5.1 ANOVA

5.1.1 ANOVA Analysis on Standardized Close Prices

To assess whether aviation accidents cause systematic changes in stock prices, we constructed an ANOVA model using standardized close prices of AIRBUS and BOEING. The stock price data was first standardized within each company using z-score normalization. This standardization ensures comparability across companies by removing differences in price scale and volatility structure. After standardization, we merged the stock data into a single dataset with a unified format.

Data Processing
From the dataset, we filtered events with EventType = 'ACC' and 'Make' in ['BOEING', 'AIRBUS'], focusing exclusively on accidents involving these two major manufacturers. For each selected accident event, we created a ±10-day time window to capture potential stock price reactions. These dates were labeled as the "LaggedPeriod." All other dates in the stock dataset were labeled as "NormalPeriod." This labeling allowed us to segment the data into treatment (LaggedPeriod) and control (NormalPeriod) periods.

However, LaggedPeriod samples were sparse—only 14 for AIRBUS and 43 for BOEING. To address this imbalance, we performed stratified random sampling from the NormalPeriod group, ensuring each company's sample size in NormalPeriod matched its LaggedPeriod count.

Modeling and Results
We then constructed an ANOVA model. The model included PeriodType (LaggedPeriod vs. NormalPeriod), Company (AIRBUS vs. BOEING), and their interaction. This setup allowed us to test both whether accident periods differ from normal trading periods and whether that effect varies by company. Although price data were standardized within each firm, Company was included as a blocking factor to control for residual structural differences.

Given the small and balanced sample—only 14 LaggedPeriod cases for AIRBUS—we used an OLS-based ANOVA, which is appropriate since ANOVA is a special case of linear regression using dummy-coded categorical variables. To address potential violations of normality and variance homogeneity, we standardized prices, balanced group sizes via stratified sampling, and focused on mean differences rather than prediction. Alternative robust methods were considered, but with such limited sample size, they could reduce statistical power. Therefore, OLS provides a valid and interpretable framework for testing whether post-accident periods show significant deviations from a company's historical average. #这段或许可以放 appendix 中

Therefore, this model tests three effects:

- The main effect of PeriodType, which evaluates whether stock prices during accident windows deviate from their usual historical level (i.e., whether they are statistically higher or lower than baseline behavior).

- The main effect of Company, capturing residual differences across BOEING and AIRBUS even after standardization.
- The interaction effect, which tests whether the effect of accident windows differs between the two companies.

Even though prices were standardized within each company, we still included C(Company) in the model to account for structural differences not removed by standardization (e.g., differences in noise, liquidity, or unobserved firm-level shocks). In this context, PeriodType functions as the treatment, and Company is used as a blocking factor. #这段或许可以放 appendix 中

The ANOVA results show significant effects for PeriodType ($F = 14.81$, $p < 0.001$), Company ($F = 12.42$, $p < 0.001$), and their interaction ($F = 7.57$, $p = 0.0069$). These findings suggest that stock prices during accident windows are significantly different from normal periods, and this effect varies across companies.

Table X. Two-Way ANOVA Results on Standardized Stock Prices by PeriodType and Company

	sum_sq	df	F	PR(>F)
C(PeriodType)	10.070927	1.0	14.810573	0.000200
C(Company)	8.443509	1.0	12.417249	0.000621
C(PeriodType):C(Company)	5.146578	1.0	7.568695	0.006947
Residual	74.798049	110.0	NaN	NaN

Supporting the statistical result, the boxplot reveals that AIRBUS's standardized close prices during LaggedPeriod are highly concentrated and consistently lower than during normal periods. BOEING also shows a downward shift during the LaggedPeriod, though with more dispersion. This indicates that both firms exhibit systematic responses following accidents, but the magnitude and volatility of the responses differ.

