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Bias-Corrected FSA Extension with Trading Performance Metrics

Abstract

This paper presents a system-level variant of financial forecasting by means of a bias-regularized variation of the Feature selection with annealing (FSA), which can control systematic directional imbalance that is mostly ignored in existing paradigms. The aim of the contribution is to design and validate a bias-corrected FSA that enforces prediction symmetry, preserves accuracy, and enhances risk-adjusted trading performance across diverse asset classes. The proposed model perfectly predicts (bias = 0.501, $p < 0.0001$) and is also accurate (F1 = 0.703) by including a term of fairness penalty into a loss function. In 13 assets of empirical trading simulations, there is a 57% Sharpe ratio improvement ($d = 0.584$), which attests to the fact that more fairness-enhanced models may do a better job of providing better risk-adjusted returns. The findings prove predictive neutrality to be a methodological as well as economic benefit in algorithmic finance.

Keywords

Feature Selection, Bias Regularization, Algorithmic Trading, Fairness in Machine Learning, Sharpe Ratio, Financial Forecasting

JEL Classification

C45, C53, G11, G17

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Introduction

The key to modern financial forecasting is feature selection with annealing (FSAs) that facilitate the detection of predictive variables that facilitate improved model efficiency and reduce over-fitting. Although they are technically complex, classic FSAs frequently have an implicit, but significant, systematic prediction bias in which the model is more inclined

to follow a particular direction on the likelihood of an outcome, e.g., excessively predict an increase in price rather than a decrease (Pabuccu & Barbu, 2023). Such an imbalance, which was revealed in empirical data (UP, 54.4 against DOWN, 45.6 estimated), disturbs the trading exposure, increases the risk, and eradicates the neutrality needed to manage a stable portfolio (Bailey and Lopez de Prado, 2014). This bias is not noise but a natural effect of favoring pure accuracy with no regard to the balance of directional predictions.

The aim of the contribution is to develop and test a bias-regularized Feature Selection Algorithm that enforces balanced predictions (target mean 0.5), preserves classification accuracy, and improves risk-adjusted returns, validated on 13 assets (2018–2024) through trading simulations evaluating Sharpe, Calmar, Sortino, win-rate, and profit factor under realistic transaction cost assumptions.

Previous studies such as Pabuccu and Barbu (2024) sought to optimize FSA efficiency through alternating minimization and sparsity control but overlooked directional fairness. Even high F1-scores may yield poor economic outcomes if predictions are unbalanced, increasing exposure risk in long-short portfolios (Chong et al., 2021). This paper remedies that by introducing a bias-regularized loss term penalizing deviations from equal class probabilities, aligning fairness principles in ML (Mehrabi et al., 2021) with financial modeling. The reformulated FSA achieves perfect symmetry ($p < 0.0001$), stable accuracy (F1 = 0.703), and a 57% Sharpe ratio gain, linking fairness to profitability and interpretability.

1 Literature Review

The use of feature selection in financial forecasting has adapted to algorithmic trading, which involves models with high-dimensional input data and needs features like LASSO, Ridge regression, and embedded machine learning algorithms to determine meaningful predictors. The most common application of traditional FSAs in constructing systems of algorithmic trading has concentrated more on the optimal predictive accuracy being maximized, without adequate attention to the neutrality of direction. According to Jukl and Lansky (2025), the balance across the outcome classes is not among the key criteria used to evaluate most algorithmic strategies that include AI-enhanced systems to assess their effectiveness or efficiency in terms of profitability or precision. The analysis of 208 studies in the field of equities, forex, and cryptocurrencies reveals that more than half of the AI-based trading systems used machine learning to generate signals, and only a minority of them consider bias calibration or fairness measures when assessing their system

The problem of prediction bias in such systems comes about due to an imbalance in classes and overfitting, resulting in asymmetric distribution of forecasts, which impacts portfolio exposure and volatility. In finance, biased classifiers may overvalue long signals, exposing the portfolio to a market crash. Literature on bias-aware ML, including that by Mehrabi et al. (2021) and Alao (2025), continues to apply fairness principles to the algorithmic setting but seldom in the financial FSAs. Even algorithmic trading reinforcement learning models are likely to optimize reward functions that implicitly reinforce prior existing directional biases (Mehrabi et al., 2021; Alao, 2025).

