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Portfolio Management Using the Black–Litterman Model and Incorporating Investor Views

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ABSTRACT

Portfolio management has consistently faced the fundamental challenge of uncertainty in estimating asset returns and risks, which has limited the practical effectiveness of classical optimization approaches, particularly the Markowitz mean–variance model. In this context, the Black–Litterman model, as a Bayesian framework, enables the derivation of more stable estimates that are consistent with market economic logic by combining market equilibrium returns with investor views. The primary objective of the present study is to propose a structured framework for portfolio management using the Black–Litterman model with the systematic incorporation of investor views grounded in fundamental analysis and asset pricing factors. From a methodological perspective, this research is applied–developmental and quantitative, and it is empirically conducted using daily stock data of manufacturing firms listed on the Tehran Stock Exchange over the period 2015 to 2023. Rather than relying on subjective judgments, investor views are extracted based on the results of regressions from the Fama–French three-factor model and are incorporated into the Black–Litterman framework in the form of relative views. After computing the implied equilibrium returns and incorporating the views, posterior Black–Litterman returns are derived, and optimal portfolio weights are determined through mean–variance optimization. The performance of the resulting portfolio is compared with that of the classical Markowitz portfolio and the baseline Black–Litterman model using return, risk, and risk-adjusted performance measures. The findings indicate that the implied equilibrium returns obtained from the Black–Litterman model are generally more conservative than historical averages and help prevent overfitting to past data. The empirical results show that incorporating Fama–French–based views leads to a significant increase in cumulative returns, improvements in the Sharpe and Sortino ratios, and reductions in the standard deviation and maximum drawdown of the portfolio compared with both the Markowitz approach and the Black–Litterman model without views. Moreover, sensitivity analysis with respect to the τ parameter demonstrates that selecting intermediate values of this parameter can establish an appropriate balance between market information and investor views. Overall, the results confirm that the structured integration of Fama–French factor analysis with the Bayesian Black–Litterman framework enhances the stability of asset allocation and improves the risk-adjusted performance of portfolios, and can therefore serve as a practical and reliable framework for investment managers in volatile and emerging markets.

Keywords: Portfolio management; Black–Litterman model; Fama–French three-factor model; investor views; portfolio optimization; Tehran Stock Exchange.

Introduction

Portfolio management has long stood at the center of both theoretical finance and practical investment decision-making, driven by the fundamental challenge of allocating capital among risky assets in a manner that balances expected return against uncertainty. Classical portfolio theory, originating from the mean–variance framework,

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provided a mathematically elegant solution to this problem by formalizing diversification and optimality under risk aversion. However, despite its conceptual importance, extensive empirical evidence has shown that traditional optimization approaches are highly sensitive to estimation errors in expected returns and covariance matrices, often resulting in unstable and counterintuitive portfolio weights. This gap between theoretical optimality and practical robustness has motivated a substantial body of research aimed at developing portfolio construction frameworks that are both economically meaningful and empirically reliable (1, 2).

Within this broader context, the Black–Litterman model has emerged as one of the most influential innovations in modern portfolio management. Originally introduced as a Bayesian extension of mean–variance optimization, the Black–Litterman framework addresses key weaknesses of classical models by anchoring expected returns to a market equilibrium and allowing investors to incorporate subjective or model-based views in a controlled and transparent manner. By combining equilibrium-implied returns with investor views through Bayesian updating, the model generates posterior return estimates that are more stable and better aligned with market structure than naïve historical averages (3, 4). This equilibrium-based anchoring is widely regarded as a critical mechanism for mitigating the overfitting and extreme allocations that often plague traditional optimization.

Over the past two decades, the Black–Litterman model has evolved from a practitioner-oriented heuristic into a rich and expanding research paradigm. Early contributions focused on clarifying the mathematical structure of the model, interpreting its parameters, and providing step-by-step implementation guidelines that made it accessible to portfolio managers and researchers alike (4). Subsequent studies extended the original framework by relaxing distributional assumptions, incorporating alternative risk measures, and embedding the model within broader Bayesian decision-theoretic perspectives (3, 5). These developments collectively repositioned the Black–Litterman model not merely as an adjustment technique, but as a general paradigm for combining heterogeneous information sources in investment management.

A central theme in the contemporary literature concerns the nature and construction of investor views. In its original formulation, the Black–Litterman model allows views to be expressed as linear combinations of asset returns, accompanied by a confidence measure reflecting uncertainty. While this flexibility is theoretically appealing, it raises practical questions regarding how views should be generated in a disciplined and reproducible manner. Early applications often relied on subjective judgments or discretionary forecasts, which, although valuable in practice, limit transparency and reproducibility in empirical research. As a result, a growing strand of literature has sought to ground investor views in observable data, econometric models, and asset pricing theory (1, 6).

One influential approach to systematic view generation involves linking the Black–Litterman framework with factor models of asset returns. Asset pricing models, such as the Capital Asset Pricing Model and its multifactor extensions, provide a theoretically grounded description of how returns relate to systematic risk factors. By exploiting estimated factor loadings and expected factor premia, researchers can construct views that are economically interpretable and empirically testable. Recent studies have demonstrated that factor-based views can improve portfolio performance by aligning expected returns with underlying sources of risk and return, rather than relying solely on historical averages (7, 8). This integration represents a meaningful step toward bridging the gap between asset pricing theory and portfolio optimization.

