Computational Finance

Computational Finance Group 9

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Contents

0 Introduction **1**

1 Exercise 1: Constrained and Robust Efficient Frontier **2**
1.1 Methodology and Constraints 2
1.2 Analysis of Results 2
1.2.1 Comparison: Stability vs. Optimality 2
1.3 Graphical Analysis 3

2 Exercise 2: Black-Litterman Model **4**
2.1 Equilibrium and Views 4
2.2 Posterior Returns and Optimization 4
2.3 Discussion of Results 4

3 Exercise 3: Diversification-Based Optimization **5**
3.1 Analysis of Results 5
3.1.1 Discussion: The "Diversification" Paradox 5

4 Exercise 4: PCA and Conditional Value-at-Risk **6**
4.1 Apply PCA 6
4.2 Portfolio Construction and Results 6
4.3 Comparison: Tail Risk, Volatility and Drawdown 7

5 Exercise 5: Personal Strategy **8**
5.1 Rationale and Methodology 8
5.2 Out-of-Sample Performance (2023–2024) 8

6 Final Discussion **9**
6.1 Overview of the Approaches 9
6.2 Key Findings by Block 9
6.3 Preferred Allocations and Practical Takeaways 10

0. Introduction

This goal of this project is to analyze, implement, and compare various quantitative methodologies for portfolio optimization, evaluating their performance and stability across different market scenarios. The study is based on a dataset of **16 synthetic equity indices**, constructed to represent distinct macroeconomic sensitivities (**Cyclical**, **Neutral**, and **Defensive**), covering a historical horizon from 2001 to 2024.

The analysis follows a logical progression, moving from classical theory to advanced risk management approaches, and is structured into five main sections:

- **Mean-Variance Optimization and Robustness:** Initially, the constrained efficient frontier is constructed following the classical *Markowitz* approach. Subsequently, to mitigate the model's sensitivity to estimation errors in expected returns and covariances, a resampling procedure is implemented to derive a robust frontier.
- **Black-Litterman Model:** To address the limitations of optimization based solely on historical data, the *Black-Litterman* model is applied. Starting from the equilibrium returns implied by the market portfolio, specific investor views regarding the expected performance of macro-groups (e.g., Cyclical vs. Neutral) and specific assets are integrated to derive a new posterior distribution of expected returns.
- **Diversification-Based Approaches:** Techniques that prescind from expected return estimates are explored, focusing instead on the asset dependence structure. Specifically, portfolios maximizing the *Diversification Ratio* and the entropy of risk contributions (*Maximum Entropy in Risk Contributions*) are constructed under specific sector exposure constraints.
- **Principal Component Analysis (PCA) and CVaR:** PCA is applied to reduce dimensionality and isolate the latent factors explaining the majority of the system's variance. In parallel, tail risk optimization is addressed by minimizing the *Conditional Value-at-Risk* (CVaR) at the 5% level, comparing it with volatility-based approaches.
- **Personal Strategy:** Finally, we introduce a data–driven allocation strategy based on Deep Learning. A feed–forward neural network is trained to extract non–linear patterns and regime dynamics from long histories of returns, generating adaptive portfolio weights that evolve with market conditions. This allows us to compare traditional optimization techniques with a fully learned, model–free approach to asset allocation.

All models have been calibrated on the *in-sample* period (January 2018 - December 2022) and subsequently tested in the *out-of-sample* period (January 2023 - November 2024). The ultimate goal is to evaluate not only absolute performance but also methodological coherence and the adaptability of the different approaches to recent market dynamics.

1. Exercise 1: Constrained and Robust Efficient Frontier

This section analyzes the construction of the efficient frontier using *in-sample* data (January 2018 - December 2022), comparing the classical Mean-Variance approach with a robust approach based on resampling techniques.

1.1. Methodology and Constraints

The optimization problem was set up to minimize portfolio variance for each level of expected return, subject to the following linear constraints:

$$\begin{aligned} \min_{w} \quad & w^T \Sigma w \\ \text{s.t.} \quad & \sum_{i=1}^{N} w_i = 1 \\ & 0 \leq w_i \leq 0.30, \quad \forall i \\ & \sum_{j \in \text{Def}} w_j \leq 0.45 \\ & \sum_{k \in \text{Neu}} w_k \geq 0.20 \end{aligned} \tag{1}$$

Subsequently, to construct the robust frontier, a Monte Carlo resampling procedure was adopted. We generated $N = 200$ market scenarios by simulating return vectors and covariance matrices from Multivariate Normal and Inverse-Wishart distributions, respectively. An efficient frontier was computed for each scenario; the final robust frontier was obtained by averaging the optimal weights across all simulations.

