Risk Management in the Airline Industry

Dissertation

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Chapter 1

INTRODUCTION

Airlines are exposed to jet fuel price risk because fuel costs account for approximately a third of total airline costs (Berghöfer and Lucey, 2014; Carter et al., 2006; IATA, 2015). Therefore, different mechanisms exist in the airline industry to deal with high, volatile kerosene prices such as passing the fuel prices on to passengers, operating fuel efficient aircraft and fuel hedging (Morrell and Swan, 2006). As air travel has evolved into a commodity market with intense competition and price sensitive customers (Yeoman and McMahon-Beattie, 2006), airlines are unable to raise fuel ticket surcharges to offset higher oil prices (Cobbs and Wolf, 2004). The fuel efficiency of passenger aircraft has been improved substantially (Airbus Group, 2015) but the purchase of new aircraft entails high capital costs (Schefczyk, 1993) and long manufacturing lead times (Jiang and Hansman, 2006). Airline managers can make use of fuel hedging as a risk management tool to counteract kerosene price risk. While fuel hedging is mostly referred to as holding a portfolio of financial derivative instruments, operational hedging in the form of operational flexibility may also be part of the risk management program (Gamba and Triantis, 2013; Smith and Stulz, 1985).

Not every firm engages in financial and operational hedging equally. Thus, the determinants of hedging have been studied intensely. The main argument for entering into derivative contracts is to lower the likelihood of encountering bankruptcy and to reduce the costs associated with financial distress (Bessembinder, 1991; Nance et al., 1993; Smith and Stulz, 1985; Warner, 1977). In addition, hedging should help in alleviating the underinvestment problem (Froot et al., 1993; Myers, 1977) and in optimizing tax expenses (Graham and Smith, 1999; Smith and Stulz, 1985). The managerial compensation structure (Breeden and Viswanathan, 1998; DeMarzo and Duffie, 1995; Smith and Stulz, 1985; Stulz, 1984) and the size of a firm (Graham and Smith, 1999; Haushalter, 2000; Smith and Stulz, 1985; Warner, 1977) are also hypothesized to influence the firm's hedging behavior. Allayannis et al. (2001), Gamba and Triantis (2013), and Mello et al. (1995) analyze the question of whether operational hedging tools are to be considered substitutes or complements to financial hedging. The studies do not provide an unequivocal answer.

As the airline industry is characterized by high leverage, low profit margins and hence a higher likelihood of incurring bankruptcy (Isin et al., 2014; Loudon, 2004), the financial distress theory as an explaining factor for hedging should be especially applicable to airlines. Several large international airlines went bankrupt in the last 10 years, like American Airlines, Delta Air Lines, Japan Airlines, and United Airlines. In this study, 8% of all sample airlines defaulted between 2005 and 2014. Regardless of the existing exposure to fuel price risk, some airlines either only hedge a small portion of their expected fuel requirements or do not hedge their fuel price risk at all. American Airlines, for example, seized their hedge program in 2014 due to their inability to "predict the future availability, price volatility or cost of aircraft fuel" (AMR Corporation, 2015, p. 19).

Thus, this thesis sheds light on the heterogeneous fuel hedging behavior of listed airlines worldwide. The question of why some airlines hedge, why others refrain from derivative usage and why airlines change their hedge portfolios frequently is addressed. The focus is on financial fuel price hedging, operational hedging and selective hedging. Operational hedging tools in this study are operating a diverse fleet, being a member of a strategic alliance and financing aircraft under operating lease contracts. The sample consists of 74 passenger airlines from 39 countries and covers the period between 2005 and 2014. The extensive hand-collected data set allows for detailed descriptive results. Unlike in many other airlines-related studies fixed effects estimation is used in the regression models to control for airline idiosyncrasies. To draw further conclusions, the sample is split into five regions: Africa, America, Asia, Europe, and Oceania. Moreover, the analysis is conducted on low-cost airlines and legacy carriers separately.

The study contributes to the existing literature in several ways: First, the analysis provides evidence of a nonlinear relation between financial hedging and debt ratios. In contrast to the results of Purnanandam (2008), the debt ratios follow a convex shape. Second, operational hedging, measured in several ways both with continuous and binary variables, is included besides determinants-related variables, therefore adding to the literature regarding the "substitute or complement" question. Third, the results regarding selective hedging support the rationale of herd behavior in the airline industry. When airlines of the same region either increased or decreased their hedge ratios, the individual airline reacted in the same direction. Fourth, the study provides evidence that prior-period hedging losses impact a firm's hedging behavior. Airlines adapted their hedge ratios more strongly when they experienced derivative losses recognized in income. Fifth, the thesis comprises the most extensive sample of international airlines in a determinant-related study to the knowledge of the author. The total revenues of the sample airlines make up 69% of the revenues of all global commercial airlines (IATA, 2018).

The thesis begins with a literature review in Chapter 2. A short introduction into financial hedging and the airline industry is followed by a description of the determinants of hedging, operational hedging tools and selective hedging. In Chapter 3, the hypotheses of this study are presented. Chapter 4 contains a detailed description of the sample and the variables employed as well as the descriptive results. The univariate and multivariate analyses of the three topics, determinants of hedging, operational hedging and selective hedging, can be found in Chapter 5. Chapter 6 summarizes the results and provides concluding remarks.

Chapter 2

LITERATURE REVIEW

The following chapter gives a review on the existing literature in the areas of the airline industry, financial hedging, the determinants of hedging, operational hedging and selective hedging. Section 2.1 is focused on the difference between fuel price risk and exposure, the volatility of the oil price and its impact on the airline industry. Subsequently, it is outlined which financial hedging instruments airlines can use to manage fuel price risk. In Section 2.2, the question of why airlines hedge is examined by summarizing existing empirical and theoretical research on the determinants of hedging. Section 2.2 is divided into the subsections relating to financial distress (2.2.1), the underinvestment problem (2.2.2), managerial motives (2.2.3), tax incentives (2.2.4), and economies of scale (2.2.5).

The question of how airlines use risk management techniques is analyzed in Section 2.3. Operational hedging can be employed by airlines as a risk management tool to counteract fuel price risk. The operational hedging tools considered in this study are fleet diversity (2.3.1), strategic alliances (2.3.2), and aircraft leasing (2.3.3). Subsection 2.3.4 concludes with focusing on the topic whether financial and operational hedging are substitutes or compliments. In addition to Section 2.3, Section 2.4 also contains answers on how airline risk managers hedge their fuel price risk, namely by adapting their hedge portfolio to changes in market conditions based on their personal views.

Appendix C comprises tabular summaries of previous empirical studies on the determinants of hedging, divided into financial distress, the underinvestment problem, economies of scale, operational hedging and selective hedging. The tables include descriptions of the study's sample, dependent and independent variables as well as regression coefficients and significance levels.

In addition to the literature to be reviewed explicitly below, there is another strand of literature on risk management and hedging with financial instruments that will not be considered in detail. This literature begins with Holthausen (1979) who considers the optimal forward hedging position of a risk-averse decision maker facing price risk. This optimal position is in complete analogy to the results derived by Arrow (1965) on the canonical portfolio problem and Mossin (1968) on insurance demand. A large number of subsequent papers extend the model of Holthausen (1979), often by analyzing the impact of various tradable or non-tradable risks on the optimal derivatives position vis-à-vis the tradable price risk. For example, Benninga et al. (1985), Kawai and Zilcha (1986), Adam-Müller (1997), and Wong (2015) incorporate revenue risks into the model. Among others, Briys et al. (1993), Broll et al. (1995), and Wong (2013) focus on cross hedging under additive basis risk while Chang and Wong (2003), Wong (2003), Benninga and Oosterhof (2004), and Adam-Müller and Panaretou (2009) allow for options in addition to linear contracts such as forward or futures contracts. Korn (2010) extends the range of available instruments to exotic derivatives. Inflation risk and delivery risk as additional sources of risk are analyzed by Adam-Müller (2000) and Adam-Müller and Wong (2003), respectively. Adam-Müller and Nolte (2011) analyze the optimal hedging portfolio under multiplicative basis risk; their paper has an empirical section in which an airline's optimal cross hedging position against jet fuel price risk is derived. In sum, this strand of literature focuses on deriving optimal derivatives positions in the framework of (mostly) single-period partial equilibrium models. The data available on companies' actual risk management position is far from sufficiently granular so as to allow to test for the explanatory power of these models. As a consequence, these contributions are neither useful for solving large, complex and, in particular, intertemporal risk management problems as faced by airlines nor for explaining their actual risk management behavior. Hence, this part of the literature will not be considered any further in this thesis.

2.1 Financial hedging and airline industry picture

Empirical research shows that the characteristics of an industry a company operates in might be a determinant for the level a firm's hedge activities (Disatnik et al., 2014; Gamba and Triantis, 2013). Jin and Jorion (2006) underline the importance of studying one single industry to control for industry factors. According to Jin and Jorion, the industry should be exposed to some price risk and should be heterogeneous in terms of hedging ratios in order to draw statistically significant conclusions, which renders the airline market a suitable industry for studying the determinants of corporate hedging.

Carter et al. (2006) and Berghöfer and Lucey (2014) show that airlines are negatively exposed to volatile jet fuel prices and that the level of hedging, defined as the percentage of next year's fuel consumption hedged, varies largely between airlines, regardless of whether the airline operates domestically or internationally.[1]

It should be noted that it is not volatility in prices itself (a random draw from a known distribution) that poses the main risk to companies but rather the uncertainty about the unknown distribution of future spot prices (Modigliani and Miller, 1958; Sercu, 2009). Risk can be defined as the "uncertainty about future spot prices" (Sercu, 2009, p. 455), whereas exposure is "what one has at risk" (Adler and Dumas, 1984, p. 42) or in other words the financial position that may be impacted be the unknown future spot price (Sercu, 2009).[2]

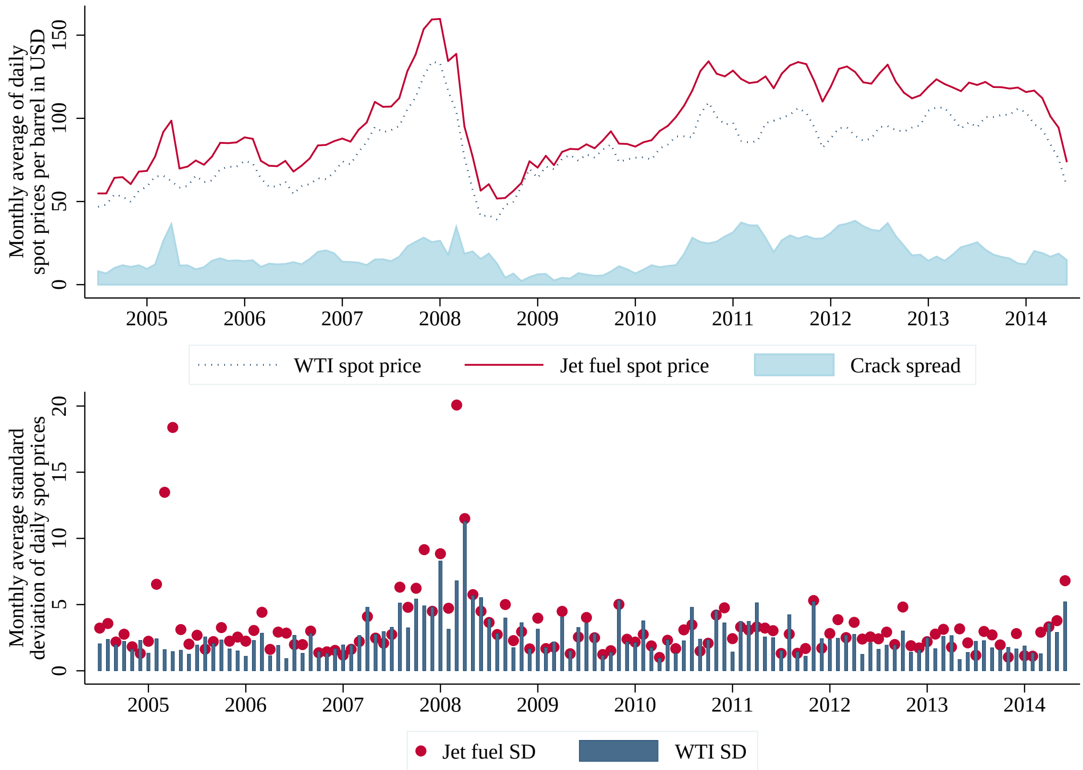
The fuel price risk of airlines becomes apparent from Figure 2.1. West Texas Intermediate (WTI) crude oil spot prices ranged from 30 to 145 U.S. dollar (USD) per barrel between 2004 and 2015. Jet fuel spot prices varied between 35 and 198 USD per barrel. The volatility of crude oil prices, measured by the monthly standard deviation of daily spot prices, peaked in October 2008 at 11.29. The standard deviation of jet fuel spot prices, on the other hand, was highest one month earlier at 20.07. Figure 2.1 also displays the crack spread, the difference between the crude oil spot price and the refined oil product (U.S. Energy Information Administration (EIA), 2011). Due to the divergence in jet fuel and crude oil prices on 12th September 2008, the spread reached the highest value of 97 USD (not visible from Figure 2.1 because of monthly average data).

Fuel price risk is especially pronounced for passenger airlines in contrast to cargo airlines. Passenger air carriers are unable to pass through increased fuel prices to their passengers as air travel has become a commodity with price sensitive customers and fierce competition between airlines (American Airlines Group, 2015; Gerner and Ronn, 2013). While network legacy carriers (NLCs) such as American Airlines, Finnair, and Lufthansa still reported in their 2014 filings that they levied fuel surcharges to pass through fuel prices to customers, low-cost competitors like Ryanair promoted their "no-fuel-surcharges policy" (Ryanair, 2015, p. 7). Although Tsoukalas et al. (2008) find that operating expenses (excluding fuel costs) of low-cost and legacy carriers converged from 1995 to 2006 in the United States (U.S.), mainly driven by an equalization of staff costs, Berghöfer and Lucey (2014) show that fuel expenses represent a larger fraction of total

[1]Seasonal demand fluctuations with high demands from June to September make airlines even more exposed to fluctuating fuel prices (Delta Air Lines, 2015; Loudon, 2004).

[2]Adler and Dumas (1984) and Sercu (2009) refer to currency risk and currency exposure yet their arguments are generalizable.

Figure 2.1: Monthly average of daily crude oil and jet fuel spot prices, crack spread and standard deviations; between January 2005 and December 2014
Data: EIA (2017)



operating costs for low-cost carriers (LCCs) than for legacy carriers.[3] The different business models in the airline industry are taken into account in this study by including only passenger airlines in the sample and by distinguishing between legacy and low-cost airlines.

Hedging is one risk management strategy to reduce an airline's fuel price risk by using financial derivatives (*financial hedging*) or real options (*operational hedging*) (Smith and Stulz, 1985; Triantis, 2000; Van Mieghem, 2003). The main goal of hedging is to reduce

[3]While the differentiation between NLCs and LCCs is not as unequivocal as it used to be, the definition of the two business models should be given here. NLCs operate hub-and-spoke systems with short and long-haul flights, whereas LCCs avail themselves of point-to-point short-haul services to smaller airports (Windle and Dresner, 1999). Moreover, air fares are usually lower with LCCs targeting more price sensitive customers. Those fares are made possible with lower service propositions (e.g. no food or drinks included on board), additional service fees (e.g. checked-in baggage), limited mileage programs, a homogeneous fleet structure, short airplane transit times, a simple class concept, and a lean organizational structure (IATA, 2006).

a company's risk[4] (Bessembinder, 1991) by shifting it to other counterparties (Triantis, 2000), whereas speculating increases risk (Hentschel and Kothari, 2001). Risk can either stem from non-tradable risk[5], such as demand uncertainty, terrorist attacks, volcanic eruptions, or changes in regulatory requirements (Icelandair, 2015), or from tradable risk e.g. changes in kerosene prices (Aretz et al., 2007).

The airline industry can avail itself of several real options, or operational hedging measures, like fleet diversity, working with strategic alliances and aircraft leasing (see Section 2.3 for more information on operational hedging).

Financial hedging, on the other hand, refers to the usage of derivative instruments for tackling tradable risk (mostly price risk), comprising forwards, futures, swaps, and options (Bessembinder, 1991; Smith and Stulz, 1985). Forwards are bilaterally specified contracts between an airline and its counterparty, for example a bank or an oil company, in which they agree to buy and sell a specified amount of jet fuel at a given time for a fixed price. The advantage of those contracts is that they are custom-made but the disadvantages are the entailed counterparty risk and low liquidity (Sercu, 2009). Airlines enter into contracts with several different banks to reduce counterparty risk. Korean Air reported trading with JP Morgan, Hana Bank and "five other financial institution" (Korean Air, 2013, p. 130). Futures, on the contrary, are standardized products traded through an exchange. As no jet fuel futures are available on an exchange, airlines have to cross hedge their fuel price risk with e.g. heating oil, gas oil or crude oil. Oil futures on WTI are traded on the New York Mercantile Exchange (NYMEX) and North Sea Brent oil futures on the Intercontinental Exchange (ICE) in London (formerly International Petroleum Exchange (IPE)) (Morrell and Swan, 2006).[6]

Cross hedging of jet fuel induces basis risk, meaning the risk that the price of jet fuel is not perfectly correlated with the underlying asset price (Haushalter, 2000).[7] Basis risk may not only arise from the difference between the hedged asset and the underlying asset but also from price source differences. Gilje and Taillard (2017) give the example

[4] Uncertain future prices can influence a firm's cash flows, its market value or its book values resulting in contractual, operating and translation exposure. Hedging can help mitigate contractual and operating exposure, which is often summarized as economic exposure (Sercu, 2009).

[5] Chod et al. (2010) refer to non-tradable risk as mismatch risk and conclude that this type of risk can be mitigated by operational flexibility, whereas tradable risk, or profit variability as they term it, is best approached by financial instruments. Section 2.3.4 discusses the different situations where operational hedging and financial hedging can be beneficial in greater depth.

[6] The maturity can be set monthly up to two years, and in half year steps up to the maximum maturity of three years. Only 1% of contracts are physically delivered at maturity (Morrell and Swan, 2006; Smith, 2009).

[7] The correlation of jet fuel and crude oil spot prices was as low as 0.22 in 2013 (calculation based on the data used in Figure 2.1).

of Canadian firms that hedge crude oil but whose local crude oil prices do not correlate perfectly with the underlying WTI crude oil prices of the NYMEX. Several studies deal with the best underlying asset for hedging jet fuel. Adams and Gerner (2012) find that gas oil presents the best future contract for cross hedging jet fuel,[8] while Lim and Turner (2016) name heating oil as the best cross hedge oil product.[9,10] Lim and Turner (2016) suggest that the difference in jet fuel prices used, European versus U.S. jet fuel prices, may explain the different results.

Apart from forwards and futures, swaps and options (including collars) are frequently used by airline managers. A collar instrument combines a long call with a short put option so that the airline is protected from rising oil prices but at the same time can benefit from the premiums received from the put option (Gerner and Ronn, 2013; Morrell and Swan, 2006). In recent years, airlines have moved to more advanced structures such as four- or five-way-collars[11] in order to reduce costs further (Mercatus Energy Advisors, 2012). Another method to reduce premium payments of financial instruments is to use Asian options: the strike price of these instruments depends on the average price over a specific period of the underlying. Premiums are lower for Asian options because the volatility of the monthly average spot price is lower than the monthly volatility of daily spot prices. Gerner and Ronn (2013) estimate a premium cost reduction of 15% for an airline that includes Asian options in its portfolio.[12]

So far, the fact that fuel price risk influences the airline industry adversely and that airline managers can mitigate those effects with financial and operational hedges has been established. Reasons for why firms in general use financial derivatives based on existing literature will be discussed in the following section.

[8]Adams and Gerner (2012) regress weekly European jet fuel spot prices against the hedge ratios of weekly one-month over-the-counter (OTC) forward prices of either Brent oil, WTI oil, heating oil, or gasoil. The hedge ratios are estimated in a separate regression with log differences of the aforementioned prices. In all three models, ordinary least squares (OLS), error correction model (ECM) and ECM with generalized autoregressive conditional heteroscedasticity (GARCH) errors, gasoil hedge ratios show the highest positive, significant coefficient. In addition, the adjusted R^2 is highest for the models where gasoil enters the regression.

[9]Lim and Turner (2016) use a similar approach to Adams and Gerner (2012) in order to estimate which underlying instrument is best used to cross hedge jet fuel prices. However, instead of using weekly one-month horizon forward prices, Lim and Turner use multiple price frequencies (daily, weekly, monthly) and hedge horizons (between one and 12 months). In most combinations, heating oil hedge ratios exhibit the highest coefficients.

[10]In Section 4.2, descriptive results are given about the type of instruments and underlying assets used by the sample airlines.

[11]If the airline is short two put options and long two call options, where the options differ by their strike prices, the airline uses a four-way collar (Mercatus Energy Advisors, 2012).

[12]As airlines in the sample either disclose whether they use options or other hedging instruments but not which type of options, Asian options usage cannot be displayed in the sample.

2.2 Determinants of hedging

The famous Proposition I by Modigliani and Miller (1958, p. 268)

> "The market value of any firm is independent of its capital structure [...]"

seems to deter any company from engaging in corporate risk management, at least under perfect market conditions. Characteristics of a perfect capital market are fairly priced bonds and shares, symmetric information, absence of tax payments, issuance, transaction and bankruptcy costs and, as said in the quote, the irrelevance of a firm's capital structure. However, capital markets are rarely perfect and thus market imperfections make a firm's capital structure matter (Berk and DeMarzo, 2017). One of those market imperfections is that debt increases a firm's likelihood to experience financial distress, which induces bankruptcy costs and lowers the profit streams for equity and bond holders. Other market imperfections, such as taxes, transaction costs and asymmetric information between managers and investors, also influence the capital structure decision of a firm (Berk and DeMarzo, 2017) and hence its hedge strategy. Smith and Stulz (1985) summarize three determinants of financial hedging, namely financial distress costs, managerial motives and tax incentives. Moreover, Froot et al. (1993) add the underinvestment problem as a subset of financial distress costs and as a reason for using financial derivatives. The fifth subsection "economies of scale" is regarded as a separate determinant only in some studies. Other researchers include economies of scale into the financial distress argument. Due to the significance of firm size for the observed hedging behavior of firms, economies of scale are classified in a separate category in this study.

In the following subsections, the theoretical background on the determinants of corporate hedging are described. Moreover, it is explained how the theories have evolved in the last decades and existing empirical findings as well as study limitations to each determinant are presented.[13] Section 2.2 hence covers the question 'why airlines hedge'. Table B.1 in Appendix B serves as an overview of selected theoretical and empirical studies discussed. The selected studies include the most-cited papers in the respective field.

In each subsection, the theoretical background is presented first before leading over to the empirical findings on each determinant. For some determinants (e.g. financial

[13] When a study is first mentioned, the methodology used is described in detail and only the regression coefficients are mentioned in subsequent citing. This approach results in textually longer subsections for the first two determinants, 'financial distress' and 'the underinvestment problem', which should not be seen as an indication for their importance.

distress), this rule is circumvented in order to set the focus on more recent hypothesis on this determinant. Due to the length and complexity of Subsections 2.2.1 and 2.2.2, tables summarizing the theoretical contributions are included in these two subsections.

2.2.1 Financial distress

The main determinant of corporate hedging discussed in the literature is the cost of financial distress. If a firm approaches bankruptcy it faces direct and indirect bankruptcy costs (Warner, 1977).

Direct costs comprise remunerations paid to the various legal advisers and consultants of the different claimholders, as well as administrative spending during the bankruptcy itself (Stulz, 1996). Warner (1977) looks at direct bankruptcy costs of 11 U.S. railway companies from 1933 to 1955. He estimates that those costs are on average 1% of a company's market value 84 months prior to filing for bankruptcy. The closer the firm moves towards insolvency, the larger the percentage of cost relative to the market value. He also finds that bankruptcy costs are a non-linear function of the market value of a firm. His findings are consistent with the notion that a large portion of bankruptcy costs are fixed costs and that the ratio of distress costs to market value is larger for smaller firms (see Subsection 2.2.5).

Indirect costs, on the other hand, are not measurable directly. A fall in demand, for example, may be a consequence of expected financial distress as customers might refrain from purchasing a product of a company with insufficient financial funds because they anticipate a lower product quality or difficulties in obtaining spare parts. It is uncertain though, which portion of the downturn is attributable to the increased likelihood of default and which portion imputable to e.g. changes in consumer behavior. Another source of indirect costs can be related to agency problems if the insolvency administrator manages the company in default less efficiently than the original managers of the company. Also, managers and other stakeholders of a financially distressed firm might require higher compensation ex-ante due to the personal risk of losing their position in bankruptcy (Stulz, 1996). Lastly, Warner (1977, p. 339) refers to the costs of "lost opportunities" in general for indirect bankruptcy costs. This thought goes hand in hand with the underinvestment theory brought forward by Myers and Majluf (1984), which will be discussed further in Subsection 2.2.2.

Without the potential occurrence of financial distress and default, shareholders would not value corporate hedging because they could reduce the impact of firm specific risk by diversifying their own portfolio (Bessembinder, 1991; Stulz, 1996).[14] If however hedging smoothens the volatility of the cash flows of a firm, the likelihood of default decreases and with that the expected costs of bankruptcy (Smith and Stulz, 1985).[15] Lowering the likelihood of bankruptcy with the help of costly hedging might not be in the primary interest of shareholders because they are only residual claimholders after bondholders have been paid (as in the "asset substitution problem"). Nonetheless, shareholders will benefit from hedging through other means. The market value of a firm that is close to distress will reflect expected bankruptcy costs by the amount of bankruptcy costs multiplied by the likelihood of default (Stulz, 1996). This means, the lower the likelihood of distress, the higher the market value and the more shareholders will benefit from hedging.[16]

Bessembinder (1991) extends the value enhancing theory of hedging by reasoning that hedging can help meeting debt obligations by shifting cash flows from strong economic periods to weaker periods. If a hedged firm is able to meet its credit obligations with a higher probability in times where it otherwise would be unable to do so without hedging, the company will be in a better position to negotiate more favorable debt terms in future times and reduce the cost of debt. This also benefits shareholders because risk premia, otherwise paid to bondholders, can be reduced (Smith and Stulz, 1985). Similar to Smith and Stulz (1985) and Bessembinder (1991), Stulz (1996) offers the idea that the goal of risk management is one of avoiding states of low net worth, or "lower-tail outcomes" (p. 8). According to Stulz' theory, high value firms should only hedge if they have more information at hand than their competitors. Firms with lower credit rating should hedge to avoid bankruptcy, and companies in default should hedge on all accounts to increase the possibility of exiting bankruptcy. Similarly, when two companies in the same industry suffer from weak economic conditions, the more indebted firm will have a higher likelihood to encounter left-tail outcomes and might be more inclined to hedge (Nance et al., 1993).

[14] Tufano (1996) finds that firms with large outside block shareholders such as insurance funds hedge less because they are better diversified and that firms with a higher percentage of managerial block ownership hedge more.

[15] Their argument rests on the above stated theory of Warner (1977) that bankruptcy costs must increase with decreasing firm market value.

[16] The results of Bodnar et al. (2011) support this theoretical reason for hedging. In their survey, 18% of respondents named "avoid large loss from unexpected price movements" as the main goal of their risk management program.

As mentioned in the introduction of the literature review, due to the complexity of this subsection, Table 2.1 gives a brief overview of the theoretical background on the financial distress rationale of using derivatives. The more recent hypothesis by Purnanandam (2008) will be discussed later in this subsection.

Table 2.1: Theoretical background on financial distress as a determinant of corporate hedging

Author	**Year**	**Key theoretical argument**
Warner	1977	Entering bankruptcy entails direct and indirect bankruptcy costs. Bankruptcy costs are a non-linear function of firm market values.
Smith and Stulz	1985	If hedging reduces cash flow volatility and by that the likelihood of default, the expected costs of bankruptcy are lowered.
Bessembinder	1991	Hedging can help meet debt obligations and by that lower the cost of debt.
Nance et al.	1993	More indebted firms should be more inclined to hedge because of the higher likelihood to encounter financial distress.
Stulz	1996	Indirect bankruptcy costs also arise due to the higher compensation requirements of managers of distressed firms.
Purnanandam	2008	Derivative usage might be a concave function of leverage, not a linear function.

Based on financial distress arguments, firms with more leverage should be more inclined to derivative usage than firms with low debt levels. The empirical studies discussed in this chapter are presented in tables in Appendix C.

In a frequently cited study by Nance et al. (1993), the authors assess the answers of 169 questionnaires completed by chief executive officers (CEOs) of Fortune 500 and Standard & Poor's (S&P) 400 companies. In a logit model they use a binary variable as the dependent variable which sets the value to one if the company uses any kind of financial derivatives (forwards, futures, swaps or options) and zero otherwise. The independent variables comprise a total of 12 variables which are grouped into five categories: tax, leverage, size, underinvestment and substitutes of hedging. All possible combinations of variables within one group are put into 48 different logit regressions. They find no statistically significant relation between hedging and debt ratios in any regression. Nance et al. note the lack of power in their study with only 169 observations and also a potential bias because they only use a combination of five (one of each topic) of their 12 possible variables.

Another study by Haushalter (2000) analyses the survey responses[17] of 100 chief financial officers (CFOs) from the U.S. oil and gas industry in relation to their fraction

[17] Nance et al. (1993) and Haushalter (2000) have to use survey data, inclusive of the disadvantages connected with questionnaires, because accounting rules did not require firms to disclose the use of derivatives until 1997 (Jin and Jorion, 2006).

of production hedged from 1992 until 1994. The univariate results of a Wilcoxon test confirm that more active hedgers, defined by hedge ratios of more than 25% of their future production, have higher leverage, lower credit ratios and a smaller dividend payout ratio. In a pooled Tobit multiple regression with the hedge ratio as the dependent variable and several determinants of hedging as the independent variables, the debt ratio coefficient is positive, statistically significant at the 5%-level or better in all four models, with the models differing by a different combination of independent variables. When analyzing each of the three sample years separately though, only the debt ratio coefficients in 1994 are statistically significantly different from zero at the 10%-level in all three models. In a two-step Cragg's model, Haushalter regresses in the first step a binary variable that takes the value of one if a company hedges a portion of their future production and zero otherwise (*the decision to hedge*). In a second step, he uses only the sample of hedgers and regresses the hedge ratio against the determinants of hedging (*the extent of hedging).* In this step, the debt ratio is not significant in the decision to hedge but positively significant at the 1%-level in all three models in the extent of hedging if only hedgers are analyzed. Haushalter concludes that leverage is an important determinant of the extent of hedging but not of the decision to hedge.

In contrast to Nance et al. (1993) and Haushalter (2000), Tufano (1996) can make use of more detailed hedging information than surveys provide because he studies the hedging data published by Ted Reeve in the "Global Gold Hedge Survey". The sample comprises 48 U.S. gold mining firms that hedge (or do not hedge) gold price risk between 1991 to 1993. The dependent variable is the annual average of quarterly option deltas of the gold hedge portfolio, which contains financial derivatives to hedge the expected gold production with a maturity of three years, scaled by the production. Besides other independent variables, Tufano (1996) employs two financial distress variables. One variable is the cost associated with producing one ounce of gold and the other represents leverage defined by the three-year average of long-term debt scaled by total assets. The regression results fail to support the bankruptcy cost motive. Neither the coefficient of the cost nor the leverage variable is statistically significant. If the most active outlier hedger is excluded from the sample and heteroskedastic standard errors are used, leverage becomes positive and significant at the 1%-level.

The three studies mentioned so far suffer from a lack of explanatory power due to the small sample sizes. Moreover, the endogenously determined decision to hedge may lead to the ambiguous results in these studies on the financial distress motive (Bartram et al., 2009). Several studies find no significant (or negative) relation between leverage and hedge ratios (Adam, 2002; Allayannis et al., 2001; Brown et al., 2006; Carter et al., 2006; Guay and Kothari, 2003; Spanò, 2007; Sprcic and Sevic, 2012). The decision to hedge is strongly interconnected with the capital structure of a firm and hence with the leverage variable employed in empirical research. A company that is fully equity-financed should not value risk management as highly as a levered firm according to the bankruptcy costs theory. If however, equity is more expensive than debt it should be beneficial to substitute equity with debt and keep the level of total firm risk constant by using risk management tools. In this way, increasing the level of hedging can at the same time allow for an increase in the level of debt (Stulz, 1996). This two-way linkage between leverage and hedging, increased leverage leading to higher likelihood of bankruptcy and hence a higher necessity to hedge and more hedging increasing debt capacity, calls for a simultaneous estimation of leverage and hedging in the regression analysis (Graham and Smith, 1999).

The following two studies by Purnanandam (2008) and Adam et al. (2017) endogenize the capital structure decision by employing an instrument variable regression to determine leverage. While older studies predict a positive, linear relationship between leverage and hedging, Purnanandam (2008) proposes a concave relation between the levels of debt and risk management. In his theory, a firm with reasonable levels of debt should engage in risk management due to the reasons brought forward before, i.e. reducing the likelihood of bankruptcy and thus the implied costs of financial distress. However, if that firm is in financial distress but still before bankruptcy, indicated by very high levels of leverage, shareholders are better off with increasing the risk by not hedging because they are only residual claim holders in the case of bankruptcy and receive the terminal value of the firm. Thus, without hedging shareholders increase the number of states in which the firm goes bankrupt but at the same time the number of the states in which the firm financially survives and shareholders are better off than debt holders. In Purnanandam's model, the extent of hedging depends on a firm's debt level, the 'distress boundary' (the state in which the company is in financial distress but not yet bankrupt), the deadweight costs of bankruptcy and the timespan of the project. Companies with high levels of leverage that operate in concentrated industries, such as the airline market, should have the highest propensity of using risk management because of a relatively greater threat to lose their competitive position in financial distress compared to companies in less concentrated industries. Purnanandam supports his model empirically by studying a sample of all CRSP and Compustat firms in 1997 whose 10-K filings are available on the Securities and Exchange Commission (SEC) website. He limits the sample to non-financial firms and firms with total assets in the highest 75%-quartile. The sample is further limited to financially exposed firms.[18] Risk management is measured either by the notional value of foreign exchange derivatives or an indicator variable which takes on the value of one if the firm uses any financial instrument for commodity price risk. The leverage variable is estimated in the first step of an instrument variable regression with the "before-financing marginal tax rate" and a "firm's nondebt tax shield" (depreciation and amortization divided by total assets) as the instruments. The predicted value of leverage enters, among others, as an independent variable in the second step with either a dummy variable for FX and commodity price risk management or the notional value of FX derivative used as the dependent variable. Only the subsample of commodity price hedgers will be discussed further. The results of the logit regression (*decision to hedge*) support the model with regards to the nonmonotonic relationship between leverage and hedging. The coefficient of leverage is positively significant at the 1%-level whereas the coefficient of the square of leverage, capturing the nonmonotic relation between debt ratio and hedging, is negatively significant at the 1%-level. The interaction term of leverage and industry concentration, indicated by one if the market shares of the top four companies in a three-digit SIC code industry are above the median and zero if they are not, is still positively significant but at the 6%-level. The results are robust to several modifications such as industry-adjusted leverage ratios, different leverage proxies, bootstrapped standard errors, and alternative instruments in the instrument variable (IV) regression. The results support Purnanandam's theory that with higher leverage hedging increases but only up to a certain level, thereafter hedge ratios decrease.

A more recent study by Adam et al. (2017) looks at the nonlinear relation of leverage and selective hedging. They use the quarterly hedging data of U.S. gold mining firms from 1989 to 1999 as edited by Ted Reeve and Scotia McLeod. Similar to Haushalter (2000), Adam et al. use a two-step procedure to first run a regression on the decision to hedge with the dependent variable being an indicator variable with the value of one if the mining company hedges its future gold production and zero otherwise. In the second regression, the hedge ratio, either defined as the portfolio delta scaled by expected production (Tufano, 1996) or the portfolio delta scaled by total gold reserves (Jin and Jorion, 2006), enters as the dependent variable. The standard deviation of the quarterly residuals of the second regression are estimated annually as a proxy for selective

[18] A firm is classified as being exposed to commodity price risk if the regression coefficients of the quarterly earnings before interest and tax (EBIT) regressed on quarterly price changes of a basket of five different commodities are significant at the 10%-level. A firm has foreign currency exposure if it discloses either foreign sales, foreign income taxes, foreign exchange (FX)-adjustments, or hedging of foreign currency exposure in its annual report (Géczy et al., 1997).

hedging. In total, four different speculation measures are calculated for robustness checks and regressed against the determinants of corporate hedging. Supporting the hypothesis of Smith and Stulz (1985), Altman's Z-score, as a proxy for the financial health of a firm, is negatively significant at least at the 5%-level. Firms with a lower likelihood of bankruptcy (higher Z-scores) hedge less. Moreover, the squared Z-score is positive and significantly different from zero at the 5%-level. Adam et al. conclude that the relation between financial soundness and selective hedging is mainly downward sloping and convex so that at higher levels of financial distress firms are more inclined to use selective hedging and speculate. The hypothesis is similar to Tufano (1996) who anticipates a negative relation between managerial shareholding or option holding and hedging for financially distressed firms. In financial distress, managers benefit from the option-like feature of their common stock holding by increasing risk through reducing or abandoning the level of continuous hedging (see Subsection 2.2.3).

Yet another explanation for the nonmonotonic relationship between leverage and hedging might be the collateral requirements for margin calls in a hedging contract. An airline that is close to bankruptcy will not have sufficient internal funds available for the required margin calls. If the airline wants to trade OTC, it will have difficulties finding a counterparty that is willing to enter a derivative contract due to counterparty risk (Morrell and Swan, 2006). See Subsection 2.3.3 for a more detailed discussion about the linkage between collateral and hedging.

2.2.2 The underinvestment problem

While Warner (1977) refers to indirect bankruptcy costs when he writes about "lost opportunities" (p. 339), Myers (1977) uses the term of "pass[ing] up valuable investment opportunities" (p. 149). The costs associated with underinvesting can be seen as a portion of indirect bankruptcy costs and hence could be classified as a subset of financial distress costs (Carter et al., 2006). Each investment opportunity a firm has at hand is similar to an option that can be exercised or not. The value of the option is reflected in the market value of the firm. If hedging, by lowering the variability of internal cash flows, can reduce the number of states in which the firm does not exercise the option to invest in a positive net present value (NPV) investment opportunity, then hedging can increase the value of the firm (Froot et al., 1993; Myers, 1977).

A prerequisite for hedging to be valuable is that a firm has exhausted other means of financing, i.e. internal funds ("ample financial slack" (Myers and Majluf, 1984, p. 188)) and issuing low-risk, tax deductible debt. Parallel to the pecking order, the issuance of equity should be the last option for a firm to generate liquidity (Brealey et al., 2017) as active shareholders would see the issuance as a signal of financial distress or as an overvalued stock price and might be inclined to sell their shares (Brealey et al., 2017; Lessard, 1991; Myers and Majluf, 1984). The costs associated with issuing equity should rise disproportionately with the numbers of shares issued due to financial distress costs, informational asymmetries between management and external shareholders[19] and other agency costs (Froot et al., 1993). Analogous to the issuance of equity, not paying any dividends to shareholders may also be a signal of bad financial health. If hedging helps meeting dividend payout expectations and reducing the number of states in which the issuance of equity becomes necessary, it could in turn help increasing market value (Lessard, 1991).[20]

A further prerequisite for hedging to be beneficial is a low correlation between investment opportunities and cash holdings. If, for example, a company has great investment opportunities but internal funds are scarce, then hedging can facilitate the investment (Froot et al., 1993).

Based on this underinvestment hypothesis, the extent of hedging should be higher for firms with more investment opportunities at hand (Bessembinder, 1991), where investment opportunities are not or not strongly correlated with internal funds available (Froot et al., 1993) and for more levered firms or firms with lower cash holdings (Nance et al., 1993).

Table 2.2 provides a short summary of the contributions to the underinvestment hypothesis. The role of cash holdings on financial hedging brought forward by Nance et al. (1993) and Gamba and Triantis (2013) will be discussed later in this subsection.

Several empirical studies look at the statistical relation between growth opportunities and hedging activities. As hedge ratios should increase with both high investment opportunities and low internal funds present, Géczy et al. (1997) interact their three proxies for growth opportunities - research and development (R&D) spending to sales, capital expenditure (CAPEX) to firm size and market-to-book (MTB) ratio (see Subsection 4.1.2 for more detail) - with a firm's debt ratio. One of the logit regressions

[19]As managers are selected by shareholders, managers are assumed to act in the interest of existing shareholders. If managers have insider information that would adversely affect existing and give an advantage to new shareholders, managers might pass up positive NPV investment opportunities by deciding against the share issue in order to protect existing shareholders (Myers and Majluf, 1984; Smith and Stulz, 1985).

[20]Likewise, the existence of convertible debt and preferred stocks could serve as an alternative to corporate hedging and hence lower derivative usage. Instead of issuing equity, a more risky firm may choose to issue convertible debt, reducing the frictions between shareholders and bondholders. Preferred stock can reduce the likelihood of financial distress because the company does not have to meet interest obligations but may forego a preferred dividend payout (Nance et al., 1993).

Table 2.2: Theoretical background on the underinvestment problem as a determinant of corporate hedging

Authors	**Year**	**Theoretical contribution**
Warner	1977	Indirect bankruptcy costs include "lost opportunities" (p. 339).
Myers	1977	Firms have to "pass up valuable investment opportunities" (p. 149) if they have used their sources of financing.
Myers and Majluf	1984	Those sources of financing follow the pecking order: internal funds, low-risk debt and equity.
Lessard	1991	Dividend payout expectations can be met better with the help of hedging.
Bessembinder	1991	Firms with more investment opportunities at hand might hedge more.
Froot et al.	1993	If the correlation between investment opportunities and availability of internal funds is low, the firm should be more inclined to hedge.
Nance et al.	1993	Firms with lower cash holdings should hedge more, i.e. cash holdings and hedging can be seen as substitutes.
Gamba and Triantis	2013	In contrast to Nance et al. (1993), Gamba and Triantis see cash holdings and hedging as complements.

includes 220 Fortune 500 non-financial firms in 1990 from different industries that are exposed to foreign currency risk. The dependent variable is a dummy variable which covers financial derivative usage (swaps, options, forwards, and futures) as reported in the footnotes of the annual reports. They find that the higher a firm's internal funds are, measured by the quick ratio, the lower is the use of hedging, statistically significantly different from zero at the 1%-level. Having more growth options, defined by R&D expenditure to sales, significantly increases the likelihood that the firm uses derivatives by about 7%. However, the interaction terms of the debt ratio and growth options are not statistically significantly different from zero.

Gay and Nam (1998) look more closely at the impact of growth opportunities and internal financing on derivative usage. Their sample includes interest rate and commodity price derivatives in addition to foreign exchange financial instruments. In total, 325 hedgers and 161 non-hedgers are analyzed for the year 1995. They add Tobin's Q, the price-earnings ratio and the cumulative abnormal return (CAR) to the growth variables of Géczy et al. (1997). In each of the five Tobit models, with the notional dollar value of the derivatives scaled by total assets as the dependent variable and one of the five growth variables as the regressor (among other control variables), the growth variable is significant and positive at least at the 5%-level. In a univariate model, Gay and Nam find that firms with large growth options (higher than the mean) and low internal funds hedge significantly more (at least at the 10%-level for three out of the five growth variables) than firms with more cash. A multiple regression with an interaction term as the independent variable, that interacts an indicator variable equaling one if a firm has lower cash than the average and relatively more growth options and one of the five growth options, supports the univariate findings for three growth variables. Lastly, the authors' results support the hypothesis that the higher the correlation between growth options and internal cash flows, the lower the propensity to hedge (all four correlation variables between cash flow and growth options, excluding Tobin's Q, are negative and statistically significantly different from zero at least at the 10%-level). Throughout the multiple regressions, the debt variable is negative and significant at the 1%-level supporting the financial distress theory discussed in Subsection 2.2.1.

Adam (2002) uses the database of gold mining firms in the US between 1989 and 1999 to focus more on expected future investment expenditure and its influence on hedging. The dependent variable are non-random future revenues, calculated as the hedged number of gold ounces multiplied by the delivery price. Adam uses the actual future investment expenses as a proxy for growth options, in contrast to other studies that use current investment expenditure. Non-random future revenues are regressed on the growth variable and control variables that capture the availability of internal and external financing, with the sample being limited to hedgers. The results support the notion that higher future growth options significantly increase derivative usage. Furthermore, Adam looks at the decision and extent to hedge (similar to Haushalter (2000) with a two-stage Cragg model) and finds in almost all of his modified regression models a negative relation between the MTB ratio and hedging, contrary to the underinvestment theory where market-to-book ratio should proxy for growth options and should show a positive relation with hedging (Nance et al., 1993). Adam conjectures that in his sample the MTB ratio could capture how mature a firm is and that with increasing maturity hedging should decrease.

More attention should be given to the study of Carter et al. (2006) because it is the first study to analyze the airline fuel hedging market with regards to the determinants of hedging. In total, they study the interest rate, FX and commodity derivative use of 29 U.S. airlines between 1992 and 2003, yielding 259 firm years. The hedge percentage of the following year's predicted fuel consumption is the continuous dependent variable regressed on the two underinvestment variables CAPEX to sales ratio and Tobin's Q. The results of the Tobit model with random effects show a positive relation between Tobin's Q and the dependent variable, the significance levels vary between 1% and 5% for the lease-adjusted sample.[21] Although CAPEX to sales is insignificant, Carter et al. (2006) conclude that the underinvestment theory explains some propensity to use derivatives. The lease-adjusted debt to asset ratio is negatively significant at the 5%-level and the credit rating variable at the 1%-level, conversely to the financial distress literature. The authors explain the positive coefficient of growth options and the negative coefficient of leverage with the underinvestment problem being the dominant factor to their results. Firms with more investment opportunities have more to lose in the case of bankruptcy and thus choose a lower level of leverage and higher credit rating (Nance et al., 1993). In their explanation, the underinvestment factor overrules the financial distress factor in the aviation industry because aircraft are sold at a discount in a recession. Airlines that have hedged their fuel consumption should not be affected as much from high oil prices and can buy aircraft at lower market values from bankrupt airlines. Carter et al. base their theory on an article by Pulvino from 1998 in which he writes "the structure of the used commercial aircraft remains, as it has been for the past 20 years, dominated by privately negotiated transactions" (p. 943). The market for commercial aircraft has changed strongly, however, since 1998 due to the emergence of the leasing market (refer to Subsection 2.3.3) and thus the underinvestment rationale brought forward by Carter et al. in the airline market will be reassessed in this thesis for a more recent time period.

Apart from growth options, another variable that is likely to influence the hedging decision due to the underinvestment problem is the level of cash holdings of a firm. As described above, cash at hand should be negatively related to the level of hedging (Nance et al., 1993), corresponding with the financial distress theory that firms with a higher propensity for default have lower levels of free cash and a higher need for hedging. Various empirical studies show a negative and significant relation between a cash variable (e.g. quick ratio, cash to sales ratio) and the decision or extent of hedging (Adam, 2002; Adam and Fernando, 2006; Adam et al., 2017; Bartram et al., 2009; Dionne and Thouraya, 2013; Gay et al., 2011; Géczy et al., 1997; Judge, 2006; Tufano, 1996). Other results, however, unveil a positive or insignificant relation (Carter et al., 2006; Purnanandam, 2008).

Gamba and Triantis (2013) offer a different idea of how cash holdings and hedging might be interconnected. They model the decision to hedge with different levels of operating flexibility and financing structure simultaneously, using average data from previous empirical studies. The researchers control for taxes, share issuance, bankruptcy, and distress costs. Operating flexibility is limited to zero or one, corresponding to

[21] The widespread use of off-balance sheet operating lease financing makes it inevitable to adjust balance sheet data by operating lease expenses. See Subsection 2.3.3.

opening or closing of production capacities (in contrast to the continuous nature of fleet diversity discussed later in Subsection 2.3.1). Gamba and Triantis find that the value of the firm under a defined risk exposure increases from a 'no cash, no hedge' position to a 'hedge, no cash' position, but only slightly. A higher increase in value can be attributed to a 'cash, no hedge' situation. Lastly, the highest value driver is a simultaneous 'cash and hedge' strategy, indicating that cash and hedging are rather complements than substitutes. The greater the correlation between the swap price and the price of the underlying asset, the larger the gain in firm value. This means by implication that the more difficult it is to hedge the underlying price uncertainty, the more valuable is cash holdings in contrast to hedging. As mentioned in Section 2.1, there are no financial contracts written on kerosene such that airlines have to cross hedge their fuel price risk with another underlying than kerosene. Consequently, cash holdings could serve as a valuable substitute of hedging or be used as a complement to support financial derivatives in the airline industry. The question of whether alternatives to financial hedging can be seen as substitutes or rather complements to financial derivatives will be analyzed further in Subsection 2.3.4.

Other studies on determinants of corporate hedging unveil ambiguous results about the relation between underinvestment variables and hedging. Allayannis and Ofek (2001) analyze currency hedge decisions for 378 non-financial firms in 1993 and find in a logit regression that the coefficient of R&D expenditures divided by total assets is positive and significant at the 5%-level. However, no significant relation is detected between the MTB ratio and the decision to hedge. The level of financial derivative usage among hedgers is not influenced by either of the two independent variables. The results of the study by Bartram et al. (2009) are equivocal: although the market-to-book ratio is negatively significant at the 1%-level in contrast to theory, the interaction term between leverage and the investment opportunity variable is positive and significant supporting the thesis by Froot et al. (1993). While Gay and Nam (1998), Géczy et al. (1997), and Nance et al. (1993) find that the existence of growth options increases hedging, Adam and Fernando (2006), Brown et al. (2006), Gay et al. (2011), Graham and Rogers (2002), Guay and Kothari (2003), Nguyen and Faff (2002), and Tufano (1996) cannot support the positive relation by finding either negative or insignificant coefficients.

There are several reasons why empirical studies may fall short of supporting the relevance of the underinvestment hypothesis. First, managers might not act according to theory. In the survey by Bodnar et al. (2011), only 46% of respondents stated that they hedged in order to be able to exercise investment options. Also, 56% of the participating CFOs denied that their cash holdings influenced their hedging decision. Second, the inclusion of leverage variables in addition to the investment opportunities variables might cause multicollinearity and is likely to lead to an imprecise estimation of the coefficients. While higher leverage should induce a firm to hedge more, investment opportunities should also increase a firm's hedge ratio. More investment opportunities, however, might be related to lower levels of debt and offset the leverage effect on hedging (Nance et al., 1993). Third, R&D variables may capture other determinants than the underinvestment effect. High R&D expenditure could mean a more difficult, more expensive access to external financing due to information asymmetry which might lead to financial distress and consequently increases the need for hedging (Froot et al., 1993). Also, the MTB ratio could stand for the financial distress argument. Ratios smaller than one mean that shareholders view the value of the firm lower than its assets, which is mostly the case when the firm is in financial distress (Nguyen and Faff, 2002). Moreover, R&D variables may pick up agency problems if a poorly performing manager wants to hide his disability to invest optimally by either spending more on R&D or by using more derivatives (Gay and Nam, 1998). Fourth, cash holdings, especially in the airline industry, may contain a large portion of restricted cash which the lessor requires the airline to have available to cover future lease payments and which is not utilizable as a reserve fund (Eisfeldt and Rampini, 2009).

2.2.3 Managerial motives

A hedging manager may have multiple motives that impact his decision making. First, transaction costs may influence the hedging behavior. When managers are assumed to be risk averse (their expected utility is a concave function of firm value) and cannot diversify the risk on their own account because of high transaction costs or because of restrictions to sell or shorten their performance-based compensation instruments, the consequence would be a full hedge position because hedging decreases the number of states where a firm defaults (see Subsection 2.2.1) (Stulz, 1984). Second, Smith and Stulz (1985) suggest that managerial compensation features such as common stock or share options may have an effect on managerial hedging behavior. In their model, the expected compensation of the manager, who is paid with share options, is a convex function of firm value. In contrast, remuneration by shares leads to more a linear function of managerial wealth. According to Jensen's inequality (see Subsection 2.2.4), if hedging reduces firm value variability, concavity of managerial compensation (shares) will lead to a full hedge position and convexity (options) to a zero hedge position. As managers are risk averse, however, managers paid with options will hedge to some extent in order to reduce risk. In sum, more option-like compensation should lead to less hedging, more share-based remuneration to more hedging.

Froot et al. (1993) challenge the full hedge position for stock rewarded managers. They criticize that Stulz (1984) includes personal hedge transaction costs in his model but not corporate hedge costs. Moreover, Froot et al. predict that the more a firm approaches financial default, the more pronounced will be the option-like feature of a stock and the less will the manager be inclined to hedge if his compensation depends on common stock, as the value of a share option increases with a higher underlying uncertainty. Similarly, Judge (2006) formulates the hypothesis that managers with shareholdings of a highly levered firm might use more speculative derivatives than firms of a financially sound firm in order to increase the value of the option of their shares by increasing cash flow variability. Gay and Nam (1998) also question the theory of Smith and Stulz (1985) by stating that option-based remuneration may not lead to less hedging due to the arrangement of stock option rewards. Long time-to-maturities of up to 10 years, option strike prices that are close to actual firm stock prices and replacement of out-of-the-money (OTM) options may prompt managers to behave more like stock than option holders, leading to an increase rather than decrease in hedge portfolios.

DeMarzo and Duffie (1995) look more closely at the informational effect of hedging, differentiating between whether the hedge position is disclosed or not and whether outsiders have information about the company's risk exposure. The assumption made in their model is that managers maximize their wage function by altering the hedge position ex-ante. If both the risk exposure and the hedge ratio is known to shareholders, managerial compensation should not influence the hedge ratio. Similarly, if only the hedge position is disclosed but risk is not, the compensation of managers is not influenced either because with the disclosure of the hedge portfolio of the firm, profit statements reflect more the actual performance of the firm, net of the underlying risk and shareholders can better evaluate the achievements of the managers. When no information about hedging or exposure is published, risk-averse managers may choose the full hedge position in order to reduce profit variability and hence salary variability.[22] Moreover, younger managers with less experience and standing might be more inclined to a full hedge position to positively influence their remuneration (DeMarzo and Duffie, 1995). Analogously, better performing managers will hedge more in order to display

[22]Nowadays, almost all international accounting standards require the disclosure of financial instrument usage though, rendering the third case scenario unlikely. The SEC, for example, extended the reporting requirements on derivative usage in 1997 (Jin and Jorion, 2006).

their performance to the public, whereas poorly performing managers may only hedge if the difference in managerial performance is small. If the difference of the ability between the two managers is large, however, the low performing manager might not hedge at all because he hopes for better profit numbers by luck (Breeden and Viswanathan, 1998).

Besides managerial ability and remuneration, another factor influencing hedging decisions is the idea that shareholders, analysts and other outsiders place a premium on the firms that hedge (in contrast to non-hedgers) because hedging is seen as a form of managerial ability and experience. Large, mostly successful companies are expected to hedge and this, in turn, increases the reputational effect of hedging if those companies remain successful with the presence of hedging (Brown, 2001; Gerner and Ronn, 2013; Morrell and Swan, 2006; Smith and Stulz, 1985).

Along with the reputational effect that concerns the perceived ability of managers, the reduction of volatility in accounting numbers is another reason for derivative usage. Forty-eight out of 73 respondents of large firms in Belgium stated in 1997 that earnings smoothing was the most important driver to use financial instruments (De Ceuster et al., 2000). To a lesser extent, 10% of the participants of the survey by Bodnar et al. (2011) reported an "increase in reported earnings predictability" as the aim of their risk management strategy. In opposition to reducing the likelihood of bankruptcy by lowering the volatility of cash flows, a reduction in earnings volatility aims more at improving the perception of analysts rather than improving the actual financial situation (Smith and Stulz, 1985). A constant growth rate in earnings is preferred over excessive rates because investors punish lower than expected performance more than they value better than forecast results (Brown, 2001). Financial instruments, as well as changes in accounting rules, can help mitigate earnings volatility (Petersen and Thiagarajan, 2000). However, the marked to market treatment of some derivatives may even exacerbate earnings volatility (Brown, 2001; Morrell and Swan, 2006). Earnings smoothing is challenging to research as accounting treatments that are used ex-ante are difficult to be discovered ex-post (Bartram et al., 2009). The variety of accounting standards in this sample compounds this difficulty and thus earnings smoothing will not be analyzed further in the remainder of this thesis.

Empirical results on managerial compensation and hedging are, again, mixed. While the results by Dionne and Thouraya (2013) and Tufano (1996) support the idea that executive stock compensation increases and option holding reduces the percentage of gold sold forward among gold producers, other studies identify no significant relation and mostly drop the managerial variables from their estimations (Allayannis and Ofek, 2001; Arnold et al., 2014; Bartram et al., 2009; Gay and Nam, 1998; Géczy et al., 1997; Graham and Rogers, 2002).

Contrary to theory, Nguyen and Faff (2002) observe a negative relationship between executive shareholding and hedging. They explain those coefficients of stock and option holdings by the idiosyncrasies of the Australian labor market. If the labor market is more competitive in Australia than in the US, it is more important for managers to improve their performance and focus less on optimizing their compensation. Similarly, Haushalter (2000) finds a negative relation between shareholding and hedge portfolios and assumes that the personal view of the manager about future price movements influences his results. If an airline manager, for example, expects kerosene prices to fall, he will reduce the hedge ratio and at the same time increase his shareholding, leading to a negative and endogenous relationship between hedging and executive shareholding. The integration of personal experience and market views will be discussed further in Section 2.4.

Managerial motives as a determinant of hedging will not be analyzed in this study. The availability of managerial share and option ownership data is limited especially for those airlines from outside the U.S..

2.2.4 Tax incentives

Corporate taxation can be a driver for the usage of financial derivatives. If the marginal effective tax rate a corporation faces is not linear but rather a convex function of the pre-tax income, the after-tax income will be a concave function of the pre-tax income. As hedging provides the possibility to reduce the variability of pre-tax income, tax expenses are expected to be reduced on average and after-tax income increased (Graham and Smith, 1999; Smith and Stulz, 1985).[23] The more pronounced the convexity of the marginal tax function is, the more should the firm be inclined to use financial derivatives (Smith and Stulz, 1985). Figure 2.2 displays a convex tax function. The higher the income before tax, the higher the marginal tax rate. The points a, b and c represent three different cases of income before tax. If, for example, a firm earns income of amount a in year 1 and income of amount b in year 2, it pays on average a tax expense of D in both years. If the firm can reduce the variability of its income before tax by hedging towards income c for each of the two years, it only pays taxes of

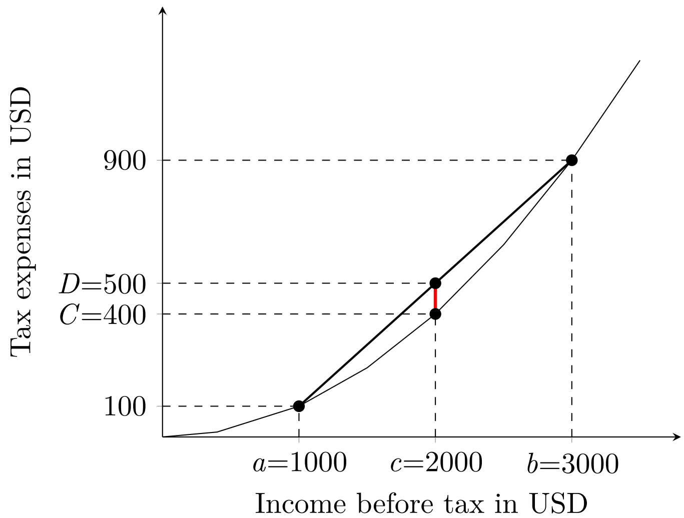
[23]Two factors influence the NPV of tax payments: the timing of taxable income and the absolute value of income. The postponement of income into later periods is the main driver of NPV. However, the timing is difficult to influence with hedging and hence the tax determinant literature concentrates on the influence hedging has on the absolute value of taxable income (Eldor and Zilcha, 2002).

C in total. The difference between D and C is the tax benefit from hedging. Jensen's inequality ($\gamma \times f(a) + (1-\gamma) \times f(b) > f(\gamma \times a + (1-\gamma) \times b)$), if and only if $f(.)$ is strictly convex (Jensen, 1906), shows that the average of the function (D) is always larger than the function of the average (C). A numerical example shows the application of Jensen's inequality in the case of a convex tax function. A convex tax function of $f(x) = 0.0001 \times x^2$, $a = 1{,}000$, $b = 3000$, and $c = 2{,}000$ is assumed. The average of the function of the income points a and b is a tax burden of 500 USD. The function of the average (C) is a tax payment of 400 USD. The tax advantage arising from hedging with a convex tax function would be 100 USD. Inserting into Jensen's formula (γ is assumed to be 0.5) yields: $0.5 \times (0.0001 \times 1000^2) + (1-0.5) \times (0.0001 \times 3000^2) = 500 > 0.0001 \times (0.5 \times 1000 + (1-0.5) \times 3000)^2 = 400$.

Not only can corporate tax expenses be reduced by hedging but also personal tax payments. In the U.S., dividend payouts are taxed at shareholder level, the purchase of shares on the other hand is not tax deductible (Graham, 2013). This means that a company that has paid out a fraction of its profits in one year and needs to raise equity in the following year adversely affects its investors. If corporate hedging reduces the variability of profits and makes share issuance less frequent, it can reduce the personal tax burden of the investors (Gamba and Triantis, 2013).

Although most empirical studies on derivatives include variables on taxation in their regressions, the selection of variables and interpretation of results is debated. Proxies that are employed to capture the tax scheme convexity or concavity include a dummy variable that equals one if the company reports tax loss carryforwards (Allayannis and

Figure 2.2: Example of the tax benefit of hedging



Ofek, 2001; Arnold et al., 2014; Judge, 2006; Nance et al., 1993), the total value of tax loss carryforwards scaled by firm value or total assets (Carter et al., 2006; Gay et al., 2011; Géczy et al., 1997; Spanò, 2007; Sprcic and Sevic, 2012; Tufano, 1996), the marginal tax rate (Dionne and Thouraya, 2013; Haushalter, 2000), and an indicator variable that signals whether the firm has profits that lie in the progressive tax region (Haushalter, 2000; Nance et al., 1993). Almost all studies fail to support the tax theory by Smith and Stulz (1985) due to insignificant results (Allayannis and Ofek, 2001; Arnold et al., 2014; Carter et al., 2006; Dionne and Thouraya, 2013; Gay and Nam, 1998; Gay et al., 2011; Géczy et al., 1997; Graham and Rogers, 2002; Judge, 2006; Spanò, 2007; Sprcic and Sevic, 2012; Tufano, 1996). A likely explanation for the insignificant results may be that most companies have taxable income that falls under a linear taxation. The closer the taxable income is to zero, the more convex the tax scheme becomes. In those convex regions, the financial distress argument may supersede the tax incentive of hedging.

Nance et al. (1993), on the other hand, find that the more investment tax credits a company has, the more likely it is to use financial derivatives, measured by a binary variable. Haushalter (2000) explains the positive and significant coefficients (significant between the 1%- and 10%-level) of the marginal tax rate in his survey results with the fact that, in the U.S., the lower the marginal tax rate of a company is, the more it faces convex tax schemes and the more it benefits from hedging.

Graham and Smith (1999) criticize the proxies employed and the usage of survey data in empirical research on tax incentives for hedging. Some tax variables such as the marginal tax rate and tax loss carryforwards are more likely to capture financial distress incentives to hedge than tax incentives. Moreover, certain tax provisions like investment tax credits do not induce a smaller convexity for all firms and in all income ranges, making a proxy variable incapable of covering the complex tax code structure.

To alleviate the methodological problems encountered with tax variables, Graham and Smith (1999) use a simulation technique to detect possible sources of a company's tax convexity in the U.S. tax system. They find that firms with volatile profits and income around zero face more convex tax schemes. Moreover, tax loss carryforwards and -backs can reduce the convexity of the tax function and even lead to tax concavities if the company expects further losses in subsequent years. Investment tax credits do not influence the tax function by much. Further, they calculate the expected reduction in tax liability from a reduction in income volatility, which arises with the usage of hedging.

Half of the 84,300 Compustat firm year observations face a convex tax schedule. If taxable income volatility was reduced by 5% (with the usage of financial derivatives), the tax liability would be 5% lower.

Even though this tax expense reduction shows that there should be a tax reason for firms to hedge, Dionne and Thouraya (2013), Graham and Rogers (2002), and Purnanandam (2008) also fail to establish a significant link between tax variables and hedging. Although they measure tax convexity as the reduction in tax expenses following a reduction in income volatility by 5% (same method as Graham and Smith (1999)) and not by a proxy, they do not find that firms hedge in response to tax incentives. Graham and Rogers (2002) conclude that firms use derivatives not because of the convexity in tax schemes but to increase their debt capacity, i.e. the leverage ratio decision of a firm and not the absolute debt limit (Brealey et al., 2017), and by that benefit from tax advantages.

Due to the insignificance of the estimation coefficients of the tax proxies analyzed in the cited studies[24] and the difficulties in calculating tax convexities with simulation methods, this study will not include tax convexity variables. In addition, the sample in this thesis comprises airlines of almost 40 different countries making it disproportionately cumbersome to analyze the tax schemes of each country individually.

2.2.5 Economies of scale

Another determinant that is extensively discussed in the literature is the size of a company. Warner (1977) finds that railroad companies with higher market values incur higher bankruptcy costs, but only in absolute terms. Relatively seen, bankruptcy costs are higher for smaller firms due to high fixed costs associated with insolvency proceedings. Smith and Stulz (1985) conclude that smaller firms should be predisposed for higher levels of hedging. Moreover, taxable incomes of smaller firms are more likely to be taxed according to the progressive tax scheme which, again, makes smaller firms more likely to hedge (Nance et al., 1993).

However, initiating and managing a hedging program entails high fixed costs which should lead to more hedging among large firms as they can benefit from economies of scale (Graham and Smith, 1999; Haushalter, 2000). Brown (2001) estimates that the costs of the FX hedging program of a manufacturing company with an annual revenue of 10 billion USD is 3.8 million USD. About 40% of the costs consist of compensation and overhead costs and 60% of bid-ask spreads. Gerner and Ronn (2013) also find that

[24] Graham (2013, p. 195) notes: "Overall, the empirical evidence suggests that the tax incentive to hedge because of tax function convexity is weak."

the decision to use collar instruments depend more on the entailed transaction costs than on the risk premium, which is the difference between the future spot price and the price of the financial instrument.[25] Economies of scale in transaction costs are especially apparent for futures, options and swaps, while forwards are customized contracts that have to be negotiated on individual terms (Nance et al., 1993). Brown (2001) calculates the costs of hedging as the difference in the six months forward exchange rate and the spot exchange rate and finds, however, that the cost of hedging is not reduced by increasing the size of the hedge portfolio.[26,27]

Apart from transaction costs and risk premia, Dionne and Thouraya (2013) propose that agency conflicts between managers and shareholders in large companies may result in relatively larger hedge portfolios compared to smaller firms. They find that managers with greater stock and option holding hedge more (in contrast to the theory that executive option holdings should reduce hedging activity, see Subsection 2.2.3) and that those managers typically lead companies with greater revenues and market value. Dionne and Thouraya theorize that the shareholders of larger firms, suffering more from agency conflicts, include more share and option compensation in managerial remuneration contracts, which in turn stimulates derivative usage.

Purnanandam (2008) questions that economies of scales are the reason why larger firms hedge more. The author suggests that firms which operate at longer horizons grow relatively larger over time and that those firms are more likely to suffer financial distress at any point in time due to the longer time frame. If they do enter bankruptcy, the likelihood that the economic climate will improve is higher for longer time periods, which the distressed firm could not take as much advantage of as a more financially sound competitor. Empirical evidence might hence rather capture the effect that firms with greater operational horizons increase in size over time than the economies of scale effect.

In contrast to the diverse empirical results on the determinants discussed so far, the findings on the relationship between firm size and hedging is more homogeneous. Most researchers find a positive effect (in most studies significant at the 1%-level) of the size

[25]Nevertheless, risk premia are non-negligible costs. Adam and Fernando (2006) calculate that a gold producer would have had to pay 25 USD yearly per ounce of gold sold forward with a maturity of 12 months, renewed monthly. Moreover, Garuda Indonesia reported premium payments of 6,528,600 USD in 2013 (Garuda Indonesia, 2015).

[26]Froot et al. (1993) mention credit risk as another source of hedging costs. They see forward contracts as a combination of a future contract and a loan, where the loan entangles credit risk making it impossible for the company to have a large position of forward contracts.

[27]The International Air Transport Association (IATA) clearing house helps especially smaller airlines to participate in fuel hedging by providing support in settling fuel hedging contracts (Morrell and Swan, 2006).

of a company on the decision to hedge (Adam, 2002; Adam et al., 2017; Allayannis and Ofek, 2001; Bartram et al., 2009; Gay et al., 2011; Géczy et al., 1997; Haushalter, 2000; Judge, 2006; Nance et al., 1993; Spanò, 2007).[28] Moreover, the use of interest rate or FX instruments is related to the use of other financial instruments such as fuel hedge derivatives, underpinning the existence of economies of scale (Carter et al., 2006; Géczy et al., 1997). Haushalter (2000) notes that positive size effects are more apparent at setting up a hedging program but once established marginal hedging costs do not seem to differ largely between extensive and less active hedgers because his and other results (Adam, 2002; Allayannis and Ofek, 2001; Gay and Nam, 1998; Guay and Kothari, 2003; Haushalter, 2000; Spanò, 2007; Tufano, 1996) are either insignificant or even negative when using the extent of hedging as the dependent variable. Again, contradicting evidence is provided in the studies of Adam and Fernando (2006), Adam et al. (2017), Carter et al. (2006), Dionne and Thouraya (2013), Gay et al. (2011), and Graham and Rogers (2002), where firm size positively effects the extent of hedging. However, Dionne and Thouraya (2013) and Gay et al. (2011) fail to support this positive significant relation in some of their models.

2.3 Operational hedging

Section 2.1 briefly outlined the key risk factors in the airline market as well as the financial instruments used to counteract fuel price risk. Section 2.2 provided a literature review of why firms in general use hedging. In this section, operational hedging as an instrument of risk management is discussed to cover the question of 'how airlines hedge'.[29] In the 2010 risk management survey of Bodnar et al. (2011) in which the authors analyze 1,161 responses of global financial and non-financial firms, they find that "operational structures and decisions" (p. 42) were employed by 83% of firms facing commodity price risk compared to 46% of companies using financial contracts. This answer emphasizes that analyzing purely the use of financial derivatives does not cover the entire scope of why and how companies manage price risk.

While the definition of financial hedging is straightforward, the delimitation of operational hedging is more difficult. Operational hedging can refer to "altering real operating decisions" (Smith and Stulz, 1985, p. 392) or "delay[ing] and adjust[ing] investment and operation decisions over time" (Triantis, 2000, p. 64). In addition,

[28]The study by Carter et al. (2006) is the only one analyzed that does not prove a positive influence of firm size on the decision to hedge.
[29]The usage of financial hedges will be analyzed in detail in Section 4.2.

operational hedging includes "various types of processing flexibility" (Van Mieghem, 2003, p. 298). Flexibility exists in many forms in the corporate finance literature and means "the ability to adapt to change" (Chod et al., 2010, p. 1031). Operational flexibility, in particular, is "the ability to operate over a range of conditions while satisfying performance specifications" (Swaney and Grossmann, 1985, p. 621).[30] The gains generated by altering real options are the "option value of operating flexibility" (Huchzermeier and Cohen, 1996, p. 109). Tufano (1998) terms the possibility to open and close production sites as "operational flexibility" (p. 1047). Similarly, Gamba and Triantis (2013) define operational flexibility as the starting or ending of production in their model on operational hedging. Allen and Pantzalis (1996), however, see operational flexibility as a hypernym for operational and financial hedging, and not only for operational hedging.

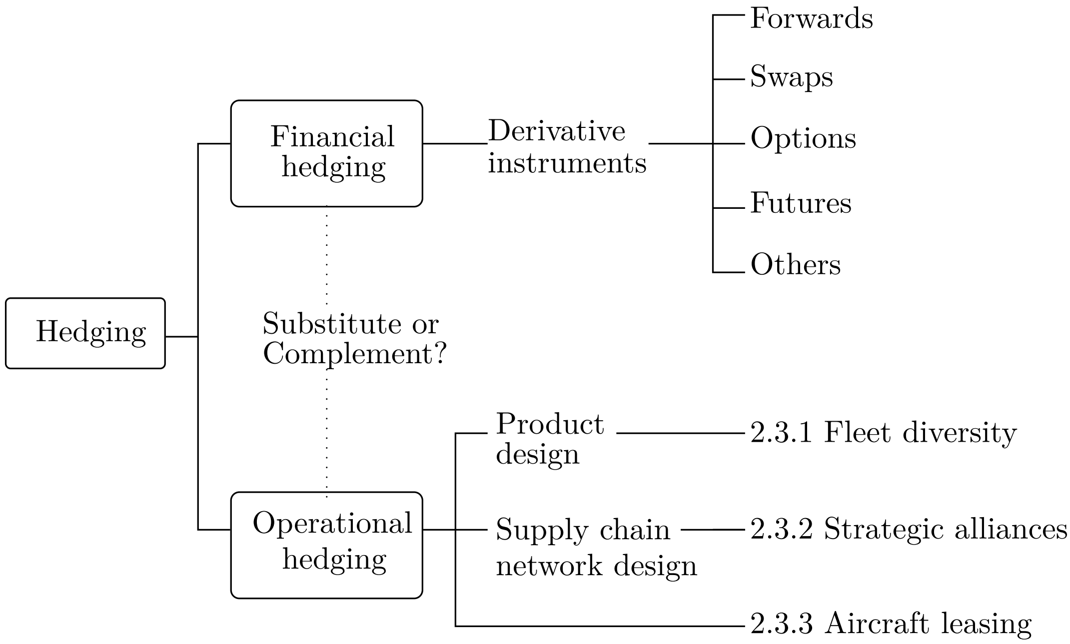
In this thesis, operational flexibility is used as a synonym for real options and operational hedging to clearly distinguish between financial hedging and operational hedging. In contrast to Allen and Pantzalis (1996), financial hedging is not seen as a subset of operational flexibility. Rather, operational flexibility can be regarded as operational hedging because it helps airlines to mitigate the impact of fuel price risk by adapting their operations to changing commodity prices.

As there are many contributions on the different types of flexibility, the next sections explain why fleet diversity (i.e. volume flexibility (Slack, 1983)) and strategic alliances (i.e. supply chain network design (Huchzermeier and Cohen, 1996)) are seen as a type of operational hedging in this study.

Figure 2.3 gives an overview of the different forms of financial and operational hedging. Section 2.1 discussed the different financial derivative instruments as a form of financial hedging. Now, the forms of operational hedging are considered. As Figure 2.3 shows, aircraft leasing is added as an operational hedging tool. Although leasing is merely a form of financing and could thus be regarded under financial hedging, aircraft leasing is integrated in Section 2.3 due to its hybrid nature of financial and operational benefits. On the one hand, leasing increases debt capacity and serves as an alternative to financial hedging. On the other hand, leasing can have direct operational implications if an operating lease contract has been designed so as to enable an airline to change aircraft types more flexibly with cancellation options. If it is easier for an airline to

[30] Production flexibility is "the ease with which [the production system] moves from one state to another, in terms of cost or organisational disruption" (Slack, 1983, p. 7).

Figure 2.3: Overview of financial and operational hedging
Based on Huchzermeier and Cohen (1996), Myers and Majluf (1984), Van Mieghem (2003), and Smith and Stulz (1985)



cancel operating lease contracts when fuel prices are high and the likelihood of default increases, aircraft leasing provides the airline with a real option to counteract fuel price risk.

Thus, the three types of operational hedging regarded in this study are fleet diversity (2.3.1), working with strategic alliances (2.3.2) and aircraft leasing (2.3.3). The question of whether financial and operational hedging are more likely to be substitutes or complements will be analyzed in Subsection 2.3.4.

2.3.1 Fleet diversity

Most research on operational and financial hedging has concentrated on exchange rate risk. Operating a production site in a foreign country, where input and output factors are denominated in the same currency, is seen as a natural operational hedge (Bartram, 2008) because a depreciation in a foreign currency increases production costs but at the same time increases revenues (Chowdhry and Howe, 1999). In the airline industry, fuel is always an input factor and an increasing fuel price will always negatively effect the operating costs of an airline (Treanor et al., 2014b). In addition, airlines that do not operate in the U.S. face currency price risk and incur higher fuel prices if the USD appreciates. Another peculiarity of the airline industry is the fact that the product air travel cannot be stored (like any other service (Kallapur and Eldenburg, 2005)) until fuel prices have decreased. Moreover, the operational hedge of grounding of an aircraft, which can be compared to shutting a mine in times of adverse factor prices (Tufano, 1998), entails large costs due to high capital (Schefczyk, 1993) and ongoing maintenance costs (Bard et al., 2001). Similar to grounding, selling or buying of aircraft is not an effective and quick response to uncertain fuel prices because of long manufacturing lead times (Jiang and Hansman, 2006). The order book of Airbus, for example, comprised 6,874 aircraft at the end of 2016, equivalent to 10 years of production or 1,060 billion Euro (EUR) based on list prices (Airbus Group, 2017b).

Availing itself of a diverse fleet structure though, can serve as a valuable operational hedging tool to counteract uncertain fuel prices. In times of high fuel prices airlines can operate smaller aircraft types[31] on routes which they usually would not service at all due to high fuel costs and thus maintain their presence on given routes without losing valuable slots (Treanor et al., 2014b). IATA (2017, p. 1) publishes "Worldwide Slot Guidelines (WSG) [...] to provide the global air transport community with a single set of standards for the management of airport slots". A slot is an approval by airport authorities for an airline to use an airport, at which traffic demand exceeds capacity, at a certain date and time. Airlines have to operate flights for at least 80% of their allocated slots otherwise they will lose the slots in the following period ("Use it or lose it rule" (IATA, 2017, p. 37)).[32]

Slack (1983) divides manufacturing flexibility into product, quality, volume, and delivery flexibility. In the context of an airline, fleet diversity is seen as an operational hedge similar to volume flexibility. The main product in the aviation market is the flight from A to B. The output capacity can be measured by the figure 'available seat miles (ASMs)', which considers two input factors for the output capacity: aircraft size and stage length. It is the sum of the number of aircraft seats multiplied with the length of a flight. The available seat miles of a wide-body aircraft type such as the Boeing 747

[31] Banker and Johnston (1993) refer to an aircraft type as a production technology that differs between the input factors (e.g. fuel consumption, minimum crew requirements and maintenance) and the output capacity (e.g. available seat miles).

[32] The importance of slots at highly frequented airports becomes apparent from various incidences. IAG, for example, bought 20 slots for the airports Gatwick and Luton from the insolvent British airline Monarch for 60 million Pound Sterling (GBP) (Hollinger and Powley, 2017-11-27). Another example of the importance of slots was the threat by the Russian government to close down the Russian airspace for Dutch carriers because the Russian cargo airline Air Bridge Cargo lost its slots at Amsterdam Schiphol airport as it did not fulfill the "Use it or lose it rule" (Sterling, 2017-10-31).

are greater in contrast to the available seat miles (ASMs) of a narrow-body aircraft like the Boeing 737 because the Boeing 747 has more seat capacity and can be operated on longer distance flights (Banker and Johnston, 1993). With a diverse fleet structure the output can be changed flexibly. The difference in output capacities between the aircraft types is the reason why fleet diversity is compared to the concept of volume flexibility. Volume flexibility means changing the output of a production system in the short term profitably (Goyal and Netessine, 2011; Slack, 1983).

Opposing views exist concerning producing above existing capacity. Slack (1983) suggests that volume flexibility is limited by the maximum output capacity and that any output in excess of that capacity is rather linked to capacity management than flexibility. Goyal and Netessine (2011, p. 180) speak of "upside flexibility" if output exceeds capacity by either enhancing existing production sites or by building new capacity. Goyal and Netessine give the example of Chrysler in 2000 for showing a lack of volume flexibility. While one car type was in high demand and the other car type in low demand, Chrysler could not switch the production between these two car types because the production lines were too inflexible to produce both cars. Similarly for an airline, if route A-B is in high demand and route A-C in low demand, the airline can react to these demand imbalances by using different sized aircraft types. If the airline availed itself only of one aircraft type, the result would be operating with excess capacity or selling tickets below costs.[33]

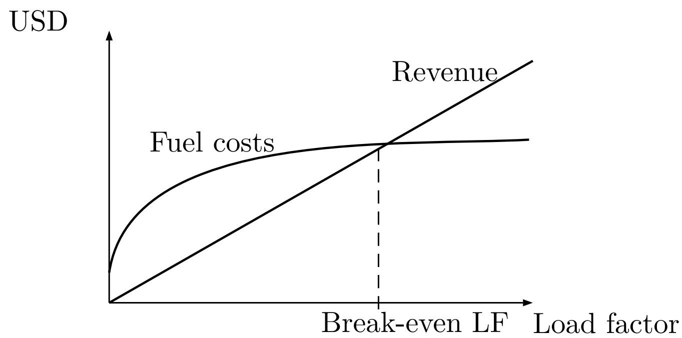
In a study about the U.S. airline market, Treanor et al. (2014b) analyze the financial and operational hedging strategies of international and regional U.S. airlines between 1994 and 2008. The authors identify fleet diversity and aircraft fuel efficiency as two operational hedging methods. Fleet diversity is calculated as the aircraft dispersion index based on the Herfindahl-Hirschman concentration index (HHI), which is also employed by Allayannis et al. (2001). The calculation will be explained in detail in Subsection 4.1.2. The results indicate that operating a diverse fleet reduces fuel price exposure[34] significantly, but only at the 10%-level. Interestingly, operational hedging (fleet diversity) decreases fuel price exposure by 2.3% whereas financial hedging (next year's fuel consumption percentage hedged) decreases exposure by only 1%. Treanor

[33]Van Mieghem (2003) highlights the importance of having different processing resources to benefit from the flexibility within the processing network. In the context of an airline, aircraft can be seen as the processing resource and diverse aircraft types, i.e. fleet diversity, is the flexibility of the processing network.

[34]Exposure is calculated based on the two-factor model employed in empirical exposure research where the airline's stock returns are regressed against market returns and jet fuel price changes.

et al. use the natural logarithm of fleet age as a proxy for fuel efficiency[35] and find that older aircraft significantly (at the 1%-level) increase exposure. One caveat of the study by Treanor et al. is that the age alone does not capture the entire fuel advantage of one aircraft type over the other. While Airbus, for example, still delivers both aircraft types, Airbus A320 and A320neo[36], the A320neo is 15% more fuel efficient than its sister aircraft (Airbus Group, 2015) although both aircraft would be considered to be of the same age in the study by Treanor et al. (2014b).

Figure 2.4: Effect of the load factor on fuel costs and revenue



However, the additional flexibility of operational hedging is costly. Specifically, those costs consist of switching costs, the time needed to carry out the change and costs associated with having excess capacity (Huchzermeier and Cohen, 1996; Slack, 1983). A diverse fleet is costly because the economies of scale of operating a large, homogeneous fleet cannot be exploited. Switching costs include flight crew and maintenance personnel training as well as the implementing costs of a new aircraft type. Moreover, spare parts and engines are not easily interchangeable (Benmelech and Bergman, 2009; Berghöfer and Lucey, 2014). Excess capacity, measured in the airline industry with (1−load factor (LF)), is costly because of a diminishing marginal effect of the load factor on an increase in fuel consumption whereas revenue is linear (assuming that all tickets are priced equally). In other words, each flight entails fixed fuel costs which can be spread over more passengers the higher the load factor is. The load factor is calculated

[35] Another way to influence fuel consumption flexibly is to change the cost index (CI) for each flight. The CI is a fraction with the time cost as the numerator and fuel costs as the denominator. The cost index that is inserted in the flight management system (FMS) of the airplane influences the climb, cruise and descent speeds of the specific flight. The faster the aircraft flies the higher the cost index, resulting in higher fuel costs due to increased consumption but at the same time resulting in lower time costs such as staff or maintenance costs (Roberson, 2007). For the Airbus 320, an increase of the CI from 0 to 100 results in a time reduction of 9 minutes and an increased fuel consumption of 400 kilogram (kg) for a flight distance of 1000 nautical miles (Airbus Group, 1998). However, CI changes cannot be incorporated in empirical research because they are not reported in airlines annual reports.

[36] "Neo" stands for "new engine option" (Airbus Group, 2017a).

with revenue passenger miles (RPMs) divided by ASMs and measures "aircraft capacity utilization" (Lazzarini, 2007, p. 353). Figure 2.4 shows that with excess capacity, fuel costs exceed the revenue of a flight up to the break-even load factor when the flight becomes profitable. Other costs are excluded for simplicity.[37] Having excess capacity, though, is the prerequisite for volume flexibility (Slack, 1983).

Another operational hedging strategy, working with strategic alliances, will be discussed in the following subsection.

2.3.2 Strategic alliances

Huchzermeier and Cohen (1996) see "supply chain network design" as an operational hedge in "sourcing, manufacturing, and distribution" (p. 100). In a similar spirit, Allen and Pantzalis (1996) define operational flexibility, i.e. operational hedging, of a multinational firm as shifting resources within the firm's network in the areas of "production, research, marketing, and financial units" (p. 643). Although there is a difference between an external strategic alliance and an internal supply chain of a multinational company, the concepts are quite similar.

There are different levels of cooperation: Fan et al. (2001) distinguish between ordinary, tactical and strategic alliances. An ordinary alliance exists if an airline outsources some part of the value chain to another airline, such as handling services at the airport. Tactical cooperation can be compared to the idea of an "implicit constellation" proposed by Lazzarini (2007), which means codesharing agreements between two airlines that is selling and marketing seats on each others flights for a specific routing or region.[38] A strategic alliance, or "explicit constellation", comprises the partnership of more than two airlines competing in the same market but working cooperatively within the alliance. A strategic alliance goes above and beyond a codeshare agreement (Lazzarini, 2007). The airlines of a strategic alliance cooperate, among others in the areas of marketing, pricing, frequent flyer programs, flight times, lounge access, and gate distribution (Brueckner and Whalen, 2000; Fan et al., 2001). Fan et al. (2001) emphasize that exclusive membership of an alliance is an essential component in characterizing a strategic alliance. Moreover, the existence of a joint frequent flyer program is an important factor for customers in being loyal to one strategic alliance because they can switch between alliance members at no cost. The three largest strategic airline alliances - Star Alliance, Oneworld and SkyTeam - evolved approximately 20 years ago (Lazzarini, 2007).

[37] Other costs, however, such as maintenance and flight crew costs do not depend on the load factor.

[38] For example, the flight A to B is performed by airline 1, the 'operating carrier', the flight B to C by airline 2, while the passenger can freely fly and transfer her baggage from A to C via B.

Empirical studies on strategic alliances or other forms of cooperation between airlines focus mostly on the impact alliances have on ticket prices[39] and airline financial performance. Brueckner and Whalen (2000) analyze how the existence of tactical alliances influences international interline fares[40] for the third quarter of 1997, where at least one segment is served by a U.S. carrier. They regress the natural logarithm of interline fares against a dummy variable covering whether the airline has a codesharing agreement, controlling for the distance flown, demand, competition and airline-specific effects, resulting in more than 46,000 observations. The results of the simple OLS regression support that airlines with a codeshare agreement offer 19.5% lower interline rates than other airlines. Several caveats exist with this study though. With an R^2 of 0.02 other regressors might explain better the variations in the dependent variable. Moreover, due to data source problems the sample omits international flights not operated by a U.S. carrier, neglecting possible lower interline fares of international competitors. Lastly, the authors assume passenger brand loyalty in their model, which can be challenged in a commodity market such as the airline industry.

Lazzarini (2007) aims to answer the questions "whether the membership of an airline constellation has any impact on carriers' operational performance, and what the drivers of membership benefit are" (p. 346). His sample comprises 75 global airlines from 54 countries between 1995 and 2000, which covers 81% of world traffic. The dependent variable is the passenger LF, a proxy for the airline's performance. Lazzarini finds a significantly (at the 5%-level) increased load factor of 1.2% points for airlines that are part of a strategic alliance (explicit constellation). If the sample is restricted to airlines being part of an explicit constellation, his results show that load factors increase significantly (at the 5%-level) by 1.1% points when the traffic of other alliance members increases by 100 billion revenue passenger kilometers (RPKs), supporting his hypothesis that airlines of a large alliance in terms of RPK outperform airlines that belong to a smaller alliance.[41]

[39] Brons et al. (2002) use 37 different studies in their meta-analysis about price elasticity in the air travel market.

[40] An interline fare means the ticket price a customer pays for traveling from her departure to her destination airport with multiple stops on different codesharing flights.

[41] One study exists about the relation between fuel hedging and alliance membership. Lin and Chang (2009) suggest that the fraction of fuel expenses (after fuel hedging) of operating expenses is lower for airlines that make use of fuel hedging. This statement neglects the fact that mostly large airlines in their sample such as Malaysian Airlines and Lufthansa use financial derivatives. Those established legacy airlines, however, usually suffer from larger operating expenses due to higher operating and personnel costs than younger airlines or LCCs. Berghöfer and Lucey (2014) show, for example, that the percentage of fuel costs (after hedging) of total operating costs is larger for LCCs in comparison to legacy carriers in all years between 2002 and 2012.

Due to the multitude of airlines in the sample, the focus is set on explicit constellations, i.e. strategic alliances, and their influence on airlines' fuel hedging behavior, not on bilateral codeshare agreements.

2.3.3 Aircraft leasing

Operational, off-balance sheet leasing can increase debt capacity similar to financial hedging (see Subsection 2.2.1), which makes operational hedging a possible alternative to financial hedging (Damodaran, 1999; Eisfeldt and Rampini, 2009). Especially in the case of the airline industry, it is essential to include leasing variables into a determinants study due to the existing magnitude of aircraft leasing (see Section 2.1).

There are two forms of lease contracts: capital or financial leasing and operating leasing. If the airline leases an aircraft under a capital lease contract, the leased aircraft will be shown in the balance sheet, similar to a debt financed purchase, and ownership is transferred from the lessor to the lessee (Narayanan, 2013). An aircraft leased under an operating lease contract will not be disclosed as an asset. The yearly rent expense is instead accounted as an operating expense in the income statement (Damodaran, 1999). Carter et al. (2006) report an average leasing ratio, either through finance or operating lease, of 60% to 70% in their sample of 29 US airlines from 1992 to 2003, implying that the debt ratios of those airlines with high operating lease aircraft are underestimated if they are not adjusted by operating lease expenses.

