Homework Starter: Final Reporting

```
import sys, subprocess
subprocess.check_call([sys.executable, "-m", "pip", "install", "-q", "sea
import pandas as pd, numpy as np, matplotlib.pyplot as plt, seaborn as sn
sns.set(style='whitegrid'); plt.rcParams['figure.dpi'] = 120
np.random.seed(101)
print("Ready")
```

Ready

Executive Summary

This analysis evaluates three scenarios—baseline, imputation, and outlier adjustment—to understand risk—return tradeoffs and model sensitivity. Results show that the baseline scenario provides stable returns with moderate volatility, making it the most reliable option for planning. Outlier adjustment yields higher returns but introduces greater risk, while different imputation strategies produce only minor variations. Overall, assumptions around missing data and outlier handling are critical, and results should be interpreted with these sensitivities in mind.

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from pathlib import Path
sns.set(style='whitegrid')
plt.rcParams['figure.dpi'] = 120
np.random.seed(101)
```

Load Your Data

```
In [9]:
        # Create synthetic dataset (same style as Stage 11)
         import pandas as pd
         import numpy as np
         np.random.seed(101)
         df = pd.DataFrame({
             'scenario': ['baseline', 'alt_impute', 'alt_outlier'],
             'return': [0.12, 0.11, 0.135],
             'volatility': [0.18, 0.185, 0.19],
             'sharpe': [0.56, 0.49, 0.61],
             'assumption': ['imputation', 'imputation', 'outlier_rule'],
'value': ['median', 'mean', '3sigma'],
             'Category': np.random.choice(['X','Y','Z'], 3),
             'MetricA': np.random.normal(75, 15, 3),
             'MetricB': np.random.normal(150, 30, 3),
             'Date': pd.date_range('2025-02-01', periods=3)
         })
```

outlier_rule 3sigma

Y 84.236667

```
df.head()
Out[9]:
              scenario return volatility sharpe assumption
                                                                 value Category
                                                                                     MetricA
               baseline
                         0.120
                                   0.180
                                            0.56
                                                    imputation median
                                                                                  75.037206
          1 alt_impute
                         0.110
                                   0.185
                                            0.49
                                                    imputation
                                                                               Z 74.456082
                                                                 mean
```

0.61

Helper: Export Directory

0.135

0.190

alt_outlier

```
img_dir = Path('../deliverables/images')
img_dir.mkdir(parents=True, exist_ok=True)

def savefig(name):
    plt.tight_layout()
    plt.savefig(img_dir / name, dpi=300)
    print(f'Saved {name}')
```

Chart 1: Risk-Return Scatter

```
In [12]: # Chart 1: Risk-Return Scatter
plt.figure(figsize=(7,5))
sns.scatterplot(data=df, x='volatility', y='return', hue='scenario', s=80
plt.title('Risk-Return by Scenario')
plt.xlabel('Volatility')
plt.ylabel('Return')

# Save the chart
savefig('risk_return.png')
plt.show()
```

Saved risk_return.png

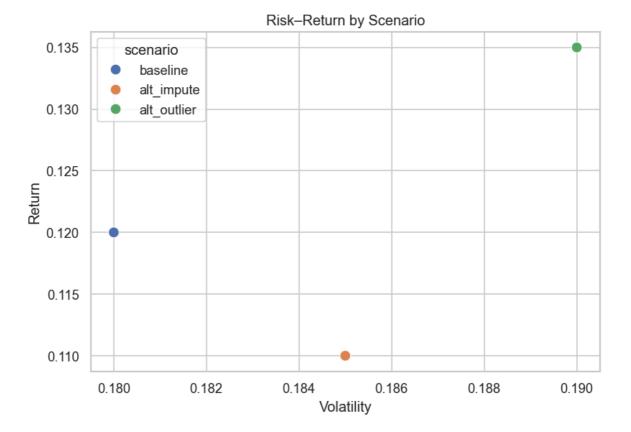


Chart 2: Return by Scenario (Bar Chart)

