ANOVA

May 7, 2025

1 Dataset Collection

We collected daily close prices for Boeing and Airbus from 2010 to 2025 using Yahoo Finance. Accident records for the same period were obtained from the National Transportation Safety Board (NTSB). Key variables used include: `Date` for aligning accident and stock data; `State` and `Country` for regional grouping; `Make` to identify manufacturer; injury counts such as `FatalInjuryCount`, `SeriousInjuryCount`, and `MinorInjuryCount` to calculate severity scores. Stock price data was linked by `Date` to generate `boeing_Close` and `airbus_Close` time series.

2 Data Processing

The Make column contains 1,542 entries labeled as Boeing and 422 as Airbus, along with 27 missing values. While the missing values represent only 0.11% of the entire dataset (0.0011), they account for approximately 1.37% of the combined Boeing and Airbus entries (0.0137). Given the small proportion and the focus of our analysis on these two manufacturers, it is reasonable to remove the rows with missing Make values without introducing significant bias.

The `State` column contains approximately 19.5% missing values. However, these are not due to random omission but stem from structural differences—nearly all missing entries come from countries where a U.S.-style state designation does not exist (e.g., Brazil, the United Kingdom, Australia). Therefore, **this missingness is considered structural rather than stochastic.** In our analysis, we account for this by limiting state-based blocking strategies to data from the United States, where the `State` information is both relevant and largely complete.

3 ANOVA

Model 1 Analysis: Effect of Manufacturer and Region on Injury Severity

Overview. In this model, we investigate whether the severity of aircraft accidents—quantified via a weighted injury score—is associated with the manufacturer (`Make`) or the incident region's activity level (`StateBlock`). The weighted score was defined as: 3×`Fatal + 2`×`Serious + 1`×`Minor`. We limited the analysis to accidents involving Boeing and Airbus, and grouped U.S. states into High / Medium / Low frequency blocks based on incident counts. Given the unbalanced sample sizes across groups, we directly applied a Type III ANOVA, which provides robust main effect estimates by adjusting for all other terms in the model.

Key Analysis Flow

- Cleaned data by removing rows with missing values in `Make`, `State`, and `Country`.
- Created a new variable `StateBlock` from state-wise accident counts.
- Computed `WeightedInjuryScore` using fatal, serious, and minor injury counts.
- Applied Type III ANOVA due to group size imbalance to assess main effects of `Make` and `StateBlock`.
- Diagnosed the model via residual plots, which indicated heteroscedasticity.
- Used Weighted Least Squares (WLS) regression to re-estimate model coefficients.
- Conducted Tukey HSD test on `StateBlock` for pairwise comparison.

Detailed Interpretation

Type III ANOVA. Given the substantial imbalance in group sizes—e.g., over 14,000 incidents in `High` versus only 1,300 in `Low`—we used Type III ANOVA, which evaluates each factor's effect after accounting for all other variables. The result showed that `Make` had no significant effect ($p = 0.965$), whereas `StateBlock` was initially significant ($p = 0.016$).

Residual Diagnostics. The Figure 1 showed a fan-shaped pattern, indicating increasing variance with fitted values. This heteroscedasticity violates ANOVA assumptions and undermines the reliability of F-tests.

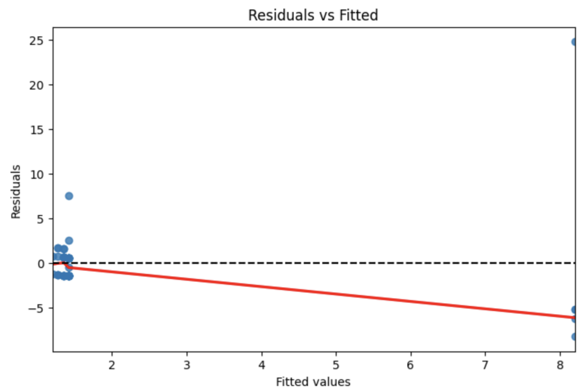
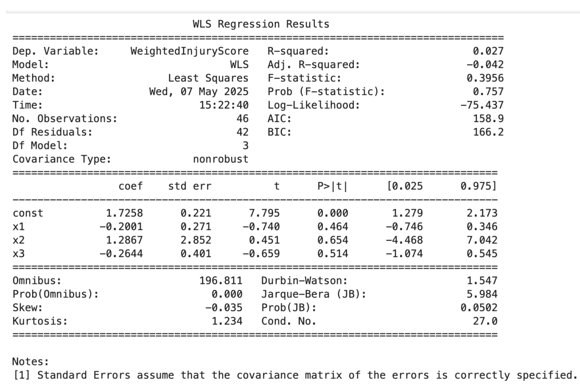


Figure 1: Residuals vs Fitted Values Plot for Model 1 Showing Heteroscedasticity

WLS Regression. To correct for heteroscedasticity, we applied WLS regression using the inverse of squared residuals as weights. As shown in **??**. The updated model showed poor fit ($R^2 = 0.027$), and neither `Make` nor `StateBlock` remained significant ($p > 0.4$ for all).