Among multifactor models, the Fama–French framework occupies a particularly prominent position due to its strong empirical support and widespread adoption in both academia and practice. Although originally developed to explain cross-sectional return patterns, its factor structure has increasingly been employed as an input to portfolio construction and strategic asset allocation. By interpreting estimated factor exposures as indicators of systematic return drivers, investors can form relative or absolute views on assets based on their exposure to market, size, value, and other risk dimensions. Prior empirical evidence suggests that portfolios constructed with factor-informed expectations tend to exhibit more robust out-of-sample performance and improved risk-adjusted returns (9, 10).

The integration of factor models with the Black–Litterman framework has been explored across diverse markets and asset classes. Empirical applications in emerging and developed markets alike indicate that the Bayesian combination of equilibrium returns and factor-based views can enhance diversification benefits and reduce sensitivity to estimation noise. Studies focusing on equity markets in Asia, Europe, and emerging economies consistently report that Black–Litterman portfolios incorporating systematic views outperform traditional benchmarks in terms of both absolute and risk-adjusted performance (9-11). These findings underscore the adaptability of the model to different market structures and institutional settings.

Parallel to factor-based developments, another important research direction has examined the treatment of uncertainty and estimation risk within the Black–Litterman model. The choice of key parameters, particularly those governing the confidence in equilibrium returns and investor views, plays a decisive role in shaping posterior expectations and portfolio weights. Mis-specification of these parameters can undermine the intended stabilizing effect of the model. Consequently, several studies have proposed refined estimation techniques, robust Bayesian priors, and sensitivity analyses to better manage uncertainty and improve the reliability of portfolio outcomes (12, 13). These contributions highlight that effective implementation of the Black–Litterman model requires careful attention not only to views themselves, but also to their associated uncertainty.

More recent research has expanded the Black–Litterman framework by incorporating advanced statistical and computational techniques. Copula-based dependence structures, regime-switching dynamics, and downside-risk measures such as Conditional Value at Risk have been integrated into the model to better capture nonlinear dependencies and tail risks (2, 13). In parallel, advances in computational economics and data science have enabled the use of simulation-based methods, such as Markov Chain Monte Carlo and evolutionary algorithms, to estimate model parameters and generate dynamic views (14). These methodological innovations reflect a broader trend toward more flexible and data-intensive portfolio optimization frameworks.

Another emerging strand of the literature explores the role of alternative information sources and learning mechanisms in Black–Litterman–type models. Rather than relying solely on traditional financial indicators, recent studies investigate how machine learning outputs, ordinal information, and heterogeneous expert signals can be systematically incorporated into the Bayesian updating process. This line of research suggests that the Black–Litterman framework is well suited to accommodating complex and non-traditional information, provided that such inputs are translated into coherent views and confidence structures (15, 16). These developments further reinforce the model's relevance in an era characterized by data abundance and informational complexity.

Despite the richness of the existing literature, several gaps remain. First, while many studies emphasize the benefits of integrating factor-based or model-driven views, fewer contributions provide a fully structured framework that explicitly links asset pricing estimation, view construction, and portfolio optimization in a transparent empirical setting. Second, much of the empirical evidence focuses on developed markets, leaving emerging and frontier markets comparatively underexplored, despite their distinct risk characteristics and informational inefficiencies. Third, there is ongoing debate regarding the relative effectiveness of different view-generation mechanisms and their impact on portfolio stability and downside risk, particularly during periods of heightened market volatility (17, 18).

Addressing these gaps is particularly important given the growing complexity of modern financial markets and the increasing demand for robust, explainable, and adaptive investment strategies. Investors and portfolio managers require frameworks that not only deliver superior performance metrics but also provide economic intuition and transparency in decision-making. The Black–Litterman model, when enriched with systematic and theory-driven views, offers a promising avenue for meeting these requirements by reconciling equilibrium market information with informed expectations about relative asset performance (5, 8).

Against this backdrop, the present study situates itself at the intersection of Bayesian portfolio optimization and asset pricing theory. Building on prior theoretical and empirical contributions, it seeks to develop and empirically evaluate a structured approach to incorporating factor-based investor views within the Black–Litterman framework. By emphasizing disciplined view construction, careful treatment of uncertainty, and comprehensive performance evaluation, the study aims to contribute to both the methodological literature and practical portfolio management. In doing so, it aligns with recent calls for integrative frameworks that combine economic theory, statistical rigor, and empirical validation in investment research (14, 16).

The aim of this study is to develop and empirically assess a structured Black–Litterman portfolio optimization framework that integrates asset pricing–based investor views to improve risk-adjusted portfolio performance.

Methods and Materials

In terms of purpose, this study is applied–developmental, and in terms of nature, it is quantitative, analytical, and model-based. The main objective is to propose a structured framework for integrating investor views based on fundamental analysis into the Black–Litterman model in order to improve asset allocation and portfolio risk management. Unlike traditional approaches that incorporate views subjectively, in this study investor views are extracted systematically based on the Fama–French three-factor model and are combined with market equilibrium returns within the Bayesian Black–Litterman framework. From an implementation perspective, the research is empirical, and the performance of the proposed model is tested using real data from Iran's capital market.

