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Black-Litterman Based Portfolio Optimization: A Hybrid Approach

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Abstract

We propose a hybrid approach that combines the time-series forecasting model and the ensemble learning algorithm to generate investor views in the Black-Litterman model. Specifically, we first use four time-series forecasting models, ARIMA, LSTM, Informer, and iTransformer, to forecast the dynamics of factors that affect the movements of assets, for example, those that are related to the market cap, trend, volatility, and momentum. Then, the ensemble learning algorithm, XGBoost, is used to integrate the results from time-series-based analyses to forecast stock returns as investor views in the Black-Litterman model for portfolio optimization. We tested the performance of our proposed hybrid model in the China A-share market, and the results indicated that the hybrid approach could significantly improve the performance of the Black-Litterman model. By comparison, the performance of different approaches, for example, a single time-series model and different hybrid models, the ARIMA-XGBoost and iTransformer-XGBoost performed much better.

Keywords

Black-Litterman, Hybrid Model, Machine Learning, Time-Series Forecasting

1. Introduction

Based on the Mean-Variance model, Sharpe (1964) and Lintner (1965) introduced the Capital Asset Pricing Model (CAPM) in the 1960s. The CAPM provides the specific model to express the theoretical relationship between the expected return and the expected risk of an asset, which moves the Mean-Variance model a big

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step forward in terms of realistic feasibility. However, the empirical record of CAPM is not good enough to validate the way it is used in practical applications (Fama & French, 2004), which reveals its theoretical shortcomings, such as the fact that the CAPM does not address the problem of overly stringent assumptions in the Mean-Variance model. For example, the CAPM assumes that investors are rational and strictly follow the Mean-Variance model rules to diversify their investments, which is inaccurate in practical investment. Meanwhile, extreme environmentalists will not invest in heavy industrial manufacturing companies that have good returns but have serious pollution problems.

In order to overcome the above shortcomings, Fischer Black and Robert Litterman proposed the Black-Litterman model in 1990 (Black & Litterman, 1990), which combines the Mean-Variance model, the CAPM, and the Bayes Theorem based investor views. The most important contribution of the Black-Litterman model is that it provides a method to combine the investors' subjective view with the CAPM market equilibrium returns to justify the value of the experience or judgment of investors that created additional return on top of the one provided by the CAPM model.

In general, the methods for generating investor views that can be found in the literature can be divided into three categories: the time-series forecasting models, the machine learning algorithms, and the hybrid approaches that combines both. Time-series models derived from mathematical formulas, such as ARIMA and GARCH, perform well in predicting data that show clear linear trends or seasonal patterns, but perform poorly in cases of multiple variables and large amounts of data that with non-linear elements or jumps. Machine learning algorithms are good at capturing nonlinear features in performing multivariate modeling, but are difficult to capture long-run dependencies and the interpretability of the generated results is poor. Therefore, the hybrid approaches are proposed that combine time-series models and machine learning algorithms aim at performing better or generate more robust outputs.

In this paper, we propose a hybrid approach that combines the time-series forecasting model and machine learning algorithms to predict returns as investor views in the Black-Litterman model and compare its performance with the two other methods: the time-series forecasting model and the machine learning algorithm. We also verified the feasibility of the hybrid approach in practical applications in the Chinese stock market. To be specific, we used the SSE50 index as a baseline and selected 22 constituent stocks of the SSE50 index as an initial portfolio. First, we choose four time-series forecasting models: ARIMA, LSTM, Informer, and iTransformer, to predict stock returns directly based on historical return time-series data. The four aboved models represent different types of time-series data prediction: ARIMA models are characterized by their flexibility in capturing sequential patterns, parsimonious parameterization, theoretical completeness, and adherence to the Box-Jenkins methodology (Zhang, 2003). These attributes make ARIMA suitable for a wide range of exponential smoothing models (McKenzie, 1984); LSTM demonstrates strong capabilities in capturing long-term dependencies and nonlinear patterns, and is particularly effective in forecasting financial time series (Chen, Zhou, & Dai, 2015); Informer and iTransformer are the latest variants of the Transformer. Research has shown that the Transformer architecture is capable of significantly reducing computational complexity across two distinct application domains, while delivering superior performance in modeling long-range temporal dependencies (Mohammadi & Pazouki, 2020). Then, we use XGBoost, an ensemble learning algorithm, to forecast stock returns based on historical stock factor data. XGBoost is a gradient boosting-based ensemble learning algorithm known for its high computational efficiency, which has led to its widespread application across various domains (Tan, Gan, & Wu, 2023). In the financial sector, it is primarily employed for default risk prediction and personal loan assessment(Ma et al., 2018; Li et al., 2020). Finally, we propose a hybrid approach that combines both to forecast stock returns. We use the time-series forecasting model to identify the factors that support the forecasting of the movements of stocks. Then XGBoost is used to predict stock returns based on the predicted stock factors. The returns obtained would be inputted into the Black-Litterman model as investor views, and we finally obtain new portfolio weights.

The innovation and contributions of this paper are summarized as follows.

