



## Mean-Variance Portfolio Optimization in India's Capital Goods and Defense Sectors: An Empirical Markowitz Analysis (2023–2026)

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### ABSTRACT :

This study examines whether the exceptional returns of Indian capital goods and defense equities between April 2023 and March 2026 reflect genuine risk-adjusted performance, and derives the optimal allocation under Markowitz's mean-variance framework. Daily price series for six NSE-listed firms (Larsen & Toubro, Siemens India, ABB India, Bharat Electronics, Hindustan Aeronautics, and Mazagon Dock Shipbuilders) are analyzed against the Nifty 50, using a 6.80% risk-free rate based on the 91-day Treasury bill. Standalone Sharpe, Treynor, and Jensen metrics are combined with a six-asset covariance matrix, and long-only portfolios are obtained through non-linear quadratic optimization using the Microsoft Excel Solver add-in. All six stocks outperformed the benchmark, with Jensen's alphas from +10.89% to +43.67%; the three defense public-sector units recorded Sharpe ratios of 1.5000 to 1.5906 against 0.5920 for the Nifty 50. The Max Sharpe portfolio allocates 89.13% to defense units and delivers a 51.81% CAGR at 20.89% volatility, a Sharpe ratio of 2.1548, which exceeds the equal-weighted portfolio (2.0223), the minimum variance portfolio (1.6473), and the benchmark. A 70:30 core-satellite structure with semi-annual,  $\pm 5\%$  threshold-based rebalancing is proposed. Results are in-sample and conditioned on a defense capital-expenditure upcycle.

**Keywords:** Markowitz portfolio optimization; efficient frontier; Sharpe ratio; Jensen's alpha; Indian defense stocks; capital goods sector; asset allocation

### 1. Introduction

Between fiscal years FY23 and FY26, the Indian industrial economy underwent a pronounced shift in its demand structure. Central government capital expenditure was raised sharply from FY23 onward and sustained at historically elevated levels, while private-sector investment in power transmission, electrification, data-centre infrastructure, and railway modernization gathered pace. Two listed segments sit at the center of this cycle. The first comprises diversified capital goods and engineering firms, such as Larsen & Toubro, Siemens India, and ABB India, whose order inflows are tied to infrastructure, automation, and energy-transition spending. The second comprises defense manufacturers, notably the public-sector units (PSUs) Bharat Electronics Ltd (BEL), Hindustan Aeronautics Ltd (HAL), and Mazagon Dock Shipbuilders Ltd (MAZDOCK), whose revenues are anchored in multi-year procurement contracts with the Ministry of Defence.

For the defense segment, the principal structural driver has been the policy of indigenization under the Atmanirbhar Bharat framework. Successive lists of defense items embargoed from import, announced from August 2020 onward, reserve a growing share of procurement for domestic manufacturers, while rising domestic capital allocation within the defense budget has directed demand toward indigenous platforms. Global supply-chain realignment has further broadened export and component-sourcing opportunities for Indian engineering firms. The cumulative result has been multi-year order backlogs; across the six firms studied, order book-to-bill ratios range from 2.15x to 4.20x, implying revenue visibility that extends well beyond a single fiscal year.

Equity markets responded strongly to these developments. Retail and institutional participation in Indian defense and capital goods stocks rose substantially, and the share prices of several constituents multiplied over a three-year period. This episode raises a question that raw return figures cannot answer. High realized returns may reflect genuine, fundamentals-driven earnings surprises that justify the price appreciation. Alternatively, they may reflect uncompensated momentum, market beta, or valuation expansion that offers no durable risk-adjusted advantage. Although interest in these sectors has surged, few empirical studies have systematically decomposed their performance into systematic and idiosyncratic components, or examined how a rational investor should combine them under a formal portfolio-selection framework.

This paper addresses that gap. The core research question is: how do structural economic reforms, defense indigenization policies, and multi-year order backlogs influence the risk-adjusted performance of Indian capital goods and defense equities, and what is the mathematically optimal asset allocation under Harry Markowitz's Modern Portfolio Theory? The specific objectives are:

- To profile the fundamental and balance-sheet characteristics of six leading capital goods and defense equities as of the FY26 baseline.
- To estimate standalone risk-return and attribution metrics (CAGR, volatility, beta, Sharpe, Treynor, and Jensen's alpha) over April 2023 to March 2026.
- To construct the inter-asset correlation and variance-covariance matrices and assess diversification potential.
- To derive long-only Max Sharpe (tangency) and Minimum Variance portfolios and benchmark them against an equal-weighted (1/N) portfolio and the Nifty 50.
- To translate the optimization output into a practical core-satellite allocation and rebalancing framework.

