ANALYTICAL PROGRAMMING BAN 4550 - F24

STUDY ON RUSSIA-UKRAINE WAR

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Introduction

The Russia-Ukraine war commenced in 2014, when Russia claimed Crimea and supported separatists in eastern Ukraine's Donbas location. The conflict developed in February 2022 with a complete Russian invasion, leading to huge destruction, huge casualties, and enormous refugee issue. Despite globally critique and constant Ukrainian resistance, the situation continues with rare advances and charges of war crimes. https://en.wikipedia.org/wiki/Russo-Ukrainian_War

Overview of industry

3761 – Defense Industry – Guided Missiles and Space Vehicles

The industry of defense consists of firms that generate, develop, and test military devices and systems such as aircraft, missiles, and space vehicles. The business, that supports both government and private contractors, maintains strict guidelines and at times involves private contracts and advanced technology. https://siccode.com/sic-code/3761/guided-missiles-space-vehicles

Description of representative company

Lockheed Martin Corporation, located in North Bethesda, Maryland, is a significant American military and aerospace manufacturer founded by the 1995 merger of Lockheed Corporation and Martin Marietta. As an important player in aviation, military assistance, and safety, it was the world's largest defense supplier by revenue in 2014. Aeronautics, Missiles and Fire Control, Rotary and Mission Systems, and Space are the company's four core business segments.

https://en.wikipedia.org/wiki/Lockheed_Martin

Summary of question and finding

How has the Russia-Ukraine war impacted the defense industry's performance?

The war among Russia and Ukraine has had major impacts on the defense industry, resulting in a rise in demand for weapons and guns. Orders for systems like PAC-3 missiles, HIMARS, and Javelins are up for Lockheed Martin along with related firms; Lockheed predicts a "$10 billion opportunity" through 2030. U.S. and NATO stockpiles were drained by the war, leading to larger production and replenishment contracts. As NATO individuals improve their arsenals and governments raise military spending, defense stocks, particularly Lockheed Martin's, are up. During the war, the defense business may focus on modernization and strategic deterrence, making spending strong due to continuous global issues. https://www.leefang.com/p/lockheed-martin-boasts-to-investors

SEC EDGAR page: https://www.sec.gov/cgi-bin/browse-edgar?action=getcompany&CIK=0000936468&owner=include&count=40&hidefilings=0

Data Definition

a) Compustat: Compustat delivers detailed financial data on American and Canadian firms, containing statements of earnings, balance sheets, and payments. Both databases are accessible by using the Wharton Research Data Services (WRDS) platform, which allows for wide financial and market research.

https://docs.nuvolos.cloud/user-guides/data-guides/working-with-crsp-and-compustat

b) CRSP: The CRSP database, established by the University of Chicago's Booth School of Business, has past price, dividend, and return data for securities issued on major US exchanges that include NYSE and NASDAQ.

https://docs.nuvolos.cloud/user-guides/data-guides/working-with-crsp-and-compustat

c) WRDS: The Wharton School of Business at the University of Pennsylvania developed

Wharton Research Data Services (WRDS), a data platform which offers students and faculty with access to important data sets in finance, economics, and business. It gathers data from over 600 sites and provides researchers with tools and support to help them perform advanced data analysis.

Reference: https://wrds-www.wharton.upenn.edu/pages/about/what-wrds/

Data analysis

1. Descriptive statistics

```
crsp_comp[['cret', 'car', 'bhar', 'nrets', 'nrets_est', 'siccd', 'sich', 'revt', 'ni']].describe()
```