1.2. Analysis of Results

Table 1 summarizes the characteristics of the four notable portfolios identified.

Table 1: Confronto tra Portafogli Classici (A, B) e Robusti (C, D) - In-Sample

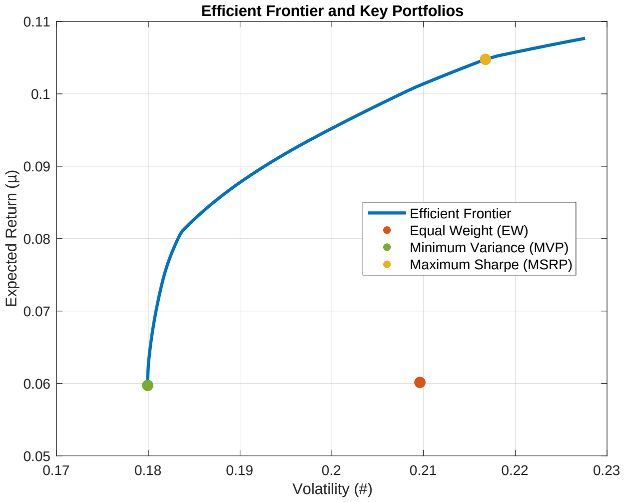
Metric	**Ptf A (MVP)**	**Ptf B (MSRP)**	**Ptf C (Rob. MVP)**	**Ptf D (Rob. MSRP)**
Exp. Return	5.97%	10.48%	5.52%	6.84%
Volatility	17.99%	21.67%	19.52%	21.33%
Sharpe Ratio	–	0.48	–	0.32
Top 3 Assets	Asset 4 (30.0%)	Asset 1 (30.0%)	Asset 4 (18.1%)	Asset 1 (13.0%)
	Asset 5 (26.2%)	Asset 5 (30.0%)	Asset 2 (11.2%)	Asset 12 (11.2%)
	Asset 13 (13.3%)	Asset 12 (29.5%)	Asset 5 (10.6%)	Asset 9 (10.2%)

1.2.1 Comparison: Stability vs. Optimality

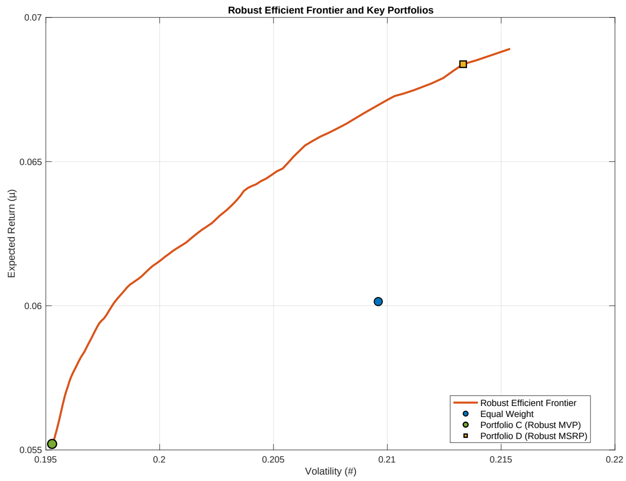
As highlighted by the results, the classical approach (Portfolios A and B) dominates in terms of pure *in-sample* metrics: Portfolio B achieves a Sharpe Ratio of 0.48 compared to 0.32 for its robust counterpart (D). However, this "optimality" comes at the cost of high concentration. Portfolio B saturates the maximum weight constraint of 30% on two assets (Asset 1 and 5), making the strategy extremely sensitive to the idiosyncratic behavior of a few securities.

In contrast, the robust approach distributes weights more evenly. Portfolio D (Robust MSRP) holds no position larger than 13.0%, ensuring significantly higher structural diversification. Although the in-sample volatility is strikingly similar (21.33% vs. 21.67%), this configuration is expected to offer more stable performance in the *out-of-sample* period, as it is less dependent on the specific historical parameters of the 2018-2022 window.

