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'You have created a monster, and it will destroy you.'
(Mary Shelly, Frankenstein, 1818)

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ZUSAMMENFASSUNG

In dieser Arbeit wird das Absicherungsverhalten von Fluggesellschaften von 2005 bis 2019 anhand eines unausgewogenen Paneldatensatzes analysiert, der insgesamt 78 Fluggesellschaften aus 39 Ländern umfasst. Der Fokus der Analyse liegt auf finanzieller und operativer Absicherung sowie dem Einfluss beidiger auf den Austoß von CO_2-Emissionen und die Entwicklung der emittierten CO_2-Emissionen. Für die Analyse wurden Probit-Modelle mit Zufallseffekten und OLS-Modelle mit festen Effekten verwendet.

Die Ergebnisse bezüglich der Beziehung zwischen Leverage und finanzieller Absicherung deuten auf eine negative Beziehung hin. Für Fluggesellschaften mit hohem Leverage deuten sie hingegen auf eine nicht-lineare konvexe Beziehung hin, was der Theorie der finanziellen Notlage widerspricht. Darüber hinaus liefern die Untersuchungen Belege dafür, dass Fluggesellschaften, die andere Arten von Derivaten, wie z.B. Zinsderivate, verwenden, mehr Treibstoffabsicherungen vornehmen.

In Bezug auf die operative Absicherung deutet die Analyse darauf hin, dass der Betrieb einer diversifizierten Flotte mehr eine Ergänzung als ein Ersatz für die finanzielle Absicherung ist. In Bezug auf die Mitgliedschaft in einer Allianz zeigen die Ergebnisse nicht, dass die Mitgliedschaft in einer Allianz ein Ersatz für finanzielle Absicherung ist, da Mitglieder von Allianzen mit größerer Wahrscheinlichkeit und in größerem Umfang Absicherungsgeschäfte tätigen.

Die Analyse zeigt, dass die relativen CO_2-Emissionen im Berichtszeitraum gesunken sind, dies gilt jedoch nicht für die absolute Menge. Über den Einfluss von finanzieller und operativer Absicherung auf die CO_2-Emissionen kann keine allgemeine Aussage getroffen werden, da die Ergebnisse uneinheitlich sind.

ABSTRACT

Within this thesis the hedging behaviour of airlines from 2005 to 2019 is analysed by using an unbalanced panel dataset consisting of a total of 78 airlines from 39 countries. The focus of the analysis is on financial and operational hedging as well as the influence of both on CO_2 emissions and the development of emitted CO_2 emissions. For the analysis Probit models with random effects and OLS models with fixed effects were used.

The results regarding the relationship between leverage and financial hedging indicate a negative relationship between leverage and financial fuel hedging and a non-linear convex relationship for highly leveraged airlines, which is contrary to the theory of financial distress. In addition, the study provides evidence that airlines using other types of derivatives, such as interest rate derivatives, engage in more fuel hedging.

In terms of operational hedging, the analysis suggests that operating a diversified fleet is a complement to, rather than a substitute for, financial hedging. With regard to alliance membership, the results do not show that alliance membership is a substitute for financial hedging, as members of alliances are more likely to engage in hedging transactions and to a greater extent.

The analysis shows that the relative CO_2 emissions fall in the period under review, but this does not apply to the absolute amount. No general statement can be made about the influence of financial and operational hedging on CO_2 emissions, as the results are mixed.

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1 INTRODUCTION

Fuel costs account for 10% to 20% of airlines' operating costs (Carter et al., 2006), which is why airlines use options such as deploying fuel-efficient aircraft, passing the additional costs on to passengers[1] or hedging fuel prices to counter the high, fluctuating kerosene prices (Morrell and Swan, 2006). The use of fuel-efficient aircraft falls under operational hedging and fuel price hedging under financial hedging, both of which are considered in this paper. Due to the inclusion of European airlines in the EU ETS, the question on how financial and operational hedging could influence the emitted CO_2 and how the amount of emitted CO_2 developed is discussed as a third part of this thesis.

Financial hedging in this context refers to the holding of financial fuel derivatives. On the one hand, it aims to prevent the probability of bankruptcy and reduce the cost of financial distress (Smith and Stulz, 1985; Froot et al., 1993; Nance et al., 1993; Gay and Nam, 1998). Within the sample period the airlines American Airlines, Delta Air Lines, Hawaiian Airlines and US Airways have filed for bankruptcy protection via Chapter 11 in the U.S. On the other hand, financial protection should help companies to avoid a suboptimal investment policy (Stulz, 1990; Froot et al., 1993). In the literature, arguments such as tax incentives (Smith and Stulz, 1985; Graham and Rogers, 1999; Sprcic and Sevic, 2012), wealth maximisation of management (Tufano, 1996; Rogers, 2002) and economies of scale (Warner, 1977; Gayand Nam, 1998; Carter et al., 2006) play a role in the hedging behaviour of companies, but are only marginally considered due to the scope of this thesis. The intensity of the use of fuel derivatives varies from airline to airline: Lufthansa, for example, has hedged around 77% of its fuel consumption over the next 12 months in the sample period, while Singapore Airlines has hedged 32%. This thesis therefore examines the hedging behaviour of global airlines, focusing on the question why airlines undertake financial hedging and why others do not.

As operational hedging instruments within this thesis fleet diversity, alliance mem-

[1] Compared to other fuel-dependent companies, the success of such a pass-through is difficult to judge. Airlines that have increased their fares and surcharges in the past have had to reverse them because their competitors did not respond with similar price increases (Cobbs and Wolf, 2004).

bership and aircraft operating leasing are considered. Compared to financial hedging, operational hedging is effective in the long term (Huchzermeier and Cohen, 1996; Van Miegham, 2003; Kim et al., 2006) and the costs can be spread over a longer time horizon. Due to that, the question on whether they are complements or substitutes is addressed as well (Allayannis et al., 2001; Chod et al., 2010; Hu et al., 2018).

In order to control emitted emissions from aircraft, the EU has included the aviation industry in its ETS since 2012. There is no general consensus in the literature on whether such a measure is suitable to significantly reduce GHG emissions (Crespo and Wang, 2019; Larsson et al., 2019), which is why the CO_2 emissions emitted by the airlines included in the sample are analysed. With regard to aircraft emissions, operational hedging should be promoted more strongly, as it has a positive effect on them compared to financial hedging (Hu et al., 2018), which is also being investigated.

The sample is described in detail at the beginning (Chapter 2), whereby the description is already focussed on the three topics. It consists of 78 airlines from 39 countries between 2005 and 2019, resulting in 924 firm years. The dataset is described and analysed by dividing it into five regions (Africa, America, Asia, Europe and Oceania) and into the two business models (low-cost and network legacy carriers). The three topics already mentioned are considered in separate chapters, starting with Financial Hedging in Chapter 3, followed by Operational Hedging in Chapter 4 and the EU ETS in Chapter 5. Each chapter begins with a summary of the literature, followed by a description of the hypotheses. This is followed by a description of the empirical analysis and finally a summary of the results. The analysis uses Probit models with random effects and OLS models with fixed effects to take into account the characteristics of the airlines. Finally, the work is summarised in Chapter 6.

One of the contributions of this paper to the existing literature is that there is a negative relationship between leverage and fuel hedging. A non-linear convex relationship between leverage and fuel hedging for highly leveraged airlines is found, which is contrary to the existing literature. Consistent with the prevailing view that hedging is costly and requires a risk management team (cf. Dolde, 1993; Géczy et al., 1997; Graham and Rogers, 2002), the finding that the use of interest rate and foreign exchange derivatives in addition to fuel hedging instruments has a positive impact on the decision to use fuel hedging instruments is consistent. Concerning operational hedging this thesis contributes to the question on whether financial and operational hedging are complements or substitutes in a way that the results indicate that they are rather complements concerning the fleet diversity and that they are not substitutes concerning alliance membership. As a fifth result, the analysis shows that the intensity of CO_2 emissions fell in the period under review, but this does not

apply to the absolute amount. Finally, it should be mentioned that this thesis analyses the largest sample of international airlines in a determinant-based study so far, as far as the author is aware. The author is also not aware of any comparable study on the development of airline emissions and the influence of financial and operational hedging on them.

2 DATA DESCRIPTION

In the following chapter, the sample selection process, the sample itself and key variables are first explained in general terms (2.1), followed by a detailed description of relevant variables and their descriptive statistics (2.2). All italicized expressions represent variables, which are summarized in a table at the end of each subsection. Table B.1[2] in Appendix B contains all variables.

The dataset consists mainly of hand-collected items from annual reports (ARs). Values that were not available, e.g. because the AR was no longer available, were supplemented as far as possible with values from the Thomson Reuters database.[3] The affected values were compared with values available in the ARs from the years before and after. If there were differences, these were negligible compared to the added value of the individual data points.

The dataset used in this thesis was initially built by Britta Pfefferle (née Berghöfer). She collected the data for the years 2005 until 2014. Following her approach the years 2015 until 2019 were added and expanded by variables needed to analyze additional aspects covered in this dissertation. As this is the same sample up to and including 2015, the figures and tables describing the data and values are very similar. This is not indicated in the remainder of the dissertation.

As Pfefferle (2019) pointed out, it makes sense to collect this type of data by hand, as several of the numbers we are interested in (e.g. fleet information) cannot be found in general databases. Furthermore, the quality of the data in general databases does not normally match the quality of hand-collected data. General income data from four different non-financial companies between 2005 and 2008 under International Financial Reporting Standards (IFRS) were analyzed by Schmitting and Wöhrmann (2013). They find that the acceptance of a hypothesis in empirical research can depend on the choice of database used and, in addition, that the figures of hand-collected and database data can differ.

[2] It is intended to make reading easier, as all explanations are contained in the text and in the tables of the individual subsections.

[3] The affected values are colour-coded (yellow) in the dataset.

2.1 General Sample Description

The data search approach is based on Pfefferle (2019). Initially, all 292 IATA members of 2019 (IATA, 2019b) were included. Through online research 16 airlines that were non-IATA members (mostly low-cost carriers (LCCs)) were added. Subsequently, the airlines' websites were manually searched for ARs, which had to be available in either German or English; otherwise the airline was excluded from the sample.[4] A search for ARs on stock exchanges was not carried out, as the relationship between effort and gain is not clear in this case. Furthermore, there would be no guarantee that the reports are written in English or German. For airlines from the United States of America (U.S.), 10-K or 20-F files were retrieved from the Electronic Data Gathering Analysis and Retrieval system (EDGAR) database using Standard Industrial Classification (SIC code[5] 4512 ('scheduled air transportation'). Variables such as operating statistics or environmental variables were partly taken from other documents publicly available on the airline's website such as a sustainability report (SR). State-owned airlines[6] were not included due to the lack of data. Due to the different business models of cargo-only airlines and airlines that are part of a tour operator[7] compared to passenger airlines, neither cargo-only nor operator-related airlines were included. Regional airlines, on the other hand, were taken into account.

The final dataset includes up to 66 airlines per year with a total of 78 different airlines from 39 countries. Table 2.1 gives an overview of how many airlines of which business model and which region are included in the dataset in the respective years. It also shows how many airlines belong to which business model in each year, regardless of the region, and how many airlines are included in the European Union Emissions Trading Scheme (EU ETS). More than three quarters of the dataset consist of so called full-service airlines, also called network-legacy carriers (NLCs). From a geographical perspective, Asian airlines (AS) dominate the dataset with just under 40%, followed by airlines from the Americas (AM), Europe (EU), Oceania (OC) and, with the smallest share, Africa (AF). The number of carriers rose to 66 between 2008 and 2012, while the lowest number of carriers (51) is included in 2005. This development resulted from airlines merging or ceasing operations. For example, in 2013, American Airlines and US Airways merged into one airline under the

[4] Pegasus Airlines, headquartered in Istanbul, for example, has no ARs on its website, which is why the airline was not included.

[5] SIC codes are four-digit numeric codes. They are assigned to companies by the US government to identify the company's main business (SICCODES.com: `https://siccode.com/page/what-is-a-sic-code`, visited on 01/12/2023).

[6] Airlines such as Air China, Qatar Airways or Emirates are state-owned.

[7] Airlines such as TUIfly are part of a tour operator.

name American Airlines after American Airlines filed for bankruptcy in 2011 (American Airlines and US Airways, 2013). An example of the suspension of operations is Air Berlin, which filed for insolvency in August 2017 and suspended its operations in October of the same year.[8]

Table 2.2 contains all airlines considered in the dataset, sorted alphabetically by airline name. The International Civil Aviation Organization (ICAO) Code ('ICAO Code') is used as identification, e.g. 'NAX' for 'Norwegian Air Shuttle'. The columns 'Airline name' (*airline*) and 'Airline Group name' refer to the name of the airline and the group to which the airline belongs, e.g. 'Norwegian Air Shuttle' and 'Norwegian Group'. Both names were taken from either the ARs or SEC filings. For simplicity, the name of the airline or an abbreviation thereof is used in this paper instead of the group name. This is usually the brand name of the airline, e.g. 'Norwegian' is used instead of 'Norwegian Group' or 'Norwegian Air Shuttle', in accordance with Pfefferle (2019).

The columns 'Country' (*ctry*) and 'Currency' (*crcy*) refer to the country where the group is headquartered and to the currency of the AR. Most airlines in the dataset are headquartered in the U.S. (15 airlines), followed by the People's Republic of China (five airlines) and the United Kingdom (UK) (four airlines). The most common currency in the dataset is US-Dollar (USD) (25 airlines), followed by Euro (EUR) (11 airlines) and Renminbi Yuan (CNY) (five airlines). The International Organization for Standardization (ISO) Code was used for both columns. The geographical affiliation of the airlines ('Region' column, *reg*) was divided into AS, AM, AF, EU and OC, as already mentioned.

The column 'ISIN' (International Securities Identification Number) has been introduced to facilitate the identification of the airline shares. Column 'LCC' indicates whether the respective airline is a LCC or NLC (dummy for low-cost carrier (*lccDm*) is either one for LCC or zero for NLC).[9]

Since not all airlines operated during the entire period, the column 'Sample Years' was added to inform about the fiscal years in the sample, which results in a total of 924 firm years.[10] Of the 78 airlines included, 35 are available over the entire period from 2005 to

[8] AirBerlin Insolvency Infomation Portal: `https://www.airberlin-inso.de/start`, visited on 11/25/2022.

[9] For this dissertation the following definitions are used combined from Gudmundsson (1998) and Nelissen et al. (2021). LCCs, in contrast to NLCs, are characterised by lower average ticket prices, a homogeneous fleet, high utilisation of aircraft and staff, low wages, high load factors, no free on-board service and short- and medium-haul flights. Another difference is the operation of point-to-point connections by LCCs and the operation of so-called hub-and-spoke networks by NLCs which also causes lower specific emissions for LCCs and higher specific emissions for NLCs. Further information can be found in Appendix B in Table B.2.

[10] For the sample years 2009 and 2010 (fiscal years ended 31 March), Japan Airlines is excluded as the company was in receivership (Pfefferle, 2019). Originally, the airline FastJet was included in the dataset.

Table 2.1: Number of airlines included in the studies, broken down by EU ETS, Non-EU ETS and by business model within regions

		2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Firm years	% of total sample
AF		1	2	2	2	2	2	2	2	2	2	2	2	2	2	2	29	3.14%
	LCC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.00%
	NLC	1	2	2	2	2	2	2	2	2	2	2	2	2	2	2	29	3.14%
AM		16	19	20	20	20	19	19	18	19	19	18	17	17	17	16	274	29.65%
	LCC	5	6	6	6	6	6	6	6	7	7	7	7	7	7	6	95	10.28%
	NLC	11	13	14	14	14	13	13	12	12	12	11	10	10	10	10	179	19.37%
AS		20	21	21	24	24	24	25	27	26	24	23	24	24	24	22	353	38.20%
	LCC	2	2	2	4	5	5	5	5	5	5	5	6	6	6	6	69	7.47%
	NLC	18	19	19	20	19	19	20	22	21	19	18	18	18	18	16	284	30.74%
EU		11	14	16	16	16	17	16	15	14	14	13	13	12	11	11	209	22.62%
	LCC	3	3	4	4	4	4	4	4	3	3	3	3	3	3	3	51	5.52%
	NLC	8	11	12	12	12	13	12	11	11	11	10	10	9	8	8	158	17.10%
OC		3	4	4	4	4	4	4	4	4	4	4	4	4	4	4	59	6.39%
	LCC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.00%
	NLC	3	4	4	4	4	4	4	4	4	4	4	4	4	4	4	59	6.39%
All		51	60	63	66	66	66	66	66	65	63	60	60	59	58	55	924	100.00%
	EU ETS	9	12	14	14	14	15	14	14	13	13	12	12	11	10	10	187	20.24%
	Non-EU ETS	42	48	49	52	52	51	52	52	52	50	48	48	48	48	45	737	79.76%
All		51	60	63	66	66	66	66	66	65	63	60	60	59	58	55	924	100.00%
	LCC	10	11	12	14	15	15	15	15	15	15	15	16	16	16	15	215	23.27%
	NLC	41	49	51	52	51	51	51	51	50	48	45	44	43	42	41	709	76.73%
All		51	60	63	66	66	66	66	66	65	63	60	60	59	58	55	924	100.00%

2019. The average period is about 12 years, with the shortest period being three years ('Transasian Airways').

The column 'Accounting standards' (*accStd*) provides information on the accounting standard used in the AR. The most commonly used accounting standard is the International Financial Reporting Standards (IFRS) (41 airlines, 50.92% of the dataset), followed by the United States Generally Accepted Accounting Principles (U.S. GAAP) (17 airlines, 20.45% of the dataset). All other accounting standards that are broadly in accordance with these are labelled accordingly with a footnote. The column 'Alliance' informs about the possible affiliation of the respective airline to one of the three biggest airline alliances (SkyTeam, Star Alliance or Oneworld).

The following section explains variables that are of general importance for the dataset and have not already been addressed in detail so far. The exact meaning of the abbreviations and an explanation of each variable is provided in Table 2.4.

Due to the heterogeneity of the balance sheet dates of the ARs (*accDate*; March, June, September and December), ARs as of 31st March are assigned to the previous year of analysis (*year*), all other cut-off dates to the current year. For example, an AR as of 31st March 2016 is assigned to the year of analysis 2015 and an AR as of 31st October 2016 to the year of analysis 2016. The currencies (*crcy*) are not uniform either. In order to standardise the currencies, all relevant figures from the ARs were first included in the dataset in the currency used for reporting in the AR and then converted to USD using the corresponding exchange rate. Exchange rates were obtained from OANDA for the period 2005 to 2014 and from Thomson Reuters Eikon from 2015 onward. For the conversion, the average of the month-end exchange rate (*xrAvg*) was used for the income statement data and the end-of-fiscal-year exchange rate (*xrEnd*) was used for the balance sheet data.[11] An overview of all variables concerned, including the allocation to the exchange rates used, can be found in Appendix B.4 Table B.3.

In the following, the role of acquisition in this sample will be analyzed. The discussion is based on Pfefferle (2019), but her sample ended in 2014. Within the sample, a total of 32 acquisitions have taken place and 27 airlines have been affected. Table 2.3 lists all acquisitions in the sample alphabetically by acquiring airline. In addition, the airline taken over, the year of acquisition and the growth in total assets due to the merger are indicated.

In the work of Lim and Hong (2014), companies are considered new companies after a merger, as the financial figures can change significantly as a result of a merger, in order to

However, as the airline is registered in the UK and operates in Zimbabwe and South Africa, an accurate attribution was not possible (FastJet PLC, 2020). For further information see Appendix B.3.

[11] The exchange rates used here correspond to the periods to which the ARs relate.

Table 2.2: General airline information

ICAO Code	Airline name	Airline Group name	Country	Region	Currency	ISIN	LCC	Sample Years	Accounting standards	Alliance
AEE	Aegean Airlines	Aegean Airlines	GR	EU	EUR	GRS495003006	No	2007-2019	IFRS	Star Alliance
EIN	Aer Lingus	Aer Lingus	IE	EU	EUR	IE00B1CMPN86	No	2006-2014[12]	IFRS	
AFL	Aeroflot	Aeroflot Group	RU	EU	USD	RU0009062285	No	2005-2019	IFRS	SkyTeam
ABY	Air Arabia	Air Arabia	AE	AS	AED	AEA003001012	Yes	2008-2019	IFRS	
BER	Air Berlin	Air Berlin	DE	EU	EUR	GB00B128C026	No	2006-2016[13]	IFRS	Oneworld
ACA	Air Canada	Air Canada	CA	AM	CAD	CA0089118776	No	2006-2019	Canadian GAAP	Star Alliance
CCA	Air China	Air China Limited	CN	AS	CNY	US00910M1009	No	2006-2019	IFRS	Star Alliance
AFR	Air France-KLM	Air France-KLM	FR	EU	EUR	FR0000031122	No	2005-2019	IFRS	SkyTeam
ANZ	Air New Zealand	Air New Zealand Group	NZ	OC	NZD	NZAIRE0001S2	No	2005-2019	NZ GAAP[14]	Star Alliance
AXM	AirAsia	AirAsia	MY	AS	MYR	MYL5099OO006	Yes	2005-2019	Malaysian FRS	
TRS	AirTran Aiways	AirTran Holdings	US	AM	USD	US00949P1084	Yes	2005-2010[15]	U.S. GAAP	
ASA	Alaska Airlines	Alaska Airlines	US	AM	USD	US0116591092	No	2005-2019	U.S. GAAP	
ANA	All Nippon Airways	ANA Holdings[16]	JP	AS	JPY	JP3429800000	No	2005-2019	Japanese GAAP	Star Alliance
AAY	Allegiant Air	Allegiant Travel Company	US	AM	USD	US01748X1028	Yes	2006-2019	U.S. GAAP	
AAL	American Airlines	American Airlines Group[17]	US	AM	USD	US02376R1023	No	2005-2019	U.S. GAAP	Oneworld
AAR	Asiana Airlines	Asiana Airlines	KR	AS	KRW	KR7020560009	No	2005-2018[18]	Korean GAAP	Star Alliance
AVA	Avianca	Avianca Holdings	CO	AM	USD	US05367G1004	No	2013-2019	IFRS	Star Alliance
BKP	Bangkok Airways	Bangkog Airways Limited	TH	AS	THB	TH4403010010	No	2014-2019	TFRS	
BAW	British Airways	British Airways	GB	EU	GBP	GB0001290575	No	2005-2010[19]	IFRS	Oneworld
CPA	Cathay Pacific	Cathay Pacific Airways Limited	HK	AS	HKD	HK0293001514	No	2005-2019	Hong Kong FRS	Oneworld
CAL	China Airlines	China Airlines	TW	AS	TWD	TW0002610003	No	2005-2019	Chinese GAAP	SkyTeam
CES	China Eastern	China Eastern Air Holding Company	CN	AS	CNY	CNE000000TR0	No	2005-2019	IFRS	SkyTeam
CSN	China Southern Airlines	China Southern Air Holding Company	CN	AS	CNY	CNE000001FG0	No	2005-2019	IFRS	SkyTeam
CAW	Comair	Comair Group	ZA	AF	ZAR	ZAE000029823	No	2005-2019		
COA	Continental Airlines	Continental Airlines	US	AM	USD	US2107953083	No	2005-2009[20]	U.S. GAAP	SkyTeam
CMP	Copa Airlines	Copa Holdings	PA	AM	USD	PAP310761054	No	2005-2019	IFRS, U.S. GAAP	Star Alliance
CYP	Cyprus Airways	Cyprus Airways	CY	EU	GBP	CY0002900716	No	2005-2011[21]	IFRS	

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[12] The takeover of Aer Lingus by IAG took place in August 2015 (The Irish Times, 2015).

[13] The company has declared itself insolvent in August 2017 (Koenen, 2017).

[14] The New Zealand (NZ) GAAP complies with the IFRS.

[15] AirTran Holdings Inc. was acquired by Southwest Airlines.

[16] The airline group name was All Nippon Airways between 2005 and 2013.

[17] The airline group name was AMR Corporation between 2005 and 2012.

[18] In April 2019, Kumho Engineering and Construction Co, main shareholder of Asiana, announced it would sell its shares. After the takeover by a consortium did not materialise in September 2020, it was announced in November 2020 that Korean Air would take over the airline (DPA, 2020).

[19] British Airways and Iberia merged in order to form IAG as of January 2011 (The Guardian, 2010).

[20] United and Continentail Airlines agreed to merge and continue to operate under the name United Airlines (Mouawad and de la Merced, 2010).

[21] Cyprus Air became a state-owned airline through state support (Kambas and Fioretti, 2015).

ICAO Code	Airline name	Airline Group name	Country	Region	Currency	ISIN	LCC	Sample Years	Accounting standards	Alliance
DAL	Delta Air Lines	Delta Air Lines	US	AM	USD	US2473617023	No	2005-2019	U.S. GAAP	SkyTeam
EZY	easyJet	easyJet	GB	EU	GBP	GB00B7KR2P84	Yes	2005-2019	IFRS	
ELY	El Al	El Al Israel Airlines	IL	AS	USD	IL0010878242	No	2005-2019	IFRS, Israeli GAAP	
EVA	Eva Air	Eva Air	TW	AS	TWD	TW0002618006	No	2005-2019	Chinese GAAP, IFRS	Star Alliance
FIN	Finnair	Finnair Group	FI	EU	EUR	FI0009003230	No	2005-2019	IFRS	Oneworld
BEE	Flybe	Flybe Group	GB	EU	GBP	GB00B4QMVR10	No	2010-2017[22]	IFRS	
GIA	Garuda Indonesia	Garuda Indonesia	ID	AS	USD	ID1000118300	No	2012-2019	Indonesian Financial Accounting Standards	SkyTeam
GLO	Gol	Gol Intelligent Airlines	BR	AM	BRL	US38045R2067	Yes	2005-2019	IFRS, U.S. GAAP	
GLA	Great Lakes	Great Lakes Aviation	US	AM	USD	US39054K1088	No	2005-2014[23]	U.S. GAAP	
CHH	Hainan Airlines	Hainan Airlines Company	CN	AS	CNY	CNE000000RT0	No	2005-2012[24]	CASBE[25]	
HAL	Hawaiian Airlines	Hawaiian Holdings	US	AM	USD	US4198791018	No	2005-2019	U.S. GAAP	
IBE	Iberia	Iberia Group	ES	EU	EUR	ES0147200036	No	2005-2010[26]	IFRS	Oneworld
ICE	Icelandair	Icelandair Group	IS	EU	ISK	IS0000013464	No	2006-2019	IFRS	
IGO	IndiGo Airlines	InterGlobe Aviation Limited	IN	AS	INR	INE646L01027	Yes	2015-2019	Ind AS	
[27]	International Airlines Group (IAG)	International Airlines Group (IAG)	GB	EU	EUR	ES0177542018	No	2011-2019	IFRS	Oneworld
JAL	Japan Airlines (JAL)	JAL Group	JP	AS	JPY	JP3705200008	No	2005-2008 2011-2019	Japanese GAAP	Oneworld
JZR	Jazeera Airways	Jazeera Airways Group	KW	AS	KWD	KW0EQ0602452	Yes	2008-2019	IFRS	
JAI	Jet Airways	Jet Airways (India)	IN	AS	INR	INE802G01018	No	2005-2018[28]	Indian GAAP	
JBU	JetBlue	JetBlue Airways Corporation	US	AM	USD	US4771431016	Yes	2005-2019	U.S. GAAP	
KQA	Kenya Airways	Kenya Airways	KE	AF	KES	KE0000000307	No	2006-2019	IFRS	SkyTeam
KAL	Korean Air	Korean Air Lines	KR	AS	KRW	KR7003490000	No	2005-2019	Korean IFRS[29]	SkyTeam
LAN	LAN	LAN Airlines	CL	AM	USD	CL0000000423	No	2005-2011[30]	IFRS, Chilean GAAP	Oneworld
LAN	LATAM	LATAM Airlines Group	CL	AM	USD	US51817R1068	No	2012-2019	IFRS	Oneworld
DLH	Lufthansa	Lufthansa Group	DE	EU	EUR	DE0008232125	No	2005-2019	IFRS	Star Alliance
MAS	Malaysia Airlines	Malaysia Airlines	MY	AS	MYR	MYL3786OO000	No	2005-2013[31]	Malaysian FRS, IFRS	Oneworld
NAX	Norwegian Air Shuttle	Norwegian Group [32]	NO	EU	NOK	NO0010196140	Yes	2005-2019	IFRS, Norwegian GAAP	
PIA	Pakistan International Airlines (PIA)	Pakistan International Airlines (PIA)	PK	AS	PKR	PIAa.KA	No	2005-2019	IFRS	

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[22] Flybe was sold to Connect Airways in July 2019 (Turner, 2019).
[23] There are no ARs available on the airline's or the SEC's website beyond 2014.
[24] There are no ARs available on the airline's website beyond 2012.
[25] Chinese Accounting Standards for Business Enterprises.
[26] British Airways and Iberia merged in order to form IAG in January 2011 (The Guardian, 2010).
[27] No code available as the combined airlines still operate under their respective names and codes, EIN, BAW and IBE, respectively.
[28] The firm suspended its operations on 17th April 2019 due to financial distress (Jet Airways, 2020).
[29] The accounting standard was Korean GAAP between 2005 and 2010.
[30] LAN Airlines took over TAM in June 2012 and they merge to form the new group LATAM Airlines Group (Alerigi, 2012).
[31] There are no ARs available on the airline's website beyond 2013.
[32] The airline group name was Norwegian Air Shuttle between 2005 and 2006.

ICAO Code	Airline name	Airline Group name	Country	Region	Currency	ISIN	LCC	Sample Years	Accounting standards	Alliance
QFA	Qantas Airways	Qantas Group	AU	OC	AUD	AU000000QAN2	No	2005-2019	AAs[33]	Oneworld
RXA	Regional Express	Regional Express Holdings	AU	OC	AUD	AU000000REX1	No	2006-2019	AASs	
RPA	Republic Airways	Republic Airways Holdings	US	AM	USD	US7602761055	No	2005-2015[34]	U.S. GAAP	
RYR	Ryanair	Ryanair Holdings	IE	EU	EUR	IE00BYTBXV33	Yes	2005-2019	IFRS	
SAS	SAS	SAS Group	SE	EU	SEK	SE0003366871	No	2005-2019	IFRS	Star Alliance
CDG	Shandong Airlines	Shandong Aviation Group	CN	AS	CNY	CNE0000014P1	No	2005-2006 2008-2014	CASBE	
SIA	Singapore Airlines	SIA Group	SG	AS	SGD	SG1V61937297	No	2005-2019	IFRS, Singapore FRS	Star Alliance
SKW	SkyWest	SkyWest	US	AM	USD	US8308791024	No	2005-2019	U.S. GAAP	
SWA	Southwest	Southwest Airlines	US	AM	USD	US8447411088	Yes	2005-2019	U.S. GAAP	
SEJ	SpiceJet	SpiceJet	IN	AS	INR	INE285B01017	Yes	2005-2019	Ind AS, Indian GAAP	
NKS	Spirit	Spirit Airlines	US	AM	USD	US8485771021	Yes	2011-2019	U.S. GAAP	
LAP	TAM	TAM	BR	AM	BRL	BRTAMMACNPR2	No	2006-2011[35]	IFRS, Brazilian GAAP	Star Alliance
THA	Thai Airways	Thai Airways International	TH	AS	THB	TH0245010010	No	2005-2019	Thai FRS	Star Alliance
TGW	Tigerair	Tiger Airways Holdings	SG	AS	SGD	SG1Z26952619	Yes	2009-2014[36]	Singapore FRS	
TNA	Transasia	Transasia Airways Corporation	SG	AS	SGD	TW0006702004	Yes	2009-2014[37]	Chinese GAAP	
THY	Turkish Airlines	Turkish Airlines Group	TR	AS	USD	US90010R1095	No	2005-2019	IFRS, Turkish GAAP	Star Alliance
UAL	United Airlines[38]	United Continental Holdings[39]	US	AM	USD	US9100471096	No	2007-2019	U.S. GAAP	Star Alliance
AWE	US Airways	US Airways Group	US	AM	USD	US90341W1080	No	2005-2012[40]	IFRS	Star Alliance
UTA	UTair	Utair Aviation	RU	AS	USD	RU0007661385	No	2007-2013[41]	IFRS	
VJC	VietJet	VietJet	VN	AS	VND	VN000000VJC7	Yes	2016-2019	VAS	
VOZ	Virgin Australia[42]	Virgin Australia Holdings[43]	AU	OC	AUD	AU000000VAH4	No	2005-2019	AASs	
VOI	Volaris	Volaris Aviation Holding Company	MX	AM	MXN	US21240E1055	Yes	2013-2019	IFRS	
VLG	Vueling	Vueling Airlines	ES	EU	EUR	ES0184591032	Yes	2007-2012[44]	IFRS	
WJA	WestJet Airlines	WestJet Airlines	CA	AM	CAD	CA9604105044	Yes	2005-2018[45]	IFRS	

[33] The Australian Accounting Standards comply with the IFRS.

[34] There are no ARs available on the airline's or SEC's website beyond this.

[35] LAN Airlines took over TAM and they merged to form the new group LATAM Airlines Group in June 2012 (Alerigi, 2012).

[36] SIA Group took over Tiger Air in February 2016 (CAPA, 2016).

[37] Transasia was shut down due to two crashes (BBC, 2016).

[38] The airline name was United Air Lines between 2007 and 2009 and United Air and Continental Airlines between 2010 and 2012.

[39] The airline group name was UAL Corporation between 2005 and 2009.

[40] American Airlines and US Airways merged and operate under American Airlines as of December 2013 (American Airlines and US Airways, 2013).

[41] There are no ARs available on the airline's website beyond 2013.

[42] The airline name was Virgin Blue between 2005 and 2011.

[43] The airline group name was Virgin Blue Holdings between 2005 and 2011.

[44] Takeover of Vueling by IAG in April 2013 (Davies, 2013).

[45] In May 2019, WestJet Airlines Ltd. announced that it would be acquired by private equity firm ONEX Corp. Accordingly, WestJet Airlines Ltd. continued operations as a privately held company (BNN, 2019).

avoid analysis problems and non-convergence problems. In contrast, Carter et al. (2006), Lin and Chang (2009), Rampini et al. (2014) and Treanor et al. (2014a) make no distinction. To control for the extraordinary asset growth due to the merger in the robustness analysis, the variable *mrgDm* was included in this thesis. It takes the value of one in the year when the acquired airline appears in the consolidated results of the acquiring airline and zero otherwise.

The variable *cpaDm* was added to test the statistical results for robustness with respect to regional U.S. airlines operating under certain agreements.[46] Regional airlines offer scheduled flights to major hubs (feeder flights). International airlines, such as American Airlines, rely on this. In this way, they can serve markets with a lower customer density that they would otherwise not have been able to serve economically with larger aircraft (American Airlines, 2020). Regional airlines benefit from such agreements 'because they are protected from some of the elements that cause volatility in airline financial performance, including variations in ticket prices, number of passengers and fuel prices.' (SkyWest, 2020, p.6). The variable has a value of one for the only two included regional U.S. airlines, Republic Airways and SkyWest, and zero otherwise. In another paper, regional airlines were not considered because they differ in many aspects from NLCs and LCCs (Zou et al., 2015). In this paper, we follow the approach of Pfefferle (2019) for the study of fuel costs by excluding airlines under CPA for the robustness analysis. Including regional airlines in the sample would make a direct comparison between airlines difficult, as fuel costs are close to zero for SkyWest and Republic Airways.[47] For the multivariate analysis of CPA airlines, we follow the approach of Rampini et al. (2014), treating them as 100% hedged with a hedge maturity of 24 months.

The variables *euetsDm* and *timeDm* were added in view of the EU-ETS. The dummy variable *euetsDm* is one if the airline is covered by the EU-ETS and zero otherwise. The variable *timeDm* is one if the year is between 2012 and 2019 and zero for the years 2005 to 2012 in order to capture the time since the airlines are included in the EU ETS.

[46] Such agreements are, for example, a fixed-fee agreement, a capacity purchase agreement (CPA) or a fuel pass-through agreement (FPA). Such a CPA, using American Airlines as an example, provides that '[...] all revenues, including passenger, in-flight, ancillary, mail and freight revenues, go to us. We control marketing, scheduling, ticketing, pricing and seat inventories. In return, we agree to pay predetermined fees to these airlines for operating an agreed-upon number of aircraft, without regard to the number of passengers on board. In addition, these agreements provide that we either reimburse or pay 100% of certain variable costs, such as airport landing fees, fuel and passenger liability insurance.' (American Airlines, 2020, p.6)

[47] 'Our fixed-fee agreements with Delta, United, American and Alaska require the respective major airline partner to either directly pay for or reimburse us for the fuel costs we incur under those agreements, thereby reducing our exposure to fuel price fluctuations.' (SkyWest, 2020, p.9)

Table 2.3: Acquisitions by airlines included in the sample (asterisks (*) indicate 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)
Alaska Airlines	Virgin America	2016	52.6% (between 2016 and 2017)
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	Finccomm	2012	48.8% (between 2012 and 2013)
Garuda Indonesia	Sriwijaya Air	2018	16.2% (between 2017 and 2018)
Gol	Varig	2007	111.8% (between 2006 and 2007)
International Airlines Group (IAG)	Aer Lingus*	2015	5.6% (between 2014 and 2015)
International Airlines Group (IAG)	Vueling*	2013	14.4% (between 2013 and 2014)
Jet Airways	Sahara Airlines Limited	2007	115.3% (between 2006 and 2007)
LAN	Aires	2010	17.6% (between 2009 and 2010)
Lufthansa	NIKI, LGW	2017	19.3% (between 2016 and 2017)
Lufthansa	British Midland	2009	27.3% (between 2008 bis 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 Airways	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	15.8% (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	Tigerair Australia	2015	1.7% (between 2014 and 2015)
Virgin Australia	SkyWest*	2013	4.5% (between 2012 and 2013)
Vueling	Clickair	2009	210.8% (between 2008 and 2009)

Table 2.4: Sample-related variables

Variable	Label	Description
accDate	Accounting date	End of financial reporting period from annual report
accStd	Accounting standard	Accounting standard used
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.
euEtsDm	EU ETS dummy	Dummy, one if the airline is established in the EEA territory, covered by the EU ETS and/or regularly operates in the EEA territory (if the verified emissions of the airline within the EU ETS represent more than 15% of the total verified emissions of the airline), zero otherwise.
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 hubs, based on UN 'Composition of macro geographical (continental) regions, geographical sub-regions, and selected economic and other groupings' (United Nations, 2023). The regions are Africa (AF), America (AM), Asia (AS), Europe (EU), and Oceania (OC).
timeDm	Time Dummy	Dummy, one in the years 2012 to 2019 and zero in the years 2005 to 2011
xrAvg	Average exchange rate	Until 2012: Average end-of-month bid exchange rate USD to local currency over the reporting period from OANDA From 2013: Average end-of-month bid exchange rate USD to local currency over the reporting period from Thomson Reuters Eikon
xrEnd	End of financial year exchange rate	Until 2012: Exchange rate USD to local currency at the end of the reporting period from OANDA From 2013: Exchange rate USD to local currency at the end of the reporting period from Thomson Reuters Eikon
year	Year of analysis	Financial years ending in March are allocated to the previous calender year, otherwise to the current year respective of whether the financial year ended in June, September, October or December.

2.2 Variable Description and Descriptive Statistics

The following section explains how the relevant variables are collected, how they are calculated if necessary, and provides initial descriptive statistics.

It is important to distinguish between three types of variables. The first includes variables that are collected exclusively from the ARs, the second includes variables that are calculated from these[48], and the third includes variables that are taken from the ARs if possible or calculated if they are not included in the AR.[49] For a better understanding, all variables that were only used to calculate other variables, but which themselves have no relevance for the statistical investigations are also listed in the tables. For reasons of space, however, these variables are not discussed in more detail in the text. Variables are ordered alphabetically in the tables and this order is largely maintained in the text. The tables are structured as follows: The first column is the name of the variable in italics as it is included in the dataset, the second is the label of the variable and the third is a description and an explanation on how the variable is collected or calculated, if needed.

The data is described in more detail, among other things, by the mean value, standard deviation (SD), illustrations and groupings within the dataset, whereby time series values or cross-sectional values are calculated depending on the variable under consideration. In order to achieve the highest possible accuracy, only individual extreme values are excluded, which are indicated in each case. The dataset is unbalanced, as not every airline considered but also not all variables are available over the entire period under consideration. However, in line with Pfefferle (2019), it is important to analyse not only the airlines that were available during the entire period, but also those that could not be included over the entire period.[50] Otherwise, there could be a survival bias and a reduction in sample size. The descriptive results serve as a first overview. This is because, due to the lack of some variables for several firm years, univariate and multivariate analyses is not suitable due to the small sample size.[51]

The order of the descriptions is as follows: First, airline-specific variables (2.2.1) are described. Then, variables related to financial hedging (2.2.2) are described, seperated into related to financial distress (2.2.2.1) and to the problem of underinvestment (2.2.2.2). Finally, variables related to operational hedging (2.2.3) and the EU ETS (2.2.4) are pre-

[48] These variables are marked with an asterisk in the tables.

[49] Where consolidated data is available, this has been used instead of company data. In order to include the most recent and adjusted figures, previous year's results were used where possible. If figures were adjusted in later ARs, the adjusted figures were included in the dataset.

[50] If only airlines that are available during the entire period were taken into account, the sample size would be reduced from a total of 78 to 35 airlines.

[51] Table B.4 in Appendix B.8 shows the absolute number and percentage of missing values of the total number of firm years for certain variables.

sented.

2.2.1 Airline Industry

Variable Description

The following subsection explains the variables relevant to the airline industry.

The total available seat miles (*asmTl*) are the number of available seat miles (ASMs) flown by an airline per year. They are a measure of passenger carrying capacity and are either directly taken from the AR or calculated as

$$\begin{aligned} asmTl &= \frac{rpmTl}{lf} = \frac{revTl}{rasm} = \text{number of flights} \times lgtAvg \\ &= \frac{fuelExp}{\text{fuel costs per ASM}} = \frac{fuelCons}{fuelConsAsm} = \frac{ASKs}{1.852}^{52}. \end{aligned}$$

rpmTl are the total revenue passenger miles (RPMs) in a given year and *lf* is the passenger load factor as reported in the AR. *rpmTl* are, according to Schefczyk (1993), the main output measure of a typical passenger airline and are either taken directly from the AR or calculated by dividing *asmTl* by *lf*. Same holds for the *lf* with the calculation rearranged for *lf*[53]. In Morrell and Swan's (2006) study, the *lf* was used to control for the effects of capacity utilisation on profitability and unit costs. Lazzarini (2007) uses the load factor similarly and in addition as a measure of operational performance. According to Schefczyk (1993) the load factor is a common indicator for airline productivity and measures how many revenue passenger kilometers (RPKs) an airline can generate per ASK, which is also done in this study. Nevertheless it does not adequately reflect overall performance and ignores all non-passenger inputs and outputs as well as most of other inputs besides aircraft capacity (Schefczyk, 1993).

rasm is total revenue per ASM and is calculated by dividing total revenues (*revTl*) by *asmTl* as reported in the income statement or in the notes. From the calculation it can be concluded that the value can be increased by increasing *revTl* or decreasing *asmTl*.

lgtAvg is the average length of one flight as reported in the AR.

fuelExp are the fuel expenses as reported in the income statement or notes.

fuelCons and *fuelConsAsm* are the annual fuel consumption in U.S. gallons (USGs) itself and per ASMs, where *fuelConsAsm*[54] is calculated by dividing *fuelCons* by *asmTl*.

[52] For airlines where instead of ASMs available seat kilometers (ASKs) were reported, ASKs are divided by 1.852, in line with the conversion table from www.eia.gov.

[53] The load factor is the number of paying passengers in relation to the number of available seats on the airline's aircraft during the period under consideration.

[54] For a better understanding of the variable, consider the following example: The length of a flight from

fuelCons is directly taken from the AR or possibly converted into USG in line with the conversion table from www.eia.gov. If the fuel consumption was not enclosed in the AR, it was calculated according to the formulas in Table 2.5. Where *fdvNm* is the nominal amount of fuel contracts outstanding, *fdvPct12m* is the hedge ratio of the next 12 months and *fuelCons*(t-1) is the fuel consumption of the previous financial year.

Based on the *asmTl* the year-on-year percentage changes in the ASMs (*asmChg*) are calculated. Costs per ASMs (*casm*) are either directly taken from the AR or calculated by dividing the total operating expenses (*opExp*) as reported in the income statement or in the notes by *asmTl*.

The variables *fuelExpAsm* and *fuelExpUSG* represent the fuel expenses scaled by *asmTl* and *fuelCons*. Both are indicators of fuel efficiency and fuel price paid. They are influenced by flight distances, aircraft fuel efficiency, jet fuel spot price, aircraft size and hedging gains and losses and are necessary to compare the fuel efficiency of different airlines. The ratio *fuelExpAsm* is influenced by the fuel price which the airline paid per USG and by its fuel hedging gains or losses. The higher the fuel price per USG, the more beneficial the use of larger aircraft. Obviously, these calculations only hold if the *lf* is 100%. Therefore the revenue per revenue passenger mile (*rrpm*) also referred to as 'the yield' in the airline industry is included in this study. It covers the combined effect of the *lf* and ASMs and is calculated by dividing *revTl* by *rpmTl*.

Table 2.5: List of airline related variables

Variable	Label	Description
*asmChg**	Percentage change in ASM	Year-on-year percentage changes in the available seat miles
asmTl	Available seat miles (ASM)	Total number of available seat miles per year; either disclosed in the AR or calculated as i) *rpmTl* / *lf* ii) *revTl* / *rasm* iii) the number of flights multiplied with the average stage lenth (*lgtAvg*) iv) *fuelExp* divided by fuel costs per ASM v) *fuelCons* / *fuelConsAsm* vi) available seat kilometers (ASKs) / 1.852

continued on next page

A to B is 500 miles which can be operated by either an Airbus 319neo (with a maximum seat capacity of 160 seats (Airbus Group, 2022)) or an Airbus 321neo (maximum seat capacity 244 seats). The A319neo has a range of 3,650 miles and the A321neo of 4,000 miles with a maximum fuel capacity of 7,060 USG for the A319neo and 8,700 USG for the A321neo. The flown ASMs by the A319neo are 500 × 160 = 80,000 and 500 × 244 = 122,000 for the A321neo. Both aircraft fly the route in one hour with a fuel consumption of approximately 970 USG for the A319neo and approximately 1,100 USG for the A321neo. Consequently, the fuel consumption per ASM of the A319neo is 970/80,000 = 0.012 USG/ASM and 1,100/122,000 = 0.009 USG/ASM of the A321neo, making the Airbus 321neo more fuel efficient on the same route.

Variable	Label	Description
casm	Cost per ASM	Total amount of operating costs per available seat mile as stated in AR or calculated as *opExp* / *asmTl*
fdvNm	Nominal amount of fuel contracts	Total nominal amount of fuel derivative contracts outstanding at year end in USG
fdvPct12m	Hedge ratio for next 12 months	Percentage of the next 12 months expected fuel consumption hedged, either reported in- or outside the notes in the AR or calculated as (*fdvNm* x *(12* / *fdvMtr*[55])) / $fuelCons_{t+1}$
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 by ASMs iii) lagged nominal amount of fuel contracts outstanding (*fdvNm*) divided by the lagged fuel percentage hedged for the expected fuel consumption in the following 12 months (*fdvPct12m)* 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 the text, i.e. 'consumption increased by X%' vi) fuel expense (*fuelExp*) divided by average fuel price per USG vii) *fuelExpAsm* × *asmTl*
*fuelConsAsm**	Fuel consumption per ASM	Calculated as *fuelCons* / *asmTl*
fuelExp	Fuel expenses	Total fuel expenses as reported in income statement (or notes), net of hedging gains or losses
*fuelExpAsm**	Fuel expense per ASM	Calculated as *fuelExp* / *asmTl*
*fuelExpUSG**	Fuel expense per USG consumed	Calculated as *fuelExp* / *fuelCons*
lf	Load factor	Passenger load factor as reported in AR or calculated as *rpmTl* / *asmTl*
lgtAvg	Average length of flight	Average length of one flight (sector length, stage length) as reported in AR - If the stage length was reported separately for long and short-haul flights (or domestic / international), the average stage lengths are weighted with *asmTl*.
opExp	Total operating expenses	Operating expenses as reported in income statement (or in the notes), including fuel expenses
*rasm**	Revenue per available seat mile	Calculated as *revTl* × *asmTl*
revTl	Total revenues	Total revenue as reported in income statement (or in the notes), including other revenues
rpmTl	Revenue passenger miles	The number of miles on which a passenger is transported, either as reported in AR or calculated as *asmTl* × *lf*.
*rrpm**	Revenue per revenue passenger mile	Revenue per RPM, calculated as *revTl* / *rpmTl* Also referred to as 'the yield' in the airline industry.

[55]The variable will be defined in Table 2.7.

Summary Statistics

According to Table 2.6 the average *asmTl* in nautical miles (NM) was 50,048 million. There appears to be wide variation between airlines, considering the SD of 54,467 million NM, with the minimum of 119 million *asmTl* reported by Great Lakes in 2014 and the maximum of 282,054 million reported by American Airlines in 2018. Minimum (4.78 million USG) and maximum (4,447 million USG) of *fuelCons* are also reported by these two airlines in the same years mentioned, with a mean of 921.62 and SD of 998.75 million USG. The average load factor was 78.2% and was more homogeneous with a SD of 6.7 percentage points. The lowest value was reported by Great Lakes in 2009 at 33.4% and the highest by Ryanair in 2018 at 96.0%. The average stage length was 839.1 NM, with a SD of 349.75. The shortest *lgtAvg* was operated by Great Lakes in 2006 at 262 NM and the longest by Cathay Pacific at 2,038 NM in 2005. *rpmTl* has an average of 40,682 and a SD of 45,156 million NM. Considering that Great Lakes reported the lowest *rpmTl* in 2014 and had an average *lf* of 46%, the maximum of 1.09 USD *rrpm* in 2014 means that they have comparatively high *revTl*. The minimum of 0.07 USD per *rpmTl* was reported by AirAsia in 2005, with the overall average being 0.21 USD per *rpmTl*.

Table 2.6: Summary statistics of the variables relevant to the airline industry

Variable	Unit	N	Mean	St. Dev.	Min	Max
*asmTl_*	NM	782	50,047.910	54,466.980	118.996	282,054.000
*fuelCons_*	USG	661	921.615	998.752	4.778	4,447.000
lf	%	801	0.782	0.067	0.334	0.960
lgtAvg	NM	356	839.101	349.749	262.000	2,037.694
*rpmTl_*	NM	770	40,682.020	45,155.660	54.262	231,284.300
rrpm	USD	770	0.208	0.100	0.066	1.090

Variables ending with '_' are denoted in millions.

Descriptive Statistics

Figure 2.1 shows the evolution of average *asmTl* (in millions) and average *fuelExpAsm* in USD between 2005 and 2019 for all airlines, LCCs and NLCs. Overall, average ASMs have increased (104.11%), with an increase of 165.96% for LCCs and 98.40% for NLCs. This includes two decreases of 0.4% between 2005 and 2006 and 1.1% between 2008 and 2009 for all airlines. These decreases are caused by a decrease for NLCs between 2005 and 2006 of 2.0% and for LCCs between 2008 and 2009 of 4.3%. Although kerosene is a commonly traded commodity, the *fuelExpAsm* of LCCs and NLCs differ. The reasons for this lie, among other things, in the age of the operating fleet and are discussed and examined in

more detail in Chapters 3 and 4. Figure 2.1 shows that the *fuelExpAsm* of NLCs is on average 25.7% higher than that of LCCs, but the general shape of the graphs is similar. Overall, there was a peak in 2008 and a low in 2016. Subsection 3.1.1 shows a chart of the monthly average daily spot prices for jet fuel and West Texas Intermediate (WTI) (Figure 3.1), which indicates that *fuelExpAsm* have a similar pattern.

