Hedging – does it add Value to the Firm?

The Effect of Financial and Operational Hedging on Risk Exposure and Firm Value of an Airline

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L.R.T. Snoeks

ABSTRACT

Fuel costs represents a substantial portion of an airline's total operating expenses and therefore, fluctuations in fuel prices can have a significant impact on an airline's profitability. In general, airlines employ two types of hedging strategies to mitigate the risks associated with these fluctuations. The first strategy is financial hedging by using financial derivatives. The second strategy is operational hedging, which we define by two proxies: fleet diversity and the operation of a young fleet. This thesis examines the effect of both financial hedging and operational hedging on the airline's risk exposure and firm value. We constructed a dataset consisting of 28 globally active airlines over the period from 2010 to 2022. Contrary to prior research, we conclude that financial hedging does not reduce risk exposure and has no positive effect on the firm value. Surprisingly, operational hedging in the form of operating a younger fleet does not seem to decrease risk exposure and even negatively affects firm value. In line with prior research, operational hedging by operating a more diversified fleet reduces the risk exposure. Additionally, we observe that fleet diversification has a positive effect on firm value. Finally, we found no statistically significant support for the joint effect of financial and operational hedging reducing risk exposure. The joint effect even has a negative effect on firm value. We argue that the discrepancies with previous studies can be attributed to the impact of the COVID-19 crisis or could be related to the differences between regions.

Keywords: Aviation, Airline, Hedging, Financial Hedging, Derivatives, Operational Hedging, Fleet Diversity, Fleet age, Risk Exposure, Firm Value

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1. INTRODUCTION

For years the effect of corporate hedging has been intensively discussed in the corporate finance literature. Based on Modigliani and Miller (1958) investors can diversify on their own under perfect, frictionless market conditions. Therefore, risk management strategies on a firm level are extraneous for investors and hedging would not create additional value. However, more recent studies suggest that markets are not perfect and frictionless (Deshmukh & Vogt, 2005) and that hedging might add value by increasing firm value (Froot, Scharfstein, & Stein, 1993; Smith & Stulz, 1985) or by reducing risk exposure (Berghöfer & Lucey, 2014; Tufano, 1998).

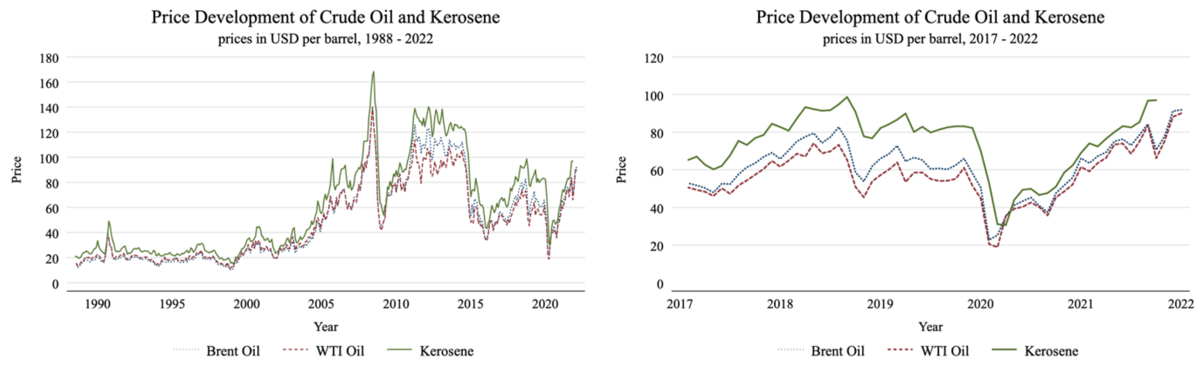
Over the past few years, a growing number of companies implemented risk management strategies to hedge interest rate risk, currency risk and commodity price risk (Carter, Rogers, & Simkins, 2006). This increase of hedging strategies also applies to the aviation industry. The aviation industry has been characterized by intense competition, especially after the deregulation in 1978 (Oum & Yu, 1998). Established airlines (legacy carriers) were confronted with the entrance of low-cost carriers (LCCs) and lost a significant percentage of their market share to them. Legacy carriers were forced to restructure to reduce costs and improve efficiency (Oum & Yu, 1998). The profit margins in an already low margin industry diminished even further.

In the aviation industry airlines are confronted with substantial operational costs, of which fuel costs constitute a substantial portion. In 2001 fuel accounted for 13% of the operating costs. This percentage rose to 22% in 2005 and reached 33% in 2012. Merkert and Swidan (2019) even found percentages as high as 50%. According to the International Air Transport Association (IATA) fuel expenses accounted for approximately 30% of the total operating costs in 2022.

These fluctuations are largely explained by the volatility of aviation fuel prices. In Figure 1, the price development of kerosene (and Brent and West Texas Intermediate (WTI) oil) is depicted. The last few years, we observed significant variations in price: in October 2018, a barrel of kerosene traded for 95 dollars, dropping to 25 dollars in April 2020, and spiking to 173 dollars in June 2022. This volatility is primarily caused by the uncertainty resulting from the COVID-19 crisis and the conflict between the Ukraine and Russia.

Figure 1:

Price Development of Crude Oil and Kerosene 1988 – 2022 (L) and 2017 – 2022 (R)



Note. The figures are based on historical weekly data from two types of crude oil (Brent crude oil and West Texas Intermediate (WTI) crude oil) and one type of jet fuel kerosene (Jet A). The data is adapted from Refinitiv Datastream.

Given the substantial amount of fuel required by airlines the volatility in jet fuel prices significantly affects airlines' operating expenses. In numerous other industries, companies can pass on the increase in operating expenses to customers. However, the exposure to market pressure caused by the intense competition gives the airlines little to no power to raise the ticket prices in response to the higher operating costs (Carter, Rogers, & Simkins, 2004). Therefore, airlines put their effort in risk management tools, like hedging activities (Berghöfer & Lucey, 2014).

Based on literature and annual reports, we observe that the majority of airlines have hedging strategies in place. We distinguish two main types of risk management tools: financial hedging and operational hedging (Berghöfer & Lucey, 2014; Lim & Hong, 2014; Smith & Stulz, 1985). Firstly, airlines apply financial hedging by using financial derivatives to mitigate the impact of currency risk, interest rate risk and mostly fuel price risk. Interestingly, fuel hedging is widely used by European and Asian airlines, while some major United States carriers – like American Airlines, Delta Air Lines and United Airlines – refrain from hedging fuel (Merkert & Swidan, 2019). This raises the question if financial hedging strategies adds value by reducing risk exposure and increasing firm value.

Secondly, airlines can hedge by altering real option decisions (operational hedging) (Smith & Stulz, 1985). According to Swidan and Merkert (2019) airlines utilize newer and more fuel-efficient aircrafts as an operational hedge. The use of more efficient planes reduces the fuel required, resulting in lower fuel costs. The proportion of total costs attributed to the fuel costs decreases, resulting in a reduced exposure to price movements of fuel. Moreover, airlines can choose to operate different types of aircrafts in the fleet (Treanor, Simkins, Rogers, & Carter, 2014). In periods of high fuel prices, certain routes might become unprofitable. Since it is costly to exit a market and reenter it later, airlines prefer to avoid exiting the (temporarily) unprofitable routes. An airline with a diversified fleet can assign a smaller aircraft to that route and thereby minimizes the level of losses. Therefore, increasing fleet diversification can be a potential operational hedging strategy.

To investigate if airlines make sound business decisions, we study the effect of financial and operational hedging on both risk exposure and firm value. Therefore, the research question of this study is:

RQ. *What is the impact of financial and operational hedging on risk exposure and the value of an airline?*

To answer the research question, we analyzed 28 of the biggest airlines – both legacy carriers and LCCs – worldwide in the period between 2010 and 2022. We only included airlines with NACE Rev. 2 code 5110 – Passenger Air Transport. Airlines that are part of a tour operator are excluded and the airlines must be publicly listed and traded on international exchanges. The data was retrieved from the Bureau Van Dijk Orbis database, Refinitiv Datastream, annual reports, and multiple other sources, resulting in a panel dataset.

We employed several models including a fixed effects models (FE) using the panel dataset to estimate the effect of financial and operational hedging on risk exposure and firm value. We concluded that financial hedging does not reduce risk exposure and has no positive effect on the firm value, which differed from previous findings. Surprisingly, operational hedging in the form of operating a younger fleet does not seem to decrease risk exposure and even has a negative effect on firm value. In line with prior research, operational hedging by operating a more diversified fleet reduced the risk exposure. Additionally, we observed that fleet diversification has a positive effect on firm value. Finally, we found no statistically significant support for the joint effect of financial and operational hedging reducing risk exposure. The joint effect even has a negative effect on firm value, as suggested by our findings.

This research contributes to the current literature in multiple ways. Firstly, we observed that the literature is mainly focused on the effect of hedging on firm value, while research on the effect on risk exposure is scarce. While Treanor, Simkins et al. (2014) found that both financial and operational hedging significantly lowered risk exposure, Berghöfer and Lucey (2014) found that both types of hedging increased risk exposure. Berghöfer and Lucey (2014) suspect that these differences were caused by the decreased volatility of kerosene prices in the period investigated. By performing a similar study with data from a period characterized by higher jet fuel price volatility, our research aims to validate or challenge the presumption of Berghöfer and Lucey (2014).

Secondly, we focused on the effect of hedging on firm value, using Tobin's Q as a measurement. While similar studies have already been conducted, these primarily relied on outdated datasets. By using a more recent dataset, we expect to acquire valuable new insights that will contribute to the existing body of literature.

Lastly, previous studies on hedging within the aviation industry predominantly focused on airlines based in the United States due to the easy access to data. In line with Berghöfer and Lucey (2014), we acknowledge the importance of exploring the effect of hedging on airlines outside the United States. Therefore, we constructed a comprehensive dataset that includes airlines from Europe, Oceania, Asia, North America, and South America.

This thesis is structured as follows: in Chapter 2 relevant literature regarding financial and operational hedging and the effect on risk exposure and firm value of airlines is discussed. In Chapter 3 the theoretical framework with the hypotheses, based on the previously discussed literature, is presented. Chapter 4 addresses the data and methodology used to conduct this research, after which the results are presented in Chapter 5. Finally, this thesis finishes with a conclusion and discussion in Chapter 6.

2. LITERATURE REVIEW

In the following chapter, we discuss the literature that is relevant for this thesis. First, we focus on hedging in general and the rationale behind it. Next, we focus on hedging in the aviation industry in specific. In section 2.3, we discuss the relation between financial and operational hedging. In section 2.4 we discuss the literature on the effect of hedging on the fuel price risk exposure of an airline. We finish this chapter with an overview on the literature on hedging and firm value in section 2.5. This literature review will be the foundation for the subsequent analysis in this thesis.

2.1 The Rationale behind hedging

The corporate finance literature is primarily based on the Capital Structure Irrelevance Theorem of Modigliani and Miller (1958). This theorem assumes: (1) perfect capital markets in the sense of no taxes, no transaction costs, no institutional frictions, no costs of bankruptcy or financial distress, and no unexploited riskless arbitrage opportunities; (2) symmetric information for all investors and managers; (3) equal access to all financial instruments for all individuals and firms; and (4) Investment decisions by firms are taken as a given (Culp, 2011).

The first proposition of this theorem implies that the value of the firm is determined by the cashflow generated by its assets and that is does not depend on its capital structure (Modigliani & Miller, 1958). Based on this proposition, Schroeck (2002) proposed an extension of the Capital Structure Irrelevance Theorem and called this the “Risk Management Irrelevance Proposition”. This variation states that under the set of conditions summed up above risk management is extraneous for investors as investors can diversify on their own (Berghöfer & Lucey, 2014). Therefore, hedging is irrelevant and should not add additional value to the firm.

Even though the Risk Management Irrelevance Proposition offers no justification for hedging, hedging is nowadays a commonly used risk management strategy (Berghöfer & Lucey, 2014; Mo, Suvankulov, & Griffiths, 2021). Van Mieghem (2011) refers to hedging as an action to mitigate a particular risk exposure. A company takes on one risk to offset another risk. Mian (1996) defines hedging as activities undertaken by the firm to mitigate the impact of uncertainties regarding price variations on the value of a firm. The goal of hedging is to lower risk exposure and to diminish the dependence on fluctuations in the underlying factor (Smith & Stulz, 1985).

Despite the theorem of Modigliani and Miller (1958) and Schroeck (2002) the current literature demonstrates situations in which hedging enhances firm value (Schrand & Unal, 1998). Hedging might add value by reducing the corporate tax burden, by reducing bankruptcy and financial distress costs (Smith & Stulz, 1985), or by mitigating the underinvestment problem (Aretz, Bartram, & Dufey, 2007).

Smith and Stulz (1985) argue that the structure of the corporate tax system provide incentives for firms to adopt hedging strategies. Marginal taxes rates are a convex, increasing function of pre-tax firm value, implying that as the value of the firm increases by an additional dollar, the imposed tax rate rises accordingly. By reducing the variability of the pre-tax value through hedging, firms lower their corporate tax liability and ultimately increase their post-tax value. Although Smith and Stulz (1985) acknowledge the positive impact of hedging, they add that the positive effect diminishes with increasing costs of hedging.

According to Modigliani and Miller (1958) the cost of financial distress is presumed to be zero. Therefore, altering the probability of financial distress does not affect the value of the firm (Mian, 1996). However, when the financial situation of a firm deteriorates, raising capital becomes more challenging and expensive (Mo et al., 2021). In that context, Carter et al. (2006) state that hedging might add value by reducing the probability and thus the expected costs of financial distress. Smith and Stulz (1985) assume that hedging reduces the likelihood of incurring bankruptcy costs and consequently decreases the expected bankruptcy costs. As these costs decline, the value of the firm increases.

However, the literature is not conclusive as several studies come with opposite conclusions. Financial distress plays a secondary role in determining hedging practices (Rampini, Sufi, & Viswanathan, 2014). Ross (1998) argues that hedging does not necessarily decrease bankruptcy costs because the firms chosen leverage increases. Based on a dataset on 90 US and Canadian gold mining firms, Fehle and Tsyplakov (2005) observe a positive relation between hedging and financial distress. Nevertheless, they argue that beyond a certain point of financial distress, the relation switches to a negative relation. The reasoning behind this reversal is that firms experiencing severe financial distress are no longer capable to afford adopting hedging strategies. Similar to the findings of Fehle and Tsyplakov (2005), Morrell and Swan (2006) argue that hedging would create exceptional value to the firm when it is on the edge of bankruptcy. However, hedging requires a guarantee that the company can cover the losses if the contract is out of the money. Firms on the verge of bankruptcy do not have the financial means to come up with the margin requirements.

Additionally, hedging might alleviate the underinvestment problem associated with external financing (Gay & Nam, 1998). When internally generated cash flows are not sufficient and external financing is expensive, firms are forced to reduce investments spendings. Hedging ensures that the firm has sufficient financial funds available to take advantage of investment opportunities and therefore adds value to the firm. Based on a set of 486 firms in the 1996 Swaps Monitor database, Gay and Nam (1998) find evidence to support the positive relation between the use of derivatives and growth opportunities of a firm. These findings support the argument that hedging alleviates the underinvestment problem.