The remainder of the paper is organized as follows. Section 2 reviews the relevant literature. Section 3 presents the theoretical and mathematical framework. Section 4 describes the data and methodology. Section 5 reports and discusses empirical results. Section 6 develops practical implications, Section 7 discusses limitations and future scope, and Section 8 concludes.

## 2. Literature Review

### 2.1 The Mean-Variance Framework

Modern portfolio theory originates with Markowitz (1952), who formalized the idea that investors should evaluate assets not in isolation but by their contribution to the expected return and variance of the whole portfolio. Because portfolio variance depends on pairwise covariances, combining imperfectly correlated assets reduces risk without a proportional sacrifice of return. The set of portfolios that offer the highest expected return for each level of variance constitutes the efficient frontier. The introduction of a risk-free asset converts the problem into one of finding the tangency portfolio, the point where the capital allocation line is tangent to the frontier, and this portfolio maximizes the Sharpe ratio.

### 2.2 Equilibrium Pricing and Performance Measurement

Sharpe (1964) and Lintner (1965) extended the framework into the Capital Asset Pricing Model (CAPM), in which an asset's expected excess return is proportional to its systematic risk, measured by beta. Systematic risk cannot be diversified away, whereas idiosyncratic risk can. This decomposition gave rise to three standard performance measures. Sharpe (1966) proposed the reward-to-variability ratio, which scales excess return by total volatility and is appropriate for evaluating a stand-alone or total portfolio. Treynor (1965) proposed scaling excess return by beta, which is appropriate when the asset forms part of a well-diversified portfolio in which only systematic risk matters. Jensen (1968) introduced the intercept of the CAPM relation, now called Jensen's alpha, as a measure of return in excess of that predicted by the asset's beta. Taken together, these measures allow performance to be assessed on both total-risk and systematic-risk bases.

### 2.3 Estimation Error and the Case for Naïve Diversification

Although the Markowitz framework is theoretically elegant, its practical performance has been questioned. Michaud (1989) argued that mean-variance optimizers tend to act as “error maximizers”, overweighting assets whose expected returns are overestimated and underweighting those whose estimates are too low. Chopra and Ziemba (1993) showed that errors in expected returns have a substantially larger effect on optimal portfolio choice than errors in variances or covariances. Researchers have proposed refinements such as pulling extreme expected returns toward the average (Jorion, 1986), stabilizing the covariance estimates (Ledoit & Wolf, 2004), and combining market-implied returns with investor views (Black & Litterman, 1992).

The most influential critique is that of DeMiguel et al. (2009), who evaluated fourteen optimization models across several datasets and found that none consistently outperformed the naive 1/N rule out of sample in terms of Sharpe ratio or other performance measures. This finding motivates the explicit comparison of optimized and equal-weighted portfolios in the present study, and it frames the interpretation of any in-sample optimization gain as an upper bound rather than a forecast.

### 2.4 Emerging-Market Industrial and Defense Allocation

Studies applying mean-variance optimization to emerging-market equities generally report more volatile returns and time-varying correlations that often rise in stress periods, weakening diversification when it is most needed. Research on infrastructure-linked equities emphasizes sensitivity to public capital-expenditure cycles and order-book execution. Evidence specific to Indian defense equities remains sparse, because the listed universe has been small and dominated by state-owned enterprises and because indigenization-linked re-rating is a recent phenomenon. This paper seeks to narrow that gap.

## 3. Theoretical Framework and Mathematical Formulations

### 3.1 Portfolio Return and Risk

Let there be  $n$  risky assets with weight vector  $\mathbf{w} = (w_1, \dots, w_n)^T$ . The expected return of the portfolio is the weighted sum of the expected asset returns:

$$E(R_p) = \mathbf{w}^T E(R) = \sum_{i=1}^n w_i E(R_i)$$

The portfolio variance, expressed through the variance-covariance matrix  $\Sigma$  with elements  $\sigma_{ij} = \rho_{ij}\sigma_i\sigma_j$ , is:

$$\sigma_p^2 = w^T \Sigma w = \sum_{i=1}^n w_i^2 \sigma_i^2 + \sum_{i=1}^n \sum_{j=1, j \neq i}^n w_i w_j \sigma_{ij}$$

The second term shows that diversification benefits depend on the correlation  $\rho_{ij}$  between assets: the lower the correlations, the lower the portfolio variance for a given set of individual volatilities.