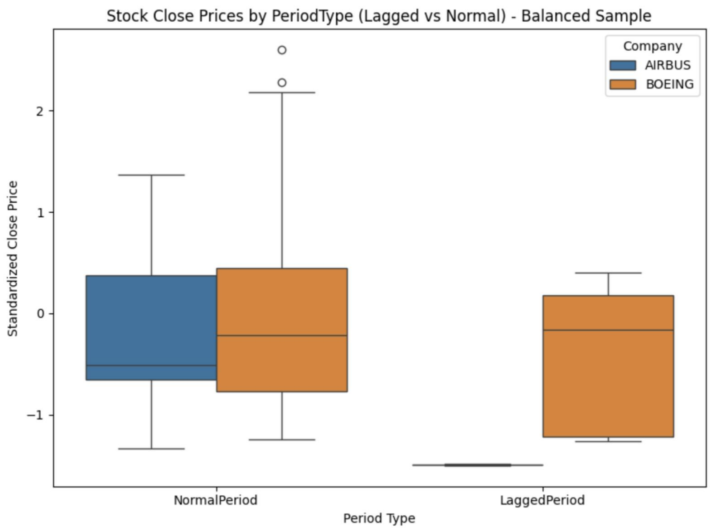

Figure X. Distribution of Standardized Close Prices by PeriodType and Company (Balanced Sample)

In summary, the ANOVA model confirms that accidents correspond to statistically significant deviations in stock prices, relative to each firm's historical average. This result justifies proceeding to further analysis of cumulative abnormal returns (CARs) in the next step, as there is strong evidence of event-induced price disruption.

5.1.2 Volatility-based Impact Assessment

To extend the findings which showed that airline accidents significantly affect average stock prices, we now examine whether such events also impact short-term volatility—a key measure of investor uncertainty and market reaction. This part shifts focus from price levels to fluctuation intensity, asking whether accidents lead to increased price instability and whether this effect differs between Airbus and Boeing.

Data Preparation

We first labeled each trading day with a PeriodType, indicating whether it falls within ±10 days of a fatal accident. Next, we also considered seasonality as a potential confounder. By averaging quarterly prices over the years (see figure below), we observed strong seasonal patterns. To account for this, we extracted each record's calendar quarter (Quarter) as a categorical covariate.

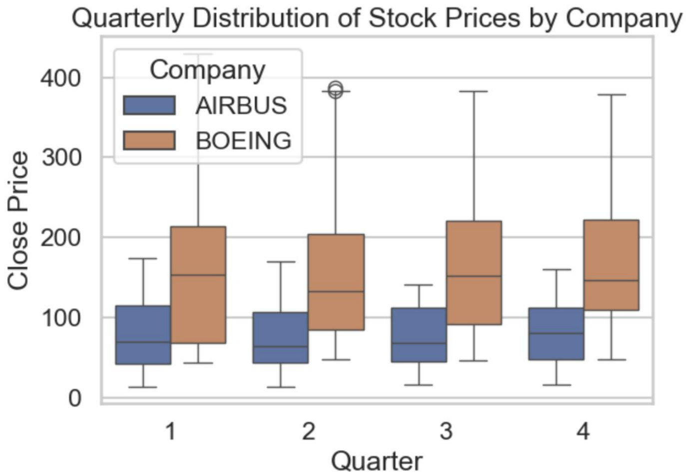

Figure 2: Quarterly distribution of closing stock prices for Airbus and Boeing, highlighting seasonal variations.

Next, we calculated the log return for each trading day, defined as the difference in the natural logarithm of consecutive closing prices. This metric captures the relative change in stock price and serves as a foundation for measuring fluctuation.

To quantify short-term volatility, we computed the 5-day rolling standard deviation of log returns. This rolling window estimate (rolling_std) reflects localized price fluctuation intensity and becomes the dependent variable in our volatility-focused ANOVA model.

Modeling and Results

We built separate models for Airbus and Boeing, applying Weighted Least Squares (WLS) to mitigate heteroscedasticity. Each model regressed rolling_std on PeriodType and Quarter.

ANOVA Output Interpretation:

The ANOVA results indicate that the accident period (PeriodType) significantly increases short-term volatility for both companies, with Airbus showing a much stronger effect ($F \approx 408$, $p \approx 0$) compared to Boeing ($F \approx 9.9$, $p \approx 0.0016$). Additionally, the Quarter variable is highly significant for both, confirming the presence of seasonal patterns in stock price volatility. These findings validate the necessity of including both structural (accident) and cyclical (quarterly) factors in the volatility model.