Section 2.1 discussed that hedging shifts risk from an airline to a counterparty that is willing to bear the risk. Similarly, aircraft lessors take the risk of funding large aircraft orders because they have easier access to financial funds with their usually better credit ratings. Lessors have grown largely in recent years to resemble large financial companies such as GECAS or AerCap (Gavazza, 2011). AerCap, that acquired one of the largest aircraft lessors (International Lease Finance Corporation (ILFC)) in 2014, owned 1,109 aircraft with a book value of 32 billion USD at the end of 2015 (AerCap Holdings, 2016). Although aircraft are specialized equipment which are usually not traded frequently, their characteristic of mobility[42] makes the secondary aircraft market relatively liquid and global. As there is no worldwide aircraft trade exchange, leased and owned aircraft are traded bilaterally. Gavazza (2011) finds that leased aircraft are 13% more traded than owned aircraft.

Apart from the difference in accounting rules, U.S. Chapter 11 bankruptcy regulations differ between operating and finance leases. If an aircraft is leased to the airline

[42] After the contract has been signed the product can be brought to the consumer without other means of transportation (Gavazza, 2011).

under an operating lease contract and that airline enters Chapter 11, the lessor still has the ownership of the aircraft and can either require the airline to make the remaining lease payments or return the aircraft to the lessor. Contrary, if the aircraft is leased under a financial lease construct, more similar to secured lending, it is part of the insolvency estate and ownership remains with the airline (Eisfeldt and Rampini, 2009). The lessor in this case has higher claims than other secured debt holders but cannot repossess the aircraft as easily as under an operating lease deal (Gavazza, 2011). Therefore, under operating leasing the lessor can lease a higher asset value to the airline because the lessor has a higher repossession ability of an operating leased aircraft under bankruptcy in contrast to an aircraft under finance lease. The disadvantage of operating leasing for the airline is that it does not have full control over the aircraft. Moreover, monthly leasing rates may be as much as 20% higher than the fictive rental rates of an owned aircraft. Those mark-ups on operating leased aircraft are justified by the lessor due to his legal, technical and market expertise (Gavazza, 2011).

Theory suggests that more indebted firms with the need for even more leverage should appraise the use of leasing more than less distressed firms because the cost of borrowing increases with debt levels and relative monitoring costs decrease (Eisfeldt and Rampini, 2009; Rampini and Viswanathan, 2013). Similar to financially distressed airlines, young airlines with high growth potential should benefit from leasing (Gavazza, 2011; Rampini and Viswanathan, 2013).

Although the debt ratios in the airline industry study of Carter et al. (2006) are adjusted by the present value of operating lease expenses, the authors do not focus specifically on the substitutional effect operating leasing might have on hedging. Rampini and Viswanathan (2013) are the first to include leasing and risk management considerations in a single model. Investments can be financed either by tangible or by intangible, liquid assets. Tangible assets, either bought or leased, are collateralizable. If the asset is leased, the company has the opportunity to borrow the entire leased asset value due to the repossession ability under leasing contracts. If the asset is debt financed, on the other hand, the firm cannot borrow the entire asset value but only a fraction of it. They therefore challenge the 'leasing for hedging substitute' theory by saying that leasing increases debt capacity, which increases the likelihood of financial distress and consequently the need for hedging. In addition, they link risk management and financing decisions with collateral requirements. In states of financial distress, a firm will face a trade-off between asset backing for either financing their investment requirements or providing collateral for margin calls in hedging contracts (Morrell and Swan, 2006). Opportunity costs arise if the available collateral is not sufficient to fund both, debt contracts for current investment decisions and derivative contracts to hedge future period risk. Similarly, Froot et al. (1993) speak of credit risk instead of collateral. A forward contract, which is a combination of a future and a debt contract, involves the same credit risk as a debt contract. If the firm does not have enough internal funds available, it may not be possible to enter into the derivative and the debt contract at the same time.

In a related study based on Rampini and Viswanathan (2013), Rampini et al. (2014) test the trade-off theory with empirical data of the airline market. The sample includes 23 U.S. passenger airlines between 1996 and 2009. In states of low net worth[43], when the firm is financially constrained, it has to decide between risk management and increasing debt for investment plans because it does not have enough collateral for both decisions simultaneously. In univariate results the researchers find that if net worth increases by one standard deviation (SD), fuel hedging increases by 0.5 SD, contrary to the financial distress theory. Also in contrast to theory, they find an average decrease of 22% in fuel price hedging if the credit rating of an airline is reduced by one grade. The univariate results are confirmed by a two-stage least squares estimation where profitability serves as an instrument for net worth. In the second step, the authors regress net worth against hedging and also find a positive significant relation. To further test the hypothesis that lower net worth leads to lower hedge ratios, they focus on firms in financial distress, defined as airlines with credit rating of CCC+ and lower. The 10 analyzed airlines hedge on average 25% of their expected fuel consumption in the two years before the financial distress. The hedge ratios decrease significantly to an average hedge ratio of 5% during the distress phase. In the two years following the bankruptcy or distress phase, hedge ratios increase again but not to pre-crisis levels.

The survey results by Bodnar et al. (2011) confirm the negative relation between required or available collateral and hedging margin calls. If margin calls were to increase on OTC derivative contracts, more than half of non-financial firms would reduce their hedge activities.

2.3.4 Substitute or complement?

One difference between financial hedging and operational hedging is that while financial hedging should reduce uncertainty, operational hedging "exploits uncertainty" (Huchzermeier and Cohen, 1996; Triantis, 2000; Van Mieghem, 2003). Also, operational hedging bears fruit in the longer term because high switching and implementation costs can be

[43]Net worth is calculated as the current cash flow of the airline plus the market value of capital minus outstanding debt plus collateral requirements for margin calls.

distributed over a longer time horizon, whereas the costs of financial instruments increase with longer maturities (Huchzermeier and Cohen, 1996). Some operational horizons may well exceed the maturities of financial derivatives, rendering financial hedging insuitable for longer time periods and making operational hedges indispensable complements (Van Mieghem, 2003). Bodnar et al. (2011) find that 31% of the survey respondents did not use financial derivatives because "exposures are more effectively managed by other means" (p.12). On the other hand, reversing an implemented operating hedge is much more costly than changing a financial hedge portfolio (Bartram et al., 2010).

The study by Mello et al. (1995) is the first one to incorporate flexibility in foreign exchange financial hedging analysis. The model assumes that a multinational enterprise (MNE) has operational flexibility with two production sites in Japan and U.S. between which they can switch as to choose the production mix with the lowest total cost. Mello et al. also assume that the debt structure of the firm is affected by both the level of operating flexibility (higher flexibility means higher fixed costs and higher leverage) as well as the hedge ratio because for each USD outstanding debt the firm buys currency derivatives to hedge the exchange rate risk between USD and Japan Yen (JPY). With a numerical example they show for two firms having the same operational flexibility and outstanding debt that the firm with financial hedges does not default in contrast to the competitor with no financial derivatives. If the example considers different levels of operational flexibility between the companies, the lower the flexibility of the firm, the higher the firm value increase through financial hedging. Mello et al. conclude from these results that financial hedging and operational hedging are substitutes because operational hedging increases firm value, reduces the likelihood of default and thus the necessity for financial hedging. Yet they also find arguments for supporting the complement theory. A more flexible firm that has the same leverage ratio as a less flexible firm has greater nominal debt outstanding due to higher asset values and hence needs more financial derivatives if it offsets the outstanding debt with financial hedging.

Allayannis et al. (2001) test whether financial hedging and operational hedging are complements or substitutes. The operational hedging strategies of the 265 sample MNEs between 1996 and 1998 are proxied by four different variables. The number of countries and the number of regions (e.g. Europe) in which the firm has operations is calculated. Moreover, two variables measure the degree of how dispersed those operating sites are across the countries and regions, i.e. the 'dispersion index'. One out of the four proxy variables enters as an independent variable in one of four OLS regressions with a dummy variable for financial hedging as the dependent variable. In addition, the proxy for FX exposure, foreign sales divided by total sales, is included in each regression. The results show that each of the four operational hedging variables is positive and significant at the 1%-level, supporting the hypothesis that financial hedging and operational hedging are complements.

Another study by Hankins (2011), which looks at the relation between operational and financial hedging, concentrates on acquisitions as a form of operational hedging. Hankins analyzes acquisitions between 1995 and 2003 of at least 50 million USD acquisition value. She measures the benefits of operational hedging as the change in operational income volatility before and after the acquisition.[44] If the change in volatility is negative, this means a (beneficial) increase of operational hedging because the acquisition has decreased the combined volatility (compared to the acquirer's volatility). The OLS regression, limited to the sample firms that acquired a firm in the time period, contains the change of the notional value of interest rate derivatives as the dependent variable one and two years *after* the acquisition, the change in operational hedging two, three and four years *before* the acquisition and other control variables. The coefficients of the change in operational hedging are almost all significantly negative, with decreasing significance levels the longer the estimation period is for operational hedging prior to the acquisition. Hankins concludes from the results that firms substitute financial hedging with operational hedging, where the acquisition serves as the operational hedge instrument.

As discussed in Subsection 2.2.2, Gamba and Triantis (2013) model operational and financial hedging as well as cash holdings simultaneously. Operational hedging means opening and closing of production capacity in their model. Based on average data from previous empirical studies, they calculate firm values for different scenarios of cash holdings and hedging strategies. They find that the increase in firm value due to financial hedging is greater for firms with lower operational flexibility, implying that financial and operational hedging are rather substitutes than complements. However, although the marginal effect of financial hedging on firm value is a decreasing function of operational flexibility, there is still a value increase if both hedging strategies are applied parallel. The more effective the financial hedge is within an industry, the higher the substitutional effect of operational and financial hedging becomes. Lastly, they analyze the case where a firm with high fixed cost and greater leverage can make use of more operational flexibility. Greater operational flexibility leads only to a slight decrease in cash holdings because cash is still needed in times of economic downturns in order to be

[44]The preacquisition volatility is the three-year income volatility of the acquirer measured with quarterly operating income volatility scaled by total assets. The change in operating volatility is calculated as the combined, fictitious operating income volatility minus the acquirer's volatility divided by the acquirer's volatility.

able to service the high fixed costs. The financial hedge portfolio, on the other hand, decreases strongly if operational hedging is increased, again supporting the substitute theory.

The three studies cited in this subsection underline the importance of analyzing financial hedging and operational hedging simultaneously. Yet they give an ambiguous answer to the question whether financial and operational hedging are complements or substitutes. Chapter 5 strives to answer this question empirically for the airline industry.

2.4 Selective hedging

Section 2.1 contained the statement that the difference between speculating and hedging is the impact those financial strategies have on a firm's risk. In this section, more attention is given on how (selective or systematic hedging) and why (determinants of selective or systematic hedging) airlines hedge. When managers assume that they can predict how commodity prices will behave or that they have superior market information available, they are tempted to adapt the size and maturity of the firm's hedge portfolios to match their personal market risk (Adam et al., 2017). In that way they hedge selectively instead of systematically in order to make profits from their derivative contracts (Adam et al., 2017; Stulz, 1996). Adam et al. (2017) use the terms selective hedging and speculation interchangeably. In the case study by Brown (2001), a financial manager stated that "We do not take speculative positions, but the extent (to which) we are hedged depends on our views." (p. 413), which opposes the assumption by Adam et al. (2017) that the terms are synonyms. The term selective hedging instead of speculation is specifically used in this thesis in order to emphasize the difference between hedging and speculation. Whether or not the firm that uses derivatives is exposed to the risky asset, is a possible differentiation between hedging and speculation. An airline that is exposed to fuel price risk uses derivatives to hedge and not to speculate. The counterparty, e.g. a financial institution, is not exposed to fuel price risk but might trade in fuel derivatives for the reason of speculation (Hentschel and Kothari, 2001). Bodnar et al. (2011) find in their survey on derivatives usage that 31% of the respondents confirmed the usage of discretionary commodity risk management. Headlines such as "Air France-KLM, Europe's biggest carrier, led cuts in fuel-cost hedging by the continent's airlines in the third quarter as prices headed for the first annual decline in six years." (Rowling, 2014-

08-14) verify that airline managers change their hedge portfolios dynamically based on changes in the oil price cycle (Cobbs and Wolf, 2004).[45] The theory on selective hedging determinants is thus closely linked to Subsection 2.2.3.

Selective hedging may even increase a firm's risk (rather than reduce it) if the financial manager reduces the hedge portfolio from a full hedge position and his market view proves to be erroneous. Due to the increase in risk, companies in good financial health should be more inclined to use selective hedging (Stulz, 1996) as well as firms that avail themselves of superior market information because of their size or their experience in that market (Adam et al., 2017). In frequently traded commodity markets such as the oil market, firms should have less opportunities to possess more information about that commodity than their competitors, leading to a reduced level of selective hedging (Stulz, 1996).

Although Haushalter (2000) does not specifically analyze selective hedging, he theorizes that the negative relation between managerial shareholding and risk management (which is contrary to the predictions that increased shareholding should lead to higher levels of hedging) could be caused by "self-selection" (p. 137). If the risk manager believes that commodity prices will develop in a positive direction, i.e. falling oil prices in the airline industry, he will increase his shareholdings in the company and reduce the level of hedging, fulfilling the definition of selective hedging. The results of the study by Yermack (1997) on 620 CEO stock option awards of Fortune 500 firms between 1992 and 1994 support the notion by Haushalter (2000). Yermack analyzes firms' CARs before (20 days) and after (120 days) the stock option award day, where the award date is not known by the public until well after the date. He finds that the company CARs in which the CEO was awarded stock options significantly outperform the market by 1.6% in the first week after the award date. Yermack concludes that CEOs take active part in and influence their option reward process in order to benefit from "good news"-stimulated stock price gains.

Brown et al. (2006) use the gold mining data by Ted Reeve (as employed before by several other researchers such as Tufano (1996) and Adam (2002)) to study the determinants of selective hedging. The level of selective hedging is measured with the standard deviation of quarterly hedge ratios. Firms with hedge ratios above the median

[45] The volatility in oil prices (see Section 2.1) is caused by the supply and demand inelasticity of oil and due to changes in market expectations. Oil users cannot easily store or adapt their oil deliveries and oil production sites cannot vary output as flexibly as needed to meet varying demand. Any shocks to the oil demand or supply lead to high levels of oil price volatility (Smith, 2009). The oil price volatility peak in October 2008 was caused by several events such as nationalization efforts in Venezuela, production site sabotage in Iraq, industrial actions in Nigeria and Scotland, and terrorist attacks in Nigeria (Smith, 2009).

are termed as active hedgers and firms below the median as less active hedgers. Almost a quarter of the 44 sample firms change their hedge ratios every four months by at least 50%. In a second step, the authors regress the SD of quarterly hedge ratios against a size, market share, financial distress, financial flexibility, and growth variable. They find that the growth variable (MTB ratio) is negative and significant at the 5%-level, implying that the more investment opportunities a company faces, the less likely it will adapt its hedge ratios. All other variables are insignificant. Changes in gold prices, however, do influence the level of hedging. When gold prices increase, gold mining firms tend to hedge more and if prices fall they hedge less.

To further explore on the question on why financial managers alter their hedge strategies, Brown et al. assess the responses of 13 gold mining financial managers. Seven managers confirmed that they changed the hedge strategy based on their personal views on how the gold price will behave and seven managers incorporated market views in their hedge portfolios. Moreover, short and long-term future price changes as well as recent gold price changes and derivative prices influence the derivative strategy. The hedge strategy of other competing market participants and previous hedging gains or losses do not influence the hedging decision strongly.

The selective hedging study by Adam et al. (2017) was discussed briefly in Subsection 2.2.1 with regards to the influence of financial distress on selective hedging. The higher the likelihood for financial distress, the more financial managers alter their hedge portfolios. Contrary to the determinants of systematic hedging, the firm size negatively influences the levels of selective hedging. Smaller firms tend to make use of more selective hedging than larger firms in the data set of Adam et al. (2017). The term of the CEO, the age of the company and managerial compensation do not have any influence on the levels of selective hedging.

In addition to personal managerial views that influence hedging decisions,[46] another behavioral aspect comes into play when analyzing the managerial impact on hedging decisions. Prior-period hedging losses significantly reduce the hedge portfolio delta and gamma of Brown (2001)'s case study company, a manufacturer that hedges its foreign exchange exposure through forward derivative instruments. While determinants such as financial distress, underinvestment, managerial compensation, and tax incentive do not appear to influence the hedge portfolio significantly, hedging losses from the previous quarter significantly increase the hedge portfolio delta and gamma at least at the 5%-

[46] Gerner and Ronn (2013) refer to those personal decision makings as "rule of thumb" hedging decisions (p. 11).

level regardless of the time horizon (three, six and nine months). These findings oppose the survey results by Brown et al. (2006, p. 2933) where hedge managers denied that the "outcome of prior hedges" influenced their hedge behavior.

Chapter 3

HYPOTHESES

Chapter 3 presents the hypotheses of the analysis. H1a to H5 relate to the determinants of hedging (Section 3.1). Hypotheses related to operational hedging are part of H6 to H9 (Section 3.2). Lastly, H10 to H12 (Section 3.3) contain hypotheses on selective hedging.

3.1 Hypotheses on the determinants of hedging

Hypothesis 1a (H1a): *High leverage airlines use more fuel price derivatives than less indebted airlines.*

Financial hedging can smoothen the volatility of firm cash flows and reduce the likelihood of financial distress and default (Smith and Stulz, 1985), implying lower direct and indirect bankruptcy costs (Warner, 1977). For highly leveraged firms, the probability of encountering financial distress is higher than for firms with low debt ratios and thus the benefits and usage of hedging should be higher for more indebted firms (Nance et al., 1993).

Hypothesis 1b (H1b): *In the cases of very high levels of debt ratios, hedging decreases, i.e. the relation between airlines' financial fuel price hedging and leverage is concave.*

In contrast to the linear relation of H1a, Purnanandam (2008) proposes a nonmonotonic relation between the levels of debt and risk management. When an airline is close to bankruptcy but still solvent, its shareholders can benefit from increasing risk by not using derivatives in order to increase the number of states in which the firm may financially survive. This notion is similar to the proposition by Tufano (1996) that holding common stock is comparable to holding a call option, written on a firms' market value. Managers that are compensated by common stock will reduce risk management activities in financial distress and by that increase a firm's risk in order to increase the option value of their stock holding. Stulz (1996), on the contrary, suggests that firms with very high leverage, i.e. that are encountering financial distress, should increase their hedge activities even more to increase the possibility of exiting bankruptcy.

Hypothesis 2 (H2): *The higher an airline's investment opportunities, the higher the firm's incentive to hedge.*

A company that has depleted its financial resources may have to abandon profitable investment projects (Myers, 1977). If hedging can lower the number of states in which investment opportunities are not being exploited, it might increase firm market value (Froot et al., 1993). Airlines with more potential investment opportunities at hand should thus benefit more from hedging than competitors with less growth options.

Hypothesis 3a (H3a): *Low levels of cash holdings are related to lower levels of risk management activities.*

If an airline has little cash at hand, it faces a trade-off between using the remaining financial funds for providing margin calls to their hedging counterparties or as collateral for raising debt from outside investors and by that finance investment opportunities (Morrell and Swan, 2006; Rampini and Viswanathan, 2010; Rampini and Viswanathan, 2013).

Hypothesis 3b (H3b): *Very high levels of cash holdings are related with lower hedge ratios. The relation between hedging and cash holdings is nonmonotonic.*

Airlines with ample financial slack should not be in need of entering costly derivative contracts. Their cash holdings are sufficient to cushion any peaks in kerosene prices.

Hypothesis 4 (H4): *Financial hedging increases with simultaneous low cash holdings and high investment opportunities.*

Low cash holdings do not necessarily mean that an airline should increase its hedging activities if there are no investment opportunities to be financed. Similarly, if the airline has high growth potential but at the same time enough internal funds, hedging should not be as beneficial as for an airline with low cash holdings and high growth options.

Hypothesis 5 (H5): *Larger firms hedge more.*

Larger firms may benefit from economies of scale in launching and operating risk management activities because transaction costs and risk premiums are spread over firm size (Graham and Smith, 1999; Haushalter, 2000). Similarly, holding various types of hedging instruments may lead to larger hedge portfolios due to expert knowledge. Moreover, agency conflicts between shareholders and managers may be more pronounced in larger companies which could lead to managerial compensation with more stock and option rewards. If larger managerial shareholding leads to more hedging, larger companies with more stock and option compensation will show higher levels of derivative usage (Dionne and Thouraya, 2013). Economies of scale may be more important at initiating a risk management division in contrast to running the established hedge department (Haushalter, 2000).

For the airline industry, this study proposes that the size of an airline's fuel bill, in addition to firm size in general, may have a positive impact on the airline's hedging behavior.

3.2 Hypotheses on operational hedging

Hypothesis 6 (H6): *The more diverse the operating fleet of an airline, the lower the need for financial fuel hedging.*

In periods of high kerosene prices, airlines with different sized aircraft can operate smaller aircraft on routes which they would otherwise not operate and by that lose valuable slots (Treanor et al., 2014a). A precondition for this notion is, though, that when kerosene prices are high, air travel decreases. Due to the fierce competition in international airline markets and high price elasticity for airline tickets (Brons et al., 2002), airlines cannot easily pass through rising kerosene prices to passengers. Thus, with increased fuel prices, airlines either keep ticket prices, the load factor and revenues stable while reducing profits, or increase ticket fares at the expense of a reduced load factor, revenues and profits. Either way, airlines suffer from increased kerosene prices and have to influence the fuel price bill by either financial or operational hedging.

Anecdotal evidence suggests that in times of high oil prices and simultaneous low demand, airlines operate smaller aircraft on longer flights and larger aircraft on shorter distances in order to reduce the overall fuel bill. In that way, airlines with a diverse fleet structure exploit the fuel price uncertainty. Larger aircraft have higher per hour fuel consumption. If they are operated on more frequented, shorter legs the relative period they are in transit, i.e. on the ground, is increased.

For example, an Airbus 321 (maximum seat capacity 236 (Airbus Group, 2017a)) with an hourly fuel consumption of 3,000 kg kerosene per hour that is operated 17.0 hours per day can fly the route Frankfurt-Hamburg-Frankfurt 4.5 times with 8.0 hours of transit, under the assumption of 1.0 hour transit between the flights. The total fuel consumption for that day would be 27,000 kg kerosene. An Airbus 319 (maximum seat capacity 156 (Airbus Group, 2017a)) with an hourly fuel consumption of 2,400 kg kerosene per hour could fly Frankfurt-Faro-Frankfurt and Frankfurt-Hamburg in the same time period. Total hours of transit would be 4.0 and fuel consumption 31,200 kg kerosene, resulting in a summed fuel consumption for both aircraft of 58,200 kg kerosene. If the airline swapped the larger aircraft for the longer distance flight (Frankfurt-Faro-Frankfurt), the total fuel consumption for both aircraft would increase to 60,600 kg kerosene. See Appendix D for a detailed calculation.

Similarly, if some route X-Y is in high demand and some route X-Z in low demand, the airline can adapt to these demand imbalances by using different sized aircraft types. If the airline availed itself only of one aircraft type, the result would be operating with excess capacity or selling tickets below costs. When analyzing fleet diversity, the costs associated with that operational hedging instrument, such as switching and implementation costs as well as maintaining excessive capacity (Huchzermeier and Cohen, 1996; Slack, 1983), must not be neglected. Therefore, switching costs are specifically included in the analysis of fleet diversity.

Hypothesis 7 (H7): *Alliance membership is a substitute for financial hedging.*

Airlines that are part of an alliance can benefit from cooperating with other alliance members in the areas of marketing, pricing, flight times etc. (Brueckner and Whalen, 2000; Fan et al., 2001). Lazzarini (2007) finds that alliance membership has a positive influence on an airline's load factor. If fuel prices increase, alliance membership may assist alliance airlines in holding load factors stable while maintaining ticket prices. Therefore, alliance membership might be related to lower levels of financial hedging.

Hypothesis 8a (H8a): *The more an airline uses leasing, the more it engages in financial risk management.*

Theory suggests that more indebted firms with the need for even more leverage should appraise the use of leasing more than less financially constrained firms because the cost of borrowing increases with debt levels. If more distressed airlines lease more aircraft than less distressed firms, higher ratios of leased aircraft should result in higher levels of risk management usage (Eisfeldt and Rampini, 2009; Rampini and Viswanathan, 2013).

Hypothesis 8b (H8b): *Aircraft operating leasing is a substitute for financial hedging.*

Leasing can have direct operational implications. If an operating lease contract includes early termination rights and cancellation options, it enables an airline to change or reduce the number of aircraft types more flexibly to counteract volatile fuel prices (Moody's, 2015). If it is easier for an airline to terminate operating lease contracts earlier when fuel prices are high and thus default is more likely, then aircraft leasing provides the airline with a real option to counteract fuel price risk. In that sense, operational leasing may be a substitute for financial hedging. The Japanese carrier Skymark, for example, had to file for bankruptcy because it could not service its advance payments for six Airbus 380 to the manufacturer because of high fuel expenses (Maki Shiraki, 2015-01-28). If the airline had operating leased the A380 instead of financed, the prepayments might not have caused the airline to become insolvent.

Hypothesis 9 (H9): *Airlines with a high number of aircraft under operating leasing and simultaneous low cash holdings show lower levels of financial fuel price hedging.*

An airline that faces financial distress will have to trade off asset backing for financing their investment requirements against providing collateral for margin calls in hedging contracts (Froot et al., 1993; Rampini and Viswanathan, 2013). With mainly operating leased aircraft in the fleet, an airline with low cash holdings has less collateral available for providing debt security or margin calls. An airline with a large number of unencumbered aircraft in its fleet and low cash holdings can still provide collateral for financial derivative contracts by pledging its fleet.

3.3 Hypotheses on selective hedging

Hypothesis 10 (H10): *Recent hedging losses, recognized in income, lead to a relatively greater adaption in hedge portfolios. Losses that are recognized in other comprehensive income (OCI) do not affect the hedge portfolios.*

Recent hedging losses significantly reduce the hedge portfolio delta and gamma of Brown (2001)'s case study company. Managers that have experienced fuel hedging losses might be more cautious in future periods (Brealey et al., 2017) to enter fuel derivative contracts. Survey results by Brown et al. (2006) controvert this argument though because financial managers stated that recent hedging gains or losses did not influence their risk management activities. The adaptions in hedge ratios are measured relatively to the other sample airlines.

Hypothesis 11 (H11): *Recent increases in regional hedge ratios lead to larger fuel derivative portfolios of an individual airline in the same region. Analogously, recent decreases in regional hedge ratios induce airlines to reduce their hedge activities.*

If airline managers are influenced by competing airlines' hedging strategies, an increase in regional average hedge ratios should lead to higher individual hedge ratios. In other words, risk managers may exhibit herd behavior. Financial managers in the gold mining industry, however, did not state that they reacted to changes in hedge portfolios of competitors (Brown et al., 2006).

Hypothesis 12 (H12): *Larger airlines are more likely to hedge selectively.*

Adam et al. (2017) suggest that larger firms are more prone to selective hedging because of greater market expertise and risk management capabilities. Their empirical findings, however, show a negative relation between firm size and speculation.

Chapter 4

DATA

Chapter 4 describes the sample, explains the variables employed (Section 4.1) and presents the main descriptive findings of the sample and variables (Section 4.2). As the data set of this study is mostly hand-collected[47] and not retrieved from one of the main data sources (e.g. Datastream), the calculation and collection methods are explained in detail.

The manual data collection is chosen because most of the variables of interest, e.g. the percentage of fuel consumption hedged, cannot be found in the general databases. Lastly, the quality of data available in databases may not always draw near the quality of hand-collected data. Schmitting and Wöhrmann (2013) analyze asset, equity, debt, and net income data from four different databases[48] of non-financial firms between 2005 and 2008 under International Financial Reporting Standards (IFRS). They find that the figures differ significantly between the data bases and hand-collected data.

4.1 Sample and variables

The sample selection process and the first descriptive characteristics of the sample are described in Subsection 4.1.1. In Subsection 4.1.2, the variables collected for this study are specified. All terms in italics represent variables that are explained in detail in tables in this section as well as in the Table F.1 of Appendix F.

[47]Otherwise, the database is named where the variable is retrieved from.
[48]The data bases comprise Worldscope (Thomson Reuters), Compustat (S&P) and Osiris (Bureau van Dijk).

4.1.1 Sample

In order to obtain as broad a sample of international, publicly listed airlines as possible, all 248 airlines that are members of the IATA as of 10th May 2014 are examined. Sixteen airlines that are non-IATA members (mostly LCCs) are added from online research. Thereafter, the airlines' websites are manually checked for annual reports. The annual report must be available in English or German.[49] If the airline is listed in the U.S., 10-K or 20-F filings are searched in the Electronic Data Gathering, Analysis, and Retrieval system (EDGAR) database with Standard Industrial Classification (SIC) code 4512 (scheduled air transportation). Operating statistics (e.g. ASM or LF) are in some cases taken from a separate documentation available on the airlines' websites. State-owned carriers such as Etihad, Emirates or Air Baltic are excluded from the sample due to data limitations.[50] Pure cargo airlines and airlines that are part of a tour operator (e.g. Air Transat, TUIfly) are also omitted because their business model diverges from that of passenger airlines substantially. Regional airlines, on the other hand, are included in the sample. Their idiosyncrasies are discussed at the end of this subsection.

The final sample comprises 74 international airlines from 39 countries.[51] Table 4.2 lists all airlines in alphabetical order with an individually assigned identification number (column 'ID'). The column 'Airline group' refers to the name of the airline group (e.g. Alaska Air Group) of the main airline[52] (column 'Airline') in the group (e.g. Alaska Airlines). The names are both retrieved from the annual report or SEC filing. The country (column 'Country') and region (column 'Region') are specified as the locations where the headquarters of the airlines are located, based on International Organization for Standardization (ISO) and United Nations (UN) declaration. Most sample airlines are based in the U.S. (15 airlines), followed by China (five airlines) and United Kingdom (four airlines). The regions are divided into Africa (AF), the Americas (AM), Asia (AS), Europe (EU), and Oceania (OC). The sample contains two airlines from Africa, 23 from the Americas, 26 from Asia, 20 from Europe, and four from Oceania. The 'International Securities Identification Number (ISIN)' is shown in the column 'ISIN' for

[49] Bangkok Air, for example, published its annual reports in Thai language only on their website and is not included in the analysis.

[50] Although TAP Portugal is officially a publicly listed company, its stock is not traded freely and has to be excluded for the analysis because variables like market capitalization cannot be calculated.

[51] Rampini et al. (2014) limit their sample to those U.S. airlines which report the fuel percentage hedged at least five years in a row. The current sample is not limited in the same way because the sample would be reduced by 11 to 64 airlines.

[52] For ease of reading, the abbreviated airline name is used instead of the airline group name in the remainder of this text. The abbreviation is mostly the brand name of the airline, e.g. Tigerair instead of Tiger Airways Holdings.

a quick reference on how to find stock information. The column 'Sample years' refers to the years of analysis of each airline.[53] The period of analysis is from 2005 until 2014. As only 40 airlines existed over the entire period (some airlines were acquired by a competitor during the sample period and 22 of the sample airlines had their initial public offering (IPO) in or after 2005), the sample comprises 621 firm years. The minimum period length is two years and the average sample period is nine years.[54] The column 'Accounting standards' reflects the accounting standards according to which the airline reports its numbers. Most of the airlines either report according to IFRS (37 airlines or 288 firm years) or U.S. Generally Accepted Accounting Principles (GAAP) (15 airlines or 140 firm years). If the local accounting standards comply with either of IFRS or U.S. GAAP, the accounting standards of that airline are classified as IFRS or U.S. GAAP.[55] Alliance membership is presented in the column 'Alliance'.

Table 4.1: The number of sample airlines and firm years, divided into regions and business models

	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	*Firm years*	
AF	1	2	2	2	2	2	2	2	2	2	*19*	*3.1%*
AM	15	18	19	19	19	18	18	17	18	18	*179*	*28.8%*
AS	20	21	21	24	24	24	25	27	26	23	*235*	*37.8%*
EU	11	14	16	16	16	17	16	15	14	14	*149*	*24.0%*
OC	3	4	4	4	4	4	4	4	4	4	*39*	*6.3%*
Airlines	*50*	*59*	*62*	*65*	*65*	*65*	*65*	*65*	*64*	*61*	***621***	*100.0%*
LCC	12	9	11	12	13	14	13	15	14	14	*127*	*20.4%*
NLC	38	50	51	53	52	51	52	50	50	47	*494*	*79.6%*
Airlines	*50*	*59*	*62*	*65*	*65*	*65*	*65*	*65*	*64*	*61*	***621***	*100.0%*

[53] Japan Airlines was in administration between January 2010 and September 2012. Therefore, the sample years 2009 (financial year end 31st March 2010) and 2010 (financial year end 31st March 2011) are excluded.

[54] Rampini et al. (2014) limit their sample of U.S. airlines to carriers with total assets above 50 million USD because of the volatility of profits of small airlines. In the sample, only Comair has an asset value of less than 50 million USD which is not excluded here because their performance is not more volatile than the average airlines' performance.

[55] Regional Express, for example, reports that "Compliance with Australian Accounting Standards ensures that the financial statements and notes of the Group comply with International Financial Reporting Standards (IFRS)" (Regional Express, 2014, p. 34). Similarly, New Zealand GAAP comply with IFRS (Air New Zealand, 2014).

Table 4.2: Sample airlines

ID	Airline	Airline group	Country	Region	ISIN	Sample years	Accounting standards	Alliance
1	Aegean Airlines	Aegean Airlines	GR	EU	GRS495003006	2007-2014	IFRS	Star Alliance
2	Aer Lingus	Aer Lingus	IE	EU	IE00B1CMPN86	2006-2014	IFRS	
3	Aeroflot	Aeroflot Group	RU	EU	US0077711085	2005-2014	IFRS	SkyTeam
4	Air Arabia	Air Arabia	AE	AS	AE000A0MX9U4	2008-2014	IFRS	
5	Air Berlin	Air Berlin	DE	EU	GB00B128C026	2006-2014	IFRS	Oneworld
6	Air Canada	Air Canada	CA	AM	CA0089118024	2006-2014	Canadian GAAP	Star Alliance
7	Air China	Air China Limited	CN	AS	US00910M1009	2006-2014	IFRS	Star Alliance
8	Air France-KLM	Air France-KLM	FR	EU	FR0000031122	2005-2014	IFRS	SkyTeam
9	Air New Zealand	Air New Zealand Group	NZ	OC	NZAIRE0001S2	2005-2014	NZ GAAP (comply with IFRS)	Star Alliance
10	AirAsia	AirAsia	MY	AS	MYL5099OO006	2005-2014	Malaysian FRS	
11	AirTran Airways	AirTran Holdings	US	AM	US00949P1084	2005-2010	U.S. GAAP	
12	Alaska Airlines	Alaska Air Group	US	AM	US0116591092	2005-2014	U.S. GAAP	
13	All Nippon Airways (ANA)	ANA Holdings (2005-2013 All Nippon Airways)	JP	AS	JP3429800000	2005-2014	Japanese GAAP	Star Alliance
14	Allegiant Air	Allegiant Travel Company	US	AM	US01748X1028	2006-2014	U.S. GAAP	
15	American Airlines	American Airlines Group (2005-2012 AMR Corporation)	US	AM	US02376R1023	2005-2014	U.S. GAAP	Oneworld
16	Asiana Airlines	Asiana Airlines	KR	AS	US04520V2034	2005-2014	Korean GAAP	Star Alliance
17	Avianca	Avianca Holdings	CO	AM	US05367G1004	2013-2014	IFRS	Star Alliance
18	British Airways	British Airways	GB	EU	GB0001290575	2005-2010	IFRS	Oneworld
19	Cathay Pacific	Cathay Pacific Airways Limited	HK	AS	US1489063081	2005-2014	Hong Kong FRS	Oneworld
20	China Airlines	China Airlines	TW	AS	TW0002610003	2005-2014	Chinese GAAP	SkyTeam
21	China Eastern Airlines	China Eastern Air Holding Company	CN	AS	CNE1000002K5	2005-2014	IFRS	SkyTeam
22	China Southern Airlines	China Southern Air Holding Company	CN	AS	US1694091091	2005-2014	IFRS	SkyTeam
23	Comair	Comair Group	ZA	AF	ZAE000029823	2005-2014	IFRS	
24	Continental Airlines	Continental Airlines	US	AM	US2107953083	2005-2009	U.S. GAAP	SkyTeam
25	Copa Airlines	Copa Holdings	PA	AM	PAP310761054	2005-2014	IFRS, U.S. GAAP	Star Alliance
26	Cyprus Airways	Cyprus Airways	CY	EU	CY0002900716	2005-2011	IFRS	
27	Delta Air Lines	Delta Air Lines	US	AM	US2473617023	2005-2014	U.S. GAAP	SkyTeam
28	easyJet	easyJet	GB	EU	GB00B7KR2P84	2005-2014	IFRS	
29	El Al	El Al Israel Airlines	IL	AS	IL0010878242	2005-2014	IFRS, Israeli GAAP	

ID	Airline name	Airline group name	Country	Region	ISIN	Years of analysis	Accounting standards	Alliance
30	EVA Air	EVA Air	TW	AS	TW0002618006	2005-2014	Chinese GAAP	Star Alliance
31	Finnair	Finnair Group	FI	EU	FI0009003230	2005-2014	IFRS	Oneworld
32	Flybe	Flybe Group	GB	EU	GB00B4QMVR10	2010-2014	IFRS	
33	Garuda Indonesia	Garuda Indonesia	ID	AS	ID1000118300	2012-2014	Indonesian Financial Accounting Standards	SkyTeam
34	Gol	Gol Intelligent Airlines	BR	AM	BRGOLLACNPR	2005-2014	IFRS, U.S. GAAP	
35	Great Lakes	Great Lakes Aviation	US	AM	US39054K1088	2005-2014	U.S. GAAP	
36	Hainan Airlines	Hainan Airlines Company	CN	AS	CNE000000RT0	2005-2012	Chinese Accounting Standards for Business Enterprises	
37	Hawaiian Airlines	Hawaiian Holdings	US	AM	US4198791018	2005-2014	U.S. GAAP	
38	Iberia	Iberia Group	GB	EU	ES0147200036	2005-2010	IFRS	Oneworld
39	Icelandair	Icelandair Group	IS	EU	IS0000013464	2006-2014	IFRS	
40	International Airlines Group (IAG)	International Airlines Group (IAG)	ES	EU	ES0177542018	2011-2014	IFRS	
41	Japan Airlines (JAL)	JAL Group	JP	AS	JP3705200008	2005-2008, 2011-2014	Japanese GAAP	Oneworld
42	Jazeera Airways	Jazeera Airways Group	KW	AS	KW0EQ0602452	2008-2014	IFRS	
43	Jet Airways	Jet Airways (India)	IN	AS	INE802G01018	2005-2014	Indian GAAP	
44	JetBlue	JetBlue Airways Corporation	US	AM	INE802G01018	2005-2014	U.S. GAAP	
45	Kenya Airways	Kenya Airways	KE	AF	KE0000000307	2006-2014	IFRS	SkyTeam
46	Korean Air	Korean Air Lines	KR	AS	KR7003490000	2005-2014	Korean IFRS, Korean GAAP	SkyTeam
47	LAN	LAN Airlines	CL	AM	CL0000000423	2005-2011	IFRS, Chilean GAAP	Oneworld
48	LATAM	LATAM Airlines Group	CL	AM	US5017231003	2012-2014	IFRS	Oneworld
49	Lufthansa	Lufthansa Group	DE	EU	DE0008232125	2005-2014	IFRS	Star Alliance
50	Malaysia Airlines	Malaysia Airlines	MY	AS	MYL3786OO000	2005-2013	Malaysian FRS, IFRS	Oneworld
51	Norwegian Air Shuttle	Norwegian Group (2005-2006 Norwegian Air Shuttle)	NO	EU	NO0010196140	2005-2014	IFRS, Norwegian GAAP	
52	Pakistan International Airlines (PIA)	Pakistan International Airlines (PIA)	PK	AS	PIAa.KA	2005-2014	IFRS	
53	Qantas Airways	Qantas Group	AU	OC	AU000000QAN2	2005-2014	Australian Accounting Standards (comply with IFRS)	Oneworld
54	Regional Express	Regional Express Holdings	AU	OC	AU000000REX1	2006-2014	Australian Accounting Standards	
55	Republic Airline	Republic Airways Holdings	US	AM	US7602761055	2005-2014	U.S. GAAP	
56	Ryanair	Ryanair Holdings	IE	EU	IE00B1GKF381	2005-2014	IFRS	

ID	Airline name	Airline group name	Country	Region	ISIN	Years of analysis	Accounting standards	Alliance
57	SAS	SAS Group	SE	EU	SE0003366871	2005-2014	IFRS	Star Alliance
58	Shandong Airlines	Shandong Aviation Group	CN	AS	SHE:200152	2005-2006, 2008-2014	Chinese Accounting Standards for Business Enterprises	
59	Singapore Airlines	SIA Group	SG	AS	SG1V61937297	2005-2014	Singapore FRS	Star Alliance
60	SkyWest	SkyWest	US	AM	US8308791024	2005-2014	U.S. GAAP	
61	Southwest	Southwest Airlines	US	AM	US8447411088	2005-2014	U.S. GAAP	
62	SpiceJet	SpiceJet	IN	AS	INE285B01017	2005-2014	Indian GAAP	
63	Spirit	Spirit Airlines	US	AM	US8485771021	2011-2014	U.S. GAAP	
64	TAM	TAM	BR	AM	BRTAMMACNPR2	2006-2011	IFRS, Brazilian GAAP	Oneworld
65	Thai Airways	Thai Airways International	TH	AS	TH0245010R19	2005-2014	Thai FRS	Star Alliance
66	Tigerair	Tiger Airways Holdings	SG	AS	SG1Z26952619	2009-2014	Singapore FRS	
67	TransAsia	TransAsia Airways Corporation	TW	AS	TW0006702004	2012-2014	Chinese GAAP	
68	Turkish Airlines	Turkish Airlines Group	TR	AS	TRATHYAO91M5	2005-2014	Turkish GAAP	Star Alliance
69	United Airlines (2007-2009 United Air Lines, 2010-2012 United Air Lines and Continental Airlines, 2013-2014 United Airlines)	United Continental Holdings (2005-2009 UAL Corporation)	US	AM	US9025498075	2007-2014	U.S. GAAP	Star Alliance
70	US Airways	US Airways Group	US	AM	US90341W1080	2005-2012	U.S. GAAP	
71	UTair	UTair Aviation	RU	EU	RU0007661385	2007-2013	IFRS	
72	Virgin Australia (2005-2011 Virgin Blue)	Virgin Australia Holdings (2005-2011 Virgin Blue Holdings)	AU	OC	AU000000VAH4	2005-2014	Australian Accounting Standards	
73	Volaris	Volaris Aviation Holding Company	MX	AM	US21240E1055	2013-2014	IFRS	
74	Vueling	Vueling Airlines	ES	EU	ES0184591032	2007-2012	IFRS	

Moreover, the sample is divided into LCCs and NLCs. Based on the definition of the two business models given in Section 2.1, the LCC dummy variable (*lccDm*) is either assigned zero or one.

In the following paragraphs, some characteristics of the sample are identified. See Table 4.4 for an overview of the sample relevant variables.

Due to the heterogeneity of the countries of incorporation studied, various reporting periods (*accDate*) and currencies (*crcy*) exist in the sample. The end dates of the reporting periods are either March, June, September or December. To compare the airlines regardless of their reporting period, reporting dates ending in March are categorized to the previous year of analysis, e.g. the *accDate* 31st March 2014 is put under *year* 2013. Reporting periods ending later than March (June, September, December) are assigned to the current year of reporting, e.g. the *accDate* 30th June 2014 is allocated to *year* 2014.[56]

The financial report data is first collected in the local currency (or the currency in which the airline reports) and then converted into USD with the relevant exchange rate extracted from OANDA. Income statement data is converted with the average of the end-of-month exchange rates (*xrAvg*) and balance sheet data with the end of financial year exchange rate (*xrEnd*).[57] For all converted variables refer to Appendix G.

Special attention must be given to how to treat acquisitions in the sample. During the sample period, 25 of 74 airlines experienced an acquisition. Total assets of the post-merger airline grew by each acquisition on average by 58.6%. Table 4.3 presents the acquisitions in the sample period, including the acquiring and acquired airline, the year of the acquisition, as well as the growth in total assets due to the acquisition. Previous research on the airline industry deals with mergers and acquisitions in different ways. While Lim and Hong (2014) treat the post-merger airline as a new airline "to avoid analysis problems and non-convergence issues resulting from structural, operational and financial changes within newly merged firms" (p. 36), Carter et al. (2006) (sample between 1992 and 2003), Isin et al. (2014) (sample between 2000 and 2012), Lin and Chang (2009) (sample between 1995 and 2005), Rampini et al. (2014) (sample between 1996 and 2009), and Treanor et al. (2014b) (sample between 1994 and 2008) do not treat post-merger airlines any differently. In this study, a merger dummy is used (*mrgDm*) in the robustness tests which takes on the value one in the year of the asset growth after the airline acquired another airline and integrated that airline into their consolidated results. This dummy allows for controlling for nonorganic asset growth due to the acquisition.

[56] If an airline changes its reporting period during the sample period, the annual report data is taken from which the entire year data is available.

[57] The exchange rates are matched to the respective reporting period, i.e. the average monthly exchange rate for a reporting period that ends on 31st March 2014 is averaged with the monthly exchange rates between 30th April 2013 and 31st March 2014.

Table 4.3: Airline acquisitions in the sample period (All acquiring airlines are in the sample; asterisks (*) identify acquired airlines that are part of the sample.)

Acquiring airline	Acquired airline	Year of acquisition	Growth in total assets due to merger
Aegean Airlines	Olympic Air	2013	47.8% (between 2012 and 2013)
Aeroflot	JSC Vladivostok Air, OJSC Saratov Airlines, JSC SAT, OJSC Rossiya airlines, JSC ORENAIR	2011	17.9% (between 2010 and 2011) and 17.1% (between 2011 and 2012)
Air Berlin	LTU	2007	73.8% (between 2006 and 2007)
American Airlines	US Airways*	2013	79.8% (between 2013 and 2014)
British Airways	L'Avion	2009	7.9% (between 2008 and 2009)
Cathay Pacific	Dragonair	2006	30.9% (between 2005 and 2006)
China Eastern Airlines	Shanghai Airlines	2010	47.4% (between 2009 and 2010)
Delta Air Lines	Northwest Airlines	2008	39.1% (between 2007 and 2008)
easyJet	GB Airways	2008	9.9% (between 2007 and 2008)
Flybe	Finncomm	2012	48.8% (between 2012 and 2013)
International Airlines Group (IAG)	Vueling*	2013	14.4% (between 2012 and 2013)
Gol	Varig	2007	111.8% (between 2006 and 2007)
Jet Airways	Sahara Airlines Limited	2007	115.3% (between 2007 and 2008)
LAN	Aires	2010	17.6% (between 2009 and 2010)
Lufthansa	British Midland	2009	27.3% (between 2008 and 2009)
Lufthansa	Swiss International Air Lines	2007	26.5% (between 2006 and 2007)
Norwegian Air Shuttle	Nordic Airlink	2007	146.6% (between 2006 and 2007)
Regional Express	Pel Air Aviation	2007	81.4% (between 2006 and 2007)
Republic Airline	Midwest Air Group, Frontier Airlines	2009	37.5% (between 2008 and 2009)
SkyWest	ExpressJet	2010	3.4% (between 2009 and 2010)
Southwest	AirTran Airways*	2011	16.8% (between 2010 and 2011)
TAM	Pantanal Linhas Aéreas	2009	15.7% (between 2009 and 2010)
Tigerair	PT Mandala Airlines	2012	7.9% (between 2010 and 2011)
United Airlines	Continental Airlines*	2010	111.9% (between 2009 and 2010)
Virgin Australia	SkyWest*	2013	4.5% (between 2012 and 2013)
Vueling	Clickair	2009	210.8% (between 2008 and 2009)

Lastly in this subsection, the characteristics of regional U.S. airlines are explained that operate under so-called capacity purchase agreements (CPAs), fixed-fee arrangements or fuel pass-through agreements (FPAs). Two regional airlines (Republic Airline and SkyWest) are part of the sample. Under a CPA "the major airline generally pays the regional airline a fixed-fee for each departure, with additional incentives based on completion of flights, on-time performance and baggage handling performance" (SkyWest, 2015, p. 7). Moreover, additional contracts most often include the reimbursement of fuel costs of regional airlines with the consequence that the major airline bears all fuel price risk. Although regional airlines mostly benefit from FPAs due to reduced risk from volatile ticket and fuel prices as well as load factors, they cannot absorb any positive trends in these factors (SkyWest, 2015). The inclusion of regional airlines in the sample impedes direct comparison between airlines because fuel expenses are almost zero for SkyWest and Republic Airline.[58] For the analysis of fuel expenses, these two carriers are therefore excluded. For the multivariate analysis, this study follows Rampini et al. (2014) and treats CPA regional airlines as 100% hedged with a hedge maturity of 24 months.[59]

Although regional carriers do not decide individually whether to hold derivative portfolios, the outcome of an FPA is similar to a 100% hedge position as fuel price risk is eliminated. Rampini et al. (2014) underline their reasoning with the fact that all seven regional airlines in their sample do not use fuel derivatives in those years where they do not operate under CPA with a major carrier.[60] Carter et al. (2006), however, do not treat airlines that operate under CPA contracts as 100% hedged. They argue that the implications of hedging and charter agreements differ if fuel prices rise. Assuming that air travel is price-elastic, travel demand would decline with rising oil and ticket prices under charter agreements, while fuel hedging would keep fuel expenses and hence ticket prices stable.

In the author's view, in the short and medium term a CPA agreement can be seen as a contract with two parts: a complex fuel hedge position for the regional carrier plus other components. The contract should be priced accordingly in competitive markets. The revenue stream for the regional carrier is stable in the short term as fuel prices are pre-arranged and are paid by the major carrier regardless of the fuel price. If the regional airline had hedged 100% of their expected fuel consumption, they would incur higher fuel prices but at the same time profit from the gains in fuel hedges. In robustness checks, a dummy variable (*cpaDm*) is included that takes on the value one for all observations of

[58]"As of December 31, 2014, all of our aircraft fuel for operations is supplied directly by our code-share partners, and thus, we do not record expense or the related revenue for those gallons of fuel" (Republic Airline, 2015, p. 33).

[59]Expiration dates of CPAs vary. Republic Airline (2015) reported agreements' durations between five and 48 months.

[60]In the sample, SkyWest did not hold any derivatives in the 10 years of analysis. Republic Airline had some fuel price derivatives outstanding in three of the 10 years with a maximum hedge ratio of 12%.

Table 4.4: Variables relating to the sample

Variable	Label	Description
accDate	Accounting date	End of financial reporting period from the annual report
accStd	Accounting standards	Accounting standards which the annual report is prepared in accordance to
airline	Name of the airline	Abbreviated name of the main airline in the airline group
cpaDm	CPA dummy	Dummy one if the airline is a regional carrier and operates under a capacity purchase agreement (CPA) for a major airline
crcy	Currency	The currency in which the airline reports their financial statement, based on ISO 4217 declaration
ctry	Country of home base	The country in which the airline has its main base (i.e. where most of its flights depart from), based on ISO 3166-1 declaration
ID	ID number of the airline in the sample	Identification number of the airline in the sample in alphabetical order
lccDm	Low-cost carrier dummy	Dummy one if the airline can be defined as a low-cost carrier according to the IATA (2006) definition
mrgDm	Merger dummy	Dummy one in the year of the asset growth after the airline acquired another airline
reg	Geographical region	The geographical region in which the airline has its main base, based on the UN "Composition of macro geographical (continental) regions, geographical sub-regions, and selected economic and other groupings" (United Nations, 2018) - The regions are Africa (AF), America (AM), Asia (AS), Europe (EU), and Oceania (OC)
xrAvg	Average exchange rate	Average of end-of-month bid exchange rate in USD to local currency over the reporting period from OANDA
xrEnd	End of financial year exchange rate	Exchange rate USD to local currency at the end of the reporting period from OANDA
year	Year of analysis	The end of year of March is categorized to the previous year (ending 31st March 2014 is 2013) and June, September, October to the current year (ending 30th June 2014 and 30th September 2014 is 2014)

Republic Airline and SkyWest (Carter et al., 2006; Lin and Chang, 2009; Treanor et al., 2014b). In an alternative robustness check, all 20 firm year observations of those two airlines are excluded (Isin et al., 2014; Rampini et al., 2014).

4.1.2 Variables

Each variable is categorized to one specific topic so that the reader can gain an overview of the relatively large number of variables used in this study. The topics, reflecting the outline of the literature review, are 'financial hedging and airline industry picture', 'financial distress', 'the underinvestment problem', 'economies of scale', 'fleet diversity', 'strategic alliances', 'aircraft leasing', and 'selective hedging'.[61] The topics follow in this subsection with the caption 'Variables relating to...'. As some variables could be allocated to several topics, the classification into one topic should not be seen as exclusive. Only variables that need explicit explanation are presented in the text and in the table, otherwise only in the table. See Table 4.5 for an example of how the variables are presented in the text and tables.

If available, the consolidated values of an airline are taken instead of the company data. In order to have the most current and restated figures at hand, previous-year results are taken. For example, *year* 2011 data is collected from the annual report 2012. In some cases, if the previous-years data is restated, $t-2$ or $t-3$ annual report data is taken (e.g. Cathay Pacific *years* 2007 and 2008 are retrieved from the annual report 2009, or the TAM annual report 2010 is used for the *years* 2007 until 2009 due to accounting changes in recognition of flight equipment reevaluation).

Variables relating to the financial hedging and airline industry picture

The variables relating to the 'financial hedging and airline industry picture' deal mainly with an airline's fuel expenses and fuel consumption. Industry-specific variables are also presented in this section. Moreover, the variables include data on fuel hedging instruments and their underlying assets, hedge ratios and hedge maturities. In this context, airlines' accounting of cash flow hedging according to IFRS and U.S. GAAP is explained.

The fuel expenses (*fuelExp*) of the airlines are reported net of hedging gains and losses in the annual reports. The total fuel consumption (*fuelCons*) is either reported by the airline in the annual report directly in U.S. gallons (USGs) or if it is reported in tons, liters or barrels, the amount is converted to USGs with the conversion table from www.eia.gov. In addition if the airline did not disclose its fuel consumption, the value is calculated with one of the following formulas:

[61] Variables on managerial motives or tax incentives are not collected because those determinants are excluded from this study.

Table 4.5: Example of the presentation of the variables relating to the topic 'financial distress'

Example text: "The second proxy for leverage is leverage ratio 2 (*lvrg2*), measured as the book value of long-term liabilities (*liaLt*) scaled by total assets (*asTl*).

Example table:

Variable	Label	Description
asTl	Total assets	Total assets as reported in the balance sheet
liaTl	Total liabilities	Total liabilities as reported in the balance sheet, calculated if they are not reported (current + non-current liabilities) - Include "liabilities subject to compromise" (Chapter 11 term)
lvrg2	Leverage ratio 2	Calculated as *liaLt*/*asTl*

i) fuel consumption in liters per 100 RPM multiplied with total RPMs (*rpmTl*)
ii) fuel consumption in liters per 100 ASM multiplied with total ASMs (*asmTl*)
iii) lagged nominal number of fuel contracts outstanding (*fdvNm*) divided by the lagged fuel percentage hedged of the expected fuel consumption in the following 12 months (*fdvPct12m*)[62]
iv) fuel consumption from the previous year ($fuelCons_{t\text{-}1}$) extrapolated with ASM percentage changes
v) fuel consumption from the previous year ($fuelCons_{t\text{-}1}$) extrapolated with information from the text, i.e. "consumption increased by X%"
vi) fuel expenses (*fuelExp*) divided by the average fuel price per USG
vii) fuel consumption per ASM (*fuelExpAsm*) multiplied with the total ASMs (*asmTl*).[63]

The total available seat miles (*asmTl*) are the number of ASMs per year flown by an airline. If the airline reported the available seat kilometers (ASKs) instead of ASMs, the value is converted with the factor 1.852. If the airline did not report its ASMs directly, it may be calculated as either

i) RPMs (*rpmTl*) divided by the load factor (*lf*)
ii) total revenues (*revTl*) divided by the revenue per available seat mile (RASM) (*rasm*)

[62] This calculation works solely if the hedge portfolio maturity (*fdvMtr*) does not exceed 12 months.

[63] For Tigerair, a special approach is applied for calculating the fuel consumption. Tigerair's ASMs are multiplied with the fuel consumption per ASM (*fuelConsAsm*) of AirAsia. The fuel consumption can be used equivalently because both airlines operate a homogeneous fleet of Airbus 320 with the same seat capacity and similar aircraft age.

iii) the number of flights multiplied with the average stage length[64] (*lgtAvg*)
iv) fuel expenses (*fuelExp*) divided by fuel costs per ASM
v) fuel consumption (*fuelCons*) divided by the consumption per ASM (*fuelConsAsm*).

For comparability the fuel consumption per ASM (*fuelConsAsm*) is calculated, which is a measure for fuel efficiency. An airline can reduce the fuel consumption per ASM by either operating the same route with a larger aircraft or by using more fuel efficient equipment. For a better understanding of the variable, consider the following example: the length of flight A to B is 500 miles which can be operated by either an Airbus 319 (with a maximum seat capacity of 156 seats (Airbus Group, 2017a)) or an Airbus 321 (maximum seat capacity 236 seats). The flown ASMs by the Airbus 319 are $500 \times 156 = 78{,}000$ and $500 \times 236 = 118{,}000$ for the Airbus 321. Both aircraft fly the route in one hour with a fuel consumption of 2,400 kg for the Airbus 319 and 3,000 kg for the Airbus 321. Consequently, the fuel consumption per ASM of the Airbus 319 is $2{,}400/78{,}000 = 0.031\,\mathrm{kg/ASM}$ and $3{,}000/118{,}000 = 0.025\,\mathrm{kg/ASM}$ of the Airbus 321, making the Airbus 321 more fuel efficient on the same route. A similar variable to *fuelConsAsm* is the variable fuel expenses per ASM (*fuelExpAsm*). The fraction is influenced by the fuel price which the airline paid per USG and also by its fuel hedging gains or losses. For simplicity, it is assumed that 1 kg kerosene costs 1 USD resulting in fuel expenses per ASM of 0.031 USD for the Airbus 319 and 0.025 USD per ASM for the Airbus 321. *fuelConsAsm* and *fuelExpAsm* are the same numbers in this example because a kerosene price of 1 USD per kg is assumed. The higher the fuel price per USG, the more beneficial the usage of larger aircraft.

Self-evidently, the fuel benefit can only be exploited if all seats are sold, i.e. the load factor is 100%. A variable that covers the combined effect of the load factor and ASMs is revenue passenger miles (RPMs), the number of miles on which a passenger is transported. It can be calculated by multiplying the load factor with ASMs (*asmTl*). The passenger load factor (*lf*) is either disclosed by the airline in the annual report or calculated as RPMs (*rpmTl*) divided by ASMs. The load factor is a standardized measure in the airline industry and simple to calculate. The disadvantage of *lf* is the sole focus on operational, passenger related aspects (Schefczyk, 1993), leaving out revenues from other business areas such as cargo or maintenance revenues (see Subsection 2.3.1). Lazzarini (2007) has to use the load factor to proxy for operational performance because some

[64] The average stage length is reported by only a few airlines. In total, stage length data is available for 38% of firms years. Thus, this variable is used for descriptive results or for ASM calculations only, not in regression analysis.

of the airlines in his sample did not report financial figures. In the current sample, an airline's productivity is measured with the load factor (Schefczyk, 1993). While Lazzarini (2007) uses the load factor to measure overall performance, this variable solely measures productivity in this study because many other factors besides load factor influence an airline's performance (Schefczyk, 1993) such as ticket prices, non-flight related revenues and customer satisfaction. Besides the load factor, other variables of interest are revenue per available seat mile (*rasm*), total revenue (*revTl*) divided by ASMs (*asmTl*), and revenue per revenue passenger mile (*rrpm*). *rrpm* is sometimes referred to as the "yield" in the airline industry and describes the average ticket revenue per RPM (Lufthansa, 2015). The following equations show the connection between the variables on operating statistics:

$$lf = \frac{rpmTl}{asmTl} \qquad rasm = \frac{revTl}{asmTl} \qquad rrpm = \frac{revTl}{rpmTl}$$

Next, the variables relating to the airlines' hedge portfolios are described. The notes of the annual reports are checked whether the airline uses any fuel hedge derivatives. If the airline had fuel hedge contracts outstanding at reporting year end, the value one is assigned to the dummy variable *fdvDm*. If the airline used fuel derivatives during the reporting year but did not have any derivatives outstanding at reporting year end, zero is assigned to *fdvDm*. Garuda Indonesia, for example, hedged 100% of its Hajj operation and 3% of its other operation but did not hedge forward for the subsequent year, hence *fdvDm* is zero. If, however, the airline reported active fuel derivative usage during the year and 12 months forward but did not disclose the notional value or fair value of fuel contracts outstanding, the value one is allocated. Besides the dummy variable for fuel derivative usage in general, a dummy variable for each underlying asset (crude oil (*fdvCo*), diesel oil (= gasoil) (*fdvDi*), heating oil (*fdvHo*), jet fuel (*fdvJf*) and unleaded gasoline (*fdvUg*)) and fuel hedge instrument (collar (*fdvCol*), forward (*fdvFwd*), future (*fdvFut*), option (*fdvOpt*), spread (= refining margin swap) (*fdvSpr*) and swap (*fdvSwp*)) is created. If the airline stated that predominantly swaps were used and no other instrument was mentioned, it is assumed that the company used swaps exclusively.

Next, the variables that refer to the accounting treatment of the airlines' hedge portfolio are presented. As already mentioned in Subsection 4.1.1, 37 airlines disclosed their data in accordance to IFRS and 15 airlines according to U.S. GAAP. Therefore, the hedge accounting rules for these two standards are described. International Accounting Standard (IAS) 39 - "Financial Instruments: Recognition and Measurement" regulates the accounting of financial instruments under IFRS (IASB, 2014), whereas Accounting

Standards Codification (ASC) 815 - "Derivatives and Hedging" (FASB, 2014) contains rules for U.S. GAAP accounting treatment. Under both standards, which "are very similar in principle" (EY, 2015, p. 193), firms can either apply cash flow hedge accounting or fair value hedge accounting. The difference between the two hedge accounting treatments is that one refers to hedging cash flow risk and the other to hedging fair value risk. Disatnik et al. (2014) present the example of the difference between fixed-rate debt (fair value interest rate risk) and floating-rate debt (cash flow interest rate risk). With a fixed-rate debt contract the company fixes its cash outflows but at the same time the fair value of its debt changes in relation to market interest rate changes. With floating-rate debt contracts, the company's future interest rate expenses are variable, exposing the firm to cash flow risk. Most airlines use fuel price cash flow hedging and have to account according to cash flow hedge accounting.

The difference in fair value and cash flow hedge accounting is that for fair value hedges, any changes in the fair value of the derivative instrument have to be recorded in the income statement immediately. Under cash flow hedge accounting only the ineffective portion of changes in the fair value of the hedging instrument[65] is recorded directly in the income statement.[66] Hedge effectiveness can be measured in several ways, for example with the "statistical correlation between the cash flows of the hedged item and those of the hedging instrument" (IASB, 2014). For a hedge to be effective the correlation must be between 80% and 125%. Gains or losses of the effective portion of the financial instrument are temporarily accounted for under OCI and reclassified to equity when the underlying transaction is realized. In Appendix E an example shows how the effective and ineffective portion of a hedging instrument are recognized under cash flow hedge accounting. Analogously, the airlines' reported gains and losses on fuel derivatives are classified under the following variables: ineffective portion of fuel derivatives recognized in income statement (*fdvPLineff*), effective portion of fuel derivatives included in OCI (*fdvPLeff*) and gains and losses on fuel derivatives that are reclassified from OCI to the income statement (*fdvPLrcl*). If the airline uses fair value hedge accounting, all changes in the fair value of the financial instrument are allocated under *fdvPLineff* because the effect is similar to the treatment of the ineffective portion under cash flow hedge accounting. For the multivariate analysis in Chapter 5, the variable *fdvPLsum* is created, which is the sum of the variables *fdvPLineff* and *fdvPLrcl*. Table 4.6 provides an overview of the recognition of gains and losses of the effective and ineffective portion

[65] A hedging instrument may consist of two or more derivatives.

[66] Aer Lingus, for example, records the ineffective portion of changes in the fair value of fuel derivatives under the income statement item "fuel and oil costs" (Aer Lingus, 2010, p. 59).

of hedging instruments. The problem in the sample with fuel hedging gains and losses is that airlines most often aggregated the gains and losses for all outstanding derivatives that are classified as cash flow hedges. Consequently, fuel hedging gains and losses cannot be separated from e.g FX derivatives gains and losses.[67]

Table 4.6: Hedge accounting of the effective and ineffective portion of derivative instruments
Source: Delta Air Lines (2015, p. 58); Southwest Airlines (2012, p. 52)

	Impact of unrealized gains and losses	
Hedge accounting	**Effective Portion**	**Ineffective portion**
Cash flow hedging	Gains / losses of the hedging instrument "parked" under OCI	Gains / losses of hedging instrument recognized in other expenses
Variable	*fdvPLeff*	*fdvPLineff*
	Gains / losses of the hedging instrument reclassified from OCI into income (mostly under fuel expenses) when the fuel derivative contract settles	
Variable	*fdvPLrcl*	
Fair value hedging	Gains / losses of the hedging instrument recorded in the income statement (e.g. Spirit Airlines its recorded gains and losses of the fuel derivative contracts in fuel expenses)	
Variable	*fdvPLineff*	

Lastly, the main dependent variable of the multivariate regression in Chapter 5, the airline's hedge ratio, is discussed. Similar to Carter et al. (2006), Lin and Chang (2009), and Rampini et al. (2014), the percentage of the next 12 months expected fuel consumption hedged at the year end is used (*fdvPct12m*).[68] This figure is either disclosed in the notes of the annual reports or calculated as the nominal number of fuel contracts outstanding at the year end (*fdvNm*) divided by the maturity of the fuel hedge portfolio (*fdvMtr*) multiplied by 12 and scaled by the next year's fuel consumption ($fuelCons_{t+1}$).[69] Flybe, for example, had 5,091,951 USG fuel hedge contracts outstanding at the reporting year end of 2010 with a maximum maturity of 24 months. The actual fuel consumption

[67]Because of the complexity of cash flow hedge accounting in contrast to fair value hedge accounting, Air Canada chose to switch from cash flow to fair value hedging in 2009 (Air Canada, 2010).

[68]Haushalter (2000) employs the fraction of the oil and gas production hedged from his survey on 177 oil and gas producing firms.

[69]Rampini et al. (2014) scale the nominal amount of fuel contracts, quoted in USD instead of USG, by the lag of the fuel expenses instead of the fuel consumption. This approach is used if the airline reported

for the year 2011 was 7,605,296 USG. The estimated hedge ratio is thus calculated as

$$fdvPct12m = \frac{fdvNm \times \frac{12}{fdvMtr}}{fuelCons_{t+1}} = \frac{5{,}091{,}951 \times \frac{12}{24}}{7{,}605{,}296} = 0.33.$$

With that formula, it is assumed for simplicity that fuel contracts are equally distributed over the entire contract maturity. In most cases, the calculated hedge ratio will underestimate the true hedge ratio as hedge ratios usually decrease over longer horizons. For Flybe, the reported fraction of the fuel consumption hedged in 2010 was 0.43 compared to the estimation of 0.33. Nevertheless, this approach is used to generate more observations for this variable. Moreover, if the airline stated that it hedged 9% for the next six months, it is assumed that it hedged pro rata and that the hedge percentage for the next 12 months was 4.5%. Equivalently, 35% for the next 15 months is equal to a next year's hedge ratio of 28%. If the hedge percentage was not reported and the fraction cannot be estimated by one of the previous approaches, the disclosed strategic hedge ratios are taken.[70] In terms of accuracy it would be better to use the deltas of the hedge portfolios (similar to e.g. Tufano (1996)) instead of hedge ratios (or nominal values) because deltas reflect whether options are in-the-money or out-of-the-money. Options that would not be executed because they are far out-of-the-money lead to large nominal hedge volumes but do not impact the portfolio deltas (Brown, 2001). However, the reported hedge data by airlines is too scarce to calculate portfolio deltas in the sample.

In addition to the hedge ratio an airline's hedge portfolio maturity (*fdvMtr*), i.e. the contract outstanding with the longest maturity, is analyzed. Hentschel and Kothari (2001) stress the importance of not analyzing merely notional values but also to look at the maturity of the hedge portfolio.

Bertus et al. (2009), for example, develop a model for calculating minimum variance hedge ratios that are superior to the classical OLS regression coefficient hedge ratios. In their model, commodity prices, the basis (see Section 2.1 for an explanation of basis risk) and convenience yields follow a random mean-reverting process. By simulation, they show that hedging jet fuel with crude oil future contracts with their calculated

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the nominal amount in USD (and not in USG) as well. This approach, however, omits the fact that reported fuel expenses are disclosed net of fuel hedge gains and losses. The monthly correction is still factored in to arrive at the 12 months forward hedge ratio.

[70] Air New Zealand published separate fuel hedging fact sheets on its website with detailed fuel hedge positions of different months. Those sheets contain the fuel hedge position as of May and August but not as of June, the end of the reporting period. For *fdvPct12m* the average of the May and August values is used.

minimum variance hedge ratios outperforms OLS regression coefficient hedge ratios and an unhedged strategy. Especially when the hedge horizon increases from four to 12 weeks, their cross-hedge effectiveness increases from the regression coefficient hedge ratio of 73.6% to 76.2%. They conclude that especially in the airline industry, where cross hedging is inevitable, different hedge ratio calculations could increase hedge effectiveness with increasing hedge horizons. The four-weeks hedge effectiveness is 48.9%, eight-weeks 48.9% and 12-weeks 76.2%. Moreover, Conlon et al. (2016) show that the correlation between crude oil spot and future prices increases with increasing maturity, based on data between 1986 and 2010. Those results confirm the empirical findings by Carter et al. (2006) that airlines increased their hedge horizons between 1992 and 2003 and underline the importance of also analyzing hedge maturities besides hedge ratios.

Variables relating to financial distress

Many empirical studies analyze the relation between risk management and the bankruptcy risk of a firm (see Subsection 2.2.1). As financial distress cannot be measured directly, researchers employ various measures as proxies for the risk of financial distress. Leverage proxies, dividend payments, credit ratings, interest coverage ratios, profit margins and other profitability measures can be used to estimate a company's bankruptcy probability. The leverage proxies used in previous studies are summarized in Table 4.8. Subsequently, the financial distress estimators used in this study are presented.

Based on the proxies that other researchers used, three different measures are constructed for estimating the sample airlines' leverage. The measures are presented in Table 4.9. The leverage ratio 1 (*lvrg1*) is calculated as interest bearing debt (IBD) (*ibd*) scaled by total assets (*asTl*). *ibd* includes all liabilities that incur interest, such as loans, financial leases, bonds, debentures, and notes payable. Other short and long-term liabilities are only included if the relevant items include interest. "Air traffic settlement liabilities", which are tickets that have already been sold but not yet flown, and trade payables are excluded because according to the airlines' notes those liabilities do not require interest payment. Most information can be retrieved from the notes section of the annual reports. Turkish Airlines reported in its notes, for example, that "other financial borrowings" from the balance sheet refer to "overnight interest-free borrowings obtained for settlement of monthly tax and social security premium payments" (Turkish Airlines, 2015, p. 128).[71] The second proxy for leverage is leverage ratio 2 (*lvrg2*), measured as the book value of long-term liabilities (*liaLt*) scaled by total assets (*asTl*),

[71] For Air Arabia "Murabaha payable" is included in *ibd* which is a form of credit in the Islamic world.

Table 4.7: Variables relating to the financial hedging and airline industry picture

Variable	Label	Description
asmTl	Available seat miles	The total number of ASMs per year, either disclosed or calculated as i) RPMs (*rpmTl*) divided by the load factor (*lf*) ii) total revenues (*revTl*) divided by RASM (*rasm*) iii) the number of flights multiplied with the average stage length iv) fuel expenses (*fuelExp*) divided by fuel costs per ASM v) fuel consumption (*fuelCons*) divided by the consumption per ASM (*fuelConsAsm*) vi) ASKs divided by 1.852
fdvCo	Underlying crude oil dummy	Dummy one if the airline used crude oil as the underlying asset for their fuel derivative contracts
fdvCol	Fuel collar dummy	Dummy one if the airline used fuel collars (a combination of short put option and long call option) as the derivative instrument
fdvDi	Underlying diesel oil dummy	Dummy one if the airline used diesel oil (=gasoil) as the underlying asset for their fuel derivative contracts
fdvDm	Fuel derivative dummy	Dummy one if the airline had outstanding fuel derivatives at the year end - If the airline used fuel derivatives during the year but did not have any derivatives outstanding at the reporting year end, zero is assigned - If, however, the airline reported active fuel derivative usage but did not disclose the notional value or fair value, the value one is assigned - Including: hedge derivatives, derivatives held for trading
fdvFut	Future fuel contract dummy	Dummy one if the airline used future fuel contracts as the derivative instrument
fdvFwd	Forward fuel contract dummy	Dummy one if the airline used forward fuel contracts as the derivative instrument
fdvHo	Underlying heating oil dummy	Dummy one if the airline used heating oil as the underlying asset for their fuel derivative contracts
fdvJf	Underlying jet fuel dummy	Dummy one if the airline used jet fuel as the underlying asset for their fuel derivative contracts
fdvMtr	Fuel derivatives maturity	Maximum maturity in months of the outstanding fuel derivative contracts
fdvNm	Nominal amount of fuel contracts	Total nominal amount of fuel contracts outstanding at the year end in USG
fdvOpt	Fuel option dummy	Dummy one if the airline used fuel options as the derivative instrument

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Variable	Label	Description
fdvPct12m	Hedge ratio for the next 12 months	Percentage of the next 12 months expected fuel consumption hedged, either reported in the text section or calculated as $(fdvNm \times (12/fdvMtr))/fuelCons_{t+1}$
fdvPct24m	Hedge ratio for the next 13-24 months	Percentage of the next 13 to 24 months expected fuel requirements hedged (excluding months 1 to 12)
fdvPct36m	Hedge ratio for the next 25-36 months	Percentage of the next 25 to 36 months expected fuel requirements hedged (excluding months 1 to 24)
fdvPct48m	Hedge ratio for the next 37-48 months	Percentage of the next 37 to 48 months expected fuel requirements hedged (excluding months 1 to 36)
fdvPLeff	Profit or loss of fuel derivatives, effective portion	Effective portion of the fuel derivatives profits or losses recognized in OCI
fdvPLineff	Profit or loss of fuel derivatives, ineffective portion	Under cash flow hedge accounting, ineffective portion of the fuel derivatives profits or losses recognized in the income statement under income on derivatives - Under fair value hedge accounting, marked to market changes of fuel derivatives directly accounted for in income
fdvPLrcl	Profit or loss of fuel derivatives, reclassified to fuel expenses	Portion of fuel derivatives profit or loss reclassified from OCI into fuel expenses when the underlying transaction is realized
fdvPLsum	Sum of the ineffective and reclassified portion of the profit or loss of fuel derivatives	Calculated as $fdvPLineff + fdvPLrcl$
fdvSpr	Fuel spread dummy	Dummy one if the airline used fuel spreads (=refining margin swaps) as the derivative instrument
fdvSwp	Fuel swap dummy	Dummy one if the airline used fuel swaps as the derivative instrument
fdvUg	Underlying unleaded gasoline dummy	Dummy one if the airline used unleaded gasoline as the underlying asset for their fuel derivative contracts

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Variable	**Label**	**Description**
fuelCons	Fuel consumption	Annual fuel consumption in USG, either reported directly or calculated as i) fuel consumption in liters per 100 RPM multiplied with RPMs ii) fuel consumption in liters per 100 ASM multiplied with ASMs iii) lagged nominal number of fuel contracts outstanding (*fdvNm*) divided by the lagged fuel percentage hedged of the expected fuel consumption in the following 12 months (*fdvPct12m*)[73] iv) fuel consumption from the previous year ($fuelCons_{t\text{-}1}$) extrapolated with ASM percentage changes v) fuel consumption from the previous year ($fuelCons_{t\text{-}1}$) extrapolated with information from the text, i.e. "consumption increased by X%" vi) fuel expenses (*fuelExp*) divided by the average fuel price per USG vii) fuel consumption per ASM (*fuelExpAsm*) multiplied with the total ASMs (*asmTl*)
fuelConsAsm	Fuel consumption per ASM	Calculated as *fuelCons*/*asmTl*
fuelExp	Fuel expenses	Total fuel expenses as reported in the income statement (or notes), net of hedging gains or losses
fuelExpAsm	Fuel expenses per ASM	Calculated as *fuelExp*/*asmTl*
lf	Load factor	Passenger load factor as reported in the annual report or calculated as *rpmTl*/*asmTl*
lgtAvg	Average length of flight	Average length of one flight (= sector length, stage length) as reported in the annual report - If the stage length was reported separately for long and short-haul flights (or domestic / international), the average stage lengths are weighted with *asmTl*
rasm	Revenue per available seat mile	Calculated as *revTl*/*asmTl*
rpmTl	Revenue passenger miles	The number of miles on which a passenger is transported, either reported directly or calculated as $asmTl \times lf$
rrpm	Revenue per revenue passenger mile	Revenue per RPM, calculated as *revTl*/*rpmTl* - Also referred to as "the yield" in the airline industry

[73]This calculation works solely if the hedge portfolio maturity (*fdvMtr*) does not exceed 12 months.

Table 4.8: Proxies on leverage used in previous research

Authors	**Leverage proxy**
Acharya et al. (2007), Carter et al. (2006), Lin and Chang (2009), and Spanò (2007)	Book value of long-term liabilities (*liaLt*) scaled by total assets (*asTl*)
Adam (2002)	Book value of long-term liabilities (*liaLt*) plus the book value of preferred stock scaled by the book value of common equity (*eqtyTl*)
Allayannis and Ofek (2001), Haushalter (2000), Gay et al. (2011), Graham and Rogers (2002), Guay and Kothari (2003), and Lee and Jang (2007)	Book value of total liabilities (*liaTl*) scaled by total assets (*asTl*) - Brealey et al. (2017) also propose this leverage ratio in order to include short-term debt - For firms regularly using short-term debt for financing, debt ratios without short-term debt may be understated
Arnold et al. (2014)	Use all possible combinations: - $liaTl/asTl$, $liaTl/(mktCap + liaTl)$ - $liaTl/mktCap$ - $liaTl/eqtyTl$ - $liaTl/asTl$ - $liaLt/(mktCap + liaTl)$ - $liaLt/mktCap$ - $liaLt/eqtyTl$ - $liaTl/asTl$ - $ibd/(mktCap + liaTl)$ - $ibd/mktCap$ - $ibd/eqtyTl$
Bartram et al. (2009)	Book value of total liabilities (*liaTl*) divided by the sum of market capitalization (*mktCap*), the book value of total liabilities (*liaTl*) and the book value of preferred stock
Dionne and Thouraya (2013)	Book value of long-term liabilities (*liaLt*) divided by the sum of market capitalization (*mktCap*), the book value of total liabilities (*liaTl*) and the book value of preferred stock
Gay and Nam (1998)	Three-year average debt-to-market value ratio
Géczy et al. (1997)	Book value of long-term liabilities (*liaLt*) scaled by the natural logarithm of market capitalization (*mktCap*), the book value of long-term liabilities (*liaLt*) and the book value of preferred stock
Guay and Kothari (2003)	Book value of total liabilities (*liaTl*) divided by the market value of assets

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Authors	Proxy variable to measure financial distress
Haushalter (2000)	Book value of total liabilities (*liaTl*) divided by the sum of market capitalization (*mktCap*) and the book value of total liabilities (*liaTl*) minus the book value of common equity (*eqtyTl*)
Judge (2006)	Uses three variables: - Gross gearing, which is the sum of the book value of total liabilities (*liaTl*) and the book value of preferred stock scaled by the sum of the book value of total liabilities (*liaTl*) and the book value of common equity (*eqtyTl*) - Net gearing, which is the sum of the book value of net debt (total liabilities (*liaTl*) minus cash and cash equivalents (*cashEq*)) and the book value of preferred stock divided by the sum of the book value of net debt and the book value of common equity (*eqtyTl*) - Industry-adjusted leverage, which is the firm's leverage scaled by the industry average leverage
Nance et al. (1993) and Tufano (1996)	Three-year average of the book value of long-term liabilities (*liaLt*) scaled by the sum of the book value of long-term liabilities (*liaLt*) plus the market capitalization (*mktCap*)
Nguyen and Faff (2002)	Book value of total liabilities (*liaTl*) scaled by the sum of the book value of total liabilities (*liaTl*) and the market capitalization (*mktCap*)

equivalent to Acharya et al. (2007), Carter et al. (2006), Lin and Chang (2009), and Spanò (2007). Long-term liabilities (*liaLt*) are the difference between total liabilities (*liaTl*)[72] and current liabilities (*liaCrt*). Lastly, the variable leverage ratio 3 (*lvrg3*) is created, which is the book value of total liabilities (*liaTl*) scaled by total assets (*asTl*). Purnanandam (2008) suggests that the relation between risk management activities and financial distress of a firm, measured by a proxy for leverage, is not linear but concave (refer to Subsection 2.2.1 for detailed information). If empirical research does not control for this non-linear relationship, statistical deductions may be biased. Therefore, this study follows the approach by Purnanandam by squaring the three leverage proxies, resulting in the variables *lvrg1Sqr*, *lvrg2Sqr* and *lvrg3Sqr*.

Apart from leverage proxies, other variables can be used to estimate a firm's likelihood to enter financial distress or bankruptcy, such as variables containing dividend payments. Comparable to Adam (2002), Adam et al. (2017), Bartram et al. (2009),

[72] "Liabilities subject to compromise" are included in total liabilities.

Carter et al. (2006), and Lin and Chang (2009) a binary variable (*divDm*) is used that takes on the value one if the firm paid any dividends in the subsequent year.[74] For robustness, the dividend yield (*divYld*) (Allayannis and Ofek, 2001; Judge, 2006; Spanò, 2007)[75] and dividend ratio (*divRto*) are used to measure the likelihood of financial distress.

Another way of measuring a firm's financial soundness is the availability and score of credit ratings. While some authors use a numerical value for a firm's credit rating (Carter et al., 2006; Judge, 2006; Rampini et al., 2014), others (Adam, 2002; Haushalter, 2000; Sprcic and Sevic, 2012) employ a dummy variable if the company avails itself of any credit rating. Unfortunately, too few airlines in the sample (178 firm years out of 621) had a credit rating of one of the three major rating agencies, Fitch, Moody's and S&P,[76] which is why credit rating variables are not used. If credit rating dummy variables were used, a bias towards overestimating the likelihood of financial distress for the airlines that did not opt for one of the three credit ratings would be introduced.

Other measures of profitability are interest coverage ratios, profit margins and return on assets. The interest coverage ratio (*intCov*), calculated as EBIT (*ebit*) divided by interest expenses (*intExp*), measures how many times the EBIT could cover for incurred interest expenses (Brealey et al., 2017). Bartram et al. (2009), Gay and Nam (1998), Judge (2006), and Nance et al. (1993) also use interest coverage ratios, mostly averaged over three years. The profit margin, on the other hand, describes the fraction of revenue that results in net income. Analogous to Bartram et al. (2009), Brown et al. (2006), and Dionne and Thouraya (2013), operating profit margins are used in order to factor in interest that has already been paid to debtholders (Brealey et al., 2017). The operating profit margin (*prfMrg*) is the sum of net income before extraordinary items (*incBfeo*) and after-tax interest (*intAtax*) scaled by total revenues (*revTl*). It is differentiated between net income (*incNet*) and net income before extraordinary items (*incBfeo*) to overcome the problem that accounting earnings and income that is used for tax expense calculations differ. In the sample, extraordinary items[77] (*eoItem*) make up 5% of net

[74] If, for example, the airline paid out dividends *in* year 2009 *for* year 2008, $divDm_{2008}$ is assigned one.

[75] Nance et al. (1993) use the three-year average of the dividend yield. Due to the short sample period, a three-year average cannot be used here.

[76] Chinese airlines, for example, had a Dagong rating or China Chengxin Securities rating.

[77] Examples of extraordinary items in the sample are: discontinued operations (Asiana, British Airways, Cyprus Airways, Icelandair, Jazeera Airways, Korean Air, Lufthansa, Malaysia Airlines, Tigerair), disposal or sale of spare engine (JetBlue), professional and legal fees, once-off pension streams and post retirement income streaming (Aer Lingus), restructuring programs (Air Berlin, Finnair, Flybe), provisions and adjustment for cargo investigation (Air Canada), reorganization costs (Air New Zealand, American Airlines, Delta Air Lines, Iberia, United Airlines), accounting changes (Alaska Airlines, China Airlines, Ryanair, US Airways), profits on disposal of investments, gains on deemed disposal of an

income before extraordinary items (excluding three outlier U.S. firm years). Graham and Smith (1999) give the example of restructuring costs, which are taxed when they occur, whereas GAAP requires the restructuring costs to be recognized in the year the restructuring program is launched.

Another measure of profitability is return on assets (*roa*), which is the sum of net income before extraordinary items (*incBfeo*) and after-tax interest (*intAtax*) scaled by total assets (*asTl*). Return on assets (ROA) states which fraction of total assets is paid to debt and equity-holders at the year end. The tax adjustment on interest payments is necessary to ensure a direct comparability between firms with different capital structures (Brealey et al., 2017). While Allayannis and Ofek (2001) regard this adjustment by calculating ROA as earnings before interest, tax and depreciation (EBITD) scaled by total assets, Lee and Jang (2007) merely divide net income by total assets.

The after-tax interest is calculated by multiplying interest expenses incurred in the reporting year with one minus the statutory tax rate (*taxSta*). Equivalent to Faccio and Xu (2015), the marginal statutory tax rate is used. The tax rate is taken from the Organisation for Economic Co-operation and Development (OECD) database ("combined corporate tax rate") or, if the country is not listed in the database, from KPMG's corporate tax rate tables.[78] Using the combined corporate tax rates means that the variable *taxSta* includes national as well as regional corporate income tax rates. The caveat with using top marginal tax rates is that they do not capture all features of the corporate tax code. Not all corporate income is taxed at the top marginal rate but rather at a non-linear tax rate including tax-loss carryforwards and carrybacks, which would be better accounted for with a simulated tax rate similar to that of Graham and Smith (1999). This simulation requires firm-specific tax and financial income data for a long estimation period (Graham, 2013), rendering this method very work-intensive. Because of the effort connected to calculating the simulated tax rate, statutory tax rates may be used in empirical research (Graham, 2013).[79]

associate (China Eastern), settlements of the United States Department of Justice cargo investigations (Cathay Pacific), subsidy income (Hainan Airlines), pre-tax lease terminations (Hawaiian Airlines), impairment losses (Japan Airlines), sales of frequent flyer program (Jet Airways), restructuring of fleet plans (Qantas), divestments of associated company (Singapore Airlines, UTair), and aircraft total losses (SpiceJet).

[78] Due to data limitations, the tax rate from the annual report for Aeroflot is used. Another special case is Air Arabia that does not pay any interest. In the KPMG database it is stated that in Saudi Arabia the maximum corporate tax rate is 55%. In the footnotes, however, KPMG notes that only oil companies are taxed at 55% and other companies not taxed at all.

[79] In addition, the variable *taxSta* is only used to calculate *intAtax*, which is included in the *roa* calculations and hence has limited impact on the results.

Table 4.9: Variables relating to financial distress

Variable	Label	Description
asTl	Total assets	Total assets as reported in the balance sheet
divDm	Dividend dummy	Dummy one if the dividend is paid in $t+1$ (not the dividend paid in t as dividends are paid in the next year's reporting period)
divPrf	Dividend payment for preference shares	Total dividends paid for preference shares (not dividend per share)
divRto	Dividend payout ratio	Calculated as $divShr/eps$
divShr	Dividend paid per share	Cash and stock dividend paid per ordinary share outstanding in year $t+1$, including interim and final dividend paid
divYld	Dividend yield	Calculated as $divShr/shrEnd$
ebit	Earnings before interest and tax	Calculated as $incBfeo + intExp - taxExp$
eoItem	Extraordinary items	Extraordinary items as reported in the income statement such as discontinued operations and other infrequent and unusual items (exceptional items, non-recurring items)
eps	Earnings per share	Calculated as $(incBfeo - divPrf)/shrTl$
eqtyDm	Negative equity dummy	Dummy one if the airline had negative *eqtyTl* in that reporting period
eqtyTl	Total equity	The book value of total equity as reported in the balance sheet
ibd	Interest bearing debt	Interest bearing debt as reported in the balance sheet (or in notes) - Including: loans, financial leases, bonds, debentures, notes payable - Other short and long-term liabilities are only included if the relevant items incur interest - Excluding: "Air traffic settlement liabilities" (=tickets already sold but not yet flown) and trade payables
incBfeo	Income before extraordinary items	Calculated as $incNet - eoItem$
incNet	Net income	Net income as reported in the income statement, after minority interests have been paid and including discontinued operations and extraordinary items
intAtax	After-tax interest	Calculated as $(1 - taxSta) \times intExp$
intCov	Interest coverage ratio	Calculated as $ebit/intExp$

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Variable	Label	Description
intExp	Interest expenses	Total interest expenses as reported in the income statement (or in notes) - Including: interest payments on finance lease obligations
liaCrt	Current liabilities	Total current liabilities as reported in the balance sheet
liaLt	Long-term liabilities	Calculated as $liaTl - liaCrt$
liaTl	Total liabilities	Total liabilities as reported in the balance sheet, calculated if they are not reported (current + non-current liabilities) - Including: "liabilities subject to compromise" (Chapter 11 term)
lvrg1	Leverage ratio 1	Calculated as $ibd/asTl$
lvrg1Sqr	Leverage ratio 1 squared	Calculated as $lvrg1 \times lvrg1$
lvrg2	Leverage ratio 2	Calculated as $(liaTl - liaCrt)/asTl = liaLt/asTl$
lvrg2Sqr	Leverage ratio 2 squared	Calculated as $lvrg2 \times lvrg2$
lvrg3	Leverage ratio 3	Calculated as $liaTl/asTl$
lvrg3Sqr	Leverage ratio 3 squared	Calculated as $lvrg3 \times lvrg3$
prfMrg	Profit margin	Calculated as $(incBfeo + intAtax)/revTl$
roa	Return on assets	Calculated as $(incBfeo + intAtax)/asTl$
taxExp	Tax expenses	Total tax expenses as reported in the income statement (or notes), including deferred and current tax expenses of that period - $(-)$ refers to a tax expense and $(+)$ to a tax benefit
taxSta	Statutory corporate income tax rate	Respective statutory corporate income tax rate of the airline's country - Source: if the country is available in the OECD Tax Database (OECD, 2018), the respective year "combined corporate income tax rate" is taken (which is the "corporate income tax rate" + "sub-central government corporate income tax rate") - If the country is not listed in the OECD database, KMPG's corporate tax rate tables are used (KPMG, 2018)

Variables relating to the underinvestment problem

The literature review (Subsection 2.2.2) highlighted the fact that, aside from the likelihood of financial distress, the existence of investment opportunities may also influence the hedging decision of a firm. In order to test this hypothesis empirically in Section 5.1, variables that may be used as a proxy for measuring the occurrence of investment opportunities are presented. Those variables comprise market-to-book ratios, price-earnings ratios, Tobin's Q, CAPEX, and cash ratios.

