README — Post-Trade Performance Analysis

Oldfield Partners | 556 Completed Trades | 2005–2025

What You Will Find Here

In this report, you will find a comprehensive post-trade performance analysis using Jupyter Notebook, Python, and statistical methods to answer the question:

> ***What drove trade performance across 556 historical trades, and which fundamental factors best predict success?***

The analysis covers 54 sectors and 40+ countries over 2005–2025, examining sector allocation, geographic exposure, temporal cycles, and company fundamentals (valuation, growth, profitability) at the time of purchase.

How I Approached The Question

Objective: Identify performance drivers across Oldfield's historical trade book and develop actionable, statistically grounded recommendations for improving future trade selection.

Methodology:

1. Load and clean the raw trade dataset (556 trades), removing 29 Error-classified observations.
2. Aggregate sector-level performance and test significance using one-sample t-tests.
3. Map Bloomberg country codes to regions and test geographic differences using ANOVA and Mann-Whitney U.
4. Construct rolling 1-year performance curves and detect outperformance/underperformance regimes.
5. Screen 11 candidate fundamental metrics for multicollinearity using Variance Inflation Factors (VIF).
6. Fit a logistic regression (HC3 robust SEs) on VIF-cleaned features to identify the top predictive factors.
7. Visualise all findings in 4 institutional-quality charts following JP Morgan *Guide to the Markets* formatting.

Key Analyses:

- **Sector Alpha** (Chart 1): Top 10 vs Bottom 10 sectors by mean annualised relative return
- **Performance Cycles** (Chart 2): Rolling 1-year returns with regime detection (2005–2025)
- **Geographic Decomposition** (Chart 3): Regional alpha with ANOVA and Mann-Whitney U tests

- **Multi-Factor Model** (Chart 4): Logistic regression marginal effects across valuation, growth, and profitability

Requirements

To reproduce this analysis, you will need:

- **Python 3.12+** with Jupyter Notebook or JupyterLab installed
- `Raw data set (2).xlsx` — the source data file must be placed in the **same folder** as the notebook. The code reads from a relative path, so no file path editing is needed
- `requirements.txt` — included in the submission. Run `pip install -r requirements.txt` before launching the notebook to install all dependencies with pinned versions

Once the above are in place, open the notebook and run all cells top-to-bottom. The first cell automatically verifies that the data file exists and that all dependencies are installed.

Libraries Imported

#	Library	Purpose
1	`pandas`	Clean, transform, and analyse the trade dataset
2	`numpy`	Numerical computation, array operations, missing value handling
3	`matplotlib`	Institutional-quality static visualisations with precise layout control
4	`seaborn`	Additional plotting utilities and colour palette support
5	`scipy.stats`	Hypothesis testing — t-tests, Pearson correlation, ANOVA, Mann-Whitney U
6	`scipy.interpolate`	Cubic spline smoothing of the temporal performance curve
7	`statsmodels`	Logistic regression with HC3 robust SEs, marginal effects, Wald tests
8	`statsmodels.stats`	Variance Inflation Factor (VIF) multicollinearity diagnostics
9	`sklearn.preprocessing`	StandardScaler to z-score features before regression

Files In This Repository

File	Description
`oldfield_revised_code.ipynb`	Main Jupyter Notebook containing all analysis code
`Raw data set (2).xlsx`	Source dataset (556 trades — place in same folder as notebook)
`requirements.txt`	Pinned dependency versions for exact reproducibility
`Post_Trade_Analysis_Report.pdf`	Written report addressing all assessment questions
`sector_performance_institutional.png`	Chart 1: Sector alpha
`performance_cycles_schroder_style.png`	Chart 2: Temporal performance cycles
`geographic_performance_institutional.png`	Chart 3: Geographic alpha decomposition
`chart4_multifactor_institutional.png`	Chart 4: Multi-factor marginal effects

Jupyter Notebook To Reference For Code

To refer to the analysis code, refer to the following notebook:

1. **Jupyter Notebook For Post-Trade Analysis** → `./oldfield_revised_code.ipynb`

Key Statistical Methods Used

Method	Where Used	Purpose
One-sample t-test	Sectors, Regions	Test if mean alpha differs from zero
One-way ANOVA	Regions	Test joint equality of regional means
Mann-Whitney U	Regions	Non-parametric distributional comparison
Pearson correlation	Sectors	Trade frequency vs performance relationship
VIF screening	Multi-factor	Remove multicollinear features before regression
Logistic regression (HC3)	Multi-factor	Model P(Hit) as function of standardised fundamentals
Wald test	Multi-factor	Joint significance of variable categories
Avg. marginal effects	Multi-factor	Translate log-odds into probability changes

Notes

- All analysis is point-in-time at purchase to avoid look-ahead bias

- The multi-factor model uses 159 of 527 trades due to missing fundamental data across all metrics
- VIF screening removed P/B Ratio (VIF = 15.1) and ROIC (VIF = 6.3) before the regression was fitted
- Significance is assessed at the 5% level throughout, with 10% flagged where relevant
- Use of AI tools was employed as appropriate for code generation and analytical support