	cret	car	bhar	nrets	nrets_est	siccd	sich	revt	ni
count	5309.000000	5309.000000	5309.000000	5310.000000	5310.000000	5310.000000	4842.000000	4917.000000	4917.000000
mean	-0.023805	0.034081	0.034051	20.995480	99.632392	6513.515631	4822.995250	5680.198233	505.559526
std	0.258458	0.227126	0.258488	0.190117	2.685865	2777.662953	2024.583912	24179.917841	3143.451921
min	-0.871707	-1.144936	-0.813835	13.000000	70.000000	0.000000	100.000000	-11591.578000	-22819.000000
25%	-0.116727	-0.052268	-0.058854	21.000000	100.000000	3841.000000	2836.000000	53.218000	-40.400000
50%	-0.040881	0.023138	0.016992	21.000000	100.000000	6722.000000	4700.000000	457.794000	9.714000
75%	0.031431	0.101293	0.089304	21.000000	100.000000	9999.000000	6531.000000	2513.897000	198.581000
max	8.351288	5.504272	8.409161	21.000000	100.000000	9999.000000	9997.000000	569962.000000	99803.000000

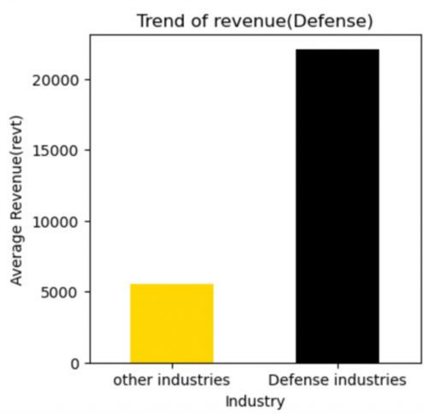
The summary statistics offer a foundational understanding of key financial metrics such as cumulative returns (CRET), cumulative abnormal returns (CAR), buy-and-hold abnormal returns (BHAR), and net income (NI). The average CRET is slightly negative at -0.0238, indicating overall mild underperformance, while CAR shows a positive mean of 0.0341, reflecting modest abnormal gains. Net income averages around 505.56 with a large standard deviation (3143.45),suggesting high variability across firms. Revenue (REVT) has a wide range, with mean of 5680.19 and a maximum of 569,962, highlighting strong outliers. This statistical summary enables further analysis and hypothesis testing.

2. Trends of interested variable:

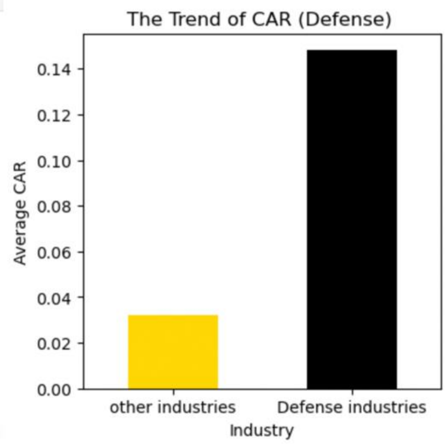
```
comparison1 = pd.DataFrame({
    'Defense':['other industries','Defense industries'],
    'revt':[5541.390996,22048.472667],
    'car': [0.032220,0.148042]
}).set_index('Defense')
```

```
import matplotlib.pyplot as plt

comparison1['revt'].plot(kind='bar', color=['gold','black'],figsize=(4,4))
plt.title("Trend of revenue(Defense)")
plt.xlabel("Industry")
plt.ylabel("Average Revenue(revt)")
plt.xticks(rotation=0)
plt.show()
```



