A Crude Awakening: Hedging Exposure in the Global Airline Industry✈

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ABSTRACT

The fear of high prices and volatility in the price of jet fuel, provides strong justification for airlines to hedge their risk as a means of migrating their exposure to price fluctuations. We determine the effectiveness of financial and operational hedging among European and U.S. airlines. More specifically, how low-cost carriers and full-service carriers reduce their exposure to jet fuel prices through hedging programs, and how effective they are in reducing stock price volatility, during the period Jan 1, 2011 – Dec 31, 2015. In contrast to Treanor, et al. (2014), we find no evidence that supports the theory that operating a diversified fleet is beneficial in reducing exposure. Rather, our paper is the first to expose a trade-off where operating a uniform fleet provides benefits in terms of cost and is positively related to operational efficiency. Results confirm the effectiveness of financial and operational hedging, where airlines use financial hedging to fine tune exposure, but that operational efficiency in terms of fuel efficiency and seating density is superior in explaining variation in exposure.

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Table of Contents

1. Introduction

The global airline industry has benefited tremendously from plunging crude oil prices and the savings in 2015 alone from lower fuel prices was $70 billion according to rating agency *Moody's* (Flottau, et al., 2015). The contraposition of cheap oil means some airlines are left with billions of dollars in losses from placing losing bets on fuel prices and ineffective fuel hedges. A recent article in *Reuters,*[1] explains that when prices fall faster and further than anyone can anticipate, some of the benefits of cheap fuel is eaten away by hedging costs (Ngai & Dastin, 2014). Airlines without hedging contracts will be the greatest beneficiaries from the fall in prices. Since airlines tend to benchmark their ticket prices against industry peers, any extra profit will most likely not be passed on to consumers (The Economist, 2015; Corones, 2014; IATA, 2015)[2]. What is certain is that the future outlook of oil prices provides one of the most important source of macroeconomic uncertainty facing the airline industry since the financial crisis, and that the substantial drop in oil prices, which in September 2014 dropped from over $100 per barrel to under $30, will produce clear winners and losers.

The fear of high prices and volatility in the price of jet fuel, provides strong justification for airlines to hedge their risk as a means of migrating their exposure to price fluctuations. Analysts and airlines alike seem to disagree on the effectiveness of hedging. Some argue that hedging is neither a core airline activity nor an area of competency, hence a practice that should be avoided. (Airfinance Journal, 2011). Even though there are large difficulties associated with fuel hedging, many airlines continue to practice this strategy. Moreover, to survive in an era of oil trading at 100 dollars per barrel, some airlines have adapted their business by switching focus to managing risk through increasing operational efficiency (Burns, 2012).

It is clear that lower oil prices and therefore lower fuel prices will stimulate airline profit when jet fuel accounts for about one-third of total operating expense, and up to 50% for low-cost carriers. This is important since the price of jet fuel is one of the dominant features in determining industry economics and predicting profitability (Figure 3), and some airlines seem to make more revenue off their hedging programs than from their core business (IATA, 2014; P.A. Laux et al., 2014). Airlines therefore stand to gain significant benefits from pursuing strategies that take advantage of the current low price of jet fuel, whereas not hedging means they are fully exposed to price fluctuations.

Therefore, we examine how airlines use financial and operational hedging strategies to reduce their exposure to the price of jet fuel. More specifically, the effectiveness of hedging

[1] Reuters is a global business and financial news service part of Thomson Reuters.

[2] IATA stands for International Air Transport Association and is the international association for the world's airlines, representing some 260 airlines or 83% of total air traffic. IATA reports airline activity and helps formulate industry policy and standards.

strategies in reducing stock price volatility of European and U.S. airlines during the period Jan 1, 2011 – Dec 31, 2015. We further investigate the strategies of low-cost carriers and if they are superior to full-service carriers in their ability to reduce exposure.

Exposure can be defined as the sensitivity of a firm's stock price to changes of the underlying financial risk, i.e. in this case the price of jet fuel (Jorion, 1990). Exposure to the commodity risk increases when fuel costs represent a large portion of total operating expense, so exposure should vary among airlines and affect basic airline strategies. We will therefore show how levels of exposure to jet fuel varies among European and U.S. airlines, and also reveal how exposure varies between low-cost carriers and full-service carriers. This will allow us to determine the effects of financial and operational hedging.

Several authors have investigated fuel hedging in the airline industry, but most of the research focuses on financial hedging in the U.S. market, and have a time period when oil prices traded around 100 dollars per barrel (Treanor, et al., 2014a; 2014b; Rampini, et al., 2014; Berghöfer & Lucey, 2014; Laux, et al., 2014). Prior research also fails to capture a modern understanding of airline hedging programs, since fleet diversity among airlines today does not reduce exposure to the same extension as other scholars found (Treanor 2014a; 2014b). In addition, most of the research focuses on U.S. airlines in isolation, neglects the impact of decreasing *psychic distance* [3] between Europe and the U.S. and the internationalization behaviour of airlines. Erased geographical borders means airlines compete on an international market, and provide rationale for looking at the aviation industry as a global industry. While some recent authors investigate the difference in exposure of airlines across continents (Berghöfer & Lucey, 2014), but none has to our knowledge considered differences in strategies between low-cost carriers and full-service carriers for the U.S. and European market. Therefore, we believe this paper can provide valuable insights to the area of hedging in the airline industry, and evaluate the impact of modern hedging practices in reducing exposure to jet fuel prices.

In order to achieve a robust measure of exposure, we use a five-year time period that extends over high and low oil prices (Jan 1, 2011 – Dec 13, 2015). We estimate yearly jet fuel exposure coefficients ($\gamma_{i,t}$) for each airline by regressing stock price return against market return and change in the price of jet fuel. A fixed effects regression based on a hand-collected panel dataset is used to estimate the effectiveness of financial and operational hedging. Observed differences between low-cost carriers and full-service airlines are tested for significance. In order to explain differences in level of exposure between low-cost carriers and

[3] The term psychic distance is a term related to international economics, where perceived distance between "home" and "foreign" constitutes as a key determinant for firms expanding into foreign markets, i.e. internationalization. Psychic distance shrinks due to similarities in culture, language, political and legal system and economic situation, and firms tend to enter markets closer to "home". The concept was first proposed by Beckerman (1956) and Linnemann (1966).

full-service carriers we investigate the trade-off in having a diverse fleet contra a uniform fleet, and the relationship between fleet diversity and operational efficiency.

The results of a fixed effects panel regression and difference tests between low-cost carriers and full-service carriers serve as the base for our contributions to research. We expose a trade-off where operating a well-diversified fleet works as diversification, whereas having a uniform fleet is better in terms of cost and is directly related to operational efficiency. Our results are contradictory to previous scholars (Treanor, et al., 2014a; 2014b), since we conclude that fleet diversity for low-cost carriers indicates high operational costs, and is statistically significant on the 1% level. Our results fail to confirm the effectiveness of operational hedging in terms of fleet diversity. These results are similar to findings of Berghöfer & Lucey (2014), but we provide further explanation as to why diversification fails to reduce exposure. According to modern portfolio theory, holding a diversified portfolio will mitigate risk (Markowitz, 1952). Our results show that this is not necessarily applicable to the airline industry. For full-service carriers, operating a well-diversified fleet does not reduce exposure nor does it provide any significant benefits of diversification because operational efficiency is negatively affected by short traveling distance and low seating density. We conclude that airlines with higher exposure hedge less, which confirms the results found by Bartram et al. (2011) who examined the effects of derivatives in a large sample of non-financial firms. Moreover, U.S. airlines are more cautious than European airlines in their use of derivatives and as a result experience higher exposure, as proposed by Bartram et al. (2008). Results also confirm that low-cost carriers have lower exposure compared to full-service carriers because they operate a uniform fleet and have higher seating density on their aircrafts. Finally, we conclude that some difference in level of exposure between the two groups is due to the fact that low-cost carriers operate younger fleets and fly shorter distances.

This paper is organized as follows: We introduce the basic motivation for this study and provide an institutional background in Section 2. The model we are estimating is presented in Section 3. Data and variable selection used to estimate exposure in order to determine effectiveness of financial and operational hedging is explained in Section 4. The final Section 5 presents results from our regression, and we explore variation in exposure between low-cost carriers and full-service carriers. We also expose a trade-off for airlines operating uniform fleets. In the final part of the section, we provide a discussion and lay out implications for future research.

2. Institutional Background

2.1 The Global Airlines Industry: The European and U.S. Market

Focusing on the European and U.S. market is beneficial for four main reasons. There is a low psychic distance from similarities in culture, language, political and legal system and economic situation, which results in comparable financial markets and business practices. Secondly, airlines in both markets compete on related international routes, purchase fuel on the same international spot market and their exposure to commodity risk is both large and easy to identify. Thirdly, the markets have a significant number of low-cost and value strategy airlines, and will allow us to determine if business strategy provides a better explanation than geographical region in determining effectives of operational and financial hedging. Lastly, access to information due to relatively similar reporting requirements simplifies comparison and data analyses.

In mid-2014, oil prices plunged due to a sudden increase in supply, which led to a following decrease in price of crude oil products such as jet fuel (Figure 1). For airlines, the cost of fuel can be as much as 50% of total operating expense, and benefits from lower fuel prices flow directly to the bottom line. This is especially true for low-cost carriers since total operating expense is lower as they are more cost effective than full-service airlines (Figure 2). The extreme case is Ryanair, since they pay lower wages to their staff, operate a uniform fleet, only fly to secondary airports and pass any additional costs on to the paying customer. In contrast, full-service carriers, have higher labor costs as they have an aging staff who have worked for the airline for many years. Full-service carriers are struggling with aging fleets, whereas low-cost carriers have younger fleets since they are relatively new entrants in the airline industry. Therefore, airline fuel costs as percentage of total operating expense is larger for low-cost carriers, than for full-service carriers (Figure 2).

Fuel cost as percentage of total operating expense is directly related to jet fuel prices, hence impact from financial hedging is directly observable when the price of jet fuel falls. Figure 2 and Figure 5 demonstrate the effectiveness of financial and operational hedging in reducing exposure. Since the financial crisis, U.S. airlines have engaged less in financial hedging and are more exposed to price fluctuations than European airlines, and thus benefit more as prices fall. Conversely, European airlines who hedge, have smoother cash outflows, but have fewer benefits from lower fuel prices due to outstanding hedging contracts.