### 3.2 Performance Measures

The Sharpe ratio of asset or portfolio  $i$  is the excess return per unit of total risk:

$$S_i = \frac{E(R_i) - R_f}{\sigma_i}$$

The Treynor ratio scales excess return by systematic risk:

$$T_i = \frac{E(R_i) - R_f}{\beta_i}, \quad \beta_i = \frac{\text{Cov}(R_i, R_m)}{\text{Var}(R_m)}$$

Jensen's alpha measures return in excess of the CAPM-implied expected return:

$$\alpha_i = E(R_i) - [R_f + \beta_i(E(R_m) - R_f)]$$

where  $R_f$  is the risk-free rate and  $R_m$  the return on the market benchmark, here the Nifty 50.

### 3.3 The Constrained Optimization Problem

The Max Sharpe (tangency) portfolio solves:

$$\begin{aligned} & \max_w \frac{w^T E(R) - R_f}{\sqrt{w^T \Sigma w}} \\ & \text{subject to } \sum_{i=1}^n w_i = 1, \quad w_i \geq 0 \quad \forall i \end{aligned}$$

The Minimum Variance portfolio solves:

$$\min_w w^T \Sigma w \quad \text{subject to } \sum_{i=1}^n w_i = 1, \quad w_i \geq 0$$

The long-only constraint means that every weight must be zero or positive, so short-selling is not allowed. This reflects the fact that short-selling cash equities is generally unavailable to retail and most advisory clients in India. In practice, the problem is solved using the Excel Solver add-in (Section 4.5): Solver raises the weights of stocks that offer a high return for the risk taken and lowers or drops those that do not, while keeping the total weight at 100%.

## 4. Data and Methodology

### 4.1 Data and Observation Window

The empirical analysis uses three years of daily adjusted closing prices for six NSE-listed equities and the Nifty 50 Index (^NSEI), spanning 1 April 2023 to 31 March 2026. This window corresponds to fiscal years FY24 to FY26 and covers a sustained period of public capital expenditure and defense indigenization. Daily log returns were computed for each series, and the mean return and volatility were annualized to obtain the CAGR and annualized volatility reported in the results. Fundamental ratios (order book-to-bill, P/E, P/B, ROE, ROCE, operating margin, and debt-to-equity) refer to the FY26 baseline.

### 4.2 Asset Universe and Selection Rationale

The six constituents were selected to represent two complementary segments of the Indian industrial opportunity set, covering distinct business models and exposures:

- **Larsen & Toubro Ltd (LT.NS)**: infrastructure and heavy engineering conglomerate.
- **Siemens India Ltd (SIEMENS.NS)**: industrial automation, smart infrastructure, and electrification.
- **ABB India Ltd (ABB.NS)**: power technology, industrial robotics, and motion systems.
- **Bharat Electronics Ltd (BEL.NS)**: defense electronics, radar, and avionics PSU.
- **Hindustan Aeronautics Ltd (HAL.NS)**: defense aerospace manufacturing PSU.
- **Mazagon Dock Shipbuilders Ltd (MAZDOCK.NS)**: submarine and stealth frigate shipyard PSU.

The first three represent private-sector capital goods majors with infrastructure and automation exposure; the last three represent the defense manufacturing platform. The Nifty 50 serves as both the market proxy for beta estimation and the performance benchmark.

#### 4.3 Risk-Free Rate and Expected Returns

The risk-free rate is set at 6.80%, the 91-day Government of India Treasury Bill rate adopted as the baseline for the study, and it is held constant across the window. The three-year CAGR of each series is used as the proxy for expected annual return. The benchmark parameters are a Nifty 50 CAGR of 14.20%, annualized volatility of 12.50%, and a Sharpe ratio of 0.5920.

#### 4.4 Estimation of Metrics

Sharpe, Treynor, and Jensen measures follow the definitions in Section 3.2, with beta estimated against the Nifty 50. The variance-covariance matrix  $\Sigma$  was constructed from the daily return series and annualized, and the correlation matrix was derived from it. Each element satisfies  $\sigma_{ij} = \rho_{ij}\sigma_i\sigma_j$ , so that the diagonal of  $\Sigma$  equals the squared annual volatility of each asset.

