Under the Hood:

A Deep Dive into Portfolio Optimisation

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The Big Question

If you had **£100,000** to invest across
stocks, bonds, gold, and commodities...

How would you split it?

- Split equally (1/18 per asset)?
- Use complex mathematical optimization?
- Something else?

We're testing this empirically.

The Research Question

Core Question

Can sophisticated portfolio optimisation models beat the naive 1/N strategy?

Why this matters:

- **For investors:** Should you pay for complex portfolio management?
- **For students:** Does classroom theory work in practice?
- **For quant enthusiasts:** Rigorous empirical comparison

This is a live debate in quantitative finance — theory vs. practice.

Our Investment Universe

Asset Class	Examples	Count
UK Equities	HSBC, BP, Shell, Tesco, AstraZeneca, etc...	15
UK Government Bonds	iShares Core UK Gilts ETF	1
Precious Metals	Invesco Physical Gold ETC	1
Commodities	WisdomTree Commodities ETF	1
Total	**Multi-Asset Portfolio**	**18**

Data period: 2015–2025 (10 years)

- Includes COVID crash, 2022 selloff, Brexit volatility
- Daily prices, monthly rebalancing

The Four Strategies We're Testing

1. **Equal Weight (1/N)** — Naive baseline
2. **Mean-Variance Optimisation (MVO)** — Markowitz (1952)
3. **Black-Litterman** — Bayesian equilibrium + views
4. **Risk Parity** — Equal risk contribution

All tested on identical data with identical methodology

Strategy 1: Equal Weight (1/N)

The Benchmark

Simplest possible: split money equally across all 18 assets

How it works:

- £5,556 to each asset (on £100k capital)
- Monthly rebalancing to maintain 1/18 weights
- No forecasting, no optimization

Why it's tough to beat

DeMiguel et al. (2009): Equal weight often beats sophisticated models due to estimation error in expected returns and covariances.

Strategy 2: Mean-Variance Optimisation

Markowitz (1952) — Foundation of Modern Portfolio Theory

Maximize return for given risk (or minimize risk for given return)

Optimization:

$$\max_{w} \frac{w^T \mu - r_f}{\sqrt{w^T \Sigma w}} \quad \text{s.t.} \quad \sum w_i = 1, \; w_i \geq 0$$

The challenge:

- Very sensitive to estimation errors in μ and Σ
- Small input changes $\rightarrow$ big portfolio changes
- Can produce extreme, unstable weights

Strategy 3: Black-Litterman

Combining Market Equilibrium with Investor Views

Overcomes MVO instability by anchoring to market equilibrium

How it works:

1. Start with equilibrium returns (from market cap weights)
2. Express views: "UK banks will outperform by 2%"
3. Blend equilibrium + views using Bayesian updating
4. Optimize portfolio with posterior returns

Key advantage: More stable than pure MVO — doesn't require perfect forecasts

Strategy 4: Risk Parity

Equal Risk Contribution, Not Equal Capital

Philosophy: diversify risk, not just money

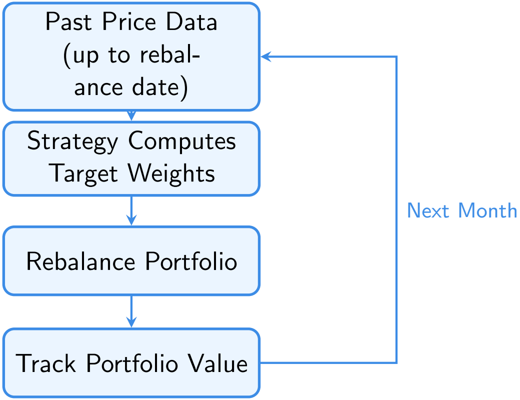
Each asset contributes equally to total portfolio risk:

$$w_i \times \frac{\partial \sigma_p}{\partial w_i} = \frac{\sigma_p}{N}$$

In practice:

- Bonds (low vol) get *more* capital
- Equities (high vol) get *less* capital
- Popular with institutional investors (e.g., Bridgewater All Weather)

How We're Testing: Backtesting Engine



Critical: No Look-Ahead Bias

Strategies only see **past data**. This prevents unrealistically good backtest results.

Code: Preventing Look-Ahead Bias

```python
for current_date in dates:
    if current_date in rebalance_dates:
        # CRITICAL: Only past data
        past_prices = self.prices.loc[:current_date]

        # Strategy uses ONLY past data
        target_weights = self.strategy.get_target_weights(
            decision_date=current_date,
            past_prices=past_prices  # No future!
        )

        # Execute rebalancing
        # ...

    # Track portfolio value
    equity_curve[current_date] = portfolio_value
```

What We're Measuring

Metric	What It Measures
Total Return	Cumulative gain/loss over 10 years
CAGR	Annualised return
Volatility	Annualised standard deviation
Sharpe Ratio	Excess return per unit of risk
Max Drawdown	Worst peak-to-trough loss
Sortino Ratio	Return per unit of downside risk
Turnover	Trading frequency (costs)

Goal: Understand risk-adjusted performance, not just returns

What Insights We're Looking For

1. **Risk-Adjusted Performance**
   - Which model has the best Sharpe ratio?
   - Is complexity worth the cost?
2. **Crisis Performance**
   - COVID crash (March 2020)
   - 2022 equity-bond selloff
   - Brexit volatility (2016)
3. **Practical Considerations**
   - Turnover costs
   - Implementation difficulty
   - Robustness to parameter choices

The Strategy Architecture

BaseStrategy Interface

All models implement this clean abstraction:

```python
class BaseStrategy(ABC):
    @abstractmethod
    def get_target_weights(
        self,
        decision_date: pd.Timestamp,
        past_prices: pd.DataFrame,  # ONLY past
        current_positions: pd.Series,
        cash: float,
    ) -> pd.Series:
        """Return target weights (sum = 1.0)"""
        raise NotImplementedError
```

Why? Fair comparison, extensibility, enforces no look-ahead bias

Example: Equal Weight Strategy

```python
class EqualWeightStrategy(BaseStrategy):
    def __init__(self, tickers: list[str]):
        self.tickers = tickers

    def get_target_weights(self, decision_date,
                           past_prices,
                           current_positions, cash):
        # Just return 1/N for all assets
        n = len(self.tickers)
        weights = pd.Series(1.0 / n,
                            index=self.tickers)
        return weights
```

Simple, but surprisingly hard to beat!

Where We Are Now

Completed:

- Data pipeline (18 assets, 2015-2025)
- Backtesting engine
- Equal weight baseline
- Black-Litterman framework

→ **In Progress:**

- MVO implementation
- Black-Litterman views
- Risk Parity solver
- Performance analysis

Coming Soon

- Full backtest results across all 4 strategies
- Regime analysis (bull/bear/crisis)
- Comprehensive research report

What This Means

Bridging the gap between theory and practice

- **For investors:** Does sophisticated management add value?
- **For students:** Testing what you learn in lectures
- **For quants:** Rigorous comparison with clean methodology

Academic finance says "here's the optimal solution"
We're asking: "does it actually work?"

Want to Follow Along?

GitHub Repository

github.com/AP-Capital-Research/deep-dive-into-portfolio-optimisation

Full Research Report

Expected publication: [Month] 2025

Questions or feedback?
Contact us at [email/contact]

Thank You

We're excited to share our findings
with the quant finance community

Stay tuned for the full results