But, other studies provide findings that do not support the underinvestment hypothesis. Mian (1996) use the market-to-book ratio as a proxy for investment decisions. This measure the likelihood that a firm will have growth options (Gay & Nam, 1998). Book value captures only the value of the assets in place, while the market value also captures the future growth options. The market-to-book ratio will therefore provide a relative measure of the growth opportunities of a firm. Mian (1996) found that hedged companies have a lower market-to-book ratio. This negative relationship contradicts the underinvestment hypothesis.

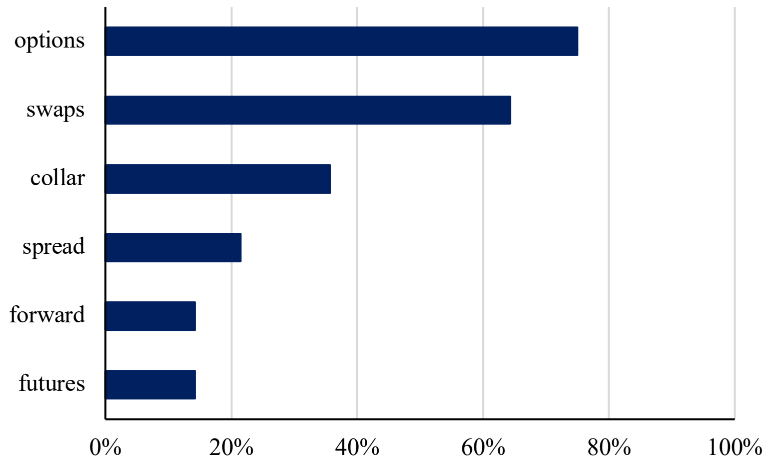
2.2 Hedging in the aviation industry

Similar to other industries, firms in the aviation industry are exposed to financial market developments. While these developments represent opportunities, they also pose various risks for airlines. As mentioned in the introduction of this research, airlines face substantial operational costs, of which fuel costs constitute a substantial portion. Given that airlines have limited control over the price movement of kerosene, these firms are – to a great extend – exposed to fuel price fluctuations. To mitigate this fuel price risk and reduce the volatility of present and future cash flows, airlines employ fuel hedging strategies (Morrell & Swan, 2006). To meet this ambition, airlines implement financial hedging strategies (Berghöfer & Lucey, 2014) or operational hedging strategies (Smith & Stulz, 1985).

A financial hedging strategy implies that airlines enter into financial derivative contracts, such as such as options, futures, and forwards (see Figure 2). By using these derivatives, airlines secure a fixed price for their required fuel consumption, which protects them to a sudden loss from increasing fuel prices (Morrell & Swan, 2006). It stabilizes a significant part of the total operating expenses and therefore has a stabilizing effect on cash flows and profits. Investors will value this stability resulting in a higher price for the airline's stock (Morrell & Swan, 2006).

Figure 2:

Distribution of Fuel Hedge Derivative Contracts used by Airlines



Note. The figure illustrates the distribution of derivative contracts used by airlines to hedge fuel. The percentage represents the proportion of airlines employing the specific type of derivative. The figure is based in hedging information from 28 airlines globally active in the period between 2010 and 2022.

Source: Annual reports

Jet fuel derivatives are usually not traded on organized exchanges and therefore the derivatives in the form of fuel forward contracts must be arranged 'over the counter' (Berghöfer & Lucey, 2014). This implies that a forward contract is a tailor-made contract between two parties, such as an airline and a fuel supplier, where one party purchases a fixed amount of fuel from the other party for a fixed price at a certain point in time (Morrell & Swan, 2006). Such arrangement reduces an airline's exposure to fuel price fluctuations resulting in a stabilization of the fuel expenses. However, these forward contracts have downsides, such as counter-party risk, margin requirements, and illiquidity problems due to the tailor-made nature of these contracts (Berghöfer & Lucey, 2014; Morrell & Swan, 2006).

To overcome this illiquidity and counter-party risk, an airline prefers to use derivatives that are traded on organized exchanges. However, the availability of jet fuel options and futures is limited (Morrell & Swan, 2006). Therefore, airlines commonly 'cross hedge' their fuel using exchanges-traded derivatives based on commodities exhibiting similar characteristics as kerosene, such as crude oil and heating oil (Berghöfer & Lucey, 2014). The upside of these contracts is that they easily can be reversed before the due date, resulting in the fact that no physical delivery is required.

However, cross hedging introduces the basis risk of the price of crude oil not being perfectly correlated to the price of kerosene (Berghöfer & Lucey, 2014), as displayed in Table 1. Airlines may be able to account for these price changes by using additional derivatives such as forward hedges (Lufthansa Group, 2023). However, the utilization of these contracts is not optimal since it entails additional costs for the airline. Additionally, we observe that the majority of oil derivatives are priced in dollars, introducing exchange rate risk for airlines with insufficient revenues in dollars (Morrell & Swan, 2006). To mitigate this exchange rate risk, it may be necessary for airlines to employ currency derivatives, resulting in additional expenses. Rao (1999) argues that these additional costs if financial hedging are as high as 1% of the total annual expenses.

Table 1:

Crude Oil and Kerosene Correlation

	Brent Oil	WTI Oil	Kerosene
Brent Oil	1		
WTI Oil	0.992***	1	
Kerosene	0.989***	0.982***	1

Note. Correlation based on historical weekly data from two types of crude oil (Brent crude oil and West Texas Intermediate (WTI) crude oil) and one type of jet fuel kerosene (Jet A). the correlation is based on prices per tonne.

$^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$

Moreover, an airline can aim to reduces its exposure to fuel prices by enhancing the fuel efficiency of its operations (Morrell & Swan, 2006). To achieve this objective, airlines might alter their real options decisions, which Smith and Stulz (1985) classify as operational hedging strategies. Operational hedging stems from the operating and investment activities of the firm (Treanor, 2008) and therefore, each industry has its own set of operational hedging methods. For most industries, risk is on the output side, while in the aviation industry the focus is primarily on risk associated with the input costs (Treanor, Simkins, et al., 2014).

Operational hedging in the aviation industry mostly relates to fleet composition and operating a more fuel-efficient fleet to mitigate the fuel price risk. In periods of high fuel prices, certain routes flown by an airline might become unprofitable. However, since exiting a route and reenter it later when conditions improve is rather costly, airlines prefer to avoid abandoning routes, even if it results in significant losses (Treanor, Simkins, et al., 2014). By operating different types of airplanes in the fleet airlines have the option to scale down the operation on the unprofitable routes by utilizing smaller, less fuel consuming aircrafts. This reduces the losses without a premature exit (Berghöfer & Lucey, 2014).

However, this strategy incurs additional costs, such as a reduced spare capacity, higher maintenance costs, increased crew costs and an increase in spare parts required (Berghöfer & Lucey, 2014). Treanor, Simkins et al. (2014) assume that these additional costs also apply on models of the same family, while Berghöfer and Lucey (2014) argue that is not per definition the case. According to Berghöfer and Lucey (2014) both airplane models of the same family (e.g. Airbus A319 and A320) can be operated interchangeable and therefore operating both types has no negative effect on the spare capacity. Additionally, planes within the same family haver similar characteristics and share similar components, reducing the maintenance costs and spare parts required. Moreover, since models of the same family require the same type rating, crew is typically allowed to operate both models, which reduces the additional crew costs significantly. Consequently, Berghöfer and Lucey (2014) propose considering the different airline families in the fleet as a measure of fleet diversification, rather than focusing on different types, to overcome the methodological issue of Treanor, Simkins et al. (2014).

The second method to operationally hedge and reduce the exposure to fluctuation fuel prices is by operating a more fuel-efficient fleet, which is predominantly proxied by operating a younger fleet (Treanor, Simkins, et al., 2014). InterGlobe Aviation Limited (2023) states that the new generation A320 aircrafts have a 15% lower fuel consumption compared to similar older-generation aircraft, while Lufthansa Group (2023) claims a 20% reduced fuel consumption of the new generation aircrafts.

2.3 Complements or Substitutes

The literature has not been conclusive on the relation between financial and operational hedging. Hutson and Laing (2014) examined a sample of 953 firms from the United States over the period 1999 – 2006. They measured operational hedging by the level of multinationality and observed that firms with a high level of multinationality are less likely to use financial derivatives, suggesting that operational hedging may substitute financial hedging.

Elliott, Huffman and Makar (2003) found a similar relation in their study on foreign currency risk. They found evidence for a negative relation between foreign-dominated debt (operational hedging) and foreign currency derivatives (financial hedging). Therefore, they conclude that operational hedging substitutes financial hedging.

Contrastingly, Kim, Mathur & Nam (2006) studied 424 firms and found that firms with a high foreign sales ratio are more inclined to use foreign currency derivatives, leading the writers to argue that operational and financial hedging complement each other, rather than being substitutes. A similar relation is found by Allayannis, Ihrig and Weston (2001). Companies use both financial and operational hedging since both types are used to manage different types of risk: financial hedging for short-term exposure and operational hedging to manage long-term exposure (Treanor, 2008).

For the aviation industry the conducted research is limited. Treanor, Carter, Rogers and Simkins (2013) examined the relation between financial hedging and three types of operational hedging: the fleet diversity, the fleet age, and the percentage of leased aircrafts. They found a positive relation between fleet diversity and financial hedging, suggesting the complementary nature of both types of hedging. Similar findings were presented by Swidan and Merkert (2019), who employed utilizing fewer engine variants as an operational hedge. They found a negative relation between the engine variants used and financial hedging, suggesting that the use of derivatives and operational hedging are complements.

2.4 Hedging and Risk Exposure

In the finance literature risk exposure is defined as the percentage change in the value of the firm resulting from a percentage change in the value of the underlying asset (Treanor, 2008). Studies demonstrated that airlines face a negative exposure to jet fuel prices (Carter, Rogers, & Simkins, 2002), indicating that an increase jet fuel price is associated with a decrease in firm value. To mitigate this risk, firms implement hedging strategies aiming to reduce their risk exposure, effectively with the goal to bring it down to zero.

Existing literature, however, presents mixed results on the relation between hedging and risk exposure. In his research on the North American gold mining industry, Tufano (1998) demonstrated that financially hedged firms are less exposed to gold price risk. Pantzalis, Simkins and Laux (2001) argued that multinational firms are less exposed to foreign exchange risk exposure when the firm spreads its activities across many foreign countries. Therefore, operational hedging through geographical dispersion contributes to mitigating risk exposure.

Treanor (2008) investigated risk exposure for 29 airlines in the United States over the period of 1994 to 2006. He did not only identify a significant negative relation between financial hedging and risk exposure, but also provided evidence supporting that operating a more diversified fleet reduces the risk exposure coefficient. Additionally, his results revealed a positive relation between fleet age and risk exposure, indicating that operating a younger fleet mitigates risk exposure. Building upon the previous work of Treanor (2008) Treanor, Simkins et al. (2014) expanded the dataset to encompasses the years 1994 to 2008. Their results provided additional evidence to support the relation between financial and operational hedging and risk exposure. Additionally, they presented that fleet diversity increases and fleet age decreases with increasing fuel prices in their examined period.

However, numerous studies did not find any evidence for the negative relation between hedging and risk exposure. In their study on 425 large U.S. corporations, Hentschel and Kothari (2001) examined if companies utilize derivative positions to systematically reduce or increase their risk exposure. Unexpectedly, they do not find compelling evidence to support that the utilization of financial derivatives leads to a reduction in risk exposure. Berghöfer and Lucey (2014) conducted a comprehensive study on 64 globally active airlines over a period from 2002 to 2012. In their study they investigated the relation between financial hedging and operational hedging through operating a more diversified fleet and risk exposure. Contrary to their expectations, they found no evidence supporting that financial hedging reduces risk exposure, even after analyzing each region separately. Contrary to previous results, they observed that operating a diversified fleet increases risk exposure, implying that operational hedging does not mitigate risk exposure. Berghöfer and Lucey (2014) proposed that the relatively low volatility of jet fuel prices during their examined period could be a potential explanation for the deviating findings.

2.5 Hedging and firm value

The effect of hedging – especially financial hedging – on firm value is widely discussed in the existing literature. As discussed before, hedging can add value by reducing the corporate tax burden, by reducing bankruptcy and financial distress costs (Smith & Stulz, 1985), or by mitigating the underinvestment problem (Aretz et al., 2007). Hedging aims to stabilize cash flows, which may improve the financial situation of the firm. Investors will value this stability resulting in a higher price for the airline’s stock (Morrell & Swan, 2006). However, we observe conflicting results on the relation between hedging and firm value.

Allayannis and Weston (2001) found in their study on currency hedging and firm value that the usage of financial derivatives results in a 4.87% increase in firm value, which translates to an average added value of $200 million for firms that adopted a financial hedging strategy (Jin & Jorion, 2006). However, Allayannis and Weston (2001) did not illustrate the source of these increased value (Carter et al., 2002). Therefore, Carter et al. (2002) adopted the methodology of Allayannis and Weston (2001) and examined the airline industry. They found a premium in the range of 12 – 16% and argue that the benefit of financial hedging comes from the reduction of the underinvestment costs. Carter et al. (2006) conducted further research and found a financial hedge premium between 5 and 10%. Additionally, they observed that the highest hedge premium occurred in years in which the fuel prices were both high and volatile. Besides a comparable hedging premium, Treanor, Rogers, et al. (2014) found that airlines hedge more of their jet fuel when fuel prices are on the rise or when the prices are already high.

In response to these findings Guay & Kothari (2003) investigated 234 large non-financial corporations that use derivatives. They found a positive effect of the usage of derivatives on firm value, but this effect is modest relative to the size of the firm. Therefore, Guay & Kothari (2003) argued that the substantial increases in firm value found in previous studies are either spurious or driven by other risk-management strategies, such as operational hedging.

However, the literature on operational hedging and firm value is not completely conclusive. Allayannis et al. (2001) investigate this relation between operational hedging and firm value. Their results suggest that operational hedging only has a positive effect on firm value if it is used in combination with financial hedging. However, Kim et al. (2006) find a strong positive relation between firm value and operational hedging measures by the geographical dispersion of a firm's subsidiaries across different countries. Treanor et al. (2013) examined the effect of operational hedging and firm value in the United States aviation industry. They employed operating a diversified fleet and operating a younger fleet as measurements of operational hedging. Their results showed that an increase of 1% of fleet diversification is associated with a 0.32% lower firm value and that reducing the average fleet age by 1 year causes the firm value to decline by 1.3%. Additionally, their results provided evidence that support a 1% increase in the financial hedge ratio increases the firm value by 0.66%. Consequently, they conclude that financial hedging has a positive effect on firm value, while operational hedging is negatively related to the value of the firm.

3. THEORETICAL FRAMEWORK

In this chapter we address the hypotheses tested in this research. the hypotheses are constructed to help answering the research question of this thesis. They are based on findings in previous literature, supplemented with standard economic theories and personal reasoning. The first four hypotheses relate to the use of hedging and fuel price characteristics. Next, we formulate one hypothesis related to the relation between financial and operational hedging. Additionally, we test four hypotheses related to the effect of hedging on fuel price risk exposure and we conclude this chapter with four hypotheses focusing on the relation between hedging and firm value.