The first ratio as a proxy for a firm's growth options is the market-to-book ratio. The MTB ratio (*mtbRto*) is calculated as the market value of equity (*mktCap*) divided by the book value of equity (*eqtyTl*). This coefficient reflects how much the invested capital by shareholders is worth under current market conditions. A MTB ratio larger than one means that each dollar invested by the shareholders has been multiplied by the amount of the ratio (Brealey et al., 2017). If market participants value the firm higher than its asset value, investment opportunities may be a driver for the investors' evaluation (Gay and Nam, 1998). Although the use of this figure as a proxy can be criticized for how accurately it really measures growth options (see Subsection 2.2.2), many researchers deploy MTB ratios in their studies. Adam (2002), for example, suggests that the MTB ratio in his sample rather captures a firm's maturity instead of its growth options. Arnold et al. (2014) also use *mktCap*/*eqtyTl*, Gay et al. (2011), Géczy et al. (1997), Graham and Rogers (2002), and Nguyen and Faff (2002) employ the reverse ratio *eqtyTl*/*mktCap*. Acharya et al. (2007), Adam (2002), Adam et al. (2017), Allayannis and Ofek (2001), Arnold et al. (2014), Brown et al. (2006), and Guay and Kothari (2003) calculate the MTB ratio with the sum of market capitalization (*mktCap*) and the book value of total liabilities (*liaTl*) scaled by the book value of total assets (*asTl*).[80] Another measure of potential growth choices is the price-earnings ratio: "Higher P/E ratios are typically associated with firms with higher growth prospects" (Gay and Nam, 1998, p. 59). It measures the multiple of dollars that has to be paid by shareholders for one dollar of earnings. The price-earnings ratio (*peRto*) is included, that is the share price at the year end (*shrEnd*) divided by earnings per share (*eps*). Arnold et al. (2014), Gay and Nam (1998), Hu and Wang (2005), and Judge (2006) either insert the earnings-price ratio or the reverse price-earnings ratio in their regression.

Tobin's Q (*tobQ*) is a more advanced indicator than the market-to-book ratio for a firm's market value compared to the replacement costs of its assets. Different forms of how to calculate Tobin's Q exist. Similar to Carter et al. (2006), Disatnik et al. (2014), Isin et al. (2014), and Spanò (2007), the approach by Chung and Pruitt (1994) is followed.[81] Chung and Pruitt (1994) suggest calculating Tobin's Q by adding the market value of common equity (*mktCap*), market value of preference shares (*shrPrfLv*)

[80] Nance et al. (1993) use the reverse fraction $asTl/(liaTl + mktCap)$.

[81] Carter et al. (2006) use the formula by Chung and Pruitt (1994) but add the book value of inventory and subtract current assets in the numerator.

and the book value of total liabilities (*liaTl*) and scaling the sum by total assets (*asTl*). In contrast to the more sophisticated formula by Lindenberg and Ross (1981), Chung and Pruitt (1994) assume that the market value of a firm's assets as well as the firm's outstanding debt is equal to its book value. The advantage of this formula is lower "data requirements and computational effort", as well as the fact that "required inputs are readily obtainable" (Chung and Pruitt, 1994, p. 71). Thus, the formula is a "compromise between analytical precision and computational effort" (Chung and Pruitt, 1994, p. 71). Chung and Pruitt regress their results to those of Lindenberg and Ross and find an R^2 on data between 1978 and 1987 of at least 0.95, and slope coefficients of 0.92 and 0.99.

In addition to the market-to-book ratio, price-earnings ratio and Tobin's Q, a firm's R&D spending or capital expenditure may be a sign for investment opportunities. R&D ratios are employed by Allayannis and Ofek (2001), Arnold et al. (2014), Gay and Nam (1998), Géczy et al. (1997), Graham and Rogers (2002), Judge (2006), Nance et al. (1993), Purnanandam (2008), and Spanò (2007). In the airline industry, there is hardly any R&D expenditure. Instead, capital expenditure (CAPEX) is used in order to measure the investment opportunities of an airline. Capital expenditure numbers are collected from investing activities inflows (*capexIn*) and outflows (*capexOut*) from the airlines' cash flow statements. The sum of the two positions is *capexNet*. Capital expenditure outflows comprise items such as capital expenditure for property, plant and equipment (PPE), investments in joint venture, purchases of non-current assets, tangible and intangible assets, payments for advances for new aircraft, investments in associates, increases in lease prepayments, acquisitions of equity method investments, increases in equipment purchase deposits, and acquisitions of subsidiaries. Purchases of financial assets and available-for-sale securities are excluded as the focus lies on investing activities in equipment, assets and associates. Increases in lease prepayments are included because this item is offset with decreases in lease prepayments from capital expenditure inflows. In total, three capital expenditure ratios are constructed: CAPEX to sales (*capRev*) (Carter et al., 2006; Judge, 2006; Lin and Chang, 2009), calculated as net capital expenditure (*capexNet*) scaled by total revenues (*revTl*), CAPEX to firm size (*capSize*)(Géczy et al., 1997), net capital expenditure (*capexNet*) divided by firm size (*size*) and CAPEX to assets (*capAs*) (Haushalter, 2000; Sprcic and Sevic, 2012), net capital expenditure (*capexNet*) scaled by total assets (*asTl*).

Due to the impact cash holdings might have on the hedging behavior (see Subsection 2.2.2), previous studies include variables that relate to a company's cash situation. Often used coefficients comprise the cash ratio (*cashRto*) (Gay et al., 2011; Géczy et al., 1997; Haushalter, 2000; Judge, 2006; Purnanandam, 2008; Spanò, 2007), calculated as the sum of cash and cash equivalents (*cashEq*) and marketable securities (*mktSec*) scaled by current liabilities (*liaCrt*), and the cash to sales ratio (*cashRev*) (Carter et al., 2006; Lin and Chang, 2009), which is cash and cash equivalents (*cashEq*) divided by total revenues (*revTl*). Cash and cash equivalent data is retrieved from the airlines' balance sheets and notes. Restricted cash and deposits for lease agreements are excluded as those cash holdings are not readily accessible by the airline and are usually "returned to the Group" at the end of the lease period (Aeroflot, 2014, p. 137). In addition, the current ratio (*crtRto*) (Nguyen and Faff, 2002) is calculated, which is the fraction of current assets (*asCrt*) to current liabilities (*liaCrt*), and the quick ratio (*qckRto*) (Adam, 2002; Adam et al., 2017; Bartram et al., 2009; Dionne and Thouraya, 2013; Sprcic and Sevic, 2012; Tufano, 1996), which is the sum of cash and cash equivalents (*cashEq*), marketable securities (*mktSec*) and current receivables (*rcvCrt*) divided by current liabilities (*liaCrt*). Lastly, the indicator variable *cashGrwDm* is introduced, which takes on the value one if an airline's annual cash ratio is below the sample average cash ratio and its annual growth options (measured by the adjusted Tobin's Q) is above the sample average growth options (Gay and Nam, 1998).

Variables relating to economies of scale

The influence of the firm size on the likelihood of using financial derivatives is discussed in previous research with mixed results (see Subsection 2.2.5). Therefore, several size variables are created to test the economies of scale related hypotheses in Chapter 5. Those variables comprise absolute financial data such as total assets, an airline's market value or operating figures.

There are many different ways of measuring a firm's size. Acharya et al. (2007), Dionne and Thouraya (2013), and Purnanandam (2008) take the logarithm of total revenue, Adam et al. (2017), Allayannis and Ofek (2001), Brown et al. (2006), Carter et al. (2006), Gay et al. (2011), Graham and Rogers (2002), Hu and Wang (2005), Judge (2006), Lin and Chang (2009), and Spanò (2007) either use the natural or common logarithm of total assets. This study follows the first approach and uses the natural logarithm of total revenues (*revTlln*). Apart from absolute balance sheet or income statement numbers, e.g. revenues and assets, researchers often employ the market value of the firm as a proxy for firm size. Dionne and Thouraya (2013), Gay and Nam (1998), Géczy et al. (1997), and Tufano (1996) calculate a firm's market value as the book value of total liabilities plus the book value of preferred stock plus the market value of equity. Brown et al. (2006), Géczy et al. (1997), Nance et al. (1993), and Nguyen and Faff (2002)

Table 4.10: Variables relating to the underinvestment problem

Variable	**Label**	**Description**
asCrt	Current assets	Total current assets as reported in the balance sheet
capAs	CAPEX scaled by total assets	Calculated as $capexNet/asTl$
capexIn	Capital expenditure (inflow)	Capital expenditure as reported in the cash flow statement under cash flow from investing activities (inflow) - Excluding: dividends received, financial assets and increases in cash in connection with mergers
capexNet	Capital expenditure (net)	Calculated as $capexOut + capexIn$ - $(-)$ means a net capital expenditure (outflow) and $(+)$ means an inflow
capexOut	Capital expenditure (outflow)	Capital expenditure as reported in the cash flow statement under cash flow from investing activities (outflow) - Including: capital expenditure for PPE, investments in joint venture, purchases of non-current assets, tangible and intangible assets, payments for advances for new aircraft, investments in associates, increases in lease prepayments, acquisitions of equity method investments, increases in equipment purchase deposits, acquisitions of subsidiaries - Excluding: financial assets, available-for-sale securities
capRev	CAPEX to sales ratio	Calculated as $capexNet/revTl$
capSize	CAPEX scaled by firm size	Calculated as $capexNet/size$
cashEq	Cash and cash equivalents	Cash and cash equivalents as reported in the balance sheet (or in notes) - Excluding: restricted cash and deposits for lease agreements
cashGrwDm	Low cash holdings, high investment opportunities dummy variable	Dummy one if the airline's annual cash ratio is below the sample average cash ratio and the annual adjusted Tobin's Q is below the sample average Tobin's Q value
cashRev	Cash to sales ratio	Calculated as $cashEq/revTl$
cashRto	Cash ratio	Calculated as $(cashEq + mktSec)/liaCrt$
crtRto	Current ratio	Calculated as $asCrt/liaCrt$
mktSec	Marketable securities	Marketable securities as reported in the balance sheet (or in notes) under current assets - Including: available-for-sale financial assets, assets held for sale, financial assets at fair value through profit, derivatives, current portion of held-to-maturity investments

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Variable	Label	Description
mtbRto	Market-to-book ratio	Calculated as $mktCap/eqtyTl$
peRto	Price-earnings ratio	Calculated as $shrEnd/eps$
qckRto	Quick ratio	Calculated as $(cashEq + mktSec + rcvCrt)/liaCrt$
rcvCrt	Current receivables	Current receivables as reported in the balance sheet (or in notes) under current assets - Including: receivables from the sale of aircraft, trade receivables, other receivables, receivables from related parties, advances to suppliers, notes receivables
tobQ	Tobin's Q	Calculated as $(mktCap + liaTl)/asTl$

ignore the book value of preferred stock. The size variable of the current study is similar to that of Dionne and Thouraya (2013), Gay and Nam (1998), Géczy et al. (1997), and Tufano (1996),[82] except for the fact that the book value of preferred stock is replaced with the market value of preference shares in order to obtain the current market value of preference shares. Thus, the variable *size* is the firm's market capitalization (*mktCap*) plus the book value of total liabilities (*liaTl*), with market capitalization being the number of common shares at year end (*shrTl*) multiplied with the share price (*shrEnd*) plus the market value of preference shares (*shrPrfLv*). If the preference shares are not traded (e.g. Korean Air, Malaysia Airlines and Shandong Airlines), the share price of the common stock is used for simplicity (Hasler, 2011). Especially Southern American airlines only list their preference shares but not their common shares. In this case, it is assumed that all shares trade at the same share price. Hence, the number of common and preference shares outstanding are added and the sum multiplied with the stock price of preference shares.[83]

In the study on the gold mining industry, Tufano (1996) employs the number of ounces of gold reserves as a measure for firm size. Analogously, the number of total aircraft in an airline's operating fleet (*acTl*) is used. This figure, however, does not cover the financing structure of the fleet, i.e. whether the aircraft are financed, finance leased or operating leased. Moreover, the total number of aircraft does not reflect the size of the aircraft types. Therefore, the total number of ASMs (*asmTl*) is also employed as a size measure in robustness tests.

[82] Haushalter (2000) subtracts the book value of equity.

[83] With that calculation the value of control and voting rights of common shares is underestimated.

Economies of scale might not only exist in setting up a hedge department but also in holding a large derivative portfolio with other contracts than fuel related contracts. Thus, interest rate and FX derivative dummies control for other derivative usage besides fuel hedging. The notes of the annual reports are checked whether the airline used FX or interest rate derivatives. If they had hedge contracts outstanding at the reporting year end, the value one is assigned to the binary variables foreign exchange rate derivative dummy (*fxdvDm*) or interest rate derivative dummy[84] (*irdvDm*). Carter et al. (2006) include an interest rate derivative dummy in their study on the airline market but not an FX derivative binary variable because their sample contains purely U.S. carriers with reduced need to hedge currency risk. Géczy et al. (1997) check if firms use any other sort of derivatives with a dummy variable.

Purnanandam (2008) uses the ratio of foreign currency sales to total sales as an additional control variable to proxy for exposure but also to proxy "for economies of scale that can be exploited in hedging foreign currency risks" (p. 721). Similarly, the variable absolute fuel expenses (*fuelExp*) is used. The larger the airline's fuel bill, the more the airline could be inclined to hedge if the economies of scale hypothesis holds true.

Variables relating to fleet diversity

The next three parts introduce the variables relating to the operational hedging tools, i.e. fleet diversity, strategic alliances and aircraft leasing. Researchers use different variables to incorporate operational hedging in their studies. Most often, those variables include figures that capture the geographical distribution of a company's operations (Purnanandam, 2008; Pantzalis et al., 2001; Spanò, 2007). Segment diversification is also part of operational hedging studies (Adam, 2002; Gay et al., 2011).

In the present study, an airline's operating fleet diversity is calculated with the approach used by Berghöfer and Lucey (2014) and Treanor et al. (2014b)[85], which is based on the Hirschmann-Herfindahl index.

The first fleet diversity measure (*fDiv1*) is calculated as

$$fDiv1 = 1 - \sum_{j=1}^{K} \left(\frac{\text{No. of aircraft models}_{\text{j}}}{\text{Total no. of aircraft}} \right)^2, \in [0, 1 - \frac{1}{K}].$$

[84]Variable rate obligations are not counted as interest rate derivatives.

[85]Treanor et al. (2014b) use alternative measures to calculate fleet diversity, such as seat capacity and aircraft style (e.g. narrow and wide-body aircraft). In unreported results, they find similar but weaker results.

Table 4.11: Variables relating to economies of scale

Variable	**Label**	**Description**
acTl	Total number of aircraft	Total number of aircraft in the operating fleet of an airline - Including: aircraft under operating lease, finance lease and owned assets - If the number was not reported in each year it might be derived from the adjacent year with deliveries and sales from the annual report text
fxdvDm	Foreign exchange rate derivative dummy	Dummy one if the airline had outstanding foreign exchange rate derivatives at the year end (e.g. cross currency swaps)
irdvDm	Interest rate derivative dummy	Dummy one if the airline had outstanding interest rate derivatives at the year end (e.g. interest rate swaps) - Variable rate obligations do not count as interest rate derivatives
mktCap	Market capitalization	Calculated as $shrCom \times shrEnd + shrPrfLv$
revTl	Total revenues	Total revenues as reported in the income statement (or notes), including other revenues
revTlln	Natural logarithm of total revenues	Calculated as $ln(revTl)$
shrCom	Ordinary shares outstanding	Total number of ordinary shares (common stock) outstanding taken from the annual report
shrEnd	Share price at the end of the financial year	Share prices are retrieved from Thomson Reuters Eikon - For the financial years not ending December, the period end date share price is used (e.g. for 31st March 2010 the share price from 31st March 2010 is taken)
shrPrf	Preference shares outstanding	Total number of preference shares (preferred stock) outstanding
shrPrfLv	Market value of preference shares	Market value of preference shares outstanding - If the preference shares are traded on an exchange, the market value is calculated as the number of preference shares outstanding multiplied with the preference share price at the year end - If the preference shares are not traded, the market value is calculated as the par value of preference shares multiplied with the number of preference shares outstanding - If neither the preference share price nor the par value is reported, it is assumed that the preference shares are traded at the common share price

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Variable	Label	Description
shrTl	Total number of shares outstanding	Total number of shares outstanding, equal to the total number of shares issued minus the number of treasury shares - Calculated as $shrCom + shrPrf$
size	Firm size of the airline	Calculated as $mktCap + liaTl$

For the calculation of the fleet diversity measures, fleet data is collected first from the notes and the main text of the airlines' annual reports. Aircraft under wet lease agreements[86] are excluded. In total, fleet data is recorded for 511 out of 621 firm years (82%). If the airline did not report the aircraft model but only the aircraft family (e.g. Air China reported "A320family" instead of Airbus 319-100), the website www.planespotters.com is checked for the current operating fleet. If the airline operated five Airbus 320 and five Airbus 319 in 2017, it is assumed that the same ratio of aircraft models applied to all years in this analysis. Some airlines reported the exact operating fleet in one reporting year and only changes in textual form in the following annual report. In this case, the fleet data is derived from the previous year with reported changes from the current year. The airlines in the sample operated 154 different aircraft models in total.

While a diverse fleet might be useful as an operational hedge to tackle volatile fuel prices, Benmelech and Bergman (2009) and Berghöfer and Lucey (2014) both highlight the fact that operating a diverse fleet entails high operating costs (see Section 2.3 for a discussion on costs of volume flexibility). In addition, Slack (1983) points out that a partly flexible production system may be inflexible due to other considerations. If the airline operates for example an Airbus 321-200 with approximately 200 seats on medium-haul flights and a Boeing 737-300 (seat capacity of 126 passengers in a two-class configuration) on short-haul flights, it gives the airline flexibility in terms of different seating capacities. On the other hand, due to flight crew training requirements those aircraft cannot be exchanged immediately. Under certain circumstances, it would be better for the airline to operate a slightly larger Airbus 320 (seating capacity of around 180 passengers) with a lower load factor.

[86] Under a wet lease agreement the lessee leases the aircraft inclusive of crew, maintenance and fuel (Rampini et al., 2014).

To factor in the disadvantages of operating a heterogeneous fleet, the second fleet diversity measure (*fDiv2*) is calculated as

$$fDiv2 = 1 - \sum_{j=1}^{K} \left(\frac{\text{No. of aircraft models in one aircraft family}_{\text{j}}}{\text{Total no. of aircraft}} \right)^2, \in [0, 1 - \frac{1}{K}].$$

An aircraft family is defined as a group containing all aircraft models that require the same license endorsements by the EASA (2017). The aircraft Airbus 320 family comprises, for example, the aircraft models A318-100, A319-100, A320-100, A320-200, A320neo, A321-100, A321-200, and A321neo. This classification captures the advantage of different seat capacities of the aircraft. Within an aircraft family, operating costs are lower due to interchangeable maintenance parts or crew requirements. Consequently, *fDiv2* is a proxy for switching costs (see Subsection 2.3.1). Higher *fDiv1* values resemble higher fleet diversity and greater operational flexibility. Higher *fDiv2* values mean higher switching costs.

For a better understanding of the two flexibility variables, consider the example of Volaris. The airline operated 18 Airbus 319 and 32 Airbus 320 in 2014. The aircraft have the advantage that they can be operated with the same flight crew, maintenance personnel and repair parts, while they offer different capacities (the Airbus 319 of Volaris has 144 seats and the Airbus 320 174 seats in all economy configuration). If one were to consider both aircraft models as the same aircraft type, the advantage of the diverse fleet (i.e. volume flexibility) would not be captured. With the formulas of this study, *fDiv1* is 0.461 for Volaris and covers these different aircraft type models. On the other hand, *fDiv2* should be as small as possible since it measures switching costs. In the case of Volaris, *fDiv2* is zero. To factor in the advantages as well as the disadvantages of operating a diverse fleet, the variable *fDivNet* is introduced. *fDivNet* is calculated as

$$fDivNet = fDiv1 - fDiv2.$$

fDivNet is the difference between *fDiv1*, the benefits of fleet diversity, and *fDiv2*, the switching costs of a diverse fleet. *fDivNet* has a bias towards airlines with only short-haul operations. If an airline offers domestic as well as long-distance flights, it has to operate different aircraft models that belong to different aircraft families. Nevertheless, *fDivNet* should constitute an appropriate proxy for the costs and benefits of fleet diversity.

Besides looking at fleet diversity, changes in an airline's operating fleet are also studied. The variable *acChg* captures the year-on-year percentage changes in the number of aircraft in an airline's fleet. Changes in an airline's capacity are accompanied by capital expenditures and investment decisions (Van Mieghem, 2003). Changes in the operating fleet are introduced in this subsection instead of Subsection 4.1.2 to underline the peculiarity of capital expenditures in the airline industry. Thus, additions to the fleet are not only used as a proxy for operational hedging in this study but also as a proxy for the underinvestment problem. As mentioned in Subsection 2.3.1, volume flexibility is compared to fleet diversity. Similarly, changes in the fleet structure can be compared to capacity expansion, where the firm can choose the expansion size, time and source of purchase (Luss, 1982). An airline can thus determine the size of the aircraft, i.e. the seat capacity, the timing, i.e. whether they buy the aircraft now or delay the purchase due to low oil prices, and the source, i.e. the manufacturer. The manufacturer influences the fleet diversity calculation as *fDiv2* values different aircraft models from the same family higher.

Another variable that would be interesting to analyze in more detail is the age of the airline's operating fleet. As stated in Subsection 2.3.1, Treanor et al. (2014b) use the natural logarithm of the airline's average fleet age as a proxy for fuel efficiency. However, not enough sample airlines reported the age of their fleet and this proxy cannot be used for the multiple regression analysis. Nevertheless, the variable *acAge* is collected for background information. *acAge* is the average age of aircraft in a fleet, either reported in the text or calculated as the sum of each aircraft's age divided by the number of aircraft. If the information is available for one reporting year only, the adjacent year's value is calculated with the reported average age extrapolated with the aircraft purchases ($(acAge_{\text{t-1}} + 1 + \textit{number of new aircraft} \times 0.5)/acTl$). This approach is contrary to Treanor et al. (2014b), who use the next available reported fleet age if the airline omits to report the age in a specific year.[87]

Variables relating to strategic alliances

To capture an airline's membership in one of the three major airline alliances, Oneworld, Skyteam and Star Alliance, the alliance websites and press releases are checked for relevant information. If the airline was a full member of any of the three alliances, the indicator variable *alliDm* is assigned one. In addition, a dummy variable is created for each of the three alliances: *alliOne* (Oneworld), *alliSky* (Skyteam) and *alliStar* (Star Alliance).

[87]Ryanair reported a fleet age of "just over three years" (Ryanair, 2011, p. 24), which is assumed to be $acAge = 3.1$.

Table 4.12: Variables relating to fleet diversity

Variable	Label	Description
acAge	Average age of the aircraft fleet	Average age of the aircraft in the fleet, either reported in the text or calculated as $\sum$ *(each aircraft's age)/acTl* - If only one year is available, the next year is calculated as the reported average age extrapolated with the aircraft purchases: $(acAge_{\text{t-1}} + 1 + \textit{number of new aircraft} \times 0.5)/acTl$
acChg	Percentage change in the number of aircraft	Year-on-year percentage changes in the number of aircraft in an airline's operating fleet
acOl	Number of aircraft under operating lease	Number of aircraft under operating lease from the annual report
fDiv1	Fleet diversity measure 1	Fleet dispersion of an airline based on the different aircraft models in the operating fleet of an airline
fDiv2	Fleet diversity measure 2	Fleet dispersion of an airline based on the different aircraft models in one aircraft family in the operating fleet of an airline
fDivNet	Combined fleet diversity measure	Calculated as *fDiv1* – *fDiv2*

Table 4.13: Variables relating to strategic alliances

Variable	Label	Description
alliDm	Alliance dummy	Dummy one if the airline was a full member of an alliance (regardless of the type of the alliance) - Information about alliance membership is obtained from the websites and press releases of the alliances
alliOne	Oneworld dummy	Dummy one if the airline was a member of Oneworld
alliSky	Skyteam dummy	Dummy one if the airline was a member of Skyteam
alliStar	Star Alliance dummy	Dummy one if the airline was a member of Star Alliance

Variables relating to aircraft leasing

The airlines in the sample and airlines in general use operating leasing extensively (Moody's, 2015). Only 1.4% of the sample firm years do not comprise operating lease expenses. The application of operating lease accounting leads to smaller balance sheets and lower leverage ratios. If airlines, however, treat leases as off-balance sheet (operating) leases, their debt and asset values will be understated, leading to the "low leverage puzzle" (Rampini and Viswanathan, 2013, p. 467). Rampini and Viswanathan (2013) show that when assets and leverage are adjusted for operating lease expenses, the seemingly small firms with low leverage ratios increase in size and leverage. The notion, supported by empirical results, that leverage ratios increase with firm size is confounded when researchers take operating lease expenses into account.

In order to estimate the debt ratios of the sample airlines correctly, and for a better comparison between airlines that use operating leases and those that do not (Damodaran, 1999), the airlines' assets and debt are adjusted by either the present value (PV) of future operating lease expenses or by a multiple of the current operating lease expenses. For both approaches, all operating lease expenses are included in the calculation, not only those that are related to aircraft lease agreements. Income from operating lease agreements, i.e. when the airline is the lessor, is disregarded in the present study. Moody's (2015) decides individually whether it regards lease income. In general, it omits lease income. The two approaches of operating lease treatment is explained in the next paragraphs.[88]

Damodaran (1999) describes how to calculate the present value of operating lease obligations. Airlines usually reported their minimum future operating lease expenses in the notes section of the annual report,[89] split into each of the subsequent five years of the reporting year and an aggregated figure 'six years and beyond'.[90] In that case, the figures can be directly inserted in a spreadsheet for calculating the present value. If an airline reported the first five years aggregated, the value is divided by five and spread over the five-year time period. Similarly, if an airline reported years one to three and years three to five individually, both values are added and divided by five.[91] If an airline disclosed five years and beyond (instead of six years and beyond) jointly, the value is divided by two and split into five years and into six years and beyond. Similar to Moody's (2015), if no 'beyond' data is reported, the expense from five years is equally distributed over the years six to 10. This approach understates short-term operating lease agreements in contrast to lessees that use longer term lease contracts (Moody's,

[88] Although the data set is adjusted by operating lease expenses, financial or capital lease expenses may impede the direct comparison between airlines. Airlines may choose to capital lease aircraft via wholly-owned subsidiaries that are based in another country to benefit from tax differences (Schefczyk, 1993).

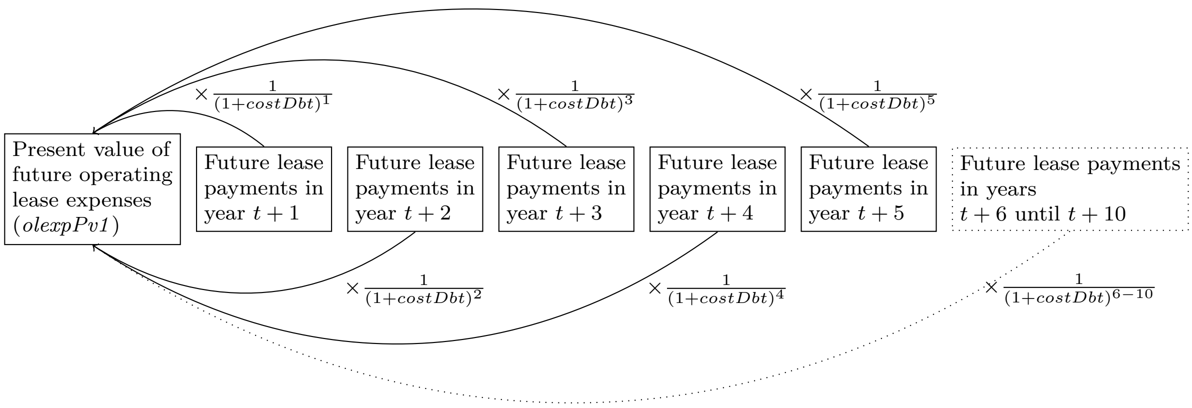
[89] EVA Air disclosed operating and capital lease expenses in one item before 2011 and separately between 2011 and 2014. The operating to total lease expense ratio of 2011 is used and this factor is multiplied with the lease data before 2011 to get an estimate of their operating lease expenses prior 2011.

[90] The 'beyond' parts means that this figure is equally distributed over the years six until 10.

[91] All Nippon Airways did not report each year of the five year forecast separately but divided the future lease commitments into a short-term and long-term portion. It is assumed that the short-term portion are the current operating lease expenses and that the long-term portion refers to future lease commitments. Thus, the long-term portion is divided by six and put under years one to five and six years and beyond.

2015). Once each of the airlines' annual future operating lease expenses are collected, partitioned into the years one, two, three, four, five, and six years and beyond, each year's payment is discounted with the relevant discount factor to the power of the equivalent year (see Figure 4.1). The sum of all discounted values is the PV of future operating lease obligations, represented by the variable *olexpPv1*.

Figure 4.1: Calculation of the present value of future operating lease commitments



The airline's individual cost of debt (*costDbt*) is employed as the discount factor.[92] The discount rate should be the pre-tax cost of debt for "unsecured and fairly risky debt" (Damodaran, 2002, p. 48). As airlines generally did not report the cost of their unsecured debt, the cost of debt is calculated as the sum of the risk-free rate (*rfRate*) and the average individual default spread (*spreadAvg*), where the risk-free rate is the monthly average yield on 10-year treasury bonds[93] from the country where the airline has its main hub. The bond yields are taken from Datastream and adapted to the different accounting dates (*accDate*). Treasury bond yields from Cyprus, Kuwait, Panama, South Africa, Turkey, and United Arab Emirates are not available on Datastream. For those countries, government and private websites as well as press releases with information on government bond issues are manually searched. Appendix H explains the calculation of the government bond yields of these six countries.

The individual default spread (*spread*) is estimated based on the synthetic rating spread tables by Damodaran (2002) and Damodaran (2016). Damodaran assigns a synthetic rating and a default spread to a firm's interest coverage ratio (*intCov*). The

[92]An individual discount rate is important as credit worthiness differs between airlines. Thus, finance costs would be higher for airlines with lower credit ratings (Moody's, 2015).

[93]For Chile (20 years) and Korea (three years) the study deviates from 10-year government bonds due to limited data available.

synthetic rating tables were prepared with historic data on interest coverage ratios and credit ratings for all U.S. companies. Although the sample comprises other countries besides the United States, the spread tables by Damodaran are used because too few of the sample airlines are rated by the main rating agencies. For the sample years 2005, 2006 and 2007, the 2002 table is used, and for years 2008 until 2014 the table from 2016 is employed. To flatten variations in interest coverage ratios, a three-year rolling average of the spread (*spreadAvg*) is calculated.

Apart from calculating the PV of future operating lease obligations, analysts, airlines and researchers also use multiples of the current operating lease expenses to adjust reported figures. Depending on the industry, different multiples exist. Moody's, for example, assigns a multiple of eight for passenger airlines. In 2015, however, they proposed to lower this multiple to five in order to better reflect the average lease duration in the airline industry instead of following the remaining useful life of the asset. Rampini and Viswanathan (2013) use a multiple of 10 for simplicity. They arrive at 10 by dividing one by the cost of capital for tangible assets of 4% plus a depreciation rate of 5% plus monitoring costs of 1%. Airlines most often use a multiple of seven in their statement adjustments (e.g. easyJet (2014) and JetBlue Airways (2015)). Garuda Indonesia published the duration and lessor for each of its aircraft and engines under operating leasing (Garuda Indonesia, 2015, p. 136). The average duration of Garuda's operating lease contracts was 13.2 years for aircraft and 4.8 year for engines.

For robustness, the annual total operating lease expenses as reported in the income statement or notes (*olexpTl*) are multiplied by five (*olexpPv5*), six (*olexpPv6*), seven (*olexpPv7*) and eight (*olexpPv8*). Some airlines did not report their operating lease expenses separately for the current year. In those cases, the annual operating lease payments are substituted with the future operating lease obligation of $t + 1$ from the previous-year report (Moody's, 2015).
Moreover, interest expenses are adjusted (*intExpAdj*) by adding one-third[94] of the yearly operating lease expenses (Moody's, 2015). The interest coverage ratio[95] is modified with

[94] The value is derived based on an implied interest rate of 6% and a multiple of six of the annual rent expense (Moody's, 2015).

[95] Besides adjusting assets and liabilities, Moody's adds two-thirds to depreciation expenses (Moody's, 2015). Damodaran (2002) also suggests adjusting operating income by adding operating lease expenses and by subtracting depreciation on the leased asset. As net income is used instead of operating income, it is assumed for simplicity that operating lease expenses are equal to the sum of imputed interest expense and deprecation and therefore can omit lease adjustments to net income (Damodaran, 1999).

the formula by Damodaran (2002):

$$intCovAdj = \frac{ebit + olexpTl}{intExp + olexpTl}.$$

Similar to Damodaran (1999) and Carter et al. (2006), the increase in the present values of future operating lease commitments are added to capital expenditure.[96] Previous studies that adjust for operating lease expenses are Carter et al. (2006) and Isin et al. (2014). Both studies follow the approach by Damodaran (1999) and add the PV of future operating lease commitments to assets, debt and Tobin's Q.

The variables in Table 4.14 are adjusted by either the PV of operating lease expenses or by changes in the PV of operating lease expenses.

Table 4.14: Variables adjusted by operating lease expenses

Variable	**Adjusted by**	**Adjusted variable**
asTl	*olexpPv1/5-8*	*asTlAdj1/5-8*
capexNet	yearly changes in *olexpPv1/5-8*	*capexNetAdj1/5-8*
capRev	yearly changes in *olexpPv1/5-8*	*capRevAdj1/5-8*
capSize	yearly changes in *olexpPv1/5-8*	*capSizeAdj1/5-8*
ebit	*intExpAdj*	*ebitAdj*
ibd	*olexpPv1/5-8*	*ibdAdj1/5-8*
intAtax	*intExpAdj*	*intAtaxAdj*
intCov	*olexpTl*	*intCovAdj*
lvrg1	*olexpPv1/5-8*	*lvrg1Adj1/5-8*
lvrg2	*olexpPv1/5-8*	*lvrg2Adj1/5-8*
lvrg3	*olexpPv1/5-8*	*lvrg3Adj1/5-8*
prfMrg	*intExpAdj*	*prfMrgAdj*
roa	*olexpPv1/5-8*	*roaAdj1/5-8*
size	*olexpPv1/5-8*	*sizeAdj1/5-8*
tobQ	*olexpPv1/5-8*	*tobQAdj1/5-8*

As mentioned in Subsection 2.3.3, leasing may have two channels through which it affects the fuel hedging strategy of an airline. First, leasing can increase debt capacity and debt usage, increase the likelihood of financial distress and thus raise the need for hedging. On the other hand, airlines that make use of operating leases have a higher

[96]Due to yearly change calculations, the earliest available firm year would be lost. Therefore, the adjustment for the earliest firm year is omitted.

degree of operational flexibility because in times of economic downturns they can reduce or cancel the operating lease agreements (Moody's, 2015), which makes operating leasing a substitute for financial fuel price hedging. The variable *olexpRev* is created, which is the current operating lease expenses (*olexpTl*) scaled by total revenues (*revTl*). With that measure, the magnitude of operating lease agreements of an airline is estimated. Moreover, the percentage of aircraft of an airline's fleet that are under operating leasing are analyzed. The fraction *acOlPct* is calculated with the number of aircraft under operarting leasing (*acOl*) divided by the total number of aircraft in the fleet (*acTl*). As some airlines did not report which aircraft in their fleet were operated under operating or finance lease and which aircraft were owned, the average operating lease expenses per Boeing 737-800 of Ryanair and per Airbus 320 of Vueling (see tables I.1 and I.2 in Appendix I) are used in order to estimate the number of aircraft under operating leasing. This procedure only works for airlines that operate a single aircraft model such as AirAsia.

In order to test H9, the variable *acOlcashDm* is introduced. It is a binary variable with the value one if the sample airline's annual cash ratio is below the sample average cash ratio and its annual percentage of aircraft under operating leasing is above the sample average. In all other cases the variable is zero.

Variables relating to selective hedging

Treanor et al. (2014a) divide their sample of hedging airlines into active and passive hedgers. They classify the airlines according to the SD of their quarterly hedge ratios and yearly percentage changes in the hedge ratios. Unfortunately, due to data limitations quarterly hedge ratios cannot be used in this study (see Subsection 5.3.4). Instead, the dummy variable *activeChg4* is created which takes on the value one for active hedgers and zero for passive hedgers. Actively hedging airlines are those airlines whose year-on-year percentage point change in its hedge ratio is in the upper quartile of the other sample airlines' year-on-year percentage point changes in hedge ratios in a given year. Passive hedgers, on the other hand, range in the lowest quartile. In contrast to Treanor et al. (2014a), the percentage point changes in hedge ratios are used instead of the percentage changes. As any changes in the hedge ratios are of interest, regardless of whether an airline increased or decreased its portfolio, the absolute value of the percentage point changes is employed. For robustness checks, active hedgers are classified as those airlines whose percentage point changes in hedge ratios range in the upper tertile (*activeChg3*=1) and passive hedgers in the lowest tertile (*activeChg3*=0). In addition,

Table 4.15: Variables relating to aircraft leasing

Variable	Label	Description
acOlcashDm	Low cash, high operating leased aircraft dummy variable	Dummy one if the airline's annual cash ratio is below the average cash ratio and its annual percentage of aircraft under operating leasing is above the sample average
acOlPct	Percentage of aircraft under operating leasing	Percentage of aircraft in an airline's fleet that were operated under operating leasing - Calculated as $acOl/acTl$
costDbt	Cost of debt	Calculated as $rfRate + spreadAvg$
intCovAdj	Adjusted interest coverage ratio	Calculated as $(ebit + olexpTl)/(intExp + olexpTl)$
intExpAdj	Adjusted interest expenses	Calculated as $intExp + \frac{1}{3} \times olexpTl$
olexpPv1	Present value of future operating lease expenses	Present value of future operating lease expenses - Calculated as the sum of future operating lease expenses of year t discounted with $(1 + costDbt)^{t}$ - Basis for the calculation of variables that end with "Adj1"
olexpPv5	Multiple (5) of annual operating lease expenses	Calculated as $5 \times olexpTl$ - Basis for the calculation of variables that end with "Adj5"
olexpPv6	Multiple (6) of annual operating lease expenses	Calculated as $6 \times olexpTl$ - Basis for the calculation of variables that end with "Adj6"
olexpPv7	Multiple (7) of annual operating lease expenses	Calculated as $7 \times olexpTl$ - Basis for the calculation of variables that end with "Adj7'
olexpPv8	Multiple (8) of annual operating lease expenses	Calculated as $8 \times olexpTl$ - Basis for the calculation of variables that end with "Adj8"
olexpRev	Operating lease expenses scaled by revenues	Calculated as $olexpTl/revTl$

... continued on next page

Variable	Label	Description
olexpTl	Total operating lease expenses	Total operating lease expenses as reported in the income statement (or notes) - Including: operating lease expenses for aircraft and rental agreements (mostly for buildings) - If the airline only reported aircraft rent and not other lease rentals separately (e.g. landing fees), but where it becomes obvious from the future operating lease commitments that not only aircraft were part of the operating lease expenses, the reported actual operating lease expenses from $t+1$ are taken - For example: the 2011 forecast of operating lease commitments of the annual report 2010 is employed as the actual total operating lease expenses 2011 - For the earliest year available (mostly 2005), the future operating lease expenses 2006 as reported in the 2005 annual report are used (which equals the current operating lease expenses of 2006 if the 2004 report is not available)
rfRate	Risk-free rate	Monthly average 10-year treasury bond yields taken from Datastream and adapted to the different *accDate* - Six countries (Cyprus, Kuwait, Panama, South Africa, Turkey, United Arab Emirates) are not available under Datastream. For those countries other web sources are searched - See Appendix H for an exact calculation
spread	Default spread	An airline's individual default spread is taken from the synthetic rating sheets of Damodaran (2002) and Damodaran (2016) and which are based on calculated interest coverage ratios - For the *years* 2008 until 2014 the table from Damodaran (2016) is used - For the *years* 2005 until 2007 the table from Damodaran (2002) is employed
spreadAvg	Three-year rolling average *spread*	The average of $spread_{t}$, $spread_{t-1}$, $spread_{t+1}$ - The average *spread* for the *year* 2005 is the average of $spread_{t}$ and $spread_{t+1}$ - The average *spread* for the *year* 2014 is the average of $spread_{t}$ and $spread_{t-1}$

the binary variables *hdgInc* and *hdgDec* are introduced. If an airline increased its hedge ratio from one year to the other, the variable *hdgInc* takes on the value one. Analogously,

Table 4.16: Variables relating to selective hedging

Variable	Label	Description
activeChg3	Active hedger dummy variable	Dummy one if the airline's absolute annual percentage point change in its hedge ratio (*fdvPct12m*) is in the highest tertile of all hedging airlines and zero if it is in the lowest tertile
activeChg4	Active hedger dummy variable	Dummy one if the airline's absolute annual percentage point change in its hedge ratio (*fdvPct12m*) is in the highest quartile of all hedging airlines and zero if it is in the lowest quartile
hdgDec	Hedge decrease dummy variable	Dummy one if the airline decreased its hedge ratio (*fdvPct12m*) from one period to another and zero otherwise
hdgInc	Hedge increase dummy variable	Dummy one if the airline increased its hedge ratio (*fdvPct12m*) from one period to another and zero otherwise
regChg	Percentage point change in regional hedge ratios	Year-on-year percentage point change in the average regional hedge ratio

for any decreases in the hedge ratio *hdgDec* will be one (Purnanandam, 2008). To further test H11, the variable *regChg* is created which is the year-on-year percentage point change in the average regional hedge ratio.

4.2 Descriptive results

Apart from the univariate and multivariate regression analysis in Chapter 5, the data set is first analyzed with descriptive methods. The data set at hand is an unbalanced panel data set because not all airline observations are available over the entire sample period. However, it is important to study all available airlines and not only those that were present for all years between 2005 and 2014 in order to avoid survivorship bias and reduction in sample size (Baum, 2007). Depending on the variable of interest either time-series values or cross-sectional values are computed. In addition, several firm years are missing for some variables, rendering univariate and multivariate analysis inappropriate due to the small sample size. Therefore, descriptive results can serve as a first overview of the given data set. Table 4.17 contains the missing firm year values for selected variables. The hedge ratio (*fdvPct12m*) is missing for 77 firm year observations, whereas the fuel hedge dummy (*fdvDm*) is available for 618 firm years. Despite missing firm years for the hedge ratio, both variables will be used as dependent variables: the hedge ratio (*fdvPct12m*), i. e. the extent of hedging, and the fuel derivative dummy (*fdvDm*), which reflects the decision to hedge.

The presentation of the descriptive results follows the same outline as in the previous chapters and sections. First, industry-specific and fuel hedge data is presented in Subsection 4.2.1. Thereafter, the descriptive results of the variables relating to financial distress (4.2.2), the underinvestment problem (4.2.3), economies of scale (4.2.4), fleet diversity (4.2.5), strategic alliances (4.2.6), and aircraft leasing (4.2.7) are discussed. Lastly, selective hedging methods of the sample airlines are analyzed (4.2.8). The results of the variables are displayed in time-series graphs and in some cases in cross-sectional form as scatter plots. For most variables, the sample is grouped into NLCs, LCCs and into the three main regions America, Europe and Asia. For reasons of clarity, the two airlines from Africa and the three airlines from Oceania are excluded in the regional presentations.

4.2.1 Financial hedging and airline industry picture

Figure 4.2 shows how the average available seat miles (in millions) changed between 2005 and 2014. While NLCs experienced a small drop in ASMs between 2005 and 2006 of 2.4%, the average ASMs of LCCs decreased slightly between 2008 and 2009 by 4.9%. The average ASMs of all sample airlines decreased by 0.9% between 2005 and 2006 and

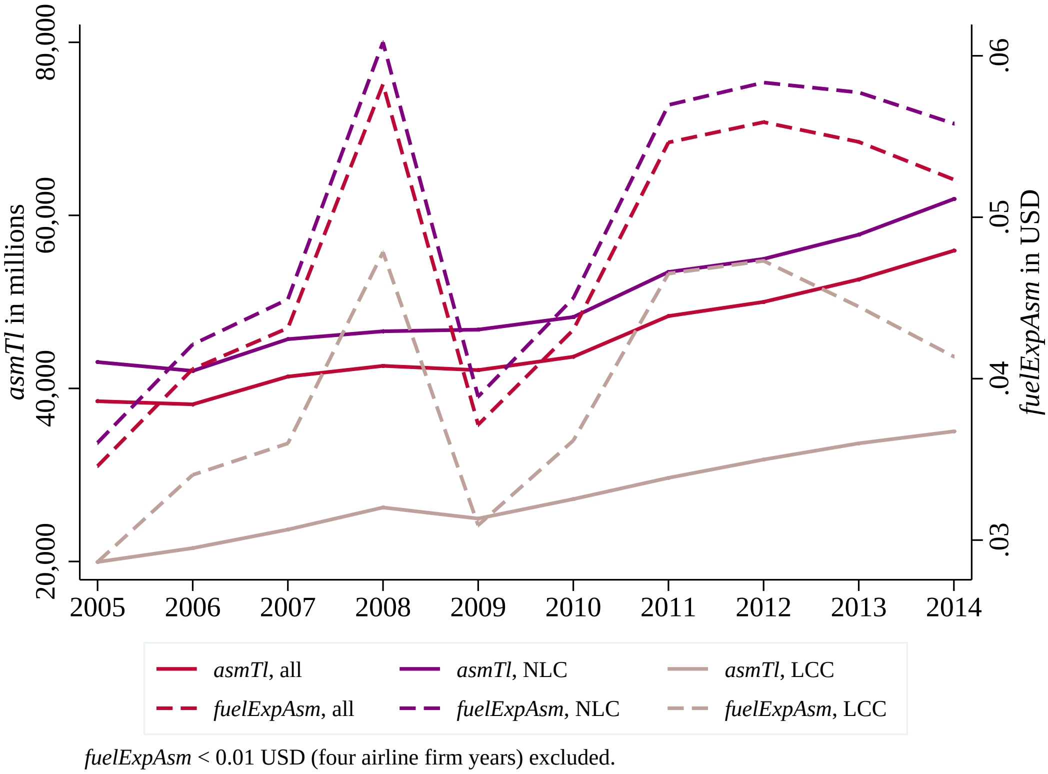
Table 4.17: Missing values of variables: absolute number of missing firm years and missing values as a percentage of the total number of firm years (621)

Variable	Missing firm years	% missing
acAge	212	34.1%
asmTl	80	12.9%
divYld	6	1.0%
fDiv1	109	17.6%
fDiv2	109	17.6%
fdvCo	136	21.9%
fdvDm	3	0.5%
fdvMtr	55	8.9%
fdvNm	147	23.7%
fdvOpt	30	4.8%
fdvPct12m	77	12.4%
fdvPct24m	116	18.7%

Variable	Missing firm years	% missing
fdvPct36m	109	17.6%
fdvPct48m	106	17.1%
fdvPLeff	111	17.9%
fdvPLineff	100	16.2%
fdvPLrcl	92	14.8%
fuelCons	156	25.1%
fuelExp	37	6.0%
olexpTl	4	0.6%
peRto	5	0.8%
shrEnd	4	0.6%
size	4	0.6%

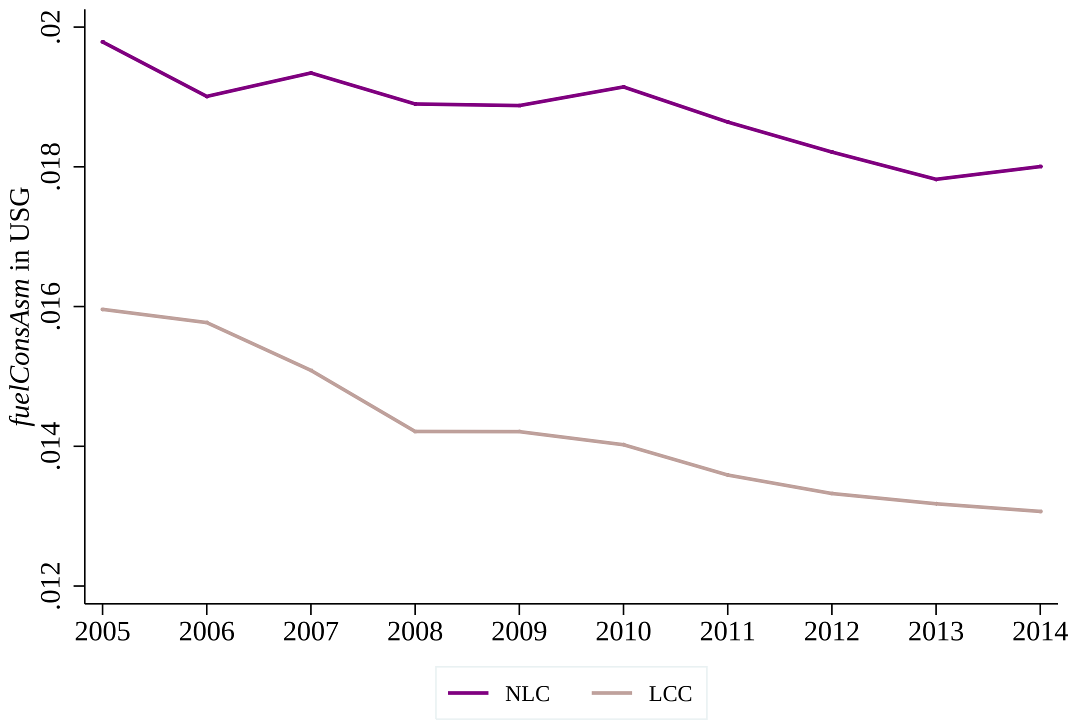
by 1.1% between 2008 and 2009. In total, the ASMs of all sample airlines increased by 45.2% in the sample period. Low-cost airlines expanded their offered seat miles by 75.7% and legacy carriers by 43.8%.

Figure 4.2: Time series: total available seat miles (*asmTl*) and fuel expenses per ASM (*fuelExpAsm*), annual average of all airlines and divided into NLCs and LCCs



The variable *fuelExpAsm* presents the average fuel expenses per ASM flown by an airline. It is both an indicator for the fuel efficiency of a flight as well as for the fuel price incurred. The number is influenced by an aircraft's fuel efficiency, the jet fuel spot price, hedging gains and losses, aircraft size, and flight distances. It is a good measure to compare the fuel expenses of different airlines. Interestingly, although fuel prices should be similar for NLCs and LCCs because kerosene is a commonly traded commodity regardless of the business model, the fuel expenses per ASM of NLCs were on average 26.3% higher than those of LCCs. Several reasons for explaining this difference, such as operating a younger, more fuel efficient fleet or benefiting from hedging gains, are examined in more detail in the following sections. Figure 4.3 demonstrates clearly the lower fuel consumption per ASM of LCCs. Low-cost airlines managed to lower their fuel consumption by 18.1% between 2005 and 2014, increasing the difference to the fuel consumption of NLCs from 24.0% in 2005 to 37.7% in 2014.

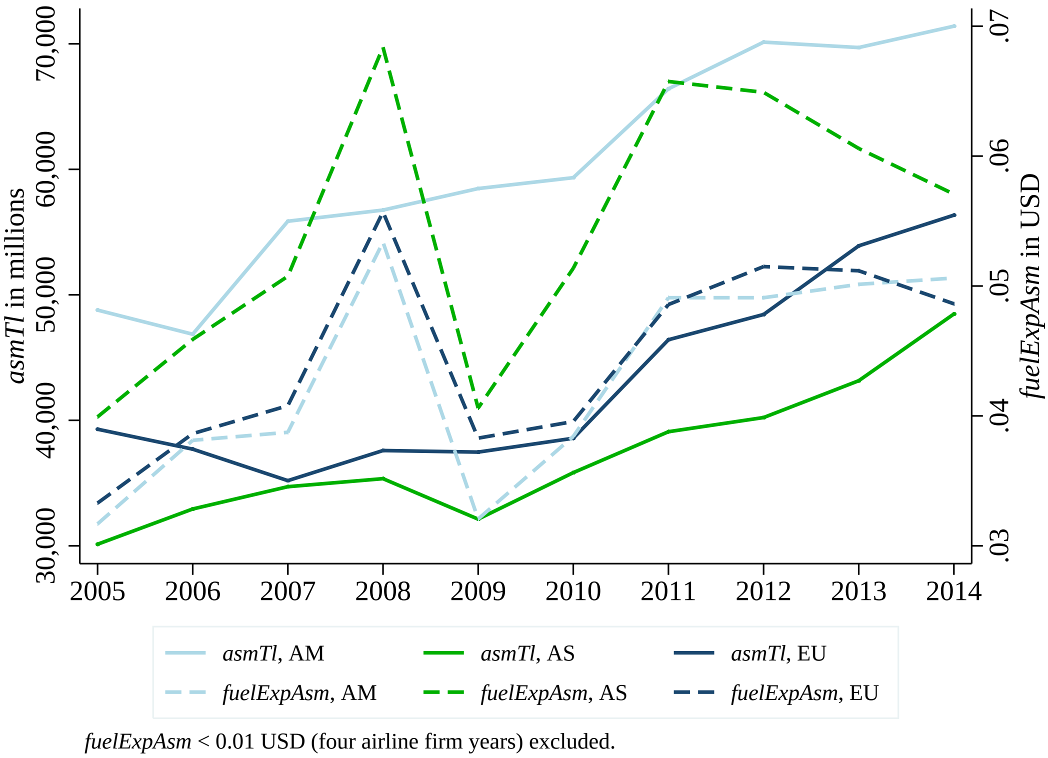
Figure 4.3: Time series: fuel consumption per ASM (*fuelConsAsm*), divided into NLCs and LCCs



fuelConsAsm < 0.01 USG (six airline firm years) excluded.

When looking at regional differences in Figure 4.4, it becomes apparent that American carriers were the largest airlines in terms of offered seat miles, followed by European and Asian airlines. Due to the demand crises in the global airline industry, the airlines reduced their ASMs in various years. While American and European carriers already lowered their supply between 2005 and 2006 (-4.9% and -4.0%), Asian airlines reduced their offered ASMs between 2008 and 2009 (-9.1%). In addition, European firms cut their ASMs a second year between 2006 and 2007 by 6.7%. The fuel expenses per ASM peaked for all airlines in 2008. Asian fuel expenses per ASM were on average 26.6% higher than American and 22.2% higher than European fuel expenses per ASM. Between 2012 and 2014, American fuel expenses increased by 3.1% to about 0.05 USD per ASM, whereas European and Asian fuel expenses declined by 12.1% and 5.6% in the same period.

Figure 4.4: Time series: total available seat miles (*asmTl*) and fuel expenses per ASM (*fuelExpAsm*), divided into regions



The fuel expenses per USG fuel consumed moved parallel to the yearly average of daily U.S. Gulf Coast jet fuel spot prices (see Figure J.1 in Appendix J). U.S. Gulf Coast jet fuel prices are not always the base for jet fuel orders among international airlines. Hawaiian Holdings (2015, p. 36), for example, stated that about two-thirds of their fuel consumption was based on Singapore jet fuel prices and one-third on U.S. West Coast jet fuel prices. In this analysis, however, U.S. Gulf Coast jet fuel spot prices are used because of easier data access. Another regional fuel price peculiarity exists in India, where fuel expenses are allegedly on average 30% or 40% higher than in other countries (SpiceJet, 2014). The Indian airlines in the sample incurred fuel expenses per USG which were on average 11% higher than those of all other sample airlines.

Similar to Cobbs and Wolf (2004), the actual fuel costs of the U.S. sample airlines[97] are compared to the annual average of daily U.S. Gulf Coast jet fuel spot prices in Figure 4.5. The actual fuel costs are calculated by dividing the fuel expenses (*fuelExp*), which are reported net of hedging gains and losses, by the fuel consumption (*fuelCons*). All

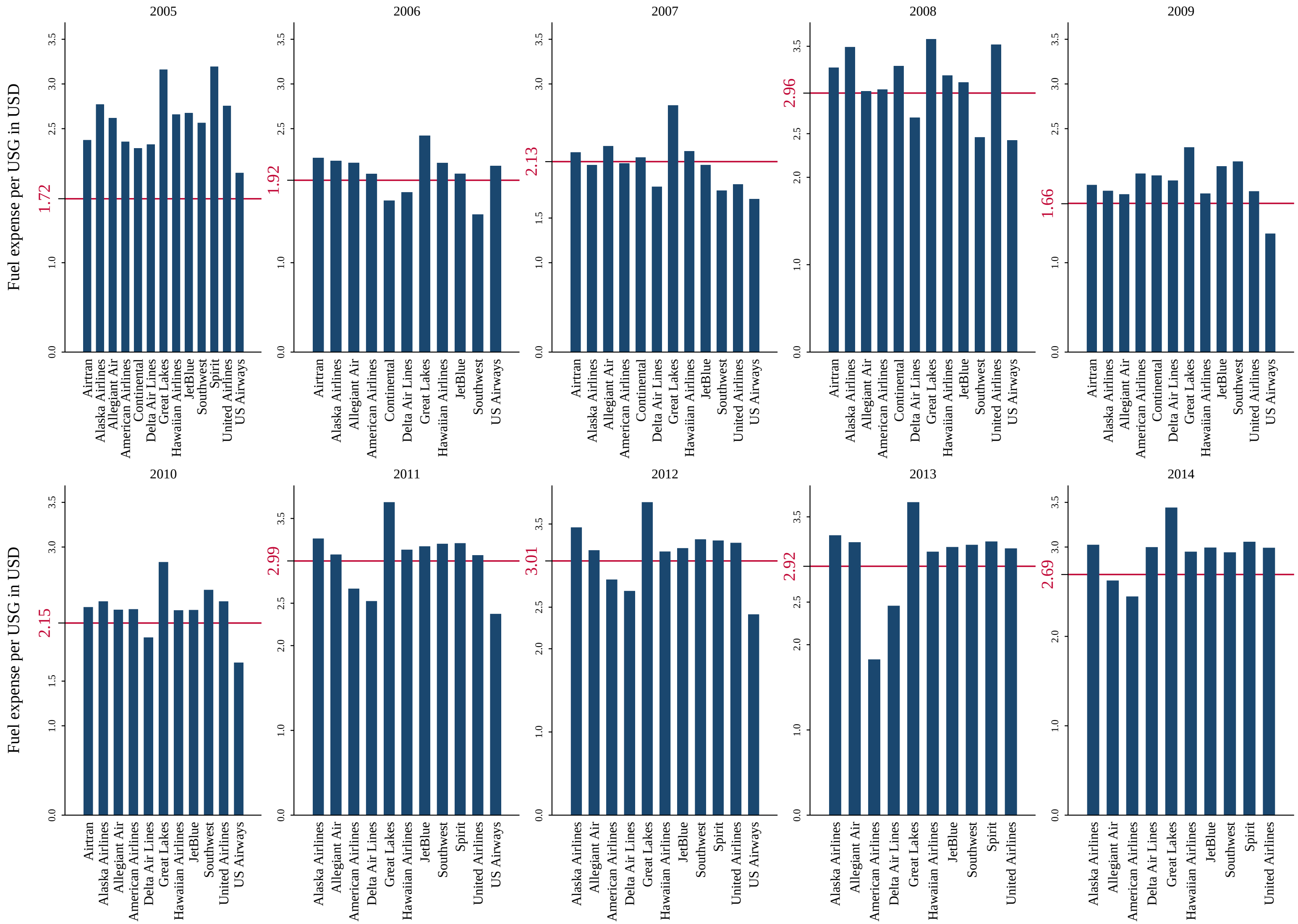
[97]For comparison all sample years of Republic Airways and SkyWest are excluded.

airlines paid a higher fuel price than the jet fuel spot price in 2005. In the following years, four (2006), seven (2007), three (2008), one (2009), two (2010), three (2011), three (2012), two (2013), and two airlines (2014) experienced lower fuel prices per USG fuel consumed than the jet fuel spot price. American Airlines was successful in reducing its fuel expenses below spot prices in five years. A likely explanation for the relatively low fuel expenses per USG for American Airlines are the hedging gains from fuel price derivatives. The airline was able to report an average fuel hedging gain of the sum of the ineffective and reclassified portion (*fdvPLsum*) of 23.4 million USD during the sample period. Eight other U.S. carriers reported average hedging losses of the ineffective and reclassified portion (*fdvPLsum*) during the sample period. Only Southwest was more successful in hedging its fuel price risk with an average *fdvPLsum* of 292.0 million USD, yet its hedging gains were more volatile.

Performance-related items are considered next. Figure 4.6 depicts the revenue earned per available seat mile (*rasm*). As expected from the business model, LCCs had the lowest *rasm* values in all sample years. European carriers were able to earn the highest revenues in all sample years. The overall increase for all sample airlines in *rasm* between 2005 and 2014 was 16.2%. The highest increment in the sample period could be seen among American airlines with 30.8%, followed by NLCs (17.2%), Asian airlines (15.2%), low-cost carriers (14.0%), and lastly European carriers (3.5%). All airlines suffered from 15.5% lower *rasm* values in 2009 compered to 2008: Asian firms -19.1%, NLCs -17.0%, European airlines -14.5%, American operators -11.9%, and LCCs -6.4%.

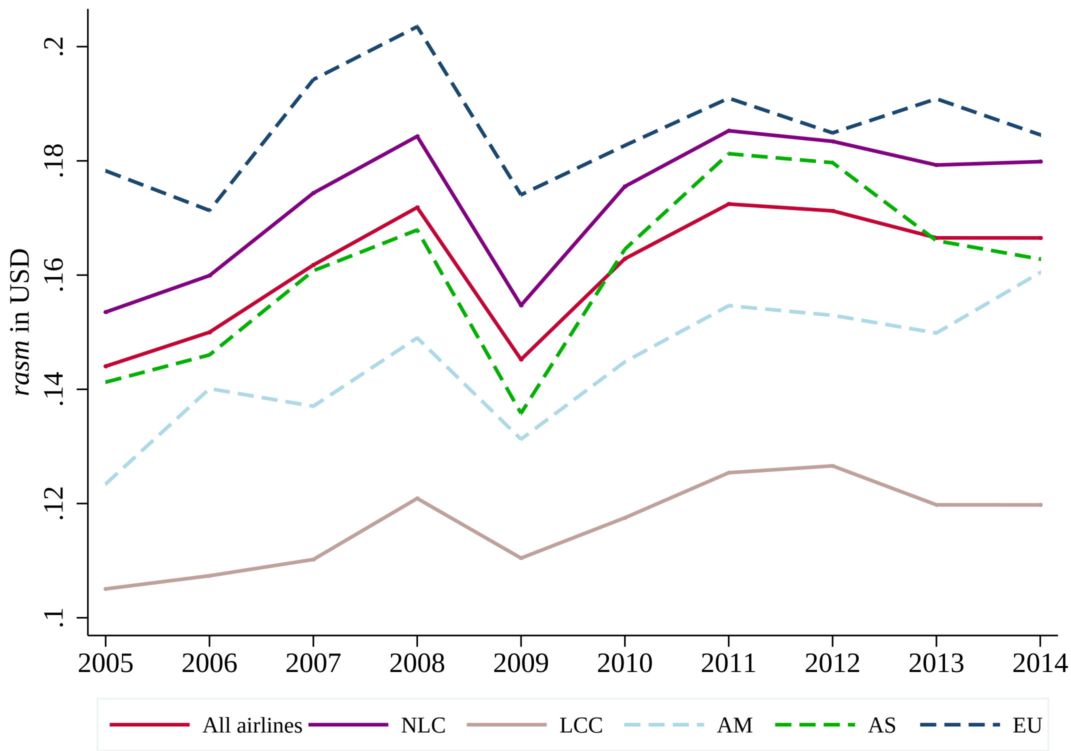
The revenue per available seat mile (*rasm*) can be increased by either higher revenues or by reducing the available seat miles. As could be seen from Figure 4.4, airlines increased their average available seat miles in the sample period. Therefore, revenues are looked at in more detail to explain the trend in *rasm*. Revenues can be raised by optimizing load factors or by increasing the yield, i.e. the revenue per revenue passenger mile (*rrpm*). Figure 4.7 shows how the load factors and *rrpm* evolved over time. Better use of existing capacities in the market becomes apparent when analyzing the load factors in the sample. Overall load factors rose by 6.0% in the sample period, with American operators being the highest driver of the average load factor with an increase of 8.2 percentage points. Asian airlines, on the other hand, could improve their load factors by 4.8 percentage points only. Network, low-cost and European carriers' load factors increased similarly by 6.0, 6.1 and 6.4 percentage points between 2005 and 2014. The comparison of trends between load factors and the yield (*rrpm*) is quite revealing. Most often, airlines operating in markets with overcapacities manage to increase their load factors by reducing ticket prices and by that the revenue incurred per transported

Figure 4.5: Time series: actual fuel expenses per USG (net of hedging gains and losses) for U.S. airlines (excluding Republic Airways and SkyWest) compared to the annual average of daily U.S. Gulf Coast jet fuel spot prices (red line) between 2005 and 2014



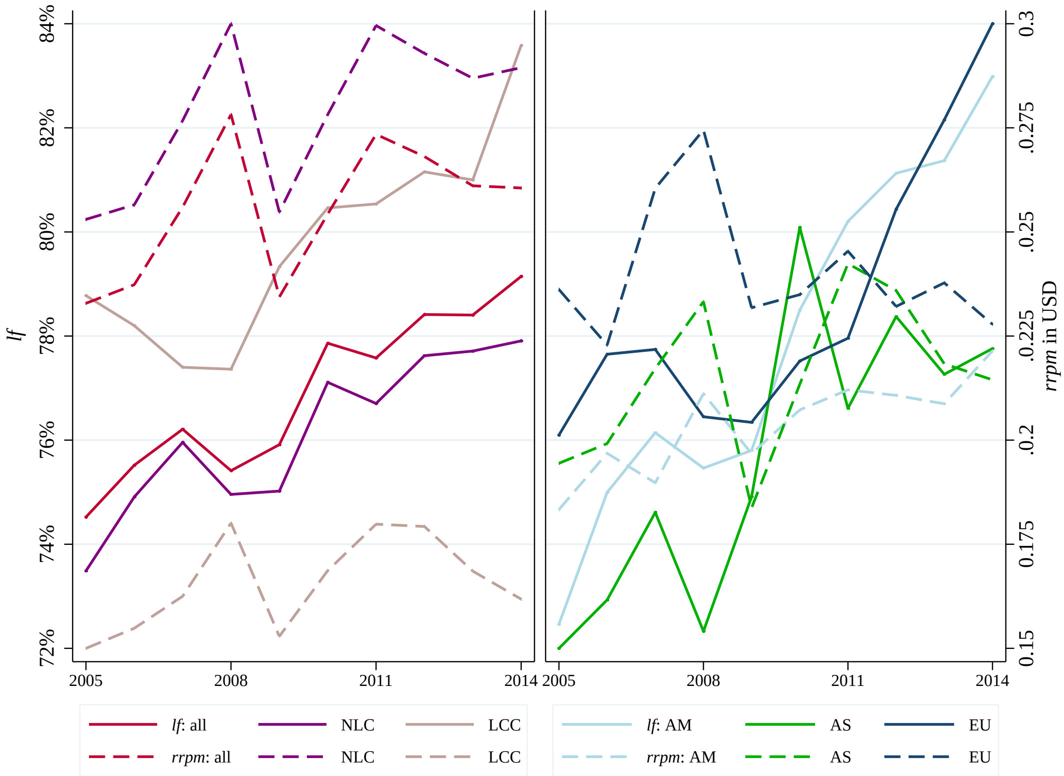
passenger. In the European airline market, *rrpm* dropped over the sample period by 3.5%. In contrast, all other subgroups could boost *rrpm* while even increasing utilization: American airlines by 22.7%, NLCs by 13.4%, Asian airlines by 10.3%, and low-cost airlines by 7.0%. The correlation factors between the annual average load factors and *rrpm* were 0.47 for all airlines, 0.83 for American carriers, 0.63 for legacy airlines, 0.32 for Asian airlines, 0.11 for LCCs, and -0.36 for European airlines. This trend speaks for existing overcapacities in the European airlines market.

Figure 4.6: Time series: total revenues per available seat mile (*rasm*), annual average of all airlines and divided into NLCs, LCCs and regions



In the following section, underlying assets, hedge instruments, hedge ratios, and hedge maturities are analyzed. On average across all sample years, airlines in the sample period (those that disclosed the type of instruments used) held 33% options, 33% swaps, 19% collars, 6% forwards, 6% spreads, and 3% futures. Figure 4.8 shows the trend over the 10 sample years. Options and collars were used 14% and 11% less in 2014 compared to 2005. Swap usage increased by 37% in the sample period. In terms of underlying assets the usage was on average across all sample years 40% jet fuel, 39% crude oil, 13%

Figure 4.7: Time series: load factor (*lf*) and total revenues per RPM (*rrpm*), annual average of all airlines and divided into NLCs, LCCs and regions

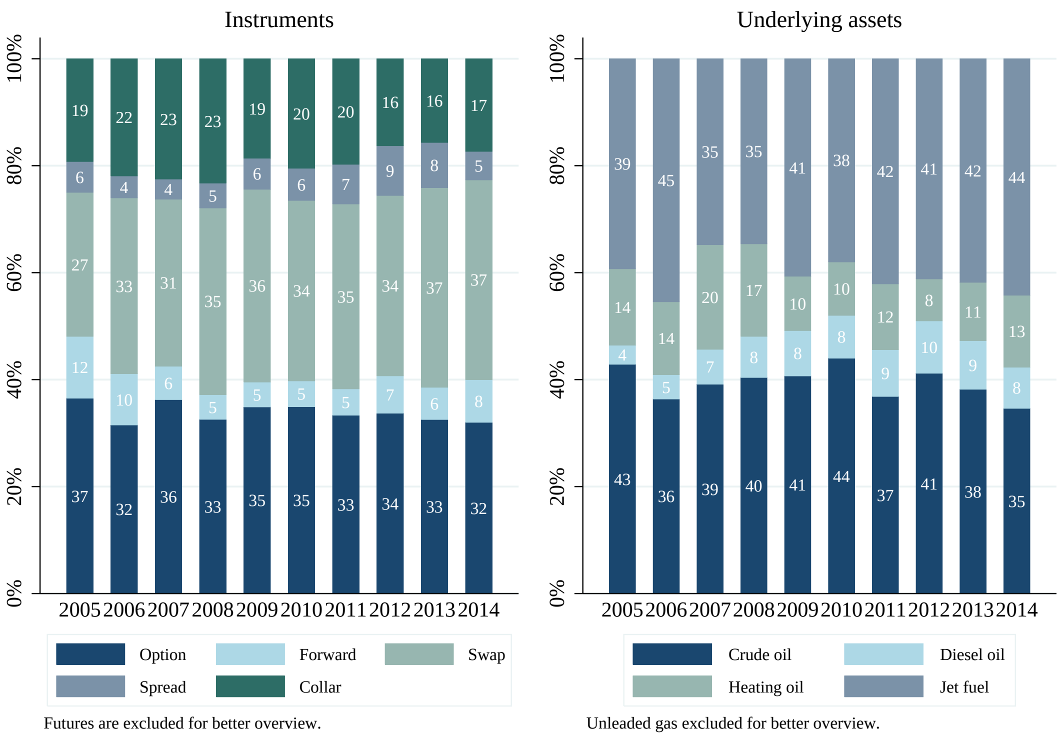


heating oil, 8% diesel oil, and 1% unleaded gas. In Figure 4.8 the decline in crude oil (-19%) and heating oil usage (-7%) can be seen over the sample period. Jet fuel as the underlying asset rose by 13% and the usage of diesel oil doubled.

Table 4.18 displays the usage of instruments and underlying assets per region. Options were the most widely used instrument in Africa (58%), America (35%) and Oceania (45%), whereas Asian (40%) and European carriers (34%) preferred to use swaps. Collars were most often part of American (25%) and Asian (19%) portfolios. Customized forward contracts were popular among European airlines (13%). In contrast to the results by Bodnar et al. (2011, p. 29), futures were not traded often by airlines. Among commodity risk management users in Bodnar et al.'s study, 34% of the companies used futures and 34% fixed pricing contracts.

It must be noted that while missing values of hedge instruments are almost zero in all regions, the information available on the underlying assets is quite scarce. Therefore, the description of the hedge portfolio instruments and underlying assets should serve as an informative overview only and will not be used in the regression analysis. The 100%

Figure 4.8: Time series: hedge portfolio instruments and underlying assets (the labels shown in the bars represent the percentages of each instrument and underlying asset)



crude oil underlying asset for African airlines, for example, arises from one firm-year observation by Kenya Airways. Kenya Aiways did not report which underlying assets they used in the other years of analysis. The second African carrier, Comair, did not use derivatives at all. Nevertheless, some interesting information can be drawn from Table 4.18: crude oil was the most commonly used underlying asset in America (43%) and Oceania (45%), whereas Asian (49%) and European (62%) companies preferred jet fuel as the underlying asset. Heating oil was merely employed by American airlines (26%)[98] and diesel oil (which is equivalent to gasoil) mainly by European (17%) and Oceanian operators (18%).

Section 2.1 explained basis risk as well as price source risk. Although in most cases the sample airlines did not display which type of crude oil, i.e. WTI or Brent crude oil, they used as the underlying asset, Southwest Airlines (2015, p. 68) pointed out that due

[98]In the U.S., heating oil contracts have been based on“ ultra-low sulfur diesel” since 2013 (EIA, 2013).

to the divergence in WTI and Brent crude oil prices from jet fuel prices it switched from WTI to Brent. The statement by Southwest confirms that price source risk is present in the airline industry:

Table 4.18: Cross-sectional: usage of hedge underlying assets and instruments per region

	Africa	**America**	**Asia**	**Europe**	**Oceania**
Instruments					
Options	58%	35%	33%	25%	45%
Swaps	33%	27%	40%	34%	38%
Collars	8%	25%	19%	13%	10%
Forwards	0%	2%	5%	13%	5%
Spreads	0%	7%	1%	9%	2%
Futures	0%	3%	0%	5%	0%
Missing values	*0.00%*	*0.01%*	*0.08%*	*0.06%*	*0.00%*
Underlying					
Jet Fuel	0%	25%	49%	62%	37%
Crude oil	100%	43%	47%	22%	45%
Heating oil	0%	26%	0%	0%	0%
Diesel oil	0%	3%	3%	17%	18%
Unleaded gas	0%	3%	0%	0%	0%
Missing values	*36.84%*	*0.02%*	*27.12%*	*32.68%*	*30.77%*

> "The Company is also subject to the risk that the fuel derivatives it uses to hedge against fuel price volatility do not provide adequate protection. A portion of the fuel derivatives in the Company's hedge portfolio are based on the market price of West Texas intermediate crude oil ("WTI"). The Company can no longer demonstrate that derivatives based on WTI crude oil prices will result in effective hedges on a prospective basis. As such, the change in fair value of all of the Company's derivatives based in WTI are recorded directly to earnings. In recent years, jet fuel prices have been more closely correlated with changes in the price of Brent crude oil (Brent). The Company has attempted to mitigate some of this risk by entering into more fuel hedges based on Brent crude."

Figure 4.9 shows the mentioned divergence in price sources. The monthly correlation between daily WTI crude oil an jet fuel spot prices was on average 0.73 in the sample period and 0.76 for Brent crude oil prices. From 2005 until 2009, the correlation between WTI crude oil and jet fuel (0.73) was 2.8% higher than that of Brent crude oil and jet fuel (0.71). However, after mid 2009 the correlation between WTI crude oil and jet fuel spot prices decreased strongly, supporting the quote by Southwest Airlines. The average correlation of WTI crude oil with jet fuel spot prices decreased by 2.1% to 0.72 between 2010 and 2014, whereas the average correlation in the same period of Brent crude oil increased by 11.5% to 0.80. The minimum correlation value between WTI and jet fuel prices of -0.43 occurred in March 2013 and the maximum value of 0.99 in January 2010. The lowest correlation (-0.28) between Brent crude oil and jet fuel prices could be observed in September 2008 and the highest correlation (0.98) in October 2010.

Figure 4.9: Monthly correlation between daily U.S. Gulf Coast jet fuel, Brent crude oil and WTI crude oil spot prices: displayed for the entire sample period (2005-2014) as well as for the periods 2005-2009 and 2010-2014 separately
Data: EIA (2017).

Apart from studying the airlines' underlying assets and instruments, the hedge ratio and the hedge maturity are analyzed. Figure 4.10 presents the difference in hedge ratios between legacy and low-cost carriers. The figure differentiates between all airlines (left side) and hedgers only (right side). Moreover, the annual standard deviation of the hedge ratios for each subgroup is shown on the second y-axis. It is a measure of how heterogeneously airlines hedged in the period of analysis. While in 2005 and 2006 the hedge ratios of LCCs exceeded the hedge ratios of NLCs by 37.1% and 47.6%, low-cost airlines had lower hedge ratios in the sample years between 2007 and 2014, regardless of whether analyzing all airlines or hedgers separately. The annual standard deviation, however, was higher for all LCCs in seven sample years, speaking for large hedge outliers among low-cost airlines. The graph on the right side underlines the variability in hedge ratios among LCCs because for hedgers the standard deviation of low-cost airlines was higher than that of legacy airlines in nine out of 10 sample years. The standard deviation peaked at 0.37 in 2005 for all LCCs and at 0.40 in 2012 for derivative using LCCs.

Figure 4.10: Time series: hedge ratios (*fdvPct12m*), annual average of all airlines and annual average for hedgers only, divided into NLCs and LCCs

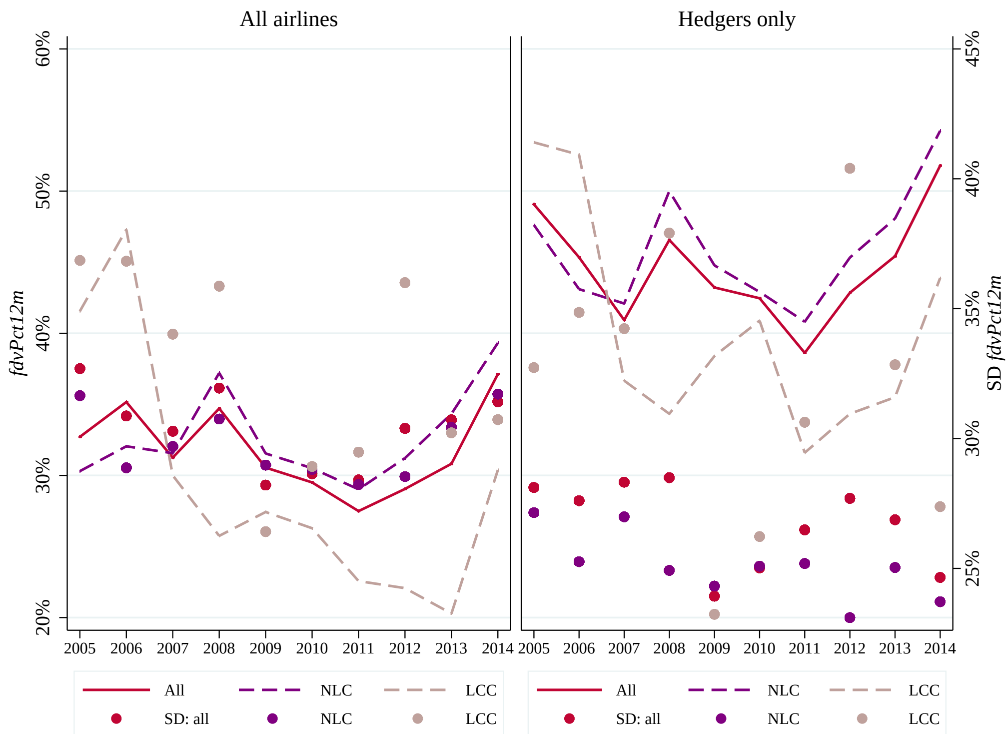


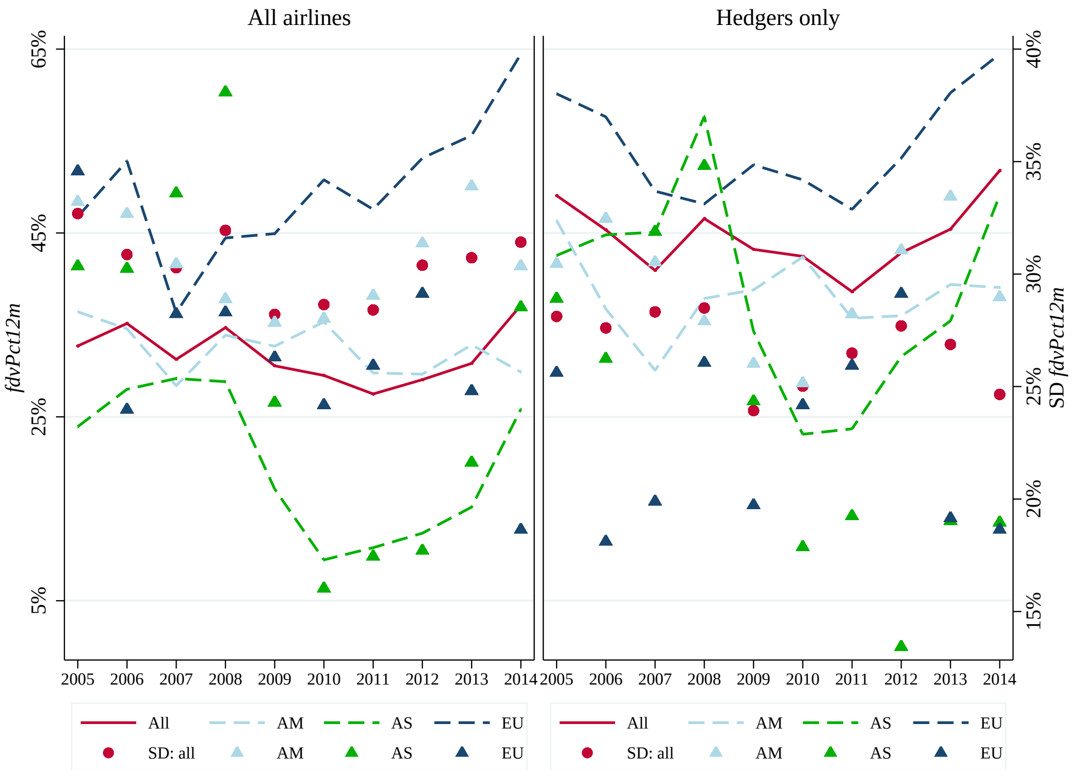
Figure 4.11 displays the hedge ratios of all airlines across the sample years as well as separately for the regions. On the left side, all airlines are displayed and on the right side only firms whose hedge ratios exceeded zero. The graph on all airlines is described first. On average across all airlines, the hedge ratios remained quite stable

around 35%, starting at 32.0% in 2005 and ending at 37.1% in 2014, which is an increase of 16.2%. The annual standard deviation varied between 0.28 and 0.33. Airlines from the Americas decreased their hedge portfolios by 12.1% from 34.0% to 30.0%. The standard deviation range was between 0.28 and 0.34. Asian airlines hedged the least of all sample airlines, less than the average airline in all sample years. Between 2008 and 2010, the Asian hedge ratios plummeted from 28.8% to 9.5%, a decrease of 67.2%. In the following three periods, the hedge ratios remained at low levels before recovering to 25.8% in 2014. Overall, Asian airlines increased their hedge ratios by 8.0% in the sample period with the largest standard deviation range between 0.16 and 0.38. As fuel prices in China "are regulated by the National Development and Reform Commission, CAAC and other government regulatory agencies" (Hainan Airlines, 2012, p. 127), Chinese airlines hedged only 4.6% of their expected fuel consumption, contributing to the low Asian hedge ratios. European carriers exhibited the highest hedge ratios among the three regions in all sample years. Besides a 31.2% drop in hedge ratios from 52.8% in 2006 to 36.3% in 2007 and a minor drop of 6.3% between 2010 and 2011, European airlines increased their hedge ratios in all sample years. Between 2005 and 2014, European carriers raised their hedge percentages by 37.8% from 46.8% to 64.5%. The standard deviation was highest in 2005 with 0.35 and lowest in 2014 with 0.19. Russian airlines did not use any derivatives until 2009 due to the lack of an acceptable hedging market for fuel prices in Russia (UTair, 2009, p. 46). The second Russian sample airline, Aeroflot, started financial fuel hedging by trading derivative contracts OTC with a Russian bank in 2010 (Aeroflot, 2011).

The graph on the right side of Figure 4.11 depicts fuel hedging airlines only. Naturally, all hedge ratios are larger than those of the entire sample. The relatively high standard deviation in hedge ratios of all Asian airlines becomes apparent in the graph when looking at the hedge ratio in 2008. In this sample year, Asian hedge ratios surpassed those of European airlines, underlining the notion that a few, hedging airlines were the driver for the large standard deviation. Due to production (Moschini and Lapan, 1995) or quantity uncertainty (Brown, 2001), firms do not know exactly how many derivative contracts they should enter. The results of the current study support this theory as airlines did not hedge 100% of their expected fuel consumption but rather a fraction of it. Hedgers in the highest percentile hedged on average 85.5% of their expected fuel consumption for the following 12 months.

The fuel price hedge maturities of all hedgers in the sample, divided into regions as well as network and low-cost carriers, can be found in Figure 4.12. The hedge maturities of American operators and low-cost carriers fluctuated between 2005 and 2012 before

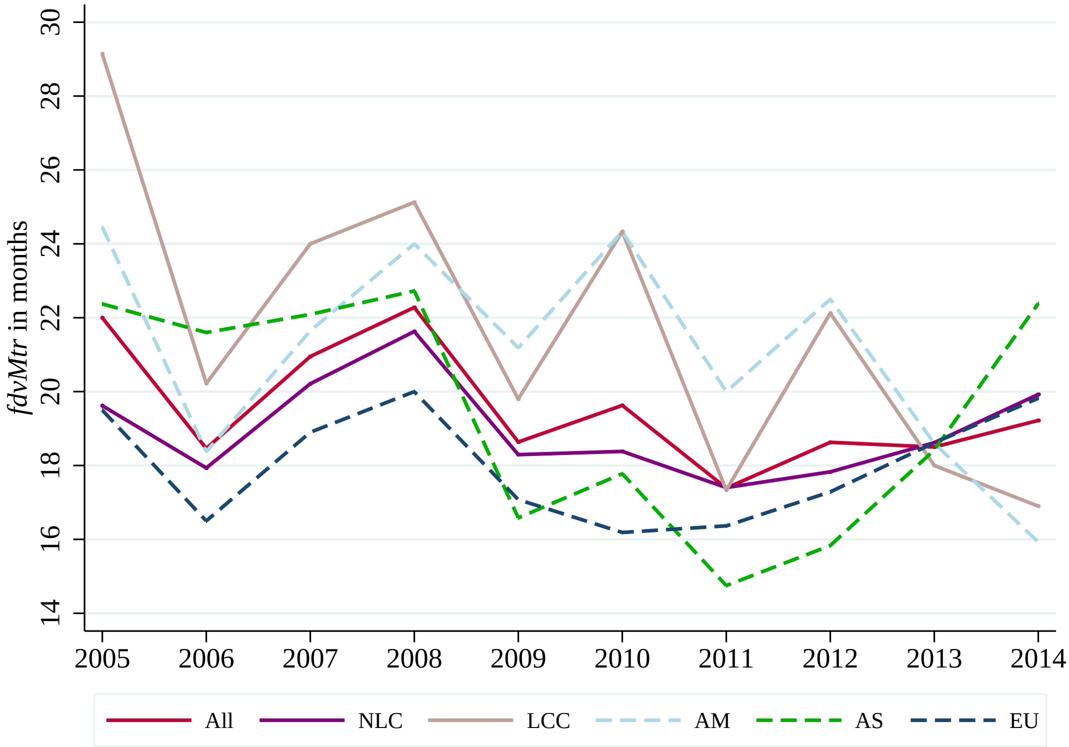
Figure 4.11: Time series: hedge ratios (*fdvPct12m*), annual average of all airlines and annual average for hedgers only, divided into regions



they fell for two periods in a row. Almost all airline groups decreased their hedge maturities in the sample period, contradicting the results by Carter et al. (2006). The airlines' hedge maturities fell by 12.6% from 22.0 months to 19.2 months on average. LCCs reduced their maturities the most by 42.0% from 29.1 to 16.9 months, followed by American carriers whose maturities dropped by 34.9% from 24.5 to 15.9 months. The reduction in portfolio maturities of LCCs and American operators was mainly influenced by the portfolio maturity of Southwest. The airline had the longest maturity in eight sample years. In 2006, Southwest had fuel contracts outstanding with a maturity of 72 months. It reduced the maturity incrementally over the sample period to 36 months in 2014. All airlines lowered the average hedge maturity between 2005 and 2006, as well as between 2008 and 2009, the sample years with the highest standard deviation in jet fuel prices (see Section 2.1). The hedge maturity of Asian, European and legacy airlines recovered to the levels of 2005 in 2014.

Figure 4.13 confirms the statement that airlines reduced their hedge maturities in recent years. The graph shows the hedge ratios of all hedging airlines for the next 12, 24,

Figure 4.12: Time series: hedge maturities (*fdvMtr*), annual average of all airlines and divided into NLCs, LCCs and regions



36, and 48 months. While the percentage hedged of the next 12 months fuel consumption slightly increased by 5.5% from 49.1% to 51.8% in the sample period, longer hedge ratios decreased between 2005 and 2014: 24 months hedge ratios by 35.7% from 19.2% to 12.4%, 36 months hedge ratios by 66.7% from 4.7% to 1.6%, and 48 months hedge ratios by 85.3% from 3.6% to 0.5%.

