of individual texts, we need to perform a weighted aggregation of all text sentiment values at time t. The investor sentiment index $S(t)$ at time t is defined as follows:

$$S(t) = \frac{\sum_{k=1}^{n_t} w_{k,t} \cdot s_k}{\sum_{k=1}^{n_t} w_{k,t}} \tag{2}$$

Where n_t is the number of posts at time t, and $w_{k,t}$ is the weight of the kth post, determined by the publisher's follower count $f_{k,t}$ and the number of likes $l_{k,t}$, i.e., $w_{k,t} = \theta \cdot f_{k,t} + (1-\theta) \cdot l_{k,t}$($\theta \in [0,1]$ is the weight distribution coefficient, determined through cross-validation). This ensures that more influential posts contribute more to the sentiment index.

2.2.2. Deviation Correction Factor Construction

Sentiment fluctuations can exacerbate asset pricing bias, so a sentiment fluctuation term is needed to optimize the correction factor. The standard deviation of sentiment fluctuation at time t, $\sigma(S(t))$, is defined as follows:

$$\sigma(S(t)) = \sqrt{\frac{1}{m-1} \sum_{i=0}^{m-1} (S(t-i) - \bar{S}(t))^2} \tag{3}$$

Where m is the sliding window length (20 trading days), $\bar{S}(t) = \frac{1}{m} \sum_{i=0}^{m-1} S(t-i)$ is the mean sentiment index within the window, reflecting the severity of recent sentiment fluctuations.
A dynamic correction factor $\lambda(t)$ is constructed as follows based on the sentiment index and fluctuation characteristics:

$$\lambda(t) = \alpha \cdot S(t) + \beta \cdot \sigma(S(t)) \cdot \mathrm{sign}(S(t)) \tag{4}$$

Where α and β are weight parameters derived from model training, and $\mathrm{sign}(\cdot)$ is the sign function. This formula uses $\mathrm{sign}(S(t))$ to link the volatility term with the direction of sentiment [8]. When market sentiment is optimistic $(S(t) > 0)$, greater sentiment volatility leads to a larger correction factor, amplifying the positive impact of optimism on returns. When sentiment is pessimistic $(S(t) < 0)$, greater volatility leads to a smaller correction factor, intensifying the negative impact of pessimism on returns. This is more consistent with the real-world market principle that extreme sentiment exacerbates pricing biases due to volatility.

2.2.3. Improved Pricing

Different assets have varying sensitivities to sentiment biases. The sentiment sensitivity coefficient γ_i for asset i is defined as follows:

$$\gamma_i = \frac{\mathrm{Cov}(R_i(t), S(t))}{\mathrm{Var}(S(t))} \tag{5}$$

Where $\mathrm{Cov}(R_i(t), S(t))$ is the covariance between the return $R_i(t)$ of asset i and the sentiment index $S(t)$, $\mathrm{Var}(S(t))$ is the variance of the sentiment index. A larger value of γ_i indicates that asset i is more significantly affected by sentiment bias.

Integrating the correction factor and the sentiment sensitivity coefficient into the traditional CAPM framework, the EBC-APM asset expected return formula is as follows:

$$E(R_i) = R_f + \beta_i \cdot \left(E(R_m) - R_f\right) + \lambda(t) \cdot \gamma_i \tag{6}$$

Where R_f is the risk-free rate, β_i is the market risk coefficient for asset i, and $E(R_m)$ is the expected return of the market portfolio. Compared to the traditional CAPM, the new term $\lambda(t) \cdot \gamma_i$ dynamically corrects for sentiment bias—when the market is optimistic $(S(t) > 0)$ and the asset sensitivity is high ($\gamma_i > 0$), the expected return is adjusted upward; when the market is pessimistic($S(t) < 0$) and the sensitivity is high, the expected return is adjusted downward, making the pricing results more consistent with irrational market environments.