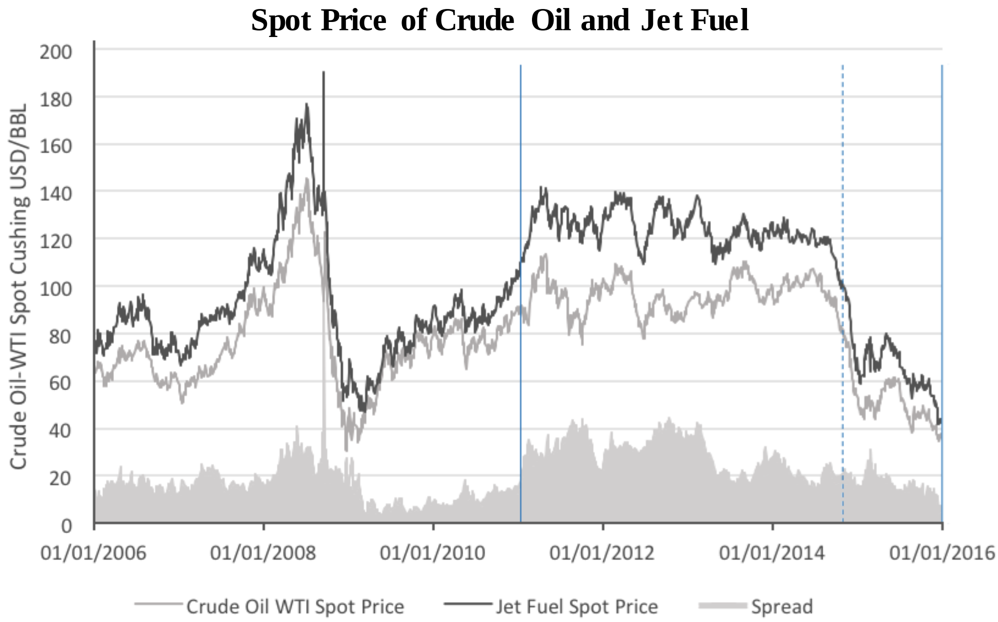

Figure 1: The sample period is denoted by the solid blue lines, where we include a period of expensive oil, Jan 2011 – Sep 2014, and a period of cheap oil, Sep 2014 – Dec 2015. The cut-off price at $90 dollars per barrel is denoted by the dashed line, where cheap oil is defined as any price below the cut-off price, and expensive oil is any price above. The period prior to and following the financial crisis is excluded from our analysis due to volatile economic conditions and irregularities in oil prices. In 2011, the world economy has started to recover from the crisis and oil prices are less volatile. The following period, beginning in mid-2014, oil prices plunged due to a sudden increase in supply with prices falling as low as to $26.68 per barrel in Jan, 2016. However, 2016 is excluded from our sample due to limited access to company data.

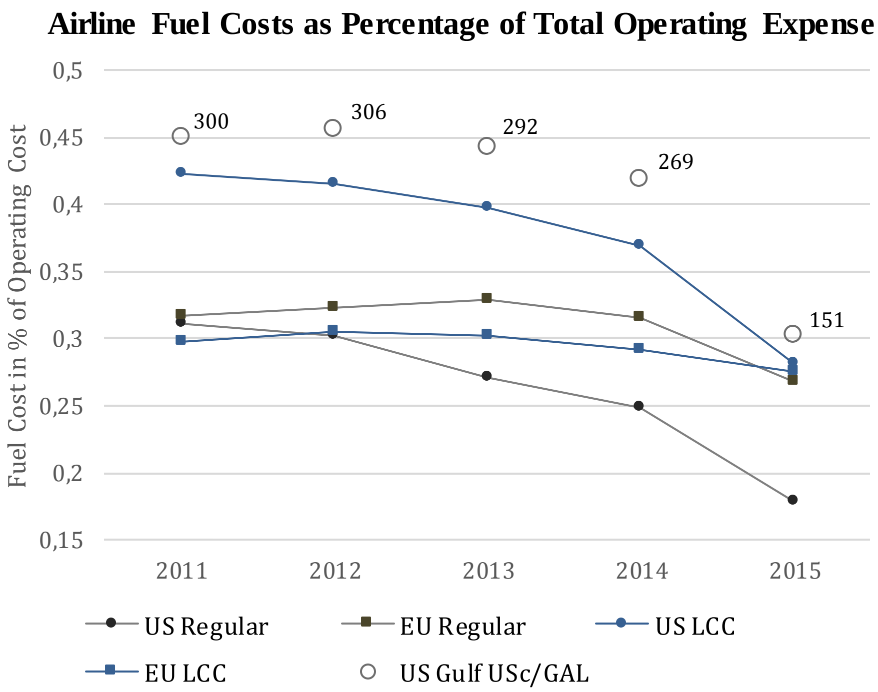

Figure 2: Airline fuel costs as percentage of total operating expense relative to average fuel prices over the sample period Jan 1, 2011 – Dec 31, 2015. Grouped by low-cost carriers and full-service carriers for European and U.S. airlines respectivley. Fuel cost in percentage of total operating expense decreases as fuel prices decline. Jet fuel represents a large portion of total costs for low-cost carriers, and is highest for European low-cost carriers, wheares the portion is half as large for U.S full-service airlines. U.S. airlines hedge less than European airlines, and are thus more exposed to changes in jet fuel prices. Data is collected from annual reports and Datastream.

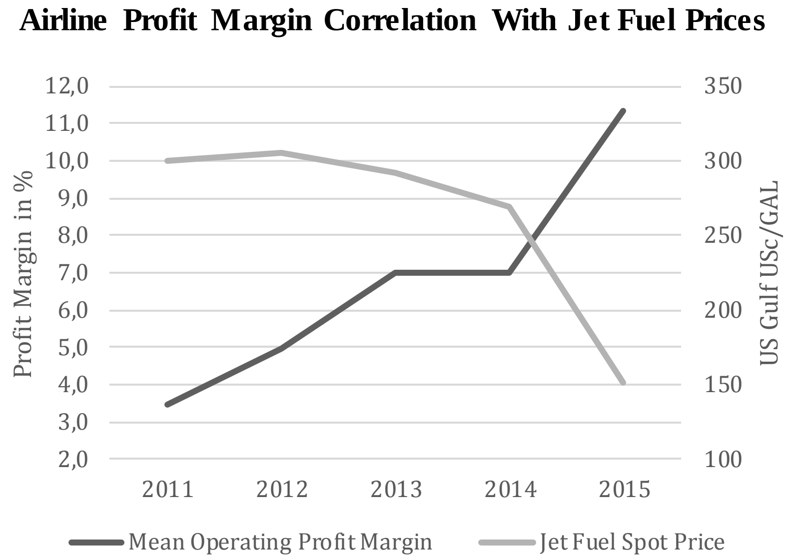

Figure 3: Profit margins of European and U.S. airlines have a negative relationship with change in jet fuel prices. This is important since the price of jet fuel is one of the dominant features in determining industry economics and predicting profitability. Mean operating profit margin in calculated using data from annual reports. Data on jet fuel prices is obtained from Datastream.

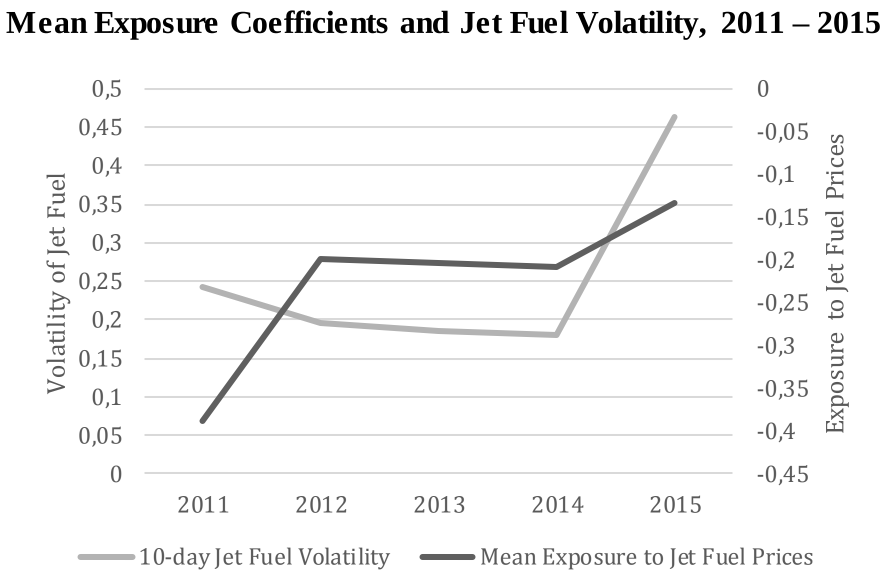

Figure 4: Fuel price exposure is calculated according to Equation (1) using weekly airline stock return, market return, trade-weighted dollar-index and change in jet fuel prices. The 10-day jet fuel volatility is averaged over a 10-day period and calculated from daily returns of U.S Gulf Coast Kerosene-Type Jet Fuel. Data from Datastream, CRSP and MSCI.

The global airline industry has struggled for a long time and was hit hard by first the 'dot.com' bubble, 9/11 and then the financial crisis in 2008 (IATA, 2012). The advent of internet and digital technologies, de-regulation has greatly disrupted the airline industry, produced new capabilities and opportunities, and has increased competition from internet-enabled innovators such as low-cost carriers. This has elicited a shift in industry behavior, where low-cost carriers have obtained a more prominent role and incumbents have been forced to re-think their business models or risk perishing. Low-cost carriers are the clear winners, whereas some incumbents are still struggling to remain buoyant. Intensified competition from low-cost carriers, ineffective cost structures and slim profit margins has increased industry consolidation, and engendered mega-mergers between full-service carriers, in an attempt to take on low-cost carriers.[4] Business travel has decreased drastically over the past 10 years and due to increased competition from low-cost carriers, travel has become cheaper and the average seat price has decreased significantly. Increasing revenue generated per passenger mile is more important than ever in order to stay competitive. When airlines are competing on price, key objectives are focused on reducing average cost per seat mile.

Besides cost management, financial hedging has long been industry praxis. Hedging in the airline industry has changed dramatically over the past 15 years. During periods of high volatility, many airlines achieved mixed results from hedging their exposure to jet fuel, where previously heavily-hedged airlines accrued such big losses that they either diminished or were forced to discontinue their hedging programs entirely. In addition, the spike in oil prices following the financial crisis of 2008 caused some airlines to incur huge losses. This spurred development of alternative risk management strategies aimed towards reducing exposure to fluctuating fuel prices in a nonviolent way. As a result, operational hedging took a more prominent role and caused an unprecedented demand for fuel efficient aircrafts. Low-cost carriers are strong advocates of operational hedging and operate a very homogeneous fleet, whereas full-service carriers tend to operate a more diverse fleet.

In recent years, major airlines in the US have achieved mixed results from hedging their exposure to jet fuel, and many were forced to rethink their hedging programs entirely. Therefore, hedging practices of US airlines tend to be reactive, increasing their hedging programs when fuel prices are low and decreasing their positions as prices rise (Figure 2). European airlines are more proactive and many airlines hedge almost all of their anticipated fuel consumption for the following year, regardless of fuel price trends, which results in less volatile outflows (Figure 2). This is important because as the drop in oil prices today means an airline profitability boost, it also means airlines are just as vulnerable when prices move against them. Therefore, as jet fuel prices fluctuate one should be able to observe the effects of airline hedging programs and determine which factors affect exposure the most. According to theory, airline stock price return and exposure to jet fuel should have a negative relationship to the

[4] In Europe, Air France merged with KLM in 2004, whereas Lufthansa has bought several subsidiaries over the past 10 years, and their ownership includes Austrian Airlines, German Wings (as of 2016, Eurowings) and Swiss International. The British-Spanish multinational airline holding company IAG, founded in 2011, consists of British Airways, low-cost airline Vueling, Iberia and Aer Lingus, as well as subsidiaries to the main operating companies. In the US, American Airlines merged with US Airways in 2013, creating the new holding company American Airline Group.

price of jet fuel, and as the price fluctuates volatility increases (Figure 4). When jet fuel represents a larger portion of total operating expense, as for low-cost carriers, one should expect that exposure should be larger. All things equal, exposure to jet fuel should increase or decrease as jet fuel prices fluctuate, allowing airlines to manage fuel price risk through a hedging program. Low-cost carriers hedge more than full-service carriers and they are successful in reducing exposure to the underlying asset, thus in line with risk management theory. The effectiveness of financial and operational hedging in reducing exposure is displayed in Figure 5.