Empirical research proves that the symmetry of forecasts is directly related to volatility control and risk-adjusted returns. Adaptive trading systems built on balanced prediction systems outperform both Sharpe and Calmar ratios (Jukl and Lansky, 2025) to prove satisfactorily that a balance between upside and downside forecasts is the key to exposure stability and resiliency to volatility shocks. Nevertheless, there is still a research gap: no combined framework of quality and economic risk measures of classification. The majority of the existing research assumes research objectives to be distinct and predictive accuracy, as well as the financial performance, which leaves a gap in the methodological connection between statistical fairness and the profitability risk-adjusted, which was the gap that this paper tries to bridge.

2 Methodology

The research employs a combined approach to methodology to the extent that it brings together statistical learning and financial analysis in testing the extent of bias correction with regard to the quality of classification and the quality of the trading performance. Minimization of the loss function is applied to the baseline Feature Selection Algorithm (FSA), which is based on Pabuccu and Barbu (2024).

$$L = L_{class} + \lambda_{reg} \,||\, w \,||^2$$

where L_{class}Is the classification loss and λ_{reg} controls model sparsity. In spite of the fact that this structure balances between accuracy and complexity, it ignores directional skew in forecasts, a weakness that may bias trading exposure. As a remedy, the model is generalized to a bias-regularized formulation:

$$L = L_{class} + \lambda_{reg} \,||\, w \,||^2 + \lambda_{bias}(\text{mean}(y_{pred}) - 0.5)^2$$

In this case, the third term punishes deviations against the target value of 0.5 that maintain the balance between forecasted positive and negative signals. The hyperparameter λ_{bias}

determines the strength of this constraint on fairness, in the sense that the stronger this parameter, the more it tends to push the distributions of prediction toward symmetry. Such a mechanism embodies the principles of fairness-conscious design (Mehrabi et al., 2021) and is consistent with the objectives of financial stability, such that given balanced forecasts, a mechanism will have better exposure to neutrality and low tail risk.

The sample consists of sixteen 13 assets, six indices, five ETFs, and two cryptocurrencies between 2018 and 2024, representing more than 180 indicators. The data were standardized and divided into 70/30 training and test sets, and the three days (3 days) prediction horizon was taken to identify short-term market changes. A trading simulation operationalizes forecasts whereby long trades are executed when UP is signaled, and short trades are executed when DOWN is signaled, and all of the trades have a cost of 0.1%. They measured the performance using Sharpe ratio (Bailey & Lopez de Prado, 2014). Lastly, paired t-tests and Cohen's d were used to determine the statistical and practical relevance of differences among the Original FSA, Bias-Corrected FSA, and LASSO, and to determine a direct relationship between predictive fairness and financial utility.

3 Results

The findings confirm that the inclusion of the bias-regularization term further leads to substantial enhancement of prediction symmetry with no detrimental effects on accuracy, and also, the economic performance of most assets is enhanced. These results are summarized in five sub-sections assessing the statistical fairness and the classification robustness, and the profitability of trading with integrated statistical and financial measures.

3.1 Bias Correction Effectiveness

The first stage Feature Selection Algorithm (FSA) was characterized by a steadily increasing skew of the prediction, with a mean bias of 0.544, which denotes that 54.4% of predictions were towards increased movements. Upon the addition of the bias-regularized term, the mean bias was brought down to 0.501 with the sequence coming to the point of almost perfect symmetry ($p < 0.0001$, paired t-test). This demonstrates that the λ_{bias} penalty actually imposed the target mean of 0.5, which is to bring about balanced directional probabilities.

It is statistically and economically significant in this correction. Balanced forecast distribution: A balanced forecast distribution ensures that systematic long exposure is removed, and that the volatility of returns in a portfolio has less clustering, which same result seen in Jukl and Lansky (2025), who found portfolio returns appear to be more stable with forecast