The statistical population of the study consists of stocks of manufacturing companies listed on the Tehran Stock Exchange. To enhance sample homogeneity and ensure consistency with fundamental analysis, firms operating in financial industries and investment funds are excluded from the sample. Stock selection is conducted based on fundamental screening criteria, including positive operating profitability and a price-to-earnings ratio lower than the historical market average. The data are collected on a daily basis over the period from 2015 to 2023, and adjusted closing prices are used to compute returns. Data sources include the TSETMC platform and audited financial statements of firms, and the effects of periods with abnormal market volatility are analytically considered in the interpretation of results.

In the analysis stage, daily stock returns are first calculated and the variance–covariance matrix is estimated. Subsequently, the Fama–French three-factor model is estimated for each stock, and expected returns based on fundamental factors are extracted. Implied market equilibrium returns are computed via reverse optimization, and investor views are defined as the differences between factor-based expected returns and equilibrium returns. These views are incorporated into the Black–Litterman Bayesian equation in the form of the Q vector and the P matrix, while accounting for their uncertainty through the Ω matrix, yielding posterior returns. Finally, mean–variance optimization is performed, and the performance of the resulting portfolio is evaluated using measures such as return, risk, and the Sharpe ratio. All computations are carried out using MATLAB software.

Findings and Results

The skewness coefficients for most assets fall within a relatively narrow range around zero. Some assets, such as R_PRD01, R_PRD03, and R_PRD13, exhibit mild positive skewness, whereas assets such as R_PRD02, R_PRD04, R_PRD07, R_PRD12, and R_PRD17 display negative skewness. This indicates that return distributions are generally fairly symmetric, with slight tendencies toward extreme losses or gains. More importantly, all kurtosis coefficients exceed the value of 3 (normal kurtosis), ranging approximately from 3.4 to 4.6, and excess kurtosis is positive for all assets. This confirms the presence of fat tails and a higher probability of extreme price shocks in daily stock returns.

Table 1. Descriptive statistics of daily returns of selected stocks

Asset Code	N (Observations)	Skewness	Standard Deviation	Mean Return	Kurtosis	Excess Kurtosis
R_PRD01	1565	0.22555	0.026886	0.00050231	4.5550	1.5550
R_PRD02	1565	−0.088232	0.020778	0.00088479	4.2072	1.2072
R_PRD03	1565	0.21870	0.025885	0.00048572	4.4513	1.4513
R_PRD04	1565	−0.11544	0.024879	0.00054691	3.9793	0.97926
R_PRD05	1565	0.055263	0.027292	0.00128180	4.4353	1.4353
R_PRD06	1565	−0.065206	0.020431	0.00041321	4.0037	1.0037
R_PRD07	1565	−0.11932	0.019229	0.00104120	4.2723	1.2723
R_PRD08	1565	−0.078631	0.016619	0.00044361	4.1044	1.1044
R_PRD09	1565	0.027367	0.027251	0.00055204	4.0208	1.0208
R_PRD10	1565	−0.036405	0.017271	0.00078964	3.9491	0.94907
R_PRD11	1565	0.060327	0.021994	0.000044903	3.4980	0.49795
R_PRD12	1565	−0.17378	0.027827	−0.0000061065	3.9488	0.94881
R_PRD13	1565	0.15589	0.020354	0.00129420	4.0728	1.0728
R_PRD14	1565	−0.024625	0.024112	0.000064967	3.4456	0.44556
R_PRD15	1565	−0.12125	0.029318	−0.00010839	3.9350	0.9350
R_PRD16	1565	0.04193	0.019312	0.00122080	4.5902	1.5902
R_PRD17	1565	−0.11474	0.015467	−0.00019471	3.8271	0.82705
R_PRD18	1565	−0.04101	0.024686	0.00084933	4.2768	1.2768
R_PRD19	1565	−0.065923	0.022409	−0.00012607	4.1763	1.1763
R_PRD20	1565	0.040678	0.015225	0.00026772	4.1661	1.1661

The results reported in Table 2 indicate that, in most cases, the implied equilibrium returns (π) are estimated to be lower than the historical average returns of the assets. For example, for assets R_PRD01, R_PRD05, R_PRD10, and R_PRD16, the difference between the historical mean and π is negative, ranging approximately from −0.00012 to −0.00024. This pattern is consistent with the logic of the Black–Litterman model, since implied equilibrium returns are obtained by combining historical information with the market risk structure and market portfolio weights, thereby smoothing potentially optimistic historical estimates toward more conservative values consistent with overall market equilibrium. In other words, by imposing equilibrium constraints, the model prevents excessive return expectations and provides estimates that are more compatible with the variance–covariance matrix and the market's degree of risk aversion.

