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Statistical Performance and Economic Value in Machine-Learning-Based Financial Forecasting

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Abstract. Though machine learning has been extensively used in financial forecasting, previous literature mainly focuses on measuring model performance based on statistical measures such as R^2 and RMSE without paying attention to whether those models create any economic benefit. In order to explore whether the improvement in statistical measures creates any economic benefit, this paper establishes a methodology of converting statistical measures into economic values and then performs a comparative analysis on four typical papers that report both kinds of measures. Three patterns about the relation between statistical measures and economic values are found from the analysis, which are positive correlation, negative correlation, and conditional correlation. Although statistical accuracy is a prerequisite for creating economic value, it is insufficient since the transformation from statistical accuracy to economic value faces several restrictions, including over-fitting, signal degradation, and mismatch of performance measures. The findings suggest that investors should not rely solely on statistical metrics for model selection, but rather incorporate risk-adjusted performance measures such as the Sharpe ratio and maximum drawdown, while also accounting for model complexity and signal persistence when constructing trading strategies.

Keywords: Machine learning, Financial forecasting, Statistical performance, Economic value, Investment strategy

1. Introduction

The past few years have witnessed the increasing use of machine learning techniques in predicting financial outcomes. Several different types of models are being extensively used to predict the outcomes such as the stock returns, volatility, and bankruptcy. For instance, Shah et al. utilized the random forest technique along with the Fama-French three factors model to predict the daily returns of the bank stocks in India [1]. Gu et al. have also shown the effectiveness of tree-based and neural network models in predicting financial data compared to the traditional econometric models [2].

Model-based traders are interested in the profitability of such strategies rather than in the precision of the models. It is possible that a very accurate model might be unable to provide profitable results while an inaccurate one could provide better risk-adjusted returns because of its robustness [3]. Traditional measures treat over-prediction and under-prediction equally which is not the case in trading as the success of the strategy is related to predicting the trend and identifying the

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market inflection points [4]. Thus, a more accurate model might lose money because of its inability to find important turning points whereas an inaccurate model would be able to earn more money. Improved prediction accuracy does not mean profitability all the time. This paradox poses the core question for discussion: Does higher statistical performance of machine learning financial predictions always guarantee the higher value of investment?

The results provide practical insights for investors. In case of correspondence between statistical accuracy and economic benefit, investors should aim to use complicated models that have lower errors. In case there is no stable relationship, then the emphasis should be put on developing a strategy and managing risks.

The remainder of the paper is organized as follows. Section 2 reviews machine-learning applications in financial forecasting and the evaluation of statistical and economic performance. Section 3 outlines the Efficient Market Hypothesis, asset-pricing models, and the bias–variance trade-off. Section 4 develops the conceptual mechanism, Section 5 compares evidence from four selected studies, and Section 6 concludes.

2. Literature review

Recent years have seen increasing use of machine learning in financial forecasting. Machine learning techniques are different from traditional linear models because they can account for nonlinear interactions between the variables. This makes machine learning more effective in dealing with high dimensionality and non-stationary nature of finance data. Rouf et al. conducted a systematic review of machine learning applications in stock prediction from 2011 to 2021, covering methods such as SVM, ANN, Random Forest, Decision Trees, Naïve Bayes, and Deep Neural Networks [5]. The review also found that combining market data with textual data significantly improves prediction accuracy. However, relatively few studies assess whether gains in predictive accuracy translate into economic value at the strategy level. A similar conclusion is corroborated by Mintarya et al. in their systematic review of 30 studies: neural networks are the most frequently used models (accounting for 46.3%), followed by LSTM (19.5%) and SVM (17.1%) [6]. However, the review also notes that the evaluation in most studies remains primarily based on statistical metrics such as accuracy.

Existing research primarily employs two categories of metrics for model evaluation. The first category consists of statistical accuracy metrics—such as Root Mean Square Error (RMSE), the coefficient of determination (R^2). The second category comprises investment value metrics—including the Sharpe ratio, annualized return, and maximum drawdown—which measure the actual economic gains generated by the model's predictions in trading. In their review, Hu, Zhao, and Khushi analyzed the evaluation metrics used in 86 studies and found that statistical error metrics (e.g., RMSE, MAPE, MAE) and economic value metrics (e.g., Sharpe ratio, rate of return) are used separately to evaluate models [7]; Shen and Shafiq developed an LSTM-based system for predicting short-term price trends in China's A-share market [8]. However, the evaluation of the models conducted by them was based purely on statistics, including such measurements as accuracy, F1-score, and confusion matrix without any regard to economic value analysis at the strategic level. Both of these studies demonstrate that there is no agreement concerning what makes a "good" model. The above observation may imply a possible disconnect between prediction and economic value.