4.2.2 Financial distress

Researchers often employ proxies such as debt ratios or dividend payout data to estimate a firm's likelihood to enter financial distress (see Subsection 4.1.2). Forty-nine airline firm years (7.9% of the sample) were in actual financial distress because they exhibited negative total equity values. Moreover, five of the 15 U.S. carriers were under Chapter 11 in the sample period. Delta Air Lines, for example, encountered Chapter 11 between

Figure 4.13: Time series: percentages of next 12 (*fdvPct12m*), 24 (*fdvPct24m*), 36 (*fdvPct36m*), and 48 months (*fdvPct48m*) fuel consumption hedged, annual average of all hedgers

2005 and 2007 during which period its share was "traded on the Pink Sheets Electronic Quotation Service" (Delta Air Lines, 2009, p. 25). The average duration of the U.S. bankruptcy cases was two years.[99,100]

In Figure 4.14 the number of airlines with negative book equity values are presented on the left side and the hedge ratios of those airlines on the right side.[101] In 2005 and 2006, mostly American carriers had negative equity, matching the mentioned Chapter 11 periods. 2007 was the only sample year with purely positive figures. After 2007, the number of American and Asian airlines with negative book equity values remained stable between one and three airlines. European and low-cost carriers had only one

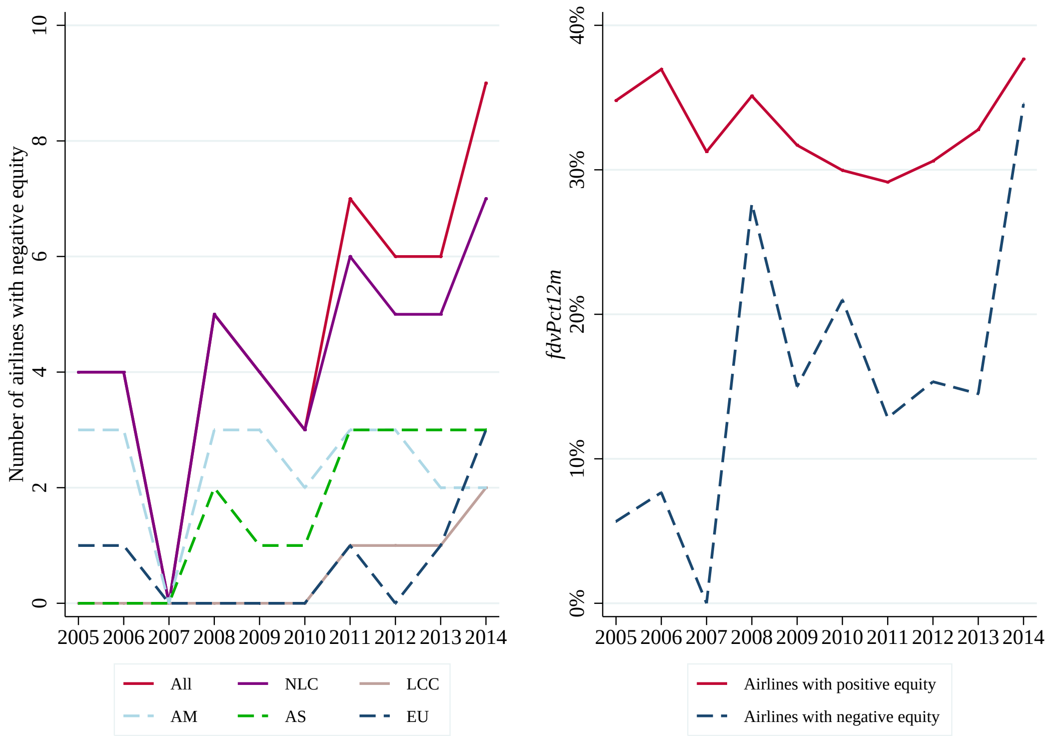
[99] American Airlines was in administration between 29th November 2011 and 21st October 2013, Delta Air Lines between 14th September 2005 and 30th April 2007, Hawaiian Airlines between 21st March 2003 and 11th March 2005, United Airlines between 9th December 2002 and 1st February 2006, and US Airways between 12th September 2004 and 27th September 2005.

[100] In contrast, Warner (1977) reports an average bankruptcy process length of 13 years among U.S. railroad companies between 1933 and 1955. The varying lengths underline the difficulty in comparing bankruptcy cases from different time periods and industries.

[101] The African airline Kenya Airways is excluded from the figure. Its book value was below zero in 2014.

airline per year between 2005 and 2013 with equity lower than zero. Between 2013 and 2014, however, the number increased to three (out of 14) European and two (out of 14) low-cost airlines. The relatively large number of legacy carriers with negative equity firm years results from the large number of NLCs firm years in the sample (496 out of 621). In all 10 sample years, the hedge ratios of negative equity airlines were lower than the hedge percentage of airlines with positive equity values. Interestingly, the hedge ratios of both groups nearly converged in 2014 with a difference of three percentage points, although theory suggests that firms in financial distress may not be able to hold derivative contracts because of margin call requirements.

Figure 4.14: Time series: the number of airlines with negative book equity values and the corresponding hedge ratios (*fdvPct12m*), annual average of all airlines and divided into NLCs, LCCs and regions



Similar to previous research, sample leverage ratios are reflected on. Debt ratio 1 (*lvrg1*), which is *ibd* scaled by total assets (*asTl*), is depicted in Figure 4.15, unadjusted on the left side and lease-adjusted (with the discount method by Damodaran (2002)) on the right side. The average (unadjusted) debt ratios 1 of all sample airlines remained stable between 2005 and 2014 with a slight plus of 0.7%. Within the sample period, debt ratios fell by 6.6% between 2006 and 2007 before rising by 12.0% from 2007 to 2008. The debt ratios stayed high in 2009 and fell by 7.6% thereafter. Due to the high number of network legacy airlines in the sample, their debt ratios moved similarly to those of the entire sample. However, the debt ratios of NLCs decreased between 2005 and 2014 by 6.5%. Low-cost airlines had 48.4% higher leverage ratios in 2014 compared to 2005. Between 2005 and 2006, low-cost airlines' debt ratios increased by 22.1% and by 13.4% between 2010 and 2011. When the leverage ratio 1 is adjusted by operating lease expenses, the rise in *lvrg1* of LCCs in the sample period is reduced to 12.8%. American carriers managed to lower their unadjusted debt ratios by 22.6% from the highest level of 0.46 in 2008 to 0.35 in 2014. Asian carriers exhibited the highest unadjusted leverage ratios in all sample years and European airlines the lowest adjusted ratios. While Asian airlines increased their unadjusted leverage ratio 1 by 1.5% between 2005 and 2014, the ratio of European airlines grew the most by 16.8%. From the right side of Figure 4.15 it becomes obvious that all airline groups made use of operating leasing since all debt ratios are inflated when adjusted by operating lease expenses. Therefore, Figure 4.35 is included in Subsection 4.2.7 to show graphically how the PV of operating lease expenses evolved in the period of analysis.

In contrast to debt ratio 1 (*lvrg1*), debt ratio 2 (*lvrg2*) is calculated as long-term liabilities (*liaLt*) divided by total assets (*asTl*). It can be seen in Figure 4.16 that, according to those calculations, American airlines (instead of Asian carriers) were the airline group with the highest leverage ratios although they reduced their adjusted leverage ratios 2 by 18.0% in the sample period. Further reductions of 7.4% could be seen among NLCs. Asian, European and low-cost carriers, on the other hand, increased their adjusted debt ratios by 3.0%, 4.4% and 9.9%. As Asian airlines' debt ratios 1 were larger than the debt ratios 2 in all sample years, the majority of Asian *ibd* contained short-term debt contracts. Figure 4.17 shows that Asian airlines financed their debt with short-term contracts more often than the average sample airline. Only European airlines made use of even more current liabilities. In 2007, European airlines' current liabilities (50.01%) surpassed slightly their long-term liabilities (49.99%).

Figure J.2 in Appendix J depicts changes in the unadjusted (*lvrg3*) and lease-adjusted leverage ratio 3 (*lvrg3Adj1*). *lvrg3* is calculated with total liabilities (*liaTl*) scaled by total assets (*asTl*). Again, American airlines started off with the highest leverage but managed to lower their (unadjusted) leverage significantly by 19.9% in the sample period. As a consequence, American airlines showed the second lowest leverage ratios 3 among all airline groups in 2014. The debt ratios of low-cost, Asian, European, and legacy airlines grew by 38.4%, 16.5%, 11.9%, and 1.4% respectively between 2005 and 2014.

Figure 4.15: Time series: unadjusted leverage ratios 1 (*lvrg1*) and lease-adjusted (*lvrg1Adj1*), annual average of all airlines and divided into NLCs, LCCs and regions

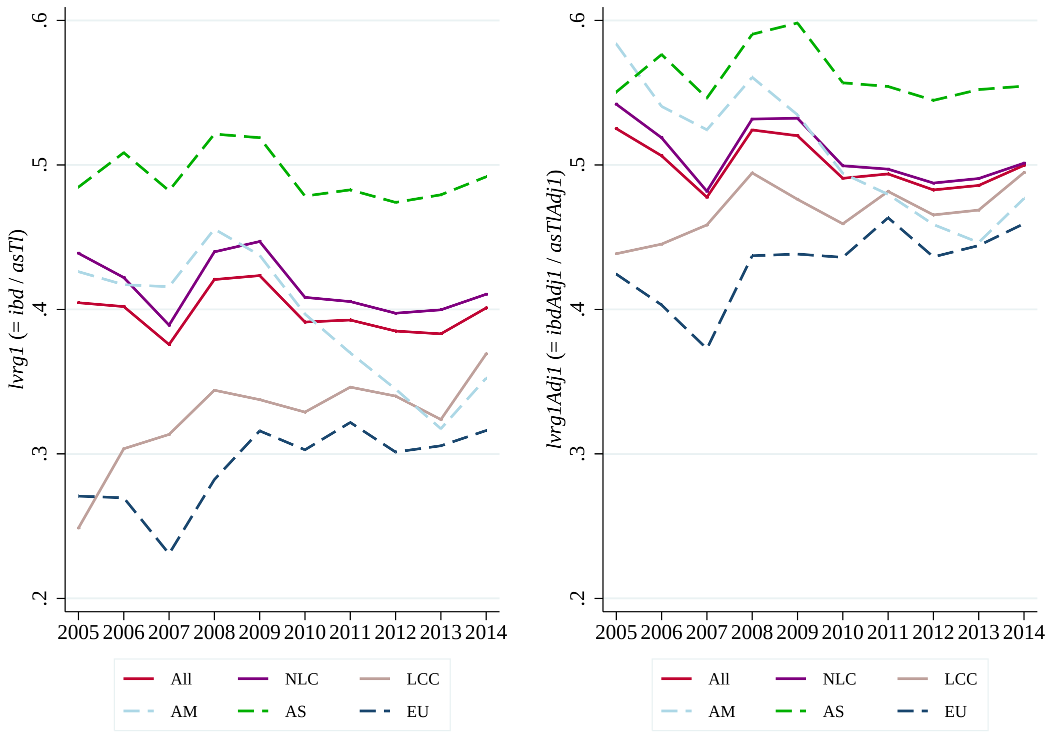


Figure 4.18 presents the lease-adjusted interest coverage ratios. Large outliers influence the unadjusted data and therefore merely values adjusted by operating lease expenses are discussed. Average adjusted interest coverage ratios plummeted in the crisis year 2008 by 64.5% from 1.94 to 0.69.[102] Low-cost airlines were the only subgroup that had interest coverage ratios above one in that sample year of 1.43. The minimum value of 0.18 was reached by Asian airlines in the same year. Besides 2008, European airlines also exhibited ratios below one in 2009 of 0.86. During the sample period, the average airline registered a decline in interest coverage ratios in the years 2008, 2011 and 2013. Overall, interest coverage ratios could be increased by 5.3% between 2005 and 2014. The largest rise was attributable to American carriers (47.2%), followed by low-cost airlines (29.3%) and Asian operators (5.7%). The large rise of American *intCovAdj* values may be attributable to the Chapter 11 proceedings in the beginning of the sample period.

[102]An interest coverage ratio below one means that EBIT did not suffice to cover for interest expenses.

Figure 4.16: Time series: unadjusted leverage ratios 2 (*lvrg2*) and lease-adjusted (*lvrg2Adj1*), annual average of all airlines and divided into NLCs, LCCs and regions

Legacy and European airlines suffered a loss in interest coverage ratios of 5.7% and 1.7%. Low-cost airlines had the highest average interest coverage ratios of 2.47 during the sample period and Asian airlines the lowest of 1.39.

Lease-adjusted profit margins developed less favorably between 2005 and 2014, as can be seen in Figure 4.19. Airlines lost on average 37.1% of their profit margins, from 5.4% in 2005 to 3.4% in 2014. The largest sample average drop of 117.9% in profit margins was again observable between 2007 and 2008 from 7.8% to -1.4%. Similar to the interest coverage ratios, network legacy and European carriers experienced the largest drops (-45.8% and -44.9%) in profit margins between 2005 and 2014. American airlines, on the other hand, could increase their profit margins between 2005 and 2014 by 31.5%, causing them to be the subgroup with the highest profit margins in 2014 of 6.4%. The Chapter 11 proceedings as well as the number of mergers (see Table 4.3) in the U.S. market may have led to the highest regional profit margins. Low-cost airlines exhibited the highest average profit margins of 7.7% in the sample period with a maximum value of 10.9% in 2009. The lowest average profit margins during the sample period were attributable

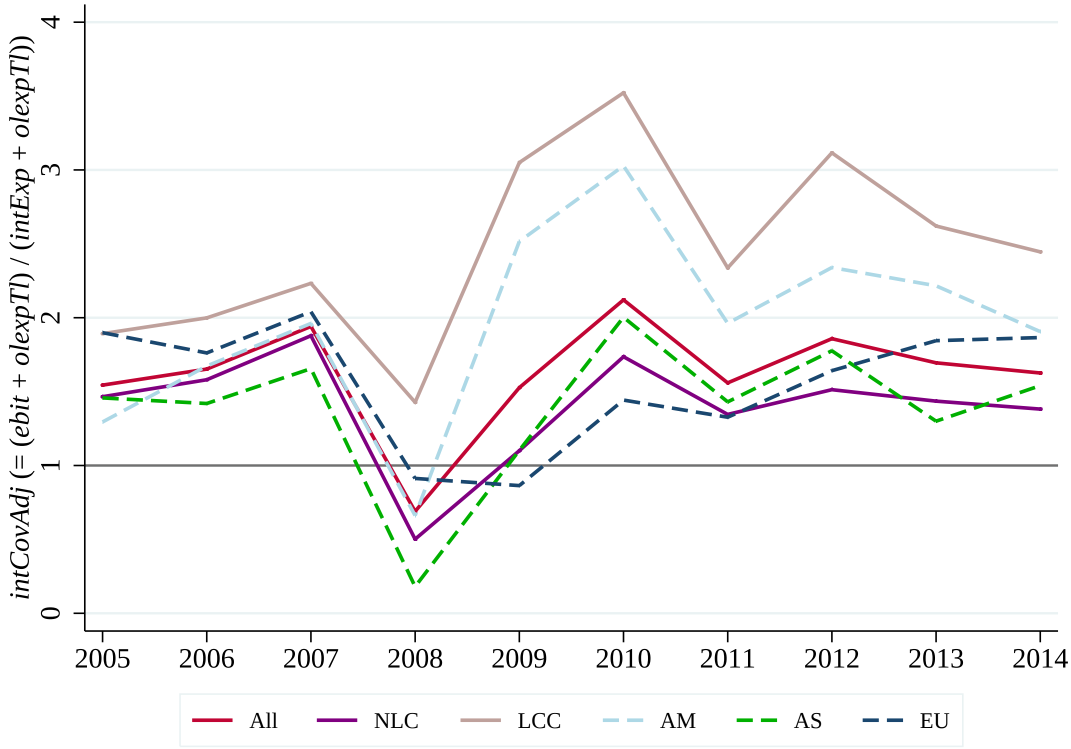
Figure 4.17: Time series: short and long-term debt ratios, annual average of all airlines and divided into NLCs, LCCs and regions

to NLCs (4.3%). In order to show the influence of the kerosene price on airline profit margins, Figure 4.19 contains the yearly average of daily U.S. Gulf Coast jet fuel spot prices (black dotted line). The correlation between those jet fuel prices and adjusted profit margins was -0.18, speaking for a negative impact of fuel prices on profit margins.

It is assumed that the cost of debt increases exponentially with the amount of debt outstanding (Froot et al., 1993). This notion can be derived from the sample as shown in Figure 4.20. The graphs on the left side depict lease-adjusted IBD (*ibdAdj1*) and total liabilities (*liaTlAdj1*) plotted against the cost of debt.[103] The size of the markers reflect an airline's lease-adjusted total assets (*asTlAdj1*). The slope is slightly negative and would thus not confirm the theory that the cost of debt increases with the amount of debt. If one regards the size of the markers in the graph on the left side, however, it becomes apparent that also the size of the firm increases with the amount of leverage. Therefore, in the graphs on the right side, *ibdAdj1* and *liaTlAdj1* are scaled by total

[103] The cost of debt (*costDbt*) is the risk-free rate (*rfRate*) plus an average spread (*spreadAvg*) that is derived from interest coverage ratios.

Figure 4.18: Time series: lease-adjusted interest coverage ratios (*intCovAdj*), annual average of all airlines and divided into NLCs, LCCs and regions



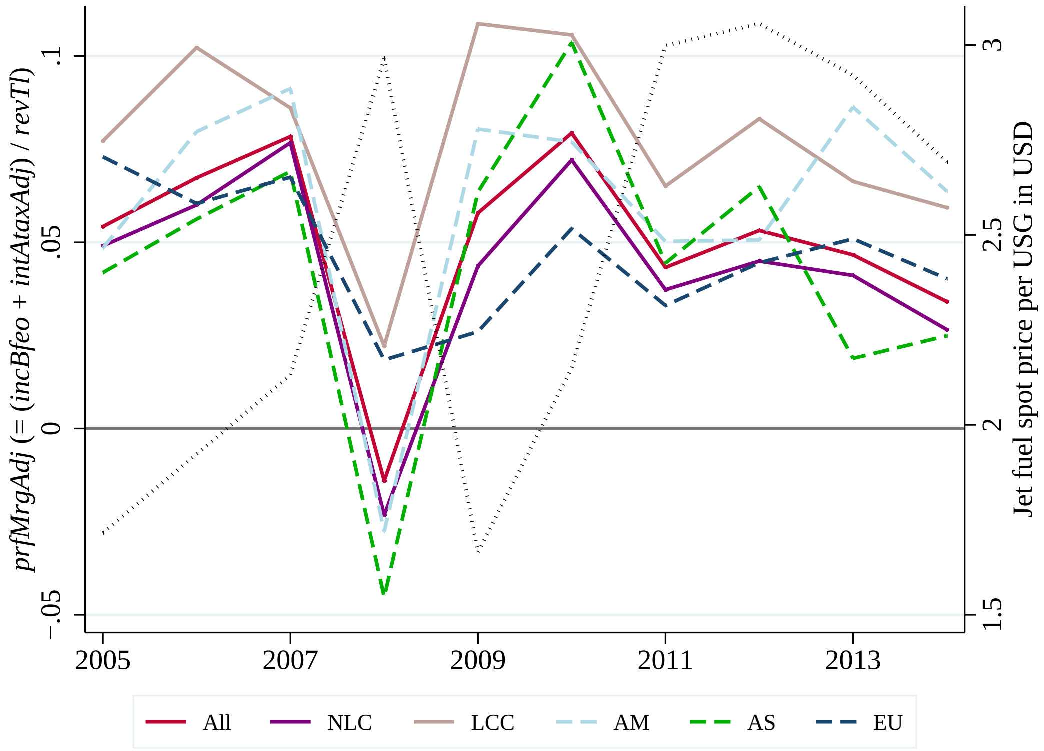
assets (all values are lease-adjusted) which equals the lease-adjusted debt ratios 1 and 3. When the size effect is controlled for, the cost of debt rises with the amount of *ibdAdj1* (slope 0.16) and total liabilities (slope 0.19).

4.2.3 The underinvestment problem

In the current sample, 44 airline firm years showed a MTB ratio (*mtbRto*) smaller than zero.[104] A market-to-book ratio between zero and one means that each dollar that has been invested by shareholders is currently worth less than the invested amount (Brealey et al., 2017). Thus, the MTB ratio could rather be a proxy for financial distress than for investment opportunities (Nguyen and Faff, 2002). In 178 firm years the MTB ratio ranged between zero and one. Consequently, 222 or 35.6% of the sample firm years had lower-than-one market-to-book ratios. Figure 4.21 illustrates the time series of the MTB ratios in the sample period, divided into the subgroups. All airlines lost on average

[104]This number diverges from the number of firm years with negative book equity values because market capitalization figures are missing for seven firm years.

Figure 4.19: Time series: lease-adjusted profit margins (*prfMrgAdj*) and jet fuel spot prices (represented by the dotted line), annual average of all airlines and divided into NLCs, LCCs and regions



27.5% of their market-to-book ratios from 2005 to 2014. The decline was most severe for low-cost carriers (-40.9%), ensued by European (-34.8%), Asian (-28.4%), American (-21.4%), and legacy airlines (-13.1%). European airlines in 2011 and Asian airlines in 2012 were the only airline groups whose market-to-book ratios were lower than one on average (0.66 and 0.74 respectively). Interestingly, the airlines' MTB ratios fell significantly between 2007 and 2008, one year before the global financial crisis (Asian by 74.2%, European by 56.2%, LCCs by 48.7%, and NLCs by 41.1%), except for the ratio of American airlines. Instead, American airlines' market-to-book ratio climbed by 63.6% in the same period before falling slightly in 2009. At the end of the sample period, American shareholders' investment was valued the highest, followed by LCCs, NLCs, Asian, and European investments.

Compared to the MTB ratio, Tobin's Q (*tobQ*) reflects the ratio of a firm's market value to the replacement costs of its assets. Tobin's Q values of less than one indicate that the replacement costs of total assets are worth more than the firm at the market. Selling

Figure 4.20: Cross-sectional: cost of debt (*costDbt*) versus lease-adjusted interest-bearing debt (*ibdAdj1*), lease-adjusted leverage ratio 1 (*lvrg1Adj1*), lease-adjusted total liabilities (*liaTlAdj1*) and lease-adjusted leverage ratio 3 (*lvrg3Adj1*), average across years for each airline (markers weighted by lease-adjusted total assets)

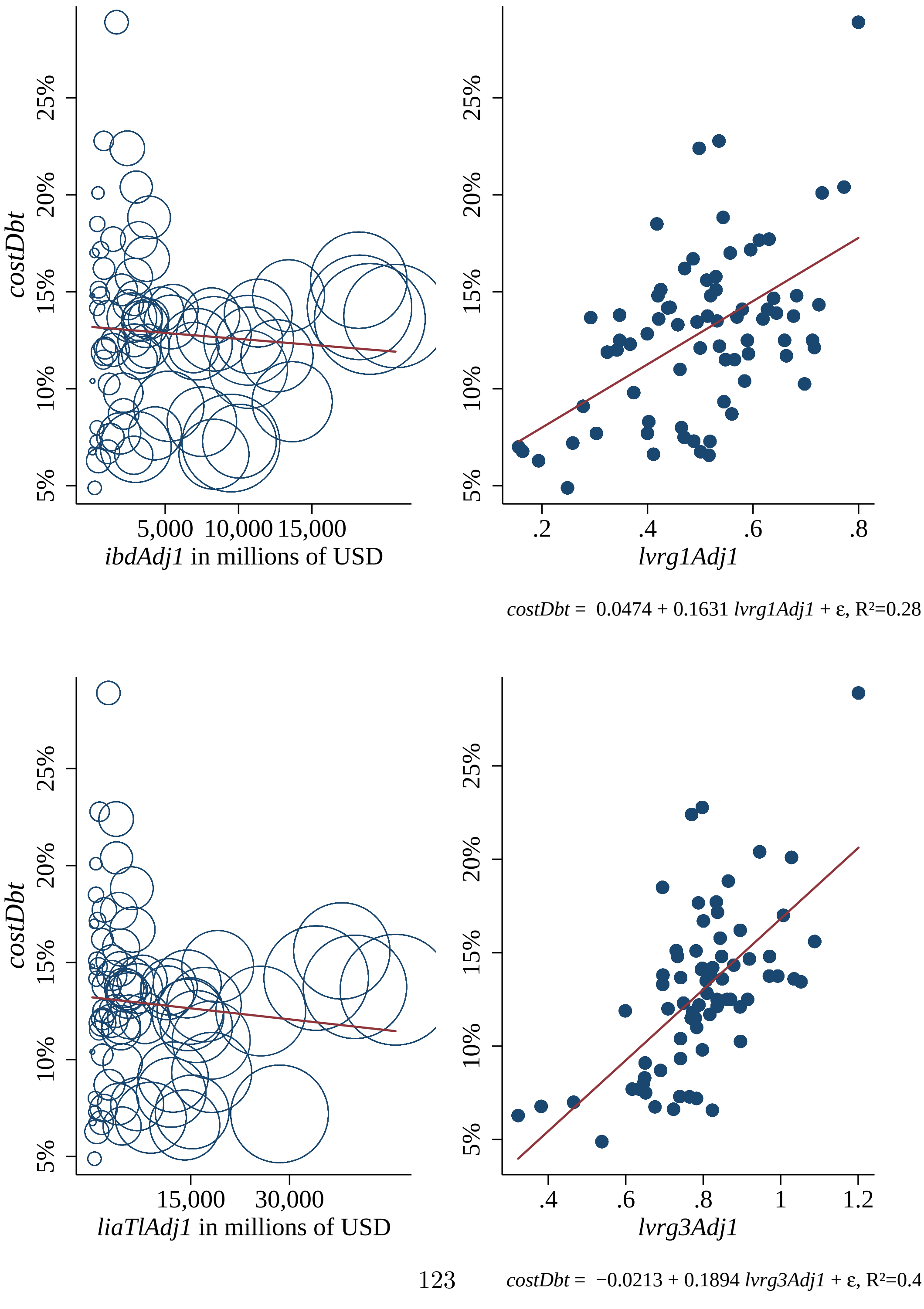
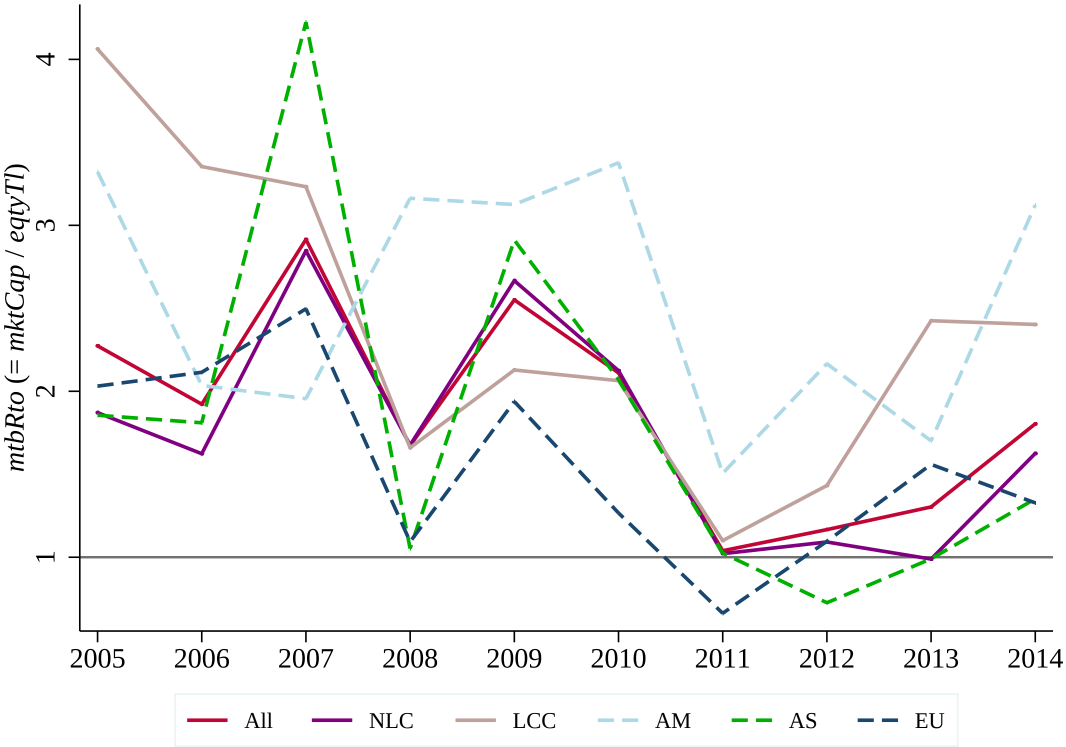


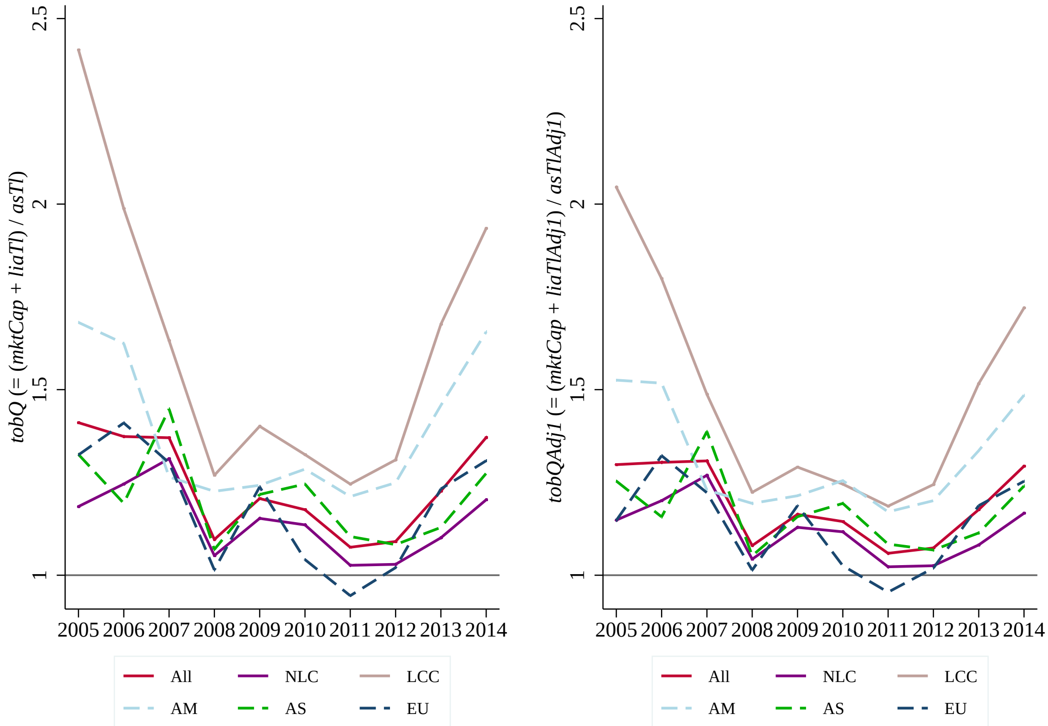
Figure 4.21: Time series: market-to-book ratios (*mtbRto*), annual average of all airlines and divided into NLCs, LCCs and regions



each of the firm's assets would give a greater benefit to shareholders and debtholders than proceeding with the firm's business (Brealey et al., 2017). Airlines had Tobin's Q values lower than one in 178 sample firm years. Averaged across the sample period, 12 airlines exhibited lease-adjusted Tobin's Q values (*tobQAdj1*) between 0.9 and 0.99. Those airlines comprised Air Arabia (0.90), Air France-KLM (0.95), Great Lakes (0.95), Finnair (0.95), SkyWest (0.96), Thai Airways (0.97), Air New Zealand (0.98), Kenya Airways (0.98), Qantas (0.98), El Al (0.99), and Aer Lingus (0.99). As can be seen in Figure 4.22, European airlines were the only group whose average adjusted Tobin's Q values were below one in a sample year (2011) with 0.95. The largest drop in adjusted Tobin's Q values occurred between 2007 and 2008. Airlines lost on average 18.0% of their adjusted Tobin's Q. The decline was spread as follows: Asian airlines -24.1%, NLCs -17.8%, LCCs -17.4%, European airlines -17.1%, and American carriers -5.2%. The adjusted Tobin's Q value of American airlines fell more strongly one year before by 22.6%. The highest adjusted Tobin's Q values were reached by low-cost airlines in 2005

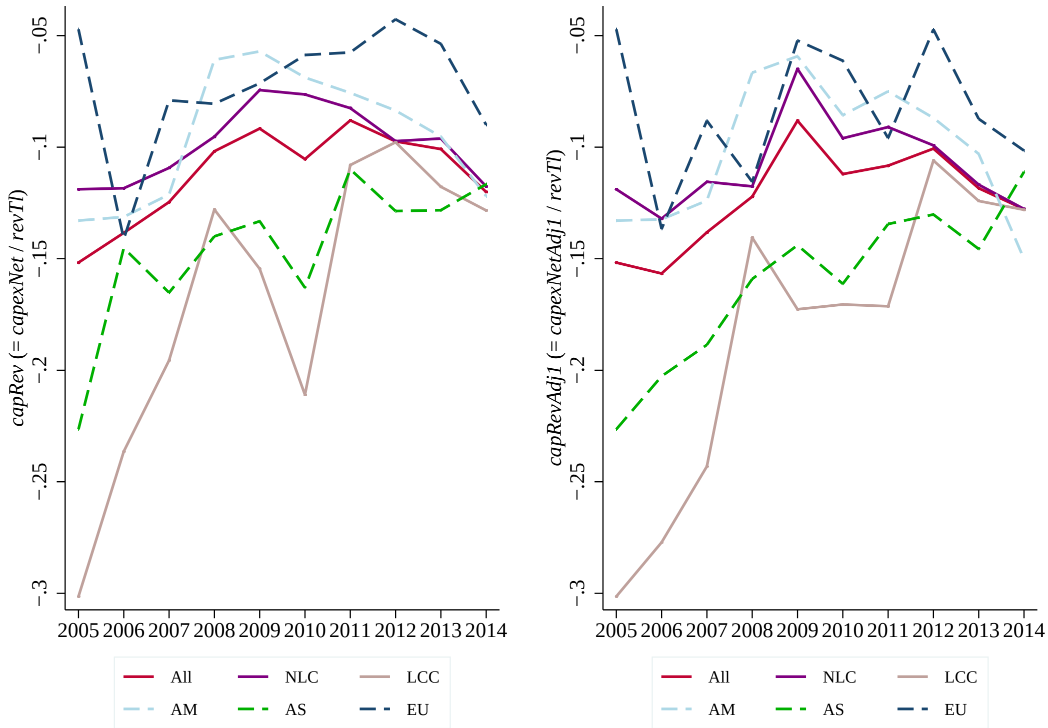
(2.01) and in 2014 (1.72). The overall change in the sample period was a decline of 2.6%. Only European and legacy airlines showed higher (9.2% and 1.6%) adjusted Tobin's Q values in 2014 compared to 2005.

Figure 4.22: Time series: unadjusted Tobin's Q (*tobQ*) and lease-adjusted (*tobQAdj1*), annual average of all airlines and divided into NLCs, LCCs and regions



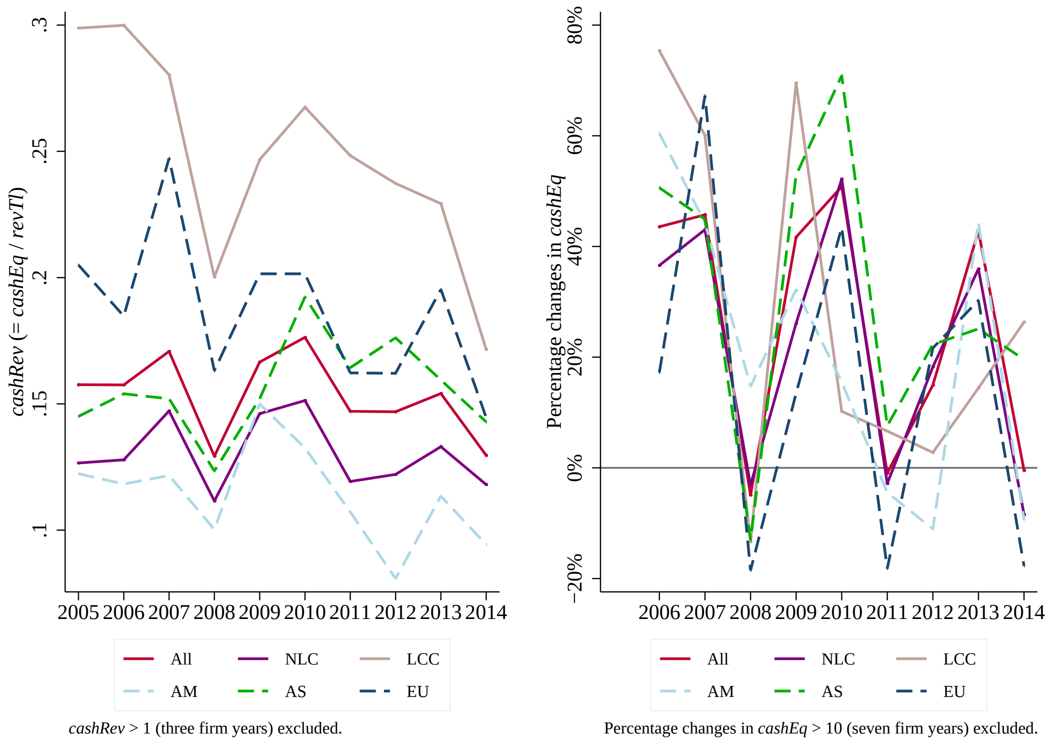
Another measure for an airline's investment opportunities is its capital expenditure. Figure 4.23 contains CAPEX scaled by total revenues (*capRev*). CAPEX scaled by total assets and scaled by firm size can be found in Figures J.3 and J.4 in Appendix J. *capRevAdj1*, which is CAPEX data adjusted by the changes in the PV of operating lease expenses (Figure J.5 in Appendix J), can be found in the right graph of Figure J.3. As a negative sign before CAPEX means an expenditure, the more negative the graph in Figure 4.23 the higher the expenditure of the airlines in that year. All sample airlines invested on average 12.1% of their total revenues in adjusted capital expenditure. European airlines exhibited the lowest expenditures (-8.4%) and low-cost airlines the highest (-17.5%). The largest decline in expenditures of all airlines was again observable between 2008 and 2009 (-27.9%). Minimum *capRevAdj1* values were visible among European carriers in 2005 (-4.7%) as well as in 2012 (-4.7%) and maximum values among LCCs in 2005 (-30.1%), 2006 (-27.7%) and 2007 (-24.3%).

Figure 4.23: Time series: unadjusted CAPEX to sales ratios (*capRev*) and lease-adjusted (*capRevAdj1*), annual average of all airlines and divided into NLCs, LCCs and regions



Apart from MTB ratios, Tobin's Q and capital expenditure measures, the cash holdings of the sample airlines are analyzed. In Figure 4.24 the cash to sales ratio (*cashRev*) is illustrated on the left side and the percentage changes in absolute cash and cash equivalent values on the right side. Low-cost airlines had the highest and American carriers the lowest cash to sales ratios in almost all sample years. Network carriers had on average 21.0% lower cash holdings than the average sample airline. Between 2007 and 2008, average sample cash to sales ratios fell by 24.3% and by 16.6% between 2010 and 2011. The cash holdings of European airlines declined by 29.5% over the sample period. The cash to sales ratio does not capture a fall in cash holdings if revenue decreases simultaneously. Therefore, percentage changes in cash and cash equivalents are also graphed on the right side in Figure 4.24. Every three years in the sample period some of the airline groups reduced their absolute cash holdings. In 2008, European, low-cost, Asian airlines, and NLCs lowered their cash holdings by 18.5%, 13.3%, 13.0%, and 3.1%. In 2011 (2014), American airlines decreased their cash holdings by 4.4% (9.4%), European carriers by 18.2% (17.7%) and network airlines by 2.8% (8.4%). For background information, time-series graphs on the cash ratio (Figure J.6), current ratio (Figure J.7) and quick ratio (Figure J.8) can be found in Appendix J.

Figure 4.24: Time series: cash to sales ratios (*cashRev*) and percentage changes in cash and cash equivalents (*cashEq*), annual average of all airlines and divided into NLCs, LCCs and regions



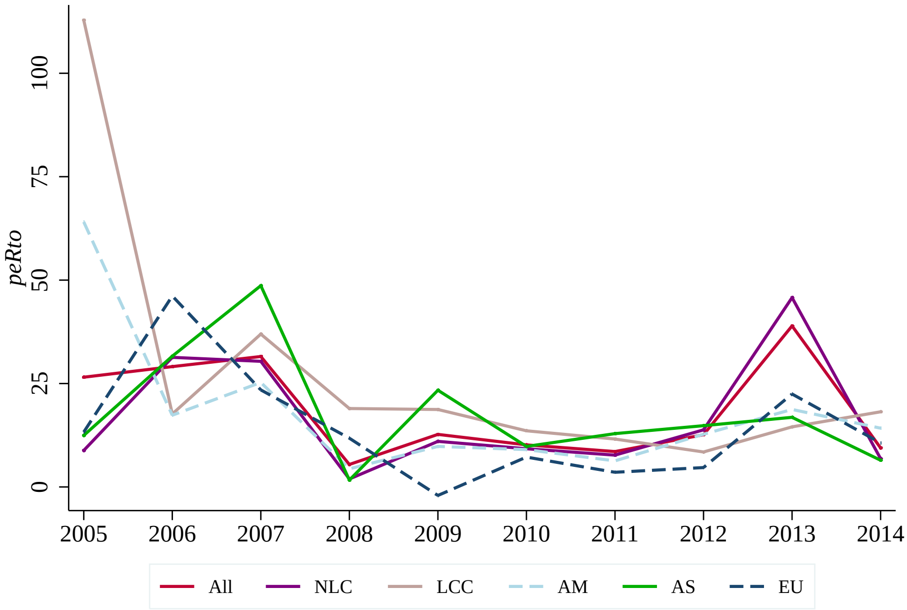
The price-earnings ratios (*peRto*) are depicted in Figure 4.25.[105] Low-cost and American carriers started in 2005 with a strong price-earnings ratio of 112.86[106] and 64.06, before dropping by 84.4% and 72.9% to 17.63 and 17.34 in 2006. European price-earnings ratios peaked one year later at 46.17 in 2006, Asian airlines in 2007 at 48.66. All airline groups faced a reduction in price-earnings ratios in the sample period, on average by 64.4%. European airlines were the only airlines that experienced a yearly

[105] The *peRto* is calculated as the share price at the year end (*shrEnd*) divided by the *eps*.

[106] The large *peRto* of the LCCs is driven by the price-earnings ratio of Gol with 610.27 in 2005.

average price-earnings ratio of less than zero (-2.06) in 2009. They also had the lowest average *peRto* during the entire sample with 14.12. At the other end, low-cost airlines' average price-earnings ratio was the highest with 27.14.

Figure 4.25: Time series: price-earnings ratios (*peRto*), annual average of all airlines and divided into NLCs, LCCs and regions



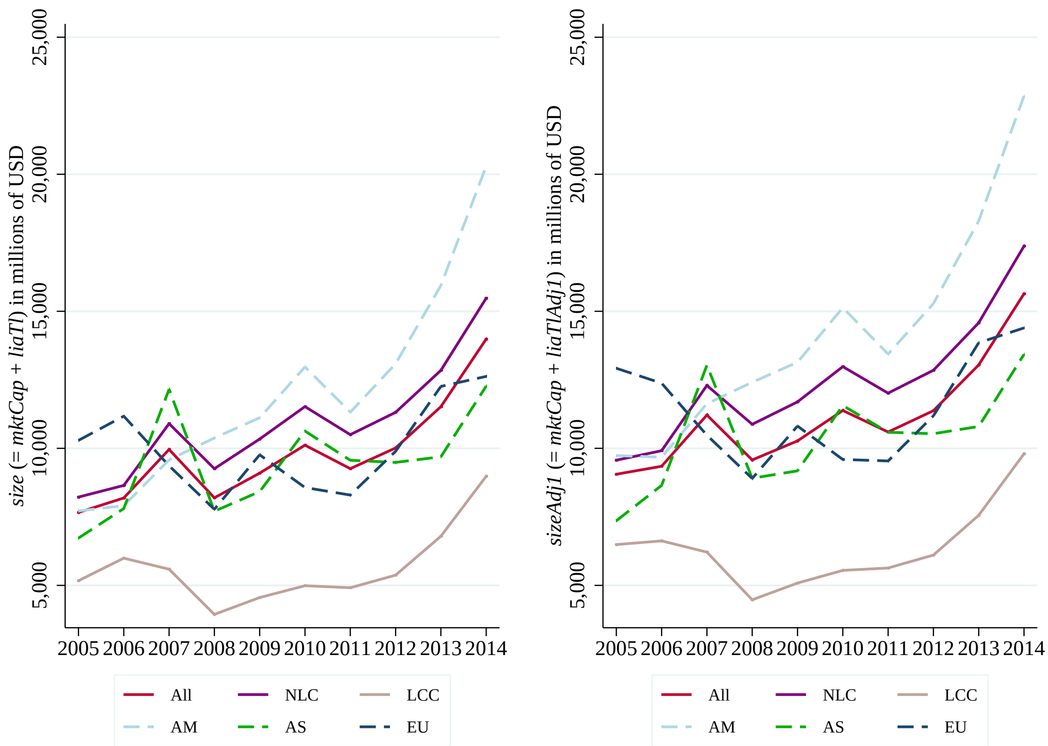
peRto < −100 (eight firm years) excluded.

4.2.4 Economies of scale

The first variable that is presented in Figure 4.26 is the size variable (*size*) which is calculated as the sum of market capitalization (*mktCap*) and total liabilities (*liaTl*). Market capitalization comprises the market value of common shares plus the market value of preference shares (see Figure J.9 in Appendix J for the time-series graph of *mktCap*). In total, 82 firm years in the sample included preference shares. Especially Southern American airlines such as Avianca, Gol, LATAM, and TAM had preference shares outstanding. The percentage of preference shares of total shares was on average 15.8%. Without the four mentioned airlines the fraction declines to 5.9%.

For comparison, undajusted size data (*size*) is presented on the left and lease-adjusted (discount method) size data (*sizeAdj1*) on the right. In the following, only lease-adjusted results are referred to. All airlines increased in firm size in the sample period, by 72.3% on average. American carriers grew the most with a plus of 130.8% to an average size of 22.9 billion USD. This rise is attributable to the mergers that happened in the U.S. market in the period of analysis (see Subsection 4.1.1). The smallest growth in size was apparent among European airlines with an increase of 11.6%. On average, airline size decreased twice in the sample period, between 2007 and 2008 by 14.9% and between 2010 and 2011 by 7.0%. Low-cost airlines were the smallest airlines in the sample with an average firm size of 6.3 billion USD. Figures J.10 and J.11 in Appendix J contain total assets (unadjusted and lease-adjusted) and total fuel expenses. The figures show the same trend because the correlation with the size variable is 0.96 for adjusted total assets and 0.90 for total fuel expenses.

Figure 4.26: Time series: unadjusted airline firm size (*size*) and lease-adjusted (*sizeAdj1*), annual average of all airlines and divided into NLCs, LCCs and regions



The number of aircraft operated in an airline's fleet and the offered available seat miles (*asmTl*) may also serve as a proxy for airline size. If the operated aircraft are smaller regional aircraft, the number of aircraft does not necessarily have to be highly correlated with the size of an airline. In the sample, however, the correlation between the total number of aircraft (*acTl*) and total assets is 0.81. The number of available seat miles is influenced by the number of operated aircraft, the average length of a flight (*lgtAvg*) and the size of an aircraft. Therefore, *asmTl* does not have to be a good proxy for firm size either if an airline operates a few, large aircraft on very long-distance flights. Again, the correlation between adjusted total assets and *asmTl* is quite high with 0.91.[107] Therefore, *acTl* and *asmTl* are used as proxies for airline firm size. Figure 4.27 graphs the time series of the number of aircraft in an airline's fleet on the left side and seat miles flown per aircraft in a fleet on the right side. American carriers operated the largest fleets with an average number of 310 aircraft. The peak was reached in 2010 with 352 aircraft. American airlines thus operated more than twice as many aircraft in their fleet as LCCs (average number of aircraft 138) and Asian airlines (133). Asian and low-cost airlines exhibited the highest increase (93.7% and 45.3%) in the number of aircraft in the sample period, from 96 to 186 and from 112 to 162 aircraft. The fleet size decreased between 2005 and 2014 for European carriers by 1.2%. Overall, fleet size increased by 19.9% in the sample period from 194 to 232 aircraft.

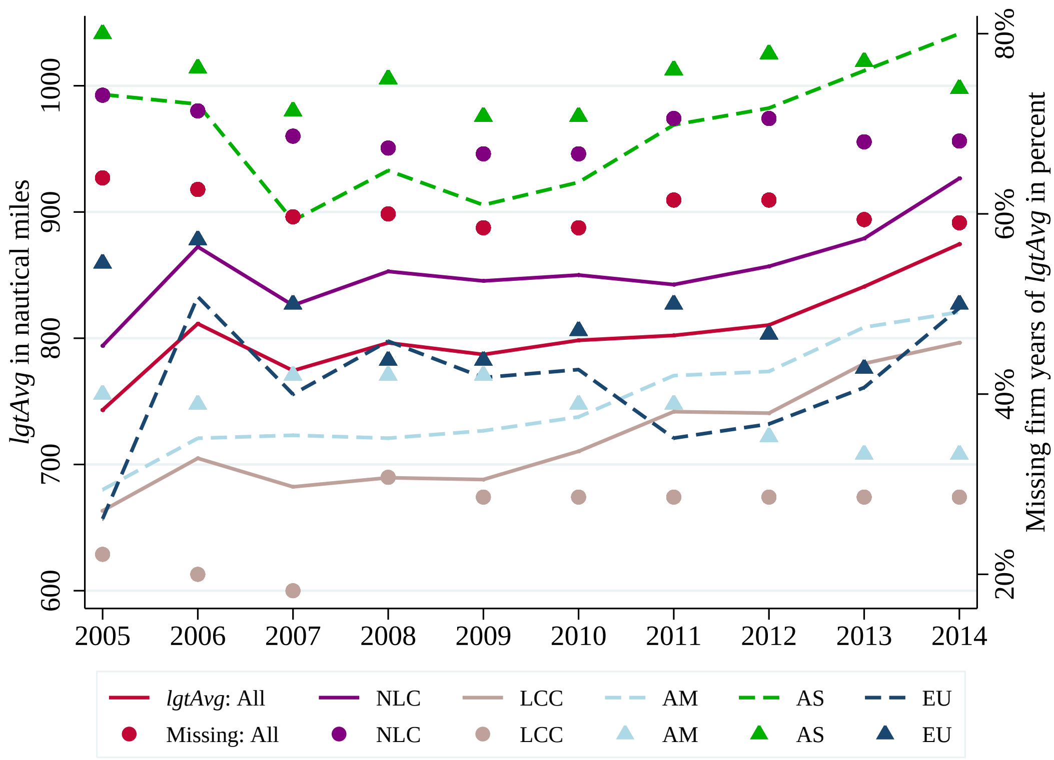
Figure 4.27: Time series: number of aircraft per airline (*acTl*) and flown available seat miles (*asmTl*) per aircraft, annual average of all airlines and divided into NLCs, LCCs and regions

[107]The correlation between *sizeAdj1* and *acTl* is 0.81 and between *sizeAdj1* and *asmTl* 0.94.

In conjunction with Figure 4.28, which shows the average stage length of each airline, some conclusions regarding the fleet can be drawn. First, while American airlines operated the largest fleets, their average flight lengths ranged in the lower region. Also, available seat miles flown per aircraft were among the lowest in contrast to the other airline groups. Asian carriers, on the other hand, had smaller fleet sizes but operated their aircraft on longer distance flights, reflected in the highest average stage length. One caveat in analyzing sector lengths in the sample is the high percentage of missing values, which can be deduced from the second y-axis in Figure 4.28. Asian airlines did not report the average stage length in 74.9% of firm years. As Cathay Pacific, the airline with the longest flights in all 10 reporting years, disclosed the flight distance in all 10 years, average Asian flight lengths were influenced mainly by that one airline. Nevertheless, some interesting insights can be gained from figures 4.27 and 4.28. Regarding the fleet structure of American and European airlines, both airline groups increased the aircraft size in their operating fleet between 2010 and 2014. Although the number of aircraft declined for American airlines in that period on average by 2.3% and the average stage lengths increased on average by 2.7%, the ASMs flown per aircraft grew by 7.3% on average. This means that American carriers switched from smaller to larger aircraft in the last four sample years. Similarly, European airlines' number of aircraft rose on average by 1.8% and the stage length by 1.7% but the seat miles flown per aircraft increased disproportionately by on average 8.1%. Asian airlines displayed the opposite trend. They expanded their number of airplanes on average by 13.0% between 2010 and 2014, while reducing the number of ASMs flown per aircraft by on average 4.3%. The average stage length increased slightly in that period by 3.1%. This means that the reduction in ASMs operated per aircraft could only arise from smaller aircraft. In Subsection 4.2.5, the sample fleet structure is examined further.

The extent of fuel price risk management may also be influenced by whether or not the airline uses other sorts of derivative instrument besides fuel hedge contracts. In Figure 4.29 the derivative usage of the sample airlines is presented. The solid red line shows the number of airlines that used fuel derivatives as part of their overall hedge portfolio in a given sample year. The green and beige solid lines reflect the number of airlines that either held exchange rate or interest rate contracts as part of their overall portfolio. The dashed lines resemble the number of airlines that held a combination of different hedge instruments. All airlines on the red dashed line, for example, employed fuel price, exchange rate and interest rate risk derivatives simultaneously. If the airlines' sole hedge instrument was fuel price derivatives, those airlines are shown on the red dotted line. The graphs demonstrate that the majority of the airlines held all three

Figure 4.28: Time series: average stage lengths (*lgtAvg*), annual average of all airlines and divided into NLCs, LCCs and regions

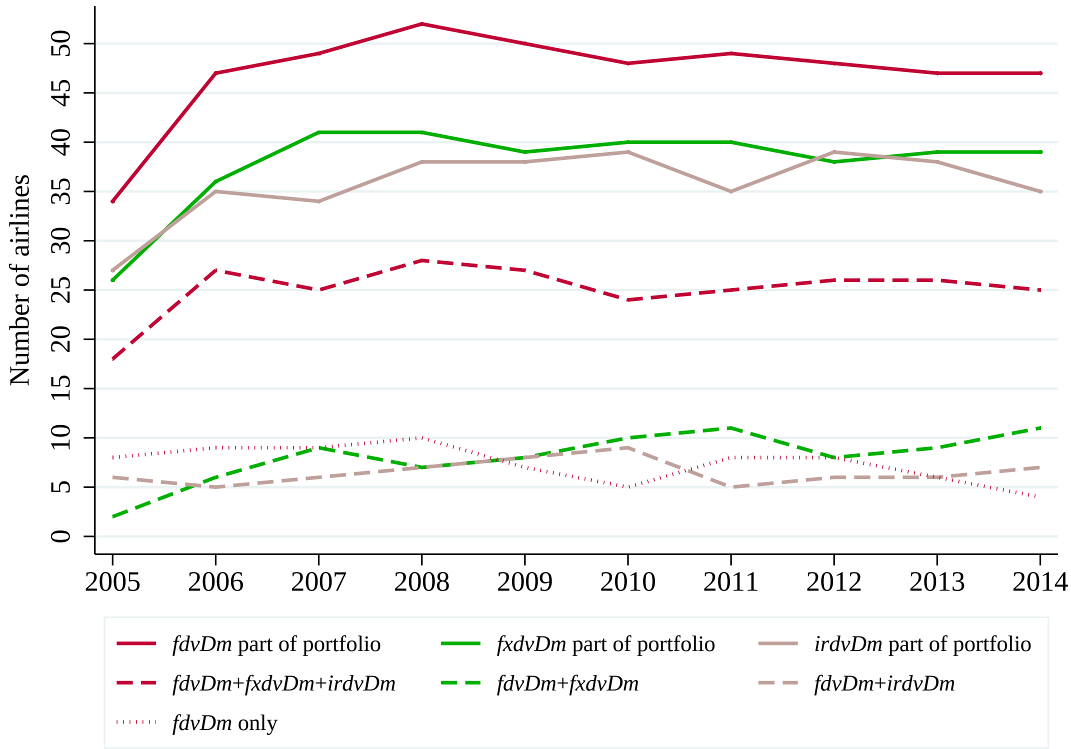


hedging instrument. About 70% of the fuel price hedging airlines also held interest rate and FX derivatives. Less than a third of the fuel hedging airlines availed themselves of purely fuel derivatives. Foreign exchange hedge instruments were more popular among airlines than interest rate instruments in eight of 10 sample years.

4.2.5 Fleet diversity

In the last subsection, the fleet structure of the sample airlines was analyzed regarding their size and average stage lengths flown. In this subsection, the fleet diversity measures *fDiv1*, *fDiv2* and *fDivNet*, as well as the variable aircraft age (*acAge*) are analyzed. Fleet diversity measures 1 and 2 are depicted in Figure 4.30. The graph on the left side shows higher values than the graph on the right side because *fDiv1* always has to be greater than *fDiv2* based on the calculation method. The average sample airline had a 27.9% larger *fDiv1* (0.67) than *fDiv2* (0.53). NLCs operated the most diverse fleet on average over the sample period with an *fDiv1* of 0.78. The highest yearly fleet diversity 1 was apparent among Asian airlines in 2007 with 0.83. As expected from the

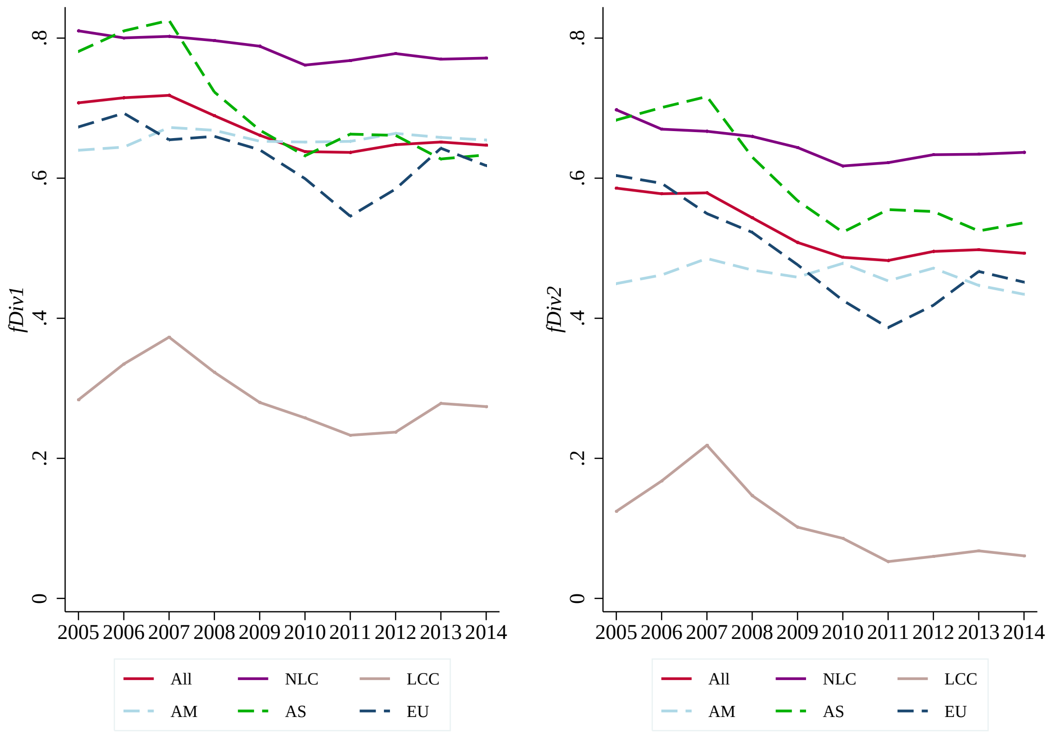
Figure 4.29: Time series: the number of airlines that use fuel price (*fdvDm*), exchange rate (*fxdvDm*) and interest rate (*irdvDm*) risk derivatives, annual average of all airlines and divided into NLCs, LCCs and regions



definition of the business model of a low-cost airline, LCCs availed themselves of the lowest average *fDiv1* of 0.29 and *fDiv2* of 0.11. The minimum values were reached in 2011 with 0.23 (*fDiv1*) and 0.05 (*fDiv2*). In contrast, Asian airlines operated a fleet with the highest *fDiv2* in 2007 with 0.72. Most airlines reduced their fleet diversity 1 in the sample period (Asian airlines -18.9%, European airlines -8.2%, NLCs -4.8%, and low-cost carriers -3.5%), except for American airlines whose *fDiv1* rose by 2.3%. All airlines reduced their switching costs (*fDiv2*) between 2005 and 2014. Low-cost airlines lowered the switching costs by 51.1%, European airlines by 25.2%, Asian operators by 21.5%, legacy carriers by 8.7%, and American airlines by 3.4%.

The measure *fDivNet* combines the advantages of operating a diverse fleet (*fDiv1*) with the disadvantages of switching costs (*fDiv2*). The greater *fDivNet*, the higher the benefits of operating a diverse fleet. *fDivNet* is presented in Figure 4.31. The average sample airline increased its net fleet diversity by 26.6% from 0.12 to 0.15 between 2005 and 2014. Except for Asian airlines, whose *fDivNet* fell by 1.1%, all airline groups

Figure 4.30: Time series: fleet diversity measure 1 (*fDiv1*) and fleet diversity measure 2 (*fDiv2*), annual average of all airlines and divided into NLCs, LCCs and regions

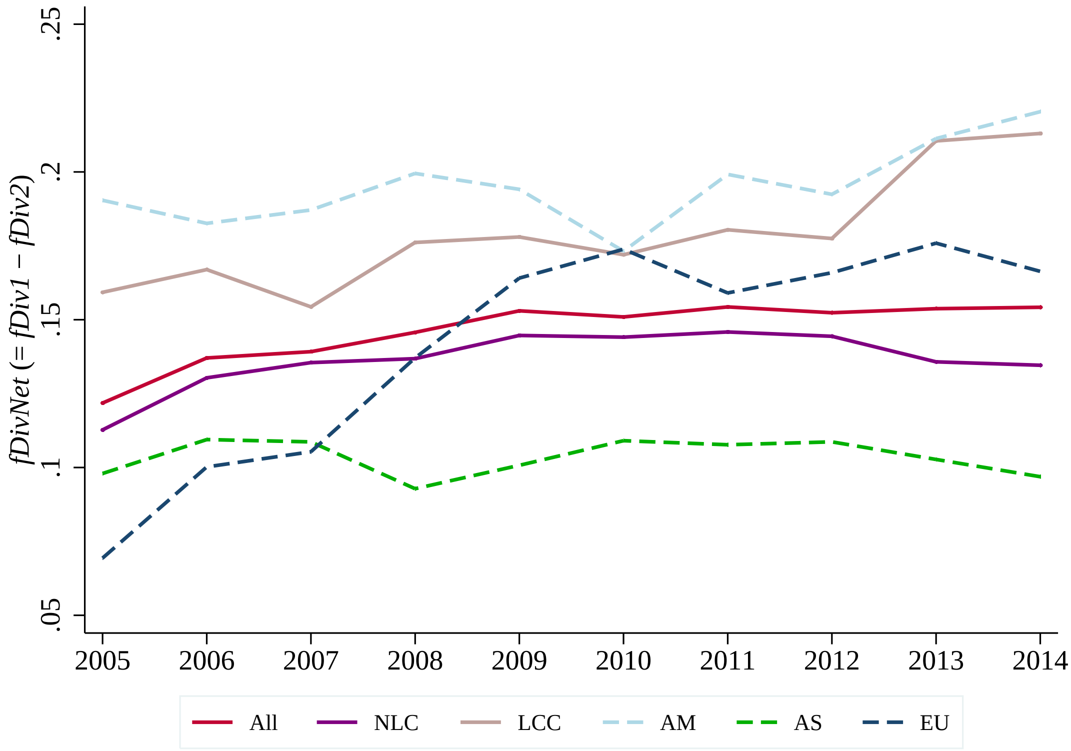


enhanced their net fleet diversity: European airlines by 139.9%, low-cost operators by 33.7%, NLCs by 19.4%, and American carriers by 15.7%. Those values show that *fDivNet* might be a good measure to analyze fleet diversity besides *fDiv1* or *fDiv2* exclusively. Almost all airlines lowered their fleet diversity but also their switching costs during the sample period and thus managed to increase the combined fleet diversity measure.

Another fleet variable of interest is the average age of an airline's operating fleet.[108] Figure 4.32 contains fleet age information on the operating fleet of the sample airlines. The second y-axis includes the percentage of firm years for which the aircraft age is missing. American airlines reported the fleet age in all sample years and Asian airlines in only 44.2% of firm years. The average age of the sample airlines rose slightly from 7.9 to 8.7 years between 2005 and 2014, an increase of 9.3%. The oldest fleet was operated by American carriers whose average aircraft age in the sample period was 9.7 years with the peak in 2012 of 11.1 years. The low-cost airlines' fleet was the youngest of all airline

[108] Treanor et al. (2014b) use the natural logarithm of the airline's average fleet age as a proxy for fuel efficiency. The younger the fleet, the higher the fuel efficiency.

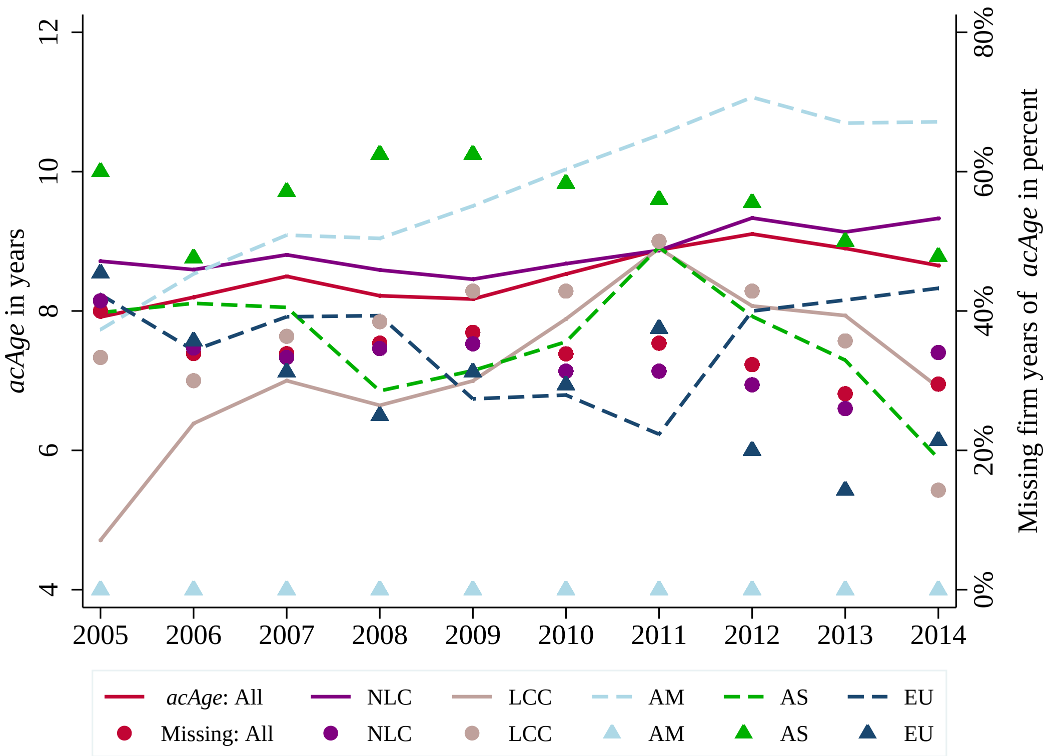
Figure 4.31: Time series: net fleet diversity measure (*fDivNet*), annual average of all airlines and divided into NLCs, LCCs and regions



groups with an average sample age of 7.1 years. The lowest value was reached in 2005 (4.7 years). Asian airlines were the only subgroup that could reduce their fleet age in the sample period, from 8.0 years to 5.9 years. The low-cost operators' fleet age grew the most by 46.6% between 2005 and 2014 because they started at the lowest age in 2005.

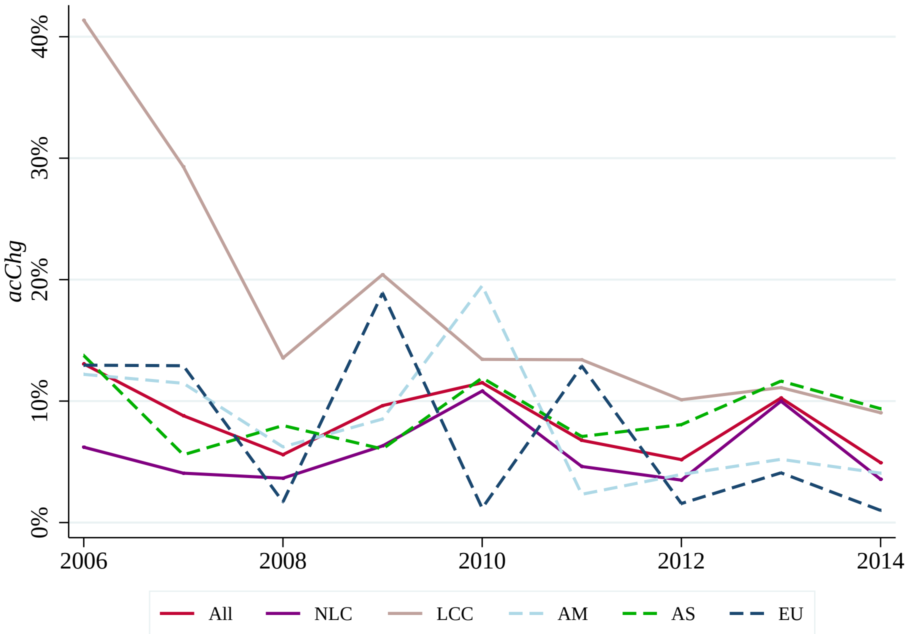
Figure 4.3 in Subsection 4.2.2 showed the difference in fuel consumption per ASM between LCCs and NLCs. While low-cost airlines lowered their fuel consumption per ASM by 18.1% between 2005 and 2014, legacy operators reduced their fuel consumption by 9.0% only. The development in aircraft age could not have been the driver for the divergence in fuel consumption between these two subgroups. LCCs increased their fleet age during the sample period by 46.6%, while NLCs by 7.0%. Two other variables might have been the contributing factor for the reduction in fuel consumption per ASM among low-cost airlines. First, the average stage lengths of low-cost airlines increased by 20.1% in the sample period in contrast to an increase in sector lengths by legacy airlines of 16.7% (see Figure 4.28). The longer a flight, the lower the fuel consumption because during the take-off phase the fuel consumption is the highest. Therefore, the fuel consumption decreases exponentially with the sector length. Second, low-cost operators increased the ASMs flown per aircraft in the fleet (see Figure 4.27) by 20.9%, in comparison to NLCs who raised the variable by 17.2%. From these numbers it follows that low-cost airlines increased the size of the aircraft in their operating fleet more than legacy airlines. This results in a lower fuel consumption per ASM flown. The low-cost airline Southwest, for example, operated 379 Boeing 737-700 with 143 seats and 29 737-800 with 175 seats (Southwest Airlines, 2015) in 2012. In 2014, the number of Boeing 737-700 increased by 2.6% whereas the number of the larger Boeing 737-800 increased by 169.0%. Another low-cost carrier that exchanged smaller for larger medium-haul airplanes was easyJet. Between 2010 and 2014, easyJet reduced the number of Airbus 319 (156 seats) by 0.6% and increased the number of Airbus 320 (180 seats) by 114.7% (easyJet, 2014).

Figure 4.32: Time series: fleet age (*acAge*) and missing values of fleet age, annual average of all airlines and divided into NLCs, LCCs and regions



Fleet diversity measures give some indication of the flexibility of an airline's operating fleet. Expansions in the fleet size are also of interest because they reflect capacity expansions in the airline industry. Therefore, Figure 4.33 contains information on the changes of the sample airlines' number of aircraft. The largest increase in the number of operated aircraft could be seen among low-cost airlines between 2005 and 2006. The airlines' fleet size rose by 41.4%. The large percentage change was driven by the fleet expansion of AirAsia (88.2%), Ryanair (62.2%), Norwegian Air Shuttle (57.1%), and Gol (54.8%). Low-cost airlines enlarged their fleets the most during the sample period, on average by 18.0% per year. The average airlines' year-on-year addition to fleet size was 8.4% in the sample. The smallest sample average growth in the number of aircraft with 5.1% occurred between 2013 and 2014. European airlines increased their fleets the least by only 1.0% between 2013 and 2014.

Figure 4.33: Time series: percentage changes in the number of aircraft (*acChg*), annual average of all airlines and divided into NLCs, LCCs and regions



4.2.6 Strategic alliances

The emergence of airline strategic alliances in the 1990s has been providing alliance members with many benefits (Lazzarini, 2007). In recent years, airlines have moved towards fostering dual partnerships which may also reach beyond the borders of the classical alliances. Lufthansa (Star Alliance) agreed with Etihad Airways (non-alliance member) to sell tickets on each others' routes cooperatively in December 2016 (Bryan and Maushagen, 2016-12-16). In March 2017, Cathay Pacific (Oneworld) and Lufthansa signed a codeshare agreement (Reuters Staff, 2017-03-27). Regardless of the increased importance of dual partnerships, the focus lies on the three strategic airline alliances in this analysis.

All sample airlines are categorized according to their alliance membership as of 31st December 2014 in Table 4.19. Moreover, the non-alliance airlines are split into LCCs and NLCs. Figure J.12 in Appendix J shows the percentage of sample airlines that were part of an alliance for each sample year, and separate for each of the three alliances. In 2014, 31 of 61 sample airlines were member of a strategic alliance. Most of the sample airlines belonged to Star Alliance (15), followed by SkyTeam (nine) and Oneworld (seven). Thirty airlines did not belong to any alliance in 2014. All 14 low-cost carriers were non-alliance members. Continental Airlines changed its alliance membership from SkyTeam to Star Alliance in 2009. Fifteen airlines (Aegean Airlines, Aeroflot, Air Berlin, Air China, China Airlines, China Eastern, China Southern, Copa Airlines, Eva Air, Garuda Indonesia, Japan Airlines, Kenya Airways, Malaysia Airlines, TAM, Turkish Airlines) entered an alliance during the sample period.

Figure 4.34: Time series: hedge ratios (*fdvPct12m*), divided into any alliance, Oneworld, Star Alliance and SkyTeam

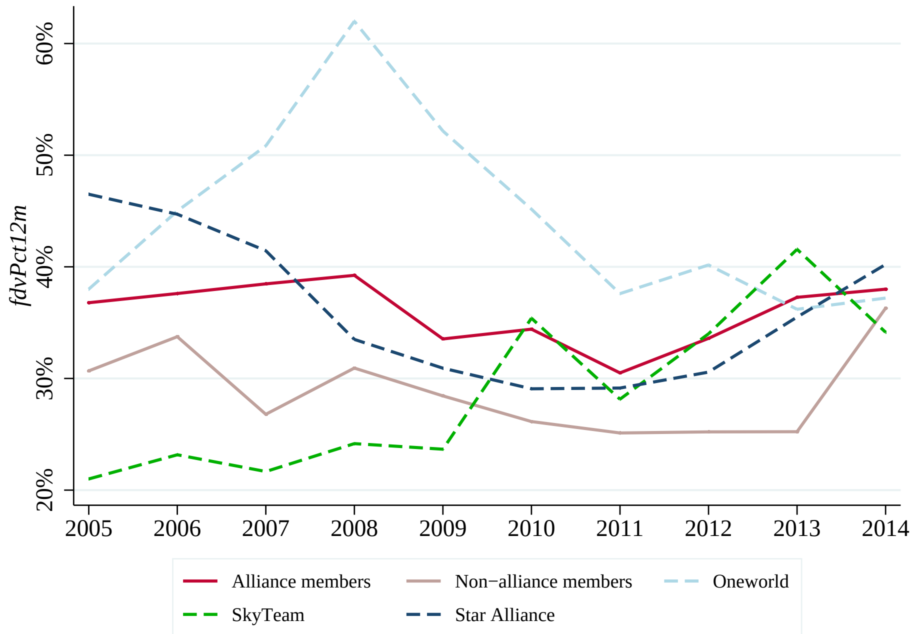


Figure 4.34 presents the average hedge ratios of the different alliances. The hedge ratios of the alliance airlines were on average 25.1% higher than those of the non-

Table 4.19: Alliance membership as of 31st December 2014 and non-alliance members divided into LCCs and NLCs (non-alliance airlines marked with an asterisk (*) entered an alliance during the sample period)

Oneworld	**SkyTeam**	**Star Alliance**	**Non-alliance NLC**	**Non-alliance LCC**
Air Berlin (2012-2013)	Aeroflot (2006-now)	Aegean Airlines (2010-now)	Aegean Airlines*	Air Arabia
American Airlines	Air France-KLM	Air Canada	Aer Lingus	AirAsia
Cathay Pacific	China Airlines (2011-now)	Air China (2007-now)	Aeroflot*	AirTran
Finnair	China Eastern (2011-now)	Air New Zealand	Air China*	Allegiant Air
IAG	China Southern (2006-now)	All Nippon Airways	Air Berlin*	easyJet
Japan Airlines (2006-now)	Delta Air Lines	Asiana	Alaska Airlines	Gol
LATAM	Garuda Indonesia (2014-now)	Avianca	China Airlines*	Jazeera Airways
Malaysia Airlines (2013-now)	Kenya Airways (2010-now)	Copa Airlines (2012-now)	China Eastern*	JetBlue
Qantas	Korean Air	Eva Air (2013-now)	China Southern*	Norwegian Air Shuttle
		Lufthansa	Comair	Ryanair
		SAS	Copa Airlines*	Southwest
		Singapore Airlines	El Al	SpiceJet
		TAM (2008-2011)	Eva Air*	Spirit
		Thai Airways	Flybe	Tigerair
		Turkish Airlines (2008-now)	Garuda Indonesia*	Volaris
		United Airlines	Great Lakes	Vueling
			Hawaiian Airlines	
			Icelandair	
			Japan Airlines*	
			Jet Airways	
			Kenya Airways*	
			Malaysia Airlines*	
			Pakistan International Airlines	
			Regional Express	
			Republic Airways	
			SkyWest	
			TAM*	
			TransAsia	
			Turkish Airlines*	
			Virgin Australia	

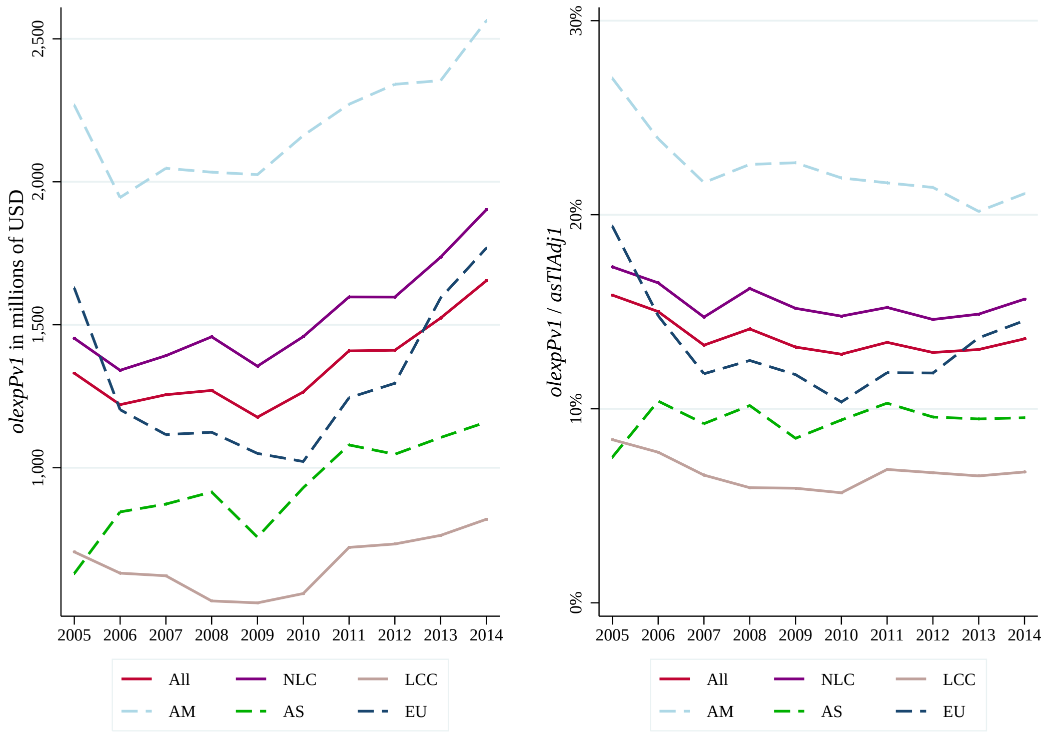
alliance airlines. In 2014, the hedge ratios of the different alliances converged. All airlines, regardless of their alliance membership, hedged between 34.1% and 40.2% of their expected fuel consumption.

4.2.7 Aircraft leasing

The sample airlines used operating lease contracts for financing their aircraft extensively. Therefore, the sample variables need to be adjusted by the PV of future operating lease expenses. The present value of future operating lease expenses in Figure 4.35 is calculated using the discount method by Damodaran (2002) (see Subsection 4.1.2). In the graph on the left side, operating lease expenses seemed to rise sharply after 2009. If the PV is scaled by adjusted total assets (*asTlAdj1*) though, the effect is flattened or even reversed. Thus, most of the increase in operating lease expenses is driven by an increase in airline asset size. American, European, low-cost, and legacy carriers showed a similar trend in the adjusted operating lease expenses. The ratio decreased between 2005 and 2007 followed by a short peak in 2008 before falling again in 2009. The Asian airlines' scaled operating lease expenses fluctuated over the sample period. In the last two years of analysis, the operating lease expenses of European airlines grew by 23.8%. A possible explanation for this regional rise could be the increased amount of outstanding debt (*lvrg1Adj1*) in the last two years of the analysis among European airlines and hence less financial flexibility to finance the aircraft. Time-series analyses of the alternative methods of the PV calculation (multiples 5 and 6 (Figure J.13), multiples 7 and 8 (Figure J.14)) can be found in Appendix J. The order in which the airline subgroups' PV of operating lease expenses scaled by adjusted total assets appear does not change - regardless of the calculation method. American airlines had the highest relative operating lease expenses, followed by NLCs, European, Asian, and low-cost airlines. The PV calculated with the discount method is in general lower than the present values calculated with multiples. For example, *olexpPv1* (discount method) is larger than *olexpPv5* (multiple 5) in 115 (of 621) firm years and larger than *olexpPv8* (multiple 8) in only 29 firm years.

Figure 4.36 depicts a times series of the percentage of aircraft that were under operating leasing (*acOlPct*) during the sample period. The dots and triangles represent the percentage of missing firm years on the second y-scale. Low-cost airlines started with the highest fractions of operating leased aircraft in their fleets of 64.9% in 2005. Eight airlines, six of which were low-cost airlines, operated purely operating leased aircraft in some sample years: the network carriers Aegean Airlines (2007) and Hawaiian

Figure 4.35: Time series: absolute present values of operating lease expenses (*olexpPv1*) and scaled by lease-adjusted total assets (*asTlAdj1*), annual average of all airlines and divided into NLCs, LCCs and regions



Airlines (2005), as well as the low-cost airlines Gol (2005), Jazeera Airways (2008, 2009), Norwegian Air Shuttle (2005), Spirit (2011-2013), Volaris (2013, 2014), and Vueling (2007-2012). Nevertheless, European airlines were the subgroup that availed themselves of the highest percentage of operating leased aircraft during the sample period. On average, 53.3% of their aircraft were under operating leasing, closely followed by LCCs with an average value of 52.5%. For comparison, American carriers had 44.3% of their aircraft under operating leasing, NLCs 40.7% and Asian airlines 36.2%. The largest increase in *acOlPct* between 2005 and 2014 was observable among Asian airlines. Besides network airlines, Asian operators were the only subgroup that increased the fraction of their operating leased aircraft in the sample period, by 51.1%. All other airlines lowered their aircraft operating lease percentages (LCCs -35.1%, American airlines -25.0% and European carriers -4.9%). Interestingly, the *acOlPct* values of each subgroup converged during the sample period, from a difference of 37.9 percentage points in 2005 to 6.9

percentage points in 2014. Four of the five subgroups had average operating lease ratios between 40.8% and 42.1% in 2014, speaking for a more homogeneous strategy towards operating leasing.

Figure 4.36: Time series: percentages of aircraft under operating leasing (*acOlPct*), annual average of all airlines and divided into NLCs, LCCs and regions

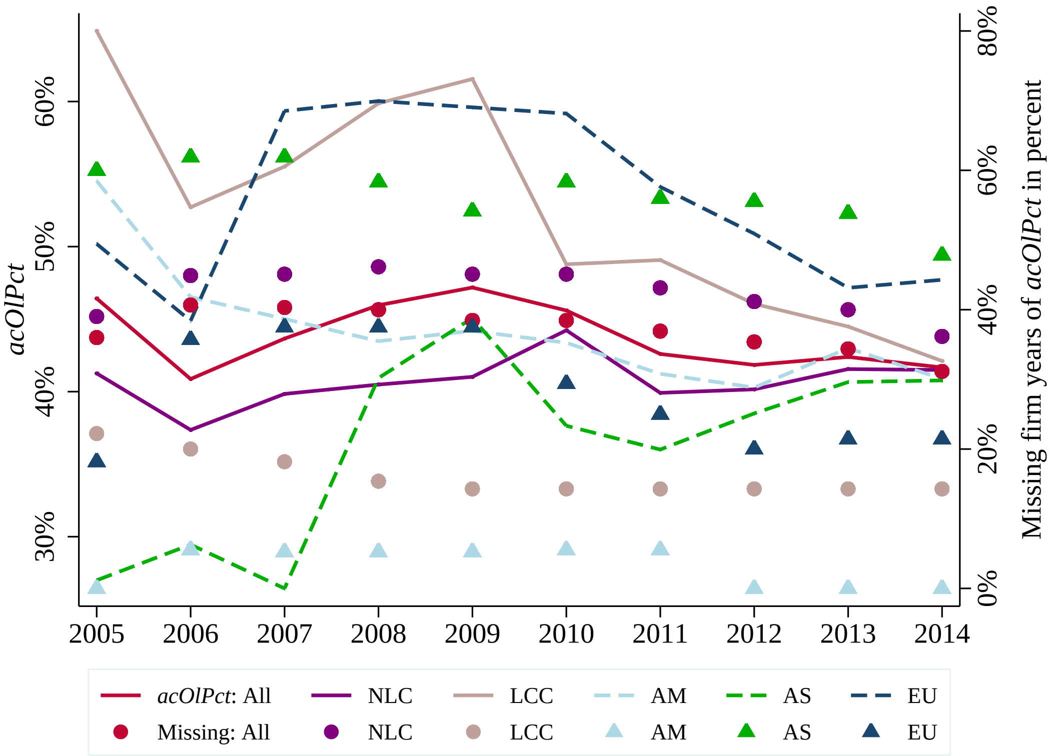
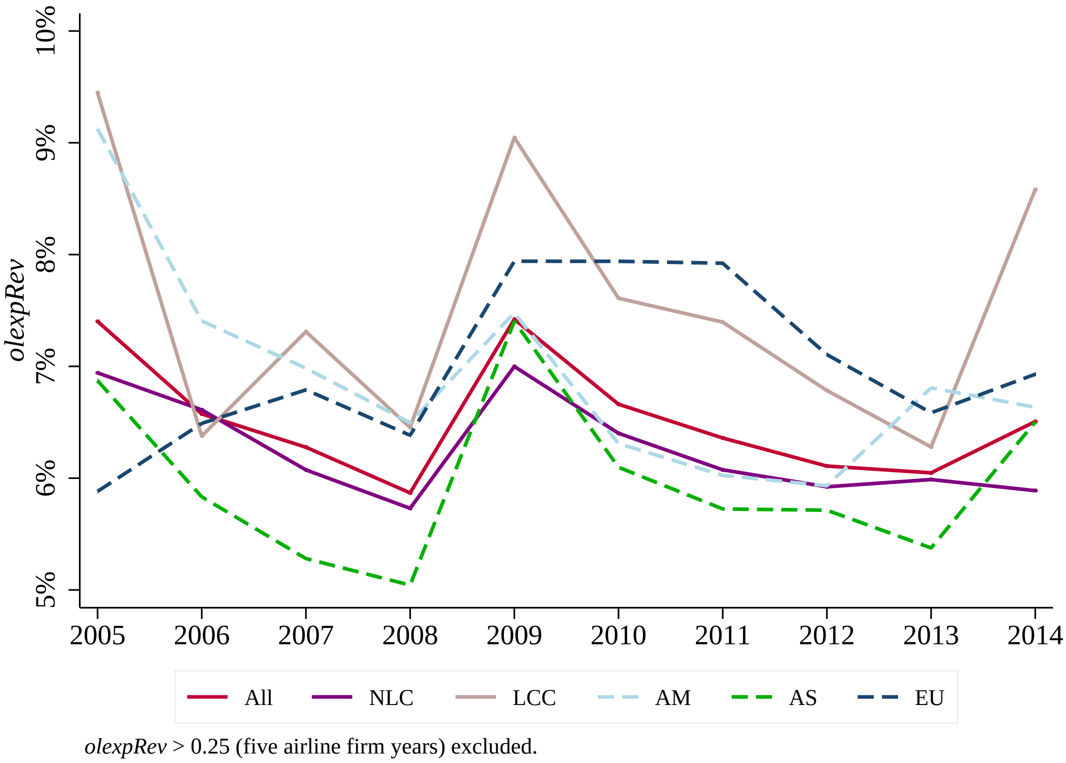


Figure 4.37 plots the current operating lease expenses scaled by total revenues (*olexpRev*) between 2005 and 2014. Current operating leases expenses (*olexpTl*) include expenses incurred for all items under operating lease contracts, not aircraft exclusively. The most noteworthy aspect in figure 4.37 is the rise in operating lease expenses between 2008 and 2009. Overall, *olexpRev* rose by 26.5% in that period. Although total revenues (see Figure J.15 in Appendix J) decreased in the same time span by 16.1%, this decline was not sufficient to explain the drop in scaled operating lease expenses. The number of aircraft under operating leasing (*acOlPct*) increased slightly by 2.7% and could not explain the plus of 26.5% either. One explanation for the large increase in current operating lease expenses could have been a higher risk premium required by aircraft lessors in 2009 for aircraft under operating leasing due to a higher risk of financial distress among airlines and hence leasing default. Vueling, for example, had to pay the

highest leasing rates in 2008 in the sample period for their Airbus 320 (see Table I.2 in Appendix I). In opposition to the relatively low results in *acOlPct* (Figure 4.36), low-cost airlines had to pay the highest average fraction of their total revenues for current operating lease expenses (7.5%) in the sample period because of the lowest average total revenue values in the sample (Figure J.15). European (7.0%), American (6.9%), network (6.3%), and Asian carriers (6.0%) followed. Although the percentage of operating leased aircraft declined by 1.7% between 2013 and 2014 and total revenues increased by 8.4%, current operating lease expenses scaled by total revenue rose by 7.6%, speaking for higher leasing rates between 2013 and 2014.