Table 2. Correlation of stock returns with Fama–French three factors

Asset	Correlation with MKT_RF	Correlation with SMB	Correlation with HML
R_PRD01	0.5944	0.0988	0.2215
R_PRD02	0.7662	−0.0943	0.0801
R_PRD03	0.7557	0.1751	0.2919
R_PRD04	0.4845	0.3389	0.3092
R_PRD05	0.7760	0.4110	0.2572
R_PRD06	0.4792	0.1982	0.0380
R_PRD07	0.7345	−0.0250	0.0047
R_PRD08	0.6057	0.5029	0.1099
R_PRD09	0.6811	0.1401	−0.0484
R_PRD10	0.7584	−0.0227	−0.0180
R_PRD11	0.7465	0.3836	0.0334
R_PRD12	0.7099	0.2657	0.1241
R_PRD13	0.5649	0.3282	0.4313
R_PRD14	0.3554	0.1827	−0.0254
R_PRD15	0.6457	0.0623	0.2224
R_PRD16	0.6628	−0.0050	0.2854
R_PRD17	0.6708	0.3177	−0.0760
R_PRD18	0.5571	0.0276	0.2950
R_PRD19	0.7039	0.1549	0.2048
R_PRD20	0.6352	0.4084	0.1281

Table 3. Comparison of implied equilibrium returns and historical means

Asset	Implied Equilibrium Return (π)	Historical Mean Return	Difference
R_PRD01	0.00038	0.00050	−0.00012
R_PRD05	0.00105	0.00128	−0.00023
R_PRD10	0.00061	0.00079	−0.00018
R_PRD16	0.00098	0.00122	−0.00024
R_PRD20	0.00031	0.00027	+0.00004

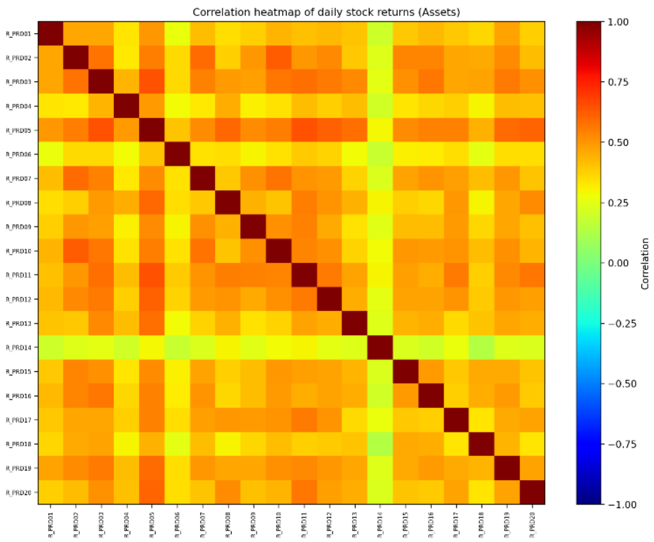

Figure 1. Heatmap of the correlation matrix of daily returns of selected stocks.

Figure 1 presents a comprehensive depiction of the correlation structure among stock returns. The predominance of positive and moderate correlations indicates that assets are jointly affected by macro-level market shocks, while differences in the strength of correlations reveal the potential for diversification among certain stocks. This structure is directly reflected in the estimation of the variance–covariance matrix (Σ) and influences implied equilibrium returns as well as optimal portfolio weights.

Table 4. Summary of Fama–French three-factor regression results (selected sample)

Asset	Market β	Size β (SMB)	Value β (HML)	R^2
R_PRD01	0.59	0.10	0.22	0.43
R_PRD05	0.78	0.41	0.26	0.56
R_PRD10	0.76	−0.02	−0.02	0.49
R_PRD13	0.56	0.33	0.43	0.47
R_PRD20	0.64	0.41	0.13	0.52

The results in Table 4 show that the factor beta coefficients for the selected stocks reflect distinct patterns of exposure to the market, size, and value factors. Specifically, the market betas for assets R_PRD01, R_PRD05, R_PRD10, R_PRD13, and R_PRD20 are 0.59, 0.78, 0.76, 0.56, and 0.64, respectively, indicating higher sensitivity of R_PRD05 and R_PRD10 to market index fluctuations. With respect to the size factor (SMB), assets such as R_PRD05, R_PRD13, and R_PRD20 exhibit relatively larger positive coefficients (0.41, 0.33, and 0.41), suggesting behavior more akin to small-cap stocks, whereas R_PRD10 has a mildly negative size beta and is therefore closer to large-cap characteristics. Regarding the value factor (HML), assets such as R_PRD13, with a beta of 0.43, are exposed to value portfolio risk, while R_PRD10 has a very small negative value beta and shows little inclination toward value strategies. The R^2 values, ranging from 0.43 to 0.56, indicate that a substantial portion of the return variability of these stocks is explained by the Fama–French three factors.