- We propose a hybrid approach based on the Black-Litterman model, which combines the time-series forecasting model and the machine learning algorithm XGBoost in portfolio optimization and verify the effectiveness of the hybrid approach in the Chinese stock market.
- We compare different methods to generate investor views in the Black-Litterman model and find that the hybrid approach has advantages over the time-series forecasting model in significantly improving the portfolio performance. And the proposed iTransformer-XGBoost hybrid model performs better.
- We also compare the impact of different holding periods on the performance of the hybrid approach. Generally speaking, the hybrid model has obvious advantages when the holding period is 5, 10, and 20 days.

2. Related Work

In 1992, Fisher Black and Robert Litterman, two researchers at Goldman Sachs, proposed the Black-Litterman model, which incorporates investor views to the Mean-Variance model via Bayes' theorem and constructs returns by weighting the average of market-implied returns and expected returns (Black & Litterman, 1990). Compared with the Mean-Variance model, the Black-Litterman model significantly reduces sensitivity to input parameters and uses 'reverse optimization' to generate a stable distribution of returns to improve the accuracy of results (Walters, 2014). Thus, the Black-Litterman model has attracted a large group of researchers from academia and industry because it addresses several limitations present in the original Mean-Variance model. The main contribution of the Black-Litterman asset allocation model is to bring out the idea of adjusting the portfolio weights based on the investor views. The investor views matrix in the Black-Litterman model is usually constructed by using historical data to make predictions about expected stock returns and risks. The precision of the investor views determines the performance of the Black-Litterman model-based portfolio optimization.

2.1. Time-Series Forecasting Model

The time-series forecasting model refers to using statistical time-series models on historical return data to predict expected returns for the Black-Litterman model. The research by Beach and Orlov (2007) can be considered as one of the earlier attempts to generate investor views in the Black-Litterman model through the EGARCH-M model (Beach & Orlov, 2007). Duqi et al. (2014) created a return volatility forecast with the EGARCH-M model, which was inputted into the Black-Litterman model to decide what investor views to include. The results indicated improved performance on returns in the U.S. stock market (Duqi, Franci, & Torluccio, 2014). Wen, Chen and Liang (2011) proposed using macroeconomic variables such as industrial value added, consumer price index, and money supply, as input parameters of the model on the basis, and using the GJR-GARCH-M model to portray return and variance of return to obtain parameters Q and Ω in the Black-Litterman model (Wen, Chen, & Liang, 2011). They found that the higher the confidence level, the greater the return obtained by the model exceeds that of the investment strategy based on the market equilibrium weights. Arisena et al. (2018) used the ARMA-GARCH time-series model to overcome the heteroscedasticity problems of stock return and formed a single view factor in the Black-Litterman model (Arisena, Noviyanti, & Zanbar, 2018). Pang (2021) utilized the GARCH family models to capture the return volatility of different sector assets and sets the level of investor confidence C with the use of ISI, a composite index of investor sentiment in CSMAR, to investigate the asset allocation strategy for the A-share sector (Pang, 2021). The results show that the asset allocation performance of the Black-Litterman model is better than that of the traditional asset allocation model. At the same time, the cumulative return keeps increasing as the investor confidence level improves. Deng (2018) established a VECM/VAR-DCC/ADCC framework to model multivariate financial time series and generate investor views for use in the Black-Litterman model (Deng, 2018).

In general, the time-series forecasting model predicts the expected return based on historical data as the investor views to input into the Black-Litterman model for portfolio optimization, which can avoid emotional bias and cognitive limitations in subjective analysis. The time-series forecasting model has a strong ability to capture linear relationships, but it is difficult to capture complex nonlinear patterns in the market, such as poor prediction accuracy under international emergencies, and has certain difficulties in modeling high-dimensional data.

2.2. Machine Learning Algorithm

With the development of technology and artificial intelligence, scholars began to use machine learning algorithms for financial analysis, such as analyzing historical data of various factors to predict return. The method of using machine learning models to generate investor views in the Black-Litterman model is called the machine learning method. Chiarawongse et al. (2012) incorporate qualitative views, taking the form of linear inequalities, into the Black-Litterman portfolio optimization framework through a Markov Chain Monte Carlo (MCMC) based simulation (Chiarawongse et al., 2012). Their work gives creative ideas on how to incorporate qualitative data into the study of investor views generation. Didenko and Demicheva (2013) applied the ensemble learning algorithm, in particular RandomForest to generate investor views for portfolio optimization (Alexander & Demicheva, 2013). Sujin Pyo and Jaewook Lee (2018) compared the prediction power of historical volatility between three machine learning models (GPR, SVR, and ANN) and the GARCH model. They found that incorporating the low-risk view into the equilibrium market portfolio enhances profitability and that this view dominates the market portfolio (Pyo & Lee, 2018). Barua and Sharma (2023) applied a deep learning network CEEMDAN-GRU to predict fear/greed technical indicators and used the XGBoost algorithm to predict returns for ten country ETFs to create relative views in the Black-Litterman model (Barua & Sharma, 2023). Hung et al. (2024) utilized the BERT model to predict stock trends as sentiments from related news articles and employed the Black-Litterman model with the GRU model to construct the portfolio. The results show that the strategy is stable and surpasses several baseline models (Hung et al., 2024).

Compared with the time-series forecasting model, machine learning algorithms perform better in high-dimensional data modeling scenarios, and can better adapt to dynamic market changes, which reduce the risk of relying on historical data. However, poor interpretability and low computational efficiency are the main challenges faced by machine learning algorithms.