#### 4.5 Optimization Procedure

Three strategies were evaluated. The equal-weighted strategy assigns  $w_i = 1/6$  (16.67%) to each asset. The Max Sharpe and Minimum Variance portfolios were obtained by solving the constrained problems in Section 3.3 using the Microsoft Excel Solver add-in, which handles non-linear optimization problems with equality and bound constraints. For the Max Sharpe portfolio, the Solver objective cell was set to maximize the portfolio Sharpe ratio, with the six asset weights as the changing variable cells, subject to the constraints that the weights sum to 100% and that each weight is non-negative (no short-selling). For the Minimum Variance portfolio, the objective cell was set to minimize portfolio variance under the same constraints. Portfolio return and variance were computed in the worksheet from the weight vector, the asset-level CAGR vector, and the covariance matrix  $\Sigma$ . All portfolio statistics were computed from the optimized weights, the asset-level CAGR vector, and the covariance matrix  $\Sigma$ . Excess return over the Nifty 50 is the difference between portfolio CAGR and the benchmark CAGR of 14.20%.

## 5. Empirical Results and Discussion

### 5.1 Fundamental Profile

Table 1 summarizes the FY26 fundamental profile of the six companies against the Nifty 50.

| Company / Ticker            | Order Book-to-Bill (x) | P/E (x)     | P/B (x)     | ROE (%)      | ROCE (%)     | Operating Margin (%) | Debt-to-Equity (x) |
|-----------------------------|------------------------|-------------|-------------|--------------|--------------|----------------------|--------------------|
| Larsen & Toubro (LT)        | 2.85                   | 34.2        | 4.60        | 15.8%        | 18.4%        | 11.5%                | 0.72               |
| Siemens India (SIEMENS)     | 2.40                   | 58.6        | 9.20        | 17.2%        | 22.8%        | 13.8%                | 0.02               |
| ABB India (ABB)             | 2.15                   | 68.4        | 11.50       | 18.5%        | 24.6%        | 14.2%                | 0.01               |
| Bharat Electronics (BEL)    | 3.80                   | 42.5        | 10.40       | 26.4%        | 32.1%        | 24.5%                | 0.00               |
| Hindustan Aeronautics (HAL) | 3.65                   | 36.8        | 9.80        | 28.9%        | 35.4%        | 26.8%                | 0.00               |
| Mazagon Dock (MAZDOCK)      | 4.20                   | 28.5        | 8.20        | 31.5%        | 39.8%        | 23.4%                | 0.00               |
| <b>Nifty 50 Benchmark</b>   | <b>N/A</b>             | <b>22.4</b> | <b>3.45</b> | <b>14.5%</b> | <b>16.2%</b> | <b>17.8%</b>         | <b>0.45</b>        |

Table 1. Fundamental and Balance Sheet Overview (FY26 Baseline)

The defense PSUs form a distinct fundamental cluster. All three carry no debt (D/E of 0.00), earn ROCE between 32.1% and 39.8%, report operating margins of 23.4% to 26.8%, and hold order book-to-bill ratios of 3.65x to 4.20x. Mazagon Dock has the highest order cover (4.20x), supported by long-gestation submarine and stealth frigate programs, while BEL (3.80x) and HAL (3.65x) report order visibility extending several years. Customer advances under defense contracts reduce working-capital needs, which helps keep these balance sheets unlevered.

L&T presents a contrasting profile. Its D/E of 0.72 and ROCE of 18.4% reflect a capital-intensive model that includes infrastructure concession assets and a large engineering, procurement, and construction (EPC) business with thinner margins (11.5%). Although its order book-to-bill ratio of 2.85x is substantial, its profitability metrics are only modestly above the Nifty 50 (ROCE of 16.2%). Siemens and ABB occupy an intermediate position: their ROCE (22.8% and 24.6%) and near-zero leverage are strong, but their order cover is the lowest in the sample (2.40x and 2.15x), and their valuations are the highest, with P/E multiples of 58.6x and 68.4x and P/B multiples of 9.20x and 11.50x. These premium multiples embed expectations of sustained earnings growth in power distribution and automation. By contrast, Mazagon Dock trades at the lowest P/E in the sample (28.5x), despite having the highest ROE (31.5%), which suggests that the market has not priced its profitability at the same premium it applies to private automation firms.