3.1 Hedging and fuel price characteristics

To help us answering the research question, multiple hypotheses will be tested. Previous studies showed that hedging programs of airlines changes over time. Additionally, fuel prices and its volatility changed over time. Carter, Rogers, and Simkins (2006) showed that the largest hedge premium occurred in the period where fuel prices were both high and volatile. moreover, Treanor, Rogers et al. (2014) provided evidence that airlines use more derivatives when fuel prices are high. Therefore, we suspect that financial hedging is positively related to the level of fuel prices and the fuel price volatility respectively, resulting in the following two hypotheses:

H.1a The (financial) fuel hedge ratio of airlines is positively related to the price level of Kerosene ($\beta_{Price} > 0$).

H.1b The (financial) fuel hedge ratio of airlines is positively related to kerosene price volatility ($\beta_{Volatility} > 0$).

In addition to financial hedging, we examine the effect of operational hedging in this study. Swidan and Merkert (2019) described fleet age as an operational hedge. The newer the aircraft, the lower the fuel required since the engines are more efficient. By operating a relatively young fleet of Boeing 737 and Airbus A320 airplanes LCCs such as Ryanair and Easyjet enhance their fuel efficiency and thus lower their fuel expenses. Treanor, Simkins, et al. (2014) provided evidence to support a negative relation between kerosene prices and fleet age. We expect to observe a similar relation in our dataset and therefore propose the following hypothesis:

H.1c All other things being equal, operational hedging – in the form operating a younger fleet – is positively related to the price level of kerosene ($\beta_{Price} < 0$).

Existing literature and annual reports showed that the diversity of airlines' fleets varies over time. We identified airlines moving to a more diversified fleet, while others adopted an opposite strategy. The study of Treanor, Simkins, et al. (2014) analyzed U.S. airlines in the period between 1994 and 2008. In 1994, airlines operated fleets that predominantly consisted of medium-sized aircrafts. Over the course of time, a general trend towards greater fleet diversification was observed. Additionally, a significant rise in fuel prices was recognized in that particular period (Treanor, Simkins, et al., 2014). Based on these findings, we suspect a positive relation between fuel price and fleet diversification and therefore formulate the following hypothesis:

H.1d *All other things being equal, operational hedging – in the form operating a more diversified fleet – is positively related to the price level of kerosene ($\beta_{Price} > 0$).*

3.2 Complements or Substitutes

Financial hedging and operational hedging can be viewed as either substitutes or compliments (Kim et al., 2006). Kim et al. (2006) argue that companies use both financial and operational hedging since both types are used to manage different types of risk exposure: financial hedging to manage short-term exposure and operational hedging to manage long-term exposure. Their findings supported this hypothesis and suggested that firms that are more operationally hedged are more likely to adopt a financial hedging strategy. Treanor (2008) performed a similar study and found that operational hedging – in the form of operating a more diversified fleet – is positively related to the use of financial derivatives, suggesting that the two types of hedging are compliments. This results in the following hypothesis:

H.2 *Airlines adopt a comprehensive hedging program that uses both financial hedging and operational hedging complementary.*

3.3 Hedging and Risk Exposure

Financial derivatives are implemented to reduce risk exposure. Based on his study of the gold mining industry, Tufano (1998) confirmed the negative relation between financial hedging and risk exposure. Additionally, Treanor (2008) investigated this relation in the aviation industry. He analyzed 29 airlines between 1994 and 2006 and found that financial hedging reduces the exposure to fuel prices. A few years later, Treanor, Simkins, et al. (2014) found similar results. In contrast, Berghöfer and Lucey (2014) did not find such significant relation and blame this lack of significant findings on the different estimation period used (2002 – 2012). Fuel prices were less volatile and thus less uncertain in their timeframe. Since hedging aims to reduce uncertainty, the effectiveness of financial derivatives reduces in periods of low uncertainty. However, since we expect increased price volatility in our estimation period, we still expect a negative relation between financial hedging and the exposure to fuel prices and propose the following hypothesis:

H.3a *All other things being equal, financial hedging is negatively related to the fuel price risk exposure of an airline* ($\beta_{Hedge} < 0$).

Reducing the exposure to fuel prices can be accomplished by lowering the proportion of fuel costs as a portion of total operating costs. This can be achieved by reducing the amount of fuel required. Operational hedging – in the form of operating a younger fleet – results in a more fuel-efficient fleet, thereby mitigating the exposure to fluctuating fuel prices. Treanor, Simkins, et al. (2014) provided statistically significant evidence for a positive relation between fleet age and risk exposure and demonstrated that reducing the average fleet age by one year leads to a reduction of 11% in the jet fuel exposure coefficient. We expect this relation to hold and therefore propose hypothesis 3b as follows:

H.3b *All other things being equal, operational hedging – in the form of operating a younger fleet – is negatively related to the fuel price risk exposure of an airline* ($\beta_{Age} > 0$).

A diverse fleet provides the airline with the ability to respond to changing market conditions. Increasing fuel prices put a downward pressure on the operational result to such an extent that a specific route might become unprofitable. An airline with a diversified fleet possesses the ability to mitigate this potential unprofitability by operating smaller, less fuel consuming aircrafts, consequently reducing its exposure to the increasing fuel prices. Treanor, Simkins, et al. (2014) found that an increase of the diversification index by 1%, reduces the risk exposure coefficient by 2.3% (significant at the 10% level). However, Berghöfer and Lucey (2014) did not find any evidence for such a relation in their study. Although not statistically significant, the sign of their coefficient even suggested a positive relation between operating a diversified fleet and fuel risk exposure. Given the increased price volatility in our estimation period, we still expect to observe a negative relation between fleet diversification and risk exposure, leading to the following hypothesis:

H.3c *All other things being equal, operational hedging – in the form of operating a more diversified fleet – is negatively related to the fuel price risk exposure of an airline* ($\beta_{Diversity} < 0$).

As can be derived from hypotheses 3a, 3b, and 3c, we expect that both financial hedging and operational hedging when used individually reduce the fuel price risk exposure of an airline. Financial and operational hedging are considered complimentary strategies, since both types of hedging are used to manage different types of risk exposure: financial hedging to manage short-term exposure and operational hedging to manage long-term exposure (Kim et al., 2006). We expect that using financial and operational hedging simultaneously amplify their effectiveness in reducing risk exposure and therefore propose the following hypothesis:

H.3d All other things being equal, a hedging strategy consisting of both financial and operational hedging is negatively related to the exposure to fuel price risk of an airline ($\beta_{Diversity/Hedge} < 0$, $\beta_{Fleet\ Age/Hedge} > 0$).

3.4 Hedging and firm value

Additionally, the research question focusses on the effect of hedging on the value of the firm. Since hedging reduces cash flow and operating margin volatility (Merkert & Swidan, 2019), the underinvestment theory implies that using financial derivatives should positively affect firm value (Berghöfer & Lucey, 2014). Based on their study analyzing 28 U.S airlines, Carter et al. (2006) found a hedge premium of 5–10% for financially hedged airlines, in line with reasoning above. Treanor (2008) conducted a study built upon the research of Carter et al. (2006) and found comparable results. In a more recent study Treanor, Rogers, Carter and Simkins (2014) refined their research based on data on U.S. airlines between 1994 and 2008. Although the effect is less pronounced, they still found a significant relation between financial hedging and firm value. Based on the literature and the rationale behind the effect of hedging on firm value, we formulate the following hypothesis:

H.4a All other things being equal financial hedging is positively related to the value of an airline ($\beta_{Hedge} > 0$)

Next, we investigate the effect of both operational hedging measures on firm's value. Operational hedges intend to reduce the cash flow volatility and mitigate risks, resulting in an possible increase of the value of firm (Kim et al., 2006). However, Allayannis and Weston (2001) argue that operational hedging alone does not lead to an increased firm value. Treanor, Carter, Rogers, and Simkins (2013) presented similar finding in their study on the U.S. aviation industry. Reducing the age of the fleet by one year reduces the value of the firm by 1.3%. Additionally, fleet diversity as an operational hedge is also negatively related to firm value. Treanor et al. (2013) argue that although operating a younger and more diversified fleet reduces risk exposure, the negative effect on firm value is not entirely illogical. The benefits of these operational hedging methods may be outweighed by the drawbacks such as the substantial implementing costs, increased maintenance costs, and reduced operational flexibility. Based on the aforementioned findings, we formulate the following hypotheses as follows:

H.4b All other things being equal, operational hedging – in the form of operating a younger fleet – is negatively related to the value of the airline ($\beta_{Fleet\ age} > 0$).

H.4c All other things being equal, operational hedging – in the form of operating a more diversified fleet – is negatively related to the value of the airline ($\beta_{Diversity} < 0$).

Finally, we investigate the interaction effect of both financial and operational hedging on the value of an airline. As proposed in hypothesis 4a, we expect a positive relation between firm value and financial hedging, while operational hedging on its own does not enhance firm value. However, Allayannis and Weston (2001) found that operational hedging increase firm value when used in combination with financial hedging. Treanor (2008) findings support that operating a younger fleet in combination with the use of financial derivatives increases firm value. We formulate hypothesis 4d as follows:

H.4d All other things being equal, a hedging strategy consisting of both financial and operational hedging is positively related to the value of the airline ($\beta_{Diversity/Hedge} > 0$, $\beta_{Age/Hedge} < 0$).

4. METHODOLOGY AND DATA

In Chapter 4 we focus on the methodological approaches and relevant data used to test the hypotheses formulated in Chapter 3. First, we provide information on how the dataset is constructed and what sources are used. Since no readily available database contains all the data required, we construct the database manually. The dataset is compiled using a variety of sources, such as the Orbis database by Bureau van Dijk, Refinitiv DataStream, Financial reports, and other relevant sources. Next, we discuss the research design to test the hypotheses related to the use of hedging strategies. We explain the chosen approach, provide some insights on the rationale behind this approach, and present the testable specification(s). subsequently, we discuss and justify the variables used in these specifications. In similar fashion, we discuss the methodology employed and provide information on the data collected to test the hypotheses related to hedging and risk exposure and hedging and firm value respectively. Finally, we outline the characteristics of the dataset based on the summary statistics.

4.1 Data and its sources

For this research data on various airlines from around the globe is collected. We select airlines based on the statistical classification of economic activity with the NACE Rev. 2 code 5110 – Passenger Air Transport. To be eligible for selection, airlines must be publicly listed and traded on international exchanges. Airlines that are part of a tour operator (e.g. TUI airlines) are excluded, due to the lack of airline level information. The period of analysis is 2010 until 2022, where the cutoff date for the annual report of 2022 is March 31st, 2023. Similar to Berghöfer and Lucey (2014) we only included airlines with an adequate number of annual reports. These criteria resulted in a panel dataset containing information on 28 airlines: 20 legacy carriers and 8 LCCs. A summary is presented in Table 2 [1].

Table 2:

Summary of Airlines

	Total	Asia and Pacific	Europe	North America	South America*	Legacy	LCC
Airlines	28	12	7	6	3	20	8
Periods	1,308	524	336	300	148	944	364
Average Periods	46.71	43.67	48	50	49.33	47.20	45.50

Note. * Includes Latin America and the Caribbean.

[1] Refer to Appendix A for a complete detailed airline overview.

Financial data on these airlines is retrieved from the Orbis database by Bureau van Dijk. Data in the Orbis is sourced from over 40 different information providers and updated daily. The database contains comprehensive financial and business information on over 20 million companies, both private and listed. Orbis contains data back to the end of the 90's and therefore covers the full period of interest. However, some data was missing in the Orbis database. Therefore, the DataStream platform provided by Refinitiv was used as an additional source. DataStream contains information on all major assets classes and features over 60 years of data, across 175 countries. Historical stock price information is derived from the Refinitiv DataStream database, since Orbis does not provide (real-time) stock price information on the selected airlines.

In addition to financial data, the dataset constructed includes hedging information. Our analysis distinguishes between two types of hedging: financial hedging and operational hedging. Airlines uses a variety of financial hedging instruments to hedge interest rate risk, currency risk and fuel price risk. However, in this study, we primarily focus on financial derivatives used to hedge fuel price risk. Data on this type of hedging and the derivatives used is collected from annual reports of the individual airlines.

For operational hedging, we retrieve the data from planespotters.net. Planespotters.net is a website dedicated to aviation enthusiasts. This platform contains current and historical data on airports, airlines, and aircrafts and is updated regularly. From this database we retrieve – on an airline level – information on both fleet composition and fleet age for the period 2010 until 2022. Refer to Appendix B for an overview of the aircrafts considered.

Next, we use Refinitiv DataStream database to collect data on jet fuel prices. We obtained some operational airline specific factor from the respective annual reports and gathered general market information from both the Federal Reserve database and the Refinitiv DataStream database.

4.2 Hedging and fuel price characteristics

Previous studies provided evidence on the relation between the use of hedging and jet fuel (price) characteristics. In this section we discuss the methodology employed to study this relation. Additionally, we provide information on the specific variables used.

4.2.1 *Research Design*

With hypotheses 1a, 1c and 1d we test the relation between the different hedging variables and the price level of jet fuel. We regressed the different hedging variables on the (natural logarithm of the) average annual price of jet fuel. By including several control variables, we tried to mitigate omitted variable biases. The regression model is presented below (Equation 1):

$$Hedge\ variable_{i,t} = \alpha_0 + \beta_{Price}\ Price_{JF,\,t} + \sum_{j=1}^{4} \beta_j\ Control\ Variable_{i,\,t} + \varepsilon_{i,\,t} \qquad (1)$$

Where:

$Hedge\ variable_{i,t}$ = *One of the following Hedge variables:*

$Hedge\ Ratio_{i,\,t}$

$ADI_{i,\,t}$

$Fleet\ Age_{i,\,t}$

$Price_{JF,\,t}$ = *Natural logarithm of the average price of jet fuel in period t*

$\varepsilon_{i,\,t}$ = *Standard error term*

The selection of the appropriate regression model depends on the dependent variable analyzed. We observed that the values of the *Hedge Ratio*$_{i,t,}$ and *Fleet age*$_{i,t}$ are continues with a lower limit of 0. Therefore, when analyzing the effect of fuel prices on those two types of hedging, we considered a left-censored Tobit model. The values of *ADI*$_{i,t}$ exhibit similar characteristics, but with an additional upper limit of 1. Therefore, we employed a both left- and right-censored Tobit model to examine the effect of fuel prices on fleet diversification. For all models, we addressed the presence of airline-specific effect by incorporating random effects and included quarter dummy variables to control for time-specific effects. Our proposed Tobit models therefore accounted for the censored nature of the dependent variable, the unobserved airline-specific effects and time-specific effects.

