Group Coursework Submission Form (PA)

Specialist Masters Programme

Please list all names of group members: (Surname, first name) 1. Sangha, Manpreet 2. Nolan, Serena 3. Bukhari, Syed	4. Quaseed, Suhail **GROUP NUMBER:** 7
MSc in: Quantitative Finance/Mathematical Trading and Finance	
Module Code: SMM265	
Module Title: Asset Pricing	
Lecturer: Dr Dirk Nitzsche	**Submission Date:** **03rd December 2025**

Declaration:

By submitting this work, we declare that this work is entirely our own except those parts duly identified and referenced in my submission. It complies with any specified word limits and the requirements and regulations detailed in the coursework instructions and any other relevant programme and module documentation. In submitting this work we acknowledge that we have read and understood the regulations and code regarding academic misconduct, including that relating to plagiarism, as specified in the Programme Handbook. We also acknowledge that this work will be subject to a variety of checks for academic misconduct.

We acknowledge that work submitted late without a granted extension will be subject to penalties, as outlined in the Programme Handbook. Penalties will be applied for a maximum of five days lateness, after which a mark of zero will be awarded.

Marker's Comments (if not being marked on-line):

Deduction for Late Submission:

Final Mark:

For Students:

Once marked please refer to Moodle for your final coursework grade, including your Peer Assessment grade.

<u>Question 1</u>

For Q1, we chose monthly data for FTSE All-Share Index Total Return Index (ASXTR), Dividend Yield (12-month trailing), UK CPI YoY (UKRPCJYR) & UK 1-Month Interbank deposit (as risk free asset). The forecasting model adapted *Pesaran, M.H. and Timmermann, A. (1994)* framework: $\text{ExcessReturn}_{t \to t+6} = \alpha + \beta_1\, DY_{t-k} + \beta_2\, CPI_{t-j} + \varepsilon_{t+6}$

$k \in 0,1,2,3$ represents the dividend yield lag $j \in 0,1,2$ represents the CPI lag

The model training window is expanded at each 6-month decision points. Each iteration adds 6 months of training data. The model implements sequential lag selection approach for each prediction (total 20 predictions):

Step 1: Calculate optimal DY lag (0,1,2,3) based on |t-stat|

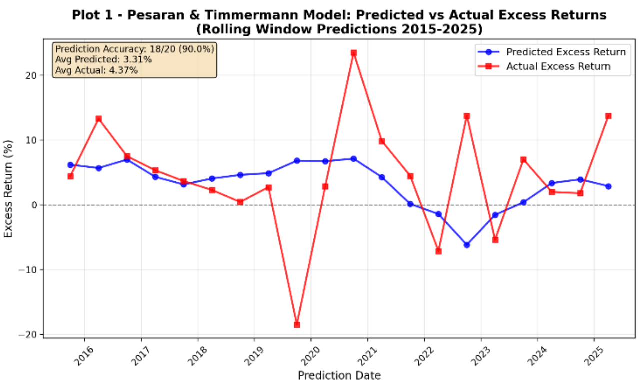
Step 2: Once optimal DY lag is determined, calculate optimal CPI lag (0,1,2) based on |t-stat|

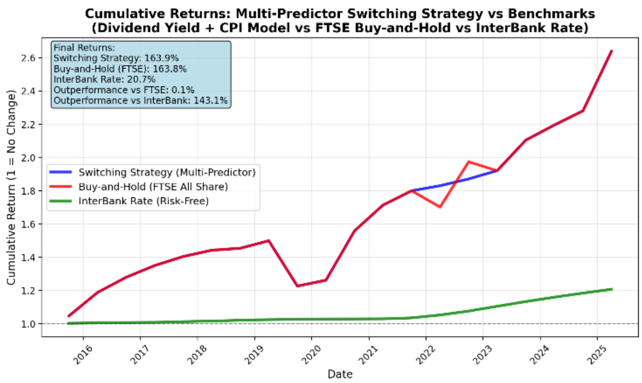
Step 3: Use optimal lags for DY and CPI to predict 6-month forward returns

Empirical results:

#	Date	Pred (%)	Actual (%)	Decision	✓/✗
1	2015-10	6.2	4.4	FTSE	✓
2	2016-04	5.7	13.3	FTSE	✓
3	2016-10	7.0	7.5	FTSE	✓
4	2017-04	4.3	5.3	FTSE	✓
5	2017-10	3.1	3.7	FTSE	✓
6	2018-04	4.0	2.3	FTSE	✓
7	2018-10	4.6	0.4	FTSE	✓
8	2019-04	4.9	2.7	FTSE	✓
9	2019-10	6.8	-18.5	FTSE	✗
10	2020-04	6.7	2.8	FTSE	✓
11	2020-10	7.1	23.5	FTSE	✓
12	2021-04	4.3	9.8	FTSE	✓
13	2021-10	0.1	4.5	FTSE	✓
14	2022-04	-1.4	-7.1	IB	✓
15	2022-10	-6.2	13.8	IB	✗
16	2023-04	-1.6	-5.4	IB	✓
17	2023-10	0.4	7.0	FTSE	✓
18	2024-04	3.4	2.0	FTSE	✓
19	2024-10	3.9	1.8	FTSE	✓
20	2025-04	2.9	13.8	FTSE	✓

- Total predicted returns 163.9% vs 163.8% nearly identical. The investment strategy achieved superior risk adjusted performance by achieving lower volatility (11.1% vs 12.3%) as it recommended switch to interbank during high inflation periods resulting in higher Sharpe ratio (0.745 vs 0.672).
- The 3-month lagged DY and current CPI remained consistent throughout investment decisions. This may reflect gradual information diffusion across market participants.
- The model correctly switched to interbank deposits during Apr-2022 till Oct-2023 when CPI reached 10.4% indicating the importance of using CPI as a predictor.
- The model predicted to remain invested in stocks during the Covid-19 market crash and subsequent recovery, indicating that the model does not capture sudden shifts in the market.





Strategy performance comparison

Metric	Model Switching Strategy	Passive Buy and Hold	Difference
Total Return 10 years	163.9%	163.8%	+0.1%
Annualised Return	10.2%	10.2%	0.0%
Volatility	11.1%	12.3%	-1.2%
Sharpe Ratio	0.745	0.672	+0.073

Model Coefficients Summary

Coefficient	Mean	Range	Interpretation
α (Intercept)	-0.056	−0.059 to −0.051	Baseline negative excess returns
β_1 (Dividend Yield)	+0.029	+0.024 to +0.034	Higher DY indicates higher returns (positive)
β_2 (CPI)	-0.008	−0.013 to −0.005	Higher CPI predicts lower returns (negative)

Model Limitations

- The coefficient estimates varied while lags remained same for DY and CPI indicating parameter instability.

Trading rule implemented

- Investment decision = FTSE All Share Index if predicted excess return > 0

- The model may not capture non-linear relationships or structural breaks.

- The analysis does not account for transaction costs whilst switching between FTSE and Interbank deposits.

- Limited monthly training sample from Apr-1997 till Oct-2015 and only 20 decision points may impact performance.

- Investment decision = Interbank rate deposit if predicted excess return < 0

The model achieved 90% accuracy(18/20) for predicting the direction of excess returns, rejecting the null hypothesis that predictions are random chance.

The forecasting model is implemented as a web application https://smm265-assetpricing.streamlit.app/. The web application is pre-loaded with input datasets we used to test model's excess returns. Please select 'Run Analysis' tab and choose between testing the model without any lags (option 1) or with optimal lags (option 2 and 3). The model investment decision accuracy improves from 80% (option 1) to 90% (option 2) and then reduces to 89.5% (option 3) reflecting that the model is responsive to additional regressors.

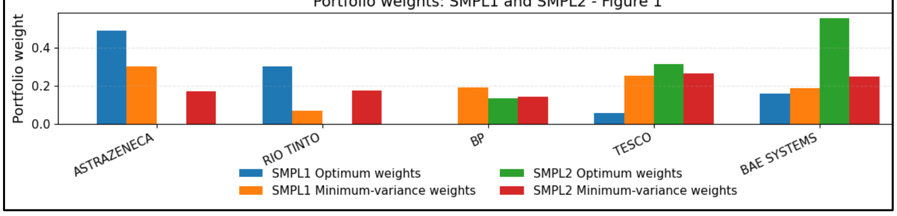
Question 2

Asset analysis

We analysed UK stocks: AstraZeneca (1), Rio Tinto (2), BP (3), Tesco (7) and BAE Systems (8). The assets were chosen to prevent sector concentration so that the correlations in the sample are driven by general UK market conditions rather than idiosyncratic sector behaviour. Using returns up to February 2020 (SMPL1), we construct both the minimum-variance portfolio and the portfolio that maximises the Sharpe ratio. These SMPL1 weights are then carried forward and tested on the later sample, October 2021 to September 2025 (SMPL2). This lets us see how the FTSE All Share index, and a risk-free investment, and we also show how the SMPL1 portfolios drift over SMPL2 when left without rebalancing.