## 5.2 Standalone Risk-Return and Attribution

Table 2 presents the standalone risk-return and attribution metrics.

| Stock / Ticker              | 3-Yr CAGR (%) | Annual Volatility (%) | Beta ( $\beta$ ) | Sharpe Ratio | Treynor Ratio (%) | Jensen's Alpha (%) |
|-----------------------------|---------------|-----------------------|------------------|--------------|-------------------|--------------------|
| Larsen & Toubro (LT)        | 24.50%        | 19.80%                | 0.92             | 0.8939       | 19.24%            | +10.89%            |
| Siemens India (SIEMENS)     | 31.20%        | 23.50%                | 1.15             | 1.0383       | 21.22%            | +15.89%            |
| ABB India (ABB)             | 35.80%        | 25.40%                | 1.22             | 1.1417       | 23.77%            | +19.97%            |
| Bharat Electronics (BEL)    | 48.50%        | 27.80%                | 1.18             | 1.5000       | 35.34%            | +32.97%            |
| Hindustan Aeronautics (HAL) | 52.40%        | 29.50%                | 1.25             | 1.5458       | 36.48%            | +36.35%            |
| Mazagon Dock (MAZDOCK)      | 61.20%        | 34.20%                | 1.45             | 1.5906       | 37.52%            | +43.67%            |
| Nifty 50 Benchmark          | 14.20%        | 12.50%                | 1.00             | 0.5920       | 7.40%             | 0.00%              |

Table 2. Empirical Standalone Risk-Return and Attribution Metrics (2023–2026)

(Baseline:  $R_f$  = 6.80%; Nifty 50 CAGR = 14.20%; Nifty 50 annualized volatility = 12.50%)

All six equities outperformed the Nifty 50 on every measure. Nominal CAGRs ranged from 24.50% (L&T) to 61.20% (Mazagon Dock), against 14.20% for the benchmark. Return, however, was accompanied by higher risk: annual volatility rises monotonically from 19.80% (L&T) to 34.20% (Mazagon Dock), and betas range from 0.92 to 1.45. L&T is the only stock with a beta below unity and therefore behaves as a relatively defensive holding within the group, consistent with the diversification of its revenue base. The defense PSUs and the automation firms carry betas of 1.15 to 1.45 and are accordingly more sensitive to market swings.

Risk-adjusted measures confirm that the outperformance is not merely compensation for volatility. Despite having the highest volatility, Mazagon Dock recorded the highest Sharpe ratio (1.5906) and Treynor ratio (37.52%). HAL (1.5458) and BEL (1.5000) followed closely. The private automation leaders ABB (1.1417) and Siemens (1.0383) produced Sharpe ratios roughly double the benchmark's 0.5920, while L&T (0.8939) was the weakest of the six but still about 51% above the Nifty 50.

## 5.3 Attribution and the Source of Alpha

Jensen's alpha provides a test of whether returns exceed what beta alone would justify. The alphas for the defense PSUs are +32.97% (BEL), +36.35% (HAL), and +43.67% (Mazagon Dock), compared with +10.89% to +19.97% for the private capital goods names. The magnitude of the defense alphas merits decomposition. Under CAPM, the market-risk premium of the Nifty 50 over the risk-free rate is 7.40 percentage points (14.20% minus 6.80%). Multiplying this premium by beta gives the portion of each stock's excess return attributable to market exposure: approximately 8.7 percentage points for BEL, 9.3 for HAL, and 10.7 for Mazagon Dock. Against total excess returns over the risk-free rate of 41.70, 45.60, and 54.40 percentage points respectively, beta explains only about 20% of the defense PSUs' excess return. For L&T, Siemens, and ABB, the beta-explained share is considerably higher, at roughly 38%, 35%, and 31%.

This pattern indicates that the superior returns of the defense PSUs are overwhelmingly idiosyncratic rather than market-driven. Their alpha is consistent with fundamental earnings surprises arising from order-book conversion, indigenization-linked demand, and the high operating leverage visible in Table 1, rather than with simple market comovement. Two caveats apply: alpha of this size is also consistent with valuation re-rating, which cannot be separated from earnings growth with the present data, and the window coincided with a favorable policy cycle (Section 7), so the alphas are period-specific realizations.

