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Pricing Fuel Risk: Oil Price Exposure, Fuel Hedging and the Stock Returns of Ryanair, Delta Air Lines and Lufthansa

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Abstract: This study examines the relationship between crude oil price fluctuations and equity returns of three international airlines, Ryanair Holdings, Delta Air Lines, and Deutsche Lufthansa, representing different business models and fuel hedging strategies. Using daily financial data, the analysis investigates airline stock return sensitivity to West Texas Intermediate (WTI) and Brent crude oil futures prices, with the S&P 500 serving as the market benchmark. The methodology combines correlation analysis, multiple regression, scenario-based sensitivity analysis, market beta estimation, and single-factor elasticity regressions. The findings reveal considerable differences in oil price exposure across airlines. Ryanair exhibits the strongest negative relationship, with estimated elasticities of −0.12 for WTI and −0.13 for Brent ($p < 0.001$), indicating that a 5% increase in oil prices is associated with an approximately 0.6% decline in its share price. Delta demonstrates weaker but statistically significant negative exposure, with elasticities of −0.06 and −0.05 ($p < 0.05$), respectively, and the highest market beta (1.44). However, oil price movements explain only a limited proportion of daily stock return variations for both airlines. Lufthansa's estimated exposure is negligible, although incomplete price observations limit the reliability of these results. Overall, the findings demonstrate heterogeneous airline equity responses to crude oil price movements, highlighting the potential importance of fuel hedging policies, operating cost structures, and market conditions. The study offers empirical insights into airline financial risk management and investment decision-making.

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1. Introduction

Fuel is one of the largest operating expenses for commercial airlines, typically accounting for roughly 20–30% of operating costs depending on the carrier and the oil price environment. Fluctuations in crude oil prices therefore affect airline profitability directly through fuel costs, and indirectly through fares, demand and the macroeconomic conditions that move oil prices in the first place. Understanding how oil price changes translate into airline equity returns matters for portfolio managers, risk analysts and corporate treasurers.

For equity investors, the question is not only whether fuel costs rise but how far oil price changes are reflected in share prices. In an efficient market, stock prices should respond to oil shocks to the extent that those shocks change expected future cash flows. Jones and Kaul (1996) find that this cash-flow channel fully accounts for the stock market reaction to oil shocks in the United States and Canada. For airlines, the cash-flow effect would seem obvious: higher fuel

prices raise costs, and competitive pressure limits how quickly they can be passed on to passengers through fares and surcharges.

The relationship is less straightforward than it first appears, however, because oil prices themselves respond to economic conditions. Kilian and Park (2009) show that the stock market's reaction depends on what drives the oil price change. Increases driven by strong global demand tend to coincide with rising equity prices, at least initially, whereas increases driven by oil-market-specific factors such as precautionary demand around supply disruptions depress stock returns. This distinction is particularly relevant for airlines, since a demand-driven oil price rise often coincides with strong travel demand, which partly offsets the higher fuel bill. The observed correlation between airline stocks and oil is therefore a net effect of cost and demand channels.

A further reason exposure differs across carriers is fuel hedging. Airlines can lock in fuel prices with futures, swaps and options, and their hedging policies vary widely. Carter et al. (2006) find that jet fuel hedging is associated with higher firm value among U.S. airlines, and Treanor et al. (2014) show that hedging reduces airlines' exposure to fuel price changes. Two airlines in the same industry can thus differ markedly in how their share prices respond to oil, depending on their hedging programmes, cost structures, revenue mix and listing markets.

Recent market episodes have made these questions more pressing. The COVID-19 pandemic grounded much of the world's fleet and coincided with the first negative settlement price in the history of WTI futures, and the Russia–Ukraine war triggered a sharp energy price shock shortly afterwards. Recent studies show that the links between oil and other markets intensify and change character during such crises (Karim et al., 2024; Djedaiet et al., 2024; Younis et al., 2025). Relationships estimated over calm periods may therefore be a poor guide to airline exposure when it matters most.

This study selects three airlines with distinct geographies, business models and hedging approaches: Ryanair, a European low-cost carrier that hedges a large share of its expected fuel requirement 12–18 months forward; Delta Air Lines, a U.S. network carrier that in recent years has relied mainly on its ownership of the Trainer refinery (Monroe Energy) rather than on financial fuel hedges; and Lufthansa, a European full-service group with a rolling multi-year hedging programme, whose primary listing on the Frankfurt Stock Exchange introduces additional currency and trading-hours effects. The two oil benchmarks, WTI (CL=F) and Brent (BZ=F), are the dominant global crude pricing standards and are expected to move almost identically, which the analysis confirms.

This thesis contributes to the literature in two ways. First, while much of the airline evidence concerns U.S. carriers, it compares a European low-cost carrier, a U.S. network carrier and a European full-service carrier within one framework, using the same data and methods for each. Second, it reports several complementary measures of exposure (correlations, elasticities, scenario impacts and market betas) and discusses how listing market, currency and trading hours affect what daily return data can reveal about oil sensitivity.

The remainder of the thesis is organised as follows. Section 2 reviews the related literature. Section 3 describes the data and methodology. Section 4 presents the empirical analysis, covering correlations, regression, sensitivity, market betas and elasticities. Section 5 discusses

the findings in light of the literature and their implications for investors, and Section 6 concludes and outlines limitations and directions for future research.

The overall aim of this thesis is to assess how crude oil price movements are reflected in the stock returns of the three carriers. To achieve this aim, the thesis pursues five specific objectives: first, to quantify the correlation between the oil benchmarks and each airline's equity returns; second, to assess how much of the variation in Delta Air Lines' daily returns is explained by oil price movements; third, to estimate the sensitivity of each airline's returns to a 5% increase in oil prices; fourth, to derive market beta coefficients relative to the S&P 500 for each asset; and fifth, to estimate the elasticity of each airline's share price with respect to oil prices and test its statistical significance.

Building on these objectives, the thesis addresses the following two research questions:

RQ1: To what extent are daily changes in crude oil prices (WTI and Brent) reflected in the stock returns of Ryanair, Delta Air Lines and Lufthansa, and how does this exposure differ across the three carriers?

RQ2: Can differences in oil price exposure across the three carriers be explained by their fuel hedging strategies, business models and listing markets?

2. Review of Literature

This chapter reviews the literature that frames the empirical analysis. It begins with studies of how oil prices affect the stock market as a whole (Section 2.1), then narrows to industries in which fuel is a major input (Section 2.2) and to recent evidence on oil–equity linkages during crises (Section 2.3). Section 2.4 reviews research on fuel hedging in the airline industry, Section 2.5 discusses methodological issues relevant to daily return data, and Section 2.6 identifies the research gap that this thesis addresses.