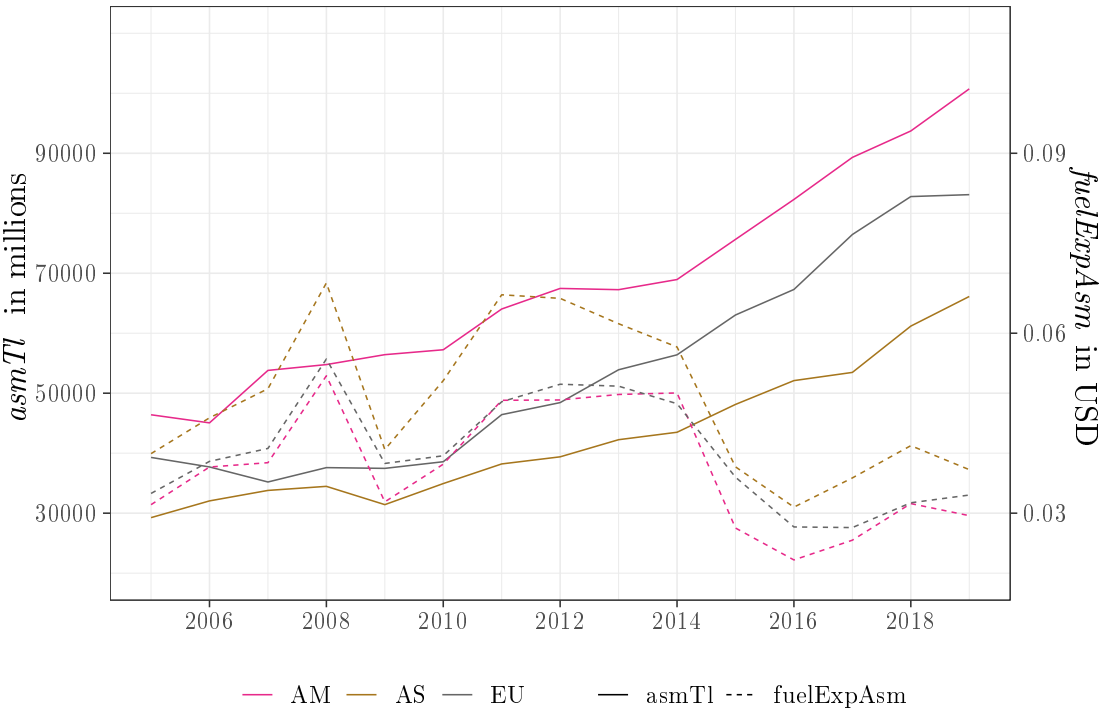
Figure 2.1: Time series: total available seat miles in millions (*asmTl*) and fuel expenses per ASM (*fuelExpAsm*), annual average of all airlines and divided into NLCs and LCCs[56]

Figure 2.2 shows the same as Figure 2.1 but split for the Americas, Asia and Europe. American airlines offer the largest amount of *asmTl*, followed by European and Asian airlines. Overall, average ASMs have increased with the biggest increase for Asia (126.02%). The shape of the lines for the regions of *fuelExpAsm* is similar to that in Figure 2.1 with the peak in 2008. Fuel costs are highest in Asia overall and lowest in the Americas, with the exception of 2011, 2014 and 2018 when they are above or equal to the European average. On average *fuelExpAsm* of Asian airlines are 30.51% higher than American and 21.17% higher than European airlines.

Figure 2.3 shows the average *fuelConsAsm* of all airlines, the two business models and

[56] $fuelExpAsm < 0.01$ USD not considered, 19 observations not considered

Figure 2.2: Time series: total available seat miles in millions (*asmTl*) and fuel expenses per ASM (*fuelExpAsm*), annual average of airlines divided into AM, AS and EU[57]

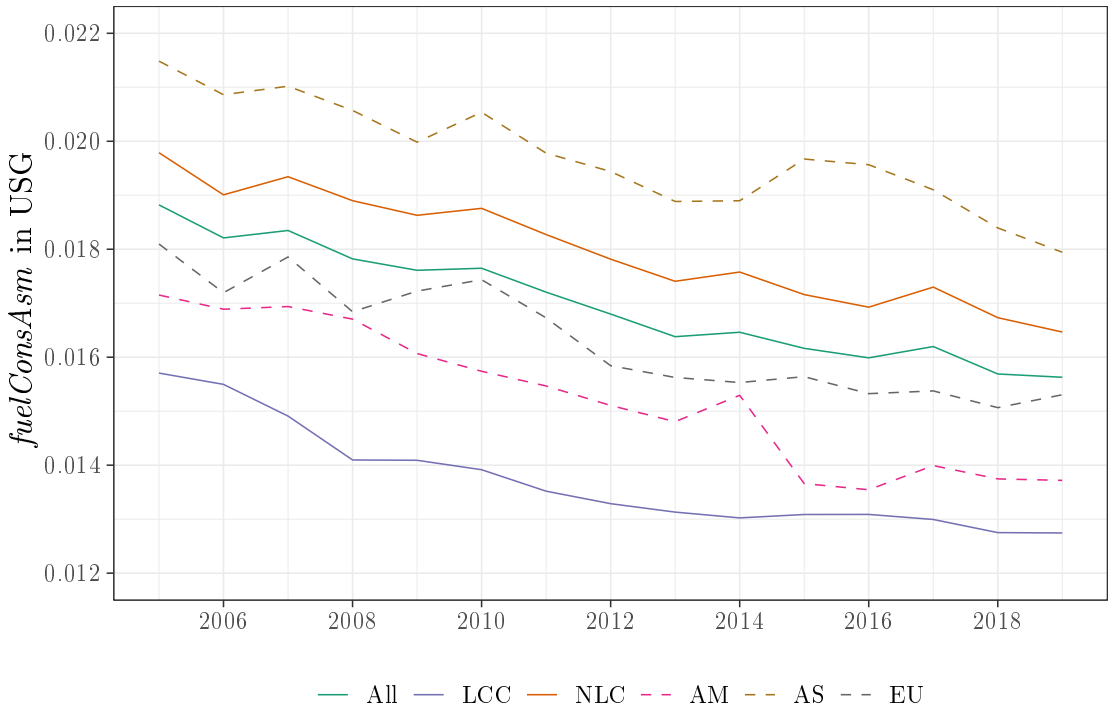


split for American, Asian and European airlines. Overall it decreased by 16.96% with American airlines having the biggest decrease (20.02%), followed by Asian (16.48%) and European airlines (15.43%). *fuelConsAsm* of LCCs is lower than that of NLCs with an overall decrease of consumption between 2005 and 2019 (LCC: 18.86%, NLC: 16.79%), with the gap increasing from 25.9% in 2005 to 29.2% in 2019. Furthermore, Figure 2.3 shows that *fuelConsAsm* for Asian airlines is the highest above that of NLCs. American airlines consume the least fuel overall in the regional comparison being beyond European airlines and only LCCs consuming less than American airlines.

In panel 1 of Figure 2.4 *rasm* is shown and indicates an overall stable development with a drop in 2009 and a decline from 2014. LCCs have the lowest values for the entire period, which is not surprising considering the business model. Until 2015, European airlines had the highest values, but over time they have moved closer to Asian airlines. Overall, *rasm* decreased by 15.91% for European airlines and 0.85% for NLCs. Asian (1.57%) and American (6.40%) airlines as well as LCCs (1.62%) have increased their *rasm*.

[57] $fuelExpAsm < 0.01$ USD not considered, 14 observations not considered

Figure 2.3: Time series: fuel consumption per ASM (*fuelConsAsm*), annual average of all airlines and divided into NLCs and LCCs

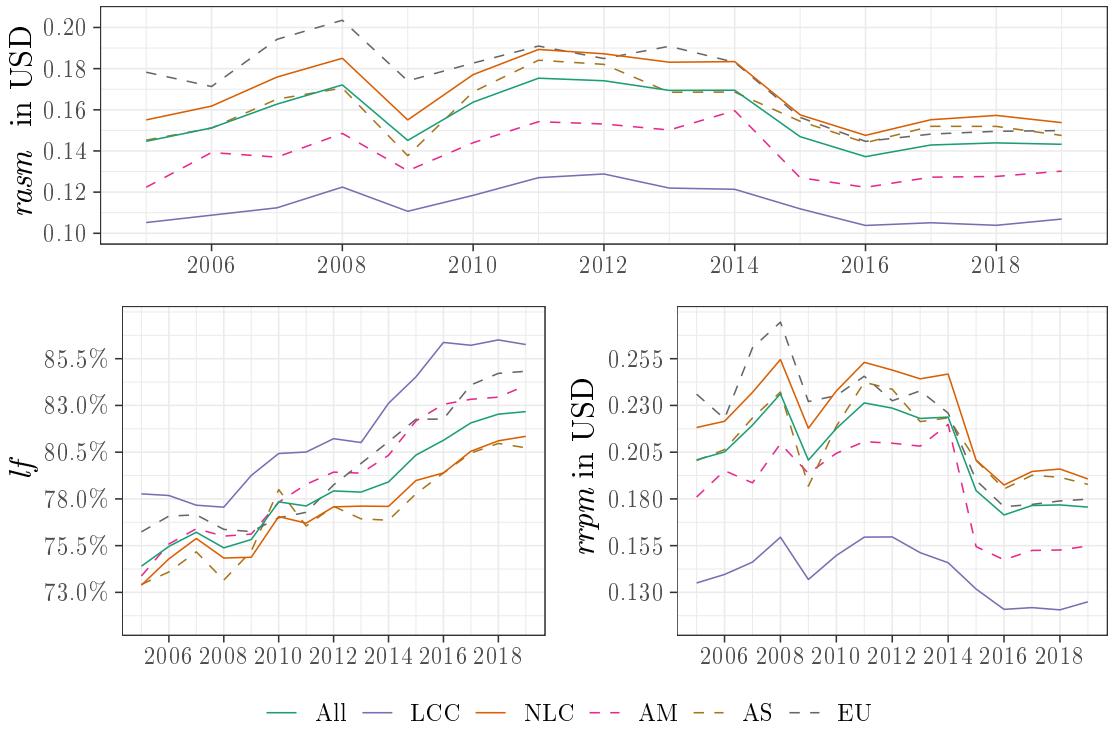


A general downward trend can be seen from 2014 until 2016, with the Americas being the most affected from 2014 to 2015 (-20.40%). Overall, ASMs have increased over the reference period (Figure 2.1). Therefore, *revTl* is looked at in more detail to explain the movements of *rasm*. In Subsection 2.2.1, the variables *lf* and *rrpm* were introduced, both of which can be used to increase *revTl*, as they inform us about aircraft utilisation and the relationship between utilisation and revenue.[58] Panel two of Figure 2.4 shows the development of the average of the two variables. There is an overall increase of 11.11% of the *lf*, with American airlines showing the largest increase of 10.19 percentage points, followed by European with 8.59 and Asian airlines with 7.31 percentage points. LCCs and NLCs each had similar increases of 7.99 and 7.96 percentage points. Looking at the development of *rrpm*, a general downward trend can be seen (-12.57%), which is due to a stronger increase of *rpm* than of *revTl*. *rrpm* of European airlines decreased the most with 23.79%, followed by American airlines with 14.49% and NLCs with 12.61%. LCCs and Asian airlines had a similar decline of 7.46% and 6.36%, respectively. Similar to *rasm*, a downward trend with subsequent stabilisation can be observed between 2014 and 2016.

[58] $rrpm = \frac{revTl}{rpmTl} = \frac{revTl}{asmTl \times lf}$.

The Americas is most affected, with a decrease of 42.30% between 2014 and 2015. The correlation factors of *lf* and *rasm* are all negative at -0.67 for all airlines, -0.60 for NLCs, -0.57 for LCCs, -0.64 for American and -0.55 for Asian airlines. European airlines stand out here as well, as the correlation factor is -0.88. This indicates that overcapacity exists in general, but especially for European airlines.

Figure 2.4: Time series: ratio of total revenue to available seat miles in USD (*rasmTl*), load factor (*lf*) and total revenue per revenue passenger mile in USD (*rrpm*), annual average of all airlines and divided into LCC, NLC as well as AM, AS and EU



2.2.2 Financial Hedging Variables

Variable Description

The following subsection introduces variables related to financial hedging. These include, among others, the type of financial contracts used, their underlying and their maturity.

One focus of this work is on fuel hedging by airlines, which is why the binary variable regarding the use of fuel derivatives (*fdvDm*) is included. A value of one is assigned if the airline had fuel derivatives outstanding at the end of the year and if the airline reported active fuel derivative usage during the current year. In all other cases a value of zero is assigned. *fdvDm* is one of two dependent variables in the multivariate analysis in Subsections 3.3.2 and 4.3.2. Furthermore, the use of foreign exchange (*fxdvDm*) and interest rate (*irdvDm*) derivatives is taken into account by means of binary variables[59]. Allayanis et al. (2001) also use these variables while Géczy et al. (1997) use only one variable indicating whether other types of derivatives are used in addition to currency derivatives.

Possible underlyings of fuel derivatives are crude oil (*fdvCo*), diesel (*fdvDi*), heating oil (*fdvHo*), jet fuel (*fdvJf*) or unleaded gasoline (*fdvUg*).

Financial contracts used are collars[60] (*fdvCol*), futures (*fdvFut*), forwards (*fdvFwd*), options (*fdvOpt*), spreads[61] (*fdvSpr*) and swaps (*fdvSwp*). Carter et al. (2006) and Morrell and Swan (2006) consider the same hedging instruments in their analyses.

The maturity of fuel derivatives is explored with the variables for the hedge ratio of the next 12 months (*fdvPct12m*), month 13 to 24 (*fdvPct24m*), month 25 to 36 (*fdvPct36m*) and month 37 to 48 (*fdvPct48m*). Except for the first variable all information is taken from the text in the ARs or seperate sheets concerning hedging. *fdvPct12m* can also be calculated in accordance with Pfefferle (2019) as

$$fdvPct12m = \frac{fdvNm \times \frac{12}{fdvMtr}}{fuelCons(t+1)},$$

[59] In this section, many binary variables are considered. If a financial contract or underlying is used by an airline, the variable is assigned a value of one and zero otherwise

[60] A collar is a combination of a long call and a short put option. The call option protects the holder against price increases, while at the same time the holder can profit from the premium of the put option (Morrell and Swan, 2006). It sets the price to be paid for the underlying between two unknown prices, thereby limiting the speculative risk to a small range of price movements (Morrell, 2021).

[61] Spread here means refinery margin swap, a commodity swap similar to an interest rate swap. It enables the payment of a fixed crack spread and thus the hedging of the refinery margin against a variable margin (Oxford Reference: `https://www.oxfordreference.com/display/10.1093/oi/authority.20110803095645237`, visited on 01/26/2024).

where *fdvMtr* is the maximum maturity of fuel contracts outstanding.[62] As already mentioned in Pfefferle (2019), it is assumed here for simplicity that the fuel contracts are evenly distributed over the entire contract term. In most cases, however, the calculated hedge ratio will underestimate the actual hedge ratio, as hedge ratios are usually not constant over longer periods of time. If an airline specifies a hedge ratio of e.g. 20% for the next six or 18 months, it is assumed that it hedges 10% or 16% for the next 12 months on a pro-rata basis. *fdvPct12m* is of special interest, as it is the second dependent variable of the multivariate regressions in Subsections 3.3.2 and 4.3.2.[63] According to Hentschel and Kothari (2001) the variable *fdvMtr* is important to analyze as one should not only analyze the notional value of a hedge (3.1.2.3).

fdvNet is the net fair value of outstanding fuel derivative contracts and is calculated as

$$fdvNet = fdvAs - fdvLia,$$

where *fdvAs* is the fair value of outstanding fuel derivative contracts (assets) and *fdvLia* is the same for liabilities.

Table 2.7: List of financial hedging related variables

Variable	Label	Description
fdvAs	Fair value of fuel derivatives (asset)	Fair value of outstanding fuel derivative contracts (asset) as reported in balance sheets (notes), including current and non-current portion
fdvCo	Underlying crude oil dummy	Dummy, one if airline used crude oil as the underlying
fdvCol	Fuel collar dummy	Dummy, one if airline used fuel collar as derivative instrument
fdvDi	Underlying diesel oil dummy	Dummy, one if airline used diesel oil (=gasoil) as underlying
fdvDm	Fuel derivative dummy	Dummy, one if the airline had outstanding fuel derivatives at 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, one is assigned. Including: hedge derivatives, derivatives held for trading
fdvFut	Future fuel contract dummy	Dummy, one if the airline used future fuel contracts
fdvFwd	Forward fuel contract dummy	Dummy, one if the airline used forward fuel contracts

continued on next page

[62] For example, Delta Airlines had outstanding *fdvNm* of 249,000,000 USG in 2017 and a hedging maturity of 17 months. Fuel consumption in 2018 totaled 4,113,000,000 USG, which is why *fdvPct12m* was calculated at 4.27% for 2017. This calculation is used to generate more observations for this variable.

[63] An alternative to using the hedge ratio would be to use portfolio deltas, as in Dionne and Triki (2013), but the available information is insufficient.

Variable	Label	Description
fdvHo	Underlying heating oil dummy	Dummy, one the if airline used heating oil as underlying
fdvJf	Underlying jet fuel dummy	Dummy, one if the airline used jet fuel as underlying
fdvLia	Fair value of fuel derivatives (liability)	Fair value of outstanding fuel derivative contracts (liability) as reported in balance sheets (notes)), including current and non-current portion
fdvMtr	Fuel derivatives maturity	Maximum maturity in months of outstanding fuel derivative contracts
fdvNet	Net fair value of fuel derivatives	Net fair value of outstanding fuel derivative contracts, calculated as *fdvNm = fdvAs – fdvLia*
fdvOpt	Fuel option dummy	Dummy, one if the airline used fuel options
fdvPct12m	Hedge percentage for next 12 months	Percentage of the next 12 months expected fuel consumption hedged, either reported in text section or calculated as (*fdvNm* x *(12 / fdvMtr*)) / $fuelCons_{t+1}$
fdvPct24m	Hedge percentage for the next 13-24 months	Percentage of the next 13 to 24 months expected fuel requirements hedged (excluding the months 1 to 12)
fdvPct36m	Hedge percentage for the next 25-36 months	Percentage of the next 25 to 36 months expected fuel requirements hedged (excluding the months 1 to 24)
fdvPct48m	Hedge percentage for the next 37-48 months	Percentage of the next 37 to 48 months expected fuel requirements hedged (excluding the months 1 to 36)
fdvSpr	Fuel spread dummy	Dummy, one if the airline used fuel spreads (=refining margin swaps)
fdvSwp	Fuel swap dummy	Dummy, one if the airline used fuel swaps
fdvUg	Underlying unleaded gasoline dummy	Dummy, one if the airline used unleaded gasoline as underlying
fxdvDm	Foreign exchange derivative dummy	Dummy, one if the airline had outstanding foreign exchange rate derivatives at year end (e.g. cross currency swap)
irdvDm	Interest rate derivative dummy	Dummy, one if the airline had outstanding interest rate derivatives at year end (e.g. interest rate swap) Variable rate obligations do not count as interest rate derivatives

Summary Statistics

The mean value (72.1%) of *fdvDm* reflects the percentage of airlines that had outstanding fuel derivative contracts with a SD of 0.45%. These contracts had an average maturity of 19 months with a relatively high SD of 11 months (Table 2.8). Southwest had the longest contract duration with 72 months in 2006. The average outstanding net fair value of fuel derivatives was -23.90 million USD with a SD of 343.13. The minimum and maximum were reached by Air France-KLM in 2008 and 2007, respectively. The average total nominal amount of fuel contracts was 409.86 million USG with a SD of 851.80. The maximum was reached by Singapore Airlines with 5,805 million USG in 2018. The average hedge ratio decreased with maturity, as the mean values of the hedge ratio of different time horizons

show. For the next 12 months, an average of 29.1% of fuel consumption was hedged, with a SD of 0.36. For the next 24 months the average hedge ratio was 8.7%, for the next 36 months 2.4% and for the next 48 months 0.6%. The maximum of *fdvPct12m* (4.76), *fdvPct24m* (4.13) and *fdvPct36m* (3.75) was reported by Air Asia in 2007 as well as that of *fdvPct48m* (0.56) but in 2005.

Table 2.8: Summary statistics of the variables relevant to financial hedging

Variable	Unit	N	Mean	St. Dev.	Min	Max
fdvDm		860	0.721	0.449	0.000	1.000
fdvMtr	months	562	19.076	11.366	0.000	72.000
*fdvNet_*	USD	810	−23.897	343.126	−3,464.567	3,321.192
*fdvNm_*	USG	675	409.858	851.795	0.000	5,804.691
fdvPct12m	%	748	0.291	0.362	0.000	4.756
fdvPct24m	%	703	0.087	0.234	0.000	4.125
fdvPct36m	%	716	0.024	0.167	0.000	3.752
fdvPct48m	%	718	0.006	0.042	0.000	0.561

Variables ending with '_' are denoted in millions.

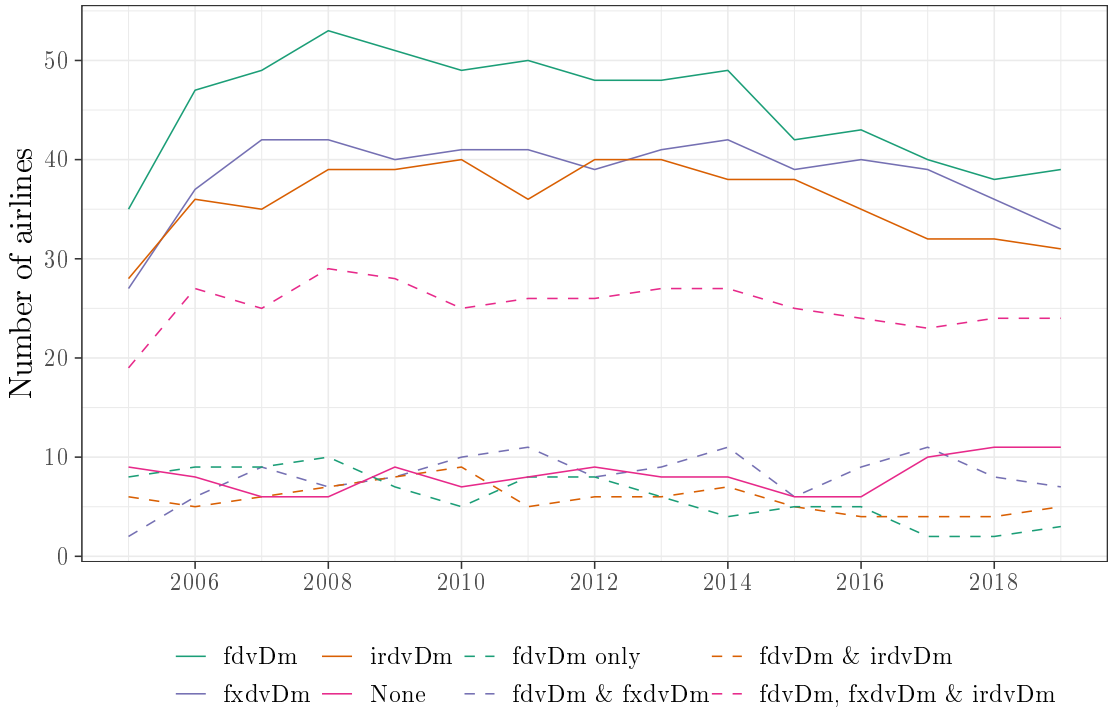
Descriptive Statistics

In Figure 2.5, the number of airlines using either fuel, foreign exchange and/or interest rate derivatives is displayed. The number of airlines using fuel derivatives is always the highest, followed by foreign exchange and interest rate derivatives, with the amount of interest rate derivatives being higher in 2005 and 2012 than foreign exchange derivatives. The number of airlines using all three derivatives at the same time is in between the usage of the just mentioned and the combinations of the three (approximately 41%). Six airlines use on average both fuel and interest rate derivatives and eight use both fuel and foreign exchange derivatives. The number of airlines using no derivatives is eight as well. Airlines using only fuel derivatives is on average six.

Figures 2.6 and 2.7 show the percentage within the sample that used collars, futures, spreads, forwards, options or swaps as hedging instruments and crude oil, diesel, heating oil or jet fuel as underlying assets of their derivatives. The number of future users in 2009, 2010 and 2011 are one, one and two, respectively. Options are used the most (33.1%) on average, followed by swaps (32.9%) and collars (17.4%), while futures (3.2%) are used the least. In between are forwards (7.7%) and spreads (5.8%).

Jet fuel (40.74%) and crude oil (40.25%) are used most frequently as underlying assets, followed by heating oil (11.58%). Diesel (7.42%) was used little at the beginning of the

Figure 2.5: Time series: number of airlines using derivatives and combinations of derivatives



period under consideration, but is used more frequently by the end, in 2012 even more frequently than heating oil. Unleaded gasoline as underlying was not included as it was only used by Southwest up to and including 2011.

Table 2.9 provides information on the use of instruments and underlying assets in the individual regions. African airlines offer the most homogeneous picture, as options, swaps and collars are used, with crude oil as underlying. Oceanian airline follow with the use of swaps, options, collars, forwards and spreads, with crude oil, jet fuel and diesel as underlying assets. European and Asian airlines use the same underlying assets as Oceania, but use all instruments. American airlines are the only ones that use all instruments and underlying assets.

Next, we focus on maturities and hedge ratios. In Figure 2.8, the average maturity of fuel derivatives between 2005 and 2019 is displayed, whereby no systematic pattern emerges. There is a general decline from 2005 to 2006 (13.67%) and 2008 to 2009 (19.43%), highest among LCCs at 22.65% for 2005 to 2006 and Asian airlines for 2008 to 2009 at 28.58% and lowest among Asian at 3.46% from 2005 to 2006 and American airlines at 13.67% from 2008 to 2009. The decline between 2008 and 2009 is consistent with the high

Figure 2.6: Time series: hedge portfolio instruments (lines represent the percentage utilisation of the individual instrument)

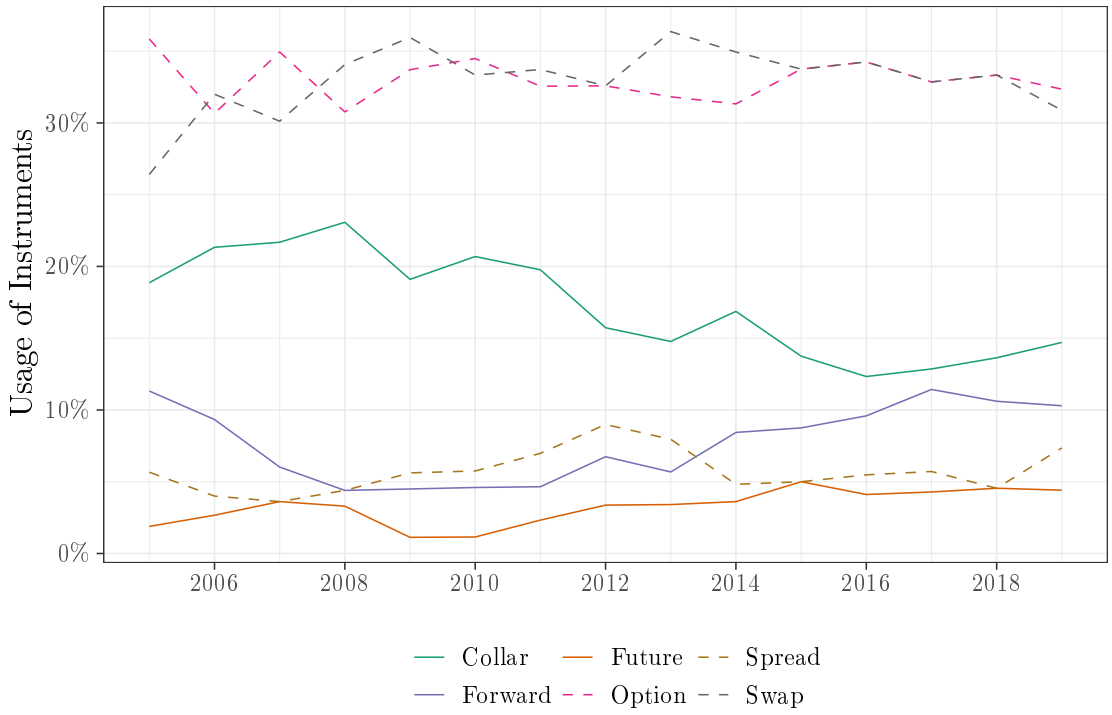


Table 2.9: Use of hedging instruments and underlying assets broken down by *reg*

	Swap	**Option**	**Collar**	**Forward**	**Future**	**Spread**
AF	28.57%	50.00%	21.43%	0.00%	0.00%	0.00%
AM	28.31%	36.66%	22.51%	1.62%	4.64%	6.26%
AS	39.39%	33.00%	16.84%	7.74%	0.34%	2.69%
EU	31.96%	26.10%	13.20%	14.66%	4.99%	9.09%
OC	40.82%	37.76%	11.22%	8.16%	0.00%	2.04%
	Jet Fuel	**Crude Oil**	**Heating Oil**	**Diesel**	**Unleaded Gasoline**	
AF	0.00%	100.00%	0.00%	0.00%	0.00%	
AM	27.43%	42.29%	24.86%	3.43%	2.00%	
AS	49.10%	49.10%	0.00%	1.80%	0.00%	
EU	59.44%	23.33%	0.00%	17.22%	0.00%	
OC	38.03%	45.07%	0.00%	16.90%	0.00%	

SD of the jet fuel price for these years, which can be seen in Figure 3.1 in Subsection 3.1.1. In between, a general increase of 19.59% in the maturity of fuel derivatives between 2006

Figure 2.7: Time series: hedge portfolio underlying assets (lines represent the percentage utilisation of the individual underlying)

and 2008 can be observed.

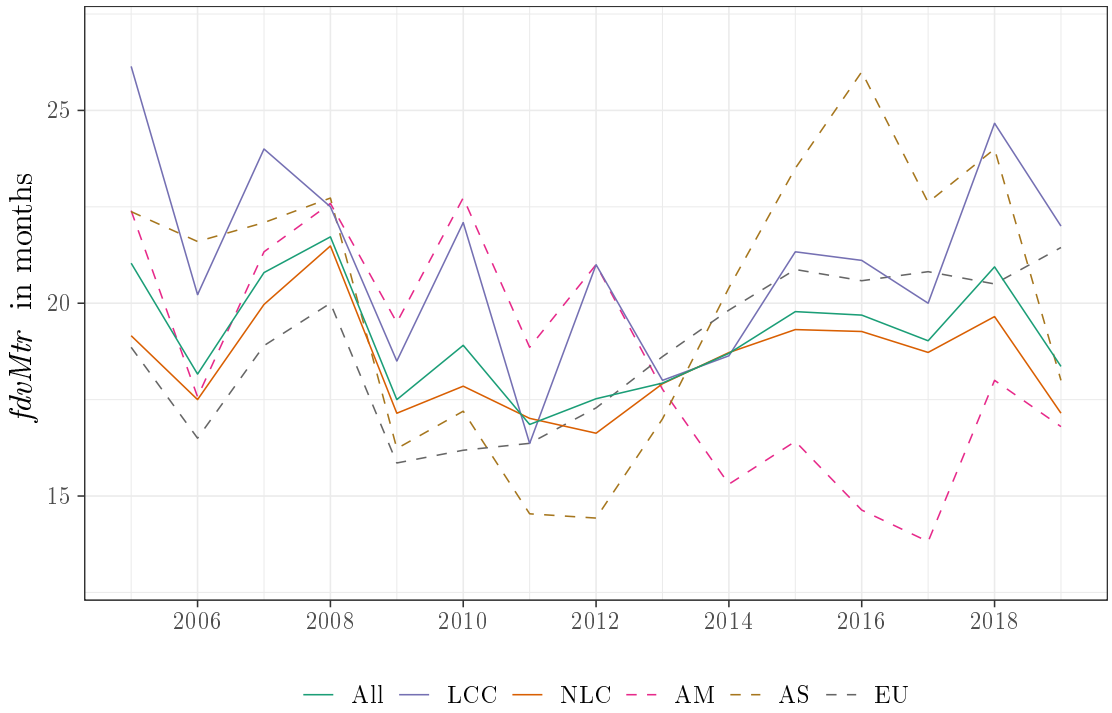
Figure 2.9 shows the average hedge ratio of contracts for 12, 24, 36 and 48 months. Hedge contracts with a maturity of 12 months show a low in 2011 (24.05%) and a high in 2014 (34.77%), but overall no general development. Contracts with a maturity of 24 months and 36 months have a high in 2007 of 15.01% and 9.37%, respectively and a low of 4.95% in 2010 and 0.87% in 2009. After the high in 2007 the hedge ratios for 36 months are rather stable in between 1.95% (2015) and 0.68% (2019). The hedge maturities for 48 months are relatively stable between 2.32% (2005) and 0% (2009 and 2016).

Figure 2.10[64] displays the average hedge ratio of the next 12 months (left y-axis) and its SD (right y-axis) including the distinction between LCCs and NLCs. Values of *fdvPct12m* greater than two are not considered, which is why four observations are not depicted, the same holds for Figure 2.11. On the left side, all airlines are included, on the right only those that hedge[65]. Overall, no general movement can be recognised over the years. The highest average hedge ratio for all airlines and NLCs, when all airlines are considered, is

[64] The legends of Figures 2.10 and 2.11 are to be understood in such a way that the dots represent the SDs of the subgroups and the lines represent the mean values.

[65] Airlines are classified as hedgers if *fdvPct12m* is different from zero.

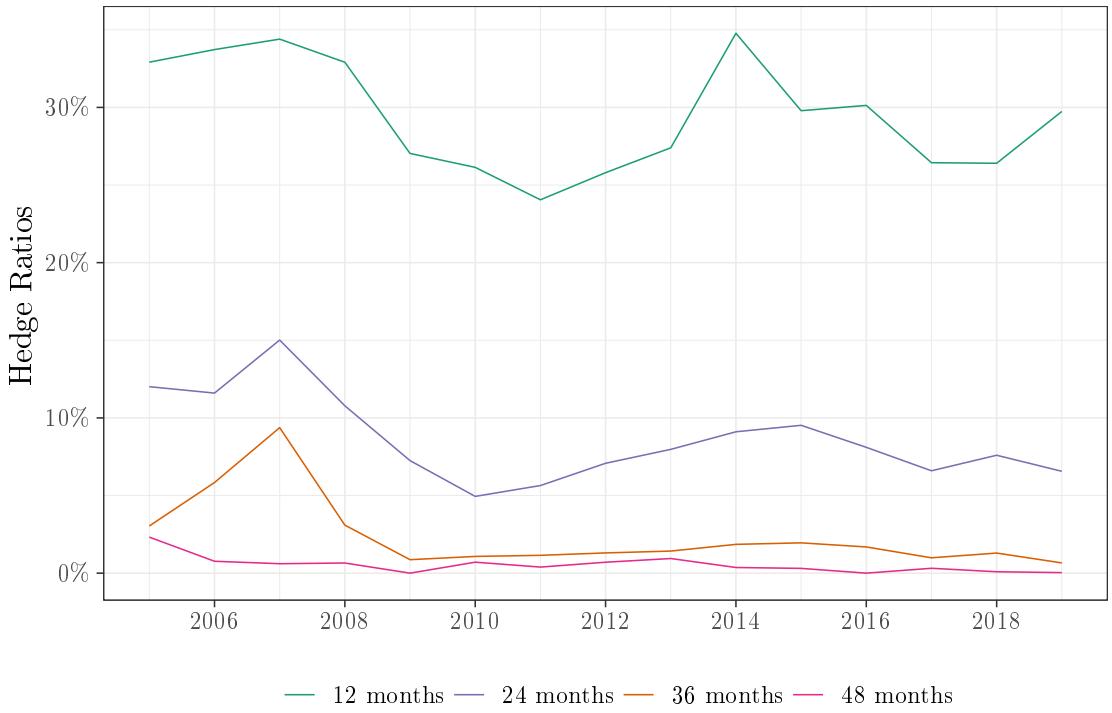
Figure 2.8: Time series: fuel derivative maturity in months (*fdvMtr*), annual average of all airlines and divided into LCC, NLC as well as AM, AS and EU



reached in 2014 with 36.77% and 36.15%, LCCs reach their peak already in 2006 with 41.43%. Looking at hedgers only, all airlines and NLCs also peak in 2014 at 50.33% and 52.36% and LCCs one year later at 56.36%. For hedgers only there is a general increase between 2011 and 2014. Comparing the left with the right panel, it is noticeable that the SD within the hedger group is less homogeneous. For all airlines and NLCs, the average SD is higher when all airlines are considered than when only hedgers are considered, for LCCs this does not hold. It indicates that higher extreme values are found for LCCs that hedge compared to the other groups. The highest SD of all LCCs and hedgers only LCCs is reached in 2015 with 0.36 and 2012 with 0.40, respectively.

Figure 2.11 shows the same as Figure 2.10, with a regional distinction. As in Figure 2.10, no general movement can be recognised over the entire observation period. The average hedge ratio of European airlines for all airlines (50.86%) and for hedgers only (56.89%) (only 2008 is an exception here, where the average hedge ratio of Asian airlines is higher) is higher than that of American (all airlines: 20.19%, hedgers only: 29.12%) and Asian airlines (all airlines: 19.76%, hedgers only: 38.51%). Similar to the previous figure for hedgers only, a general increase in the hedge ratio can be observed between 2012

Figure 2.9: Time series: percentages of next 12 (*fdvPct12m*), 24 (*fdvPct24m*), 36 (*fdvPct36m*), and 48 months (*fdvPct48m*) fuel consumption hedged, annual average of all hedgers



and 2014. Comparing the SD of all airlines and hedgers only, the same as for Figure 2.10 applies, it is more homogeneous when all airlines are considered. In this case, there is no clear outlier up or down. The highest SD value can be found when all airlines are considered in 2008 for Asian airlines (0.35). Same holds for hedgers only but with a value of 0.33.

Figure 2.10: Time series: hedge ratios for the next 12 months (*fdvPct12m*), annual average of all airlines and divided into LCC, NLC

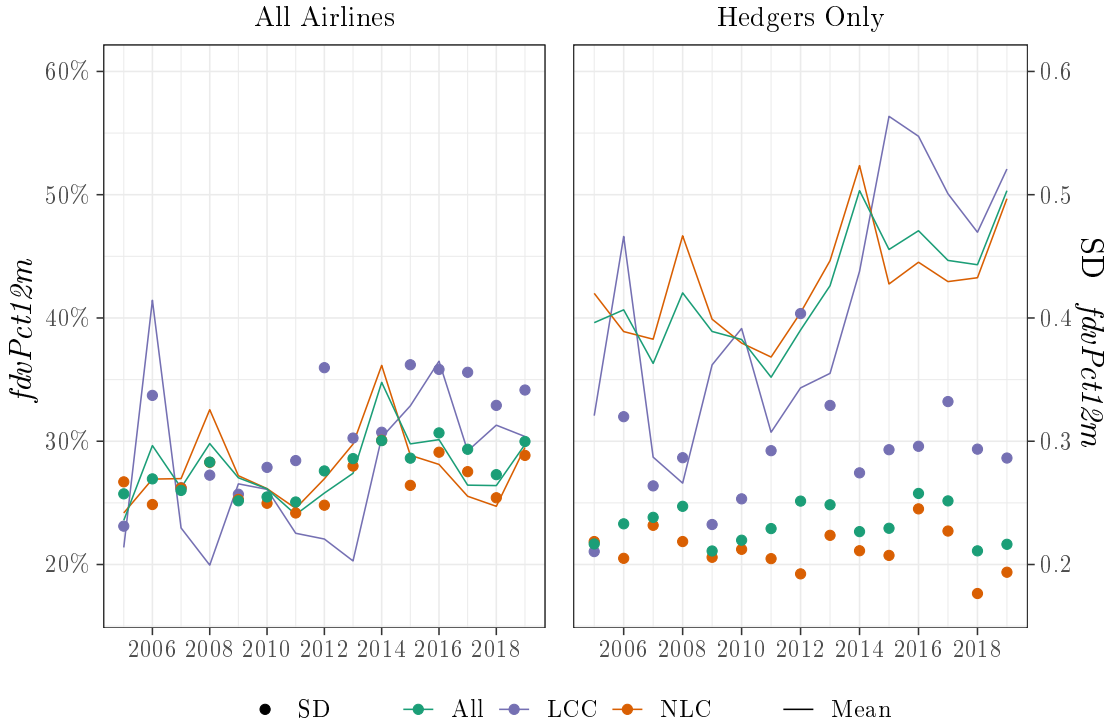
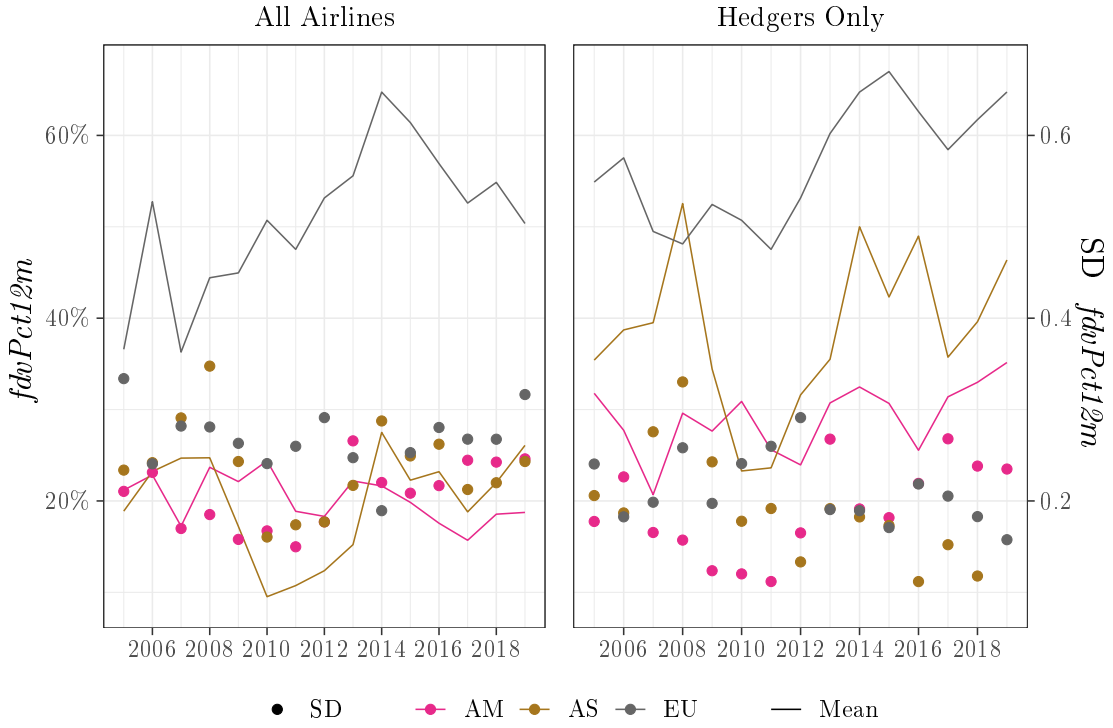


Figure 2.11: Time series: hedge ratios for the next 12 months (*fdvPct12m*), annual average of all airlines divided into AM, AS and EU



2.2.2.1 Financial Distress

Variable Description

This subsection focuses on financial distress motives for financial hedging. An overview of the relevant literature can be found in Subsection 3.1.2.1. In order to be able to examine the relevant hypotheses within this study, the associated variables will now be presented.

Starting with variables related to dividends, we first consider *divDm* (Adam, 2002; Carter et al., 2006; Bartram et al., 2009; Lin and Chang, 2009; Adam et al., 2017). It is a binary variable that takes the value of one if the airline pays dividends in the following year, as dividends for year t are always paid in $t+1$. In order to compare the payment of dividends between different airlines, the dividend payout ratio (*divRto*) and dividend yield (*divYld*) are included. *divRto* (Haushalter, 2000) indicates how much of a firm's net earnings are distributed as dividends. It is calculated by dividing the dividends per share (*divShr*) by the earnings per share (*eps*). With *eps* being calculated as

$$eps = \frac{incBfeo - divPrf}{shrTl},$$

where *incBfeo* is the income before extraordinary items and is calculated by subtracting extraordinary items (*eoItem*)[66] from net income (*incNet*).[67] *divPrf* are the total dividends paid for preference shares. *shrTl* is the total number of outstanding shares and is calculated by adding the total number of ordinary shares (*shrCom*) and the total number of preference shares (*shrPrf*). The *divYld* (Nance et al., 1993; Allayannis and Ofek, 2001; Nguyen and Faff, 2002; Judge, 2006; Spanò, 2007; Treanor et al., 2013) is an indicator on how much return a shareholder receives through dividends per dollar invested. It is a useful metric for investors to compare their investment in an airline's ordinary shares to other investment opportunities (Morrell, 2021) and is calculated by dividing *divShr* by the share price at the end of the financial year (*shrEnd*).

Two well-known financial performance measures are the earnings before interest and taxes (*ebit*) and the interest coverage ratio (*intCov*). *ebit* is calculated as

$$ebit = incBfeo + intExp - taxExp,$$

[66] Exceptional items include, for example, gains or losses on sales or restructuring costs (Finnair, 2020), an exceptional non-cash net operating charge (IAG, 2020) or a loss from discontinued operations (Korean Air, 2016).

[67] A distinction is made between *incNet* and *incBfeo* to deal with the problem that accounting income and the income used to calculate the tax charge differ (Pfefferle, 2019).

where *intExp* are the interest and *taxExp* the tax expenses[68]. The *intCov* is calculated by dividing *ebit* by *intExp* and is used to asses whether a firm has the ability to meet its interest obligations. According to Morrell (2021), it is one of the most important ratios in the airline industry. If its value is not significantly above one, there is little profit left to distribute to shareholders or reinvest in the company (Morrell, 2021). Within the literatur, the *intCov* is also used by Judge (2006) and by Nance et al. (1993), Gay and Nam (1998) and Bartram et al. (2009) with the last three using the three-year average. The lease-adjusted interest coverage ratio (*intCovAdj*) is calculated based on Damodaran (2012) by

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

where *olexpTl* are the total operating lease expenses as reported in the income statement or in the notes (Subsection 2.2.3).[69]

To account for negative equity values, the dummy variable *eqtyDm* is included. It is assigned a value of one if the book value of total equity (*eqtyTl*) is negative and zero otherwise.

The ratio of debt to total assets is measured using three different leverage ratios. These are used to test the common hypothesis in the literature that companies hedge to increase their debt capacity and thus reduce the risk of financial distress (Smith and Stulz, 1985; Graham and Rogers, 2002). In general, a high leverage ratio means that the company may have borrowed too much and is overleveraged relative to its ability to service the debt out of future cash flows. The first leverage ratio (*lvrg1*) is calculated by scaling interest bearing debt (*ibd*) by the book value of total assets (*asTl*). Similar leverage ratios are used by Haushalter (2000), Graham and Rogers (2002), Guay and Kothari (2003) and Spanò (2007). The second leverage ratio (*lvrg2*) (Carter et al., 2006; Spanò, 2007; Lin and Chang, 2009; Treanor et al., 2013) is calculated as

$$lvrg2 = \frac{liaTl - liaCrt}{asTl} = \frac{liaLt}{asTl},$$

where *liaTl* is the book value of total liabilities, *liaCrt* is the book value of current liabilities and *liaLt* is the book value of long-term liabilities. The last leverage ratio (*lvrg3*) is calculated by dividing the book value of long-term liabilities (*liaLt*) by *asTl*. In accordance with Pfefferle (2019) for all three leverage ratios, the leverage ratio squared is calculated (*lvrg1Sqr*, *lvrg2Sqr* and *lvrg3Sqr*) based on Purnanandama (2008). He uses these to control for what he believes to be a non-monotonic relationship between risk management and a

[68] *taxExp* is positive in the case of a tax benefit and negative in the case of a tax expense, see Table 2.10.
[69] The calculation of the lease adjusted variables can be found in Table B.5 in Appendix B.6.

company's financial distress. This aims at preventing biases of statistical conclusions.

The profit margin (*prfMrg*) and the return on assets (ROA, *roa*) are included as performance measures to evaluate the firm's profitability. *prfMrg* is calculated as

$$prfMrg = \frac{incBfeo + intAtax}{revTl},$$

where *intAtax* is the after-tax interest and is itself calculated by adjusting the interest expense (*intExp*) by the statutory corporate income tax (*taxSta*) with $(1 - taxSta)$. The adjustment is necessary to be able to compare firms with different capital structures (Brealey et al., 2023, p.839). For the statutory corporate income tax, the so-called combined corporate income tax rate is used as described in Table 2.10.[70] This is why *taxSta* contains both regional and national corporate tax rates. Using only the highest marginal tax rate would not reflect all features of the corporate tax code, as not all corporate income is taxed at this rate. A more sensible approach would be to use a simulated tax rate as in Graham and Smith (1999). However, such a simulation requires company-specific tax and financial income data over a long period of time. Another alternative approach would be to use an effective tax rate, but as the average of several years is used due to outliers, too many firm years would be lost. As suggested by Graham (2013) statutory tax rates can be used in empirical research. ROA measures the return available to equity and debt investors per dollar of a company's total assets and is calculated according to Brealey et al. (2023, p. 837) as

$$roa = \frac{intAtax + incBfeo}{asTl}.$$

Other studies do not adjust *intAtax* (Lee and Jang, 2007; Gay et al., 2011) and use earnings before taxes scaled by the book value of total assets (Graham and Rogers, 2002) or earnings before interest and tax deductions scaled by total assets (Allayannis and Ofek, 2011) as ROA.

In addition, several papers (Adam, 2002; Carter et al., 2006; Judge, 2006; Sprcic and Sevic, 2012; Rampini et al., 2014) use a variable related to credit rating to assess a company's internal resources. A poor credit rating is indicative of situations where financing is particularly costly (Rampini et al., 2014). As already mentioned in Pfefferle (2019), many of the airlines considered do not have a credit rating of the three major rating agencies[71], which is why such a variable is not included in the analysis.

[70] Air Arabia is an exception here. According to KPMG (2023), the UAE corporate tax rate is between zero and 55%. In fact, only foreign oil companies (55%) and branches of foreign banks (20%) pay taxes on their profits. As a result, Air Arabia is assigned a tax rate of zero.

[71] Fitch, Moody's and S&P.

Table 2.10: List of financial distress related variables

Variable	Label	Description
asTl	Total assets	Total assets as reported in 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 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 has negative *eqtyTl* in that reporting period
eqtyTl	Total equity	Book value of total equity as reported in balance sheet
ibd	Interest bearing debt	Interest bearing debt as reported in balance sheet (or in the notes) - Including: loans, financial leases, bonds, debentures, notes payable Other short and long-term liabilities are only included if the relevant items include 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 income statement, after minority interests have been paid and including discontinued operation and extraordinary items
*intAtax**	After-tax interest	Calculated as (1 - *taxSta*) × *intExp*
*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 income statement (or in the notes) - Including: interest payments on finance lease obligations
liaCrt	Current liabilities	Total current liabilities as reported in balance sheet
*liaLt**	Long-term liabilities	Calculated as *liaTl* - *liaCrt*
liaTl	Total liabilities	Total liabilities as reported in balance sheet, calculate 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* × *lvrg1*

continued on next page

Variable	Label	Description
*lvrg2**	Leverage ratio 2	Calculated as (*liaTl* - *liaCrt*) / *asTl* = *liaLt* / *asTl*
*lvrg2Sqr**	Leverage ratio 2 squared	Calculated as *lvrg2* × *lvrg2*
*lvrg3**	Leverage ratio 3	Calculated as *liaTl* / *asTl*
*lvrg3Sqr**	Leverage ratio 3 squared	Calculated as *lvrg3* × *lvrg3*
*prfMrg**	Profit margin	Calculated as (*incBfeo* + *intAtax*) / *revTl*
*roa**	Return on assets	Calculated as (*incBfeo* + *intAtax*) / *asTl*
shrCom	Ordinary shares outstanding	Total number of ordinary shares (common stock) outstanding taken from AR[72]
shrEnd	Share price at end of the financial year	Share prices are retrieved from Thomson Reuters Eikon - For the financial years not ending 31st December, the period end date share price is used (e.g. for 31st March the share price from 31st March is taken).
shrPrf	Preference shares outstanding	Total number of preference shares (preferred stock) outstanding
*shrTl**	Total number of shares outstanding	Total number of shares outstanding, equal to the total number of shares issued minus treasury shares. - Calculated as *shrCom* + *shrPrf*
taxExp	Tax expense	Total tax expenses as reported in income statement (or in the notes), including deferred and current tax expense 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, 2023), 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, 2023).[73]

Summary Statistics

Looking at Table 2.11, the binary variable *divDm* shows that on average 49.9% of the airlines pay dividends. The variables *divRto* and *divYld* provide information about the amount of dividends paid. With an average value of 0.17, *divRto* was below one. *divYld*, with an average value of 0.015, means that investors received on average less than two cents per dollar invested as a dividend. As already mentioned in Subsection 2.2.2.1, it makes sense to use *intCovAdj* instead of *intCov* due to extreme outliers. This is confirmed by the high SD of *intCov* (71.44), compared to 2.25 for *intCovAdj*. The minimum of -5.13 for

[72]The number of ordinary shares is always the undiluted amount, as it would go beyond the scope of this paper to determine the number of diluted ordinary shares for each airline.

[73]The OECD data is largely consistent with the KPMG figures. Counterexamples are, for example, the USA and Japan, whereby the values were taken from the OECD source.

intCovAdj was reached by Delta Air Lines in 2007 and the maximum of 25.35 by Allegiant Air in 2010. Allegiant Air had the highest average *intCovAdj* value of 10.65 compared to the second highest value of 6.17 for Japan Airlines. For this reason, Allegiant Air is excluded from the robustness checks of the multivariate analysis.

The summary statistics for the three leverage ratios contained in Table 2.11 confirm that the leverage ratios adjusted for leasing have increased, where the average value of *lvrg1* increased the most by 0.11. The largest *lvrg1* value with 1.08 was observed at Pakistan International Airlines (PIA) in 2018.[74] Compared to the average value of *lvrg1* (0.39), the average value of *lvrg2* is slightly higher at 0.41. The maximum of *lvrg2* is reached by Delta Air Lines in 2006 with 1.40, Delta Air Lines being under Chapter 11 at that time. The highest value for *lvrg3* is reached by Jet Airways in 2018 with 2.14, meaning that *liaTl* were more than double of *asTl*.