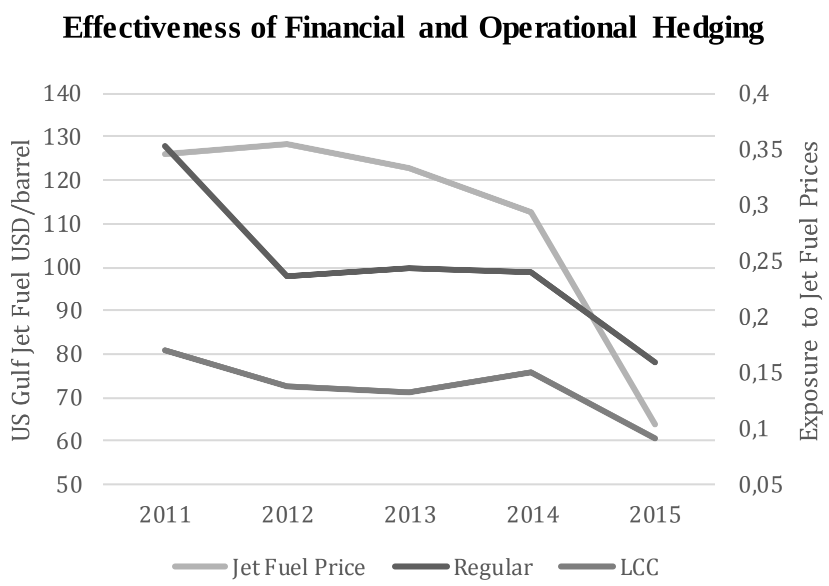

Figure 5: Airline average yearly exposure for low-cost carriers and full-service carriers compared to change in jet fuel. Jet fuel prices calculated using weekly returns of U.S Gulf Coast Kerosene-Type Jet Fuel. Exposure to jet fuel is calculated according to Equation (1). Data from Datastream and CRSP.

2.2 Hedging and the Airline Industry

Hedging is a risk management strategy used to reduce or offset the probability of loss from fluctuations in the price of the underlying asset. The aim of risk management programs is thus to systematically manage such risk exposure, so as to provide protection in the event of unfavourable outcomes and thereby maintain firm value. Financial hedging means investing in financial instruments, usually derivative contracts such as forwards, futures, options and swaps. Hedgers can either do so to avoid risk or engage in pure speculation, according to the government agency CFTC. Others argue that behaviour of hedgers and speculators is best described as a continuum between pure risk avoidance and pure speculation (Working, 1953; Gray, 1960; Hieronymus 1977; Peck 1979). Most non-financial hedgers are essentially speculating on price direction, according to Kaufmann (2010), which Stulz (1996) describes as "taking a view on the market". This indicates information asymmetry and that firms engage in speculation rather than in hedging (Culp and Miller, 1995; Dolde, 1993). In their 10k report Delta (2013) states that, "We actively manage our fuel price risk through a hedging program intended to reduce the financial impact from changes in the price of jet fuel… and rebalance the hedge portfolio from time to time according to market conditions," thus saying that their hedging programs depend on their market view. Several other airlines disclose similar statements in their annual reports, and Ryanair specifically say that they hedge bets on oil prices to take advantage of price movements. If and how derivatives are being used for the purpose of speculation is hard to prove, however the main objective of airlines engaging in financial hedging is to reduce their exposure to jet fuel.

Regardless if the purpose is to reduce exposure or take advantage of price movements, financial hedging used by airlines can essentially take one of two forms: enter forward contracts to buy jet fuel at a pre-determined price for future delivery at a pre-specified date, or place a bet on future prices by selling forward contracts. The outcome is financially the same, and placing the wrong bet on fuel prices can turn gains into losses. For example, many airlines were fully hedged during the successful bull run leading up to the financial crisis in 2008, and when it ultimately crashed into the bear market, ineffective hedges slashed airline profits and put the industry on the verge of bankruptcy. Specifically, Ryanair lost €169 million in 2009, Southwest Airlines had its first loss in 17 years and reported a loss of $120 million in the third quarter of 2008, and American Airlines reported a net loss of $360 million during the same period (The Economist, 2008; Rowling, 2014). Inappropriate risk management programs caused hedging contracts to decline in value due to sliding fuel prices, which in turn led to cuts in fuel-cost hedging among airlines. "The financial crisis was the trigger for airlines to scale back the tenure of their hedges," according to a recent *Bloomberg* article, and many airlines ceased to hedge after prices fell and shifted focus to search for other ways of spreading risk (Rowling, 2014).

In contrast to financial hedging, operational hedging in the airline industry means operating a diverse fleet and fuel efficient aircrafts, and is a way to spread risk without exposing the airline to unfavourable movements in the price of jet fuel. An article in *The Economist* (1996) describes operational hedging as a real option to reduce overall risk exposure and thus provides a better match of costs to revenues. Such operational flexibility allows the airline to respond to unexpected price movements by reducing the overall exposure to jet fuel, but unlike financial hedging, operational hedging does not provide opportunities to make money off highs and lows in the price of oil.

2.3 Incentives to Hedge

Under the assumption of perfect capital markets, hedging activities should not be able to increase firm value (Modigliani & Miller, 1958). According to financial theory, firms should be risk neutral, as individual investors can reduce idiosyncratic risk from a specific investment through diversification. However, market imperfections seem to engender behavior that points to the contrary. There are several reason to why firms can benefit from hedging, where the potential to increase firm value is the most prominent. Based on the Modigliani-Miller theorem, Smith and Stulz (1985) present a framework to demonstrate how hedging can increase firm value by exploring market imperfections. They find evidence that hedging can add value by lowering taxes and reducing costs of financial distress caused by solvency concerns (Gruber and Warner, 1977; Diamond, 1984). These findings are confirmed by Froot et al. (1993), who specifically look at how hedging adds value by reducing volatility of internal cash flows during times of economic downturn. They conclude that hedging improves access to internal funding, which reduces the risk of rejecting attractive investment opportunities due to financial constraint (Lessard, 1990; Pulvino, 1998). Hedging also lowers cash flow volatility and makes future outflows more predictable, hence has the potential to increase firm value. Carter et al. (2006) and Allayannis and Weston (2001), support this theory and show that companies that hedge have statistically significant hedging premiums.

Another reason firms engage in hedging is managerial risk aversion. Managers are presumably more risk averse than the average investor as they have more to lose if the firm fails (Smith and Stulz, 1985) and this creates an incentive for managers to reduce risk exposure through hedging. There is a speculative aspect of hedging, where some airlines engage in financial hedging in order to make a profit and are able to make more money of their hedging programs than their core business (Morrell & Swan, 2006). In conclusion, firms engage in hedging hoping to make cash flows more predictable, reduce risk and potentially increase firm value.

2.4 Does Hedging Reduce Exposure?

Our work does not take aim to evaluate if hedging adds value, but rather to determine the effectiveness of different strategies in reducing exposure. There are several mechanics behind how hedging can reduce risk exposure. For example, financial hedging stabilizes earnings over time by regulating cash outflows in advance. However, since future prices are a function of the underlying spot price, hedging using forwards or futures does not remove the effect of price movements in the underlying asset, but only transfers the effect forward in time. This entails that only sensitivity to short term volatility can be hedged by using derivatives. On the other hand, operational hedging lowers exposure to jet fuel by reducing the overall fuel consumption. Apart from operating more fuel efficient fleet, airlines can also reduce exposure by increasing passenger load factor and seating density[5]. Fitting more people on each plane, translates into increased fuel efficiency as fuel consumption per passenger per mile travelled declines. Recent publications by the ICCT[6] (Kwan & Rutherford, 2014), provide evidence that seating density and load factor can explain about 85% of variation in fuel efficiency among airlines. Friberg (2015) discusses how operational hedging can reduce risk exposure and that real options are key elements in risk management strategies used by airlines.

To test the hypothesis that hedging reduces risk exposure, Jin and Jorion (2006) examined the relation between stock price sensitivity and commodity prices in the oil and gas industry. By comparing exposure with each company's individual hedging strategy, they confirm that a firm's commodity beta is negatively correlated with hedging activities. However, in contrary to previous research, they find no evidence that hedging can increase firm value. The results from Jin and Jorion's article confirm those of Tufano (1996), who conducted a study on risk exposure in the gold mining industry. He examined how the usage of financial derivatives has the potential to decrease exposure to fluctuating commodity prices, and found that strategies vary largely across firms, and that those with higher hedge ratios experience less exposure. Tufano (1998), looked at operational hedging and found that the real option exploited by gold producers, is their ability to hold back on production when commodity prices are low, and finds that operational hedging is just as effective as financial hedging in reducing exposure (Dixit and Pindyck, 1994). Treanor et al. (2014), examines both financial and operational hedging in the U.S. airlines industry, and conclude that airlines use a combination of financial and operational hedging to reduce their exposure to jet fuel prices, but that operational hedging is more efficient, and that financial hedging is of far less economic importance (Petersen and Thiagarajan, 2000). These results are in line with Guay and Kohari's (2003) study of hedging activities in a broad sample of non-financial corporations, who find that financial derivatives reduce risk exposure, but that hedging positions relative to the size of the firm are too small to have any major impact on firm value (Brown, 2001). This implies that financial hedging reduces exposure, but might be of less economic importance compared to operational hedging.

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[5] Passenger load factor (LF) measures capacity utilization of scheduled flights and is reported as the percentage of seats filled of total available seats. It is a common measure used in the airline industry to compare how efficient airlines are in filling seats. Seating density, or average seating configuration, measures aircraft capacity and differs among airlines. For example, low-cost carriers will tend to increase the number of seats on an aircraft, compared to full-service carriers, even though they operate the same aircraft model.

[6] ICCT stands for the International Council on Clean Transportation. The ICCT is an independent non-profit organization, and provide technical and scientific analysis to environmental regulators.

3. Data

3.1 Data Selection

In order to calculate exposure to jet fuel prices for each airline, we use weekly return in U.S. Gulf Coast Kerosene-Type Jet Fuel and weekly stock return for 32 U.S. and European airlines during the period Jan 1, 2011 – Dec, 31 2015. Two indices are used as proxies for the market return; the equally-weighted market index provided by CRSP[7] for the U.S. market, and the MSCI Europe Index (in USD) retrieved from Datastream for the European market. Since oil is quoted in dollars, we include the Trade-Weighted U.S. Dollar Index, obtained from the economic research department of the Federal Reserve Bank of St. Louis, to account for currency exposure faced by European airlines.

We identified 36 airlines using the Sector Industrial Classification (SIC) code 4512, Scheduled Air Transportation, and 4 cargo airlines with SIC 4513, Air Courier Services. The sample was then adjusted to only include U.S. airlines and cargo airlines with active operations during the period Jan 1, 2011 – Dec 31, 2015. Airline and industry specific data such as passengers carried, passenger load factor (LF), available seat miles (ASM) and revenue passenger miles (RPM) for the remaining 16 U.S. airlines was extracted from Compustat[8]. Daily stock returns for each airline and additional firm specific financial data, such as long-term debt to total assets (LTDA), was obtained from CRSP, Compustat or hand-collected from 10-K reports. There is no equivalent to a SIC code for the European airline industry, so the identification process of European airlines was more complicated. First, we limited our data search to only include IATA[9] members and airlines based in Europe, and retrieved an initial list of 384 airlines from the ICAO[10] database. We then matched the airlines with an additional list from IATA of active airlines during the period of Jan 1, 2011 – Dec 31, 2015. The two data samples were then merged in order to retrieve a list of active European airlines during our sample period. In a final step, we manually cross-checked each airline with European stock exchanges and limited our sample to listed airlines. Stock returns and additional firm specific financial data for the remaining 16 European airlines was extracted using Thomson Reuters Datastream. Data that could not be retrieved from Compustat or Datastream was hand-collected

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[7] Centre for Research in Security Prices, Chicago Booth

[8] Airline Industry specific data for cargo airlines are reported as available ton miles (ATM) and revenue ton miles (RTM). Reported in kilometres as ASK and RPK for European airlines.