2.1 Oil Prices and the Stock Market

Research on oil prices and equity markets asks two related questions: whether stock prices respond to oil price changes, and whether that response is rational. Jones and Kaul (1996) study four developed markets with post-war quarterly data. In the United States and Canada, the stock market reaction to oil shocks is fully accounted for by their effect on current and expected future real cash flows. In Japan and the United Kingdom, the cash-flow channel does not fully account for it, which suggests that those markets overreact to oil news. Their framework supports the basic premise of this thesis: if oil affects a firm's expected cash flows, it should be visible in that firm's stock returns.

Kilian and Park (2009) refine this view by showing that the response depends on the source of the oil price change. Using a structural VAR model, they separate oil supply shocks, shocks to aggregate demand for industrial commodities and oil-market-specific demand shocks. Positive global demand shocks raise both oil prices and stock prices, whereas oil-specific demand shocks, often associated with precautionary buying during supply concerns, lower stock returns. Supply shocks matter less than is commonly assumed. The implication for this thesis is that a single oil coefficient estimated over a long sample averages over different kinds of shocks with

opposite effects. Simple regression estimates should therefore be read as average exposures, not as structural effects.

2.2 Oil Price Exposure in Transport and Travel Industries

Because aggregate market indices combine firms that gain and lose from higher oil prices, later studies examine industries where fuel is a major input. Nandha and Brooks (2009) analyse transport sector returns across a large international sample of countries and find evidence that oil prices affect transport returns, particularly in developed markets. Mohanty et al. (2014) focus on the U.S. travel and leisure industry and find significant negative oil price exposure for several sub-industries, including airlines. They also find that the exposure varies over time and differs between oil price increases and decreases. These results suggest that a single, constant exposure coefficient may hide important variation, and they motivate the rolling-window extensions discussed in Section 6.1.

For airlines, these industry-level findings have a clear economic basis. Fuel is one of the largest components of operating costs, and competitive pressure in passenger markets limits how quickly higher costs can be passed on through fares. Airline profits are therefore more directly exposed to fuel prices than those of most other industries, and the transport-sector literature would lead one to expect airlines to show some of the strongest negative oil exposures. At the same time, sector-level studies average across firms with very different cost structures and hedging policies. They cannot show whether exposure differs between, for example, a low-cost carrier and a network carrier, which is the comparison at the centre of this thesis.

2.3 Oil–Equity Linkages During Crises

A fast-growing recent literature uses connectedness and dynamic-correlation models to study how oil interacts with equity and other asset markets, much of it focused on the COVID-19 pandemic and the Russia–Ukraine war. Karim et al. (2024) find a sudden breakdown in correlations after the COVID-19 shock and identify oil as a major transmitter of volatility before the pandemic. Younis et al. (2025) report that oil, gold, Bitcoin and Gulf Cooperation Council stock markets were more interconnected during the COVID-19 crisis than during the Russia–Ukraine conflict, with WTI among the main transmitters of risk spillovers during the Israel–Palestine conflict. Using a TVP-VAR framework, Attarzadeh et al. (2024) find that volatility shocks are most significant in the crude oil market. Riahi et al. (2024) find that WTI crude oil had a positive effect on stock index returns in the countries most affected by the pandemic. The sign of the oil–equity relationship is therefore not fixed across markets and periods.

Several studies also find that these relationships are asymmetric and depend on market conditions and the time horizon. Djedaiet et al. (2024) show that oil price fluctuations affect gold returns asymmetrically, more strongly during declines, and that correlations with Brent changed as the COVID-19 pandemic and the Russia–Ukraine conflict progressed. Matsui and Knottenbelt (2024) find that increases in oil implied volatility spill over to stock market volatility (the VIX) more strongly than decreases of the same size. Kamal and Bouri (2025) and Zhang and Hamori (2025) show that spillovers and diversification benefits depend on the time scale and on whether markets are in normal, bullish or bearish phases. Georgescu (2026) finds that dependence structures among technology stocks, Bitcoin, gold and oil are unstable over time, with lower-tail dependence intensifying during market stress. For investors, Tarchella et

al. (2024) show that the hedging and safe-haven value of oil, gold and cryptocurrencies for G7 equity markets depends on market conditions and on the country concerned.

Although none of these studies examines airlines directly, they carry two lessons for this thesis. First, a single correlation or regression coefficient estimated over a sample that includes COVID-19 and the 2022 energy shock averages over regimes in which the oil–equity relationship may differ considerably. Second, hedging relationships are state-dependent, which bears directly on the investment implications drawn in Section 5.3.

2.4 Fuel Hedging and Airline Value

The airline industry has been a central setting for studying corporate risk management, because fuel is a large, volatile and hedgeable cost. Carter et al. (2006) examine U.S. airlines and find that jet fuel hedging is positively associated with firm value, measured by Tobin's Q. They attribute the effect to reduced underinvestment: hedged airlines are better placed to invest when high fuel prices put competitors under financial strain. Treanor et al. (2014) study both financial hedging and operational hedging and show that fuel hedging reduces airlines' exposure to jet fuel price changes. Together, these studies imply that differences in hedging policy should produce observable differences in oil price exposure across carriers. This is the main hypothesis this thesis uses to interpret differences between Ryanair, Delta and Lufthansa.

The literature also suggests why hedging need not eliminate share price exposure. Financial hedges are typically placed for a limited horizon, so a lasting change in oil prices eventually feeds through to unhedged future fuel purchases. Hedging programmes also differ in their instruments, coverage ratios and horizons, and some carriers rely on operational rather than financial hedges, for example through fleet decisions or, in Delta's case, ownership of a refinery. Equity investors, who value a firm on its long-run cash flows, may therefore continue to price oil risk even for heavily hedged airlines. Whether hedging reduces measured exposure is consequently an empirical question, and the comparison of Ryanair, Delta and Lufthansa provides a natural setting in which to examine it.

2.5 Methodological Considerations

Daily financial returns rarely satisfy the classical OLS assumptions. Their volatility changes over time and they are frequently fat-tailed, so conventional standard errors can understate or overstate the precision of estimated exposures. White (1980) provides a heteroskedasticity-consistent covariance estimator, and Newey and West (1987) extend it to allow for autocorrelation as well. Following this literature, inference in this thesis should rely on robust standard errors rather than on the conventional OLS formula. This matters most for borderline results such as Delta's Brent elasticity ($p = 0.021$).