The average values of *prfMrg* and *prfMrgAdj* were 0.04 and 0.06. The minimum of both values were -0.44 and -0.42 (Jet Airways in 2018). The highs of 0.35 and 0.36 were achieved by Air Asia in 2007. *roa* and *roaAdj* also measure the profitability of a company, so it is not surprising that the summary statistics are very similar to those of *prfMrg* and *prfMrgAdj*.[75]

Descriptive Statistics

In the literature, financial distress is measured by different variables (3.1.2.1). In the context of this work, it is determined by variables like *eqtyDm, lvrg1* or *divRto*, which were explained in the sections before. *eqtDm* is displayed in Figure 2.12 in the left panel. If an airline has negative book equity value, it can be assumed that it is in financial distress, which is the case in 8.43% of the firm years. In addition, eight years are considered in which US airlines were under Chapter 11[76]. Figure 2.12 shows that the number of airlines with negative book equity value has increased, reaching a high of nine in 2014 and a low of zero in 2007. It can be seen that the total number is mainly driven by NLCs (76.73% of the sample) and by American airlines until 2011, which is due to airlines being under Chapter 11. The right panel of Figure 2.12 displays the *fdvPct12m* for airlines with positive and negative equity value. *fdvPct12m* of airlines with positive equity value is always above that of airlines with negative equity value. In 2014, the values are almost the same (0.29%

[74] PIA was among the ten highest *lvrg1* values six times, with the value of *lvrg1* being higher than one in two more firm years (2017, 2015).

[75] See also the correlation matrix D.3 with a correlation value of 0.90. Pearson correlation coefficient was calculated as it is the most common measure of linear correlation.

[76] Delta Air Lines (2005-2007), Hawaiian Airlines (2005), US Airways (2005) and American Airlines (2011-2013)

Table 2.11: Summary statistics of the variables relevant to financial distress

Variable	N	Mean	St. Dev.	Min	Max
divDm	868	0.463	0.499	0.000	1.000
divRto	868	0.170	0.560	−6.378	5.351
divYld	864	0.015	0.029	0.000	0.256
intCov	867	11.219	71.435	−211.100	1,320.673
intCovAdj	867	1.853	2.246	−5.134	25.354
lvrg1	869	0.389	0.188	0.000	1.080
lvrg1Adj1	864	0.496	0.167	0.070	1.073
lvrg2	869	0.414	0.172	−0.489	1.399
lvrg2Adj1	864	0.516	0.151	0.045	1.319
lvrg3	869	0.760	0.225	0.082	2.142
lvrg3Adj1	864	0.796	0.193	0.200	1.997
prfMrg	869	0.041	0.087	−0.440	0.352
prfMrgAdj	865	0.059	0.086	−0.415	0.358
roa	869	0.029	0.075	−0.450	0.295
roaAdj1	863	0.025	0.057	−0.328	0.1996

difference).

Figure 2.13 displays the unadjusted (left, *lvrg1*) and lease-adjusted[77] (right) leverage 1 ratios *lvrg1Adj1*.[78] Overall, *lvrg1* decreased for all airlines by 16.73% with Asian airlines having the biggest decline of 24.55% and LCCs having the least of 3.06%, but there is no recognisable general development. Asian airlines had the highest *lvrg1* and European Airlines the lowest for the entire period. A local minimum of unadjusted values was reached for all airlines in 2007 with a decline of 2.66 percentage points, immediately followed by a peak in 2008. Comparing the left with the right panel shows that all groups have used operating leases, as *lvrg1Adj1* is shifted upwards for all of them.[79]

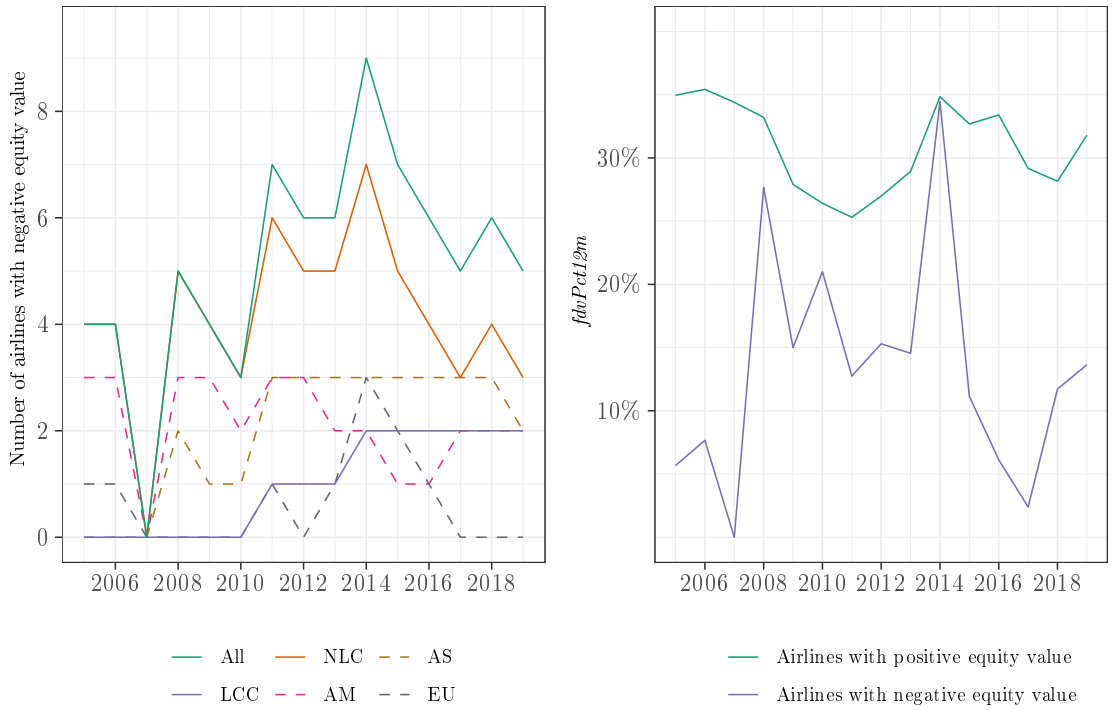
Comparing *lvrg2* from Figure 2.14 with *lvrg1* from Figure 2.13, it is noticeable that we can see a similar picture of an overall decrease (7.13%). The only subgroup with an increase are LCCs with 16.80%. Moreover, it is not Asian but American airlines that show the highest values and not only European airlines with the lowest values but also LCCs. *lvrg2Adj1* shows a similar picture, with an overall decrease of 5.12%, driven by the decrease of 12.74% of American airlines and 7.39% of NLCs. Over time, the distances between the

[77] Lease-adjusted in accordance with Damodaran (2012), see Subsection 3.1.2.2.

[78] 2019 is not considered for lease adjusted variables as new accounting standards were introduced for almost all airlines in the sample from 2019 onwards. See Subsection 4.1.1.3 for further information. Figures including 2019 can be found in Appendix B.8.

[79] The following airlines have not reported operating lease expenses for the years in brackets: Asiana Airlines (2005), Jazeera Airways (2010-2013), Regional Express (2015) and Shadong Airlines (2008).

Figure 2.12: Time series: Number of airlines with negative equity value (*eqtyDm*), annual average of all airlines and divided into NLCs, LCCs and regions and fuel derivative hedge ratio for the next 12 months (*fdvPct12m*) for airlines with positive and negative equity value



values of *lvrg2Adj1* become significantely smaller and converge from an interval between 47.46% and 62.91% in 2005 to an interval between 48.08% and 54.89% in 2018.[80]

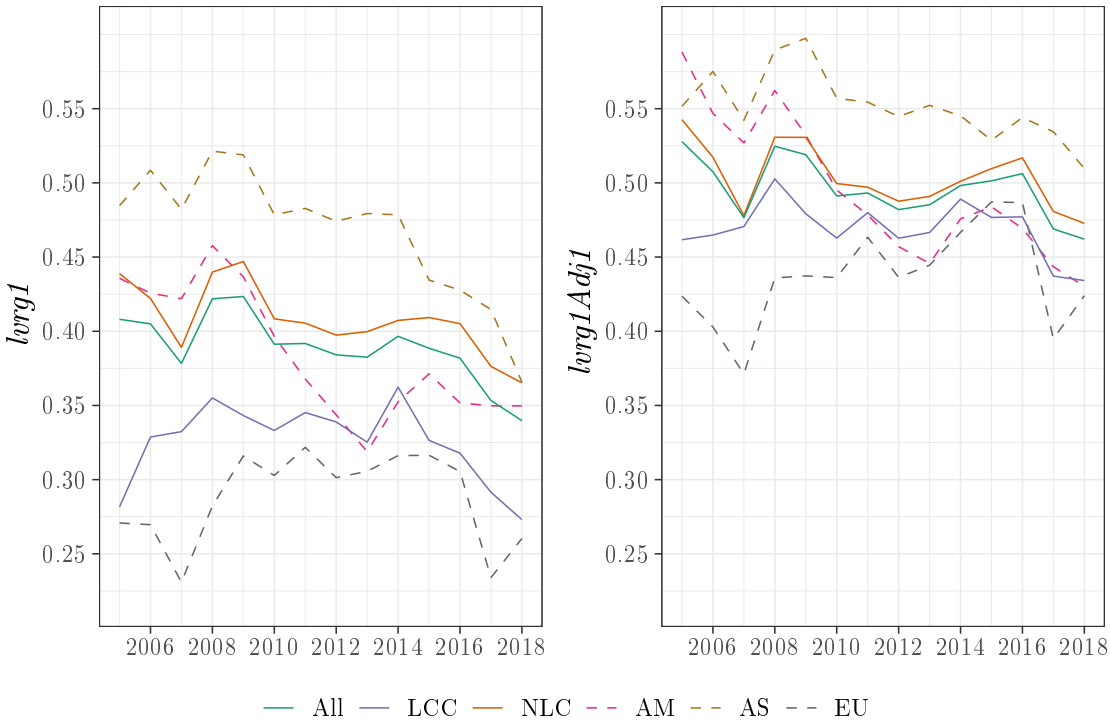
Figure 2.15 shows the lease-adjusted interest coverage ratios (*intCovAdj*).[81] For the period between 2005 and 2018, the average *intCovAdj* increased by 44.66%, with American airlines having the biggest increase of 113.68% and Asian airlines having the lowest with 17.83%. In 2008, the year of the financial crisis, the values for all but the LCCs fell below one and then rose above one again in 2009, with the exception of the European airlines, for which the value was above one again from 2010. The highest value of 4.38 was reached by LCCs in 2016.

Figure 2.16 shows lease-adjusted profit margins (*prfMrgAdj*) and the jet fuel spot price per barrel in USD between 2005 and 2018. The correlation between the *prfMrgAdj* and the spot price of jet fuel is -0.35, clearly showing the negative impact of the spot price of jet fuel on profit margins. Between 2006 or 2007 and 2008 there is a general decline,

[80] Figure B.3 in Appendix B.8 shows the same as Figures 2.13 and 2.14 but for the variables *lvrg3* and *lvrg3Adj1*.

[81] *intCov* is subject to extreme outliers, which is why *intCovAdj* is considered here.

Figure 2.13: Time series: unadjusted leverage ratios 1 (*lvrg1*) and lease-adjusted (*lvrg1Adj1*), annual average of all airlines and divided into NLCs, LCCs and regions



which could be related to the significant increase in the jet fuel spot price between 2006 and 2008 (54.13%). Immediately thereafter, margins recovered and remained at similar levels until 2014. Between 2014 and 2016, a general upward trend in *prfMrgAdj* can be observed, which can be explained by the downward trend in spot prices for jet fuel between 2014 and 2016.

In Figure 2.17, the variables *lvrg1Adj1* and *lvrg3Adj1* are plotted against *costDbt*. The size of the points reflects the leasing-adjusted total assets (*asTlAdj1*[82]) of the airlines. The two debt ratios are plotted in order to control for the size effect. We can see that the slope is positive (0.19 (*lvrg1Adj1*), 0.2 (*lvrg3Adj1*)), which is consistent with the theory, where it is assumed that the cost of debt increases exponentially with the amount of outstanding debt (Froot et al., 1993; see Subsection 3.1.2.1).

[82] *asTlAdj1* is calculated as $asTl + olexpPv1$. *olexpPv1* is explained in Table 2.15.

Figure 2.14: Time series: unadjusted leverage ratios 2 (*lvrg2*) and lease-adjusted (*lvrg1Adj2*), annual average of all airlines and divided into NLCs, LCCs and regions

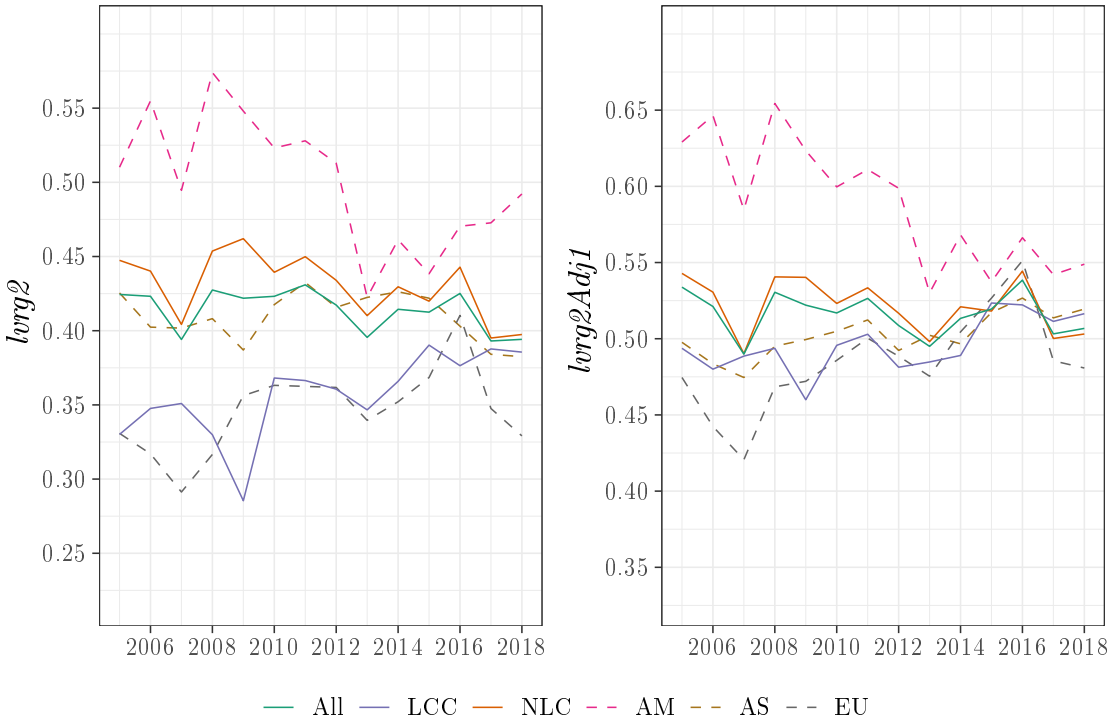


Figure 2.15: Time series: lease-adjusted interest coverage ratios (*intCovAdj*), annual average of all airlines and divided into NLCs, LCCs and regions

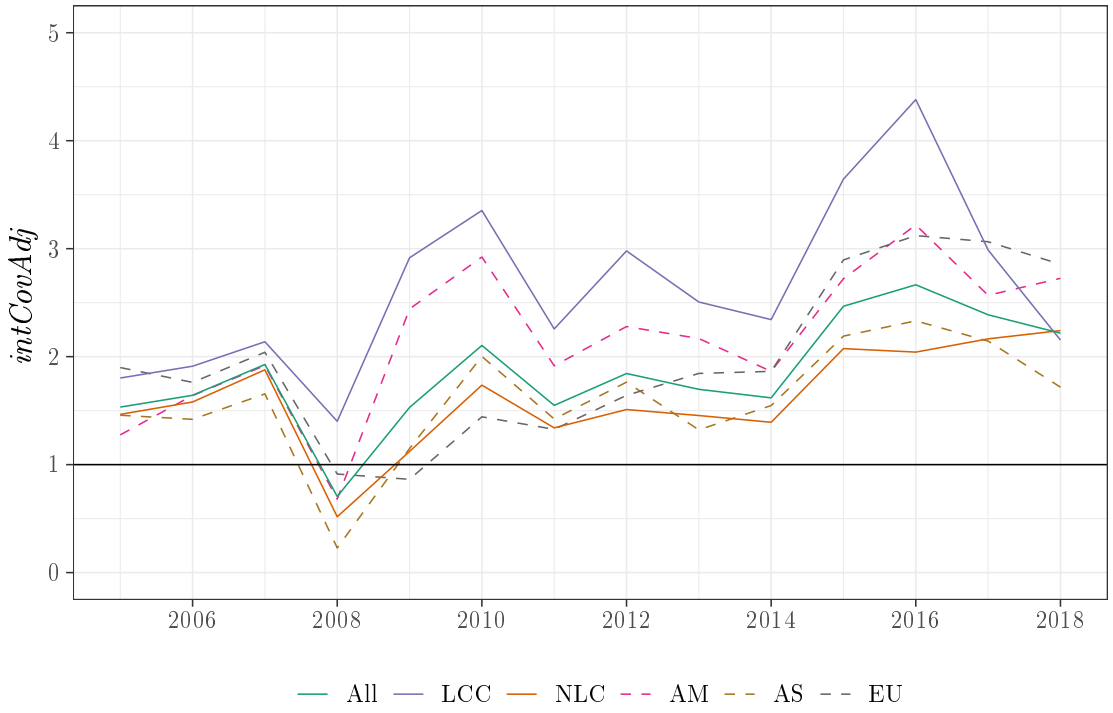


Figure 2.16: Time series: lease-adjusted profit margin (*prfMrgAdj*), annual average of all airlines and divided into NLCs, LCCs and regions and yearly average of jet fuel spot price per barrel in USD

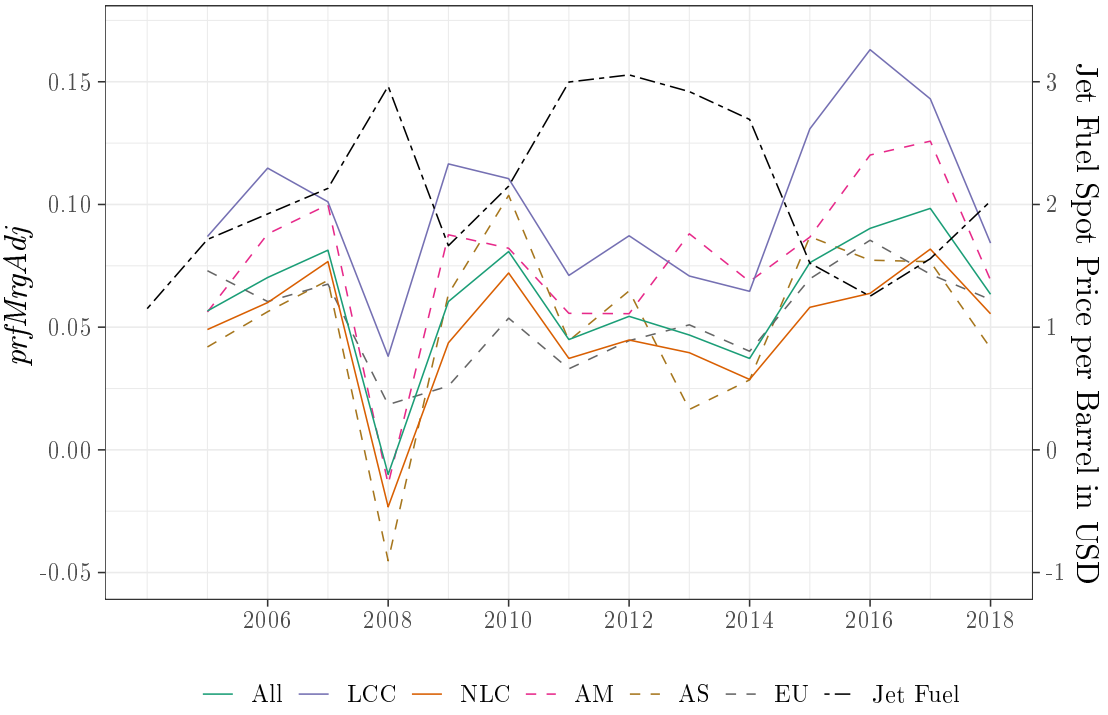
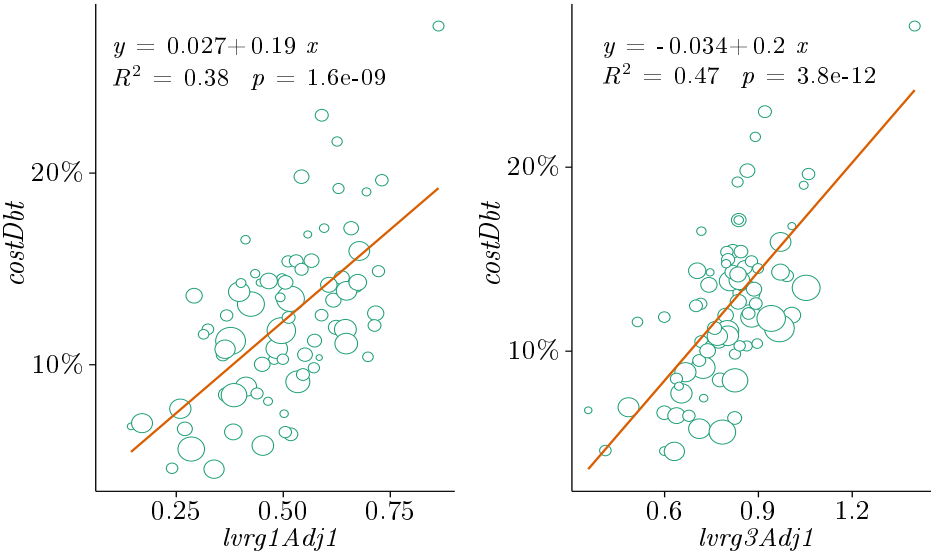


Figure 2.17: Cross-sectional: cost of debt (*costDbt*) versus lease-adjusted variables (leverage ratio 1 (*lvrg1Adj1*) and leverage ratio 3 (*lvrg3Adj1*), average across years for each airline (weighted by lease-adjusted total assets (*asTlAdj1*))



2.2.2.2 Underinvestment

Variable Description

Apart from financial distress, there are other reasons why hedging can be attractive for companies. We therefore want to analyze variables relevant to the underinvestment problem (3.1.2.2) described below, for example capital expenditures or the market-to-book ratio.

Starting with ratios connected to investments we first need to define the calculation of the net capital expenditure (CAPEX, *capexNet*)[83], which is calculated by adding the CAPEX inflow (*capexIn*) to the outflow (*capexOut*). To arrive at the first ratio (*capAs*), CAPEX is divided by *asTl* (Haushalter, 2000; Sprcic and Sevic, 2012). The second ratio is the investment to sales ratio (*capRev*), which is calculated by scaling *capexNet* by *revTl* (Allayannis and Weston, 2001; Carter et al., 2006; Judge, 2006; Lin and Chang, 2009, Treanor et al., 2013). The last ratio (*capSize*) (Géczy et al., 1997) is investment scaled by the firm size of the airline (*size*), where the size is calculated by adding the market capitalization of the airline (*mktCap*) to *liaTl*. The market capitalization itself is calculated as

$$mktCap = shrCom \times \frac{shrEnd}{xrEnd} + shrPrfMv,$$

[83] A negative value means a cash outflow and a positive value means a cash inflow.

where *shrPrfMv* is the market value of the preference shares. Other studies use R&D dummies, expenses or other ratios (Dolde, 1993; Nance et al., 1993; Géczy et al., 1997; Gey and Nam, 1998; Allayannis and Ofek, 2001; Graham and Rogers, 2002; Judge, 2006; Spanò, 2007; Purnanandam, 2008), but these are hardly existent in the airline industry, which is why the investment opportunity ratios are used.

In order to account for liquidity, liquidity ratios are included. One of them is the cash to sales ratio (*cashRev*) (Carter et al., 2006; Lin and Chang, 2009) which is calculated by dividing the cash and cash equivalents (*cashEq*) by *revTl*. The second one is the cash ratio (*cashRto*) (Haushalter, 2000; Judge, 2006; Spanó, 2007) and is calculated as

$$cashRto = \frac{cashEq + mktSec}{liaCrt},$$

where *mktSec* are the marketable securities. Cash ratios are of interest as the cash holdings might have an impact on the firm's hedging behavior (Subsection 3.1.2.1 and 3.1.2.2). One further ratio is the quick ratio (*qckrto*) (Tufano, 1996; Géczy et al., 1997; Adam, 2002; Purnanandam, 2008; Bartram et al., 2009; Gay et al., 2011; Sprcic and Sevic, 2012; Dionne and Triki, 2013; Adam et al., 2017), which is calculated as

$$qckRto = \frac{cashEq + mktSec + rcvCrt}{liaCrt},$$

where *rcvCrt* are the current receivables. It helps to identify current assets that can be easily and readily converted into cash (Morrell, 2021). In order to measure the capability of the firm to meet its short-term liabilities the current ratio (*crtRto*) (Nguyen and Faff, 2002) is included as well. It is calculated by dividing the current assets (*asCrt*) by *liaCrt*. According to Morrell (2021), a value of one is considered largely sound in the aviation industry. A value significantly above or below one might indicate that the airline is generating more cash than it can profitably reinvest (above) or that it is not generating enough cash to meet its short-term obligations (below) (Morrell, 2021).

To measure the availability of internal funds (3.1.2.2), the market-to-book (MTB) ratio (*mtbRto*) is included. It is calculated by scaling *mktCap* by *eqtyTl* and is either used in this form (Gay and Nam, 1998; Allayannis and Ofek, 2001; Adam, 2002; Nguyen and Faff, 2002; Judge, 2006; Bartram et al., 2009; Adam et al., 2017)[84] or the inverse (*eqtyTl*/*mktCap*), which is called book-to-market ratio (Froot et al., 1993; Nance et al., 1993; Géczy et al., 1997; Gay et al., 2011). The MTB ratio is of special interest as the underinvestment problem is most pronounced for firms with valuable investment opportunities (Graham and

[84] Although they all use the MTB ratio, the calculations differ. Going into more detail about the individual calculations would go beyond the scope of this work.

Rogers, 2002). Nevertheless, the use of it is disputed, as discussed in Subsection 3.1.2.2. In general, a *mtbRto* exceeding one means that the value of the company's assets when utilised exceeds the historical costs (Berk and DeMarzo, 2023, p. 66).

The price-earnings ratio (*peRto*) (Gay and Nam, 1998; Judge, 2006) is used to gauge the market value. The basic idea is that the value of the share should be proportional to the amount of income it can generate for its shareholders. It is calculated by dividing *shrEnd* by *eps* (Berk and DeMarzo, 2023, p. 79).

A similar indicator for the market value of a company compared to the replacement cost of its assets is Tobin's Q (*tobQ*) (Gay and Nam, 1998; Treanor et al., 2013). Carter et al. (2006) use Tobin's Q to measure investment opportunities. In accordance with Pfefferle (2019) who based her calculation on Chung and Pruitt (1994)[85] it is calculated as

$$tobQ = \frac{mktCap + liaTl}{asTl}.$$

Table 2.12: List of underinvestment problem related variables

Variable	Label	Description
asCrt	Current assets	Total current assets as reported in balance sheet
*capAs**	CAPEX scaled by total assets	Calculated as *capexNet / asTl*
capexIn	Capital expenditure (inflow)	Capital expenditure as reported in cash flow statement under cash flow from disinvestment activities (cash inflow) - Excluding: dividends received, financial assets and increase in cash in connection with mergers
*capexNet**	Capital expenditure (CAPEX) (net)	Calculated as *capexOut + capexIn* (-) means a net capital expenditure (cash outflow) (+) means an inflow
capexOut	Capital expenditure (outflow)	Capital expenditure as reported in cash flow statement under cash flow from investing activities (cash outflow) - Including: capital expenditure for PPE, investment in joint venture, purchase of non-current assets, tangible and intangible assets, payments for advances for new aircraft, investment in associated firms, increase in lease prepayments, acquisition of equity method investments, increase in equipment purchase deposits, acquisition of subsidiary - Excluding: purchase of financial assets and available-for-sale securities
*capRev**	CAPEX to sales ratio	Calculated as *capexNet / revTl*

continued on next page

[85] Chung and Pruitt (1994) use an approximated Q. It gets by with basic financial and accounting information and does not require complex calculations like Tobin's Q of Lindenberg and Ross (1981). Chung and Pruitt (1994) examine the approximated Q using regressions and conclude that it explains the variability of the Tobin's Q of Linberg and Ross (1994) at least 96.6% of the firm years.

Variable	Label	Description
*capSize**	CAPEX scaled by firm size	Calculated as *capexNet / size*
cashEq	Cash and cash equivalents	Cash and cash equivalents as reported in balance sheet (or in the notes) - Excluding: restricted cash and deposits for lease agreements
cashRev	Cash to sales ratio	Calculated as *cashEq / revTl*
*cashRto**	Cash ratio	Calculated as *(cashEq + mktSec) / liaCrt*
*crtRto**	Current ratio	Calculated as *asCrt / liaCrt*
eqtyTl	Total equity	Book value of total equity as reported in balance sheet
*mktCap**	Market capitalization	Calculated as *shrCom* x *shrEnd/xrEnd + shrPrfMv*
mktSec	Marketable securities	Marketable securities as reported in balance sheet (or in the 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
*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 balance sheet (or in the notes) under current assets. Including: receivables from sale of aircrafts, trade receivables, other receivables, receivables from related parties, advances to suppliers, notes receivables
shrPrfMv	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.
*size**	Firm size of the airline	Calculated as *mktCap + liaTl*
*tobQ**	Tobin's Q	Calculated as *(mktCap + liaTl) / asTl*

Summary Statistics

Table 2.13 shows the summary statistics for the variables relevant to the underinvestment problem. The CAPEX ratios (*capAs, capRev* and *capSize*) do not change substantially when adjusted for leasing. The lowest value for *capAsAdj1* and *capRevAdj1* of -0.50 and -1.31 were achieved by AirAsia in 2006, as well as the highest values of 0.51 and 1.31 in 2018. For *capSizeAdj1* the lowest value of -0.36 is reached by Regional Express in 2010 and the highest value of 0.50 is reached by AirAsia in 2018. Negative values in this context mean an investment.

In terms of liquidity ratios, it is worth noting that the minimum of *cashRev* and *cashRto* are reached by SpiceJet in 2013, while the maximum of the two is reached by AirAsia in 2009 and Air Arabia in 2008. The means of the two are 15.3% and 58.4%. The minimum and maximum of *crtRto* and *qckRto* are reached by GoI in 2019 with 11.1% and Great Lakes in 2005 with 559.7% as well as 6.7% and 439.2% by AirAsia in 2005. As mentioned earlier, the dataset has outliers, which is reflected in the SD of *mtbRto* and *peRto*. The lowest *mtbRto* is stated by Jet Airways in 2011 due to a relatively low market capitalization and a negative *eqtyTl* value.[86] The highest *mtbRto* with 72.18 is reached by Air Canada in 2015 due to a decrease of 99.49% in *eqtyTl* compared to 2018. The lowest *peRto* is stated by JetBlue in 2006 with -2,522 and the highest by Qantas in 2013 with 1,393 both due to low *eps*, which is negative in the case of JetBlue and positive for Qantas. The minimum of *tobQ* and *tobQAdj* are from the same firm year (Great Lakes in 2014), while the maximum is different with 9.01 for *tobQ* and 6.81 for *tobQAdj* both by GoI in 2018. The mean of *tobQAdj1* is slightly smaller as well as the SD.

Table 2.13: Summary statistics of the variables relevant to the underinvestment problem

Variable	N	Mean	St. Dev.	Min	Max
capAs	869	−0.081	0.086	−0.613	0.472
capAsAdj1	863	−0.059	0.089	−0.500	0.513
capRev	869	−0.109	0.131	−1.168	0.804
capRevAdj1	866	−0.095	0.164	−1.305	1.305
capSize	865	−0.069	0.073	−0.497	0.457
capSizeAdj1	859	−0.052	0.077	−0.358	0.502
cashRev	869	0.153	0.150	0.001	1.012
cashRto	869	0.584	0.465	0.009	3.811
crtRto	869	0.948	0.535	0.111	5.597
mtbRto	865	1.169	12.526	−281.921	72.180
peRto	864	13.112	116.392	−2,522.051	1,392.965
qckRto	869	0.807	0.501	0.067	4.392
tobQ	865	1.283	0.589	0.571	9.007
tobQAdj1	860	1.222	0.460	0.571	6.809

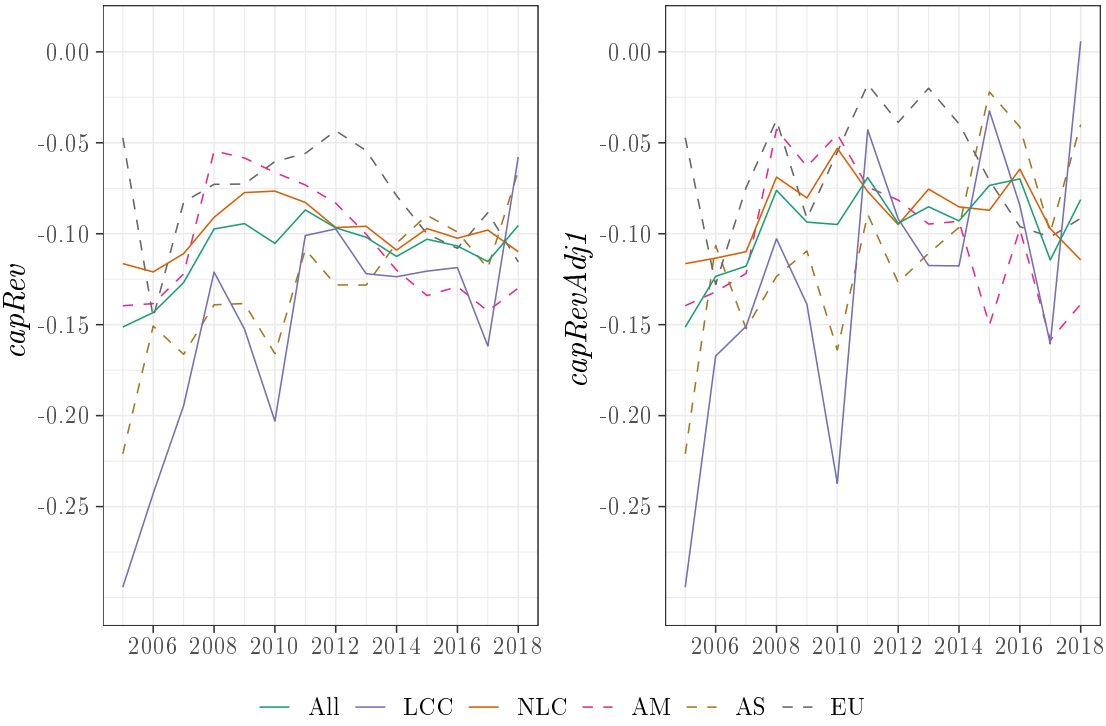
Descriptive Statistics

Figure 2.18 displays one measure for investments of an airline, the unadjusted (*capRev*) and lease-adjusted CAPEX to sales ratio (*capRevAdj1*). Appendix B.8 contains the Figures for *capAs* and *capAsAdj1* (Figure B.9) and *capSize* and *capSizeAdj1* (Figure B.10).

[86] The values of *eqtyTl* remain negative up to and including 2018, but the ratio of *mktCap* and *eqtyTl* changes so that there are no more outliers.

Overall, airlines spent an average of 9.94% of their total revenue in lease-adjusted capital expenditure during the period under review[87], with LCCs investing 12.44%, NLCs 9.32%, American 10.96%, Asian 10.92% and European airlines investing 7.03% on average. The overall high and low of *capRevAdj1* in the sample is reached by LCCs, with -0.29 in 2005 and 0.01 in 2018, which is also the only positive value.

Figure 2.18: Time series: unadjusted (*capRev*) and lease-adjusted CAPEX to sales ratio (*capRevAdj1*), annual average of all airlines and divided into NLCs, LCCs and regions

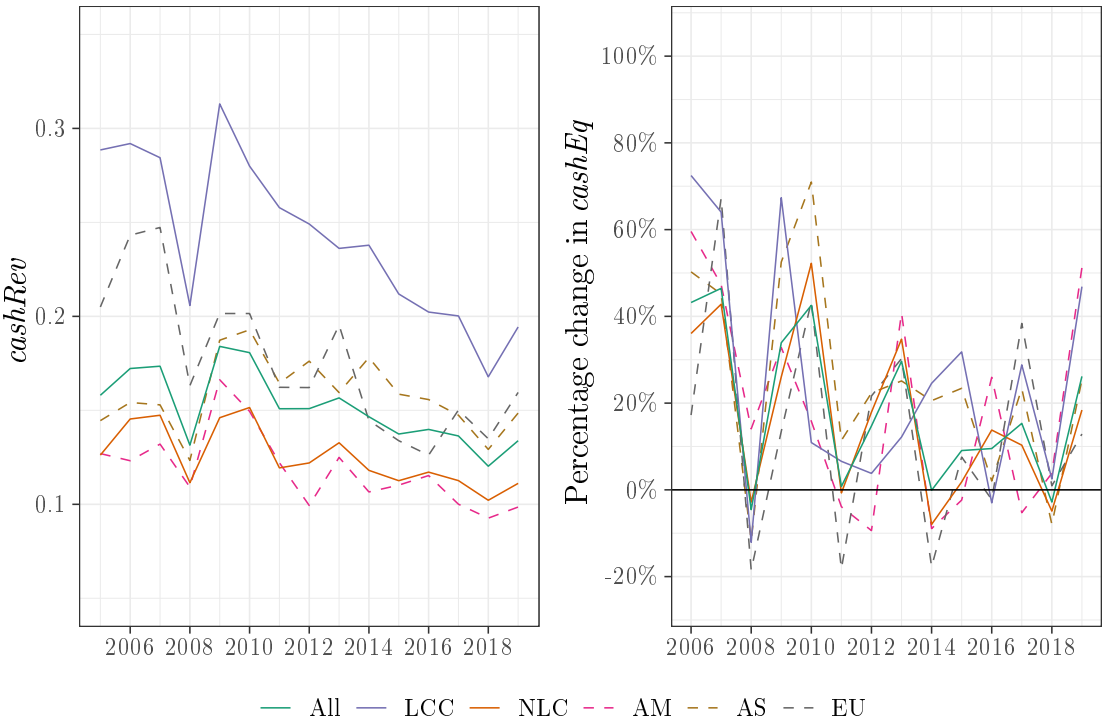


Next, consider the cash positions of airlines. In Figure 2.19 the cash to sales ratio (*cashRev*) is displayed in the left panel. In the right panel, the percentage change in cash and cash equivalents (*cashEq*) is displayed as *cashRev* on the left does not capture changes in *cashEq* when *revTl* changes similarly. Overall, the average *cashRev* declined by 15.29% with American and European Airlines decreasing by 22.39% and 22.18%, NLCs decreasing by 11.90% and Asian airlines being the only ones with an increase of 2.79%. The *cashRev* of LCCs is the highest for the whole sample period but also declined the most by 32.64%. The largest decline was between 2007 and 2008[88] with an average of 24.21%, followed by 2009 to 2010 with 16.52% and 2017 to 2018 with 11.81%. The percentage change in *cashEq*

[87] Negative values here mean expenditure.
[88] Financial crisis 2007-2008.

shows a general low point for 2008, which falls in the period of the financial crisis between 2007 and 2008. Beyond this, no general trend is recognisable. For further background information on liquidity ratios, Figures concerning the *cashRto* (B.11), *qckRto* (B.12) and *crtRto* (B.13) are included in Appendix B.8.

Figure 2.19: Time series: cash to sales ratio (*cashRev*) and percentage changes in cash and cash equivalents (*cashEqChg*), annual average of all airlines and divided into NLCs, LCCs and regions[89]



Taking a closer look at the availability of internal funds, we start with the *mtbRto* in Figure 2.20. The *mtbRto* was below zero in 75 firm years (8.12%) and between zero and one in 249 firm years (26.95%). Overall, the average *mtbRto* of all airlines declined by 44.14%, with American airlines recording the largest decline of 77.06%. All groups fell below one in one or more years (One: American, LCCs, European, NLCs; Two: Asian), with the global low for LCCs being 0.08 in 2018[90]. In addition to the *mtbRto*, the value of the MSCI World Transportation Index[91] is displayed in Figure 2.20. The correlation

[89] $cashEqChg > 5$ excluded, nine observations not considered

[90] This low value results from the negative values of GoI (-17.44) and SpiceJet (-16.72). Excluding these two values, the average *mtbRto* for LCCs in 2018 would be 2.53.

[91] The MSCI World Transportation Index comprises large and medium-sized shares that belong to the transport industry. On 31 January 2024, 3.02% of the index consisted of passenger airlines. (msci.com: `https://www.msci.com/documents/10199/1495ddee-9f80-43ed-81fa-4dc7c618d5ec`, visited on 02/12/2024)

between the *mtbRto* and the index is -0.36.[92]

Figure 2.20: Time series: market-to-book ratios (*mtbRto*), annual average of all airlines and divided into NLCs, LCCs and regions[93]

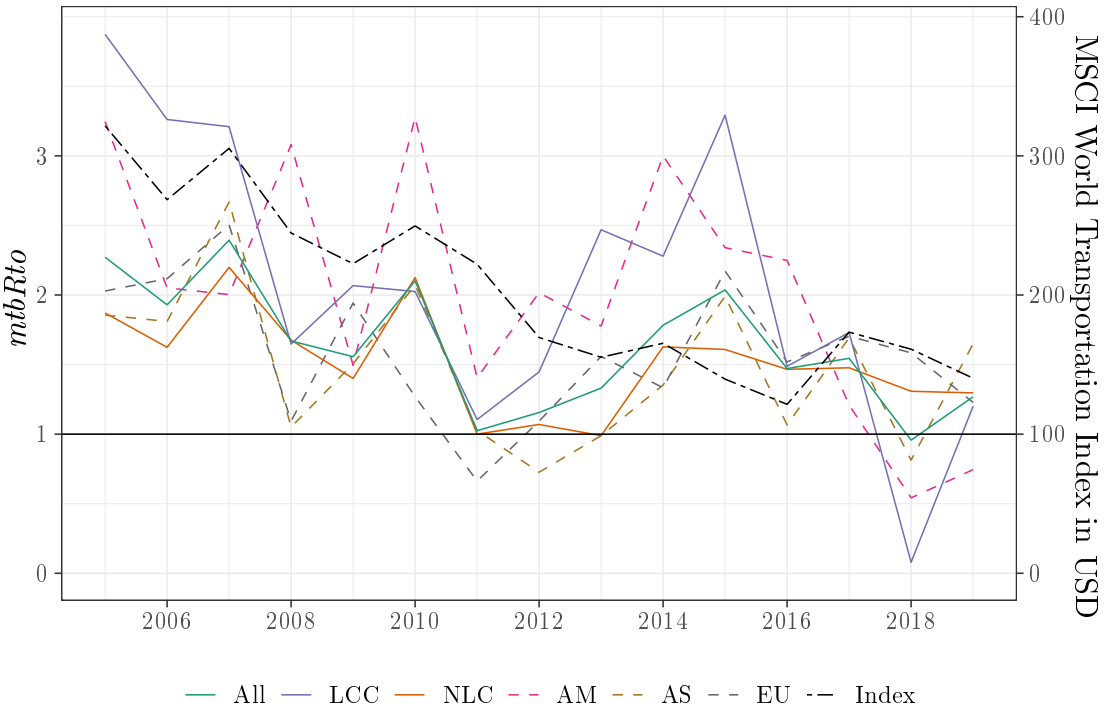


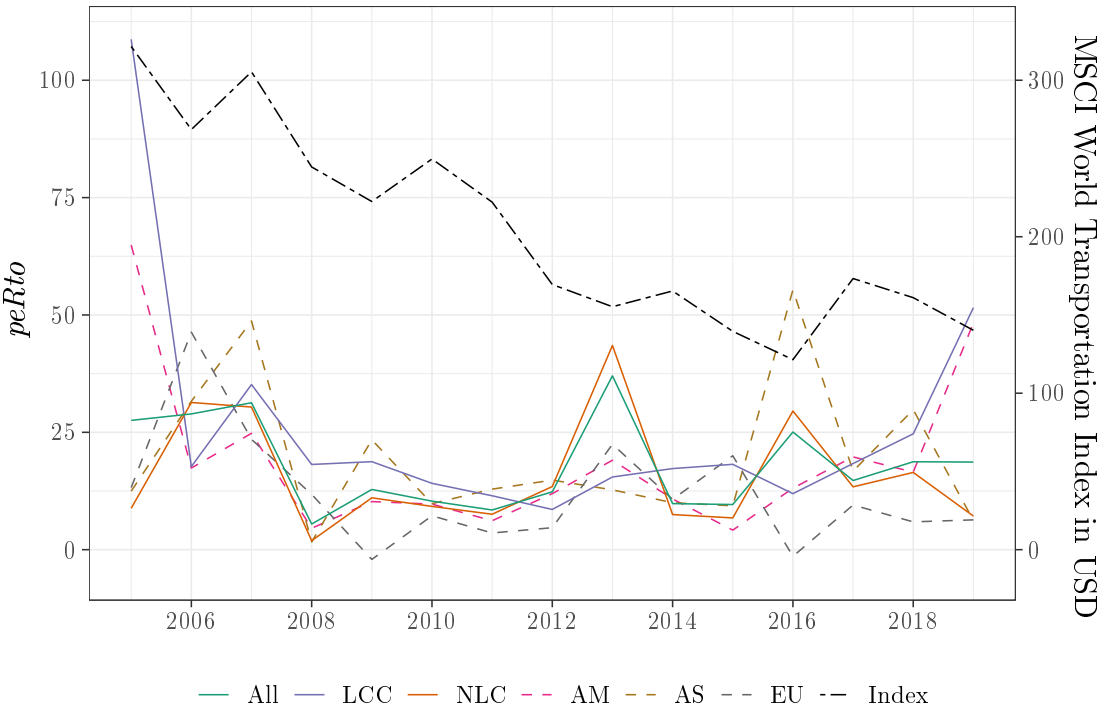
Figure 2.21 shows the average annual price-earnings ratios (*peRto*) and the MSCI World Transportation Index. Overall, no general trend can be recognised. The highest *peRto*s were achieved in 2005 by LCCs (17.71) and American airlines (17.39) before dropping to 17.71 (LCCs) and 17.39 (American) the most during the sample period. Comparing the index and the *peRto*, it is noticeable that there are major differences. The correlation with the index is 0.09, which emphasises the need for cautious interpretation due to the small number of passenger airlines included in the index.

The annual average of unadjusted (*tobQ*) and lease-adjusted Tobin's Q (*tobQAdj1*) are both shown in Figure 2.22. It shows that only European airlines had an annual average value below one for *tobQ* (0.94) and *tobQAdj1* (0.95) for the year 2011. Overall, the value

[92] Caution is required when interpreting the correlation here, as passenger airlines account for less than 5% of the index. Other indices such as the S&P Composite 1500 Passenger Airlines (Sub Ind) or the MSCI World Passenger Airline Industry Price Index were also considered, but either the prices were not available via Thomson Reuters Eikon or other sources such as `https://www.onvista.de/`, or no further information on the index itself or no information on the composition of the index was available.

[93] $\|mtbRto\| > 20$ not considered, 13 observations not taken into account

Figure 2.21: Time series: price-earnings ratio (*peRto*), annual average of all airlines and divided into NLCs, LCCs and regions[94]

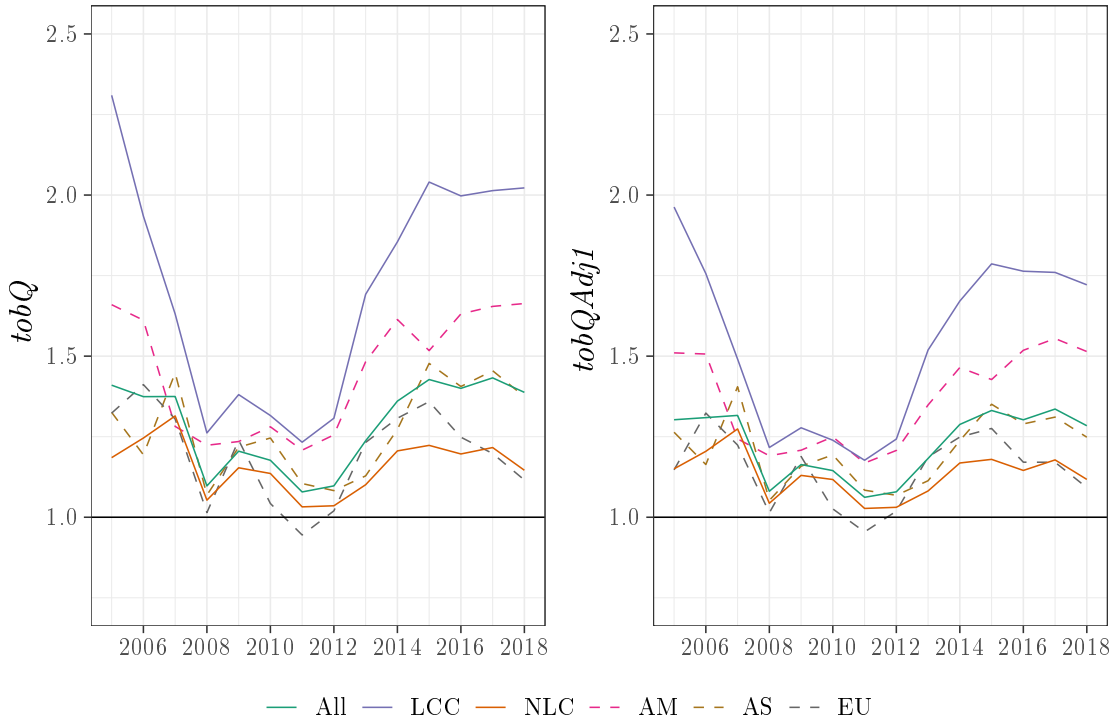


of *tobQ* and *tobQAdj1* is below one in 248 firm years (27.04% and 27.22%)[95] and no general trend can be identified for the two variables over the entire period. There appears to be a general decline between 2005 and 2008, followed by an unstable phase until 2012, after which an upward trend can be recognised. The largest overall change occurred between 2007 and 2008, with an average decline of 17.88%, with Asian (25.11%) and then European carriers (17.17%) recording the largest decline. LCCs recorded a decrease of 18.40% and NLCs of 18.10%. American airlines recorded the strongest decrease already in the previous year with 17.48%.

[94] $peRto > -100$ excluded, 10 observations not considered

[95] The difference in percentages results from the different number of total observations, *tobQAdj1* is available for 911 and *tobQ* for 917 firm years.

Figure 2.22: Time series: unadjusted ($tobQ$) and lease-adjusted Tobin's Q ($tobQAdj1$), annual average of all airlines and divided into NLCs, LCCs and regions



2.2.3 Operational Hedging

Variable Description

The following part deals with variables specific to operational hedging. These variables are all related either to fleet diversity, alliance membership or aircraft leasing. Within the literature, various variables are used to include operational hedging in studies. These variables usually include the geographical distribution (Pantzalis et al., 2001) or flexibility in capacity or quantity of production (Slack, 1983; Goyal and Netessine, 2011; Treanor, 2012) of a company's operations.

Starting with variables related to the fleet, consider the average age of the aircraft fleet ($acAge$) first. It is either taken from the AR or is calculated as

$$acAge = \frac{\sum_i A_i}{acTl},$$

where A_i is the age of the individual aircraft i and $acTl$ is the total number of aircraft in the respective airline's fleet.[96] If the required information is only available for one year, the value for the next year is interpolated according to the following formula:

$$acAge(t) = acAge(t\text{-}1) + \frac{acAge(t\text{-}1) + 1 + \text{number of new aircraft}^{97} \times 0.5}{acTl(t)}.$$

A similar variable was already used as a proxy for fuel efficiency by Treanor et al. (2014a). In contrast to this study, they use the natural logarithm of the weighted average age of the different aircraft operated by the airline and the next possible reported age in case of missing data. To be as accurate as possible, this variable is not rounded to the nearest integer as in Treanor et al. (2014a) and Pfefferle (2019). The variable itself should only be used in further statistical analyses taking into account that it was only available in 73.84% of firm years (Table B.4 in Appendix B.8).

The airlines' ownership of aircraft is represented by the variables *acFl* (aircraft under finance lease), *acOl* (aircraft under operating lease) and *acOw* (aircraft owned). Where no ownership information was provided in the ARs, the total number of aircraft was classified as *acOw*. If there is only a split between leased and owned aircraft, the number of leased aircraft was classified as *acOl*. In case of a combination of owned and financially leased

[96] The information is often taken from the notes, whereby it is assumed that the information relates to the end of the financial year.