[9] The International Air Transport Association (IATA) is the trade association for the world's airlines, including 260 active airlines and 83% of the world's total air traffic.

[10] International Civil Aviation Organization (ICAO) is a specialized agency of the United Nations that manage the administration and governance of the Convention on International Civil Aviation.

from each company's annual report or 10-K filing[11]. Fleet size and average fleet age for U.S. and European airlines was retrieved from annual reports, and then matched with IATA's Active Aircraft Database. We adjust fleet size and fleet composition for each airline on a yearly basis, and only include active aircrafts in our sample. Data on fleet composition and each aircraft's individual seating configuration was acquired from IATA and Ch-aviation[12]. Table 1 provides an overview of the final sample of airlines used in our study.

Table 1. Overview of Airline Sample: European based airlines are denoted as EU, and US is the number of American airlines in our sample. Also reported is the number of airlines that hedge some portion of their anticipated fuel consumption for 2 or more consecutive years. Note that an airline is either EU or US, and low-cost carrier or full-service carrier. If an airline has entered a fuel-pass agreement, the airline's fuel cost is locked, and the airline in question is treated as a hedger. This agreement serves as a substitute to hedging for the regional carrier, as any risk exposure is transferred to the mainland carrier.

Variable	**EU**	**US**	**Total**
Low-Cost Carrier	6	5	11
Full-Service Carrier	10	9	19
Air Courier Services		2	2
Total No. of Airlines	16	16	32
Financial Hedging Program > 2 years	16	7	23
Fuel-Pass Agreement		3	3

4. Methodology

4.1 The Empirical Model

To test the hypothesis that airlines use hedging to reduce their exposure to the price of jet fuel, we use a two-stage fixed-effects regression model. First, we estimate each airline's exposure to jet fuel, defined as the sensitivity of firm value to change in the underlying financial risk. Second, we determine the effectiveness of financial and operational hedging in reducing exposure. The first regression is based on the risk exposure formula presented by Jorion (1990), with stock price return being the dependent variable, and the value-weighted market return and change in jet fuel being the independent variables. For European airlines we add the trade-

[11] European airlines disclose available seat kilometres (ASK), revenue passenger kilometres (RPK). For comparative purposes, all data is converted to miles and gallons.
[12] Private airline intelligence provider based in Switzerland.

weighted dollar index to our base case, since jet fuel prices are quoted in dollars. Equation (1) estimates the exposure coefficient for each European and U.S. airline[13].

$$R_{i,t} = \alpha_i + \beta_{i,y} R_{M,t} + \gamma_{i,y} R_{JF,t} + \delta_i R_{USD,t} \cdot EU_i + \varepsilon_{i,t} \quad (1)$$

Where,

$R_{i,t} = daily\ stock\ return\ for\ airline\ i$
$R_{M,t} = return\ for\ the\ corresponding\ value\ weighted\ market\ index\ for\ day\ t$
$\beta_{i,y} = market\ risk\ factor\ for\ airline\ i\ for\ year\ t$
$R_{JF,t} = daily\ percentage\ change\ in\ jet\ fuel\ prices\ for\ day\ t$
$\gamma_{i,y} = coefficient\ representing\ exposure\ to\ jet\ fuel\ for\ airline\ i$
$R_{USD,t} = change\ in\ the\ trade\ weighted\ U.S.\ dollar\ index\ for\ day\ t$
$EU_i = dummy\ variable\ that\ assumes\ value\ 1\ if\ airline\ i\ is\ EU\ and\ 0\ if\ US$

In the second regression, the dependent variable is the absolute value of the estimated jet fuel coefficient ($\gamma_{i,y}$), which represents each airline's yearly exposure to jet fuel prices (Table 4). The independent variables used in the second regression are explained in section 4.2, and are as follows: PERHEDGE is the independent financial hedging variable, ADI and LNAGE are the independent operational hedging variables, and FUELBURN, LNSEATING and LNDIS are the independent fuel efficiency variables. We also include control variables for firm size such as LNTA and LTDA, as well as dummy variables REG, LCC and USEU used for sub-group comparison. The variables are calculated for each airline and averaged annually, i.e. we regress the dependent variable against the independent variables for every airline for each of the five consecutive years over the sample period.[14] Equation (2) estimates how much our chosen variables can explain the variation in exposure as predicted by the coefficients estimated in Equation (1).

$$\begin{aligned} |\gamma_{i,y}| = \alpha_0 + \alpha_1 PERHEDGE_{i,y} + \alpha_2 ADI_{i,y} + \alpha_3 LNAGE_{i,y} + \alpha_4 FUELBURN_{i,y} \\ + \alpha_5 LNSEATING_{i,y} + \alpha_6 LNDIS_{i,y} + \sum_{j=1}^{5} \beta_j Control\,Var_{i,y} + \varepsilon_{i,y} \end{aligned} \quad (2)$$

Where,

$$\sum_{j=1}^{5} \beta_j Control\,Var_{i,y} = \beta_1 LNTA + \beta_2 LTDA + \beta_3 REG + \beta_4 LCC + \beta_5 USEU$$

[13] The trade-weighted U.S. dollar index is only used for European airlines. In the regression, a country dummy is used where $i\epsilon EU = 1$ for European airlines, and otherwise 0.
[14] Treanor et Al. (2014) perform a similar regression based on annually averaged quarterly data. Quarterly data is available for U.S. airlines, but not for European. Due to this limitation, we conduct the calculations for both U.S. and European airlines on annual data for comparable reasons.

4.2 Variable Selection

The hedge ratio is disclosed in the annual report or 10-K filing as, *the percentage hedged of next years estimated fuel consumption*, for which the fuel price has already been locked in. Financial positions generally consist of swaps, calls, forwards and futures, and the most common underlying commodities are crude oil, jet fuel and heating oil. The variable PERHEDGE is included to account for any variation in exposure due to differences in hedging ratios, where 0 means the airline is fully exposed to any change in the price of jet fuel, and 1 means the firm has hedged their entire anticipated fuel consumption for the next 12 months (Table 3).

In the area of operational hedging, Treanor et al. (2014), present evidence that exposure is correlated with fleet diversity, and that firms who operate a diverse fleet are less exposed to jet fuel prices. They argue that fleet diversity, which allows the airlines to choose when to operate the more cost-efficient aircrafts, increases the airline’s ability to react to changing market conditions. To account for fleet diversity, an Aircraft Dispersion Index (ADI) is calculated according to Equation (3) using the Herfindahl-Hirschman Index.

$$\mathrm{ADI_i} = 1 - \sum_{\mathrm{j}=1}^{\mathrm{K}} \frac{(\mathrm{No.\,of\,Aircraft}_j)^2}{(\mathrm{Total\,No.\,of\,Aircraft}_i)^2} \tag{3}$$

Where, K is the total number of different aircraft models that is operated by airline *i*, and No. of Aircraft is the number of aircrafts for each different type of model *j*, and the Total No. of Aircrafts is the total number of aircrafts in the fleet of airline *i*. The ADI is calculated for each airline on a yearly basis and assumes a value between 0 and 1; where 0 implies the airline operates a uniform fleet of only one model, and a high value indicates a more diversified fleet (Table 2).

Another factor affecting level of exposure relates to the average flight length. Different flight routes and various flight lengths in a combination with passenger load factor have an impact on cost structure. For example, short distance flights are generally associated with higher operational costs for airport fees and stand by time, but often have a higher load factor, whereas airlines with long-haul or transatlantic operations have lower passenger load factor and are more exposed to oil prices as fuel becomes a larger portion of their operational expense. To account for the impact of these factors, the natural logarithm of distance ($\mathrm{LNDIS}_{i,y}$) is included, which measures distance traveled per passenger as capacity utilization for airline i for year y, calculated according to Equation (4)[15].

$$LNDIS_{i,y} = ln\left(\frac{passenger\ load\ factor\ \times available\ seat\ miles}{Total\ No.Passengers}\right) \quad (4)$$

Table 2: Summary statistics of ADI for each airline. Calculated according to Equation (3). Value of 0 means the airline only operates one aircraft model, whereas high values indicate a well-diversified fleet. Only active aircrafts, both fully owned and leased, that are used by the airline in question, or operated by its subsidiaries, are included in an airline's operational fleet. An active aircraft is defined as such if it has been active partially or throughout the year in question, whereas an aircraft that is stored is inactive and therefore not part of the operational fleet.

EU - AIRLINE	**2011**	**2012**	**2013**	**2014**	**2015**	**Avg.**
AEGAN AIRLINES	0,58	0,50	0,36	0,41	0,38	0,45
AER LINGUS GROUP	0,43	0,43	0,45	0,53	0,53	0,47
AEROFLOT	0,68	0,70	0,73	0,75	0,78	0,73
AIR BERLIN	0,74	0,76	0,78	0,79	0,79	0,77
AIR FRANCE-KLM	0,87	0,85	0,85	0,85	0,85	0,85
EASYJET	0,37	0,41	0,42	0,45	0,48	0,43
FINNAIR	0,85	0,84	0,81	0,81	0,81	0,82
FLYBE GROUP	0,34	0,45	0,47	0,51	0,53	0,46
ICELANDAIR GROUP	0,00	0,00	0,00	0,00	0,14	0,03
INTL CONSOL AIRLINES GR.	0,79	0,77	0,74	0,72	0,68	0,74
JET2 - DART GROUP	0,51	0,53	0,56	0,63	0,67	0,58
LUFTHANSA GROUP	0,90	0,91	0,90	0,90	0,91	0,90
NORWEGIAN	0,46	0,36	0,26	0,23	0,04	0,27
RYANAIR	0,00	0,00	0,00	0,04	0,02	0,01
SAS	0,51	0,50	0,64	0,63	0,62	0,58
TURKISH AIRLINES	0,76	0,59	0,80	0,79	0,79	0,75
Airline average	0,57	0,55	0,56	0,57	0,56	0,56
US - AIRLINE	**2011**	**2012**	**2013**	**2014**	**2015**	**Avg.**
AIR TRANSPORT SER. GR.	0,00	0,05	0,26	0,25	0,28	0,17
ALASKA AIR GROUP	0,35	0,35	0,33	0,31	0,29	0,33
ALLEGIANT AIR	0,07	0,22	0,40	0,47	0,59	0,35
AMERICAN AIRLINES	0,76	0,76	0,77	0,78	-	0,77
AMERICAN AIRLINES GR.	0,58	0,58	0,63	0,66	0,84	0,66
DELTA AIRLINES	0,84	0,84	0,84	0,85	0,86	0,85
FEDERAL EXPRESS	0,78	0,85	0,84	0,84	0,84	0,83
GREAT LAKES AVIATION	0,31	0,34	0,32	0,32	0,32	0,32
HAWAIIAN AIRLINES	0,59	0,64	0,66	0,64	0,62	0,63
JETBLUE AIRWAYS	0,42	0,42	0,45	0,50	0,54	0,47
REPUBLIC AIRWAYS	0,36	0,51	0,49	0,40	0,32	0,42
SKYWEST	0,23	0,21	0,20	0,27	0,35	0,25
SOUTHWEST AIRLINES	0,45	0,43	0,38	0,33	0,31	0,38
SPIRIT AIRLINES	0,45	0,51	0,53	0,53	0,57	0,52
UNITED CONTINENTAL	0,82	0,81	0,80	0,78	0,77	0,80
VIRGIN AMERICA	-	0,31	0,31	0,31	0,29	0,31
Airline average	0,47	0,49	0,51	0,52	0,52	0,50

[15] Berghöfer & Lucey (2014) used a combination of LNDIS and LF to account for fuel efficiency and average flight length. Since the impact of load factor is included in the variable LNDIS, it is redundant to include LF separately in the analysis.