The volatility of oil itself also varies over time, and GARCH-family models are the standard tool for modelling it. Darie and Miron (2023) apply a GARCH(1,1) model to WTI, and Matsui et al. (2025) show that augmenting GARCH models with implied volatility improves one-day-ahead volatility forecasts for crude oil. Dynamic conditional correlation (DCC-GARCH) models, used in several of the studies reviewed above, allow the correlation itself to vary over time and are a natural extension of the constant correlations reported in Section 4.1. Finally, the oil series used here are continuous front-month futures. Matsui et al. (2022) show that oil futures volatility and the futures basis depend on contract maturity, trading volume and open interest.

Rolling from one contract to the next can also introduce artificial jumps into a continuous futures return series, which should be checked when constructing the CL=F and BZ=F returns.

2.6 Research Gap

Existing airline studies concentrate mainly on U.S. carriers and on the link between hedging and firm value, and they typically use monthly or quarterly data. The recent literature on oil–equity linkages during crises, in turn, focuses on market indices and on alternative assets such as gold and Bitcoin rather than on individual firms in oil-intensive industries. There is less direct evidence comparing the daily oil sensitivity of carriers with different business models, hedging policies and listing venues, particularly ones that include European airlines whose shares trade in different currencies and time zones. This thesis addresses that gap by applying a common set of methods to Ryanair, Delta Air Lines and Lufthansa, and by examining how far observed differences in exposure can be linked to hedging, cost structure and market listing.

Two further gaps follow from the literature reviewed above. First, most studies report a single measure of exposure, whereas investors and risk managers typically need several complementary measures, such as correlations, elasticities and scenario impacts, that can be compared across firms. Second, few studies discuss explicitly how the practical features of daily data, including non-synchronous trading hours, currency denomination and the construction of continuous futures series, affect estimated exposure for firms listed in different markets. This thesis responds to both gaps by reporting several related measures for each carrier and by discussing these data issues alongside the results. The research questions set out in Section 1 follow directly from these gaps.

3. Data and Methodology

This chapter describes the data used in the analysis and the methods applied to them. Section 3.1 sets out the data sources, sample and return calculations, and Section 3.2 describes the five analytical methods used to measure oil price exposure.

3.1 Data Sources

Daily closing price data for Ryanair Holdings (RYAAY), Delta Air Lines (DAL), Deutsche Lufthansa (LHA.DE), West Texas Intermediate (WTI) crude oil futures (CL=F), Brent crude oil futures (BZ=F), and the S&P 500 index (^GSPC) were obtained from Yahoo Finance. The financial time series were aligned according to their respective trading dates to ensure consistency across instruments traded on different exchanges. Daily logarithmic returns were calculated as \(r_t = \ln(P_t/P_{t-1})\), where \(P_t\) and \(P_{t-1}\) represent the closing prices on consecutive valid trading observations. The use of logarithmic returns facilitates the analysis of proportional price changes and reduces the influence of trends associated with raw price levels. Accordingly, the empirical framework employs daily returns to examine the relationships between crude oil price fluctuations and airline stock performance through correlation analysis, regression modelling, sensitivity analysis, market beta estimation, and elasticity analysis.

The three airlines were selected to provide variation in business model, hedging approach and listing market. Ryanair is represented by its American Depositary Receipt (RYAAY), which trades on NASDAQ in U.S. dollars; Delta by its New York Stock Exchange listing (DAL); and

Lufthansa by its primary listing on the Frankfurt Stock Exchange (LHA.DE), which trades in euros. Oil prices are measured with continuous front-month futures for WTI (CL=F), traded on NYMEX, and Brent (BZ=F), traded on ICE, the two most widely used crude oil benchmarks. The S&P 500 index serves as the market benchmark for the beta estimates. Because the series trade on different exchanges, in different currencies and with different closing times, the alignment of trading dates and the treatment of holidays can affect the results; these issues are discussed further in Sections 4.1 and 4.4.

3.2 Analytical Methods

Five complementary methods are used to measure the relationship between oil prices and airline stock returns. Correlation analysis describes the direction and strength of co-movement; multiple regression measures how much of Delta's return variation is explained by oil; sensitivity analysis translates the estimated elasticities into the impact of a specific oil price shock; beta analysis measures each asset's exposure to the overall equity market; and elasticity regressions estimate the size and significance of each airline's oil exposure. Together, these methods address the five research objectives set out in Section 1.

3.2.1 Correlation Analysis

Pearson correlation coefficients were computed for all pairs of the five series to measure the direction and strength of their linear co-movement, with particular attention to the airline–oil and airline–airline pairs. For two series x and y, the coefficient is defined as

$$\rho(x, y) = \mathrm{Cov}(x, y) / (\sigma x \, \sigma y)$$

and ranges from −1 (perfect negative co-movement) to +1 (perfect positive co-movement). A negative correlation between an airline and oil is expected, because higher oil prices raise fuel costs. Correlation is a symmetric, unit-free measure: it shows whether two series move together, but not how large the response of one is to a given change in the other, which is why it is complemented by the regression-based measures below. Correlations are also sensitive to how the data are prepared. Correlations computed on price levels can be inflated by common trends over the sample, so the analysis is intended to be based on daily returns.

3.2.2 Multiple Regression

A multiple regression was estimated with Delta's daily returns as the dependent variable and WTI and Brent futures returns as regressors:

$$R(DAL,t) = \alpha + \beta 1 \, R(WTI,t) + \beta 2 \, R(Brent,t) + \varepsilon(t) \qquad (1)$$

where R denotes a daily log return and ε(t) is an error term. Because the two oil series are almost perfectly correlated, their individual coefficients β1 and β2 are not separately identified: the regression cannot distinguish the effect of WTI from that of Brent. The model is therefore used only to measure the joint explanatory power of oil prices, summarised by the coefficient of determination (R^2). The residuals were inspected for systematic bias and heteroscedasticity by plotting them against the fitted values.

3.2.3 Sensitivity Analysis

The sensitivity analysis translates the elasticities estimated in Section 4.5 into the expected change in each airline's daily return for a hypothetical 5% increase in WTI or Brent:

$$\Delta R(i) = \gamma(i) \times 5\% \quad (2)$$

where γ(i) is the oil price elasticity of airline i from Equation (4). A 5% one-day rise in oil prices is large but not unusual in volatile periods, so it provides an intuitive stress scenario for comparing the carriers. Because the analysis rescales the elasticity coefficients, it presents the same evidence in a more accessible form rather than providing independent evidence. It also assumes that the response is linear and symmetric, so that the effect of a 5% rise is five times the effect of a 1% rise and equal in size to the effect of a 5% fall. The literature reviewed in Section 2.3 suggests that these assumptions may not hold during crises.