[97] Number of new aircraft is calculated as $acTl(t) - acTl(t\text{-}1)$, which implies that in case the number is reduced from one year to another it can also be negative.

aircraft, the total number was classified as *acOw*. Fleet data is compiled first from the notes and then, if needed, from the text in the AR. Aircraft under a so-called wet lease agreements[98] were not taken into account. The percentage of operating leased aircraft (*acOlPct*) is calculated by dividing *acOl* by *acTl*. In case the annual share of operating leased aircraft of an airline is above the annual average of the sample and at the same time the annual cash ratio of this airline is below the annual average cash ratio of the sample, a dummy variable (*acOlcashDm*) was introduced which takes the value one. A value of one in this case implies a relatively high percentage of operating leased aircraft in the fleet and simultaneously low cash holdings. In all other cases, this variable has a value of zero.

In total, fleet data is available for 775 out of 924 firm years, or 83.87%. Not all airlines indicate the exact type of their aircraft, e.g. SAS (2020) has indicated 'Boeing 737 NG' instead of Boeing 737-500, 737-600, 737-700 or 737-800. In this case, the website www.planespotters.com was consulted for the currently operated fleet. In some cases, fleet information is not consistent, with accurate information available one year and only textual changes the next. In this case, last year's fleet data was used and updated with the current year's changes. In total, the airlines in the sample use 168 different aircraft models.

The percentage change in the total number of aircraft in an airline's operating fleet compared to the previous year is represented by *acChg*. This variable is of interest because fleet changes might be associated with high costs and investments (Van Mieghem, 2003).

Changes to the fleet structure can lead to greater flexibility, measured in this study by three fleet diversity measures, that can, for example, increase the airline's capacity, be it by increasing the total seat capacity or by expanding an aircraft family to better respond to changes in demand. In this study, the diversity of an airline's operating fleet is calculated using the approach of Treanor et al. (2013) and Berghöfer and Lucey (2014). This measure was for example also used by Bai et al. (2022) for the fleet diversity of tramp shipping companies. The calculation of the diversity measure is based on the Hirschmann-Herfindahl concentration index (HHI).

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

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

where K is the number of aircraft models operated by the airline. A value of zero for *fDiv1* represents minimal fleet diversity, which is also called a standardized fleet within the literature (Narcizo et al., 2020). Higher values represent greater fleet diversity and

[98] A wet lease is an agreement for the use of an aircraft with crew (including engineers) and their salaries, all maintenance for the aircraft and insurance (Gavazza (2010).

operational flexibility. For example, EasyJet's fleet between 2005 and 2011 consisted of several aircraft types (Airbus A319, A320 and Boeing B737-700, B737-300). Therefore, the value of *fDvi1* was unequal to zero. As of 2012, the fleet consisted of only one type of aircraft, which meant that *fDiv1* was zero. The mean values of this example for *fDiv1* reflect low fleet diversity combined with high flexibility.

The second fleet diversity measure (*fDiv2*), is introduced by Pfefferle (2019) and is calculated as

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

An aircraft family referred to in the formula is defined as a group comprising all aircraft models for which EASA (2023) requires the same licence endorsements.[99] For example, the Boeing 747 100-300 aircraft family includes the B747-100, B747-200, B747-300 and B747-SP aircraft types. Within an aircraft family, operating costs are lower due to interchangeable maintenance parts or crew requirements (Pfefferle, 2019). Compared to *fDiv1* the values of *fDiv2* are generally lower, as the numerator within the sum is lower when calculating *fDiv2*. It follows that *fDiv2* is an indicator of switching costs and higher values mean higher switching costs. Using again the example of EasyJet, we can see that *fDiv2* had values between 0.02 and 0.5 between 2005 and 2011, and also a value of zero from 2012 onward. The decreasing *fDiv2* values indicate decreasing switching costs.

To take into account the advantages and disadvantages of a diverse fleet, Pfefferle (2019) has used the variable *fDivNet*, which is calculated as

$$fDivNet = fDiv1 - fDiv2, \quad > 0.$$

fDivNet is intended to be an indicator of the benefits (*fDiv1*) and at the same time the switching costs (*fDiv2*) of a diverse fleet. The higher the value, the greater the benefits of operating a diverse fleet.

The dummy variable *fDiv1AgeDm* has a value of one in case the airlines' *fDiv1* is above the annual average and simultaneously the age of the airlines' fleet (*acAge*)[100] is above the annual average. In all other cases it has a value of zero.

In order to investigate the influence of an airline's membership in one of the three major

[99] In the USA, for example, this is organised by the Federal Aviation Administration (faa.gov: `https://www.faa.gov/aircraft`, visited on 02/16/2024).

[100] It has already been established that data for *acAge* are not available in 26.16% of the firm-years considered, but these largely coincide with the missing firm-years of *fDiv1*, which is why the variable *fDiv1AgeDm* is available in 70.24% and is included in the statistical analyses.

alliances (Oneworld, SkyTeam or Star Alliance; Subsection 4.1.1.2), the dummy variable *alliDm* is introduced. It is assigned a value of one if membership exists and zero otherwise. In addition, for each of the three alliances (*alliOne*, *alliSky* and *alliStar*) a dummy variable is introduced for which the same procedure as for *alliDm* applies. For reliable information in this regard, the ARs, websites and press releases were consulted. An overview of all airlines that were members of an alliance during the period under consideration can be found in Table 2.14. For airlines that were members for only part of the period, the period of membership is indicated.[101]

Table 2.14: Members of a strategic alliance as of 31.12.2019

Oneworld	**SkyTeam**	**Star Alliance**
Air Berlin (2012 - 2016)	Aeroflot (2006 - 2019)	Aegean Airlines (2010 - 2019)
American Airlines	Air France-KLM	Air Canada
British Airways	China Airlines (2011 - 2019)	Air China (2007 - 2019)
Cathay Pacific	China Eastern (2011 - 2019)	Air New Zealand
Finnair	China Southern (2007 - 2019)	All Nippon Airways
Iberia	Continental Airlines (2005 -	Asiana
IAG	2008)	Avianca
Japan Airlines (2007 - 2019)	Delta Air Lines	Continental Airlines (2009)
LAN	Garuda Indonesia (2014 -	Copa Airlines (2012 - 2019)
LATAM	2019)	Eva Air (2013 - 2019)
Malaysia Airlines (2013)	Kenya Airways (2009 - 2019)	Lufthansa
Qantas	Korean Air	SAS
		Singapore Airlines
		TAM (2008 - 2011)
		Thai Airways
		Turkish Airlines (2008 - 2019)
		United Airlines
		US Airways (2005 - 2012)

As a final part of operational hedging, let us now turn to leasing. Leasing, especially operational leasing, is very popular in the aviation industry and has become widespread since the 1990s (Carter et al., 2006; Chen et al., 2018). This is also reflected in the dataset, as operational leasing is used in 96.42% of the firm years under consideration.[102] The use of operational leasing, accounted for as off-balance sheet leasing, causes the debt and asset value of the company to be underestimated (Subsection 4.1.1.3) and difficulty in comparing

[101] Only the ARs from 2005 to 2009 are available for Continental Airlines, which is why it is only considered for this period. The airline was a member of SkyTeam from 2005 to 2008 and a member of Star Alliance from 2009 onward. Continental Airlines and United agreed to merge and continued to operate under United Airlines.

[102] If 2019 is not taken into account, operational leasing is used in 98.73% of the firm years.

related financial ratios between companies (Morales-Díaz and Zamora-Ramírez, 2018). To compensate for this underestimation and to establish a better comparability of airlines with and without operating leases, the debt and asset values are adjusted.[103] Damodaran (1999) and Moody's (2016) adjust values using either the present value (PV) of future operating lease commitments or a multiple of current operating lease expenses.[104]

The disclosure of future operating lease obligations is usually made individually for the following five years (*olexpYr1*, *olexpYr2*, *olexpYr3*, *olexpYr4*, *olexpYr5*) in the notes to the ARs and a single value is disclosed for the period after these five years (*olexpYr5b*) (Moody's, 2016), e.g. under 'Thereafter'[105] (JetBlue, 2020).[106] If the airline provides a common value for the first three, the first five or years two to five or three to five, these values are divided by three, five, four or three accordingly. In case of a single indication for the entire period, half of the total value shall be divided between the first five years and half for the period beyond. If there is no indication for the following period, the expense of years one to five shall be divided equally between them. The PV of future operating lease payments is then calculated as described in Formula (2.1) by discounting the value of each year to the power of that year using the appropriate discount factor (*costDbt*).[107] According to Moody's (2016), this approach underestimates the present value of very short and overestimates the present value of very long leases.[108]

$$\begin{aligned} olexpPv(t) = & \frac{olexYr1}{(1+costDbt)^1} + \frac{olexYr2}{(1+costDbt)^2} + \frac{olexYr3}{(1+costDbt)^3} + \\ & \frac{olexYr4}{(1+costDbt)^4} + \frac{olexYr5}{(1+costDbt)^5} + \sum_{i=6}^{10} \frac{olexYr5b}{(1+costDbt)^i} \end{aligned} \tag{2.1}$$

costDbt is calculated by adding the risk-free rate (*rfrate*) and the three-year rolling average of the spread (*spreadAvg*). The *rfrate* is the monthly average of the 10-year Treasury bond yield at the balance sheet date available on Datastream. No or incomplete data are

[103] The dataset is adjusted for the different treatments of operating and finance lease costs as described above. However, when comparing airlines, it should be noted that it is still possible for an airline to lease an aircraft through a subsidiary in order to benefit from the tax advantages in the country of that subsidiary (Schefczyk, 1993).

[104] Income from leases is usually not included, but Moody's (2016) considers the possibility of including the value of rental income if the rental income is significant.

[105] By 'Thereafter' or similar expressions, the years six to ten are meant.

[106] Lufthansa, for example, states that the leasing contracts of aircraft have a term of between six and eleven years, but provides no further details (Lufthansa, 2017).

[107] This calculation is based on the specifications of Damodaran (1999).

[108] Short leases are underestimated as they could be extended if the assets are needed for longer, and long leases are overestimated as they usually have conditional terms. They often contain cancellation clauses and can be terminated earlier for less than the full payment (Moody's, 2016).

available for Kuwait, Panama, Turkey and Saudi Arabia.[109] To calculate *spreadAvg*, the average of the respective default spreads (*spread*) of the previous, current and next year of the airlines is calculated.[110] The individual default spread of each airline was taken from a table of synthetic ratings by Damodaran (2002, 2016 and 2022) based on the interest coverage ratio.

intExp is adjusted (*intExpAdj*) as well by adding one third of *olexpTl* in accordance with Moody's (2016). Another study in which the values are adjusted in accordance with Damodaran (1999) is Carter et al. (2006). For more information on his approach see Subsection 3.1.2.2. To measure the scale of operating lease agreements, operating lease expenses scaled by total revenues (*olexpRev*) have been added.

As mentioned above, in addition to calculating the PV of future operating lease obligations for adjustment purposes, there is also the possibility of using so-called industry multipliers. Moody's (2016) suggests a multiplier of five for passenger airlines. Some airlines themselves usually use a multiplier of seven (easyJet, 2019; Finnair, 2020). In accordance with Pfefferle (2019) *olexpTl* are multiplied by five (*olexpPv5*), six (*olexpPv6*), seven (*olexpPv7*) and eight (*olexpPv8*). In the event that airlines do not report their current operating lease expenses, the *olexpYr1* from the previous year was used in accordance with Moody's (2016).

From 1st January 2019 (IFRS 16) and 15th December 2018 (ASC 842) onward new international accounting standards had to be recognized (Subsection 4.1.1.3).[111] Against this background, for the most part there will no longer be any differences between the adjusted and unadjusted values, as operating leases are treated in the same way as finance leases.[112] According to both accounting standards, contracts with a term of less than 12 months continue to be considered as operating leases. In IFRS 16 contracts with an acquisition value of less than approximately 5,000 USD continue to be considered as operating leases (International Accounting Standards Board, 2016). Under ASC 842 such a threshold is not established (Financial Accounting Standards Board, 2016). Within this

[109] A description of the collection process of *rfrate* for these countries can be found in Appendix B.7.

[110] For the years 2005 and 2019, only the current year and the following year (2005) or the previous year (2018) are considered.

[111] Delta Air Lines has already published its AR for the year ending 31 December 2018 in accordance with the new regulation (Delta Air Lines, 2019).

[112] The airlines Air New Zealand, All Nippon Airways, Bangkok Airways, Comair, Garuda Indonesia, Japan Airlines, Qantas, Regional Express, Sas, Thai Airways, VietJet and Virgin Australia are excluded from this. The new accounting standard was either not taken into account, only at a later date or the accounting date for the financial year 2019 was not affected by it. For example, Virgin Australia's *accDate* is 30th June, but as the new accounting standards only applied to ARs from 01st January 2019 or 18th December 2018, Virgin Australia's AR as at 30th June 2019 was not affected.

thesis, amounts are only considered if they are above 1% of $asTl$.[113] Due to these changes the financial year 2019 is excluded in the univariate and multivariate analyses.

Table 2.15: List of operational hedging related variables

Variable	Label	Description
$acAge$	Average age of aircraft fleet	Average age of 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 ($acAge_{t-1}$ + 1 + new number of aircraft x 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
$acFl$	Number of aircraft under finance lease	Number of aircraft under finance lease (=financial lease, capital lease) if reported in the AR
$acOl$	Number of aircraft under operating lease	Number of aircraft under operating lease if reported in the AR
$acOlcashDm$*	Low cash, high operating leased aircraft dummy variable	Dummy, one if the airline's annual cash ratio is below the annual average cash ratio and its annual percentage of aircraft under operating leasing is above the annual sample average
$acOlPct$*	Percentage of operating lease aircraft	Percentage of aircraft in airline's operating fleet under operating leasing, calculated as $acOl$ / $acTl$
$acOw$	Number of owned aircraft	Number of owned aircraft if reported in the AR
$acTl$	Total number of aircraft	Total number of aircraft in operating fleet Including: aircraft under operating lease, finance lease and owned assets.[114] If the number was not reported in each year it might be derived from the adjacent year with deliveries and sales from the text of the AR.
$alliDm$	Alliance dummy	Dummy, one if the airline was a 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 is a member of Oneworld
$alliSky$	Skyteam dummy	Dummy, one if the airline is a member of Skyteam
$alliStar$	Star Alliance dummy	Dummy, one if the airline is a member of Star Alliance
$costDbt$*	Cost of debt	Calculated as $rfRate$ + $spreadAvg$
$fDiv1$*	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 the airline
$fDiv1AgeDm$	Combined fleet diversity and aircraft age dummy variable	Dummy, one if the airlines' fleet diversity measure is above the annual sample average and simultaneously the age of the airlines' fleet is above the annual sample average

continued on next page

[113] Jet Airways stated in their AR of the financial year 2019, that their operating leases were classified as short-term which is why they are included as operating lease (Jet Airways, 2020).

[114] Aircraft of the Boeing 737 Max 8 model that have been grounded since 13 March 2019 at the latest are also included, as there was no standardised grouding schedule.

Variable	Label	Description
*fDivNet**	Combined fleet diversity measure	Calculated as *fDiv1* - *fDvi2*
*intExpAdj**	Adjusted interest expenses	Calculated as *intExp*+1/3 x *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 x *olexpTl* - Basis for the calculation of variables that end with 'Adj5'
*olexpPv6**	Multiple (6) of annual operating lease expenses	Calculated as 6 x *olexpTl* - Basis for the calculation of variables that end with 'Adj6'
*olexpPv7**	Multiple (7) of annual operating lease expenses	Calculated as 7 x *olexpTl* - Basis for the calculation of variables that end with 'Adj7'
*olexpPv8**	Multiple (8) of annual operating lease expenses	Calculated as 8 x *olexpTl* - Basis for the calculation of variables that end with 'Adj8'
olexpYr1	Future lease payments in year t+1	Operating lease expenses in year t+1 as reported income statement (or notes)
olexpYr2	Future lease payments in year t+2	Operating lease expenses in year t+2 as reported income statement (or notes)
olexpYr3	Future lease payments in year t+3	Operating lease expenses in year t+3 as reported income statement (or notes)
olexpYr4	Future lease payments in year t+4	Operating lease expenses in year t+4 as reported income statement (or notes)
olexpYr5	Future lease payments in year t+5	Operating lease expenses in year t+5 as reported income statement (or notes)
olexpYr5b	Future lease payments in year t+6 until t+10	Operating lease expenses in year t+6 until t+10 as reported income statement (or notes)
*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 between 2004 and 2014. Of these only Kuwait, Panama, South Africa, Turkey and United Arab Emirates are included after 2014. The values of South Africa are available from 2015 onward, which is why the described calculation is sufficient. For the other countries other web sources are searched. The calculations for the years 2004 until 2014 can be found in Pfefferle (2019, p. 258-259). - See Appendix B.7 for an exact calculation.
spread	Default spread	An airline's individual default spread is taken from the synthetic rating sheets of Damodaran (2002), Damodaran (2016) and Damodaran (2022) and which are based on calculated interest coverage ratios - For the years 2015 until 2019 the table from Damodaran (2022) is used - 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 used
*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 2019 is the average of $spread_t$ and $spread_{t-1}$

Summary Statistics

The average age of the airlines' fleet (*acAge*) is approximately 8.6 years with a minimum of just above one (Air Arabia in 2014) and a maximum of more than 24 years (Allegiant Air in 2013). The variable *acOlcashDm* shows that on average in 19.8% of the firm years the

percentage of operating leased aircraft is higher than the annual average and simultaneously the airline's annual cash ratio is lower than the annual average. In this context, 41.8% of the airlines' operating fleet were operating leased aircraft. In 23 out of 600 firm years *acOlPct* had a value of one with mostly LCCs (Gol, Jazeera Airways, Norwegian Air Shuttle, Spirit, Volaris and Vueling). Four out of these 23 firm years were NLCs with Aegan Airlines, Garuda Indonesia and Hawaiian Airlines.

Concerning *fDiv1* it is not surprising that the minimum value of zero is in all 45 firm years reported by LCCs due to the business model.[115] The most diverse fleet was operated by Air France-KLM in 2009 with a value of 0.95, the second highest value was reached by WestJet in 2018 (0.75). By construction, *fDiv2* is smaller than *fDiv1* which can also be seen by the mean values of 0.51 and 0.67, respectively. The maximum of the switching costs is reached by Air France-KLM in 2005 with 0.89. In general Air France-KLM had high values for *fDiv2*, it is represented eight times in the ten highest values. The lowest value of zero is represented in 127 firm years all being LCCs but Aegan Airlines and Regional Express. The maximum of *fDivNet* is reached by Spirit in 2017 with 0.66, due to a value of zero for *fDiv2*.[116] Compared to this the highest value reached by a NLC is 0.40 by SkyWest in 2009. Overall, the mean value of *fDivNet* is 0.16. In 29.5% of the observed firm years *fDiv1* was higher than the annual average while simultaneously the age of the airlines' fleet was higher than the annual average as indicated by *fDiv1AgeDm*.

The eight highest total operating lease expenses are reported by United Airlines, with the highest value of 2,910 million USD in 2012. In eight cases a value of zero was reported for *olexpTl*. The mean value is 382.04 million USD. WestJet and SpiceJet are the two airlines with the ten highest values of *olexpRev* with values between 0.35 and 0.71, whereby WestJet reaches the maximum in 2009. Compared to this the mean is 0.08.

Descriptive Statistics

Figure 2.23 shows the percentage change in the number of aircraft. An increase or decrease in size means an increase or decrease in capacity. Overall a general increase in fleet size is visible by an average of 7.07%. LCCs enlarged their fleet the most by 12.30%, followed by Asian (8.23%), American (7.30%), European airlines (6.68%) and NLCs (5.42%). The largest increase occurred from 2005 to 2006 for LCCs at 41.4% and the smallest from 2018 to 2019 for European airlines at 0.72%.

[115] A key feature of the business model of LCCs is that they generally have a homogeneous fleet consisting of only one type of aircraft (Table B.2). In addition, the correlation factor between *fDiv1* and *lccDm* is -0.75.

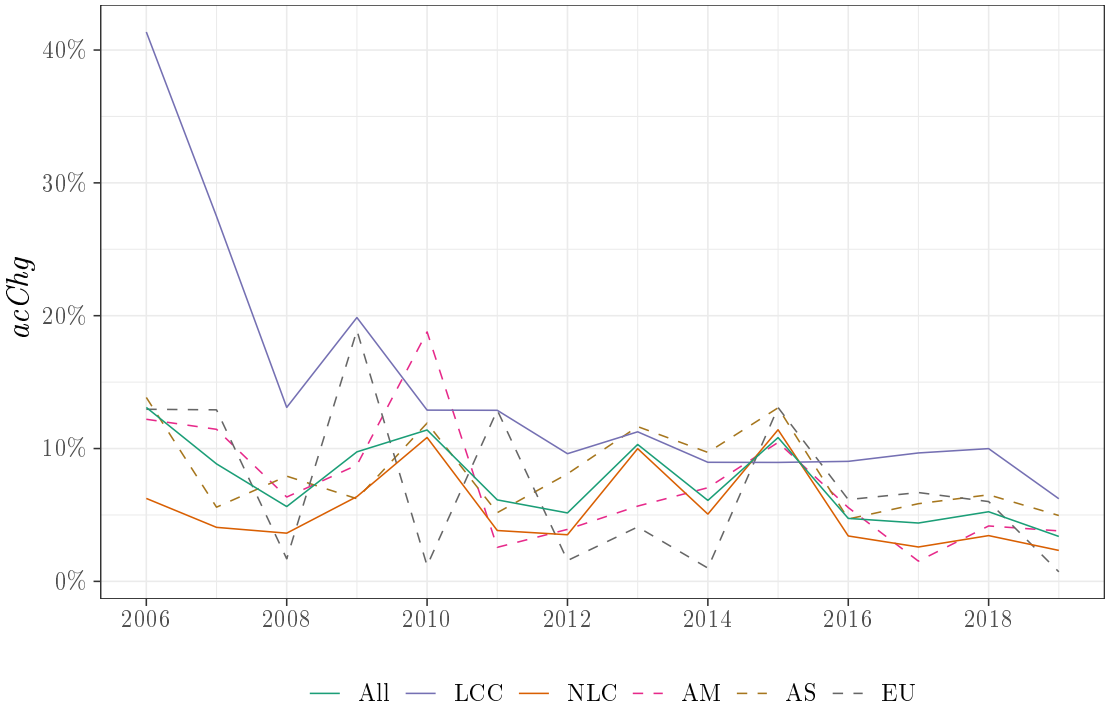
[116] A value of zero for *fDiv2* means that the airline operates only one aircraft family and has due to that no switching costs, see Subsection 2.2.3.

Table 2.16: Summary statistics of the variables relevant to operational hedging

Variable	Unit	N	Mean	St. Dev.	Min	Max
acAge	years	640	8.597	3.741	1.300	24.640
acOlcashDm		600	0.198	0.399	0.000	1.000
acOlPct	percentage	600	0.418	0.266	0.000	1.000
alliDm		869	0.455	0.498	0.000	1.000
fDiv1		728	0.673	0.259	0.000	0.951
fDiv2		728	0.514	0.294	0.000	0.892
fDivNet		728	0.160	0.138	0.000	0.664
fDiv1AgeDm		607	0.295	0.456	0.000	1.000
olexpRev	percentage	865	0.076	0.076	0.000	0.707
*olexpTl_*	USD	865	382.042	437.009	0.000	2,910.000

Variables ending with '_' are denoted in millions.

Figure 2.23: Time series: percentage change in the number of aircraft (*acChg*), annual average of all airlines and divided into LCC, NLC as well as AM, AS and EU

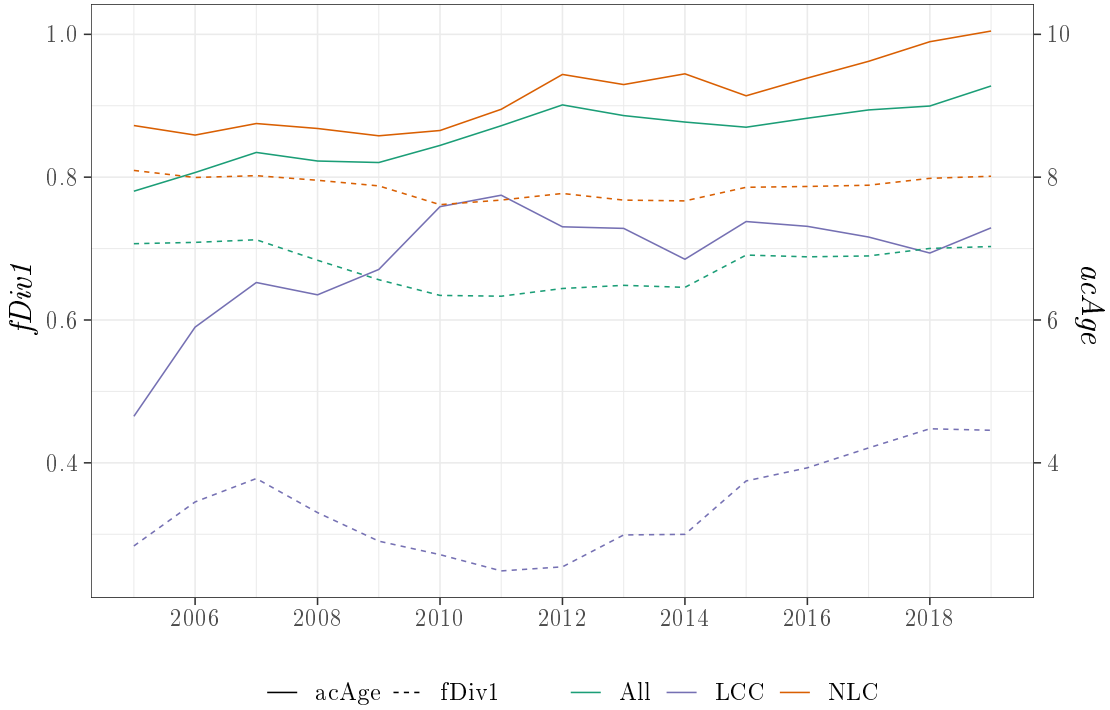


In Figure 2.24 average *fDiv1* and *acAge*[117] of an airlines' fleet are displayed. It contrasts

[117]The variable *acAge* needs to be considered with caution as it is missing in 26.16% of the considered firm years (Table B.4 in Appendix B.8).

two important characteristics of the fleet, which are of interest in addition to the change in fleet size. It can be seen that the average *acAge* has increased from 7.8 to 9.3 years while fleet diversity only slightly decreased. NLCs use younger aircraft (2005: 8.7, 2019: 10) in the beginning with approximately the same fleet diversity during the sample period (2005: 0.81, 2019: 0.80). In comparison, LCCs use older aircraft (2004: 4.7, 2019: 7.3) in the end of the period under review with a more diverse fleet (2004: 0.28, 2019: 0.45) than in the beginning.

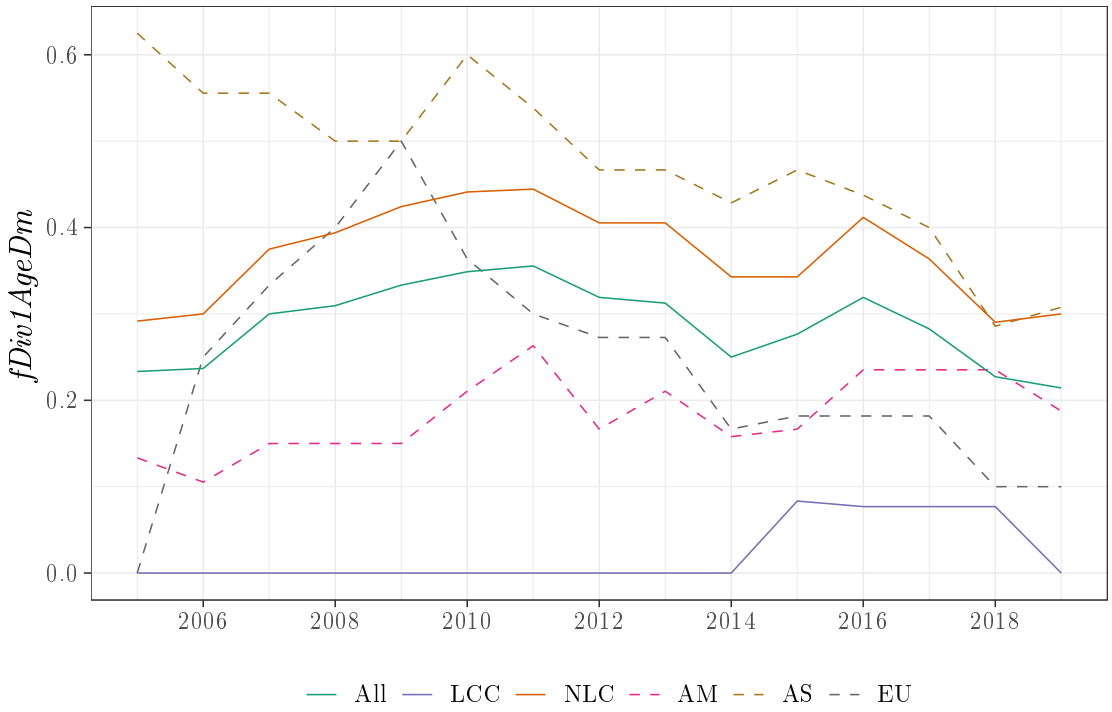
Figure 2.24: Time series: fleet diversity measure one (*fDiv1*) and average aircraft age (*acAge*), annual average of all airlines and divided into LCC and NLC (extension based on Treanor et al. (2014)



In Figure 2.25 the average dummy variable *fDiv1acAgeDm* across the fleets of all airlines is displayed. A general trend cannot be recognised. With the exception of 2009 and 2018, the average value for Asian airlines is always above that of all other groups. This implies that Asian airlines had the most diversified fleets while at the same time the oldest fleets. It can bee seen that the average *fDiv1acAgeDm* for LCCs is never above the sample average and at zero% for the years 2005 until 2014 and again in 2019.

Figure 2.26 shows the average *fDiv1* and *fDiv2*. NLCs had the highest *fDiv1* values for all years except 2007 and 2008 (Asian airlines) with an average of 0.79. LCCs were

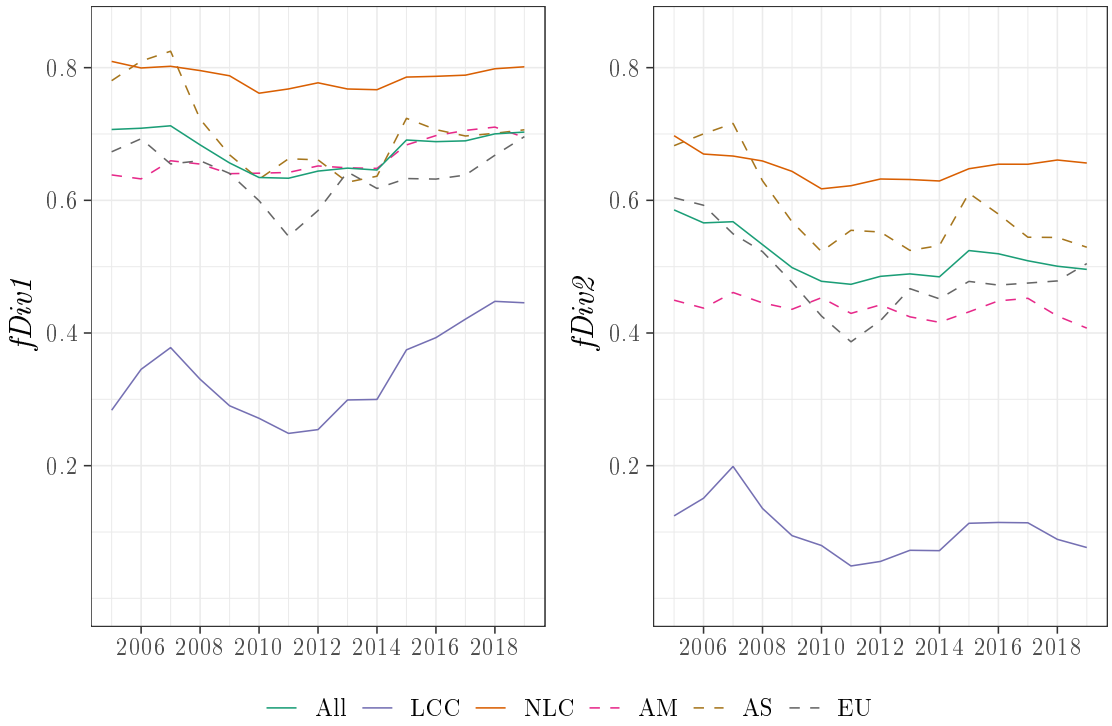
Figure 2.25: Time series: combined fleet diversity measure one and average aircraft age dummy variable (*fDiv1acAgeDm*), annual average of all airlines and divided into LCC and NLC as well as AM, AS and EU



below all other groups with an average *fDiv1* of 0.34, which is in line with the definition of their business model. In contrast to *fDiv1*, the values of *fDiv2* generally decreased (All: 15.31% with LCCs: 38.39%, Asian: 22.43%, European: 16.42%, American: 9.37% and NLCs: 5.90%), meaning the switching costs were reduced generally with an average value of 0.51. The highest value for *fDiv2* was reached by Asian airlines in 2007 (0.72) and the lowest by LCCs in 2011 (0.05).

The combination of *fDiv1* and *fDiv2* is shown in Figure 2.27. Overall, the average *fDivNet* increased by 70.72% within the sample period. European airlines increased *fDivNet* the most with 175.96% from 0.07 to 0.19, followed by LCCs (131.65%), Asian (80.68%), American airlines (52.26%) and NLCs (29.49%). Figure 2.27 shows that the general reduction of switching costs and a less pronounced increase or decrease in fleet diversity has a positive effect on the combined fleet diversity measure. Asian airlines, for example, were able to reduce both fleet diversity measures, resulting in an increase in *fDivNet*. LCCs were also able to reduce switching costs, but saw an overall increase in *fDiv1*, which nevertheless resulted in a significant increase in *fDivNet*.

Figure 2.26: Time series: fleet diversity measures (*fDiv1, fDiv2*), annual average of all airlines and divided into LCC, NLC as well as AM, AS and EU



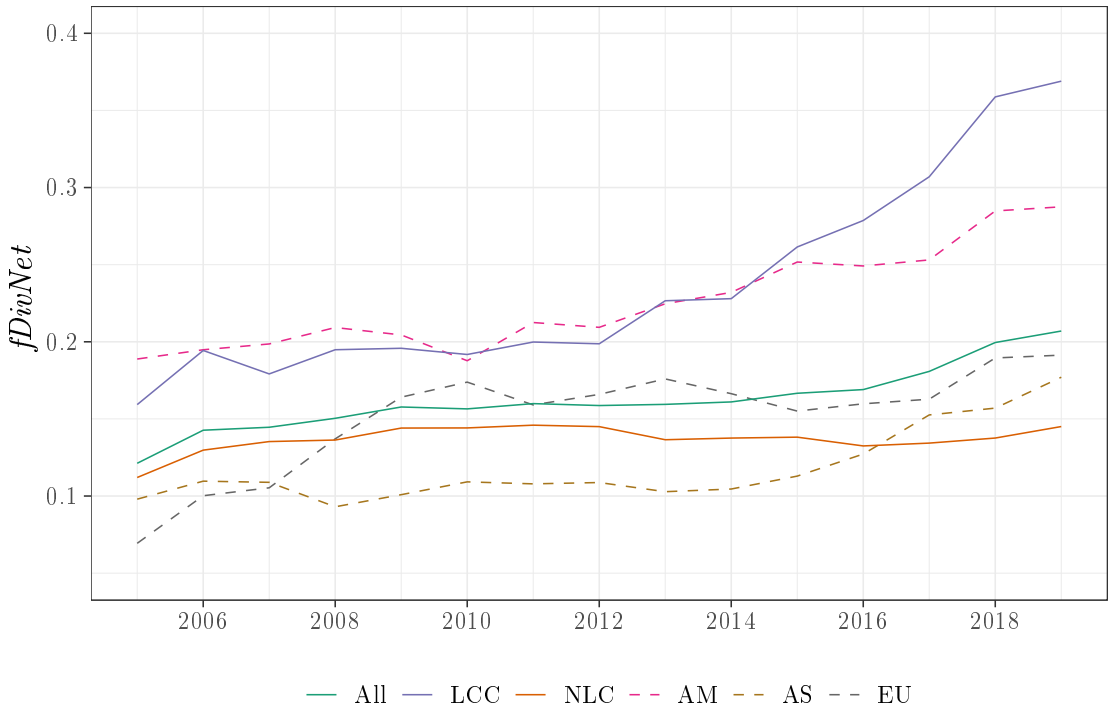
Starting with the descriptive statistics for alliance members Figure 2.28 shows the average *fdvPct12m* by alliance and non-alliance members and by membership of the three largest alliances. Up to and including 2015, the hedge ratio of alliance members was higher than that of non-alliance members, from 2016 onwards it is the other way round.[118] In terms of alliance membership, members of the OneWorld alliance have the highest average hedge ratios (39.75%), followed by Star Alliance (34.97%) and SkyTeam (22.98%).

Table 2.14 lists all airlines that were, have become or are members of an alliance in the period under consideration. A total of 18 airlines joined an alliance in the period under review; these are indicated with the respective year in the brackets. Of particular interest in Table 2.14 is Continental Airlines. The table shows that Continental Airlines is the only airline to have changed alliances, as it was a member of SkyTeam from 2005 to 2008 and became a member of Star Alliance in 2009.[119] In 2019, 30 out of 56 (53.57%) airlines were members of an alliance. The group of LCCs (15) is a true subset of the non-alliance

[118] The author is not aware of any obvious reason for this observation.

[119] Continental Airlines and United agreed to merge and continued to operate under United Airlines in 2010/2011.

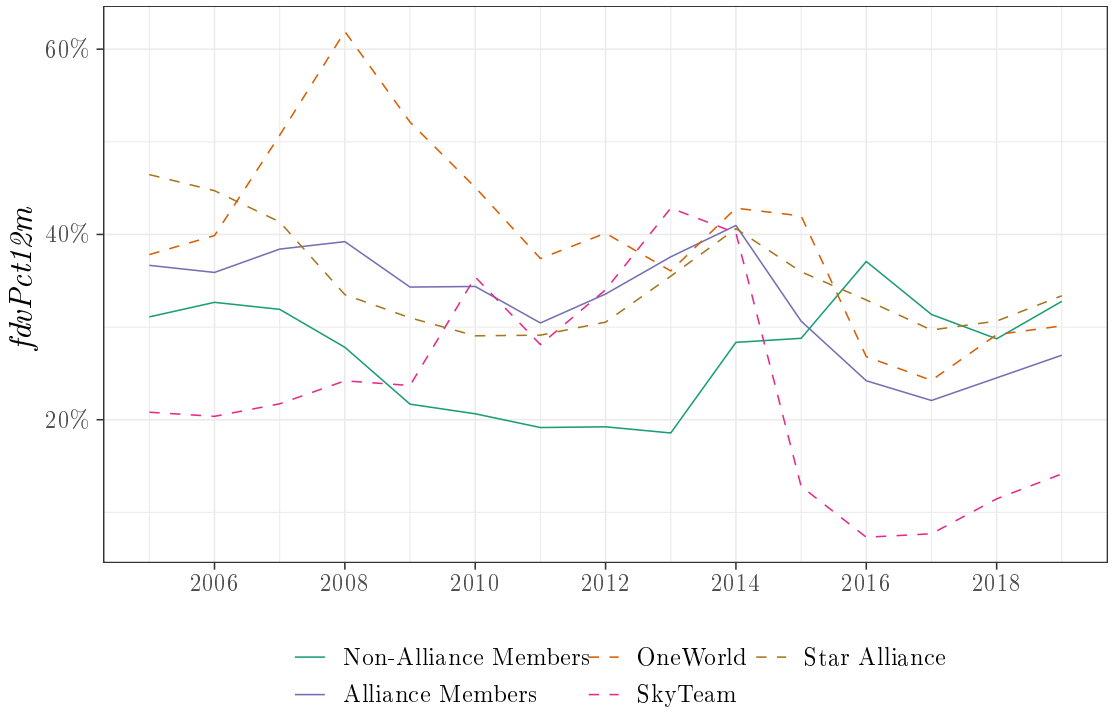
Figure 2.27: Time series: combined fleet diversity measure (*fDivNet*), annual average of all airlines and divided into LCC, NLC as well as AM, AS and EU



members (26). For more information, see Appendix B.8 Figure B.15, where members of all alliances and members of the top three alliances are shown scaled by average *asmTl*. Overall, Figure B.15 shows a percentage increase in alliance membership in general (except for 2010) from 23.87% to 58.77%. Star Alliance had the least members in the beginning (7.20%) and the most in the end (24.07%).

As already mentioned, due to the change in accounting standards, the representations connected to operational leasing do not include 2019. In Appendix B.8 the relevant Figures (B.16 - B.24) can be found including 2019. Figure 2.29 shows the percentage of an airline's aircraft under operating lease (*acOlPct*) between 2005 and 2018. However, this figure should be viewed with reservations, as there are no values for *acOl* in 30.84% of the 869 firm years (Table B.4 in Appendix B.8). In general, there is a decrease in *acOlPct*, from 47.22% in 2005 to 36.23% in 2018. The exception are Asian airlines, which were the only ones to increase their share (21.43%). Despite the increase, Asian airlines have on average the least aircraft under operating lease in their fleet. LCCs started with the global high in 2005 of 64.87%, followed by an overall decline to 50.03%. Figure 2.29 shows that the

Figure 2.28: Time series: hedge ratio for the next 12 months (*fdvPct12m*), annual average of airlines being and not being a member in an alliance and divided into Oneworld, SkyTeam and Star Alliance

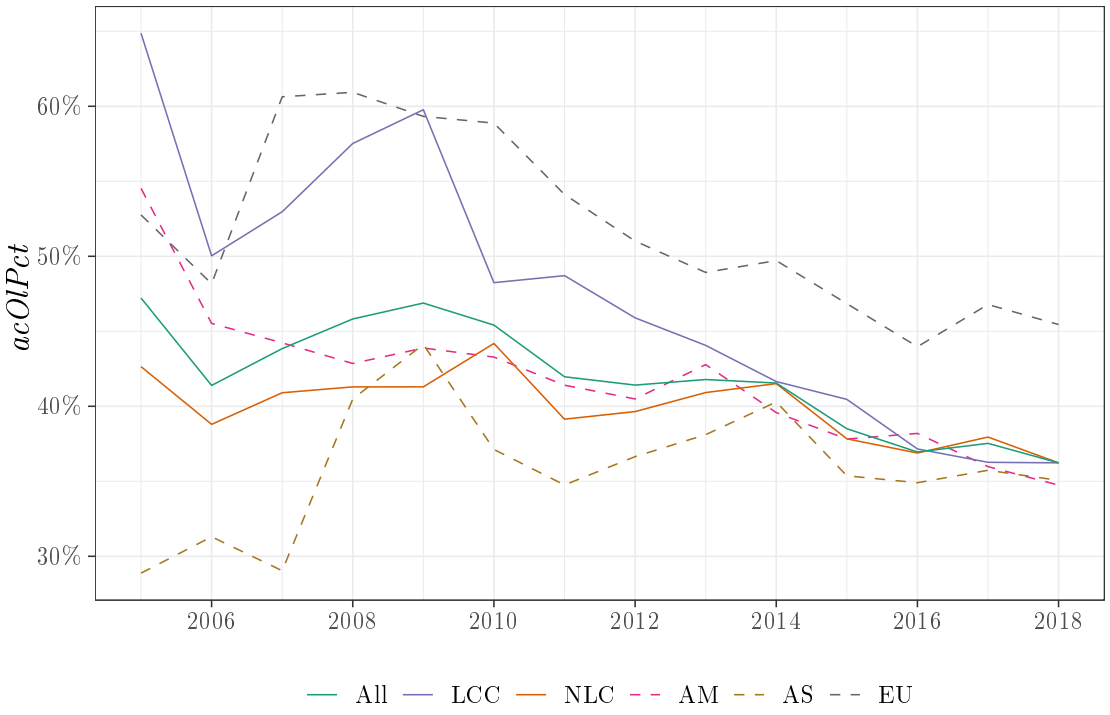


percentage shares of all groups, with the exception of European airlines, have continued to converge over the period under consideration, so that in the end they lie in an interval of 34.75% to 36.23%. A total of nine airlines used pure operating lease fleets in the reporting period.[120]

Another option for airlines to continue operating aircraft even though they sell them is the so-called sale-and-leaseback. According to Morrell (2021), this happens when airlines decide to realise the capital value of the aircraft, for example to cover capital needs for new aircraft or investments or if they have cash flow problems. Following Pfefferle (2019), these transactions are analysed using changes in *acOlPct*, which is shown in Figure 2.30. It shows the relation of *acOlPct* and *fdvPct12m* on the left and the relation of percentage changes in *acOlPct* with *fdvPct12m* on the right. It does not allow any further interpretation, as the regression has no statistical significance. The same applies to Figure B.17 in Appendix B.8, which includes the year 2019.

[120] Aegan Airlines (2007), Garuda Indonesia (2017-2019), Gol (2005), Hawaiian Airlines (2005), Jazeera Airways (2008.2009), Norwegian Air Shuttle (2005), Spirit (2011-2013), Volaris (2013-2018) and Vueling (2007-2012)

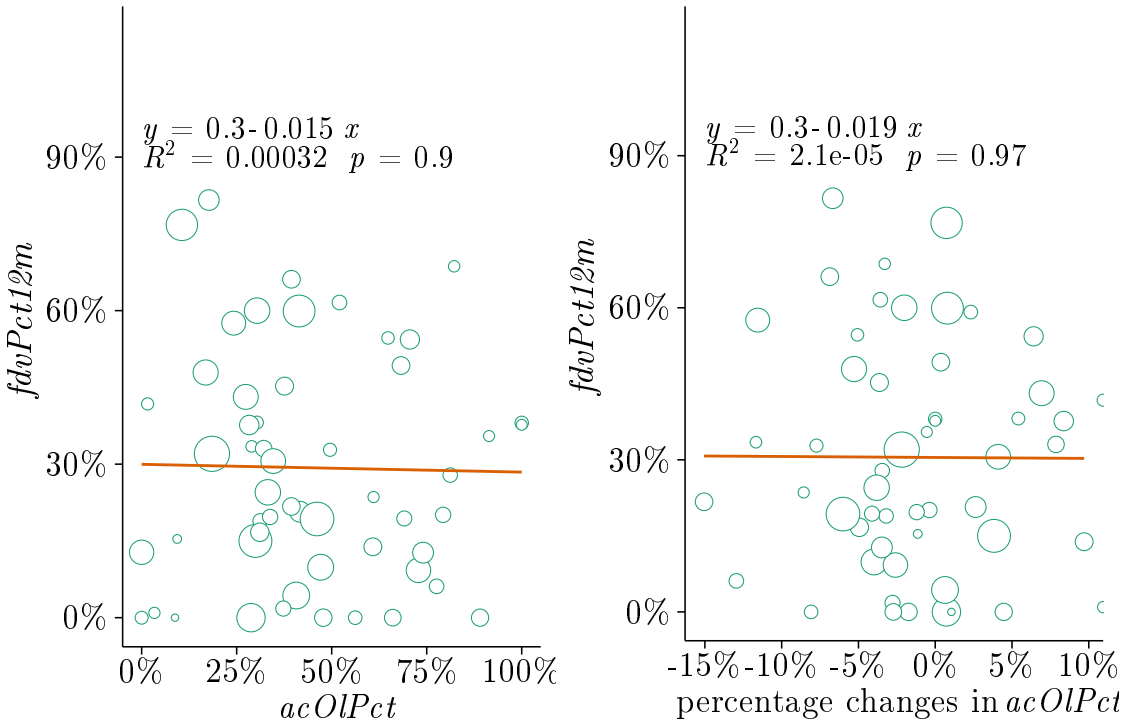
Figure 2.29: Time series: percentage of aircraft under operating lease within the fleet (*acOlPct*), annual average of all airlines and divided into LCC, NLC as well as AM, AS and EU



In addition, some airlines used their aircraft or aircraft parts as collateral. For example, Air New Zealand stated that they used 'aircraft and aircraft related assets with a carrying value of $3,230 millions as at 30 June 2019' (Air New Zealand, 2019, p.15) as collateral for secured loans and finance lease obligations. Lufthansa, on the other hand, stated that they used 'aircraft with a carrying amount of 2,550m' (Lufthansa, 2020, p.168) as collateral for current financing contracts. In addition, easyJet, for example, had 'two separate revolving credit facilities of $500 million and £250 million respectively' (easyJet, 2018, p.146) to cushion the impact of potential business disruptions. Furthermore, according to JetBlue hedging 'contracts and agreements do not completely protect us against price volatility, are limited in volume and duration in the respective contract, and can be less effective during volatile market conditions and may carry counterparty risk. Under the fuel hedge contracts we may enter from time to time, counterparties to those contracts may require us to fund the margin associated with any loss position on the contracts. Meeting our obligations to fund these margin calls could adversely affect our liquidity.' (JetBlue, 2020,

[121] In accordance with Pfefferle (2019) Jazeera Airways is excluded, as it acquired a leasing company in 2010 and entered the market as a lessor.

Figure 2.30: Cross-sectional: correlation between the variables percentage of operating lease aircraft (*acPlOct*) and percentage change in *acOlPct* with hedge ratios for the next 12 months (*fdvPct12m*), average across years for each airline (weighted by lease-adjusted total assets (*asTlAdj1*))[121]

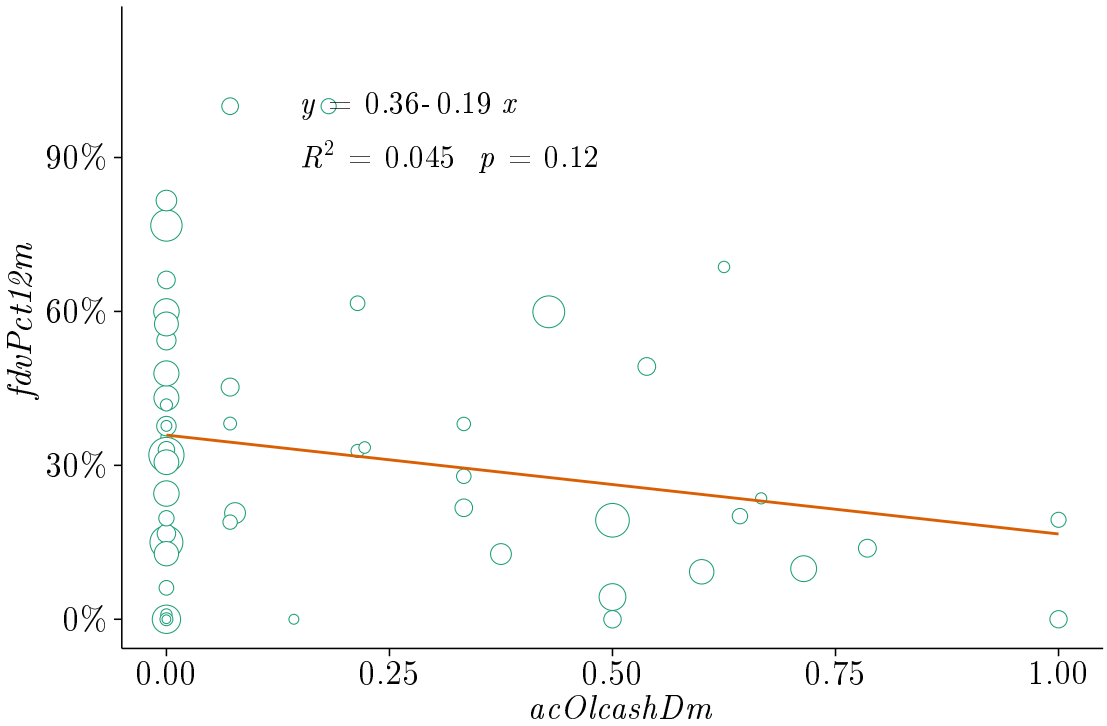


p.17). Figure 2.31 shows the relation between an airline's hedge ratio (*fdvPct12m*) and cash holdings relative to the proportion of aircraft in an airline's fleet that are under operating lease (*acOlcashDm*). It shows that there is no systematic connection. The above citations therefore appear to be isolated cases.

The airlines examined here have made extensive use of operating leasing.[122] To account for the use of operating leases, the sample variables must be adjusted for the present value of future operating lease expenses (*olexpPv*).[123] Figure 2.32 shows the ratio of *olexpPv1* to *asTlAdj1*. For all groups except American airlines, the global trough was reached in 2007, with Asian airlines showing the lowest value at 0.11. American airlines reached their global low in 2018 at 0.12. Asian airlines had the lowest overall ratio until 2015, when they were undercut by American airlines. The overall global high for all groups was reached by

[122]Out of a total of 924 firm years, operating lease expenses were reported in 874 (94.49%). Looking at the sample without 2019, in 857 out of 869 (98.62%) firm years operating lease expenses are reported.
[123]This is calculated using the approach of Damodaran (2012) (Subsection 4.1.1.3).