Although extensive research has demonstrated the forecasting potential of machine-learning algorithms, model-evaluation criteria remain inconsistent. Most studies emphasize statistical accuracy without examining the mechanisms through which predictive improvements may create

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investment value. Accordingly, this study asks whether improvements in statistical performance are consistently associated with improvements in economic performance and, if not, what explains the divergence.

3. Theoretical foundation

3.1. Efficient Market Hypothesis (EMH)

The Efficient Market Hypothesis (EMH) was systematically stated by Fama and provides a basic theory explaining the informational efficiency of capital markets. According to this theory, in an efficient market, the prices of assets will quickly adjust to incorporate all the information available; hence, investors cannot earn abnormal profits by making use of any past or public information [9]. Fama has defined market efficiency in three types, namely: weak-form efficiency (information reflected in prices is historical in nature), semi-strong form efficiency (information reflected in prices is public in nature), and strong form efficiency (all information is reflected in prices) [9].

The EMH provides a benchmark for evaluating whether forecasts contain exploitable information. Under weak-form efficiency, past prices and trading data should not generate persistent abnormal returns; under semi-strong-form efficiency, publicly available information should likewise be rapidly incorporated into prices. Documented anomalies challenge strict versions of market efficiency, although they may also reflect risk compensation, data mining, or implementation frictions. This debate motivates the examination of whether machine-learning forecasts deliver robust out-of-sample and post-cost economic gains [10, 11].

3.2. Capital asset pricing model, CAPM

Asset pricing theories are concerned with the determination of prices and the determinants of asset prices. The capital asset pricing model (CAPM), which was developed by Sharpe in 1964 and Lintner in 1965, is regarded as the basis for asset pricing theory. The CAPM suggests that the price of an asset depends entirely on its market risk. Other forms of risk can be diversified away and are not rewarded.

Subsequent research showed that market risk is not enough to account for cross-section variations in stock returns. Taking the CAPM model as their basis, Fama and French proposed a three-factor model using the size factor (SMB) and value factor (HML) in order to better explain variations in returns [12]. Carhart added a momentum factor (UMD) to develop a four-factor model [13].

The theories are used as a theoretical framework to determine the predictive ability of the models discussed in this paper. Under the multi-factor model theory, stock returns may be decomposed into risk premia related to known factors and a part that is unrelated to known factors. If the stock returns created by the prediction model can be fully described by known factors, then there is no economic content to the model; on the other hand, if the model reveals stock return information which is not contained in the factor models, it indicates that the prediction model is meaningful.

3.3. Bias-variance trade-off

The bias–variance trade-off describes the tension between model flexibility and out-of-sample generalization. According to this theory, prediction error is broken down into bias and variance. High bias arises when a model is too restrictive to capture relevant structure, whereas high variance arises when a model is overly sensitive to sample-specific fluctuations. There is an inverse relation

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between the two; the increase in complexity of a model is likely to reduce bias and increase variance.

Bias-variance trade-off is especially important in financial forecasting. Market financial data is characterized by the low signal-to-noise ratio, which means that the predictable component of stock price movement is significantly smaller than the noise component. Uncontrolled pursuit of statistical precision in fitting the model on the training data can result in over-fitting noise rather than the real pattern. Besides the degradation of the out-of-sample predictive capability, this approach is even more dangerous for investments because of the fact that investment strategy based on such models will produce many incorrect trading signals leading to losses as a result of transaction costs and wrong direction estimation. Thus, the model that exhibits the highest statistical precision on the training data set is not always the most accurate one in terms of the out-of-sample prediction—the model that is less precise on the training data, but produces stronger signals might be even more profitable.