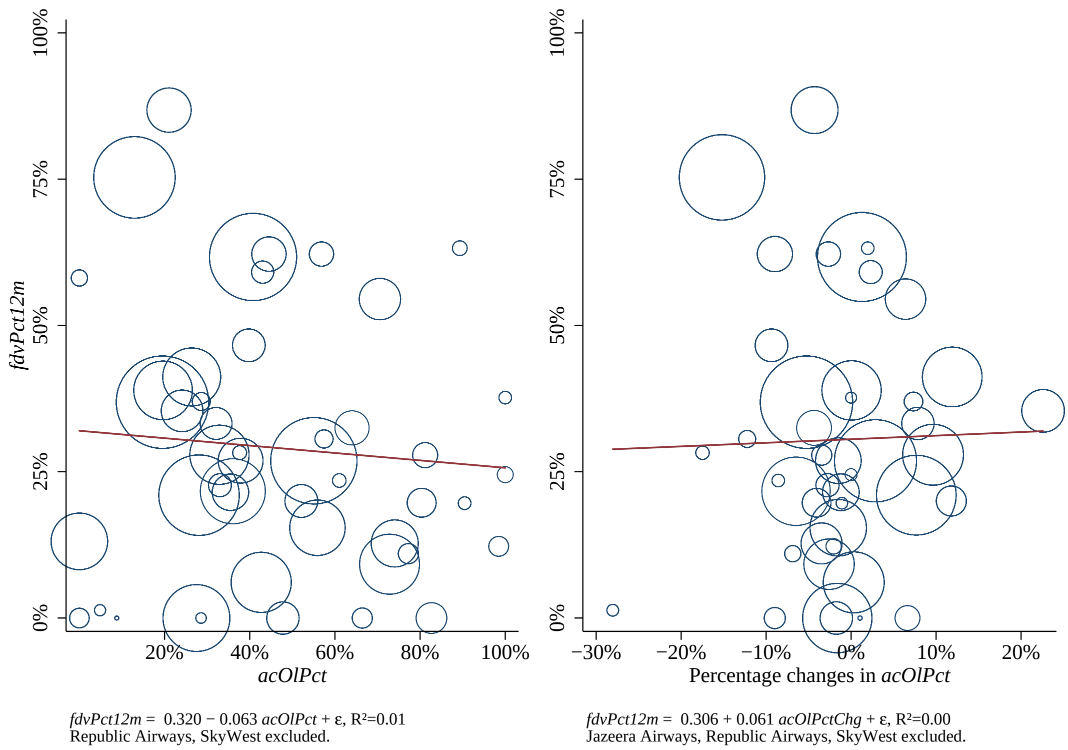
Figure 4.37: Time series: current operating lease expenses scaled by total revenues (*olexpRev*), annual average of all airlines and divided into NLCs, LCCs and regions



Besides operating lease contracts, another financial procedure that is commonly used in the airline industry are sale-and-leaseback transactions. Airlines can sell their owned aircraft to a lessor and lease them back under operating or finance lease contracts (Brealey et al., 2017). Rampini and Viswanathan (2013) propose that especially mature firms with low cash holdings might make use of sale-and-leaseback transactions. Sale-and-leaseback transactions can be analyzed with changes in the variable *acOlPct*. Those transactions are reflected in positive changes in *acOlPct* and can be viewed as a signal of financial distress. The positive slope of 0.061 in the graph on the right side in Figure 4.38 supports H1a. The magnitude of the slope is quite small though. A one standard deviation change in the changes of *acOlPct* would have led to changes in the hedge ratios of 0.5%.

Jazeera Airways is excluded as an outlier from the cross-sectional analysis of the changes in the percentage of operating leased aircraft in Figure 4.38. The airline acquired a leasing company in 2010 and entered the leasing market as a lessor. It bought all eight aircraft that were originally under operating leasing. In 2014, it sold all aircraft, leased them back and abandoned the leasing industry in order to focus towards their “core business, the passenger airline business” (Jazeera Airways, 2015, p. 8). The variable *acOlPct* dropped from 100% to 0% and back to 100%, a change of -100% and 100%.

Figure 4.38: Cross-sectional: correlation between the percentages of operating leased aircraft (*acOlPct*), percentage changes of *acOlPct* and hedge ratios (*fdvPct12m*), average across years for each airline (markers weighted by lease-adjusted total assets)



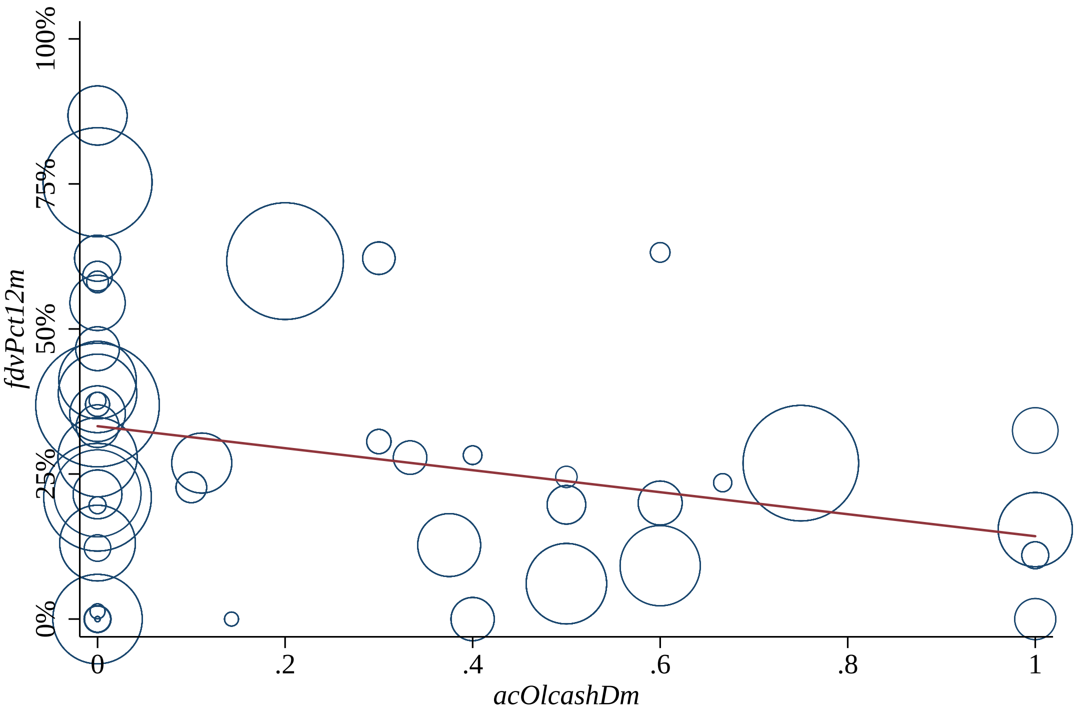
Several airlines mentioned the collateral requirements regarding their fuel hedge contracts. While Alaska Airlines was not required to post any margins at the end of 2014

(Alaska Air Group, 2015), other airlines such as Delta Air Lines had to collateralize any losses in their fuel hedge contracts with their counterparties (Delta Air Lines, 2009). The amount and type of collateral varied between the airlines. Continental Airlines provided margin calls of 7.9% of its cash and cash equivalents in 2009, El Al 63.3% in 2014, JetBlue 40.5% in 2008, Southwest Airlines 50.7% in 2014, and United Airlines 47.3% in 2008. US Airways further provided letters of credit besides cash collateral in 2008. The airline also mentioned the likely impact collateral requirements might have on its financial situation: "Since the third quarter of 2008, we have not entered into any new transactions as part of our fuel hedging program due to the impact collateral requirements could have on our liquidity resulting from the significant decline in the price of oil and counterparty credit risk arising from global economic uncertainty" (US Airways, 2009, p. 59). Apart from cash and letters of credit, airlines also provided aircraft as a security to financial counterparties (easyJet, 2014). Therefore, the variable *acOlcashDm* combines the cash holding of an airline with its fraction of aircraft under operating leasing. The proposed negative relation between hedge ratios and the binary variable (H9) is reflected in the negative slope in Figure 4.39. Most of the airlines had an average *acOlcashDm* of zero during the sample period. Four airlines (Avianca, China Eastern, Garuda Indonesia, and Norwegian Air Shuttle) showed an average value of one, implying that these airlines had relatively low cash holdings and an operating lease intense fleet in all sample years.

4.2.8 Selective hedging

Although many airlines had systematic hedge programs in place, their guidelines still allowed diversions from the set strategic values and to hedge selectively. Aer Lingus, for example, set up a "systematic fuel hedging policy" in 2009 but allowed the treasury department to deviate from those guidelines in the "event of unusual market conditions" (Aer Lingus, 2010, p. 65). Flybe "temporarily suspended" its hedge activities due to "unusual trading conditions" in 2011 (Flybe Group, 2011, p. 87) and Southwest allowed to change its derivative positions "based on its expectation of future market prices, as well as its perceived exposure to cash collateral requirements" (Southwest Airlines, 2015, p. 67). Air France-KLM changed its systematic hedge strategy because of its derivative losses in 2008 both in terms of maturity and hedge ratio (Air France-KLM, 2010), thus indirectly applying selective hedging. El Al adapted its financial risk hedging policy in 2011 due to improved IT capabilities and "deepened [...] capabilities in the field of financial exposure" (El Al, 2011, p. 89).

Figure 4.39: Cross-sectional: correlation between the binary variable *acOlcashDm* and hedge ratios (*fdvPct12m*), average across years for each airline (markers weighted by lease-adjusted total assets)



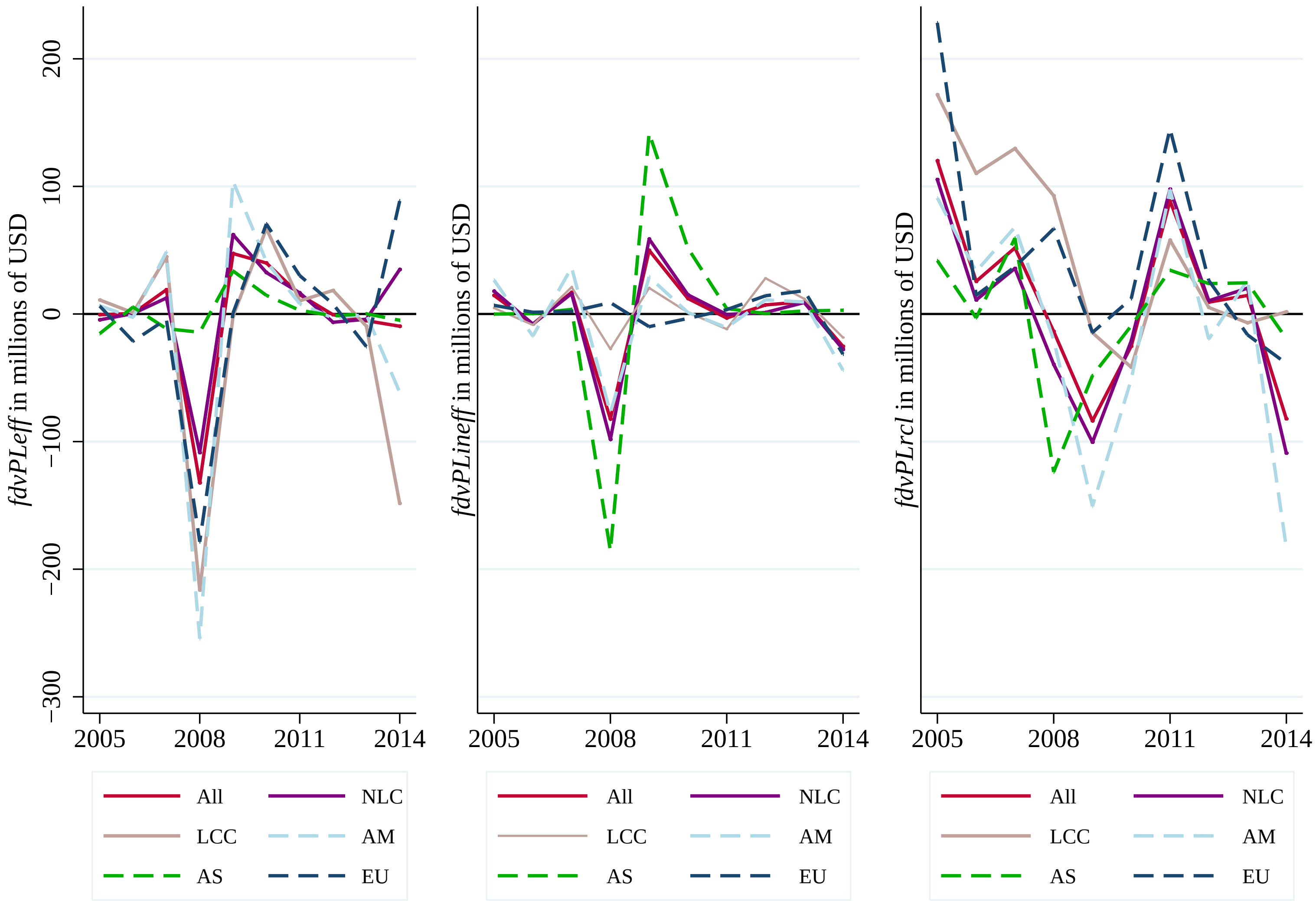
fdvPct12m = 0.333 − 0.190 *acOlcashDm* + ε, R^2=0.06

For the selective hedging hypothesis (H10), the effective (*fdvPLeff*), ineffective (*fdvPLineff*) and reclassified (*fdvPLrcl*) portions of the profits and losses of fuel price contracts are presented in Figure 4.41. Due to the peak in kerosene price levels and volatility in September 2008 (see Section 2.1), the airlines incurred the highest losses on their outstanding fuel price contracts in 2008. American operators experienced the largest losses in the effective portion of their hedging instruments of 254.4 million USD, whereas Asian airlines had ineffective losses of 185.7 million USD in 2008. The average sample airline was subjected to effective and ineffective losses of 132.3 million USD and 82.3 million USD. As the effective portion is temporarily accounted for under OCI until the fuel contract settles, the largest average losses of hedging instruments were reclassified from OCI to income in 2009 (-83.7 million USD). The highest combined loss of the ineffective and reclassified portion (both recognized in income) could be seen among Asian carriers in 2008 of 309.4 million USD (depicted in Figure J.16 in Appendix J). H10 suggests that fuel hedging managers adapt their hedge portfolios more actively after they incurred large losses recognized in income. This hypothesis is supported by the descriptive results because Asian airlines reduced their hedge portfolios by 67.2% between 2008 and 2010 after their large ineffective losses in 2008. The highest effective profits were made by American airlines in 2009 (104.1 million USD) and the highest ineffective profits by Asian operators in 2009 (141.7 million USD) both due to the drop in the oil price at the end of 2008.

Figure 4.40 shows the regional changes in hedge ratios. From 2005 to 2006, 2012 to 2013 and 2013 to 2014 all airlines, regardless of their region or business model, increased their hedge portfolios. Between 2006 and 2007, all airlines decreased their hedge activities, low-cost airlines the most by 15.5 percentage points, mainly driven by the percentage point reductions in the individual hedge ratios of Norwegian Air Shuttle (-38.0), Southwest (-25.0) and Ryanair (-25.0). On average, the airlines showed an increase in hedge ratios in five sample years. If all adaptions in the derivative position, increases and decreases, are considered as positive changes, low-cost airlines were the most active hedgers with an average change of 11.7 percentage points, followed by European airlines with 9.7 percentage points and American carriers with 8.8 percentage points.

Figure 4.40: Time series: percentage point changes in the regional hedge ratios, annual average of all airlines of a region and divided into NLCs, LCCs and regions

Figure 4.41: Time series: effective (*fdvPLeff*), ineffective (*fdvPLineff*) and reclassified portions (*fdvPLrcl*) of hedging instruments gains and losses, annual average of all airlines and divided into NLCs, LCCs and regions



Chapter 5

ANALYSIS

In order to test the hypotheses from Chapter 3, Chapter 5 presents the univariate and multivariate regression results. The content of this chapter follows the same outline as in the previous parts. In Section 5.1 determinants-related hypotheses are analyzed. Thereafter, Section 5.2 contains the results for the hypotheses that refer to the operational hedging theory. Lastly, Section 5.3 discusses selective hedging hypotheses. Each of the sections is structured similarly. The sections start with summary statistics of the variables of interest and lead to their univariate (5.1.1, 5.2.1 and 5.3.1) and multivariate analysis (5.1.2, 5.2.2 and 5.3.2). Due to the multitude of proxies employed, the alternative model specifications are examined in the robustness Subsections 5.1.3, 5.2.3 and 5.3.3. Model limitations (5.1.4, 5.2.4 and 5.3.4) are shown thereafter. The sections terminate with discussing the results (5.1.5, 5.2.5 and 5.3.5).

5.1 Analysis of the determinants of international airlines' fuel hedging

In Table 5.1 the summary statistics relating to the airline industry picture and fuel hedging variables are depicted in alphabetical order. In the textual description, the industry variables are discussed prior to the fuel hedging variables. All variables ending with "_" are in millions.

The average total available seat miles (*asmTl*) published by the airlines was 45.5 billion nautical miles. The difference in sample airline size becomes apparent when including the standard deviation as well as minimum and maximum values. While the U.S. airline Great Lakes offered a total of 119.0 million seat miles in 2014, American Airlines flew 265.7 billion seat miles in 2014. Similarly, the fuel consumption (*fuelCons*) ranged between 4.8 million USG (Great Lakes) and 4,332.0 million USG (American Airlines) with a standard deviation of 916.1 million USG. The load factor (*lf*) values were more homogeneous with an SD of 6.9 percentage points. The airlines sold on average 76.9% of their ASMs. The lowest value of 33.0% and the highest value of 91.0% were reached by Great Lakes in 2009 and by easyJet in 2014. The airlines earned on average 0.22 USD with each revenue passenger mile (*rrpm*). The low-cost airline AirAsia had a yield, as *rrpm* is often referred to, of only 0.07 USD in 2005, whereas Great Lakes showed *rrpm* of 1.08 USD in 2014. The high yield of Great Lakes was mainly driven by its short flight distances: the shortest average stage length (*lgtAvg*) of 262.0 nautical miles was observable for Great Lakes in 2006. Thus, Great Lakes operated short flights with relatively high ticket prices. The longest flights were operated by Cathay Pacific in all ten sample years. The airline's focus on long-distance flights is reflected in its fleet structure. In 2014, 79.5% of Cathay's fleet were long-range aircraft.

The sample airlines had fuel hedge contracts outstanding in 76.2% of sample firm years, reflected in the dummy variable *fdvDm*. The average hedge ratio 12 months forward (*fdvPct12m*) was 31.7%. The longer the hedge maturity, the lower the hedge ratio. The airlines hedged on average 9.1%, 2.8% and 0.7% 24, 36 and 48 months forward.[109] The average fuel hedge maturity (*fdvMtr*) was 14.3 months. The U.S. LCC Southwest held the fuel hedge portfolio with the longest maturity of 72 months in 2006. Thereafter Southwest reduced the portfolio gradually to 36 months in 2009 due to large derivative losses incurred in 2008 in the effective portion (*fdvPLeff*) of 1.5 billion USD (see Table 5.27 for summary statistics of the selective hedging variables).

Table 5.2 contains the summary statistics of the financial distress variables. The sample airlines paid dividends (*divDm*) to their shareholders in 40.7% of sample years. In 2009, 44 out of 65 airlines did not pay dividends, the year with the lowest number of airlines paying dividends. The average dividend payout ratio (*divRto*) in the sample period was 0.15 and the average dividend yield (*divYld*) 0.01. Thirteen airlines experienced a dividend payout ratio smaller than zero in the sample period, with TAM having the lowest value of -6.39 in 2006.[110] The lowest annual sample average dividend payout ratio was 0.004 in 2008.

[109] The percentages exceeding 100.0% were attributable to AirAsia, who disclosed notional portfolio values only and not hedge ratios directly. Therefore, the hedge ratio was calculated as discussed in Subsection 4.1.2 leading to hedge ratios surpassing 100.0%.

[110] The low ratio of TAM is caused by the calculation method of the dividend payout ratio. TAM's ratio in 2006 was negative because its dividend payments on preference shares exceeded the net income before extraordinary items.

Table 5.1: Summary statistics of the financial hedging and airline industry variables

	Obs.	Mean	SD	MIN	MAX
*asmTl_* (in NM)	544	45462.513	49221.602	118.996	265657.000
fdvDm	618	0.762	0.426	0.000	1.000
fdvMtr (in months)	566	14.295	12.762	0.000	72.000
*fdvNet_* (in USD)	574	−9.826	352.654	−3464.567	3321.192
*fdvNm_* (in USG)	474	360.579	802.006	0.000	8604.000
fdvPct12m	545	0.317	0.302	0.000	1.000
fdvPct24m	505	0.091	0.260	0.000	4.120
fdvPct36m	512	0.028	0.193	0.000	3.750
fdvPct48m	515	0.007	0.049	0.000	0.560
*fuelCons_* (in USG)	470	845.666	916.051	4.778	4332.000
lf	558	0.769	0.069	0.330	0.910
lgtAvg (in NM)	246	805.492	340.729	262.000	2037.690
*rpmTl_* (in NM)	537	36328.116	40359.370	54.738	217838.750
rrpm (in USD)	537	0.218	0.111	0.066	1.081

Variables ending with "_" in millions

The preference of using the adjusted interest coverage ratio instead of the unadjusted variable in this study becomes apparent when analyzing the summary statistics of the two variables. The SD of the unadjusted interest coverage ratio (*intCov*) is quite high with 60.78. The standard deviation is reduced to 1.96 when adjusted values (*intCovAdj*) are used. The sample average adjusted EBIT was 1.62 times higher than the incurred interest expenses. The negative interest coverage ratios stem from negative EBIT values. In 2008, the average sample airlines' EBIT did not suffice to cover the interest expenses. Adjusted interest coverage ratios were on average 0.69 in that sample year. The U.S. low-cost airline Allegiant Air had the seven highest adjusted interest coverage ratios in the sample period. The airline belongs to the leisure travel company Allegiant Travel Company and therefore diverges from the business model of a "pure" airline.[111] The airline is excluded from the multivariate analysis in robustness checks.

In general, the data set suffers from large minimum and maximum outliers. Therefore, the data set is winsorized at the 1% and 99%-level for the univariate and multivariate analysis.

The values in Table 5.2 show that all three leverage ratios rise when they are adjusted by operating lease expenses. The average leverage ratio 1 (*lvrg1*), which is calculated

[111] In 2014, 64% of Allegiant's operating revenue arose from scheduled service revenue.

as IBD scaled by total asstes, increases the most by a quarter when it is lease adjusted (*lvrg1Adj1*). The sample airlines' average adjusted IBD was half of the average adjusted total assets. The four highest leverage ratios could be found for Pakistan International Airlines and Great Lakes. Their interest-bearing debt nearly exceeded their total assets with leverage ratios between 0.94 and 0.92. The average adjusted leverage ratio 2 (*lvrg2Adj1*) was almost identical to *lvrg1Adj1* with 0.52. The maximum value of 1.32 was reached by Delta Air Lines in 2006. Delta Air Lines incurred high liabilities subject to compromise in 2005 and 2006 due to its Chapter 11 proceedings. As liabilities subject to compromise are included under long-term and total liabilities, the maximum leverage ratios 2 and 3 exceed one. Besides Delta Air Lines, Pakistan International Airlines also had very high leverage ratios in the sample period. Its adjusted leverage ratio 3 (*lvrg3Adj1*) was 1.73 in 2014. The sample airlines' total liabilities exceeded the total assets in 47 airline firm years, leading to a high *lvrg3Adj1* of 0.79.

The average sample profit margin (*prfMrg*) increases from 0.02 to 0.05 when lease payments are taken into account. AirAsia had the highest adjusted profit margins (*prfMrgAdj*) in 2007 and 2010 with 0.36 and 0.34. The negative minimum values of -0.41 and -0.37 arose from net losses. The summary statistics of the ROA variables (*roa*, *roaAdj1*) are close to those of the profit margin because of a high correlation factor of 0.82 between these two variables (see the correlation matrix in Table L.1 in Appendix L).

The statistics of the underinvestment variables are summarized in Table 5.3. The year-on-year percentage change of the number of aircraft (*acChg*) was 250.6% for United Airlines in 2010 due to its merger with Continental Airlines. Air Canada, at the other end, showed a reduction in the number of aircraft of -38.0% because the airline changed its reporting standards and excluded the formerly included aircraft of its CPA airline JAZZ. The impact mergers had on the sample airlines' capacity expansion is reflected in the correlation factor of 0.41 between the variables *mrgDm* and *acChg*. Moreover, in five of the nine sample firm years with the highest *acChg* values a merger occurred.

The CAPEX variables do not change considerably when they are adjusted by changes in the PV of operating lease expenses. The sample airlines invested on average 7.6% of their adjusted total assets (*capAsAdj1*), 12.1% of their revenues (*capRevAdj1*) or 6.6% of their firm size (*capSizeAdj1*). Kenya Airways had the lowest *capAsAdj1* value of -42.5% in 2014 because it increased its fleet size by a quarter by buying ten new aircraft.[112] As the Indian low-cost airline SpiceJet withdrew previously placed margin deposits in 2014, it had the maximum *capAsAdj1* value of 44.5%. The Asian LCC AirAsia invested

[112]Note that a capital outflow, i.e. an investment, is signaled by a negative sign.

Table 5.2: Summary statistics of the financial distress variables

	Obs.	Mean	SD	MIN	MAX
divDm	619	0.407	0.492	0.000	1.000
divRto	619	0.147	0.558	−6.385	5.322
divYld	614	0.012	0.024	0.000	0.191
intCov	619	7.830	60.777	−211.102	1320.673
intCovAdj	617	1.623	1.962	−5.134	25.354
lvrg1	621	0.398	0.185	0.000	0.937
lvrg1Adj1	619	0.500	0.163	0.094	0.939
lvrg2	621	0.422	0.197	−0.489	1.399
lvrg2Adj1	619	0.516	0.152	0.076	1.319
lvrg3	621	0.756	0.198	0.082	1.745
lvrg3Adj1	619	0.793	0.174	0.199	1.727
prfMrg	621	0.015	0.086	−0.410	0.311
prfMrgAdj	617	0.050	0.082	−0.368	0.358
roa	621	0.023	0.072	−0.450	0.217
roaAdj	616	0.033	0.053	−0.192	0.206

All variables (except for *divDm*) are dimensionless ratios

more than its revenues in 2007 and 2006, resulting in the minimum adjusted CAPEX to sales ratio (*capRevAdj1*) of -102.1%. The airline also had the highest average increase in fleet size of 35.2% in the sample period. Due to the calculation method of the adjusted net capital expenditure, the Kuwaiti low-cost carrier Jazeera Airways had an adjusted CAPEX to sales ratio of 50.1% in 2010. The airline bought all its formerly operating leased aircraft in 2010. Therefore, the negative change in the PV of operating lease expenses resulted in a positive net capital expenditure and by that in a positive adjusted CAPEX to sales ratio.

The sample airlines held on average 15.8% of their revenues as cash (*cashRev*). SpiceJet depleted its cash holdings in 2013, leading to a cash to sales ratio of 0.1%. Air Arabia, Jazeera Airways and Aer Lingus, at the other end, had larger cash holdings than revenues in 2009, 2014 and 2006 respectively. The sample average cash ratio (*cashRto*) was 0.60, the current ratio (*crtRto*) 0.99 and the quick ratio (*qckRto*) 0.83. The high standard deviations of the MTB (*mtbRto*) and price-earnings ratio (*peRto*) show that the two variables suffer from large outliers. The minimum value (-281.9) of the *mtbRto* occurred for Jet Airways in 2011 due to a small negative equity value of 2 million USD. Similarly, JetBlue showed the lowest *peRto* (2,522.1) in 2006 and Qantas the highest price-earnings ratio (1,394.5) in 2013 because of small net income values. JetBlue reported net losses of 1 million USD and Qantas a net income of approximately 2 million USD.

Table 5.3: Summary statistics of the underinvestment variables

	Obs.	Mean	SD	MIN	MAX
acChg	444	0.083	0.212	−0.380	2.506
capAs	621	−0.082	0.088	−0.476	0.305
capAsAdj1	619	−0.076	0.086	−0.425	0.445
capRev	621	−0.111	0.139	−1.144	0.319
capRevAdj1	621	−0.121	0.153	−1.021	0.501
capSize	616	−0.070	0.074	−0.404	0.239
capSizeAdj1	614	−0.066	0.075	−0.404	0.256
cashRev	621	0.158	0.162	0.001	1.012
cashRto	621	0.598	0.476	0.002	3.811
crtRto	621	0.994	0.578	0.094	5.597
mtbRto	616	1.406	11.937	−281.934	35.334
peRto	615	11.681	129.752	−2522.051	1394.542
qckRto	621	0.834	0.519	0.067	4.392
tobQ	616	1.233	0.467	0.571	5.380
tobQAdj1	614	1.185	0.382	0.571	4.629

All variables (except for *acChg*) are dimensionless ratios

Table 5.4 exhibits the summary statistics of the economies of scale variables. The sample airlines operated an average fleet size (*acTl*) of 209 aircraft. As Jazeera Airways was founded in 2005, the airline operated only six aircraft in 2008. The largest fleet of 1,262 aircraft was held by United Airlines in 2010, closely followed by American Airlines with a fleet of 1,187 aircraft in 2013. The different airline sizes also become apparent when looking at fuel expenses and revenues. The fuel expenses (*fuelExp*) ranged between 16.4 million USD (Great Lakes in 2014) and 13.2 billion USD (United Airlines in 2012). The South African airline Comair showed the smallest revenue (*revTl*) and firm size (*size*) values in 2005. While American Airlines was the largest airline in 2014 with total revenues of 42.7 billion USD, Delta Air Lines had a slightly larger adjusted firm size value (*sizeAdj1*) of 94.6 billion USD than American Airlines (89.0 billion USD) in the same year.

Table 5.4: Summary statistics of the economies of scale variables

	Obs.	Mean	SD	MIN	MAX
acTl	512	208.777	224.749	6.000	1262.000
*fuelExp_* (in USD)	584	1998.054	2332.050	16.435	13138.000
fxdvDm	618	0.613	0.487	0.000	1.000
irdvDm	618	0.579	0.494	0.000	1.000
*revTl_* (in USD)	621	6782.056	8398.804	42.828	42650.000
revTlln (ln)	621	21.875	1.392	17.573	24.476
*size_* (in USD)	616	9844.161	12093.558	24.232	85902.453
*sizeAdj1_* (in USD)	614	11200.169	13533.143	35.347	94640.328

Variables ending with "_" in millions

5.1.1 Univariate analysis

In the following subsection, the univariate analysis of the variables related to the determinants argument is presented. For each topic (financial distress, the underinvestment problem, economies of scale), two univariate analyses are carried out. In the first analysis, the sample firm years are divided into firm years with the fuel derivative dummy (*fdvDm*) being one (hedgers) and zero (non-hedgers). In the second analysis, the categorization into two groups is based on the airlines' hedge ratios. All airlines enter the analysis, hedgers as well as non-hedgers. If the airline's hedge ratio (*fdvPct12m*) is above the sample median hedge ratio, this airline firm year is categorized as "high ratios" and "low ratios" otherwise.[113] For robustness, Tables K.1, K.2 and K.3 in Appendix K contain alternative differences-of-means tests between airlines whose hedge ratios are above the sample average hedge ratio and airlines whose hedge ratios are below the sample average hedge ratio.

For the univariate analysis Stata's two-sample t test using groups with unequal variance is employed. Without the *unequal* function it would be assumed that both analyzed groups have the same variance, which is not the case in the sample.[114]

[113] Although the median hedge ratio is employed to split the sample into two groups in the second analysis, the two groups do not always show the same number of observations. The missing values of the hedge ratio as well as of the variable of interest lead to the different number of observations. The sample airlines reported their hedge ratios (*fdvPct12m*) in 545 firm years. If, for example, airlines with high hedge ratios disclosed their number of aircraft (*acTl*) more often than airlines with relatively low hedge ratios, the result is that the second group ("low ratios") is smaller than the first group ("high ratios"), as can be seen in Table 5.10.

[114] Also, using the pooled standard error formula would lead to biased results because the formula requires the same number of observations for each group or otherwise the same variance (Stock and Watson, 2007).

In Table 5.5 the *t* test results between hedgers and non-hedgers for the financial distress variables are exhibited. The first column contains the abbreviated variable name, the second and third column the mean value and the number of observations for the first group, the fourth and fifth column the mean value and the number of observations for the second group, the sixth column the differences in the means of the two groups, the seventh column the standard errors, and the last column the total number of observations. The significance levels are displayed with asterisks behind the difference values. The univariate results do not show any difference in the means of the dividend variables (*divDm*, *divRto*, *divYld*) between hedgers and non-hedgers. Moreover, the means of the unadjusted and adjusted profitability measures (*intCov*, *intCovAdj*, *prfMrg*, *prfMrgAdj*) do not differ significantly. Hedgers, however, had significantly (5%) lower adjusted ROA values (*roaAdj1*). As lower return on assets can be viewed as a sign of a proximity to financial distress, the univariate results support the hypothesis H1a. On the other hand, the results demonstrate that hedgers had significantly (1%) lower leverage ratios 1 than non-hedgers, failing to support H1a. The mean *lvrg2*, *lvrg2Adj1*, *lvrg3* and *lvrg3Adj1* values did not differ significantly between the two groups. Overall, the univariate results are ambiguous regarding H1a. Especially the insignificant difference of means of the leverage ratios 2 and 3 may arise because the univariate analysis does not take account of the nonlinear relation between leverage and hedging proposed in H1b.

Table 5.6 comprises the results of the differences-of-means test between airlines with high hedge ratios and low hedge ratios. The results are similar to those of the previous table. In the firm years with relatively high hedge ratios, airlines showed significantly lower unadjusted and adjusted leverage ratios 1. In addition, leverage ratios 3 were significantly smaller among airlines that used fuel price derivatives extensively. The unadjusted interest coverage ratio was smaller for airlines with relatively high hedge ratios, whereas the adjusted ratio remains insignificant. All other variables are not significant. The results of the *t* test when the sample average is used to split the sample into airlines with high and low hedge ratios can be found in Table K.1 in Appendix K. In this case, airlines with high hedge ratios showed significantly lower unadjsuted interest coverage ratios, adjusted profit margins and unadjusted as well as adjusted ROA values. Again, the univariate results of the second analysis are mixed with regards to the financial distress hypothesis.

Tables 5.7 and 5.8 provide the *t* test results of the underinvestment variables. The variable *cashGrwDm*, which identifies airlines with relatively large growth options and simultaneous low cash holdings, was significantly (5%) smaller for airlines that chose

Table 5.5: Differences-of-means test between hedgers (*fdvDm*=1) and non-hedgers (*fdvDm*=0): financial distress variables

	Hedgers		Non-hedgers		*t* test		
	Mean	Obs.	Mean	Obs.	Diff.	SE	Obs.
divDm	0.395	471	0.448	145	0.053	0.047	616
divRto	0.152	471	0.148	145	−0.004	0.029	616
divYld	0.012	467	0.011	144	0.000	0.002	611
intCov	4.508	470	8.502	146	3.994	2.162	616
intCovAdj	1.491	470	1.782	145	0.291	0.148	615
lvrg1	0.369	471	0.485	147	0.116***	0.020	618
lvrg1Adj1	0.477	471	0.573	145	0.096***	0.017	616
lvrg2	0.426	471	0.413	147	−0.013	0.021	618
lvrg2Adj1	0.520	471	0.493	145	−0.027	0.015	616
lvrg3	0.747	471	0.783	147	0.036	0.021	618
lvrg3Adj1	0.787	471	0.812	145	0.025	0.019	616
prfMrg	0.016	471	0.017	147	0.001	0.009	618
prfMrgAdj	0.047	470	0.059	145	0.012	0.008	615
roa	0.020	471	0.033	147	0.013	0.007	618
roaAdj1	0.029	470	0.043	144	0.013*	0.005	614

* $p<0.05$, ** $p<0.01$, *** $p<0.001$

to use fuel hedging (Table 5.7) and for airlines with relatively high hedge ratios (Table 5.8). These results fail to support H4. The capital expenditure variables (*capAs*, *capRev*, *capSize*) did not differ significantly between airlines with and without fuel derivatives, as well as between airlines with high and low hedge ratios. While the difference in the MTB ratios is not significant in either of the two tables, the Tobin's Q values differed significantly between the groups. Hedgers had significantly (10%) fewer investment opportunities at hand than non-hedgers. In addition, airlines with high hedge ratios displayed lower adjusted Tobin's Q values than airlines with low hedge ratios, significant at the 5%-level. Therefore, H2 is not supported by the univariate analysis. The cash ratio, current ratio and quick ratio were significantly greater for firm year observations with *fdvDm* being one. The significance levels vary between 1% and 10%. Similarly, airlines with relatively high hedge ratios exhibited greater cash, current and quick ratios, significant at the 10%-level. These results support H3a. The alternative *t* test results in Table K.2 in Appendix K also support H3a as the cash, current and quick ratios are significantly greater for airlines whose hedge ratio was above the sample average hedge

Table 5.6: Differences-of-means test between airlines with high hedge ratios (hedge ratio above sample median) and low hedge ratios (hedge ratio below sample median): financial distress variables

	High ratios (>med.)		Low ratios (<=med.)		*t* test		
	Mean	Obs.	Mean	Obs.	Diff.	SE	Obs.
divDm	0.417	271	0.408	272	−0.009	0.042	543
divRto	0.154	271	0.152	272	−0.002	0.027	543
divYld	0.012	271	0.011	268	−0.001	0.002	539
intCov	4.110	271	7.512	272	3.402*	1.599	543
intCovAdj	1.531	271	1.660	272	0.129	0.117	543
lvrg1	0.348	271	0.435	274	0.087***	0.016	545
lvrg1Adj1	0.455	271	0.540	272	0.085***	0.014	543
lvrg2	0.417	271	0.425	274	0.009	0.017	545
lvrg2Adj1	0.511	271	0.517	272	0.006	0.013	543
lvrg3	0.733	271	0.772	274	0.040*	0.017	545
lvrg3Adj1	0.773	271	0.808	272	0.035*	0.015	543
prfMrg	0.019	271	0.018	274	0.000	0.007	545
prfMrgAdj	0.049	271	0.058	272	0.009	0.007	543
roa	0.022	271	0.029	274	0.006	0.006	545
roaAdj1	0.031	271	0.038	271	0.006	0.004	542

* p<0.05, ** p<0.01, *** p<0.001

ratio. Furthermore, the results in Table K.2 also fail to support H2. While all CAPEX variables are insignificant, the market-to-book ratio, the price-earnings ratio and the unadjusted as well as the adjusted Tobin's Q values are significantly smaller for airlines with relatively high hedge ratios.

The economies of scale variables, presented in Tables 5.9, 5.10 and K.3, support H5. Hedgers (Table 5.9) were significantly larger than non-hedgers regardless of the variable examined: the total number of aircraft (*acTl*), fuel expenses (*fuelExp*), total revenues (*revTl*), and firm size (*size*, *sizeAdj1*). Hedgers also held a greater number of currency (*fxdvDm*) and interest rate derivatives (*irdvDm*), analogous to the argument that economies of scale exist with holding multiple types of derivatives because of expert knowledge within a firm. All variables, except *acTl*, are significant at the 1%-level. With regards to the extent of hedging (Table 5.10), airlines with high hedge ratios had significantly (10%) greater fuel expenses, greater revenues (1%), held more further derivatives (1%), and were significantly larger in firm size (5%). Only the number of aircraft (as well as the fuel expenses in Table K.3) did not differ significantly.

Table 5.7: Differences-of-means test between hedgers (*fdvDm*=1) and non-hedgers (*fdvDm*=0): under-investment variables

	Hedgers		Non-hedgers		*t* test		
	Mean	Obs.	Mean	Obs.	Diff.	SE	Obs.
acChg	0.081	377	0.097	65	0.016	0.029	442
capAs	−0.078	471	−0.094	147	−0.016	0.009	618
capAsAdj1	−0.072	471	−0.088	145	−0.016	0.008	616
capAsAdj5	−0.072	470	−0.087	145	−0.015	0.010	615
capRev	−0.105	471	−0.123	147	−0.018	0.013	618
capRevAdj1	−0.116	471	−0.139	147	−0.022	0.015	618
capSize	−0.068	467	−0.077	146	−0.009	0.007	613
capSizeAdj1	−0.063	467	−0.074	144	−0.010	0.007	611
cashGrwDm	0.158	467	0.319	144	0.161***	0.043	611
cashRev	0.158	471	0.156	147	−0.002	0.018	618
cashRto	0.639	471	0.434	147	−0.205***	0.042	618
crtRto	1.026	471	0.859	147	−0.167**	0.054	618
mtbRto	1.770	467	1.858	146	0.088	0.266	613
peRto	14.413	467	11.333	145	−3.080	3.264	612
qckRto	0.863	471	0.689	147	−0.173***	0.044	618
tobQ	1.196	467	1.321	146	0.124**	0.044	613
tobQAdj1	1.159	467	1.247	144	0.088*	0.035	611

* $p<0.05$, ** $p<0.01$, *** $p<0.001$

5.1.2 Multivariate analysis

Hypotheses H1a to H5 presented in Chapter 3 regarding the determinants of hedging are analyzed with different regression models in this subsection. First, regression results with the fuel derivative dummy (*fdvDm*) as the dependent variable will be discussed. Thereafter, the hedge ratio (*fdvPct12m*) is the dependent variable in the regression models.

Statistical methods provide the possibility to either reject or not reject the null hypothesis in favor of the theoretically developed alternative hypothesis (Stock and Watson, 2007). The null hypothesis of H1a, for example, is that the coefficient of the leverage variable is not statistically significantly different from zero and that the leverage of a firm does not influence its hedging behavior. If the leverage coefficient, however,

Table 5.8: Differences-of-means test between airlines with high hedge ratios (hedge ratio above sample median) and low hedge ratios (hedge ratio below sample median): underinvestment variables

	High ratios (>med.)		Low ratios (<=med.)		*t* test		
	Mean	Obs.	Mean	Obs.	Diff.	SE	Obs.
acChg	0.081	235	0.093	175	0.012	0.021	410
capAs	−0.078	271	−0.089	274	−0.012	0.007	545
capAsAdj1	−0.070	271	−0.083	272	−0.013	0.007	543
capAsAdj5	−0.070	271	−0.082	272	−0.012	0.007	543
capRev	−0.103	271	−0.116	274	−0.014	0.011	545
capRevAdj1	−0.110	271	−0.133	274	−0.022	0.012	545
capSize	−0.068	271	−0.074	270	−0.006	0.006	541
capSizeAdj1	−0.062	271	−0.070	268	−0.008	0.006	539
cashGrwDm	0.096	271	0.272	268	0.176***	0.033	539
cashRev	0.160	271	0.156	274	−0.004	0.014	545
cashRto	0.708	271	0.516	274	−0.192***	0.037	545
crtRto	1.113	271	0.914	274	−0.199***	0.045	545
mtbRto	1.619	271	1.934	270	0.315	0.223	541
peRto	11.614	271	14.141	269	2.527	3.483	540
qckRto	0.939	271	0.751	274	−0.188***	0.039	545
tobQ	1.165	271	1.292	270	0.126***	0.036	541
tobQAdj1	1.133	271	1.227	268	0.095**	0.029	539

* p<0.05, ** p<0.01, *** p<0.001

is statistically significantly different from zero, indicated by a predefined significance probability (the p-value[115]) of for example 1%, the null hypothesis can be rejected in favor of the alternative hypothesis (Stock and Watson, 2007).

Table 5.11 contains the results of five different random effects probit models that were run on different independent variables with the same regressand, the binary fuel hedge variable *fdvDm*. The nonlinearity imposed by a probit model allows the regressand to be censored between zero and one (Stock and Watson, 2007).[116] Random effects are chosen because with fixed effects Stata eliminates all observations in which the dependent variable does not change over time (Stock and Watson, 2007). As many airlines used

[115]The p-value resembles the probability of randomly drawing a statistic similar to the null hypothesis (Stock and Watson, 2007).
[116]The nonlinearity is achieved by the use of the standard normal cumulative probability distribution function (Stock and Watson, 2007).

Table 5.9: Differences-of-means test between hedgers (*fdvDm*=1) and non-hedgers (*fdvDm*=0): economies of scale variables

	Hedgers		Non-hedgers		*t* test		
	Mean	Obs.	Mean	Obs.	Diff.	SE	Obs.
acTl	218.449	428	162.171	82	−56.278*	25.039	510
*fuelExp_*	2200.864	459	1239.909	123	−960.955***	199.651	582
fxdvDm	0.705	471	0.320	147	−0.385***	0.044	618
irdvDm	0.671	471	0.286	147	−0.385***	0.043	618
*revTl_*	7810.438	471	3542.875	147	−4267.563***	619.631	618
revTlln	22.177	471	20.901	147	−1.275***	0.144	618
*size_*	11121.317	467	5831.278	146	−5290.038***	1015.428	613
*sizeAdj1_*	12612.363	467	6718.533	144	−5893.830***	1141.840	611

* p<0.05, ** p<0.01, *** p<0.001

Variables ending with "_" in millions of USD

Table 5.10: Differences-of-means test between airlines with high hedge ratios (hedge ratio above sample median) and low hedge ratios (hedge ratio below sample median): economies of scale variables

	High ratios (>med.)		Low ratios (<=med.)		*t* test		
	Mean	Obs.	Mean	Obs.	Diff.	SE	Obs.
acTl	226.852	263	200.880	208	−25.972	21.722	471
*fuelExp_*	2173.662	271	1743.972	250	−429.690*	203.398	521
fxdvDm	0.723	271	0.471	274	−0.252***	0.041	545
irdvDm	0.712	271	0.442	274	−0.271***	0.041	545
*revTl_*	8290.884	271	5227.385	274	−3063.499***	721.067	545
revTlln	22.255	271	21.441	274	−0.814***	0.116	545
*size_*	11256.541	271	7926.926	270	−3329.614**	1007.619	541
*sizeAdj1_*	12765.738	271	9169.906	268	−3595.832**	1137.827	539

* p<0.05, ** p<0.01, *** p<0.001

Variables ending with "_" in millions of USD

fuel price hedging in all sample years, there was no change in the dependent variable within an entity in many cases. The coefficients are estimated by maximum likelihood (Baum, 2007).

There are multiple approximate measures for one hypothesis in this study. Therefore, a base regression is first defined which is adapted subsequently with the alternative regressors (Stock and Watson, 2007). The Akaike information criterion (AIC) serves as the quality characteristic for the model selection. The lower the AIC value, the higher the relative quality of one model compared to the other model (Akaike, 1973). In order to arrive at the multiple regression with the lowest AIC factor, a base regression containing one independent variable of each topic relating to the determinants hypotheses is established. The initial base regression comprises the variables that were predominantly used in previous research. Thereafter, the independent variable of the examined topic is exchanged by another proxy variable. If the new regression model displays a lower AIC value than the base regression, the base regression is adapted accordingly and the new regression model becomes the new base regression. The alternative regressors of the other topics are exchanged subsequently. With this iterative process multiple combinations of proxies are used, leading to the regression model with the (almost) lowest AIC value. As this process is performed manually, not all combinations of variables are tested. Although variables selection procedures such as stepwise deletion would be available in order to accomplish the automatic selection of variables whose coefficients show a high significance level with the dependent variable, the caveats of those procedures (e. g. statistical noise) exceed the computational ease. Thus, expert knowledge and profound theoretical reasoning should be favored in variables selection instead of data mining (Harrell, 2001). In some cases, when the AIC values of two models differ by less than seven, the base regression is not adapted if the variables selected are better suited for testing the discussed hypotheses. Regression models with differences in AIC values equal to or smaller than seven are of a similar quality and ergo facilitate similar statistical inferences (Burnham and Anderson, 2004).

In Table 5.11 the model number as well as the dependent variable employed is shown in the header of the table. Model 1 is the base regression in all regression tables for better comparison. The abbreviated variable labels are presented on the left side. The random effects coefficient estimate of each regressor is exhibited, including the p-value in parentheses and the significance level as asterisks. The intercept of the regression line is presented as "intercept". Moreover, the number of observations (N), the AIC value, and whether year dummies are included in the model are depicted at the bottom of the table. Model specifications with alternative approximate measures for each topic are discussed in Subsection 5.1.3. The base regression in Model 1 does not contain time fixed effects in contrast to Model 2, which includes time fixed effects. The AIC value of Model 2 with year dummies is higher than the AIC value of Model 1. As the coefficient estimates and p-values do not differ strongly between Models 1 and 2, year dummies are omitted in the later regression. Model 4 is presented to demonstrate that a regression model with purely leverage ratio variables does not represent the data better than the base regression with a lower AIC value.

The base regression comprises the financial distress variables *lvrg1Adj1*, *lvrg1Adj1Sqr* and *intCovAdj*. The inclusion of the nonlinearity of the leverage ratio (H1b) follows from the significance of the squared term as well as from the higher AIC value in Model 3, in which the squared terms are excluded. The coefficient estimate on leverage is negative and significantly different from zero at the 5%-level in Models 1, 2 and 5. The results do not support hypothesis H1a. On the contrary, if the leverage ratio (*lvrg1Adj1*) increased by 0.01, the probability of fuel derivative usage would decrease by 14.2%. The coefficient estimates in a probit regression cannot be interpreted in the same way as in a linear regression model though. Due to the nonlinear nature of the calculation method in a probit regression, an increase from 0.2 to 0.3 may not allow for the same inferences as an increase from 0.5 to 0.6. Therefore, probit results should rather be used to explain tendencies than concrete values (UCLA: Statistical Consulting Group, 2018). The results also fail to support hypothesis H1b as the coefficient on the squared leverage ratio (*lvrg1Adj1Sqr*) is positive, statistically significantly different from zero at the 5%-level. In cases of very high leverage ratios airlines rather increased their hedge activities in the sample period. The negative coefficient on *lvrg1Adj1* and the positive coefficient on the quadratic indicate a convex relation between debt ratios and the likelihood of hedging. A possible explanation is that airlines with increasing debt ratios face a trade-off between providing margin calls or securing their remaining funds for investment opportunities. At very high leverage ratios, airlines hedge on all accounts to the seize the opportunity to exit the phase of financial distress. See Subsection 5.1.5 for more details.

The underinvestment hypothesis H2 is not supported by the data. The coefficient on the adjusted Tobin's Q variable is not significant in any of the four models. The results, on the other hand, support H3a. The positive coefficient estimates on the cash ratio (*cashRto*) are significantly different from zero at the 5%-level in Models 1, 2 and 5. Higher cash ratios increase the probability of derivative usage. The nonlinearity imposed by hypothesis H3b is in accordance with expectations. Very high levels of cash holdings (*cashRtoSqr*) lead to a lower likelihood of hedging. The coefficient estimate on the binary variable *cashGrwDm* is positive but not significantly different from zero in Model 5. H4 is therefore not supported by the data.

The results with regards to the economies of scale hypotheses are mixed. While the coefficient on the number of aircraft (*acTl*) is not significant in any of the four models, the estimates on the interest rate (*irdvDm*) and foreign exchange derivative dummies (*fxdvDm*) are positive and statistically significantly different from zero between the 1% and 5%-level. The results imply that airlines with a hedge portfolio that includes other derivatives are more likely to also hold fuel price derivatives. A likely answer for the insignificant coefficient on the size variable is the importance of fuel hedging in the airline industry. As total fuel expenses account for approximately a third of airlines' total operating costs (IATA, 2015), the impact of the overall fuel bill is as severe for small airlines as it is for large airlines. This statement is further discussed in Subsection 5.1.5.

In Table 5.12 regression models with the hedge ratio as the dependent variable are shown. If the regressand is a continuous variable, OLS estimators with fixed effects and heteroskedastic-robust standard errors can be used.[117] The fixed effects model is necessary to control for potential omitted variables in the data set "when the omitted variables vary across entities (states) but do not change over time" (Stock and Watson, 2007, p. 356). Examples of the omitted variable bias are discussed in Subsection 5.1.4. In a fixed effects regression model each airline is assigned a dummy variable that controls for all omitted idiosyncrasies of that airline, which do not change in the sample period. Without the introduction of the airline-specific binary variable (the entity fixed effect), random effects estimators could be used but only if these estimators were consistent. The Hausman test compares the estimators of the random effects and fixed effects regression models, and tests whether the random effects estimators are consistent. In the current sample, the null hypothesis that the random effects model leads to valid inferences has to be rejected and the fixed effects model applies (Baum, 2007). If an omitted variable changed during the sample period among one entity, time fixed effects needed to be included. In order to prevent this bias, year dummies are included in the regression analysis. A joint F test of the year dummies is not statistically significantly different from zero however, implying that time fixed effects are not necessary and that there are no omitted variables that are constant across entities but change over time (Baum, 2007).[118]

Due to the nature of fixed effects models, variables with an entity standard deviation of zero cannot be included in the model (Baum, 2007). Therefore, the binary LCC (*lccDm*) or regional variable (*reg*) cannot enter the regression because none of the sample

[117] The fixed effects estimator can be employed for the unbalanced panel data set because there is more than one observation for each airline (Baum, 2007).

[118] Moreover, the AIC value of the regression model that includes year dummies is greater than the AIC value of the equivalent model without year dummies. The lower AIC value indicates that a model without year dummies is of higher statistical quality.

Table 5.11: Random effects probit models, hedge dummy as the dependent variable

	BASE (1) fdvDm	(2) fdvDm	(3) fdvDm	(4) fdvDm	(5) fdvDm
lvrg1Adj1	-14.22^{**}	-13.63^{**}	-1.872	-2.135	-14.09^{**}
	(0.012)	(0.018)	(0.173)	(0.620)	(0.013)
lvrg1Adj1Sqr	12.18^{**}	11.50^{**}		2.036	12.03^{**}
	(0.023)	(0.037)		(0.605)	(0.026)
intCovAdj	-0.733^{***}	-0.716^{***}	-0.607^{***}		-0.736^{***}
	(0.000)	(0.000)	(0.000)		(0.000)
tobQAdj1	0.418	0.477	0.331		0.457
	(0.329)	(0.313)	(0.435)		(0.312)
cashRto	3.021^{**}	3.043^{**}	0.339		2.970^{**}
	(0.016)	(0.020)	(0.453)		(0.020)
cashRtoSqr	-1.317^{**}	-1.370^{**}			-1.304^{**}
	(0.020)	(0.021)			(0.022)
acTl	0.000664	0.000775	0.000596		0.000647
	(0.537)	(0.486)	(0.582)		(0.547)
irdvDm	1.208^{***}	1.275^{***}	1.184^{***}		1.199^{***}
	(0.003)	(0.002)	(0.004)		(0.003)
fxdvDm	1.101^{***}	1.060^{***}	0.935^{**}		1.110^{***}
	(0.005)	(0.008)	(0.015)		(0.005)
cashGrwDm					-0.0995
					(0.782)
intercept	4.011^{**}	3.723^{**}	2.108^{*}	2.632^{**}	3.993^{**}
	(0.014)	(0.035)	(0.054)	(0.027)	(0.014)
N	504	504	504	616	504
AIC	248.9	264.3	253.7	381.5	250.8
Year dummies	no	yes	no	no	no

p-values in parentheses

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

airlines changed either their business model or their region during the sample period. Similarly, variables that change from one period to another but do not vary between airlines in one period, such as the yearly oil price, cannot be part of a fixed effects model (Baum, 2007). The fixed effects estimates will control for any impact that the *lccDm*, region or the yearly oil price might have.

Regarding the type of standard error it is essential to employ heteroskedastic-robust standard errors in contrast to homoskedasticity-only standard errors. Under homoskedasticity it is presumed that the variance of the error term is the same regardless of the value of the independent variable. If, for example, the variance of the hedge ratio (the dependent variable) is not the same for airlines with high leverage (the independent variable) and airlines with low leverage, only heteroskedastic-robust standard errors lead to valid statistical inferences (Baum, 2007; Stock and Watson, 2007). Stock and Watson (2007) emphasize the importance of using heteroskedastic-robust standard errors because "economic theory rarely gives any reason to believe that the errors are homoskedastic" (p. 166). Apart from heteroskedasticity, serial correlation may also lead to inconsistent error terms. Especially in time-series and panel data, potential serial correlation exists if the error terms are correlated between time periods. The Stata command *xtserial*, based on a test proposed by Wooldridge (2001), enables the researcher to test for serial correlation in panel data (Drukker, 2003). The test results negate the existence of serial correlation among the error terms.

Table 5.12 displays the regression results of the fixed effects models. The header of the table contains the model number and the regressand. The abbreviated variable labels are presented on the left side. The raw estimators are shown, followed by the significance level in asterisks. The p-values are in parentheses. The intercept is given underneath the variables. The table concludes with the number of observations (N), the AIC value, adjusted[119] and normal R^2 values and whether year dummies are included in the model. Tables including fixed effects model specifications with alternative approximate measures for each topic are discussed for robustness in Subsection 5.1.3.

The base regression in Model 1 includes the adjusted leverage ratio 1 (*lvrg1Adj1*), its squared term (*lvrg1Adj1Sqr*), the adjusted interest coverage ratio (*intCovAdj*), the price-earnings (*peRto*) and current ratios (*crtRto, crtRtoSqr*), the adjusted firm size (*sizeAdj1*), and interest rate (*irdvDm*) as well as currency derivative dummies (*fxdvDm*). Corresponding to the results of the decision to hedge (*fdvDm*), the leverage ratio is negatively related to the extent of hedging. The coefficient estimate is significantly

[119]As the inclusion of additional independent variables inflates the R^2 value, the adjusted R^2 is also reported.

Table 5.12: Firm fixed effects models (with heteroskedastic-robust standard errors), hedge ratio as the dependent variable

	BASE (1) fdvPct12m	(2) fdvPct12m	(3) fdvPct12m	(4) fdvPct12m	(5) fdvPct12m
lvrg1Adj1	-1.462^{***}	-1.292^{***}	-0.103	-1.304^{***}	-1.166^{***}
	(0.000)	(0.001)	(0.321)	(0.000)	(0.001)
lvrg1Adj1Sqr	1.254^{***}	1.083^{***}		1.186^{***}	1.072^{***}
	(0.000)	(0.001)		(0.000)	(0.001)
intCovAdj	-0.0261^{***}	-0.0258^{***}	-0.0206^{**}		
	(0.002)	(0.003)	(0.013)		
peRto	-0.000186	-0.000183	-0.000138		-0.000202
	(0.279)	(0.293)	(0.427)		(0.245)
crtRto	-0.0179	-0.0141	-0.0598		-0.0424
	(0.776)	(0.825)	(0.340)		(0.507)
crtRtoSqr	0.0103	0.00964	0.0250		0.0182
	(0.603)	(0.629)	(0.204)		(0.361)
sizeAdj1_	-0.000000208	-0.00000137	-0.000000707		-0.00000122
	(0.893)	(0.421)	(0.652)		(0.428)
irdvDm	0.0785^{***}	0.0807^{***}	0.0847^{***}		0.0777^{***}
	(0.006)	(0.006)	(0.004)		(0.008)
fxdvDm	0.00478	0.00620	0.000338		0.00664
	(0.863)	(0.823)	(0.990)		(0.812)
cashGrwDm					0.0107
					(0.632)
intercept	0.705^{***}	0.729^{***}	0.392^{***}	0.641^{***}	0.588^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N	538	538	538	543	539
AIC	-597.7	-593.6	-582.9	-586.6	-588.5
Adj. R^2	0.761	0.763	0.754	0.750	0.757
R^2	0.796	0.801	0.790	0.784	0.792
Year dummies	no	yes	no	no	no

p-values in parentheses

Variables ending with "_" in millions of USD

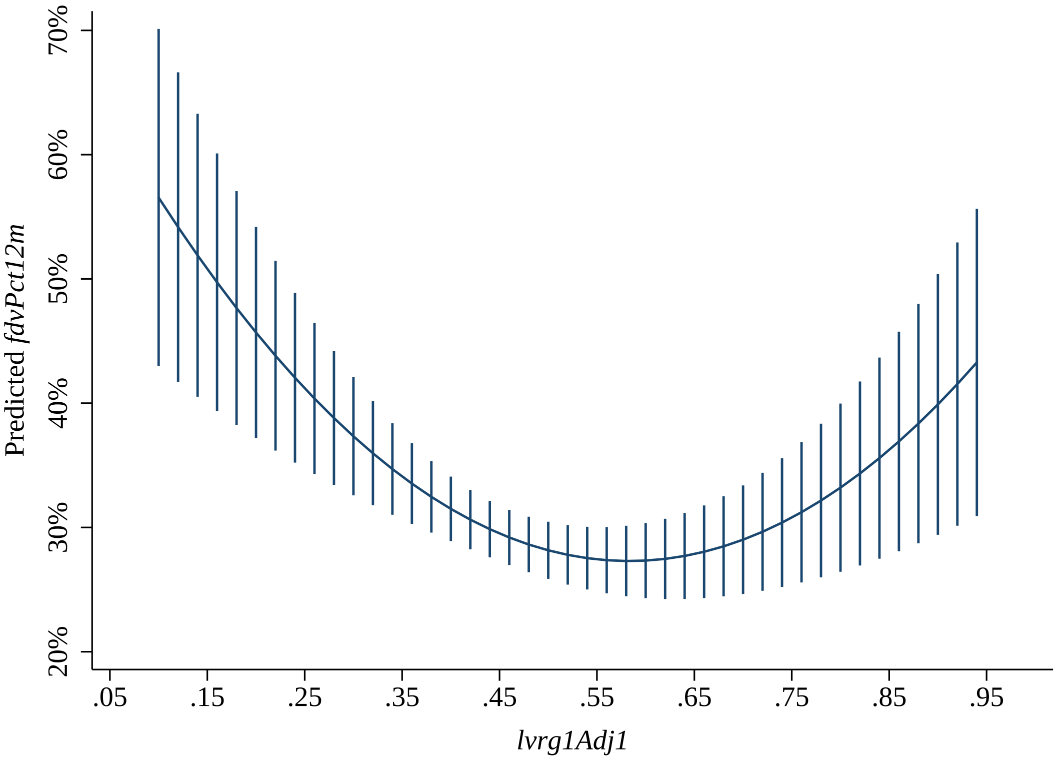
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

different from zero at the 1%-level in four out of five models. H1a is not supported. A one (within) SD increase in leverage ratio 1 (0.07) would reduce the airlines' hedge ratio by 10.23 (0.07×1.462) percentage points. The estimate on the interest coverage ratio is also negative and significant despite a negative correlation between *lvrg1Adj1* and *intCovAdj* in the sample. Higher interest coverage ratios indicate a better financial situation and contradict the negative coefficient of the leverage ratio. However, the magnitude of the leverage coefficient greatly exceeds that of the interest coverage ratio. Therefore, the effect of leverage on the hedge ratio is stronger than the effect of the interest coverage ratio. Moreover, the estimates of the interest coverage ratio as well as the profit margin may be distorted by the large fluctuations of the two variables over the sample period (see Figures 4.18 and 4.19). The within SD of *intCovAdj* (*prfMrgAdj*) was 1.28 (0.06) with an average value of 1.62 (0.05). In comparison, the adjusted leverage ratio 1 was more stable in the sample period with a standard deviation of 0.07 and an average value of 0.50.

Airlines with very high leverage (*lvrg1Adj1Sqr*) significantly (1%) increased their hedge ratios, opposing the argument in hypothesis H1b. The negative coefficient on *lvrg1Adj1* and the positive coefficient on *lvrg1Adj1Sqr* speak for a nonlinear relation between leverage and the extent of hedging, comparable to the probit regression results. The predicted hedge ratios in Figure 5.1 follow a U-shape. The hedge ratios are predicted at different leverage ratios while all other independent variables are set to their mean values (Williams, 2012). The spikes reflect the 95% confidence interval. The results on leverage remain consistent when year dummies are included in Model 2. If the relation between the hedge ratio and leverage is assumed to be linear as in Model 3, the leverage ratio does not significantly influence the extent of hedging. In contrast to the probit model, the leverage ratio significantly reduces the extent of hedging in absence of other independent variables in Model 4.

To further analyze the nonlinear relationship between leverage and the extent of hedging, the approach by Purnanandam (2008) is followed who divides his sample into two groups, one group with leverage ratios in the lower 70th percentile and the other group in the upper tertile. The results in Table 5.13 provide strong evidence of the nonlinear relationship as the fixed effects estimate on leverage is negative for airlines with low leverage ratios and positive for airlines with high leverage ratios. Airlines with leverage ratios in the lowest 70th percentile reduced their hedge ratio by 3.50 percentage points if the debt ratio increased by 0.1. The estimate is statistically significantly different from zero at the 5%-level. Highly indebted airlines increased their hedge ratio by 3.04 percentage points for an increase in leverage of 0.1. The p-value of the estimate

Figure 5.1: Predicted hedge ratios (*fdvPct12m*) at different leverage ratios (*lvrg1Adj1*) with a 95% confidence interval, based on fixed effects estimation with the remaining independent variables set at their mean values



is 0.101 and thus slightly exceeds the 10%-level. The quadratic leverage term is excluded in the regression as the nonlinearity is achieved by dividing the sample into airlines with relatively high and low leverage ratios.

Moreover, analogous to Rampini et al. (2014), the focus is set on the sample airlines in actual financial distress, i. e. whose book equity is below zero. The positive relation between leverage ratios and negative equity values in the sample is shown by a correlation factor of 0.30 between *lvrg1Adj1* and the negative equity dummy variable (*eqtyDm*) (see Table L.1 in Appendix L). In addition, the debt ratio of the firm years with negative equity values ranges between 0.41 and 0.94, with a mean value of 0.68 (values not shown in any table). Airlines in the highest quartile of *lvrg1Adj* exhibited debt ratios between 0.61 and 0.94, with a mean value of 0.70. Therefore, airlines with negative equity values and airlines with high leverage ratios can be viewed as airlines under financial distress.

The average hedge ratios in the two years prior to the distress phase (defined as years with negative equity values) are compared against the hedge portfolio during the

Table 5.13: Firm fixed effects models (with heteroskedastic-robust standard errors), airlines with low leverage (in the lower 70th percentile) and airlines with high leverage (in the highest tertile)

	(1) Low leverage airlines fdvPct12m	(2) High leverage airlines fdvPct12m
lvrg1Adj1	-0.350^{**}	0.304
	(0.024)	(0.101)
intCovAdj	-0.0110	-0.0728^{***}
	(0.238)	(0.000)
peRto	-0.000262	0.0000927
	(0.250)	(0.660)
crtRto	-0.118	0.0669
	(0.140)	(0.454)
crtRtoSqr	0.0301	-0.00766
	(0.231)	(0.785)
sizeAdj1_	-0.000000205	-0.00000288
	(0.902)	(0.401)
irdvDm	0.0978^{***}	0.0282
	(0.004)	(0.598)
fxdvDm	-0.0190	-0.0552
	(0.558)	(0.237)
intercept	0.563^{***}	0.0881
	(0.000)	(0.544)
N	375	163
Adj. R^2	0.732	0.888
R^2	0.782	0.916

p-values in parentheses
Variables ending with "_" in millions of USD
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

crisis and in the two years following the crisis. The sixteen airlines shown in Table 5.14 hedged on average 23.4% of their expected fuel consumption prior to the crisis years, 22.1% during the crisis and 23.3% following the crisis. The averaged values give the impression that the distress phase does not have an impact on the hedging behavior of the concerned airlines. However, when individually considered in Figure 5.2, all airlines (except for Air France-KLM) changed their hedge portfolios before, during and after the distress phase. Aeroflot, Air Berlin, Kenya Airways, and United Airlines increased their hedge portfolio during the crisis compared to pre-crisis years. On the other hand, Air Canada, American Airlines, Delta Air Lines, Gol, and US Airways lowered their hedge ratios during the distress phase. In the post-crisis phase, American Airlines reduced the hedge ratio. Delta Air Lines and United Airlines, on the contrary, increased their hedge activities after the crisis. While Delta Air Line's hedge portfolio reached above pre-crisis level, United Airlines' hedge ratio remained below pre-crisis levels. No information is available for two airlines (China Eastern, Cyprus Airways). Four airlines (Great Lakes, Jet Airways, Pakistan International Airlines, SpiceJet) did not hedge in either of the three periods.

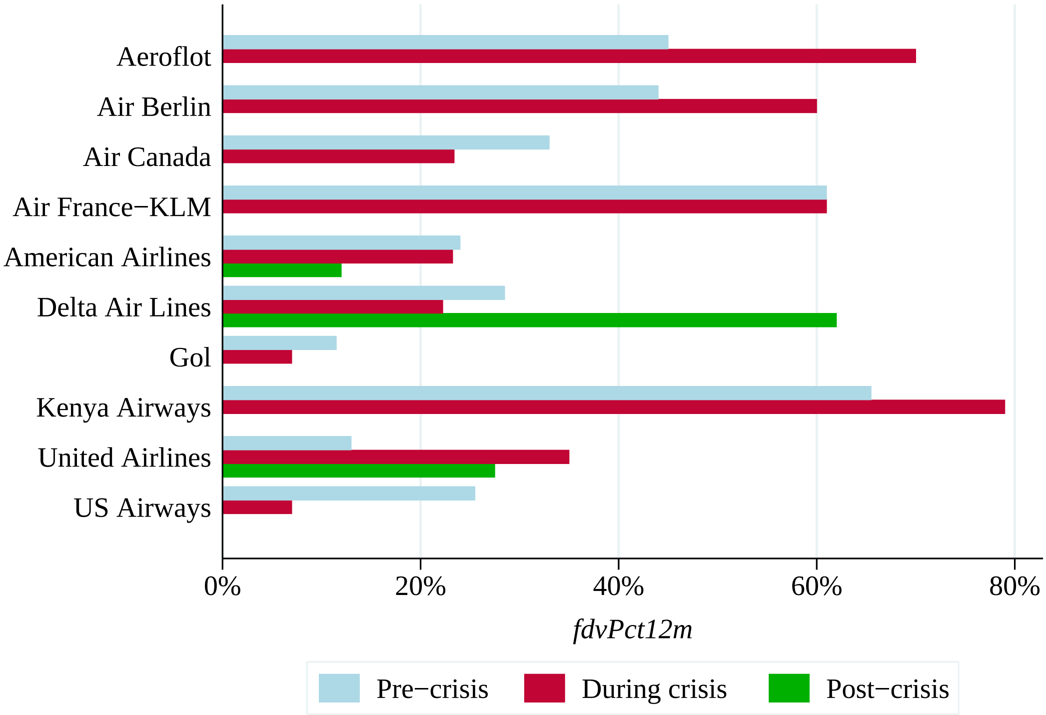
Table 5.14: Airlines in financial distress, defined as years with negative equity values

Airline	**Pre-crisis**	**Crisis**	**Post-crisis**
Aeroflot	2012-2013	2014	x
Air Berlin	2011-2012	2013-2014	x
Air Canada	2008-2009	2010-2014	x
Air France-KLM	2012-2013	2014	x
American Airlines	x	2005-2006	2007
American Airlines	2007	2008-2013	2014
China Eastern	2006-2007	2008	2009-2010
Cyprus Airways	x	2005-2006	2007-2008
Cyprus Airways	2009-2010	2011	x
Delta Air Lines	x	2005-2006	2007-2008
Delta Air Lines	2009-2010	2011-2012	2013-2014
Gol	2012-2013	2014	x
Great Lakes	x	2005-2006	2007-2008
Jet Airways	2009-2010	2011-2014	x
Kenya Airways	2012-2013	2014	x
Pakistan International Airlines	2006-2007	2008-2014	x
SpiceJet	2009-2010	2011-2014	x
United Airlines	2006-2007	2008-2009	2010-2011
US Airways	2006-2007	2008-2009	2010-2011

The results in Table 5.12 fail to support H3a, H3b and H4. The coefficient estimates on the current ratio, its quadratic term and the price-earnings ratio are all insignificant in Models 1, 2, 3, and 5. Neither the existence of growth options nor the levels of cash holdings influence the airlines' hedge ratios. Apparently, the level of cash holdings affects the decision to hedge but not the extent of hedging. The coefficient on the variables that reflect potential growth options might be insignificant due to generally low investment opportunities in the airline industry and due to an increased importance of operating leasing among distress airlines (refer to Subsection 5.1.5 for more details).

Similar to the probit regression models, the coefficient on the size variable (*sizeAdj1*) is not statistically significantly different from zero. Hypotheses H5 cannot be supported.

Figure 5.2: Hedge ratios (*fdvPct12m*) of the sample airlines in a financial crisis (i. e. with negative equity values): pre-crisis, during the crisis and post-crisis



China Eastern, Cyprus Airways, Great Lakes, Jet Airways, Pakistan International Airlines, and SpiceJet excluded.

The fixed effects estimates on the binary interest rate derivative variable (*irdvDm*) is positive and significantly different from zero at the 1%-level in all models. These results support H5. In contrast to the probit results, the currency derivative dummy (*fxdvDm*) does not influence the hedge ratios of the airlines. Thus, holding currency derivatives affects the decision to hedge but not the extent of hedging.

5.1.3 Robustness

The results discussed so far will be tested on robustness. First, the variables on each topic are replaced by alternative approximate measures in the probit and fixed effects models. Only the table with the proxy variables on the financial distress topic is printed in this subsection, the other tables can be found in Appendix M (alternative random effects probit models) and Appendix N (alternative fixed effects models). Second, the sample is restricted in various ways for the probit and fixed effects models (Tables 5.16

and N.4). Third, probit model regression analysis is performed on the sample airlines divided into the regions America, Asia, Europe and divided by the business models low-cost and network airlines (Table 5.17).

Table 5.15 contains the alternative probit regression results regarding the financial distress proxy variables. The magnitude and significance level of the adjusted leverage ratio 1 is reduced when the adjusted interest coverage ratio is exchanged by either the adjusted profit margin, the adjusted ROA, the dividend dummy, or the dividend yield (Models 2 to 5). The sign remains the same, higher leverage reduces the likelihood of hedging. The p-value rises slightly above the 10%-level if the interest coverage ratio is swapped for the dividend dummy or the dividend yield. Consistent results are obtained when *lvrg1Adj8* is used in Model 8. The p-value and magnitude of the linear and squared coefficient rise strongly. The significance level changes when *lvrg1Adj1* is replaced by *lvrg2Adj1* (*lvrg3Adj1*). The algebraic signs are the same but the p-values increase to 0.408 (0.115) for the linear coefficient and to 0.687 (0.146) for the quadratic term. The insignificance of the long-term debt ratio coefficient (*lvrg2Adj1*) may issue from the importance short-term debt played in financing European and Asian airlines' debt (see Subsection 4.2.2).

In Table M.1 in Appendix M the underinvestment variables *tobQAdj1* and *cashRto* are replaced. Similar to the coefficient estimates on the Tobin's Q variable, the estimates of the coefficients of the MTB ratio, the price-earnings ratio, *acChg*, and the CAPEX ratios (*capAsAdj1*, *capRevAdj1*, *capSizeAdj1*) are not statistically significantly different from zero. The results regarding the cash argument are robust to replacing the cash ratio by the quick ratio. The coefficient estimate on *qckRto* is positive and statistically significantly different from zero at the 5%-level, whereas the coefficient of the quadratic term is negative and significant. The p-values of the alternative current ratio slightly exceed 0.1. However, the algebraic signs are consistent. The linear coefficient is positive and the coefficient on the quadratic term is negative.

The results in Table M.2 in Appendix M show that all proxy variables on firm size (*fuelExp*, *revTl*, *sizeAdj1*, *asmTl*) are not related to the likelihood of using fuel price derivatives. The coefficient estimates of the interest rate and FX derivative dummies remain positive and statistically significantly different from zero at least at the 5%-level in all seven models.

The fixed effects regression models with alternative financial distress variables can be found in Table N.1 in Appendix N. The base regression results are robust to exchanging the interest coverage ratio for the adjusted profit margin, adjusted return on assets, dividend dummy, or dividend yield (Models 2 to 5). The magnitude of the leverage coefficient is reduced but the significance level remains at the 1%-level in all models. The coefficients increase in magnitude when *lvrg1Adj8* is used. The results are not robust, though, when leverage ratio 1 is replaced by *lvrg2Adj1*. The coefficient on the adjusted leverage ratio 2 is still negative but not statistically significantly different from zero. The estimate on the squared terms is positive, yet the p-value greatly exceeds the 10%-level. The coefficient estimate on *lvrg3Adj1* is positive and statistically significantly different from zero at the 10%-level. The p-value of the quadratic term is marginally greater than 0.1. The insignificance of leverage ratio 2 can again stem from the importance short-term debt played among Asian and European debt financing.

The robustness results regarding the underinvestment proxy variables in Table N.2 in Appendix N are mixed. While the Tobin's Q coefficient is positive and statistically significantly different from zero at the 5%-level, implying that airlines with greater investment opportunities showed higher hedge ratios, all other proxies on the underinvestment argument (*mtbRto*, *capAsAdj1*, *capRevAdj1*, *capSizeAdj1*) are as insignificant as the *peRto* in the base regression. Therefore, the possible existence of growth options do not seem to influence the hedging behavior of the sample airlines. Tobin's Q is more likely to capture the effect of financial distress in the sample because a third of the sample airlines exhibited Tobin's Q values below one. If lower Tobin's Q values are associated with a greater likelihood of financial distress, the positive coefficient of Tobin's Q reflects the negative coefficient of the debt ratio. The results on cash holdings are robust as the cash ratio and the quick ratio are not significant.

The regression results in Table N.3 in Appendix N show that the coefficients on the alternative approximate measures of firm size (*revTl*, *fuelExp*, *asmTl*, *acTl*) are not statistically significantly different from zero. The results are robust as the coefficient on the size variable (*sizeAdj1*) in the base regression is not significant either. The results are robust regarding the interest rate and currency derivative dummy. All estimates on *irdvDm* are positive and statistically significantly different from zero at the 1%-level. The coefficients on *fxdvDm* are not significant.

In Table 5.16 the random effects probit regression models with various sample restrictions are presented. The results do not change considerably when Republic Airways and SkyWest, the two airlines under a capacity purchase agreement (CPA), are either dropped from the sample (Model 2) or given a CPA dummy (Model 3). The results also remain consistent when a merger dummy (*mrgDm*) is included in Model 4. When the U.S. low-cost airline Allegiant Air, which is part of the tour operator Allegiant Travel Company, is removed from the sample the coefficient estimates on the leverage ratio change in magnitude from -14.22 to -13.86. Similar to Isin et al. (2014) and Bartram

Table 5.15: Random effects probit models with different financial distress proxies

	BASE (1) fdvDm	(2) fdvDm	(3) fdvDm	(4) fdvDm	(5) fdvDm	(6) fdvDm	(7) fdvDm	(8) fdvDm
lvrg1Adj1	-14.22^{**}	-9.829^{*}	-11.75^{*}	-7.108	-8.319			
	(0.012)	(0.087)	(0.052)	(0.170)	(0.104)			
lvrg1Adj1Sqr	12.18^{**}	9.947^{*}	10.65^{*}	6.936	8.052^{*}			
	(0.023)	(0.076)	(0.067)	(0.162)	(0.097)			
intCovAdj	-0.733^{***}					-0.679^{***}	-0.639^{***}	-0.821^{***}
	(0.000)					(0.000)	(0.000)	(0.000)
tobQAdj1	0.418	0.227	0.355	-0.104	-0.242	0.318	0.331	
	(0.329)	(0.601)	(0.415)	(0.799)	(0.547)	(0.455)	(0.442)	
cashRto	3.021^{**}	3.065^{**}	3.006^{**}	1.201	0.869	2.558^{**}	2.698^{**}	3.314^{***}
	(0.016)	(0.020)	(0.022)	(0.330)	(0.468)	(0.045)	(0.037)	(0.008)
cashRtoSqr	-1.317^{**}	-1.101^{*}	-1.259^{**}	-0.604	-0.400	-1.058^{*}	-1.179^{**}	-1.420^{**}
	(0.020)	(0.060)	(0.033)	(0.278)	(0.460)	(0.066)	(0.044)	(0.012)
acTl	0.000664	0.000354	0.000484	0.000850	0.000526	0.000868	0.000618	0.000584
	(0.537)	(0.762)	(0.674)	(0.480)	(0.635)	(0.463)	(0.584)	(0.577)
irdvDm	1.208^{***}	1.342^{***}	1.138^{***}	1.097^{***}	1.085^{***}	1.163^{***}	1.233^{***}	1.208^{***}
	(0.003)	(0.002)	(0.007)	(0.009)	(0.007)	(0.005)	(0.003)	(0.002)
fxdvDm	1.101^{***}	1.155^{***}	1.183^{***}	1.064^{**}	1.074^{***}	0.950^{**}	0.998^{**}	1.156^{***}
	(0.005)	(0.008)	(0.005)	(0.012)	(0.008)	(0.017)	(0.011)	(0.003)
prfMrgAdj		-14.07^{***}						
		(0.000)						
roaAdj1			-21.91^{***}					
			(0.000)					
divDm				-1.033^{***}				
				(0.003)				
divYld					-10.47^{*}			
					(0.089)			
lvrg2Adj1						-4.411		
						(0.408)		
lvrg2Adj1Sqr						2.183		
						(0.687)		
lvrg3Adj1							-12.63	
							(0.115)	
lvrg3Adj1Sqr							7.620	
							(0.146)	
lvrg1Adj8								-16.53^{***}
								(0.003)
lvrg1Adj8Sqr								12.96^{***}
								(0.008)
tobQAdj8								0.511
								(0.267)
intercept	4.011^{**}	2.305	3.042^{*}	2.568	2.780^{*}	2.168	5.426^{*}	5.041^{***}
	(0.014)	(0.167)	(0.077)	(0.103)	(0.077)	(0.187)	(0.094)	(0.004)
N	504	504	504	504	504	504	504	505
AIC	248.9	245.7	247.3	267.1	274.4	254.4	253.8	250.1

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

et al. (2009), the sample is limited to IFRS users (Model 6) and to U.S. GAAP users (Model 7).[120] The results are robust among IFRS users as the coefficient estimates on the leverage variables remain significantly different from zero at least at the 10%-level. If the sample is restricted to U.S. GAAP airlines, the results change considerably. Neither of the significant coefficient estimates of the base regression is significant. The number of observations is reduced from 504 airline firm years in the base regression to 134 airline firm years in Model 7.

The alternative fixed effects results with sample restrictions can be found in Table N.4 in Appendix N. The fixed effects estimates do not change substantially when the regional airlines (Model 2) and Allegiant Air (Model 5) are excluded or when a CPA (Model 3) or merger dummy (Model 4) is included. In contrast to the probit results, the coefficient estimates on leverage remain robust for both groups, airlines accounting according to IFRS (Model 6) and according to U.S. GAAP (Model 7). The signifiance level remains at least at the 5%-level, the magnitude of the leverage coefficient and the squared term even increase. The debt ratio apparently influences the extent of hedging but not the decision to hedge of U.S. GAAP airlines. The coefficient on the interest rate derivative dummy is only statistically significantly different from zero for IFRS airlines, not for U.S. GAAP firms.

The sample is divided into the three main regions and into the two business models in Table 5.17. Models 2, 3 and 4 show the regression results of the probit models on American, Asian and European airlines. Model 5 contains NLCs whereas Model 6 treats LCCs. As fixed effects control for any omitted variables that change between entities but are constant over time, it is not necessary to split the sample into regions and business models for the fixed effects regression analysis.

The results on the relation between debt ratios and the likelihood of financial fuel price hedging are robust to restricting the sample to Asian airlines (Model 3) and to low-cost carriers (Model 6). The magnitude of the coefficient on *lvrg1Adj1* and *lvrg1Adj1Sqr* increases strongly for these two models. The coefficients remain significantly different from zero at least at the 10%-level. The p-values of the *lvrg1Adj1* coefficients rise above 0.1 for American (Model 2), European (Model 4) and legacy airlines (Model 5), yet the algebraic signs are consistent with the base regression (Model 1). Interestingly, the quadratic term of the debt ratio is negative among American carriers. Therefore, a second probit regression is run on American airlines, without the inclusion of the squared

[120]The large difference in AIC values between Models 1 to 5 and Models 6 and 7 arises due to the lower number of observations in the last two models. Stata uses the formula proposed by Akaike (1973) to calculate the shown AIC value in Table 5.16. This formula does not include the number of observations (StataCorp, 2013d). Sugiura (1978) proposes a finite sample correction of the original AIC formula for small sized samples. Due to the computational effort, the AIC value is not corrected here.

Table 5.16: Alternative random effects probit models with different sample restrictions

	BASE (1) fdvDm	(2) fdvDm	(3) fdvDm	(4) fdvDm	(5) fdvDm	(6) fdvDm	(7) fdvDm
lvrg1Adj1	−14.22**	−14.18**	−14.18**	−14.21**	−13.86**	−15.91*	−4.237
	(0.012)	(0.011)	(0.011)	(0.012)	(0.033)	(0.081)	(0.741)
lvrg1Adj1Sqr	12.18**	11.70**	11.70**	12.18**	12.09**	17.96**	−5.213
	(0.023)	(0.028)	(0.028)	(0.023)	(0.046)	(0.040)	(0.693)
intCovAdj	−0.733***	−0.722***	−0.722***	−0.733***	−0.797***	−0.692**	−1.188
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.018)	(0.110)
tobQAdj1	0.418	0.453	0.453	0.416	0.579	0.0241	−0.227
	(0.329)	(0.280)	(0.280)	(0.335)	(0.228)	(0.973)	(0.839)
cashRto	3.021**	2.910**	2.910**	3.021**	3.025**	5.597**	4.807
	(0.016)	(0.018)	(0.018)	(0.017)	(0.022)	(0.011)	(0.297)
cashRtoSqr	−1.317**	−1.311**	−1.311**	−1.317**	−1.341**	−2.594***	−1.766
	(0.020)	(0.019)	(0.019)	(0.021)	(0.025)	(0.006)	(0.392)
acTl	0.000664	0.000336	0.000337	0.000661	0.000750	−0.000471	−0.000818
	(0.537)	(0.743)	(0.743)	(0.540)	(0.514)	(0.859)	(0.716)
irdvDm	1.208***	1.240***	1.240***	1.208***	1.176***	1.903**	1.468
	(0.003)	(0.001)	(0.001)	(0.003)	(0.005)	(0.042)	(0.168)
fxdvDm	1.101***	1.160***	1.160***	1.100***	1.306***	2.015***	0.0266
	(0.005)	(0.002)	(0.002)	(0.005)	(0.003)	(0.006)	(0.983)
cpaDm			10.25				
			(0.998)				
mrgDm				0.0139			
				(0.982)			
intercept	4.011**	3.985**	3.985**	4.009**	3.773**	2.184	6.829
	(0.014)	(0.013)	(0.013)	(0.014)	(0.044)	(0.382)	(0.144)
N	504	484	504	504	495	231	134
AIC	295.4	290.6	297.2	301.6	281.2	164.3	111.1
Specification	none	CPA excl.	CPA dummy	Merger dummy	Allegiant excl.	IFRS only	US GAAP only

p-values in parentheses

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

term (not shown in any table). In this case, the coefficient on *lvrg1Adj1* changes to -26.02 and is statistically significantly different from zero at the 1%-level. The nonlinear assumption between leverage and the likelihood of hedging does not apply for American carriers.

The results regarding the adjusted interest coverage ratios are robust in all subsamples except for the European sample. The results of the variables relating to the underinvestment problem (*tobQAdj1*, *cashRto*, *cashRtoSqr*) are not robust. Both the p-values as well as the algebraic signs differ between the base regression and Models 2 until 5. Merely the coefficients on the *cashRto* and its squared term of low-cost airlines coincide with the coefficients in Model 1. Greater cash ratios were associated with a higher likelihood of financial hedging up to a certain level, thereafter the likelihood decreased. These results support H3a and H3b. The coefficient estimates on the total number of aircraft are not robust. While the *acTl* coefficient in Models 1 and 5 is positive and insignificant, the coefficient is negative and insignificant for American and Asian airlines. European and low-cost airlines exhibited coefficients which were positive and statistically significantly different from zero at the 10% and 1%-level. Airlines with more aircraft in their fleet were more likely to use financial fuel price instruments, supporting H5. The algebraic sign of the coefficients on *irdvDm* and *fxdvDm* are constant in all six models. The p-value of the two binary variables ranged between 0.003 and 0.868. The overall mixed results on the regional subsamples show the importance of using fixed effects estimators in the regressions with the hedge ratio as the regressand. The entity fixed effect controls for any omitted variable, such as the region, that might explain the dependent variable.