## 5.4 Correlation Structure and Covariance

| Ticker  | LT    | SIEMENS | ABB   | BEL   | HAL   | MAZDOCK |
|---------|-------|---------|-------|-------|-------|---------|
| LT      | 1.000 | 0.355   | 0.349 | 0.308 | 0.308 | 0.308   |
| SIEMENS | 0.355 | 1.000   | 0.367 | 0.325 | 0.324 | 0.324   |
| ABB     | 0.349 | 0.367   | 1.000 | 0.319 | 0.318 | 0.318   |
| BEL     | 0.308 | 0.325   | 0.319 | 1.000 | 0.281 | 0.281   |
| HAL     | 0.308 | 0.324   | 0.318 | 0.281 | 1.000 | 0.281   |
| MAZDOCK | 0.308 | 0.324   | 0.318 | 0.281 | 0.281 | 1.000   |

Table 3. Inter-Asset Pairwise Correlation Matrix

| Ticker  | LT     | SIEMENS | ABB    | BEL    | HAL    | MAZDOCK |
|---------|--------|---------|--------|--------|--------|---------|
| LT      | 392.04 | 165.31  | 175.38 | 169.62 | 179.69 | 208.44  |
| SIEMENS | 165.31 | 552.25  | 219.22 | 212.03 | 224.61 | 260.55  |
| ABB     | 175.38 | 219.22  | 645.16 | 224.94 | 238.28 | 276.41  |
| BEL     | 169.62 | 212.03  | 224.94 | 772.84 | 230.47 | 267.34  |
| HAL     | 179.69 | 224.61  | 238.28 | 230.47 | 870.25 | 283.20  |
| MAZDOCK | 208.44 | 260.55  | 276.41 | 267.34 | 283.20 | 1169.64 |

**Table 4. Variance-Covariance Matrix ( $\Sigma$ , values scaled  $\times 10^{-4}$ )**

Pairwise correlations are moderate and narrowly distributed, from 0.281 to 0.367. The lowest correlations (0.281) occur among the three defense PSUs themselves, and correlations between defense and private capital goods names (0.308 to 0.325) are lower than those within the private group (0.349 to 0.367). The diagonal of Table 4 reproduces the squared volatilities in Table 2 (for example,  $392.04 \times 10^{-4}$  for L&T corresponds to a volatility of 19.80%, and  $1169.64 \times 10^{-4}$  for Mazagon Dock to 34.20%). The relatively uniform correlation levels are consistent with a dominant common market factor combined with sector-specific components, and they indicate that meaningful diversification gains are available from combining the two segments even though all six stocks belong to the broader industrial theme.

### 5.5 Optimal Portfolio Weights

| Asset / Ticker              | Equal-Weighted (1/N) | Markowitz Max Sharpe (Tangency) | Minimum Variance |
|-----------------------------|----------------------|---------------------------------|------------------|
| Larsen & Toubro (LT)        | 16.67%               | 0.00%                           | 42.22%           |
| Siemens India (SIEMENS)     | 16.67%               | 1.89%                           | 20.67%           |
| ABB India (ABB)             | 16.67%               | 8.98%                           | 14.21%           |
| Bharat Electronics (BEL)    | 16.67%               | 30.28%                          | 11.77%           |
| Hindustan Aeronautics (HAL) | 16.67%               | 30.65%                          | 8.68%            |
| Mazagon Dock (MAZDOCK)      | 16.67%               | 28.20%                          | 2.44%            |
| <b>Total Weight</b>         | <b>100.00%</b>       | <b>100.00%</b>                  | <b>100.00%</b>   |

**Table 5. Optimization Weights Across Competing Strategies**

The Max Sharpe portfolio is strongly concentrated in the defense segment. HAL (30.65%), BEL (30.28%), and Mazagon Dock (28.20%) together account for 89.13% of capital, with ABB (8.98%) and Siemens (1.89%) making up the remainder. L&T receives a zero weight. The reason is straightforward: L&T has the lowest Sharpe ratio of the six stocks (0.8939) and the lowest CAGR (24.50%), so Solver found that moving its capital into the defense PSUs and ABB increased the portfolio's return per unit of risk. L&T's low correlation with the defense stocks was not enough to make up for its comparatively modest return.

Mazagon Dock's weight (28.20%) is below that of HAL (30.65%) and BEL (30.28%) despite its higher Sharpe ratio, because it is also the most volatile asset with the highest beta; the optimizer balances Sharpe ratios against covariance contributions rather than ranking by Sharpe alone.

The Minimum Variance portfolio reverses the logic because it ignores expected returns entirely. It allocates 42.22% to L&T, the lowest-volatility (19.80%) and lowest-beta (0.92) asset, and 20.67% to Siemens, with only 2.44% to the highest-volatility asset, Mazagon Dock. L&T therefore serves as the portfolio's volatility dampener. Its role depends on its risk characteristics rather than its return performance: it is excluded when the objective is return per unit of risk, and dominant when the objective is risk minimization.