Figure 2.31: Cross-sectional: correlation between binary variable for low cash ratio and high percentage of aircraft under operating lease (*acOlcashDm*) and hedge ratios for the next 12 months (*fdvPct12m*), average across years for each airline (weighted by lease-adjusted total assets (*asTlAdj1*))



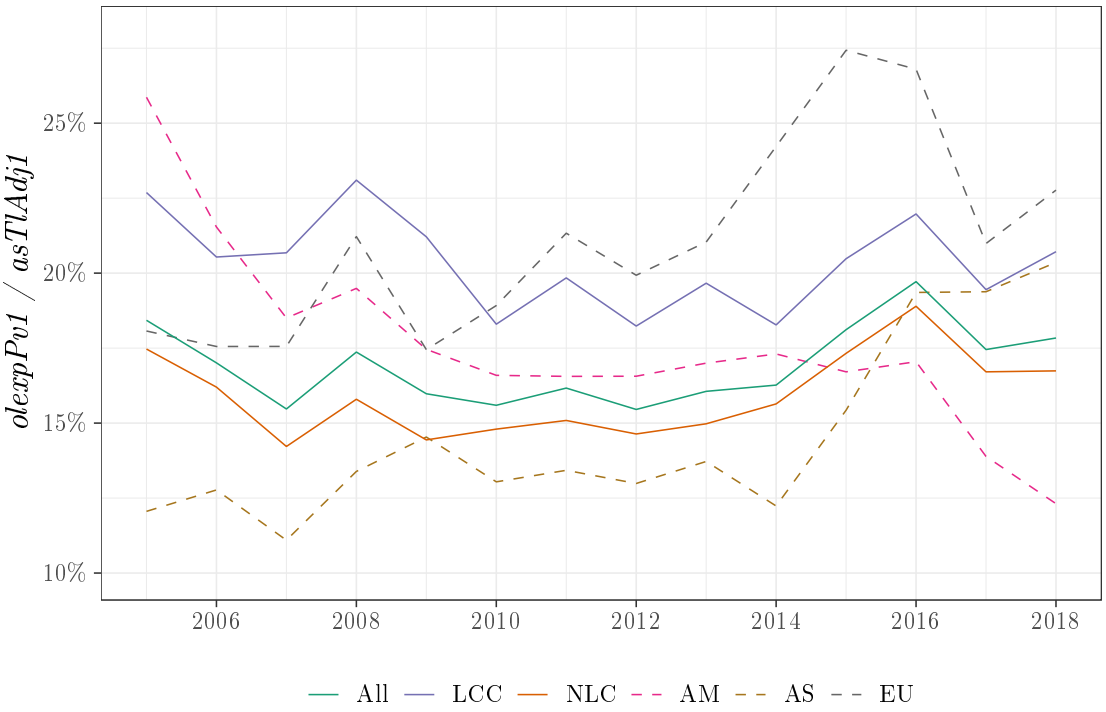
European airlines in 2015 at 0.27.[124]

Figure 2.33 shows current operating lease expenses in relation to total revenue (*olexpRev*), total operating lease expenses (*olexp*) and total revenue (*revTl*). LCCs had the highest value of *olexpRev*, which is in line with Figure 2.29.[125] The ratio increased over time as *revTl* increased more than *olexp*, although the percentage of operating lease aircraft decreased. LCCs generally had the lowest *revTl* during the observation period. In general, both *olexp* and *revTl* have increased by 91.40% and 66.20%, respectively. For *olexp*, Asian airlines recorded the highest increase with 123.08%, followed by European (89.12%) and American airlines (27.96%). For *revTl*, on the other hand, American airlines recorded the highest increase with 171.30%, followed by Asian (81.82%) and European airlines (64.91%). LCCs increased their *olexp* by 64.22% compared to 73.63% for NLCs. The opposite was

[124] Figures with the time series of alternative methods for calculating the present value (*olexpPv5* (multiple five) B.20, *olexpPv6* (multiple 6) B.21, *olexpPv7* (multiple 7) B.22 and *olexpPv8* (multiple 8) B.23) are included in Appendix B.8. Overall, they differ only slightly compared to Figure 2.32.

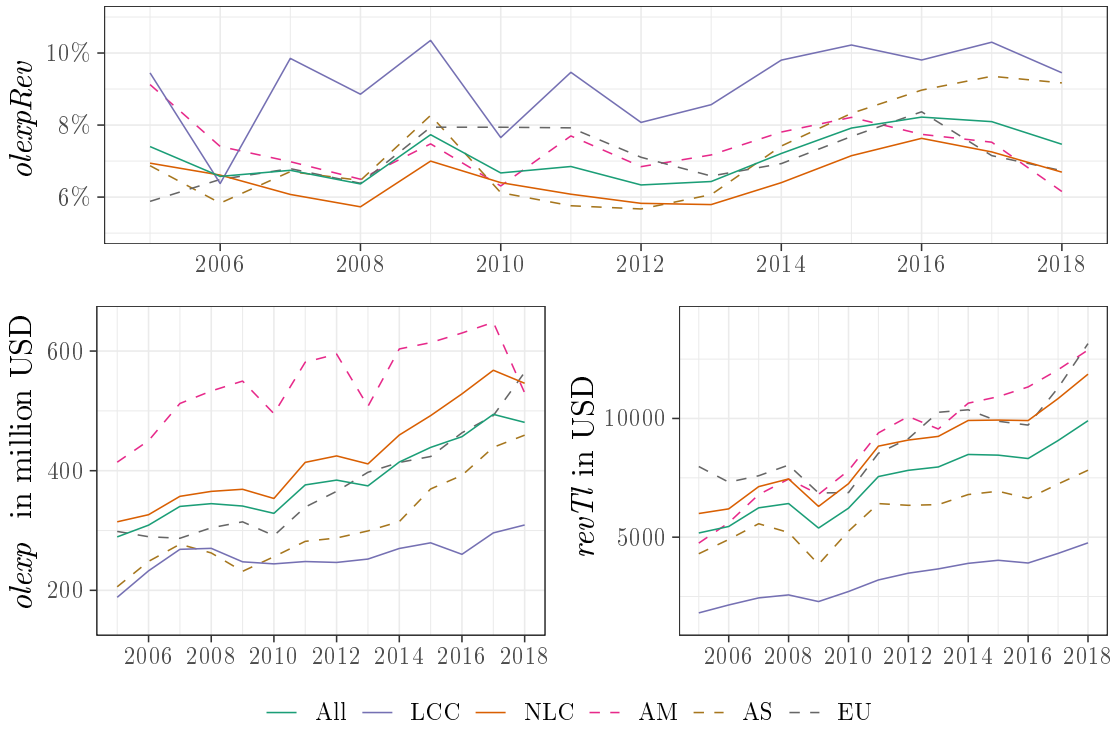
[125] LCCs have spent the most revenue on operational leasing and also have the highest proportion of aircraft in their fleet under operational lease.

Figure 2.32: Time series: present values of operating lease expenses (*olexpPv1*) scaled by lease-adjusted total assets (*asTlAdj1*), annual average of all airlines and divided into NLCs, LCCs and regions



true for *revTl*, where LCCs recorded an increase of 163.07% and NLCs of 97.89%. Most striking in the upper part of Figure 2.33 are the two overall increases between 2008 and 2009 (21.48%) and between 2012 and 2016 (29.72%). Between 2008 and 2009 and 2010 and 2016, there is a decrease in *revTl*, but only by 16.10% and 6.34% respectively. According to Figure 2.29, the number of aircraft under operating lease increased by 2.31% for 2008 and 2009 and decreased by 10.77% for the second period, which also cannot fully explain the high increase. Another explanation could be the high increase in *olexp* of 18.90% especially between 2012 and 2016.

Figure 2.33: Time series: operating lease expenses scaled by revenues (*olexpRev*), total operating lease expenses *olexpTl* and total revenues (*revTl*), annual average of all airlines and divided into LCC, NLC as well as AM, AS and EU[126]



[126] *olexpRev* > 0.5 excluded, 10 observations excluded

2.2.4 EU ETS

Variable Description

The following section introduces variables for the EU ETS in detail, for example, the total amount of CO_2 emissions produced.

The variable *aEmEu* are the freely allocated emissions for a specific airline by the EU. Connected to this are the emissions verified by the respective airline and reported to the EU (*vEmEu*). The total amount of CO_2 emissions emitted by the airlines (CO_2Tl) are either taken from the AR, Corporate Social Responsibility Report (CSR), SR or are calculated as

$$CO_2Tl = S1Em + S2Em + S3Em = S1Em + S23Em.$$

Within the formulas *S1Em* are all Scope 1 emissions (direct GHG emissions) in tonnes, *S2Em* are all Scope 2 emissions (indirect GHG emissions from consumption of purchased electricity, heat or steam) in tonnes and *S3Em* are all other indirect emissions (Scope 3) in tonnes not covered by Scope 2 emissions. The percentage change in CO_2 emissions is measured by the variable CO_2Chg.

In order to compare the emissions, different ratios are included in this study. CO_2Pkm are the CO_2 emissions per passenger kilometer in gram and are taken from the AR, CSR or SR. CO_2 emissions per RPM (CO_2Rpm) are either taken from the reports or are calculated as

$$\frac{CO_2Tl \times 1,000,000}{rpmTl}.$$

Total CO_2 emissions scaled by $asmTl$ (CO_2Asm) are calculated in the same manner, but divided by $asmTl$

$$\frac{CO_2Tl \times 1,000,000}{asmTl}.$$

The price per aviation allowance of the EU ETS is given by $EuaaAP$ and is calculated as

$$\frac{\sum_{\text{i}}(\text{allowance price auction}_i \times \text{number of allowances sold auction}_i)}{\#\text{of auctioned allowances for respective year}}.$$

Table 2.17: List of EU ETS related variables

Variable	Label	Description
aEmEU	Allocated emissions by the EU	Freely allocated emissions for the airline by the EU (`https://www.eea.europa.eu/data-and-maps/data/european-union-emissions-trading-scheme-17`, visited on 04/15/2020)

continued on next page

Variable	Label	Description
CO_2Tl	Total amount of CO_2 in tonnes	Total amount of CO_2 in tonnes per year either taken from AR, CSR or SR. If not available in one of the mentioned reports is is calculated as - $S1Em + S2Em + S3Em$ - $S1Em + S23Em$
CO_2Chg	Percentage change of CO_2 emissions	Calculated as ($CO_2Tl(t)$ - $CO_2Tl(t-1)$) / $CO_2Tl(t-1)$
CO_2Pkm	CO_2 emissions per passenger kilometer	CO_2 emissions per passenger kilometer in gram taken from AR, CSR or SR
CO_2Rpm	CO_2 emissions per revenue passenger miles	CO_2 emissions per RPM either taken from AR or calculated as CO_2Tl x 100,0000 / $rpmTl$
CO_2Asm*	CO_2 emissions per ASM	CO_2 emissions per ASM calculated as $CO_2Tl \times$ 100,0000 / $asmTl$
$EuaaAP$	EU Aviation Allowances Price	Cost per allowance in the allocated country calculated as $\sum$ (allowance price of respective auction x number of allowances sold in respective auction) / # of auctioned allowances for respective year (if e.g. EU and DE were allocated both geographical areas were taken into account)
$S1Em$	Scope 1 Emissions	All direct GHG emissions in tonnes either taken from AR, CSR or SR
$S2Em$	Scope 2 Emissions	Indirect GHG emissions from consumption of purchased electricity, heat or steam in tonnes. Either taken from AR, CSR or SR.
$S3Em$	Scope 3 Emissions	Other indirect emissions in tonnes, such as the extraction and production of purchased materials and fuels, transport-related activities in vehicles not owned or controlled by the reporting entity, electricity-related activities (e.g. T&D losses) not covered in Scope 2, outsourced activities, waste disposal, etc. Either taken from AR, CSR or SR
$vEmEu$	Verified Emissions by EU	Emissions verified for the airline by the EU (`https://www.eea.europa.eu/data-and-maps/data/european-union-emissions-trading-scheme-17`, visited on 04/15/2020)

Summary Statistics

The summary statistics in Table 2.18 show that the average $CO_2Tl_$ were 13.80 million tonnes with a minimum of 0.51 (Comair in 2012) and a maximum of 65.39 million tonnes (American Airlines in 2018). The changes in $CO_2Tl_$ were on average 0.04 percent with a SD of 0.12. The total CO_2 emissions in relation to RPM and ASM averaged at 178.78 and 214.78 per ASM and RPM, respectively. The minima were reached by Volaris in 2017 with 73.87 per ASM and 76.60 by Finnair in 2018 per RPM. Both maxima were reached by China Airlines in 2016.[127] The average freely allocated amount of emissions by the EU were 0.83 million with a SD of 2.16. Compared to this the average amount of verified emissions to the EU was 1.01 million, which indicates that the airlines had to buy additional certificates. The largest number of freely allocated emission certificates were

[127] China Airlines is six times amongest the ten highest values for CO_2Rpm and CO_2Asm.

granted to Air France-KLM in 2012 and the highest verified emissions were reported by Ryanair in 2019. The difference in N between *vEmEU_* and *aEmEU_* results from airlines from outside the EU that have verified their emissions but were not allocated any emissions because they were not included in the EU ETS. The average price per allocated allowance averaged at 12.30 EUR with a SD of 7.77 EUR. The average of 0.20 of *euetsDm* shows that on average 20% of the airlines included in the dataset are included in the EU ETS. The average Scope 1, 2 and 3 emissions were 13.2, 0.08 and 2.08 with SDs of 10.78, 0.12 and 3.69 million tonnes, respectively.

Table 2.18: Summary statistics of the variables relevant to the EU ETS

Variable	Unit	N	Mean	St. Dev.	Min	Max
*aEmEU_*	certificates	278	0.833	2.163	0.000	19.966
CO_2Asm	gram per ASM	375	178.775	47.151	73.870	329.271
CO_2Chg	percentage	328	0.044	0.117	−0.473	0.774
CO_2Rpm	gram per RPM	378	214.781	67.503	76.600	423.010
$CO_2Tl_$	tonnes	379	13.798	11.916	0.513	65.385
EuaaAP	price per allowance	210	12.297	7.774	5.820	28.425
euetsDm	dummy	924	0.202	0.402	0.000	1.000
*S1Em_*	tonnes	318	13.161	10.783	0.226	42.300
*S2Em_*	tonnes	255	0.084	0.118	0.0003	0.519
*S3Em_*	tonnes	157	2.083	3.687	0.000	24.781
*vEmEU_*	certificates	294	1.010	2.176	0.000	10.530

Variables ending with '_' are denoted in millions

Descriptive Statistics

The airline industry was included in the EU ETS from 2012 onward[128], which is why Figure 2.34 shows the total verified and freely allocated emission allowances of the airlines considered from 2012 to 2019. The year 2012 is an exception as the freely allocated emissions more than double the amount of verified emissions. From 2013 onward, the ratio changes and the freely allocated emissions are less than the verified emissions. From 2013 onwards, a general increase in *vEmEu* can be observed. The situation is somewhat different for *aEmEu*, where there is a decline up to and including 2018 and an increase between 2018 and 2019.[129]

[128] For further information see Subsection 5.1.2.

[129] The increase from 2018 to 2019 is entirely due to the inclusion of EasyJet's two subsidiaries *easyJet Europe Airline GMBH* and *easyJet UK Limited*.

Figure 2.34: Time series: verified (*vEmEu*) and freely allocated (*aEmEu*) emission rights by EU in millions

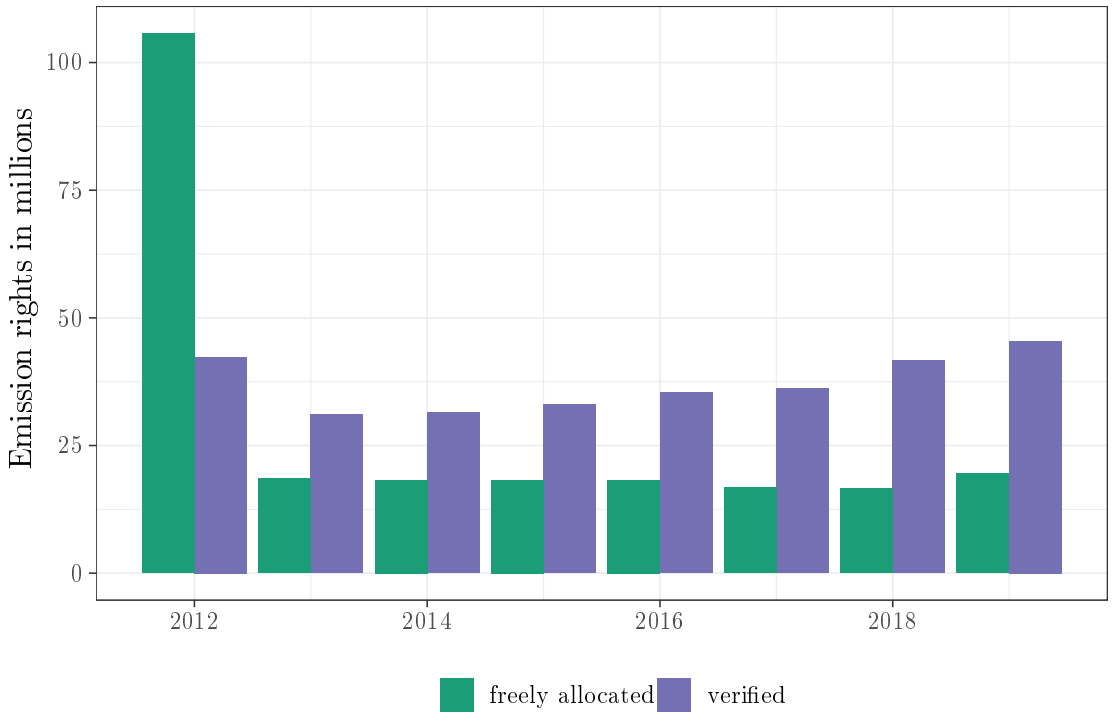
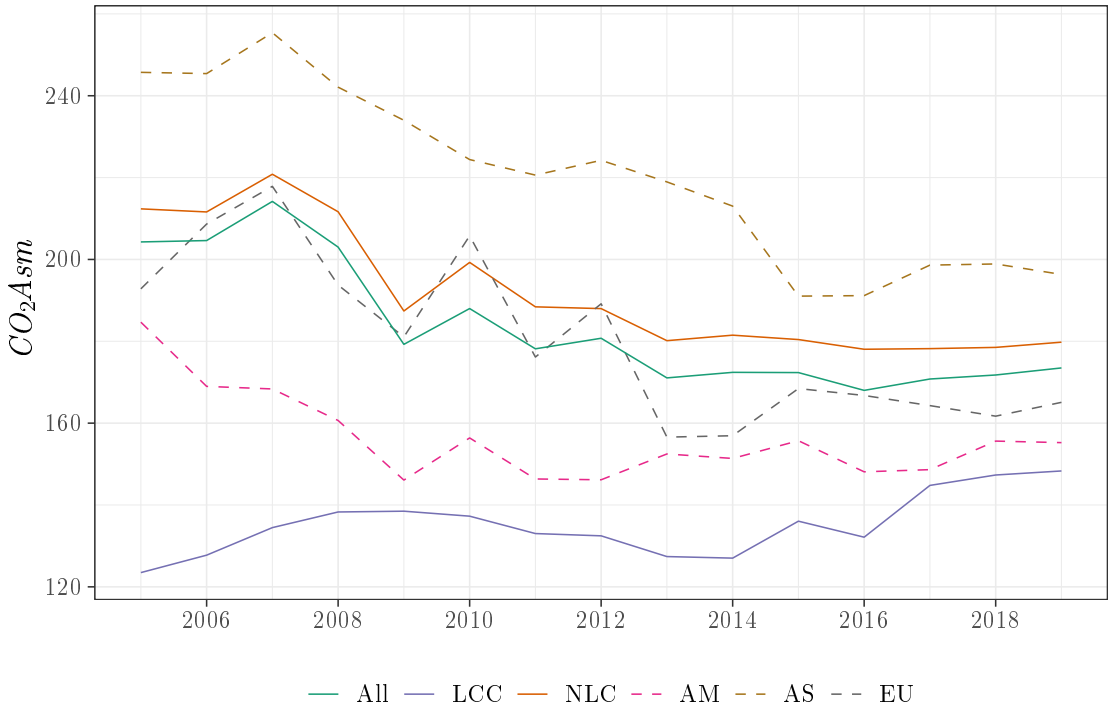


Figure 2.35 shows the percentage change in CO_2 emissions ($CO_2 Chg$). A general development is not visible.

Figure 2.36 shows the average CO_2 emissions scaled by $asmTl$ ($CO_2 Asm$). It can be seen that they have decreased over the period considered (15.07%). The largest overall decrease is seen for Asian airlines with 20.10%, followed by American (15.94%), NLCs (15.34%) and European airlines (14.38%). The only exception are LCCs, which increased their value by 20.11%, but still have the lowest values over the entire period with an average of 135.22 grams per ASM. Just above this are American airlines with an average of 156.32 grams per ASM and, at some distance, European airlines with 180.33. The highest values for the whole period have Asian airlines with 219.99 grams per ASM. It can also be seen that the values have converged over time.

Figure 2.35: Time series: percentage change in CO_2 emissions ($CO_2\,Chg$), annual average of all airlines and divided into LCC, NLC as well as AM, AS and EU

Figure 2.36: Time series: CO_2 emissions per available seat miles (CO_2Asm), annual average of all airlines and divided into LCC, NLC as well as AM, AS and EU



3 FINANCIAL HEDGING

3.1 Literature Review

The following chapter provides an overview of the relevance of hedging in the airline industry (Subsection 3.1.1) and financial hedging in this context (Subsection 3.1.2). Subsection 3.1.2 is again divided into sections on financial distress (3.1.2.1), the problem of underinvestment (3.1.2.2) and related issues (3.1.2.3), such as tax incentives, maximising managerial wealth and economies of scale. The corresponding hypotheses on financial hedging in aviation are presented in Section 3.2 and the empirical analyses in Section 3.3. The chapter concludes with a summary of the results in Section 3.4. Additional information can be found in Appendix D, with references in the text to the individual items in the Appendix.

3.1.1 Hedging relevance in the Airline Industry

Hedging generally involves the reduction of a risk, whereby risks can be divided into two different categories. On the one hand, there are non-tradable risks, such as regulatory risks due to climate change, crises, wars, political unrest, natural disasters or human resources (Lufthansa Group, 2020). Alternatively, there are risks that can be traded, such as fluctuations in the prices of raw materials that are pertinent to the business. In the next three subsections, we deal in particular with the risk of fuel price volatility for airlines.[130]

This paper distinguishes between two types of hedging. Both aim to reduce the uncertainty of cash flows and thereby the risk a company is exposed to, where the risk is reduced by shifting it to other counterparties. On the one hand, there is so-called finan-

[130]Sprcic and Sevic (2012) define financial risk as the risk to which companies are exposed through price changes that directly or indirectly influence the value of the company. How and how intensively risks such as fuel price are managed often plays a major role in the success or failure of a company. Therefore, it can be said that financial risk management is one of the most important corporate functions that contributes to maximising shareholder wealth (Sprcic and Sevic, 2012).

cial hedging (Subsection 3.1.2). This involves mitigating risk associated with securities positions, exchange rate fluctuations, or commodity prices. This is crucial for airlines as they are exposed to significant jet fuel price fluctuations. To protect against unfavorable price movements, they can purchase or sell derivatives which might create counterparty risk. One part of financial hedging is selective hedging, which focuses on the behaviour of companies or managers who take their own market views into account when determining the company's hedging strategy. Due to the scope of this work, this topic was not dealt with further.[131]

On the other hand, there is operational hedging (Subsection 4.1.1), where risks are hedged through operational activities or real options[132]. In case of airlines such an operational hedge could be a diverse fleet or membership in a strategic alliance (Triantis, 2000).[133]

As already mentioned, the airlines analysed here mainly use cash flow hedges for fuel prices. Cash flow hedges are used to hedge the risk of variable cash flows from assets or liabilities that are attributable to a specific risk, in this case the fuel price risk, and can have an impact on profit and loss. In addition to cash flow hedging, there is also fair value hedging, which occurs in the literature analysed. Fair value hedges are used to minimise the risk of changes in the fair value of liabilities, assets or other firm commitments that could affect profit or loss.

The cost of jet fuel is an important cost factor for airlines and accounts for between 10% and 20% of total operating costs. As with other commodities, the volatility of jet fuel prices is very high (Carter et al., 2006) and airlines cannot avoid being exposed[134] to jet fuel prices. 'Airlines are inherently "short" jet fuel (i.e., they benefit if jet fuel prices decline), thus they should be negatively exposed to short-term increases of jet fuel prices.' (Treanor et al., 2014a, p. 150).

According to Morell and Swan (2006), airlines use hedging to stabilise their profits in the event of a sudden rise in crude oil prices. Airlines have three ways of dealing with fuel prices: Increasing the fuel efficiency of their operations, passing on the additional costs to

[131] For further information on this topic see i.e. Dolde, 1993; Stulz, 1996; Bodnar and Gebhardt, 1998; Adam and Fernando, 2006; Brown et al., 2006 or Adam et al., 2017.

[132] Triantis (2000) cites Airbus SE as an example of such real options. By developing a family of commonality aircraft and flexible production lines, Airbus can manufacture different aircraft in the same production facility. This allows them to respond flexibly and quickly to its customers' orders.

[133] According to Treanor et al. (2013), operational hedges are a consequence of a company's real options, which give the option holder greater operational flexibility.

[134] Exposure is the fact of being exposed to a risk without protection. Smithson and Simkins (2005) define it as the sensitivity of a company's stock price to changes in the underlying asset value. They define it as the sensitivity of the stock returns to returns on owning and underlying asset.

passengers[135], and hedging fuel prices. Airlines typically hedge between one and two thirds of their fuel costs, usually with a view to the next six months. A few airlines hedge volumes for more than one year in the future and almost none for more than two years (Morrell and Swan, 2006). Cobbs and Wolf (2004) propose a strategy that involves a dynamic hedging programme that is actively managed through the use of derivatives over the oil price cycle.[136] In essence, the practice of financial hedging involves managing the risks by using derivatives like forwards, futures, options, swaps (Bessembinder, 1991), and collars (Morrell and Swan, 2006). Similar to exchange rate risk, companies try to absorb these price changes through the use of such financial derivatives.[137] However, financial contracts on jet fuel are not traded directly on commodity exchanges.[138] Airlines therefore often use financial instruments with alternative oil price underlyings with similar price movements, known as cross hedging, for their fuel hedging strategy. Due to the characteristics of jet fuel, underlying alternatives such as crude oil (West Texas Intermediate (WTI) in the US, Brent in Europe) or heating/fuel oil are used (Carter et al., 2006; Morell and Swan, 2006; Adams and Gerner, 2012). The trading centers for oil futures are the New York Mercantile Exchange (NYMEX) and the Intercontinental Exchange (ICE) in London (until 2005 the International Petroleum Exchange (IPE)). Contracts are available for each month up to two years and thereafter semi-annually up to three years (Morrell and Swan, 2006). Adams and Gerner (2012) conclude that for a hedging horizon of up to three months, the use of crude oil is suboptimal and gasoline is more effective as an alternative underlying. In contrast, Lim and Turner (2016) conclude that heating oil is the better underlying for cross hedging with jet fuel, regardless of the hedging horizon.[139]

[135] Compared to other fuel-dependent companies, e.g. Fedex, the success of such a concept in the aviation industry is hard to predict. Airlines that have increased their fares and surcharges have had to reverse this because their competitors did not respond with a similar price increase (Cobbs and Wolf, 2004).

[136] If the oil price is at the low point of the cycle, the relatively low price is hedged, as the probability of a further price fall is considered lower than that of a price rise. In the middle of the cycle, a certain price range is set, foregoing potential savings from price falls while hedging against further price rises. If the oil price is at the upper end of the price cycle, the company hedges against losses from further price increases, while it can benefit from price decreases (Cobbs and Wolf, 2004).

[137] For example, in 2012, Delta Air Lines bought an oil refinery in addition to hedging as part of their strategy to cushion the rising cost of refining margin, as fuel costs were their largest single expense (Delta Air Lines, 2013). This has brought them many benefits, such as protection against price changes in all oil prices. However, this purchase also brings with it all the risks associated with running an oil refinery (Turner and Lim, 2015).

[138] Futures for aviation fuel are only traded on the relatively small Japanese market. However, other contracts are traded over the counter (Morrell and Swan, 2006). They are very illiquid, which makes them quite expensive and means that they are not available in sufficient quantities for an airline's total jet fuel consumption (Cobbs and Wolf, 2004).

[139] In general, the approach of the two papers is very similar. Adam and Gerner (2012) use weekly European jet fuel spot prices (Amsterdam-Rotterdam-Antwerp) between June 1995 and June 2010 with maturities of one, three, six, nine and 12 months as dependent variable and the hedging ratios of weekly one-month OTC forward prices for Brent, WTI, heating oil or gasoline as independent variable. For a

The risk that the settlement price of the hedging instrument deviates from the price of the hedged underlying is called basis risk. To illustrate this, consider an example. In the following, the underlying of the hedging instrument is crude oil and the hedged underlying is jet fuel. The basis risk of our example can then be measured by the correlation between the price change of crude oil and the price change of jet fuel.[140] The lower the correlation, the greater the basis risk (Haushalter, 2000).[141]

Figure 3.1 provides an overview of the spot prices for WTI crude oil, jet fuel and the associated fluctuations. The price of WTI has fluctuated between 26 and 145 USD per barrel between 2004 and 2019, while that of jet fuel has ranged between 33 and 198 USD per barrel. The upper part of the chart also shows the crack spread[142]. The price peak for both was reached in 2008.[143] From the figure it can already be guessed that they are highly correlated, which is confirmed by the calculation of the correlation average of 0.97. The lowest correlation was reached in July 2013 with -0.08. The lower part shows the volatility of the two by the average monthly SD, which peaks for both in 2008: WTI 11.04 (October) and jet fuel 19.59 (September).

Regarding the suitability of the airline industry for an investigation of the determinants of corporate hedging, Carter et al. (2006) and Jin and Jorion (2006) are of the opinion that the airline industry is particularly well suited for the investigation of the determinants of corporate hedging. Jin and Jorion (2006) suggest that when choosing a sample, it is important to ensure that the companies being considered are from the same industry, which ensures similarity of industry-related factors. When selecting the sample, it was important to Jin and Jorion (2006) that for the industry under consideration financial exposure is important and that the companies differ sufficiently in terms of their hedging ratio. Carter et al. (2006) agree with them as the airline industry is largely homogeneous

24-month term, only forwards for Brent and gasoline are continuously available. Lim and Tuner (2016) use daily data from Bloomberg Professional Service for the period from 15 April 1994 to 17 February 2010 and regress US Gulf Coast spot jet fuel prices with daily, weekly or monthly frequency against hedge ratios with time horizons of one, three, six, nine and 12 months. One reason for the different conclusions could be that European jet fuel is more strongly correlated with gasoline and jet fuel from the US Gulf Coast is more strongly correlated with fuel oil.

[140] From the data on which Figure 3.1 is based, it can be seen that the correlation between WTI and jet fuel was lowest in 2013, at 0.13.

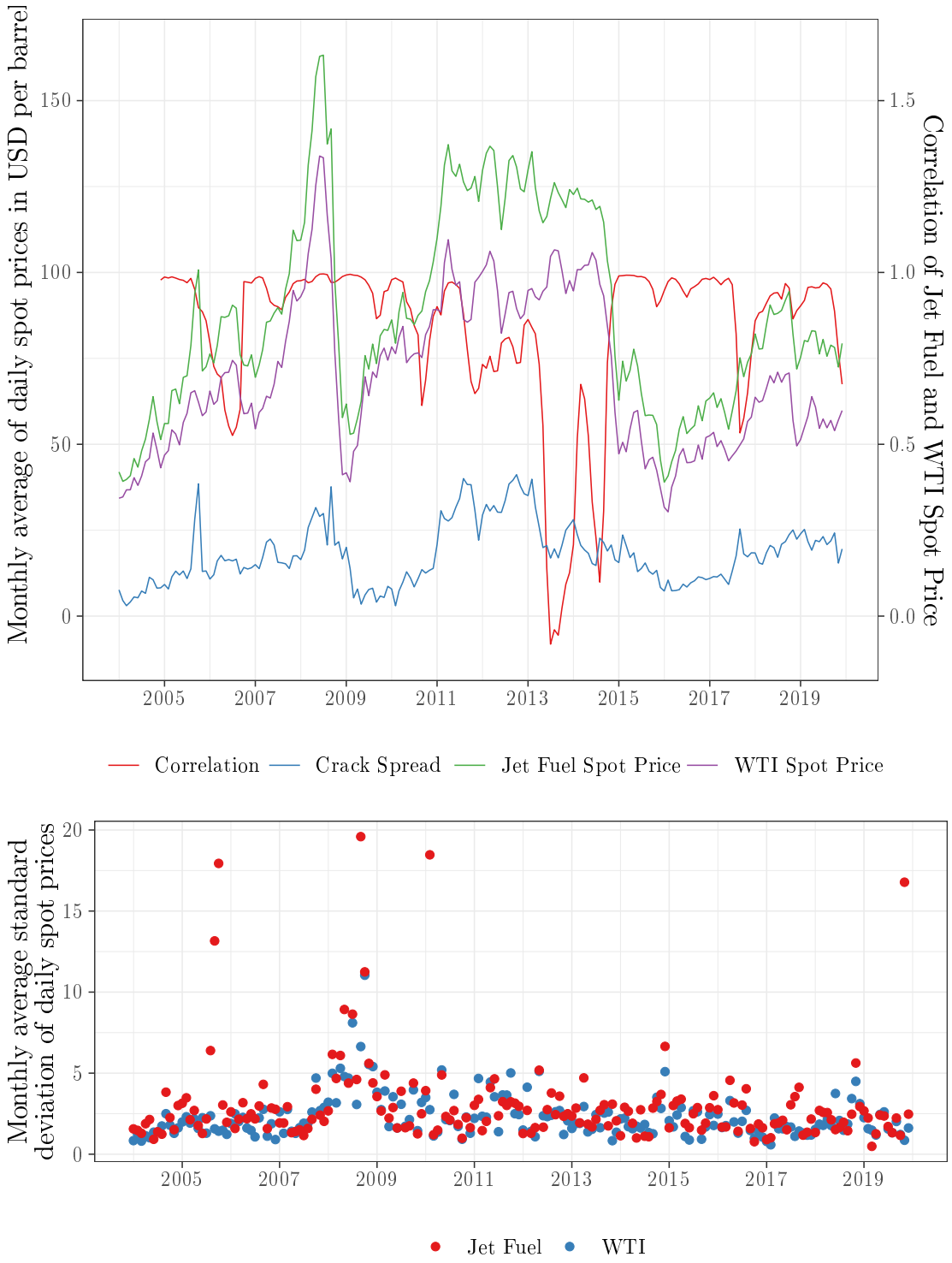
[141] For example, to measure the basis risk associated with hedging, Haushalter (2000) uses a variable to indicate the location of production. It is defined as the share of the firm's total production in the regions where the spot price for the underlying asset is most correlated with the price of the derivatives relative to the firm's total production.

[142] The crack spread is the difference between the price of crude oil (in this case: WTI) and the price of its refined products (in this case: jet fuel).

[143] These peaks can be explained by several significant upheavals in 2008, such as a strike by Nigerian union workers that reduced ExxonMobil's production by 780,000 barrels of oil per day (Smith, 2009).

and competitive, cf. Froot et al. (1993).

Figure 3.1: Monthly average of daily crude oil spot prices, jet fuel spot prices and crack spread including the correlation and standard deviations; between January 2004 and December 2019 (extension based on Pfefferle (2019), Data: EIA (2023a) and EIA (2023b))



3.1.2 Determinants of Financial Hedging

In the world of perfect capital markets as outlined by Modigliani and Miller (1958), there is no reason for companies to hedge. However, perfect markets do not correspond to reality, which is why hedging can be of interest to companies. Within financial economics, there are various hypotheses based on market imperfections as to why risk management can make sense for companies. The basic idea is to create a portfolio that offers deterministic future values, the so-called 'perfect hedge' (Van Mieghem, 2003, p. 297). Another view on this is that risk management leading to a reduction in return volatility is called hedging (Hentschel and Kothari, 2001). According to Mello and Parsons (2000), optimal hedging maximises a firm's liquidity[144] when it is most valuable. They are able to show that hedging can reduce the risk of costly financial distress, reduce the impact of external financial constraints and enable value-maximising investments (Mello and Parsons, 2000).

Two different explanatory approaches are explained below - one that focuses on maximising shareholder value and one that focuses on managerial self-interest. The former approach strives to enhance shareholder value by executing strategies like hedging to reduce the potential cost of financial distress, tackling the underinvestment problem linked to expensive debt financing, and curtailing anticipated taxes (Myers, 1977; Warner, 1977; Stulz, 1984; Smith and Stulz, 1985; Lessard, 1989; Bessembinder, 1991; Froot et al., 1993; Nance et al., 1993; Mello et al., 1995; Stulz, 1996; Géczy et al., 1997; Gay and Nam, 1998; Leland, 1998; Chowdhry and Howe, 1999; Graham and Smith, 1999; Haushalter, 2000; Allayannis et al., 2001; Allayannis and Ofek, 2001; Allayannis and Weston, 2001; Pantzialis et al., 2001; Adam, 2002; Graham and Rogers, 2002; Guay and Kothari, 2003; Carter et al., 2006; Jin and Jorion, 2006; Morell and Swan, 2006; Ding et al., 2007; Bartram, 2008; Bolton et al., 2011; Gay et al., 2011; Hankins, 2011; Merkert and Hensher, 2011; Dionne and Triki, 2013; Gamba and Triantis, 2014; Turner and Lim, 2015; Adam et al., 2017; Swidan and Merkert, 2019). The second approach focuses on managers who aim to maximise their private wealth through risk management (Stulz, 1984; Smith and Stulz, 1985; DeMarzo and Duffie, 1995; Tufano, 1996; Géczy et al., 1997; Gay and Nam, 1998; Adam, 2002; Rogers, 2002; Brown et al., 2006; Lin and Chang, 2009).

In addition to the various reasons for hedging and their consideration, the studies considered in the following can also be differentiated on the basis of the dependent variable in the empirical analysis. On the one hand, there are studies that consider a binary variable as the dependent variable that describes whether hedging takes place or not (e.g. Nance et al., 1993; Géczy et al., 1997). Other works consider the extent of hedging (e.g. Tufano, 1996; Haushalter, 2000), e.g. the notional amount of derivatives scaled by total assets (Gay

[144] Slack in the form of unused liquid assets, e.g. excess cash (Mello and Parsons, 2000).

and Nam, 1998) or the percentage hedged in the following year (Carter et al., 2006), as the dependent variable, and still other works consider both (e.g. Carter et al., 2006; Bartram et al., 2009). These different approaches lead to differences in the results, as independent variables can influence the decision to hedge or the decision on the extent of hedging differently.

Besides the topics briefly mentioned, there is another part of literature that deals with risk management and hedging with financial instruments in terms of an optimal derivative position. Baron (1970) and Sandmo (1971) develop a generalised model of optimal production under price uncertainty in a competitive equilibrium. To incorporate futures trading into the theory of a firm, i.e. to set future prices at which outputs or inputs are traded, this generalised model is extended by Danthine (1978), Holthausen (1979) and Feder et al. (1980) to a two-date or one-period model for a tradable risk that incorporates optimal hedging decisions. Subsequently, this model was extended in various directions, e.g. for exchange rates, commodity prices and the related scope of foreign exchange and commodity forwards or futures (Benninga et al., 1985 and Kawai and Zilcha, 1986). For further additions, cf.: Briys et al., 1993; Broll et al., 1995; Adam-Müller, 1997; Adam-Müller, 2000; Adam-Müller and Wong, 2003; Chang and Wong, 2003; Wong, 2003; Benninga and Oosterhof, 2004; Adam-Müller and Panaretou, 2009; Korn, 2010 and others.

Nevertheless, brief reference should be made to a paper that analyses the optimal hedging portfolio under multiplicative basis risk (Adam-Müller and Nolte, 2011). The paper uses the cross hedging position of an airline to demonstrate the ideal way to hedge against jet fuel price risk. Due to insufficient data[145], the literature regarding this topic is not extensively discussed in this section.

3.1.2.1 Financial Distress

The argument for risk management in relation to financial distress[146] is that risk management can increase the expected value of a business by reducing the likelihood of financial distress (Smith and Stulz, 1985) and the associated costs by reducing the variability of cash flows (e.g. Froot et al., 1993). Survey results of US non-financial companies show that 49% of respondents cited managing the volatility of cash flows and 42% cited managing the volatility of accounting results as the primary reason for hedging (Bodnar et al., 1996).

By reducing deadweight costs and increasing debt capacity, a company can benefit from

[145] Data is not sufficient to test the explanatory power of the models.

[146] Purnanandam (2008) distinguishes between financial distress and insolvency. Financial distress is defined as a state of low cash flows in which the company makes losses without being insolvent, in other words the state between solvency and insolvency.

the tax shield of debt or a reduction in the agency costs of excess free cash flows, leading to an increase in value (Smith and Stulz, 1985). According to Stulz (1996), companies should only make bets with a positive expected value that have no influence on the probability of financial distress. Those that significantly increase this probability should not be made, as they may not be profitable if the cost of a bad outcome is too high (Stulz, 1996).

Hedging reduces the volatility of a firm's cash flows and thus reduces the expected costs of financial distress (Smith and Stulz, 1985; Froot et al., 1993; Nance et al., 1993; Gay and Nam, 1998). In addition, if a company is experiencing financial difficulties, its shareholders may be tempted to abandon projects that have a positive net present value (NPV), especially if the profits primarily benefit senior claim holders. Hedging the market value of a company not only reduces the possibility of financial distress, but also the likelihood that shareholders will see it as favourable to abandon valuable projects (Myers, 1977; Bessembinder, 1991; Froot et al., 1993). The argument that a company can reduce the cost of financial distress through hedging activities is supported by the positive correlation between the amount of hedging and financial leverage as documented by Haushalter (2000), Nguyen and Faff (2002) and Purnanandam (2008).

Bessembinder (1991) notes that less attention has been paid to corporate risk hedging because shareholders do not value corporate hedging. Indeed, shareholders can reduce company-specific risks by diversifying their own portfolios (Bessembinder, 1991; Stulz, 1996). However, the potential costs of financial distress or default make hedging attractive for shareholders.

The responses of 73 Belgian non-financial companies surveyed by de Ceuster et al. (2000) showed that more than 60% of the companies do not consider hedging as important for increasing the market value are in contrast to the above reasons for hedging. For 45% of them hedging is of importance because of earnings volatility, which is consistent with Bodnar and Gebhard's (1999) survey results of German companies. These results for European companies contrast with the results for US companies of Bodnar et al. (1995) and Bodnar et al. (1996)[147], where the two main reasons for hedging are to reduce the volatility of cash flows and reported accounting profits.

Concerning the reasons of a company for hedging, Brown (2001) studies a single company which formulates the objective of its hedging programme as minimising the impact of exchange rate fluctuations by maximising dollar cash flows. He examines the quarterly and annual SD of income changes and arrives at a quarterly and annual decline of 22% and 10.2%, respectively. Forecast horizons of three, six and nine months are considered

[147] A survey concerning the use of derivatives was mailed to US non-financial firms in 1994 and again in 1995.

and the dependent variables are the deltas and gammas of the hedge portfolio. He finds a significant positive impact on the portfolio deltas for the three- and six-month horizons when comparing the current spot rate to both the 12-month high and the 12-month low. The change in the spot rate over the last three months is also positive and significant for the portfolio deltas over the nine-month period. This suggests that the company tends to hedge less when the foreign currency appreciates against the USD (Brown, 2001).

Bartram et al. (2009) conclude that the determinants of the use of derivatives are endogenously related to other financial and operational decisions and that the traditional tests of the above theories are not well suited to explain these determinants. The study analyzes derivatives, including foreign exchange, interest rates, and commodity price derivatives, held by 7,319 non-financial firms from 50 countries in either 2000 or 2001. The findings partly contradict the financial distress and underinvestment hypotheses (Subsection 3.1.2.2). With respect to the first hypothesis, they agree that derivatives users have higher leverage and less liquid assets (e.g. Myers, 1977; Smith and Stulz, 1985). However, contrary to theory, they conclude that users are more profitable (positive significant interaction between use of derivatives and profit margin both at the 1% level).

Within the literature, there is no unanimous opinion on the correlation between the use of derivatives and leverage. On the one hand, it is argued that there is a positive correlation and a resulting higher firm value (Nance et al., 1993; Graham and Rogers, 2002). On the other hand, the results are attributed to the correlation between the use of derivatives and other risk management options, such as operational hedging (Allayannis et al., 2001; Guay and Kothari, 2003) or the reduction of financial distress costs (Dionne and Triki, 2013). Guay and Kothari (2003) try to reconcile the contradictory findings on whether economic theories of hedging predict the use of derivatives by firms (Géczy et al., 1997; Allayannis and Ofek, 1998). They note that the size of derivative positions held by most companies is economically small compared to the risks at the corporate level.

The study of 100 oil and gas companies between 1992 and 1994 carried out by Haushalter (2000) allows for the separation of the determinants of the hedging decision and hedging volume, by using the so-called Cragg Model[148] (Cragg, 1971). The use of different dependent variables and thus different statistical models has led to sometimes contradictory results. The use of Tobit models for the hedged portion of the company's annual oil and gas production shows a statistically positive significance for the leverage value. Probit regressions for the dependent variable hedge dummy show no statistical significance.

[148]The Cragg model is used when two outcomes are to be considered separately. One is the probability of a binary decision (e.g. the decision to hedge production) and the other is the level of that decision (e.g. the share of production to be hedged) (Haushalter, 2000).

Haushalter (2000) concludes that the cost of hedging[149] and the underlying risk of the instruments available for hedging appear to be more important determinants of this decision.

Using a two-step model (Heckman-Two-Step-Estimator), Adam (2002)[150] examines whether, and if so, to what extent the use of derivatives influences a firm's financing strategies. First, the probability that a company engages in hedging is estimated, where the dependent variable is a hedging dummy. In the second step, the dependent variable is the hedge ratio[151] to capture the extent to which gold mining companies engage in hedging. Adam (2002), in line with Allayannis and Ofek (2001), finds that less diversified firms are more likely to engage in hedging. Using the same sample, Dionne and Triki (2013) run a Tobit regression with random effects for the dependent variable delta percentage (fraction of planned gold production that is being hedged over the next three years) for the years 1991 to 1999. For the two independent variables (leverage and cash cost) of financial distress, they find a positive significance at the 1% level. From this, they conclude that companies are putting in place hedges to reduce financial distress costs.

Purnanandam (2008) tests his model using non-financial firms whose 10-K files for 1996 and 1997 were available on the US Security and Exchange Commission (SEC) website. He uses both a dummy variable for the decision to hedge and the notional value of derivatives scaled by total assets for the extent of hedging. For an investigation of the dynamic behaviour of hedging and leverage decisions of firms, a smaller dataset of 200 manufacturing firms (one digit SEC code 2) is used for the years 1996 to 1999. Companies with a moderate increase in leverage (as a proxy for financial distress) are more likely to adjust their hedging position. If the increase in leverage is very high, this probability decreases and companies are more likely to reduce their hedging efforts, resulting in a non-monotonic relationship between the levels of risk management and leverage (Purnanandam, 2008).

In his study of 441 UK non-financial firms for 1995, Judge (2006) finds strong evidence of the relationship between the decision to hedge and the expected cost of financial distress. Although these results may be mainly due to his definition of hedging[152], the determinants of the cost of financial distress appear to be more important for his UK sample than for

[149] Bodnar et al. (1996) find as well evidence that one of the main reasons why firms do not hedge is that the cost of hedging would exceed the profit.

[150] The sample *Gold and Silver Hedge Outlook* (a quarterly survey conducted by Ted Reeve) was used. He examined 92 North American gold mining companies between 1989 and 1999, with regard to their derivative use strategy. Adam (2002) examines whether hedging increases the likelihood that future investments will be internally financed. This sample was also used in whole or in part in the following papers: Tufano, 1996; Brown et al., 2006; Dionne and Triki, 2013; Adam et al., 2017.

[151] The total hedge ratio is defined as either the ratio of portfolio delta to expected production (Tufano, 1996) or the ratio of portfolio delta to total reserves (Jin and Jorion, 2006).

[152] Unlike other studies, Judge (2006) includes all hedgers, not just those using derivatives.

samples of US firms (e.g. Nance et al., 1993). For further research, he divides his sample into derivative users and non-derivative users and finds evidence that larger firms, firms with more cash, firms more likely to experience financial distress[153], firms with exports or imports, and firms with more short-term debt are more likely to hedge using derivatives. In line with Spanò (2007), he finds a negative significance for the measure of liquidity, which is represented by the cash ratio, and the probability of hedging. Moreover, like Bartram et al. (2009), he finds evidence that the interest coverage ratio is negatively significant for the probability of hedging.

Gamba and Triantis (2014) analyze the impact of commonly used risk management strategies on enhancing the value of a firm. Their research includes exploring the potential benefits of reducing expected tax payments (Smith and Stulz, 1985; Graham and Rogers, 2002), lowering borrowing costs (Froot et al., 1993) and reducing the likelihood of financial distress and default costs (Smith and Stulz, 1985). They conclude that the strongest motivation is the avoidance of default costs (cf. Froot et al. (1993); Guay and Kothari (2003); Jin and Jorion (2006)) and estimate that the limit of hedging by derivatives in the presence of other risk management mechanisms is on average no higher than 2% of the firm value. In their opinion, liquidity, measured in terms of cash holdings, is one of the most important risk management tools (Gamba and Triantis, 2014). The analysis of the economic impact of derivative positions on a sample of non-financial derivative users shows that the potential gains from derivatives are relatively small compared to cash flows and cannot be responsible for an increase in the market value (Guay and Kothari, 2003) of, for example, 10.2% (Carter et al., 2006). Jin and Jorion (2006) show that the relationship between hedging and the firm value of 119 U.S. oil and gas producers between 1998 and 2001 is neither statistically nor economically significant. On the other hand, Gamba and Triantis (2014) show that this effect may be significantly higher for companies with a key risk that can be effectively hedged. Haushalter (2000) has shown this for oil and gas companies, Allayannis and Weston (2001)[154] have shown this for currency hedging activities and the firm value of export companies, and Carter et al. (2006) have shown this for

[153] Judge (2006) measures corporate creditworthiness using the credit rating in form of the Qui-score to assess the ability of companies to meet their obligations.

[154] Allayannis and Weston (2001) investigate whether firms with exchange rate risk that use foreign currency derivatives have a higher market value. The starting point is a sample of 720 large non-financial firms between 1990 and 1995 and Tobin's Q is used as a proxy for market value. They find positive significance for the use of foreign currency derivatives and the market value of the firms. Furthermore, they show that companies exposed to currency risk and using currency derivatives have an average firm market value 4.87% higher than companies not using currency derivatives. Companies that start a hedging policy experience an increase in value compared to companies that do not hedge or discontinue hedging, while companies that discontinue hedging experience a loss in value compared to companies that hedge (Allayannis and Weston, 2001).

jet fuel hedging and airline market value, which is in contrast to Jin and Jorion (2006). One explanation for the different results could be information asymmetries or operational hedges (Jin and Jorion, 2006).

In a capital-intensive industry such as aviation, debt and liquidity are crucial for hedging activities. Airlines typically take on debt to purchase aircraft, which makes it difficult for financially distressed airlines to engage in hedging activities as they cannot always provide the necessary collateral (Rampini et al., 2014). Financial hedging contracts require cash collateral that financially distressed airlines are unable to provide or that cause them to terminate existing hedges (Swidan and Merkert, 2019). Morell and Swan (2006) agree and show that hedging can be of great value to financially distressed airlines, but they may not have the necessary cash resources. At the same time, they point out that hedging fuel costs could be an outward sign of attentive management rather than a fundamental economic benefit (Morell and Swan, 2006). According to Carter et al (2006), non-financial hedges can illustrate the financial health of a company in addition to risk management abilities. It has been shown that the use of fuel hedging or its impact on airline operating costs and profits is statistically negligible (Lim and Hong, 2014).

Rampini et al. (2014) examine the trade-off between capital structure and risk management. They use a dataset consisting of 23 US airlines between 1996 and 2006. To this end, they examine the behaviour of airlines with low net worth[155], as this is where they can run into the conflict between financing and risk management. By using averages for the entire sample, they can show that airlines with higher net worth, higher cash flows and higher credit ratings hedge a larger portion of their expected fuel costs. An increase of one SD in the market value of net worth, scaled with the company's market value, results in an increase in the proportion of next year's hedged fuel expenses by 0.5 SDs. They find statistically significant evidence that a one step reduction in credit rating reduces the proportion of expected jet fuel expenses hedged by 22%. The results of this univariate analysis are confirmed by the multivariate analysis using two-stage least squares models. In addition, they take a closer look at the airlines under distress in the sample (airlines with a rating of CCC+ or worse). They note a 20% point reduction (from 25% to 5%) in the coverage of expected fuel expenses in the year before the distress occurs. Although figures recover in the first two years after the event, they do not reach pre-event levels (Rampini et al., 2014).