5.1.4 Limitations

In order to be able to draw valid statistical inferences from the regression analysis, the coefficient estimates have to be internally and externally valid. A study is externally valid when the sample allows for statistical inferences that are applicable for a wider population, i.e. when the results are generalizable. Internal validity is at threat when one or more of the following six phenomena are present: omitted variable bias, misspecification of the functional form, measurement error, simultaneous causality, sample selection bias, and incorrect calculation of standard errors. In all six cases the estimates are biased as the regressor is correlated with the error term (Stock and Watson, 2007). The omnipresent problem of endogeneity in corporate finance research goes hand in hand with the threats to internal validity. Endogenous variables are those variables

Table 5.17: Random effects probit models, hedge dummy as the dependent variable (divided into regions and business models)

	BASE (1) fdvDm	(2) fdvDm	(3) fdvDm	(4) fdvDm	(5) fdvDm	(6) fdvDm
lvrg1Adj1	-14.22^{**}	-1.339	-74.62^{**}	-22.74	-12.17	-17.30^{**}
	(0.012)	(0.910)	(0.012)	(0.254)	(0.170)	(0.027)
lvrg1Adj1Sqr	12.18^{**}	-6.222	62.03^{**}	18.02	10.62	14.76^{*}
	(0.023)	(0.608)	(0.016)	(0.351)	(0.172)	(0.082)
intCovAdj	-0.733^{***}	-0.848	-1.094^{***}	-0.730	-0.950^{***}	-0.711^{***}
	(0.000)	(0.128)	(0.009)	(0.121)	(0.000)	(0.000)
tobQAdj1	0.418	-0.500	3.050^{*}	-2.088^{*}	0.539	0.130
	(0.329)	(0.629)	(0.088)	(0.083)	(0.494)	(0.772)
cashRto	3.021^{**}	3.661	3.497	2.957	1.845	4.284^{**}
	(0.016)	(0.352)	(0.193)	(0.246)	(0.449)	(0.029)
cashRtoSqr	-1.317^{**}	-1.502	-3.540^{**}	-1.524	-0.165	-1.865^{**}
	(0.020)	(0.417)	(0.022)	(0.172)	(0.918)	(0.024)
acTl	0.000664	-0.00114	-0.00136	0.0170^{*}	0.000324	0.0119^{***}
	(0.537)	(0.559)	(0.763)	(0.064)	(0.825)	(0.007)
irdvDm	1.208^{***}	1.675^{*}	1.242	0.933	1.936^{***}	0.0808
	(0.003)	(0.096)	(0.109)	(0.211)	(0.003)	(0.868)
fxdvDm	1.101^{***}	0.397	2.446^{**}	2.343^{**}	1.387^{**}	0.418
	(0.005)	(0.721)	(0.044)	(0.031)	(0.016)	(0.360)
intercept	4.011^{**}	5.874	18.51^{**}	7.037	3.841	4.064^{**}
	(0.014)	(0.187)	(0.011)	(0.190)	(0.177)	(0.021)
N	504	175	165	126	388	116
AIC	248.9	81.79	103.2	47.15	169.8	78.07
Region/ Business model	ALL	AM	AS	EU	NLC	LCC

p-values in parentheses

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

that are correlated with the error term,[121] causing the endogeneity problem. As the error term is unobservable, the existence of endogeneity cannot be tested (Roberts and Whited, 2013). Therefore, the six sources of endogeneity are discussed in this subsection and it is analyzed whether those sources are present in this study.

Omitted variable bias results when an independent variable which both explains the dependent variable and is correlated with another regressor is excluded from the regression (Stock and Watson, 2007). The omitted variable appears among the error term and as the omitted variable is correlated with another independent variable, the error term will be correlated with one of the regressors, fulfilling the definition of endogeneity. The omission of variables may either arise due to the impossibility of collecting data or due to wrong theoretical assumptions (Roberts and Whited, 2013). An example of an unobservable omitted variable in the current sample could be the cultural background of the airline managers. If, for example, European risk managers are in general more risk averse, the hedge portfolios will be influenced by their risk behavior. The attitude towards risk will most likely also influence how the finance department structures the debt ratios. Therefore, cultural background fulfills the two conditions of omitted variable bias: culture determines the hedging behavior and is correlated with the leverage ratios. If the cultural background does not change in the sample period, however, the fixed effects estimates will control for that omitted variable and the results will not be biased. An omitted variable that changes over time (hence is not controlled for by fixed effects) could be the managerial ability of the risk manager. If a poorly performing manager tries to hide his lack of ability by buying into hedge contracts and if smaller airlines rather hire poorly performing managers, then managerial ability both determines the regressand and is correlated with an explanatory variable. The fixed effects estimates in this case will be biased. A subset of omitted variable bias is the misspecification of the functional form. When a linear regression is assumed although the true regression line is nonlinear, the estimators are biased (Stock and Watson, 2007). The ignored squared term has the same impact as an omitted variable. In the current study, the squared terms of the leverage and cash variables are included to avoid this misspecification.

Another potential source of inconsistent and biased regression estimators is the measurement error or errors-in-variables. This error arises when the independent variable is measured incorrectly (Stock and Watson, 2007) or when an approximate measure is used that does not reflect the true, unobservable variable of interest (Roberts and Whited, 2013). In this study, several measurement errors are likely to impact the results.

[121] Historically, endogeneous variables where those variables that were determined within the model in multiple equations (Stock and Watson, 2007).

First, transmission errors during the collection process cannot be ruled out because the data is hand-collected. Second, as some airlines did not report directly the numbers of interest, some values are estimated based on expert knowledge (see Chapter 4). Third, several approximate measures that were also extensively used in previous research may not fully resemble the unobservable variables of interest. The MTB ratio, for example, is used as a proxy variable for investment opportunities. Market-to-book ratios exceeding one may identify firms with potential growth options as market participants value the firm higher than its actual book value. If, however, the MTB ratio is smaller than one (as it is the case in 224 firm years in this sample), the variable may rather capture financial distress than investment opportunities (Nguyen and Faff, 2002). Similarly, Tobin's Q is an inexact, approximate measure for investment opportunities (Roberts and Whited, 2013). Fourth, the use of book measures leads to incorrectly measured variables. Due to data availability, researchers most often have to rely on book measures although accounting numbers do not reflect the true value of the firm. For one thing, book values are only available at a single point in time. For another thing, book values do not include all items of interest, such as the value of a brand name (Brealey et al., 2017). Moreover, the various accounting standards in this sample may differ drastically rendering a direct comparison inadequate.

A further reason for regression estimators to be biased and inconsistent is simultaneous causality. Simultaneous causality, or simultaneity bias, emerges when not only the regressor affects the regressand but also the regressand the regressor (Roberts and Whited, 2013; Stock and Watson, 2007). In previous studies on the determinants of hedging, the variables relating to the financial distress theory are a major source of simultaneity bias. It is assumed that leverage (the regressor) influences a firm's hedge behavior (the regressand). At the same time a larger hedge position may allow a company to incur larger levels of debt, i. e. increase its debt capacity. Therefore, causality between hedging and leverage could run in both directions (Graham and Smith, 1999). Simultaneous causality is a source of bias in this study.

As the amount of information published differs greatly between the sample airlines, this study suffers from sample selection bias. Sample selection bias is induced when the sample is chosen in a way that is influenced by the availability of the data of the dependent variable (Stock and Watson, 2007). In the current sample only those airlines enter the regression analysis that publish their hedging behavior. If primarily financially sound airlines disclose their hedge portfolios, the regression estimators on leverage would be biased downwards. Another bias that is related to sample selection bias is survivorship bias. If the study was restricted to a balanced panel data set (Baum, 2007), only those airlines that existed in the entire sample period would be analyzed and the estimators would be biased. Thus it is important to include all airlines: those that either incurred bankruptcy in the sample period, those that were merged with another airline and those that started business later in the sample period.

Lastly, incorrectly calculated standard errors further lead to biased estimators. The internal validity should be assured in this study as a result of the usage of heteroskedastic-robust standard errors.

A solution to resolve omitted variable bias, errors-in-variables and simultaneous causality is to run an instrument variables regression. Purnanandam (2008) and other researchers use IV regressions to predict leverage because leverage variables are likely to cause bias. Purnanandam (2008) uses the "before-financing simulated marginal tax rate" and a "firm's nondebt tax shield", which is depreciation and amortization divided by total assets, as instruments to predict the leverage of a firm. Due to the unavailability of simulated tax rates and due to the computational effort, instrument variables regression is not part of this study.

5.1.5 Discussion

The results and implications of the univariate and multivariate results regarding the determinants hypotheses are discussed in detail. H1a proposes a positive relation between financial distress and hedging whereas H1b speaks of decreasing hedge activities at high levels of leverage. The results, on the contrary, indicate a nonlinear, convex relation between debt ratios and the decision to hedge as well as the extent of hedging. At low debt ratios the sample airlines had relatively large hedge portfolios. Medium levels of leverage were, on average, associated with low hedge ratios. Highly indebted airlines made use of more hedging but their hedge ratios remained below the hedge activities of the airlines with lower leverage ratios.

Several research papers find either negative or insignificant results between financial distress and hedging (Adam, 2002; Allayannis et al., 2001; Brown et al., 2006; Carter et al., 2006; Guay and Kothari, 2003; Spanò, 2007; Sprcic and Sevic, 2012), contrary to the financial distress theory. Most previous studies assume a linear relation between financial distress and derivative usage. If the squared term is excluded in the probit models (see Model 3 in Table 5.11) as well as in the fixed effects OLS regression in this study (see Model 3 in Table 5.12), the coefficient on the linear debt ratio becomes insignificant. Therefore, the conflicting results in previous research may arise due to a misspecification of the functional form of the regression models.

A likely explanation of the current results being in opposition to the results of Adam et al. (2017) and Purnanandam (2008), whose studies include nonlinearity in the regression models and find a concave relation between leverage and hedging, is the different sample period and industry studied. Purnanandam (2008) analyzes selected CRSP and Compustat firms from various industries in 1997 only. The sample of Adam et al. (2017) contains U.S. gold mining firms from 1989 to 1999. The sample firms in this study are taken from a single industry and cover a more recent period.

The results regarding the financial distress variables of Carter et al. (2006), who study the U.S. airline industry between 1992 and 2003, are similar to the current results. Their results show that the coefficient estimate on the lease-adjusted leverage ratio is negative and statistically significantly different from zero at least at the 10%-level. Airlines tend to hedge their fuel requirements to a smaller extent when their debt ratios increase. Carter et al. (2006) draw a different conclusion from their results though. They argue that airlines with greater investment opportunities face higher distress costs, choose lower debt ratios and higher hedge ratios because they have more to lose than airlines with lower distress costs. Whether the sample airlines of Carter et al. (2006) also reduced their hedge portfolios at very high debt ratios cannot be assessed because they do not include quadratic debt ratios in their study. Similar to Carter et al. (2006) and consistent with the current results, Rampini and Viswanathan (2013) find a negative relation between net worth[122] and hedging in the U.S. airline industry between 1996 and 2009. Moreover, airlines with a downgrade in credit ratings reduce their fuel hedge ratios.[123] Rampini and Viswanathan (2013) conclude that the trade-off between providing margin calls or raising debt for investment opportunities is causing the negative relation.

The negative linear coefficient on the leverage ratio in this study supports the argument that airlines with low leverage ratios hold larger hedge portfolios. This argument is in contradiction to the financial distress theory. A likely explanation for this relation could be that airlines value financial fuel price instruments as an insurance against volatile fuel prices regardless of their good financial position. Airlines with low debt ratios have the financial flexibility to enter costly derivative contracts and seize that opportunity to further secure their financial health in future periods. Airlines with medium debt ratios face a trade-off between paying margin calls for financial instrument contracts[124] or allocating funds to investment opportunities. Highly indebted airlines

[122]Net worth is calculated as the current cash flow of the airline plus the market value of capital minus outstanding debt plus collateral requirements for margin calls (see Chapter 2).

[123]As discussed in Chapter 4, credit ratings are excluded in this study due to a lack of credit rating data.

[124]The potential amount of margin calls was presented in Subsection 4.2.7. Some airlines posted as much as 50% of their cash and cash equivalents as hedge margins.

ramp up their hedge activities in order to avoid bankruptcy and to exit the financial distress phase, which seems rational in light of expected indirect and direct bankruptcy costs (see Subsection 2.2.1). The descriptive results in Section 4.2 showed that airlines with negative equity values increased their hedge ratios strongly between 2005 and 2014, almost reaching the hedge ratios of airlines with positive equity values. Moreover, the analysis of hedge ratios before, during and after the crisis of financially distressed airlines in Subsection 5.1.2 presented four airlines that increased their hedge ratios during the crisis. It remains unclear which counterparties are willing to enter into fuel price contracts with highly indebted airlines. A likely counterparty could be the financial institution that holds a large portion of the financial liabilities of the indebted airline. In that case, the financial instution could sell derivative instruments to the airline in the expectation that the airline overcomes the financial distress phase with the help of fuel hedging and by that repays its outstanding debt.[125]

The financial distress results may suffer from simultaneous causality. If airlines with a sophisticated risk management program manage to counteract volatile fuel prices better with a large hedge portfolio, those airlines may be less in need to increase their debt contracts. In this case, the dependent variable explains the independent variable and the estimators are biased. In future studies, IV regressions could be used to test for the nonlinear relation between hedging and leverage in the airline industry.[126]

The hypotheses referring to the underinvestment problem are partially supported. In the multivariate analysis the coefficient estimates on Tobin's Q are not statistically significantly different from zero in the probit models. The coefficients on the alternative growth options approximate measures, MTB ratio and price-earnings ratio, are not significant either in robustness tests. Neither are any of the CAPEX variables significant. Apart from the positive and significant OLS estimate of the adjusted Tobin's Q value, neither of the variables relating to the underinvestment argument are significant in the fixed effects regressions. The results of the probit and fixed effects models clearly fail to support H4.

The results on the growth variables are in contrast to the results of previous research. Géczy et al. (1997) and Gay and Nam (1998), for example, find a positive relation between investment opportunities and derivative usage. The studies comprise firms from various industries. If growth options and capital expenditure are homogeneous within an

[125]The role managerial compensation plays for an airline's hedging behavior near bankruptcy, especially the option-like feature of managerial shareholding, was left out from this study and should be part of future research.

[126]Potential instruments could be the before-financing marginal tax rate and a firm's nondebt tax shield as proposed by Purnanandam (2008).

industry, less profitable firms with less internal funds need to rely more on debt financing and exhibit higher debt ratios (Brealey et al., 2017). Therefore, the analysis of a single industry in this study may lead to the weak evidence regarding the underinvestment variables.

The study by Carter et al. (2006) deals with a single industry, yet finds a positive relation between growth options and hedge ratios. However, their significant results may be driven by biased estimators due to the usage of random effects instead of fixed effects estimation. Random effects do not control for any omitted airline idiosyncrasies that are constant during the sample period. Moreover, they base their conclusion that higher growth options lead to more hedging on the positive and significant coefficient on the Tobin's Q variable. The results are not robust to alternative approximate measures as the CAPEX to sales variable is insignificant. In addition, their sample encompasses an earlier time period (1992 until 2003). Carter et al. explain the benefit of hedging in times of high oil prices by buying aircraft from distressed airlines at a discount. If, however, airlines in financial distress rather lease aircraft under operating lease contracts, which they can terminate flexibly in times of economics difficulties, then the potential bargain buys of airlines in good financial health become less important. The correlation factor between the adjusted debt ratio 1 and the percentage of aircraft under operating leasing in this study is 0.16. Therefore, the insignificant results regarding the growth variables in this study may originate from a changed operating leasing behavior of financially distressed airlines.

Tobin's Q may identify firms with investment opportunities or otherwise firms in financial distress. A third of the sample airlines had Tobin's Q values lower than one. Consequently, the positive and significant estimates of the Tobin's Q variable in the fixed effects models may capture the financial distress theory. Airlines with greater debt ratios and lower Tobin's Q values hedge less. Lastly, the coefficient estimates on the capital expenditure variables could be insignificant because the airline industry is an industry with relatively low levels of R&D spending and investment opportunities. Apart from renewing the fleet with more fuel-efficient aircraft, game-changing innovations are virtually non-existent or, if at all, driven by aircraft manufacturers and equally available to all airlines.

The probit results support H3a. The coefficient estimate on the cash ratio as well as the alternative quick ratio is positive, significantly different from zero at the 5%-level. The results are robust to several sample restrictions. Merely the coefficient of airlines accounting in accordance with U.S. GAAP is not significant. When the cash ratio is replaced by the current ratio, the p-values rise above 0.1 but the algebraic signs remain unchanged. Higher levels of cash holdings are related with a higher likelihood of financial fuel price hedging. The probit results partially support H3b as the estimate of the squared cash ratio is negative and statistically significantly different from zero at the 5%-level. Airlines with very high cash holdings exhibited a lower likelihood of holding fuel price derivatives. The extent of hedging does not seem to be influenced by cash holdings. Neither the OLS estimate on the cash ratio, nor on the quick ratio, nor on the current ratio is significant. These results contradict H3b. The interaction term of low cash holdings and high growth options is not significant in either the probit or the OLS models. H4 is not supported.

The positive relation between cash holdings and the decision to hedge is in opposition to the existing theory. Most previous studies find a negative and significant relation between a cash variable and hedging. These studies assume a linear relation though. If the squared cash ratio is excluded in the probit model (see Model 3 in Table5.11), the coefficient estimate changes to being insignificant. Hence, the concave relation between the cash ratio and the probability of hedging represents the data set best. Airlines decided against hedging more often at low levels of cash holdings. Similar to the implications of the debt ratio, airlines preserved their relatively low funds by not providing margins calls for hedge contracts. At very high levels of cash holdings airlines were in the comfortable position to use their cash holdings to cushion any peaks in kerosene prices and did not have the necessity to enter into costly fuel price derivatives.

On the one hand, the univariate results show that hedgers and airlines with greater hedge ratios were larger than those in the other group. They were more likely to hold currency and interest rate derivatives. On the other hand, in the random effects as well as in the fixed effects models neither of the proxies for firm size is significant. The results are robust to all model specifications and fail to support H5 with regards to firm size. The decision to hedge and the hedge ratios are not impacted by the size of an airline. The coefficient estimates on the interest rate and FX derivative binary variable are positive and statistically significantly different from zero between the 1% and 5%-level in all models. Airlines with a more diverse hedge portfolio were more likely to enter into fuel price contracts. Therefore, H5 is partially supported. While the fixed effects OLS estimator on the interest rate derivative dummy is positive and significantly different from zero at the 1%-level, the estimate of the currency derivative dummy is not significant. Airlines that held interest rate derivatives exhibited larger hedge ratios.

Most previous studies find a positive and significant relation between firm size and hedging, except for Carter et al. (2006) who analyze the U.S. airline market. An explanation for the insignificant results with regards to airline size could be the importance of fuel price risk in the airline industry. Fuel costs accounted for a third of airlines' total costs in 2014 (IATA, 2015), demonstrating the likely strong impact of fuel price changes on airline profitability. While the absolute fuel bill differs between the airlines, the relative fuel bill is equally attributable to large airlines as it is to small airlines. Therefore, airline size may not have influenced the hedging behavior of the sample airlines. In addition, the IATA clearing house provides support in managing financial instruments (IATA, 2018). Sixty-eight of the 74 sample airlines were members of the IATA clearing house.[127] As the clearing house is available to all members regardless of their firm size, small airlines are equally supported in setting up hedge contracts. This support may remove any potential impact of airline firm size on hedge activities.[128] In addition, the sample comprises joint-stock airlines only. If airlines that trade their stock on an exchange are more likely to be larger in size, then the insignificant results may be driven by sample selection.

Setting up a hedge department entails high costs and requires risk management expertise (Graham and Smith, 1999; Haushalter, 2000). This theory is reflected in this study as airlines held different financial instruments to protect themselves against various price risks. Figure 4.29 in Subsection 4.2.4 presented less than 10 airlines that held fuel price derivatives exclusively. All other airlines included at least one other financial instrument in their risk management strategy. The results support the assumption by Haushalter (2000) that positive size effects unfold especially in setting up a hedge department. Both binary derivative variables had positive effects on the likelihood of hedging, whereas only interest rate derivatives impacted the extent of hedging.

5.2 Analysis of international airlines' operational hedging

The summary statistics of the operational hedging variables are shown in Table 5.18. The binary variable *acOlcashDm* identifies those airlines whose cash ratio of a given year is lower than the average cash ratio of all sample airlines in the respective year and a higher than average percentage of aircraft under operating leasing in a given year. In 21.3% of the 390 available firm year observations airlines showed an *acOlcashDm* of one. In 2008, 41.1% of the sample airlines had low cash holdings and a higher number of operating leased aircraft. The sample airlines' fleets comprised on average 43.8% of

[127] Three of the six airlines not being part of the IATA clearing house were not member of the IATA either.
[128] The influence of agency conflicts in large companies on hedging behavior cannot be analyzed in this study because managerial shareholding is not part of the analysis.

aircraft under operating leasing. Eight airlines operated a purely leased fleet in 17 firm years (*acOlPct*=100%). At the other end, the fleet of six airlines did not comprise any aircraft under operating leasing (*acOlPct*=0%) in 32 firm years.

The first fleet diversity measure, *fDiv1*, ranged between 0.00 and 0.95. The higher the number, the more diverse an airline's fleet. As the business model of LCCs is characterized by a homogeneous fleet, it is not surprising that all 36 firm years with an *fDiv1* of zero can be attributed to low-cost airlines. The correlation factor between *fDiv1* and *lccDm* is -0.78. On the contrary, the European network carrier Air France-KLM was the airline with the highest *fDiv1* values in all ten sample years, followed by Lufthansa, Japan Airlines and SAS. Due to its calculation method, *fDiv2* is with an average value of 0.52 smaller than the average *fDiv1* with 0.67. As *fDiv2* reflects the switching costs of operating a diverse fleet, Air France-KLM operated the fleet with the highest costs. The variable *fDivNet* (see p. 89) combines the advantages of a diverse fleet (*fDiv1*) while respecting the entailed costs (*fDiv2*). The Brazilian low-cost airline Gol displayed the highest *fDivNet* value in 2006 with 0.64 because it operated a single aircraft family (Boeing 737) with three different aircraft models (Boeing 737-300, Boeing 737-700, Boeing 737-800).

The total operating lease expenses (*olexpTl*) reached a maximum value of 2.9 billion USD for United Airlines in 2012. The airline operated 541 of its 948 aircraft under operating leasing in that year. Jazeera Airways (2010, 2011, 2012, 2013) and Allegiant Air (2012) were the airlines with operating lease expenses of zero. When the operating lease expenses are scaled by total revenues (*olexpRev*), the Indian low-cost airline SpiceJet paid 70% of its revenues for aircraft, engines and other operating leased items in 2006. Due to this large outlier (the sample average *olexpRev* was 6.8%), the variable *olexpRev* is also winsorized at the 1% and 99%-level

5.2.1 Univariate analysis

This subsection encloses the univariate analysis of the operational hedge variables. Comparable with the tables in Subsection 5.1.1, Table 5.19 shows the results of the differences-of-means test between hedgers and non-hedgers and Table 5.20 between airlines with relatively high hedge ratios (above the sample median) and relatively low hedge ratios (below the sample median).

The dummy variable *acOlcashDm* does not differ between the hedgers and non-hedgers in Table 5.19 such that H9 can be rejected. Hedgers operated a significantly (5%) greater percentage of aircraft under operating leasing (*acOlPct*) in contrast to

Table 5.18: Summary statistics of the operational hedging variables

	Obs.	Mean	SD	MIN	MAX
acOlcashDm	390	0.213	0.410	0.000	1.000
acOlPct	390	0.438	0.275	0.000	1.000
alliDm	621	0.433	0.496	0.000	1.000
fDiv1	512	0.670	0.271	0.000	0.951
fDiv2	512	0.523	0.294	0.000	0.892
fDivNet	512	0.147	0.130	0.000	0.636
olexpRev	617	0.068	0.052	0.000	0.701
*olexpTl_* (in USD)	617	339.745	395.435	0.000	2910.000

Variable ending with "_" in millions

non-hedgers. These results contradict H8b. H7 is not supported by the results in Table 5.19 either because the mean of the binary alliance variable (*alliDm*) was greater for hedgers than for non-hedgers, statistically significantly different from zero at the 1%-level. Hedgers had a significantly more diverse fleet than non-hedgers. The mean of both fleet diversity variables, *fDiv1* and *fDiv2*, was significantly greater for airlines with hedge activities, contrary to hypothesis H6. The difference of the means of *fDivNet* was not statistically significantly different from zero. As total operating lease expenses (*olexpTl*) were significantly greater for hedgers, H8a is supported by the univariate results. The average of operating lease expenses scaled by revenues (*olexpRev*) did not differ significantly.

When the sample is divided into airlines with hedge ratios above the sample median and airlines with hedge ratios below the sample median in Table 5.20, the results change compared to Table 5.19. Airlines with relatively small hedge portfolios had significantly (5%) more aircraft under operating lease with simultaneous low cash holdings, supporting H9. The percentage of aircraft under operating leasing did not differ significantly between the two groups. Airlines with high hedge ratios were more likely to be alliance members and operated a more diverse fleet with higher switching costs. Again, the groups did not differ significantly in *fDivNet*. The differences of the means of the absolute and scaled operating lease expenses were not statistically significantly different from zero.

In order to integrate the likely impact of being a member of an alliance and to test H7, Table 5.21 contains the results of differences-of-means tests between alliance and

Table 5.19: Differences-of-means test between hedgers (*fdvDm*=1) and non-hedgers (*fdvDm*=0): operational hedging variables

	Hedgers		Non-hedgers		t test		
	Mean	Obs.	Mean	Obs.	Diff.	SE	Obs.
acOlcashDm	0.212	326	0.219	64	0.007	0.057	390
acOlPct	0.456	326	0.342	64	-0.114^{**}	0.042	390
alliDm	0.493	471	0.231	147	-0.261^{***}	0.042	618
fDiv1	0.694	428	0.543	82	-0.152^{***}	0.037	510
fDiv2	0.545	428	0.408	82	-0.137^{***}	0.037	510
fDivNet	0.149	428	0.134	82	-0.015	0.015	510
olexpRev	0.066	470	0.069	145	0.004	0.005	615
*olexpTl_*	361.394	470	232.217	145	-129.177^{***}	32.019	615

* p<0.05, ** p<0.01, *** p<0.001

Variable ending with "_" in millions of USD

Table 5.20: Differences-of-means test between airlines with high hedge ratios (hedge ratio above sample median) and low hedge ratios (hedge ratio below sample median): operational hedging variables

	High ratios (>med.)		Low ratios (<=med.)		t test		
	Mean	Obs.	Mean	Obs.	Diff.	SE	Obs.
acOlcashDm	0.15	196	0.27	173	0.12^{**}	0.04	369
acOlPct	0.43	196	0.45	173	0.02	0.03	369
alliDm	0.50	271	0.35	274	-0.15^{***}	0.04	545
fDiv1	0.71	263	0.59	208	-0.12^{***}	0.03	471
fDiv2	0.57	263	0.44	208	-0.13^{***}	0.03	471
fDivNet	0.14	263	0.15	208	0.01	0.01	471
olexpRev	0.06	271	0.07	272	0.01	0.00	543
*olexpTl_*	361.28	271	310.68	272	-50.60	31.03	543

* p<0.05, ** p<0.01, *** p<0.001

Variable ending with "_" in millions of USD non-alliance carriers. Alliance members had a greater likelihood of engaging in hedge activities as well as greater hedge extents. The difference in the binary hedge variables (*fdvDm*) and in the hedge ratios (*fdvPct12m*) was statistically significantly different from zero at the 1% and 5%-level. The univariate results therefore fail to support H7. A likely explanation for the positive relation between alliance membership and fuel price hedging is given in Subsection 5.2.5. The non-alliance airlines had significantly larger adjusted profit margins (*prfMrgAdj*) and cash ratios (*cashRto*). Moreover, they showed higher levels of capital expenditure scaled by total assets (*capAsAdj1*) and adjusted Tobin's Q values (*tobQAdj1*). Their total operating lease expenses were lower than those of the alliance airlines. The adjusted leverage ratios 1 (*lvrg1Adj1*) of non-alliance airlines exceeded significantly the debt ratios of alliance members. The fleet diversity measures *fDiv1*, *fDiv2* and *fDivNet* were significantly lower for non-alliance members. As all sample alliance members were legacy carriers, reflected in the mean value of the *lccDm* of zero, the lower fleet diversity measure of non-alliance members reflects the business model of low-cost airlines. The adjusted interest coverage ratio (*intCovAdj*), market-to-book ratio (*mtbRto*), adjusted return on assets (*roaAdj1*), and *cashGrwDm* variables did not differ significantly.

Although the different business models are not specifically part of any hypotheses, *t* test results between LCCs and legacy airlines are presented in Table 5.22. Moreover, as the LCC binary variable cannot enter the fixed effects regressions,[129] the univariate analysis may yield interesting insights. The second column of Table 5.22 contains the mean values for selected variables of low-cost airlines and the fourth column average values of legacy airlines. The business model does not seem to influence financial fuel price hedging. Both financial hedging variables, *fdvPct12m* and *fdvDm*, are not significantly different between the two groups. While the hedge ratio was slightly larger among legacy airlines, LCCs held financial fuel price instruments marginally more often. The overall financial situation was better for low-cost carriers than for network airlines. LCCs showed significantly greater adjusted interest coverage ratios, adjusted profit margins, cash ratios, MTB ratios and adjusted Tobin's Q values. Moreover, low-cost airlines had lower adjusted leverage ratios and greater capital expenditure scaled by total assets. As expected, LCCs operated a significantly less diverse fleet (*fDiv1*) with lower switching costs (*fDiv2*). Interestingly, although the *fDiv1* value of low-cost airlines

[129] As stated previously, variables with an entity standard deviation of zero, such as *lccDm*, cannot be included in fixed effects models (Baum, 2007).

Table 5.21: Differences-of-means test between alliance (*alliDm*=1) and non-alliance airlines (*alliDm*=0): selected variables

	Alliance		Non-alliance		t test		
	Mean	Obs.	Mean	Obs.	Diff.	SE	Obs.
fdvPct12m	0.358	231	0.287	314	−0.071**	0.025	545
fdvDm	0.872	266	0.679	352	−0.193***	0.032	618
intCovAdj	1.456	267	1.636	350	0.180	0.110	617
lvrg1Adj1	0.477	269	0.517	350	0.040**	0.013	619
prfMrgAdj	0.041	267	0.057	350	0.016**	0.006	617
roaAdj1	0.028	267	0.036	349	0.007	0.004	616
capAsAdj1	−0.065	269	−0.084	350	−0.020**	0.006	619
cashGrwDm	0.197	264	0.194	350	−0.003	0.032	614
cashRto	0.498	269	0.658	352	0.160***	0.032	621
mtbRto	1.825	264	1.762	352	−0.064	0.219	616
tobQAdj1	1.117	264	1.225	350	0.108***	0.026	614
fDiv1	0.848	244	0.507	268	−0.341***	0.018	512
fDiv2	0.718	244	0.346	268	−0.372***	0.020	512
fDivNet	0.131	244	0.162	268	0.031**	0.011	512
*olexpTl_*	536.532	267	173.038	350	−363.494***	26.763	617
lccDm	0.000	269	0.361	352	0.361***	0.026	621

* p<0.05, ** p<0.01, *** p<0.001

Variable ending with "_" in millions of USD

was 0.49 lower than the value of network airlines, LCCs managed to have a 0.04 greater net fleet diversity value. This implies that despite the low-cost airlines' homogeneous fleet structure, their fleet strategy allowed for operational flexibility at very low costs.[130]

5.2.2 Multivariate analysis

In Table 5.23 the results of several multiple regression models relating to the different operational hedging variables can be found. As the dependent variable is the decision

[130] It must not be neglected, though, that the majority of low-cost carriers do not operate long-distance flights. If an airline offers short, medium and long-haul flights, it automatically needs a more diverse fleet than an airline without long-distance flights.

Table 5.22: Differences-of-means test between legacy (*lccDm*=0) and low-cost airlines (*lccDm*=1): selected variables

	LCCs		Legacy airlines		t test		
	Mean	Obs.	Mean	Obs.	Diff.	SE	Obs.
fdvPct12m	0.283	125	0.327	420	0.043	0.032	545
fdvDm	0.764	127	0.762	491	−0.002	0.042	618
intCovAdj	2.143	127	1.406	490	−0.737***	0.171	617
lvrg1Adj1	0.471	126	0.507	493	0.036*	0.017	619
prfMrgAdj	0.076	127	0.043	490	−0.033***	0.009	617
roaAdj1	0.039	126	0.031	490	−0.008	0.006	616
capAsAdj1	−0.097	126	−0.070	493	0.027**	0.009	619
cashGrwDm	0.230	126	0.186	488	−0.044	0.042	614
cashRto	0.912	127	0.506	494	−0.406***	0.051	621
mtbRto	2.342	127	1.645	489	−0.697**	0.226	616
tobQAdj1	1.418	126	1.117	488	−0.301***	0.043	614
acOlPct	0.518	107	0.407	283	−0.110**	0.036	390
fDiv1	0.284	117	0.784	395	0.501***	0.022	512
fDiv2	0.103	117	0.647	395	0.545***	0.018	512
fDivNet	0.181	117	0.137	395	−0.044*	0.020	512
*olexpTl_*	178.127	127	369.786	490	191.659***	23.610	617

* p<0.05, ** p<0.01, *** p<0.001

Variable ending with "_" in millions of USD

to hedge (*fdvDm*), a probit model with random effects is used. Contrary to H6, the relationship between the fleet diversity measure (*fDiv1*) and the binary hedge variable is positive and statistically significant at the 5% and 10%-level in Models 1, 2 and 3.[131] Operational hedging, in the form of operating a diverse fleet, seems to be a complement rather than a substitute to financial fuel price hedging in the current sample. In the t test results between alliance and non-alliance members, it became apparent that alliance members showed higher levels of hedging and also greater fleet diversity measures. The positive coefficient on *fDiv1* may thus capture the positive effect of alliance membership

[131] Model 2 contains year dummies. The AIC value of Model 2 is higher than that of Model 1. Therefore, the further regression models in Table 5.23 do not include time fixed effects.

on hedging. The binary alliance variable (*alliDm*) is therefore added in Model 3. The magnitude as well as the significance level of the fleet diversity coefficient is reduced in comparison to the base regression, yet the coefficient is still statistically significantly different from zero at the 10%-level. The relation between alliance membership and the decision to hedge is positive but not significantly different from zero. When *fDiv1* is dropped from the analysis in Model 4 the p-value of the *alliDm* coefficient increases to 0.144. H7 is not supported by the multivariate results. Model 5 exhibits that total operating lease expenses are negatively associated with the hedge dummy variable. The coefficient on *olexpTl* is statistically significantly different from zero at the 5%-level, failing to support H8a. The correlation factor between *lvrg1Adj1* and *olexpTl* is 0.06. The negative coefficient on total operating lease expenses may consequently capture the financial distress theory. Airlines with greater debt ratios show greater levels of operating lease expenses and hedge less.

In Model 6 the operating lease expenses are exchanged for the percentage of operating leased aircraft (*acOlPct*). The coefficient on *acOlPct* is not statistically significant. Thus, H8b cannot be supported by the data. Lastly, the results also fail to support H9 as the coefficient on the dummy variable *acOlcashDm* is positive and not significant. However, the number of observation is greatly reduced from 504 in Model 5 to 385 in Models 6 and 7 due to limited fleet data, which may be the reason for the insignificant estimates of *acOlPct* and *acOlcashDm*. As expected from the univariate analysis, the coefficient estimate on the low-cost dummy is insignificant in Model 8. The type of business model does not seem to influence the decision to hedge.

The relationship between different operational hedge variables and the extent of hedging is presented in Table 5.24. As the regressand, the hedge ratio, is a continuous variable, OLS regressions with entity fixed effects and heteroskedastic-robust standard errors are chosen. The coefficient on the fleet diversity measure is positive and significant at the 1%-level, regardless of whether time fixed effects are excluded (Model 1) or included (Model 2). According to the coefficient estimates in Model 1, a one (within) standard deviation increase in *fDiv1* (0.06) would lead to an increase in hedge ratios of 2.3 percentage points (0.06×0.379). To factor in the likely impact of alliance membership, the variable *alliDm* is included in Model 3. The coefficient estimate on *fDiv1* remains significantly different from zero at the 1%-level. The magnitude even increases from 0.379 to 0.404. Therefore, the positive (complementary) relation between fleet diversity and hedging is not driven by alliance membership. The estimate on *alliDm* is positive and significant at the 5%-level. The significance level of the coefficient on the alliance dummy rises to 10% when *fDiv1* is dropped from the analysis in Model 4. Hypotheses

Table 5.23: Random effects probit models with different operational hedging variables

	BASE (1) fdvDm	(2) fdvDm	(3) fdvDm	(4) fdvDm	(5) fdvDm	(6) fdvDm	(7) fdvDm	(8) fdvDm
lvrg1Adj1	-14.15^{**}	-14.18^{**}	-14.76^{**}	-14.74^{***}	-14.08^{**}	-16.09^{**}	-15.31^{**}	-14.23^{**}
	(0.013)	(0.016)	(0.011)	(0.010)	(0.014)	(0.010)	(0.013)	(0.011)
lvrg1Adj1Sqr	12.13^{**}	12.04^{**}	12.77^{**}	12.76^{**}	12.08^{**}	14.78^{**}	13.79^{**}	12.19^{**}
	(0.025)	(0.033)	(0.021)	(0.019)	(0.026)	(0.012)	(0.018)	(0.023)
intCovAdj	-0.719^{***}	-0.718^{***}	-0.753^{***}	-0.773^{***}	-0.791^{***}	-0.698^{***}	-0.684^{***}	-0.733^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
tobQAdj1	0.395	0.479	0.487	0.531	0.459	−0.265	−0.311	0.422
	(0.357)	(0.311)	(0.273)	(0.227)	(0.294)	(0.595)	(0.531)	(0.329)
cashRto	3.305^{***}	3.331^{**}	3.446^{***}	3.302^{**}	3.083^{**}	5.594^{***}	5.976^{***}	3.037^{**}
	(0.009)	(0.012)	(0.008)	(0.011)	(0.017)	(0.001)	(0.000)	(0.017)
cashRtoSqr	-1.320^{**}	-1.363^{**}	-1.396^{**}	-1.430^{**}	-1.325^{**}	-2.573^{***}	-2.684^{***}	-1.320^{**}
	(0.019)	(0.021)	(0.016)	(0.014)	(0.023)	(0.000)	(0.000)	(0.020)
acTl	−0.00000344	−0.0000485	−0.000427	−0.0000665	0.00442^{*}	−0.000332	−0.000326	0.000648
	(0.997)	(0.967)	(0.719)	(0.955)	(0.057)	(0.753)	(0.754)	(0.553)
irdvDm	1.177^{***}	1.217^{***}	1.174^{***}	1.184^{***}	1.113^{***}	1.515^{***}	1.503^{***}	1.209^{***}
	(0.003)	(0.003)	(0.004)	(0.004)	(0.007)	(0.003)	(0.003)	(0.003)
fxdvDm	1.115^{***}	1.081^{***}	1.057^{**}	1.020^{**}	1.203^{***}	1.012^{**}	0.947^{**}	1.101^{***}
	(0.005)	(0.007)	(0.010)	(0.012)	(0.003)	(0.028)	(0.037)	(0.005)
fDiv1	1.806^{**}	1.840^{*}	1.621^{*}					
	(0.048)	(0.061)	(0.095)					
alliDm			0.467	0.643				
			(0.301)	(0.144)				
olexpTl_					-0.00198^{**}			
					(0.044)			
acOlPct						0.215		
						(0.804)		
acOlcashDm							0.515	
							(0.262)	
lccDm								−0.0490
								(0.939)
intercept	2.791	2.796	2.928^{*}	3.914^{**}	4.036^{**}	4.266^{**}	3.983^{**}	4.009^{**}
	(0.101)	(0.124)	(0.090)	(0.017)	(0.016)	(0.021)	(0.028)	(0.014)
N	504	504	504	504	504	385	385	504
AIC	246.8	262.5	247.7	248.6	245.9	193.6	192.3	250.9
Year dummies	no	yes	no	no	no	no	no	no

p-values in parentheses
Variable ending with "_" in millions
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

H6 and H7 have to be rejected. Fleet diversity and alliance membership both positively impact the extent of hedging. The fixed effects results do not support H8a. The estimator of total operating lease expenses is negative and significant at the 10%-level. Airlines with greater operating leasing had smaller hedge portfolios. Analogous to the probit results, the negative estimator may reflect the financial distress theory. The insignificant coefficient estimates on *acOlPct* and *acOlcashDm* fail to support hypotheses H8b and H9. The coefficients may be impacted by the low number of observations in Models 6 and 7.

5.2.3 Robustness

The robustness tests on the random effects probit models of Subsection 5.2.2 are depicted in Tables O.1 and O.2 in Appendix O. While Table O.1 summarizes various sample specifications with the operational hedge variable *fDiv1*, Table O.2 further contains the binary alliance variable (*alliDm*) in all seven models. The coefficient estimate on *fDiv1* is robust to excluding CPA airlines (Model 2), including a CPA (Model 3) or merger dummy (Model 4), and to dropping Allegiant Air from the analysis (Model 5). The estimates remain positive and statistically significantly different from zero at least at the 10%-level. When the sample is either restricted to airlines accounting in accordance with IFRS (Model 6) or U.S. GAAP (Model 7), the p-value increases above the 10%-level. The insignificant coefficient estimate on *alliDm* in Model 3 of Table 5.23 is robust to almost all sample specifications (Table O.2).[132] When U.S. GAAP airlines are analyzed separately, the estimate on *alliDm* becomes negative. The results imply that for U.S. GAAP airlines the likelihood for financial fuel hedging falls with alliance membership. However, the coefficient estimate is not statistically signficantly different from zero.

Robustness tests on the variables *olexpTl*, *acOlPct* and *acOlcashDm* can also be found in Appendix O. The coefficient estimates on *olexpTl* in Table O.3 are not robust to excluding CPA airlines (Model 2) or including a CPA dummy (Model 3). Moreover, for airlines that report in accordance with U.S. GAAP (Model 7) the estimate is not significant. The p-value of the operating lease expenses coefficient ranges between 0.028 and 0.288. Additionally, the magnitude and algebraic sign remain similar to the base regression. The results relating to *acOlPct* and *acOlcashDm* are robust to the sample restrictions. Neither of the coefficient estimates are significant in Tables O.4 and O.5.

Tables P.1 and P.2 in Appendix P show the alternative fixed effects models. The operational hedging variable *fDiv1* enters the models in Table P.1. The results are

[132]The regression model in which Allegiant Air is dropped from the sample is excluded from Table O.2 in order to preserve clarity.

Table 5.24: Firm fixed effects models (with heteroskedastic-robust standard errors) with different operational hedging variables

	BASE (1) fdvPct12m	(2) fdvPct12m	(3) fdvPct12m	(4) fdvPct12m	(5) fdvPct12m	(6) fdvPct12m	(7) fdvPct12m
lvrg1Adj1	-2.037^{***}	-1.808^{***}	-2.035^{***}	-1.460^{***}	-1.332^{***}	-2.044^{***}	-2.029^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
lvrg1Adj1Sqr	1.862^{***}	1.634^{***}	1.854^{***}	1.250^{***}	1.142^{***}	1.876^{***}	1.862^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
intCovAdj	-0.0297^{***}	-0.0298^{***}	-0.0300^{***}	-0.0266^{***}	-0.0294^{***}	-0.0220^{**}	-0.0213^{**}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.030)	(0.032)
peRto	-0.000296	-0.000297	-0.000293	-0.000181	-0.000208	-0.000309^{*}	-0.000313^{*}
	(0.120)	(0.125)	(0.122)	(0.291)	(0.227)	(0.093)	(0.089)
crtRto	0.0113	0.0136	0.0266	-0.00555	-0.0260	0.100	0.0938
	(0.879)	(0.856)	(0.719)	(0.930)	(0.678)	(0.202)	(0.234)
crtRtoSqr	0.00354	0.00339	-0.000392	0.00718	0.0125	-0.0285	-0.0277
	(0.877)	(0.883)	(0.986)	(0.717)	(0.526)	(0.227)	(0.240)
sizeAdj1__	-6.21×10^{-8}	-0.00000114	-0.000000596	-0.000000628	0.00000125	-0.000000756	-0.000000821
	(0.970)	(0.528)	(0.717)	(0.688)	(0.468)	(0.629)	(0.598)
irdvDm	0.0951^{***}	0.0950^{***}	0.0861^{***}	0.0728^{**}	0.0853^{***}	0.0938^{***}	0.0989^{***}
	(0.003)	(0.004)	(0.008)	(0.012)	(0.003)	(0.007)	(0.003)
fxdvDm	0.0116	0.0118	0.0107	0.00377	0.00551	0.0241	0.0232
	(0.722)	(0.718)	(0.741)	(0.891)	(0.842)	(0.489)	(0.505)
fDiv1	0.379^{***}	0.392^{***}	0.404^{***}				
	(0.002)	(0.002)	(0.001)				
alliDm			0.0810^{**}	0.0680^{*}			
			(0.047)	(0.072)			
olexpTl__					-0.000143^{*}		
					(0.054)		
acOlPct						-0.0362	
						(0.629)	
acOlcashDm							-0.0104
							(0.705)
intercept	0.587^{***}	0.590^{***}	0.535^{***}	0.677^{***}	0.709^{***}	0.787^{***}	0.772^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N	466	466	466	538	538	364	364
AIC	-482.6	-476.8	-485.4	-599.6	-600.1	-444.4	-444.3
Adj. R^2	0.734	0.735	0.736	0.762	0.763	0.788	0.788
R^2	0.776	0.782	0.778	0.798	0.798	0.822	0.822
Year dummies	no	yes	no	no	no	no	no

p-values in parentheses
Variables ending with "_" in millions of USD
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

robust in Models 2, 3, 4, and 5. The coefficient on *fDiv1* is positively significant at the 1%-level. The coefficient estimate is still positive in Models 5 and 6, yet the p-value strongly exceeds 0.1. The coefficient of zero on *cpaDm* in Model 3 arises from a within panel variance of zero. None of the CPA airlines changed their agreements during the sample period. The binary variable was always one for the two CPA airlines. The results regarding the coefficient on the alliance variable are robust as can be seen in Models 1 to 5 in Table P.2. When the sample is reduced to IFRS users in Model 6, the magnitude of the coefficient slightly decreases and the p-value increases to 0.277. The *alliDm* is dropped in Model 7 because none of the U.S. GAAP airlines changed their alliance membership in the sample period.

The alternative fixed effects models with the operational hedge variable *olexpTl* can be found in Table P.3. While the results are robust to the sample restrictions in Models 2 to 5, the coefficient of the European sample is insignificant. The significance of the coefficient estimate changes to the 1%-level for U.S. GAAP carriers in Model 7. Higher operating lease expenses are related with lower levels of hedging, opposing H8b. A one (within) standard deviation (198.61) increase in total American operating lease expenses would be related with a 10.4 (198.61×-0.000523) percentage points lower hedge ratio. The strong evidence among American carriers may result from the large amount of operating lease contracts in the Americas (see Subsection 5.3.5 for further discussion). The coefficient estimates on *acOlPct* in Table P.4 and on *acOlcashDm* in Table P.5 are robust. All coefficients are insignificant.

A cluster analysis of the sample airlines can be found in Table Q.1 in Appendix Q. With cluster analysis, researchers aim to allocate a large set of observations into several groups with the groups being as distinct to each other while the observations within a group are as close to each other as possible (Anderberg, 1973). Cluster analysis is different from statistical hypothesis testing in the way that it serves to find the appropriate hypothesis and not to support or reject it (Duda et al., 2001). Congruent with the multivariate results of Subsections 5.1.2 and 5.2.2, the airlines of Cluster 1 hedged the lowest fraction of their expected fuel requirements 12 months forward (*fdvPct12m*) in contrast to the airlines of Clusters 2 and 3. As the panel data set is collapsed to time-series data in the cluster analysis, any time-varying component cannot be captured. The cluster analysis mirrors the regression results in showing the negative relation between debt ratios and hedging, the positive relation between Tobin's Q and hedging, the positive relation between cash ratios and hedging and the negative relation between operating lease expenses and hedging. Due to the similar results between the cluster analysis and the multivariate regressions, a further inclusion of the cluster results (e.g. inclusion of cluster dummies) is not pursued.

5.2.4 Limitations

The most pervasive limitation regarding the operational hedging variables is sample selection bias. The number of observations is greatly reduced when the variables containing the fraction of aircraft under operating leasing, *acOlPct* and *acOlcashDm*, are included in the regression models. While the fraction is published in 390 firm years, the regression models only incorporate 364 observations. If rather financially sound firms publish their number of aircraft under operating leasing and if those airlines are more likely to hedge (according to the regression results in this study), the coefficient estimates on *acOlPct* and *acOlcashDm* are biased upwards, in opposite direction to the theory in H8b.

The other sources of inconsistent estimators discussed in Subsection 5.1.4 are also likely to be present among the operating hedge variables. In order to prevent the misspecification of the functional form, all operating hedge variables are included with their squared terms in unreported results. As neither of the quadratic coefficients is significant nor the AIC value lower for the models containing the squared term, a nonlinear relationship between operational and financial hedging is not likely. Measurement error in the fleet diversity variables or the leasing variables cannot be ruled out. Simultaneous causality may also cause the estimators on the operational hedge variables to be biased. The theory in H8b suggests that a higher fraction of aircraft under operating leasing leads to lower hedge ratios. If, however, greater hedge ratios are related with a better financial situation in which operating leasing is less necessary, the negative causality between financial hedging and aircraft operating leasing runs in both directions. The incorrect calculation of the standard error is evaded by employing heteroskedastic-robust standard errors.

5.2.5 Discussion

The probit models fail to support three of the five operational hedging hypotheses. The likelihood of hedging is not influenced by either the alliance dummy (H7), the percentage of aircraft under operating leasing (H8b) or collateral constraints (H9). The random effects estimate on total operating lease expenses is negative and statistically significantly different from zero at the 5%-level.[133] Airlines with greater total operating lease expenses showed a lower propensity to employ financial fuel price hedging. These results stand in contrast to H8a. If airlines with a lower credit rating have greater difficulties in finding counterparties for debt contracts and therefore rather finance aircraft under

[133]When airlines under a CPA are excluded, the p-value rises above 0.1.

operating lease contracts, the negative coefficient on operating lease expenses could reflect the financial distress theory. The multivariate determinants results in Subsection 5.1 indicate a negative relation between debt ratios and financial hedging. Larger debt ratios and greater operating lease expenses could both reflect a greater likelihood of financial distress. The extent of hedging is also influenced by operating lease expenses. The fixed effects estimates on $olexpTl$ are statistically significantly different from zero at the 10%-level, except for the European sample. The significance level of the American carriers rises to the 1%-level. A possible explanation for the increased significant results is the extensive use of operating lease contracts of American carriers. They showed the highest PV of future operating lease expenses and the highest fraction relative to total assets (see Figure 4.35 in Subsection 4.2.7).

The random effects as well as the OLS results fail to support H6. On the contrary, the fixed effects estimators of the fleet diversity measure are positive and statistically significantly different from zero at the 1%-level and the random effects estimators at the 5%-level. The results are robust to including an alliance binary variable and to different sample restrictions. The positive coefficient implies that operational hedging, in the form of operating a heterogeneous fleet, is a complement to financial hedging. The results are in accordance with the evidence of Allayannis et al. (2001), Mello et al. (1995), and Gamba and Triantis (2013). A diverse fleet is a risk management tool for a longer time horizon while financial hedging can be adapted more flexibly. Long lead times among aircraft manufacturers due to immense aircraft backlogs inhibit airlines to adapt their fleet structures in the short term. Financial contracts, at the other end, can be unwound quickly as many airlines demonstrated in 2008 (see Section 5.3). Thus, the sample airlines availed themselves of financial and operating hedging simultaneously.

The OLS results do not support H7. The fixed effects coefficients on the alliance binary variable are positive and statistically significantly different from zero at the 5%-level. Being a member of an airline alliance had a positive impact on airlines' hedge ratios. The argument that alliance membership is similar to an operational hedge and should therefore be negatively related with fuel hedging cannot be supported. Similar to the results regarding H6, operational hedging is a complement to financial hedging. As all alliance members were network legacy carriers, it could be assumed that the business model is driving the positive results. The t test results between NLCs and LCCs do not show a significant difference in hedge ratios or the hedge dummy though. Moreover, the low-cost binary variable is not significant in the probit results. The business model does not explain the positive coefficient of the alliance dummy. In Table 5.25 the mean value of selected variables between legacy alliance members and legacy non-alliance members is presented. This distinction is important as the results in Table 5.21 are mainly driven by the difference between non-alliance low-cost and alliance legacy airlines. Alliance legacy airlines were significantly more likely to enter into financial fuel derivatives and to hold larger hedge portfolios. Moreover, the non-alliance legacy airlines had larger leverage ratios, statistically significantly different from zero at the 1%-level. Therefore, the financial distress theory may be the explaining factor for the positive alliance variable. If rather financially sound airlines with a good reputation and low debt ratios are invited to join an alliance, then the positive alliance coefficient mirrors the negative debt ratio coefficient. The question of simultaneous causality arises: either alliance airlines have greater hedge portfolios because they are selected based on their lower debt ratios and lower debt ratios are related with a greater hedge activity; or strategic alliances expect their airlines to hedge financially because investors see hedging as a sign of managerial ability (Brown, 2001; Morrell and Swan, 2006).

To further test this potential source of simultaneity bias, six airlines that joined an alliance and reported their hedge ratios in all sample years are analyzed. Table 5.26 reports t test results between prior-alliance years and alliance years. The six airlines exhibited a greater likelihood of hedging, larger hedge portfolios and greater hedge maturities after the entry. The difference of the variables does not differ significantly though. Due to the small number of observations in Table 5.26, Figure 5.3 depicts the time series of the hedge ratios of those six airlines. Except for TAM, the airlines exhibited greater hedge ratios after the admittance to an alliance. The question of whether alliance entrance increases the hedging behavior remains unclear. Although the descriptive results indicate a positive relation between hedge ratios and alliance entrance, the t test results do not provide significant evidence. Eleven alliance airlines did not hold any fuel derivatives in one or more sample firm years. Four of the eleven airlines did not have access to a derivative market in some or all sample years (Aeroflot, Air China, China Eastern, and China Southern Airlines). Otherwise, the magnitude and significance of the *alliDm* variable may be even higher.

Hypotheses H8b and H9 are not supported by the fixed effects results. The negative and insignificant coefficient estimate on *acOlPct* may be impacted by the number of observations. If financially sound airlines with greater hedge ratios operated less aircraft under operating leasing and if those airlines were more likely to disclose their fleet data, the estimate on *acOlPct* would be biased downwards. Similarly, the variable *acOlcashDm* may suffer from a low number of observations.

Table 5.25: Differences-of-means test between network alliance (*alliDm*=1, *lccDm*=0) and network non-alliance airlines (*alliDm*=0, *lccDm*=0): selected variables

	NLC alliance		NLC non-alliance		t test		
	Mean	Obs.	Mean	Obs.	Diff.	SE	Obs.
fdvPct12m	0.358	231	0.289	189	−0.069*	0.030	420
fdvDm	0.872	266	0.631	225	−0.241***	0.038	491
intCovAdj	1.456	267	1.346	223	−0.110	0.108	490
lvrg1Adj1	0.477	269	0.543	224	0.066***	0.014	493
prfMrgAdj	0.041	267	0.046	223	0.005	0.006	490
roaAdj1	0.028	267	0.034	223	0.005	0.005	490
capAsAdj1	−0.065	269	−0.077	224	−0.013	0.007	493
cashGrwDm	0.197	264	0.174	224	−0.023	0.035	488
cashRto	0.498	269	0.515	225	0.017	0.033	494
mtbRto	1.825	264	1.434	225	−0.391	0.233	489
tobQAdj1	1.117	264	1.116	224	−0.001	0.024	488
fDiv1	0.848	244	0.681	151	−0.168***	0.016	395
fDiv2	0.718	244	0.534	151	−0.184***	0.019	395
fDivNet	0.131	244	0.147	151	0.016	0.010	395
*olexpTl_*	536.532	267	170.140	223	−366.391***	27.547	490

* p<0.05, ** p<0.01, *** p<0.001

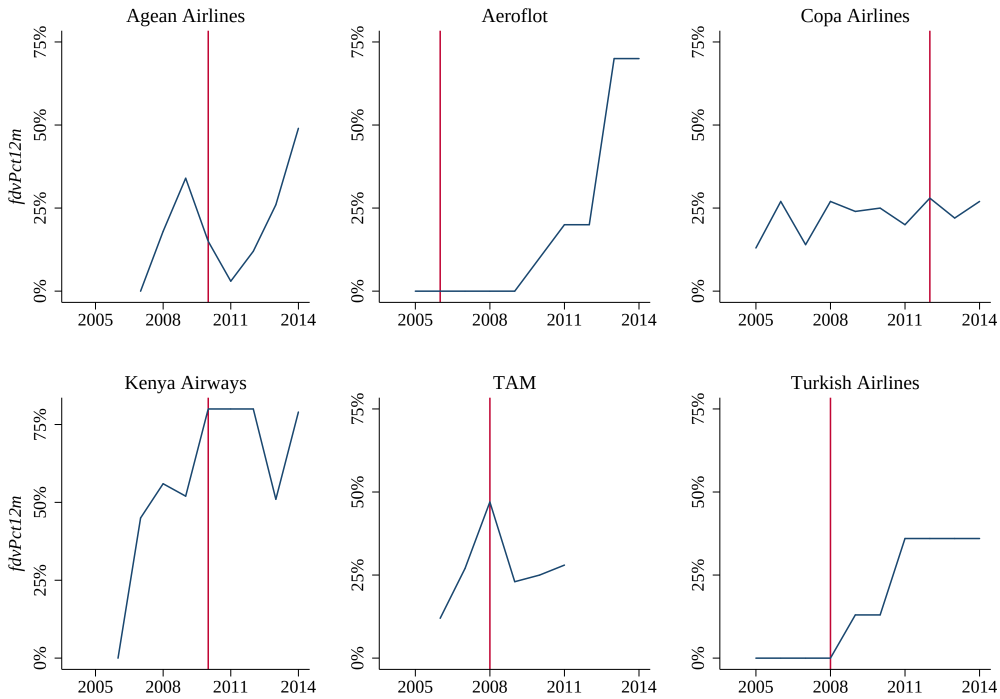
Variable ending with "_" in millions of USD

Table 5.26: Alternative differences-of-means test of six airlines (Aegean Airlines, Aeroflot, Copa Airlines, Kenya Airways, TAM, Turkish Airlines) before and after their alliance entry

	Alliance years		Non-alliance years		t test		
	Mean	Obs.	Mean	Obs.	Diff.	SE	Obs.
fdvDm	0.714	42	0.667	21	−0.048	0.127	63
fdvPct12m	0.265	41	0.188	21	−0.077	0.056	62
fdvMtr	15.071	42	13.429	21	−1.643	3.067	63

* p<0.05, ** p<0.01, *** p<0.001

Figure 5.3: Time series: hedge ratios (*fdvPct12m*) of alliance airlines that entered a strategic alliance during the sample period (date of entry marked with red line)



5.3 Analysis of international airlines' selective hedging

This section contains the analysis regarding the selective hedging behavior of the sample airlines. First, the summary statistics are discussed. Second, Subsection 5.3.1 presents differences-of-means tests of selected variables between active and passive hedgers. Third, multiple regression models are enclosed in Subsection 5.3.2. Lastly, in Subsections 5.3.3, 5.3.4 and 5.3.5 robustness results, limitations and the discussion of all results are given.

The summary statistics clearly indicate a selective hedging behavior of the sample airlines. The year-on-year percentage point changes in the average hedge ratios of all airlines within a region (*regChg*) can be seen in Table 5.27. The mean value was 0.5 percentage points and the SD 6.2 percentage points. The highest increase in hedge ratios occurred among African airlines by 22.5 percentage points followed by Oceanian carriers with 14.2 percentage points between 2006 and 2007. In the same time period, European airlines reduced their hedge ratios the most by 16.5 percentage points. American firms changed their hedge portfolios the least, with a standard deviation of 3.8 and an average percentage point change of -7.0.

The individual year-on-year percentage point changes in the hedge ratios are reflected in the variable *fdvPct12mChg*. AirAsia reduced its hedge portfolio by 78.0 percentage points from 100.0% to 22.0% between 2008 and 2009 due to large losses incurred in 2008 of 641 million Malaysian Ringgit (approximately 197 million USD), or 24.3% of its revenues. AirAsia's well-known CEO, Tony Fernandes, stated in his CEO report (AirAsia Berhad, 2009, p. 30):

> Excessive speculation drove oil prices to levels unprecedented in history. [...] We were of the opinion that such price levels were unsustainable. Nevertheless, we bought into fuel hedges as a precaution to protect the business from this unpredictable market volatility. When the credit crisis unfolded in the latter half of 2008, the true value of oil began to crystallise, and our fuel hedges which we entered into as an insurance measure became liabilities. While other airlines whined and moaned, and continue to pay the now exceedingly high prices for their hedged oil, we reviewed our hedging structures in depth, bit the bullet, and decided to unwind our hedges. But even with our swift action, the damage amounted to RM641 million, including margins held by the now bankrupt Lehman Brothers. [...] While the cost of unwinding the hedges was high, we are now one of the rare airlines with clean balance sheets and transparent earnings. We currently purchase fuel at the spot market price, enjoying the low price.

The second largest decrease in its hedge ratio was made by Southwest in 2008 of -60.0 percentage points. The company reacted to large losses in its portfolio by entering into further derivative contracts, offsetting the original hedge contracts (Southwest Airlines, 2009). In 2014, Southwest unwound its entire hedge portfolio again, the third largest decrease in hedge ratios of -43.0 percentage points in the sample. In both cases, Southwest replied to the "precipitous decline in fuel prices" (Southwest Airlines, 2009, p. 58) and to the "precipitous decline in oil and jet fuel prices" (Southwest Airlines, 2015, p. 159), respectively. At the other end, Delta Air Lines increased its hedge ratio by 53.2 percentage points from 2012 to 2013. Delta Air Lines made headlines with buying a refinery in 2012. In 2014, the refinery delivered as much as approximately 56% of Delta's fuel requirements (Delta Air Lines, 2015, p. 35). Nevertheless, the airline entered into fuel hedge contracts which covered 100% of its expected fuel consumption in 2014. Thai

Airways reported to take "a more proactive approach to jet fuel price hedging" (Thai Airways, 2012, p. 56), reflected in the second largest plus of 52.4 percentage points between 2010 and 2011.

The sample airlines changed the maturity of their fuel price derivative positions (*fdvMtrChg*) on average by 0.3 months, with an SD of 6.7 months. Four airlines reduced the maturity by 24 months from one period to another: Southwest (from 60 to 36 months) and Air France-KLM (from 48 to 24 months) between 2008 and 2009, AirTran (from 48 to 24 months) between 2005 and 2006, and China Southern (from 24 months to an unhedged position) between 2007 and 2008. As mentioned in Subsection 4.2.8, Southwest and Air France-KLM specifically changed their hedge strategy due to large derivative losses in 2008. AirTran and China Southern did not state explicitly why they lowered or ceased their hedge activities. China Southern experienced large losses in their fuel hedge portfolio two years prior to the termination of the hedge activities. No data is available for AirTran regarding its fuel hedge gains or losses in the years prior to the reduction in hedge maturity. Delta Air Lines was the airline with the largest increase in hedge maturity of 32 months between 2006 and 2007. The airline emerged from Chapter 11 in April 2007 under which it was not allowed to enter into fuel price contracts more than 12 months forward "without approval from the Bankruptcy Court or the Creditors Committee" (Delta Air Lines, 2007, p. 25).

The largest ineffective loss (*fdvPLineff*) of 1.1 billion USD was recorded in 2008 by Air China. In the following year, Air China accounted ineffective derivative profits of 400.0 million USD. China Eastern had the highest profits of the ineffective portion in 2009 with 777.4 million USD. The largest loss of the reclassified (*fdvPLrcl*) portion was disclosed by Delta Air Lines in 2014 with 2.3 billion USD. The sample airlines' average profits in fuel contracts exceeded the losses in the sample period: the average ineffective portion was a loss of 1.3 million USD while the reclassified portion amounted to a profit of 4.8 million USD.[134]

5.3.1 Univariate analysis

Table 5.28 presents the t test results of selected variables between active and passive hedgers. Active hedgers in these tables are defined as those airlines whose absolute annual percentage point change in hedge ratios is in the highest quartile of all hedging airlines in that year (*activeChg4*=1) and zero if it is in the lowest quartile

[134] Effective profits and losses are not regarded here because they are parked under OCI and not recognized in income until the underlying contract settles.

Table 5.27: Summary statistics of the selective hedging variables

	Obs.	Mean	SD	MIN	MAX
fdvPct12mChg	467	0.012	0.142	−0.780	0.530
fdvMtrChg	487	0.303	6.736	−24.000	32.000
*fdvPLeff_* in (USD)	510	−4.116	180.559	−1528.000	2288.709
*fdvPLineff_* (in USD)	521	−1.330	91.436	−1138.281	777.365
*fdvPLrcl_* (in USD)	529	4.768	189.055	−2300.000	1196.022
regChg	467	0.005	0.062	−0.165	0.225

Variables ending with "_" in millions

(*activeChg4*=0). The differences-of-means tests between active and passive hedgers, defined by tertiles instead of quartiles, are presented in Appendix R. The results are virtually the same.

The *t* test results support H10. The derivative profits and losses of *t-1* recognized in income (*fdvPsumt1*, *fdvLsumt1*) are significantly larger among active hedgers as well as the profits recognized in income of *t-2* (*fdvPsumt2*). Consistent with H10 the means of the effective portion of the profits and losses (*fdvPefft1*, *fdvPefft2*, *fdvLefft1*, *fdvLefft2*) do not differ significantly. H12 is also supported by the results. All approximate size measures, except for the number of aircraft, are larger for actively hedging airlines, statistically significantly different from zero at the 1%-level. Active hedgers had greater fuel expenses and total revenues than passive hedgers. They held more interest rate and currency derivatives and were larger in firm size. The results are robust to the alternative definition of selective hedging in Table R.1.[135]

5.3.2 Multivariate analysis

The results of the multivariate analysis regarding the selective hedging hypotheses are presented in Tables 5.29 and 5.30. To begin with, hypotheses H10 and H12 are discussed with the results of Table 5.29. The dependent variable in the models is the binary selective hedging variable *activeChg4*. Therefore, a probit model with random effects is employed. Model 1 includes fuel derivative profits and losses of *t-1* (*fdvPsumt1*, *fdvPefft1*, *fdvLsumt1*, *fdvLefft1*), whereas Model 2 contains profits and losses of *t-2* (*fdvPsumt2*, *fdvPefft2*, *fdvLsumt2*, *fdvLefft2*).

[135]In the alternative *t* test results in Table R.1 the means of *fdvLsumt2* are significantly different at the 10%-level.

Table 5.28: Differences-of-means test between active (*activeChg4*=1) and passive hedgers (*activeChg4*=0): selective hedging variables

	Active hedgers		Passive hedgers		t test		
	Mean	Obs.	Mean	Obs.	Diff.	SE	Obs.
*fdvPsumt1_*	68.6	81	9.2	158	−59.4**	20.6	239
*fdvLsumt1_*	−71.5	81	−1.2	158	70.3**	23.4	239
*fdvPefft1_*	26.2	85	6.5	160	−19.7	15.6	245
*fdvLefft1_*	−43.9	85	−0.9	160	43.0	23.4	245
*fdvPsumt2_*	94.4	67	9.0	138	−85.3**	25.2	205
*fdvLsumt2_*	−41.2	67	−7.6	138	33.6	18.6	205
*fdvPefft2_*	27.1	72	6.3	141	−20.8	11.1	213
*fdvLefft2_*	−34.2	72	−2.3	141	31.9	20.4	213
acTl	216.6	108	211.9	112	−4.7	29.6	220
*fuelExp_*	2350.5	111	1347.8	146	−1002.7***	289.0	257
*revTl_*	7828.6	111	4184.7	165	−3643.9***	983.5	276
revTlln	22.1	111	21.2	165	−1.0***	0.2	276
*sizeAdj1_*	13459.0	110	7211.6	164	−6247.4***	1652.7	274
irdvDm	0.7	111	0.4	165	−0.4***	0.1	276
fxdvDm	0.7	111	0.3	165	−0.4***	0.1	276

* p<0.05, ** p<0.01, *** p<0.001

Variables ending with "_" in millions of USD

Hypothesis H10 can be tested by analyzing the coefficient estimates on the fuel derivative profit and loss variables. For easier interpretation of the results, the profits and losses are disaggregated into profits (*fdvPsumt1*, *fdvPsumt2*, *fdvPefft1*, *fdvPefft2*) and losses (*fdvLsumt1*, *fdvLsumt2*, *fdvLefft1*, *fdvLefft2*). The coefficient estimate on the lagged sum of the reclassified and ineffective portion of fuel derivative losses (*fdvLsumt1*) is negative and statistically significantly different from zero at the 10%-level in Model 1. These results weakly support H10. As losses are recorded with a negative algebraic sign, the negative coefficient means a positive relation with the dependent variable. Airlines that experienced prior-period losses in their fuel hedge portfolios adapted their hedge portfolios more actively. The effective portion of derivative losses, temporarily accounted for under other comprehensive income, does not have any impact on selective hedging as the coefficient estimate on *fdvLefft1* is not statistically significant. Neither prior-period profits of the effective portion (*fdvPefft1*) nor of the ineffective portion (*fdvPsumt1*) of fuel derivatives affect the airlines' selective hedging behavior. All coefficient estimates on derivative profits and losses of period *t-2* in Model 2 are not statistically significantly different from zero, indicating that hedging managers are not influenced by portfolio gains or losses that date back more than one period.

H12 is partially supported by the results. The coefficient estimate on the size variable is insignificant in both models.[136] The coefficient estimate on the interest rate derivative variable is positive and significantly different from zero at the 10%-level in Model 1 and at the 5%-level in Model 2. The currency derivative coefficient is also statistically significantly different from zero at the 5%-level in Model 2. Airlines that held interest rate or currency derivatives were more prone to hedge selectively.

The impact of the competing airlines' hedging behavior on the sample airlines' hedge portfolios is discussed with the help of the results in Table 5.30. The dependent variable of the random effects probit Model 1 is a binary variable that takes on the value one if the sample airline increased its hedge ratio from one period to another (*hdgInc*). Model 2 includes any decreases in the individual hedge portfolio as the dependent variable (*hdgDec*). The results of Models 1 and 2 support H11. An increase in regional hedge ratios (*regChg*) is associated with an increase in the individual hedge ratio because the coefficient estimate on *regChg* in Model 1 is positive, statistically significantly different from zero at the 1%-level. If the regional competitors decreased their hedge activities, the individual airline would also lower its hedge ratio, reflected by the negative coefficient estimate on *regChg* in Model 2. The coefficient is significantly different from zero at the 1%-level. The p-value of the *fdvPsumt1* coefficient in Model 1 slightly exceeds the 10%-level with 0.146. The positive coefficient relates prior-period derivative profits, recognized in income, to an increase in hedge ratios. Similarly, the p-value of the estimate on *fdvLsumt1* is marginally greater than 0.1 with 0.116. The negative coefficient indicates that prior-period derivative losses, recognized in income, led to decreases in hedge ratios.

[136]The size variable remains insignificant even if the dummy variables on interest rate and FX derivatives are excluded in unreported results.

Table 5.29: Random effects probit models with active hedgers binary variable (highest quartile) as the dependent variable

	(1) activeChg4	(2) activeChg4
fdvPsumt1__	0.00401	
	(0.559)	
fdvLsumt1__	-0.0936^{*}	
	(0.070)	
fdvPefft1__	-0.00927	
	(0.374)	
fdvLefft1__	0.00202	
	(0.592)	
sizeAdj1__	-0.0000709	0.0000176
	(0.223)	(0.546)
irdvDm	3.285^{*}	1.656^{**}
	(0.059)	(0.040)
fxdvDm	1.007	1.853^{**}
	(0.271)	(0.012)
fdvPsumt2__		0.00221
		(0.364)
fdvLsumt2__		-0.0000548
		(0.985)
fdvPefft2__		-0.00129
		(0.719)
fdvLefft2__		-0.000398
		(0.891)
intercept	-2.490^{***}	-2.483^{***}
	(0.001)	(0.000)
N	233	201

p-values in parentheses

Variables ending with ”__” in millions

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

Table 5.30: Random effects probit models with hedge ratio increase and decrease binary variables as the dependent variable

	(1) hdgInc	(2) hdgDec
fdvPsumt1_	0.00129	0.000286
	(0.146)	(0.735)
fdvLsumt1_	−0.000382	−0.00108
	(0.581)	(0.116)
fdvPefft1_	−0.000533	0.0000380
	(0.592)	(0.968)
fdvLefft1_	0.000303	−0.000615
	(0.617)	(0.290)
regChg	5.803***	−5.381***
	(0.000)	(0.000)
intercept	−0.762***	−0.853***
	(0.000)	(0.000)
N	371	371

p-values in parentheses

Variables ending with "_" in millions

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

5.3.3 Robustness

In order to test whether the multivariate results of Subsection 5.3.2 are robust, robustness tests are discussed in the following. Table 5.31 presents the results of two random effects probit models with *activeChg3* as the dependent variable. *activeChg3* identifies active hedgers based on their absolute year-on-year percentage point changes of hedge ratios being in the highest tertile of the percentage point changes of all sample airlines. The number of observations in Table 5.31 is greater than the number of observations in Table 5.29 because of the classification in tertiles compared to quartiles. The results on H10 are robust to the classification of selective hedgers. The coefficient estimate on *fdvLsumt1* remains negative and statistically significantly different from zero at the 1%-level. The magnitude as well as the p-value decrease. The coefficients on *fdvPsumt1*, *fdvPefft1*, *fdvLefft1*, *fdvPsumt2*, *fdvLsumt2*, *fdvPefft2*, and *fdvLefft2* are still insignificant. The results regarding interest rate and currency derivatives are mixed. The coefficient estimates on *irdvDm* are positive and significantly different from zero at least at the 10%-level in Models 1 and 2. The *fxdvDm* estimate is positive and significantly different from zero in both models. The size coefficient remains insignificant.

Table 5.32 shows the regression Model 1 of Table 5.29 with different sample restrictions. The sample is not restricted to U.S. GAAP airlines due to an otherwise insufficient number of observations. The results on H10 are robust to all sample restrictions. The coefficient estimates on *fdvLsumt1* are negative and statistically different from zero at least at the 10%-level in all models. The effective portion of the derivative profits and losses (*fdvPefft1*, *fdvLefft1*) as well as the derivative profits recognized in income (*fdvPsumt1*) are still not affecting the dependent variable. However, when merely airlines are analyzed reporting in accordance with IFRS (Model 6), the results change considerably. The coefficient estimate on *fdvPsumt1* changes to being negative and statistically significantly different from zero at the 10%-level. IFRS airlines with prior-period profits, recognized in income, reduced their level of selective hedging. The estimate on *fdvLsumt1* increases strongly in magnitude and significance, supporting the previous results. The magnitude of the *fdvLsumt1* coefficient greatly exceeds the magnitude of the *fdvPsumt1* coefficient. Therefore, the airlines in Model 6 reacted more strongly to prior-period losses than to prior-period profits: When they incurred hedging losses recognized in income (*fdvLsumt1*), they adapted their hedge ratios more strongly than they reduced the adaptions with prior-period gains (*fdvPsumt1*). H10 is partially not supported as the estimates on the profits and losses that are temporarily accounted for under OCI (*fdvLefft1*, *fdvPefft1*) are significantly different from zero. The negative coefficient on *fdvPefft1* corresponds to the negative coefficient on *fdvPsumt1*. Regardless of where the profits on fuel financial instruments were recorded, either under OCI (*fdvPefft1*) or in income (*fdvPsumt1*), those profits led to a reduction in adaptions in hedge portfolios. The positive coefficient estimate on *fdvLefft1* is significantly different from zero at the 5%-level. If the airline reported effective derivative losses in *t-1*, it reacted with less adaptions in its hedge portfolio. The results in Model 6 have to be analyzed with reservations though as the number of observations is relatively low with 99 observations.[137]

The robustness tests regarding the economies of scale hypothesis H12 are mixed. The coefficient estimate on the size variable is insignificant in five of the six models. The size coefficient is negative and statistically different from zero at the 1%-level for IFRS reporting airlines, opposing H12. The interest rate derivative coefficient is positive and significantly different from zero at least at the 10%-level in five of the six models. The coefficient on *fxdvDm* is not significant in either of the six models.

[137]The difference in AIC values between Models 1 to 5 and Model 6 is attributable to the low number of observations (see footnote on p. 176.)

Table 5.31: Random effects probit models with active hedgers binary variable (highest tertile) as the dependent variable

	(1) activeChg3	(2) activeChg3
fdvPsumt1_	0.00405	
	(0.159)	
fdvLsumt1_	-0.0151^{***}	
	(0.007)	
fdvPefft1_	-0.00715	
	(0.336)	
fdvLefft1_	0.00179	
	(0.187)	
sizeAdj1_	0.0000173	0.0000256
	(0.332)	(0.163)
irdvDm	1.122^{**}	0.843^{*}
	(0.025)	(0.064)
fxdvDm	0.917^{**}	1.137^{**}
	(0.038)	(0.012)
fdvPsumt2_		0.00332
		(0.105)
fdvLsumt2_		-0.00220
		(0.479)
fdvPefft2_		-0.00163
		(0.550)
fdvLefft2_		-0.000487
		(0.874)
intercept	-1.658^{***}	-1.723^{***}
	(0.000)	(0.000)
N	265	230

p-values in parentheses

Variables ending with "_" in millions

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

Table 5.32: Alternative random effects probit models with different sample restrictions, selective hedging

	(1) activeChg4	(2) activeChg4	(3) activeChg4	(4) activeChg4	(5) activeChg4	(6) activeChg4
fdvPsumt1_	0.00401	0.00351	0.00356	0.00420	0.00400	-0.0673^{*}
	(0.559)	(0.586)	(0.578)	(0.546)	(0.568)	(0.073)
fdvLsumt1_	-0.0936^{*}	-0.0961^{*}	-0.0950^{*}	-0.0946^{*}	-0.0924^{*}	-0.435^{***}
	(0.070)	(0.082)	(0.080)	(0.061)	(0.075)	(0.001)
fdvPefft1_	−0.00927	−0.00958	−0.00950	−0.00939	−0.00922	-0.275^{***}
	(0.374)	(0.376)	(0.375)	(0.373)	(0.378)	(0.002)
fdvLefft1_	0.00202	0.00198	0.00197	0.00212	0.00202	0.315^{**}
	(0.592)	(0.580)	(0.587)	(0.601)	(0.582)	(0.018)
sizeAdj1_	−0.0000709	−0.0000778	−0.0000762	−0.0000714	−0.0000712	-0.000615^{***}
	(0.223)	(0.162)	(0.174)	(0.224)	(0.245)	(0.000)
irdvDm	3.285^{*}	3.710^{***}	3.615^{***}	3.250^{**}	3.092	5.473^{***}
	(0.059)	(0.007)	(0.008)	(0.041)	(0.121)	(0.001)
fxdvDm	1.007	0.812	0.816	1.003	1.026	1.118
	(0.271)	(0.363)	(0.361)	(0.277)	(0.282)	(0.459)
cpaDm			−26.20			
			(0.998)			
mrgDm				0.280		
				(0.847)		
intercept	-2.490^{***}	-2.319^{***}	-2.285^{***}	-2.524^{***}	-2.313^{***}	0.341
	(0.001)	(0.003)	(0.003)	(0.001)	(0.003)	(0.778)
N	233	215	233	233	227	99
AIC	150.3	147.8	149.7	152.3	149.2	68.77
Specification	none	CPA excl.	CPA dummy	Merger dummy	Allegiant excl.	IFRS only

p-values in parentheses

Variables ending with "_" in millions

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

5.3.4 Limitations

Analogous to the limitations of the operational hedging variables, sample selection bias exists among the selective hedging variables. The selection of the sample airlines is influenced by the availability of data on the reported profits and losses of the fuel hedge portfolio. Many airlines aggregate the profits and losses of all of their derivative positions, regardless of whether they hedge interest rate, currency or fuel price risk. If airlines with large derivative losses aggregate their hedge positions, they do not enter the analysis in Section 5.3. If those airlines adapt their hedge portfolios more often because of recent losses, the estimators will be biased.

Besides sample selection bias, the estimators relating to the selective hedging hypotheses may be biased due to omitted variables. Similar to the limitations in Subsection 5.1.4, the cultural background of hedging managers might be an omitted variable. Managers emanating from a more risk averse culture may choose to adapt their hedge portfolios more often. At the same time, risk averse managers may take any action possible in order to reduce losses associated with those hedge portfolios. Hence, the omitted variable cultural background explains the dependent variable and is correlated with another independent variable.

The manual collection of the annual report data makes the existence of errors-in-variables likely. Especially the nonuniform presentation (due to the multitude of accounting standards in this sample) of profits and losses associated with financial instruments complicated the data collection. Moreover, simultaneous causality of those profits and losses may result in inconsistent estimators. While it is assumed that greater losses of financial instruments lead to adaptions in fuel price risk management, strong changes in hedge portfolios may result in greater derivative losses. If hedging managers are of the opinion that they have superior information regarding the development of the oil price, they may increase or decrease their hedge portfolios more often. If their market views turn out to be incorrect, the consequence might be large losses in the derivative position. Ergo, causality between derivative losses and selective hedging runs in both directions.

5.3.5 Discussion

Although the t test results provide evidence that selective hedgers were larger in size, the coefficient on the size variable is not significant in the multivariate analysis. The sample selection process may be causing the insignificant results (see Subsection 5.3.4). The interest rate and currency derivative variables, however, are positively related with the selective hedging dependent variable, partially supporting H12. Airlines with a diverse hedge portfolio were more likely to change their hedge ratios more often during the sample period. A possible reason for this positive relation could be that more experienced risk managers are more likely to employ different types of derivatives contracts. Those risk managers may be more confident and of the opinion that they hold superior market information, leading them to alter their hedge portfolios more often based on personal market views.

The probit results show that prior-period losses, recognized in income, are positively related to selective hedging, supporting H10. Moreover, neither profits nor losses parked under OCI affect the selective hedging behavior. Prior-period losses, recognized in income, that date back more than one period do not influence the hedging behavior either. The current results are an example of how behavioral finance impacts managerial decision making. People are more reluctant to lose money than they are content about winning money (Brealey et al., 2017). Thaler and Johnson (1990) propose that risk-taking is influenced differently by prior gains or losses. With the experience of prior losses, the readiness to take further risk is lowered, especially when the possibility to break-even in the second attempt is not given or significantly reduced. Applying this argument to the current study, the hedging manager who experienced a prior-period derivative loss without the outlook of derivative profits in the subsequent period was more risk-averse and thus adapted the hedge portfolio more selectively. The direction of the adaption, an increase or a decrease in hedge ratios, is not captured by the variable *activeChg4*. The results in Table 5.30, however, provide weak evidence that prior losses led to a reduction in hedge ratios. The results confirm the findings of Brown (2001) who observes a change in hedge portfolios of the case study company with prior-period hedging losses. The findings are in opposition to Brown's survey results in which managers denied the adaption in hedge portfolios due to hedging losses. However, the denial may spring from the unwillingness to admit that their actions were driven by behavioral reactions.

The findings on the impact of regional changes support H11. The coefficients on the changes in regional hedge ratios are statistically significantly different from zero at the 1%-level. When airlines from the same region increased their hedge ratios, the individual sample airline reacted with an increase in its hedge ratio. Correspondingly, the individual airline reduced its hedge portfolio when their competitors showed a negative change in their hedge percentages. The responses of the sample hedging managers resemble the theory of herd behavior. Skilled managers may prefer to forego investment opportunities although they hold private information that predicts a positive outcome if other managers forego investments accordingly. The skilled managers fear the reputational effect in case their private information turn out to be wrong (Scharfstein and Stein, 1990). Similarly, the airline hedging managers react to changes in their competitors' hedge activities. When the airline managers believe that kerosene prices go up, they will strengthen their derivative position to protect the airline from high fuel bills. A single risk manager who is of the opinion that the price level will fall, does not dare to remain unhedged. If kerosene prices rise drastically, the single manager may put his airline at risk of financial distress and himself at risk of losing his reputation. If kerosene prices fall, all airlines will equally face losses in their hedge portfolios.

Chapter 6

CONCLUSION AND IMPLICATIONS

The uncertainty and volatility of the oil price calls for risk management strategies in the airline industry. Jet fuel spot prices ranged from 35 to 198 USD per barrel between 2005 and 2014. Fuel price risk can be managed by financial hedging or operational hedging. Financial hedging comprises derivative instruments written on various underlyings that are correlated with the jet fuel price. Operating a diverse fleet, financing aircraft under operating lease contracts and being a member of an alliance can be seen as operational hedging tools. Although all sample airlines were exposed to jet fuel price risk, the hedging behavior was not homogeneous. While some airlines hedged continuously the same fraction of their expected fuel requirements, other airlines either changed their hedge portfolios frequently or did not hold any financial instruments at all.

This study examines the hedging behavior of the global airline industry. Based on a literature review, 12 hypotheses are formulated related to the three main topics of this thesis: financial hedging, operational hedging and selective hedging. Seventy-four airlines from 39 countries are analyzed between 2005 and 2014. The sample is divided into five regions (Africa, America, Asia, Europe, and Oceania) and into low-cost airlines as well as network legacy airlines. The data collection process and the variables employed in the study are explained in detail. This allows for replicability of the hand-collected data. For a better understanding of the rich data set, extensive descriptive results are presented.

The descriptive results unveil that the fuel expenses per ASM of the network airlines were on average 26.3% higher than those of the LCCs although kerosene prices should not differ between the two business models. The fuel consumption per ASM was 31.3%

lower for low-cost airlines due to longer flights and larger aircraft. The analysis of the hedge portfolio is influenced strongly by the availability of fuel hedging information in the annual reports. While American carriers disclosed almost gapless information on their hedging behavior, the information of the other regions was less complete. Overall, the sample airlines used options, swaps and collars written on either jet fuel or crude oil[138] the most as their types of financial instruments and underlying assets. The sample average hedge ratio remained quite stable in the sample period. Asian carriers exhibited the lowest hedge ratios whereas European airlines had the highest hedge percentages in all sample years. The average hedge maturity decreased by 12.6% from 22.0 months in 2005 to 19.2 months in 2014. Apart from fuel hedging contracts, nine out of 10 airlines held interest rate or currency derivatives. All airlines increased in size during the sample period, by 72.3% on average as measured by firm size. American airlines grew the most by 130.8%, reflecting the consolidation wave in the U.S. airline market after several Chapter 11 proceedings. United Airlines operated the largest fleet in 2010 with 1,262 aircraft. The sample airlines reduced their operational flexibility with regards to fleet diversity. The first fleet diversity measure, calculated with a dispersion index based on the number of different aircraft models in an airline's fleet, decreased by 9.4%. The second fleet diversity measure, which regards the number of aircraft models in an aircraft family and thus captures the switching costs, dropped by 18.9%. The net fleet diversity measure increased by 26.6%, which indicates that the sample airlines valued higher operating flexibility while observing the entailed switching costs. Due to the nature of their business model, LCCs had the most homogeneous fleets.

The multivariate analysis comprises random effects probit models for the decision to hedge and entity fixed effects OLS regressions for the extent of hedging, i. e. the hedge ratio. The hedge ratio is the percentage of fuel requirements hedged 12 months forward. The panel data set is winsorized at the 1% and 99%-level. All variables are lease-adjusted as the airlines used operating leasing in 98.6% of sample firm years. The debt ratios, for example, increase by about a quarter when adjusted by the present value of future operating lease commitments.

The regression results provide strong evidence of a nonlinear relationship between leverage and hedging, proposed by Purnanandam (2008). The results are in opposite directions to his results though. Airlines with a low leverage showed a high propensity of hedging as well as high hedge ratios. Hedge ratios decreased with increasing leverage before they rose again at very high levels of debt ratios. The hedge ratios of highly

[138]Airlines switched from WTI to Brent crude oil contracts during the sample period because the correlation between WTI and jet fuel prices decreased strongly between 2010 and 2014.

indebted airlines remained below the hedge ratios of the airlines with low leverage. A linear increase in leverage ratios of one SD was related with a decrease in hedge ratios of 10.23 percentage points. The results are confirmed when the regression is run separately on airlines with low leverage and airlines with high leverage. A likely explanation for the convex relation is that airlines in good financial health value the insurance character of financial instruments to maintain their financial situation. Airlines with higher leverage face a trade-off between providing margin calls and allocating funds to investment opportunities. Highly indebted airlines use financial instruments to evade the impending distress phase. Without the inclusion of the quadratic leverage term, the OLS estimate on the debt ratio is insignificant, similar to the results of various previous studies. Therefore, the existing ambiguous research results regarding the financial distress theory may stem from the assumption of a linear relationship between leverage and hedging; thus from a misspecification of the functional form of the regression equation.

Unlike the results of Carter et al. (2006), this study mainly fails to support the underinvestment theory. Most coefficient estimates on the approximate measures of growth options and capital expenditure are insignificant. Carter et al. (2006) find positive coefficients on growth opportunities, measured with Tobin's Q, and hedging. They propose that airlines with greater financial flexibility due to hedging purchase aircraft of distressed airlines at a discount. The contradicting results of this study may arise from the fact that a later sample period was chosen. If airlines under financial distress rather lease aircraft under operating lease contracts, the possibility of purchasing aircraft at a discount is lowered. Financially distressed airlines are able to terminate operating lease contracts early and return the aircraft to the lessor. Moreover, as a third of the sample airlines exhibited Tobin's Q values lower than one, Tobin's Q may be more likely to reflect financial distress than growth options. The positive and significant OLS estimate of Tobin's Q is compatible with the negative coefficient on leverage.

The notion of economies of scale in financial hedging is partially supported by the study results. While airline firm size does not influence the propensity or extent of hedging, holding currency or interest rate derivatives is positively related with the likelihood of engaging in financial fuel hedging. A hedge portfolio that includes interest rate derivatives comprises significantly more fuel derivative contracts. FX financial instruments do not significantly influence airlines' hedge ratios. The insignificant coefficient on firm size may result from the equally strong impact of the fuel price on the airlines' fuel bills regardless of their size. Total fuel expenses account for approximately a third of airlines' total operating costs (IATA, 2015). In addition, the existence of the IATA clearing house, which helps airlines in settling derivative contracts, is uniformly available to large as to small airlines.

The *t* test results of the operational hedging variables show that hedgers were significantly (1%) more likely to be an alliance member. Alliance airlines had lower debt ratios, statistically significantly different from zero at the 5%-level, supporting the negative relation between leverage and hedging. Low-cost airlines were not part of any alliance. As LCCs had lower yet insignificant hedge ratios and lower debt ratios, the *t* test results may be influenced not only by alliance membership but also by the different business models. Therefore, low-cost airlines are excluded from a second univariate analysis. In this analysis, alliance legacy carriers exhibited a significantly greater likelihood of hedging, larger hedge ratios and lower debt ratios in contrast to non-alliance network airlines, supporting the notion that lower leverage is associated with more hedging. The significance level of the leverage ratio improves from 5% to 1%.