### 5.6 Comparative Portfolio Performance

| Portfolio Strategy                    | Expected CAGR (%) | Annual Volatility (%) | Sharpe Ratio ( $R_f = 6.8\%$ ) | Alpha over Nifty 50 (%) |
|---------------------------------------|-------------------|-----------------------|--------------------------------|-------------------------|
| <b>Markowitz Max Sharpe Portfolio</b> | <b>51.81%</b>     | <b>20.89%</b>         | <b>2.1548</b>                  | <b>+37.61%</b>          |
| Equal-Weighted Portfolio (1/N)        | 42.27%            | 17.54%                | 2.0223                         | +28.07%                 |
| Minimum Variance Portfolio            | 33.63%            | 16.29%                | 1.6473                         | +19.43%                 |
| Benchmark Nifty 50 Index              | 14.20%            | 12.50%                | 0.5920                         | 0.00% (Baseline)        |

**Table 6. Comparative Risk-Return Performance of Portfolios vs. Benchmark**

Note: "Alpha over Nifty 50" denotes the portfolio CAGR minus the Nifty 50 CAGR of 14.20%, that is, the arithmetic excess return over the benchmark.

The ranking by Sharpe ratio is unambiguous: Max Sharpe (2.1548), Equal-Weighted (2.0223), Minimum Variance (1.6473), and Nifty 50 (0.5920). Three

observations follow.

First, every constructed portfolio dominates the benchmark by a wide margin. The Max Sharpe portfolio earns 51.81% against 14.20% while taking 8.39 percentage points more volatility, and even the Minimum Variance portfolio, with 16.29% volatility, delivers a CAGR of 33.63%.

Second, the gain from optimization over naive diversification is positive but modest in Sharpe terms. Moving from the equal-weighted to the Max Sharpe portfolio raises the Sharpe ratio from 2.0223 to 2.1548, a relative improvement of 6.55%, and lifts expected return by 9.54 percentage points, from 42.27% to 51.81%. This improvement comes at the cost of 3.35 percentage points of additional volatility (20.89% versus 17.54%). This modest gain is consistent with Section 2.3: with similar correlations and uniformly strong in-sample performance,  $1/N$  already approximates the tangency Sharpe ratio, so the optimizer's advantage lies mainly in return enhancement for investors who can tolerate higher volatility.

Third, the Minimum Variance portfolio reduces volatility from 20.89% to 16.29% relative to the tangency portfolio, a reduction of 4.60 percentage points, but it does so at the expense of 18.18 percentage points of CAGR and a markedly lower Sharpe ratio. The portfolio's beta of approximately 1.08 (against approximately 1.28 for the Max Sharpe portfolio) shows that even the risk-minimizing allocation retains meaningful market exposure. A risk-averse client prioritizing capital preservation would nonetheless find the Minimum Variance portfolio attractive, since its Sharpe ratio remains almost three times that of the Nifty 50.

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## 6. Practical Implications and Portfolio Recommendations

### 6.1 Core-Satellite Model Portfolio

A strict tangency portfolio is a fragile basis for client advice, given its sensitivity to estimated inputs (Michaud, 1989) and its concentration of about 89% in a single policy-driven theme. A core-satellite structure offers a more robust implementation that retains the empirical insight of the optimization while limiting concentration risk. The proposed model allocates:

- **Growth core (70%):** defense PSUs, namely HAL, BEL, and Mazagon Dock, which carry the highest Sharpe ratios, alphas, and order cover. Equal allocation within the core gives approximately 23.33% each.
- **Volatility-dampening satellite (30%):** private capital goods majors, namely ABB, Siemens, and L&T, which carry lower betas and volatility and are less exposed to defense-budget cycles. Equal allocation gives 10% each.

Applying the study's return and covariance estimates to this structure produces illustrative figures of a CAGR of approximately 46.97%, an annual volatility of approximately 18.93%, and a Sharpe ratio of approximately 2.12, corresponding to an excess return of approximately 32.77 percentage points over the Nifty 50. These values are derived by the authors from Tables 2 and 4 and are not part of the optimizer output. The Sharpe ratio lies between the Max Sharpe (2.1548) and equal-weighted (2.0223) portfolios, with a volatility roughly 2 percentage points below the tangency portfolio. In effect, the structure retains most of the risk-adjusted benefit of the optimal portfolio while including L&T, which the optimizer excluded, as an explicit hedge against a reversal in defense sentiment or order-flow disappointment. The proportions can be calibrated to client risk tolerance.

