Oil and Airline Stocks: An Empirical Study Using Bloomberg Data

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Abstract

This report investigates the relationship between crude oil prices (CL1 Comdty) and major U.S. airline equities (DAL, AAL, UAL) using Bloomberg Terminal data and Python-based econometric modeling. The analysis examines correlations, simple regressions, and multiple regressions with the SPX market factor. We find that oil alone explains very little variation in airline returns, but with SPX included, oil betas turn negative as expected.

1 Introduction

Airline companies are among the most fuel-intensive businesses in the world, and jet fuel expenses are directly related to the price of crude oil. Because fuel represents one of the largest and most volatile components of airline operating costs, movements in oil prices are often believed to have a significant impact on airline profitability and, therefore, equity performance. Higher oil prices increase operating costs and may compress margins, while lower oil prices can improve profitability and enhance investor sentiment.

This project investigates whether short-term changes in crude oil prices (CL1 Comdty) systematically affect the daily stock returns of three major U.S. airlines: Delta Air Lines (DAL), American Airlines Group (AAL) and United Airlines Holdings (UAL). The study further examines whether the influence of oil persists after controlling for general market movements, represented by the S&P 500 Index (SPX).

To formally examine this relationship, we evaluate the following statistical hypotheses:

- $\mathbf{H_0}$**:** Crude oil price returns have no effect on airline stock returns.
- $\mathbf{H_1}$**:** Crude oil price returns negatively affect airline stock returns.

These hypotheses are tested using Bloomberg analytics (HRA, CRP, CMT) combined with Python-based econometric models. The analysis assesses whether oil prices alone explain return movements of airline passengers and how the relationship changes when broader market conditions (SPX) are incorporated. As required by the course project instructions [1], the analysis uses Bloomberg as the primary data source.

2 Data Collection via Bloomberg

Data were collected directly from the Bloomberg Terminal. The Excel files exported from Bloomberg begin on December 31, 2014, while the Bloomberg HRA regressions display a start date of January 1, 2015, which is a market holiday with no trading activity. Since the first return in Python is computed from the December 31, 2014 closing price to the next available trading day, January 2, 2015, both the Python regressions and the Bloomberg HRA analysis effectively use the same initial return observation. This ensures full consistency between the two methods.

- **HP**: Historical Price Table for each equity and CL1.
- **HRA**: Historical Regression Analysis for weekly returns.
- **CRP**: Comparative Returns.
- **CMT**: Correlation Matrix.
- **GP**: Historical Price Graph.

The following securities were downloaded:

- **CL1 Comdty** – WTI Crude Oil front-month futures
- **DAL US Equity** – Delta Air Lines
- **AAL US Equity** – American Airlines
- **UAL US Equity** – United Airlines
- **SPX Index** – S&P 500 (used as market factor)

The daily PX_LAST series were exported to Excel and later merged in Python [3].

3 Methodology and Data Extraction

This project uses a two-stage workflow that combines Bloomberg Terminal tools with Python-based analysis. Bloomberg is used as the primary data source for prices, correlations, and single-factor regressions, while Python is used only for the extended analysis that Bloomberg does not directly provide.

3.1 Data Extraction via Bloomberg Terminal

All historical price data was obtained directly from Bloomberg using the **HP** (Historical Price) function. For each ticker (CL1, DAL, AAL, UAL, SPX), daily PX_LAST values were exported to Excel from 2015–2025.

In addition to prices, Bloomberg analytics was used to generate the initial exploratory results.

- **CRP** – Comparative returns chart for long-run performance.
- **CMT** – Correlation matrix for weekly returns.
- **HRA** – Simple linear regression of airline returns on oil.

These Bloomberg-generated charts and tables are directly included in the report and form the basis for the initial interpretation of the relationship between oil and airline equities.

3.2 Python Analysis (Only for Extended Modeling)

Python was used only for modeling steps that require deeper econometric analysis not provided by Bloomberg's HRA function. Specifically:

- Merging exported Bloomberg price files into one dataset.
- Computing daily log returns for all assets.
- Reproducing summary statistics and correlations for verification.
- Running multiple regression models that include the market factor (SPX), which Bloomberg's HRA does not support with multiple independent variables.