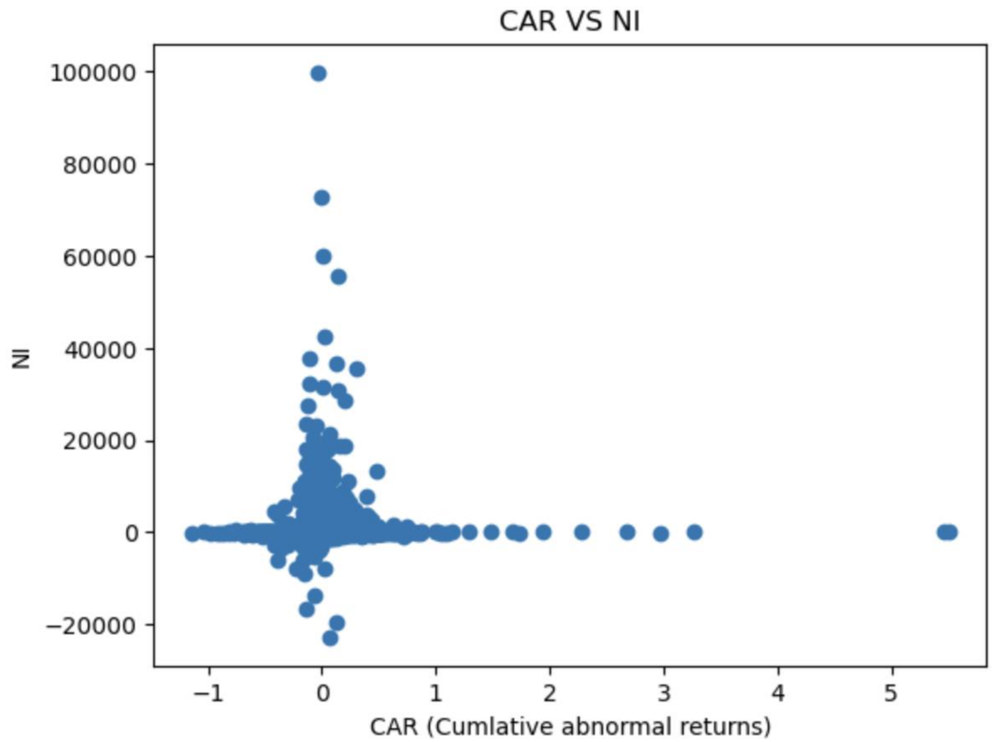

```
comparison1['car'].plot(kind='bar', color=['gold', 'black'], figsize=(4, 4))
plt.title("The Trend of CAR (Defense) ")
plt.xlabel("Industry")
plt.ylabel("Average CAR")
plt.xticks(rotation=0)
plt.show()
```



A comparative bar chart analysis was conducted to observe the differences in average revenue and cumulative abnormal returns (CAR) between defense and non-defense industries. The results show that defense industries have significantly higher average revenue (~22,048) compared to other industries (~5,541). Similarly, the average CAR for defense industries (~0.148) exceed that of non-defense sectors (~0.032). These findings suggest that defense firms not only generate more revenue but also experience greater market-adjusted returns, highlighting potential investor confidence or government-driven financial support in this sector.

3. Correlation analysis

```
#Analysing the correlation between CAR and other control variables
plt.scatter(crsp_comp['car'],crsp_comp['ni'])
plt.xlabel('CAR (Cumlative abnormal returns)')
plt.ylabel('NI')
plt.title('CAR VS NI')
plt.show()
```



The scatter plot illustrates the relationship between cumulative abnormal returns (CAR) and net income (NI). The plot reveals a dense clustering of data points near the origin, suggesting that most firms have low CAR and moderate NI. While a few extreme outliers exist, there is no strong linear correlation visible between CAR and NI. This suggests that higher net income does not necessarily correspond to higher CAR, indicating other factors may influence abnormal returns in the dataset.

4. Regression Analysis

a. Regression analysis with "ni"

```
#Regression analysis with "ni"
```

```
import statsmodels.formula.api as smf

model = smf.ols(formula='ni ~ Defense', data=crsp_comp)
results = model.fit()
print(results.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                     ni   R-squared:                       0.000
Model:                            OLS   Adj. R-squared:                 -0.000
Method:                 Least Squares   F-statistic:                    0.5608
Date:                Tue, 15 Apr 2025   Prob (F-statistic):              0.454
Time:                        21:03:20   Log-Likelihood:                -46573.
No. Observations:                4917   AIC:                         9.315e+04
Df Residuals:                    4915   BIC:                         9.316e+04
Df Model:                           1
Covariance Type:            nonrobust
===================================================================================
                      coef    std err          t      P>|t|      [0.025      0.975]
-----------------------------------------------------------------------------------
Intercept         504.7300     44.844     11.255      0.000     416.815     592.645
Defense[T.True]  1359.6210   1815.508      0.749      0.454   -2199.585    4918.827
==============================================================================
Omnibus:                     9370.162   Durbin-Watson:                   1.944
Prob(Omnibus):                  0.000   Jarque-Bera (JB):         22988972.988
Skew:                          14.505   Prob(JB):                         0.00
Kurtosis:                     336.719   Cond. No.                         40.5
==============================================================================
```