Additionally, we investigated the relation between financial hedging and the price volatility of kerosene. To test this hypothesis, we regressed the financial hedge ratio on the price volatility of kerosene. The specification of this model is presented below:

$$Hedge\ Ratio_{i,t} = \alpha_0 + \beta_{volatility}\,\sigma_{JF,t} + \sum_{j=1}^{4} \beta_j\ Control\ Variable_{i,t} + \varepsilon_{i,t} \tag{2}$$

Where:

$Hedge\ Ratio_{i,t}$ = *percent of next year's fuel requirements hedged for airline i in period t*

$\sigma_{JF,t}$ = *Natural logarithm of the rice volatility of jet fuel in in period t*

$\varepsilon_{i,t}$ = *Standard error term*

Given that the dependent variable in this model is *Hedge Ratio*$_{i,y}$, which is a continuous variable with a lower limit of 0, we utilized a Tobit model. We included random effects to account for airline-specific effects and included quarter dummy variables to control for time-specific effects.

4.2.2 *Variables*

According to Berghöfer and Lucey (2014) the financial hedging strategy of an airline is defined by the percentage of next year's fuel requirements hedged. Therefore, the first dependent variable in this analysis is the *Hedge Ratio*$_{i,y}$ which we defined as the percentage of next year's fuel requirements hedged. We collected this information from the airlines' annual reports and 10-K fillings.

$$Hedge\ Ratio_{\ i,t} = percentage\ of\ next\ year's\ fuel\ requirement\ hedged_{i,t} \tag{3}$$

Additionally, we employed different types of operational hedges as dependent variables. The first dependent variable relates to diversification of an airline's fleet. In periods of high fuel prices airlines might experience downwards pressure on the operational results to such an extent that a specific route might become unprofitable. An airline with a diversified fleet possesses the ability to mitigate this potential unprofitability by operating smaller, less fuel consuming aircrafts, consequently reducing its exposure to fuel prices. In line with previous studies, we estimate the degree of an airline's fleet diversification based on the Hirschman-Herfindahl index (Berghöfer & Lucey, 2014; Treanor, Simkins, et al., 2014). At the end of the respective financial year, we estimated the first measure of fleet diversification according to the following equation:

$$ADI_{Model,i,t} = 1 - \sum_{j=1}^{N} \left(\frac{Number\ of\ Aircraft\ of\ Model_j}{Total\ Number\ of\ Aircraft\ in\ the\ Fleet_i}\right)^2 \tag{4}$$

$ADI_{Model,i,t}$ has a value between 0 and 1, where 0 implies an airline with an undiversified fleet and 1 an airline with a completely diversified fleet. *N* is the total number of aircraft models in airline *i*. The data required to construct this variable is derived from the planespotters.net database, annual reports, and airline's websites.

Based on Berghöfer and Lucey (2014) we construct an alternative measure of fleet diversity to overcome the methodological issue of the previous diversification measure as proposed by Treanor, Simkins et al. (2014). Here we consider the similarities between different aircraft models resulting in the following formula:

$$ADI_{Family,\,i,\,t} = 1 - \sum_{j=1}^{N} \left(\frac{Number\ of\ Aircraft\ of\ Family_j}{Total\ Number\ of\ Aircraft\ in\ the\ Fleet_i}\right)^2 \qquad (5)$$

$ADI_{Family,i,y}$ again has a value between 0 and 1. In this formula *N* is the total number of aircraft families operated by airline i. By focusing on families, we acknowledge the similarities between for example the Boeing 737-700 and the larger Boeing 737-800. Note that we consider the passenger and freighter versions of a type not as the same model or family since they cannot be operated interchangeably (Berghöfer & Lucey, 2014). The data required is derived from the planespotters.net database, annual reports, and airline's websites.

Next, an airline can operationally hedge by operating a younger fleet (Swidan & Merkert, 2019; Treanor, Simkins, et al., 2014). Newer aircraft are in general more fuel efficient, resulting in lower fuel costs and thus a lower exposure to fuel price risk. The information on fleet age is collected from the Planespotters database and subsequently subjected to a natural logarithmic transformation. The variable will be further referred to as *Fleet age:*

$$Fleet\ Age_{i,\,t} = Ln\left(Fleet\ age_{i,\,t}\right) \qquad (6)$$

When studying the relation between the different types of hedging and the price level of jet fuel, we used the (natural logarithm of the) average jet fuel price within fiscal quarter *q* as the independent variable. We specifically focus on the financial quarter, to account for the variation in financial quarter- and year-end dates among airlines. As explained in the theoretical framework chapter, we expect airlines to hedge more in periods of high fuel prices and therefore expect a positive relation between hedging and the price level of fuel ($\beta_{Price} > 0$ for financial hedging an operational hedging by operating a diversified fleet, and ($\beta_{Price} < 0$ for operational hedging by operating a younger fleet). We obtained information on American, European, and Asian jet fuel prices from the Refinitiv DataStream database.

For the testing of hypothesis 1b, we utilized the natural logarithm of the annual volatility of jet fuel prices within fiscal quarter q. previous research provided evidence for a positive relation between price volatility and financial hedging and therefore we expect to observe a positive coefficient *($\beta_{Price} > 0$)*. This variable is derived from the price level of fuel as obtained from the Refinitiv DataStream dataset.

Next, we included a set of control variables to help address potential biases, increase the explanatory power of the model, and improve its accuracy. The first control variable relates to the size of the firm. A strong positive relation is found between the firm size and financial hedging (Graham & Rogers, 2002; Haushalter, 2000; Mian, 1996). To control for this effect, we included the natural logarithm of the total assets of airline i in quarter q. we obtain this information from the Orbis database and refer to this variable as *Size*:

$$Size_{i,t} = Ln(Total\ Assets_{i,t}) \tag{7}$$

Additionally, the capital structure of the firm may influence a firm's decision to apply hedging strategies at all (Carter et al., 2006). This stems from the logic that a higher level of debt – and thus a higher probability of financial distress – creates an incentive for the firm to apply hedging strategies (Graham & Rogers, 2002; Haushalter, 2000). Therefore, the ratio of long-term debt to total assets is used to control for leverage and thus for differences in capital structures (Carter et al., 2002). The variables to construct this ratio are collected from the Orbis database and we name the long-term debt to asset ratio *Leverage:*

$$Leverage_{i,t} = \frac{Long-Term\ Debt_{i,t}}{Total\ Assets_{i,t}} \tag{8}$$

Because of market imperfections, firms with more growth opportunities hedge more to mitigate the underinvestment problem (Froot et al., 1993). Given the significant positive relation between hedging and growth opportunities (Graham & Rogers, 2002), Treanor et al. (2013) argued that firms protect their future growth options by hedging. Among others, Graham and Rogers (2002) found a significant positive relation between hedging and growth opportunities. To capture this effect, we included the ratio of capital expenditures to sales as a proxy for investment opportunities. We collected the information on these variables from the Orbis database and name the variable IO:

$$IO_{i,\,t} = \frac{Capital\ Expenditures_{i,\,t}}{Total\ Sales_{i,\,t}} \tag{9}$$

Finally, we include quarter dummy variables to capture time-related effects that are not already included in the model. These variables will not be reported in the results.

4.3 Complements or substitutes

In this section, we study the relation between financial and operational hedging and investigate if the two types of hedging are complements or substitutes. Previous studies provided evidence on the two types of hedging being complements. In the following sections we discuss the methodology to test this relationship and provide information on the variables used.

4.3.1 *Research Design*

To test hypothesis 2, our approach is similar to the approach of Treanor et al. (2013), implying that we regressed the airlines' use of financial hedging against our operational hedging variables. Additionally, we included several control variables to account for the potential effect these variables have on the use of financial derivatives. The specification is presented below:

$$\begin{aligned} Hedge\ Ratio_{\,i,\,t} \\ &= \alpha_0 + \beta_{Diversity}\ ADI_{i,\,t} + \beta_{Fleet\ age}\ Fleet\ Age_{i,\,t} \\ &+ \sum_{j=1}^{4} \beta_j\ Control\ Variable_{i,\,t} + \varepsilon_{i,\,t} \end{aligned} \tag{10}$$

Where:

$Hedge\ Ratio_{\,i,t}$	=	$Hedge\ Ratio_{i,t}$
		$Hedge\ Dummy_{i,t}$
$ADI_{i,\,t}$	=	*Aircraft dispersion index for airline i in period t*
$Fleet\ Age_{i,\,t}$	=	*The natural logarithm of the average fleet age of airline i in period t*
$\varepsilon_{i,\,t}$	=	*Standard error term*

we performed the regression analysis using a Tobit model with random effects, which is similar to the approach of Treanor et al. (2013). We considered a Tobit model well-suited, since the dependent variable is a continuous variable with a lower limit of 0. By incorporating random effect into the model, we addressed airline-specific characteristics potentially influencing the relationship and thus account for heterogeneity. Our proposed Tobit model therefore accounted for both the censored nature of the dependent variable and unobserved airline-specific effects.

To verify the robustness and reliability of our findings, we undertook several robustness checks. First, we incorporated two different types of operational hedging to investigate the relation between financial hedging and operational hedging. Regarding operational hedging by operating a more diversified fleet we went even further and included an additional measurement of Fleet diversification (ADI_{Family}). Additionally, we subjected the Tobit regressions to multiple iterations with different combinations of the independent variables. Finally, we extended the analysis by using a Logit random effects model with the binary *Hedge Dummy* as the dependent variable.

4.3.2 *Variables*

According to Berghöfer and Lucey (2014) the financial hedging strategy of an airline is defined by the percentage of next year's fuel requirements hedged. Therefore, the dependent variable in this analysis is the $Hedge\ Ratio_{i,t}$ as explained in Chapter 4.2.2.

The additional dependent variable which we used in the Logit models is $Hedge\ Dummy_{i,t}$. This binary dummy variable has a value of one if the airline's percentage of next year's fuel hedged is greater than zero, and zero otherwise.

$$Hedge\ Dummy_{\ i,t} = \begin{cases} 0, & Hedge\ Ratio_{i,t} = 0 \\ 1, & Hedge\ Ratio_{i,t} > 0 \end{cases} \tag{11}$$

The model contained two independent variables. The first variable is the aircraft dispersion index of airline i in period t ($ADI_{i,t}$) as a measurement of fleet diversity. Based on previous literature, we consider operational hedging and financial hedging complements. Therefore, we expect a positive relation between the fleet diversification of airline i and its percentage of next year's fuel requirements hedged ($\beta_{Diversity} > 0$).

The second variable of interest is $Fleet\ Age_{i,t}$. Since previous literature found evidence to consider financial hedging and operational hedging as compliments, we expect a negative relation between the age of an airline's fleet and financial hedging ($\beta_{Fleet\ age} < 0$).

Additionally, we included a set of control variables to help address potential biases, increase the explanatory power of the model, and improve its accuracy. The first control variable is related to the size of the firm. Given the strong positive relation between firm size and financial hedging (Graham & Rogers, 2002; Haushalter, 2000; Mian, 1996) controlling for size prevent under- or overestimation. Therefore, we included the *Size* variable as set out in section 4.2.2.

Additionally, the capital structure of the firm may influence a firm's decision to apply hedging strategies at all (Carter et al., 2006). This stems from the logic that a higher level of debt – and thus a higher probability of financial distress – creates an incentive for the firm to apply hedging strategies (Graham & Rogers, 2002; Haushalter, 2000). We controlled for this effect by including the variable *Leverage* (see section 4.2.2):

The third control variable relates to the growth potential of a firm. Graham and Rogers (2002) found a significant positive relation between hedging and growth opportunities. To prevent omitted variable biases, we included the variable *IO,* which we introduced in section 4.2.2. Finally, a year dummy variable is included to account for time-specific effects. However, this variable will not be reported in the results.

4.4 Hedging and risk exposure

In this section, we focus on the relation between hedging and risk exposure. in line with the empirical literature, we expect a negative relation between hedging and risk exposure. Next, we set out the methodology applied and provide information on the variables used.

4.4.1 *Research Design*

Hypothesis 3a to 3d all relate to the relation between hedging and exposure to fuel price risk. To test these hypotheses, we utilized – similar to the approaches of Treanor (2008), Berghöfer and Lucey (2014), Treanor, Simkins, et al. (2014) – a two-step procedure based on Jorion's (1990) risk exposure formula. In the first step we used a panel dataset with weekly data and estimated each airline's weekly fuel risk exposure coefficient by means of Equation 12:

$$R_{i,w} = \alpha_0 + \gamma_{i,q} R_{JF,w} + \beta_{i,q} R_{mkt,w} + \varepsilon_{i,w} \tag{12}$$

Where:

$R_{i,w}$ = *The weekly stock price return of airline i for week w*

$R_{JF,w}$ = *The weekly percent change in jet fuel prices for week w*

$R_{mkt,w}$ = *The weekly return for the equally weighted market index for week w*

$\gamma_{i,q}$ = *The jet fuel risk factor of airline i for week w*

$\beta_{i,q}$ = *The market factor of airline i for week w*

$\varepsilon_{i,w}$ = *Standard error term*

In the second step, we used a panel dataset with quarterly data. We regressed the absolute value of the quarterly averaged jet fuel risk factors ($|\gamma^{avg}|$) obtained in the previous step on financial and operational hedge variables, along with a set of control variables. We write this second step as:

$$\begin{aligned}\left|\gamma_{i,t}^{avg}\right| = \alpha_0 + \beta_{Hedge}\, Hedge\ Ratio_{i,t} + \beta_{Diversity}\, ADI_{i,t} \\ + \beta_{Fleet\ age}\, Fleet\ Age_{i,t} \\ + \beta_{Hedge/Diversity}\, Hedge\ Ratio_{i,t} ADI_{i,t} \\ + \beta_{Hedge/Fleet\ Age} Hedge\ Ratio_{i,t} Fleet\ Age_{i,t} \\ + \sum_{j=1}^{4} \beta_j\, Control\ Variable_{i,t} + \varepsilon_{i,t}\end{aligned} \tag{13}$$

Where:

$\left\|\gamma_{i,t}^{avg}\right\|$	=	*The absolute value of annual averaged weekly jet fuel risk factor for airline i in period t*
$Hedge\ Ratio_{i,t}$	=	*percent of next year's fuel requirements hedged for airline i in period t*
$ADI_{i,t}$	=	*Aircraft dispersion index for airline i in period t*
$Fleet\ Age_{i,t}$	=	*The natural logarithm of the average fleet age of airline i in period t*
$Hedge\ Ratio_{i,y} ADI_{i,y}$	=	*Joint effect of Hedge ratio and fleet diversification for airline i in period t*
$Hedge\ Ratio_{i,y} Fleet\ age_{i,y}$	=	*Joint effect of hedge ratio and the average fleet age of airline t in period t*
$\varepsilon_{i,t}$	=	*Standard error term*

Based on the outcome of a Hausman test, we performed the regression analysis using a fixed effects model. Additionally, we included quarter dummy variables to control for time-related effects that are not already captured by the other variables in the model. Similar to the approach of Berghöfer and Lucey (2014), we clustered the standard errors on airline level to control for potential autocorrelation and heteroscedasticity.

4.4.2 *Variables*

For the first step of the analysis, we used airline *i*'s weekly return for week *w* as the dependent variable $R_{i,w}$. The variable is derived from the weekly stock prices of the corresponding airlines, which we collected from Refinitiv DataStream.