Importantly, Python was **not** used to duplicate the EDA and single-factor regressions already performed using Bloomberg. Instead, its purpose was to extend the analysis by incorporating market controls and quantifying how the oil–airline relationship changes in a multi-factor environment.

4 Bloomberg Exploratory Data Analysis

4.1 Price Performance

Figures 1 and 2 present the normalized price performance of crude oil (CL1) and the three main U.S. airline stocks over the period 2015-2025. Each series is indexed to 100 at the start date to facilitate a direct comparison of relative performance.

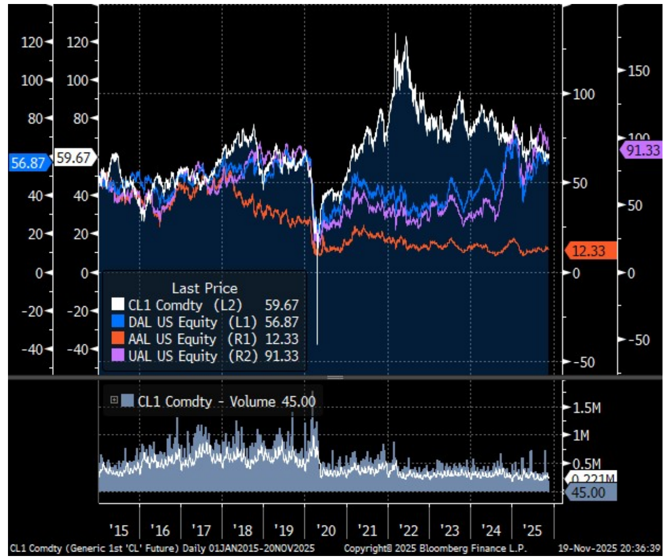

Figure 2: Bloomberg long-term price comparison of CL1, DAL, AAL, and UAL (2015–2025).

Several patterns emerge from the long-run price trajectories. Crude oil displays large cyclical swings driven by supply-demand shocks, geopolitical events, and global macroeconomic conditions. In contrast, the airline stocks exhibit more stable but clearly equity–market–driven trends. All three airlines experienced a sharp decline during the 2020 period associated with COVID-19, followed by a gradual recovery in subsequent years.

Among the carriers, UAL and DAL show stronger post-pandemic rebounds, while AAL underperforms consistently throughout the sample, reflecting differences in balance-sheet strength and operational efficiency. Overall, while crude oil undergoes pronounced cycles, the airline equities move more closely together and appear driven primarily by market-wide factors rather than oil price movements. This visual observation already hints at a potentially weak direct relationship between oil prices and airline equity performance, which is later confirmed by the correlation and regression results.

4.2 Bloomberg Correlation Matrix

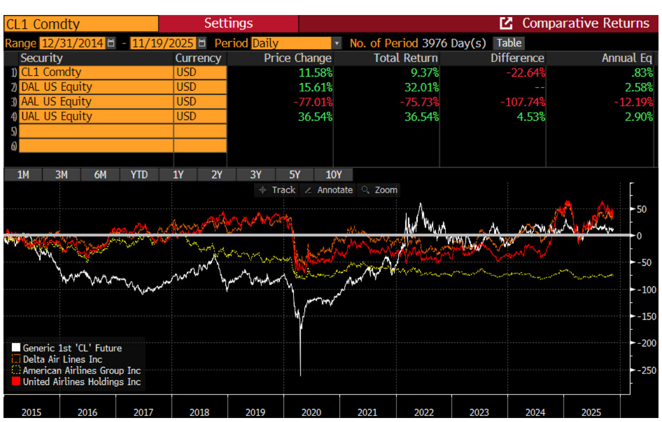

Figure 1: Bloomberg Comparative Returns (2015–2025).

Security	CL1	DAL	AAL	UAL
11) CL1	1.000	0.118	0.066	0.066
12) DAL	0.118	1.000	0.810	0.864
13) AAL	0.066	0.810	1.000	0.845
14) UAL	0.066	0.864	0.845	1.000

Figure 3: Bloomberg weekly return correlations.