Both passenger load factor (LF) and available seat mile (ASM) are global performance metrics commonly used in the airline industry. ASM is a measure of an airline's total carrying capacity available to generate revenue, i.e. refers to how many seat miles are actually available for purchase by customers. Revenue passenger miles (RPM), is calculated by multiplying the number of paying passengers by the distance traveled. Dividing RPM with ASM yields the passenger load factor (LF), which is the percentage of ASM that the airline actually sells.[16]

Another important aspect of operational hedging is fuel efficiency as it directly reduces an airlines fuel consumption. Treanor et al. (2014), use fleet age as a proxy for fuel efficiency, and find it to be statistically significant in reducing exposure. However, even if an old aircraft is expected to be less fuel efficient than a new aircraft, fleet age fails to take into account individual aircraft composition in terms of fuel burn rate and seating density. The ICCT[17] identifies aircraft fuel burn and overall seating density as the two major drivers of airline fuel efficiency. Their results show that approximately 80% of variation among carriers can be explained by these two factors. Therefore, to strengthen our model we add two additional proxies for fuel efficiency. Differences in aircraft fuel burn rate (FUELBURN) and seating configuration (LNSEATING) are estimated according to Equation (5.1) and Equation (5.2) respectively.

$$FUELBURN^{avg}{}_{i,y} = \sum_{j=1}^{K} RL_j - \left(MV_j \times \frac{No.of\ Aircraft_j}{Total\ No.of\ Aircrafts\ in\ fleet_j} \right) \tag{5.1}$$

$$LNSEATING = \ln\left(\frac{No.of\ seats\ on\ aircraft_j}{eRGF[m^2]} \right) \tag{5.2}$$

Where, $FUELBURN_{i,y}$ for airline i for year y is the metric value (MV)[18] to a reference line (RL), weighted by its corresponding fraction of the airline's fleet, where MV_j is the MV for aircraft model j as calculated by Equation (5.3), and k is the number of different aircraft models. MV is a function of an aircraft's specific air range (SAR)[19], which is the distance per unit fuel

[16] For example, an airplane with 100 passengers that flies 250 miles has generated 25,000 RPMs and if the airline has a fleet of 100 aircrafts with the same capacity, total RPM of the airline is 2,500,000. If total ASM is 3,000,000, then the airline has a LF of 83,33%

[17] The International Council on Clean Transportation (ICCT) is an independent nonprofit organization that provides analysis to environmental regulators and regularly publish studies and reports on airline fuel efficiency.

[18] Metric value (MV) is used as a proxy for aircraft fuel burn, as developed by ICAO

[19] Value collected from from Piano 5, a statistical program for aviation purposes that can process, rank and plot an entire aircraft database automatically. It includes a code extension to calculate values of ICAO's metric for aviation CO2 emissions. The maximum SAR is calculated using Piano 5 for each aircraft type at three postulated weights (High, Mid, Low). Piano selects the optimum combination of

burned, and an aircraft's reference geometric factor (RGF), a close proxy for the pressurized floor area of the aircraft in an attempt to quantify cabin size, as seen in Equation (5.4).

$$MV_j = \frac{\left(\frac{1}{SAR}\right)_{avg}}{RGF^{0.24}} \tag{5.3}$$

$$RGF = eRGF[m^2] = fuselage\ width \times cabin\ length \tag{5.4}$$

The reference line is calculated by plotting MV_j against $MTOW_j$, for each aircraft model operated by the airlines in our sample, where MTOW is an indicator of aircraft size and assigned by the aircraft producer. This means that even if you alter the number of seats in an aircraft, the maximum MTOW does not change as the maximum load of any aircraft is constant. We use a similar technique to that proposed by ICCT where the reference line is a combination of two separate ones, allowing us to control for smaller aircrafts with MTOW's below 55 tons (Figure 6, Appendix). To conclude, FUELBURN in percentage relative to average will be used as a proxy for aircraft fuel burn in combination with overall seating density (LNSEATING) and the capacity utilization variable LNDIS. This will allow us to control for several operational factors that affect an airline's average fuel efficiency.

Previous research has also shown that hedging is related to firm size and financial leverage. For example, Haushalter (2000) conclude that larger firms are more prone to hedge than smaller firms, as they have a cost advantage in managing hedging programs. Haushalter also showed that firms with high financial leverage, and thereby greater exposure to financial risk, tend to engage more in hedging. Similar results are presented by Geczy, et al. (1997), who find that firms in financial distress are more likely to use currency derivatives to reduce the volatility in their cash flow. However, these results were complemented by Carter et al. (2006), who found that firms in financial distress hedge less, as high debt-ratios often limit a firm's ability to hedge. Therefore, to control for the potential effect of firm size and leverage, LNTA, the natural logarithm of total assets, and LTDA, long term debt over assets, are included. Natural logarithms are preferable since they can be interpreted as approximate proportional differences.

We use a dummy variable to control for geographical location (USEU), separating airlines based in North America and Europe, in order to explain variation in exposure among airlines. We also include a dummy variable for regional carriers (REG), where North America

Mach number and altitude that maximizes SAR, at a 99% confidence interval according to the following equations:

$High\ Gross\ Weight\ (HGW) = 0.92 \times MTOW$

$Mid\ GW = avg(HGW + LGW)$

$Low\ GW = 0.45 \times MTOW + 0.63 \times MTOW^{0.924}$

and Europe are considered two separate regions and airlines only operating within one region is considered a regional carrier. These firms have the possibility to enter into fuel pass-through agreements with larger mainland carriers. In compensation for agreeing to serve local routes for the mainland carrier, the regional carrier receives fuel at a pre-specified price. This agreement serves as a substitute to hedging for the regional carrier, as any risk exposure is transferred to the mainland carrier. Therefore, carriers with fuel-pass agreements are considered as full-hedgers. Information regarding fuel passes are disclosed in an airline's annual report or 10-K filing. Low-cost carriers have different cost structure than full-service carriers, and can only affect certain parts of their operational expense, such as wages or stand by time between flights, since jet fuel is traded on a global market at global spot prices. Therefore, fuel cost for low-cost carriers represents a larger portion of their total operating expense. To account for the potential variation between low-cost carriers and full-service carriers, the dummy variable LCC is included. Summary statistics of variables used in the regression are presented in Table 3.

Table 3: Summary statistics of key variables.

Variable	Mean	Std. Dev.	Min	Max
Total Assets in $ m.	12033	14523	510	54121
Long Term Debt over Assets	0.26	0.14	0.00	0.60
Average Fleet Age	9.77	4.85	2.00	22.88
Number of Aircraft Models, k	5.49	3.75	1.00	18.00
Total Fleet Size	226	216	22	928
ADI (aircraft dispersion index)	0.54	0.26	0.00	0.91
PERHEDGE (% hedged of next years estimated fuel consumption)	0.41	0.31	0.00	1.00
LNDIS (distance, measured as LF x ASM)	6.93	0.41	6.00	7.77
FUELBURN (fuel burn rate in % relative to average)	0.09	0.06	-0.11	0.16
LNSEATING (seating density)	0.33	0.14	0.11	0.59

5. Results

Table 4 reports yearly jet fuel exposure coefficients for each airline in the sample period, estimated from Equation (1). This results in 7614 weekly observations, generating 151 unique beta values, of which six are omitted due to insufficient observations. Of the remaining 145 observations, 80% have negative exposure to price fluctuations in jet fuel, and exposure varies among years; 64% of airlines have negative exposure in 2013, in 2015 the proportion was 93%. The average exposure for the entire sample is -0.24, or -0.20 if adjusted for outliers, which implies that a 1% movement in the price of jet fuel has an impact on the average airline stock by 0.24% (0.20%). The observed fall in annual average beta value, presented at the bottom of

Table 4, implies an overall decline in exposure as a function of time, and seems to correlate with a corresponding decline in oil prices (Figure 1). In comparison to our findings, Treanor et al. (2014), and Berghöfer and Lucey (2014), both observe a lower mean exposure of -0.13, and that 72% and 68% respectively of the firms in their samples on average were negatively exposed to jet fuel prices. The higher percentage of airlines with negative exposure in our sample is most likely a result from a combination of volatile and peaking oil prices and airlines tightening their hedging programs after the financial crisis.

Table 4: Estimated jet fuel exposure coefficients ($\gamma_{i,y}$). Annual exposure to change in the U.S. Gulf Coast Kerosene-Type Jet Fuel is calculated using weekly returns in the price of jet fuel and weekly stock returns. The exposure coefficient $(\gamma_{i,y})$ is estimated using Equation (1): $R_{i,t} = \alpha_i + \beta_{i,y} R_{M,t} + \gamma_{i,y} R_{JF,t} + \varepsilon_{i,t} + \delta_i R_{USD,t} \cdot EU_i + \varepsilon_{i,y}$. Average exposure for years 2011 – 2015 is presented for each airline along with the average exposure for all firms on an annual basis. The annual exposure adjusted for outliers is also presented. The column Strategy reports if an airline is a low-cost carrier (LCC), regional carrier (REG) or Cargo carrier.

AIRLINE	Strategy		2011	2012	2013	2014	2015	Avg.
AEGAN AIRLINES			-0.34	-0.01	-0.36	0.02	-0.02	-0.14
AER LINGUS GROUP			-0.51	-0.09	0.16	-0.93	-0.27	-0.33
AEROFLOT			0.02	0.15	0.24	-0.37	-0.20	-0.03
AIR BERLIN	LCC		0.01	0.17	-0.66	-0.16	-0.07	-0.14
AIR FRANCE-KLM			-0.47	-0.66	-0.24	-0.09	-0.28	-0.35
AIR TRANSPORT SER. GR.	Cargo		0.05	-0.19	-0.41	-0.19	0.15	-0.12
ALASKA AIRGROUP		REG	-0.54	-0.24	-0.34	-0.04	-0.23	-0.28
ALLEGIANT TRAVEL CO	LCC		-0.48	-0.31	-0.03	-0.04	-0.12	-0.20
AMERICAN AIRLINES GR.						-0.19	-0.25	-0.22
DELTA AIR LINES			-0.72	-0.43	-0.40	-0.16	-0.12	-0.37
EASYJET	LCC	REG	-0.56	-0.26	0.14	-0.15	-0.08	-0.18
FEDERAL EXPRESS	Cargo		-0.49	-0.02	0.10	-0.06	-0.03	-0.10
FINNAIR			-0.07	0.32	0.18	-0.22	-0.24	0.00
FLYBE GROUP	LCC		0.70	0.03	0.08	-0.29	0.06	0.11
HAWAIIAN AIRLINES			-0.67	-0.59	-0.54	-0.49	-0.38	-0.53
ICELANDAIR GROUP			-0.14	0.13	0.04	-0.20	-0.15	-0.06
INTL CONSOL AIR. GR.			-0.81	-0.34	-0.23	-0.23	-0.20	-0.36
JET2 - DART GROUP	LCC		0.13	0.10	0.53	-0.15	-0.09	0.11
JETBLUE AIRWAYS	LCC	REG	-0.86	-0.63	-0.52	-0.34	0.05	-0.46
LUFTHANSA GROUP			-0.44	-0.41	-0.24	-0.43	-0.23	-0.35
NORWEGIAN	LCC		-0.31	0.28	0.06	-0.27	-0.08	-0.06
REPUBLIC AIRWAYS			-0.21	0.25	-0.23	-0.12	-0.06	-0.07
RYANAIR	LCC	REG	-0.34	-0.08	0.08	-0.17	-0.11	-0.12
SAS			-0.16	-0.23	-0.13	-0.17	-0.21	-0.18
SKYWEST		REG	-0.12	-0.33	-0.57	-0.23	-0.10	-0.27
SOUTHWEST AIRLINES	LCC	REG	-0.57	-0.44	-0.33	-0.09	-0.20	-0.33
SPIRIT AIRLINES	LCC	REG	0.60	-0.23	-0.68	0.16	-0.16	-0.06
TURKISH AIRLINES			-0.41	-0.26	-0.78	-0.26	-0.03	-0.35
UNITED CONTINENTAL			-1.10	-0.48	-0.62	-0.20	-0.17	-0.51
US AIRWAYS GROUP			-1.36	-0.95				-1.16
VIRGIN AMERICA	LCC						-0.20	-0.20
Total			-0.35	-0.20	-0.20	-0.21	-0.13	-0.24
Adjusted for outliers (4 obs. removed)			-0.29	-0.17	-0.20	-0.18	-0.13	-0.20