The independent variable is the weekly change in kerosene prices for week *w,* which we denoted as $R_{JF,w}$. We calculated this weekly return for American kerosene, European jet fuel, and Asian jet fuel respectively. We matched these returns with the corresponding airlines based on their homebase. The information on fuel prices is gathered from Refinitiv DataStream.

Additionally, we included a control variable to improve the accuracy of our model. This variable is $R_{mkt,w}$, which is defined as weekly return for the equally weighted market index on which airline *i* is listed for week *w*. Including $R_{mkt,w}$ captures the general market effect on the airline's stock price return. This information is retrieved from the Refinitiv DataStream database.

As described in the research design sub-section, we took the quarterly average of the weekly jet fuel risk factor estimated in the first step. We denoted this variable as γ^{avg}. The absolute value of γ^{avg} ($|\gamma^{avg}|$) for airline *i* in quarter *q* functioned as the dependent variable for the second step. We used the absolute value as the objective of hedging is to reduce the fuel exposure of an airline towards zero (Berghöfer & Lucey, 2014; Treanor, 2008). Since this variable is estimated by our own analysis, no external source can be referred to.

In the second step of this analysis, three independent variables of interest are included. The first independent variable relates to financial hedging and is the $Hedge\ Ratio_{i,t}$, as described in chapter 4.2.2. Since we expect a negative relation between financial hedging and risk exposure, we expect to observe a negative coefficient ($\beta_{Hedge} < 0$). Including this variable will provide insights in the effect of financial hedging on the risk exposure.

The second independent variable relates to operating a diversified fleet as an operational hedge. To measure the diversity of the fleet, we constructed two Aircraft Dispersion indices ($ADI_{i,t}$) as described in chapter 4.2.2. A more diversified fleet provides the airline with more flexibility, potentially reducing its exposure to fuel price risk ($\beta_{Diversity} < 0$). By including this variable, we may gain insight into how this measure of operational hedging affects risk exposure.

Finally, we included the variable *Fleet Age*$_{i,t}$ as described in chapter 4.2.2 to study the effect of operating a younger fleet on the exposure to fuel price risk. A younger fleet implies a more fuel-efficient fleet and thus a lower exposure to fuel price risk. Therefore, we expect a positive relation the average fleet age and the risk exposure coefficient ($\beta_{Fleet\ age} > 0$)

To mitigate the omitted variable bias as much as possible, we included several control variables. Since the size of a firm is positively related to risk exposure (Tufano, 1998), we included the variable *Size* as described in Section 4.2.2. additionally, Treanor, Simkins, et al. (2014) argued that leverage has a positive effect on risk exposure. Therefore, the variable *Leverage* as described in section 4.2.2 is incorporated in the model.

Next, we control for the average flight distance of the respective airlines. The longer the average flight sector, the higher the possibility that the airline operate a more diversified fleet (Berghöfer & Lucey, 2014). However, due to technical limitations the smaller, more fuel-efficient planes are not always capable to function as a substitute for the larger aircrafts. Hence, operating a diversified fleet does not always reduce the risk exposure. To mitigate this bias, we included the natural logarithm of the average flight distance of airline *i* in period *t* and named this variable *Distance*. The information for this variable is collected from the annual reports:

$$Distance_{i,t} = Ln\left(average\ Flight\ Distance_{i,t}\right) \tag{14}$$

Finally, we included quarter dummy variable to account for time-specific effects. However, this variable will not be reported in the results.

4.5 Hedging and firm value

Finally, we study the relation between hedging and value of the firm. In line with the empirical literature, we expect a positive relation between financial hedging and the value of the firm. However, based on literature focused on the aviation industry, a negative relation between operational hedging and firm value was found. Although, in combination with financial hedging, operational hedging seems to add value. Next, we discuss the methodology to test our hypotheses and provide information on the variables used.

4.5.1 *Research design*

To investigate the effect of hedging on firm value, we tested hypotheses 4a to 4d. We used an approach employed by Treanor, Rogers, et al. (2014) and regressed the natural logarithm of Tobin's Q on the different hedging variables and included the interaction effect between financial and operational hedging. To complete the model, we included several control variables. The regression model is presented below (Equation 15):

$$\begin{aligned} Tobin's\,Q_{i,t} = {} & \alpha_0 + \beta_{Hedge} Hedge\,Ratio_{i,t} + \beta_{Diversity} ADI_{i,t} \\ & + \beta_{Fleet\,age}\,Fleet\,Age_{i,t} \\ & + \beta_{Hedge/Diversity} Hedge\,Ratio_{i,t} ADI_{i,t} \\ & + \beta_{Hedge/Fleet\,age} Hedge\,Ratio_{i,t} Fleet\,Age_{i,t} \\ & + \sum_{j=1}^{5} \beta_j\,Control\,Variable_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{15}$$

Where:

$Tobin's\,Q_{i,y}$	=	*The natural logarithm of Tobin's Q as described in Equation 16*
$Hedge\,Ratio_{i,y}$	=	*percent of next year's fuel requirements hedged for airline i in period t*
$ADI_{i,y}$	=	*Aircraft dispersion index for airline i in period t*
$Fleet\,Age_{i,y}$	=	*The natural logarithm of the average fleet age of airline i in period t*
$Hedge\,Ratio_{i,y} ADI_{i,y}$	=	*Joint effect of Hedge ratio and fleet diversification for airline i in period t*
$Hedge\,Ratio_{i,y} Fleet\,age_{i,y}$	=	*Joint effect of hedge ratio and the average fleet age of airline t in period t*
$\varepsilon_{i,w}$	=	*Standard error term*

A Hausman test suggested that a fixed effects model is the appropriate model to investigate the relationship. This fixed effects model controls for airline-specific variations that are not already captured by the other variables. Additionally, we included quarter dummy variables to control for time-related effects that are not already captured by the other variables in the model. We clustered the standard errors on airline level to control for potential autocorrelation and heteroscedasticity.

4.5.2 *Variables*

The dependent variable relates to the firm value. We utilized the natural logarithm of Tobin's Q as a proxy for firm value since it is one of the most used proxies in the empirical literature. Tobin's Q is defined as the market value of the firm divided by its replacement cost (Treanor, 2008). Studies such as Lindenberg and Ross' (1981) proposed a variety of procedures to calculate Tobin's Q. However, these calculations are so complex that it imposes limitations on the practical applicability. Therefore, Chung and Pruitt (1994) developed an approximation of Tobin's Q. Carter et al. (2006) preferred this approximation over more complex alternatives, as this complexity would reduce the sample size drastically. Hence, we used the following estimation of *Tobin's Q*:

$$Tobin's\ Q_{i,t} = Ln\left(\frac{MVE_{i,t} + PS_{i,t} + DEBT_{i,t}}{Total\ Assets_{i,t}}\right) \tag{16}$$

Where:

MVE	=	*The product of a firm's share price and the number of common stock shares outstanding*
PS	=	*The liquidation value of the firm's outstanding preferred stock*
$DEBT_{i,t}$	=	*The value of the firm's short term liabilities net of its short-term assets, plus the book value of the firm's long-term debt*
$Total\ Assets_{i,t}$	=	*The Book value of the total assets of the firm*

Given the logarithmic transformation, a *Tobin's Q* value > 0 implies that the firm is overvalued relative to the book value of its assets, while a value < 0 implies undervaluation. The variables required for the estimation of *Tobin's Q* are derived from both Refinitiv DataStream and the Orbis Database.

The first independent variable is $Hedge\ Ratio_{i,t}$. as described in chapter 4.2.2. According to hypothesis 4a we expect a positive relation between financial hedging and firm value. Therefore, we predict to observe a positive coefficient ($\beta_{Hedge} > 0$).

Additionally, we test the effect of operational hedging on firm value. Therefore, we include the fleet diversification variable ($ADI_{i,t}$) and the variable $Fleet\ Age_{i,t}$. We expect a negative relation between operational hedging and firm value ($\beta_{Diversity} < 0$, $\beta_{Fleet\ age} > 0$).

However, in hypothesis 4d, we argued that using operational hedging and financial hedging together provides additional value to the firm compared to the value added by solely using both the hedging strategies (Treanor, 2008). To test this hypothesis, we included the variables $Hedge\ Ratio_{i,t}ADI_{i,t}$ and $Hedge\ Ratio_{i,t}Fleet\ Age_{i,t}$. We therefore expect $\beta_{Hedge/Diversity} > 0$ and $\beta_{Hedge/Fleet\ age} < 0$.

We incorporated five different control variables in the model. First, we controlled for size. Since the literature shows inconsistent results on the effect of size on firm value, we cannot rule out its potential effect. Omitting to account for this potential relationship might result in biased findings. Therefore, we included the variable *Size* as specified in section 4.2.2. Since Treanor, Rogers, et al. (2014) reported a significant positive effect of leverage on firm value we included the control variable *Leverage* as discussed in section 4.2.2.

Thirdly, we controlled for profitability, since the market is likely to reward profitable firms, resulting in higher firm values. According to Allayannis and Weston (2001) a positive relation between profitability and firm value can be expected. To control for the effect of profitability, we included the return on assets (*ROA*). The data required for the *ROA* variable is collected from the Orbis database.

$$ROA_{i,y} = \frac{Operating\ Income_{i,y}}{Total\ Assets_{i,y}} \tag{17}$$

The fourth potential factor influencing firm value might be the investment opportunities a firm has. The greater the investment opportunities, the more likely the firm is valued higher by the market (Carter et al., 2002). A similar positive relation is found by Allayannis and Weston (2001). Froot et al. (1993) argued that hedging results in more investment opportunities for the firm. To capture this factor, we utilized the *IO* variable as described in section 4.2.2. Finally, we included a year dummy variable to account for time-specific effects. However, this variable will not be reported in the results.

4.6 Descriptive statistics

In Table 3 below we provide the summary statistics of the variables discussed above. We provide information on the number of observations, the mean, the standard deviation, the minimum value, and the maximum value.

We observed a total of 28 airlines for 13 consecutive years. This resulted in 1,456 airline-quarter observations. However, we were only able to retrieve financial hedging information on 1,308 of these observations. The average firm value measured by Tobin's Q was 0.77 ranging between 0.19 and 3.52. We observed that airlines hedge on average 35.10% of their next year's fuel requirements. The average diversification index was 0.709 considering ADI_{Type} and 0.551 considering ADI_{Family}. The average fleet age was 8.16 years ($e^{2.099}$= 8.16).

Table 3:

Descriptive Statistics of Variables

	Obs. (*N*)	mean	Std. Dev.	Min	Max
Tobin's Q	1,387	-0.255	0.357	-1.651	1.259
Hedge Ratio	1,308	0.351	0.326	0	1.090
ADI_{Type}	1,456	0.709	0.250	0	0.951
ADI_{Family}	1,456	0.551	0.324	0	0.897
Fleet Age	1,456	2.099	0.402	0.721	3.042
$Price_{JF}$	1,456	91.17	30.62	31.02	166.1
σ_{JF}	1,456	5.728	4.222	1.566	24.57
Size	1,452	23.40	0.994	19.94	25.00
Leverage	1,452	0.316	0.158	0.00533	1.394
ROA	1,452	0.0328	0.0733	-0.281	0.195
IO	1,452	11.57	7.217	0.410	70.64
Distance	1,396	7.556	0.411	6.777	8.656
Legacy	1,456	0.714	0.452	0	1
Number of Airlines	28				

Note. *Tobin's Q, Fleet Age, Size* and *Distance* are the natural logarithmic transformation of the respective variables.

5. RESULTS

In this chapter we present the statistical outcomes of the analysis performed as described in methodology section of Chapter 4. First, we provide our results on the relation between fuel price characteristics and the different types of hedging. Next, we examine if financial hedging and operational hedging are used as complements or substitutes. We display the results of this analysis in section 5.2. Thirdly, we present the results on the effect of financial and operational hedging on the fuel price risk exposure of the airlines. Lastly, present our findings concerning the relationship between financial and operational hedging and the airline's value. These outcomes are presented in section 5.4.

5.1 Hedging and fuel price characteristics

In this section we present our results on the relation between the price characteristics of jet fuel and the different types of hedging. Given the high Wald χ^2 values of the 5 models we confirm that the set of independent variables are collectively significant at the 1% level.

First, Table 4 model 1 describes the regression output of the regression of the *Hedge ratio* on the (natural logarithm of the) average fuel prices of each quarter. In contrast to our hypothesis, we observe a negative coefficient that is statistically significant on a 10% level ($p = 0.058$). These results suggest that an airline tends to hedge more fuel when fuel prices are relatively low. Consequently, we reject hypothesis 1a.

Next, we examined the relation between the volatility of jet fuel prices and the financial hedge ratio of airlines. The results of this analysis are displayed in Model 2. We find no significant relation between the price volatility of jet fuel and the percentage of next year's fuel hedged by an airline ($p = 0.728$), and thus no support for hypothesis 1b.

Thirdly, we observe that higher fuel prices are associated with an older fleet in model 3. The significant coefficient ($p = 0.000$) with the value of 0.8385 suggest that an increase of the fuel price by 1% is associated with a 0.84% increase in fleet age. Since we hypothesized that rising fuel prices would incentivize an airline to operate a younger, more fuel-efficient fleet, the results lead us to the rejection of hypothesis 1c.

Furthermore, we investigated the relationship between in operational hedging in the form of operating a diversified fleet and jet fuel prices in similar fashion. We expect that higher fuel prices incentivize airlines to operate a more diversified fleet. In Model 4 we utilize AD_{Type} to measure the fleet diversification. The coefficient in this model has an unexpected negative sign, suggesting that higher jet fuel prices are associated with a less diversified fleet. However, this coefficient is not statistically significant (p = 0.218).

Furthermore, we employed *ADI* $_{Family}$ to measure the diversity of an airline's fleet in Model 5. We observe the similar unexpected negative sign as in Model 4. However, in this instance the coefficient is statistically significant (p = 0.000). Therefore, a 1% increase in jet fuel price leads to a decrease in the airline's fleet diversity in such way that *ADI* $_{Family}$ decreases by 0,77%. For this reason, we reject hypothesis 1d.