2.3. Hybrid Approach

Some researchers attempted to combine econometric modeling and the machine learning algorithm to come up with a hybrid approach to predict returns and input them as investor views into the Black-Litterman model. Mahmut Kara et al. (2019) used the GARCH model to predict stock indicators and then transformed the predicted factors into expected returns using Support Vector Regression (SVR). The predicted returns are then inputted into the Black-Litterman model as the investor views matrix, to update portfolios based on rolling data (Kara, Ulucan, & Atici, 2019). They found that the results were more accurate than those obtained by using econometric models or machine learning algorithms to generate investor views separately. Hadi Rezaei et al. (2021) found that the portfolio constructed by the hybrid CEEMD-CNN-LSTM model had high return, low extreme exposure and low risk (Rezaei, Faaljou, & Mansourfar, 2021). Barua and Sharma (2022) found that the hybrid multivariate CNN-BiLSTM model provided significantly better predictions for out-of-sample index closing prices than when CNN or BiLSTM was used alone (Barua & Sharma, 2022).

3. Research Design

3.1. Data

Dataset. We choose the market data for the constituent stocks of the Shanghai Stock Exchange 50 (SSE 50) Index in 2446 trading days from June 1, 2014 to May 31, 2024 as our dataset, with the first 80% being the training set and the last 20% being the test set. The data is obtained from the CSMAR database. The data sample interval includes major events such as the US-China trade war that began in 2018 and the global epidemic of COVID-19 in 2020-2023. In addition, the SSE 50 index has switched between bulls and bears several times during the sample interval. In summary, we believe that the data sample can reflect the volatility of the financial market.

Since the SSE 50 index was released on January 2, 2004, its constituent stocks adjust on average every six months based on a combination of sample stability and the dynamic tracking principle. Considering that the stability of the stocks would affect the performance of the portfolio, we selected a total of 22 stocks that had been included in the SSE 50 Index for more than three years to rebuild our portfolio, based on the constituent stocks listed in the SSE 50 Index as of June 1, 2022. Therefore, the data we used to test the model start from June 1, 2022, which means that no future information is used in our testing. The constituent stocks of the portfolio included in this paper are shown in **Table 1**.

Table 1. Constituent stocks.

Code	Stock	Sector
600000	Pudong Development Bank	Banking
600028	China Petrochemical Corporation	Petrochemical
600030	CITIC Securities	Security
600036	China Merchants Bank	Banking
600048	Poly Developments and Holdings Group	Real Estates
600050	China United Telecommunications	Communication
600104	SAIC MOTOR	Automotive
600309	WANHUA	Manufacture
600519	KweichowMoutai	Food and Beverage
600887	Yili	Food and Beverage
601088	China Shenhua Energy	Mining Industry
601166	Industrial Bank of China	Banking
601211	Guotai Junan	Security
601288	Agricultural Bank of China	Banking
601318	PAIC	Insurance
601336	New China Life	Insurance

Continued

601398	ICBC	Banking
601601	China Pacific	Insurance
601628	China Life	Insurance
601668	CSCEC	Construction
601688	Huatai	Security
601857	CNPC	Petrochemical

Factors. Regarding the sample data feature, a total of 14 factors in two categories (market factors and technical factors) are selected. Market factors are those that can be visualized directly on the candlestick chart. A total of five market factors were selected for the analysis. Among these, the opening price, closing price, daily high price, and daily low price were used to represent the dynamics of the stock price, while the daily trading volume was used as a representation of stock liquidity. On the other hand, this paper selects a total of eight technical factors in four categories: scale factors, volatility factors, trend factors, and momentum factors. These technical factors and their calculation formulas are shown in **Table 2**.

Table 2. Technical factors.

Type	Factors	Meaning	Formula
Scale	Market Capitalisation	The total value of circulating stocks	$\text{CLOSE} \times N_{\text{outstanding shares}}$
Volatility	ATR	Average true range of stock fluctuations	$\text{ATR}_t = \frac{\text{ATR}_{t-1} \times (n-1) + \text{TR}_t}{n}$
Trend	ADXR	Average directional movement index rating	$\frac{\text{ADX}(\text{today}) + \text{ADX}(n \text{ days ago})}{2}$
	EMA	Exponential Moving Average	$\frac{Value_{\text{today}} \times \text{Smoothing}}{1+\text{Days}} + \text{EMA}_{\text{yesterday}} \times \left(1 - \frac{\text{Smoothing}}{1+\text{Days}}\right)$
	MACD	Moving Average Convergence Divergence	$\text{EMA}_{12} - \text{EMA}_{26}$
	MACDsignal	9-day exponential moving average of MACD	EMA(MACD,9)
	SMA	Simple Moving Average	$\frac{\text{CLOSE}_1 + \ldots + \text{CLOSE}_n}{n}$
Momentum	RSI	Relative Strength Index	$100 - \frac{100}{1 + \frac{\text{Average gain during up days}}{\text{Average loss during down days}}}$

3.2. Assumption

No short-selling. Short-selling is not allowed in the Shanghai A-share market, but the direct output result of the Black-Litterman model has no restrictions on the positive and negative weights, so the output results of negative values must be eliminated. The negative weight in the results indicates that the Black-Litterman model is bearish on that stock and believes that its price will go down.