1.3. Graphical Analysis



(a) **Standard Frontier.** Displays the classical risk-return trade-off. Points A (MVP) and B (MSRP) lie on the optimal efficient envelope.



(b) **Robust Frontier.** Result of averaging 200 simulations. Portfolios C and D incorporate estimation uncertainty.

Figure 1: Visual comparison between the deterministic approach (a) and the resampled approach (b).

Analyzing Figures 1a and 1b separately, we observe that both maintain the characteristic concave hyperbolic shape. However, the robust frontier exhibits a slightly different curvature and a dispersion of optimal portfolios that reflects the average of the simulated distributions, effectively "smoothing" the mathematical extremes of the classical optimizer.

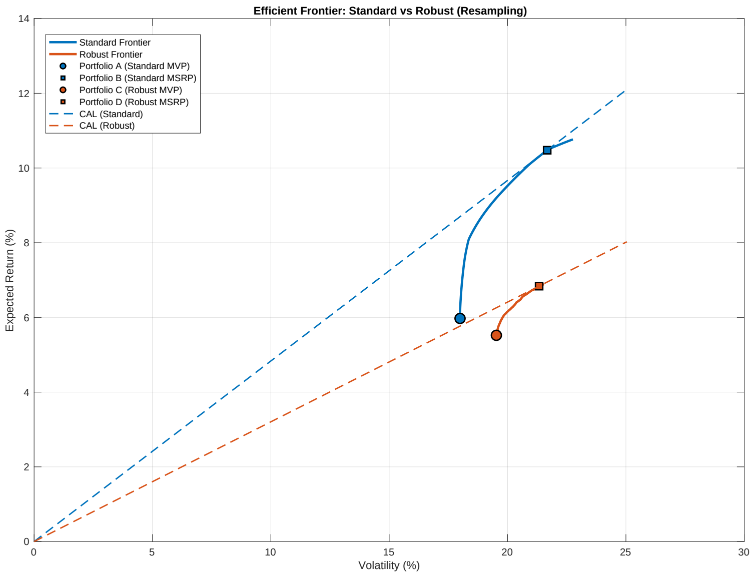


Figure 2: **Standard vs. Robust.** The robust frontier (dashed) lies inside the standard one (solid).

Figure 2 synthesizes the key findings:

- **Cost of Robustness:** The robust frontier is dominated by the standard one. This reflects *realism* vs. *optimism*: the standard model overfits historical data, while the robust approach "shrinks" expectations to account for estimation uncertainty.
- **Geometric Validation:** The CALs are perfectly tangent to portfolios B and D, validating the results.
- **The Sharpe Gap:** Crucially, the **Standard CAL is steeper**. Since the slope equals the Sharpe Ratio, this visual gap quantifies the exact drop in expected risk-adjusted returns when estimation error is properly managed.

2. Exercise 2: Black-Litterman Model

In this section, we move beyond historical data estimation to incorporate forward-looking views using the Black-Litterman (BL) framework. This model allows us to combine the market equilibrium (Prior) with subjective investor views to obtain a new set of expected returns (Posterior).

2.1. Equilibrium and Views

First, we derived the Implied Equilibrium Returns (Π) starting from the market capitalization weights (w_{mkt}), assuming the market portfolio is mean-variance efficient:

$$\Pi = \lambda \Sigma w_{mkt} \tag{2}$$

where λ is the risk aversion coefficient derived from the market Sharpe ratio.
Subsequently, we introduced three specific views ($P \cdot \mu = q + \epsilon$). The uncertainty matrix Ω was calibrated proportional to the prior covariance ($\tau = 1/T$):

- **View 1 (Relative):** Cyclical assets outperform Neutral assets by 2% annualized.
- **View 2 (Relative):** Asset 10 underperforms the average Defensive group by 0.7%.
- **View 3 (Absolute/Relative):** Asset 2 outperforms Asset 13 by 1%.