3.2.4 Beta Analysis

Market betas were estimated with the market model, regressing each asset's daily returns on the daily returns of the S&P 500 index:

$$R(i,t) = \alpha(i) + \beta(i)\, R(m,t) + \varepsilon(i,t) \quad (3)$$

where R(m,t) is the market return. The beta coefficient β(i) measures systematic risk: the expected percentage change in the asset's return for a 1% change in the market return. A beta of 1 indicates that the asset moves in line with the market, a beta above 1 that it amplifies market movements and a beta below 1 that it dampens them. Betas were estimated for the three airlines and for both oil benchmarks, which shows how strongly each asset, including oil itself, is linked to the U.S. equity market. Because LHA.DE trades in Frankfurt and closes before the U.S. market, its same-day beta against the S&P 500 is expected to be biased downwards by non-synchronous trading.

3.2.5 Elasticity Analysis

Oil price elasticities were estimated with separate OLS regressions of each airline's daily log returns on the daily log returns of each oil benchmark:

$$R(i,t) = \alpha(i) + \gamma(i)\, R(oil,t) + \varepsilon(i,t) \quad (4)$$

Because both variables are log differences, the slope coefficient γ(i) is the elasticity of the share price with respect to the oil price, that is, the percentage change in the airline's share price associated with a 1% change in the oil price. A negative γ(i) indicates that the airline's share price falls when oil prices rise. Six regressions were estimated, one for each combination of airline and oil benchmark. Coefficients were treated as statistically significant at the 5% level using [heteroscedasticity-robust (White, 1980) / Newey–West (1987)] standard errors. Because the regressions include only oil returns, the estimates measure total oil exposure, which may partly reflect the correlation between oil and the wider market.

4. Empirical Analysis

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This section presents the empirical results. Section 4.1 reports the correlation analysis, Section 4.2 the multiple regression for Delta Air Lines, Section 4.3 the sensitivity analysis, Section 4.4 the market betas, Section 4.5 the elasticity estimates, and Section 4.6 summarises the results across methods. The implications of these results are discussed in Section 5.

4.1 Correlation Analysis

Table 1 and Figure 1 report the pairwise correlations between the five series over the study period. Table 1 gives the exact coefficients, and the heatmap shows the pattern visually, with blue cells indicating negative and red cells positive correlation. Three groups of relationships stand out: the correlation between the two oil benchmarks, the correlations between the airlines and oil, and the correlation between the airlines themselves. Figure 1 is labelled as computed on closing prices rather than returns. Because correlations between price levels can be inflated by common trends over the sample, the coefficients below should be confirmed on daily returns, as described in Section 3.2.1.

Table 1. Pairwise Correlation Coefficients Between Oil Benchmarks and Airline Stocks

Asset	CL=F	BZ=F	RYAAY	LHA.DE	DAL
CL=F	1.00	0.99	-0.49	n/a	-0.33
BZ=F	0.99	1.00	-0.50	n/a	-0.33
RYAAY	-0.49	-0.50	1.00	n/a	0.80
LHA.DE	n/a	n/a	n/a	1.00	n/a
DAL	-0.33	-0.33	0.80	n/a	1.00

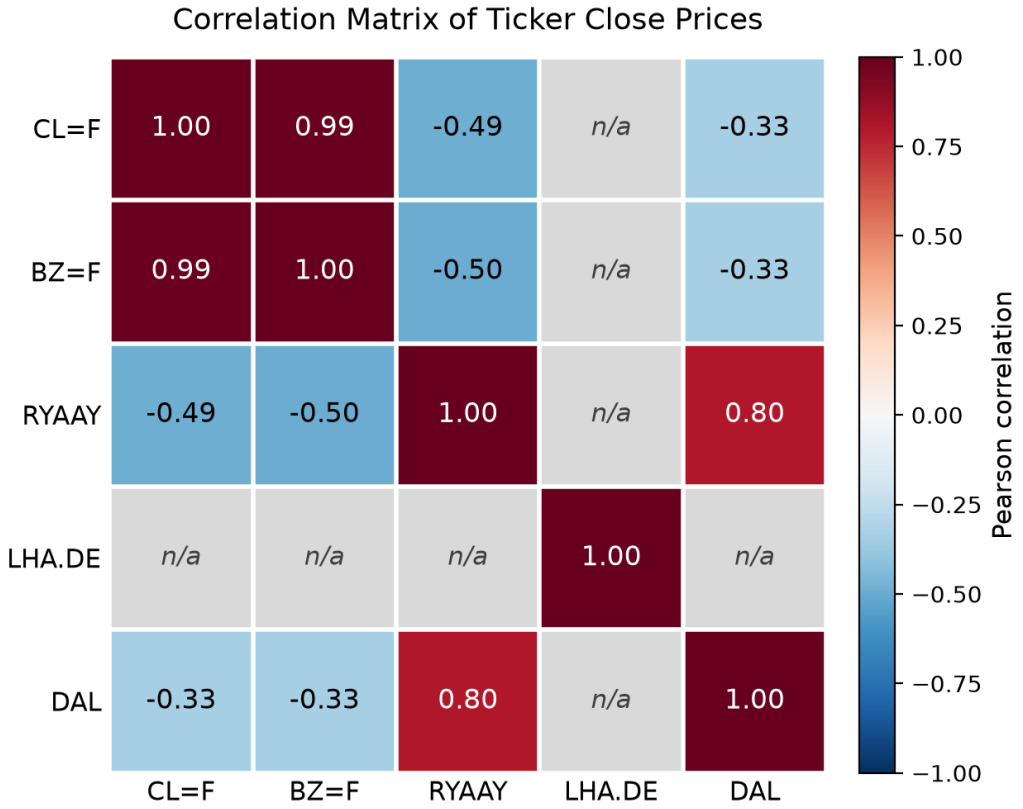


Figure 1. Correlation Matrix Heatmap — Ticker Close Prices (CL=F, BZ=F, RYAAY, LHA.DE, DAL). n/a = not available because of missing LHA.DE data.

4.1.1 Inter-Oil Correlation

WTI and Brent are almost perfectly correlated (0.99), as expected given the integration of global crude markets. Their shared variance, approximately the square of the correlation, is about 98%, so any result obtained with one benchmark should be closely reproduced with the other. This is confirmed throughout the analysis: the sensitivity and elasticity estimates for WTI and Brent differ only marginally for each airline. The small differences that remain reflect factors such as the different delivery locations and quality of the two crudes, and the spread between them, which can widen temporarily during supply disruptions. The two benchmarks therefore carry essentially the same information, and reporting both serves as a robustness check rather than as two independent measures.