Frictionless Capital Markets. To simplify theoretical analysis, the traditional CAPM generally assumes that there is no friction in the capital market.

3.3. Experiment Design

Figure 1 provides a step-by-step overview of the research methodology employed in this study.

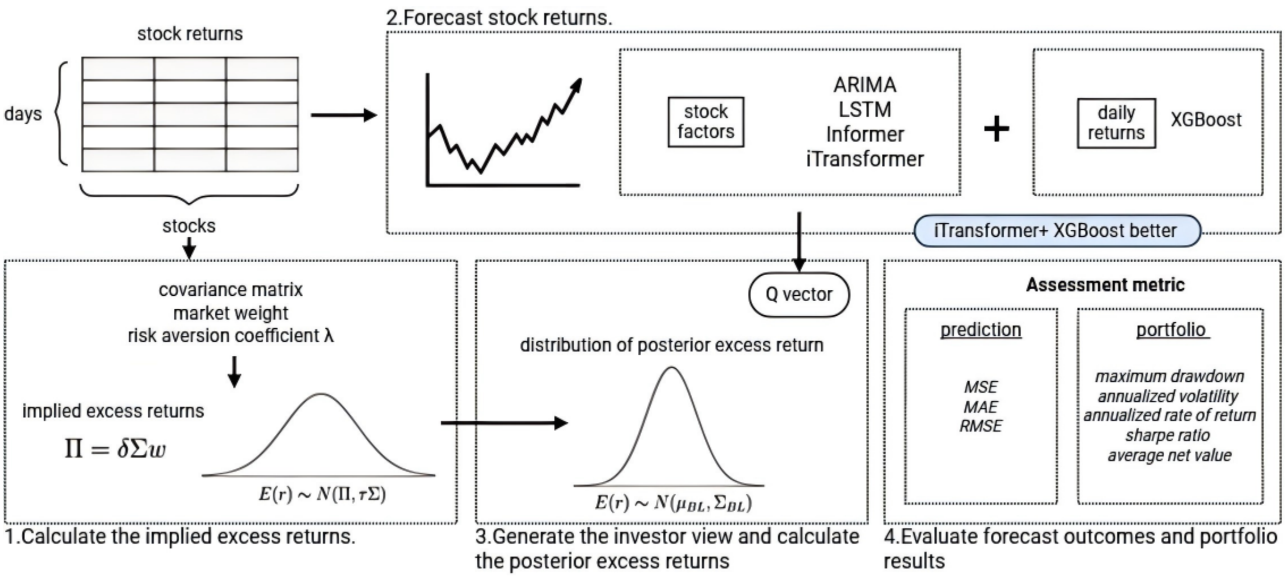

Figure 1. The overall process of the research method.

The advantage of the hybrid model is that it uses the time-series model to predict stock factors to reduce the impact of stock factor lags and accurately generate investor views. Therefore, the key of experiment design is to analyze the gains brought about by the hybrid model relative to the single time-series model.

In this paper, our experiments consist of two steps. The design of the experiments is also demonstrated in **Figure 2**.

The first step is a time-series forecasting problem essentially. Specifically, we treat the factors and return forecasting problem as a time-series forecasting problem, that is, we perform factors and return prediction based on historical return data. We trained four models for time-series forecasting: the conventional statistical model ARIMA, the long short-term memory network (LSTM), which is widely used in time-series problems, and two Transformer variants: Informer and iTransformer. The latter two can predict multivariable time series due to the incorporation of the attention mechanism. We train these four models on the

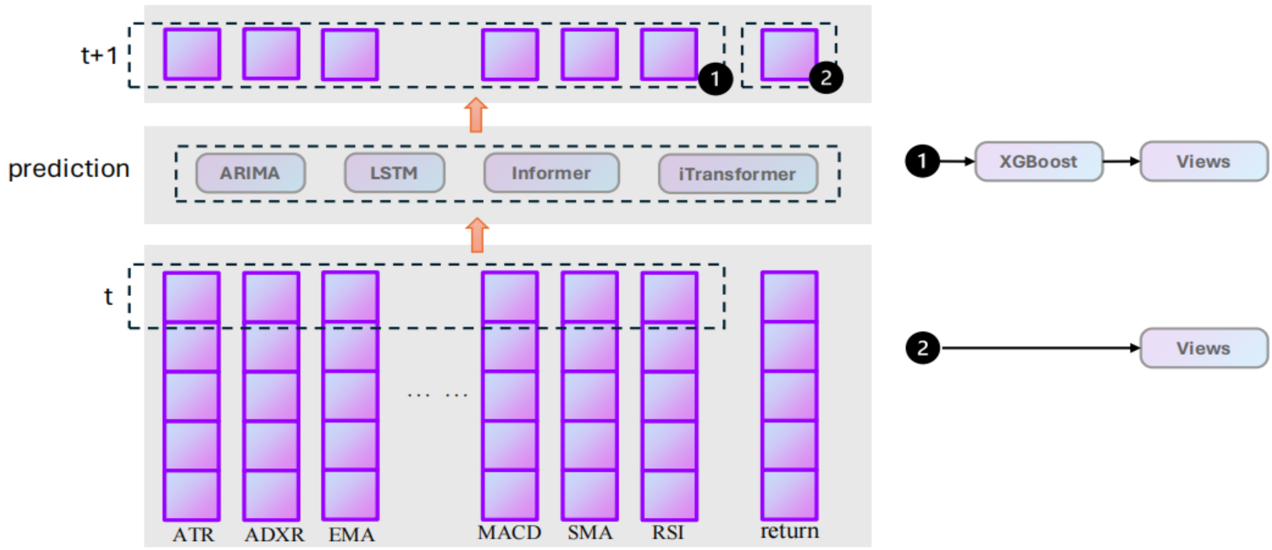

Figure 2. Experiment design.

data in the training set and adjust the model parameters according to specific metrics to maximize the predictive capabilities of the four models.