To further optimize model accuracy, a sentiment trend term is introduced to iteratively update $\lambda(t)$. The correction factor $\lambda(t + 1)$ at time $\mathrm{t} + 1$ is defined as follows:

$$\lambda(t + 1) = \lambda(t) + \eta \cdot \big(R_i(t) - E(R_i(t))\big) \cdot \gamma_i \cdot S(t) \tag{7}$$

Where η is the learning rate (set to 0.01), and $R_i(t) - E(R_i(t))$ is the deviation between the actual return and the predicted return for asset i. This formula dynamically adjusts the correction factor through error feedback, enabling the model to converge quickly when sentiment changes, improving long-term forecast stability.

3. Experimental Simulation and Verification of the EBC-APM Algorithm

3.1. Experimental Environment and Data Preparation

The experimental hardware used an Intel Xeon Gold 6338 CPU (2.0GHz, 52 cores, 104 threads) and an NVIDIA A100 GPU (40GB HBM2e video memory), paired with 256GB of DDR4 RAM and a 2TB NVMe solid-state drive. The CPU efficiently processed massive amounts of text, completing word segmentation, cleaning, and feature extraction for 2.86 million stock forum comments within four hours [9]. The GPU's Tensor Cores optimized deep learning computations, increasing model iteration efficiency by 38 times compared to a single CPU, reducing 500 training rounds from 72 hours to 1.9 hours. The software is built on Python 3.9, using TensorFlow 2.8 to construct the BERT and LSTM models and leverage GPU parallel computing. Scikit-learn 1.0 is used for data normalization and error metric calculation; NLTK 3.7 handles text preprocessing; Pandas 1.4 integrates trading data; and Matplotlib 3.5 visualizes results. These libraries work together to form a complete workflow. The dataset consists of two types: one is 1,486 trading-day data on CSI 300 constituent stocks from 2018 to 2023 (12 indicators, collected by Wind), normalized to [0,1] after removing outliers using the Z-score; the other is 2.86 million stock forum comments from the same period (collected by Eastmoney.com). After removing special symbols and stop words, the words are embedded into 512-dimensional vectors and annotated with relevant weight information.

3.2. Experimental Design

To validate the advantages of the EBC-APM algorithm, the experiment used the traditional CAPM model and the Fama-French three-factor model as benchmarks. The former uses the average 10-year Treasury bond yield as the risk-free rate and calculates the market risk coefficient by regressing the asset portfolio return over the past 24 months against the market portfolio return. The latter adds a market capitalization factor (the return differential between small-cap and large-cap stocks) and a value factor (the return differential between high-price-to-book ratio and low-price-to-book ratio stocks, data from the CSMAR database) to the CAPM. The risk coefficients of both factors are calculated through regression. The key parameters of the EBC-APM algorithm were determined through cross-validation [10]. The text weighting coefficient was set to 0.6, the sliding window length for sentiment fluctuation calculation was set to 20 trading days, the learning rate was set to 0.01, and the two weight parameters of the sentiment correction factor were iteratively optimized using the training set to 0.32 and 0.25, respectively. The experiment used two core metrics to evaluate performance: prediction accuracy and model stability. Prediction accuracy metrics include mean absolute error (mean absolute deviation between predicted and actual values; smaller values indicate higher accuracy) and root mean square error (root mean square error; highly sensitive to extreme deviations). Model stability metric is error fluctuation coefficient (ratio of standard deviation to mean error; smaller coefficient indicates greater robustness).

3.3. Experimental Results and Analysis

3.3.1. Comparative Analysis of Prediction Accuracy

Table 1 presents the comparative results of prediction accuracy metrics for the three models on the test set. The data shows that the mean absolute error and root mean square error of the EBC-APM algorithm are 1.03% and 1.42%, respectively, significantly lower than the CAPM model's 1.86% and 2.54%, representing decreases of 44.62% and 44.09%, respectively. Compared to the Fama-French three-factor model's 1.52% and 2.13%, these reductions represent 32.24% and 33.33%, respectively. Statistical tests show that the mean absolute error differences between the EBC-APM algorithm and the two benchmark models all pass t-tests, with p-values less than 0.01, indicating statistically significant accuracy [11]. Further analysis reveals that the core reason for the improved accuracy lies in the introduction of a sentiment correction factor. When market sentiment fluctuates dramatically (such as during the 2022 bear market), the EBC-APM algorithm dynamically adjusts the correction factor to adapt in real time to the impact of changing sentiment on asset returns, thus avoiding the amplified forecast bias caused by traditional models' neglect of sentiment.