WLS Regression Results

Dep. Variable:	WeightedInjuryScore	R-squared:	0.027
Model:	WLS	Adj. R-squared:	-0.042
Method:	Least Squares	F-statistic:	0.3956
Date:	Wed, 07 May 2025	Prob (F-statistic):	0.757
Time:	15:22:40	Log-Likelihood:	-75.437
No. Observations:	46	AIC:	158.9
Df Residuals:	42	BIC:	166.2
Df Model:	3		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	1.7258	0.221	7.795	0.000	1.279	2.173
x1	-0.2001	0.271	-0.740	0.464	-0.746	0.346
x2	1.2867	2.852	0.451	0.654	-4.468	7.042
x3	-0.2644	0.401	-0.659	0.514	-1.074	0.545

Omnibus:	196.811	Durbin-Watson:	1.547
Prob(Omnibus):	0.000	Jarque-Bera (JB):	5.984
Skew:	-0.035	Prob(JB):	0.0502
Kurtosis:	1.234	Cond. No.	27.0

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Figure 2: WLS Regression Summary Table for Model 1

Post Hoc Comparison (Tukey's HSD). To identify which levels of `StateBlock` differ significantly, we applied Tukey's Honest Significant Difference (HSD) test.

The results showed that:

- `High` vs. `Low` states differ significantly ($p = 0.009$).
- `Low` vs. `Medium` states also show significant difference ($p = 0.028$).
- However, `High` vs. `Medium` states did not differ significantly ($p = 0.997$).

This indicates that the `Low`-incident states have systematically different injury scores compared to both `High` and `Medium` blocks, suggesting that lower exposure (or fewer cases) might be associated with higher injury severity per case.

Conclusion

Although the initial Type III ANOVA suggested that `StateBlock` had a significant effect, residual diagnostics revealed clear heteroscedasticity, potentially undermining the validity of the F-tests. After applying Weighted Least Squares (WLS) to address variance inequality, no predictors remained significant. However, post-hoc Tukey's HSD tests revealed that `Low` frequency states significantly differ from both `High` and `Medium` blocks. This suggests potential regional disparities in injury severity that warrant further investigation. Meanwhile, `Make` (Airbus vs. Boeing) consistently showed no association with injury severity.

Model 2: One-Way ANOVA on Standardized Prices (Airbus vs Boeing)

Overview. Initial analysis on raw close prices indicated a significant mean difference between Airbus and Boeing stock prices. However, this difference likely stemmed from inherent scale discrepancies. To address this, we standardized closing prices within each company using z-score normalization and then applied one-way ANOVA.

- The dependent variable is the standardized closing price.
- The independent variable is the company label (Airbus vs Boeing).
- Timeframe was aligned from 2010 onward to ensure comparable periods.

Rationale. Raw stock prices are influenced by company-specific factors such as initial offering, historical valuation, and currency denomination. Standardization removes scale effects and allows fair comparison of relative fluctuations and trends between companies.

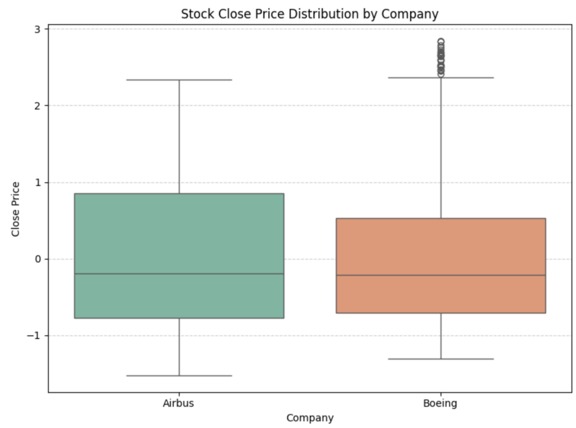


Figure 3: Boxplot of Standardized Close Prices (2010–2025) by Company

Boxplot Visualization. **??** shows that after standardization, the distributions for Airbus and Boeing stock prices appear similar in range and central tendency.

ANOVA and Post-Hoc Results. The one-way ANOVA yielded an F-statistic near 0 with $p = 1.0$, indicating no significant difference between company means. Tukey's HSD post-hoc test confirmed this: the mean difference was 0.0, with adjusted $p = 1.0$.

Conclusion. Although the raw prices showed a significant difference, standardizing the data revealed that Airbus and Boeing stock prices behave similarly in relative terms. This underscores the importance of addressing scale effects before conducting comparative statistical tests.