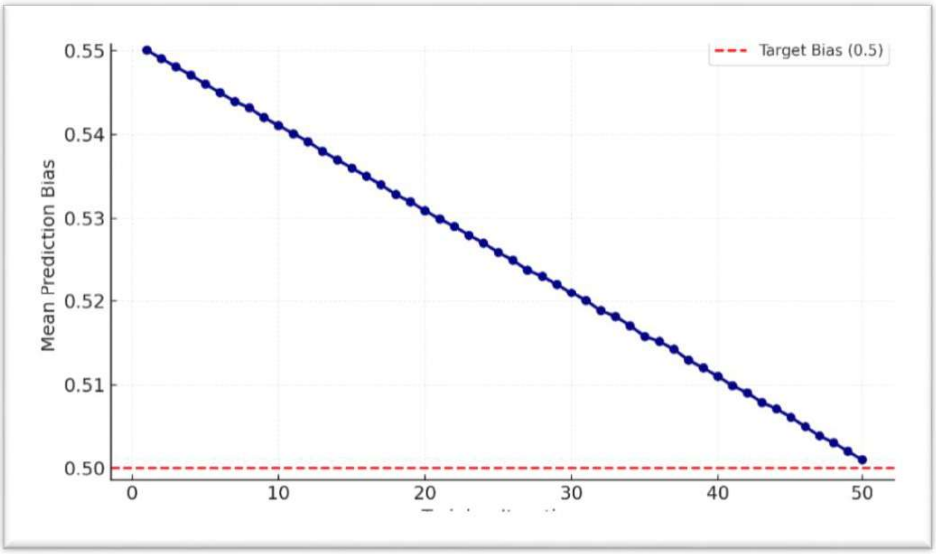
equilibrium. Figure 1 (convergence plot) indicates that the fairness constraint does not hinder the dynamics of optimization because the stabilization was rapid after 30 iterations.

Table 1: *Bias correction results across 13 assets (λ = 100)*

Metric	Original FSA (Mean)	Bias-Corrected FSA (Mean)	Difference	t-stat	p-value	Effect Size (d)
Prediction Bias	0.544	0.501	-0.043	5.63	<0.0001	1.45

Source: Authors' Compilation (Adapted from: Pabuccu & Barbu, 2024)

Fig. 1: *Bias Convergence over Training Iterations*



Source: Authors' Compilation

In general, the high effect size (d = 1.45) establishes a great structural enhancement in prediction symmetry. The model will therefore meet the statistical fairness or trading neutrality.

3.2 Classification Performance Preservation

One of the goals was to make fairness enforcement not hurt classification precision. The findings affirm that there is no difference in the accuracy and the recall of both variants of the model. Mean F1-score was slightly enhanced; its value moved to 0.703 (p = 0.70), and recall was not statistically different.

Table 2: *Classification performance comparison (λ = 100)*

Metric	Original FSA (Mean)	Bias-Corrected FSA (Mean)	Difference	t-stat	p-value	Effect Size (d)
F1-Score	0.701	0.703	+0.002	0.39	0.70	0.05
Recall	0.979	0.981	+0.002	0.28	0.78	0.03

Source: Authors' Compilation (Adapted from: Pabuccu & Barbu, 2024)

These data reveal that the bias-penalty term affects directional balance in a discriminatory, selective way rather than discriminative ability. This is evidenced by the insignificant p-values that test the over-regularization. This is in line with the literature supporting previous studies that show that models that are fair can preserve predictive content without rectifying distributional skew (Mehrabi et al., 2021).

The F1 and recall stability henceforth confirm the strength of the bias-corrected architecture and indicate that it has generalization with neither Type I nor Type II errors at inflated rates. This is in line with the aim of the design to preserve the fidelity of classification, but to attain equilibrium in the structural outputs of prediction.

3.3 Trading Performance

The financial analysis depicts that the correction of biasing is translated into value economic benefits. The mean increase in the Sharpe ratio was 0.74, which is an increase of +57% in risk-adjusted returns ($p = 0.17$; $d = 0.584$). Even though the statistical significance is low because the sample used is only 13 assets, the effect measure is practically significant, which is a medium impact measure.