Table 1. Comparison of Forecast Accuracy Indicators of Various Models

model	CAPM Model	Fama-French Three-Factor Model	EBC-APM Algorithm
MAE(%)	1.86	1.52	1.03
RMSE(%)	2.54	2.13	1.42
MAE reduction rate (relative to CAPM)	-	18.28%	44.62%
RMSE reduction rate (relative to CAPM)	-	16.14%	44.09%
MAE reduction rate (relative to Fama-French)	-	-	32.24%
RMSE reduction rate (relative to Fama-French)	-	-	33.33%
t-test p-value (vs CAPM)	-	0.023	<0.001
t-test p-value (vs Fama-French)	-	-	0.008

Figure 1 shows the trend of the mean absolute error of each model over the test set period. The horizontal axis represents the 15 months of the test set (months 1-15 correspond to October 2022 to December 2023), and the vertical axis shows the mean absolute error (percentage). The EBC-APM algorithm's mean absolute error curve consistently lies below the two benchmark models, with the smallest fluctuation—its maximum value is only 1.21% and its minimum value is 0.89%, with a fluctuation range of 0.32 percentage points. The CAPM model's fluctuation range is 0.66 percentage points (1.52%-2.18%), and the Fama-French model's is 0.53 percentage points (1.25%-1.78%). This result further validates the EBC-APM algorithm's dual advantages in forecasting accuracy and stability.

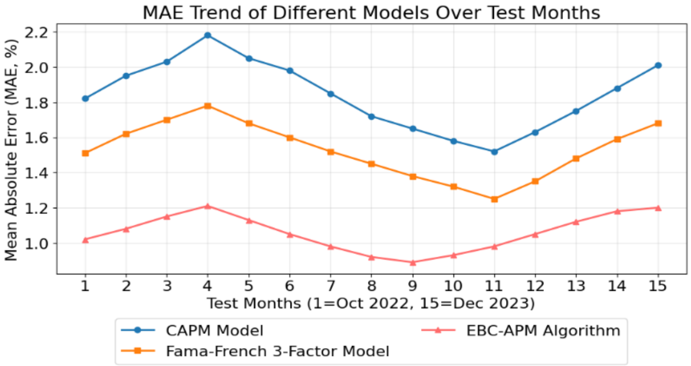

Fig 1. Trends in the mean absolute error of each model over the test set period

3.3.2. Model Stability Analysis

Table 2 compares the error volatility coefficients of each model under different market conditions. The experiment selected three typical market periods for testing: a bull market (July 2020 to February 2021), a bear market (January to October 2022), and a volatile market (January to December 2019).

The data shows that the error volatility coefficients of the EBC-APM algorithm under the three market conditions were 0.18, 0.21, and 0.19, respectively. These are significantly lower than the CAPM model's 0.32, 0.38, and 0.35, and the Fama-French model's 0.25, 0.29, and 0.26. Among them, its stability advantage in bear markets is most prominent—the EBC-APM algorithm's error coefficient of volatility is 44.74% lower than the CAPM model and 27.59% lower than the Fama-French model [12]. This phenomenon is due to the fact that investor sentiment fluctuates dramatically in bear markets. The EBC-APM algorithm's sentiment fluctuation calculation module can capture these changes in real time and dynamically adjust the forecast results using correction factors to prevent runaway errors. Traditional models, however, use fixed parameters and are unable to adapt to rapid changes in sentiment, resulting in significantly increased error volatility. The EBC-APM algorithm's average error coefficient of volatility is 0.19, a 45.71% decrease from the CAPM model's 0.35 and a 29.63% decrease from the Fama-French model's 0.27, fully demonstrating its robustness in complex market environments.