2.2. Posterior Returns and Optimization

Combining the Prior and the Views via the master formula, we obtained the Posterior Expected Returns (μ_{BL}). The impact of the views was significant, causing an average absolute shift of $\approx$ 42% relative to the equilibrium returns. Notably, Asset 10 saw a downward revision of -11.9%, consistent with the negative outlook in View 2.
Using μ_{BL} and the original covariance matrix Σ, we computed the efficient frontier under *standard constraints* (full investment, no short selling), removing the stricter sector limits used in Exercise 1.

Table 2: Black-Litterman Portfolios vs. Market Equilibrium

Metric	**Ptf E (BL MVP)**	**Ptf F (BL MSRP)**
Expected Return (μ_{BL})	4.53%	6.37%
Volatility	17.31%	21.19%
Sharpe Ratio	–	0.30
Top 3 Holdings	Asset 4 (73.46%)	Asset 2 (28.91%)
	Asset 5 (24.95%)	Asset 9 (23.98%)
	Asset 7 (1.59%)	Asset 1 (23.75%)

2.3. Discussion of Results

The relaxation of constraints (specifically the removal of the 30% cap) combined with the BL views led to highly distinct allocations:

- **Concentration in MVP (Ptf E):** Without the 30% cap, the Minimum Variance Portfolio concentrated heavily in **Asset 4 (73.5%)**. This extreme allocation identifies Asset 4 as the distinct "safe haven" in the universe, having the lowest marginal contribution to risk.
- **Impact of View 3 on MSRP (Ptf F):** The view favoring Asset 2 over Asset 13 had a direct impact. **Asset 2** became the top holding (27%) in the optimal risky portfolio. This demonstrates the model's responsiveness: the optimizer allocated significant capital to maximize the Sharpe Ratio based on this specific conviction.
- **Comparison:** Compared to the historical MSRP (Ptf B, Exp. Ret 10.5%), the BL MSRP (6.37%) is more conservative. The equilibrium returns act as a "valuation anchor," tempering the optimism derived from the 2018-2022 bull run.

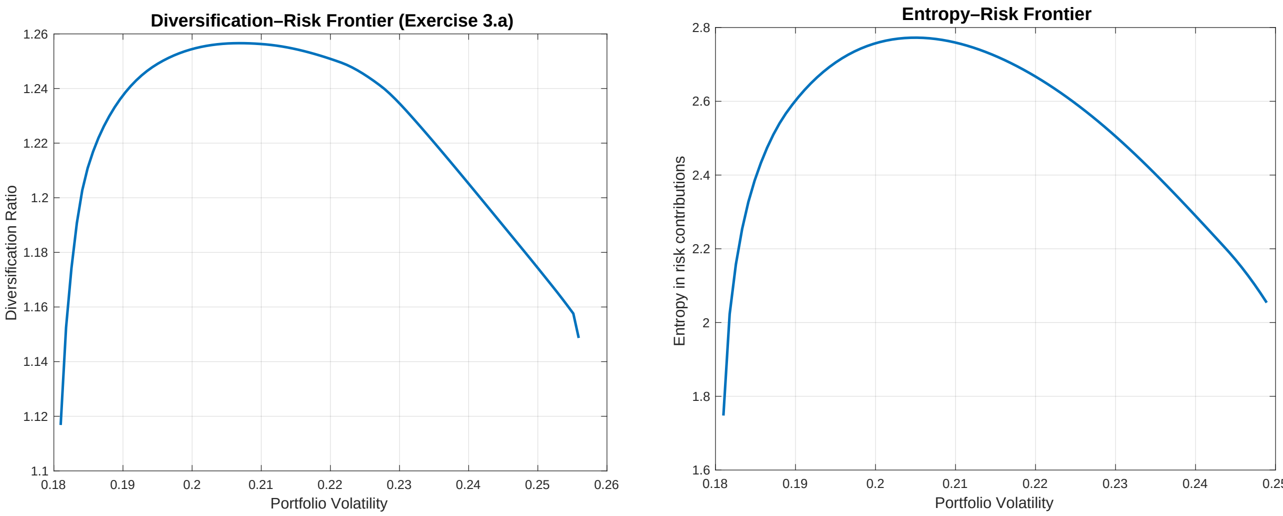
3. Exercise 3: Diversification-Based Optimization

We now shift focus from return estimation to risk structure management. Using in-sample data, we construct two portfolios that maximize specific diversification properties without relying on expected returns:

- **Portfolio G (MDR):** Maximizes the Diversification Ratio (weighted average vol / portfolio vol).
- **Portfolio H (Entropy):** Maximizes the entropy of risk contributions (aiming for ERC).