Table 4:

The Relation Jet Fuel Price Characteristics and Hedging

	Tobit / Random Effects				
	Hedge Ratio		*Fleet Age*	*ADI* $_{Tyoe}$	*ADI* $_{Family}$
	(1)	(2)	(3)	(4)	(5)
Price $_{JF}$	-0.6491*		0.8385***	-0.1560	-0.7713***
	(0.3429)		(0.2205)	(0.1267)	(0.0891)
σ_{JF}		-0.0123			
		(0.0445)			
Size	-0.0684***	-0.0684***	-0.0937***	0.1539***	0.0446***
	(0.0234)	(0.0234)	(0.0135)	(0.0079)	(0.0066)
Leverage	0.1268**	0.1198**	-0.2466***	-0.0050	-0.0657***
	(0.0549)	(0.0549)	(0.0396)	(0.0227)	(0.0206)
IO	-0.0025**	-0.0025**	-0.0042***	0.0013***	0.0016***
	(0.0010)	(0.0010)	(0.0007)	(0.0004)	(0.0003)
Legacy	-0.1706	-0.1624	0.3600**	0.2492***	0.6903***
	(0.1844)	(0.1818)	(0.1565)	(0.0523)	(0.0729)
Constant	4.5095***	1.7152***	0.3216	-2.4208***	2.3293***
	(1.5937)	(0.5784)	(1.0269)	(0.5868)	(0.4193)
Observations	1,308	1,308	1,452	1,452	1,452
Number of Airlines	28	28	28	28	28
Wald χ^2	208.3	205.3	981.7	684	334.7
Prob > χ^2	0	0	0	0	0

Note. This table displays the results of equations 1 and 2. Both models include quarter dummy variables, which are not reported. Standard errors are in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5.2 Complements or substitudes

To test if financial hedging and operational hedging are complements or substitutes (hypothesis 2) we regressed the hedge ratio on the operational hedging variables and included several control variables as specified in Equation 10 in the previous chapter. The outcomes of this analysis are presented in Table 5.

Model 1 outlines the results of a Tobit random effects model with the *Hedge Ratio* as the dependent variable and ADI_{Type} as one of the independent operational hedging variables. Model 2 is present the results of a Tobit model with ADI_{Family} as one of the independent variables. Given the high Wald χ^2 values (Model 1: Wald χ^2 = 216.8, Model 2: Wald χ^2 = 226.6) we confirm that the set of independent variables are collectively significant at the 1% level.

Both models show a significant coefficient for fleet diversity at the 1% level. The coefficient for fleet diversity in Model 1 is positive and significant (p = 0.006), indicating a 1% increase of fleet diversity, increases the hedge ratio by 0.25%. When considering ADI_{Family} as the measure of fleet diversification (Model 2), we once more observe a positive significant coefficient (p = 0.000). In this instance a 1% increase of fleet diversity corresponds to a 0.60% increase in the hedge ratio. These results provide support for the positive relation between operational hedging in the form of operating a more diversified fleet and the financial hedge ratio of airline.

Furthermore, Model 1 presents a significant negative relationship between the fleet age and the hedge ratio of an airline. The significant coefficient (p = 0.002) indicates that a reduction of the average fleet age by 1% results in an increase of the hedge ratio by 0.15%. Model 2 also provide a negative coefficient, although its magnitude is less pronounced. In this model, a 1% reduction of the average fleet age corresponds to a 0.06% increase in the hedge ratio. However, this coefficient is not significant (p = 0.125), suggesting that this relation in Model 2 may not be as robust as in Model 1.

Additionally, we perform a series of supplementary analyses to assess the robustness of our models. We present these analyses in Appendix C. We performed the Tobit model analyses with different combinations of the independent variables. Furthermore, we ran several Logit random effect models with *Hedge Dummy* as the dependent variable. This binary dummy variable has a value of one if the airline's percentage of next year's fuel hedged is greater than zero, and zero otherwise. The outcomes of these additional analyses align with the findings from Model 1 and 2, enhancing the reliability of our findings.

In chapter 3 we proposed the hypothesis that airlines adopt a comprehensive hedging program that uses both financial and operational hedging complementary. Our analysis provides no evidence to reject this hypothesis. Therefore, the results support that airlines may indeed use financial hedging and operational hedging complementary.

Table 5:

The Relation between Financial and Operational Hedging

	Tobit / Random Effects	
	Dependent variable: Hedge Ratio	
	(1)	(2)
Fleet age	-0.1483***	-0.0657
	(0.0469)	(0.0428)
ADI $_{Type}$	0.2454***	
	(0.0887)	
ADI $_{Family}$		0.6014***
		(0.1344)
Size	-0.1153***	-0.0690***
	(0.0272)	(0.0251)
Distance	-0.0082	-0.0295
	(0.0450)	(0.0447)
Leverage	0.0981*	0.1341**
	(0.0557)	(0.0563)
IO	-0.0034***	-0.0039***
	(0.0010)	(0.0010)
Legacy	-0.1749	-0.5080**
	(0.2056)	(0.2068)
Constant	2.9870***	1.9743***
	(0.7192)	(0.6768)
Observations	1,308	1,308
Number of Airlines	28	28
Wald χ^2	216.8	226.6
Prob > χ^2	0.00	0.00

Note. This table displays the results of Equation 10. Both models include quarter dummy variables, which are not reported. Standard errors are in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5.3 Hedging and risk exposure

To test hypotheses 3a to 3d, we employed a two-step analysis as described in the previous chapter. In the first step we estimated the quarterly averaged jet fuel exposure coefficients (γ^{avg}) for each individual airline *i* for each quarter *q*. Table 6 reports a summary of the coefficients.

Table 6:

Summary Statistics of the Jet Fuel Exposure Coefficient

	Total	Asia and Pacific	Europe	North America	South America[1]	Legacy	LCC
Obs. (*N*)	1,370	590	340	296	144	998	372
Mean γ	-0.0676	-0.1153	-0.0016	-0.1172	0.0713	-0.1099	0.0448
Median γ	-0.0805	-0.1095	-0.0033	-0.1151	-0.0072	-0.0967	-0.0085
Std. dev γ	0.5833	0.4980	0.6154	0.5798	0.7749	0.5416	0.6707
Min γ	-2.1441	-2.1441	-1.9607	-1.9991	-1.9499	-2.1441	-1.9499
Max γ	3.8587	2.7383	2.2356	2.8260	3.8586	2.8260	3.8587
% negative γ	58.91%	64.58%	50.59%	60.81%	50.69%	61.62%	51.34%

Note. [1] Includes Latin America and the Caribbean. This table displays the results of Equation 12

We estimated a total of 1,370 coefficients, with 590 Asian and pacific, 340 European, 296 north American and 144 South American exposure coefficients. We observe an overall mean (median) coefficient of –0.0676 (–0.0805) and that 58.91% of the estimated coefficients is negative. We observe that airlines from the Asian and pacific region exhibit the highest percentage of negative coefficients (64.48%), while only half of the coefficients are negative for European and south American airlines (50.59% and 50.69%). Additionally, we observe that Legacy carriers have more negative coefficients and lower mean and median values compared to the LCCs. The highest exposed airline is the Brazilian GOL Airlines with an exposure coefficient of 3.8587 in the first quarter of 2016.

The absolute values of these jet fuel exposure coefficients function as the dependent variable in the second step of the analysis, as described in the previous chapter. To determine the most efficient model between a random effects model and a fixed effects model, we conduct a Hausman test. The null hypothesis assumes that both models are equally efficient. With a χ^2-value of 108.04 (p = 0.0001) we reject the null hypothesis, implying that a fixed effects model is the more appropriate model compared to the random effects model. The results of the fixed effects models are presented in Table 7. Models 1 and 2 control for fleet diversity with the variable ADI_{Type}, while models 3 and 4 report the results using ADI_{Family} representing fleet diversity. Given the F-statistic around 5.00 for all models we confirm that the set of independent variables are collectively significant at the 1% level.

Table 7:

Financial Hedging, Operational Hedging, and Jet Fuel Risk Exposure

	Fixed Effects		Fixed Effects	
	Dependent variable: $\left\|\gamma_{i,t}^{avg}\right\|$		*Dependent variable:* $\left\|\gamma_{i,t}^{avg}\right\|$	
	(1)	(2) Interaction	(3)	(4) interaction
Hedge Ratio	0.0267	-0.2920	0.0340	-0.2995
	(0.0740)	(0.4149)	(0.0740)	(0.3931)
Fleet age	0.1002	0.0455	0.0342	-0.0423
	(0.0954)	(0.1204)	(0.0945)	(0.1284)
ADI $_{Type}$	-0.1778	-0.2567		
	(0.1815)	(0.2343)		
ADI $_{Family}$			-0.4296*	-0.4783*
			(0.2352)	(0.2450)
Hedge Ratio x Fleet age		0.1207		0.1557
		(0.1851)		(0.1747)
Hedge Ratio x ADI $_{Type}$		0.0616		
		(0.3056)		
Hedge Ratio x ADI $_{Family}$				-0.0456
				(0.1944)
Size	-0.0199	-0.0102	-0.0501	-0.0474
	(0.0614)	(0.0629)	(0.0590)	(0.0594)
Distance	0.0092	0.0206	0.0257	0.0422
	(0.0975)	(0.0988)	(0.0976)	(0.0994)
Leverage	0.3563***	0.3583***	0.3382***	0.3393***
	(0.1167)	(0.1168)	(0.1167)	(0.1170)
Constant	0.3645	0.2357	1.2009	1.2096
	(1.5943)	(1.6165)	(1.5889)	(1.5915)
Observations	1,278	1,278	1,278	1,278
Number of Airlines	28	28	28	28
(adjusted) R^2	0.2001	0.2005	0.2017	0.2022
F-statistic	4.960***	4.805***	5.010***	4.856***

Note. This table displays the results of Equation 13. Models 1 and 3 report the results of our fixed effects model, Models 2 and 4 include the interaction effects. All models are clustered on Airline ID to control for heteroskedasticity and autocorrelation. All models include quarter dummy variables, which are not reported. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

In contrast to our expectations as set out in hypothesis 3a, Models 1 and 3 provide positive coefficients for the *Hedge Ratio* variable, although not statistically significant (p = 0.719 and p = 0.646 respectively). Models 2 and 4 display the anticipated negative sign, but similar to models 1 and 3, the coefficients lack statistical significance (p = 0.482 and p = 0.446 respectively). The findings do not provide evidence for a negative relation between financial hedging and the jet fuel risk price exposure. Therefore, we reject hypothesis 3a.

To test hypothesis 3b, we focus on the coefficient of the *Fleet Age* variable. Models 1 to 3 exhibit positive coefficients as anticipated. However, none of the coefficients are statistically significant. Based on our data and analysis, we cannot conclude that operational hedging in the form of operating a younger fleet reduces the exposure to fuel price risk, resulting in the rejection of hypothesis 3b.

Although support for hypothesis 3c is not provided by Models 1 and 2 (ADI_{Type}), Models 3 and 4 present evidence supporting a negative association between ADI_{Family} and the airline's exposure to fuel prices. The estimated coefficients reported in Models 3 and 4 are statistically significant at a 10% significance (p = 0.068 and p = 0.051) and have a negative value (–0.4296 and –0.4783 for Model 3 and 4 respectively). Based on the methodology of Treanor, Simkins, et al. (2014), the coefficient of –0.4296 suggests that for the average airline in our dataset the jet fuel price exposure coefficient declines by 1.04% if the airline increases its fleet diversity in such way that the ADI_{Type} variable rises by 1% [2]. Therefore, hypothesis 3c is supported by the results of our analysis.

Lastly, we examined the joint effect of the two types of operational hedging and financial hedging on the risk exposure. Consistent with hypothesis 3d, we anticipate a positive coefficient for the *Hedge Ratio x Fleet age* variable and a negative coefficient for the *Hedge Ratio x ADI* variable. The coefficient of the former shows the expected positive sign, although it lacks statistical significance. The coefficient of the *Hedge Ratio x ADI* variable displays the expected negative sign when utilizing ADI_{Family} to measure fleet diversity, although we cannot consider this coefficient significant. Given this lack of significance we find no support for our hypothesis and therefore we reject hypothesis 3d.

[2] The 1.04% decline is calculated by multiplying the coefficient on the fleet diversity variable (-0.4296) from Table 7 Model 3 by the 1% change (0.01) and dividing the result by the average of the absolute values of the quarterly averaged jet fuel risk factors ($|\gamma^{avg}|$) (0.4112)

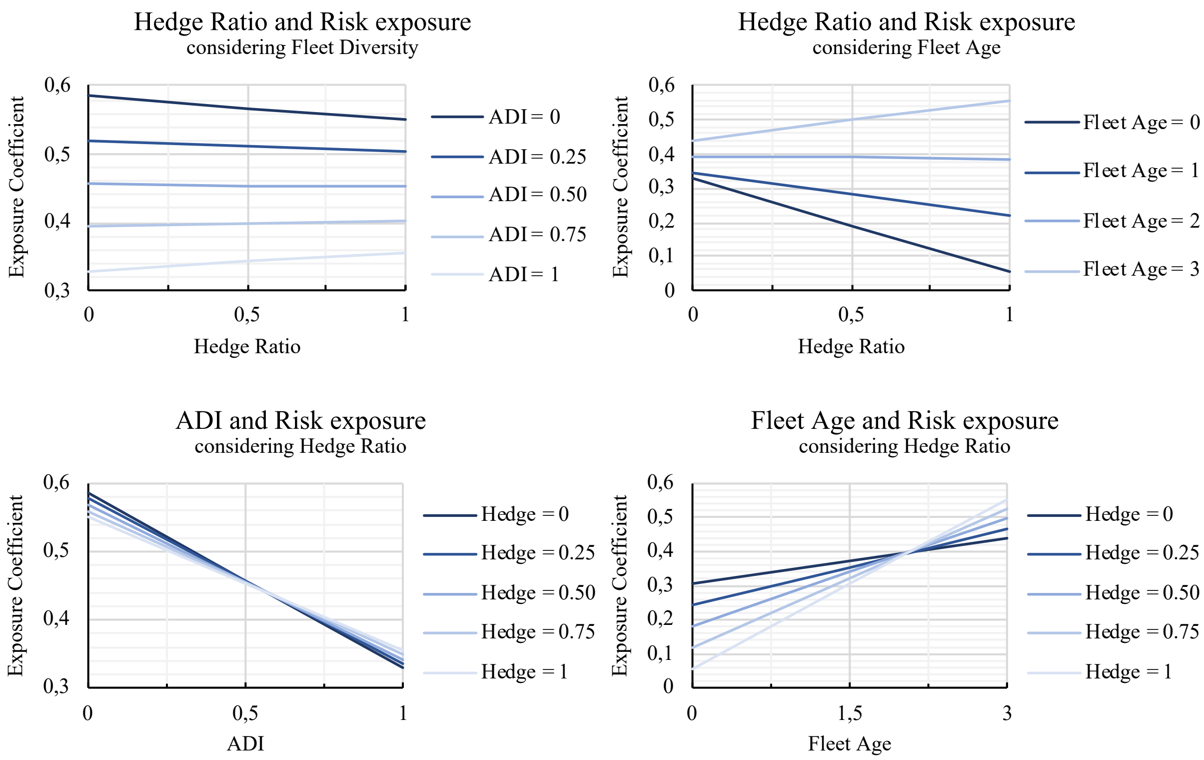
The lack of significance raises some questions. Therefore, we aim to visualize the relationship between the different types of hedging and risk exposure. These relations are presented in Figure 3. Given an average fleet age of 8.16 years (Table 3), we observe that an increase in hedge ratio leads to a decrease in risk exposure for an airline with an undiversified fleet, while it increases the exposure coefficient of an airline with a fully diversified fleet.

Moreover, as depicted in Figure 3b, we observe that for an airline with an average ADI_{Type} of 0.709 and an older fleet, the risk exposure increases if the hedge ratio increases. However, for a company with a similar diversification ratio but a younger fleet, risk exposure decreases with an increasing hedge ratio.