The multivariate results support the *t* test results regarding alliance membership. The OLS estimator on the binary alliance variable is positive and significant. Alliance membership positively impacted the hedge ratios of the airlines. Therefore, alliance membership can be seen as a complement to financial fuel price hedging. Again, the financial distress theory may be the cause for the positive relation. If rather financially sound airlines with a good reputation are being invited into an airline alliance and if those airlines tend to hold larger hedge portfolios, then the positive alliance coefficient reflects the negative leverage coefficient.

The business model does not have any influence on the hedging behavior of the sample airlines. Neither the univariate analysis nor the LCC dummy variable in the multivariate analysis yield significant results.

Fleet diversity affects the decision to hedge as well as the extent of hedging. If fleet diversity increased by a one standard deviation, hedge ratios would rise by 2.3 percentage points. Thus, operational hedging in the form of operating a diverse fleet can serve as a complement to financial hedging. Financial hedge contracts are effective in the short term whereas operational hedging tools exploit uncertainty in the longer term (Huchzermeier and Cohen, 1996; Triantis, 2000; Van Mieghem, 2003). The percentage of aircraft under operating leasing, hence less colleteralizable assets for providing margin calls, does not influence the sample airlines' hedging activities.

Selective hedging is defined as adapting the size and maturity of the hedge portfolio based on the personal view of the hedging managers (Adam et al., 2017). The sample airlines adapted their hedge ratios frequently. AirAsia, for example, reduced the hedge ratio by 78.0 percentage points in 2008 due to derivative losses of a fifth of its revenues. Southwest reacted to the ”precipitous decline in oil and jet fuel prices“ (Southwest Airlines, 2015, p. 35) by lowering the percentage of fuel consumption hedged by 43.0 percentage points in 2014. In this study, selective hedgers are termed active hedgers and represent those airlines, whose absolute value of the year-on-year percentage point changes in hedge ratios range in the highest tertile or quartile. Passive hedgers range in the lowest tertile or quartile. The multivariate analysis fails to provide evidence that airline size influences the selective hedging behavior. The results support the argument that prior-period derivative losses that are recognized in income lead to higher levels of selective hedging. Losses that date back more than one period do not influence the selective hedging behavior. Derivative profits and losses which are parked under OCI are not related with hedge portfolio adaptions. These results show that managers seem to act in accordance with the behavioral finance theory (an excellent overview of the behavioral finance literature can be found in Baker and Wurgler (2013)). The willingness to take further risk is lowered with the experience of recent losses. Moreover, risk managers appear to follow herd behavior in their hedging strategy. When their regional competitors either increased or decreased their hedge ratios, the individual airline equally adapted the hedge portfolio.

All regression results are validated with different robustness checks. The independent variables of the base regression are replaced by various alternative approximate measures for robustness tests. Furthermore, a binary merger variable is included to control for the non-organic growth due to mergers and acquisitions. During the sample period, 25 sample airlines acquired another airline, resulting in an average growth in total assets of 58.6%. Moreover, the peculiarity of the two U.S. regional airlines, SkyWest and Republic Airline, which operate under capacity purchase agreements is taken account of. The two airlines are either excluded in the robustness analysis or given a CPA dummy variable. Lastly, the sample is restricted to airlines that report in accordance with IFRS or U.S. GAAP.

A caveat of this study is that due to data limitations on tax related variables the author is not able to run instrument variables regressions. IV regressions are a solution to resolve several causes of bias present in this study. Any omitted variables bias is in large part controlled for by entity fixed effects estimation. If, however, a variable that changes during the sample period is omitted from the analysis, the estimators may be biased. The hand-collection of the panel data and the usage of approximate measures may cause measurement error. Moreover, the two-way linkage between leverage and hedging could result in simultaneous causality. As the sample is restricted to airlines that publish their hedging behavior and fleet data, the study could suffer from sample selection bias.

Further research may concentrate on including managerial compensation and tax incentives in the study for a more comprehensive approach. IV regression analysis could improve the statistical quality. The relation between herd behavior and selective hedging is also an interesting topic for future studies.

The study contributes to the existing body of knowledge especially with regards to the financial distress theory. The nonlinear nature of the leverage variable represents the relation between debt ratios and hedging in the airline industry best. The results might hold more generally in all industries in which leverage ratios are heterogeneous with some firms near bankruptcy. In addition, the results show that the two operational hedging tools, strategic alliance membership and fleet diversity, serve as complements to financial hedging. Lastly, the study provides evidence that the attitude towards risk and herd behavior can influence a firm's selective hedging activities.

A List of abbreviations

AIC Akaike information criterion

ASC Accounting Standards Codification

ASK available seat kilometer

ASM available seat mile

CAPEX capital expenditure

CAR cumulative abnormal return

CEO chief executive officer

CFO chief financial officer

CI cost index

CPA capacity purchase agreement

EBIT earnings before interest and tax

EBITD earnings before interest, tax and depreciation

ECM error correction model

EDGAR Electronic Data Gathering, Analysis, and Retrieval system

EIA U.S. Energy Information Administration

EUR Euro

FMS flight management system

FPA fuel pass-through agreement

FX foreign exchange

GAAP Generally Accepted Accounting Principles

GARCH generalized autoregressive conditional heteroscedasticity

GBP Pound Sterling

HHI Herfindahl-Hirschman concentration index

IAG International Airlines Group

IAS International Accounting Standard

IATA International Air Transport Association

IBD interest bearing debt

ICE Intercontinental Exchange

IFRS International Financial Reporting Standards

ILFC International Lease Finance Corporation

IPE International Petroleum Exchange

IPO initial public offering

ISIN International Securities Identification Number

ISO International Organization for Standardization

IV instrument variable

JPY Japan Yen

kg kilogram

LCC low-cost carrier

LF load factor

MNE multinational enterprise

MTB market-to-book

NLC network legacy carrier

NPV net present value

NYMEX New York Mercantile Exchange

OCI other comprehensive income

OECD Organisation for Economic Co-operation and Development

OLS ordinary least squares

OTC over-the-counter

OTM out-of-the-money

PPE property, plant and equipment

PV present value

R&D research and development

RASM revenue per available seat mile

ROA return on assets

RPK revenue passenger kilometer

RPM revenue passenger mile

S&P Standard & Poor's

SD standard deviation

SEC Securities and Exchange Commission

SIC Standard Industrial Classification

U.S. United States

UAE United Arab Emirates

UN United Nations

USD U.S. dollar

USG U.S. gallon

WTI West Texas Intermediate

B Selected studies on the determinants of hedging

Table B.1: Selected studies on the determinants of hedging, the sequence is not in chronological order but as the studies are appearing in the text

Determinant	Author	Year	Title	Journal title
2.2.1 Financial distress	**Theoretical background**			
	Warner	1977	"Bankruptcy Costs: Some Evidence"	Journal of Finance
	Stulz	1996	"Rethinking risk management"	The Journal of Applied Corporate Finance
	Smith and Stulz	1985	"The Determinants of Firms' Hedging Policies"	The Journal of Financial and Quantitative Analysis
	Bessembinder	1991	"Forward Contracts and Firm Value: Investment Incentive and Contracting Effects"	Journal of Financial & Quantitative Analysis
	Nance et al.	1993	"On the determinants of corporate hedging"	The Journal of Finance
	Empirical studies			
	Nance et al.	1993	"On the determinants of corporate hedging"	The Journal of Finance
	Haushalter	2000	"Financing policy, basis risk, and corporate hedging: Evidence from oil and gas producers"	The Journal of Finance
	Tufano	1996	"Who Manages Risk? An Empirical Examination of Risk Management Practices in the Gold Mining Industry"	The Journal of Finance
	Purnanandam	2008	"Financial distress and corporate risk management: theory and evidence"	Journal of Financial Economics
	Adam et al.	2017	"Why do firms engage in selective hedging? Evidence from the gold mining industry"	Journal of Banking and Finance
2.2.2 The underinvestment problem	**Theoretical background**			
	Myers	1977	"Determinants of corporate borrowing"	Journal of Financial Economics
	Myers and Majluf	1984	"Corporate financing and investment decisions when firms have information that investors do not have"	Journal of Financial Economics
	Froot et al.	1993	"Risk Management: Coordinating Corporate Investment and Financing Policies"	The Journal of Finance
	Lessard	1991	"Global competition and corporate finance in the 1990s"	Journal of Applied Corporate Finance
	Bessembinder	1991	"Forward Contracts and Firm Value: Investment Incentive and Contracting Effects"	Journal of Financial & Quantitative Analysis
	Empirical studies			
	Géczy et al.	1997	"Why firms use currency derivatives"	The Journal of Finance

	Gay and Nam	1998	“The underinvestment problem and corporate derivatives use”	Financial Management
	Adam	2002	“Do firms use derivatives to reduce their dependence on external capital markets?”	European Finance Review
	Carter et al.	2006	“Does hedging affect firm value? Evidence from the US airline industry”	Financial Management
	Gamba and Triantis	2013	“Corporate Risk Management: Integrating Liquidity, Hedging, and Operating Policies”	Management Science
	Allayannis et al.	2001	“Exchange-rate hedging: Financial versus operational strategies”	American Economic Review
2.2.3 Managerial motives	**Theoretical background**			
	Stulz	1984	“Optimal Hedging Policies”	The Journal of Financial and Quantitative Analysis
	Smith and Stulz	1985	“The Determinants of Firms’ Hedging Policies”	The Journal of Financial and Quantitative Analysis
	Empirical studies			
	DeMarzo and Duffie	1995	“Corporate incentives for hedging and hedge accounting”	Review of Financial Studies
2.2.4 Tax incentives	**Theoretical background**			
	Smith and Stulz	1985	“The Determinants of Firms’ Hedging Policies”	The Journal of Financial and Quantitative Analysis
	Graham and Smith	1999	“Tax incentives to hedge”	The Journal of Finance
	Empirical studies			
	Nance et al.	1993	“On the determinants of corporate hedging”	The Journal of Finance
	Haushalter	2000	“Financing policy, basis risk, and corporate hedging: Evidence from oil and gas producers”	The Journal of Finance
	Graham and Smith	1999	“Tax incentives to hedge”	The Journal of Finance
2.2.5 Economies of scale	**Theoretical background**			
	Warner	1977	“Bankruptcy Costs: Some Evidence”	The Journal of Finance
	Smith and Stulz	1985	“The Determinants of Firms’ Hedging Policies”	The Journal of Financial and Quantitative Analysis
	Purnanandam	2008	“Financial distress and corporate risk management: theory and evidence”	Journal of Financial Economics
	Empirical studies			
	Dionne and Thouraya	2013	“On Risk Management Determinants: What Really Matters?”	The European Journal of Finance
	Purnanandam	2008	“Financial distress and corporate risk management: theory and evidence”	Journal of Financial Economics

C Previous empirical findings on the determinants of hedging

Table C.1: Previous empirical findings on the financial distress determinant

Author	Year	Sample	Dependent variable	Independent variable	Statistical impact on hedging
Adam	2002	Gold mining firms (1989-1999)	Fixed future income stream (number of ounces hedged multiplied by delivery price)	Financing net cash flow	Not significant
				Operating net cash flow	Not significant
			Gold price hedge dummy	Dividend dummy	Not significant
				Profit margin	Not significant
				Credit rating dummy	Not significant
				Debt ratio	Not significant
				Aggressive financing policy: Dummy one if the debt ratio is above the industry median and the quick ratio below the industry median	Not significant
				Conservative financing policy: Dummy one if the debt ratio is below industry median and the quick ratio above the industry median	In one out of two models negative significant at 10%-level
Adam et al.	2017	92 gold mining firms (1989-1999)	Gold price hedge dummy	Dividend dummy	Negatively significant at 5%-level
				Debt ratio	Not significant
			Hedge ratio	Dividend dummy	Negatively significant at 1%-level
Allayannis and Ofek	2001	378 S&P 500 non-financial firms (1993)	FX hedge dummy	Debt ratio	Negatively significant at 5%-level
				Dividend yield	Not significant
				ROA	Not significant
			Notional value of currency derivatives scaled by total assets	Debt ratio	Not significant
				Dividend yield	Not significant
				ROA	Not significant
Bartram et al.	2009	7,319 non-financial firms from 50 countries (2000)	Hedge dummy (FX, interest rate and commodity price risk)	Debt ratio	Positively significant at 1%-level
				EBIT scaled by interest expenses (three-year average)	Negatively significant at 10%-level
				Dividend dummy	Positively significant at 1%-level
				Gross profit margin	Positively significant at 1%-level

			Hedge dummy from the simultaneous equation (second step)	Debt ratio	Positively significant at 1%-level
				Dividend dummy	Positively significant at 1%-level
Carter et al.	2006	29 U.S. airlines (1992-2003)	Percentage of next year's fuel consumption hedged	Debt ratio (lease-adjusted)	Negatively significant at 5%-level
				Credit rating (lease-adjusted)	Negatively significant at 1%-level
			Fuel hedge dummy	Debt ratio (lease-adjusted)	Not significant
				Credit rating (lease-adjusted)	Not significant
Dionne and Thouraya	2013	36 North American gold mining firms (1992-1999)	Number of gold ounces sold forward scaled by the expected consumption over the next three years	Debt ratio	Positively significant at 1%-level
				Operating costs of producing one ounce of gold	Positively significant at 1%-level
Gay and Nam	1998	325 derivative users and 161 non-users (1995)	Notional dollar value of outstanding currency, interest rate and commodity derivative contracts scaled by total assets	Debt ratio (three-year average)	Positively significant at 1%-level
				Interest coverage ratio (three-year average)	Not significant
				Convertible debt scaled by firm market value	Not significant
				Preferred stock scaled by firm market value	Not significant
				Debt ratio (three-year average) (including a dummy one for firms with lower than average cash holdings and greater than average growth options)	Positively significant at 1%-level
				Interest coverage ratio (three-year average)	Not significant
				Convertible debt scaled by firm market value	Not significant
				Preferred stock scaled by firm market value	Not significant
Gay et al.	2011	1,541 non-financial U.S. firms (1992-1996) and 1,341 non-financial U.S. firms (2002-2004)	Notional dollar value of outstanding currency, interest rate and commodity derivative contracts scaled by total assets	Debt ratio	Not significant
			Hedge dummy	Debt ratio	Not significant

Géczy et al.	1997	372 Fortune 500 U.S. non-financial firms (1990) with ex-ante currency exposure	FX hedge dummy	Debt ratio	Not significant
Graham and Rogers	2002	442 U.S. non-financial firms (March until December 1995) with ex-ante currency and interest rate exposure	Sum of net (long/short) position of currency and interest rate hedges scaled by total assets	Debt ratio	Positively significant at 1%-level
				Sum of current liabilities and long-term floating rate debt scaled by total assets	Not significant
Guay and Kothari	2003	234 large, derivative using non-financial Compustat firms (1995)	Notional value of outstanding currency, interest rate and commodity derivatives scaled by total assets	Debt ratio	Not significant
				Change in the annual cash flow from operations scaled by total assets (three-year average)	Not significant
Haushalter	2000	Survey responses of 100 CFOs of oil and gas producing firms (1992-1994)	Fraction of production hedged	Dividend payment scaled by income	Not significant
				Credit rating dummy	Negatively significant between 5 and 10%-level
				Debt ratio	Positively significant at 1-5%-level
				Dummy one if the debt ratio is above the sample median	Not significant
				Production costs per barrel oil	Not significant
				Basis risk: the percentage of a firm's production located in highly correlated regions such as Lousiana and Texas (+)	Positively significant at 1%-level
			Hedge dummy	Debt ratio	Not significant
				Basis risk: the percentage of a firm's production located in highly correlated regions such as Lousiana and Texas (+)	Positively significant at 1%-level
		Hedgers only	Fraction of production hedged	Debt ratio	Positively significant at 1%-level
				Dividend payment scaled by income	Negatively significant at 1%-level

Judge	2006	441 non-financial FT500 firms (1995)	Hedge dummy (hedging for any financial price exposure)	Interest coverage ratio	Negatively significant at 1%-level
				Credit rating (qui-score)	Negatively significant at 1%-level
				Dummy one if the firm is a net receiver of interest	Negatively significant at 1%-level
				Gross gearing	Positively significant at 1%-level
				Net gearing	Positively significant at 1%-level
				Industry-adjusted leverage	Positively significant at 1%-level
			Hedge dummy (derivative usage)	Interest coverage ratio	Not significant
				Credit rating (qui-score)	Negatively significant at 1%-level
				Dummy one if the firm is a net receiver of interest	Not significant
				Gross gearing	Positively significant at 5%-level
				Net gearing	Not significant
				Industry-adjusted leverage	Not significant
Lin and Chang	2009	69 airlines from 32 countries (1995-2005)	Percentage of next year's fuel consumption hedged	Dividend dummy	Not significant
				Debt ratio	Positively significant at 10%-level
			Fuel hedge dummy	Dividend dummy	Not significant
				Debt ratio	Not significant
Nance et al.	1993	Survey responses of 169 CEOs of Fortune 500 and S&P 400 companies (1986)	Hedge dummy (any use of forwards, futures, swaps, options)	EBIT scaled by interest expenses	Not significant
				Debt ratio	Not significant
				Dividend yield	Positively significant at 1%-level
				Preferred stock scaled by firm value	Not significant
Nguyen and Faff	2002	239 (1999) and 230 (2000) non-financial Australian firms with derivative usage	Hedge dummy (any use of forwards, futures, swaps, options)	Debt ratio	Positively significant at 1%-level
				Dividend yield (quarterly average)	Not significant
			Notional value of derivatives outstanding scaled by total assets	Debt ratio	Positively significant at 1%-level

				Dividend yield (quarterly average)	Positively significant at 1%-level
Rampini et al.	2014	23 large U.S. airlines (1996-2009)	Percentage of next year's fuel consumption hedged	Total market value of net worth	Not significant
				Total book value of net worth	Positively significant at 10%-level
				Total book value of net worth scaled by total assets	Positively significant at 1%-level
				Total market value of net worth scaled by total assets	Positively significant at 1%-level
				Credit rating dummy	Positively significant at 1%-level
				Change in the market value of net worth	Positively significant at 10%-level
				Change in the book value of net worth	Not significant
				Change in the book value of net worth scaled by total assets	Not significant
				Change in the market value of net worth scaled by total assets	Positively significant at 10%-level
				Change in the credit rating dummy	Positively significant at 1%-level
Spanò	2007	443 British non-financial firms (1999-2000)	FX hedge dummy	Dividend yield	Positively significant at 10%-level
				Debt ratio	Not significant
				Long-term debt scaled by total debt	Not significant
		Derivative users only (169 firms)	Fair value of FX derivatives scaled by firm market value	Dividend yield	Not significant
				Debt ratio	Not significant
				Long-term debt scaled by total debt	Not significant
Sprcic and Sevic	2012	157 Croatian non-financial firms (2005), data from annual reports and survey	Hedge dummy (any use of financial, operational or natural hedging)	Credit rating dummy	Positively significant at 5%-level
		186 Slovenian non-financial firms (2005), data from annual reports and survey	Hedge dummy (any use of financial, operational or natural hedging)	Credit rating dummy	Not significant
Tufano	1996	48 North American gold mining firms (1990-1993)	Percentage of gold sold forward divided by total production of the next three years	Production costs per gold ounce	Not significant
				Long-term debt ratio (three-year average)	Positively significant at 1%-level (excluding the largest outlier)

Table C.2: Previous empirical findings on the underinvestment problem determinant

Author	Year	Sample	Dependent variable	Independent variable	Statistical impact on hedging
Adam	2002	Gold mining firms (1989-1999)	Fixed future income stream (number of ounces hedged multiplied by the delivery price)	Actual future investment expenditure	Positively significant at 5%-level
				Change in the cash position excluding hedge cash flows	Not significant
				Net cash holdings	Not significant
			Gold price hedge dummy	MTB ratio	Negatively significant at 1%-level
				Quick ratio	Negatively significant at 1-5%-level
Adam et al.	2017	92 gold mining firms (1989-1999)	Gold price hedge dummy	MTB ratio	Negatively significant at 1%-level
				Quick ratio	Negatively significant at 10%-level
			Hedge ratio	MTB ratio	Not significant
				Quick ratio	Negatively significant at 1%-level
Allayannis and Ofek	2001	378 S&P 500 non-financial firms (1993)	FX hedge dummy	R&D scaled by total sales	Positively significant at 5%-level
				MTB ratio	Not significant
			Notional value of currency derivatives scaled by total assets	R&D scaled by total sales	Not significant
				MTB ratio	Not significant
Bartram et al.	2009	7,319 non-financial firms from 50 countries (2000)	Hedge dummy (FX, interest rate and commodity price risk)	Quick ratio	Negatively significant at 1%-level
				MTB ratio	Negatively significant at 1%-level
				Interaction term of the debt ratio and MTB ratio	Positively significant at 5%-level
			Hedge dummy from the simultaneous equation (second step)	Quick ratio	Negatively significant at 10%-level
Carter et al.	2006	29 U.S. airlines (1992-2003)	Percentage of next year's fuel consumption hedged	Cash flow to sales ratio (lease-adjusted)	Not significant
				Cash flow to sales ratio (not lease-adjusted)	Positively significant at 5%-level
				Cash to sales ratio (lease-adjusted and not lease-adjusted)	Not significant
				CAPEX to sales ratio (lease-adjusted and not lease-adjusted)	Not significant
				Tobin's Q (lease-adjusted)	Positively significant at 1%-level

				Tobin's Q (not lease-adjusted)	Positively significant at 5%-level
			Fuel hedge dummy	Cash flow to sales ratio (lease-adjusted and not lease-adjusted)	Positively significant at 10%-level
				Cash to sales ratio (lease-adjusted and not lease-adjusted)	Not significant
				CAPEX to sales ratio (lease-adjusted and not lease-adjusted)	Not significant
				Tobin's Q (lease-adjusted and not lease-adjusted)	Not significant
Dionne and Thouraya	2013	36 North American gold mining firms (1992-1999)	Number of gold ounces sold forward scaled by the expected consumption over the next three years	Quick ratio	Negatively significant at 5%-level
				Acquisitions expenditure scaled by firm market value	Not significant
				Acquisitions expenditure scaled by firm market value	Not significant
Gay and Nam	1998	325 derivative users and 161 non-users (1995)	Notional dollar value of outstanding currency, interest rate and commodity derivative contracts scaled by total assets	R&D expenditure scaled by firm size	Positively significant at 5%-level
				MTB ratio	Positively significant at 5%-level
				Tobin's Q	Positively significant at 5%-level
				Price-earnings ratio	Positively significant at 1%-level
				Market-adjusted CAR	Positively significant at 5%-level
				R&D expenditure scaled by firm size (including a dummy one for firms with lower than average cash holdings and greater than average growth options)	Not significant
				MTB ratio	Not significant
				Tobin's Q	Not significant
				Price-earnings ratio	Not significant
				Market-adjusted CAR	Not significant
				Dummy one for firms with lower than average cash holdings and greater than average growth options	Positively significant at 1%-level (in one out of five models)
Gay et al.	2011	1,541 non-financial U.S. firms (1992-1996) and 1,341 non-financial U.S. firms (2002-2004)	Notional dollar value of outstanding currency, interest rate and commodity derivative contracts scaled by total assets	Book-to-market ratio	Not significant

				Quick ratio	Negatively significant at 1%-level (entire sample); positively significant at 1%-level (1992-1996); not significant (2002-2004)
			Hedge dummy	Book-to-market ratio	Not significant
				Quick ratio	Negatively significant at 1%-level (entire sample); negatively significant at 10%-level (1992-1996); negatively significant at 1%-level (2002-2004)
Géczy et al.	1997	372 Fortune 500 U.S. non-financial firms (1990) with ex-ante currency exposure	FX hedge dummy	R&D expenditure scaled by total sales	Positively significant at 1%-level
				Book-to-market ratio	Not significant
				Quick ratio	Negatively significant at 1%-level
				Interaction term: debt ratio with book-to-market ratio	Positively significant at 10%-level
				Interaction term: debt ratio with R&D expenditure (scaled by total sales)	Not significant
Graham and Rogers	2002	442 U.S. non-financial firms (March until December 1995) with ex-ante currency and interest rate exposure	Sum of net (long/short) position of currency and interest rate hedges scaled by total assets	R&D expenditure scaled by total assets	Not significant
				Book-to-market ratio	Not significant
				Interaction term: debt ratio with book-to-market ratio	Positively significant at 10%-level
				Dummy one if negative book-to-market ratio	Negatively significant at 1%-level
Guay and Kothari	2003	234 large, derivative using non-financial Compustat firms (1995)	Notional value of oustanding currency, interest rate and commodity derivatives scaled by total assets	MTB ratio	Positively significant at 10%-level
				Change in annual cash and short-term investments scaled by total assets (three-year average)	Positively significant at 10%-level
Haushalter	2000	Survey responses of 100 CFOs of oil and gas producing firms (1992-1994)	Fraction of production hedged	Investment expenditure scaled by the market value of assets	Positively significant at 5%-level (in one out of three models)

				Cash ratio	Not significant
Judge	2006	441 non-financial FT500 firms (1995)	Hedge dummy (hedging for any financial price exposure)	Cash ratio	Negatively significant at 5%-level
			Hedge dummy (derivative usage)	Cash ratio	Not significant
Lin and Chang	2009	69 airlines from 32 countries (1995-2005)	Percentage of next year's fuel consumption hedged	CAPEX to sales ratio	Not significant
				Tobin's Q	Not significant
				Cash flow to sales ratio	Not significant
				Cash to sales ratio	Not significant
			Fuel hedge dummy	CAPEX to sales ratio	Not significant
				Tobin's Q	Not significant
				Cash flow to sales ratio	Not significant
				Cash to sales ratio	Not significant
Nance et al.	1993	Survey responses of 169 CEOs of Fortune 500 and S&P 400 companies (1986)	Hedge dummy (any use of forwards, futures, swaps, options)	R&D expenditure scaled by firm value	Positively significant between 5 and 21%-level (in 48 regressions)
Nguyen and Faff	2002	239 (1999) and 230 (2000) non-financial Australian firms with derivative usage	Hedge dummy (any use of forwards, futures, swaps, options)	MTB ratio	Not significant
				Cash ratio	Negatively significant at 1%-level
				Current ratio	Not significant
			Notional value of derivatives outstanding scaled by total assets	MTB ratio	Negatively significant at 10%-level
				Cash ratio	Not significant
				Current ratio	Not significant
Spanò	2007	443 British non-financial firms (1999-2000)	FX hedge dummy	R&D expenditure dummy	Positively significant at 1%-level
				Tobin's Q	Not significant
				Cash ratio	Negatively significant at 5%-level
		Derivative users only (169 firms)	Fair value of FX derivatives scaled by firm market value	R&D expenditure dummy	Not significant
				Tobin's Q	Not significant
				Cash ratio	Not significant
Sprcic and Sevic	2012	157 Croatian non-financial firms (2005), data from annual reports and survey	Hedge dummy (any use of financial, operational or natural hedging)	Investment expenditure scaled by total assets	Positively significant at 5%-level

				Quick ratio	Not significant
		186 Slovenian non-financial firms (2005), data from annual reports and survey	Hedge dummy (any use of financial, operational or natural hedging)	Investment expenditure scaled by total assets	Negatively significant at 10%-level
				Quick ratio	Not significant
Tufano	1996	48 North American gold mining firms (1990-1993)	Percentage of gold sold forward divided by total production of the next three years	Exploration expenditure scaled by firm value	Negatively significant 10%-level
				Average dollar value of attempted acquisitions of previous three years	Not significant
				Quick ratio	Negatively significant at 5%-level (excluding the largest outlier)

Table C.3: Previous empirical findings on the economies of scale determinant

Author	Year	Sample	Dependent variable	Independent variable	Statistical impact on hedging
Adam	2002	Gold mining firms (1989-1999)	Fixed future income stream (number of ounces hedged multiplied by the delivery price)	Net sales (excluding hedge cash flows)	Positively significant at 1%-level
					Not significant
				Firm size (market value of total assets)	Not significant
			Gold price hedge dummy	Firm size (market value of total assets)	Positively significant at 1%-level
Adam et al.	2017	92 gold mining firms (1989-1999)	Gold price hedge dummy	Log of firm size (see Adam (2002))	Positively significant at 1%-level
			Hedge ratio	Log of firm size	Positively significant at 10%-level
Allayannis and Ofek	2001	378 S&P 500 non-financial firms (1993)	FX hedge dummy	Log of total assets	Positively significant at 10%-level
				Exposure: foreign sales scaled by total sales	Positively significant at 10%-level
				Exposure: total trade scaled by total production	Positively significant at 1%-level
			Notional value of currency derivatives scaled by total assets	Log of total assets	Not significant
				Exposure: foreign sales scaled by total sales	Positively significant at 5%-level
				Exposure: total trade scaled by total production	Positively significant at 1%-level
Bartram et al.	2009	7,319 non-financial firms from 50 countries (2000)	Hedge dummy (FX, interest rate and commodity price risk)	Natural logarithm of firm size	Positively significant at 1%-level
				Exposure: foreign sales/assets/income scaled by total sales/assets/income	Positively significant at 1%-level
				Exposure: foreign debt scaled by total debt	Positively significant at 1%-level
			Hedge dummy from the simultaneous equation (second step)	Net FX exposure: percentage of foreign sales minus percentage of foreign assets	Negatively significant at 10%-level
Brown	2001	Case study firm	Hedge portfolio delta (for three, six and nine months)	Exposure: exchange rate implied volatility	Negatively significant at 1%-level (nine months delta)
				Cost of hedging: difference between six months forward and spot exchange rate	Negatively significant at 5%-level (three months delta)
			Hedge portfolio gamma (for three, six and nine months)	Exposure: exchange rate implied volatility	Negatively significant at 1%-level (three and six months gamma)

				Cost of hedging: difference between six months forward and spot exchange rate	Positively significant at 10%-level (three months delta)
Carter et al.	2006	29 U.S. airlines (1992-2003)	Percentage of next year's fuel consumption hedged	Natural logarithm of total assets (lease-adjusted)	Positively significant at 5%-level
				Natural logarithm of total assets (not lease-adjusted)	Positively significant at 10%-level
				Interest rate derivative dummy	Positively significant at 10%-level
			Fuel hedge dummy	Natural logarithm of total assets (lease-adjusted and not lease-adjusted)	Not significant
				Interest rate derivative dummy	Positively significant at 5%-level
Dionne and Thouraya	2013	36 North American gold mining firms (1992-1999)	Number of gold ounces sold forward scaled by the expected consumption over the next three years	Natural logarithm of total sales	Positively significant at 1%-level
Gay and Nam	1998	325 derivative users and 161 non-users (1995)	Notional dollar value of outstanding currency, interest rate and commodity derivative contracts scaled by total assets	Logarithm of firm size	Not significant
				Logarithm of firm size (including a dummy one for firms with lower than average cash holdings and greater than average growth options)	Not significant
Gay et al.	2011	1,541 non-financial U.S. firms (1992-1996) and 1,341 non-financial U.S. firms (2002-2004)	Notional dollar value of outstanding currency, interest rate and commodity derivative contracts scaled by total assets	Natural logarithm of total assets	Positively significant at 1%-level (entire sample); positively significant at 1%-level (1992-1996); not significant (2002-2004)
				Exposure: foreign sales scaled by net sales	Positively significant at 1-5%-level
			Hedge dummy	Natural logarithm of total assets	Positively significant at 1%-level
				Exposure: foreign sales scaled by net sales	Positively significant at 1%-level
Géczy et al.	1997	372 Fortune 500 U.S. non-financial firms (1990) with ex-ante currency exposure	FX hedge dummy	Other derivative dummy	Positively significant at 1-5%-level
				Firm size (book value of debt plus market value of equity)	Positively significant at 1%-level
				Exposure: foreign net income scaled by total sales	Positively significant between 5 and 10%-level
				Exposure: dummy one if the firm has foreign denominated debt	Positively significant at 1-5%-level

				Exposure: amount of industry imports scaled by total industry output	Positively significant at 1%-level
Graham and Rogers	2002	442 U.S. non-financial firms (March until December 1995) with ex-ante currency and interest rate exposure	Sum of net (long/short) position of currency and interest rate hedges scaled by total assets	Logarithm of total assets	Positively significant at 1%-level
				Exposure: foreign sales scaled by total sales	Positively significant at 5%-level
Guay and Kothari	2003	234 large, derivative using non-financial Compustat firms (1995)	Notional value of oustanding currency, interest rate and commodity derivatives scaled by total assets	Logarithm of total assets	Not significant
Haushalter	2000	Survey responses of 100 CFOs of oil and gas producing firms (1992-1994)	Fraction of production hedged	Firm size	Not significant
			Hedge dummy	Firm size	Positively significant at 5%-level
		Hedgers only	Fraction of production hedged	Firm size	Not significant
Judge	2006	441 non-financial FT500 firms (1995)	Hedge dummy (hedging for any financial price exposure)	Natural logarithm of total assets	Positively significant at 1%-level
				Exposure: foreign sales scaled by total sales	Positively significant at 1%-level
			Hedge dummy (derivative usage)	Natural logarithm of total assets	Positively significant at 1%-level
				Exposure: foreign sales scaled by total sales	Positively significant at 1%-level
Lin and Chang	2009	69 airlines from 32 countries (1995-2005)	Percentage of next year's fuel consumption hedged	Natural logarithm of total assets	Positively significant at 1%-level
				FX dummy	Not significant
			Fuel hedge dummy	Natural logarithm of total assets	Positively significant at 1%-level
				FX dummy	Positively significant at 1%-level
Nance et al.	1993	Survey responses of 169 CEOs of Fortune 500 and S&P 400 companies (1986)	Hedge dummy (any use of forwards, futures, swaps, options)	Firm size	Positively significant between 1 and 31%-level (in 48 regressions)

Nguyen and Faff	2002	239 (1999) and 230 (2000) non-financial Australian firms with derivative usage	Hedge dummy (any use of forwards, futures, swaps, options)	Firm size	Positively significant at 1%-level
			Notional value of derivatives outstanding scaled by total assets	Firm size	Not significant
Spanò	2007	443 British non-financial firms (1999-2000)	FX hedge dummy	Natural logarithm of total assets Exposure: overseas tax scaled by firm market value	Positively significant at 1%-level Positively significant at 5%-level
		Derivative users only (169 firms)	Fair value of FX derivatives scaled by firm market value	Natural logarithm of total assets Exposure: overseas tax scaled by firm market value	Not significant Positively significant at 5%-level
Sprcic and Sevic	2012	157 Croatian non-financial firms (2005), data from annual reports and survey	Hedge dummy (any use of financial, operational or natural hedging)	Total sales	Not significant
		186 Slovenian non-financial firms (2005), data from annual reports and survey	Hedge dummy (any use of financial, operational or natural hedging)	Total sales	Not significant
Tufano	1996	48 North American gold mining firms (1990-1993)	Percentage of gold sold forward divided by total production of the next three years	Firm size Number of ounces as reserves	Not significant Negatively significant at 10%-level (excluding the largest outlier)

Table C.4: Previous empirical findings on operational hedging

Author	Year	Sample	Dependent variable	Independent variable	Statistical impact on hedging
Adam	2002	Gold mining firms (1989-1999)	Gold price hedge dummy	HHI based on the industry book value of total assets	Not significant
				HHI based on industry sales	Positively significant at 1-5%-level
Carter et al.	2006	29 U.S. airlines (1992-2003)	Percentage of next year's fuel consumption hedged	FPA dummy	Negatively significant at 1%-level
			Fuel hedge dummy	FPA dummy	Negatively significant at 5%-level
Dionne and Thouraya	2013	36 North American gold mining firms (1992-1999)	Number of gold ounces sold forward scaled by the expected consumption over the next three years	U.S. based firm dummy	Not significant
Gay et al.	2011	1,541 non-financial U.S. firms (1992-1996) and 1,341 non-financial U.S. firms (2002-2004)	Hedge dummy	HHI based on segements	Positively significant at 5%-level (entire sample); positively significant at 5%-level (1992-1996); not significant (2002-2004)
Guay and Kothari	2003	234 large, derivative using non-financial Compustat firms (1995)	Notional value of outstanding currency, interest rate and commodity derivatives scaled by total assets	Segment diversification (entropy measure)	Positively significant at 5%-level
				Geographic diversification (entropy measure)	Positively significant at 5%-level
Haushalter	2000	Survey responses of 100 CFOs of oil and gas producing firms (1992-1994)	Fraction of production hedged	Diversification: oil and gas revenues scaled by total revenues	Not significant
				Diversification: oil revenues scaled by oil and gas revenues	Positively significant at 1-5%-level
Lin and Chang	2009	69 airlines from 32 countries (1995-2005)	Percentage of next year's fuel consumption hedged	FPA dummy	Negatively significant at 5%-level
			Fuel hedge dummy	FPA dummy	Negatively significant at 1%-level
Spanò	2007	443 British non-financial firms (1999-2000)	FX hedge dummy	Dummy one if the firm is multinational	Not significant
		Derivative users only (169 firms)	Fair value of FX derivatives scaled by firm market value	Dummy one if the firm is multinational	Not significant
Tufano	1996	48 North American gold mining firms (1990-1993)	Percentage of gold sold forward divided by total production of the next three years	Non-mining related assets scaled by total assets	Not significant

Table C.5: Previous empirical findings on selective hedging

Author	Year	Sample	Dependent variable	Independent variable	Statistical impact on hedging
Adam et al.	2017	92 gold mining firms (1989-1999)	Selective hedge activity (based on production)	Z-score	Negatively significant at 1%-level
				Z-score squared	Positively significant at 1%-level
				Firm size (see Adam (2002))	Negatively significant at 10%-level
				CEO tenure	Not significant
			Selective hedge activity (based on gold reserves)	Z-score	Negatively significant at 5%-level
				Z-score squared	Positively significant at 5%-level
				Firm size (see Adam (2002))	Negatively significant at 1%-level
				CEO tenure	Not significant
Brown	2001	Case study firm	Hedge portfolio delta (for three, six and nine months)	Market view: percentage difference between current spot rate and highest spot rate in previous 12 months	Positively significant at 10%-level (six months delta) and 5%-level (three months delta)
				Market view: percentage difference between current spot rate and lowest spot rate in previous 12 months	Positively significant at 1%-level (three and six months delta)
				Percentage change in oil spot price over last 60 days	Positively significant at 5%-level (nine months delta)
			Hedge portfolio gamma (for three, six and nine months)	Market view: percentage difference between current spot rate and highest spot rate in previous 12 months	Not significant
				Market view: percentage difference between current spot rate and lowest spot rate in previous 12 months	Negatively significant at 5%-level (six months delta) and 10%-level (three months delta)
				Percentage change in oil spot price over last 60 days	Positively significant at 10%-level (six months delta) and 5%-level (three months delta)
Brown et al.	2006	44 gold mining firms (1992-1998)	SD of quarterly hedge ratios	Z-score	Not significant
				Operating profit margin	Not significant
				Log of total assets	Not significant
				MTB ratio	Negatively significant at 5%-level
				Exposure: market share of projected gold production	Not significant

D Example of the fuel advantage of operating a diverse fleet

An Airbus 321 with an hourly fuel consumption of 3,000 kg kerosene per hour that is operated 17.0 hours per day can fly the route Frankfurt (FRA) - Hamburg (HAM) - FRA (Operation A) 4.5 times with 8.0 hours of transit, under the assumption of 1.0 hour transit between the flights. The total fuel consumption for that day would be 27,000 kg kerosene. An Airbus 319 with an hourly fuel consumption of 2,400 kg kerosene per hour could fly FRA - Faro (FAO) - FRA and FRA - HAM (Operation B) in the same time period. Total hours of transit would be 4.0 and fuel consumption 31,200 kg kerosene, resulting in a summed fuel consumption for both aircraft of 58,200 kg kerosene. If the airline swapped the larger aircraft (Airbus 321) for the longer distance flight (FRA - FAO - FRA), total fuel consumption for both aircraft would increase to 60,600 kg kerosene.

From	Until	Operation A	Operation B
6:00 AM	7:00 AM	FRA - HAM	FRA - FAO
7:00 AM	8:00 AM	*Transit*	
8:00 AM	9:00 AM	HAM - FRA	
9:00 AM	10:00 AM	*Transit*	*Transit*
10:00 AM	11:00 AM	FRA - HAM	FAO - FRA
11:00 AM	12:00 PM	*Transit*	
12:00 PM	1:00 PM	HAM - FRA	
1:00 PM	2:00 PM	*Transit*	*Transit*
2:00 PM	3:00 PM	FRA - HAM	FRA - FAO
3:00 PM	4:00 PM	*Transit*	
4:00 PM	5:00 PM	HAM - FRA	
5:00 PM	6:00 PM	*Transit*	*Transit*
6:00 PM	7:00 PM	FRA - HAM	FAO - FRA
7:00 PM	8:00 PM	*Transit*	
8:00 PM	9:00 PM	HAM - FRA	
9:00 PM	10:00 PM	*Transit*	*Transit*
10:00 PM	11:00 PM	FRA - HAM	FRA - HAM

	Operation A	Operation B
Transit hours	8	4
Flight hours	9	13
Fuel consumption A319	21,600 kg $= 2{,}400\,\text{kg} \times 9$	31,200 kg $= 2{,}400\,\text{kg} \times 13$
Fuel consumption A321	27,000 kg $= 3{,}000\,\text{kg} \times 9$	39,000 kg $= 3{,}000\,\text{kg} \times 13$
Sum fuel consumption (if A319 operated on FRA - FAO - FRA)	**58,200 kg**	
Sum fuel consumption (if A321 operated on FRA - FAO - FRA)	**60,600 kg**	

E Example of financial instrument cash flow hedge accounting

This example shows how cash flow hedges are accounted for under IFRS. The fair value of the hedged item, fuel expenses of −1,000,000 USD in t_0, decreases by 10% to −1,100,000 USD in t_1. The airline uses 10 different contracts (the hedging instrument) to hedge the incurred fuel expenses. The fair value of the portfolio is 1,000,000 USD in t_0. If the fair value of the hedging instrument increased by 10% (case A), the hedge effectiveness of the instrument would be 100% because the change in the fair value of the instrument equals the change of the hedged item. Therefore, the gain in the fair value of the hedging instrument (100,000 USD) would be accounted under other comprehensive income. If, however, the fair value of one or all of the contracts decreased in t_1 (case B) so that the fair value of the portfolio was (1,060,000 USD), the hedge effectiveness would decrease to 60% (= 6%/10%). The loss of the ineffective portion of the hedging instrument ($100{,}000 - 70{,}000 = 30{,}000$) would be directly accounted under losses in the income statement and the effective portion of the gain in the fair value ($= 9 \times 10{,}000 = 90{,}000$) under OCI.

	Hedged item: fuel expenses			Hedging instrument		
					case A	case B
	t_0	t_1		t_0	t_1	t_1
				100,000 USD	110,000 USD	110,000 USD
				100,000 USD	110,000 USD	110,000 USD
				100,000 USD	110,000 USD	110,000 USD
				100,000 USD	110,000 USD	110,000 USD
				100,000 USD	110,000 USD	70,000 USD
				100,000 USD	110,000 USD	110,000 USD
				100,000 USD	110,000 USD	110,000 USD
				100,000 USD	110,000 USD	110,000 USD
				100,000 USD	110,000 USD	110,000 USD
				100,000 USD	110,000 USD	110,000 USD
	−1,000,000 USD	**−1,100,000 USD**	Sum portfolio:	**1,000,000 USD**	**1,100,000 USD**	**1,060,000 USD**
Change in cash flows:		−100,000 USD 10%			100,000 USD 10%	60,000 USD 6%
Hedge effectiveness:					**100%**	**60%**

Accounting:

		case A	case B
	t_0	t_1	t_1
Derivative asset in balance sheet	1,000,000	1,100,000	1,060,000
Gain in other comprehensive income (OCI)		100,000	90,000
Loss in income statement			−30,000
Fuel expenses	−1,000,000	−1,100,000	−1,100,000

F List of the variables employed in the study

Table F.1: Description of the variables employed in the study

Variable	Label	Description
acAge	Average age of the aircraft fleet	Average age of the aircraft in the fleet, either reported in the text or calculated as $\sum$ *(each aircraft's age)*$/acTl$ - If only one year is available, the next year is calculated as the reported average age extrapolated with the aircraft purchases: $(acAge_{\text{t-1}} + 1 +$ *number of new aircraft* $\times 0.5)/acTl$
accStd	Accounting standards	Accounting standards which the annual report is prepared in accordance to
acChg	Percentage change in the number of aircraft	Year-on-year percentage changes in the number of aircraft in an airline's operating fleet
acOl	Number of aircraft under operating lease	Number of aircraft under operating lease from the annual report
acOlcashDm	Low cash, high operating leased aircraft dummy variable	Dummy one if the airline's annual cash ratio is below the average cash ratio and its annual percentage of aircraft under operating leasing is above the sample average
acOlPct	Percentage of aircraft under operating leasing	Percentage of aircraft in an airline's fleet that were operated under operating leasing - Calculated as $acOl/acTl$
activeChg3	Active hedger dummy variable	Dummy one if the airline's absolute annual percentage point change in its hedge ratio (*fdvPct12m*) is in the highest tertile of all hedging airlines and zero if it is in the lowest tertile
activeChg4	Active hedger dummy variable	Dummy one if the airline's absolute annual percentage point change in its hedge ratio (*fdvPct12m*) is in the highest quartile of all hedging airlines and zero if it is in the lowest quartile
acTl	Total number of aircraft	Total number of aircraft in the operating fleet of an airline - Including: aircraft under operating lease, finance lease and owned assets - If the number was not reported in each year it might be derived from the adjacent year with deliveries and sales from the annual report text
airline	Name of the airline	Abbreviated name of the main airline in the airline group
alliDm	Alliance dummy	Dummy one if the airline was a full member of an alliance (regardless of the type of the alliance) - Information about alliance membership is obtained from the websites and press releases of the alliances
alliOne	Oneworld dummy	Dummy one if the airline was a member of Oneworld
alliSky	Skyteam dummy	Dummy one if the airline was a member of Skyteam
alliStar	Star Alliance dummy	Dummy one if the airline was a member of Star Alliance
asCrt	Current assets	Total current assets as reported in the balance sheet
asmTl	Available seat miles	The total number of ASMs per year, either disclosed or calculated as i) RPMs (*rpmTl*) divided by the load factor (*lf*) ii) total revenues (*revTl*) divided by RASM (*rasm*) iii) the number of flights multiplied with the average stage length iv) fuel expenses (*fuelExp*) divided by fuel costs per ASM v) fuel consumption (*fuelCons*) divided by the consumption per ASM (*fuelConsAsm*) vi) ASKs divided by 1.852
asTl	Total assets	Total assets as reported in the balance sheet

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Variable	Label	Description
$asTlAdj1$	Total assets adjusted by operating lease expenses 1	Calculated as $asTl + olexPv1$
$asTlAdj5$	Total assets adjusted by operating lease expenses 5	Calculated as $asTl + olexPv2$
$asTlAdj6$	Total assets adjusted by operating lease expenses 6	Calculated as $asTl + olexPv3$
$asTlAdj7$	Total assets adjusted by operating lease expenses 7	Calculated as $asTl + olexPv4$
$asTlAdj8$	Total assets adjusted by operating lease expenses 8	Calculated as $asTl + olexPv5$
$capAs$	CAPEX scaled by total assets	Calculated as $capexNet/asTl$
$capAsAdj1$	CAPEX scaled by total assets adjusted by operating lease expenses 1	Calculated as $capexNetAdj1/asTlAdj1$
$capAsAdj5$	CAPEX scaled by total assets adjusted by operating lease expenses 5	Calculated as $capexNetAdj5/asTlAdj5$
$capAsAdj6$	CAPEX scaled by total assets adjusted by operating lease expenses 6	Calculated as $capexNetAdj6/asTlAdj6$
$capAsAdj7$	CAPEX scaled by total assets adjusted by operating lease expenses 7	Calculated as $capexNetAdj7/asTlAdj7$
$capAsAdj8$	CAPEX scaled by total assets adjusted by operating lease expenses 8	Calculated as $capexNetAdj8/asTlAdj8$
$capexIn$	Capital expenditure (inflow)	Capital expenditure as reported in the cash flow statement under cash flow from investing activities (inflow) - Excluding: dividends received, financial assets and increases in cash in connection with mergers
$capexNet$	Capital expenditure (net)	Calculated as $capexOut + capexIn$ - $(-)$ means a net capital expenditure (outflow) and $(+)$ means an inflow
$capexNetAdj1$	Capital expenditure (net) adjusted by operating lease expenses 1	Calculated as $capexNetAdj1 = capexNet + \textit{Yearly absolute change in olexpPv1}$ - For missing values, assume that absolute change equals zero as not to lose to many observations
$capexNetAdj5$	Capital expenditure (net) adjusted by operating lease expenses 5	Calculated as $capexNetAdj5 = capexNet + \textit{Yearly absolute change in olexpPv5}$ - For missing values, assume that absolute change equals zero as not to lose to many observations
$capexNetAdj6$	Capital expenditure (net) adjusted by operating lease expenses 6	Calculated as $capexNetAdj6 = capexNet + \textit{Yearly absolute change in olexpPv6}$ - For missing values, assume that absolute change equals zero as not to lose to many observations
$capexNetAdj7$	Capital expenditure (net) adjusted by operating lease expenses 7	Calculated as $capexNetAdj7 = capexNet + \textit{Yearly absolute change in olexpPv7}$ - For missing values, assume that absolute change equals zero as not to lose to many observations
$capexNetAdj8$	Capital expenditure (net) adjusted by operating lease expenses 8	Calculated as $capexNetAdj8 = capexNet + \textit{Yearly absolute change in olexpPv8}$ - For missing values, assume that absolute change equals zero as not to lose to many observations

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Variable	Label	Description
capexOut	Capital expenditure (outflow)	Capital expenditure as reported in the cash flow statement under cash flow from investing activities (outflow) - Including: capital expenditure for PPE, investments in joint venture, purchases of non-current assets, tangible and intangible assets, payments for advances for new aircraft, investments in associates, increases in lease prepayments, acquisitions of equity method investments, increases in equipment purchase deposits, acquisitions of subsidiaries - Excluding: financial assets, available-for-sale securities
capRev	CAPEX to sales ratio	Calculated as $\mathit{capexNet}/\mathit{revTl}$
capRevAdj1	CAPEX to sales ratio adjusted by operating lease expenses 1	Calculated as $\mathit{capexNetAdj1}/\mathit{revTl}$
capRevAdj5	CAPEX to sales ratio adjusted by operating lease expenses 5	Calculated as $\mathit{capexNetAdj5}/\mathit{revTl}$
capRevAdj6	CAPEX to sales ratio adjusted by operating lease expenses 6	Calculated as $\mathit{capexNetAdj6}/\mathit{revTl}$
capRevAdj7	CAPEX to sales ratio adjusted by operating lease expenses 7	Calculated as $\mathit{capexNetAdj7}/\mathit{revTl}$
capRevAdj8	CAPEX to sales ratio adjusted by operating lease expenses 8	Calculated as $\mathit{capexNetAdj8}/\mathit{revTl}$
capSize	CAPEX scaled by firm size	Calculated as $\mathit{capexNet}/\mathit{size}$
capSizeAdj1	CAPEX scaled by firm size adjusted by operating lease expenses 1	Calculated as $\mathit{capexNetAdj1}/\mathit{sizeAdj1}$
capSizeAdj5	CAPEX scaled by firm size adjusted by operating lease expenses 5	Calculated as $\mathit{capexNetAdj5}/\mathit{sizeAdj5}$
capSizeAdj6	CAPEX scaled by firm size adjusted by operating lease expenses 6	Calculated as $\mathit{capexNetAdj6}/\mathit{sizeAdj6}$
capSizeAdj7	CAPEX scaled by firm size adjusted by operating lease expenses 7	Calculated as $\mathit{capexNetAdj7}/\mathit{sizeAdj7}$
capSizeAdj8	CAPEX scaled by firm size adjusted by operating lease expenses 8	Calculated as $\mathit{capexNetAdj8}/\mathit{sizeAdj8}$
cashEq	Cash and cash equivalents	Cash and cash equivalents as reported in the balance sheet (or in notes) - Excluding: restricted cash and deposits for lease agreements
cashGrwDm	Low cash holdings, high investment opportunities dummy variable	Dummy one if the airline's annual cash ratio is below the sample average cash ratio and the annual adjusted Tobin's Q is below the sample average Tobin's Q value
cashRev	Cash to sales ratio	Calculated as $\mathit{cashEq}/\mathit{revTl}$
capSize	CAPEX scaled by firm size	Calculated as $\mathit{capex}/\mathit{size}$
cashRto	Cash ratio	Calculated as $(\mathit{cashEq} + \mathit{mktSec})/\mathit{liaCrt}$
costDbt	Cost of debt	Calculated as $\mathit{rfRate} + \mathit{spreadAvg}$
cpaDm	CPA dummy	Dummy one if the airline is a regional carrier and operates under a capacity purchase agreement (CPA) for a major airline

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Variable	Label	Description
crcy	Currency	The currency in which the airline reports their financial statement, based on ISO 4217 declaration
crtRto	Current ratio	Calculated as $asCrt/liaCrt$
ctry	Country of home base	The country in which the airline has its main base (i.e. where most of its flights depart from), based on ISO 3166-1 declaration
divDm	Dividend dummy	Dummy one if the dividend is paid in $t+1$ (not the dividend paid in t as dividends are paid in the next year's reporting period)
divPrf	Dividend payment for preference shares	Total dividends paid for preference shares (not dividend per share)
divRto	Dividend payout ratio	Calculated as $divShr/eps$
divShr	Dividend paid per share	Cash and stock dividend paid per ordinary share outstanding in year $t+1$, including interim and final dividend paid
divYld	Dividend yield	Calculated as $divShr/shrEnd$
ebit	Earnings before interest and tax	Calculated as $incBfeo + intExp - taxExp$
ebitAdj	Earnings before interest and tax adjusted by operating lease expenses	Calculated as $incBfeo + intExpAdj - taxExp$
eoItem	Extraordinary items	Extraordinary items as reported in the income statement such as discontinued operations and other infrequent and unusual items (exceptional items, non-recurring items)
eps	Earnings per share	Calculated as $(incBfeo - divPrf)/shrTl$
eqtyDm	Negative equity dummy	Dummy one if the airline had negative *eqtyTl* in that reporting period
eqtyTl	Total equity	The book value of total equity as reported in the balance sheet
fDiv1	Fleet diversity measure 1	Fleet dispersion of an airline based on the different aircraft models in the operating fleet of an airline
fDiv2	Fleet diversity measure 2	Fleet dispersion of an airline based on the different aircraft models in one aircraft family in the operating fleet of an airline
fDivNet	Combined fleet diversity measure	Calculated as $fDiv1 - fDiv2$
fdvCo	Underlying crude oil dummy	Dummy one if the airline used crude oil as the underlying asset for their fuel derivative contracts
fdvCol	Fuel collar dummy	Dummy one if the airline used fuel collars (a combination of short put option and long call option) as the derivative instrument
fdvDi	Underlying diesel oil dummy	Dummy one if the airline used diesel oil (=gasoil) as the underlying asset for their fuel derivative contracts
fdvDm	Fuel derivative dummy	Dummy one if the airline had outstanding fuel derivatives at the year end - If the airline used fuel derivatives during the year but did not have any derivatives outstanding at the reporting year end, zero is assigned - If, however, the airline reported active fuel derivative usage but did not disclose the notional value or fair value, the value one is assigned - Including: hedge derivatives, derivatives held for trading
fdvFut	Future fuel contract dummy	Dummy one if the airline used future fuel contracts as the derivative instrument
fdvFwd	Forward fuel contract dummy	Dummy one if the airline used forward fuel contracts as the derivative instrument
fdvHo	Underlying heating oil dummy	Dummy one if the airline used heating oil as the underlying asset for their fuel derivative contracts

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Variable	Label	Description
fdvJf	Underlying jet fuel dummy	Dummy one if the airline used jet fuel as the underlying asset for their fuel derivative contracts
fdvLefft1	Losses of fuel derivatives $t-1$, effective portion	Effective portion of the fuel derivative losses of $t-1$ recognized in OCI
fdvLefft2	Losses of fuel derivatives $t-2$, effective portion	Effective portion of the fuel derivative losses of $t-2$ recognized in OCI
fdvLsumt1	Sum of the ineffective and reclassified portion of the losses of fuel derivatives $t-1$	Calculated as $\mathit{fdvLinefft1} + \mathit{fdvLrclt1}$
fdvLsumt2	Sum of the ineffective and reclassified portion of the losses of fuel derivatives $t-2$	Calculated as $\mathit{fdvLinefft2} + \mathit{fdvLrclt2}$
fdvMtr	Fuel derivatives maturity	Maximum maturity in months of the outstanding fuel derivative contracts
fdvNm	Nominal amount of fuel contracts	Total nominal amount of fuel contracts outstanding at the year end in USG
fdvOpt	Fuel option dummy	Dummy one if the airline used fuel options as the derivative instrument
fdvPct12m	Hedge ratio for the next 12 months	Percentage of the next 12 months expected fuel consumption hedged, either reported in the text section or calculated as $(\mathit{fdvNm} \times (12/\mathit{fdvMtr}))/\mathit{fuelCons}_{t+1}$
fdvPct24m	Hedge ratio for the next 13-24 months	Percentage of the next 13 to 24 months expected fuel requirements hedged (excluding months 1 to 12)
fdvPct36m	Hedge ratio for the next 25-36 months	Percentage of the next 25 to 36 months expected fuel requirements hedged (excluding months 1 to 24)
fdvPct48m	Hedge ratio for the next 37-48 months	Percentage of the next 37 to 48 months expected fuel requirements hedged (excluding months 1 to 36)
fdvPefft1	Profits of fuel derivatives $t-1$, effective portion	Effective portion of the fuel derivatives profits of $t-1$ recognized in OCI
fdvPefft2	Profits of fuel derivatives $t-2$, effective portion	Effective portion of the fuel derivative profits of $t-2$ recognized in OCI
fdvPLeff	Profit or loss of fuel derivatives, effective portion	Effective portion of the fuel derivative profits or losses recognized in OCI
fdvPLineff	Profit or loss of fuel derivatives, ineffective portion	Under cash flow hedge accounting, ineffective portion of the fuel derivatives profits or losses recognized in the income statement under income on derivatives - Under fair value hedge accounting, marked to market changes of fuel derivatives directly accounted for in income
fdvPLrcl	Profit or loss of fuel derivatives, reclassified to fuel expenses	Portion of fuel derivatives profit or loss reclassified from OCI into fuel expenses when the underlying transaction is realized
fdvPLsum	Sum of the ineffective and reclassified portion of the profit or loss of fuel derivatives	Calculated as $\mathit{fdvPLineff} + \mathit{fdvPLrcl}$
fdvPsumt1	Sum of the ineffective and reclassified portion of the profits of fuel derivatives $t-1$	Calculated as $\mathit{fdvPinefft1} + \mathit{fdvPrclt1}$
fdvPsumt2	Sum of the ineffective and reclassified portion of the profits of fuel derivatives $t-2$	Calculated as $\mathit{fdvPinefft2} + \mathit{fdvPrclt2}$
fdvSpr	Fuel spread dummy	Dummy one if the airline used fuel spreads (=refining margin swaps) as the derivative instrument

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Variable	Label	Description
fdvSwp	Fuel swap dummy	Dummy one if the airline used fuel swaps as the derivative instrument
fdvUg	Underlying unleaded gasoline dummy	Dummy one if the airline used unleaded gasoline as the underlying asset for their fuel derivative contracts
fuelExpAsm	Fuel expense per ASM	Calculated as *fuelExp*/*asmTl*
fuelCons	Fuel consumption	Annual fuel consumption in USG, either reported directly or calculated as i) fuel consumption in liters per 100 RPM multiplied with RPMs ii) fuel consumption in liters per 100 ASM multiplied with ASMs iii) lagged nominal amount of fuel contracts outstanding (*fdvNm*) divided by the lagged fuel percentage hedged of the expected fuel consumption in the following 12 months (*fdvPct12m*)[139] iv) fuel consumption from the previous year ($fuelCons_{t-1}$) extrapolated with ASM percentage changes v) fuel consumption from the previous year ($fuelCons_{t-1}$) extrapolated with information from text, i.e. "consumption increased by X%" vi) fuel expense (*fuelExp*) divided by average fuel price per USG vii) fuel consumption per ASM (*fuelExpAsm*) multiplied with the total ASMs (*asmTl*)
fuelConsAsm	Fuel consumption per ASM	Calculated as *fuelCons*/*asmTl*
fuelExp	Fuel expenses	Total fuel expenses as reported in the income statement (or notes), net of hedging gains or losses
fuelExpAsm	Fuel expenses per ASM	Calculated as *fuelExp*/*asmTl*
fuelExpUSG	Fuel expense per USG consumed	Calculated as *fuelExp*/*fuelCons*
fxdvDm	Foreign exchange rate derivative dummy	Dummy one if the airline had outstanding foreign exchange rate derivatives at the year end (e.g. cross currency swaps)
hdgDec	Hedge decrease dummy variable	Dummy one if the airline decreased its hedge ratio (*fdvPct12m*) from one period to another and zero otherwise
hdgInc	Hedge increase dummy variable	Dummy one if the airline increased its hedge ratio (*fdvPct12m*) from one period to another and zero otherwise
ibd	Interest bearing debt	Interest bearing debt as reported in the balance sheet (or in notes) - Including: loans, financial leases, bonds, debentures, notes payable - Other short and long-term liabilities are only included if the relevant items incur interest - Excluding: "Air traffic settlement liabilities" (=tickets already sold but not yet flown) and trade payables
ibdAdj1	Interest bearing debt adjusted by operating lease expenses	Calculated as *ibd* + *olexPv1*
ibdAdj5	Interest bearing debt adjusted by operating lease expenses	Calculated as *ibd* + *olexPv2*
ibdAdj6	Interest bearing debt adjusted by operating lease expenses	Calculated as *ibd* + *olexPv3*
ibdAdj7	Interest bearing debt adjusted by operating lease expenses	Calculated as *ibd* + *olexPv4*
ibdAdj8	Interest bearing debt adjusted by operating lease expenses	Calculated as *ibd* + *olexPv5*
ID	ID number of the airline in the sample	Identification number of the airline in the sample in alphabetical order

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[139]This calculation works solely if the hedge portfolio maturity (*fdvMtr*) does not exceed 12 months.

Variable	Label	Description
incBfeo	Income before extraordinary items	Calculated as $incNet - eoItem$
incNet	Net income	Net income as reported in the income statement, after minority interests have been paid and including discontinued operations and extraordinary items
intAtax	After-tax interest	Calculated as $(1 - taxSta) \times intExp$
intAtaxAdj	After-tax interest adjusted by operating lease expenses	Calculated as $(1 - taxSta) \times intExpAdj$
intCov	Interest coverage ratio	Calculated as $ebit/intExp$
intCovAdj	Adjusted interest coverage ratio	Calculated as $(ebit + olexpTl)/(intExp + olexpTl)$
intExp	Interest expenses	Total interest expenses as reported in the income statement (or in notes) - Including: interest payments on finance lease obligations
intExpAdj	Adjusted interest expenses	Calculated as $intExp + \frac{1}{3} \times olexpTl$
irdvDm	Interest rate derivative dummy	Dummy one if the airline had outstanding interest rate derivatives at the year end (e.g. interest rate swaps) - Variable rate obligations do not count as interest rate derivatives
mktCap	Market capitalization	Calculated as $shrCom \times shrEnd + shrPrfLv$
lccDm	Low-cost carrier dummy	Dummy one if the airline can be defined as a low-cost carrier according to the IATA (2006) definition
lf	Load factor	Passenger load factor as reported in the annual report or calculated as $rpmTl/asmTl$
lgtAvg	Average length of flight	Average length of one flight (= sector length, stage length) as reported in the annual report - If the stage length was reported separately for long and short-haul flights (or domestic / international), the average stage lengths are weighted with $asmTl$
liaCrt	Current liabilities	Total current liabilities as reported in the balance sheet
liaLt	Long-term liabilities	Calculated as $liaTl - liaCrt$
liaLtAdj1	Long-term liabilities adjusted by operating lease expenses 1	Calculated as $liaTlAdj1 - liaCrt$
liaLtAdj5	Long-term liabilities adjusted by operating lease expenses 5	Calculated as $liaTlAdj5 - liaCrt$
liaLtAdj6	Long-term liabilities adjusted by operating lease expenses 6	Calculated as $liaTlAdj6 - liaCrt$
liaLtAdj7	Long-term liabilities adjusted by operating lease expenses 7	Calculated as $liaTlAdj7 - liaCrt$
liaLtAdj8	Long-term liabilities adjusted by operating lease expenses 8	Calculated as $liaTlAdj8 - liaCrt$
liaTl	Total liabilities	Total liabilities as reported in the balance sheet, calculated if they are not reported (current + non-current liabilities) - Including: "liabilities subject to compromise" (Chapter 11 term)
liaTlAdj1	Total liabilities adjusted by operating lease expenses	Calculated as $liaTl + olexpPv1$
liaTlAdj5	Total liabilities adjusted by operating lease expenses	Calculated as $liaTl + olexpPv5$
liaTlAdj6	Total liabilities adjusted by operating lease expenses	Calculated Calculated as $liaTl + olexpPv3$
liaTlAdj7	Total liabilities adjusted by operating lease expenses	Calculated Calculated as $liaTl + olexpPv7$

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Variable	Label	Description
liaTlAdj8	Total liabilities adjusted by operating lease expenses	Calculated Calculated as $liaTl + olexpPv8$
lvrg1	Leverage ratio 1	Calculated as $ibd/asTl$
lvrg1Adj1	Leverage ratio 1 adjusted by operating lease expenses 1	Calculated as $ibdAdj1/asTlAdj1$
lvrg1Adj5	Leverage ratio 1 adjusted by operating lease expenses 5	Calculated as $ibdAdj5/asTlAdj5$
lvrg1Adj6	Leverage ratio 1 adjusted by operating lease expenses 6	Calculated as $ibdAdj6/asTlAdj6$
lvrg1Adj7	Leverage ratio 1 adjusted by operating lease expenses 7	Calculated as $ibdAdj7/asTlAdj7$
lvrg1Adj8	Leverage ratio 1 adjusted by operating lease expenses 8	Calculated as $ibdAdj8/asTlAdj8$
lvrg1Sqr	Leverage ratio 1 squared	Calculated as $lvrg1 \times lvrg1$
lvrg2	Leverage ratio 2	Calculated as $(liaTl - liaCrt)/asTl = liaLt/asTl$
lvrg2Adj1	Leverage ratio 2 adjusted by operating lease expenses 1	Calculated as $(liaTlAdj1 - liaCrt)/asTlAdj1$
lvrg2Adj5	Leverage ratio 2 adjusted by operating lease expenses 5	Calculated as $(liaTlAdj5 - liaCrt)/asTlAdj5$
lvrg2Adj6	Leverage ratio 2 adjusted by operating lease expenses 6	Calculated as $(liaTlAdj6 - liaCrt)/asTlAdj6$
lvrg2Adj7	Leverage ratio 2 adjusted by operating lease expenses 7	Calculated as $(liaTlAdj7 - liaCrt)/asTlAdj7$
lvrg2Adj8	Leverage ratio 2 adjusted by operating lease expenses 8	Calculated as $(liaTlAdj8 - liaCrt)/asTlAdj8$
lvrg2Sqr	Leverage ratio 2 squared	Calculated as $lvrg2 \times lvrg2$
lvrg3	Leverage ratio 3	Calculated as $liaTl/asTl$
lvrg3Adj1	Leverage ratio 3 adjusted by operating lease expenses 1	Calculated as $liaTlAdj1/asTlAdj1$
lvrg3Adj5	Leverage ratio 3 adjusted by operating lease expenses 5	Calculated as $liaTlAdj5/asTlAdj5$
lvrg3Adj6	Leverage ratio 3 adjusted by operating lease expenses 6	Calculated as $liaTlAdj6/asTlAdj6$
lvrg3Adj7	Leverage ratio 3 adjusted by operating lease expenses 4	Calculated as $liaTlAdj7/asTlAdj7$
lvrg3Adj8	Leverage ratio 3 adjusted by operating lease expenses 8	Calculated as $liaTlAdj8/asTlAdj8$
lvrg3Sqr	Leverage ratio 3 squared	Calculated as $lvrg3 \times lvrg3$
mktCap	Market capitalization	Calculated as $shrCom \times shrEnd + shrPrfLv$
mktSec	Marketable securities	Marketable securities as reported in the balance sheet (or in notes) under current assets - Including: available-for-sale financial assets, assets held for sale, financial assets at fair value through profit, derivatives, current portion of held-to-maturity investments
mrgDm	Merger dummy	Dummy one in the year of the asset growth after the airline acquired another airline
mtbRto	Market-to-book ratio	Calculated as $mktCap/eqtyTl$

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Variable	Label	Description
olexpPv1	Present value of future operating lease expenses	Present value of future operating lease expenses - Calculated as the sum of future operating lease expenses of year t discounted with $(1 + costDbt)^{t}$ - Basis for the calculation of variables that end with "Adj1"
olexpPv5	Multiple (5) of annual operating lease expenses	Calculated as $5 \times olexpTl$ - Basis for the calculation of variables that end with "Adj5"
olexpPv6	Multiple (6) of annual operating lease expenses	Calculated as $6 \times olexpTl$ - Basis for the calculation of variables that end with "Adj6"
olexpPv7	Multiple (7) of annual operating lease expenses	Calculated as $7 \times olexpTl$ - Basis for the calculation of variables that end with "Adj7'
olexpPv8	Multiple (8) of annual operating lease expenses	Calculated as $8 \times olexpTl$ - Basis for the calculation of variables that end with "Adj8"
olexpRev	Operating lease expenses scaled by revenues	Calculated as $olexpTl/revTl$
olexpTl	Total operating lease expenses	Total operating lease expenses as reported in the income statement (or notes) - Including: operating lease expenses for aircraft and rental agreements (mostly for buildings) - If the airline only reported aircraft rent and not other lease rentals separately (e.g. landing fees), but where it becomes obvious from the future operating lease commitments that not only aircraft were part of the operating lease expenses, the reported actual operating lease expenses from $t + 1$ are taken - For example: the 2011 forecast of operating lease commitments of the annual report 2010 is employed as the actual total operating lease expenses 2011 - For the earliest year available (mostly 2005), the future operating lease expenses 2006 as reported in the 2005 annual report are used (which equals the current operating lease expenses of 2006 if the 2004 report is not available)
peRto	Price-earnings ratio	Calculated as $shrEnd/eps$
prfMrg	Profit margin	Calculated as $(incBfeo + intAtax)/revTl$
prfMrgAdj	Profit margin adjusted by operating lease expenses	Calculated as $(incBfeo + intAtaxAdj)/revTl$
qckRto	Quick ratio	Calculated as $(cashEq + mktSec + rcvCrt)/liaCrt$
rasm	Revenue per available seat mile	Calculated as $revTl/asmTl$
rcvCrt	Current receivables	Current receivables as reported in the balance sheet (or in notes) under current assets - Including: receivables from the sale of aircraft, trade receivables, other receivables, receivables from related parties, advances to suppliers, notes receivables
reg	Geographical region	The geographical region in which the airline has its main base, based on the UN "Composition of macro geographical (continental) regions, geographical sub-regions, and selected economic and other groupings" (United Nations, 2018) - The regions are Africa (AF), America (AM), Asia (AS), Europe (EU), and Oceania (OC)
regChg	Percentage point change in regional hedge ratios	Year-on-year percentage point change in the average regional hedge ratio
revTl	Total revenues	Total revenues as reported in the income statement (or notes), including other revenues
revTlln	Natural logarithm of total revenues	Calculated as $ln(revTl)$

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Variable	Label	Description
rfRate	Risk-free rate	Monthly average 10-year treasury bond yields taken from Datastream and adapted to the different *accDate* - Six countries (Cyprus, Kuwait, Panama, South Africa, Turkey, United Arab Emirates) are not available under Datastream. For those countries other web sources are searched - See Appendix H for an exact calculation
roaAdj1	ROA adjusted by operating lease expenses 1	Calculated as $(intAtaxAdj + incBfeo)/asTlAdj1$
roaAdj5	ROA adjusted by operating lease expenses 5	Calculated as $(intAtaxAdj + incBfeo)/asTlAdj5$
roaAdj6	ROA adjusted by operating lease expenses 6	Calculated as $(intAtaxAdj + incBfeo)/asTlAdj6$
roaAdj7	ROA adjusted by operating lease expenses 7	Calculated as $(intAtaxAdj + incBfeo)/asTlAdj7$
roaAdj8	ROA adjusted by operating lease expenses 8	Calculated as $(intAtaxAdj + incBfeo)/asTlAdj8$
rpmTl	Revenue passenger miles	The number of miles on which a passenger is transported, either reported directly or calculated as $asmTl \times lf$
rrpm	Revenue per revenue passenger mile	Revenue per RPM, calculated as $revTl/rpmTl$ - Also referred to as "the yield" in the airline industry
shrCom	Ordinary shares outstanding	Total number of ordinary shares (common stock) outstanding taken from the annual report
shrEnd	Share price at the end of the financial year	Share prices are retrieved from Thomson Reuters Eikon - For the financial years not ending December, the period end date share price is used (e.g. for 31st March 2010 the share price from 31st March 2010 is taken)
shrPrf	Preference shares outstanding	Total number of preference shares (preferred stock) outstanding
shrPrfLv	Market value of preference shares	Market value of preference shares outstanding - If the preference shares are traded on an exchange, the market value is calculated as the number of preference shares outstanding multiplied with the preference share price at the year end - If the preference shares are not traded, the market value is calculated as the par value of preference shares multiplied with the number of preference shares outstanding - If neither the preference share price nor the par value is reported, it is assumed that the preference shares are traded at the common share price
shrTl	Total number of shares outstanding	Total number of shares outstanding, equal to the total number of shares issued minus the number of treasury shares - Calculated as $shrCom + shrPrf$
size	Firm size of the airline	Calculated as $mktCap + liaTl$
sizeAdj1	Firm size of the airline adjusted by operating lease expenses 1	Calculated as $mktCap + liaTlAdj1$
sizeAdj5	Firm size of the airline adjusted by operating lease expenses 5	Calculated as $mktCap + liaTlAdj5$
sizeAdj6	Firm size of the airline adjusted by operating lease expenses 6	Calculated as $mktCap + liaTlAdj6$
sizeAdj7	Firm size of the airline adjusted by operating lease expenses 7	Calculated as $mktCap + liaTlAdj7$
sizeAdj8	Firm size of the airline adjusted by operating lease expenses 8	Calculated as $mktCap + liaTlAdj8$

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Variable	**Label**	**Description**
spread	Default spread	An airline's individual default spread is taken from the synthetic rating sheets of Damodaran (2002) and Damodaran (2016) and which are based on calculated interest coverage ratios - For the *years* 2008 until 2014 the table from Damodaran (2016) is used - For the *years* 2005 until 2007 the table from Damodaran (2002) is employed
spreadAvg	Three-year rolling average *spread*	The average of $spread_{t}$, $spread_{t\text{-}1}$, $spread_{t+1}$ - The average *spread* for the *year* 2005 is the average of $spread_{t}$ and $spread_{t+1}$ - The average *spread* for the *year* 2014 is the average of $spread_{t}$ and $spread_{t\text{-}1}$
taxExp	Tax expenses	Total tax expenses as reported in the income statement (or notes), including deferred and current tax expenses of that period - $(-)$ refers to a tax expense and $(+)$ to a tax benefit
taxSta	Statutory corporate income tax rate	Respective statutory corporate income tax rate of the airline's country - Source: if the country is available in the OECD Tax Database (OECD, 2018), the respective year "combined corporate income tax rate" is taken (which is the "corporate income tax rate" + "sub-central government corporate income tax rate") - If the country is not listed in the OECD database, KMPG's corporate tax rate tables are used (KPMG, 2018)
tobQ	Tobin's Q	Calculated as $(mktCap + liaTl)/asTl$
tobQAdj1	Tobin's Q adjusted by operating lease expenses 1	Calculated as $(mktCap + liaTlAdj1)/(asTlAdj1)$
tobQAdj5	Tobin's Q adjusted by operating lease expenses 5	Calculated as $(mktCap + liaTlAdj5)/(asTlAdj5)$
tobQAdj6	Tobin's Q adjusted by operating lease expenses 6	Calculated as $(mktCap + liaTlAdj6)/(asTlAdj6)$
tobQAdj7	Tobin's Q adjusted by operating lease expense 7s	Calculated as $(mktCap + liaTlAdj7)/(asTlAdj7)$
tobQAdj8	Tobin's Q adjusted by operating lease expenses 8	Calculated as $(mktCap + liaTlAdj8)/(asTlAdj8)$
xrAvg	Average exchange rate	Average of end-of-month bid exchange rate in USD to local currency over the reporting period from OANDA
xrEnd	End of financial year exchange rate	Exchange rate USD to local currency at the end of the reporting period from OANDA
year	Year of analysis	The end of year of March is categorized to the previous year (ending 31st March 2014 is 2013) and June, September, October to the current year (ending 30th June 2014 and 30th September 2014 is 2014)

G Variables converted with the average and year-end exchange rate

Adjusted with the average exchange rate	**Adjusted with the year-end exchange rate**
eoItem	*asCrt*
fdvPLeff	*asTl*
fdvPLineff	*capexNet*
fdvPLrcl	*cashEq*
fuelExp	*divPrf*
incBfeo	*divShr*
incNet	*eqtyTl*
intExp	*ibd*
revTl	*liaCrt*
taxExp	*liaTl*
olexpPv	*mktCap*
olexpTl	*mktSec*
	rcvCrt

H Calculation of the government bond yields for certain countries

Cyprus

The government bond yields of Cyprus are taken from the ministry of finance website, on which the ministry uploads statistics on risk indicators such as outstanding securities in the domestic market with maturities and weighted average yields (=government registered development stocks) (Ministry of Finance of Cyprus, 2013). As there are no yields available for 2008 and 2010, the adjacent year values are used.

Kuwait

There is no information on Kuwait bond yields available which is why the United Arab Emirates (UAE) bond yields from Air Arabia for 2008 and 2009 have to be employed.

Panama

From the two press releases "The Republic of Panama, rated Baa2/BBB/BBB, has priced a US$1.25bn 10-year bond at a final yield of 4.089%, according to market sources" (Reuters Staff, 2014-09-15) and "The Republic of Panama is set to raise US$1.25bn through the issuance of a new 10-year bond, which was launched on Wednesday at a final spread of 178bp over US Treasuries, according to market sources" (Scigliuzzo, 2015-03-11), it is assumed that the bond yield for 2014 is 4.089. For the other years of analysis, 178 basis points are added to the U.S. government bond yields.

South Africa

South African bond yields are derived from the website of the Federal Reserve Bank of St. Louis. They provide 10-year bond yield graphs based on OECD data (FRED, Federal Reserve Bank of St. Louis, 2016).

Turkey

Between 2010 and 2014, Turkish treasury bond yields are available on Datastream. Before 2010, 13.625% is assumed to be the yield based on the following press release: "The World Bank [...] has issued the first global benchmark bond denominated in New Turkish Lira (TRY). The TRY 500 million sized bond is a syndicated transaction lead-managed by ABN AMRO, JP Morgan and TD Securities, and the Co-Lead managers are Danske Bank, Deutsche Bank, KBC, RBC and UBS. The bond pays a coupon of 13.625%

and has a maturity of 10 years, extending 5 years beyond the longest outstanding Turkish Government domestic bond. It is also the largest TRY-denominated security at this part of the maturity curve" (The World Bank, 2007-04-25).

United Arab Emirates

The United Arab Emirates sold government bonds twice in the reporting period: "Abu Dhabi's department of finance sold a $2.5bn tranche of 5-year bonds yielding 2.125 per cent and which mature on May 3, 2021, and another $2.5bn tranche of 10-year bonds yielding 3.125 per cent. Those bonds mature on May 3, 2026, according to market participants" (Kassem, 2016-04-26) and "Abu Dhabi government bonds maturing in 2019 are yielding about 3.2 per cent, down from 4.8 per cent six months ago. Qatari bonds that also mature in 2019 are yielding 3 per cent, less than half of their 6.5 per cent yield when they were first sold in 2009" (Fitch, 2011-08-22). Therefore, the bond yields for Air Arabia are assumed to be 3.125% for 2014 and 2013, 3.2% for 2012 and 2011, 4.8% for 2010, 6.5% for 2009, and 5.0% for the other years of analysis.