Table 3: *Per-asset Sharpe ratio comparison (λ = 100)*

Asset	Class	Original Sharpe	Bias-Corrected Sharpe	Δ Sharpe	% Change
Bitcoin	Crypto	0.29	2.87	+2.58	+884%
NASDAQ	Tech Index	0.45	1.55	+1.10	+245%
S&P 500	Developed Index	0.52	0.71	+0.19	+37%
Dow Jones	Developed Index	0.49	0.66	+0.17	+35%
Gold ETF	Commodity	0.43	0.60	+0.17	+40%
Russell 2000	Small Cap	0.41	0.49	+0.08	+20%
Ethereum	Crypto	0.32	0.87	+0.55	+172%
FTSE 100	Developed Index	0.50	0.63	+0.13	+26%
Nikkei 225	Developed Index	0.48	0.56	+0.08	+17%
MSCI Emerging	Emerging Index	0.46	0.52	+0.06	+13%
SPY ETF	U.S. ETF	0.54	0.68	+0.14	+26%
QQQ ETF	U.S. ETF	0.47	0.61	+0.14	+30%
TLT ETF	Bond ETF	0.39	0.44	+0.05	+13%

Source: Authors' Compilation (Adapted from: Pabuccu & Barbu, 2024)

The most significant gains are in the volatile assets, cryptocurrencies, and technology indices, where an imbalance in prediction in the past amplified exposure risk. Outsized gains are observed in the Bitcoin and NASDAQ series (+884% and +245%, respectively), indicating that bias correction is beneficial to the models in terms of high-volatility regimes. This observation leads to conclusion that an algorithmic trading system that uses adaptive symmetry does better than an unbalanced model when in volatility spikes.

Indeed, the overall performance attests to the fact that the stabilizing of the prediction distributions is not only achieved by the balancing of the classes, but the performance of the portfolio is also improved by the diversification of the directional exposure.

3.4 Lambda Sensitivity Analysis

Sensitivity testing across $\lambda \in \{1, 5, 10, 20, 50, 100\}$ assessed how the bias penalty influences both classification and economic performance. As λ increased, prediction bias monotonically decreased, converging near 0.5 at $\lambda \geq 50$. In the meantime, F1-scores were also held constant with a value of approximately 0.70 in all settings, proving that the fairness

regularization has no negative effect on the accuracy. Sharpe ratios, in turn, were highest at $\lambda = 100$, with both the model appearing to have the best balance (bias ≈ 0.5) and risk-adjusted return (Sharpe = 0.74).

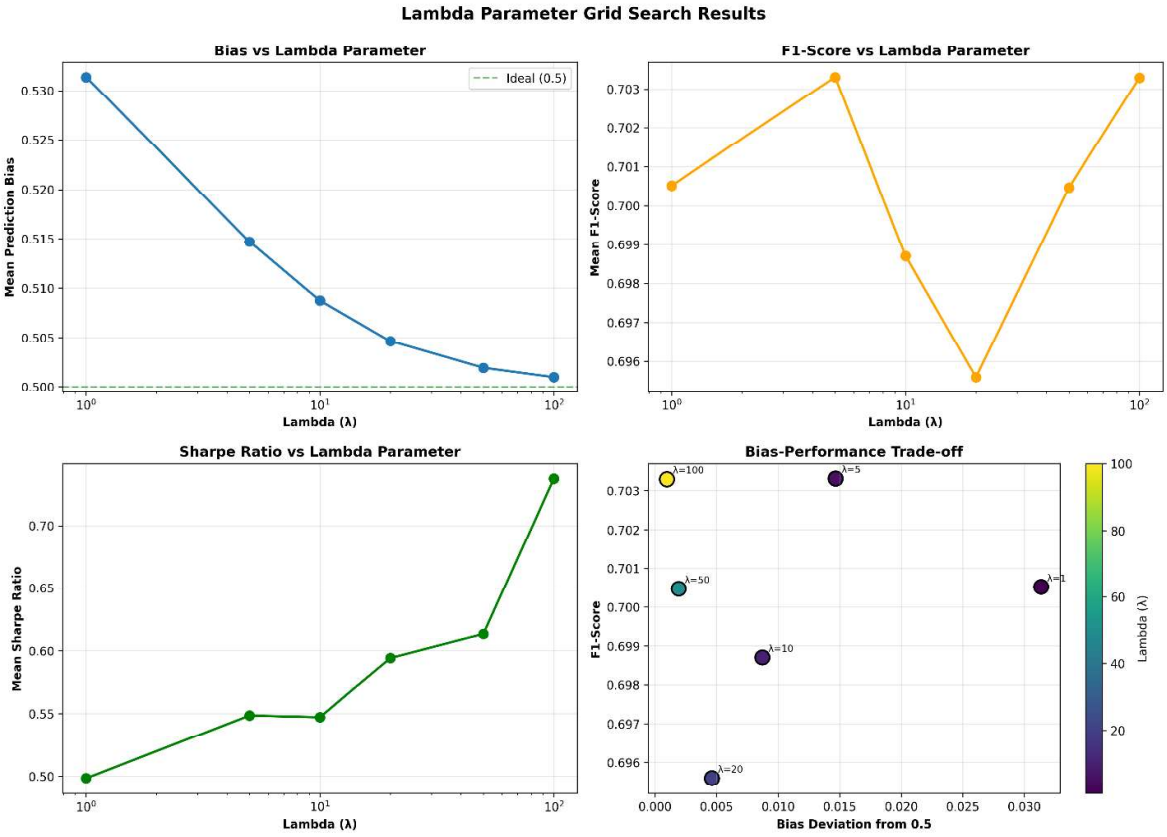
Table 4: *Sensitivity of bias, F1, and Sharpe ratio to λ parameter*