The second step is to utilize the results of the time-series forecasting model to generate investor views, in which we set up a control experiment. In experiment 1, the four time-series models mentioned in the first step are used only to predict stock factors, and then we train the XGBoost model to predict daily returns based on the predicted stock factors data as XGBoost is particularly good at dealing with multi-factor regression problems. These obtained returns would be inputted into the Black-Litterman model as the investor views to optimize stock weights of portfolio. In experiment 2, the predicted return obtained by the four time-series models would be directly inputted into the Black-Litterman model as investor views for portfolio optimization without any transform. The Black-Litterman model uses the investor views obtained from these two methods to update the portfolio.

3.4. Evaluation Metric

For the time-series forecasting model, we use three metrics to measure the forecasting efficiency of the model: the Mean Squared Error (MSE), Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). The calculation formulas for MSE, MAE and RMSE are shown in Equations (1-(3).

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{1}$$

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - \hat{y}_i\right| \tag{2}$$

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2} \tag{3}$$

Meanwhile, we verify the effectiveness of investor views generated by comparing portfolio performance. In this paper, we choose five criteria to evaluate portfolio performance: maximum drawdown, annualized volatility, annualized rate of return, Sharpe ratio, and average net value of portfolio during the test window. The evaluation metric and their calculation formulas are shown in Equations (4)-(8).

$$\text{Maximum Drawdown} = max_{i,j:j>i}\left(\frac{V_j - V_i}{V_i}\right) \tag{4}$$

where $V(i)$ represents the portfolio net value on Day i.

$$\text{Annualized Volatility} = \sigma_{return} \times \sqrt{n} \tag{5}$$

where σ_{return} represents the standard deviation of daily returns, and n represents the investment strategy execution days in one year ($n = 250$ in this paper).

$$\text{Annualized Return} = \frac{V_T - V_0}{V_0} \div \frac{n}{365} \times 100\% \tag{6}$$

where V_T represents the portfolio maturity value, V_0 represents the portfolio initial value and $n = 726$ represents the trading days over the test window 2021-2023.

$$\text{Sharpe Ratio} = \frac{R_p - R_f}{\sigma_p} \tag{7}$$

where R_p represents the annualized return, σ_p represents the annualized volatility, and R_f is the risk-free rate. In this paper, R_f is set to the average of Treasury yields over the test window 2021-2023.

$$\text{Average Value} = \frac{1}{m}\sum_{i=1}^{m} V_i \tag{8}$$

where V_i represents the portfolio net value on day i and $m = n/\text{holding period}$ over the test window 2021-2023.

4. Experiment

4.1. Time-Series Forecast

In this section, we trained four time-series models: ARIMA, LSTM, Informer and iTransformer to predict return and stock factors in **Table 2**. Given the distinct technical principles underlying the four models, the configuration settings for each model are tailored accordingly to align with their respective frameworks. Informer and iTransformer can handle longer time series as input, whereas LSTM and ARIMA struggle with performance when processing long sequences. Therefore, different window periods are set for each model. The input lengths of ARIMA and LSTM are set to 12 days, while those of Informer and iTransformer are set to 32 days. The entire dataset comprises a total of 2,446 trading days over 10 years and includes market data such as opening prices, closing prices, trading volumes. These features are further processed to calculate the factors listed in **Table 2**, which are used for time-series forecasting. Approximately 70% of the data is allocated for model training and validation, while data from June 1, 2022 to May

31, 2024 is reserved for historical testing. This ensures that all the information used to train the model comes from periods prior to June 1, 2022, avoiding artificially high investment returns.

During the training process of the four models, since there are multiple metrics: MSE, MAE, and RMSE and multiple factors, so we choose the most important one, the MSE of the closing price, as the target of model optimization. Subsequently, the four models were trained and fine-tuned to prepare for application in subsequent tasks. The MSE, MAE and RMSE between the predicted closing price and the observed closing price are shown in **Figure 3**. Both traditional statistical models and deep neural network models optimized for time-series tasks have good performance. However, this result does not represent the performance of the model after it is integrated into the hybrid approach.