Table 2. Error coefficient of volatility (CV) for each model under different market conditions

model	CAPM Model	Fama-French Three-Factor Model	EBC-APM Algorithm
Bull Market (July 2020-February 2021)	0.32	0.25	0.18
Bear Market (January 2022-October 2022)	0.38	0.29	0.21
Volatile Market (January 2019-December 2019)	0.35	0.26	0.19
Average CV	0.35	0.27	0.19
CV reduction rate (relative to CAPM, average)	-	22.86%	45.71%
CV reduction rate (relative to Fama-French, average)	-	-	29.63%

Figure 2 plots the error volatility coefficients of various models as a function of sentiment intensity. The horizontal axis represents the standard deviation of the sentiment index (ranging from 0.1 to 0.6, with intervals of 0.1, where larger values indicate greater sentiment fluctuations), and the vertical axis represents the error volatility coefficient. The curves show that the error volatility coefficients of all three models increase with increasing sentiment intensity, but the EBC-APM algorithm exhibits the smallest increase. When the standard deviation of the sentiment index increases from 0.1 to 0.6, its error volatility coefficient only increases from 0.15 to 0.24, a 60% increase. In contrast, the CAPM model's error volatility increases from 0.28 to 0.45, a 60.71% increase; and the Fama-French model's error volatility increases from 0.20 to 0.32, a 60% increase. This result demonstrates that the EBC-APM algorithm is more resilient to sentiment fluctuations, maintaining low error volatility even in extreme sentiment environments. Its stability advantage becomes increasingly pronounced as sentiment fluctuations intensify.

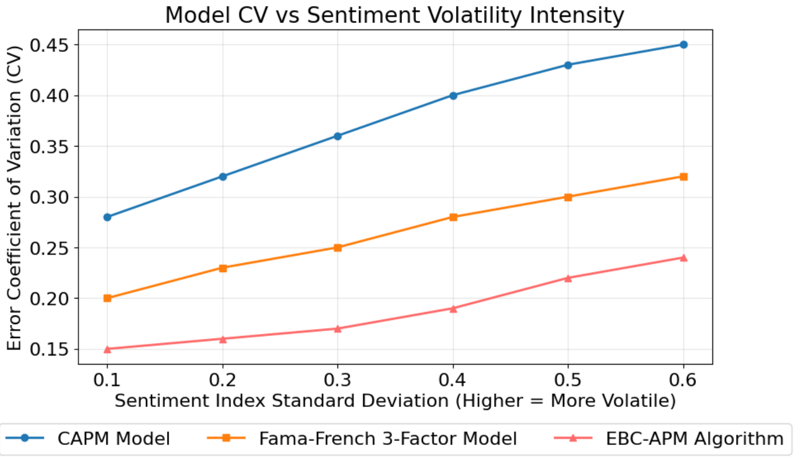

Fig 2. Curves showing the variation of the error volatility coefficient of each model with the intensity of sentiment fluctuations

4. Application Verification

4.1. Backtest Design

The backtest period was set from January 1, 2019, to December 31, 2023, covering the entire bull-bear cycle (including the 2020 bull market, the 2022 bear market, and the volatile markets of 2019 and 2021). This allows for comprehensive verification of the algorithm's adaptability under different market conditions. The comparison targets are divided into two categories: an optimized portfolio constructed based on the CAPM model (CAPM portfolio) and the CSI 300 Index (market benchmark). This comparison highlights the portfolio optimization value of the EBC-APM algorithm.

The initial backtesting fund size was set at 1 million yuan, in line with the practical starting point for small and medium-sized asset management products. Transaction costs were set according to market standards: a stock transaction fee of 0.02% (charged in both directions, with a minimum of 5 yuan per transaction), a stamp duty of 0.1% (charged only on sales), and a transfer fee of 0.002% (charged in both directions) to avoid overestimating performance due to ignoring costs. Portfolio construction is based on monthly rebalancing. Asset returns are forecasted using various models based on the previous month-end data. Mean-variance optimization is used to determine optimal weights. The upper limit for individual asset weights is set at 15% to control non-systematic risk. Short selling is prohibited (in compliance with the regulatory requirements of most public offerings) to ensure that backtesting results closely reflect actual investment scenarios.