4.1.2 Airline–Oil Inverse Relationship

Ryanair shows the strongest negative correlation with oil (−0.49 with WTI; −0.50 with Brent), and Delta a moderate negative correlation (−0.33 with both benchmarks). The sign is consistent with the economic argument that higher fuel costs compress airline margins and therefore reduce the value investors place on airline shares. The difference in magnitude between the two carriers is notable: Ryanair's correlation with oil is roughly one and a half times as large as Delta's, which suggests that its share price is more closely tied to fuel prices. This ranking is the first indication of a pattern confirmed by the regression-based measures in Sections 4.3 and 4.5. Even a correlation of −0.5, however, leaves most of the variation in each series unrelated to the other, so oil is far from the only influence on airline share prices.

4.1.3 Airline Inter-Correlation

RYAAY and DAL are strongly positively correlated (0.80), consistent with common industry-wide drivers such as travel demand, the macroeconomic cycle and investor sentiment towards the sector. This correlation is considerably stronger than either airline's correlation with oil, which indicates that sector-wide factors matter more for airline share prices than oil prices alone. It also implies that holding both stocks provides only limited diversification within the airline sector.

No correlations could be computed for Lufthansa: the LHA.DE row and column of Figure 1 are marked n/a, which indicates missing or constant data in that series rather than weak co-movement. This is an important diagnostic result in its own right. Lufthansa is a large and actively traded stock, and in a correctly constructed dataset it would be expected to show at least moderate correlation with the other airlines. The missing values therefore point to a problem in the downloading or alignment of the LHA.DE series, which also affects the beta and elasticity results reported below.

4.2 Multiple Regression Analysis (DAL)

A multiple regression model was estimated with Delta Air Lines' daily returns as the dependent variable, and WTI (CL=F) and Brent (BZ=F) daily futures returns as independent variables, as specified in Equation (1). The model addresses the second research objective: to assess how much of the variation in Delta's daily returns can be attributed to oil price movements. Delta was chosen for this analysis because it is the largest of the three carriers and is listed on the same

U.S. market as the oil futures, which avoids the time-zone mismatch that affects LHA.DE. The results are presented in two parts: overall model performance (Section 4.2.1) and residual diagnostics (Section 4.2.2).

4.2.1 Model Performance

Table 2. Multiple Regression Model Summary — DAL Returns on WTI and Brent Returns

Metric	Value	Interpretation
R-Squared	0.308	30.8% of variance explained
Independent Variables	CL=F, BZ=F	WTI & Brent returns
Dependent Variable	DAL Returns	Daily log returns

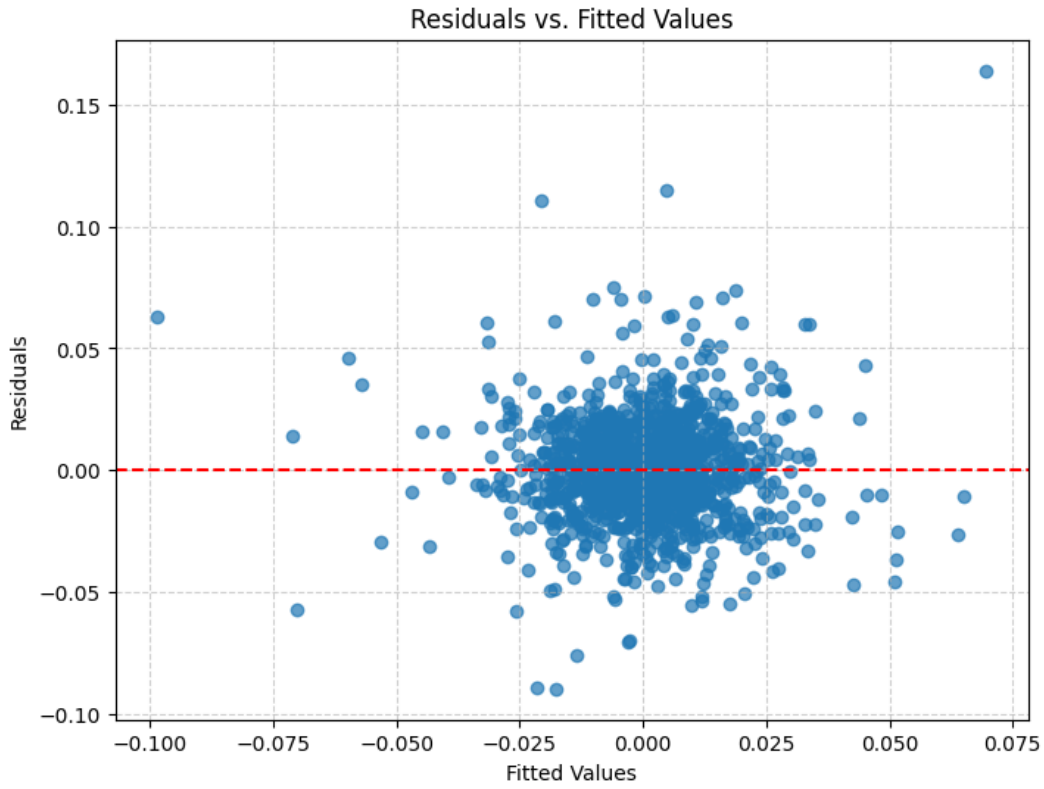


Figure 2. Residuals vs. Fitted Values — DAL Multiple Regression Model

The R^2 of 0.308 reported in Table 2 implies that the two oil series jointly account for about 31% of the daily variance in Delta's returns, leaving about 69% unexplained. Most of the variation is therefore driven by other factors, including broad market movements, company-specific news, demand shocks and operating leverage. Because WTI and Brent are almost perfectly correlated, the second benchmark adds very little information, and the individual coefficients on the two series should not be interpreted separately.

The R^2 should also be read with caution. The single-benchmark elasticity regressions in Section 4.5 imply a considerably weaker relationship between oil and Delta's returns than an R^2 of 0.308 would suggest, so this figure should be verified by re-estimating the model on daily returns before it is relied upon.

4.2.2 Residual Diagnostics

Figure 2 plots the residuals against the fitted values. The residuals are centred on zero with no visible trend, indicating no major systematic bias in the model.

However, the residuals are fat-tailed, with several outliers beyond ±0.10, and their dispersion is uneven, which is consistent with heteroscedasticity and volatility clustering. This does not bias the OLS coefficients, but it makes conventional standard errors unreliable, so inference should rely on heteroscedasticity-robust standard errors. GARCH-family models are a natural extension.