As shown in Figure 3, the correlation matrix highlights two key patterns:

- Oil's correlation with airline stocks is extremely low (0.06–0.12), indicating minimal direct co-movement.
- Airline stocks are highly correlated with one another (0.81–0.86), reflecting shared exposure to industry and market-wide factors.

5 Bloomberg Regression Analysis

Bloomberg's HRA function was used to run simple linear regressions of airline weekly returns against crude oil (CL1) returns. These regressions provide an initial view of the direct sensitivity of each airline to oil price movements.

5.1 AAL vs Oil

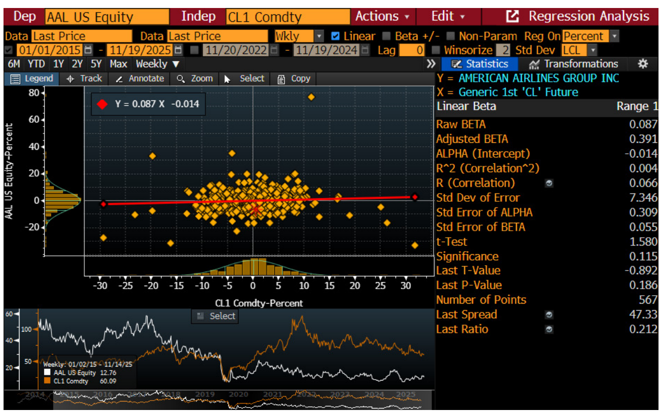

Figure 4: Bloomberg Regression: AAL on CL1.

As shown in Figure 4, the regression between AAL weekly returns and crude oil yields a very small beta of 0.087 and an R^2 of only 0.004. Oil explains almost none of AAL's short-term return variability, and the relationship is statistically weak and economically insignificant.

5.2 DAL vs Oil

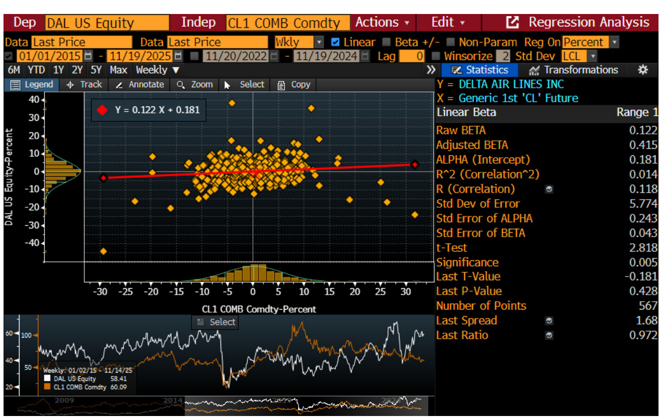

Figure 5: Bloomberg Regression: DAL on CL1.

As shown in Figure 5 DAL exhibits a slightly higher oil beta of 0.122, but the explanatory power remains extremely low with $R^2 \approx 0.01$. This suggests that although DAL has a marginally stronger sensitivity to oil, crude oil prices do not meaningfully drive its weekly return fluctuations.

5.3 UAL vs Oil

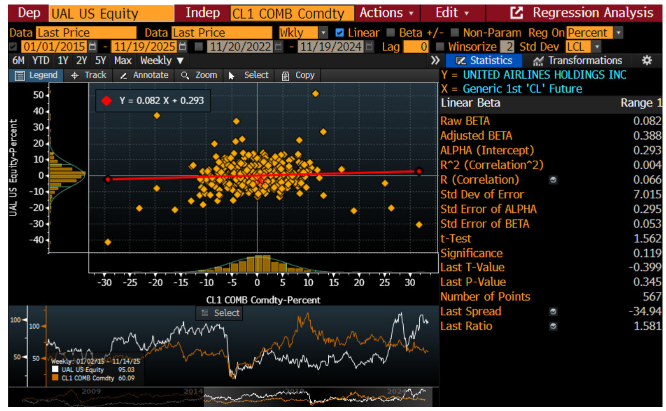

Figure 6: Bloomberg Regression: UAL on CL1.