Figure 3c visualizes the relation between risk exposure and fleet diversification. It shows that regardless of the level of financial hedging, an increase in fleet diversity reduces the risk exposure. However, airlines with a lower financial hedge ratio exhibit a more pronounced negative effect of fleet diversity on risk exposure compared to a more financially hedged airline.

Figure 3:

Financial Hedging, Operational Hedging, and Jet Fuel Risk Exposure



Note. Fleet age is the natural logarithmic transformation of the respective variable. in Figure 3a and c we assume an airline with an average fleet age of 8.16 years (*Fleet Age* = 2.099, fleet age = $e^{2.099}$= 8.16) (Table 3). In Figure 3b and d we assume an airline with the average dispersion index of 0.551 (ADI_{Type}=0.551) (Table 3)

Lastly, we provide a visual representation of the relationship between fleet age and risk exposure in Figure 3d. Irrespective of the hedge ratio, we observe that operating a younger fleet, results in a lower risk exposure coefficient. Based on the slope of the lines, we argue that an increased hedge ratio magnifies the impact of operating a younger fleet on risk exposure.

5.4 Hedging and firm value

To test hypotheses 4a to 4d and examine the effect of the two types of hedging on firm value, we regressed (the natural logarithm of) *Tobin's Q* on the different hedging variables and included the interaction effect between financial and operational hedging. To complete the model, we included several control variables. To determine the most efficient model between a random effects model and a fixed effects model, we conducted a Hausman test. The null hypothesis assumes that both models are equally efficient. With a χ^2-value of 675.55 (p = 0.0000) we rejected the null hypothesis, implying that a fixed effects model is the more appropriate model compared to the random effects model. The results of the fixed effects models are presented in Table 8.

In Model 1 we utilized ADI_{Type} to measure fleet diversity. The model has an F-statistic of 14.88, indicating that the model is significant (p = 0.0000). Additionally, the model's explanatory power is 43,78%. In Model 2 we employed ADI_{Family} as the measurement of fleet diversity, resulting in a significant model (F-statistic = 15.64, p = 0.0000) with an explanatory power of 45.01%.

First, we consider the effect of financial hedging on firm value. In Model 1, the positive coefficient suggests a positive effect of hedging on firm value. On the other hand, Model 2, which utilizes ADI_{Family}, displays a negative coefficient. However, the lack of significance of both these coefficients indicates that there is insufficient evidence to support our hypothesis that financial hedging adds value to the firm. Therefore, we reject hypothesis 4a.

Both models report a significant positive coefficient for the variable *Fleet Age* (p = 0.000 and p = 0.000 respectively), indicating a positive relation between fleet age and firm value, measured by Tobin's Q. The coefficients suggest that a 1% increase in fleet age results in respectively a 0.23% and 0.28% increase in firm value. This significant relation implies that operational hedging by operating a younger fleet has a negative effect on the value of a firm, which support hypothesis 4b.

For the fleet diversification variables, we also observe significant positive coefficients (p = 0.000 and p = 0.000 respectively), which suggests a positive relation between fleet diversification and firm value. A 1% increase in ADI_{type} is associated with a 0.62% increase in firm value, while an increase of 1% in ADI_{Family} results in a 0.60% increase of the Tobin's Q. However, these results do not support our hypothesis that operational hedging in the form of operating a more diversified fleet is negatively related to firm value.

Table 8:

Financial Hedging, Operational Hedging, and Firm Value

	Fixed Effects *Dependent variable: Tobin's Q*	
	(1)	(2)
Hedge Ratio	0.0106	-0.2190
	(0.2077)	(0.1968)
Fleet age	0.2279***	0.2824***
	(0.0603)	(0.0630)
ADI_{Type}	0.6238***	
	(0.1143)	
ADI_{Family}		0.6010***
		(0.1244)
Hedge Ratio x Fleet Age	0.3861***	0.2940***
	(0.0934)	(0.0871)
Hedge Ratio x ADI_{Type}	-1.1929***	
	(0.1534)	
Hedge Ratio x ADI_{Family}		-0.8667***
		(0.0992)
Constant	-0.3696	-0.2750
	(0.7705)	(0.7543)
Observations	1,295	1,295
(adjusted) R^2	0.4378	0.4501
Number of airlines	28	28
F-statistic	14.88***	15.64***

Note. This table displays the results of equation 15. Models 1 and 2 report the results of our fixed effects model. Both models include the control variables *Size*, *Leverage*, *ROA*, *IO* and quarter dummy variables, which are not reported. Refer to appendix D for the complete model. Standard errors are in parentheses.

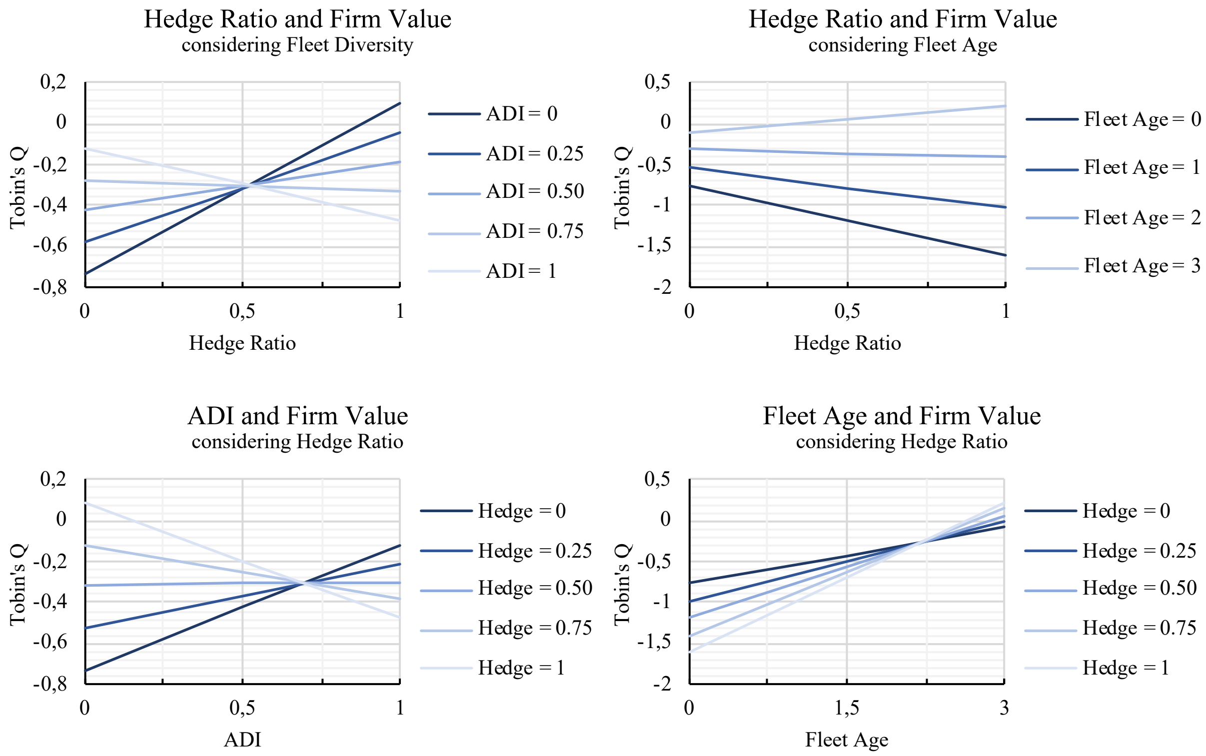
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Finally, we investigate the joint effect of financial and operational hedging on the value of an airline. Focusing on the joint effect between operating a younger fleet and the hedge ratio, we hypothesized a positive joint effect and thus a negative coefficient. However, the results of both models reveal positive significant coefficients (p = 0.000 and p = 0.001). Furthermore, we expect to observe positive coefficients for the *Hedge ratio x ADI* variables, However, the results of both models provide is with significant negative coefficients (p = 0.000 and p = 0.000). Because of these contradicting results, we reject the hypothesis that that a hedging strategy that consists of both financial and operational hedging is positively related to the value of an airline.

Analogue to our analyses concerning risk exposure, we visualized the relation between the different types of hedging and firm value and presents these relations in Figure 4. Considering an average fleet age of 8.16 years (refer to Table 3), we observe that an increase in hedge ratio is associated with an increase in firm value for an airline with an undiversified fleet, while airline with a diversified fleet experiences a decrease in firm value when the hedge ratio increases (Figure 4a).

Figure 4:

Financial Hedging, Operational Hedging, and Firm Value



Note. Tobin's Q and *Fleet age* are the natural logarithmic transformations of the respective variables. In Figure 4a and c we assume an airline with an average fleet age of 8.16 years (*Fleet Age* = 2.099, fleet age = $e^{2.099}$= 8.16) (Table 3). In Figure 4b and d we assume an airline with the average dispersion index of 0.551 (ADI_{Type} =0.551) (Table 3)

Furthermore, we observe in Figure 4b that for an airline with an average ADI_{Type} of 0.709 and an older fleet, the firm value increases if the hedge ratio increases. However, for a company with a similar diversification ratio but a younger fleet, the firm value decreases with an increasing hedge ratio.

Figure 4c visualizes the relationship between firm value and fleet diversification. It reveals that operating a more diversified fleet is linked to a rise in firm value for the financially unhedged firm. However, for airlines that utilize a financial hedging strategy, we observe that an increase in the fleet diversity results in a lower firm value.

Lastly, Figure 4d offers a visual representation of the relationship between fleet age and firm value. Irrespective of the hedge ratio, we observe that operating a younger fleet corresponds with a lower firm value. Based on the slope of the lines, we argue that an increased hedge ratio magnifies the negative impact of operating a younger fleet on firm value.

6. CONCLUSION AND DISCUSSION

For years the effect of corporate hedging has been intensively discussed in corporate finance literature. Despite the weak theoretical justification for hedging, it is a commonly used risk management strategy nowadays (Berghöfer & Lucey, 2014; Mo et al., 2021). Prior research provided us with mixed results, with some papers supporting the added value of hedging, while other studies found either a negative effect or no significant effect at all.

The purpose of this thesis was to add additional insights on hedging in the aviation industry by investigating a relatively recent period characterized by more volatile fuel prices. Additionally, we acknowledged the importance of exploring the effect of hedging on airlines outside the United States and therefore included airlines from around the globe. This study examined the effect of both financial hedging and operational hedging on the airline's risk exposure and firm value. Therefore, the research question was:

RQ. *What is the impact of financial and operational hedging on risk exposure and the value of an airline?*

We collected airline-specific data, data on jet fuel prices, and general market data to construct a panel dataset containing information on 28 globally active airlines. We analyzed these airlines in the period between 2010 and 2022.

In contrast to previous studies, we found that fuel price characteristics are negatively related to both financial and operational hedging. This relation implies that airlines financially hedge less, reduce their fleet diversity, and increase their fleet age if fuel prices increase. Secondly, our findings indicate that airlines use financial hedging and operational hedging complementary. Surprisingly, we found no evidence that financial hedging reduces risk exposure or has a positive effect on firm value. Moreover, operational hedging in the form of operating a younger fleet does not seem to decrease risk exposure and even negatively affects firm value. However, operational hedging by operating a more diversified fleet reduces the risk exposure and has a positive effect on firm value. Finally, we found no statistically significant support for the joint effect of financial and operational hedging reducing risk exposure. The joint effect even has a negative effect on firm value, as suggested by our findings.

Although some findings align with our hypotheses and previous results, we observed multiple unexpected results. First, we note that our observed negative relation between financial hedging and fuel price characteristics contradicts with previous findings. We argue that our findings hold some logic, as they align with the principle of hedging being potentially more effective when fuel prices are low. However, the divergence of our results compared to previous findings warrants a deeper exploration into the potential factors contributing to these contrasting outcomes. COVID-19 is identified as a potential factor and therefore, this period is excluded from the analysis. We observe indeed a shift from a negative to a positive mathematical sign, However, the coefficient becomes insignificant. Similarly, we identify the COVID-19 crisis as a potential explanation for our deviating findings on financial hedging and risk exposure compared to the broader consensus in the existing literature. The COVID-19 crisis may have influenced this relation as it had a significant impact on the whole aviation industry. Yet, excluding the COVID-19 period did not provide us with a significant coefficient, although the mathematical sign suggests that financial hedging reduces the risk exposure, which is in line with our hypothesis and the majority of previous findings. Additionally, our unexpected negative relation between financial hedging and firm value might be explained by inclusion of the COVID-19 crisis. While firm value almost immediately dropped because of the crisis, liquidating a financial hedge portfolio was not instantly realized. Airlines would still hold a significant number of hedging derivatives, while simultaneously experiencing a decrease in firm value. To validate this, we excluded the COVID-19 crisis from our analysis and did indeed observe a shift to a significant positive relation (see Appendix E).

Another potential explanation for the discrepancies between our findings and previous literature might be related to the companies examined. As previous studies predominantly concentrated their research on the United States airline industry, we took a much broader perspective by examining a global sample of airlines. To address this potential source of divergence, we conducted subgroup analyses for each region. This analysis provided evidence to support that financial hedging reduces the risk exposure for European airlines. Additionally, we observed that operating a younger fleet reduces the risk exposure solely for North American airlines, implying a relation that aligns with prior studies. Furthermore, we concentrated on the relation between hedging and firm value. Through subgroup analysis, we investigated this relationship across different regions. The results revealed a positive association between financial hedging and firm value for all regions, although this relation was only statistically significant for the North American airlines (see Appendix F). Furthermore, the relation between fleet age and firm value across all regions is statistically significant. We observed that for Asian and North American airlines operational hedging through operating a younger fleet has a positive effect on the value of the firm. Finally, when solely focusing on airlines from North America, we observed a negative association between diversification of the fleet and firm value.

This study provided interesting insights on the effect of hedging on risk exposure and firm value. However, it is essential to acknowledge the limitations of this study. First, the sample size of 28 airlines may be considered a relatively small sample. Especially when conducting the region-specific subgroup analyses, the small number of airlines from specific regions may affect the statistical power and reliability of our analysis and therefore we must interpret our results with care. Nevertheless, expanding our dataset with a larger number of airlines offers a compelling avenue to further investigate the impact of hedging. This would provide a broader representation of the global aviation industry and would provide more reliable findings in our subgroup analysis.

Secondly, the unprecedented disruptions caused by the COVID-19 virus seem to have obscured the patterns of hedging behavior. However, the real impact of the pandemic on hedging behavior remains uncertain and requires additional research. Potential avenues for further research are qualitative studies with airline executives to gain a better understanding of the decisions made in the pandemic, or additional quantitative studies to analyze hedging and its impact before, during and after the pandemic.

Finally, the aviation industry is a complex industry with numerous factors influencing the relation between hedging, risk exposure and firm value. Even though, we carefully selected several key factors, the limited number of control variables may have resulted in incomplete explanations and biased relations. For future research, our dataset can be expanded with more relevant control variables to increase the robustness of our findings.

The strengths of this study are twofold. We are the first study to include the COVID-19 period in our sample. Additionally, we constructed a sample containing airlines from all around the globe, acknowledging the differences between the U.S. airline industry and other regions.