### 6.2 Threshold-Based Rebalancing Rule

Because the defense PSUs have appreciated faster than the satellite holdings, an unmanaged portfolio would drift toward higher concentration and higher risk. A threshold-based rebalancing rule is therefore recommended. The portfolio should be reviewed semi-annually, and rebalancing back to target weights should be triggered when any holding's weight deviates from its target by more than  $\pm 5\%$  in absolute terms, or when the core-to-satellite split moves outside the 65:35 to 75:25 band. Combining calendar review with a drift threshold limits unnecessary turnover and associated transaction costs while still enforcing risk discipline when strong performance causes concentration. Each rebalancing should also include re-estimation of the covariance matrix and a review of order-book and valuation data.

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## 7. Limitations and Future Scope

Several limitations qualify the results. First, parameter instability is a central concern. The three-year sample coincided with a major defense capital-expenditure upcycle and an indigenization-driven re-rating. The estimated returns, alphas, and Sharpe ratios therefore reflect an unusually favorable regime, and the optimizer's heavy defense allocation is a direct consequence of in-sample returns that may not persist. Historical CAGR is also used as the estimate of expected return, which makes the optimal weights highly sensitive to the sample window (Chopra & Ziemba, 1993). All results are in-sample, and no out-of-sample validation was conducted; given the findings of DeMiguel et al. (2009), the optimization advantage over  $1/N$  should be expected to shrink out of sample.

Second, the analysis is subject to simplified measurement choices. The risk-free rate is fixed at 6.80% for the entire window, although short-term yields varied over the period. Jensen's alpha is computed by comparing realized CAGR against the CAPM-implied return, using the benchmark's CAGR as the market return, rather than through a regression with formal standard errors; no statistical significance tests are therefore reported. The correlation and covariance estimates are treated as constant, whereas correlations in emerging markets typically rise during stress periods.

Third, trading frictions are not modeled. Brokerage, securities transaction tax, stamp duty, impact costs, and bid-ask slippage are excluded, and the

rebalancing rule in Section 6 would incur such costs in practice. Liquidity differences and capacity constraints for PSU stocks with limited free float are also outside scope. The sample is restricted to six prominent stocks, so conclusions about the wider sectors should be drawn cautiously, and selection of sector leaders may bias results upward.

Fourth, the model contains no forward-looking Bayesian priors. Future research could apply the Black-Litterman approach (Black & Litterman, 1992) to combine market-implied returns with views based on order-book data and earnings forecasts, use more stable estimates of returns and covariances (Jorion, 1986; Ledoit & Wolf, 2004), and cap individual weights to produce more diversified allocations. Further extensions include testing on out-of-sample data, including a wider set of defense and capital goods stocks, and adding transaction costs.

## 8. Conclusion

This paper evaluated whether the strong performance of Indian capital goods and defense equities from April 2023 to March 2026 represents genuine risk-adjusted return, and derived long-only mean-variance optimal allocations for six leading stocks. Three conclusions emerge.

First, the defense PSUs (BEL, HAL, and Mazagon Dock) combine unlevered balance sheets, ROCE of 32.1% to 39.8%, and order book-to-bill ratios of 3.65x to 4.20x, and they delivered Sharpe ratios of 1.5000 to 1.5906 and Jensen's alphas of +32.97% to +43.67%. Beta explains only about 20% of their excess returns, which supports an interpretation based on fundamental earnings strength rather than market co-movement, subject to the caveat that valuation re-rating cannot be isolated.

Second, the Markowitz Max Sharpe portfolio, which allocates 89.13% to the three defense PSUs, achieved a CAGR of 51.81% at 20.89% volatility and a Sharpe ratio of 2.1548. This outperformed the equal-weighted portfolio (2.0223), the Minimum Variance portfolio (1.6473), and the Nifty 50 (0.5920). L&T's zero weight in the tangency portfolio results from its having the lowest Sharpe ratio of the six stocks (0.8939), whereas its 42.22% weight in the Minimum Variance portfolio reflects its role as the lowest-risk asset.

Third, the improvement from optimization over equal weighting is real but modest (6.55% in Sharpe terms), and it is based entirely on in-sample estimates drawn from a favorable policy cycle. For practical advisory use, a 70:30 core-satellite portfolio with semi-annual,  $\pm 5\%$  threshold-based rebalancing captures most of the risk-adjusted benefit while limiting concentration. The findings are best interpreted as evidence of a strong fundamental case for including defense PSUs in Indian industrial equity portfolios, not as a guarantee that the optimal weights will persist.

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