I Average operating lease expenses per Boeing 737-800 and Airbus 320

Table I.1: Operating lease expenses per Boeing 737-800 of Ryanair in USD

Year of analysis	Total operating lease expenses of Ryanair	Number of 737-800 under operating leasing	Operating lease expenses per 737-800
2014	137,913,646	51	2,704,189
2013	136,022,514	51	2,667,108
2012	126,452,693	59	2,143,266
2011	124,822,240	59	2,115,631
2010	128,428,447	51	2,518,205
2009	134,793,399	55	2,450,789
2008	110,464,979	43	2,568,953
2007	102,823,993	35	2,937,828
2006	74,622,291	32	2,331,947
2005	57,661,342	21	2,745,778

Table I.2: Operating lease expenses per Airbus 320 of Vueling in USD

Year of analysis	Total operating lease expenses of Vueling	Number of Airbus 320 under operating leasing	Operating lease expenses per Airbus 320
2014	234,954,226	80	2,936,927
2013	187,440,409	68	2,756,477
2012	154,618,474	53	2,917,330
2011	148,565,069	47	3,160,958
2010	125,452,317	36	3,484,787
2009	102,424,172	37	2,768,221
2008	97,462,226	18	5,414,568
2007	87,189,852	25	3,632,910
2006	47,012,560	16	2,938,285
2005	no information	no information	no information

J Time-series graphs

Figure J.1: Time series: fuel expenses per USG fuel consumed compared to the jet fuel spot price (represented by the solid black line), annual average of all airlines and divided into NLCs, LCCs and regions

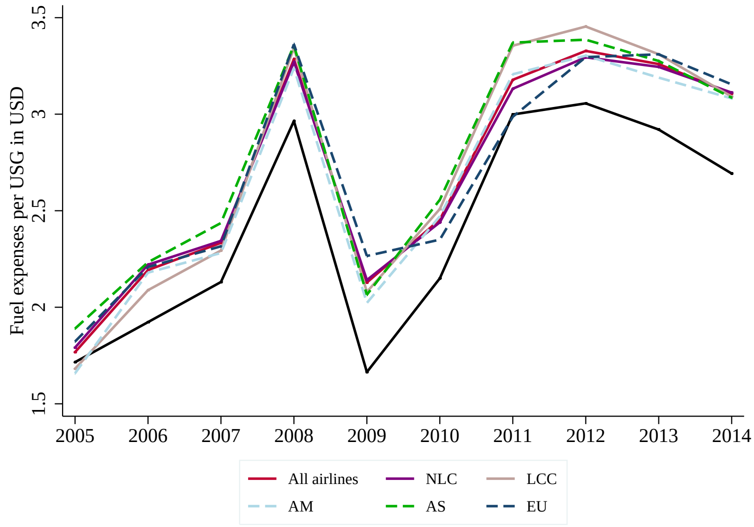


Figure J.2: Time series: unadjusted leverage ratios 3 (*lvrg3*) and lease-adjusted (*lvrg3Adj1*), annual average of all airlines and divided into NLCs, LCCs and regions

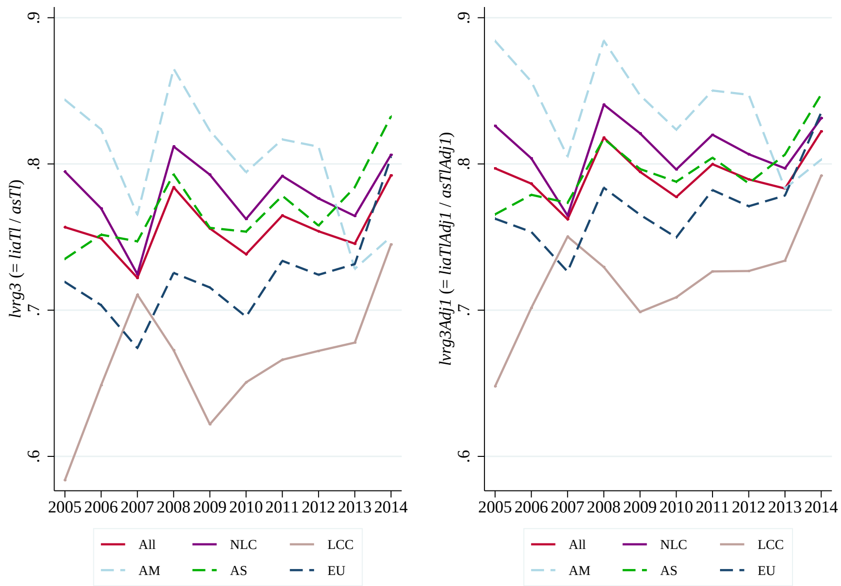


Figure J.3: Time series: unadjusted CAPEX scaled by total assets (*capAs*) and lease-adjusted (*capAsAdj1*), annual average of all airlines and divided into NLCs, LCCs and regions

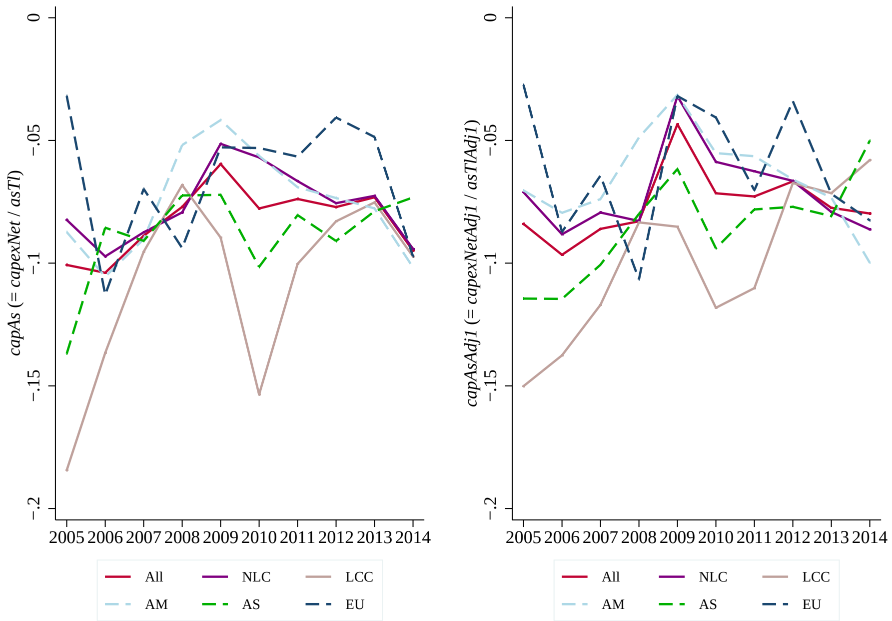


Figure J.4: Time series: unadjusted CAPEX scaled by airline firm size (*capSize*) and lease-adjusted (*capSizeAdj1*), annual average of all airlines and divided into NLCs, LCCs and regions

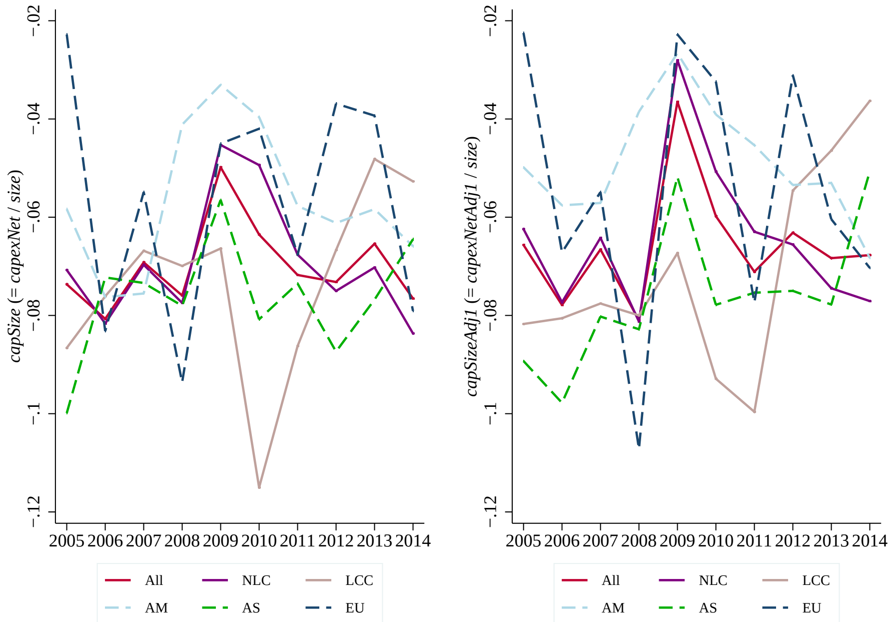


Figure J.5: Time series: absolute changes in the present values of operating lease expenses (*olexpPv1*), annual average of all airlines and divided into NLCs, LCCs and regions

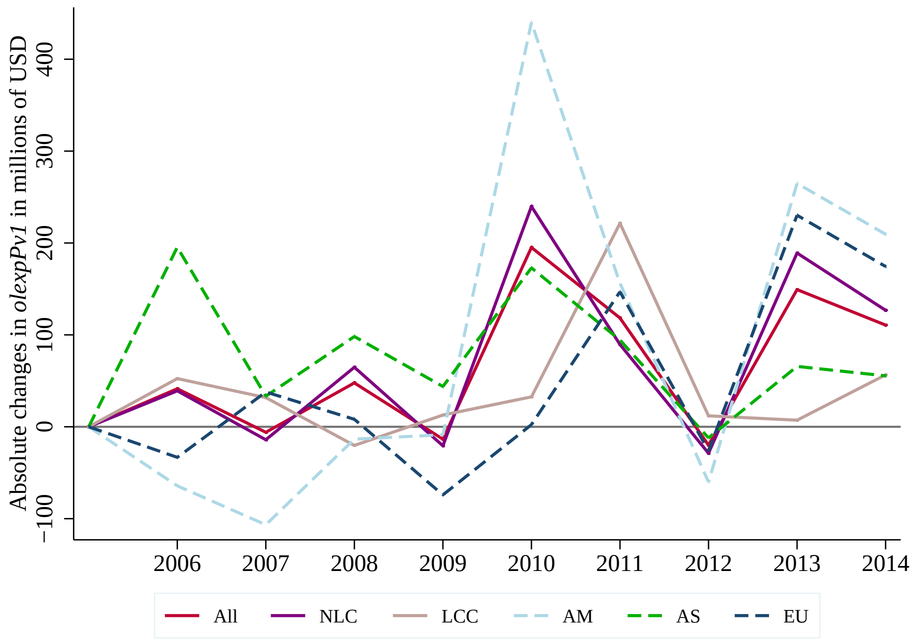


Figure J.6: Time series: cash ratios (*cashRto*), annual average of all airlines and divided into NLCs, LCCs and regions

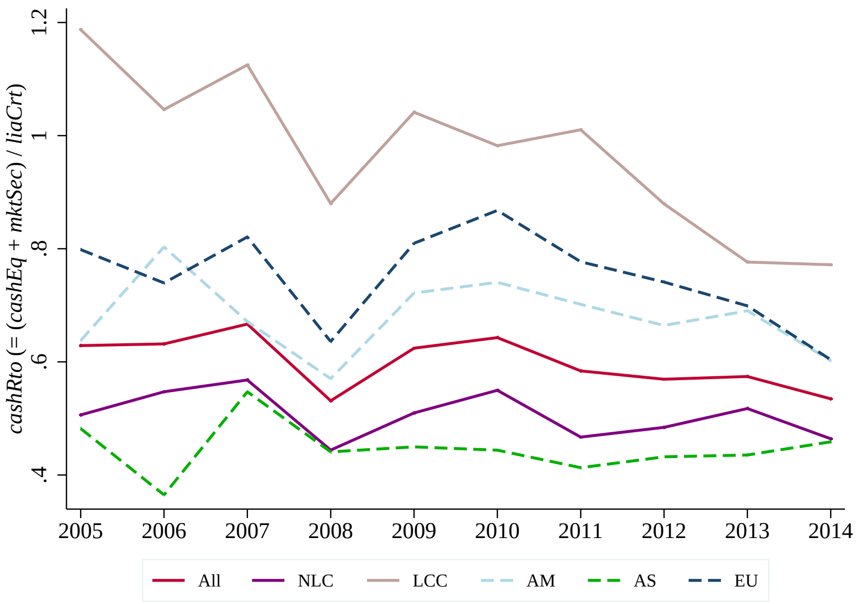


Figure J.7: Time series: current ratios (*crtRto*), annual average of all airlines and divided into NLCs, LCCs and regions

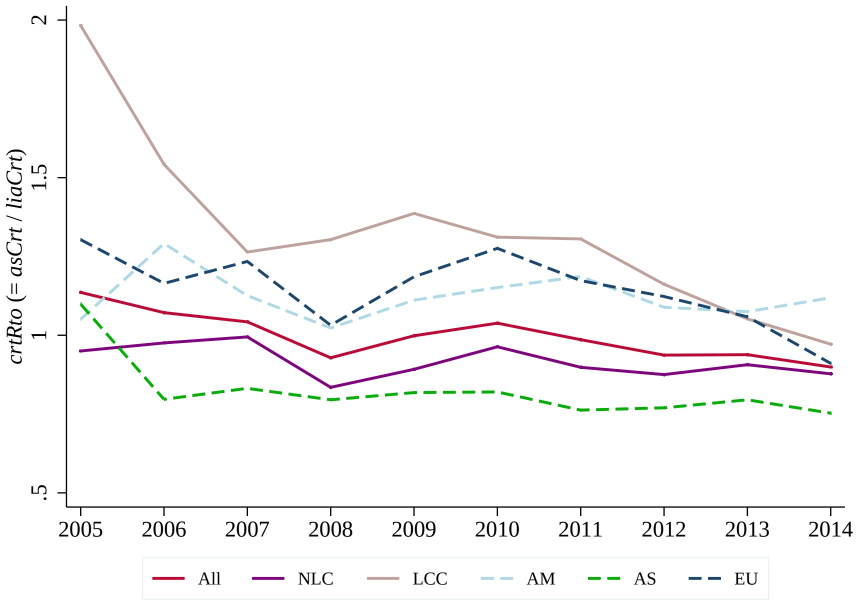


Figure J.8: Time series: quick ratios (*qckRto*), annual average of all airlines and divided into NLCs, LCCs and regions

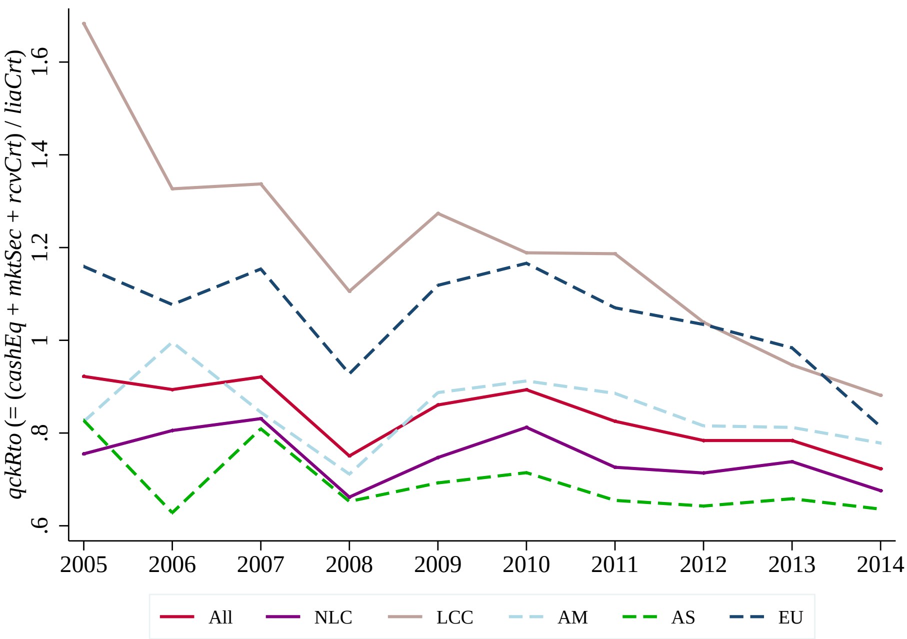


Figure J.9: Time series: market capitalization (*mktCap*), annual average of all airlines and divided into NLCs, LCCs and regions

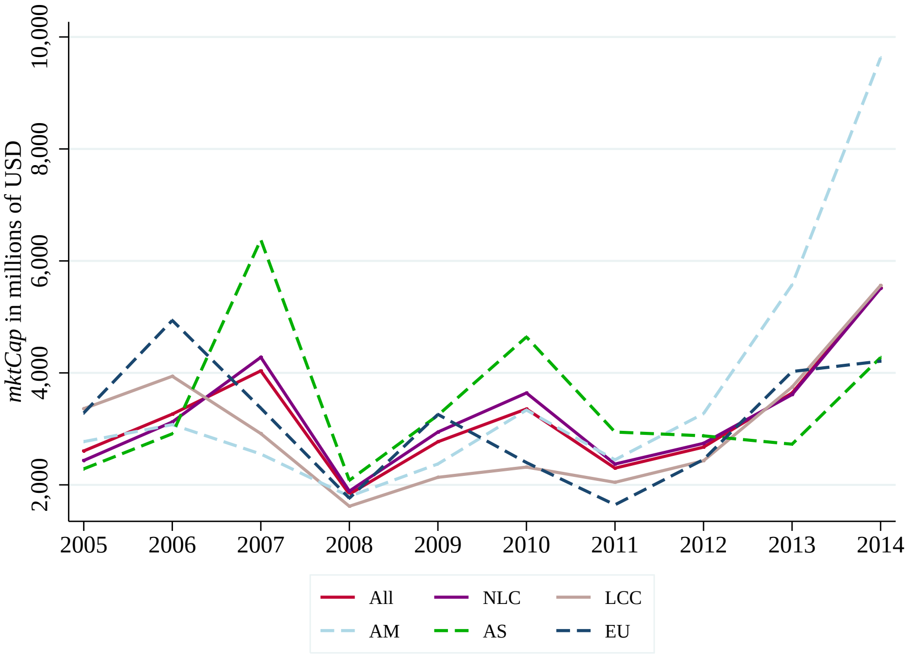


Figure J.10: Time series: unadjusted total assets (*asTl*) and lease-adjusted (*asTlAdj1*), annual average of all airlines and divided into NLCs, LCCs and regions

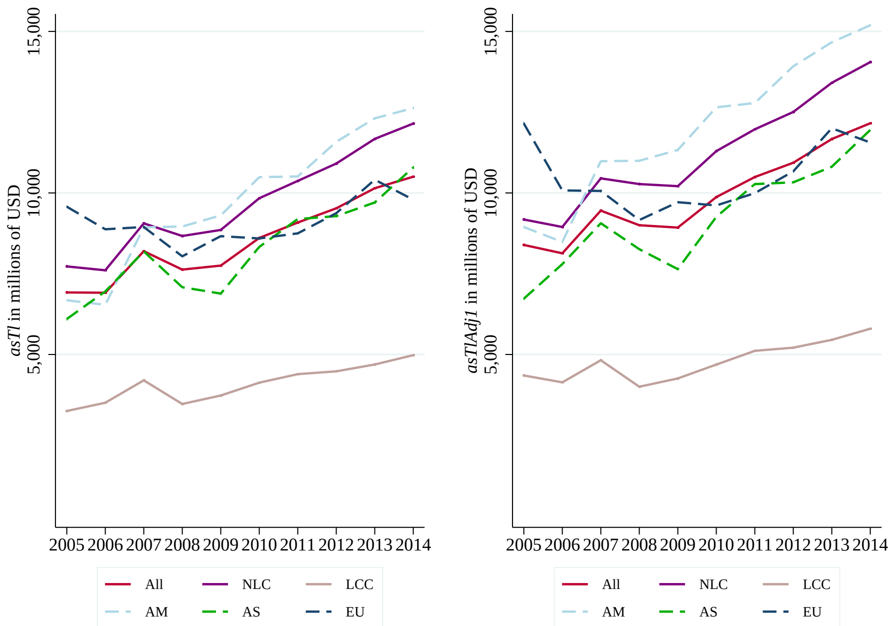


Figure J.11: Time series: total fuel expenses (*fuelExp*), annual average of all airlines and divided into NLCs, LCCs and regions

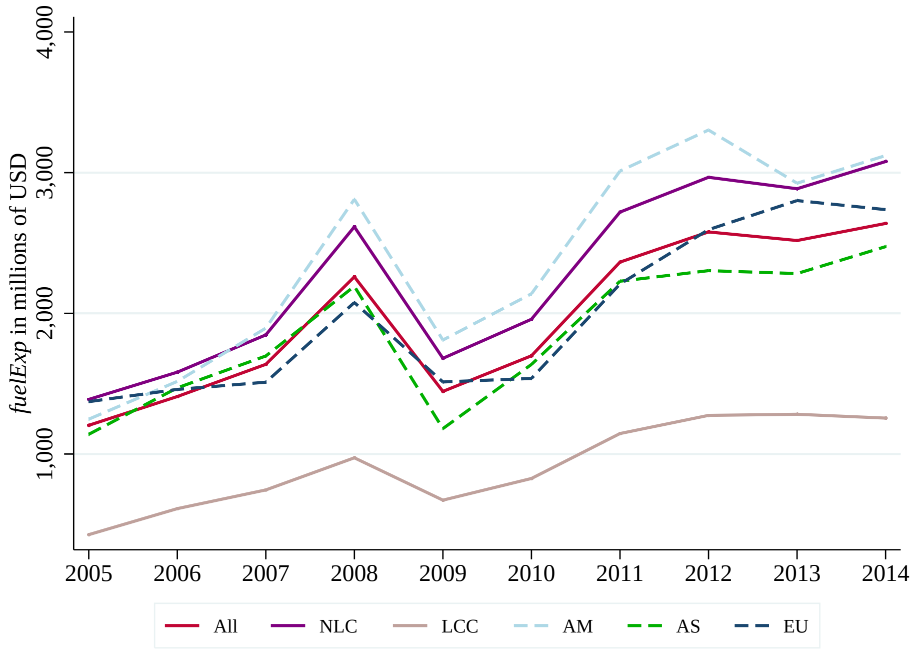


Figure J.12: Time series: alliance membership (*alliDm*) in percentage of the sample airlines, divided into any alliance, Oneworld, Star Alliance and SkyTeam

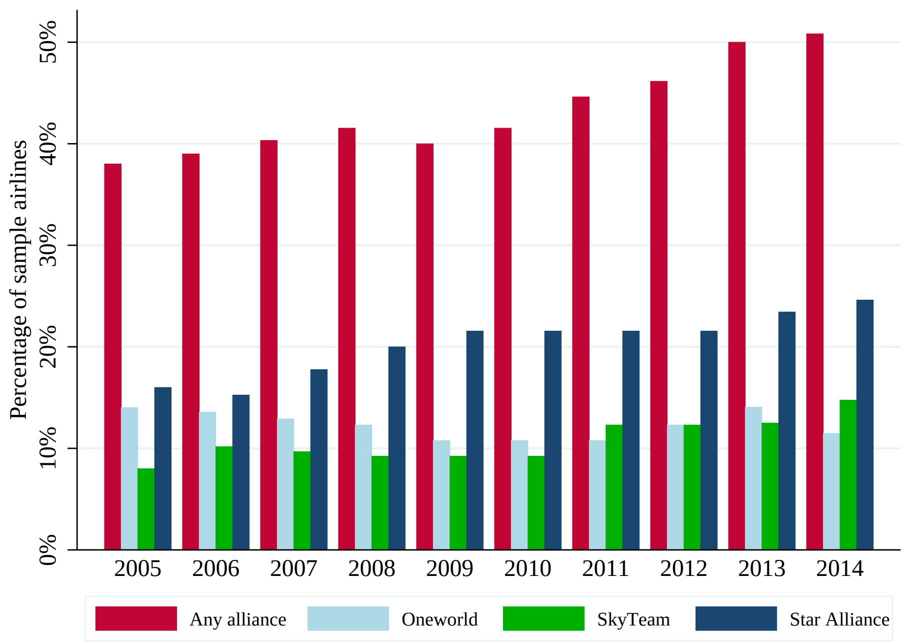


Figure J.13: Time series: absolute present values of operating lease expenses (*olexpPv5*) and (*olexpPv6*) as well as scaled by lease-adjusted total assets (*asTlAdj1*), annual average of all airlines and divided into NLCs, LCCs and regions

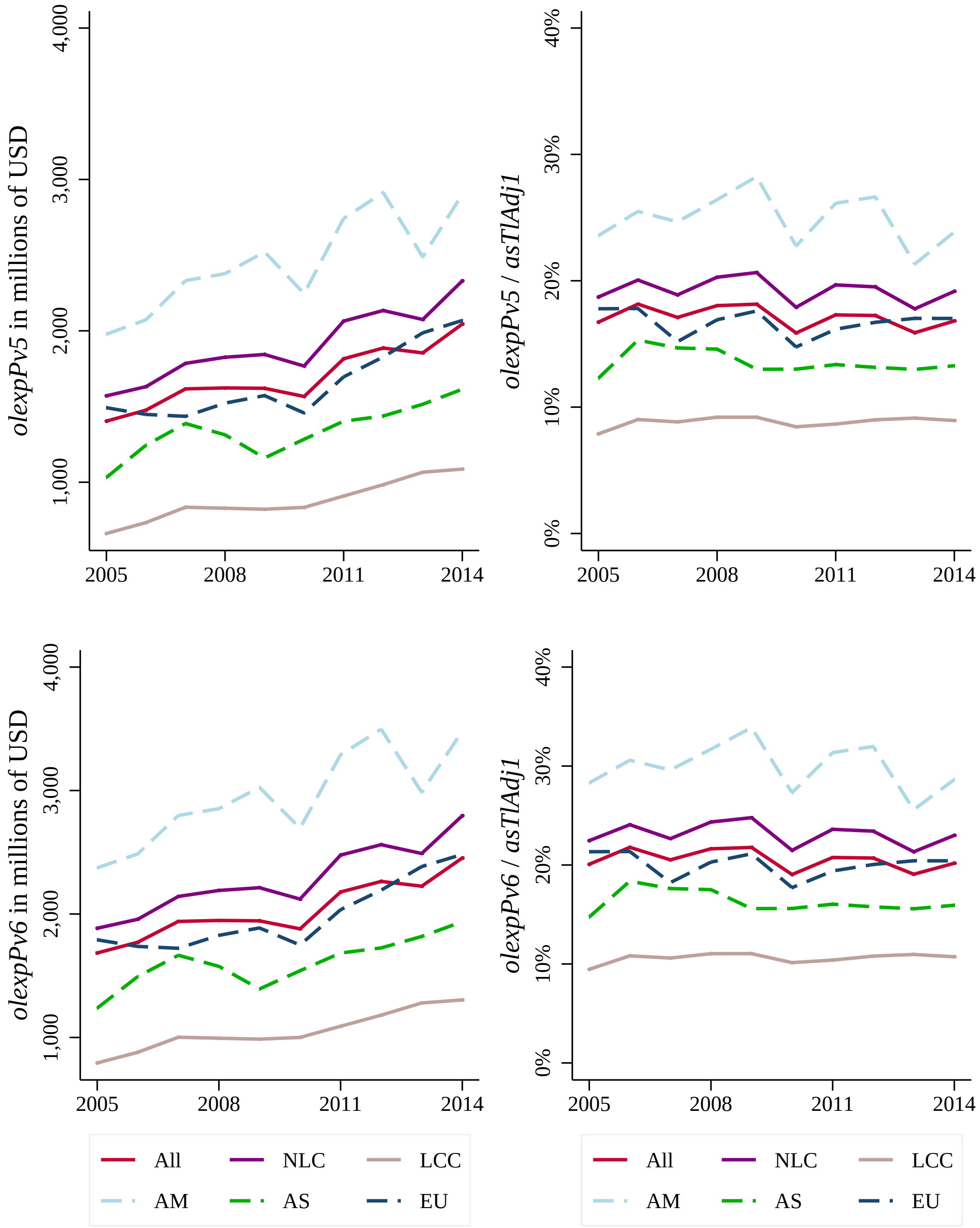


Figure J.14: Time series: absolute present values of operating lease expenses (*olexpPv7*) and (*olexpPv8*) as well as scaled by lease-adjusted total assets (*asTlAdj1*), annual average of all airlines and divided into NLCs, LCCs and regions

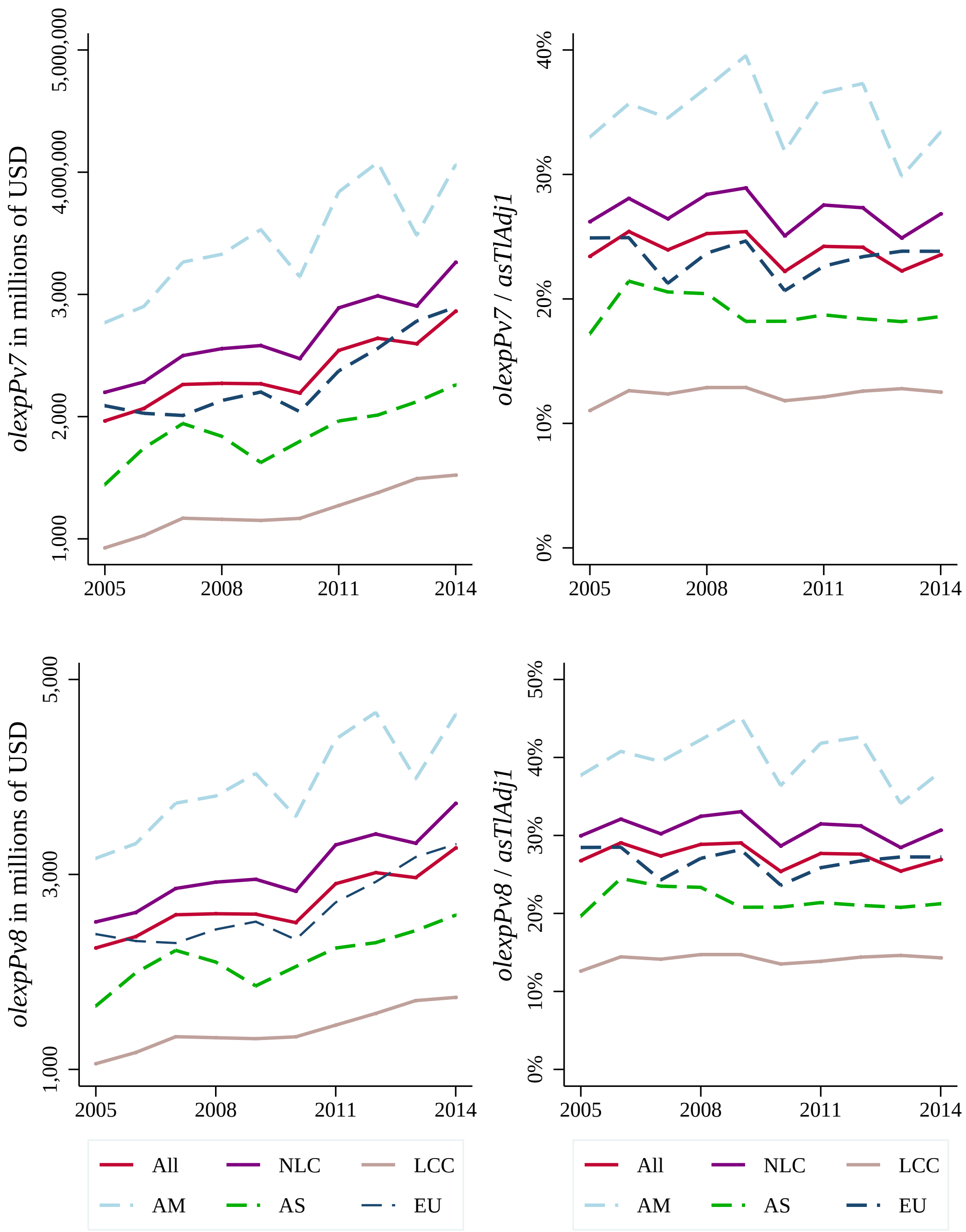


Figure J.15: Time series: total revenues (*revTl*), annual average of all airlines and divided into NLCs, LCCs and regions

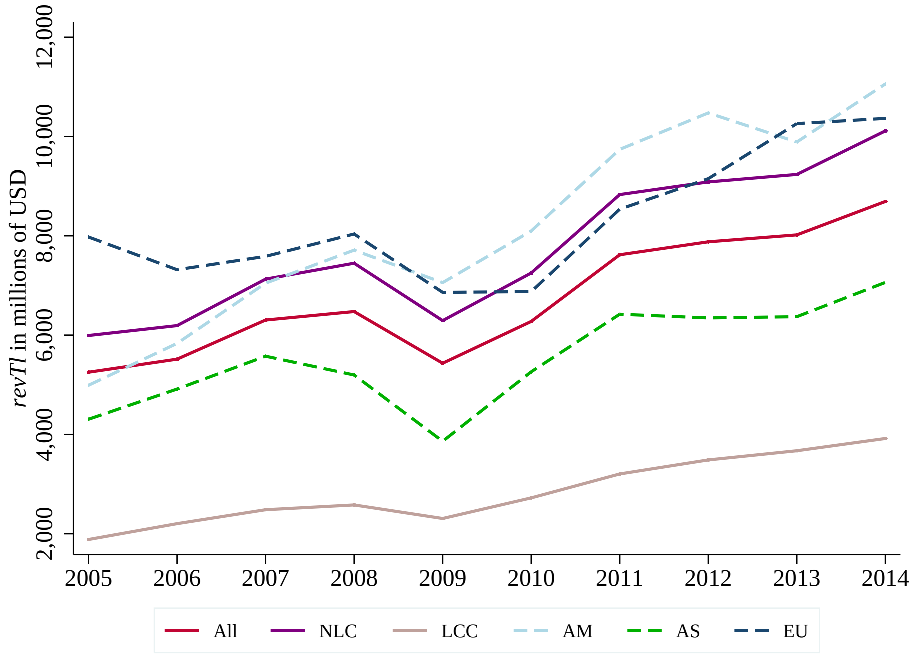
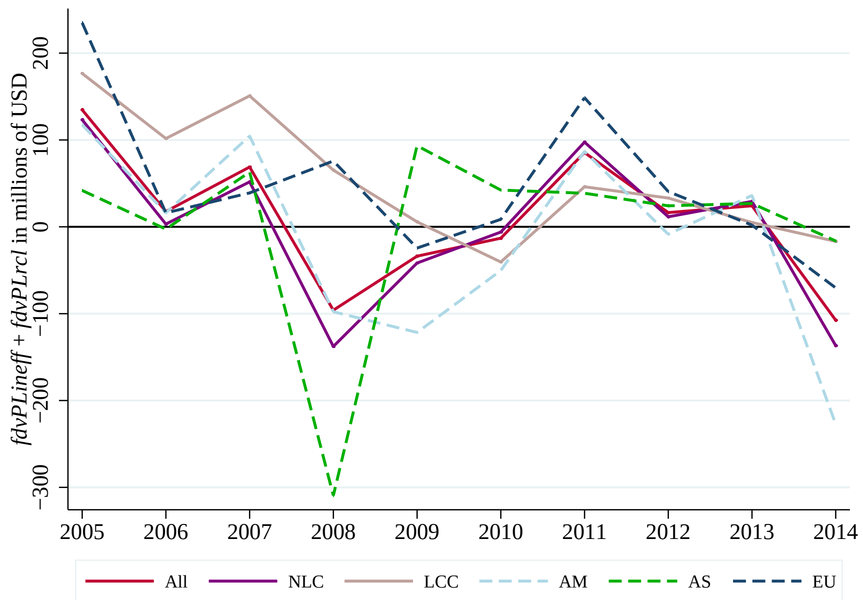


Figure J.16: Time series: sums of the ineffective (*fdvPLineff*) and reclassified portions (*fdvPLrcl*) of the profits and losses of fuel derivatives, annual average of all airlines and divided into NLCs, LCCs and regions



K Alternative differences-of-means tests

Table K.1: Alternative differences-of-means test between airlines with high hedge ratios (hedge ratio above sample average) and low hedge ratios (hedge ratio below sample average): financial distress variables

	High ratios (>avg.)		Low ratios (<=avg.)		t test		
	Mean	Obs.	Mean	Obs.	Diff.	SE	Obs.
divDm	0.406	239	0.418	304	0.012	0.043	543
divRto	0.148	239	0.156	304	0.008	0.027	543
divYld	0.012	239	0.012	300	−0.001	0.002	539
intCov	3.965	239	7.267	304	3.302*	1.526	543
intCovAdj	1.480	239	1.687	304	0.207	0.116	543
lvrg1	0.344	239	0.428	306	0.084***	0.015	545
lvrg1Adj1	0.453	239	0.533	304	0.081***	0.014	543
lvrg2	0.415	239	0.425	306	0.010	0.016	545
lvrg2Adj1	0.511	239	0.517	304	0.006	0.013	543
lvrg3	0.732	239	0.768	306	0.036*	0.016	545
lvrg3Adj1	0.772	239	0.805	304	0.032*	0.014	543
prfMrg	0.015	239	0.021	306	0.006	0.007	545
prfMrgAdj	0.045	239	0.060	304	0.014*	0.006	543
roa	0.019	239	0.030	306	0.011*	0.006	545
roaAdj1	0.029	239	0.039	303	0.010*	0.004	542

* p<0.05, ** p<0.01, *** p<0.001

Table K.2: Alternative differences-of-means test between airlines with high hedge ratios (hedge ratio above sample average) and low hedge ratios (hedge ratio below sample average): underinvestment variables

	High ratios (>avg.)		Low ratios (<=avg.)		t test		
	Mean	Obs.	Mean	Obs.	Diff.	SE	Obs.
acChg	0.071	209	0.102	201	0.031	0.022	410
capAs	−0.078	239	−0.088	306	−0.009	0.007	545
capAsAdj1	−0.069	239	−0.082	304	−0.012	0.007	543
capAsAdj5	−0.070	239	−0.081	304	−0.011	0.007	543
capRev	−0.105	239	−0.113	306	−0.009	0.011	545
capRevAdj1	−0.111	239	−0.130	306	−0.019	0.012	545
capSize	−0.070	239	−0.072	302	−0.001	0.006	541
capSizeAdj1	−0.063	239	−0.068	300	−0.005	0.006	539
cashGrwDm	0.088	239	0.260	300	0.172***	0.031	539
cashRev	0.161	239	0.155	306	−0.006	0.014	545
cashRto	0.710	239	0.534	306	−0.176***	0.038	545
crtRto	1.122	239	0.927	306	−0.195***	0.045	545
mtbRto	1.395	239	2.078	302	0.684**	0.210	541
peRto	8.894	239	16.033	301	7.139*	3.401	540
qckRto	0.940	239	0.770	306	−0.170***	0.039	545
tobQ	1.133	239	1.304	302	0.171***	0.035	541
tobQAdj1	1.107	239	1.238	300	0.131***	0.028	539

* $p<0.05$, ** $p<0.01$, *** $p<0.001$

Table K.3: Alternative differences-of-means test between airlines with high hedge ratios (hedge ratio above sample average) and low hedge ratios (hedge ratio below sample average): economies of scale variables

	High ratios (>avg.)		Low ratios (<=avg.)		t test		
	Mean	Obs.	Mean	Obs.	Diff.	SE	Obs.
acTl	229.039	233	202.013	238	−27.026	21.173	471
*fuelExp_*	2143.937	239	1817.923	282	−326.014	206.366	521
fxdvDm	0.724	239	0.497	306	−0.227***	0.041	545
irdvDm	0.711	239	0.471	306	−0.241***	0.041	545
*revTl_*	8390.609	239	5469.862	306	−2920.747***	753.193	545
revTlln	22.274	239	21.511	306	−0.762***	0.113	545
*size_*	11140.086	239	8371.895	302	−2768.191**	1026.099	541
*sizeAdj1_*	12604.107	239	9682.228	300	−2921.879*	1152.527	539

* p<0.05, ** p<0.01, *** p<0.001

Variables ending with "_" in millions of USD

Table K.4: Alternative differences-of-means test between airlines with high hedge ratios (hedge ratio above sample average) and low hedge ratios (hedge ratio below sample average): operational hedging variables

	High ratios (>avg.)		Low ratios (<=avg.)		t test		
	Mean	Obs.	Mean	Obs.	Diff.	SE	Obs.
acOlcashDm	0.14	168	0.26	201	0.12**	0.04	369
acOlPct	0.42	168	0.45	201	0.03	0.03	369
alliDm	0.50	239	0.37	306	−0.13**	0.04	545
fDiv1	0.71	233	0.61	238	−0.11***	0.03	471
fDiv2	0.57	233	0.45	238	−0.12***	0.03	471
fDivNet	0.14	233	0.16	238	0.01	0.01	471
olexpRev	0.07	239	0.07	304	0.00	0.00	543
*olexpTl_*	362.15	239	315.33	304	−46.82	30.69	543

* p<0.05, ** p<0.01, *** p<0.001

Variable ending with "_" in millions of USD

L Correlation matrices

Table L.1: Correlation matrix between hedging and financial distress variables

	fdvPct12m	fdvDm	fdvMtr	divDm	divRto	divYld	eqtyDm	intCovAdj	lvrg1Adj1	lvrg3Adj1	prfMrgAdj	roaAdj1
fdvPct12m	1.00											
fdvDm	0.63	1.00										
fdvMtr	0.62	0.66	1.00									
divDm	0.03	-0.05	0.09	1.00								
divRto	-0.01	-0.00	0.02	0.30	1.00							
divYld	0.02	0.00	-0.02	0.58	0.33	1.00						
eqtyDm	-0.12	-0.11	-0.12	-0.24	-0.07	-0.14	1.00					
intCovAdj	-0.07	-0.13	-0.05	0.29	0.10	0.23	-0.18	1.00				
lvrg1Adj1	-0.21	-0.27	-0.26	-0.35	-0.16	-0.36	0.30	-0.44	1.00			
lvrg3Adj1	-0.09	-0.08	-0.13	-0.41	-0.22	-0.40	0.58	-0.49	0.74	1.00		
prfMrgAdj	-0.00	-0.05	-0.03	0.35	0.15	0.29	-0.32	0.53	-0.27	-0.49	1.00	
roaAdj1	-0.06	-0.11	-0.07	0.34	0.11	0.25	-0.35	0.60	-0.36	-0.51	0.88	1.00

Table L.2: Correlation matrix between hedging and underinvestment variables

	fdvPct12m	fdvDm	fdvMtr	acChg	capAsAdj1	capRevAdj1	capSizeAdj1	cashRev	cashRto	crtRto	mtbRto	peRto	qckRto	tobQAdj1
fdvPct12m	1.00													
fdvDm	0.55	1.00												
fdvMtr	0.53	0.58	1.00											
acChg	-0.03	-0.02	-0.09	1.00										
capAsAdj1	0.07	0.03	0.00	-0.25	1.00									
capRevAdj1	-0.02	-0.02	-0.02	-0.32	0.87	1.00								
capSizeAdj1	0.04	-0.00	-0.04	-0.19	0.95	0.79	1.00							
cashRev	-0.00	0.04	-0.11	0.19	0.01	-0.13	0.05	1.00						
cashRto	0.16	0.15	0.06	0.10	0.06	0.00	0.14	0.65	1.00					
crtRto	0.17	0.03	0.00	0.11	0.08	0.01	0.13	0.45	0.82	1.00				
mtbRto	-0.10	-0.06	-0.07	0.06	0.00	-0.00	0.08	0.04	0.01	-0.04	1.00			
peRto	-0.03	-0.01	0.02	-0.03	0.04	0.11	0.04	0.05	-0.02	-0.01	0.04	1.00		
qckRto	0.12	0.10	-0.01	0.14	0.03	-0.04	0.09	0.62	0.92	0.91	-0.02	-0.00	1.00	
tobQAdj1	-0.14	-0.13	-0.15	0.15	-0.20	-0.17	0.06	0.14	0.22	0.08	0.39	0.03	0.15	1.00

Table L.3: Correlation matrix between hedging and economies of scale variables

	fdvPct12m	fdvDm	fdvMtr	acTl	fuelExp	fxdvDm	irdvDm	revTl	revTlln	size	sizeAdj1
fdvPct12m	1.00										
fdvDm	0.54	1.00									
fdvMtr	0.55	0.57	1.00								
acTl	0.16	0.11	0.23	1.00							
fuelExp	0.05	0.11	0.19	0.79	1.00						
fxdvDm	0.18	0.32	0.04	-0.05	0.18	1.00					
irdvDm	0.16	0.32	0.28	0.06	0.23	0.39	1.00				
revTl	0.14	0.13	0.23	0.79	0.95	0.20	0.24	1.00			
revTlln	0.23	0.33	0.32	0.69	0.79	0.31	0.39	0.80	1.00		
size	0.09	0.09	0.20	0.80	0.92	0.18	0.26	0.92	0.77	1.00	
sizeAdj1	0.08	0.09	0.19	0.83	0.93	0.17	0.24	0.93	0.78	1.00	1.00

Table L.4: Correlation matrix between financial hedging and operational hedging variables

	fdvPct12m	fdvDm	fdvMtr	acOlcashDm	acOlPct	alliDm	fDiv1	fDiv2	fDivNet	olexpRev	olexpTl
fdvPct12m	1.00										
fdvDm	0.51	1.00									
fdvMtr	0.54	0.58	1.00								
acOlcashDm	-0.16	-0.01	-0.13	1.00							
acOlPct	-0.05	0.15	-0.07	0.42	1.00						
alliDm	-0.04	0.04	-0.03	0.02	-0.11	1.00					
fDiv1	0.10	0.14	0.15	0.01	-0.12	0.66	1.00				
fDiv2	0.07	0.06	0.07	-0.01	-0.20	0.66	0.88	1.00			
fDivNet	0.05	0.16	0.15	0.06	0.20	-0.11	0.10	-0.38	1.00		
olexpRev	-0.01	0.13	-0.06	0.40	0.74	-0.20	-0.12	-0.16	0.11	1.00	
olexpTl	-0.09	0.02	0.05	0.18	0.09	0.54	0.45	0.43	-0.02	0.05	1.00

M Alternative random effects probit models

Table M.1: Random effects probit models with different underinvestment proxies

	BASE (1) fdvDm	(2) fdvDm	(3) fdvDm	(4) fdvDm	(5) fdvDm	(6) fdvDm	(7) fdvDm	(8) fdvDm	(9) fdvDm
lvrg1Adj1	-14.22^{**}	-13.31^{**}	-13.49^{**}	-17.65^{**}	-13.90^{**}	-13.51^{**}	-13.71^{**}	-14.77^{**}	-16.08^{***}
	(0.012)	(0.017)	(0.016)	(0.013)	(0.012)	(0.013)	(0.014)	(0.010)	(0.006)
lvrg1Adj1Sqr	12.18^{**}	11.35^{**}	11.29^{**}	16.89^{**}	11.86^{**}	11.54^{**}	11.66^{**}	12.40^{**}	13.84^{**}
	(0.023)	(0.032)	(0.035)	(0.013)	(0.024)	(0.026)	(0.028)	(0.023)	(0.013)
intCovAdj	-0.733^{***}	-0.677^{***}	-0.700^{***}	-0.762^{***}	-0.656^{***}	-0.642^{***}	-0.688^{***}	-0.726^{***}	-0.757^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
tobQAdj1	0.418							0.505	0.497
	(0.329)							(0.249)	(0.252)
cashRto	3.021^{**}	3.069^{**}	2.993^{**}	2.383	3.098^{**}	2.984^{**}	3.025^{**}		
	(0.016)	(0.013)	(0.018)	(0.245)	(0.011)	(0.014)	(0.016)		
cashRtoSqr	-1.317^{**}	-1.293^{**}	-1.281^{**}	-0.715	-1.315^{**}	-1.265^{**}	-1.282^{**}		
	(0.020)	(0.020)	(0.024)	(0.525)	(0.017)	(0.022)	(0.022)		
acTl	0.000664	0.000710	0.000688	0.000597	0.000392	0.000298	0.000622	0.000766	0.000738
	(0.537)	(0.501)	(0.524)	(0.690)	(0.693)	(0.763)	(0.557)	(0.507)	(0.515)
irdvDm	1.208^{***}	1.129^{***}	1.206^{***}	1.958^{***}	1.229^{***}	1.197^{***}	1.181^{***}	1.251^{***}	1.269^{***}
	(0.003)	(0.004)	(0.003)	(0.004)	(0.001)	(0.002)	(0.003)	(0.003)	(0.002)
fxdvDm	1.101^{***}	1.115^{***}	1.084^{***}	1.245^{**}	1.130^{***}	1.127^{***}	1.092^{***}	1.060^{**}	1.097^{***}
	(0.005)	(0.004)	(0.006)	(0.028)	(0.003)	(0.003)	(0.005)	(0.010)	(0.007)
mtbRto		-0.0309							
		(0.439)							
peRto			0.00509						
			(0.152)						
acChg				0.814					
				(0.371)					
capAsAdj1					-1.039				
					(0.560)				
capRevAdj1						0.167			
						(0.873)			
capSizeAdj1							-0.259		
							(0.897)		
crtRto								1.509	
								(0.141)	
crtRtoSqr								-0.488	
								(0.108)	
qckRto									2.989^{**}
									(0.039)
qckRtoSqr									-1.215^{**}
									(0.033)
intercept	4.011^{**}	4.196^{***}	4.277^{***}	5.466^{***}	4.105^{***}	4.149^{***}	4.284^{***}	4.423^{**}	4.176^{**}
	(0.014)	(0.009)	(0.009)	(0.010)	(0.010)	(0.009)	(0.008)	(0.012)	(0.014)
N	504	504	504	442	509	509	504	504	504
AIC	248.9	249.3	247.3	191.9	256.8	257.1	249.9	251.7	249.8

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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Table M.2: Random effects probit models with different economies of scale proxies

	BASE (1) fdvDm	(2) fdvDm	(3) fdvDm	(4) fdvDm	(5) fdvDm	(6) fdvDm	(7) fdvDm
lvrg1Adj1	−14.22**	−13.16**	−8.665	−9.399**	−9.959**	−9.991**	−11.79**
	(0.012)	(0.021)	(0.102)	(0.047)	(0.036)	(0.035)	(0.021)
lvrg1Adj1Sqr	12.18**	11.20**	7.556	5.882	6.337	6.388	8.037*
	(0.023)	(0.040)	(0.137)	(0.166)	(0.137)	(0.134)	(0.076)
intCovAdj	−0.733***	−0.697***	−0.668***	−0.611***	−0.643***	−0.646***	−0.586***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
tobQAdj1	0.418	0.340	0.345	0.293	0.324	0.325	0.128
	(0.329)	(0.426)	(0.436)	(0.440)	(0.392)	(0.393)	(0.740)
cashRto	3.021**	2.984**	2.749**	1.933	1.961*	2.000*	1.475
	(0.016)	(0.017)	(0.037)	(0.100)	(0.086)	(0.078)	(0.210)
cashRtoSqr	−1.317**	−1.334**	−1.345**	−1.030*	−1.014*	−1.023**	−0.698
	(0.020)	(0.019)	(0.024)	(0.054)	(0.053)	(0.050)	(0.213)
acTl	0.000664	0.000743	0.000954				
	(0.537)	(0.509)	(0.439)				
irdvDm	1.208***			1.036***	1.262***	1.249***	1.084***
	(0.003)			(0.006)	(0.001)	(0.001)	(0.003)
fxdvDm	1.101***	1.505***		0.807**	0.790**	0.789**	0.769**
	(0.005)	(0.000)		(0.020)	(0.022)	(0.022)	(0.025)
fuelExp_				−0.0000425			
				(0.651)			
revTl_					−0.00000545		
					(0.851)		
sizeAdj1_						0.00000106	
						(0.945)	
asmTl_							0.00000156
							(0.728)
intercept	4.011**	4.285**	4.170***	4.150***	4.091***	4.022***	4.859***
	(0.014)	(0.010)	(0.010)	(0.008)	(0.009)	(0.008)	(0.005)
N	504	504	504	576	609	609	536
AIC	248.9	256.6	271.3	314.3	332.9	333.0	288.1

p-values in parentheses
Variables ending with "_" in millions
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

N Alternative fixed effects models

Table N.1: Firm fixed effects models (with heteroskedastic-robust standard errors) with different financial distress proxies

	BASE (1) fdvPct12m	(2) fdvPct12m	(3) fdvPct12m	(4) fdvPct12m	(5) fdvPct12m	(6) fdvPct12m	(7) fdvPct12m	(8) fdvPct12m
lvrg1Adj1	-1.462^{***}	-1.200^{***}	-1.205^{***}	-1.186^{***}	-1.169^{***}			
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)			
lvrg1Adj1Sqr	1.254^{***}	1.071^{***}	1.080^{***}	1.065^{***}	1.066^{***}			
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)			
intCovAdj	-0.0261^{***}					-0.0217^{***}	-0.0219^{***}	-0.0336^{***}
	(0.002)					(0.007)	(0.009)	(0.000)
peRto	−0.000186	−0.000165	−0.000181	−0.000174	−0.000204	−0.000171	−0.000165	−0.000141
	(0.279)	(0.341)	(0.298)	(0.320)	(0.240)	(0.327)	(0.346)	(0.411)
crtRto	−0.0179	−0.0243	−0.0306	−0.0376	−0.0477	−0.0368	−0.0512	−0.0158
	(0.776)	(0.700)	(0.631)	(0.552)	(0.447)	(0.555)	(0.434)	(0.803)
crtRtoSqr	0.0103	0.0142	0.0150	0.0162	0.0192	0.0186	0.0186	0.0112
	(0.603)	(0.473)	(0.453)	(0.416)	(0.333)	(0.349)	(0.363)	(0.573)
sizeAdj1_	−0.000000208	−0.000000584	−0.000000828	−0.000000951	−0.00000119	−0.000000357	−0.000000398	
	(0.893)	(0.706)	(0.594)	(0.538)	(0.438)	(0.820)	(0.800)	
irdvDm	0.0785^{***}	0.0789^{***}	0.0763^{***}	0.0723^{**}	0.0752^{***}	0.0852^{***}	0.0858^{***}	0.0828^{***}
	(0.006)	(0.007)	(0.009)	(0.013)	(0.010)	(0.004)	(0.003)	(0.004)
fxdvDm	0.00478	0.00660	0.00735	0.00746	0.00729	0.00244	0.00357	0.0122
	(0.863)	(0.813)	(0.793)	(0.790)	(0.795)	(0.930)	(0.899)	(0.661)
prfMrgAdj		-0.279^{**}						
		(0.023)						
roaAdj1			−0.255					
			(0.151)					
divDm				−0.0270				
				(0.190)				
divYld					−0.298			
					(0.460)			
lvrg2Adj1						−0.590		
						(0.112)		
lvrg2Adj1Sqr						0.409		
						(0.252)		
lvrg3Adj1							-0.759^{*}	
							(0.089)	
lvrg3Adj1Sqr							0.382	
							(0.108)	
lvrg1Adj8								-1.553^{***}
								(0.000)
lvrg1Adj8Sqr								1.091^{***}
								(0.001)
sizeAdj8_								−0.000000772
								(0.594)
intercept	0.705^{***}	0.602^{***}	0.605^{***}	0.611^{***}	0.602^{***}	0.509^{***}	0.687^{***}	0.834^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
N	538	538	538	538	538	538	538	539
AIC	−597.7	−592.2	−588.5	−588.1	−586.7	−585.4	−583.2	−598.3
Adj. R^2	0.761	0.759	0.757	0.757	0.756	0.756	0.755	0.761
R^2	0.796	0.794	0.793	0.793	0.792	0.792	0.791	0.796

p-values in parentheses
Variables ending with "_" in millions of USD
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table N.2: Firm fixed effects models (with heteroskedastic-robust standard errors) with different underinvestment problem proxies

	BASE (1) fdvPct12m	(2) fdvPct12m	(3) fdvPct12m	(4) fdvPct12m	(5) fdvPct12m	(6) fdvPct12m	(7) fdvPct12m	(8) fdvPct12m	(9) fdvPct12m
lvrg1Adj1	−1.462***	−1.427***	−1.270***	−1.432***	−1.421***	−1.431***	−1.849***	−1.467***	−1.564***
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
lvrg1Adj1Sqr	1.254***	1.227***	1.088***	1.226***	1.209***	1.228***	1.736***	1.237***	1.326***
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
intCovAdj	−0.0261***	−0.0262***	−0.0300***	−0.0269***	−0.0266***	−0.0263***	−0.0305***	−0.0254***	−0.0268***
	(0.002)	(0.002)	(0.000)	(0.001)	(0.001)	(0.002)	(0.001)	(0.003)	(0.001)
peRto	−0.000186							−0.000179	−0.000179
	(0.279)							(0.296)	(0.299)
crtRto	−0.0179	−0.0239	−0.0177	−0.0226	−0.0248	−0.0211	0.0859		
	(0.776)	(0.706)	(0.777)	(0.718)	(0.694)	(0.737)	(0.293)		
crtRtoSqr	0.0103	0.0113	0.00800	0.0109	0.0114	0.0108	−0.0252		
	(0.603)	(0.569)	(0.686)	(0.582)	(0.564)	(0.587)	(0.323)		
sizeAdj1_	−0.000000208	−0.000000517	−0.00000104	−0.000000329	−0.000000346	−0.000000300	−0.000000910	−0.000000278	−0.000000298
	(0.893)	(0.749)	(0.512)	(0.832)	(0.823)	(0.846)	(0.604)	(0.857)	(0.848)
irdvDm	0.0785***	0.0789***	0.0836***	0.0804***	0.0799***	0.0779***	0.124***	0.0779***	0.0761***
	(0.006)	(0.007)	(0.004)	(0.006)	(0.006)	(0.007)	(0.001)	(0.007)	(0.008)
fxdvDm	0.00478	0.00365	−0.000246	0.00202	0.00196	0.00359	0.0393	0.00604	0.00585
	(0.863)	(0.895)	(0.993)	(0.942)	(0.944)	(0.897)	(0.258)	(0.827)	(0.832)
mtbRto		0.00143							
		(0.647)							
tobQAdj1			0.0618**						
			(0.040)						
capAsAdj1				−0.0856					
				(0.368)					
capRevAdj1					−0.0488				
					(0.407)				
capSizeAdj1						−0.0195			
						(0.856)			
acChg							0.0592		
							(0.130)		
cashRto								−0.0643	
								(0.414)	
cashRtoSqr								0.0368	
								(0.332)	
qckRto									0.0300
									(0.721)
qckRtoSqr									−0.0152
									(0.656)
intercept	0.705***	0.699***	0.598***	0.696***	0.698***	0.698***	0.714***	0.725***	0.723***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N	538	538	538	538	538	538	407	538	538
AIC	−597.7	−596.6	−601.3	−597.3	−597.2	−596.4	−436.2	−598.2	−597.3
Adj. R^2	0.761	0.761	0.763	0.761	0.761	0.761	0.739	0.761	0.761
R^2	0.796	0.796	0.798	0.796	0.796	0.796	0.784	0.796	0.796

p-values in parentheses
Variables ending with "_" in millions of USD
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table N.3: Firm fixed effects models (with heteroskedastic-robust standard errors) with different economies of scale proxies

	BASE (1) fdvPct12m	(2) fdvPct12m	(3) fdvPct12m	(4) fdvPct12m	(5) fdvPct12m	(6) fdvPct12m	(7) fdvPct12m
lvrg1Adj1	−1.462***	−1.456***	−1.521***	−1.431***	−1.483***	−1.760***	−1.994***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
lvrg1Adj1Sqr	1.254***	1.251***	1.304***	1.223***	1.264***	1.551***	1.808***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
intCovAdj	−0.0261***	−0.0261***	−0.0254***	−0.0256***	−0.0272***	−0.0312***	−0.0301***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
peRto	−0.000186	−0.000185	−0.000169	−0.000188	−0.000189	−0.000252	−0.000219
	(0.279)	(0.280)	(0.328)	(0.273)	(0.289)	(0.176)	(0.248)
crtRto	−0.0179	−0.0175	0.00153	−0.0221	−0.0262	−0.0196	0.0187
	(0.776)	(0.780)	(0.981)	(0.726)	(0.688)	(0.791)	(0.802)
crtRtoSqr	0.0103	0.0103	0.00378	0.0111	0.0120	0.0166	−0.000188
	(0.603)	(0.604)	(0.848)	(0.575)	(0.556)	(0.480)	(0.993)
sizeAdj1_	−0.000000208	−0.000000186	-6.22×10^{-8}				
	(0.893)	(0.904)	(0.968)				
irdvDm	0.0785***	0.0798***		0.0805***	0.0809***	0.0860***	0.0999***
	(0.006)	(0.004)		(0.005)	(0.006)	(0.008)	(0.002)
fxdvDm	0.00478		0.0246	0.00475	0.00460	0.00220	0.0203
	(0.863)		(0.361)	(0.863)	(0.875)	(0.946)	(0.535)
revTl_				−0.00000220			
				(0.436)			
fuelExp_					−0.00000565		
					(0.480)		
asmTl_						0.000000163	
						(0.787)	
acTl							−0.000112
							(0.334)
intercept	0.705***	0.704***	0.740***	0.712***	0.739***	0.795***	0.841***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N	538	538	538	538	516	473	466
AIC	−597.7	−599.7	−591.0	−598.4	−552.3	−478.3	−474.5
Adj. R^2	0.761	0.762	0.758	0.761	0.750	0.730	0.729
R^2	0.796	0.796	0.793	0.797	0.787	0.770	0.771

p-values in parentheses
Variables ending with "_" in millions
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table N.4: Alternative firm fixed effects models (with heteroskedastic-robust standard erros) with different sample restrictions

	BASE (1) fdvPct12m	(2) fdvPct12m	(3) fdvPct12m	(4) fdvPct12m	(5) fdvPct12m	(6) fdvPct12m	(7) fdvPct12m
lvrg1Adj1	-1.462^{***}	-1.462^{***}	-1.462^{***}	-1.460^{***}	-1.645^{***}	-1.585^{***}	-1.774^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.004)	(0.009)
lvrg1Adj1Sqr	1.254^{***}	1.260^{***}	1.254^{***}	1.249^{***}	1.403^{***}	1.503^{***}	1.549^{**}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.015)
intCovAdj	-0.0261^{***}	-0.0258^{***}	-0.0261^{***}	-0.0262^{***}	-0.0266^{***}	-0.00278	-0.0176
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.818)	(0.321)
peRto	-0.000186	-0.000185	-0.000186	-0.000180	-0.000198	-0.000100	-0.000673
	(0.279)	(0.292)	(0.279)	(0.296)	(0.255)	(0.673)	(0.109)
crtRto	-0.0179	-0.0191	-0.0179	-0.0162	-0.0145	-0.0397	0.176
	(0.776)	(0.774)	(0.776)	(0.796)	(0.819)	(0.684)	(0.128)
crtRtoSqr	0.0103	0.0107	0.0103	0.00964	0.00855	-0.00457	-0.0385
	(0.603)	(0.620)	(0.603)	(0.627)	(0.669)	(0.884)	(0.248)
sizeAdj1__	-0.000000208	-0.000000211	-0.000000208	-0.000000128	-0.000000205	-0.00000260	-0.000000945
	(0.893)	(0.894)	(0.893)	(0.934)	(0.896)	(0.370)	(0.607)
irdvDm	0.0785^{***}	0.0826^{***}	0.0785^{***}	0.0785^{***}	0.0786^{***}	0.113^{***}	0.0392
	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)	(0.009)	(0.398)
fxdvDm	0.00478	0.00346	0.00478	0.00685	0.00322	0.0339	0.0405
	(0.863)	(0.903)	(0.863)	(0.806)	(0.909)	(0.381)	(0.468)
cpaDm			0				
			(.)				
mrgDm				-0.0217			
				(0.515)			
intercept	0.705^{***}	0.674^{***}	0.705^{***}	0.704^{***}	0.761^{***}	0.701^{***}	0.697^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N	538	518	538	538	529	249	133
AIC	-597.7	-555.6	-597.7	-596.2	-580.6	-329.9	-159.4
Adj. R^2	0.761	0.703	0.761	0.761	0.758	0.801	0.831
R^2	0.796	0.747	0.796	0.796	0.793	0.837	0.863
Specification	none	CPA excl.	CPA dummy	Merger dummy	Allegiant excl.	IFRS only	US GAAP only

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

O Alternative random effects probit models with operational hedge variables

Table O.1: Alternative random effects probit models with different sample restrictions, *fDiv1*

	BASE (1) fdvDm	(2) fdvDm	(3) fdvDm	(4) fdvDm	(5) fdvDm	(6) fdvDm	(7) fdvDm
lvrg1Adj1	−14.15**	−14.12**	−14.12**	−14.17**	−13.58**	−15.89*	−4.050
	(0.013)	(0.012)	(0.012)	(0.013)	(0.037)	(0.082)	(0.762)
lvrg1Adj1Sqr	12.13**	11.68**	11.68**	12.14**	11.87*	17.93**	−6.522
	(0.025)	(0.030)	(0.030)	(0.025)	(0.052)	(0.041)	(0.652)
intCovAdj	−0.719***	−0.709***	−0.709***	−0.720***	−0.776***	−0.689**	−1.208*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.021)	(0.080)
tobQAdj1	0.395	0.435	0.435	0.398	0.552	0.0235	−0.727
	(0.357)	(0.301)	(0.301)	(0.358)	(0.250)	(0.974)	(0.533)
cashRto	3.305***	3.190**	3.190**	3.308***	3.264**	5.598**	4.553
	(0.009)	(0.010)	(0.010)	(0.009)	(0.014)	(0.011)	(0.355)
cashRtoSqr	−1.320**	−1.310**	−1.310**	−1.321**	−1.330**	−2.588***	−1.564
	(0.019)	(0.018)	(0.018)	(0.020)	(0.025)	(0.007)	(0.494)
acTl	−0.00000344	−0.000293	−0.000293	−0.000000264	0.000127	−0.000499	−0.00402
	(0.997)	(0.780)	(0.780)	(1.000)	(0.914)	(0.854)	(0.230)
irdvDm	1.177***	1.206***	1.206***	1.178***	1.147***	1.897**	1.431
	(0.003)	(0.002)	(0.002)	(0.003)	(0.006)	(0.046)	(0.201)
fxdvDm	1.115***	1.174***	1.174***	1.117***	1.311***	2.015***	−0.0466
	(0.005)	(0.002)	(0.002)	(0.005)	(0.003)	(0.006)	(0.972)
fDiv1	1.806**	1.677*	1.678*	1.808**	1.732*	0.0712	7.705
	(0.048)	(0.054)	(0.054)	(0.048)	(0.076)	(0.961)	(0.143)
cpaDm			8.219				
			(0.976)				
mrgDm				−0.0252			
				(0.966)			
intercept	2.791	2.842*	2.843*	2.793	2.537	2.133	4.041
	(0.101)	(0.087)	(0.087)	(0.101)	(0.194)	(0.431)	(0.397)
N	504	484	504	504	495	231	134
AIC	246.8	242.7	244.7	248.8	233.7	128.4	78.34
Specification	none	CPA excl.	CPA dummy	Merger dummy	Allegiant excl.	IFRS only	US GAAP only

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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Table O.2: Alternative random effects probit models with different sample restrictions, *alliDm*

	BASE (1) fdvDm	(2) fdvDm	(3) fdvDm	(4) fdvDm	(5) fdvDm	(6) fdvDm
lvrg1Adj1	-14.76^{**}	-14.88^{***}	-14.88^{***}	-14.75^{**}	-15.90^{*}	-8.283
	(0.011)	(0.009)	(0.009)	(0.011)	(0.082)	(0.520)
lvrg1Adj1Sqr	12.77^{**}	12.42^{**}	12.42^{**}	12.76^{**}	17.96^{**}	-0.0509
	(0.021)	(0.024)	(0.024)	(0.021)	(0.041)	(0.997)
intCovAdj	-0.753^{***}	-0.747^{***}	-0.747^{***}	-0.753^{***}	-0.689^{**}	-1.108^{*}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.021)	(0.069)
tobQAdj1	0.487	0.545	0.545	0.486	0.0287	-1.005
	(0.273)	(0.209)	(0.209)	(0.277)	(0.968)	(0.434)
cashRto	3.446^{***}	3.359^{***}	3.359^{***}	3.445^{***}	5.604^{**}	5.377
	(0.008)	(0.008)	(0.008)	(0.009)	(0.011)	(0.256)
cashRtoSqr	-1.396^{**}	-1.404^{**}	-1.404^{**}	-1.396^{**}	-2.589^{***}	-1.914
	(0.016)	(0.014)	(0.014)	(0.017)	(0.007)	(0.412)
acTl	-0.000427	-0.000865	-0.000865	-0.000429	-0.000549	-0.0000669
	(0.719)	(0.454)	(0.454)	(0.720)	(0.851)	(0.982)
irdvDm	1.174^{***}	1.205^{***}	1.205^{***}	1.174^{***}	1.894^{**}	1.100
	(0.004)	(0.002)	(0.002)	(0.004)	(0.046)	(0.295)
fxdvDm	1.057^{**}	1.116^{***}	1.116^{***}	1.057^{**}	2.014^{***}	0.410
	(0.010)	(0.004)	(0.004)	(0.011)	(0.006)	(0.711)
fDiv1	1.621^{*}	1.401	1.401	1.621^{*}	0.0677	10.26
	(0.095)	(0.132)	(0.132)	(0.095)	(0.963)	(0.105)
alliDm	0.467	0.574	0.574	0.468	0.0262	-5.119
	(0.301)	(0.201)	(0.201)	(0.302)	(0.965)	(0.142)
cpaDm			10.44			
			(0.998)			
mrgDm				0.00674		
				(0.991)		
intercept	2.928^{*}	3.026^{*}	3.026^{*}	2.927^{*}	2.124	2.342
	(0.090)	(0.072)	(0.072)	(0.090)	(0.434)	(0.570)
N	504	484	504	504	231	134
AIC	247.7	242.9	244.9	249.7	130.4	77.05
Specification	none	CPA excl.	CPA dummy	Merger dummy	IFRS only	US GAAP only

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table O.3: Alternative random effects probit models with different sample restrictions, *olexpTl*

	BASE (1) fdvDm	(2) fdvDm	(3) fdvDm	(4) fdvDm	(5) fdvDm	(6) fdvDm	(7) fdvDm
lvrg1Adj1	−13.83**	−13.93**	−13.93**	−13.88**	−12.74**	−13.37	−4.015
	(0.014)	(0.013)	(0.013)	(0.014)	(0.049)	(0.236)	(0.753)
lvrg1Adj1Sqr	11.94**	11.68**	11.68**	11.96**	11.23*	16.72	−5.222
	(0.026)	(0.029)	(0.029)	(0.026)	(0.064)	(0.114)	(0.697)
intCovAdj	−0.780***	−0.764***	−0.764***	−0.783***	−0.866***	−1.016***	−1.169
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.009)	(0.114)
tobQAdj1	0.407	0.439	0.439	0.416	0.610	−0.513	−0.264
	(0.345)	(0.303)	(0.303)	(0.340)	(0.214)	(0.560)	(0.815)
cashRto	3.102**	2.999**	2.999**	3.109**	3.130**	6.231**	4.555
	(0.015)	(0.017)	(0.017)	(0.015)	(0.020)	(0.021)	(0.324)
cashRtoSqr	−1.333**	−1.327**	−1.327**	−1.337**	−1.351**	−2.902**	−1.678
	(0.021)	(0.020)	(0.020)	(0.020)	(0.027)	(0.012)	(0.416)
acTl	0.00343*	0.00264	0.00264	0.00345*	0.00410**	0.0158*	0.000831
	(0.068)	(0.159)	(0.159)	(0.067)	(0.048)	(0.087)	(0.801)
irdvDm	1.161***	1.194***	1.194***	1.162***	1.100***	2.774*	1.352
	(0.004)	(0.003)	(0.003)	(0.004)	(0.009)	(0.059)	(0.223)
fxdvDm	1.209***	1.235***	1.235***	1.217***	1.478***	3.266***	0.0609
	(0.002)	(0.002)	(0.002)	(0.003)	(0.001)	(0.006)	(0.962)
olexpTl_	−0.00194**	−0.00155	−0.00155	−0.00195**	−0.00235**	−0.00955**	−0.00141
	(0.048)	(0.115)	(0.115)	(0.048)	(0.031)	(0.038)	(0.429)
cpaDm			11.01				
			(1.000)				
mrgDm				−0.0933			
				(0.880)			
intercept	4.052**	4.039**	4.039**	4.063**	3.618*	1.841	7.169
	(0.014)	(0.013)	(0.013)	(0.014)	(0.053)	(0.559)	(0.127)
N	504	484	504	504	495	231	134
AIC	246.6	243.9	245.9	248.6	231.6	117.1	80.64
Specification	none	CPA excl.	CPA dummy	Merger dummy	Allegiant excl.	IFRS only	US GAAP only

p-values in parentheses

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

Table O.4: Alternative random effects probit models with different sample restrictions, *acOlPct*

	BASE (1) fdvDm	(2) fdvDm	(3) fdvDm	(4) fdvDm	(5) fdvDm	(6) fdvDm	(7) fdvDm
lvrg1Adj1	−16.09**	−16.53***	−16.53***	−16.08**	−15.81**	−24.31***	−1.557
	(0.010)	(0.007)	(0.007)	(0.010)	(0.043)	(0.009)	(0.910)
lvrg1Adj1Sqr	14.78**	14.58**	14.58**	14.77**	14.97**	23.09***	−12.71
	(0.012)	(0.012)	(0.012)	(0.012)	(0.035)	(0.008)	(0.415)
intCovAdj	−0.698***	−0.681***	−0.682***	−0.698***	−0.798***	−0.524*	−1.299*
	(0.001)	(0.000)	(0.000)	(0.001)	(0.002)	(0.052)	(0.090)
tobQAdj1	−0.265	−0.197	−0.197	−0.266	−0.231	−0.369	−0.201
	(0.595)	(0.688)	(0.688)	(0.596)	(0.683)	(0.567)	(0.863)
cashRto	5.594***	5.309***	5.310***	5.593***	5.930***	5.432***	2.755
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.006)	(0.598)
cashRtoSqr	−2.573***	−2.501***	−2.501***	−2.572***	−2.772***	−2.591***	−1.030
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.003)	(0.656)
acTl	−0.000332	−0.000556	−0.000556	−0.000334	−0.000337	−0.00129	−0.00211
	(0.753)	(0.578)	(0.578)	(0.752)	(0.775)	(0.542)	(0.460)
irdvDm	1.515***	1.514***	1.514***	1.514***	1.630***	1.399**	1.475
	(0.003)	(0.002)	(0.002)	(0.003)	(0.006)	(0.042)	(0.173)
fxdvDm	1.012**	1.097**	1.097**	1.011**	1.289**	1.881***	0.490
	(0.028)	(0.013)	(0.013)	(0.028)	(0.018)	(0.003)	(0.713)
acOlPct	0.215	0.167	0.167	0.212	0.124	−0.777	4.550
	(0.804)	(0.837)	(0.837)	(0.808)	(0.900)	(0.454)	(0.212)
cpaDm			8.713				
			(0.991)				
mrgDm				0.0129			
				(0.984)			
intercept	4.266**	4.411**	4.413**	4.265**	4.122*	5.626**	7.770
	(0.021)	(0.015)	(0.015)	(0.021)	(0.076)	(0.038)	(0.115)
N	385	365	385	385	376	187	134
AIC	193.6	189.4	191.4	195.6	179.9	119.0	79.57
Specification	none	CPA excl.	CPA dummy	Merger dummy	Allegiant excl.	IFRS only	US GAAP only

p-values in parentheses

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

Table O.5: Alternative random effects probit models with different sample restrictions, *acOlcashDm*

	BASE (1) fdvDm	(2) fdvDm	(3) fdvDm	(4) fdvDm	(5) fdvDm	(6) fdvDm	(7) fdvDm
lvrg1Adj1	−15.31**	−15.67***	−15.66***	−15.31**	−15.09*	−22.81**	−1.507
	(0.013)	(0.010)	(0.010)	(0.014)	(0.051)	(0.012)	(0.914)
lvrg1Adj1Sqr	13.79**	13.46**	13.46**	13.79**	14.04**	21.95**	−12.79
	(0.018)	(0.020)	(0.020)	(0.018)	(0.047)	(0.011)	(0.424)
intCovAdj	−0.684***	−0.667***	−0.667***	−0.684***	−0.769***	−0.504*	−1.504
	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.063)	(0.115)
tobQAdj1	−0.311	−0.243	−0.243	−0.311	−0.281	−0.345	−0.226
	(0.531)	(0.617)	(0.617)	(0.533)	(0.615)	(0.601)	(0.859)
cashRto	5.976***	5.671***	5.671***	5.977***	6.196***	5.261***	8.128
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.009)	(0.217)
cashRtoSqr	−2.684***	−2.604***	−2.604***	−2.685***	−2.840***	−2.513***	−2.944
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.004)	(0.267)
acTl	−0.000326	−0.000545	−0.000545	−0.000326	−0.000338	−0.00102	−0.00149
	(0.754)	(0.579)	(0.579)	(0.755)	(0.771)	(0.639)	(0.600)
irdvDm	1.503***	1.511***	1.510***	1.503***	1.606***	1.466**	1.539
	(0.003)	(0.002)	(0.002)	(0.003)	(0.005)	(0.043)	(0.193)
fxdvDm	0.947**	1.023**	1.023**	0.947**	1.208**	1.682**	0.0726
	(0.037)	(0.018)	(0.018)	(0.038)	(0.024)	(0.010)	(0.960)
acOlcashDm	0.515	0.541	0.541	0.515	0.435	0.200	1.296
	(0.262)	(0.230)	(0.230)	(0.262)	(0.372)	(0.773)	(0.314)
cpaDm			7.491				
			(0.955)				
mrgDm				−0.00117			
				(0.999)			
intercept	3.983**	4.100**	4.098**	3.983**	3.862*	4.856*	7.530
	(0.028)	(0.020)	(0.020)	(0.028)	(0.089)	(0.057)	(0.147)
N	385	365	385	385	376	187	134
AIC	192.3	188.0	190.0	194.3	179.1	119.5	79.85
Specification	none	CPA excl.	CPA dummy	Merger dummy	Allegiant excl.	IFRS only	US GAAP only

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

P Alternative fixed effects models with operational hedge variables

Table P.1: Alternative firm fixed effects models (with heteroskedastic-robust standard errors) with different sample restrictions, *fDiv1*

	BASE (1) fdvPct12m	(2) fdvPct12m	(3) fdvPct12m	(4) fdvPct12m	(5) fdvPct12m	(6) fdvPct12m	(7) fdvPct12m
lvrg1Adj1	−2.037***	−2.064***	−2.037***	−2.029***	−2.328***	−2.370***	−1.793***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.010)
lvrg1Adj1Sqr	1.862***	1.886***	1.862***	1.848***	2.110***	2.276***	1.573**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.016)
intCovAdj	−0.0297***	−0.0300***	−0.0297***	−0.0298***	−0.0297***	−0.00669	−0.0180
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.594)	(0.316)
peRto	−0.000296	−0.000298	−0.000296	−0.000287	−0.000321*	−0.000109	−0.000674
	(0.120)	(0.127)	(0.120)	(0.133)	(0.095)	(0.660)	(0.110)
crtRto	0.0113	0.0184	0.0113	0.0130	0.0177	−0.0200	0.178
	(0.879)	(0.816)	(0.879)	(0.861)	(0.812)	(0.843)	(0.127)
crtRtoSqr	0.00354	0.000425	0.00354	0.00281	0.0000830	−0.0161	−0.0384
	(0.877)	(0.987)	(0.877)	(0.902)	(0.997)	(0.619)	(0.252)
sizeAdj1__	-6.21×10^{-8}	-6.86×10^{-8}	-6.21×10^{-8}	5.08×10^{-8}	-6.95×10^{-8}	−0.00000157	−0.000000976
	(0.970)	(0.967)	(0.970)	(0.975)	(0.966)	(0.595)	(0.599)
irdvDm	0.0951***	0.0988***	0.0951***	0.0949***	0.0944***	0.182***	0.0394
)	(0.003)	(0.004)	(0.003)	(0.004)	(0.004)	(0.000)	(0.399)
fxdvDm	0.0116	0.0106	0.0116	0.0145	0.0108	0.0446	0.0388
	(0.722)	(0.751)	(0.722)	(0.658)	(0.745)	(0.328)	(0.494)
fDiv1	0.379***	0.380***	0.379***	0.391***	0.399***	0.0636	0.0431
	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.688)	(0.860)
cpaDm			0				
			(.)				
mrgDm				−0.0320			
				(0.370)			
intercept	0.587***	0.558***	0.587***	0.576***	0.653***	0.816***	0.671***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.006)
N	466	446	466	466	457	218	133
AIC	−482.6	−442.0	−482.6	−481.6	−467.9	−289.7	−157.4
Adj. R^2	0.734	0.664	0.734	0.734	0.729	0.796	0.829
R^2	0.776	0.718	0.776	0.777	0.772	0.834	0.863
Specification	none	CPA excl.	CPA dummy	Merger dummy	Allegiant excl.	IFRS only	US GAAP only

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table P.2: Alternative firm fixed effects models (with heteroskedastic-robust standard errors) with different sample restrictions, *alliDm*

	BASE (1) fdvPct12m	(2) fdvPct12m	(3) fdvPct12m	(4) fdvPct12m	(5) fdvPct12m	(6) fdvPct12m	(7) fdvPct12m
lvrg1Adj1	-2.035^{***}	-2.063^{***}	-2.035^{***}	-2.025^{***}	-2.327^{***}	-2.360^{***}	-1.793^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.010)
lvrg1Adj1Sqr	1.854^{***}	1.877^{***}	1.854^{***}	1.839^{***}	2.103^{***}	2.271^{***}	1.573^{**}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.016)
intCovAdj	-0.0300^{***}	-0.0303^{***}	-0.0300^{***}	-0.0301^{***}	-0.0299^{***}	-0.00532	-0.0180
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.672)	(0.316)
peRto	-0.000293	-0.000297	-0.000293	-0.000283	-0.000319^{*}	-0.0000976	-0.000674
	(0.122)	(0.128)	(0.122)	(0.136)	(0.096)	(0.693)	(0.110)
crtRto	0.0266	0.0350	0.0266	0.0288	0.0333	-0.00193	0.178
	(0.719)	(0.658)	(0.719)	(0.697)	(0.656)	(0.985)	(0.127)
crtRtoSqr	-0.000392	-0.00397	-0.000392	-0.00126	-0.00391	-0.0203	-0.0384
	(0.986)	(0.875)	(0.986)	(0.956)	(0.865)	(0.531)	(0.252)
sizeAdj1__	-0.000000596	-0.000000603	-0.000000596	-0.000000484	-0.000000612	-0.00000272	-0.000000976
	(0.717)	(0.720)	(0.717)	(0.769)	(0.712)	(0.381)	(0.599)
irdvDm	0.0861^{***}	0.0887^{**}	0.0861^{***}	0.0858^{***}	0.0854^{***}	0.179^{***}	0.0394
	(0.008)	(0.011)	(0.008)	(0.009)	(0.009)	(0.000)	(0.399)
fxdvDm	0.0107	0.0101	0.0107	0.0139	0.00985	0.0435	0.0388
	(0.741)	(0.763)	(0.741)	(0.671)	(0.766)	(0.339)	(0.494)
fDiv1	0.404^{***}	0.409^{***}	0.404^{***}	0.418^{***}	0.426^{***}	0.0972	0.0431
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.545)	(0.860)
alliDm	0.0810^{**}	0.0810^{*}	0.0810^{**}	0.0826^{**}	0.0820^{**}	0.0591	0
	(0.047)	(0.053)	(0.047)	(0.043)	(0.045)	(0.227)	(.)
cpaDm			0				
			(.)				
mrgDm				-0.0349			
				(0.326)			
intercept	0.535^{***}	0.504^{***}	0.535^{***}	0.522^{***}	0.599^{***}	0.761^{***}	0.671^{***}
	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)	(0.006)
N	466	446	466	466	457	218	133
AIC	-485.4	-444.5	-485.4	-484.5	-470.7	-289.6	-157.4
Adj. R^2	0.736	0.667	0.736	0.736	0.731	0.796	0.829
R^2	0.778	0.721	0.778	0.779	0.774	0.836	0.863
Specification	none	CPA excl.	CPA dummy	Merger dummy	Allegiant excl.	IFRS only	US GAAP only

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table P.3: Alternative firm fixed effects models (with heteroskedastic-robust standard errors) with different sample restrictions, *olexpTl*

	BASE (1) fdvPct12m	(2) fdvPct12m	(3) fdvPct12m	(4) fdvPct12m	(5) fdvPct12m	(6) fdvPct12m	(7) fdvPct12m
lvrg1Adj1	−1.332***	−1.326***	−1.332***	−1.324***	−1.499***	−1.490***	−1.153*
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.007)	(0.073)
lvrg1Adj1Sqr	1.142***	1.147***	1.142***	1.130***	1.277***	1.425***	0.926
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.004)	(0.125)
intCovAdj	−0.0294***	−0.0291***	−0.0294***	−0.0296***	−0.0298***	−0.00587	−0.0164
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.638)	(0.319)
peRto	−0.000208	−0.000206	−0.000208	−0.000200	−0.000215	−0.000133	−0.000633
	(0.227)	(0.240)	(0.227)	(0.244)	(0.215)	(0.576)	(0.105)
crtRto	−0.0260	−0.0286	−0.0260	−0.0242	−0.0225	−0.0410	0.119
	(0.678)	(0.667)	(0.678)	(0.699)	(0.722)	(0.674)	(0.273)
crtRtoSqr	0.0125	0.0135	0.0125	0.0118	0.0108	−0.00334	−0.0277
	(0.526)	(0.533)	(0.526)	(0.553)	(0.588)	(0.915)	(0.373)
sizeAdj1__	0.00000125	0.00000131	0.00000125	0.00000142	0.00000118	−0.00000101	0.00000300
	(0.468)	(0.455)	(0.468)	(0.413)	(0.497)	(0.759)	(0.125)
irdvDm	0.0853***	0.0910***	0.0853***	0.0856***	0.0849***	0.121***	0.0366
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.006)	(0.396)
fxdvDm	0.00551	0.00373	0.00551	0.00826	0.00432	0.0384	0.0316
	(0.842)	(0.895)	(0.842)	(0.767)	(0.878)	(0.324)	(0.542)
olexpTl__	−0.000143*	−0.000150*	−0.000143*	−0.000149**	−0.000135*	−0.000110	−0.000523***
	(0.054)	(0.050)	(0.054)	(0.045)	(0.072)	(0.299)	(0.000)
cpaDm			0				
			(.)				
mrgDm				−0.0285			
				(0.394)			
intercept	0.709***	0.677***	0.709***	0.708***	0.758***	0.686***	0.808***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N	538	518	538	538	529	249	133
AIC	−600.1	−558.1	−600.1	−599.0	−582.4	−329.2	−178.1
Adj. R^2	0.763	0.705	0.763	0.762	0.759	0.801	0.854
R^2	0.798	0.749	0.798	0.798	0.795	0.837	0.882
Specification	none	CPA excl.	CPA dummy	Merger dummy	Allegiant excl.	IFRS only	US GAAP only

p-values in parentheses

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

Table P.4: Alternative firm fixed effects models (with heteroskedastic-robust standard errors) with different sample restrictions, *acOlPct*

	BASE (1) fdvPct12m	(2) fdvPct12m	(3) fdvPct12m	(4) fdvPct12m	(5) fdvPct12m	(6) fdvPct12m	(7) fdvPct12m
lvrg1Adj1	-2.044^{***}	-2.107^{***}	-2.044^{***}	-2.046^{***}	-2.472^{***}	-2.711^{***}	-1.720^{**}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.012)
lvrg1Adj1Sqr	1.876^{***}	1.945^{***}	1.876^{***}	1.871^{***}	2.234^{***}	2.571^{***}	1.521^{**}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.017)
intCovAdj	-0.0220^{**}	-0.0222^{**}	-0.0220^{**}	-0.0221^{**}	-0.0232^{**}	−0.00128	−0.0200
	(0.030)	(0.034)	(0.030)	(0.028)	(0.030)	(0.938)	(0.266)
peRto	-0.000309^{*}	−0.000311	-0.000309^{*}	−0.000301	-0.000340^{*}	−0.000145	−0.000639
	(0.093)	(0.102)	(0.093)	(0.102)	(0.068)	(0.596)	(0.130)
crtRto	0.100	0.122	0.100	0.104	0.113	0.0380	0.191
	(0.202)	(0.152)	(0.202)	(0.186)	(0.153)	(0.756)	(0.103)
crtRtoSqr	−0.0285	−0.0377	−0.0285	−0.0300	−0.0337	−0.0345	−0.0426
	(0.227)	(0.159)	(0.227)	(0.204)	(0.159)	(0.361)	(0.207)
sizeAdj1_	−0.000000756	−0.000000767	−0.000000756	−0.000000629	−0.000000759	−0.00000230	−0.000000644
	(0.629)	(0.633)	(0.629)	(0.688)	(0.630)	(0.504)	(0.731)
irdvDm	0.0938^{***}	0.106^{***}	0.0938^{***}	0.0958^{***}	0.0913^{***}	0.225^{***}	0.0255
	(0.007)	(0.005)	(0.007)	(0.006)	(0.009)	(0.001)	(0.603)
fxdvDm	0.0241	0.0214	0.0241	0.0269	0.0213	0.0502	0.0247
	(0.489)	(0.551)	(0.489)	(0.441)	(0.549)	(0.420)	(0.674)
acOlPct	−0.0362	−0.0276	−0.0362	−0.0247	−0.0294	0.0443	−0.136
	(0.629)	(0.724)	(0.629)	(0.745)	(0.698)	(0.660)	(0.392)
cpaDm			0				
			(.)				
mrgDm				−0.0333			
				(0.343)			
intercept	0.787^{***}	0.739^{***}	0.787^{***}	0.779^{***}	0.905^{***}	0.865^{***}	0.734^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N	364	344	364	364	355	179	133
AIC	−444.4	−401.4	−444.4	−443.5	−428.8	−214.1	−158.3
Adj. R^2	0.788	0.711	0.788	0.788	0.784	0.786	0.830
R^2	0.822	0.759	0.822	0.823	0.819	0.829	0.864
Specification	none	CPA excl.	CPA dummy	Merger dummy	Allegiant excl.	IFRS only	US GAAP only

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table P.5: Alternative firm fixed effects models (with heteroskedastic-robust standard errors) with different sample restrictions, *acOlcashDm*

	BASE (1) fdvPct12m	(2) fdvPct12m	(3) fdvPct12m	(4) fdvPct12m	(5) fdvPct12m	(6) fdvPct12m	(7) fdvPct12m
lvrg1Adj1	-2.029^{***}	-2.097^{***}	-2.029^{***}	-2.034^{***}	-2.461^{***}	-2.768^{***}	-1.734^{**}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.010)
lvrg1Adj1Sqr	1.862^{***}	1.936^{***}	1.862^{***}	1.862^{***}	2.224^{***}	2.607^{***}	1.516^{**}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.016)
intCovAdj	-0.0213^{**}	-0.0218^{**}	-0.0213^{**}	-0.0218^{**}	-0.0226^{**}	-0.00308	-0.0228
	(0.032)	(0.035)	(0.032)	(0.028)	(0.031)	(0.845)	(0.205)
peRto	-0.000313^{*}	-0.000314^{*}	-0.000313^{*}	-0.000303	-0.000343^{*}	-0.000155	-0.000727^{*}
	(0.089)	(0.098)	(0.089)	(0.100)	(0.065)	(0.570)	(0.083)
crtRto	0.0938	0.118	0.0938	0.0988	0.108	0.0528	0.166
	(0.234)	(0.169)	(0.234)	(0.211)	(0.175)	(0.669)	(0.149)
crtRtoSqr	-0.0277	-0.0375	-0.0277	-0.0294	-0.0331	-0.0370	-0.0400
	(0.240)	(0.163)	(0.240)	(0.214)	(0.168)	(0.331)	(0.227)
sizeAdj1_	-0.000000821	-0.000000819	-0.000000821	-0.000000670	-0.000000813	-0.00000230	-0.000000867
	(0.598)	(0.609)	(0.598)	(0.669)	(0.605)	(0.503)	(0.635)
irdvDm	0.0989^{***}	0.110^{***}	0.0989^{***}	0.0994^{***}	0.0954^{***}	0.214^{***}	0.0451
	(0.003)	(0.002)	(0.003)	(0.003)	(0.005)	(0.001)	(0.330)
fxdvDm	0.0232	0.0208	0.0232	0.0265	0.0206	0.0552	0.0253
	(0.505)	(0.562)	(0.505)	(0.448)	(0.562)	(0.355)	(0.652)
acOlcashDm	-0.0104	-0.00922	-0.0104	-0.0101	-0.00842	0.0200	-0.0664
	(0.705)	(0.755)	(0.705)	(0.713)	(0.761)	(0.626)	(0.120)
cpaDm			0				
			(.)				
mrgDm				-0.0350			
				(0.312)			
intercept	0.772^{***}	0.728^{***}	0.772^{***}	0.770^{***}	0.894^{***}	0.894^{***}	0.721^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N	364	344	364	364	355	179	133
AIC	-444.3	-401.4	-444.3	-443.5	-428.7	-214.1	-160.4
Adj. R^2	0.788	0.711	0.788	0.788	0.784	0.786	0.833
R^2	0.822	0.759	0.822	0.823	0.819	0.829	0.866
Specification	none	CPA excl.	CPA dummy	Merger dummy	Allegiant excl.	IFRS only	US GAAP only

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Q Cluster analysis

There exists a multitude of ways to cluster a data set (Anderberg, 1973). The formation of the clusters in this study is based on the following procedure: first, a cluster analysis with Stata's average linkage function is performed. Clustering with average linkage is a hierarchical (or agglomerative) clustering method (Anderberg, 1973). Each observation forms its own group in the beginning. Thereafter, the two groups which are closest in their average similarity of cluster variables are merged. This process is repeated until all observations are part of one large group (StataCorp, 2013b). To determine the appropriate number of clusters, the formula by Duda et al. (2001) is employed as a stopping rule. The greater the index, the more distinct the clustering. The Duda-Hart-Stork index indicates that three clusters are the most appropriate number of clusters for the data set at hand. Lastly, cluster analysis using Stata's *kmeans* function is run on the cluster variables *lvrg1Adj1*, *intCovAdj*, *tobQAdj1*, and *cashRto*.[140] With the *kmeans* function, the clustering starts with a predefined number of clusters (three clusters in this study). Due to the predefined number of clusters, *kmeans* belongs to the nonhierarchical clustering methods. In nonhierarchical clustering methods, each observation is first assigned to an initially partitioned cluster and subsequently may change to another cluster based on the chosen algorithm (Anderberg, 1973). *kmeans* assigns the observations to the cluster which matches the most with regards to the mean value of the cluster variables (StataCorp, 2013a). In order to avoid that an airline is in Cluster 1 in one year and in Cluster 2 in the second year, the panel data set is collapsed to a cross-sectional data set. The mean value of the variable of interest is computed for all observations of an airline over the period of analysis.

Table Q.1 shows the cluster variables, the descriptive variables and the regions in the first column. The mean values of the variables for each cluster are presented in columns two, four and six. The third, fifth and seventh column contain the number of observations for each cluster. Cluster 1 contains 36 airlines, the majority are Asian airlines (16), followed by American (10), European (8), African (1), and Oceanian carriers (1). That cluster is characterized by the highest adjusted leverage ratio (*lvrg1Adj1*), the lowest adjusted interest coverage ratio (*intCovAdj*), the lowest adjusted Tobin's Q (*tobQAdj1*) and the lowest cash ratio (*cashRto*). The descriptive variables indicate that Cluster 1 is the largest in terms of the number of aircraft (*acTl*), operates the most heterogeneous

[140] The separate procedure of first running average linkage before *kmeans* is necessary because the Duda-Hart-Stork stopping rule only works for hierarchical cluster analysis (StataCorp, 2013c).

fleet (*fDiv1*) and shows the highest level of operating lease expenses (*olexpTl*). The airlines of Cluster 1 show the lowest levels of hedge ratios which is in line with the financial distress theory.

Cluster 2 is the smallest cluster with only 10 airlines, five Asian, two American, two European, and one Oceanian airline. It is the most financially sound cluster with the lowest debt ratio, the highest adjusted interest coverage ratio, the highest Tobin's Q, the largest cash ratios, and the lowest operating lease expenses. Moreover, the airlines of Cluster 2 operate the smallest and least diverse fleets. Half of the airlines of that cluster are low-cost airlines and less than a third belong to an alliance. The hedge ratio lies between Cluster 1 and Cluster 3.

The cluster variables of the 28 airlines of Cluster 3 lie between the airlines of Cluster 1 and Cluster 3. In addition, their size, fleet diversity and total operating lease expenses range between the other two clusters. Merely the hedge ratio is the highest of all three clusters, which does not correspond to the multivariate results.

Table Q.1: Clusteranalysis: mean cross-sectional airline average values of selected variables of the three clusters

	Cluster 1		Cluster 2		Cluster 3	
	Mean	Obs.	Mean	Obs.	Mean	Obs.
Cluster variables						
lvrg1Adj1	0.579	36	0.333	10	0.464	28
intCovAdj	0.854	36	3.576	10	1.688	28
tobQAdj1	1.152	36	1.345	10	1.169	28
cashRto	0.444	36	0.975	10	0.666	28
Descriptive variables						
acTl	226.976	30	112.355	10	198.912	25
fdvPct12m	0.219	36	0.290	10	0.387	25
fDiv1	0.716	30	0.444	10	0.667	25
*olexpTl_*	435.235	36	166.471	10	265.127	28
lccDm	0.194	36	0.500	10	0.143	28
alliDm	0.448	36	0.287	10	0.467	28
Regions						
AF		1		0		1
AM		10		2		11
AS		16		5		6
EU		8		2		8
OC		1		1		2

Variables ending with "_" in millions of USD

Table Q.2: Sample airlines divided into the three clusters

Cluster 1	**Cluster 2**	**Cluster 3**
Air Berlin	Air Arabia	Aegean Airlines
Air Canada	Allegiant Air	Aer Lingus
Air France-KLM	Copa Airlines	Aeroflot
AirTran Airways	easyJet	Air China
American Airlines	Japan Airlines	Air New Zealand
Asiana	Jazeera Airways	AirAsia
China Airlines	Regional Express	Alaska Airlines
China Eastern Airlines	Ryanair	All Nippon Airways
China Southern Airlines	Singapore Airlines	Avianca
Continental Airlines	Turkish Airlines	British Airways
Cyprus Airways		Cathay Pacific
Delta Air Lines		Comair
El Al		Great Lakes
EVA Air		Hawaiian Airlines
Finnair		Iberia
Flybe		Icelandair
Garuda Indonesia		IAG
Gol		JetBlue
Hainan Airlines		LAN
Jet Airways		Lufthansa
Kenya Airways		Qantas
Korean Air		Republic Airways
LATAM		Shandong Airlines
Malaysia Airlines		SkyWest
Norwegian Air Shuttle		Southwest
Kenya Airways		Spirit
PIA		TAM
SAS		TransAsia
SpiceJet		
Thai Airways		
Tigerair		
United Airlines		
US Airways		
UTair		
Virgin Australia		
Volaris		
Vueling		

R Alternative differences-of-means tests with selective hedging variables

Table R.1: Alternative differences-of-means test between active (*activeChg3*=1) and passive (*activeChg3*=0) hedgers: selective hedging variables

	Active hedgers		Passive hedgers		t test		
	Mean	Obs.	Mean	Obs.	Diff.	SE	Obs.
*fdvPsumt1_*	55.3	111	9.8	165	−45.5**	15.6	276
*fdvLsumt1_*	−64.2	111	−2.3	165	61.9***	17.6	276
*fdvPefft1_*	23.7	112	6.2	167	−17.4	12.1	279
*fdvLefft1_*	−35.8	112	−3.5	167	32.3	17.9	279
*fdvPsumt2_*	80.2	92	9.1	145	−71.0***	19.2	237
*fdvLsumt2_*	−38.8	92	−7.8	145	31.0*	14.0	237
*fdvPefft2_*	23.3	96	6.5	148	−16.8	8.7	244
*fdvLefft2_*	−30.2	96	−2.2	148	28.0	15.6	244
acTl	226.9	147	208.4	121	−18.5	26.8	268
*fuelExp_*	2403.1	152	1383.6	155	−1019.5***	254.4	307
*revTl_*	8304.6	152	4318.3	174	−3986.3***	899.2	326
revTlln	22.2	152	21.2	174	−1.0***	0.1	326
*sizeAdj1_*	13663.8	150	7419.0	173	−6244.8***	1468.2	323
irdvDm	0.7	152	0.4	174	−0.3***	0.1	326
fxdvDm	0.7	152	0.4	174	−0.4***	0.1	326

* p<0.05, ** p<0.01, *** p<0.001

Variables ending with "_" in millions of USD

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