Financial hedging and operating a younger fleet do not seem to reduce risk, while operating a diversified fleet has a positive effect in mitigating risk. While no effect of financial hedging was found on firm value, operating a younger fleet reduces firm value and diversification of the fleet has a positive effect on the value. While our study may have certain limitations in providing recommendations for airlines, our findings do suggest that hedging does not necessarily benefit the firm. Therefore, we would encourage airlines to carefully review their current risk management strategy.

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APPENDICES

Appendix A

Table 9A:

List of Airlines

Airline	Continent	Headquarters
Air Canada	North America	Saint-Laurent, Canada
Air China	Asia	Beijing, China
Air France - KLM	Europe	Paris, France
American Airlines	North America	Fort Worth, United States
ANA Holdings	Asia	Tokyo, Japan
Cathay Pacific Airways	Asia	Lantau, Hong Kong
China Airlines	Asia	Taoyuan, Taiwan
China Eastern Airlines	Asia	Shanghai, China
China Southern Airlines	Asia	Guangzhou, China
Copa Holdings	North America	Panama City, Panama
Delta Air Lines	North America	Atlanta, United States
Deutsche Lufthansa	Europe	Cologne, Germany
Easyjet	Europe	Luton, England
EVA Airways	Asia	Taoyuan, Taiwan
Gol Linhas Áereas Inteligentes	South America	Rio de Janeiro, Brazil
Interglobe Aviation	Asia	Gurgaon, India
International Airlines Group	Europe	London, Kingdom
Japan Airlines	Asia	Tokyo, Japan
Jet2	Europe	Leeds, United Kingdom
Jetblue Airways	North America	New York, United States
Korean Air Lines	Asia	Seoul, South Korea
LATAM Airlines	South America	Santiago, Chile
Qantas Airways	Australia	Mascot, Australia
Ryanair	Europe	Swords, Ireland
Singapore Airlines	Asia	Singapore City, Singapore
Southwest Airlines	North America	Dallas, United States
United Airlines	North America	Chicago, United States
Wizz Air	Europe	Budapest, Hungary

Note. Airlines sorted on alphabetic order.

Source: Annual reports

Appendix B

Table 10A:

List of Aircraft Type and Families

Manufacturer	Family	Type
Airbus	Airbus A220	A220-100, A220-300
Airbus	Airbus A300	A300-100, A300-200, A300-600
Airbus	Airbus A310	A310-200, A310-300
Airbus	Airbus A320	A318-100
		A319-100
		A320-100, A320-200, A320neo
		A321-100, A321-200, A321neo
Airbus	Airbus A330	A330-200, A330-300, A330-900
Airbus	Airbus A340	A340-200, A340-300, A340-600
Airbus	Airbus A350	A350-900, A350-1000
Airbus	Airbus A380	A380-800
ATR	ATR 42/72	ATR42-300, 42-500, 42-600, 72-200
		72-500, 72-600
Boeing	Boeing B717	B717-200
Boeing	Boeing B727	B727-200
Boeing	Boeing B737	B737-200, B737-300, B737-400
		B737-500, B737-600
		B737-700, B737-800, B737-900
		B737-Max 8, B737-Max 9, B737-Max 10
Boeing	Boeing B747	B747-100, B747-200, B747-300, B747-400
		B747-8
Boeing	Boeing B757	B757-200
Boeing	Boeing B767	B767-200, B767-300
Boeing	Boeing B777	B777-200, B777-300
Boeing	Boeing B787	B787-8, B787-9, B787-10
Bombardier Inc.	Bombardier CRJ/ CL65	CL600-100, CL600-200, CL600-700
		CL600-900, CL600-1000
Bombardier Inc.	AVRORJ/Bae146	RJ70, RJ85, RJ100, BA 146-100
		BA 146-200, BA 146-300
Bombardier Inc.	Bombardier Dash 8	DHC-8-100, DHC-8-200
		DHC-8-300, DHC-8-400
British Aerospace/ AVRO	Jetstream 41	Jetstream 41
British Aerospace/ AVRO	BAC 1-11	BAC -200, BAC-500
British Aerospace/ AVRO	Bae ATP	ATP
COMAC	COMAC ARJ21	ARJ21-700
COMAC	COMAC C919	C919
Dornier	DO 328-100	DO 328-100
Dornier	DO 328-300	DO 328-300

Embraer	Embraer 120	E120
Embraer	Embraer 135/ 145	E135, E145
Embraer	Embraer 170	E170, E175, E190, E195, E195-E2
Fokker	Fokker 70-100	F70, F100
Fokker	Fokker 50	F50
Lockheed	Lockheed L-1011	L-1011
McDonnell Douglas	DC8	DC8
McDonnell Douglas	DC9-10-50	DC9-10, DC9-20, DC9-30, DC9-40, DC9-50
McDonnell Douglas	DC9-80	MD-81, MD-82, MD-83, MD-87, MD-88
McDonnell Douglas	DC10	DC10-10, DC10-30
McDonnell Douglas	MD11	MD11
Saab	Saab 340	Saab 340
Saab	Saab 2000	Saab 2000
Viking Air Limited	DHC-6	DHC-6-300

Note. Airplane manufacturers sorted on alphabetic order.

Sources: planespotters.net, annual reports, EASA Typerating and licence endorsement list Fligth crew – Fixed wing: 24 july 2023

Appendix C

Table 11A:

The Relation between Financial and Operational Hedging (det.)

	Tobit / Random Effects *Dependent variable: Hedge Ratio*					Logit / Random Effects *Dependent variable: Hedge dummy*				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Fleet age	-0.0970**			-0.1483***	-0.0657	-5.1494***			-4.0545***	-0.4486
	(0.0428)			(0.0469)	(0.0428)	(1.3642)			(1.2122)	(1.3610)
ADI $_{Type}$		0.1348*		0.2454***			20.3503***		22.2145***	
		(0.0810)		(0.0887)			(4.2411)		(3.7888)	
ADI $_{Family}$			0.6287***		0.6014***			29.5982***		27.7089***
			(0.1329)		(0.1344)			(3.6473)		(2.8978)
Size	-0.0869***	-0.0769***	-0.0553**	-0.1153***	-0.0690***	-3.0109***	-3.0848***	-2.2696***	-3.2855***	-2.7581***
	(0.0251)	(0.0243)	(0.0235)	(0.0272)	(0.0251)	(1.0440)	(0.8486)	(0.7149)	(0.6304)	(0.7751)
Distance	-0.0125	-0.0302	-0.0405	-0.0082	-0.0295	-4.6550**	-8.2105***	-7.0733***	-5.6789***	-6.3516***
	(0.0449)	(0.0445)	(0.0442)	(0.0450)	(0.0447)	(1.8976)	(2.0198)	(2.1070)	(1.9883)	(1.7428)
Leverage	0.0973*	0.1288**	0.1516***	0.0981*	0.1341**	3.5008**	4.1028**	5.0230***	3.3346*	4.4341***
	(0.0558)	(0.0552)	(0.0552)	(0.0557)	(0.0563)	(1.6444)	(2.0114)	(1.6515)	(1.7047)	(1.6651)
IO	-0.0028***	-0.0028***	-0.0038***	-0.0034***	-0.0039***	-0.1988***	-0.2558***	-0.2595***	-0.2706***	-0.2536***
	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0340)	(0.0620)	(0.0427)	(0.0436)	(0.0368)
Legacy	-0.1144	-0.1901	-0.5474***	-0.1749	-0.5080**	-4.3242**	-6.2353***	-17.1197***	-1.0090	-9.8217***
	(0.1966)	(0.1871)	(0.2006)	(0.2056)	(0.2068)	(2.0428)	(1.8563)	(2.9931)	(1.9674)	(2.5096)
Constant	2.3849***	2.0537***	1.6198**	2.9870***	1.9743***	131.7017***	131.5986***	110.0625***	122.5617***	110.9703***
	(0.6814)	(0.6485)	(0.6341)	(0.7192)	(0.6768)	(24.6895)	(27.3718)	(21.4729)	(17.9107)	(21.2889)
Observations	1,308	1,308	1,308	1,308	1,308	1,300	1,300	1,300	1,300	1,300
Number of id	28	28	28	28	28	28	28	28	28	28
Wald χ^2	211.2	207	224	216.8	226.6	137.6	87.66	144	165.5	194.5
Prob > χ^2	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00

Appendix D

Table 12A:

Financial Hedging, Operational Hedging, and Firm Value

	Fixed Effects *Dependent variable: Tobin's Q*	
	(1)	(2)
Hedge Ratio	0.0106	-0.2190
	(0.2077)	(0.1968)
Fleet age	0.2279***	0.2824***
	(0.0603)	(0.0630)
ADI_{Type}	0.6238***	
	(0.1143)	
ADI_{Family}		0.6010***
		(0.1244)
Hedge Ratio x Fleet Age	0.3861***	0.2940***
	(0.0934)	(0.0871)
Hedge Ratio x ADI_{Type}	-1.1929***	
	(0.1534)	
Hedge Ratio x ADI_{Family}		-0.8667***
		(0.0992)
Size	-0.0611**	-0.0659**
	(0.0308)	(0.0286)
Leverage	1.0389***	1.0884***
	(0.0646)	(0.0642)
ROA	1.0317***	1.0132***
	(0.1402)	(0.1371)
IO	0.0040***	0.0034***
	(0.0010)	(0.0010)
Constant	-0.3696	-0.2750
	(0.7705)	(0.7543)
Observations	1,295	1,295
(adjusted) R^2	0.4378	0.4501
Number of airlines	28	28
F-statistic	14.88***	15.64***

Note. This table displays the results of equation 15. Models 1 and 2 report the results of our fixed effects model. Both models include quarter dummy variables, which are not reported. Standard errors are in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix E

Table 13A:

Financial Hedging, Operational Hedging, and Firm Value (det.)

	Fixed Effects *Dependent variable: Tobin's Q*			Fixed Effects *Dependent variable: Tobin's Q*		
	(1) Total	(2) *Year* < 2020	(3) *Year* ≥ 2020	(4) Total	(5) *Year* < 2020	(6) *Year* ≥ 2020
Hedge Ratio	0.0106	0.6590**	0.2503	-0.2190	0.3688	-0.0979
	(0.2077)	(0.2620)	(0.6260)	(0.1968)	(0.2526)	(0.5242)
Fleet age	0.2279***	0.3567***	-0.0650	0.2824***	0.3288***	0.2430
	(0.0603)	(0.0728)	(0.2237)	(0.0630)	(0.0726)	(0.2216)
ADI $_{Type}$	0.6238***	0.4585***	-0.0748			
	(0.1143)	(0.1421)	(0.3653)			
ADI $_{Family}$				0.6010***	0.1608	4.0430***
				(0.1244)	(0.1946)	(0.9674)
Hedge Ratio x Fleet Age	0.3861***	0.0841	0.0386	0.2940***	0.0816	0.0214
	(0.0934)	(0.1152)	(0.2424)	(0.0871)	(0.1100)	(0.2356)
Hedge Ratio x ADI $_{Type}$	-1.1929***	-1.0280***	-0.5242			
	(0.1534)	(0.1814)	(0.4019)			
Hedge Ratio x ADI $_{Family}$				-0.8667***	-0.9266***	0.2093
				(0.0992)	(0.1103)	(0.1907)
Size	-0.0611**	0.0462	-0.4639***	-0.0659**	0.0018	-0.4362***
	(0.0308)	(0.0353)	(0.1498)	(0.0286)	(0.0348)	(0.1369)
Leverage	1.0389***	0.7238***	0.3725**	1.0884***	0.6865***	0.1334
	(0.0646)	(0.0996)	(0.1884)	(0.0642)	(0.0952)	(0.1827)
ROA	1.0317***	3.0041***	-0.5668***	1.0132***	2.8447***	-0.6258***
	(0.1402)	(0.2201)	(0.1831)	(0.1371)	(0.2135)	(0.1779)
IO	0.0040***	0.0054***	0.0019	0.0034***	0.0053***	0.0014
	(0.0010)	(0.0013)	(0.0014)	(0.0010)	(0.0013)	(0.0013)
Constant	-0.3696	-3.0273***	10.8386***	-0.2750	-1.6808*	7.3080**
	(0.7705)	(0.8505)	(3.5350)	(0.7543)	(0.9020)	(3.5306)
Observations	1,295	987	308	1,295	987	308
(Adjusted) R^2	0.4378	0.5167	0.4314	0.4501	0.5356	0.4624
F-statistic	14.88***	19.04***	8.510***	15.64***	20.54***	9.647***

Note. This table displays the results of equation 15. Models 1 and 2 report the results of our fixed effects model. Both models include quarter dummy variables, which are not reported. Standard errors are in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix F

Table 14A:

Financial Hedging, Operational Hedging, and Firm Value per Continent

	Fixed Effects *Dependent variable: Tobin's Q*				
	(1) Global	(2) North America	(3) Europe	(4) Asia & Pacific	(5) South America
Hedge Ratio	0.0106	1.6283**	0.6844	0.2920	2.3770
	(0.2077)	(0.8237)	(0.5910)	(0.6168)	(2.0626)
Fleet age	0.6238***	-0.5328*	1.4619***	-0.3835***	1.4607***
	(0.1143)	(0.3219)	(0.4225)	(0.1208)	(0.4094)
ADI $_{Type}$	0.2279***	-0.3058**	0.1200	0.4964***	0.9527
	(0.0603)	(0.1235)	(0.2798)	(0.0630)	(0.6817)
Hedge Ratio x Fleet Age	0.3861***	-0.4440	0.0792	-0.0867	-0.5098
	(0.0934)	(0.3530)	(0.3186)	(0.1059)	(0.9443)
Hedge Ratio x ADI $_{Type}$	-1.1929***	-0.7124**	-1.8420***	-0.0871	-1.8313***
	(0.1534)	(0.2956)	(0.5150)	(0.6544)	(0.6666)
Size	-0.0611**	0.1509	0.2255***	-0.4204***	-0.1166
	(0.0308)	(0.0953)	(0.0683)	(0.0367)	(0.1155)
Leverage	1.0389***	-0.2372	0.4097	0.9486***	1.4797***
	(0.0646)	(0.2030)	(0.2539)	(0.0785)	(0.2210)
ROA	1.0317***	1.1628***	1.1095***	0.0781	1.8809***
	(0.1402)	(0.4189)	(0.4241)	(0.1439)	(0.5032)
IO	0.0040***	-0.0031	0.0052*	0.0013	0.0079
	(0.0010)	(0.0026)	(0.0029)	(0.0008)	(0.0055)
Constant	-0.3696	-3.1198	-7.1295***	8.5931***	-0.9758
	(0.7705)	(2.3727)	(1.6742)	(0.8569)	(2.5333)
Observations	1,295	297	329	521	148
(Adjusted) R^2	0.4378	0.8638	0.6380	0.6709	0.8455
Number of Airlines	28	6	7	12	3
F-statistic	14.88***	24.41***	7.390***	14.43***	7.755***

Note. This table displays the results of equation 15 per continent. The models report the results of our fixed effects model. all models include quarter dummy variables, which are not reported. Standard errors are in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.