Regression results are reported in Table 5, which displays the direct relationship between exposure to jet fuel prices and the effectiveness of operational and financial hedging. Coefficients are estimated from Equation (2) using panel data regression with fixed effects, as suggested by the results from a Hausman's test (Table 8, Appendix**).** Robust standard errors are used to adjust for heteroscedasticity within the sample, caused by seasonal variability between years. The absolute value of each airline's jet fuel exposure coefficient is regressed against selected variables using a fixed effect model, as defined in Section 4. The result from the full model is presented in Model 2, while Model 1 is without robust standard errors. The altered models, Model 3 and Model 4, present relative effects between different fuel efficiency variables. Model 3 excludes the variables fleet age (LNAGE) and fleet diversity (ADI) to determine the effect of fuel efficiency, defined as fuel burn (FUELBURN) and seating density (LNSEATING), estimated according to Equation (5.1) and Equation (5.2). The variables are proposed by the ICCT to explain most of the variation in fuel efficiency among airlines, but our results only confirm FUELBURN to be statistically significant at the 5% level. Long term debt to asset (LTDA) is excluded from Model 3, as it holds no explanatory value when testing for fuel efficiency. Model 4 replaces fuel burn and seating density with fleet age as a proxy for fuel efficiency, which increases explanatory value of LNTA, but does not prove to be a superior proxy for fuel efficiency than fuel burn. Model 5 presents a standardized OLS regression and is included for comparative reasons only.

The results displayed in Table 5 identifies three key variables that strengthen the explanatory value of the model: firm size, hedge ratio and fuel efficiency. The estimated coefficient for firm size (LNTA) is negative (-0.313), and statistically significant at the 5% level, suggesting that larger firms face less exposure than smaller firms. This result is in line with the finding of Haushalter (2000), who concluded that larger firms hedge more since they have an advantage in financing their hedging programs. In contrast, Treanor et al. (2014), find no relation between firm size and exposure, while Berghöfer and Lucey (2014) find size to be negatively correlated (-0.066) and statistically significant at the 5% level. The estimated coefficient for financial hedging (PERHEDGDE), or simply the hedge ratio, is positive (0.332) and statistically significant at the 1% level. This implies that financial hedging increases exposure, which is opposite to what is expected as hedging programs are used to reduce price volatility in the underlying asset. Our results are contradictory to previous research, which in most cases confirm that financial hedging is successful in reducing exposure. Treanor et al. (2014) find the coefficient for the hedge ratio to be negative and statistically significant at the 1% level, whereas Berghöfer and Lucey (2014) find the coefficient to be positive but not statistically significant.

We also conduct the regression on European and U.S. airlines separately, as well as for Low-cost carriers and full-service carriers, and reach the same conclusion that financial hedging does not reduce exposure. There are several reasons for why our results differ from previous research. First, there is variation in the airlines analyzed and our sample period. Most other research focuses on U.S. airlines, where larger airlines engage in hedging, whereas smaller airlines compensate financial hedging with fuel-pass agreements. Our results confirm that size is successful in reducing exposure, and when airlines with high LNTA also hedge more, collinearity between the variables might eliminate some of the effect from financial hedging, also emphasized by Berghöfer and Lucey (2014). However, LNTA and PERHEDGE has a correlation value of 0.015, which is the lowest among our variables. Second, our results could also differ from previous research due to a different sample period since we include a time period where prices are less volatile, but that captures a sudden drop in prices. There are two reasons to why the hedge ratio coefficient could be positive, either financial derivatives are used in excess by firms facing higher exposure or because derivatives are used to a greater extent during times of high fuel prices. Excess use of financial hedging in times of high fuel prices will appear in the results as if financial hedging would increase exposure, due to the positive correlation between exposure and oil prices. In our sample, the coefficient for the hedge ratio is negative during the period of low fuel prices in 2014 and 2015. Consequently, this would indicate that airlines primarily use financial hedging to fine tune their jet fuel exposure in accordance with fluctuating oil prices. Lastly, the estimated coefficient for fuel efficiency (FUELBURN) is negative (-3.864), and statistically significant at the 10% level in Model 2 and at the 5% level in revised Model 3. This indicates that exposure to jet fuel prices can be reduced by improving fuel efficiency, and this result is to be expected as lower fuel consumption means lower exposure. It is also in line with the findings of Treanor et al (2014), who use fleet age as a proxy for fuel efficiency, instead of fuel burn, and find it to be statistically significant at the 1% level. Model 4 confirms that fleet age can be used as a proxy for fuel efficiency, as the estimated coefficient for fleet age (LNAGE) is negative (-0.185) and statistically significant at the 5% level, and implies that older aircrafts are less fuel-efficient. However, fleet age adds less explanatory value to the model than the fuel efficiency variables used by the ICCT, as fleet age neglects to take into account configuration of individual aircrafts. Moreover, our results fail to confirm the findings of Treanor et al. (2014), since we find no indication that estimated coefficients for fleet diversity (ADI) reduce exposure. Rather, we find the coefficient to be positive (0.220), but not statistically significant. This is similar to the results of Berghöfer and Lucey (2014), who find ADI to be positive (0.351), but statistically significant at the 10% level. All things equal, our results suggest that a more diverse fleet can lead to higher exposure, and that ADI as an operational hedging strategy is ineffective in reducing exposure.

Table 5: The Effectiveness of Operational and Financial Hedging. The table presents the relation between exposure to jet fuel and operational and financial hedging. Coefficients are estimated using fixed effects regression using Equation (2): $|\gamma_{i,y}| = \alpha_0 + \alpha_1 PERHEDGE_{i,y} + \alpha_2 ADI_{i,y} + \alpha_3 LNAGE_{i,y} + \alpha_4 LNFUELE_{i,y} + \alpha_5 LNDIS_{i,y} + \sum_{j=1}^{5} \beta_j Control\ Var_{i,y} + \varepsilon_{i,y}$. Model 1 and Model 2 include all variables used in the final model, where Model 1 is presented without robust standard errors. Model 3 excludes ADI and LNAGE to estimate the effectiveness of FUELE (FUELBURN + LNSEATING) as a measure of fuel efficiency. LTDA is excluded, as it holds no explanatory value. Model 4 excludes ADI, FUELBURN and LNSEATING to estimate the effectiveness of LNAGE as measure of fuel efficiency. OLS regression including all variables is added for comparative reasons.

	Model 1 Fixed effect	Model 2 Fixed effect, robust	Model 3 Fixed effect, robust	Model 4 Fixed effect, robust	Model 5 OLS
LNTA	-0.313**	-0.313**	-0.278**	-0.395***	0.009
	(0.121)	(0.144)	(0.127)	(0.117)	(0.016)
LTDA	0.452	0.452		0.272	-0.065
	(0.373)	(0.418)		(0.379)	(0.158)
LNAGE	-0.111	-0.111		-0.185**	-0.094*
	(0.141)	(0.088)		(0.086)	(0.056)
ADI	0.220	0.220			0.178**
	(0.300)	(0.272)			(0.078)
PERHEDGE	0.332**	0.332***	0.306***	0.331***	0.034
	(0.157)	(0.119)	(0.106)	(0.113)	(0.057)
LNDIS	0.105	0.105	0.108	0.247	0.102**
	(0.266)	(0.334)	(0.332)	(0.333)	(0.051)
FUELBURN	-3.864**	-3.864*	-3.558**		-0.797
	(1.782)	(1.970)	(1.636)		(0.564)
LNSEATING	0.005	0.004	-0.078		0.134
	(0.630)	(0.593)	(0.652)		(0.140)
Constant	2.456	2.456	2.143	2.172	-0.357
	(1.844)	(2.021)	(2.053)	(2.065)	(0.362)
Prob > F	0.0072	0.0027	0.0002	0.0010	0.0798
Observations / Firm years	128	128	128	135	128
Number of groups	28	28	28	30	28
R-squared	0.4874	0.4874	0.4654	0.5910	0.0824
R-squared, within	0.198	0.198	0.156	0.158	

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Due to concerns regarding correlation between the independent variables, which can give rise to problems with multicollinearity, a collinearity diagnostic test is conducted, as suggested by Belsley et al. (1980) (Table 9, Appendix). Results show limited dependency between variables, except for fleet age (LNAGE) and distance travelled per passenger (LNDIS). To further determine the degree of the problem, a simple correlation test is conducted in Stata. The results are presented in Table 10 (see Appendix), and confirm that fleet age appears to have some correlation with the variable for fuel burn, which is to be expected as both variables are proxies for fuel efficiency. The variable for distance travelled per passenger shows signs of correlation with several other variables, but is of less concern as it does not add to the explanatory value of the regression model. Overall correlation between independent variables is low, hence concerns for correlation within the sample can be discarded. Based on these results, we conclude that the model holds, but exhibits some signs of multicollinearity. However, the limitations are redundant as they have no effect on explanatory value.

To explore how business strategy effects the level of exposure, airlines are grouped into sub-groups conditional on operational strategy, i.e. low-cost carrier or full-service, and geographical location. Table 6 reports difference in level of exposure between low-cost carriers and full-service carriers, as well as variation between European and U.S. airlines. The average exposure coefficient for low-cost carriers and full-service carriers differs by 51% and is -0.135 and -0.264 respectively. To test if the difference is statistically significant, we conduct a chi-squared test on the estimated exposure coefficient, obtained using Equation (1), grouped by low-cost carriers and full-service (Table 11, Appendix). We reject the null-hypothesis that the mean exposure for low-cost carriers is the same for full-service carriers (Prob > chi2 = 0.0007), and results suggest that the operational strategy implemented by low-cost carriers is substantially superior in reducing exposure to jet fuel prices. Table 6 also reports the difference in exposure and hedge ratios between European and U.S. airlines. European airlines have an average exposure of -0.05 for low-cost carriers and -0.22 for full-service carriers, and U.S. airlines have an average exposure of -0.26 and -0.33. Results show that European airlines are considerably less exposed to jet fuel prices than U.S. airlines, and that there is a substantial difference in hedging ratios. On average, European airlines have a hedge ratio of 68% for low-cost carriers and 53% for full-service carriers, while corresponding numbers for U.S. airlines are 14% and 17%. In other words, European airlines use more financial hedging and as a result face lower exposure. This contradicts some of the results from the regression (Table 5**)**, which indicated that hedging would increase exposure, and findings are more in line with previous research (Jin & Jorion, 2006).