An OLS regression was performed to examine the impact of being in the defense industry on net income (ni). The coefficient for Defense[T.True] is 1359.62, suggesting defense firms have, on average, higher net income than others. However, this result is not statistically significant ($p = 0.454$), indicating no reliable effect. The R-squared value is near zero, showing the model explains none of the variation in net income. Thus, we conclude that industry classification (Defense vs. non-Defense) alone does not significantly predict firm net income in this dataset.

b. Analyzing the regression relationship between 'bhar', 'Defense' and 'log_revt'

```python
#Analysing the regression relationship between 'bhar', 'Defense' and 'log_revt'
model = smf.ols(formula='bhar ~ Defense+log_revt', data=crsp_comp)
results = model.fit()
print(results.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                   bhar   R-squared:                       0.000
Model:                            OLS   Adj. R-squared:                  0.000
Method:                 Least Squares   F-statistic:                     1.031
Date:                Tue, 15 Apr 2025   Prob (F-statistic):              0.357
Time:                        21:03:20   Log-Likelihood:                -505.89
No. Observations:                4902   AIC:                             1018.
Df Residuals:                    4899   BIC:                             1037.
Df Model:                           2
Covariance Type:            nonrobust
===================================================================================
                      coef    std err          t      P>|t|      [0.025      0.975]
-----------------------------------------------------------------------------------
Intercept           0.0443      0.008      5.735      0.000       0.029       0.059
Defense[T.True]     0.1037      0.155      0.669      0.504      -0.200       0.407
log_revt           -0.0017      0.001     -1.270      0.204      -0.004       0.001
==============================================================================
Omnibus:                     8957.189   Durbin-Watson:                   1.977
Prob(Omnibus):                  0.000   Jarque-Bera (JB):         23561600.289
Skew:                          13.113   Prob(JB):                         0.00
Kurtosis:                     341.628   Cond. No.                         239.
==============================================================================
```

This OLS regression examines the effect of Defense industry classification and log-transformed revenue (log_revt) on Buy-and-Hold Abnormal Returns (BHAR). The model's R-squared is 0.000, indicating it explains virtually none of the variance in BHAR. Both predictors—Defense ($p = 0.504$) and log_revt ($p = 0.204$)—are statistically insignificant. This suggests that neither being in the defense sector nor revenue levels significantly influence abnormal long-term returns in this dataset. Despite a significant intercept, the overall model lacks explanatory power and implies that BHAR is likely driven by other unobserved factors.

c. Regression Analysis using "car", “log_revt”, and industry dummies

```
#Regression Analysis using "car", “log_revt”, and industry dummies
```

```
crsp_comp['sic2'] = (crsp_comp['siccd']/100).astype(int)
model=smf.ols(formula='car~Defense+C(sic2)+log_revt',data=crsp_comp)
```

```
import numpy as np
crsp_comp = crsp_comp.dropna()
crsp_comp = crsp_comp.replace([np.inf, -np.inf], np.nan).dropna()
crsp_comp['sic2'] = ((crsp_comp['siccd'] / 100).astype(int) + 1e-6)
model = smf.ols(formula='car ~ Defense + C(sic2) + log_revt', data=crsp_comp)
```

```
results = model.fit()
print(results.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                    car   R-squared:                       0.113
Model:                            OLS   Adj. R-squared:                  0.099
Method:                 Least Squares   F-statistic:                     8.386
Date:                Tue, 15 Apr 2025   Prob (F-statistic):           5.13e-79
Time:                        21:03:21   Log-Likelihood:                 411.58
No. Observations:                4818   AIC:                            -677.2
Df Residuals:                    4745   BIC:                            -204.1
Df Model:                          72
Covariance Type:            nonrobust
========================================================================================
                           coef    std err          t      P>|t|      [0.025      0.975]
----------------------------------------------------------------------------------------
Intercept                0.1042      0.058      1.796      0.073      -0.010       0.218
Defense[T.True]          0.1058      0.132      0.802      0.422      -0.153       0.365
C(sic2)[T.1.000001]      0.1215      0.102      1.185      0.236      -0.079       0.322
```

