1 Introduction

Relative performance analysis is a way of evaluating investments by comparing how a stock performs against a market benchmark (such as an *index*) instead of just looking at its absolute return. This approach helps investors and fund managers see whether a stock or strategy is doing better or worse than the overall market. It is often used to find opportunities that can generate extra profit, test whether an investment strategy is effective, and build portfolios that aim to consistently beat the market.

The main idea is to separate market-wide effects from company- or sector-specific factors. Outperforming the benchmark or index suggests unique drivers of success, while underperforming may signal problems or opportunities for recovery, which managers can take advantage of when deciding what to buy or sell.

For this assignment, we focus on *monthly relative performance* prediction against the US Monash Index [1], which is a custom benchmark designed to represent the broader US equity market. The assignment employs a two-tier assessment structure that accommodates different levels of analytical sophistication and academic achievement targets.

- **Basic Binary classification Task**: Predict whether each stock will outperform or underperform the US Monash Index benchmark. This provides hands-on experience with relative performance analysis and forms the core competency expected of all students.
- **Advanced Regression Task**: Forecast the exact magnitude of excess returns relative to the benchmark. This requires deeper understanding of market dynamics and more advanced modeling techniques, and is intended for students aiming for high distinction grades.

The monthly relative performance calculation follows this methodology:

- Calculate monthly stock returns: For each stock, compute the percentage change from month-start opening price to month-end closing price using the formula: Monthly Stock Return = (Month-end Closing Price - Month-start Opening Price) / Month-start Opening Price × 100%
- Calculate monthly *excess returns*: Determine the relative performance by subtracting the corresponding US_MONASH_Index monthly return: Excess Return = Monthly Stock Return - US_MONASH_Index Return
- Generate prediction targets: For the basic task, convert excess returns into binary classification targets where positive excess returns indicate outperformance (target = 1) and negative excess returns indicate underperformance (target = 0). For the advanced task, use the continuous excess return values directly as regression targets.

[1] The Monash Index is defined and described in Section A.4.

This framework enables the analysis of 616 US stocks across diverse sectors and market capitalisations, providing a comprehensive foundation for understanding systematic factors that drive relative performance in equity markets and developing predictive models that can inform real-world investment decisions across both classification and regression paradigms.

2 Task Description

This assessment aims to practice your exploratory data analysis and machine learning skills by building predictive models for monthly stock relative performance. You will work in groups to predict whether US stocks will outperform or underperform the US Monash Index benchmark, with an optional advanced component for groups targeting high distinction grades.