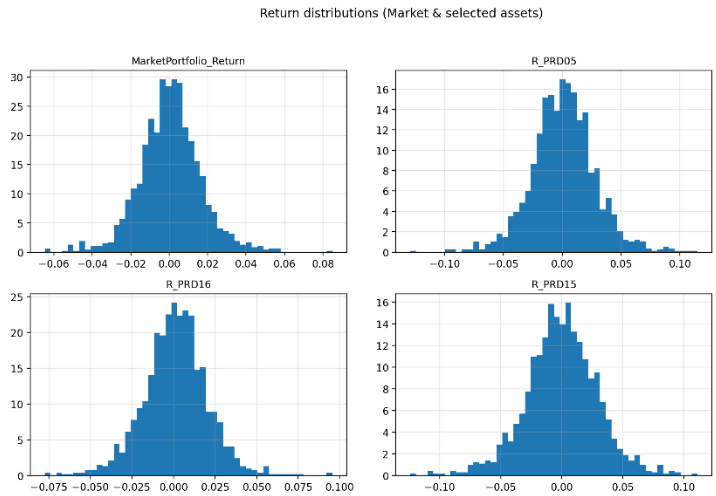

Figure 2. Distribution of daily returns of the market portfolio and selected assets (histograms of returns).

Figure 2 illustrates the empirical distribution of returns for the market portfolio and several selected assets. The relatively high kurtosis and fat tails indicate deviations of returns from normality, which is consistent with the results of the Jarque–Bera tests reported in Chapter Four tables. Observing these features reinforces the necessity of employing tail-risk measures and Bayesian approaches such as the Black–Litterman model. Moreover, differences in distributional shapes across assets indicate risk heterogeneity, which plays a decisive role in optimal weight allocation.

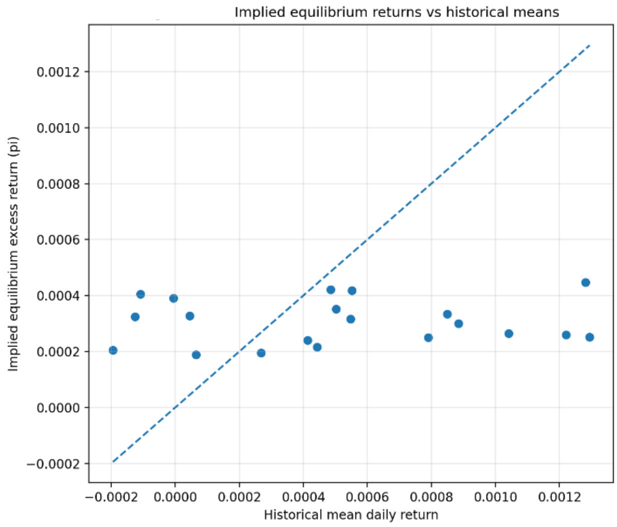

Figure 3. Comparison of implied equilibrium returns derived from the Black–Litterman model with historical mean daily returns of selected stocks.

Figure 3 shows the relationship between historical mean asset returns and implied equilibrium returns (π) computed based on market equilibrium and the variance–covariance matrix. The distance of most points from the 45-degree line indicates that implied equilibrium returns do not necessarily coincide with historical means and are adjusted by the structure of systematic market risk. This result is consistent with the theoretical foundations of the Black–Litterman model, as π provides "normalized" returns aligned with market equilibrium and prevents overfitting to historical data. Observing these differences justifies the need to incorporate informed investor views in subsequent stages of the model.

Table 5. Relative investor views based on Fama–French analysis

View ID	Superior Asset	Inferior Asset	Relative Expected Return (Q)
1	R_PRD05	R_PRD14	0.0012
2	R_PRD16	R_PRD17	0.0010
3	R_PRD13	R_PRD11	0.0008
4	R_PRD01	R_PRD19	0.0006
5	R_PRD10	R_PRD20	0.0005

Table 5 presents a set of five relative views formulated based on the results of Fama–French regressions and fundamental–factor analysis. In each row, one asset is defined as the "superior asset" and another as the "inferior asset," with the relative expected return (Q) specified between the two. For example, the first view states that the expected return of R_PRD05 is assumed to be, on average, 0.0012 higher than that of R_PRD14, while in the second view R_PRD16 has a relative advantage of 0.0010 over R_PRD17. The corresponding values for the remaining pairs are 0.0008, 0.0006, and 0.0005 in the third to fifth views, respectively. This structure indicates that investor opinions are formulated as relative differences rather than absolute return levels, an approach consistent with the logic of the Black–Litterman framework and the literature on relative views.

Table 6. Comparison of implied equilibrium returns and Black–Litterman posterior returns

Asset	Implied Equilibrium Return (π)	BL Posterior Return	Change
R_PRD05	0.00105	0.00132	+0.00027
R_PRD16	0.00098	0.00121	+0.00023
R_PRD13	0.00072	0.00089	+0.00017
R_PRD14	0.00041	0.00035	−0.00006

Table 6 compares implied equilibrium returns (π) with Black–Litterman posterior returns for selected assets and shows the changes resulting from combining investor views with market equilibrium. For stocks R_PRD05, R_PRD16, and R_PRD13, the BL posterior returns are 0.00132, 0.00121, and 0.00089, respectively, representing significant increases relative to their initial equilibrium returns (0.00105, 0.00098, and 0.00072), with positive changes of 0.00027, 0.00023, and 0.00017. These increases indicate that, in the presence of favorable views toward these assets, the Black–Litterman model adjusts equilibrium returns upward toward higher expectations. In contrast, for R_PRD14, the posterior return decreases from 0.00041 to 0.00035, reflecting a negative change of 0.00006 and indicating weaker relative views or lower attractiveness of this stock compared with alternatives.