Company	Company No.	SMPL1 Optimum	SMPL1 Min Var	SMPL2 Optimum	SMPL2 Min Var
AstraZeneca	1	0.488503	0.300564	0	0.169969
Rio Tinto	2	0.300189	0.069719	0	0.175789
BP	3	0	0.192213	0.133932	0.142302
Tesco	7	0.055489	0.252862	0.312107	0.263728
BAE Systems	8	0.15582	0.184643	0.553962	0.248211

Portfolio weights: SMPL1 and SMPL2 - Figure 1

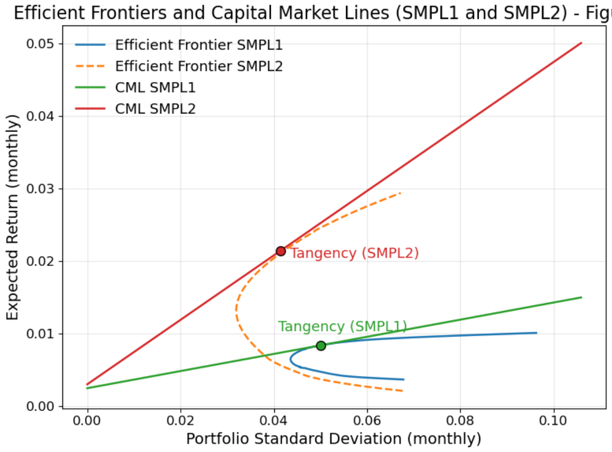


The SMPL1 optimum portfolio allocates 41% to AstraZeneca and 35% to Rio Tinto, indicating that these two shares provided the highest risk-adjusted returns in the pre-2020 period. By contrast, the SMPL1 minimum-variance portfolio distributes weights more evenly, with 29% in BP, 27% in Tesco, and 25% in BAE Systems, reflecting that these stocks exhibited lower volatility compared to the rest of the group. In the latter sample, the optimal allocation shifts, with Tesco's weight increasing to 32% and BAE Systems rising markedly to 48%, highlighting the stronger and more consistent post-pandemic performance of these firms. The SMPL2 minimum-variance portfolio remains more balanced, assigning 28% to Tesco, 26% to BP, and 29% to BAE, as changes in volatility and correlations among these assets alter the risk-return profile.

Efficient Frontier

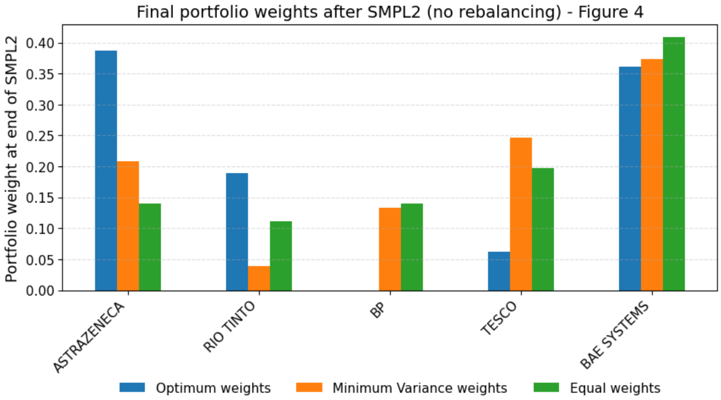
Figure 2 shows that the SMPL1 frontier sits much lower, reaching only around 0.8–1.1% expected monthly return even at higher volatility levels of 7–10%, whereas SMPL2 achieves roughly 2.5–3% returns at similar or lower volatility (4–6%). The tangency portfolios highlight this contrast: SMPL1's tangency occurs near σ ≈ 0.045 with E[r] ≈ 0.010, while SMPL2 delivers over twice the return (≈ 0.022) at almost identical risk. As a result, the SMPL1 CML has a shallow slope (Sharpe ratio around 0.10–0.12), whereas SMPL2's is far steeper (roughly 0.40–0.45), indicating a much stronger risk–return trade-off in the later period. These numerical differences reflect the underlying market conditions: pre-2020 UK stocks displayed tight co-movement and limited dispersion, flattening the frontier, while the post-2021 sample shows greater divergence and higher realised returns, pushing both the frontier and the tangency point upward.