Table X. Type II ANOVA summary of weighted least squares models examining the effect of accident period and seasonal quarter on short-term volatility for Airbus and Boeing.

		sum_sq	df	F	PR(>F)
Airbus	C(PeriodType)	408.402814	1.0	408.638531	1.672662e-86
	C(Quarter)	59891.183065	3.0	19975.250143	0.000000e+00
	Residual	3903.746876	3906.0	NaN	NaN
Boeing	C(PeriodType)	9.902544	1.0	9.910649	0.001656
	C(Quarter)	950085.167749	3.0	316954.273701	0.000000
	Residual	3765.917562	3769.0	NaN	NaN

Residual Pattern Discussion:
Residual plots for both companies suggest that while the WLS models reduce heteroskedasticity, they do not completely eliminate it. For Airbus, the residuals show mild funneling patterns and some remaining structure. For Boeing, the residuals exhibit larger outliers, potentially due to extreme market responses or data irregularities. This motivates the need for more sophisticated volatility models such as GARCH to better capture time-varying variance.

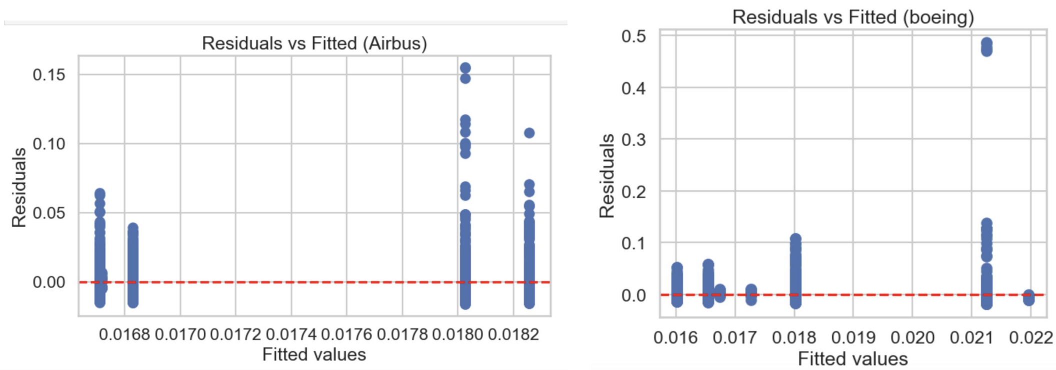

Figure X: Residuals vs. Fitted Values for Volatility Models (Airbus and Boeing)

Interaction Effect Test
To examine whether the reaction strength differs between the two companies, we constructed a combined model that includes an interaction term between PeriodType and Company and used Type II ANOVA to test the significance of the interaction. Below shows the results:

TableX: ANOVA Results: Testing the Interaction Between Accident Period and Company on Rolling Volatility

	sum_sq	df	F	PR(>F)
C(PeriodType)	0.000026	1.0	0.081746	7.749528e-01
C(Company)	0.000503	1.0	1.579429	2.088811e-01

C(Quarter)	0.012489	3.0	13.075398	1.629906e-08
C(PeriodType):C(Company)	0.000060	1.0	0.188221	6.644137e-01
Residual	2.444490	7678.0	NaN	NaN

It can be seen that:

- Both PeriodType and Company have significant main effects on volatility.
- The interaction term is not significant ($p \approx 0.66$), suggesting no evidence that one company reacts more intensely than the other during accident windows.

Conclusion

This model confirms that accident periods significantly increase stock price volatility for both Airbus and Boeing. While Airbus exhibits a stronger response, this difference is not statistically significant. The presence of seasonality further justifies its inclusion as a control factor. These results indicate that fluctuation intensity, not just price level, is sensitive to aviation accidents. The patterns observed also highlight volatility clustering, motivating the use of GARCH models to better capture time-dependent volatility structure.