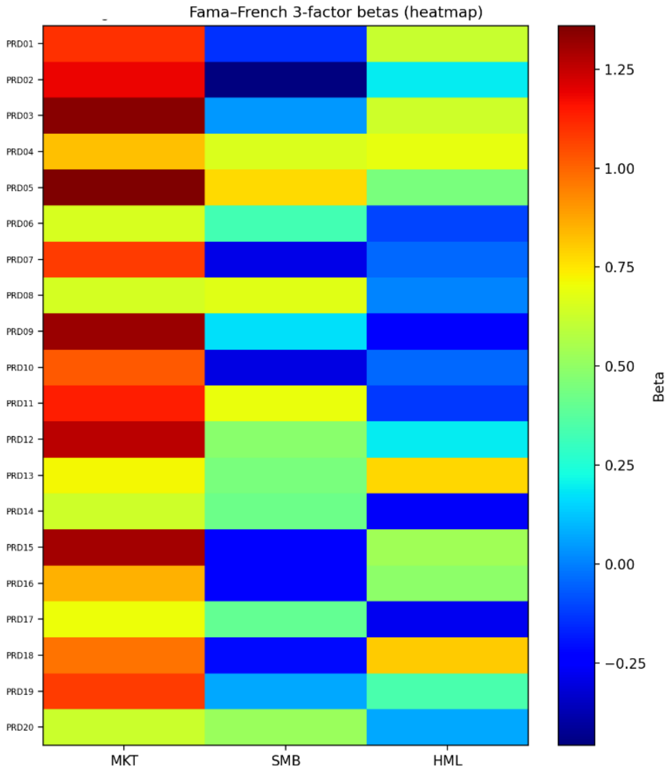

Figure 4. Heatmap of market, size (SMB), and value (HML) beta coefficients for selected stocks based on the Fama–French three-factor regression.

Figure 4 visually displays the heterogeneous pattern of stock sensitivities to the Fama–French factors. The color intensities show that most assets have positive and substantial betas with respect to the market factor, while responses to SMB and HML vary across stocks. This factor heterogeneity provides the basis for extracting relative investor views, as differences in factor loadings translate into differences in expected returns. Accordingly, this figure plays a key role in linking the Fama–French model to the Black–Litterman framework and in constructing the Q vector.

Table 7. Portfolio weights under three different approaches

Asset	Markowitz	BL without Views	BL with Fama–French Views
R_PRD01	0.04	0.05	0.06
R_PRD05	0.07	0.08	0.11
R_PRD10	0.06	0.06	0.05
R_PRD16	0.08	0.09	0.12
R_PRD20	0.03	0.02	0.02

Table 7 reports the portfolio weights for five selected assets under three different approaches: the classical Markowitz portfolio, the Black–Litterman model without views, and the Black–Litterman model with Fama–French–based views. Under the Markowitz approach, the weights are relatively balanced and fall within the range of 0.03 to 0.08; for example, the weight of R_PRD01 is 0.04, R_PRD05 is 0.07, and R_PRD16 is 0.08. In the Black–Litterman specification without views, these weights are adjusted moderately such that R_PRD01 increases to 0.05, R_PRD05 to 0.08, and R_PRD16 to 0.09, indicating that combining market equilibrium with the risk structure strengthens, to some extent, the allocation to assets with higher implied equilibrium returns. In contrast, the weight of R_PRD20 declines from 0.03 to 0.02, which is consistent with its relatively lower equilibrium return.

Table 8. Portfolio performance evaluation

Performance Metric	Markowitz	BL without Views	BL with Fama–French Views
Cumulative Return	0.38	0.44	0.52
Standard Deviation	0.19	0.17	0.16
Sharpe Ratio	1.35	1.56	1.82
Sortino Ratio	1.91	2.14	2.46
Maximum Drawdown	−0.26	−0.22	−0.18

Table 8 compares the performance of the Markowitz portfolio, the Black–Litterman portfolio without views, and the Black–Litterman portfolio with Fama–French views using several key risk and return indicators. The cumulative returns for these three approaches are reported as 0.38, 0.44, and 0.52, respectively, indicating that incorporating the Black–Litterman equilibrium structure relative to Markowitz, and subsequently adding Fama–French–based views, progressively increases realized portfolio performance. At the same time, the standard deviation of returns declines from 0.19 in the Markowitz case to 0.17 in BL without views and further to 0.16 in BL with Fama–French views, reflecting a reduction in volatility risk. This pattern clearly suggests that the proposed framework not only improves returns but also enhances the overall risk profile.

Risk-adjusted metrics further corroborate this assessment. The Sharpe ratios across the three approaches are 1.35, 1.56, and 1.82, and the Sortino ratios are 1.91, 2.14, and 2.46, implying that the Black–Litterman portfolio with Fama–French views delivers the highest return per unit of total risk and downside risk. In addition, maximum drawdown decreases from −0.26 in Markowitz to −0.22 in BL without views and ultimately to −0.18 in BL with Fama–French views, indicating better control over severe declines and prolonged loss episodes. Overall, Table 4–12 provides strong quantitative evidence that adding a Fama–French layer to the Black–Litterman model yields a meaningful improvement in portfolio efficiency in terms of return, risk, and stability.