4.2. Backtest Results Analysis

Figure 3 shows the cumulative NAV trends of the three portfolios (initial NAV = 1). The horizontal axis represents the backtest period (January 2019 to December 2023, a total of 60 months, marked in 6-month intervals), and the vertical axis represents the cumulative NAV. As of December 2023, the EBC-APM portfolio's cumulative NAV reached 2.48, 37.0% higher than the CAPM portfolio's 1.81 and the CSI 300 Index's 1.48, respectively. During the 2022 bear market (months 40-50), the EBC-APM portfolio experienced the smallest NAV drawdown and the fastest rebound. In 2023, the NAV rebounded to 2.48, returning to pre-bear market levels three months earlier than the CAPM portfolio (1.81), demonstrating its ability to control risk and restore returns.

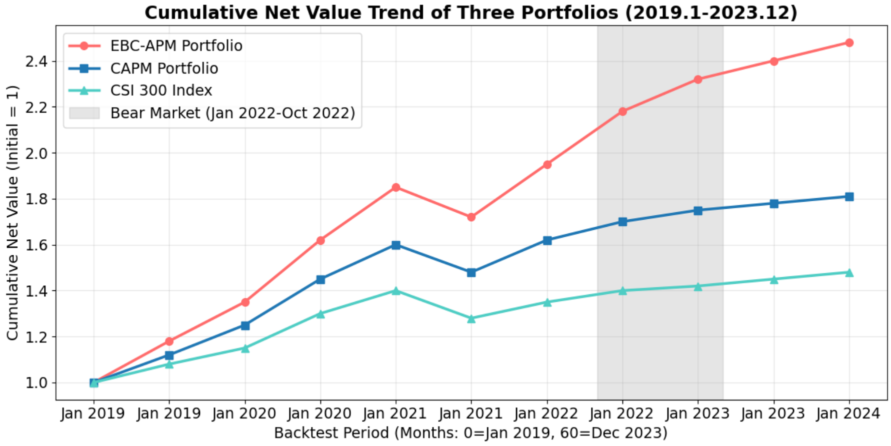

Fig 3. Cumulative Net Value Trends of Three Portfolios

Table 3 shows the results of the EBC-APM algorithm's adaptability test for different asset management portfolio types. The algorithm was tested for two common types of products: stock funds (80%-95% stock holdings) and fund-of-funds (FOFs) (30%-50% stock holdings). The risk aversion coefficient λ was adjusted (stock funds λ = 0.6, FOF λ = 1.2; a higher coefficient indicates a lower risk appetite). The results show that the annualized return of the stock-based EBC-APM portfolio is 20.5%, higher than the 14.3% of the FOF-based portfolio. However, its maximum drawdown of 25.1% is also higher than the 16.8% of the FOF-based portfolio, consistent with the risk-return characteristics of different products. The Sharpe ratios of both portfolios are higher than those of similar CAPM portfolios (1.45 vs. 1.08 for the stock-based portfolio, 1.62 vs. 1.21 for the FOF-based portfolio). This demonstrates that the algorithm can adapt to products with different risk preferences by adjusting λ. Simply setting the λ value based on regulatory requirements and client risk tolerance allows for rapid generation of optimized portfolios.