Lin and Chang (2009) investigate whether hedging jet fuel increases the market value

[155]Rampini et al. (2014) calculate net worth as the sum of the current cash flow, the value of capital less debt and the payout of the contingent claims used for hedging.

of 69 airlines worldwide between 1995 and 2005. Their regression analysis[156] shows that hedging jet fuel is valuable for airlines, and the hedging premium is about 12%, which is 7% higher than estimated by Allayannis and Weston (2001), who studied 720 non-financial firms between 1990 and 1995. They examine different subsamples and show that the firm value of US airlines participating in fuel hedges is higher by 13.61% than the value of firms without hedging (cf. Cobbs and Wolf, 2004). This is higher than the 10.2% increase in firm value from fuel hedging found by Carter et al. (2006), which Carter et al. (2006) interpret as 'hedging premium (i.e., the added firm value attributable to hedging)' (Carter et al., 2006, p. 54).[157] In contrast, Lin and Chang (2009) conclude that non-US and alliance airlines do not increase their firm value through fuel hedging. In addition, fuel hedging has been shown to be worth more in volatile times than in stable times, leading to the conclusion that airlines can avoid firm value losses from rising oil prices by taking hedging measures. Consistent with Smith and Stulz (1985) and Froot et al. (1993), Lin and Chang (2009) find evidence that hedging is important for non-US, non-alliance airlines and in times of stable prices with respect to financial distress. They agree with Froot et al. (1993) and Carter et al. (2006) that for US airlines, airlines without alliances and airlines in the stable phase, mitigating underinvestment problems is an important reason for hedging, which is discussed in more detail in the following subsection. In addition, alliance airlines and airlines in a volatile period, hedge against fuel price risk to maintain their higher profitability (Lin and Chang, 2009).

3.1.2.2 Underinvestment

Overall, there seems to be a consensus in the literature that companies without risk management may be forced to pursue sub-optimal investment policies. Due to capital market imperfections, a close relationship might be established between a firm's investments and cash flows. In the case of low cash flows, raising further funds (i.e. issuing equity[158]) is often costly, so value-maximising investments can possibly not be made. By removing this

[156] They use a Tobit regression for the dependent variable on the percentage of fuel hedging requirements in the next year and a Logit regression for the dummy variable on whether the firm's hedging ratio is greater than or equal to zero (Lin and Chang, 2009).

[157] Carter et al. (2006) also find positive significance for the interaction between capital expenditure and hedging in terms of firm value. They conclude that higher capital expenditures are associated with higher firm value for airlines that engage in hedging. A company that hedges is valued on average 7.3% higher than a company that does not hedge.

[158] The issuance of equity or the retention of dividends can be interpreted by shareholders as a sign of financial distress and result in the sale of their shares (Myers and Majluf, 1984; Lessard, 1991). Thus, if hedging helps to reduce the likelihood of equity issuance, it can help to increase market value (Lessard, 1991).

dependency through risk management, the value of a company can be increased (e.g. Stulz, 1990; Lessard, 1989; Froot et al., 1993). Employing derivatives for hedging corporate risk can enhance the value of the firm alleviating underinvestment problems. This is achieved by lowering the impact of additional investment on the worth of senior claims, thereby enabling shareholders to receive a more substantial proportion of the additional benefits resulting from new investments. Hedging increases the ability of firms to fulfill obligations that would have otherwise been unattainable (Bessembinder, 1991).

According to the pecking order theory, raising external capital should be avoided whenever possible, as external capital is more expensive than internal capital for firms facing asymmetric information issues with respect to the attractiveness of their projects. Nevertheless this can create an incentive to hedge risks and ensure that sufficient funds are available to avoid underinvestment. Froot et al. (1993) show that hedging allows firms to have sufficient internal funds to take advantage of profitable investment opportunities by reducing the variability of internal funds. Consistent with this, Nance et al. (1993) and Géczy et al. (1997) conclude that firms that hedge have greater opportunities for growth. Stulz (1996) comes to a similar conclusion, stating that companies should manage risk in a way that preserves their financial flexibility to implement their investment strategies. In his opinion, risk management can be seen as a direct substitute for equity. The more a company hedges its financial risk, the less equity it needs to support its business (Stulz, 1996).

Another reason why hedging can be a value-enhancing activity is that it reduces the likelihood that a firm will need to use capital markets for more expensive external than internal financing by reducing the variability of cash flows (Froot et al., 1993; Stulz, 1996). The more closely their cash flows are linked to collateral values and thus to the possibility of debt financing, the more companies will want to hedge their risks. Conversely, the more closely their cash flows are correlated with future investment opportunities, the less companies will want to hedge (Froot et al., 1993). Consistent with that, derivatives are used to reduce the volatility of cash flows that might otherwise prevent companies from investing in valuable growth opportunities (Lessard, 1991; Stulz, 1990; Géczy et al., 1997).

Géczy et al. (1997) conduct a statistical study of 372 industrial firms with foreign currency exposure[159] from Fortune's 500 companies in 1990. The dependent variable is a dummy variable for the use of currency derivatives. Using a Logit regression, they show that the higher the quick ratio, which represents more internally available funds, the

[159] A company is exposed to foreign exchange risk when either foreign sales, foreign currency denominated debt, foreign tax expense, foreign currency surcharges or foreign currency hedging are included in the AR (Géczy et al., 1997).

lower the probability of using currency derivatives, corroborating evidence is provided by Gay and Nam (1998) and Gay et al. (2011). With the same regression they show that potential underinvestment costs increase the incentives to hedge, as the ratio of research and development (R&D) spending (measure of investment opportunities) to sales is positive and significant at the 1% level for the dependent variable, consistent with e.g. Froot et al. (1993) or Nance et al. (1993). This suggests that the incentive to reduce underinvestment costs through the use of derivatives is greater when a firm's external financial flexibility is lower (Géczy et al., 1997).[160]

Similar results are obtained by Allayannis and Ofek (2001), who use a two-stage Cragg model for the currency hedging of 378 non-financial S&P 500 companies in 1993. They conclude that the relationship between R&D relative to total sales and the decision to hedge is positive and significant at the 5% level (cf. Gay and Nam, 1998 and Graham and Rogers, 2002). On average, companies use currency derivatives to reduce exchange rate risk rather than for speculative purposes, which suggests that the use of derivatives can be a value-enhancing strategy for companies (Allayannis and Ofek, 2001).

Consistent with Froot et al. (1993) and Géczy et al. (1997), Purnanandam (2008) finds a strong relationship between R&D expenses and hedging for foreign currency hedging decisions. In contrast to commodity hedging, the results for foreign currency hedging show a positive and significant relationship for high-growth companies. The author concludes that these companies have a tendency to engage in strong foreign currency hedging to manage their risks, while taking less action to mitigate commodity risk (Purnanandam, 2008).

Nance et al. (1993) use survey data[161] from the Chief Executive Officers (CEOs) of 169 Fortune 500 and S&P 400 companies on corporate hedging behaviour. Using Logit regressions where the dependent variable is a binary hedging variable that has a value of one if the firm uses forwards, futures, swaps and/or options and zero otherwise, they examine the impact of hedging. They conclude that companies that hedge have lower fixed asset coverage, more growth opportunities and employ fewer hedging substitutes. Companies that use hedging instruments have more growth opportunities in their investment portfolio,

[160] In their study of Croatian and Slovenian companies, Sprcic and Sevic (2012) come to a similar conclusion: a company's decision to hedge is positively related to investment opportunities. In addition, they can show that more liquid companies are more likely to hedge.

[161] Only since the early 1990s have companies been required to disclose information such as the notional amount of derivatives used in the footnotes of their ARs. Until then, this information was kept secret and was considered a very important part of strategic competitiveness (Allayannis and Ofek, 2001). Prior to that, survey data was used to examine the determinants of derivative use (Allayannis and Weston, 2001). The SEC adjusted its reporting requirement for the use of derivatives in 1997 (Jin and Jorion, 2006). In Europe, on the other hand, there is virtually no accurate disclosure of the use of derivatives in the financial statements (de Ceuster et al., 2000).

which can be inferred from the fact that companies with more investment opportunities have both lower leverage and hedge more. They conclude that the aim of firms with more growth opportunities is to reduce the variance of firm value (Nance et al., 1993).

Stulz (1996) has a different concept. According to him, the goal of a company's risk management is the 'elimination of costly lower-tail outcomes' (p. 8) rather than minimizing variance. This means that the expected costs of financial distress should be reduced while the company should still be able to take advantage of possible comparable benefits in risk-bearing capacity. With this in mind, risk management can be seen as buying 'well-out-of-the-money put options designed to limit the downside risk' (Stulz, 1996, p. 24). Furthermore, he sees risk management as a direct substitute for equity, or in other words, the use of risk management to effectively reduce exposure increases a company's debt capacity. This is consistent with the argument that hedging mitigates a potential underinvestment problem.

In examining the relationship between the underinvestment problem[162] and a firm's use of derivatives, Gay and Nam (1998) examine up to 161 firms that do not use derivatives and up to 325 firms that use derivatives using a Tobit regression. They show that firms with greater investment opportunities tend to use more derivatives to hedge their risks and to be able to finance investment opportunities. Furthermore, they can show that among comparable companies with good investment opportunities, those companies that have a low cash balance make greater use of derivatives.

Adam and Fernando (2006), by examining the average total cash flows from derivatives of each company for their sample of 92 gold mining companies, show that hedging was very profitable for most companies during the sample period.

In contrast to this, Bartram et al. (2009) find that derivative users have lower capital expenditures, engage in less R&D (cf. Graham and Rogers, 2002) and have lower MTB ratios (negative significant interaction between use of derivatives and MTB ratio at the 1% level). In line with these findings, Mian (1996) finds a negative relationship between the decision to hedge and the MTB ratio in his study of 3,022 non-financial firms for the year 1992. Allayannis and Ofek (2001), in line with Nguyen and Faff (2002) and Adam et al. (2017), find no or negative evidence for the significance of the MTB ratio in relation to the hedging decision. Nguyen and Faff (2002) question whether the MTB ratio really measures the growth opportunities of a company. According to them, this is only the case if the MTB ratio is greater than one. If it is not, it means that market participants

[162] According to Gay and Nam (1998), an underinvestment problem occurs when firms have to curtail investment at times when debt financing is too expensive and internal cash flows are insufficient to support investment opportunities.

consider the value of the company to be lower than its assets, which is usually the case in financial difficulties. Therefore, a low MTB ratio may also indicate financial distress and a higher probability of using derivatives (Nugyen and Faff, 2002). However, the effect regarding the use of derivatives for the interaction between MTB value and leverage ratio is positive (Bartram et al., 2009), consistent with Géczy et al. (1997) and Graham and Rogers (2002). Furthermore, as with financial distress, Tufano (1996) finds no relationship between risk management and the share of investment opportunities of firms.

Adam (2002) examines whether gold mining companies hedge their sales/production, cash flows or capital expenditures. He shows that companies that are more dependent on the gold price hedge more than companies that produce multiple metals. By finding that companies with higher liquidity are less likely to hedge, he concludes that companies hold liquid assets as a substitute for hedging. From the negative relationship between the MTB ratio and the decision to hedge, he concludes that companies with lower growth opportunities or underperformance are more likely to hedge (Adam, 2002).

Carter et al. (2006) examine the hedging behaviour of 29 US airlines between 1992 and 2003 and focus on jet fuel as a single, homogeneous and volatile input commodity. They justify this decision on the one hand with the considerable price risk for airlines associated with the volatility of fuel prices[163] and on the other hand with the fact that the airlines are faced with considerable financial distress costs.

They conclude that fuel price risk is of economic importance to airlines. The reasons already mentioned for investments (e.g. Froot et al., 1993) why companies engage in hedging are also relevant for airlines. On the one hand, it is about structuring internal cash flows in such a way that future commitments, e.g. the purchase of an aircraft, can be entered into. On the other hand, hedging can improve the liquidity situation in times of crisis, and the hedging airline might not have to resort to external financing to make investments (Carter et al., 2006). Consistent with that, Pulvino (1998) believes that cash reserves can be a valuable source of investment when current internally generated funds are insufficient and external financing is costly. Carter et al. (2006) point out that hedging fuel costs can help airlines manage a potential underinvestment problem, which is again consistent with Froot et al. (1993). Since many aircraft are leased through operations and the value of these aircraft therefore does not appear on the airlines' balance sheets, some values are adjusted using a procedure explained by Damodaran (2012)[164].

[163] Carter et al. (2006) calculate that fuel accounts for an average of 13.6% of operating costs and the annualised volatility of fuel prices, as measured by monthly averages from 1992 to 2003, is about 27%.

[164] This method is used to determine the PV of future operating lease obligations, which is then added to assets and liabilities (Damodaran, 2012). In Carter et al. (2006), capital expenditures-to-sales, Tobin's

Carter et al. (2006) use a Tobit random effects model for the dependent variable of the percentage of next year's fuel demand hedged, with and without the adjustment. Both models show positive significance of Tobin's Q. From this, they conclude a key prediction of the underinvestment hypothesis, which is that airlines with more productive investment opportunities hedge more (Carter et al., 2006). Consistent with this, Treanor et al. (2013) find positive significance for US airline growth potential and the percentage of next year's fuel consumption hedged.

As described above, the airline industry is very capital intensive. Pulvino (1998) shows that airlines can face significant distress costs and aircraft sold by financially distressed airlines in so-called 'distress sales' (p. 941) are sold at a significantly lower price than the average market price[165]. Against this background, he suggests that airlines may want to hedge against rising fuel prices if this strategy allows them to invest in aircraft (and other assets) of financially distressed airlines at discount prices (Pulvino, 1998).

3.1.2.3 Others

Tax Incentives

In addition to the above-mentioned incentives to hedge, e.g. in case of financial distress, the reduction in the volatility of profits can also lead to a decrease in the NPV of expected taxes. The reason for risk management in taxation is given by the fact that a convex tax function can induce companies to hedge in order to reduce their expected tax liabilities (Graham and Smith, 1999).[166] Expected tax liabilities are reduced through risk management by holding taxable profits to a certain extent (Smith and Stulz, 1985; Graham and Rogers, 1999; Sprcic and Sevic, 2012) or by reducing the volatility of taxable income (Stulz, 1996), whereby the more convex the tax plan is, the more the expected taxes decrease (Nance et al., 1993).[167] Smith and Stulz (1985) further conclude that the convexity of the tax function induces firms to hedge and thereby increases their value.

In line with this, Graham and Smith (1999) find that 50% of their sample of more than 80,000 firm-years face a convex effective tax schedule, and of these, a quarter can achieve significant tax savings through hedging (reduction of volatility of 5% delivers approximately

Q, LT debt-to-assets and ln(assets) are adjusted in this way.

[165]Market values are difficult to determine in this context because, in contrast to the financial market, the market for aircraft mainly involves privately negotiated transactions (Pulvino, 1998).

[166]For companies with a convex tax progression, the effective marginal tax rate is low if the taxable income is low. If the taxable income is high, the marginal tax rate is high. If such a company engages in hedging transactions, the expected taxes are lower overall, as the tax increase in the case of low income is lower than the tax reduction in the case of high income (Graham and Smith, 1999).

[167]This conclusion follows from Jensen's inequality (Jensen, 1905).

5.4% tax savings). The study indicates that small to medium-sized companies, whose expected profits fluctuate around zero, have the highest tax incentive to hedge.

However, most studies on this topic do not support Smith and Stulz's (1985) theory. One of these studies is the study by Tufano (1996), who finds no relationship between risk management and the extent of the convexity of tax plans (cf. Mian, 1996; Géczy et al., 1997; Haushalter, 2000; Allayannis and Ofek, 2001; Purnanandam, 2008). It should be mentioned that Haushalter (2000), for example, does not reach a clear conclusion. On the one hand, his study supports the view that there is no significant relationship between a company's risk management and its tax function, on the other hand, he finds a positive statistical significance for the relationship between hedging and the convexity of the marginal tax rate, which supports the theory of e.g. Smith and Stulz (1985).

As mentioned earlier, hedging can reduce the volatility of cash flows and increase debt capacity, which according to Stulz (1996) and Leland (1998) can also lead to greater tax benefits. Empirical support for this hypothesis is provided by Graham and Rogers (2002). They use a Tobit model to examine the tax incentives for the hedging of 442 non-financial US firms facing ex ante currency and/or interest rate risk with fiscal years ending from March 1995 until December 1995. First, they fail to find a relationship between a firm's hedging behaviour and tax convexity[168]. They conclude that firms engage in hedging to increase their debt capacity, but not because of the convexity of the tax function. They find that tax benefits of additional debt financing are an important source of the value of hedging (cf. Stulz, 1996 and Leland, 1998). On average, hedging with derivatives increases leverage by 3.03%, with increased debt tax benefits averaging at 1.11% of the company's market value. They conclude that debt capacity is not increased by the decision to hedge, but rather by how much a company hedges (Graham and Rogers, 2002).

Carter et al. (2006) cannot fully confirm the result of Graham and Rogers (2002) for airlines. Their first result implies a positive relationship between leverage and hedging behaviour. However, Carter et al. (2006) find a insignificant and a negative and significant relationship at the 5% level for the unadjusted for lease and adjusted for lease value. The second finding of Graham and Rogers (2002), that there is no evidence of a relationship between hedging behaviour and tax convexity, is confirmed by Carter et al. (2006). Consistent with this, Gay and Nam (1998) and Gay et al. (2001) cannot find a significant relation between tax loss carry forwards and hedging.

[168]Their independent variable for tax convexity is not significant for the dependent variable (net derivatives scaled by the book value of assets). The variable used was calculated based on Graham and Smith (1999). In this method, the convexity-related benefits of hedging are quantified by calculating the tax saving resulting from the reduction in volatility (Graham and Rogers, 2002).

In comparison to other studies, Graham and Smith (1999) do not employ a survey or regression analysis. Instead, they utilize a simulation to investigate the tax benefits of hedging. They point out that utilizing a regression analysis could pose difficulties in interpreting results because some variables may be relevant to both financial distress and tax arguments. Graham and Smith (1999) propose that the overall advantage of hedging is determined by the sum of various motives.

Managerial Wealth Maximisation

A risk-averse manager[169] who is underdiversified in terms of wealth and firm-specific human capital is likely to either demand additional compensation or suffer from a utility loss to bear such a undiversified total wealth position (Stulz, 1984). This gives the manager an incentive to reduce risk, and hedging can potentially reduce the required risk premium that shareholders have to pay (Smith and Stulz, 1985), so managerial incentives for risk taking are related to hedging behaviour (Tufano, 1996; Rogers, 2002). Stulz (1996) adds that managers should only be rewarded for taking risks that are expected to increase shareholder wealth. In other words, returns that are higher than what shareholders could have earned if they had taken the same risk. This view implies that for a concave function of managerial compensation (stock ownership), the optimal hedging strategy corresponds to full hedging and for a convex function (option holdings) it corresponds to no hedging (both are implied by Jensen's inequality). This statement is supported by the empirical findings of Tufano (1996) and Dionne and Triki (2013).

The study by Tufano (1996) examines the extent of risk-taking by 48 listed North American gold mining companies between 1990 and 1996. He finds significant differences in hedging behaviour between the companies. Hedging is low for companies with low management share ownership, in contrast to companies where management share ownership was higher. Only management share ownership and the type of management compensation contracts are found to be important systematic determinants (Tufano, 1996). Brown et al. (2006) also examine hedging ratios in gold mining companies and conclude that only a small part of the variation in hedging ratios can be explained by traditional theories of risk management.

Spanò (2007) examines 443 British non-financial companies between 1999 and 2000, in particular the behaviour of managers in relation to hedging. Using a two-stage model, both the decision to hedge and, in a second step, its extent are examined. The decision itself

[169]The expected utility function of a risk-averse manager is a concave function of firm value (Smith and Stulz, 1985).

depends mainly on already mentioned factors such as the reduction in tax liabilities. The level of hedging utilized by managers is heavily influenced by their motives. Companies tend to achieve a position closer to the perfectly balanced hedging position when the managers' wealth is only marginally impacted by the firms value. However, when the manager's wealth is significantly impacted by the company's value, they may not use derivatives optimally. Additionally, if managers own a larger percentage of stocks, they tend to act in the interest of shareholders, which partially balances out the mentioned effect of managerial risk aversion (Spanò, 2007).

Since managers are risk-averse, even managers with a convex compensation will engage in some hedging to reduce risk, but in a smaller extent than the hedging of managers with a concave compensation function (Smith and Stulz, 1985). Consistent with that, Gay and Nam (1998) and Lin and Chang (2009) find a positive relationship between the use of derivatives and managerial wealth invested in the firm for non-US airlines.

In contrast to the studies mentioned so far in this subsection, studies such as Géczy et al. (1997) or Haushalter (2000) find no or a negative significance impact of managerial risk aversion or share ownership on the hedging behaviour of companies. Géczy et al. (1997) find that companies with high institutional ownership tend to hedge with currency derivatives (cf. Graham and Rogers, 2002).

Nguyen and Faff (2002) find a negative relationship between executive share ownership and the extent of derivatives use. Their findings are likely to be driven by the competition within the Australian executive labor market. Due to this competition, managers tend to prioritize shareholder interests and participate in hedging programs that add value, rather than solely focusing on their own personal wealth (Nguyen and Faff, 2002).

In contrast to the above studies, DeMarzo and Duffie (1995) and Breeden and Viswanathan (2016) focus on the informational effect of financial risk management and managerial reputation.[170] DeMarzo and Duffie (1995) analyse various cases related to information structure. They conclude that hedging can serve as a signal for external investors to better observe the manager's skills and for managers to demonstrate their skills in the labour market. Therefore, it is expected that reputational consequences of hedging will be most severe for younger managers (DeMarzo and Duffie, 1995). According to Breeden and Viswanathan (2016), if there are sufficiently large differences in the skills of managers, there is an equilibrium in which a manager with higher skills hedges and a manager with

[170] DeMarzo and Duffie (1995) use the terms financial risk management and hedging as substitutes. In their model, the hedging decision and the manager's compensation are linked, with the manager adjusting the hedging decision ex ante with knowledge of the level of risk and seeking to maximise his compensation.

lower skills does not because his hedging costs are higher. If the difference in skills increases and reputational effects become more important at the same time, the less skilled manager might hedge. Consistent with this, Tufano (1996) finds that companies with managers who have been in business shorter are more likely to have risk management in place. However, he finds no correlation between the age of managers and the extent of risk management. Furthermore, Bodnar et al. (1996) find that two of the main reasons for companies not to hedge are lack of knowledge and concerns about the perception of using derivatives.

Economies of scale

Studies on the relationship between size and risk management of a company have established a link between the two (e.g. Mian, 1996). Since small firms are more likely to experience financial difficulties c.p., one would expect them to be more likely to resort to hedging than large firms, which is confirmed empirically by Warner (1977). He is able to show that due to financial costs being less than proportional to firm size, small firms should tend to hedge more, which is consistent with the findings by e.g. Gay and Nam (1998) and Carter et al. (2006). Warner (1977) examines 11 bankrupt railways between 1933 and 1955[171] on the basis of the ratio of bankruptcy costs to the market value of the companies at different points in time before bankruptcy. Bankruptcy costs consist of direct costs such as lawyers' and accountants' fees on the one hand and indirect costs such as lost sales and profits on the other (Warner, 1977; Stulz, 1996), which is why Warner (1977) also refers to them as 'lost opportunities' (p. 339). He concludes that bankruptcy costs average at either 1% or 2.5% of the market value of railways 84 or 36 months before bankruptcy.

Stulz (1996) looks at bankruptcy costs from a different angle: by avoiding bankruptcy, risk management increases the value of a company by approximately the amount of bankruptcy costs.

Furthermore, the marginal benefits may be exceeded by the marginal costs of hedging, making hedging (especially for small businesses) not economically worthwhile. Therefore, some companies may not hedge at all, even though they are exposed to financial risks (Sprcic and Sevic, 2012). This is in line with the findings that larger companies are more likely to hedge their risk (e.g. Nance et al., 1993; Mian, 1996; Géczy et al., 1997; Haushalter, 2000; Nguyen and Faff, 2002; Gay et al., 2011; Dionne and Triki, 2013) and potentially to a greater extent than smaller companies (Graham and Rogers, 1999; Adam, 2002; Adam et al., 2017). Nearly all studies using a binary dependent variable find a positive significance for firm size as an explanatory variable for hedging. For example,

[171] The railways studied were in bankruptcy proceedings under Section 77 of the Bankruptcy Act between 1933 and 1955. Further information on this can be found in Wehle (1934).

Adam (2002), Bartram et al. (2009), Treanor et al. (2013) and Adam et al. (2017) find a positive effect of company size on the extent of hedging. Gay and Nam (1998) find that for firms that hedge only their interest rate risk, there is a negative relationship between firm size and the extent of hedging. For the entire sample they find no significance, which is consistent with the results of Allayannis and Ofek (2001). Haushalter (2000) attributes this difference to the fact that economies of scale can be particularly important in establishing or maintaining a hedging program and that the costs associated with these activities can be significant. In his view the marginal costs of increasing the level of hedging do not appear to be significant economies of scale.

In line with Purnanandam (2008), Hentschel and Kothari (2001) point out that not only the nominal value of a derivative position should be considered for the extent of risk, but also other aspects such as the maturity of the derivatives.

It appears that risk management is more widespread in large companies than in small ones (Dolde, 1993; Culp and Miller, 1995b), apparently due to economies of scale reflecting the high fixed costs, i.e. computer hardware and knowledge, of setting up such a program (Dolde, 1993; Nance et al., 1993; Géczy et al, 1997; Haushalter, 2000; Graham and Rogers, 2002). In his survey of Fortune 500 companies, Dolde (1993) receives the response of 244 companies. 85% of these responded that they used either swaps, forwards, futures or options with larger companies using more derivatives than smaller ones. Dolde (1993) finds evidence for Stulz's (1996) view that there are reasons for small firms to hedge more than for large ones, e.g. the higher probability of default caused by unhedged risks. Smaller companies hedge a significantly larger share of their exchange rate and interest rate risks when they include their assessment of future market movements (Dolde, 1993).

In their survey-based study, Bodnar et al. (1996) examine the use of derivatives by US non-financial firms for the year 1994. 350 of the firms surveyed responded, showing that overall 41% of them use derivatives. 59% of these are large firms (market value over 250 million USD) and this percentage decreases as size decreases, which supports that larger firms hedge more. Most of these firms use derivatives to manage foreign exchange risk (76%) and interest rate risk (73%). 37% of them use derivatives to manage commodity price risk.

Overall, Lin and Chang (2009) can show for all airlines that economies of scale and the use of currency derivatives play an important role in explaining fuel hedging behaviour. Treanor et al. (2013) find no significance between economies of scale and the decision to hedge for their sample of US airlines between 1994 and 2006. When using a non-binary

variable to measure the impact of firm size on the extent of hedging behaviour, the results differ. In addition, the influence of company size on hedging behaviour for global airlines is investigated by Carter et al. (2006). Their empirical studies show that firm size has a positively significant influence on the hedging behaviour.

3.2 Hypotheses

Hypothesis 1a (H1a): 'Highly levered airlines use more fuel price derivatives than less levered airlines.'
Firms use financial hedging to reduce the probability of financial distress (Smith and Stulz, 1985) and the associated costs by reducing the variability of cash flows (Froot et al., 1993; Gay and Nam, 1998). Firms with higher leverage are more likely to experience financial distress than firms with low leverage, which is why firms with higher leverage are more likely to hedge (Nance et al., 1993; Bartram et al., 2009). Purnanandam (2008) finds that highly levered firms in concentrated industries have higher incentives to hedge.

Hypothesis 1b (H1b): 'In the cases of very high leverage, hedging decreases.'
The hypothesis implies a non-monotonic relation between an airlines' financial fuel price hedging and leverage. According to Purnanandam (2008), the relationship between hedging and leverage mentioned in H1a is reversed at a very high level of leverage and is negative.

Hypothesis 2 (H2): 'Airlines with more investment opportunities hedge more.'
By reducing the variability of cash flows through hedging, a company can reduce the likelihood that it will need expensive external financing instead of internal financing for an investment opportunity (Froot et al., 1993; Stulz, 1996). This also applies to airlines, which is why airlines with more attractive investment opportunities should hedge more than airlines with less attractive investment opportunities (Carter et al., 2006).

Hypothesis 3a (H3a): 'Low levels of cash holdings are related to lower levels of risk management activities.'
According to Judge (2006) (cf. Nguyen and Faff, 2002; Spanò, 2007), companies with lower liquidity are less likely to hedge with derivatives, as companies that do not hedge with derivatives do not have sufficient liquidity to pay option premiums or cash deposits for futures contracts.

Hypothesis 3b (H3b): 'Very high levels of cash holdings are related to lower hedge ratios.'
The hypothesis implies a non-monotonic relation. An airline with sufficient financial resources does not need to hedge, as the financial resources are sufficient to absorb changes in fuel prices.

3.3 Empirical Analysis

This section first deals with the analysis of variables related to financial hedging with the univariate analysis in Subsection 3.3.1 and then the multivariate analysis in Subsection 3.3.2. Subsequently, the results are checked for their robustness in Subsection 3.3.3 and the limitations are described in Subsection 3.3.4. The interpretation of the results can be found in Section 3.4.

The author is aware of the criticism of the common practice of statistical reporting (Hirschauer et al., 2022). Therefore, the univariate analysis is used first to describe the data as accurately as possible, and tests such as the Hausman Test[172] or robustness analysis are used in the context of multivariate analysis to present the procedure and the results as accurately as possible.

Due to the strong change in the lease-adjusted values as a result of the changes in accounting standards, data from 2019 is not included in the following analysis.[173]

3.3.1 Univariate Analysis

In the following, the univariate analysis is carried out for variables relevant to financial distress and the underinvestment problem by using 'Student's t-Test' from the package *stats* of *R*.[174] For this purpose, the dataset is divided into hedgers and non-hedgers based on whether *fdvDm* is equal to one or zero (Table 3.1). In a second, step the dataset is divided into airlines with high hedge ratios, if *fdvPct12m* is above the median of the sample, and low hedge ratios otherwise (Table 3.2). For robustness reasons, a third subdivision is made using the mean instead of the median of the hedge ratio, which can be found in Appendix D.3.

The tables used for the presentation are structured in a way that the variable under investigation is named in the first column. Columns two and four show the mean and columns three and five the number of observations (N) of the groups being compared. The calculations related to the t-test are given in columns six to eight. Column six gives the difference between the means (diff.) and a possible significance. Column seven displays the Standard Error (SE) and column eight the total number of observations (N).

As seen in the previous part, the dataset contains some outliers, which is why the

[172] The Hausman test, sometimes called the Durbin-Wu-Hausman test, is a test to determine whether a regression model should be applied with, random or fixed effects.

[173] See the figures which include 2019 for the relevant lease-adjusted variables in Appendix B.8.

[174] The default setting of the function assumes unequally distributed variances without further specification. This is intentional due to the different sample sizes and variances.

dataset is winsorised at the 1% and 99% levels for the univariate and multivariate analysis.

Table 3.1 shows the difference-in-means tests of hedgers and non-hedgers for variables significant for financial distress. For the variables related to dividends, only the difference for *divDm* ist significantly higher (at the 10% level) with higher values for non-hedgers. For *intCov* and *prfMrg* as well as for the lease-adjusted variables none of the differences are significant. For *roa* and *roaAdj* there is a significant difference at the 10% and 5% level, respectively with hedgers having lower values. This can be interpreted as indirect support for H1a, since lower ROAs normally implies a higher probability of financial distress. *lvrg1* and *lvrg3*, as well as the lease-adjusted variables, show a significant difference at the 1% level, whereas this is not true for *lvrg2* and *lvrg2Adj1*. The significant difference in the leverage ratios does neither support H1a nor H1b. As Pfefferle (2019) notes, the non-significant difference for *lvrg2* and *lvrg2Adj1* may be due to the fact that the univariate analysis does not account for the non-linear relationship proposed in H1b.

Table 3.1: Difference-in-means test of the variables relevant to financial distress for hedgers (*fdvDm* = 1) and non-hedgers (otherwise)

	hedgers		non-hedgers		t-Test		
variable	mean	N	mean	N	diff.	SE	N
divDm	0.442	620	0.510	239	0.069*	0.038	859
divRto	0.171	620	0.141	239	−0.031	0.030	859
divYld	0.016	618	0.013	238	−0.003	0.002	856
intCov	7.407	619	9.686	239	2.279	2.205	858
intCovAdj	1.796	619	1.898	240	0.102	0.163	859
lvrg1	0.355	620	0.477	240	0.121***	0.015	860
lvrg1Adj1	0.463	618	0.577	238	0.114***	0.013	856
lvrg2	0.414	620	0.412	240	−0.003	0.014	860
lvrg2Adj1	0.512	618	0.519	238	0.007	0.012	856
lvrg3	0.745	620	0.796	240	0.051***	0.020	860
lvrg3Adj1	0.781	618	0.830	238	0.049***	0.017	856
prfMrg	0.039	620	0.045	240	0.006	0.007	860
prfMrgAdj	0.056	619	0.065	238	0.010	0.007	857
roa	0.026	620	0.037	240	0.011*	0.006	860
roaAdj1	0.035	618	0.046	237	0.010**	0.005	855

*p<0.1; **p<0.05; ***p<0.01

In Table 3.2 the same as above is displayed for hedgers with low and high hedging ratios. The results differ in that the difference of *divDm*, *roa* and *roaAdj* is not significant. Moreover, the differences between *lvrg2* and *lvrg2Adj1* are significant at the 5% and 1% level, respectively, with hedgers with low ratios having higher values.

Table D.5 in Appendix D contains the results for the dataset divided by the mean of

Table 3.2: Difference-in-means test of the variables relevant to financial distress for hedgers with low ($\leq$ median of *fdvPct12m*) and hedgers with high hedge ratios ($>$ median of *fdvPct12m*)

	high ratios		low ratios		t-Test		
variable	mean	N	mean	N	diff.	SE	N
divDm	0.476	374	0.442	373	−0.034	0.036	747
divRto	0.178	374	0.130	373	−0.048	0.040	747
divYld	0.017	374	0.013	371	−0.003	0.002	745
intCov	9.045	374	8.351	372	−0.695	1.973	746
intCovAdj	1.913	374	1.838	374	−0.074	0.148	748
lvrg1	0.325	374	0.446	374	0.121***	0.014	748
lvrg1Adj1	0.437	374	0.552	372	0.115***	0.012	746
lvrg2	0.340	374	0.427	374	0.027**	0.013	748
lvrg2Adj1	0.500	374	0.534	372	0.036***	0.011	746
lvrg3	0.734	374	0.788	374	0.055***	0.017	748
lvrg3Adj1	0.770	374	0.824	372	0.054***	0.014	746
prfMrg	0.042	374	0.043	374	0.002	0.006	748
prfMrgAdj	0.058	374	0.062	372	0.004	0.006	746
roa	0.030	374	0.032	374	0.002	0.005	748
roaAdj1	0.038	374	0.040	371	0.002	0.004	745

*p<0.1; **p<0.05; ***p<0.01

fdvPct12m, which do not significantely differ from the results displayed in Table 3.2.

As for the variables relevant to financial distress, Table 3.3 and 3.4 contain the univariate analysis for variables relevant to the underinvestment problem. Besides *capAs* for hedgers and non-hedgers, none of the CAPEX ratios (*capAs, capRev and capSize*) or the lease-adjusted ratios shows a significant difference. The significant difference at the 5% level is negative, indicating higher investment of non-hedgers. The values of *mtbRto* and *peRto* are not significantly different for hedgers and non-hedgers. For *tobQ* and *tobQAdj1*, the difference for hedgers and non-hedgers is significant at the 1% and 5% level, indicating that hedgers had significantly lower investment opportunities than non-hedgers. None of these significant differences can be interpreted as support for H2. In case of *cashRto, crtRto* and *qckRto* there is a significant difference at the 1%, 5% and 1% level respectively, with hedgers having higher values. This results can be interpreted as support for H3a, as low levels of cash holdings seem to be related to hedging activities. In addition, the variable *acChg* is included in this table from where one can see that the costs and investments associated with the fleet do not significantly differ for hedgers and non hedgers.

Compared to Table 3.3, Table 3.4 differs in that the difference for low and high hedging ratios for *capAs* is not significant. The significance of the differences of *tobQ* and *tobQAdj* is reduced to 5% and 1%, respectively. The differences of *mtbRto* and *peRto* are not

Table 3.3: Difference-in-means test of the variables relevant to the underinvestment problem for hedgers (*fdvDm* = 1) and non-hedgers (otherwise)

	hedgers		non-hedgers		t-Test		
variable	mean	N	mean	N	diff.	SE	N
achChg	0.072	519	0.082	134	0.009	0.014	653
capAs	−0.078	620	−0.093	240	−0.015**	0.007	860
capAsAdj1	−0.058	618	−0.064	237	−0.007	0.007	855
capAsAdj5	−0.054	618	−0.054	238	−0.0001	0.007	856
capRev	−0.105	620	−0.124	240	−0.018	0.010	860
capRevAdj1	−0.092	618	−0.108	239	−0.016	0.013	857
capSize	−0.068	618	−0.074	239	−0.005	0.005	857
capSizeAdj1	−0.051	616	−0.055	236	−0.004	0.006	852
cashRto	0.614	620	0.495	240	−0.119***	0.040	860
crtRto	0.972	620	0.874	240	−0.098**	0.046	860
mtbRto	1.715	618	1.338	239	−0.377	0.275	857
peRto	13.251	618	10.086	238	−3.165	5.646	856
qckRto	0.835	620	0.692	240	−0.143***	0.042	860
tobQ	1.234	618	1.360	239	0.126***	0.042	857
tobQAdj1	1.189	616	1.269	237	0.080**	0.032	853

*p<0.1; **p<0.05; ***p<0.01

significant again, not supporting H2. The differences for *cashRto*, *qckRto* and *crtRto* are again significant at the 1% level. The results support H3a, as hedgers with a low cash ratio have lower cash holdings. They cannot support H3b, as very high levels of cash holdings are supposed to be related to lower hedge ratios for the relation between hedging and cash holdings to be non-monotonic.

Table D.6 in the Appendix D contains the results for the dataset divided by the mean of *fdvPct12m*. The results only differ for *tobQ* and *tobQAdj1* as the significance increases to the 1% and 5% level, respectively.

3.3.2 Multivariate Analysis

Two dependent variables are used for the following multivariate analysis. *fdvDm* is used for the decision to hedge and *fdvPct12m* for the extent of hedging. As for the independent variables, all those already used in previous studies were used[175]. An iterative process was then conducted to find the most appropriate composition of independent variables for the first model. Based on the Akaike information criterion (AIC)[176], further variables

[175]Table D.1 in Appendix D.1 provides an overview of the relevant studies and the independent and dependent variables used therein

[176]The AIC is concerned with the trade-off between the goodness of fit and the simplicity of a model. For a number of models, it estimates the quality of each model compared to every other model.

Table 3.4: Difference-in-means test of the variables relevant to the underinvestment problem for hedgers with low (≤ median of *fdvPct12m*) and hedgers with high hedge ratios (> median of *fdvPct12m*)

	high ratios		low ratios		t-Test		
variable	mean	N	mean	N	diff.	SE	N
achChg	0.078	338	0.076	251	−0.002	0.014	589
capAs	−0.078	374	−0.088	374	−0.009	0.006	748
capAsAdj1	−0.059	374	−0.061	371	−0.002	0.006	745
capAsAdj5	−0.055	374	−0.052	372	0.002	0.006	746
capRev	−0.104	374	−0.117	374	−0.013	0.009	748
capRevAdj1	−0.092	374	−0.102	373	−0.010	0.012	747
capSize	−0.068	374	−0.071	372	−0.003	0.005	746
capSizeAdj1	−0.052	374	−0.053	369	−0.0007	0.005	743
cashRto	0.661	374	0.519	374	−0.142***	0.035	748
crtRto	1.024	374	0.894	374	−0.131***	0.040	748
mtbRto	1.769	374	1.430	372	−0.339	0.234	746
peRto	8.630	374	12.578	371	3.948	8.146	745
qckRto	0.895	374	0.721	374	−0.174***	0.037	748
tobQ	1.238	374	1.335	372	0.097**	0.043	746
tobQAdj1	1.191	374	1.255	370	0.063*	0.034	744

*p<0.1; **p<0.05; ***p<0.01

were added or variables of particular interest were added in line with Pfefferle (2019). To test the models, *regsubsets*[177] was used to determine the explanatory power of the variables.

The tables are always constructed in the same way. At the top in the middle, the dependent variable is indicated and below it a number in brackets indicates which model it is, with model (1) always being the base model. The independent variables used are listed on the left side of the tables. Below that, depending on the method, it is indicated whether dummy variables for years or specifications for the entire dataset were used, such as only considering airlines reporting according to IFRS. Then, depending on the method, only the AIC value and the number of observations (N) are given or also R^2 and the adjusted R^2 are displayed. Below the tables there is an explanation of the asterisks indicating significance. In case of homoscedasticity within the regression models, robust heteroscedastic SEs are calculated, which is indicated below the tables. The SEs or robust heteroscedastic SEs are in brackets.

Starting with the hedging decision in Table 3.5, five different random effect probit

[177] *regsubsets* is a function from the *leaps* package of *R* and performs a search for the best variables to predict the dependent variable in a linear regression using R^2 as static model selection

models[178] are included, the first and the second of which contain all the variables of the so-called base model. The variables *lvrg1Adj1, lvrgAdj1Sqr* and *intCovAdj* are variables related to financial distress, *tobQAdj, cashRto* and *cashRtoSqr* to the underinvestment problem and *irdvDm* and *fxdvDm* are related to the use of interest rate and foreign exchange derivatives. The difference between the two models is that the second model includes year dummies. There is only the significant difference that the coefficient of *lvrg1Adj1Sqr* is positively significant in model (2) and not in model (1), and the AIC value of model (2) is higher, which is why year dummies are not considered any further. In model (3), a linear relationship between leverage as well as the cash ratio and the decision to hedge is tested by excluding *lvrg1Adj1Sqr* and *cashRtoSqr*. In model (4), the variables *irdvDm* and *fxdvDm* are excluded. Model (5) only consists of *lvrg1Adj1* and *lvrg1Adj1Sqr*. The results cannot be interpreted as support for H1a as the coefficient of *lvrg1Adj1* is negative and significant at the 5% level in model (1) and at the 1% level in models (2) and (3).[179] Since the coefficient of *lvrg1Adj1Sqr* is positive but not significant in model (1) and significant at the 5% level in model (2), the results for H1b cannot be interpreted as supportive either. In model (3), the coefficient of *lvrg1Adj1* stays negatively significant at the 1% level, implying a negative linear relationship. The insignificant coefficient of *tobQAdj1* in all models cannot be interpreted as support for H2. The coefficient of *cashRto* is positively significant at the 1% in models (1) and (2), which implies a positive influence of cash holdings on the decision to hedge. The negative and significant (at the 1% level) coefficients of *cashRtoSqr* imply lower hedging activity at very high cash holdings and may indicate the non-monotonic relationship from H3b. The positive and significant coefficients of *irdvDm* and *fxdvDm* imply a more likely decision for fuel hedging in case of the use of interest rate and foreign exchange derivatives. When *irdvDm* and *fxdvDm* are excluded in model (4), the coefficient of *lvrg1Adj1Sqr* is positive and significant at the 1% level. Model (5) implies that leverage only has no impact on the decision to hedge.

The base model for airline fixed effects[180] OLS regression concerning the extend of hedging in Table 3.6 includes *lvrg1Adj1, lvrg1Adj1Sqr* and *intCovAdj* as independet variables

[178] A binomial regression is chosen because it is a form of regression suited when the dependent variable is binary and the independents are of any type (Hosmer et al., 2013). Since probit models are estimated using maximum likelihood estimation, we do not need robust SEs as heteroscedasticity is automatically taken into account (Wooldridge, 2020). For further information on the data analysis process see Appendix C.

[179] Interpreting the sign of the coefficient is sufficient to detect a positive or negative effect, but the magnitude cannot be easily calculated and interpreted in probit models, which is why it is not done here (Wooldridge, 2020).

[180] Variables that are constant over time cannot be included because they are not considered by the fixed effects transformation. Such variables in this study are for example *cpaDm* or *lccDm*. Nevertheless year dummy variables can be used (Wooldridge, 2020).

Table 3.5: Random effects probit models for different financial hedging variables

	Dependet variable: *fdvDm*				
	(1)	(2)	(3)	(4)	(5)
lvrg1Adj1	−5.694**	−10.143***	−2.216***	−7.903***	2.449
	(2.777)	(2.990)	(0.692)	(2.807)	(2.044)
lvrg1Adj1Sqr	3.050	6.070**		5.215**	−2.614
	(2.328)	(2.562)		(2.306)	(1.992)
intCovAdj	−0.266***	−0.259***	−0.299***	−0.260***	
	(0.060)	(0.065)	(0.059)	(0.064)	
tobQAdj1	0.138	0.127	0.259	0.162	
	(0.224)	(0.222)	(0.203)	(0.194)	
cashRto	1.866***	1.603***	−0.058	2.594***	
	(0.550)	(0.530)	(0.197)	(0.550)	
cashRtoSqr	−0.665***	−0.744***		−1.072***	
	(0.207)	(0.224)		(0.267)	
irdvDm	1.324***	1.374***	1.667***		
	(0.307)	(0.326)	(0.251)		
fxdvDm	0.921***	1.112***	0.827***		
	(0.267)	(0.289)	(0.195)		
(Intercept)	1.681*	3.501***	2.683***	3.560***	1.473**
	(0.860)	(1.022)	(0.581)	(0.960)	(0.583)
Year dummies	No	Yes	No	No	No
AIC	467.642	476.321	472.248	501.107	528.566
N	851	851	851	853	856

*p<0.1; **p<0.05; ***p<0.01
Standard errors in parentheses

for financial distress, *peRto, crtRto* and *crtRtoSqr* are included due to the underinvestment problem and *irdvDm* and *fxdvDm* are variables concerning the use of interest rate and foreign exchange derivatives. In model (2), year dummies are included, but these are not considered further as model (2) does not differ much from model (1) with regard to the coefficients and the AIC value. H1a and H1b cannot be supported as *lvrg1Adj1* and *lvrg1Adj1Sqr* are not significant in the models considered. When a linear relationship between leverage and the extent of hedging is tested (model (3)), the significance of *lvrg1Adj1* is not affected, not supporting the theory of a linear relationship. The coefficient of *intCovAdj* is negatively significant in all models where the variable is included. The coefficients of *peRto* are negative and significant at the 10% level, which might imply a negative relationship between a firm' investment opportunities and the extent of hedging, which is in contrast to H2. The results concerning hypotheses H3a are not in support of it, as the coefficient of *crtRto* is not significant. The coefficients of *crtRtoSqr* are positive and significant at the 10% level, which is in contrast to the results concerning the decision to

hedge, not supporting H3b. The significance of *irdvDm* and *fxdvDm* is mainly positive, supporting the results of Table 3.5 that the decision and the extent of hedging is positively influenced by the usage of interest rate and foreign exchange derivatives. When the two variables are excluded in model (4), the coefficients of *peRto* and *crtRtoSqr* are insignificant compared to model (1). The extent of hedging is, as the decision to hedge, not affected by leverage only (model (5)).

Table 3.6: Airline fixed effects models for different financial hedging variables

	Dependent variable: *fdvPct12m*				
	(1)	(2)	(3)	(4)	(5)
lvrg1Adj1	−0.181	−0.115	−0.095	−0.108	0.015
	(0.243)	(0.244)	(0.073)	(0.244)	(0.243)
lvrg1Adj1Sqr	0.067	−0.009		0.045	−0.009
	(0.233)	(0.234)		(0.231)	(0.234)
intCovAdj	−0.015***	−0.015***	−0.015***	−0.015***	
	(0.004)	(0.004)	(0.004)	(0.004)	
peRto	−0.0001*	−0.0001*	−0.0001*	−0.0001	
	(0.00004)	(0.00004)	(0.00004)	(0.00004)	
crtRto	−0.072	−0.070	0.009	−0.044	
	(0.044)	(0.045)	(0.027)	(0.043)	
crtRtoSqr	0.021*	0.021*		0.014	
	(0.012)	(0.012)		(0.012)	
irdvDm	0.095***	0.092***	0.086***		
	(0.020)	(0.020)	(0.022)		
fxdvDm	0.031*	0.031*	0.026		
	(0.017)	(0.017)	(0.018)		
Year dummies	No	Yes	No	No	No
AIC	−604.686	−597.165	−601.495	−586.866	−574.521
N	742	742	742	744	746
R^2	0.767	0.772	0.767	0.759	0.751
Adjusted R^2	0.738	0.739	0.738	0.730	0.724

*p<0.1; **p<0.05; ***p<0.01
Robust standard errors in parentheses

Table 3.7[181] contains five further random effects probit models concerning the decision to hedge where only American, Asian or European airlines (models (2) to (4)) are considered and in models (5) and (6) the dataset is divided into NLCs and LCCs.[182] Only for

[181] In Table 3.7 model (4) Cyprus Airways had to be excluded (seven observations) due to a relatively high *cashRto* and *intCovAd*, otherwise the regression would not have been successful.

[182] Since fixed effects models control for all omitted variables that change between units but are constant over time, a similar fixed effects table is not needed.

the coefficient of *irdvDm* the significance is the same in model (2) as in model (1). The coefficients of the variables *lvrg1Adj1, cashRto, cashRtoSqr* and *fxdvDm* are not significant any longer and the coefficient of *intCovAdj1* is significant at the 5% level. In model (3), the negative significance of *lvrg1Adj1* is now at 1% and the coefficient of *lvrg1Adj1Sqr* is positive and significant at the 1% level as well. The coefficient of *cashRto* is not significant any longer and the coefficient of *cashRtoSqr* is negatively significant at the 5% level instead of the 1% level. The significance of *irdvDm* vanishes. Model (4) is different compared to the base model in that the significance of *lvrg1Adj1, intCovAdj1, cashRto* and *cashRtoSqr* completely vanishes and that of *irdvDm* decreases from the 1% to the 5% level. Only the formerly insignificant variable *tobQAdj1* is negatively significant at the 5% level. In model (5), the coefficient of *lvrg1Adj1* is again insignificant, but other than that it is the same as the base model. The same holds for model (6), but the coefficient of *cashRto, cashRtoSqr* and *fxdvDm* decrease to a significance level of 10%, 5% and 10%. respectively.

Table 3.7: Random effects probit models for different financial hedging variables for different regions and business models

	Dependent variable: *fdvDm*					
	(1)	(2)	(3)	(4)	(5)	(6)
lvrg1Adj1	-5.694^{**}	5.798	-24.804^{***}	5.175	-4.764	-3.239
	(2.777)	(9.860)	(8.327)	(8.530)	(3.101)	(5.172)
lvrg1Adj1Sqr	3.050	-8.935	16.058^{***}	-10.108	2.243	2.162
	(2.328)	(9.901)	(6.185)	(7.877)	(2.544)	(4.924)
intCovAdj	-0.266^{***}	-0.278^{**}	-0.518^{***}	0.049	-0.333^{***}	-0.265^{***}
	(0.060)	(0.132)	(0.155)	(0.144)	(0.103)	(0.087)
tobQAdj1	0.138	0.328	0.451	-1.592^{**}	0.226	0.076
	(0.224)	(0.469)	(0.492)	(0.655)	(0.411)	(0.226)
cashRto	1.866^{***}	4.201	1.416	0.155	3.359^{***}	1.786^{*}
	(0.550)	(2.675)	(0.943)	(2.114)	(1.075)	(0.917)
cashRtoSqr	-0.665^{***}	-1.316	-0.743^{**}	-0.674	-1.649^{**}	-0.759^{**}
	(0.207)	(1.321)	(0.299)	(0.848)	(0.725)	(0.349)
irdvDm	1.324^{***}	2.089^{***}	0.198	1.323^{**}	1.479^{***}	1.409^{***}
	(0.307)	(0.775)	(0.393)	(0.544)	(0.310)	(0.500)
fxdvDm	0.921^{***}	0.741	1.477^{***}	2.518^{***}	1.381^{***}	-1.106^{*}
	(0.267)	(0.585)	(0.404)	(0.721)	(0.308)	(0.616)
(Intercept)	1.681^{*}	-0.879	8.026^{***}	1.279	1.210	2.287
	(0.860)	(2.964)	(2.941)	(2.728)	(1.170)	(1.493)
Region		AM	AS	EU		
Business Model					NLC	LCC
AIC	467.642	146.964	191.910	62.128	322.129	154.199
N	851	256	318	188	659	192

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

3.3.3 Robustness

In order to check the robustness of the results discussed, this subsection presents tables with further results. Each table includes the already known base models as model (1), and in subsequent models additional variables are added and previously used ones are excluded. Appendix D.4 shows further random effects probit models with specific subgroups of the dataset based on variables such as *cpaDm*, accounting standards[183], regional groups or the two different business models. The same is done for airline fixed effects models in Appendix D.5.