Efficient Frontiers and Capital Market Lines (SMPL1 and SMPL2) - Figure 2



Terminal wealth results

Weights	Terminal Wealth
Optimum weights	1482.94
Minimum Variance weights	1742.89
Equal weights (no rebalancing)	1701.17
FTSE All Share index	1247.05
Risk free investment	1153.63



How differently SMPL1-based strategies translated into the post-2021 environment is demonstrated by the ranking of terminal-wealth outcomes. Because its SMPL1 allocations load on stocks whose covariances remained relatively low in SMPL2, the minimum-variance portfolio ends up strongest at £1742.89 reducing exposure to co-movement tends to preserve wealth more effectively when volatility is high and sector behaviour diverges. The equal-weight portfolio performs similarly well at £1701.17, benefitting from spreading risk across names that recovered at different speeds. By contrast, the SMPL1 optimum portfolio fares worse: its weights embed return forecasts from pre-2020 that did not hold once return premia and correlations shifted. The FTSE All-Share and risk-free benchmarks trail for the same reason (they capture broad market risk but not the specific cross-sectional patterns that drove performance in the later sample.)

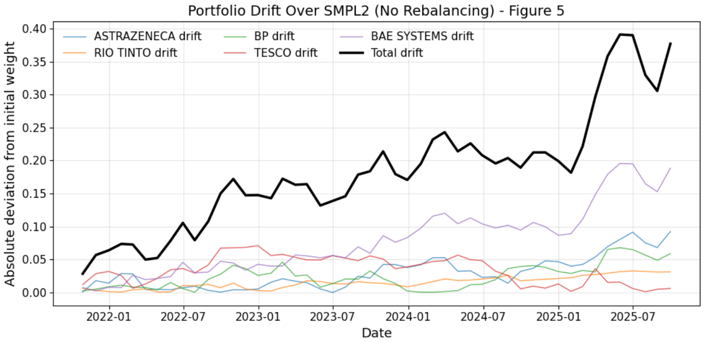


Figure 5 shows how the SMPL1 minimum-variance portfolio changes when held through SMPL2 without rebalancing. The total drift exceeds 0.35 by 2025 - the portfolio held at the end is far from the SMPL1 allocation. The asset-level lines show the source of this shift: BAE Systems' weight rises sharply, while Rio Tinto and Tesco decline, pulling the portfolio toward a more concentrated risk profile.

Conclusion and recommendation

Portfolios built only from historical mean–variance optimisation often appear strong in-sample but rarely maintain that performance when market conditions change. This pattern appears clearly in our results. The efficient frontier from SMPL1 does not carry into SMPL2. When recalculated on the later sample it shifts upward in volatility and loses return. The SMPL1 optimum and minimum-variance portfolios also show large changes out of sample, and the terminal wealth results underline this. The minimum-variance and equal-weight strategies produce the highest outcomes in SMPL2, while the SMPL1 optimum portfolio drops well behind despite appearing attractive in the earlier period. The change in the capital market line and the drift in portfolio weights in Figure 5 reflect how the SMPL1 allocation adapts once exposed to different return and covariance patterns.

These results capture some well-known shortcomings of mean–variance optimisation. The approach is highly susceptible to estimation error, and modest changes in expected returns or covariances can result in large changes in the weights. This paradigm is consistent with the study of Jorion (1992), which identifies strong sample sensitivity in estimated optimal portfolios, and also with the work of Britton-Jones (1999), who demonstrates that many estimated weights are statistically indistinguishable from zero. This reliance on backward-looking inputs may therefore generate unstable allocations that work during one period and then fail in the next. A better approach would be to have diversification across the various sectors and to rebalance periodically, ensuring that the weight of any one asset does not become excessive and that the portfolio adjusts automatically to any changes in return premium or correlation structure.

References:

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