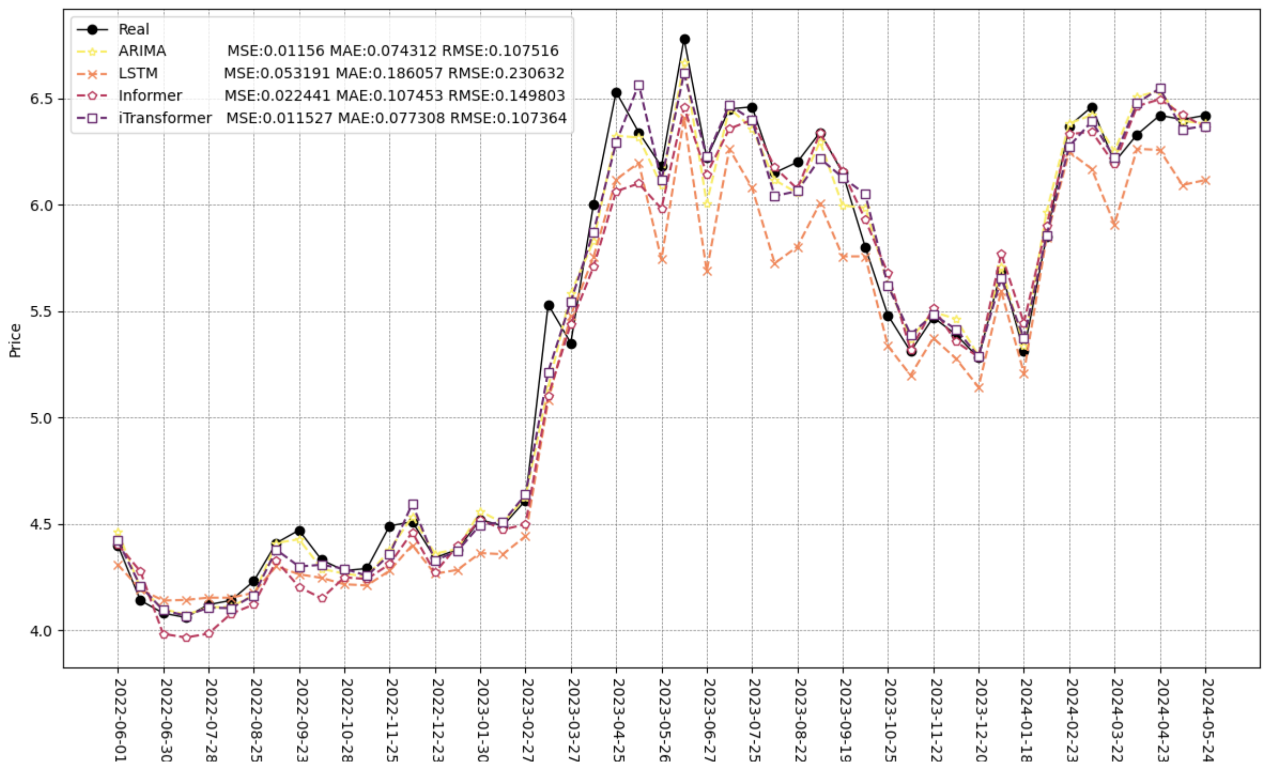

Figure 3. Model Training Metrics: MSE, MAE and RMSE.

4.2. Hybrid Approach

In experiment 1, we employ the hybrid approach to optimize the portfolio. To be specific, we use ARIMA, LSTM, Informer and iTransformer these four models to predict the stock factors. Then, we use the XGBoost algorithm to predict daily stock returns based on the predicted stock factors, which will be inputted as the investors views into the Black-Litterman model. Simultaneously, the controlled experiment 2 focuses only on historical daily returns, using the time-series forecasting model to predict return and then converting them as investor views matrix in the Black-Litterman model.

The comparison of the performance of the four hybrid models and the SSE 50 index is shown in **Figure 4**. Hybrid models pay attention to historical data, learn trend patterns from historical data, generate views on future trends, and flexibly allocate positions among investable stocks, achieving higher holding period returns. In contrast, the constituent stocks and weight adjustments of the SSE50 index, which serves as the baseline, focus more on market size and liquidity, and the constituent stocks also follow the principle of stability, so they are far less flexible than the investment model.