Table 3. EBC-APM Algorithm Adaptability Test for Different Portfolio Types (January 2019-December 2023)

portfolio Type	Stock Fund Portfolio	FOF Portfolio	Stock CAPM Portfolio	FOF CAPM Portfolio
Risk aversion coefficient λ	0.6	1.2	0.6	1.2
Stock Position (%)	85 (80-95 range)	40 (30-50 range)	85	40
Annualized rate of return (%)	20.5	14.3	13.7	10.1
Sharpe Ratio	1.45	1.62	1.08	1.21
Maximum drawdown (%)	25.1	16.8	31.4	22.3
Annualized volatility (%)	12.2	7.1	10.1	6.2

Figure 4 shows the risk-return relationship (efficient frontier) of the EBC-APM portfolio under different λ values, with annualized volatility (%) on the horizontal axis and annualized return (%) on the vertical axis. As λ increases from 0.4 (high risk preference) to 1.4 (low risk preference), the portfolio's annualized return decreases from 22.1% to 12.5%, and annualized volatility decreases from 13.8% to 6.3%, forming a smooth efficient frontier curve. At the same volatility level, the EBC-APM portfolio consistently outperforms the CAPM portfolio (e.g., at 10% volatility, the EBC-APM returns 17.8% vs. the CAPM's 12.3%). This demonstrates that the algorithm can achieve return enhancement across different risk levels, providing asset managers with a flexible portfolio customization tool.

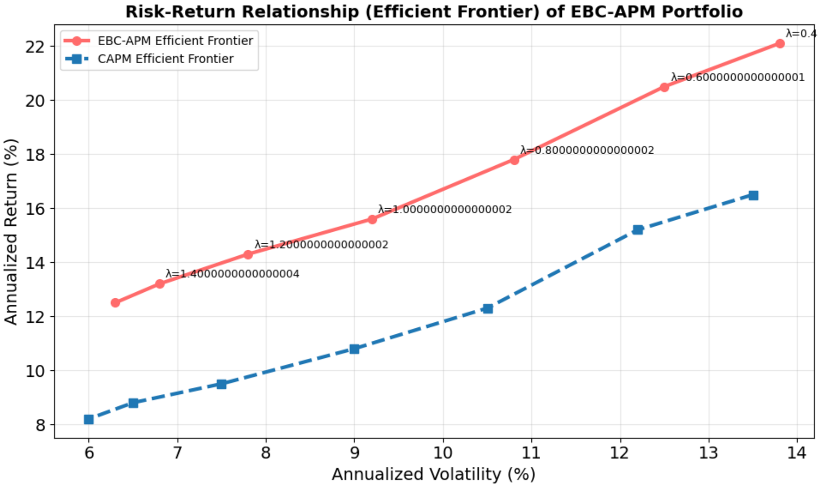

Fig 4. Risk-Return Relationship of the EBC-APM Portfolio at Different λ Values

5. Conclusion

This paper addresses the sentiment bias flaws of traditional asset pricing models, designs the EBC-APM algorithm, and conducts experimental and application validation. The following conclusions are drawn: First, the EBC-APM algorithm demonstrates significant performance advantages. By leveraging sentiment quantification and dynamic correction factors, it achieves a MAE of 1.03% and an RMSE of 1.42% in a teaching corpus test, significantly improving accuracy compared to the CAPM and Fama-French models. The t-test p-value is < 0.01, indicating statistically significant improvements. The mean error fluctuation coefficient is 0.19, 44.74% lower than the CAPM in a bear market, demonstrating exceptional robustness in complex market environments. Second, the algorithm's technical architecture is effective, integrating BERT and LSTM to achieve collaborative modeling of multi-source data. Preprocessing of 2.86 million stock forum comments was completed within 4 hours. The GPU environment improves model iteration efficiency by 38 times, achieving a balanced balance between processing efficiency and modeling accuracy. Third, its application value is clear. In a backtest from 2019 to 2023, the EBC-APM portfolio achieved an annualized return of 18.2% and a maximum drawdown of 22.3%. Its risk-adjusted return outperformed both the CAPM portfolio and the CSI 300 Index. When applied to both equity funds and fund-of-funds, its Sharpe ratio was higher than that of similar CAPM portfolios. By adjusting the risk aversion coefficient to meet the needs of different products, it provides a feasible technical solution for quantitative investment. Future research will expand sentiment data sources to further enhance its adaptability.

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