Starting with financial distress, Table 3.8 contains alternative random effects probit models concerning *fdvDm*. In models (2) to (5), *intCovAdj* is excluded and instead *prfMrgAdj1, roaAdj1, divDm* and *divYld* are added one by one.[184] It is noticeable that the significance (at the 5% level) of *lvrg1Adj1* is not robust and is only present in model (1). The coefficients of *prfMrgAdj* and *roaAdj1* are negative and significant at the 1% level, suggesting a negative influence on the decision to hedge. The coefficients of the variables concerning dividends are negative and significant, at the 1% level for *divDm* and at the 5% level for *divYld*, which implies that paying dividends has a negative influence on the decision the hedge. In models (6) and (7), the two leverage variables are replaced by other leverage ratios (*lvrg2Adj1, lvrg2Adj1Sqr, lvrg3Adj1, lvrg3Adj1Sqr*). *intCovAdj* is included again. For both pairs, the squared terms are positive and the linear terms are negative, with *lvrg2Adj1* and *lvrg2Adj1Sqr* being significant at the 10% level. These results support the results from Table 3.5, where the same is true for *lvrg1Adj1* and *lvrg1Ajd1Sqr*. In model (8), *lvrg1Adj1, lvrg1Adj1Sqr* and *tobQAdj1* are excluded and instead *lvrg1Adj8, lvrg1Adj8Sqr* and *tobQAdj8* are included. The coefficient of *lvrg1Adj8* is negative and positive for *lvrg1Adj8Sqr* with significances at the 1% level. These results support the rejection of hypotheses H1a and H1b. This contradicts with the concave relationship between leverage and the decision to hedge. *irdvDm* and *fxdvDm* are positively significant in all eight models, which underlines the positive effect of the usage of other derivatives concerning the decision to hedge fuel price risk.

To further test the robustness of financial distress theory, Table 3.9 includes alternative airline fixed effects models with the same included variables as in Table 3.8, besides *tobQAdj1*. The insignificance of the variables concerning leverage does not change in any of the models and the added leverage variables are insignificant as well. These results

[183] The AIC value decreases significantly if only airlines that report in accordance with the same accounting standard are taken into account.

[184] This is done due to the correlation of *intCovAdj1* with the added variables and as they are related to financial distress as well.

Table 3.8: Random effects probit models with different financial distress variables

	Dependent variable: *fdvDm*							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
lvrg1Adj1	−5.694**	1.081	−0.265	−0.586	−2.429			
	(2.777)	(2.417)	(2.625)	(2.318)	(2.314)			
lvrg1Adj1Sqr	3.050	−2.532	−1.609	−1.152	1.237			
	(2.328)	(2.276)	(2.423)	(2.181)	(2.097)			
intCovAdj	−0.266***					−0.231***	−0.327***	−0.372***
	(0.060)					(0.066)	(0.067)	(0.083)
tobQAdj1	0.138	0.149	0.218	−0.086	−0.113	0.087	0.363	
	(0.224)	(0.197)	(0.202)	(0.172)	(0.170)	(0.263)	(0.228)	
cashRto	1.866***	2.348***	2.228***	1.997***	1.984***	2.124***	1.753***	2.326***
	(0.550)	(0.495)	(0.594)	(0.491)	(0.521)	(0.544)	(0.491)	(0.610)
cashRtoSqr	−0.665***	−0.682***	−0.708***	−0.688***	−0.639***	−0.713***	−0.784***	−0.875***
	(0.207)	(0.192)	(0.217)	(0.209)	(0.204)	(0.215)	(0.241)	(0.248)
irdvDm	1.324***	1.290***	1.202***	1.229***	1.192***	1.096***	1.419***	1.269***
	(0.307)	(0.268)	(0.324)	(0.254)	(0.271)	(0.300)	(0.267)	(0.299)
fxdvDm	0.921***	1.173***	1.010***	1.081***	1.110***	1.026***	0.701***	1.075***
	(0.267)	(0.268)	(0.355)	(0.225)	(0.297)	(0.296)	(0.206)	(0.325)
prfMrgAdj		−6.394***						
		(1.248)						
roaAdj1			−9.146***					
			(1.933)					
divDm				−0.946***				
				(0.221)				
divYld					−7.633**			
					(3.346)			
lvrg2Adj1						−5.338*		
						(2.865)		
lvrg2Adj1Sqr						4.610*		
						(2.703)		
lvrg3Adj1							−3.444	
							(2.120)	
lvrg3Adj1Sqr							0.927	
							(1.029)	
lvrg1Adj8								−13.485***
								(3.621)
lvrg1Adj8Sqr								8.299***
								(2.850)
tobQAdj8								0.286
								(0.293)
(Intercept)	1.681*	−0.307	0.059	0.797	0.614	1.149	3.079**	4.660***
	(0.860)	(0.714)	(0.787)	(0.717)	(0.693)	(0.784)	(1.203)	(1.223)
AIC	467.642	462.385	464.853	467.754	482.003	473.558	470.974	466.836
N	851	850	850	851	851	851	851	852

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$
Standard errors in parentheses

underline that H1a and H1b cannot be supported. As for the other added variables, with the exception of *prfMrgAdj*, they are all insignificant. The negative and significant (at the 5% level) coefficient of *prfMrgAdj* is consistent with the coefficient of *intCovAdj* in relation to the decision to hedge and implies that a firm's profitability has a negative impact on the level of hedging.

Chaining to the underinvestment problem, Table 3.10 contains alternative random effects probit models. In models (2) to (6), *tobQAdj* is excluded and instead *mtbRto, peRto, capsAsAdj1, capRevAdj1* and *capSizeAdj1* are added one by one for the same reason as for financial distress. The positive significance of *cashRto* and negative significance of *cashRtoSqr*, both at the 1% level, do not change in models (2) to (6), underlining the robustness of the results. The coefficients of *mtbRto* and *peRto* are not significant, suggesting that valuation ratios have little impact on the decision to hedge. The coefficients of the variables concerning CAPEX are positive, but are only significant for *capAsAdj1* and *capSizeAdj1* at the 10% level. These results imply a positive influence on the decision to hedge, which could be interpreted as support for H2. However, it should be borne in mind that these variables measure actual investments rather than investment opportunities. In models (7) and (8) *cashRto* and *cashRtoSqr* are excluded and *tobQAdj* is again included as well as *crtRto, crtRtoSqr, qckRto* and *qckRtoSqr* are included pairwise. The insignificance of *tobQAdj1* is not changed by the inclusion of the other variables. The coefficient of *qckRto* is positively significant and the coefficient of *qckRtoSqr* is negativly significant at the 1% level. These results support the results concerning *cashRto* and *cashRtoSqr* and the interchangeability.

To further test the robustness of the underinvestment problem, Table 3.11 includes alternative airline fixed effects models. In models (2) to (6), the *peRto* is excluded and *mtbRto, tobQAdj1, capAsAdj1, capRevAdj1* and *capSizeAdj1* are included in order to test other variables that could be relevant for investment opportunities or investments. The significance of the coefficient of *crtRto* changes, which is negative and significant at the 10% level in models (2), (4) and (5) instead of not significant. The significance of *crtRtoSqr* disappears in model (3) instead of being positive and significant at the 10% level, which implies that the results are not robust to the inclusion of other variables related to the underinvestment problem. Besides *tobQAdj1*, none of the added independent variables are significant, indicating that investments do not seem to influence the extent of hedging. The coefficient of *tobQAdj1*, on the other hand, is positive and significant at the 1% level. In models (7) and (8) *crtRto* and *crtRtoSqr* are excluded and *cashRto, cashRtoSqr, qckRto* and *qckRtoSqr* are pairwise included. None of the added variables are significant.

Table 3.9: Airline fixed effects model with financial distress variables

	Dependent variable: *fdvPct12m*							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
lvrg1Adj1	−0.181	0.133	0.086	0.076	0.065			
	(0.243)	(0.246)	(0.245)	(0.243)	(0.243)			
lvrg1Adj1Sqr	0.067	−0.190	−0.128	−0.100	−0.090			
	(0.233)	(0.239)	(0.237)	(0.234)	(0.234)			
intCovAdj	−0.015***					−0.013***	−0.012***	−0.016***
	(0.004)					(0.004)	(0.004)	(0.005)
peRto	−0.0001*	−0.0001	−0.0001*	−0.0001*	−0.0001**	−0.0001*	−0.0001*	−0.0001*
	(0.00004)	(0.00004)	(0.00004)	(0.00004)	(0.00004)	(0.00004)	(0.00004)	(0.00004)
crtRto	−0.072	−0.061	−0.066	−0.070	−0.070	−0.060	−0.060	−0.080*
	(0.044)	(0.043)	(0.044)	(0.045)	(0.044)	(0.045)	(0.046)	(0.044)
crtRtoSqr	0.021*	0.021*	0.021*	0.021*	0.021*	0.019	0.021	0.023*
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.013)	(0.013)	(0.012)
irdvDm	0.095***	0.097***	0.096***	0.094***	0.095***	0.092***	0.091***	0.094***
	(0.020)	(0.020)	(0.021)	(0.021)	(0.021)	(0.020)	(0.020)	(0.020)
fxdvDm	0.031*	0.032*	0.029*	0.027	0.027	0.027	0.025	0.036**
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.016)	(0.017)	(0.018)
prfMrgAdj		−0.283**						
		(0.117)						
roaAdj1			−0.219					
			(0.149)					
divDm				−0.009				
				(0.017)				
divYld					−0.272			
					(0.301)			
lvrg2Adj1						−0.235		
						(0.179)		
lvrg2Adj1Sqr						0.222		
						(0.167)		
lvrg3Adj1							0.105	
							(0.159)	
lvrg3Adj1Sqr							−0.045	
							(0.057)	
lvrg1Adj8								−0.019
								(0.254)
lvrg1Adj8Sqr								−0.140
								(0.224)
N	742	741	741	742	742	742	742	742
R^2	0.767	0.765	0.763	0.763	0.763	0.766	0.766	0.767
Adjusted R^2	0.738	0.736	0.734	0.734	0.734	0.738	0.737	0.739
AIC	−604.686	−598.321	−592.566	−592.401	−593.321	−603.329	−602.397	−606.023

*p<0.1; **p<0.05; ***p<0.01
Robust standard errors in parentheses

Table 3.10: Random effects probit models with different underinvestment problem variables

	Dependent variable: *fdvDm*							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
lvrg1Adj1	−5.694**	−5.760**	−5.651*	−7.701**	−7.582**	−5.090*	−2.205	−4.806
	(2.777)	(2.852)	(2.946)	(3.259)	(3.335)	(2.951)	(2.301)	(3.050)
lvrg1Adj1Sqr	3.050	3.227	3.117	4.456	4.421	2.581	0.096	2.399
	(2.328)	(2.392)	(2.431)	(2.721)	(2.748)	(2.603)	(2.022)	(2.639)
intCovAdj	−0.266***	−0.258***	−0.254***	−0.247***	−0.251***	−0.269***	−0.296***	−0.263***
	(0.060)	(0.058)	(0.057)	(0.055)	(0.055)	(0.058)	(0.060)	(0.063)
tobQAdj1	0.138						0.216	0.200
	(0.224)						(0.202)	(0.249)
cashRto	1.866***	1.895***	1.889***	1.689***	1.696***	1.859***		
	(0.550)	(0.543)	(0.562)	(0.519)	(0.519)	(0.530)		
cashRtoSqr	−0.665***	−0.669***	−0.668***	−0.666***	−0.660***	−0.670***		
	(0.207)	(0.206)	(0.208)	(0.207)	(0.207)	(0.205)		
irdvDm	1.324***	1.306***	1.298***	1.066***	1.114***	1.076***	1.681***	1.176***
	(0.307)	(0.312)	(0.316)	(0.285)	(0.282)	(0.278)	(0.263)	(0.315)
fxdvDm	0.921***	0.917***	0.932***	1.172***	1.180***	1.096***	0.845***	1.031***
	(0.267)	(0.280)	(0.280)	(0.303)	(0.317)	(0.283)	(0.197)	(0.290)
mtbRto		0.011						
		(0.022)						
peRto			0.000					
			(0.001)					
capAsAdj1				1.903*				
				(1.056)				
capRevAdj1					0.795			
					(0.567)			
capSizeAdj1						2.268*		
						(1.269)		
crtRto							−0.110	
							(0.331)	
crtRtoSqr							0.038	
							(0.075)	
qckRto								1.322***
								(0.476)
qckRtoSqr								−0.319***
								(0.115)
(Intercept)	1.681*	1.816**	1.803**	2.811***	2.699**	2.006**	2.717***	1.456
	(0.860)	(0.863)	(0.897)	(1.045)	(1.072)	(0.924)	(0.841)	(0.964)
AIC	467.642	467.812	468.053	470.631	471.985	464.968	475.981	476.044
N	851	851	851	853	853	850	851	851

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$
Standard errors in parentheses

Table 3.11: Airline fixed effects model with underinvestment problem variables

	Dependent variable: *fdvPct12m*							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
lvrg1Adj1	−0.181	−0.161	−0.024	−0.192	−0.188	−0.156	−0.314	−0.234
	(0.243)	(0.242)	(0.249)	(0.245)	(0.243)	(0.245)	(0.263)	(0.243)
lvrg1Adj1Sqr	0.067	0.060	−0.083	0.072	0.071	0.048	0.185	0.108
	(0.233)	(0.233)	(0.240)	(0.234)	(0.233)	(0.236)	(0.245)	(0.233)
intCovAdj	−0.015***	−0.015***	−0.018***	−0.015***	−0.015***	−0.015***	−0.016***	−0.015***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
peRto	−0.0001*						−0.0001*	−0.0001*
	(0.00004)						(0.00004)	(0.00004)
crtRto	−0.072	−0.075*	−0.061	−0.077*	−0.076*	−0.073		
	(0.044)	(0.045)	(0.043)	(0.045)	(0.045)	(0.045)		
crtRtoSqr	0.021*	0.021*	0.017	0.022*	0.022*	0.021*		
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)		
irdvDm	0.095***	0.092***	0.090***	0.098***	0.099***	0.090***	0.089***	0.092***
	(0.020)	(0.021)	(0.020)	(0.021)	(0.021)	(0.020)	(0.022)	(0.021)
fxdvDm	0.031*	0.030*	0.027	0.037**	0.036**	0.033*	0.025	0.027
	(0.017)	(0.017)	(0.017)	(0.018)	(0.018)	(0.017)	(0.018)	(0.017)
mtbRto		0.002						
		(0.002)						
tobQAdj1			0.056***					
			(0.017)					
capAsAdj1				0.024				
				(0.082)				
capRevAdj1					−0.015			
					(0.053)			
capSizeAdj1						0.087		
						(0.097)		
cashRto							−0.010	
							(0.042)	
cashRtoSqr							−0.003	
							(0.011)	
qckRto								−0.061
								(0.054)
qckRtoSqr								0.017
								(0.018)
N	742	742	742	742	743	741	742	742
R^2	0.767	0.766	0.769	0.765	0.765	0.766	0.765	0.765
Adjusted R^2	0.738	0.738	0.741	0.736	0.736	0.737	0.736	0.737
AIC	−604.686	−603.185	−613.861	−600.832	−600.861	−601.371	−598.689	−600.421

*p<0.1; **p<0.05; ***p<0.01
Robust standard errors in parentheses

Further tables concerning the base model are included in Appendices D.4 and D.5. Table D.7[185] contains six further random effect probit models, where only certain subgroups of the dataset are considered (model (2) without airlines under CPA (Republic Airways and SkyWest), model (5) without Allegiant Air[186], model (6) and (7) only include airlines which report under IFRS and US GAAP, respectively) or certain variables are added to the base model (model (3) *cpaDm* and model (4) *mrgDm*). The explanatory power of the base model does not change when regional airlines are excluded or when *cpaDm* is added. In contrast, when *mrgDm* is included, *lvrg1Adj1* is no longer negative and significant at the 5% level but at the 10% level and *mrgDm* itself is not significant. In model (5), *lvrg1Adj1* is not significant, but other than that the significances stay the same. In model (6), only *irdvDm* and *fxdvDm* are still positive and significant at the 1% level and *intCovAdj1* is negatively significant at the 10% instead of the 1% level. If only airlines that prepare their accounts in accordance with US GAAP are taken into account, only the significance of the coefficient of *irdvDm* is robust. The coefficients of *cashRto* and *cashRtoSqr* are still significant at the 10% and 5% level respectively.[187]

Table D.8 in Appendix D.5 includes the same subgroups as Table D.7 and includes further alternative airline fixed effects models for *fdvPct12m*. The results are robust for the exclusion of airlines under CPA and the addition of *mrgDm*. When Allegiant Air is excluded, the significance of the coefficient of *crtRto* changes to negative and significant at the 10% level instead of insignificance. When only airlines reporting under IFRS are considered besides the significance of *irdvDm*, which is reduced to the 5% level, all other formerly significant variables are no longer significant. When only airlines reporting under US GAAP are considered, leverage seems more important for the extent of hedging as the coefficients of *lvrg1Adj1* and *lvrg1Adj1Sqr* are negative and significant at the 5% and positive and significant at the 1% level, respectively. The previously negative and significant (at the 10% level) coefficient of *peRto* is now significant at the 1% level. The coefficient of *crtRto* is now negative and significant at the 5% level and the significance of the coefficient of *crtRtoSqr* is increased to the 5% level. In addition, the coefficient of *fxdvDm* is positive and significant at the 5% level.

[185] In Table D.7 model (7) Delta Air Lines had to be excluded (14 observations) due to outliers of *intCovAdj* and *tobQAdj1*, otherwise the regression would not have been successful.

[186] Allegiant Air is excluded as it has the highest average *intCovAdj* of 10.65 compared to the second highest value of 6.13.

[187] If one reduces the dataset to airlines reporting according to IFRS and US GAAP, the number of observations is reduced, which is reflected in the AIC value, as *R* calculates them as a function of each other.

3.3.4 Limitations

Regarding the general limitations of the studies, some points are discussed in more detail below, where Wooldridge (2020) was used as source.

A model is said to be underspecified if a variable relevant to the model that is correlated with at least one other independent variable is omitted. Instead of estimating the model including the variable in question, the variable is considered part of the error term and the model is misspecified. Due to the correlation of the omitted variable with another independent variable, the error term is correlated with a regressor, which leads to endogeneity. The bias resulting from this is also called omitted variable bias. Connected to this is the functional form misspecification of a regression model, which means that the relationship between the dependent and observed explanatory variables is not correctly accounted for. Omitting a relevant explanatory variable leads to a functional form misspecification, which generally leads to biased estimators. To circumvent this situation, for example, *cashRtoSqr* and *crtRtoSqr* were included in the models.

In some collection processes, variables truly affecting the dependent variable cannot be collected. For example, within this work in Subsection 2.2.2.1 it is mentioned that the combined corporate income tax rate is used for the statutory corporate income tax, which is why national and regional tax rates are included. A more sensible approach would be to use a simulated tax rate (Subsection 2.2.2.1). The so-called measurement error is the difference between the desired variable and the one approximated or collected instead. As the data is collected by hand, transmission errors cannot be ruled out. In addition, since some airlines did not report the desired variables, they were approximated based on the approach of Pfefferle (2019).

The use of book values instead of market values should also be mentioned here, as book values have to be used due to the unavailability of market values in the AR. The disadvantages are that they are only available at the time of the AR and not continuously throughout the financial year and that the ARs are prepared under different accounting standards.[188]

Using a sample that is restricted to the availability of the dependent variable can lead to sample selection bias. In this paper, for example, this would mean only looking at airlines that hedge without including those that do not hedge. Nevertheless, there is a sample bias in this paper as only airlines that disclose their hedging behaviour were included in the regression analysis and there are large differences in the provision of data between airlines.

Another source of bias is simultaneity, which arises when one or more independent variables are jointly determined with the dependent variable. It is known that this problem can

[188] This problem is addressed by considering only IFRS and US GAAP airlines in the robustness checks.

exist between variables related to hedging and leverage. For example, to better understand the simultaneity problem, Dionne and Triki (2013) developed an estimation procedure that can be applied to a model with two simultaneous equations with two censored dependent variables using a panel dataset. However, this procedure is beyond the scope of this study, which is why simultaneity may be a source of bias in this study.

3.4 Results

The positive relationship between leverage and the use of fuel price derivatives resulting from H1a can neither be supported by the results regarding the decision to hedge nor regarding the extent of hedging. In both cases, the coefficients are either negative and significant (see Table 3.5) or not significant (see Table 3.6). The negative slope in Figure 2.30 on the right side suggests a negative relationship as well. These results are in contrast to the positive and significant coefficients of leverage in relation to the extent of hedging reported by Haushalter (2000) and Dionne and Triki (2013). On the other hand, these results here are consistent with the results of Haushalter (2000) with regard to the decision to hedge, as he finds no significant relationship. He concludes that the cost of hedging and the underlying risk of the instruments to be hedged appear to be more important determinants of the hedging decision (Haushalter, 2000).

H1b, on the contrary, assumes a non-monotonic and concave relationship between very high leverage ratios and hedging, which cannot be supported by the results either. In case of the decision to hedge, the results show a positive relationship either significant or non-significant (see Table 3.5). With regard to the extent of hedging, the results show no significance (see Table 3.6). Rather, the results indicate a non-linear convex relationship between leverage and the decision to hedge or the extent of hedging, based on the inverse signs of the linear and squared terms. Pfefferle (2019) concludes that airlines with a very high level of debt should always take out insurance in order to be protected in the event of a financial distress. In contrast to these results, Purnanandam (2008) finds a linear and concave relationship between leverage and hedging. The different results are likely due to the different samples, as Purnanandam examines nonfinancial CRSP and COMPUSTAT firms for the fiscal year 1997 with the current study based on a dataset of firms from a single industry between 2005 and 2018. In contrast to the financial distress theory, similar results concerning the relationship between leverage and hedging are found by Géczy et al., 1997; Allayannis and Ofek, 2001; Adam, 2002; Guay and Kothari, 2003; Carter et al., 2006; Spanò, 2007; Sprcic and Sevic, 2012 and Adam et al., 2017. Whether the relationship between leverage and hedging is linear or not cannot be answered unambiguous. Concerning the extent of hedging, there seems to be a negative linear relationship (see Table 3.5 model (3)), which is not true for the extent of hedging, where there is no indication of a relationship (see Table 3.6 model (3)).

One explanation could be that airlines use fuel derivatives to hedge their risk as insurance against fluctuating fuel prices, regardless of how good their financial position is (Pfefferle, 2019). Another could be that they hedge the exposure due to the high share

of fuel costs in an airline's operating costs and the high volatility of fuel prices (Carter et al., 2006). In both cases, airlines with low leverage ratios have the financial option to take derivative positions to secure their financial position in the future and to protect their ability to meet pre-agreed purchase commitments (Carter et al., 2006; Pfefferle, 2019). When considering the univariate analysis, *lvrg1Adj1* and *lvrg1Adj1Sqr* are both significantely higher for non-hedgers (see Table 3.1) and for hedgers with low hedge ratios (see Table 3.2). This could lead to the interpretation that more indebted airlines do not hedge or hedge less than airlines that are less indebted. The two European NLCs Lufthansa and Air France-KLM are an example of this behaviour, both are headquartered in Europe, have the same business model and similar average ASMs. Lufthansa has an average *lvrg1Adj1* value between 2005 and 2018 of 0.28 and *fdvPct12m* of 0.77, while the values for Air France-KLM are 0.42 and 0.60 respectively. The complete opposite is Aeroflot with an average value of 0.64 for *lvrg1Adj1* and an average hedge ratio of 0.14. These examples show that there may not be a standardised concept in the industry.

Figure 2.12 in Subsection 2.2.2 shows that the percentage hedge for the next 12 months of airlines with negative equity value nearly reached the one of airlines with positive equity value in 2014. Before and after that year, the percentage hedged of airlines with negative equity value is strictly lower. According to Pfefferle (2019) it is not known which counterparties would enter into fuel derivative contracts with highly indebted airlines. According to her, a likely counterparty could be the financial institution which holds a large portion of the financial liabilities, with the expectation that the indebted airline might overcome the phase of financial distress with the hedging positions and be able to repay the outstanding financial liabilities.

Similar to the present results are the findings of Carter et al. (2006), who examine 29 U.S. airlines between 1992 and 2003. The coefficient of the lease-adjusted leverage ratio is negatively significant at the 5% level for the amount of jet fuel hedged. Their conclusion is different, however, as they argue that underinvestment costs are a subset of the costs of financial distress, so companies with more investment opportunities could lose more in the event of distress and therefore choose lower leverage ratios and higher hedge ratios.

In addition to the results regarding the relationship between leverage and hedging, it can be concluded from Table 3.8 based on the negative and significant coefficients of *prfMrgAdj, roaAdj, divDm* and *divYld* that profitable airlines opt less for hedging. This result is only confirmed for the extent of hedging (see Table 3.9) for *prfMrgAdj*, whereby the coefficients of the other variables are negative but not significant.

The results concerning the underinvestment hypotheses are mixed. When the decision to hedge is considered, the coefficients of *tobQAdj1* are not significant in any of the models (see Table 3.5), which is in line with the results of Carter et al. (2006), Spanò (2007) and Lin and Chang (2009). When other variables concerning the underinvestment problem are added, only the coefficients of *capAsAdj1* and *capSizeAdj1* are positive and significant at the 10% level, and all other coefficients are insignificant (see Table 3.10). This positive significance of *capAsAdj1* and *capSizeAdj1* is in line with previous studies by i.e. Nance et al. (1993), Gèczy et al. (1997), Allayannis and Ofek (2001) and Sprcic and Sevic (2012).

Concerning the extent of hedging, the coefficients of *peRto* are negative and significant at the 10% level, which is robust when other variables like the *cashRto* are added to the models (see Table 3.6). Besides *tobQAdj1* (positive and significant at the 1% level), none of the alternatively added investment opportunities variables have significant coefficients (see Table 3.11). The results of the models cannot support H2, but when the robustness test are considered the results seem rather mixed. The positive significance of the coefficients of *tobQAdj1* is in line with Gay and Nam (1998), Carter et al. (2006) and Treanor et al. (2013) and the theory by Froot et al. (1993). The studies by Carter et al. (2006) and Treanor et al. (2013) also refer to airlines, but only to US airlines between 1992 and 2003 and 1994 and 2006, respectively. Carter et al. (2006) conclude from the positive significance of Tobin's Q that airlines with more investment opportunities engage in more hedging. Based on these results and the negative effect of leverage on the amount of jet fuel hedged, they argue that airlines facing higher costs of financial distress optimally choose lower leverage ratios. Since underinvestment costs are a subset of the costs of financial distress, companies with greater investment opportunities have a higher loss of value in the event of distress (Carter et al., 2006). In line with this is that in approximately 27% of the firm years Tobin's Q is less than one, indicating that airlines with greater leverage ratios and lower Tobin's Q hedge less. However, other coefficients, e.g. the CAPEX to sales ratio, are not significant in the results of Carter et al. (2006), Lin and Chang (2009) and Treanor et al. (2013).

The results from the univariate analysis can be interpreted as support for H3a, but the coefficients of *cashRto* are positive and significant at the 1% level in the multivariate analysis (see Table 3.5). The result is not robust for airlines reporting under IFRS, American, Asian or European airlines (see Table 3.7). Replacing the *cashRto* by the *qckRto* results in a positive significant coefficient as well, not supporting that lower cash holdings are related to lower levels of risk management activities (see Table 3.10 model (8)). The results of the airline fixed effects OLS models cannot provide support for H3a, as the coefficient of the *peRto* is negative and significant at the 10% level (see Table 3.6), which is

robust for subsets besides when only airlines under IFRS are considered (see Table D.8). The positive relationship between levels of cash and the decision to hedge is in opposite to most previous studies (e.g. Adam, 2002; Nguyen and Faff, 2002; Judge, 2006; Spanò, 2007; Bartram et al., 2009; Dionne and Triki, 2013; Adam et al., 2017), where they find a negative significant or no significant relation (see Table D.2). What characterizes these studies is the assumption of a linear relationship, which corresponds to model (3) from Table 3.5, in which there is no significance (in line with Gèczy et al., 1997; Haushalter, 2000; Nguyen and Faff, 2002; Judge, 2006; Spanò, 2007 and Sprcic and Sevic, 2012). In accordance with Pfefferle (2019), it can be concluded that the change in significance of the cash ratio shows that the assumption of a concave relationship between levels of cash holdings and hedge ratios is most appropriate.

The results for H3b of the probit models support that very high levels of cash holdings are related with lower hedge ratios, as the coefficient of *cashRtoSqr* is negative and significant (see Table 3.5), which is supported by the negative significant coefficient of *qckRtoSqr* in the robustness checks (see Table 3.10). The results on the extent of hedging are inconclusive, as the coefficient of *crtRtoSqr* is either not significant or positive and significant. The coefficients of *cashRtoSqr* and *qckRtoSqr* are not significant, which do not support H3b (see Table 3.11).

The mixed results with regard to the level of cash holdings and hedging behaviour are also reflected in the example of Lufthansa and Air France-KLM used above. With an average *cashRto* of 0.45 (Lufthansa) and 0.41 (Air France-KLM), the two airlines are relatively close to each other, but as already noted above, the hedge ratios of 0.77 and 0.60 are comparatively far apart. The same holds for the two US LCCs JetBlue and Southwest, with an average *cashRto* of 0.58 and 0.62 and an average *fdvPct12m* of 0.17 and 0.48, respectively. No standardised procedure can be derived from this and it can also be interpreted as contradiction to the hypotheses.

Both binary variables for the usage of further types of derivatives have a positive impact on the decision to hedge (see Table 3.5). For the extent of hedging, the influence of *irdvDm* seems stronger than that of *fxdvDm*, as the significance is reduced generally to the 10% level (see Table 3.6) and turns into not significant for some robustness checks (see Tables 3.9 and 3.11). These results confirm what was already seen in Figure 2.5. The airlines considered use several types of derivatives, on average only 10 of them do not use derivatives at all. This can be explained by the fact that hedging is costly and requires a risk management team (Dolde, 1993; Nance et al., 1993; Géczy et al., 1997; Haushalter, 2000; Graham and Rogers, 2002). When the two binary variables are not considered, the coefficient of

lvrg1Adj1Sqr is positive and significant at the 5% level compared to the base model (see Table 3.5 model (4)) and the coefficients of *peRto* and *crtRtoSqr* are insignificant compared to the base model (see Table 3.6 model (4)). The result regarding *lvrg1Adj1Sqr* can be interpreted as a contradiction to H1a and H1b, as the coefficients are significant if the use of other derivatives is not taken into account.

4 OPERATIONAL HEDGING

4.1 Literature Review

In Chapter 3.1, the importance of risk management for the aviation industry was already explained. Furthermore, the concept of financial hedging and its application in the aviation industry were discussed and analysed. In addition, companies have the possibility of operational hedging, which is discussed in the following chapter. It provides an overview of operational hedging in general and its relevance in the aviation industry. In Section 4.1.1, a closer look is taken at the determinants of operational hedging.

The hypotheses on operational hedging are presented in Section 4.2. The empirical analysis is described in Section 4.3, which is divided into three subsections. The first subsection contains the univariate analysis of the dataset (4.3.1) and the second subsection the multivariate analysis (4.3.2). In the third subsection (4.3.3), the limitations of the analyses are discussed.

The chapter concludes with a summary of the results (4.4). Additional information can be found in Appendix E, with references in the text to the individual items.

4.1.1 Determinants of Operational Hedging

Operational hedging is not as easy to define as financial hedging. Van Mieghem (2003), for example, interprets it as 'risk mitigation through offsetting actions in a processing network that do not involve financial instruments' (p. 271). Chod et al. (2010) refer to operational hedging as being closely related to flexibility and 'risk mitigation using operational instruments' (p. 1032). Smith and Stulz (1985) refer to it in a way that 'a firm can hedge by altering real operating decisions; for instance, a merger can produce effects similar to those of hedging through financial contracts.' (p. 392). This is in line with the view of Hankins (2011), who believes that acquisitions can be considered as operational hedges as they reduce potentially costly volatility. In the case of the aviation industry, Ramos and

Veiga (2014) define operational hedging as a group of strategies that focus on improving operational fuel efficiency, including fleet fuel efficiency, optimising flight schedules and fleet allocations, and fuel-efficient practices such as flying slower.

Based on Guay and Kothari's (2003) findings that hedging intensity is not only dependent on, for example, jet fuel derivatives, but on a broader, more sophisticated risk management program, theoretical models have been developed that combine financial and operational approaches into a common risk management strategy (Bolton et al., 2011; Gamba and Triantis, 2014). This combines the use of derivatives with operational measures such as operational diversification and flexibility.

According to Huchzermeier and Cohen (1996), operational flexibility is the flexibility to switch between different production strategies and locations. Operational flexibility can be seen as an effective hedge against a company's exchange rate risk by quantifying the expected gains from switching to alternative strategies (Huchzermeier and Cohen, 1996). For the purposes of this paper, operational flexibility is considered synonymous with operational hedging. Operational flexibility offers airlines the opportunity to protect themselves against changes in fuel prices or demand, for example.

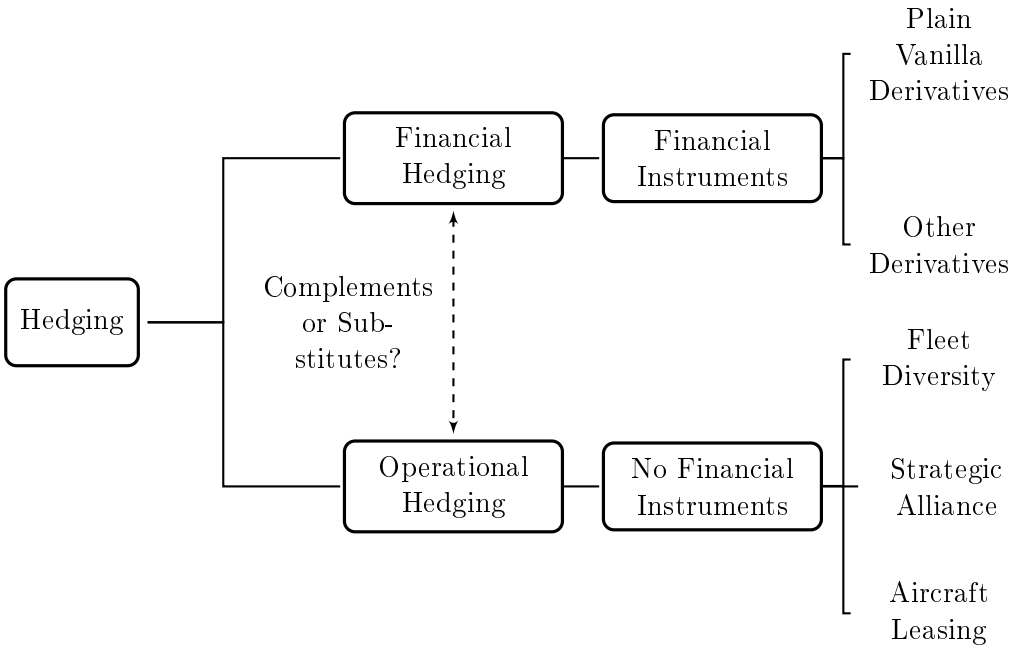
Figure 4.1 gives an overview of the differences between financial and operational hedging. Financial hedging with financial instruments has already been explained in detail in Section 3.1. In case of operational hedging, three types are considered below: Fleet diversity (4.1.1.1), membership in a strategic alliance (4.1.1.2) and aircraft leasing (4.1.1.3). A fourth part (4.1.1.4) discusses, whether financial and operational hedging are substitutes or complements.

4.1.1.1 Fleet Diversity

Operating costs make up a large part of airlines' costs (see Subsection 3.1.2). It therefore makes sense for airlines to respond to rising fuel prices or falling demand by adjusting the aircraft they use accordingly. In uncertain situations, a diverse fleet can allow the airline to wait until more information is available and react flexibly to high or low fuel prices by using their aircraft differently. For example, in times of high fuel prices the airline can deploy a smaller aircraft. The smaller aircraft causes proportionally fewer losses than a larger aircraft, but the airline can still serve the market. Airlines with a less diversified or possibly uniform fleet cannot take these measures (Treanor, 2012).

In the airline industry, fleet diversity is considered an operational hedge that can be used to manage the capacity or quantity of flights. Operational capacity is expressed in

Figure 4.1: Overview of financial and operational hedging (based on Huchzermeier and Cohen (1996), Van Mieghem (2003), Morrell and Swan (2006) and Pfefferle (2019)).



terms of ASMs. A diverse fleet allows the use of aircraft of different sizes on the same route, thereby controlling ASMs as the output (Slack, 1983). In Slack's (1983) sense, the maximum number of possible ASMs is the upper limit of volume range flexibility. The expansion of ASMs is a matter of long-term capacity management, not flexibility. However, this additional flexibility has its costs. Firstly, the cost of the change itself (switching costs), for example the training of board and ground staff, and secondly, the cost of providing the capability to change, i.e. maintaining a diverse fleet (Slack, 1983). According to him, flexibility in the context of production is the ability to assume different positions or alternatively a range of states. Slack (1983) divides flexibility into product, quality, supply and quantity flexibility, with the latter playing a role in this paper.[189] Similarly, Goyal and Netessine (2011) distinguish between product and volume flexibility. Product flexibility involves the ability to produce multiple products with the same facilities and reallocate capacity according to demand. Volume flexibility, on the other hand, involves the production of a single product at a given capacity and is referred to as up- and downward flexibility when production can be profitably increased or decreased depending on demand (Goyal and Netessine, 2011). As an example of the mismatch between supply and demand, Goyal and Netessine (2011) cite the example of Chrysler in 2000. Chrysler

[189] Airlines also have quality flexibility, but this is not measured in this paper.

misjudged the demand for newly introduced cars and underestimated the subdued demand for an already introduced minivan. Due to inflexible production technology, Chrysler was unable to adjust production to demand and lost about two billion USD.

In the literature, fleet diversity[190] is a commonly used indicator of operational risk management in various transport industries (Bai at al., 2022). Alexandridis et al. (2018) suggest that a well-diversified fleet can reduce exposure to market movements, similar to Treanor et al. (2014a) who find an overall reduction in risk exposure. In contrast, Berghöfer and Lucey (2014) find that an increase in fleet diversity leads to an increase in risk exposure and operating costs. This is consistent with Bai et al.'s (2022) finding that an appropriate level of diversity better reduces risk exposure, as they assume a trade-off between risk diversification and the challenges of operating a diversified fleet.

There is some consensus within the literature that operating costs are not changed by financial hedging through derivatives (e.g. Chowdhry and Howe, 1999; Zhao and Huchzermeier, 2015; Swidan and Merkert, 2019). The age of the aircraft is also not significant for operating costs (Merkert and Hensher, 2011), from which one can conclude that the use of younger aircraft is not suitable as an operational hedge (Swidan and Merkert, 2019). There is a positive influence of aircraft age on the jet fuel hedging status. Swidan and Merkert (2019) conclude that airlines hedge more with financial derivatives when their fleet is older. With regard to the age of a fleet, Bai et al. (2022) conclude that a young fleet increases risk as it is associated with high costs and thus increases the pressure on the company to perform well.

Considering only operational hedging, it was found that by reducing the variance of operating costs, expected profitability can be increased (Mello et al., 1995; Chowdhry and Howe, 1999; Ding et al., 2007). Fleet commonality is one type of operational hedging that leads to significant reductions in operating costs (Merkert and Hensher, 2011; Alamdari and Fagan, 2005; Kipli, 2007; Brüggen and Klose, 2010). Airlines align their fleet strategy not only with maintenance costs but also with demand requirements, service frequency or competition (Wei and Hansen, 2003).

[190] In this context, fleet standardisation should not be confused with fleet commonality. The former refers to the homogeneity of the fleet in terms of the number of aircraft of an aircraft manufacturer, aircraft families or aircraft models. The latter refers to the common characteristics of aircraft within the fleet, such as similar components, common spare parts and crew interchangeability. To calculate fleet commonality, a large number of different aspects of flight equipment would have to be considered, making the measurement very complex. Therefore, instead of fleet commonality, researchers use indices of fleet standardisation or fleet diversity, as in this paper (Narcizo et al., 2020).

According to Treanor's (2012) study using real option analysis on publicly traded US airlines from 1994 to 2008, having a diverse fleet is beneficial during periods of high fuel prices providing an operational hedge against fuel prices. This finding is consistent with the research conducted by Berghöfer and Lucey (2014). A 1% increase in fleet diversity[191] reduces the exposure to jet fuel prices by about 2.3%. Furthermore, Treanor et al. (2014) agree with Treanor (2012) that when fuel prices rise, an airline's operating fleet becomes more uniform as the airline switches to smaller aircraft. Conversely, it becomes more diverse when fuel prices fall (Treanor, 2012; Treanor et al., 2014).[192]

4.1.1.2 Strategic Alliances

As early as 1985, almost all of the 50 largest commuter air carriers[193] had entered into so-called code-sharing agreements with a major airline, representing more than 75% of the passengers carried by the commuter airline industry (Oster and Pickerell, 1986). The so-called airline alliances have become more established in aviation since the 1990s with the three largest being Star Alliance, SkyTeam and Oneworld (Lazzarini, 2007).

In the literature, there are various definitions as well as different levels of such alliances. Lazzarini (2007) distinguishes between two types of 'constellations' (p. 345). He understands constellations in general as an association of autonomous companies that compete with each other in the same or a similar industry in terms of customers and members. 'Explicit constellations' (Lazzarini, 2007, p. 346) are associations of several companies that formally act together. This includes joint decision-making, unification of the member's frequent-flyer programs, shared lounges, coordinated schedule and joint investments in brand names and technological platforms (Brueckner and Whalen, 2000; Fan et al., 2001; Lazzarini, 2007). In contrast, there are 'implicit constellations' (Lazzarini, 2007, p. 346), where not all companies are linked, but there is a bilateral link between two companies. The most common bilateral constellations are the already mentioned code-sharing agreements, where two airlines offer routes as a single composite product (Lazzarini, 2007).[194]

In comparison, Fan et al. (2001) distinguish between three different levels of cooper-

[191] Treanor (2012) uses a similar fleet diversity measure to what is used in this study, also based on HHI.

[192] It is not possible to make a statement here about the adjustment period for the company pension plan, as there is no standardised procedure or general parameter for measuring it.

[193] 'Commuter air carrier means an air carrier as established by § 298.3(b) that carries passengers on at least five round trips per week on at least one route between two or more points according to its published flight schedules that specify the times, days of the week, and places between which those flights are performed.' (Code of Federal Regulations: `https://www.govinfo.gov/app/collection/cfr/2022/title14/chapterII/subchapterA/part298`, visited on 04/14/2023). Commuter airline in this context is a legal definition of the US Code of Federal Regulations.

[194] Alliances also engage in code-sharing, whereby several routes are offered by not just two but several airlines (Lazzarini, 2007).

ation, namely ordinary[195], tactical and strategic. Tactical cooperations are comparable to Lazzarini's (2007) implicit constellations and strategic cooperation to explicit constellations. Fan et al. (2001) emphasise that a distinctive feature of strategic alliances is the pooling of frequent flyer programmes, as there is no additional cost to the customer when switching airlines within the strategic alliance. See Table 4.1 for a better overview.

Table 4.1: Cooperative relationships between airlines - key characteristics (based on Fan et al., 2001).

Types of relationships and examples of cooperation	**Ordinary cooperation**	**Tactical cooperation**	**Strategic cooperation (alliances)**
Equity exchange	Possible	Possible	Possible
Outsource logistics at out-stations	Possible	Possible	Possible
Code-sharing and related arrangements	No	Yes	Very often
Reciprocal frequent flyer benefits	No	Possible	Yes
Exclusive membership; joint marketing entity	No	No	Yes

To investigate the operational performance of airlines in the above constellations, Lazzarini (2007) uses the load factor of 75 global airlines between 1995 and 2000 as the dependent variable. His utilized dataset covers approximately 81% of the global passenger traffic in 2000. He finds an increase in the load factor of 1.2% with significance at the 1% level for airlines that are part of an alliance compared to non alliance members. For the subset containing only members of an alliance, he finds an increase in the load factor of 1.1% (significant at the 1% level) when traffic coming from other alliance members increases by 100 billion RPKs. For implicit constellations, however, he cannot confirm any of the results, i.e. implicit constellations appear not to have a significant influence on operating performance (Lazzarini, 2007).

The impact of international airline alliances on airfares is examined by Brueckner and Whalen (2000) using a sample of flights in the third quarter of 1997[196]. For the OLS re-

[195] For example, transferring the handling of general sales or airport functions to another carrier (Fan et al., 2001).

[196] The original sample was restricted to make the empirical work tractable, e.g. one segment of the route flown must always be operated by US carriers, and routes with prices below 100 USD and with more than two carriers were dropped, resulting in 46,620 observations (Brueckner and Whalen, 2000).

gression, the natural logarithm of the interline[197] fare was used as the dependent variable and regressed on the dummy variable for code-sharing agreements. Airlines with such an agreement thus charge 19.5% less, although it should be mentioned that the value of R^2 is only 0.02. If further regressors are added (e.g. a variable for demand), the effect increases to 24.2% with a R^2 of 0.43 which underlines the robustness of the result.

Purely bilateral code-sharing agreements are not included in this analysis due to the high number of airlines in the dataset considered, in accordance with Pfefferle (2019).

4.1.1.3 Aircraft Leasing

In general, there are two types of leasing[198], operating leasing and finance or capital leasing. In a finance lease, the lessee acquires ownership of the asset at the end of the lease term and the structure is similar to a debt contract, with the lender no longer having a claim on the asset at maturity and the lessee (often) making one higher payment. The lessee is considered the owner of the asset and the lease serves as collateral. As a result, the asset is subject to the Chapter 11 automatic stay[199], which prohibits realisation or foreclosure of the asset (Eisefeldt and Rampini, 2009; Gavazza, 2010).

With an operating lease, on the other hand, the asset is returned to the lessor at maturity and the contract bears no resemblance to a debt contract. Furthermore, the lessor is considered the owner of the leased asset and can more easily repossess the aircraft in the event of non-fulfilment of a lease agreement prior to bankruptcy than in the case of a finance lease (Gavazza, 2011). This repossession option implicitly makes it possible for the lessor to extend more credit than a lender whose claim is secured by the same asset. As a result, the leasing's debt capacity exceeds that of a secured loan (Eisfeldt and Rampini, 2009). The expense for operating leases is recognised in the income statement as an operating expense and not in the balance sheet as it is the case with finance leases. For this reason, operating leases are also referred to as off-balance sheet financing (Damodaran, 1999). Operating leases can be seen as a option, as they can be terminated earlier in the

[197] Interline in this context means the agreement between airlines that allows passengers to use flights that may be operated by different airlines as one complete journey. For example, passengers no longer have to recheck in if the connecting flight is operated by a different airline than the previous one.

[198] Leasing is a contract between the lessor (the owner) and the lessee (another party) whereby the lessor allows the lessee to use the asset for an agreed period of time in return for the regular payment of a rent (Gavazza, 2010; Morrell, 2021).

[199] 'The automatic stay provides a period of time in which all judgments, collection activities, foreclosures, and repossessions of property are suspended and may not be pursued by the creditors on any debt or claim that arose before the filing of the bankruptcy petition.' (Chapter 11 - Bankruptcy Basics: `https://www.uscourts.gov/services-forms/bankruptcy/bankruptcy-basics/chapter-11-bankruptcy-basics`, visited on 06/03/2024.

event of high fuel prices, thus avoiding a potential payment default. Table 4.2 provides an overview.

Table 4.2: Operational vs. Financial Hedging - key characteristics (based on Chen et al., 2018).

	Operating Leases	**Finance Leases**
Aircraft type selection	Chosen and reordered by leasing company, with aircraft types in common use.	Assigned by airline but ordered by leasing company.
Lease term	Flexible and can be months or years, which are much shorter than the useful life of an aircraft.	Approximately equal to depreciation duration of an aircraft.
Airline's options at the end of lease term	Renew the lease or terminate the lease.	Renew the lease, terminate the lease, or purchase the aircraft.
Rent	High.	Low.
Depreciation Cost	Covered by leasing companies.	Covered by airlines.
Influence of airline's balance sheet	No effect on assets or debt of the airline. Rent is part of the operation cost of the airline.	Leased aircraft are assets of the airline. Rent is part of the debt of the airline.
Advantages for airline finance	Advantageous to reduce debt ratio of the airline because rent is not classified as debt.	Depreciation costs and interest expenses can be deducted from the airline's taxable income.
Airline's goal	Adjust fleet capacity in the short term.	Financing.

For ARs or Financial Reports as of 1 January 2019 (IFRS 16) and as of 15 December 2018 (ASC 842), new accounting standards had to be recognized (International Accounting Standards Board, 2016; Financial Accounting Standards Board, 2016). Both are of interest for this study and will have a significant impact on the financial statements and key ratios. Payment obligations from contracts previously classified as operating leases now have to be recognized as interest-bearing lease liabilities and right-of-use asset on the balance sheet (Finnair, 2020).

Leasing in the aviation industry has increased from 0.5% of the total fleet in 1970 to 40% in 2014 (Chen et al., 2018). Carter et al. (2006), for example, use a sample of airlines with an average of between 60% and 70% of the airlines' fleet leased in each year. This underlines the importance of leasing in the airline industry, which is why the inclusion of corresponding variables in this study is important.[200]

[200] Within the analysed dataset, an average of 53% of the aircraft in the fleet are leased.

The largest lessor of aircraft at this point in time is AerCap Holdings N.V. (AerCap)[201] with approximately 70 billion USD total assets, 16.2 billion USD of equity and approximately 1,800 aircraft (Gavazza, 2011; AerCap, 2023). The leasing companies have extensive technical and legal knowledge of the aircraft market through their work and keep track of the airlines' needs and the use of the aircraft. This and the separation of ownership and control creates costs, which is why the instalments for leased aircraft are higher than for owned aircraft (Eisfeldt and Rampini, 2009; Gavazza, 2010). Gavazza (2010) documents that leasing rates are on average 20% higher than implicit rental rates.

Aircraft are not traded on central markets like bonds and the number of transactions is comparably low. Gavazza (2011) finds empirical evidence that leased aircraft are 13% more likely to be traded than owned aircraft.

As already discussed in Subsection 3.1.2.1, access to debt capital is often more expensive for already indebted companies, which is why leasing should be attractive for them. Empirical evidence that more financial constrained firms lease a considerably larger fraction of their capital is provided by Sharpe and Nguyen (1995) and Eisfeldt and Rampini (2009). In their study on corporate investment, Eisfeldt and Rampini (2009) conclude that attention should not be limited to capital expenditures, but that leased capital should also be considered. For example, not taking leasing into account when measuring investment cash flow sensitivities to assess the impact of financial constraints can be misleading. As described above, companies with financial constraints lease more, potentially miscalculating investment cash flow sensitivities and likely overstating them. Gavazza (2011) mentions young airlines with volatile capital needs in this context. In addition, leasing transfers some of the risk of aircraft ownership to the lessor. Leasing can therefore be seen as a reduction in economic risk, which also explains the cost differences between operational and financial hedging. This is of particular interest to airlines, as airline profits and the value of aircraft are almost perfectly correlated (Gavazza, 2011). Gavazza (2011) reports that approximately one third of all aircraft currently in operation by major airlines are under operating lease. Moreover, the utilisation of leased aircraft is higher than that of owned aircraft and they have shorter holding periods.

In their dynamic model of corporate finance that takes into account the role of leasing capital, Rampini and Viswanathan (2013) conclude that companies with large financial constraints hedge less on the one hand and lease more on the other. The increase in leasing increases the implicit debt of companies, leads to an increase in the volatility of net assets and may cause companies to engage in risk management. Leasing allows

[201] AerCap acquired International Lease Finance Corporation (ILFC) in 2014 (AerCap, 2013) and GE Capital Aviation Services (GECAS) from General Electric in 2021 (AerCap, 2021).

constrained firms to grow faster. In addition, mature companies suffering from severe cash flow shocks can stop hedging and use so-called sale-and-lease-back agreements[202] (Rampini and Viswanathan, 2013).

4.1.1.4 Complements or Substitutes?

There is no clear opinion in the literature on whether operational and financial hedging complement or substitute each other. The following section provides an overview of existing research on this topic, beginning with the opinion that they are complementary.

Allayannis et al. (2001) analyze the exchange rate risks of 265 US multinational non-financial firms between 1996 and 1998 and find evidence supporting the notion that operational hedging is a complement to financial hedging and not a substitute. They show that operational hedging alone does not increase firm value, but that it does when combined with financial hedging. Kim et al. (2006) arrive at the same conclusion by examining the interplay of operational and financial risk of exporting firms in the period from 1996 to 2000. Within the univariate analysis, they already find that the average financial hedge ratio for non-operationally and operationally hedged companies is 0.38 and 0.14, and the proxies for operational and financial hedging are positively correlated. In their multivariate analysis, they run two regressions that are of particular interest for this paper. The dependent variables are a dummy variable for the use of derivatives and the financial hedging ratio[203]. Both regressions show a significant positive relationship (at the 1% level) between operational and financial hedging, leading to the conclusion that they are complementary. Furthermore, Kim et al. (2006) find that both are associated with an increase in firm value, confirming the findings of Allayannis and Weston (2001) and Carter et al. (2006).