4. Conceptual framework and mechanism analysis

4.1. Forward transmission mechanism

Statistical efficiency gains are expected to translate into economic value creation for investment strategy. The machine learning models provide predictions on the future direction of return movements through finding patterns in the influencing factors on the stock performance. With increasing accuracy of model prediction, the real information in the signals becomes higher, and thus, the portfolio based on those signals would be able to make correct decision on buying and selling more often, resulting in creating positive excess returns. The basic principle underlying such transmission is that gains in statistical efficiency generate informational advantages, which in turn lead to excess returns.

For the positive examples studied in Chapter 5 of this paper, both the LSTM model in Paper A and the XGBoost model in Paper B show such positive transmission, which suggests that statistical efficiency gain can be translated into economic value creation under certain circumstances.

4.2. Inhibitory mechanism

Over-fitting happens when the model picks up on noise in the data set rather than the patterns. In accordance with the bias-variance trade-off, the more complex the model is, the less biased it will be, but the higher the variance will be. Due to the low signal-to-noise ratio inherent in financial data, complex models, seeking to increase their statistical precision, often pick up on noise. According to Bagchi et al., as the number of factors increases from 1 to 350, performance increases and then starts falling down again: not enough factors cause under-fitting, whereas too many factors make the model pick up noise, which in turn degrades its performance out of sample [14]. This shows that there exists an optimal level of model capacity, the crossing of which results in the loss of the model's generalization ability due to excessive focus on statistical precision. Trading strategies based on overfitted models create lots of spurious signals, which result in wrong direction and cost money. This pattern is consistent with, but does not by itself establish, an overfitting explanation for the XGBoost results reported in Study C in section 5.

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4.3. Signal decay mechanisms

The predictive power of signals in financial markets does not stay valid for an indefinite period after being identified. According to Liu, there exist systematic variations in the speed at which the decay of the predictive power of certain factors occurs: momentum signals usually decay very quickly during a crisis, while value signals stay almost constant. Ignoring this asymmetric decay results in continual weight misallocation [15]. From a theoretical point of view, when a certain signal is widely used and traded by market participants, then the price abnormality that it reflects gets quickly corrected, resulting in the decline of its predictive power. Thus, if a model exhibits a very good fit to the data sample, then its predictive ability to generate economic profit out-of-the-sample is greatly restricted by the nature of the signal. The META case study (Paper D of Chapter 5 of the thesis) could be explained in this way: although the model had a very high R^2 for the sample, the returns generated by the strategy were lower than the benchmark—presumably due to the rapid decay of the signal out-of-the-sample.

However, there is an inconsistency between the standards used for evaluating statistical prediction and its economic value. An increase in statistical prediction accuracy does not automatically lead to increased economic utility or profitability. The statistical metric assigns equal weight to overpredictions and underpredictions, whereas trading gains depend on whether the forecast is directionally correct, rather than on how close the forecasted value is to the actual value. The economic value that some models exhibit in statistical tests vanishes when trading costs are included into account. It accounts for the fact that the model which is statistically optimal is not economically optimal; one can gain higher risk-adjusted returns from a less precise model.

5. Comparative analysis based on literature evidence

5.1. Statistical performance of models

There are several metrics can be used to demonstrate the performance of different models. For all the models in this article, values of R^2 and RMSE are picked as main metrics. The table below lists out the accuracy metrics of different models from different backgrounds.

Table 1. Performance of statistical predictions in out-of-sample analysis – selected literature

Study	Model	R^2	RMSE
Study A [16]	LR	-0.0426	15.65
Study A [16]	RF	0.0024	14.39
Study A [16]	NN	0.0030	14.21
Study A [16]	LSTM	0.0057	14.06
Study A [16]	Factor-Gan	0.0112	13.93
Study B [17]	OLS	0.89	—
Study B [17]	XGBoost	0.0227	—
Study C [18]	Linear	-0.06596	0.01953
Study C [18]	RandomForest	-0.05145	0.01952
Study C [18]	Ridge	-0.00421	0.01898

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Table 1. (continued)

Study C [18]	XGBoost	-0.00296	0.01897
Study D [19]	ConvLSTM/AAPL	0.9220	0.0260
Study D [19]	ConvLSTM/META	0.9770	0.0256
Study D [19]	ConvLSTM/SBUX	0.9043	0.0290
Study D [19]	ConvLSTM/TSLA	0.9118	0.0394

Note: bold data perform the best statistically in their own study

Within Study A, Factor-GAN achieves the strongest reported out-of-sample predictive performance, with an R^2 of 1.12% and an RMSE of 13.93%. Study B reports a higher out-of-sample R^2 for XGBoost than for OLS, while Study C reports only small and negative out-of-sample R^2 values for all models. Study D evaluates the same ConvLSTM architecture across four stocks; these cross-asset results should not be treated as a controlled model comparison.