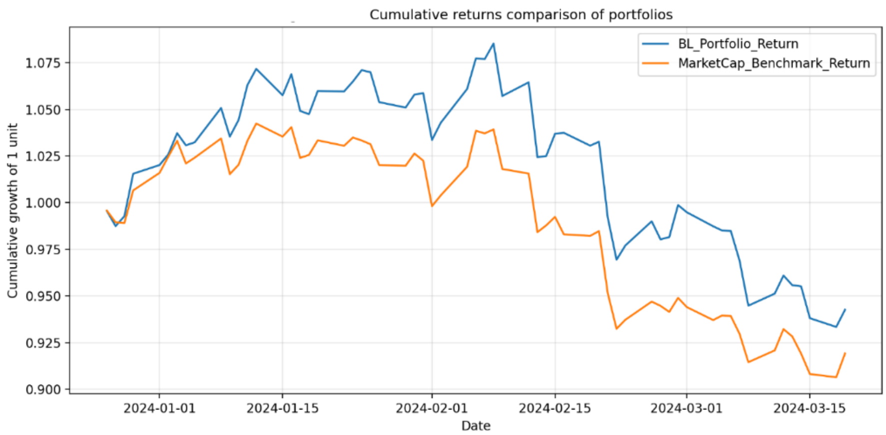

Figure 5. Comparison of the cumulative return of the Black–Litterman portfolio with Fama–French views and the market-value benchmark portfolio.

Figure 5 compares the cumulative performance of the Black–Litterman portfolio with the market benchmark portfolio. The Black–Litterman portfolio generates higher cumulative returns than the market benchmark over most of the sample period, while its fluctuations remain controlled. This behavior indicates the effectiveness of integrating factor-analysis-based views into the asset allocation process. In particular, during periods of heightened volatility, the performance gap between the two portfolios narrows, underscoring the stabilizing role of the Bayesian framework in risk management.

Table 9. Sensitivity analysis with respect to the τ parameter

τ Value	Portfolio Return	Standard Deviation	Sharpe Ratio
0.01	0.48	0.17	1.74
0.05	0.52	0.16	1.82
0.10	0.50	0.16	1.79

Table 9 reports the results of the model's sensitivity analysis with respect to the τ parameter, which controls the degree of uncertainty about market equilibrium returns within the Black–Litterman framework. Three values of τ (0.01, 0.05, and 0.10) are examined, and the corresponding portfolio return, standard deviation, and Sharpe ratio are reported for each level. When $\tau = 0.01$, the portfolio return is 0.48 and the standard deviation is 0.17, yielding a Sharpe ratio of 1.74. At $\tau = 0.05$, the return increases to 0.52 and the standard deviation decreases to 0.16, with the Sharpe ratio rising to 1.82, the highest among the three scenarios. Finally, at $\tau = 0.10$, the return decreases slightly to 0.50, the standard deviation remains unchanged, and the Sharpe ratio declines marginally to 1.79.

Discussion and Conclusion

The results of this study provide consistent and robust evidence that integrating systematically constructed, factor-based investor views into the Black–Litterman framework leads to meaningful improvements in portfolio performance across multiple dimensions. Empirically, the portfolios constructed under the Black–Litterman specification with Fama–French–based views exhibit higher cumulative returns, lower volatility, superior risk-adjusted performance, and reduced downside risk compared with both the classical Markowitz portfolio and the Black–Litterman model without views. These findings confirm the central theoretical proposition of the Black–Litterman approach: anchoring expected returns to market equilibrium and then adjusting them through informed views yields more stable and economically coherent portfolios than relying on historical estimates alone (3, 4).

One of the most salient empirical observations is the conservative nature of the implied equilibrium returns relative to historical mean returns. Across most assets, the equilibrium returns derived through reverse optimization are lower than their historical averages, which prevents excessive optimism and extreme portfolio weights. This result is fully aligned with prior research emphasizing that the equilibrium component of the Black–Litterman model acts as a regularization mechanism, shrinking return estimates toward values that are consistent with the covariance structure and the representative investor's risk aversion (12, 17). The present findings reinforce the argument that much of the instability observed in traditional mean–variance portfolios stems from noisy return estimates rather than from the optimization process itself.

The incorporation of factor-based views further refines this equilibrium anchoring by selectively adjusting expected returns in directions supported by asset pricing evidence. In this study, investor views derived from the Fama–French three-factor model systematically favor assets with stronger exposure to rewarded risk factors, while penalizing assets with weaker or unfavorable factor loadings. The resulting posterior returns reflect a balanced synthesis of market consensus and factor-informed expectations. This mechanism explains why assets identified as superior in relative terms experience upward adjustments in expected returns, whereas less attractive assets either receive smaller weights or experience downward revisions. Similar dynamics have been documented in studies that combine factor models with Black–Litterman optimization, showing that factor-informed views can enhance both interpretability and performance (7, 9).