Results from Table 12 (see Appendix) show differences in mean values between European and U.S. airlines, and the differences in both hedge ratio and fuel efficiency are statistically significant at the 1% level, and the difference in exposure is significant at the 10% level. Similar results are presented by Berghöfer and Lucey (2014). Table 7 provides an understanding for how low-cost carriers and full-service carriers differ in their strategies, where low-cost carriers on average operate younger and more uniform fleets with higher seating density, and fly shorter distances per passenger. All four variables are statistically significant at the 1% level, and we conclude that the variables indeed can explain the variation in exposure between low-cost carriers and full-service carriers. The results clearly show that low-cost carriers are superior in reducing their exposure to jet fuel. Most noticeable is the 43.8%

difference in the ADI and the 82.8% difference in LNSEATING, suggesting that fleet configuration has a major impact on exposure.

Table 6: Difference in Exposure between LCC and Full-Service Carriers. Difference in mean value of the exposure coefficient between LCCs and full-service carriers, including geographical separation between EU and U.S. Results reveal the exposure coefficient on average is 51% lower for LCCs than for full-service carriers, indicating that the strategy implemented by LCCs significantly reduce exposure. The results also reveal that the exposure coefficient is lower for European airlines than for airlines in the U.S., and that European airlines has a substantially higher hedge ratio. This result implies a relation between financial hedging and low exposure.

		Exposure to jet fuel				Financial Hedging	
GROUP	**Country**	**Mean**	**Std. Dev.**	**Min**	**Max**	**Airlines hedging**	**Hedge Ratio**
LCC	Total	-0.13	0.31	-0.86	0.70	91%	44%
Full-service		-0.26	0.29	-1.36	0.32	86%	39%
LCC	EU	-0.05	0.27	-0.66	0.70	100%	68%
	US	-0.26	0.32	-0.86	0.60	80%	14%
Full-service	EU	-0.22	0.25	-0.93	0.32	91%	53%
	US	-0.33	0.33	-1.36	0.25	73%	17%

Table 7: Difference in Mean Values of Variables between LCCs and Full-Service Carriers. T-test for statistical significance in differences between mean values of variables for LCCs and full-service carriers. Data is hand-collected on a yearly basis from annual reports. Information regarding fuel burn rate is obtained from aircraft manufactures and Piano5. Seating density of each aircraft is obtained from Ch-aviation. The table illustrate how strategy differs between LCCs and full-service carriers. LCCs operate younger and more uniform fleets, as confirmed by the difference in mean values between fleet age (LNAGE) and fleet diversity (ADI). LCCs also fly shorter distances (LNDIS) and have higher seating density (LNSEATING) than full-service carriers.

Variables	LCC	Full-Service	Difference
LNTA	8.126	8.817	-0.691**
			(0.233)
LTDA	0.235	0.277	0.042
			(0.025)
LNAGE	1.995	2.248	-0.253**
			(0.089)
ADI	0.417	0.598	-0.181***
			(0.043)
PERHEDGE	0.438	0.523	-0.085
			(0.058)
LNDIS	6.749	7.051	-0.302***
			(0.076)
FUELBURN	0.091	0.105	0.013
			(0.009)
LNSEATING	0.469	0.254	0.213***
			(0.017)

Standard errors in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Table 13 (see Appendix) reports the difference in operational efficiency between low-cost carriers and full-service carriers. Operational efficiency is defined as high if fuel costs represent a large portion of total operating expense. Results suggest that fleet diversity (ADI) is directly related to high operational costs for low-cost carriers, and that operational efficiency for full-service carriers is negatively affected by short flights and low seating density. The coefficients are estimated by regressing the dependent variable, fuel cost as percentage of total operating expense, against the four independent variables, identified from the t-test in Table 7. The result from the regression show that operational efficiency for low-cost carriers increases with a lower ADI, indicating that operating a diverse fleet means higher operational costs, hence the trade-off of having a uniform fleet is better in terms of cost. This is in line with the results of Berghöfer and Lucey (2014), who also show that increased fleet diversity entails higher expense for maintenance and crew. For full-service carriers, operational efficiency seems to improve as the travel distance increases in combination with higher seating density on aircrafts.

6. Discussion

The oversupplied oil market in the years of 2014 and 2015 has precipitated the dramatic fall in the price of jet fuel, and the benefits from lower prices has flown directly to the bottom line of airlines. Hedging has become an increasingly important instrument in the risk management toolbox of airlines, but the quantity of research conducted on the subject is still limited. This article examines the effects of both financial and operational hedging in the airline industry, and aims to complement the findings of Treanor et al. (2014), and Berghöfer and Lucey (2014). We look at a different time period than previous scholars, in order to determine the effectiveness of hedging in a modern airline industry, which is characterized by consolidating full-service carriers and thriving low-cost carriers, and now under the presence of plunging oil prices. We also focus our research on operational hedging in terms of operational efficiency, and our findings present both supporting and contradictive results to previous research.

The airline industry offers ideal conditions to analyse the effects of hedging, as it has a concentrated risk exposure aimed towards a single commodity: jet fuel. We find evidence that suggests that level of exposure is correlated with commodity prices, and that airlines face less exposure during periods of low oil prices. Airlines adjust their hedge ratio in accordance to current spot prices, and trade less with derivatives when fuel prices are low. This implies that financial hedging is used to fine tune exposure to current market conditions, making it more short term in perspective compared to operational hedging. In other words, financial derivatives are used by airlines to offset changes in exposure caused by movements in commodity prices. We further find that fuel efficiency is an important instrument for airlines in reducing exposure to jet fuel prices. Both of these findings are in line with the results presented by Treanor et al

(2014). However, in contrast to Treanor et al. (2014) we find no evidence that fleet diversity reduces exposure. Our results indicate that operating a diverse fleet reduces efficiency, and thereby increases exposure. These results support the findings presented by Berghöfer and Lucey (2014), and is most likely due to the increase in maintenance and crew cost combined with operating several different aircraft models.

We also look at discrepancies between airlines grouped by different strategies and geographical location, and find a significant difference in the exposure between low-cost carriers and full-service carriers. Our results show that low-cost carriers on average have a 51% lower exposure coefficient than full-service carriers, and that this superiority can be explained by operating a uniform fleet with high seating density. We find no difference in the hedge ratio, suggesting that operational efficiency could be more important in reducing exposure than previously believed. This supports the proposition by Treanor et al. (2014), that the economic value created by operational hedging is greater than that of financial hedging. However, even if this holds true, financial hedging is still a profound practice for reducing exposure in the short term.

One of the main findings suggested by Treanor et al. (2014) is the impact from fleet diversity in reducing exposure and has the potential to increase economic value. This is interesting, since neither Berghöfer & Lucey (2014), nor our results, provide any evidence to support this claim. Treanor et al. (2014) had a sample period of 1994 to 2008, which is a period not influenced by low-cost carriers. However, the mean value and standard deviation in the ADI between our two samples is almost identical, suggesting that fleet composition of airlines has not particularly changed over time. There is no clear answer to why this discrepancy is apparent, which suggest that certain aspects are not accounted for. For example, Ryanair only operates one type of aircraft and maintain one of the youngest fleets in our sample. This approach has reduced their cost for training pilots, cabin crews and mechanics, but it has also reduced maintenance and fuel expense since their fleet is relatively new. In effect, having a low ADI has allowed them to both increase efficiency and reduce exposure. However, this strategy does not come without a cost, as it gives them a disadvantage on certain routes, as their fleet is not optimized for all distances. This serves as the base of the trade-off we expose, where the benefits from operating a uniform fleet outweighs the benefits from flexibility in operating a diversified fleet.

Financial hedging entails higher risk, but high return, and can be beneficial in the short run. However, most of the losses from hedging in the airlines industry is due to ineffective financial hedges. Operational hedging is less risky, but comes at a higher cost and does not provide the same short-term economic benefits as financial hedging. In the long run, operational efficiency is superior in reducing exposure, but airlines can still stand to benefit from placing "right bets" on oil prices. The implications from our analysis would be that full-service carriers should have a clear separation of long-haul and short-haul with a focus in reducing operational risk. For low-cost carriers, effective hedging programs seem to be essential in combination with operational efficiency.

For future research one would like to extend the study to determine if our results have an implication on the valuation of airlines. This could be accomplished by looking at changes in stock price valuation. Preliminary analyses show that low-cost carriers in our sample may have outperformed full-service carriers, since they have an excess return of 3.5% compared to 2.5%. This would suggest that the hedging strategies of low-cost carriers are more effective. We would also recommend a more complete exploration of the trade-off between the benefit from having a diversified fleet, and the cost advantage of having a uniform fleet. Such a study should would provide valuable insight for airline managers faced with difficult choices that will have profound long-term implications on competitive outcomes. Rethinking operational strategies might serve as a stepping stone to revised thinking in managing risk and uncertainty in the modern global airline industry.

Conclusion

Airlines do not face the same exposure to jet fuel prices. Our results confirm that stock price return is negatively correlated with fuel prices, and that financial and operational hedging is effective in reducing exposure to the price of jet fuel. Exposure of airlines varies as the price of jet fuel changes, where high fuel prices increases exposure, and conversely, low fuel prices decreases exposure. Our results show that airlines who use financial derivatives and hedge a larger portion of next years anticipated fuel consumption are less exposed than airlines who hedge less or do not hedge at all. U.S. airlines hedge less than European airlines, and are thus more exposed. When the cost of fuel represents a large portion of an airline's operating expense, the airline in question is more exposed and has a greater incentive to engage in financial hedging. This holds for our sample, and we confirm that low-cost carriers' hedge more than full-service carriers, and as a result experience less exposure. Some airlines even mange to obtain a positive exposure due to placing right bets on fuel prices, i.e. are effective in their financial hedging strategies. Hedging behaviour and level of exposure varies between European and U.S. airlines, but our results show that level of exposure varies more among airlines based on strategy, where exposure is lower for low-cost carriers than full-service carriers. Our results confirm that larger airlines are more likely to engage in financial hedging, and that a high degree of leverage or limited access to capital markets from previously ineffective hedging programs, reduces the airline's ability to hedge.

Increasing fleet diversity will not reduce exposure to jet fuel prices. Airlines who have a well-diversified fleet are according to theory more flexible in their ability to react to changing market conditions, as they have the ability to choose which aircrafts to operate and thus reducing their exposure. We find contradictory results, and find that airlines operating a uniform fleet are less exposed than airlines who operate a diversified fleet. Our results indicate that low-cost carriers, who adopt a reverse strategy and only operate a few different aircraft models, have a cost advantage and are thus actually better at handling exposure. We also find a positive relationship between having a uniform fleet and operational efficiency, where increasing fuel efficiency reduces an airline's exposure to the price of jet fuel. Low-cost carriers are more fuel efficient than full-service carriers since they operate younger fleets, fly shorter distances and have higher seating density. Observed variation among airlines in fuel efficiency can be explained by adjusting for fuel burn and seating density. If an airline has an average fuel burn rate below the reference line and an overall seating density above the average they are more energy efficient, hence we observe a negative relationship to fuel burn and a positive relationship to seating density. In addition, low-cost airlines are more energy efficient than regular airlines, since they have higher seating density and lack first-class seating. Airlines can effectively decrease their exposure by increasing passenger load factor since certain costs arise regardless of the number of seats sold. This allows for capacity utilization, thus lowering the cost of jet fuel per revenue generated mile and increasing actual revenue generated per flight. The longer the flight distance, the costlier it is to have unused capacity, hence airlines with longer routes are more exposed and low-cost carriers with shorter routes are thus less exposed than full-service carriers.