Taken together, the diagnostics suggest that the model captures the average relationship between oil and Delta's returns without obvious bias, but that its standard errors, and any confidence intervals based on them, should be treated with caution. The presence of large outliers also means that a small number of extreme trading days, such as days of severe market stress, may have a disproportionate influence on the estimates.

4.3 Sensitivity Analysis

Table 3 converts the elasticities from Section 4.5 into the expected change in each airline's daily return for a hypothetical 5% one-day increase in WTI or Brent, using Equation (2). A 5% daily oil move is large but has occurred repeatedly in recent years. The scenario is a stress test: it asks how much each airline's share price would be expected to fall on a day when oil prices rise sharply, holding other factors constant. The results are shown in Table 3 and Figure 3. Because the impacts are linear transformations of the elasticities, their ranking across carriers is identical to the elasticity ranking reported in Section 4.5.

Table 3. Estimated Impact of a 5% Oil Price Increase on Airline Daily Returns

Airline	5% ↑ in CL=F	5% ↑ in BZ=F	Sensitivity Rank
RYAAY	≈ −0.59%	≈ −0.64%	1 (Most Sensitive)
DAL	≈ −0.29%	≈ −0.25%	2 (Moderate)
LHA.DE	≈ 0.00%	≈ 0.00%	3 (Insensitive)

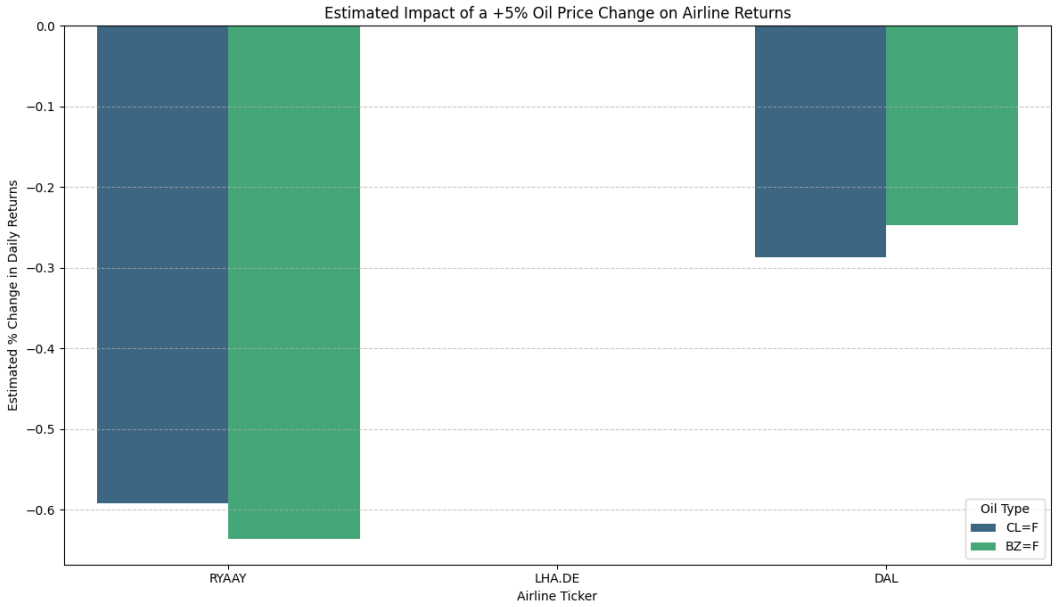


Figure 3. Estimated Impact of a +5% Oil Price Change on Airline Daily Returns (CL=F vs. BZ=F)

4.3.1 Ryanair (RYAAY)

Ryanair shows the largest negative response, with estimated return impacts of about −0.59% (WTI) and −0.64% (Brent). Because a low-cost carrier keeps its other costs low, fuel makes up a particularly large share of its cost base, so fuel price changes weigh heavily on margins. That this sensitivity appears despite Ryanair's extensive forward hedging suggests investors price the effect of oil on future, not-yet-hedged fuel costs and on demand. Its USD-denominated ADR listing may also contribute through exchange-rate effects.

An impact of around −0.6% on a single day is economically meaningful, although it is small relative to the large daily price swings that airline stocks commonly experience. Its importance lies less in any single day than in its cumulative effect: a sustained period of rising oil prices, made up of many daily increases, would weigh persistently on Ryanair's share price.

4.3.2 Delta Air Lines (DAL)

Delta shows a smaller response, of about −0.29% (WTI) and −0.25% (Brent) for a 5% oil price increase. Its scale, diversified revenue (loyalty programme, cargo and premium cabins) and the natural hedge provided by its refinery plausibly dampen the effect, although it remains statistically significant. The estimated impact on Delta is between about 40% and 50% of that on Ryanair, consistent with Delta's lower correlation with oil in Section 4.1. The difference between the WTI and Brent estimates is small and reverses the ordering seen for Ryanair, a reminder that the two benchmarks carry essentially the same information and that small differences between them should not be over-interpreted. For investors, the result suggests that Delta's share price is less sensitive to fuel price shocks than Ryanair's, although its high market beta (Section 4.4) means that it remains a volatile stock overall.

4.3.3 Lufthansa (LHA.DE)

Lufthansa's estimated response is effectively zero for both benchmarks. Because the same LHA.DE series produces no computable correlations in the correlation matrix (Figure 1) and a market beta of exactly 0.0000 (Section 4.4), this result most likely reflects a data problem, such as missing prices or zero returns introduced when aligning Frankfurt and U.S. trading calendars, rather than genuine insensitivity. Lufthansa is shown in Table 3 for completeness, but its zero values should not be read as evidence that its shares are insulated from oil price shocks. The LHA.DE results should be re-estimated before they are interpreted.

4.4 Beta Analysis (vs. S&P 500)

Market betas measure each asset's systematic risk relative to the S&P 500, estimated with Equation (3). A beta of 1.0 means the asset tends to move one-for-one with the market; a beta above 1.0 indicates amplified sensitivity, and a beta below 1.0 dampened sensitivity. Table 4 reports the estimated betas for the three airlines and the two oil benchmarks, together with a broad risk classification. Including the oil benchmarks shows how strongly oil itself is linked to the U.S. equity market. This matters for interpreting the oil elasticities: if oil and the market move together, part of an airline's apparent oil exposure may in fact reflect market exposure.