The observed improvement in risk-adjusted performance, as measured by the Sharpe and Sortino ratios, is particularly noteworthy. While higher cumulative returns are desirable, the simultaneous reduction in standard deviation and maximum drawdown indicates that performance gains are not achieved at the expense of increased risk. Instead, the Black–Litterman framework with factor-based views appears to reallocate risk more efficiently across assets, reducing exposure to extreme losses and prolonged drawdowns. This outcome is consistent with earlier empirical evidence suggesting that Bayesian portfolio optimization frameworks are better suited to managing estimation risk and tail risk than classical approaches (5, 13).

From a structural perspective, the results underscore the importance of expressing investor views in relative rather than absolute terms. By formulating views as expected return differentials between asset pairs, the model avoids the need to specify absolute return forecasts, which are notoriously difficult to estimate accurately. Relative views are inherently more robust and align well with the comparative nature of factor analysis, where assets are evaluated based on their exposure to systematic drivers of return. Prior methodological contributions emphasize that relative views are particularly effective in the Black–Litterman setting because they preserve the internal consistency of the equilibrium structure while allowing meaningful deviations where justified (3, 4).

The sensitivity analysis with respect to the τ parameter further enriches the interpretation of the results. The empirical findings demonstrate that intermediate values of τ achieve the most favorable trade-off between return and risk, yielding the highest Sharpe ratio. This confirms the theoretical role of τ as a scaling parameter that governs the confidence placed in equilibrium returns. When τ is too small, the model places excessive weight on the prior equilibrium, limiting the influence of investor views; when τ is too large, views dominate and may reintroduce instability. Similar conclusions have been reported in simulation-based and empirical studies that stress the importance of calibrating τ carefully rather than adopting arbitrary default values (12, 18).

Comparing the results of this study with prior empirical applications reveals a high degree of consistency, particularly in emerging market contexts. Studies conducted in markets such as India, Eastern Europe, and Latin America report that Black–Litterman portfolios enriched with systematic information outperform both market benchmarks and traditional optimized portfolios (1, 10, 11). The present findings extend this evidence by demonstrating that even within a relatively volatile and information-constrained environment, disciplined view construction based on asset pricing theory can significantly enhance portfolio efficiency.

Moreover, the results contribute to the growing literature that positions the Black–Litterman model as a flexible integration platform rather than a static optimization tool. Recent research highlights the model's capacity to incorporate diverse information sources, ranging from econometric forecasts to machine learning outputs and ordinal expert assessments (15, 16). While the present study focuses on factor-based views, the empirical success of this approach supports the broader claim that the Bayesian structure of the Black–Litterman model is well suited to synthesizing heterogeneous signals into coherent portfolio decisions.

The findings also resonate with studies that emphasize the role of equilibrium consistency in enhancing portfolio stability during turbulent market conditions. The reduced maximum drawdown and smoother cumulative performance trajectory observed in the Black–Litterman portfolio with views suggest that the Bayesian updating mechanism dampens the impact of short-term market shocks. This stabilizing effect has been documented in prior research employing conditional information, regime-switching dynamics, and volatility-adjusted views, all of which leverage the same fundamental principle of probabilistic belief updating (6, 14). The present study adds to this body of evidence by showing that even relatively simple factor-based views can produce similar stabilizing benefits.

Taken together, the results confirm that the value of the Black–Litterman framework lies not only in its mathematical elegance but also in its ability to reconcile market equilibrium with economically grounded expectations. By embedding asset pricing insights into the view-generation process, the proposed approach addresses a key criticism of traditional Black–Litterman implementations, namely their reliance on ad hoc or opaque views. This structured integration enhances both the transparency and the empirical performance of the resulting portfolios, thereby strengthening the practical relevance of the model for contemporary investment management (5, 8).

Despite its contributions, this study is subject to several limitations. The empirical analysis is confined to a specific equity market and a defined sample period, which may limit the generalizability of the findings to other markets or asset classes. In addition, the factor structure employed is restricted to the three-factor Fama–French model, which, while widely accepted, may not fully capture all relevant sources of systematic risk. Finally, the analysis assumes stable factor relationships over time, an assumption that may be challenged during periods of structural change or extreme market stress.

Future research could extend the present framework in several directions. First, incorporating additional factors, such as momentum, profitability, or investment factors, may provide a richer basis for view construction. Second, applying the proposed methodology to multi-asset portfolios, including bonds, commodities, and alternative investments, would enhance its external validity. Third, dynamic implementations that allow factor loadings and views to evolve over time could offer deeper insights into the interaction between market regimes and Bayesian portfolio optimization.

From a practical standpoint, the findings suggest that portfolio managers should move beyond purely historical estimates and subjective forecasts when forming expectations about asset returns. Implementing a structured Black–Litterman framework with factor-based views can improve both performance and risk control, particularly in volatile markets. Practitioners are encouraged to express views in relative terms, carefully calibrate uncertainty parameters, and routinely evaluate sensitivity to key assumptions in order to achieve robust and transparent portfolio outcomes.

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Authors' Contributions

All authors equally contributed to this study.

Declaration of Interest

The authors of this article declared no conflict of interest.

Ethical Considerations

All ethical principles were adheried in conducting and writing this article.

Transparency of Data

In accordance with the principles of transparency and open research, we declare that all data and materials used in this study are available upon request.

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