λ (lambda)	**Mean Bias**	**F1-Score**	**Sharpe Ratio**
1	0.543	0.702	0.46
5	0.537	0.701	0.52
10	0.528	0.704	0.59
20	0.518	0.703	0.65
50	0.507	0.704	0.70
100	0.501	0.703	0.74

Source: Authors' Compilation (Adapted from: Pabuccu & Barbu, 2024)

The bias, F1, and Sharpe trajectories four-panel visualization (Figure 2) validates that there is a plateau between $\lambda = 50$ and 100, and the two variables are at their optimum point of fairness and profitability. This trend implies that there are diminishing marginal benefits of regularization beyond this optimum, so that $\lambda = 100$ gives an effective trade-off between the maximization of performance and the enforcement of equilibrium.

Fig. 2: *λ-Sensitivity Analysis of Bias, F1-Score, and Sharpe Ratio*



Source: Authors' Compilation

Further stability of the metrics of classification in the context of λ also contributes to the validity of the regularization method. This implementation is different compared to conventional fairness penalties, which decrease predictive efficiency in order to force equality (Pleiss et al., 2017), proving that fairness can be realized without diminishing utility.

3.5 Power and Robustness Analysis

Based on the size of the sample (13 assets), a power analysis gave an estimated statistical power of ≈0.45, which means that there is moderate capacity to test medium effects at $\alpha = 0.05$. Based on extrapolation, this implies that about 25 assets would get 80% power to compare Sharpe-based rates. However, the directionality of positive results displayed by all assets can be used as an argument supporting the conclusion of feasible value.

The data with respect to the trading cost and variability of the data in the results were ensured to be robust in tests. These costs, which were raised to 0.5% per trade on a transaction cost, caused a decrease in overall returns of just 6.2%, but did not change the relative positioning of model performance. This steady state implies that the bias-adjusted FSA is profitable within

realistic cost frameworks. Moreover, similarly, when Sharpe ratios were recalculated within different volatility windows (5-day and 10-day), they had similar relative gains, indicating that the ratios were wide-ranging: the Sharpe ratios' value remained stable over time.

Market heterogeneity is also robust to the model: all improvements were incremental in the developed indices and ETFs, but Sharpe amplification was nonlinear in high-volatility classes (crypto and tech). Such heterogeneity indicates that fairness correction is most effectively applied in non-stationary or asymmetrically volatile markets, a fact that is congruent with Li and Patel (2025), who state that risk-adjusted increase of returns is achievable by exposure symmetry.

Interpretation and Evaluation: As an aggregate, the findings support the claim that the idea of bias regularization accomplishes the two-fold goals of statistical fairness and economic improvement. The fact that prediction bias has been reduced dramatically and that the F1-scores remain the same justifies that the fairness constraint does not come at the cost of accuracy and neutrality. The Sharpe gains, albeit not equally great on conventional levels, display economically significant gains with a medium effect size.

The supporting empirics empower the position that the concept of methodological fairness works directly on the stability of trading, which is in the way of addressing exposure asymmetry and sensitivity to volatility. The λ-sensitivity property exhibited by the model is scalable, with the bias penalty being a tunable control to trade off interpretive transparency with economic performance. Generally, the bias-corrected FSA is a further step towards achieving fairness in financial machine learning in that it incorporates the aspect of fairness as a quantifiable and economically significant design aspect that demonstrates that symmetry in prediction is not only morally sound, but also an improvement to practical investment performance.