Table 4. Market Betas Relative to the S&P 500

Ticker	Asset Type	Beta vs. S&P 500	Risk Classification
CL=F	WTI Crude Futures	0.1784	Low Systematic Risk
BZ=F	Brent Crude Futures	0.1658	Low Systematic Risk
RYAAY	Ryanair ADR	0.9453	Market-Like Risk
LHA.DE	Lufthansa (FRA)	0.0000	No Market Correlation
DAL	Delta Air Lines	1.4435	High Systematic Risk

4.4.1 Interpretation by Asset

The two oil benchmarks have low betas of 0.18 (WTI) and 0.17 (Brent), meaning their returns respond only weakly to U.S. equity market movements. Oil prices are driven largely by factors specific to the oil market, such as OPEC+ production decisions and geopolitical events, rather than by the equity market cycle. The positive betas nonetheless indicate some common exposure to global economic conditions, which is why the single-factor oil elasticities in Section 4.5 may partly capture market effects.

Ryanair's beta of 0.95 is close to one, indicating that RYAAY broadly moves in line with the U.S. market. Because RYAAY is an ADR traded on NASDAQ during U.S. hours, part of this co-movement reflects U.S. investor sentiment and EUR/USD movements, not only the airline's fundamentals. Combined with its strong negative oil exposure, this means that Ryanair carries two distinct sources of risk: general market risk and oil price risk.

Lufthansa's estimated beta of exactly zero is not economically plausible for a large listed airline: even a stock without a U.S. listing co-moves with global markets. Non-synchronous trading (Frankfurt closes before the U.S. market) would bias the estimate towards zero, but not to exactly zero. The value most likely reflects the data problem in the LHA.DE series noted in Section 4.1. The estimate should be recomputed against both the S&P 500 and a European index such as the DAX or STOXX Europe 600, with lagged market returns included to address non-synchronous trading.

Delta's beta of 1.44 is the highest of the assets studied and indicates that it amplifies market movements: on average, a 1% move in the S&P 500 is associated with a 1.44% move in DAL in the same direction. This is typical of airlines, given their exposure to the business cycle, discretionary consumer spending, high operating leverage and leveraged balance sheets. It also implies that Delta's share price is driven more by general market conditions than by oil prices, which is consistent with its relatively low oil elasticity.

4.5 Elasticity Analysis

Elasticities were estimated with separate OLS regressions of each airline's daily log returns on each oil benchmark's daily log returns, as specified in Equation (4). The slope coefficient is the percentage change in the airline's share price associated with a 1% change in the oil price. Coefficients with p-values below 0.05 are treated as statistically significant. Table 5 reports the coefficient, p-value and significance for each of the six regressions. These results address the fifth research objective and form the basis for the sensitivity analysis in Section 4.3.

Table 5. Oil Price Elasticity Estimates by Airline and Benchmark

Airline	Oil Benchmark	Elasticity Coeff.	P-Value	Significance
RYAAY	CL=F (WTI)	−0.1183	1.05e−11	✓ Highly Significant
RYAAY	BZ=F (Brent)	−0.1272	5.48e−12	✓ Highly Significant
LHA.DE	CL=F (WTI)	−0.0002	0.9915	✗ Insignificant
LHA.DE	BZ=F (Brent)	−0.0002	0.9917	✗ Insignificant
DAL	CL=F (WTI)	−0.0573	0.0044	✓ Significant
DAL	BZ=F (Brent)	−0.0494	0.0207	✓ Significant

4.5.1 Ryanair — Highest Oil Elasticity

Ryanair has the largest and most precisely estimated oil elasticity of the three carriers. A 1% rise in WTI is associated with a 0.118% fall in RYAAY's share price on the same day (0.127% for Brent), and both coefficients are highly significant ($p < 0.001$). Statistical significance should not be confused with explanatory power, however: oil explains only a modest share of the daily variation in Ryanair's returns.

Interpretation: because fuel is a large share of a low-cost carrier's cost base, changes in fuel prices weigh heavily on its margins. Within the airline sector, RYAAY therefore carries meaningful negative oil exposure. Because oil explains only a modest share of its returns, however, it is not a close substitute for a short oil position.

4.5.2 Delta Air Lines — Moderate, Significant Elasticity

Delta's elasticity is smaller but statistically significant: −0.057 for WTI ($p = 0.004$) and −0.049 for Brent ($p = 0.021$). The lower magnitude is consistent with its diversified revenue base across loyalty, cargo and premium segments and with the natural hedge provided by its refinery.

Both coefficients are significant at the 5% level, but the Brent estimate is closer to the threshold, so its significance depends more heavily on the choice of standard errors discussed in Section 2.5. For both benchmarks, Delta's elasticity is less than half of Ryanair's, confirming the ranking found in the correlation and sensitivity analyses. Taken together with its high market beta, the result suggests that Delta's share price is driven more by general market conditions than by oil prices.

4.5.3 Lufthansa — Statistically Insignificant Elasticity

Lufthansa's coefficients are essentially zero (−0.0002 for both benchmarks; $p \approx 0.99$). As discussed in Sections 4.1 and 4.4, this most likely reflects incomplete LHA.DE data rather than evidence that Lufthansa's share price is unaffected by oil. No conclusion about Lufthansa's oil exposure is drawn until the series is corrected and the regressions are re-estimated. If the corrected data confirm a low exposure, this would be consistent with Lufthansa's extensive hedging programme; if they reveal a significant negative exposure, it would suggest that hedging does little to insulate airline share prices from oil price shocks.

4.6 Summary of Results

Table 6 brings together the results of the correlation, sensitivity and elasticity analyses for each carrier. For the two carriers with reliable data, the methods agree: Ryanair is the most oil-exposed and Delta is moderately exposed. Because the correlation, sensitivity and elasticity measures are closely related transformations of the same co-movement, their agreement is a consistency check rather than independent confirmation. The Lufthansa estimates are reported for completeness but are classified as inconclusive because of the data problem identified in Section 4.1.

Table 6. Summary of Oil Price Exposure Measures by Airline

Airline	Correlation (Oil)	Sensitivity	Elasticity	Overall Verdict
RYAAY (Ryanair)	−0.49 / −0.50	Highest	−0.12 / −0.13*	Most Oil-Exposed
DAL (Delta)	−0.33 / −0.33	Moderate	−0.06 / −0.05*	Moderately Exposed
LHA.DE (Lufthansa)	≈ 0	None	≈ 0 (n.s.)	Inconclusive (data issue)

* Statistically significant at $p < 0.05$

5. Discussion

This section interprets the empirical results in light of the literature reviewed in Section 2, considers what they imply for the role of fuel hedging and business models, and draws out their implications for investors.

5.1 Comparison with Prior Literature

The negative oil exposure found for Ryanair and Delta is consistent with the cash-flow channel documented by Jones and Kaul (1996) and with industry-level evidence of negative oil price exposure for transport and travel stocks (Nandha & Brooks, 2009; Mohanty et al., 2014). Higher oil prices raise expected fuel costs, and investors appear to reflect this in airline share prices on the same trading day.