UAL's regression as shown in Figure 6 yields a beta of 0.082 and an R^2 of 0.004, nearly identical to AAL. This reinforces the conclusion that crude oil prices have almost no direct predictive power for UAL's returns, and any observed sensitivity is too weak to be economically useful.

6 Python-Based Extended Analysis

Python was used exclusively for the components of the analysis that Bloomberg does not support directly. Since Bloomberg already provides comparative performance, correlations, and single-factor regressions, these steps were not replicated. Instead, Python focused on multi-factor modeling and synchronized return computation.

6.1 Data Preparation

The Bloomberg-exported PX_LAST series for CL1, DAL, AAL, UAL, and SPX were merged into a single time-aligned dataset. Daily log returns were computed to ensure consistent measurement across assets and to prepare the data for multi-factor regression analysis.

6.2 Multi-Factor Regression with Market Control

Bloomberg's HRA function supports only one independent variable. To incorporate both crude oil and the market factor (SPX), Python was used to estimate the following model:

$$R_{air,t} = \alpha + \beta_{oil} R_{oil,t} + \beta_{mkt} R_{SPX,t} + \epsilon_t.$$

This extended specification allows us to evaluate whether the crude oil effect remains significant once broader market movements are accounted for.

6.3 Results

Ticker	α	β_{oil}	$t(\beta_{oil})$	β_{SPX}	Adj. R^2
DAL	-0.0005	-0.0433	-2.961	1.3358	0.330
AAL	-0.0011	-0.0872	-4.578	1.4637	0.255
UAL	-0.0005	-0.0404	-2.177	1.4968	0.278

Table 1: Multiple regression estimates with t-statistics for oil sensitivity.

Key findings: After controlling for broader market movements, the oil beta (β_{oil}) becomes *negative and statistically significant* for all airlines, with t-statistics ranging from -2.18 to -4.58. This confirms that higher crude oil returns are associated with lower airline stock returns once market effects are accounted for. In contrast, the market factor (β_{SPX}) remains strongly positive and highly significant across all regressions, indicating that SPX is the dominant driver of airline return variation. The multi-factor model explains 25–33% of the variation in daily airline returns, substantially improving upon the near-zero explanatory power of the simple Bloomberg HRA regressions.

7 Conclusion

This study examined whether fluctuations in crude oil prices explain the daily returns of major U.S. airline stocks. Using Bloomberg for data extraction, comparative performance, correlation analysis, and single-factor regressions, and Python for multi-factor modeling, we evaluated both the direct and market-adjusted relationships.

Hypothesis Testing

H_0: Oil price returns have no effect on airline stock returns.
H_1: Oil price returns negatively affect airline stock returns.

Test 1: Simple regression (Bloomberg HRA) All R^2 values were below 1%, and oil betas were small and slightly positive.
Result: Fail to reject H_0. Oil alone does not meaningfully explain airline returns.

Test 2: Multi-factor regression (Python) After adding SPX as a market control, all oil betas turned negative and were statistically significant based on their t-values (ranging from -2.18 to -4.58).
Result: Reject H_0 in the presence of market control. Oil has a negative effect on airline returns, but only after accounting for market-wide movements.

Overall Conclusion

The relationship between oil and airline stocks is more nuanced than simple correlation suggests. Oil alone has very limited explanatory power, but the multi-factor model reveals the theoretically expected negative sensitivity once market effects are incorporated. Airline equities are primarily driven by broad market conditions (SPX), with crude oil acting as a secondary but statistically significant risk factor.

References

[1] Stevens Institute of Technology. "FE 511: Intro to Bloomberg and Thomson-Reuters – Final Project Guidelines." Instructor: Jingyi Wei, Fall 2025.

[2] Bloomberg Terminal Data: CL1 Comdty, DAL US, AAL US, UAL US, SPX Index. Historical prices and analytics retrieved via HP, HRA, CRP, and CMT.

[3] PX_LAST time-series data exported from Bloomberg (2015–2025) and merged in Python for multi-factor regression analysis.