5.2. Economic value of each literature

The selected studies report the Sharpe ratio as a measure of risk-adjusted return. Maximum drawdown (MDD), where available, measures the largest peak-to-trough decline in portfolio value over the evaluation period. Lower absolute drawdown indicates smaller realized downside exposure, although sign conventions must be standardized before comparison.

Table 2. Summary of out-of-sample economic prediction performance across selected literature

Study	Model	Sharpe Ratio	Max Drawdown (%)
Study A [16]	LR	-0.02	Not reported
Study A [16]	RF	0.71	Not reported
Study A [16]	NN	0.75	Not reported
Study A [16]	LSTM	1.00	Not reported
Study A [16]	Factor-GAN	1.29	9.77
Study B [17]	OLS	1.17	21.04
Study B [17]	XGBoost	1.76	18.59
Study C [18]	Buy_Hold	0.19	43.12
Study C [18]	Linear	-0.00	23.29
Study C [18]	RandomForest	-0.05	29.57
Study C [18]	Ridge	0.12	21.07
Study C [18]	XGBoost	-0.19	39.94
Study D [19]	ConvLSTM/AAPL	1.13	17.97
Study D [19]	Buy_Hold/AAPL	1.03	28.26
Study D [19]	ConvLSTM/META	1.18	42.72
Study D [19]	Buy_Hold/META	1.42	49.07

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Table 2. (continued)

Study D [19]	ConvLSTM/SBUX	2.10	5.41
Study D [19]	Buy_Hold/SBUX	1.03	14.29
Study D [19]	ConvLSTM/TSLA	0.57	57.89
Study D [19]	Buy_Hold/TSLA	0.39	64.91

Note: data with bold letter have the best economic value based on Sharpe ratio and Max Drawdown.

For the study A, LSTM has a Sharpe ratio of 1.00, which is the highest among this study. And for study B, XGBoost performs the best economically because it has higher Sharpe value 1.76 and smaller MDD, better than OLS.

Study C shows that XGBoost has the lowest Sharpe ratio (−0.19) and a relatively large maximum drawdown (39.94% in absolute terms). Among the forecasting models, Ridge has a higher Sharpe ratio (0.12) and a smaller maximum drawdown (21.07%), but the buy-and-hold benchmark has a higher Sharpe ratio of 0.19.

Finally, for the last study D, it evaluates the economical performance of ConvLSTM model on four types of stock. For AAPL, the model performance is better because of the increased Sharpe ratio value (1.13 vs 1.03) and decreased MDD (17.97% vs 28.26%). ConvLSTM also increased the Sharpe ratio (2.10 vs 1.03) and reduced the maximum drawdown (5.41% vs 14.29%) of SBUX. META has a lower ConvLSTM Sharpe ratio than buy-and-hold (1.18 vs. 1.42), but it also has a smaller maximum drawdown (42.72% vs. 49.07%).

5.3. Relationship between statistical performance and economic value

In this section, the performances of both statistical and economic values of models are contrasted to find out if a highly accurate model necessarily means high investment value.

In study A, a more advanced model will be accompanied by higher investment from a financial perspective. The LSTM model is more advanced and has better performance with higher excess returns, making it more profitable for investment in the long run.

Similarly, in study B, similar to study A, the more advanced, more complex, and more resistant to overfitting XGBoost model has higher excess returns. Based on the high performance of the model, the conclusions made based on this model are going to be more valuable and thus make the investment in the long run more profitable.

However, not all complex and highly accurate models necessarily imply more future investment value; Study C provides an example of this situation. Even though the XGBoost model performed with the highest accuracy, it had significantly lower returns compared to other models, including Ridge regression.