The magnitudes, however, are modest. Elasticities of about −0.12 for Ryanair and −0.05 to −0.06 for Delta mean that oil explains only a small fraction of daily return variation. This is consistent with Kilian and Park (2009), who show that the stock market response to oil depends on the source of the shock. If part of the oil price increases in the sample reflect strong global demand, which also supports air travel, the cost and demand effects partly offset each other, and a single average coefficient understates the response to supply-driven shocks. The recent literature on crisis periods (Karim et al., 2024; Djedaiet et al., 2024) also suggests that the oil–

equity relationship is unstable over time, so full-sample estimates should be read as averages across different market regimes.

5.2 Fuel Hedging, Business Model and Listing Effects

The hedging literature predicts that carriers with more extensive hedging programmes should show lower oil price exposure (Carter et al., 2006; Treanor et al., 2014). The results do not support a simple version of this prediction. Ryanair, which hedges a large share of its expected fuel requirement in advance, shows the largest exposure, while Delta, which relies mainly on the natural hedge provided by its refinery, shows a smaller one.

Several explanations are possible. Financial hedges cover only a limited horizon, so a persistent oil price change still affects fuel costs beyond the hedged period, and equity investors price that longer-term effect. Fuel is also a larger share of total costs for a low-cost carrier, so the same change in fuel prices has a proportionally larger effect on Ryanair's margins. Finally, RYAAY is a U.S.-listed ADR, so its returns also reflect EUR/USD movements, which are themselves related to oil prices. Distinguishing between these explanations would require data on hedge ratios and an augmented model that includes market and exchange rate factors.

For Lufthansa, no conclusion can be drawn. The near-zero estimates coincide with clear signs of a data problem in the LHA.DE series, so they cannot be used to test the hedging hypothesis until the series is corrected and the analysis re-estimated.

5.3 Investment Implications

The results have several implications for investors and analysts. They are discussed below from three perspectives: using airline stocks to manage oil price risk, allocating capital within the airline sector, and the further analysis needed before conclusions can be drawn about Lufthansa.

5.3.1 For Oil-Hedging Portfolios

Airline stocks are at best a partial hedge against oil price risk. RYAAY offers the strongest negative oil exposure of the three and DAL a weaker one. However, because oil explains only a modest share of their daily returns, both carry substantial non-oil risk, so investors using them as an oil hedge would face considerable basis risk.

Hedge effectiveness depends on how closely the hedging instrument tracks the risk being hedged, and correlations of −0.33 to −0.50 imply that much of the variation in airline returns is unrelated to oil. An investor seeking protection against rising oil prices would therefore achieve a far more reliable hedge with oil futures or options. Airline stocks may be more useful in the opposite direction: an investor holding airline shares who wishes to reduce their oil exposure could hedge part of it with oil futures, using the estimated elasticities as a guide to the appropriate hedge ratio.

5.3.2 For Airline Sector Allocation

DAL's beta of 1.44 makes it the most market-sensitive carrier with reliable estimates, so it can be expected to amplify market drawdowns. RYAAY's near-unity beta combined with its

negative oil exposure leaves it vulnerable to rising oil prices and falling equity markets at the same time, as in a stagflationary shock.

The two carriers therefore offer different risk profiles. Delta behaves primarily as a high-beta exposure to the equity market and the economic cycle, with a smaller oil exposure, while Ryanair combines market-like systematic risk with the strongest oil exposure of the three. Investors who expect oil prices to rise may wish to underweight Ryanair relative to Delta, while those who expect a broad market downturn may prefer the lower-beta stock. In both cases, the estimates are averages over the sample period and may change over time, particularly during crises.

5.3.3 For Fundamental Analysis

Lufthansa's oil exposure cannot be assessed from the current results. Once the data are corrected, comparing its estimated exposure with the hedge ratios disclosed in its annual reports would allow a direct test of whether its multi-year hedging programme dampens the market's reaction to oil prices.

More generally, the Lufthansa results show the importance of checking data quality before drawing conclusions. Taken at face value, an estimated exposure of zero could lead an analyst to conclude that Lufthansa is a safe holding during oil price spikes, when in fact the result reflects missing data. Analysts using automated data sources should routinely check for missing values, stale prices and misaligned trading calendars, especially when combining securities listed on different exchanges.

6. Conclusion

This thesis set out to measure how crude oil price movements are reflected in the stock returns of Ryanair, Delta Air Lines and Lufthansa, using correlation analysis, multiple regression, scenario-based sensitivity analysis, market betas and elasticity estimates. For the two carriers with reliable data, the different methods give a consistent picture: Ryanair is the most oil-exposed, and Delta is moderately exposed.

Three conclusions follow. First, oil price increases are associated with statistically significant declines in the share prices of Ryanair and Delta, with Ryanair the more exposed of the two. Second, the economic size of this exposure is modest relative to the other drivers of daily airline returns, so airline equities are at best a partial hedge against, or proxy for, oil price risk. Third, differences in exposure across carriers do not align simply with the extent of their financial fuel hedging, which suggests that cost structure, listing market and currency effects also shape how oil shocks are priced. Lufthansa's exposure remains an open question pending corrected data.

6.1 Limitations and Future Research

This study has several limitations. First, the Lufthansa results could not be interpreted because the LHA.DE price series appears to be incomplete; the series should be checked and the analysis re-estimated against a European market index such as the DAX or STOXX Europe 600, with lagged returns included to account for non-synchronous trading. Second, the single-factor elasticity regressions do not control for market returns, so part of the estimated oil exposure may reflect general market risk; an augmented market model that includes both market and oil

returns would separate the two. Third, the multiple regression for Delta leaves most of the variation in returns unexplained ($R^2 = 0.308$, subject to the check noted in Section 4.2), and its residuals are heteroscedastic and fat-tailed, so inference depends on robust standard errors, and a constant-coefficient specification may hide changes in exposure over time.

Future research could extend this work in several directions. GARCH-family, rolling-window or dynamic conditional correlation models would show whether airline oil exposure varies over time, and splitting the sample into pre-COVID-19, COVID-19 and post-2022 sub-periods would reveal whether it changes during crises, as the literature finds for other assets (Karim et al., 2024; Djedaiet et al., 2024). Decomposing oil price changes into supply and demand shocks (Kilian & Park, 2009) would sharpen the economic interpretation of the results. Finally, including additional airlines such as United Airlines and easyJet would strengthen the cross-sectional conclusions, and incorporating the hedge ratios disclosed in annual reports would allow a direct test of whether fuel hedging reduces the oil exposure of airline stocks.

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