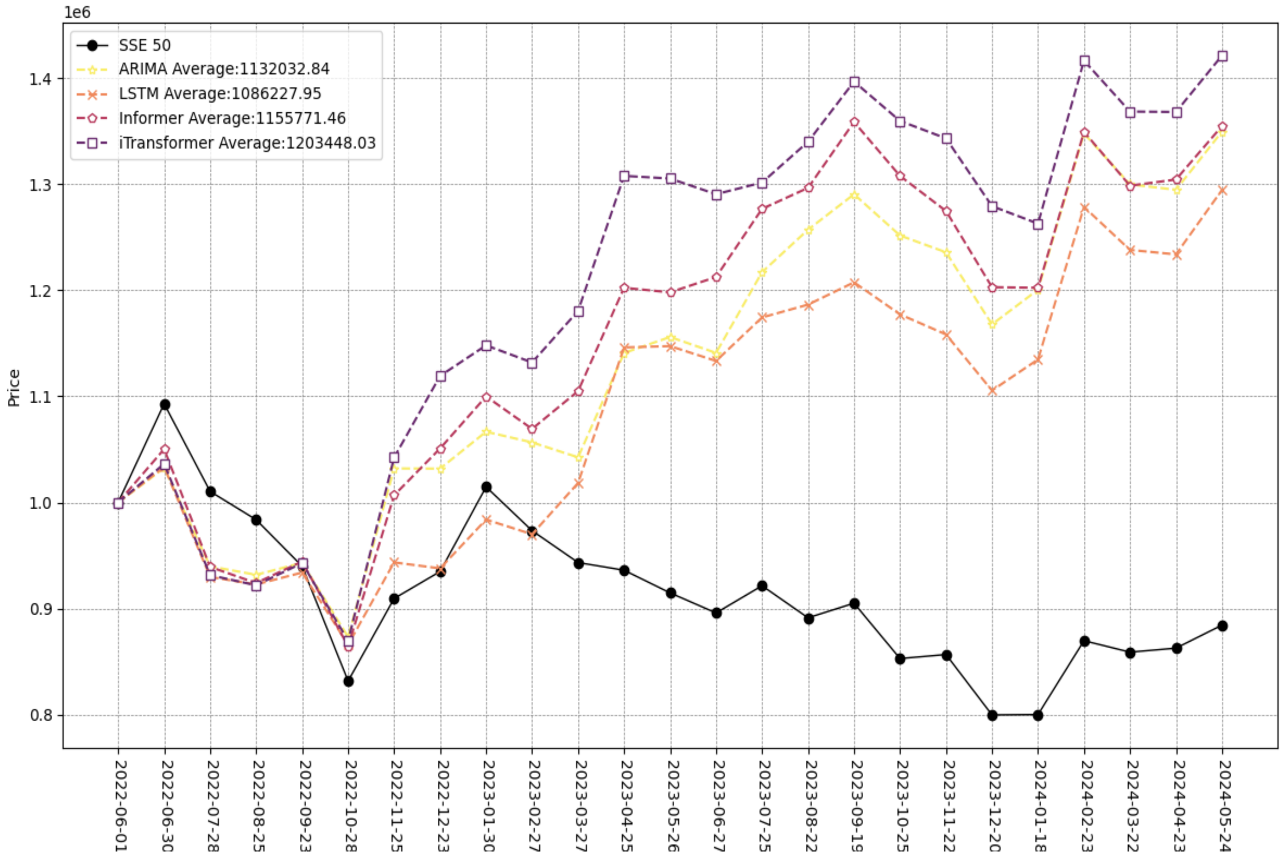

Figure 4. Hybrid models compared with SSE 50.

The comparison of the performance of the four hybrid models and the four single time-series forecasting models is shown in **Figure 5**. We can see that the four hybrid models perform significantly better than the baseline SSE 50 index, with the iTransformer-XGBoost model performing the best. Moreover, hybrid models obviously outperform the single time-series forecasting models. When comparing each hybrid model with its corresponding time-series model, LSTM-XGBoost, iTransformer-XGBoost, and ARIMA-XGBoost all perform better than their corresponding single time-series forecasting models, LSTM, iTransformer, and ARIMA, during the testing period. The hybrid model focuses on more information besides yield, including not only market data but also factors such as trends and momentum. The ability to process more data and extract meaningful information from it is the advantage of the hybrid model. Therefore, we could draw the conclusion that these four hybrid models are effective in significantly improving portfolio performance.

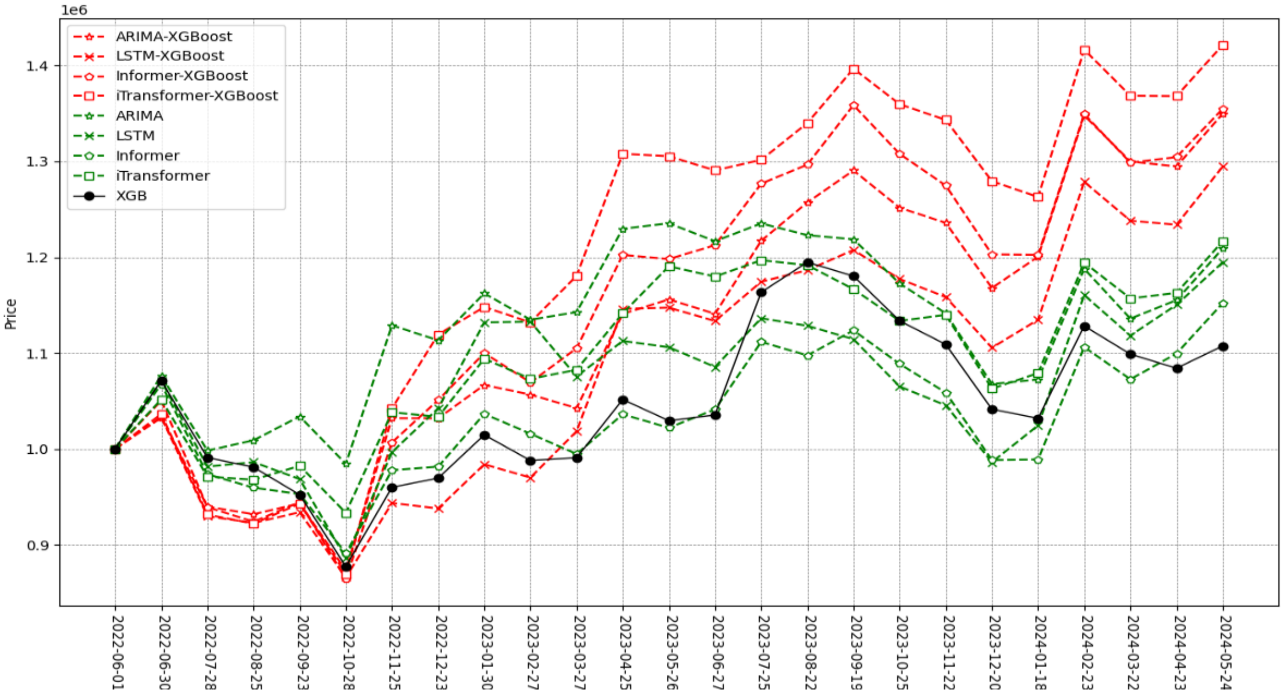

Figure 5. Hybrid models compared with time-series forecasting models and single XGBoost.