Our findings conclude that airlines are successful in decreasing their exposure to jet fuel, and that financial and operational hedging are both effective, but that operational efficiency is most effective. In contrast to other scholars, we find no evidence that supports the theory that operating a diversified fleet is beneficial in reducing exposure. Rather, we expose a trade-off where operating a uniform fleet provides benefits in terms of costs and is positively related to operational efficiency. This explains much of the variation among airlines, where low-cost carriers manage to have lower exposure to jet fuel than full-service carriers even though the cost of jet fuel represents a larger portion of their operational expense.

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Appendix

Figure 6: Aircraft Fuel Burn

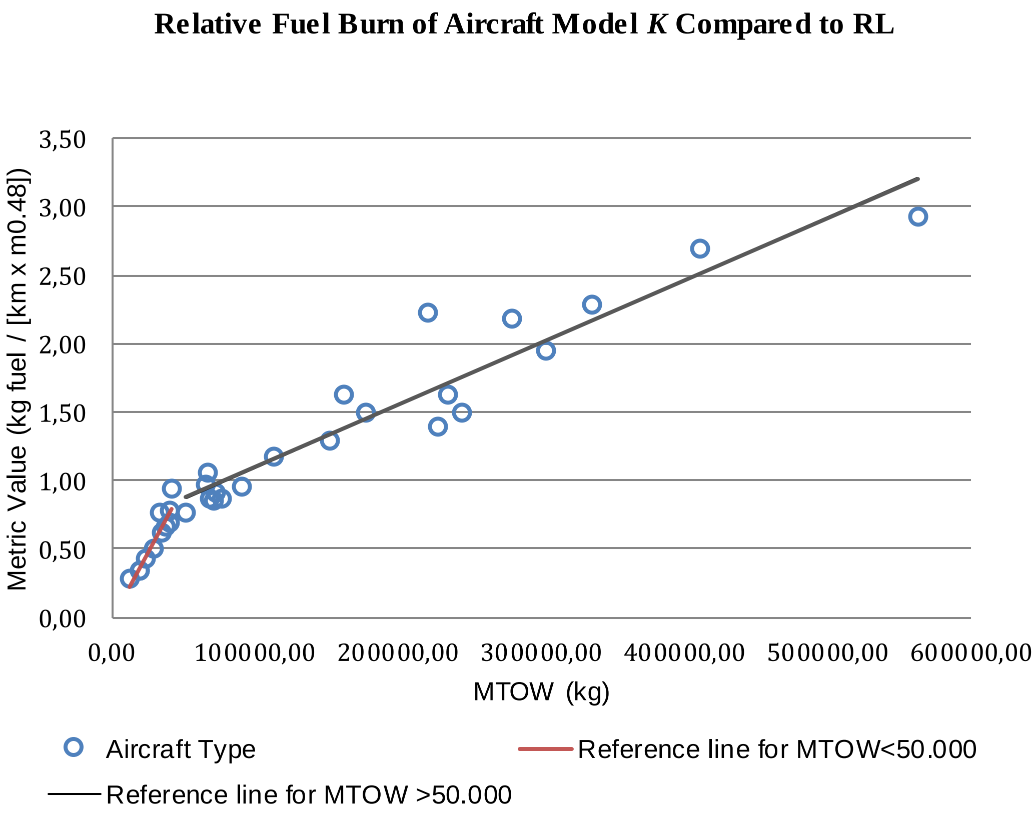

Figure 6: Two reference lines (RL) are calculated to normalize results for different size aircrafts observed in our sample during the period of Jan 1, 2011 – Dec 31, 2015. MTOW is a proxy for size and load. FUELBURN is expressed as the percentage difference in the airline's MV to the average of the sample, where an average for each airline is calculated by weighting the 'MV to RL' of each aircraft in the fleet. Intuitively, this means that a negative $FUELBURN_i$ (below the reference line) implies the airline's average aircraft is more fuel efficient than that of the average airline in the sample, and a positive $FUELBURN_i$ (above the reference line) indicates that the airline´s average aircraft burns more fuel than the average.

Table 8: Hausman's Test

Table 8: Hausman's Test. Hausman's test conducted to determine if fixed or random effect should be used in regression. Null hypothesis that difference in the coefficients is not systematic is rejected at the 0.0078 level, indicating that fixed effect should be used.

Variables	(b) fixed	(B) random	(b-B) Difference	sqrt(diag(V_b-V_B)) S.E.
LNTA	-0.313	0.008	-0.321	0.119
LTDA	0.452	-0.070	0.522	0.333
LNAGE	-0.111	-0.106	-0.005	0.126
ADI	0.220	0.182	0.039	0.285
PERHEDGE	0.332	0.045	0.287	0.141
LNDIS	0.105	0.112	-0.006	0.258
FUELBURN	-3.864	-0.923	-2.941	1.683
LNSEATING	0.004	0.131	-0.127	0.605

b = consistent under Ho and Ha

B = inconsistent under Ha, efficient under Ho

Test: Ho: difference in coefficients not systematic

chi2(8) = (b-B)'[(V_b-V_B)^(-1)](b-B) = 20.76

Prob >chi2 = 0.0078

Table 9: Collinearity

Table 9: Collinearity Diagnostics of Variables Used in the Regression. Test for multicollinearity between independent variables as suggested by Belslet et al. (1980). If the variance inflation factor (VIF) is above 2.60 and the tolerance level is below 0.40, there are reasons for concern regarding collinearity. The estimated coefficients for fleet age (LNAGE), fuel burn (FUELBURN) and distance travelled per passenger (LNDIS) show signs of collinearity.

	VIF	SQRT VIF	Tolerance	R-Squared
LNTA	1.57	1.25	0.64	0.36
LTDA	1.49	1.22	0.67	0.33
LNAGE	2.78	1.67	0.36	0.64
ADI	1.45	1.20	0.69	0.31
PERHEDGE	1.33	1.15	0.75	0.25
LNDIS	2.27	1.51	0.44	0.56
FUELBURN	2.37	1.54	0.42	0.58
LNSEATING	1.54	1.24	0.65	0.35
Mean	1.85			

Table 10. Correlation

Table 10: Correlation Matrix for Variables of Regression Model. Test for correlation between independent variables. Variables for FUELBURN and LNAGE show signs of correlation. This is expected since both variables are measures of fuel efficiency. Overall there is low correlation between variables.

e(V)	V(1)	V(2)	V(3)	V(4)	V(5)	V(6)	V(7)	V(8)
V(1) LNTA	1							
V(2) LTDA	0.193	1						
V(3) LNAGE	0.129	-0.286	1					
V(4) ADI	0.431	0.105	0.090	1				
V(5) PERHEDGE	0.015	0.151	-0.060	-0.080	1			
V(6) LNDIS	0.406	-0.088	0.387	0.392	-0.298	1		
V(7) FUELBURN	0.272	-0.011	-0.512	0.266	0.086	0.201	1	
V(8) LNSEATING	-0.152	-0.223	-0.286	-0.318	-0.128	-0.381	0.025	1

Table 11. Chi-squared Test

Table 11: Chi-squared Test on Difference in Mean Exposure. Test for statistical significance in the difference of the exposure coefficients between LCCs and full-service carriers. Coefficients are estimated using Equation (1): $R_{i,t} = \alpha_i + \beta_{i,y} R_{M,t} + \gamma_{i,y} R_{JF,t} + \varepsilon_{i,t} + \delta_i R_{USD,t} \cdot EU_i + \varepsilon_{i,t}$ grouped by LCC and full-service carriers. Result from chi-squared test reject the null-hypothesis that mean exposure for LCCs and full-service carriers are the same. The result confirm that LCCs have lower exposure than full-service carriers.

Variables	Coefficients	Std. Err.	z	P>|z|	[95% Conf. Int.]	
LCC Mean						
Return jet fuel ($R_{JF,t}$)	-0.130	0.025	-5.210	0.000	-0.178	-0.081
Return market ($R_{M,t}$)	0.932	0.052	17.970	0.000	0.830	1.034
Dollar index ($R_{USD,t}$)	1.811	0.279	6.480	0.000	1.263	2.359
constant	0.002	0.001	2.570	0.010	0.001	0.004
Full-Service Mean						
Return jet fuel ($R_{JF,t}$)	-0.247	-0.024	10.180	0.000	-0.294	-0.199
Return market ($R_{M,t}$)	1.073	0.047	22.680	0.000	0.980	1.165
Dollar index ($R_{USD,t}$)	1.132	0.198	5.730	0.000	0.745	1.520
constant	0.001	0.001	1.760	0.079	0.000	0.003

Chi-squared test

Test [LCC Mean]return jet fuel = [Full-service Mean]return jet fuel

(1) [LCC Mean]return jet fuel - [Full-service Mean]return jet fuel = 0

chi2(1) = 11.41

Prob > chi2 = 0.0007

Number of observations = 7614

Table 12. Difference in Strategy between EU and US

Table 12: Difference in Mean Values of Variables between EU and US. T-test for statistical significance in differences between mean values of variables grouped by EU and US. Table illustrate how strategy differs between airlines based in EU and US. Difference in hedge ratio and fuel efficiency is statistically significant at the 1% level, and difference in exposure and fleet age is statistically significant at the 10% level. These results demonstrate that airlines in the US have higher exposure than European airlines, and that it is most likely due to their 63% lower hedge ratio.

	EU	US	Difference
beta	-0.158	-0.284	0.126 *
			(0.049)
LNTA	8.457	8.710	-0.253
			(0.237)
LNAGE	2.064	2.288	-0.224 *
			(0.089)
ADI	0.556	0.491	0.064
			(0.045)
PERHEDGE	0.577	0.362	0.215 ***
			(0.054)
LNDIS	6.958	6.908	0.050
			(0.079)
FUELBURN	0.113	0.079	0.034 ***
			(0.009)
LNSEATING	0.326	0.347	-0.022
			(0.025)

Standard errors in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Table 13. Operational Efficiency

Table 13: Variables Affecting Operational Efficiency. The table indicates what variables affect efficiency, estimated using fuel cost as percentage of total operating expense for each airlines on a yearly basis. Dependent variable is fuel cost as percentage of total operating expense, independent variables are the following: the natural logarithm of fleet age (LNAGE), fleet diversity (ADI), distance (LNDIS) and seating density (LNSEATING). The independent variables are chosen based on the results from the t-test presented in Table 7, and only include variables that tested significant in explaining the difference between low-cost carriers and full-service carriers. If fuel is a large portion of total operating expense, operational efficiency is assumed to be high. Two separate regressions are conducted, one by LCC and one by full-service carriers. Results suggest that differences between LCCs is due to differences in fleet diversity, where high fleet diversity is directly related to high operational costs. Lower operational efficiency among full-service carriers is due to some carriers flying longer distances and having lower seating density, thus explaining the difference in operational efficiency among full-service carriers.

	LCC	Full-Service
LNAGE	0.002	-0.071**
	(0.017)	(0.024)
ADI	-0.210***	-0.086*
	(0.055)	(0.040)
LNDIS	0.080*	0.181***
	(0.033)	(0.025)
LNSEATING	0.280*	0.353***
	(0.134)	(0.099)
Constant	-0.251	-0.856***
	(0.261)	(0.155)
R-squared	0.493	0.458
N. of cases	49	83

Standard errors in parentheses
* p<0.05, ** p<0.01, *** p<0.001