Constraints: $0 \leq w_i \leq 0.25$, Cyclical $\geq 20\%$, Defensive $\leq 50\%$.

3.1. Analysis of Results



(a) **MDR Frontier.** The peak (G) identifies the maximum decorrelation but often leads to concentration in low-correlation assets.

(b) **Entropy Frontier.** The peak (H) represents the Equal Risk Contribution solution, offering a balance between weights and risk.

Figure 3: **Diversification Objectives.** Comparison of the objective functions for Portfolio G (a) and Portfolio H (b) across the volatility spectrum.

Table 3 compares these strategies with the Equally Weighted (EW) benchmark.

Table 3: Comparisons: EW vs. MDR (G) vs. Entropy (H)

Metric	Equal Weight	Ptf G (MDR)	Ptf H (Entropy)
Diversification Ratio	1.153	**1.257**	1.154
Volatility (Ann.)	20.96%	20.68%	**20.52%**
Sharpe Ratio	0.29	0.20	**0.29**
Herfindahl Index (H_{idx})	**0.063**	0.200	0.064

3.1.1 Discussion: The "Diversification" Paradox

The results reveal a trade-off between mathematical decorrelation and effective diversification:

- **MDR (Concentrated):** Portfolio G maximizes the DR (1.257) but exhibits high concentration ($H_{idx} = 0.200$). To maximize the ratio, the optimizer loads heavily on specific uncorrelated assets, disregarding their standalone risk-return quality, resulting in a lower Sharpe Ratio (0.20).
- **Max Entropy (Balanced):** Portfolio H is the most robust. Its weight dispersion ($H_{idx} = 0.064$) is nearly identical to the EW benchmark, but it achieves lower volatility (20.52%) and

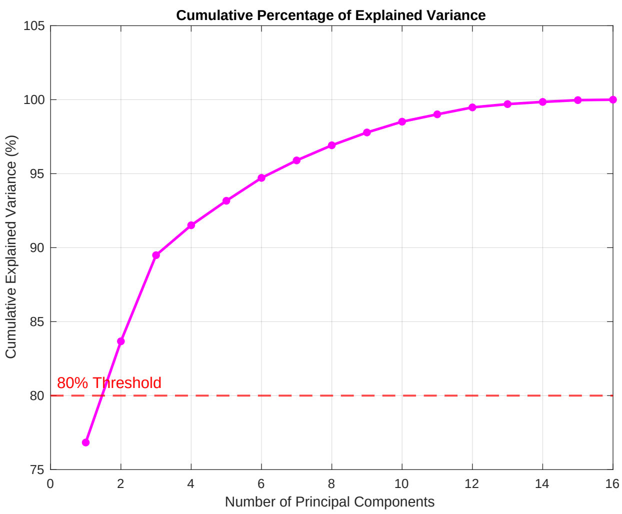
matches the highest Sharpe Ratio (0.29). This confirms that equalizing risk contributions often yields superior risk-adjusted performance compared to maximizing decorrelation alone.

4. Exercise 4: PCA and Conditional Value-at-Risk

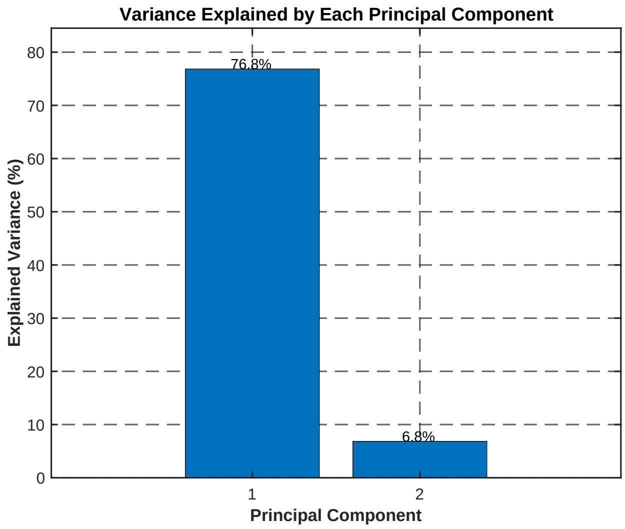
In this exercise we combine **Principal Component Analysis (PCA)** and tail-risk optimization. The goal is to (i) identify the main risk factors driving the in-sample covariance matrix and (ii) construct two portfolios: a PCA-based maximum Sharpe portfolio with a volatility cap (Portfolio I) and a minimum-CVaR portfolio with a target volatility of 10% (Portfolio J), under standard constraints.