Model 3: WLS ANOVA with Interaction – Do Airbus and Boeing React Differently to Fatal Accidents?

Research Goal and Methodology

This model investigates whether the stock price responses of Airbus and Boeing differ significantly between periods surrounding fatal accidents and normal trading periods. To address this, we use Weighted Least Squares (WLS) regression with an ANOVA framework, including an interaction term between `PeriodType` (Fatal vs. Normal) and `Company` (Airbus vs. Boeing), while controlling for seasonality through the `Month` variable as a blocking factor.

Part 1: Separate Analysis of Airbus and Boeing

We first fit separate WLS models for each company. We estimate weights as the inverse of the squared residuals from an initial OLS fit. Results indicate:

- **Airbus:** `PeriodType` significantly impacts stock price after controlling for month, $F = 4287.4$, $p < 0.0001$.
- **Boeing:** A similarly strong effect is observed, with $F = 12875.3$, $p < 0.0001$.

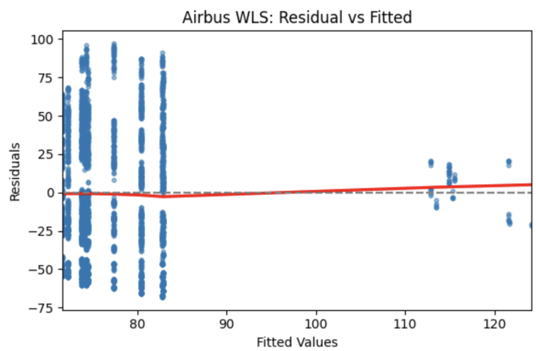


Figure 4: Airbus WLS: Residuals vs Fitted Values

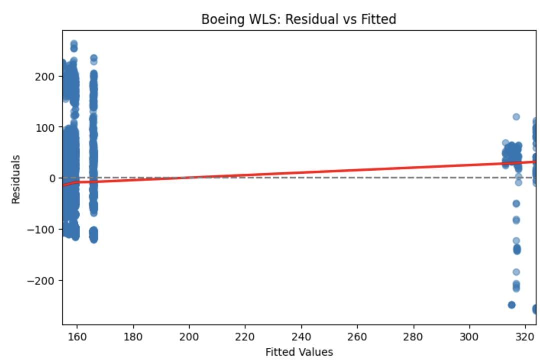


Figure 5: Boeing WLS: Residuals vs Fitted Values

As shown above, both residual plots exhibit substantial variability in the low fitted value region. This suggests that even after applying WLS, conditional heteroskedasticity may persist. These findings support the motivation for applying volatility models such as GARCH in subsequent analysis, which explicitly model time-varying variance.

Part 2: Interaction Analysis – Do the Two Companies React Differently?

We then fit a combined WLS model with an interaction term between `PeriodType` and `Company`, again controlling for month as a block.

- The interaction term `PeriodType:Company` is highly significant: $F = 1039.3$, $p < 0.0001$.
- This implies that the change in stock price from normal to fatal accident periods is not uniform across companies – the market reacts differently to Boeing and Airbus.

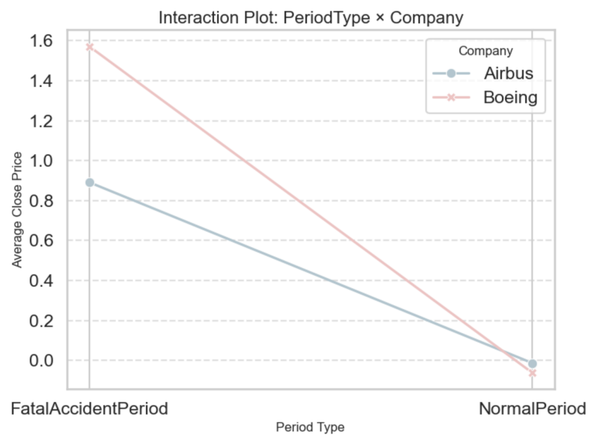


Figure 6: Interaction Plot: PeriodType × Company Effects on Average Close Price

As shown in the interaction plot, Airbus shows a moderate decrease in stock price during fatal accident periods, while Boeing's stock price drops more steeply. This non-parallel trend line supports the statistical evidence of a significant interaction effect.

Conclusion and Implications

Our findings suggest:

- `PeriodType` has a significant effect on stock price for both Airbus and Boeing after accounting for month.
- A significant **interaction effect** indicates that the magnitude of stock price response to fatal accidents differs between the two companies.
- The residual plots show clear patterns of volatility, particularly at the lower fitted value range, underscoring the need for GARCH modeling in future steps.

This model not only confirms the significance of fatal accidents in influencing stock prices but also highlights how company-specific factors modulate that response. It provides a solid foundation for follow-up analysis using volatility-sensitive models like GARCH.