We also compared the performance of the models under different holding periods: 5, 10 and 20 days. As shown in **Tables 3-5**, ARIMA-XGBoost and iTransformer-XGBoost consistently outperform the other models, and the net values of the four portfolios, compared to the baseline SSE 50 are also listed.

Table 3. Portfolio performance comparison (Holding Period = 5).

Model	Max Drawdown	Return	Volatility	SP Ratio	Average Value	Incresed with SSE50
ARIMA-XGBoost	19.6%	31.81%	41.02%	0.71	1,200,761.87	30.52%
LSTM-XGBoost	17.63%	11.81%	36.4%	0.26	1,045,566.86	13.65%
Informer-XGBoost	19.93%	26.1%	40.55%	0.58	1,166,372.54	26.78%
iTransformer-XGBoost	18.06%	33.24%	41.53%	0.74	1,235,449.21	34.29%
ARIMA	20.03%	12.75%	41.53%	0.25	1,057,799.99	14.98%
LSTM	19.69%	20.82%	37.31%	0.49	1,075,153.65	16.86%
Informer	18.34%	11.01%	33.74%	0.25	1,053,455.27	14.50%
iTransformer	17.07%	29.4%	42.26%	0.64	1,166,834.41	26.83%
XGBoost	16.66%	9.85%	35.32%	0.21	1,085,074.3	17.94%
SSE 50	26.84%	−8.7%	34.68%	−0.32	920,012.65	

Table 4. Portfolio performance comparison (Holding Period = 10).

Model	Max Drawdown	Return	Volatility	SP Ratio	Average Value	Incresed with SSE50
ARIMA-XGBoost	17.73%	25.06%	62.81%	0.36	1110974.98	20.95%
LSTM-XGBoost	20.89%	19.24%	60.37%	0.28	1059743.95	15.37%
Informer-XGBoost	21.03%	23.56%	65.35%	0.32	1144004.66	24.54%
iTransformer-XGBoost	21.99%	24.37%	68.67%	0.32	1120412.9	21.97%
ARIMA	18.76%	12.78%	56.63%	0.18	1049432.63	14.25%
LSTM	18.8%	22.94%	58.6%	0.35	1104860.97	20.28%
Informer	17.93%	7.9%	53.91%	0.1	1030419.53	12.18%
iTransformer	17.58%	16.37%	59.06%	0.23	1077541.91	17.31%
XGBoost	19.73%	4.86%	58.56%	0.04	1036380.37	12.83%
SSE 50	26.84%	−8.7%	55.3%	−0.2	918562.74	

Table 5. Portfolio performance comparison (Holding Period = 20).

Model	Max Drawdown	Return	Volatility	SP Ratio	Average Value	Incresed with SSE50
ARIMA-XGBoost	15.42%	26.32%	94.97%	0.25	1132032.84	23.67%
LSTM-XGBoost	16.21%	22.17%	85.39%	0.23	1086227.95	18.67%
Informer-XGBoost	17.71%	26.7%	96.75%	0.25	1155771.46	26.27%
iTransformer-XGBoost	16.09%	31.71%	101.32%	0.29	1203448.03	31.48%
ARIMA	13.58%	15.73%	84.11%	0.16	1131376.3	23.60%
LSTM	17.3%	14.65%	91.85%	0.13	1068018.23	16.68%
Informer	16.54%	11.44%	81.22%	0.11	1033493.04	12.91%
iTransformer	11.25%	16.3%	74.83%	0.18	1097613.4	19.91%
XGBoost	18.12%	8.08%	84.23%	0.07	1047361.14	14.42%
SSE 50	26.84%	−8.7%	86.42%	−0.13	915338.79	

5. Conclusion

In this paper, we propose a hybrid approach that combines the time-series forecasting model and the XGBoost algorithm to generate investor views in the Black-Litterman model and verify its effectiveness in portfolio optimization in the Chinese stock market. The experimental results show that the hybrid model outperforms both the single time-series forecasting model and the market baseline. This suggests that hybrid models, regardless of what the specific time-series forecasting model used, consistently achieve higher portfolio returns compared to the baseline SSE 50. From a theoretical analysis, the single time-series forecasting model has the limited ability to extract deep market information under multivariate models and large data samples, while ensemble learning can capture more complex market information while maintaining strong robustness, thus making up for the shortcomings of a single time-series model. We also compared the performance of hybrid models with a single time-series forecasting model under different holding periods. No matter which evaluation metric is used for comparison, the ARIMA-XGBoost and iTransformer-XGBoost hybrid models outperform the single time-series forecasting model and the baseline. Therefore, we believe that the hybrid approach combines the interpretability of time-series models and the feature extraction capabilities of machine learning models, thus achieving excellent performance in investor views generation that cannot be achieved by any single model, thereby improving the performance of the Black-Litterman model in portfolio optimization.

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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