In study D, the economic value of high accuracy is viewed in a completely different way. In this case, various stocks were evaluated in terms of their performance using a single ConvLSTM strategy. The model had outstanding fitting accuracy for all four stocks and surpassed the buy-and-hold strategy in case of AAPL, SBUUX, and TSLA. In the case of META, however, the results were opposite: even though the ConvLSTM strategy had the highest accuracy (as well as the highest R^2) of all strategies in regard to this particular stock, its Sharpe ratio was lower than that of the buy-and-hold strategy. Thus, in this case, high statistical accuracy did not mean economic value: when the fitting accuracy of the model regarding a particular stock is extremely high, errors in predicting its direction prevent obtaining excess returns.

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5.4. Discussion of the phenomenon

Three types of relationships between statistical performance and economic value can be observed in the comparative analysis of Section 5.3. To clarify the reasons behind the formation of these relationships, this section utilizes the mechanistic approach formulated in Chapter 4.

Positive relationship takes place where model complexity is compatible with data features. By achieving balance in bias and variance, a moderately complex model can recognize the underlying patterns of factor returns instead of capturing the noise. Thus, any gains in statistical precision result in strategy returns.

Negative relationship results from multiple interactions of mechanisms. As part of the effort to create an ideal fit in-sample, the complex model fits the noise present in financial data with low signal-to-noise ratios. The spurious signals created in the process become useless very quickly out-of-sample. Moreover, whereas RMSE evaluates prediction regardless of overestimation or underestimation, trading profitability depends on the accuracy of the predictions of direction. The example of XGBoost from Paper C with the lowest RMSE, worst Sharpe ratio (-0.19) and maximum drawdown of -39.94% directly shows how this mechanism works.

Conditional correlations provide an indication of the extent to which the intensity of the above-mentioned mechanisms changes depending on market and security-specific factors. In particular, in Paper D, the same ConvLSTM model produced statistically significant excess returns for AAPL, SBUX, and TSLA, but was inferior to the benchmark for META, which had the highest R^2 (0.977), suggesting that signal quality is different for different assets. Statistical accuracy becomes economic significance more easily in case of relatively stable factor return patterns, while in case when statistical patterns mainly come from the idiosyncratic nature of the particular sample period, they quickly lose their economic significance.

Thus, the interaction between statistical performance and economic value is affected by all three dimensions mentioned above (model complexity, signal quality, and market environment), and can be explained by a single mechanism framework.

6. Conclusion

This research paper attempts to solve the fundamental problem of whether a gain in statistical efficiency would mean a gain in investment value through a theoretical and empirical analysis of the same. Theoretical analysis entails formulating a framework through which statistical efficiency gets translated into economic value while empirical analysis involves conducting a comparative study of four research papers that include statistics as well as economic value. It has been established that statistical efficiency is necessary but not sufficient for economic value; the relationship is seen in many different forms.

More specifically, there are three types of relationships between statistical performance and economic performance: positive, negative, and conditional correlations. tudies A and B illustrate positive alignment, whereas the XGBoost evidence in Study C and the META evidence in Study D show that the statistically strongest result is not necessarily the most economically attractive. There are three main reasons for such differences. First, the problem of over-fitting makes models interpret noise as a signal and thus decreases their ability to generalize. Second, the decay of the signal means that the forecasting accuracy decreases with time. Third, the mismatch between the statistical criteria and trading performance means that low error does not necessarily imply accurate directionality. The interaction of these three factors results in complex models fitting noise and producing decaying signals. Finally, this becomes reflected in live trading as wrong directionality and losses.

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The above results provide reference for investors to select models: statistical measures cannot serve as the only benchmark, and risk-adjusted performance measures such as Sharpe Ratio and maximum drawdown must be taken into account in a comprehensive manner; the negative effects brought by overfitting must be taken into consideration, and the out-of-sample testing must be applied strictly; the real-time features of signals must be taken into account, and the weights of strategies must be readjusted dynamically according to their decaying rate.

This study has several limitations. The literature sample is small, and the selected studies differ in data frequency, market setting, prediction target, sample period, and evaluation protocol. Moreover, the proposed mechanisms are derived conceptually rather than tested directly. The future research can increase the sample size of the literatures, adopt targeted empirical solution, and even apply the analytical framework to other asset classes.

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