This regression explores the relationship between cumulative abnormal returns (CAR), defense industry classification, log revenue (log_revt), and industry fixed effects (via SIC code dummies). The model explains about 11.3% of the variance in CAR ($R^2 = 0.113$), a notable improvement from prior models. However, the Defense variable remains statistically insignificant ($p = 0.422$), suggesting no meaningful impact of industry classification on CAR. The F-statistic (8.386, $p < 0.001$) indicates that the overall model is statistically significant. This implies that while individual predictors may be weak, the combination of industry effects and revenue contributes meaningfully to explaining CAR.

d. Filtering profitable companies

```
#Filtering profitable companies and fitting an OLS regression model to examine the impact of Defense and log_revt on car.
```

```
crsp_comp_profit=crsp_comp[(crsp_comp['ni']>=0)]
```

```
model = smf.ols(formula='car ~ Defense+log_revt', data=crsp_comp_profit)
results = model.fit()
print(results.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                    car   R-squared:                       0.018
Model:                            OLS   Adj. R-squared:                  0.017
Method:                 Least Squares   F-statistic:                     24.09
Date:                Tue, 15 Apr 2025   Prob (F-statistic):           4.26e-11
Time:                        21:03:21   Log-Likelihood:                 1179.3
No. Observations:                2679   AIC:                            -2353.
Df Residuals:                    2676   BIC:                            -2335.
Df Model:                           2
Covariance Type:            nonrobust
===================================================================================
                      coef    std err          t      P>|t|      [0.025      0.975]
-----------------------------------------------------------------------------------
Intercept           0.1125      0.010     11.628      0.000       0.093       0.131
Defense[T.True]     0.1739      0.156      1.114      0.265      -0.132       0.480
log_revt           -0.0098      0.001     -6.887      0.000      -0.013      -0.007
==============================================================================
Omnibus:                     1739.573   Durbin-Watson:                   1.992
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            85139.927
Skew:                           2.436   Prob(JB):                         0.00
Kurtosis:                      30.185   Cond. No.                         357.
==============================================================================
```

This OLS regression was conducted on a filtered dataset containing only profitable firms (ni >= 0) to evaluate the impact of Defense classification and log_revt on cumulative abnormal returns (CAR). The R-squared is 0.018, meaning the model explains 1.8% of the variance in CAR. While the Defense variable is **not statistically significant** (p = 0.265), **log_revt** shows a **significant negative relationship** with CAR (p < 0.001), indicating that higher revenues are associated with slightly lower abnormal returns in profitable firms. This suggests diminishing returns or overvaluation effects in larger firms.

Business implication

For Lockheed Martin, the research underscores increased demand for defense equipment due to geopolitical tensions, presenting opportunities to enhance production and capitalize on strategic military contracts. Both companies must adapt their strategies to evolving market demands shaped by external events.

Limitations of this research

This research might have some issues because the data we used isn't perfect. Some important information might be missing, or the numbers we have could have small errors. Also, we didn't look at a lot of companies, so the results might not show the full picture of what's happening in the energy and defense industries. Lastly, the methods we used, like looking at straight-line relationships between factors, might not fully explain more complicated patterns or the effects of big global events.

Potential project

Predictive analytics involves using historical data and machine learning techniques to forecast future outcomes. It provides actionable recommendations based on predictive models, optimizing decision-making processes.