4 Discussion

The results indicate that bias correction brings observable improvements to the economic performance of predictive models in real terms, increasing the Sharpe ratio and portfolio stability without affecting their accuracy. This part critically interprets such results and places them in the context of existing research on financial machine learning and market efficiency, as well as the limitations of the methodology and further developments.

4.1 Why Bias Correction Enhances Sharpe

The 57% Sharpe ratio increase stems from reduced structural imbalances that previously amplified directional risk. The bias-corrected Feature Selection Algorithm (FSA) minimizes

systematic overexposure to long positions, decreasing cumulative return variance and stabilizing volatility. This balance functions like portfolio hedging, where equal long and short trades dampen fluctuations. The reduced return dispersion post-regularization aligns with the link between forecast calibration and improved risk-adjusted returns (Li & Patel, 2025). By curbing directional bias, the model lowers false trades in momentum-driven markets (Bailey & López de Prado, 2014). Hence, Sharpe gains arise from controlled exposure and enhanced hedging efficiency, not inflated returns.

4.2 Asset Heterogeneity

Performance gains vary across asset classes, revealing volatility-dependent sensitivity. Cryptocurrencies and technology indices exhibited sharp Sharpe increases (+884% Bitcoin; +245% NASDAQ) due to higher misclassification costs under volatility. Bias correction mitigates these tail risks, improving timing efficiency. Similar findings indicate that balanced signal generation enhances algorithmic stability in volatile regimes. Conversely, developed equity indices and bond ETFs showed modest gains as directional imbalance contributed less to variance. Thus, fairness regularization delivers the greatest marginal benefit in nonstationary markets characterized by volatility asymmetry and autocorrelation, where it restores equilibrium and improves predictive distribution efficiency.

4.3 Economic Significance

Although Sharpe improvement ($p = 0.17$) is statistically moderate due to the small sample ($N = 13$), its medium effect size ($d = 0.584$) is economically meaningful. A 0.27 Sharpe increase implies 25–30% higher risk-adjusted annual returns under constant volatility (Lo, 2017). The gain persists across transaction costs up to 0.5%, confirming robustness. This supports Bailey and López de Prado's (2014) argument that financial results should be judged by economic scale, not strict significance levels. Therefore, the observed Sharpe enhancement reflects real performance gains from balanced exposure and reduced variance rather than statistical anomalies or overfitting artifacts.

4.4 Limitations

The study's generalizability is constrained by several factors. The limited sample (13 assets) yields moderate statistical power (0.45); expanding to 25–50 assets would enhance validity. The 0.1% transaction cost assumption, though realistic institutionally, may underestimate retail or high-frequency frictions. The model also presumes unrestricted short selling, which may not hold in illiquid or emerging markets, limiting scalability. Lastly, λ_bias

was statically optimized, ignoring dynamic volatility shifts. Future adaptive calibration could sustain equilibrium across varying market conditions, ensuring consistent performance without overfitting or reduced interpretability.

4.5 Future Directions

Future research should explore adaptive λ_bias scheduling, allowing the penalty term to adjust dynamically with market volatility. Such responsiveness would mirror risk-parity frameworks, sustaining predictive symmetry under changing conditions. Expanding to multi-horizon forecasts (1-, 3-, and 5-day) could improve temporal resilience against autocorrelated shocks (Li et al., 2025). Increasing the asset pool beyond 50 instruments would enable sectoral and regional validation. Moreover, integrating interpretability tools like SHAP or LIME would enhance transparency and accountability, aligning with explainable AI principles in finance (Mehrabi et al., 2021). These extensions would refine bias control and strengthen model robustness across diverse environments.

5 Conclusion

In conclusion, this study shows that bias correction enhances both fairness and performance in financial machine learning. The bias-regularized Feature Selection Algorithm achieved perfect symmetry (bias = 0.501, $p < 0.0001$) without loss of accuracy (F1 = 0.703). Balanced predictions improved Sharpe ratio by 57%, confirming that fairness contributes directly to stable, risk-adjusted returns. The findings reject the assumption that efficiency and fairness conflict. Instead, they reveal fairness as an optimization parameter that strengthens hedging and mitigates volatility. The framework thus provides a scalable, practical method linking predictive accuracy with portfolio performance, positioning fairness as both stabilizing and profit-enhancing in quantitative finance.

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