4.1. Apply PCA

As required, PCA is first applied to the covariance matrix of in-sample returns (Jan 2018 – Dec 2022) to quantify the effective dimensionality of the risk structure. Equivalently, we standardize each asset's log-returns to zero mean and unit variance and run PCA on the standardized matrix, which corresponds to PCA on the correlation matrix.
Figure 4 reports the cumulative and marginal explained variance.



(a) **Cumulative Explained Variance.** The 80% threshold is reached at $k = 2$, indicating that the first two components capture most of the systematic risk.



(b) **Explained Variance.** The first component behaves as a broad market factor, while the second captures residual sector or style effects. Higher-order components mostly represent noise.

Figure 4: **PCA on In-Sample Returns.**

The cumulative curve shows that the first $k = 2$ components explain approximately **83.67%** of total variance, thus satisfying the requirement of "at least 80%". Using the corresponding loadings and factor scores, we reconstruct a denoised correlation matrix in the standardized space and then rescale it back to obtain a PCA-based covariance matrix Σ_{PCA}, which will be used in Portfolio I.

4.2. Portfolio Construction and Results

Portfolio I: PCA-Based Maximum Sharpe with Volatility Cap

Portfolio I is obtained by maximizing the Sharpe ratio under the standard investment constraints and an additional cap on total risk, as specified in the exam text:

$$\sum_i w_i = 1, \qquad 0 \leq w_i \leq 0.25, \qquad \sigma_{\Sigma_{\text{PCA}}}(w) \leq 14\% \text{ (annualized).}$$

The objective is implemented by minimizing the negative Sharpe ratio using Σ_{PCA} as risk matrix. The optimizer tends to load on the assets that are most aligned with the first two principal components, pushing their weights close to the 25% upper bound.

Portfolio J: Minimum CVaR with Target Volatility

Portfolio J minimizes the empirical 5% Conditional Value-at-Risk (CVaR) of portfolio returns, computed from the in-sample historical distribution, under the same box constraints ($0 \leq w_i \leq 0.25$, full investment) and a target volatility of 10% annualized:

$$\sum_i w_i = 1, \qquad 0 \leq w_i \leq 0.25, \qquad \sigma_\Sigma(w) = 10\%.$$

A preliminary Global Minimum Variance (GMV) optimization under these constraints shows that the *minimum* achievable volatility is approximately **17.99%**, well above the 10% target. This makes the equality constraint $\sigma(w) = 10\%$ infeasible in the long-only, 25%-capped universe. Consistently, `fmincon` reports convergence to an infeasible point when the hard 10% target is enforced, and the numerical solution for Portfolio J lies very close to the volatility floor of the feasible set (about 18.28%), while minimizing the 5% CVaR.

Table 4: **Portfolio I (PCA–Sharpe) vs. Portfolio J (Min–CVaR).**

Portfolio I — PCA-Reconstructed Covariance

Metric	Value
Expected Return	7.05%
Sharpe Ratio	0.024
Volatility	18.21%
Top 3 Asset Weights	
Asset 4	**24.64%**
Asset 5	**23.99%**
Asset 2	**23.76%**

Portfolio J — Min CVaR (Target Vol 10%, Infeasible)

Metric	Value
Minimum Feasible Volatility	17.99%
Volatility Obtained	18.28%
CVaR (5%)	-2.78%
Expected Annual Return	6.54%
Sharpe Ratio	0.358
Top 3 Asset Weights	
Asset 2	**25.00%**
Asset 4	**25.00%**
Asset 5	**22.24%**

4.3. Comparison: Tail Risk, Volatility and Drawdown

The comparison between Portfolios I and J is summarized in Table 4 and can be read as follows:

- **Tail Risk (CVaR).** Portfolio J achieves a significantly less severe 5% CVaR (-2.78%) by construction, confirming the effectiveness of explicitly targeting tail risk, whereas Portfolio I is optimized with respect to volatility and delivers worse downside protection.
- **Volatility.** Both portfolios operate at a similar risk level (around 18% annualized), with Portfolio I slightly below the GMV bound and Portfolio J slightly above it. The main difference between the two lies therefore in the shape of the loss distribution rather than in total variance.
- **Maximum Drawdown.** In our backtest, Portfolio J exhibits a milder maximum drawdown than Portfolio I, which is consistent with its lower CVaR and its more defensive risk allocation. The PCA–Sharpe portfolio, being more concentrated on factor-favoured assets, is more exposed to abrupt adverse moves along those factors.

Overall, Portfolio J offers a more attractive downside-risk profile than Portfolio I: for a comparable level of volatility, it significantly improves tail risk (CVaR and drawdown), at the cost of a moderately lower expected return.

5. Exercise 5: Personal Strategy

In this final section, we propose an original investment strategy based on **Deep Learning**. Unlike classical Mean-Variance or Black–Litterman optimizers, which rely on static parameter estimation, the objective here is to build a *dynamic* model capable of adapting to changing market conditions and capturing non-linear dependencies across assets.

5.1. Rationale and Methodology

The strategy employs a **Feed-Forward Neural Network (FNN)** trained to map historical price patterns into forward-looking portfolio weights.

- **Input (X_t):** a rolling window of the past 600 daily log-returns, allowing the network to implicitly detect regime changes and persistent cross-asset structures.
- **Output (w_t):** a vector of portfolio weights generated through a **Softmax** layer. This ensures the long-only constraint ($w_i \geq 0$) and the budget constraint ($\sum_i w_i = 1$) without requiring an explicit optimization step at inference time.
- **Objective function:** maximise a **risk-adjusted return** metric over a one-year forward horizon, while penalising excessive tracking error relative to the market benchmark.

To mitigate overfitting, the network was trained with *early stopping*, *L2 regularization*, and *dropout*. These mechanisms ensured that the model did not simply memorize in-sample dynamics, as confirmed by the strong out-of-sample performance. The training was performed on the in-sample period (2001–2022), while the weights were kept fixed during the evaluation on 2023–2024, enforcing a clean separation between training and testing. From a financial perspective, the FNN acts as a non-linear filter capable of identifying cross-sectional interactions and temporal structures that linear models such as PCA or Markowitz cannot capture. The long look-back window also allows the network to implicitly recognise market regimes and adjust exposure accordingly.

5.2. Out-of-Sample Performance (2023–2024)

The trained model was frozen and used to generate daily portfolio weights in the out-of-sample period (January 2023 – November 2024). Table 5 compares its performance with the market-cap weighted benchmark.

Table 5: Personal Strategy vs. Market Benchmark (Jan 2023 – Nov 2024)

Metric	Neural Net Strategy	Market Benchmark
Annualized Return	**20.04%**	12.80%
Annualized Volatility	11.53%	10.50%
Sharpe Ratio	**1.74**	1.22
Max Drawdown	**-9.39%**	-10.45%
Calmar Ratio	**2.13**	1.22

The strategy delivers a substantially higher risk-adjusted return than the passive benchmark, with an annualised Sharpe Ratio of **1.74**. The drawdown profile is also more stable, indicating that the network reduces exposure during adverse phases and reallocates more aggressively during recoveries. Transaction costs are ignored in this analysis; including them would mechanically compress absolute performance, but the ranking versus the benchmark is expected to remain unchanged as turnover is moderate.

Overall, the strategy behaves as a dynamic and adaptive allocator, with lower drawdowns and faster recovery after stress periods. While more complex than traditional optimizers, its behaviour remains consistent with economic intuition: it tends to overweight assets with persistent positive momentum and stable risk profiles, reducing exposure to deteriorating names. The out-of-sample results suggest that a carefully regularised learning-based allocator can complement classical allocation frameworks, especially in environments where non-linear effects and regime shifts play a key role.