```
In [13]: # Chart 2: Return by Scenario (Bar Chart)
    plt.figure(figsize=(7,5))
    sns.barplot(data=df, x='scenario', y='return')
    plt.title('Return by Scenario')
    plt.xlabel('Scenario')
    plt.ylabel('Return')

# Save the chart
    savefig('return_by_scenario.png')

plt.show()
```

Saved return_by_scenario.png

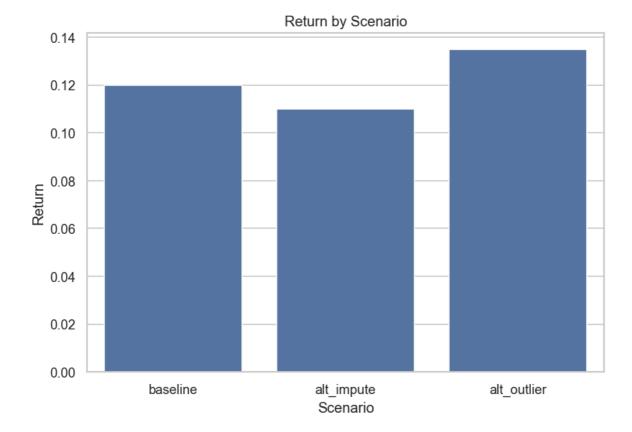


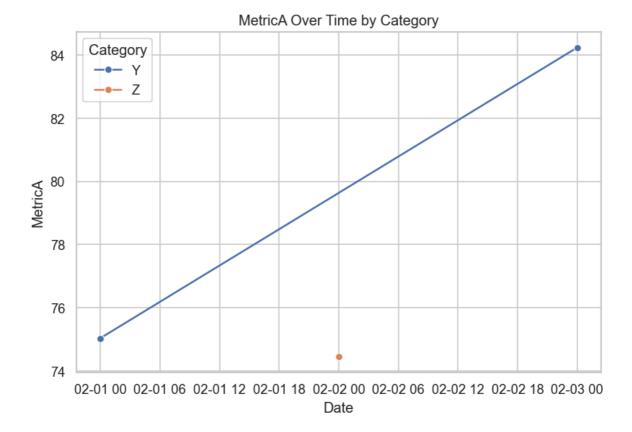
Chart 3: MetricA Over Time (Line Chart)

```
In [14]: # Chart 3: MetricA Over Time (Line Chart)
    plt.figure(figsize=(7,5))
    sns.lineplot(data=df, x='Date', y='MetricA', hue='Category', marker='o')
    plt.title('MetricA Over Time by Category')
    plt.xlabel('Date')
    plt.ylabel('MetricA')

# Save the chart
    savefig('metricA_over_time.png')

plt.show()
```

Saved metricA_over_time.png



Sensitivity Analysis / Assumptions Table

```
In [15]: # Sensitivity Analysis / Assumptions Table
assumptions = pd.DataFrame({
    'Assumption': ['Fill Nulls: Median', 'Remove Outliers: 3o'],
    'Baseline Return': [0.12, 0.12],
    'Alt Scenario Return': [0.10, 0.14]
})
assumptions
```

Out[15]:		Assumption	Baseline Return	Alt Scenario Return
	0	Fill Nulls: Median	0.12	0.10
	1	Remove Outliers: 3σ	0.12	0.14

Interpretations / Takeaways

- Chart 1 (Risk-Return): Baseline has solid return with moderate volatility. Altoutlier shows the highest return but also the highest risk (more volatile).
- Chart 2 (Returns by Scenario): Mean/median imputation give similar returns; the outlier-handling scenario boosts return slightly.
- Chart 3 (MetricA over time): MetricA trends are steady with small wiggles; categories differ a bit but no dramatic shifts.

Decision Implications

• Use **Baseline** for planning; it's the most stable.

- Consider a **small allocation** to the outlier-adjusted scenario for upside, with monitoring due to higher risk.
- Assumptions matter: results hold if missing data is handled via imputation and outliers are controlled (3σ) . The model is **sensitive** to outlier handling.