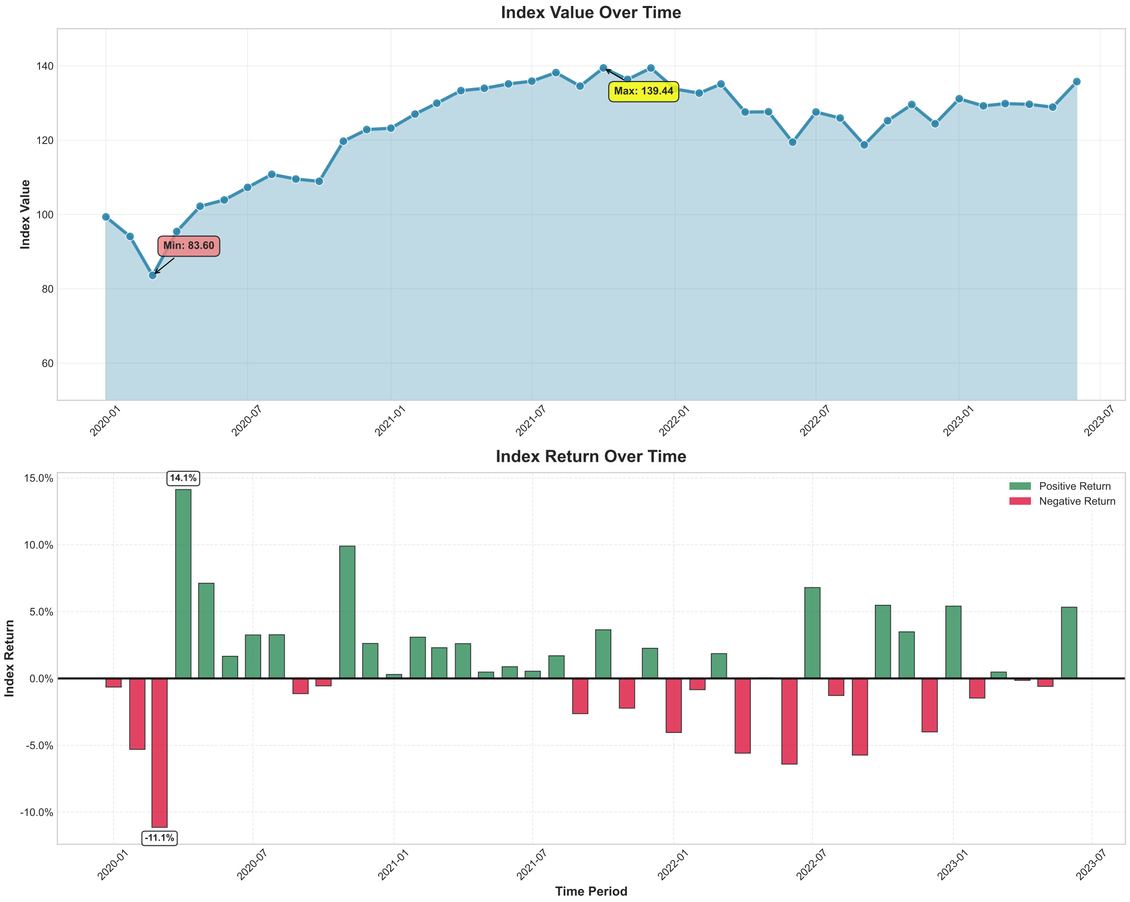

Figure 1: This figure illustrates the Monash Index performance across 43 months, highlighting key market dynamics. The top panel shows index values ranging from a low of 83.60 (Mar 2020) to a peak of 139.67. The bottom panel displays monthly returns with color-coded bars (green=positive, red=negative), featuring extreme values of -11.1% (Mar 2020) and +14.1% (Apr 2020).

2.1 Prediction Task

Basic Task (Required for all groups): Develop at least three different types of classification models to predict binary relative performance for July 2023 using various features extracted from historical stock data spanning January 2020 to June 2023. The binary target indicates whether each stock will outperform (target = 1) or underperform (target = 0) the US Monash Index benchmark during July 2023.

Advanced Task (Optional for High Distinction candidates): Develop regression models to predict the continuous excess return values (stock return minus US Monash Index return) for July 2023. This task requires more sophisticated modeling approaches and deeper understanding of market dynamics.

General Requirements: Select the best-performing model for final predictions and submission. Apply appropriate data preprocessing methods, feature selection, and feature extraction techniques. Implement proper time series validation to avoid look-ahead bias.

Note: Different input variables for the same algorithm (e.g., linear regression) are considered the same type of model. Linear regression and KNN regressor, for example, are considered different types.

2.2 Analysis Task

- Identify key input variables and outliers that significantly influence the predictive outcomes for relative performance against the US Monash Index benchmark. Your group should conduct comprehensive analysis of feature relationships and market patterns that drive relative performance.
- Provide statistical evidence to support your findings, such as feature importance scores, correlation analysis with the benchmark index, and sector-based performance patterns. Include analysis of how different features perform across various market conditions and time periods.
- Explain which features (including newly created ones) are particularly useful for estimating relative stock performance and why. Consider the relationship between individual stock characteristics and the underlying construction methodology of the US Monash Index, including sector weightings and market capitalisation effects.

2.3 Report

Write a comprehensive group report documenting your approach and results, including detailed methodology and collaborative analysis findings.

- Description of at least **three** different models your group tried for the basic classification task, and any additional models used for the advanced regression task. Include rationale for model selection and comparison of performance across different approaches.

- Explanation of your data preprocessing and feature engineering techniques, particularly those designed to capture relative performance signals and market benchmark relationships. Document the collaborative process used to develop and validate these features.
- Analysis of model predictions and performance, including comparison between classification and regression approaches if both were attempted.
- Evidence-based discussion of feature importance and their relationship to relative stock performance against the US Monash Index benchmark, including any insights about sector rotation, market capitalisation effects, or temporal patterns discovered through your group analysis.

2.4 Evaluation Metric

Basic Task (Binary Clssification): Given a test set and the corresponding predicted binary values, the key metric to evaluate your classification model is F_1[2] Score, which balances precision and recall for the positive class (outperformance prediction).

$$F_1 = \frac{2}{\text{Recall}^{-1} + \text{Precision}^{-1}}$$

Advanced Task (Regression): Given a test set $\{(\mathbf{x}_1, y_i), ..., (\mathbf{x}_n, y_n)\}$ and the corresponding predicted values $\{\hat{y}_1, ...\hat{y}_n\}$, the key metric to evaluate your final model is Root Mean Squared Error (RMSE), defined as:

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

- RMSE in Python can be computed as the square root of Mean Squared Error (MSE)[3];
- RMSE in R can be computed by following the lecture or the tutorial[4].

[2] https://scikit-learn.org/stable/modules/generated/sklearn.metrics.f1_score.html

[3] https://scikit-learn.org/stable/modules/generated/sklearn.metrics.mean_squared_error.html

[4] https://www.geeksforgeeks.org/root-mean-square-error-in-r-programming