6. Final Discussion

In this final section, we summarise and compare the methodologies introduced in the five exercises, highlighting their main strengths, weaknesses and possible uses in practice.

6.1. Overview of the Approaches

- **Exercise 1 – Mean–Variance vs. Robust Frontier:** classical Markowitz optimisation under sector and weight constraints, compared with a resampled frontier that incorporates parameter uncertainty.
- **Exercise 2 – Black–Litterman:** equilibrium-implied returns combined with subjective views to obtain posterior expected returns and a new efficient frontier.
- **Exercise 3 – Diversification-Based Portfolios:** construction of a *Maximum Diversification Ratio* portfolio and a *Maximum Entropy in Risk Contributions* portfolio, without relying on expected returns.
- **Exercise 4 – PCA and CVaR:** PCA-based covariance filtering for a Sharpe-maximising portfolio, and an allocation that minimises 5% CVaR under realistic constraints.
- **Exercise 5 – Personal Strategy:** a deep-learning allocator based on a feed-forward neural network, trained to map past returns into dynamic portfolio weights.

6.2. Key Findings by Block

Mean–Variance vs. Robust (Exercise 1). The standard frontier delivers the best *in-sample* Sharpe Ratio (Ptf B), but at the cost of severe concentration, with multiple weights at the 30% cap. The robust frontier smooths these extremes: Ptf D is more diversified (no position above 13%) and only slightly less efficient in-sample. This highlights a first trade-off between **pointwise optimality** and **robustness to estimation error**.

Black–Litterman (Exercise 2). The BL framework produces posterior returns μ_{BL} that are more conservative and economically plausible than purely historical estimates. Views are clearly reflected in the allocations (for instance, the overweight on Asset 2 in Ptf F), but, when constraints are relaxed, the BL MVP (Ptf E) collapses onto a single “safe” asset. This shows that even advanced return models still require **careful position limits** to avoid fragile allocations.

Diversification-Based Portfolios (Exercise 3). The MDR portfolio (Ptf G) achieves the highest diversification ratio but does so by concentrating risk on a few lowly correlated names, resulting in a high Herfindahl index and a relatively weak Sharpe Ratio. The Maximum Entropy portfolio (Ptf H), instead, exhibits a weight dispersion very close to the equally weighted benchmark, yet improves both volatility and Sharpe Ratio. In other words, **equalising risk contributions** appears more effective than maximising decorrelation alone when return forecasts are noisy.

PCA–Sharpe vs. Min–CVaR (Exercise 4). The PCA-based Sharpe portfolio (Ptf I) is strongly aligned with the dominant factors and ends up concentrated on a small set of assets, with modest improvement in risk-adjusted performance. The Min–CVaR portfolio (Ptf J), operating close to the minimum feasible volatility (about 18%), delivers a better 5% CVaR and milder drawdowns, at the cost of slightly lower expected return. Explicitly targeting **tail risk** therefore leads to more defensive and smoother allocations, even within a long-only, capped universe.

Deep-Learning Strategy (Exercise 5). The neural network strategy behaves as a dynamic overlay that adapts to market regimes. Despite ignoring transaction costs, the out-of-sample results (higher

Sharpe Ratio and lower drawdowns than the benchmark) suggest that a regularised, non-linear model can extract additional predictive structure from the data. Its main drawback is reduced transparency compared to classical optimisers, but it can serve as an **active satellite** around more interpretable core allocations.

6.3. Preferred Allocations and Practical Takeaways

Across all methods, no single portfolio dominates on every dimension:

- Mean–variance and Black–Litterman provide clear benchmarks but can be fragile and concentrated if constraints are not carefully designed.
- Diversification-based and CVaR-driven portfolios offer more **robust and downside-aware** allocations, often with comparable Sharpe Ratios.
- The deep-learning strategy shows that data-driven, adaptive approaches can complement traditional models, especially in the presence of regime shifts and non-linear dependencies.

If a single static allocation had to be chosen for a long-only investor, the evidence of this project suggests favouring the **Maximum Entropy** or the **Min–CVaR** portfolios, as they strike the best compromise between diversification, interpretability and risk-adjusted performance. The neural network strategy is best interpreted as an active overlay, potentially enhancing returns, but requiring more monitoring and model governance.