Treanor et al. (2013) agree with Allayannis et al. (2001) and Kim et al. (2006) that operational and financial hedging appear to be complementary, but do not conclude that the use of either hedging method increases firm value. Rather, in their empirical study of US airlines, they conclude that operational hedging and the use of fuel derivative contracts alone, which lock in the price of fuel, reduce value, while the use of financial derivatives increases value.

Chod et al. (2010) examine the relationship between operational flexibility[204] and fi-

[202] Sale and leaseback arrangements are used by airlines when they own an aircraft and want to continue using it, but want to realise the capital value of the aircraft. This may be for reasons of cash flow fluctuations or to meet capital requirements for new aircraft or investments (Morrell, 2021).

[203] Financial hedge ratio is calculated as the total notional amount of currency derivatives divided by total foreign activities (Kim et al., 2006).

[204] Flexibility here refers to the ability to adapt to change and is closely linked to the concept of operational

nancial hedging. In their opinion they can be both, complements and substitutes, which is consistent with the conclusion of Géczy et al. (2000). If product flexibility tends to increase (decrease) the value of financial protection, they are complements (substitutes) (Chod et al., 2010). Guay and Kothari (2003) report that companies use derivatives only to refine an overall risk management programme that is likely to include operational hedges. Laing et al. (2020) cannot find any evidence that operational hedging impacts financial hedging in their study of 32 US oil and gas companies between 2000 and 2015.

In contrast, Hankins (2011) finds evidence that operational and financial hedging are substitutes. In order to arrive at this conclusion she examines the impact of acquisitions[205] as a form of operational hedging on the use of derivatives for hedging purposes by bank holding companies between 1995 and 2003. For this purpose, the dataset is restricted to firms that made acquisitions during this period and for which data is available for at least three years prior to the acquisition. She examines the impact of the measure of operational hedging (expected percentage change in operational volatility) prior to the acquisition as one of the independent variables in an OLS regression on the change in the use of derivatives one or two years after the acquisition as the dependent variable. The coefficients for the measure of operational hedging are almost all significantly negative, with the significance decreasing with increasing time horizon. This implies that the contribution of acquisition to reducing volatility is followed by a decline in financial hedging (Hankins, 2011). Consistently, Smith and Stulz (1985) and Van Mieghem (2007) consider an acquisition to be an operational hedge if it limits potentially costly volatility, taking into account the cost of the hedge.

Another example are Huchzermeier and Cohen (1996). They show that international expansion can increase flexibility in sourcing and reduce price uncertainty and find that operational hedging can provide a long-term hedge against exchange rate risk, which is in line with Hankins (2011) regarding the substitutability of operational and financial hedges.

In their study, Mello et al. (1995) develop a model that includes both flexibility and financial hedging. They study a multinational company[206] that can hedge its exchange rate risk through financial markets and has flexibility in sourcing its production. As a reason for financial hedging of the company within their model, they assume agency costs arising

hedging (Chod et al., 2010).

[205] To avoid errors in the data, only acquisitions with a value of at least 50 million USD were taken into account.

[206] The company under consideration has one production site in Japan and one in the USA, with the production costs per unit given in Japan Yen (YEN) or USD in each case. The company will produce in the country with the lowest production costs, with fixed costs in USD when moving from one country to the other (Mello et al., 1995).

from outstanding liabilities. Using various examples, they examine the value of financial hedging and how it interacts with flexibility. First, they consider two firms with the same operational flexibility and identical outstanding debt. The effective use of financial hedges increases the value of the company compared to the value of the company without hedging. Second, they consider two firms with comparable debt structures and different flexibility. The lower the flexibility, the lower the company value, which is proportionally more influenced by hedging. From the previous two insights, Mello et al. (1995) conclude that hedging and flexibility are substitutes. In the third example, they consider two except for flexibility completely identical companies. The more flexible company has more notional debt and therefore requires a larger number of derivatives for effective hedging, which suggests that companies with greater flexibility hedge more, being the complement to the first result. Finally, they conclude that hedging depends not only on flexibility, but also on the relationship between flexibility and a company's liability structure.

In their empirical study of 31 of the world's leading tanker shipping companies, Bai et al. (2022) examine the effectiveness of financial hedging and operational risk management. The results show that financial hedging can only effectively reduce fuel price risk, while operational risk management can effectively reduce both fuel price risk and freight rate[207] risk. In addition, fleet age and trade diversity can reduce fuel price risk.

Gamba and Triantis (2014) examine the impact of different levels of operational flexibility on optimal financial risk management and the resulting value. They show that these are largely substitutes, e.g. the level of cash is non-monotonically related to the level of flexibility. Moreover, they show that higher levels of flexibility reduce the benefits of hedging, of cash holdings or both. This result is consistent with empirical results derived by Allayannis et al. (2001), Hankins (2001), Pantzalis et al. (2001) and Bartram (2008). For industries where hedging can be very effective, i.e. where the correlation between the available derivatives and the main risks is very high, a stronger negative relationship between operating flexibility and financial risk management will likely be observed (Gamba and Triantis, 2014).

To investigate the incentives to improve airlines' operational fuel efficiency, Hu et al. (2018) consider financial hedging as a substitute for operational hedging. They find that operational improvements lead to higher expected profit levels when efficiency is sufficiently high, but financial hedges are more effective in reducing airline profit volatility or risk exposure.

[207] In the transport sector, the freight rate is the price for the carriage of goods. It is limited to the transport of goods; its counterparts in passenger transport are, for example, the transport tariff (public transport) or the air fare (air transport).

Operational and financial hedging differ in their effect, regardless of the approach and means. The former is effective in the long term and capitalises on the volatility of the firm's cash flows, while the latter is effective in the short term and reduces the volatility of the firm's cash flows (Huchzermeier and Cohen, 1996; Van Mieghem, 2003; Kim et al., 2006).[208] According to Hu et al. (2018), financial hedging is more effective in reducing the volatility of the airline's profits and risk exposure, while operational hedging is more likely to increase the expected profit when it is effective. In addition, the longer the planning horizon, the lower the costs of operational hedging, as the conversion costs can be spread over several periods, while they are higher for financial hedging. Financial hedging is also less flexible in terms of instruments. For example, only instruments for the most important currencies are available for currency hedging, whereas there are no such restrictions for operational hedging.

[208] For example, the planning horizon of a production plant may be longer than ten years. Operational hedging can be used here, but not financial hedging, as such time horizons are usually not available for derivatives. This makes operational hedging indispensable in such situations, however, operational hedging also generates additional costs (Van Mieghem, 2003).

4.2 Hypotheses

Hypothesis 1 (H1): 'The more diverse the fleet of an airline, the lower the use of financial fuel hedging.'

Given the volatility of fuel prices, airlines with a diversified fleet can make use of it by flexibly deploying different aircraft sizes according to demand and use it as an operational hedge against fuel prices (Treanor, 2012). Empirical evidence for the reduction of fuel price exposure by the increase in fleet diversity was found by Berghöfer and Lucey (2014).

Hypothesis 2 (H2): 'Alliance membership is a substitute for financial fuel hedging.'

Regarding the benefits of alliance membership, Lazzarini (2007) finds an increase in the load factor for alliance members (significant at the 1% level), and Brueckner and Whalen (2000) find that alliance members charge lower prices for their flights. In case of rising fuel prices, membership in an alliance could protect members from a fall in load factors and ticket prices. Membership in an alliance may therefore be associated with a lower level of financial fuel price hedging. They also benefit from e.g. shared lounges and investments in brand names (Brueckner and Whalen, 2000; Fan et al., 2001; Lazzarini, 2007).

Hypothesis 3a (H3a): 'The more an airline uses leasing, the more it engages in financial risk management.'

Access to further debt capital is more expensive for more indebted companies, as costs increase with the level of debt. Operational leasing, in turn, increases implicit debt, which increases the volatility of the firm's net worth. To offset this volatility, the firm can engage in risk management (Eisfeldt and Rampini, 2009; Rampini and Viswanathan, 2013). Thus, if distressed airlines lease more aircraft than less distressed ones, the proportion of leased aircraft in the fleet should lead to higher risk management.

Hypothesis 3b (H3b): 'Aircraft operating leasing is a substitute for financial fuel hedging.'

Generally speaking operational hedging can simultaneously reduce fuel price risk and transportation costs (in a transport sector), while financial hedging only reduces fuel price risk (Bai et al., 2022). According to Moody's (2016) 'Leases are contractual commitments for future cash outlays and failure to make the contractual payments can result in adverse consequences that eventually lead to a default.' (p. 9), which is why operating leases can be seen as a real option in case an earlier termination is possible in case of high fuel prices

and a default can be avoided.

Hypothesis 4 (H4): 'Airlines with a higher number of aircraft under operating leasing and simultaneous low cash holdings show lower levels of financial fuel hedging.'

According to Rampini and Viswanathan (2013) firms with large financial constraints hedge less and lease more. With a high number of operating lease aircraft in the fleet and at the same time low cash balances, airlines have less collateral to provide for financial hedges.

Hypothesis 5 (H5): 'Airlines with an older fleet use more financial fuel hedging.'

In the opinion of Swidan and Merkert (2019) airlines hedge more with financial derivatives when their fleet is older. Furthermore Bai et al. (2022) find that fleet age can reduce fuel price risk. The high financial costs of young fleets exert greater pressure to enter into contracts and make younger fleets more vulnerable to market fluctuations.

Hypothesis 6 (H6): 'Airlines with a more diverse operating and simultaneously younger fleet use less financial fuel hedging.'

Due to the combination of high diversity and low fleet age, it can be assumed that airlines can react flexibly to customer demand and deploy younger aircraft with lower fuel consumption, which are utilised accordingly. The combination of low fleet age and flexibly deployable aircraft could therefore lead to lower fuel consumption, which could make financial hedging less relevant.

4.3 Empirical Analysis

The following analysis of operational hedging begins with the univariate (Subsection 4.3.1) and is followed by the multivariate analysis (Subsection 4.3.2).

Due to the strong change in the lease-adjusted values as a result of the changes in accounting standards, 2019 is not included in the following analyses.[209]

4.3.1 Univariate Analysis

The following tables show the difference-in-means tests for variables relevant for operational hedging.

Starting with Table 4.3, we take a look at the differences between hedgers and non-hedgers. Hedgers have a value of one for *fdvDm* and non-hedgers a value of zero. The fleet age of hedgers and non-hedgers is significantly different at the 10% level, with hedgers having a lower value, which implies that H5 may have to be rejected. For *acOlcashDm*, there is no significant difference, suggesting that hedgers and non-hedgers do not differ significantly concerning their cash holdings and amount of aircraft under operating lease. H4 can possibly not be accepted. In contrast, the difference in *acOlPct* is significant at the 1% level. Hedgers have on average 9.4% more aircraft under operating lease in their fleet than airlines that do not hedge, which points in a different direction than H3b. The difference for *alliDm* is significant at the 1% level, indicating that membership in an alliance is not a substitute for financial hedging, which can be seen as a contradiction to H2. The mean values of *fDvi1* and *fDiv2* of hedgers are higher than those of non-hedgers with significance levels at 1%. This shows that hedgers have on average a higher fleet diversity while simultaneously having higher switching costs, which can be interpreted as contradiction to H1. In total, the difference in *fDivNet* is not significant. The difference of *fDiv1acAgeDm* is significantly different as well at the 1% level. Hedgers have a lower value which can be interpreted as support for H6. The two groups do not differ significantly in terms of expenditure on operating leases (*olexpTl_*). However, when the expenditure is put in relation to total income (*olexpRev*), hedgers spend significantly (at the 5% level) less, which points in another direction than H3a.

Table 4.4 shows the same variables, but splits the dataset into airlines with low and high hedging ratios. The difference of *acAge* is not significantly different for hedgers with high and low hedge ratios. It is noticeable that the significance of *acOlcashDm* and *acOlPct* is reversed, so that *acOlcashDm* is significantly (at the 1% level) higher for airlines with low hedging ratios and *acOlPct* is not significantly different. This provides evidence for H4,

[209] See also the figures which include 2019 for the relevant lease-adjusted variables in Appendix B.8.

Table 4.3: Difference-in-means test of the variables relevant to operational hedging for hedgers ($fdvDm = 1$) and non-hedgers ($fdvDm = 0$)

	hedgers		non-hedgers		t-Test		
variable	mean	N	mean	N	diff.	SE	N
acAge	8.440	518	9.350	119	0.909*	0.36	637
acOlcashDm	0.195	488	0.214	112	0.020	0.032	600
acOlPct	0.433	488	0.339	112	−0.093***	0.021	600
alliDm	0.512	642	0.298	218	−0.214***	0.037	860
fDiv1	0.689	590	0.611	133	−0.079***	0.021	723
fDiv2	0.534	590	0.440	133	−0.095***	0.023	723
fDiv1AgeDm	0.268	496	0.407	108	0.139***	0.038	604
fDivNet	0.155	590	0.171	133	0.016	0.012	723
olexpRev	0.071	641	0.089	216	0.018**	0.007	857
*olexpTl_*	380.000	641	374.000	216	−6.180	37.400	857

*p<0.1; **p<0.05; ***p<0.01

Variables ending with '_' are denoted in millions.

but against H3b. Besides the insignificance of *fDiv1AgeDm*, nothing changed compared to Table 4.3. In summary, the univariate analysis does not deliver a clear picture concerning H4 and all the others mentioned previously.

Table 4.4: Difference-in-means test of the variables relevant to operational hedging for Hedgers with high (> median of *fdvPct12m*) and low hedge ratios (≤ median of *fdvPct12m*)

	high ratios		low ratios		t-Test		
variable	mean	N	mean	N	diff.	SE	N
acAge	8.440	313	8.960	249	0.528	0.280	562
acOlcashDm	0.156	308	0.251	247	0.095***	0.029	555
acOlPct	0.417	308	0.421	247	0.003	0.020	555
alliDm	0.497	374	0.409	374	−0.088**	0.036	748
fDiv1	0.705	366	0.626	285	−0.079***	0.019	651
fDiv2	0.551	366	0.459	285	−0.092***	0.021	651
fDiv1AgeDm	0.263	308	0.319	235	0.056	0.033	543
fDivNet	0.155	366	0.167	285	0.012	0.010	651
olexpRev	0.068	374	0.080	372	0.013**	0.005	746
*olexpTl_*	363.000	374	400.000	372	36.500	31.700	746

*p<0.1; **p<0.05; ***p<0.01

Variables ending with '_' are denoted in millions.

In Appendix E, a similar table (E.3) to Table 4.4 is included, where instead of the

median of *fdvPct12m* the mean is used as criterion. Only for *olexpTl_* the significance increases from the 5% to the 1% level and for *acOlcashDm* the significance decreases to the 5% level. Besides that no significance is changed.

Tables 4.5 and 4.6 show the results of the difference-in-means tests of generally relevant variables for alliance and non-alliance members and for the two different business models in order to get a better overview of the industry and test H2.

From the significant difference (at the 1% level) of *fdvDm* in Table 4.5, it can be concluded that members of alliances are more likely to opt for hedging than non-members, which does not lead to support for H2. With the exception of *intCovAdj1*, the variables relevant to financial distress are all significantly higher for alliance members, with *lvrg1Adj1* and *roaAdj1* both at the 5% level and *prfMrgAdj1* at the 1% level. *capAsAdj1* (at the 10% level) and *tobQAdj1* (at the 1% level) are both significantly higher for non-alliance members, while the difference in *mtbRto* is not significant. All three variables are related to the underinvestment problem. Regarding fleet diversity, all three differences are significant at the 1% level, with members of an alliance having significantly higher values of *fDiv1* and *fDiv2*. The opposite is true for *fDivNet*, where non-alliance members have a significantly higher value, implying that non-alliance members have a greater benefit from operating a diverse fleet. *olexpTl_* are significantly (at the 1% level) higher for alliance members, which is not surprising, as alliance members account for an average of 75,023 million ASMs and non-members for 24,556 million ASMs. *lccDm* has a mean of zero for alliance members, showing that only NLCs are alliance members.

There is no significant difference between the two business models in terms of hedging behaviour (see Table 4.6). Concerning the variables relevant to financial distress, all are significantly different for LCCs and NLCs, with *intCovAdj1*, *prfMrgAdj1* and *roaAdj1* significantly higher for LCCs at the 1% level, whereby the difference of *intCovAdj1* is striking, as it is 0.97. *lvrg1Adj1* is significantly (at the 5% level) lower for LCCs. Besides the difference of *tobQAdj1*, none of the variables related to the underinvestment problem are significantly different, with *tobQAdj1* being significantly higher for LCCs at the 1% level. In terms of fleet diversity, *fDiv1* and *fDiv2* of LCCs and NLCs differ significantly at the 1% level, with the values of NLCs being higher. This difference is not really surprising, as the definition of LCCs includes a homogeneous fleet (see Table B.2). Nevertheless LCCs have a significantly higher average value for *fDivNet* (at the 1% level), which implies that although the fleet is less diverse they manage to operate at relatively lower switching costs. LCCs have significantly lower (at the 1% level) operating lease expenses compared to NLCs.

Table 4.5: Difference-in-means test of selected variables for alliance members (*alliDm* = 1) and non-alliance members (*alliDm* = 0)

	alliance		non-alliance		t-Test		
variable	mean	N	mean	N	diff.	SE	N
fdvDm	0.835	394	0.672	466	−0.163***	0.029	860
fdvPct12m	0.327	339	0.297	409	−0.030	0.020	748
intCovAdj1	1.735	393	1.926	474	0.181	0.134	867
lvrg1Adj1	0.482	392	0.506	472	0.024**	0.011	864
prfMrgAdj1	0.049	393	0.067	472	0.018***	0.005	865
roaAdj1	0.033	392	0.042	471	0.009**	0.003	863
capAsAdj1	−0.053	391	−0.064	472	−0.010*	0.006	863
cashRto	0.471	395	0.679	474	0.208***	0.029	869
mtbRto	1.667	392	1.648	473	−0.022	0.216	865
tobQAdj1	1.117	389	1.306	471	0.189***	0.028	860
fDiv1	0.839	362	0.510	366	−0.329***	0.013	728
fDiv2	0.707	362	0.322	366	−0.385***	0.015	728
fDivNet	0.131	362	0.188	366	0.057***	0.009	728
*olexpTl_*	580.124	393	209.957	472	−370.167***	27.050	865
lccDm	0.000	395	0.422	474	0.422***	0.023	869

*p<0.1; **p<0.05; ***p<0.01

Variables ending with '_' are denoted in millions.

4.3.2 Multivariate Analysis

The procedure within the multivariate analysis is the same as in Subsection 3.3.2.[210]

4.3.2.1 Decision to Hedge

Table 4.7 presents ten random effects probit models[211] with different operational hedging variables for the dependent variable *fdvDm*, where *lvrgAdj1, lvrgAdj1Sqr, intCovAdj, tobQAdj, cashRto, cashRtoSqr, irdvDm* and *fxdvDm* form the basic framework (see Subsection 3.3.2). The first three models include *fDiv1* as a proxy for fleet diversity, which is positive and significant at the 10% level. The results can be interpreted as contradiction to H1, which implies a decline in financial fuel hedging in case of a more diverse fleet. The models differ from each other in that model (2) includes year dummies. The other models do not include year dummies because the AIC value of model (2) is higher than that of model (1) and the significance of *fDiv1* is not changed. Model (3) differs

[210] Table E.1 in Appendix E contains information on the relevant studies, the models used and the dependent and independent variables.

[211] Appendix C contains further information on how the data was analyzed.

Table 4.6: Difference-in-means test of selected variables for low-cost ($lccDm = 1$) and network-legacy carriers ($lccDm = 0$)

	LCC		NLC		t-Test		
variable	mean	N	mean	N	diff.	SE	N
fdvDm	0.705	193	0.759	667	0.054	0.144	860
fdvPct12m	0.284	178	0.319	570	0.035	0.025	748
intCovAdj1	2.577	200	1.611	667	−0.966***	0.207	867
lvrg1Adj1	0.469	199	0.503	665	0.034**	0.014	864
prfMrgAdj1	0.099	200	0.046	665	−0.053***	0.008	865
roaAdj1	0.056	199	0.033	664	−0.023***	0.005	863
capAsAdj1	−0.063	199	−0.058	664	0.004	0.009	863
cashRto	0.901	200	0.490	669	−0.412***	0.047	869
mtbRto	1.996	199	1.555	666	−0.441	0.284	865
tobQAdj1	1.527	198	1.129	662	−0.398***	0.052	860
fDiv1	0.331	179	0.785	549	0.454***	0.017	728
fDiv2	0.101	179	0.648	549	0.547***	0.014	728
fDivNet	0.230	179	0.137	549	−0.093***	0.016	728
*olexpTl_*	260.601	200	413.486	665	152.885***	27.241	865

*p<0.1; **p<0.05; ***p<0.01

Variables ending with '_' are denoted in millions.

by including *alliDm* as an additional independent variable, as alliance members showed significantly higher usage of fuel hedging and fleet diversity measures in Table 4.5. Compared to model (1) nothing is changed and the coefficient of *alliDm* is negative but not significant. Model (4) includes only *alliDm* in addition to the basic framework, where the coefficient is again negative and insignificant. The insignificance of *alliDm* in both cases does not deliver support for H2. In model (5), *olexpTl_* is added in order to investigate whether airlines leasing more engage more in financial risk management. *olexpTl_* is negative and significant at the 1% level, which can be interpreted as contradiction to H3a, as the hypothesis would have suggested a positive relationship. As the coefficient of *acOlPct* is positive and not significant in model (6)[212], the results cannot be interpreted as support for H3b, which suggests that operating leasing is a substitute for financial hedging. In model (7), the added independent variable is *acOlcashDm*, which is positive and significant at the 5% level, which can be interpreted as contradiction to H4. The results of model (8) are in contradiction to the univariate analysis, as *lccDm* is not significant, suggesting that the business model has no impact on the hedging decision. The coefficients of

[212]The number of observations of models (6), (7), (9) and (10) is lower compared to the other models due to missing fleet information.

acAge and *fDiv1AgeDm* are both insignificant, hence not providing support for H5 and H6.

In addition to Table 4.7, tables for robustness checks are included in Appendix E.4 or hereafter.

First, the same models as in Table 4.7 without *irdvDm* and *fxdvDm* are considered in Table E.4. The coefficient of *lvrg1Adj1* remains negative in all eight models, but the significance changes in models (1) to (3) as well as (8) to (10). The formerly significant coefficient of *lvrg1Adj1Sqr* in model (2) Table 4.7 is not significant in model (2) Table E.4. The other variables of the base model did not change in any of the models. The coefficients of *fDiv1* in models (1) to (3) are still positive, but the significance is increased to the 5% level in models (1) and (2). The coefficient of *acOlPct* is now positive and significant at the 10% level and the coefficients of *lccDm* and *acAge* are now negative and significant at the 5% and 10% levels, respectively. The coefficients for the variables *alliDm, olexpTl, acOlcashDm* and *fDiv1AgeDm* have not changed.

For each additional variable related to operational hedging (*fDiv1, alliDm, olexpTl_ acOlPct, acOlcashDm, acAge* and *fDiv1AgeDm*) to the basic framework one individual table is included with the same different sample restrictions. Where the first model has no sample restrictions, the second one excludes regional airlines, the third includes *mrgDm*, in the fourth Allegiant Air is excluded and in the fifth only airlines which report under IFRS are considered[213]. Regarding the robustness of the models for *fDiv1*, it stays significant when *mrgDm* is added, while the significance vanishes for all other cases (Table E.5). In Table 4.8, the models for *alliDm* are included. The coefficient is insignificant in all cases, except when only airlines reporting under IFRS are included, the coefficient is negative and significant at the 1% level, which supports H2. The models (Table E.6) regarding *olexpTl_* show that the significance for all sample restrictions remains at the 1% level. The results for *acOlPct* are robust to any of the sample restrictions and are insignificant for all models (Table E.7). In Table E.8 the models for *acOlcashDm* are included, but the significance at the 1% level is not robust. It decreases to the 5% level for models (2), (3) and (4) and is insignificant in model (5). The insignificance for *acAge* is robust to all sample restrictions (Table E.9). The coefficient of *fDiv1AgeDm* is negatively significant at the 10% level when regional airlines are excluded and when airlines reporting under IFRS are included only. The significance rises to the 5% level when Allegiant Air is excluded, which supports H6 (Table E.10).

[213] Again, the AIC value decreases significantly if only airlines that report in accordance with the same accounting standard are taken into account.

Table 4.7: Random effects probit models with operational hedging variables

	Dependet variable: *fdvDm*									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
lvrg1Adj1	−7.087*	−8.808***	−7.035*	−5.678**	−6.796**	−4.635	−4.403	−7.707**	−6.934*	−6.902*
	(4.187)	(3.230)	(4.258)	(2.820)	(2.958)	(3.903)	(3.685)	(3.188)	(4.034)	(4.095)
lvrg1Adj1Sqr	4.825	5.970**	4.791	3.033	3.849	3.051	2.660	4.582*	3.718	4.155
	(3.522)	(2.950)	(3.572)	(2.380)	(2.596)	(3.298)	(3.187)	(2.710)	(3.377)	(3.606)
intCovAdj	−0.265***	−0.246***	−0.264***	−0.266***	−0.291***	−0.196***	−0.209***	−0.259***	−0.287***	−0.279***
	(0.064)	(0.071)	(0.064)	(0.061)	(0.067)	(0.071)	(0.066)	(0.060)	(0.078)	(0.079)
tobQAdj1	0.056	0.180	0.051	0.138	0.070	−0.090	−0.117	0.087	0.566*	0.217
	(0.245)	(0.248)	(0.247)	(0.225)	(0.232)	(0.242)	(0.222)	(0.209)	(0.326)	(0.287)
cashRto	2.582***	1.823***	2.576***	1.860***	1.864***	1.842***	2.236***	2.126***	2.513***	2.868***
	(0.625)	(0.669)	(0.629)	(0.574)	(0.509)	(0.628)	(0.629)	(0.587)	(0.650)	(0.741)
cashRtoSqr	−0.798***	−0.681***	−0.795***	−0.663***	−0.699***	−0.686***	−0.746***	−0.760***	−0.902***	−0.975***
	(0.215)	(0.222)	(0.215)	(0.211)	(0.213)	(0.229)	(0.229)	(0.219)	(0.254)	(0.279)
irdvDm	1.463***	1.458***	1.477***	1.325***	1.321***	1.671***	1.809***	1.254***	1.113***	1.464***
	(0.393)	(0.371)	(0.396)	(0.311)	(0.278)	(0.426)	(0.446)	(0.269)	(0.316)	(0.368)
fxdvDm	0.895***	0.985***	0.902***	0.922***	1.137***	0.797*	0.844***	1.033***	0.689***	0.737**
	(0.273)	(0.306)	(0.273)	(0.271)	(0.251)	(0.454)	(0.325)	(0.284)	(0.264)	(0.335)
fDiv1	1.120*	1.161*	1.208*							
	(0.588)	(0.688)	(0.646)							
alliDm			−0.099	−0.011						
			(0.280)	(0.275)						
*olexpTl_*					−0.001***					
					(0.000)					
acOlPct						1.058				
						(0.863)				
acOlcashDm							0.725**			
							(0.322)			
lccDm								−0.507		
								(0.372)		
acAge									−0.051	
									(0.049)	
fDiv1AgeDm										−0.712
										(0.444)
(Intercept)	1.097	1.989*	1.069	1.685*	2.706***	1.422	1.419	2.482**	2.669*	2.281*
	(1.529)	(1.129)	(1.571)	(0.870)	(0.929)	(1.215)	(1.167)	(1.032)	(1.468)	(1.333)
Year dummies	No	Yes	No	No	No	No	No	No		
N	717	717	717	851	850	596	596	851	633	600
AIC	383.711	396.341	385.585	469.640	463.486	319.972	317.276	468.865	358.775	322.567

*p<0.1; **p<0.05; ***p<0.01
Standard errors in parentheses
Variables ending with '_' are denoted in millions

Table 4.8: Alternative random effects probit models inclusive *alliDm* with different sample restrictions

	Dependent variable: *fdvDm*				
	(1)	(2)	(3)	(4)	(5)
lvrg1Adj1	−7.035*	−8.526**	−7.073	−2.929	−6.524
	(4.258)	(3.803)	(4.551)	(3.497)	(4.069)
lvrg1Adj1Sqr	4.791	5.806*	4.834	1.605	4.405
	(3.572)	(3.264)	(3.777)	(3.109)	(3.415)
intCovAdj	−0.264***	−0.268***	−0.264***	−0.226***	−0.126
	(0.064)	(0.064)	(0.064)	(0.072)	(0.088)
tobQAdj1	0.051	0.062	0.047	0.137	−0.077
	(0.247)	(0.241)	(0.249)	(0.240)	(0.239)
cashRto	2.576***	2.417***	2.572***	1.838***	0.787
	(0.629)	(0.641)	(0.637)	(0.602)	(0.913)
cashRtoSqr	−0.795***	−0.774***	−0.795***	−0.579***	−0.439*
	(0.215)	(0.221)	(0.215)	(0.201)	(0.251)
irdvDm	1.477***	1.392***	1.471***	1.264***	1.545***
	(0.396)	(0.334)	(0.412)	(0.336)	(0.549)
fxdvDm	0.902***	0.940***	0.897***	1.180***	1.600***
	(0.273)	(0.269)	(0.277)	(0.360)	(0.461)
fDiv1	1.208*	1.010	1.199*	1.288	1.741*
	(0.646)	(0.655)	(0.657)	(0.849)	(0.933)
alliDm	−0.099	−0.029	−0.097	−0.248	−0.838**
	(0.280)	(0.280)	(0.281)	(0.311)	(0.410)
mrgDm			0.064		
			(0.515)		
(Intercept)	1.069	1.682	1.088	0.168	1.754
	(1.571)	(1.330)	(1.713)	(1.173)	(1.577)
Specifications		excl. CPA		excl. Allegiant Air	IFRS only
N	717	692	717	704	351
AIC	385.585	379.619	387.570	373.641	188.249

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$
Standard errors in parentheses

4.3.2.2 Extent of Hedging

Table 4.9 presents nine airline fixed effects[214] linear regression or OLS models for different operational hedging variables for the dependent variable *fdvPct12m*. The basic framework consists of the variables *lvrgAdj1, lvrgAdj1Sqr, intCovAdj, perRto, crtRto, crtRtoSqr, irdvDm* and *fxdvDm* (see Subsection 3.3.2). The first three models include *fDiv1* as a proxy for fleet diversity, which is insignificant, which can be interpreted as contradiction to H1. The models differ from each other in the same way as for random effects probit models. In accordance with the previous subsection, the coefficient of *alliDm* is insignificant in models (3) and (4) and does not seem to influence the relationship between the fleet diversity and hedging extent, not supporting H2. In Model (5), *olexpTl_* is added in order to investigate whether airlines leasing more engage more in financial risk management. *olexpTl_* is negatively significant at the 5% level, which contradicts H3a, as the hypothesis would have suggested a positive relationship. Both variables concerning aircraft operating lease (*acOlPct* and *acOlcashDm*) are not significant, failing to support H3b and H4. The same holds for *acAge* and *fDiv1AgeDm*, not supporting H5 and H6.

Again, for reasons of robustness, a table with the same models as in Table 4.9 without *irdvDm* and *fxdvDm* and tables for each additional variable to the base model are included in Appendix E.5 or in the following.

When *irdvDm* and *fxdvDm* are excluded, the coefficients of *lvrg1Adj1* and *lvrg1Adj1Sqr* do not change. The coefficients of *intCovAdj* in models (8) and (9) are insignificant instead of significant at the 10% level. Only in models (6) to (9) the coefficients of *peRto* are significant at the same level. The coefficients for *cashRto* and *cashRtoSqr* are not significant in any of the models.

In contrast to the random effects probit models, a model for airlines reporting under the US GAAP accounting standard only can be computed as the sixth model for the airline fixed effects models. This was not possible for the random effects probit model because there was insufficient data from the sampling restriction to estimate the model.

Concerning the robustness of the models for *fDiv1*, it stays insignificant in all subsamples (Table E.12). In Table E.13, the models for *alliDm* are included, where the coefficient stays insignificant as well for all models. The models regarding *olexpTl_* show that the significance for all sample restrictions remains, although it decreases from the 5% level to the 10% level when airlines reporting under IFRS are considered only. The coefficients of

[214] Results of Hausmann-Test suggested fixed effects. The variable *lccDm* cannot be considered here, in contrast to the random effects probit model, because it is constant over time and a fixed effects model is used (Wooldridge, 2020).

Table 4.9: Airline fixed effects model with operational hedging variables

	Dependet variable: *fdvPct12m*								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
lvrg1Adj1	−0.241	−0.134	−0.229	−0.174	−0.154	−0.174	−0.199	−0.119	−0.236
	(0.335)	(0.337)	(0.341)	(0.247)	(0.242)	(0.349)	(0.350)	(0.333)	(0.363)
lvrg1Adj1Sqr	0.121	0.001	0.112	0.061	0.042	0.046	0.056	0.048	0.127
	(0.347)	(0.348)	(0.352)	(0.237)	(0.231)	(0.367)	(0.367)	(0.351)	(0.383)
intCovAdj	−0.016***	−0.015***	−0.016***	−0.015***	−0.016***	−0.015***	−0.014***	−0.009*	−0.009*
	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)
peRto	−0.0001**	−0.0001*	−0.0001**	−0.0001*	−0.0001*	−0.0001***	−0.0001***	−0.0001**	−0.0001**
	(0.00004)	(0.00004)	(0.00004)	(0.00004)	(0.00004)	(0.00003)	(0.00003)	(0.00003)	(0.00003)
crtRto	−0.080	−0.080	−0.077	−0.070	−0.081*	0.006	−0.001	−0.005	−0.007
	(0.051)	(0.052)	(0.051)	(0.044)	(0.044)	(0.049)	(0.050)	(0.046)	(0.051)
crtRtoSqr	0.024*	0.024*	0.023*	0.021*	0.023*	−0.010	−0.011	−0.010	−0.011
	(0.013)	(0.013)	(0.013)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.013)
irdvDm	0.112***	0.107***	0.111***	0.094***	0.093***	0.116***	0.119***	0.081***	0.095***
	(0.022)	(0.023)	(0.022)	(0.020)	(0.020)	(0.025)	(0.024)	(0.021)	(0.021)
fxdvDm	0.036*	0.035	0.035	0.030*	0.031*	0.042*	0.041*	0.065***	0.070***
	(0.022)	(0.022)	(0.022)	(0.017)	(0.017)	(0.022)	(0.022)	(0.022)	(0.024)
fDiv1	0.141	0.145	0.152						
	(0.139)	(0.138)	(0.140)						
alliDm			0.026	0.017					
			(0.041)	(0.039)					
*olexpTl_*					−0.0001**				
					(0.00003)				
acOlPct						−0.077			
						(0.068)			
acOlcashDm							−0.007		
							(0.018)		
acAge								0.003	
								(0.005)	
fDiv1AgeDm									−0.002
									(0.020)
Year dummies	No	Yes	No	No	No	No	No	No	No
N	646	646	646	742	741	552	552	558	539
R^2	0.734	0.741	0.734	0.767	0.768	0.766	0.766	0.774	0.770
Adjusted R^2	0.699	0.700	0.699	0.738	0.739	0.736	0.735	0.742	0.737
AIC	−447.833	−438.691	−446.418	−602.980	−605.095	−430.766	−429.510	−464.185	−441.749

*p<0.1; **p<0.05; ***p<0.01
Robust standard errors in parentheses
Variables ending with '_' are denoted in millions

acOlPct, *acOlcashDm*, *acAge* and *fDiv1AgeDm* remain insignificant for all models (Tables E.14 to E.16).

4.3.3 Limitations

Particularly noteworthy is the difference in the number of observations between the models, especially those containing *acAge*, *acoOlPct*, *acOlcashDm* and *fDiv1AgeDm*. The dataset itself consists 924 observations. Due to the change in accounting standards, the firm year 2019 had to be excluded, reducing the number of available observations to 869. Due to missing variables, the maximum number of observations for the random effects probit models is 719 and for the airline fixed effects model is 742. The minimum of the two models is 596 and 552, respectively. When robustness checks are taken into account, the minimum of the two further decreases to 319 and 362 for the fixed effects model for IFRS only and 177 for the fixed effects model for US GAAP only.

As for the general limitations, these have already been discussed in Subsection 3.3.4, but should nevertheless also be mentioned here with regard to the operational hedging variables.

Due to the approximation and calculation of the fleet diversity variables, measurement errors cannot be excluded at this point.

To avoid any misspecification of the functional form of a model and an underspecified model, all relevant operational hedging variables (*fDiv1*, *olexpTl_* and *acOlPct*) including their squared terms were added to the regressions. Only the relevant results are added in Appendix E, with regressions for *olexpTl_* and *acOlPct* concerning the extent of hedging in Table E.18. The coefficient of *olexpTlSqr_* has the same sign as for *olexpTl_*, which underlines the contradiction against H3a. For the variable *acOlPctSqr*, the results are significant at the 10% level, but the AIC value increases when the squared variable is included. If *acOlPctSqr* is included in the model, not only is the variable itself positive and significant, but *acOlPct* is also significant at the 10% level, but negative. These results can be interpreted as support for H3b, as a higher percentage of aircraft under operating leasing indicates less hedging and vice versa.

Table 4.10: Alternative airline fixed effects models for *olexpTl_* with different sample restrictions

	Dependent variable: *fdvPct12m*					
	(1)	(2)	(3)	(4)	(5)	(6)
lvrg1Adj1	−0.154	−0.154	−0.137	−0.131	−0.411	−0.837**
	(0.242)	(0.244)	(0.241)	(0.275)	(0.359)	(0.388)
lvrg1Adj1Sqr	0.042	0.043	0.022	0.019	0.192	0.738**
	(0.231)	(0.233)	(0.230)	(0.253)	(0.332)	(0.353)
intCovAdj	−0.016***	−0.016***	−0.017***	−0.018***	0.002	−0.020***
	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.007)
peRto	−0.0001*	−0.0001*	−0.0001*	−0.0001*	−0.00004	−0.0001***
	(0.00004)	(0.00004)	(0.00004)	(0.00004)	(0.0002)	(0.00002)
crtRto	−0.081*	−0.084*	−0.080*	−0.084*	−0.076	0.146**
	(0.044)	(0.046)	(0.044)	(0.045)	(0.064)	(0.068)
crtRtoSqr	0.023*	0.023*	0.023*	0.023*	0.002	−0.029*
	(0.012)	(0.012)	(0.012)	(0.012)	(0.015)	(0.017)
irdvDm	0.093***	0.096***	0.093***	0.092***	0.097**	0.052**
	(0.020)	(0.021)	(0.020)	(0.020)	(0.040)	(0.023)
fxdvDm	0.031*	0.031*	0.034*	0.033*	0.032	0.047
	(0.017)	(0.017)	(0.018)	(0.018)	(0.027)	(0.029)
*olexpTl_*	−0.0001**	−0.0001**	−0.0001**	−0.0001**	−0.0001*	−0.0001**
	(0.00003)	(0.00003)	(0.00003)	(0.00003)	(0.0001)	(0.0001)
mrgDm			−0.042*			
			(0.024)			
Specifications		excl. CPA		excl. Allegiant Air	IFRS only	US GAAP only
N	741	716	741	728	362	177
R^2	0.768	0.715	0.768	0.764	0.771	0.854
Adjusted R^2	0.739	0.680	0.739	0.735	0.737	0.830
AIC	−605.095	−559.274	−605.095	−582.445	−294.994	−169.978

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$
Robust standard errors in parentheses
Variables with '_' are denoted in millions

4.4 Results

If we look at the statistical results on H1, a clear picture emerges. Neither the univariate analysis nor the two regressions of the multivariate analysis support the hypothesis. In case of the fixed effects OLS models (see Table 4.9), the coefficient is not significant. The coefficient is positive and significant at the 10% level in the random effects probit models (see Table 4.7), which indicates a rejection of H1. This implies that operating a diverse fleet is rather a complement to financial hedging, which is in line with the results of Allayanis et al. (2001), Kim et al. (2006) and Treanor (2013). It should also be kept in mind that hedging through a diverse fleet is set for a longer time horizon than financial hedging. Financial hedging is more flexible in short-term situations and operational hedging is less restricted in terms of instruments (Huchzermeier and Cohen, 1996; Van Mieghem, 2003; Kim et al., 2006), so it can be assumed that the airlines analysed use both at the same time. With regard to fleet diversity and hedging behaviour of comparable airlines, we return to the examples of Lufthansa and Air France-KLM, as well as JetBlue and Southwest. The average *fDvi1* is close to each other at 0.91 (Lufthansa) and 0.94 (Air France-KLM), while the average hedge ratio is 0.77 (Lufthansa) and 0.60 (Air France-KLM). In the second example, the average hedge ratios are further apart at 0.17 (JetBlue) and 0.48 (Southwest), while *fDiv1* is also further apart at an average of 0.44 and 0.51 respectively. Here, too, the examples also show that there are different approaches within the industry.

The same clear picture emerges for *alliDm*, as neither the univariate analysis nor the multivariate analyses support H2. Both the random-effects probit models and the fixed-effects OLS models (see Tables 4.7 and 4.9) fail to provide evidence that alliance membership is a substitute for financial hedging as the coefficients are not significant in any case. The negative and significant differences of both difference-in-means tests (see Tables 4.3 and 4.4) can be interpreted as a rejection of H2, as more hedgers decide in favour of hedging and carry it out to a greater extent. The distinction between non-alliance and alliance members in Table 4.5 supports this, as the difference is negative for *fdvPct12m* and negative and significant for *fdvDm*, with alliance members hedging to a greater extent. It should also be noted that Table 4.5 shows that only NLCs are members of alliances. Table 4.6 shows that the business model has no influence on hedging behaviour, so a closer look at NLCs and their alliance membership seems reasonable, as suggested by Pfefferle (2019). Table 4.11 shows the difference-in-means tests of selected variables for alliance and non-alliance NLCs. There is no significant difference in the extent of hedging, but the decision to hedge is significantly different, with alliance member NLCs being more likely to enter into fuel hedging contracts. The non-alliance members had a significantly lower

intCovAdj1 and *lvrg1Adj1*, suggesting that the costs of financial distress are the reason for the negative significance of the univariate tests for H2.

Table 4.11: Difference-in-means test of selected variables for alliance NLCs (*lccDm* = 0 and *alliDm* = 1) and non-alliance NLCs (*lccDm* = 0 and *alliDm* = 0)

	alliance NLC		non-alliance NLC		t-Test		
variable	mean	N	mean	N	diff.	SE	N
fdvDm	0.835	394	0.648	273	−0.187***	0.034	667
fdvPct12m	0.327	339	0.308	231	−0.019	0.024	570
intCovAdj1	1.735	393	1.433	274	−0.302**	0.123	667
lvrg1Adj1	0.482	392	0.533	273	0.051***	0.013	665
prfMrgAdj1	0.049	393	0.043	272	−0.006	0.006	665
roaAdj1	0.033	392	0.032	272	−0.001	0.004	664
capAsAdj1	−0.053	391	−0.065	273	0.080	0.006	664
cashRto	0.471	395	0.517	274	0.046	0.030	669
mtbRto	1.667	392	1.395	274	−0.273	0.221	666
tobQAdj1	1.117	389	1.146	273	0.029	0.022	662
fDiv1	0.839	362	0.681	187	−0.158***	0.011	549
fDiv2	0.707	362	0.534	187	−0.174***	0.013	549
fDivNet	0.131	362	0.147	187	0.016*	0.070	549
*olexpTl_*	580.124	393	172.718	272	−407.406***	26.734	665

*p<0.1; **p<0.05; ***p<0.01

Robust standard errors in parentheses

Variables ending with '_' are denoted in millions

There is inconclusive evidence on the two hypotheses on the impact of leasing on financial risk management (H3a and H3b). *olexpTl_* and *acOlPct* are either insignificant or negative and significant at the 5% level, respectively, in the univariate analysis (see Tables 4.3 and 4.4), suggesting neither that increased use of leasing increases financial risk management nor that operating leases are a substitute for financial hedging. The coefficients of *olexpTl_* are negative and significant at the 1% level in the random effects probit (see Table 4.7) and at the 5% level (see Table 4.9) in the fixed effects OLS models. For *acOlPct*, the random effects probit models are only positive and significant when *irdvDm* and *fxdvDm* are excluded (see Table E.4) and the fixed effects OLS models are not significant in any case (see Table E.14). Again the four airlines already mentioned should be used as an example. As already mentioned, Lufthansa's average hedge ratio is 16.83% higher than that of Air France-KLM. At 0.11, *acOlPct* at Lufthansa is lower than that of 0.41 at Air France-KLM. A similar picture emerges for JetBlue and Southwest, where Southwest's hedging ratio is 31.12% higher than JetBlue's and *acOlPct* is 0.31 for JetBlue

and 0.17 for Southwest. In both cases, the airline with the lower average hedge ratio has more aircraft under operating lease. Taking a look at, for example, United Airlines with average values of 0.19 (hedge ratio) and 0.46 ($acOlPct$), it is again visible that the airlines behave differently.

The univariate analysis for H4 is not as clear as for the other hypotheses. If only hedgers and non-hedgers are considered (see Table 4.3), this can be interpreted as rejection, and if hedgers with high and low hedge ratios are considered (see Table 4.4), this can be interpreted as support. The multivariate analyses show mixed evidence for H4. Within the fixed effects OLS model the coefficients are not significant for $acOlcashDm$ (see Tables 4.9 and E.15). The random effects probit models show positive significance (see Tables 4.7 and E.8), indicating that airlines with a higher number of aircraft under operating lease and at the same time low cash holdings are more likely to hedge, which is the opposite of H4. Due to these results from the statistical analyses, the opinion of Rampini and Viswanathan (2013) cannot be supported.

For H5, only the univariate analysis concerning hedgers and non hedgers shows some significant results (see Table 4.3), which is not in support of it, leading to the conclusion that the age of an ailines' fleet has no impact on the hedging behavior. These results are in line with Treanor et al. (2013) and in contrast to the conclusions of Swidan and Merkert (2019), according to which airlines' financial hedging ratios are higher when their fleet is older.

The results of the multivariate analyses for H6 are not significant either (see Tables 4.7 and 4.9). Nevertheless, the univariate analysis shows a significant difference at the 1% level between hedgers versus non-hedgers (see Table 4.3). These results indicate that $fDiv1AgeDm$ is lower for carriers that hedge, supporting H6. The overall results are not clear.

In line with the results regarding the operational hedging variables Berghöfer and Lucey (2014) cannot find any evidence that operational hedges reduce aviation fuel risk, which is consistent with the results of Laing et al. (2020) for US oil and gas companies.

5 THE EU ETS

5.1 Literature Review

The following chapter summarizes the literature on the EU ETS, its impact on the aviation industry, the resulting additional costs for the airlines affected and potential measures to manage these costs. First, consider a historical perspective and the originated mechanisms (5.1.1) followed by a special focus on the aviation industry (5.1.2). Second, consider more general aspects of the EU ETS such as the question on whether the inclusion of airlines in the EU ETS leads to a reduction in CO_2 emissions is examined in more detail (5.1.3). Then, the possible additional costs arising from inclusion in the EU ETS and ways to compensate for these costs are examined (5.1.4). Finally, Subsection 5.1.5 considers further impacts of the EU ETS.

The corresponding hypotheses are presented in Section 5.2. The empirical analysis is described in Section 5.3, which is divided into two subsections. The first subsection contains the univariate analysis (5.3.1), the second the multivariate analysis (5.3.2).

The chapter concludes with a summary of the results (5.4). Additional information related to this chapter can be found in Appendix F, with references in the text to the individual items in the Appendix.

5.1.1 General

The EU ETS emerged from the specifications of the Kyoto Protocol in 1997. The Kyoto Protocol established legally binding green house gas (GHG) reduction targets for 37 industrialized countries for the period of 2008 to 2012, the so-called first commitment period (European Union, 2015).

The respective EU ETS Directive was adopted in 2003 (Directive, 2003/87/EC) and the EU ETS itself came into effect on 1st January 2005. It is the first international and, so far, largest emissions trading scheme for reducing GHG emissions. It includes about 45% of total GHG emissions in the EU caused by about 11,000 power stations and industrial facil-

ities in the 28 EU Member States as well as in Iceland, Liechtenstein and Norway or caused by flights between these countries.[215] The EU ETS currently covers three gases from different sectors, which are easy to measure, report and verify. The scheme takes into account carbon dioxide (CO_2), which is produced in electrictiy and heat generation, in engery-intensive industries (e.g. oil refineries, steels mills and iron or aluminium production)[216] and in civil aviation, as well as, since 2013, nitrous oxide (N_2O) from production of nitric, adipic and glyoxylic acids and glyoxal and perfluorocarbons ($PFCs$) from aluminium production (European Commission, 2016).[217] Under the EU ETS, CO_2 is considered the most important GHG and is used as a measurement unit, the carbon dioxide equivalent (CO_2e), to indicate the global warming potential of GHGs (European Union, 2015).[218]

The system itself is a so-called 'cap and trade' system, which permits emission allowances to be traded in such a way that the total amount of emissions does not exceed the cap. For example, in 2013, the limit for European Union Allowances (EUAs) to be allocated was 2,084,301,856.[219] At the end of each year, participants must forfeit one allowance for each ton of CO_2 equivalent (tCO_2e) emitted. For non-compliance, participants must pay penalties of 100 EUR per tonne of CO_2 (tCO_2). Fines are imposed when emissions exceed the number of allowances, they increase with European Union (EU) inflation starting from 2013.

Each allowance freely allocated, auctioned or obtained either from another participant's surplus or from the owner's own surplus entitles the owner to emit GHGs equivalent to the global warming potential of one metric ton of CO_2.[220] Figure 5.1 illustrates the process: Depending on whether participant A has a surplus of emission allowances, he can sell them to another participant, participant B, if the latter has a shortage of emission allowances, and vice versa. If participant B needs further emission allowances or needs them in general, they can also be purchased in an auction.

These auctions take place within a specific auction calendar, which is set well in advance

[215] The United Kingdom was a member of the European Union until 31st December 2020.

[216] A detailed table on the substances and sectors covered by the EU ETS can be found in Appendix F Table F.1.

[217] Methane (CH_4), sulphur hexafluoride (SF_6) and hydrofluorocarbons ($HFCs$) are currently not considered under the EU ETS (European Union, 2015).

[218] CO_2 is henceforth used as a reference. All other greenhouse gases considered are converted to the CO_2e, where CO_2 is given a value of one as a base (Umweltbundesamt, 2021).

[219] The share of free allowances is different for different industries (European Commission, 2016).

[220] Part of the allowances for certain sectors are allocated free of charge to avoid potential risks, e.g. shifting production to a country with lower emission targets (European Commission, 2016). Detailed information, e.g. on the individual sectors, on the allocation of free allowances can be viewed here: `https://www.eea.europa.eu/data-and-maps/dashboards/emissions-trading-viewer-1`, visited on 03/14/2024.

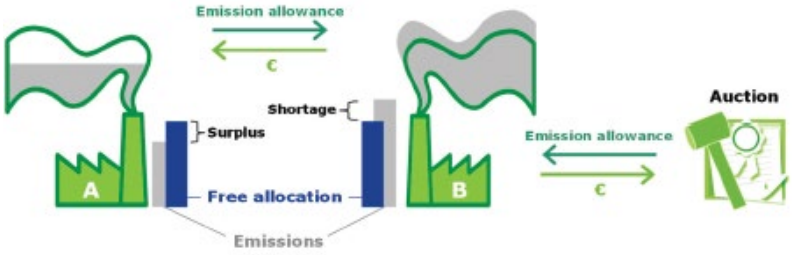


Figure 5.1: EU ETS emission allowances process (European Union, 2015)

by the auction platforms after consulting the European Commission (EC) and asking for its opinion in order to provide certainty on the auctioning schedule to the market.[221] The various auction platforms for the respective Member State and the dates of the auctions can be found in Figure 5.2 (European Union, 2015). The revenues from the auctioning of EU emissions trading allowances flow into the national budgets of the Member States. At least 50% of this should be used for climate or energy-related purposes. Member States report to the Commission on how the auctions' proceeds are used. In addition to the auctions, futures, options and forward contracts (OTC) on allowances as the underlying are traded on the secondary market (ICAP, 2022).

Auction platform	States	Auction timing
EEX	25 Participating Member States/ EEA EFTA States	Weekly auctions on Mondays, Tuesdays and Thursdays
EEX	Germany	Weekly auctions on Fridays
ICE	United Kingdom	Fortnightly auctions on Wednesdays
EEX	Poland	Monthly auctions on Wednesdays

Figure 5.2: EU ETS auction platforms (based on European Union, 2015)

The chronology of the EU ETS can be divided into four phases, as illustrated by Figure 5.3.

Figure 5.3: EU ETS timeline (based on European Union, 2015)

The so-called pilot phase or phase I ran from 1st January 2005 to 31st December 2007. Its primary purpose was to ensure that the Member States could meet their Kyoto Protocol

[221] All emission allowances under the EU's general emissions cap that are not allocated to operators free of charge will be auctioned (DEHSt, 2023).

obligations and that the EU ETS would function effectively prior to 1st January 2008. It served to put in place the necessary infrastructure, such as monitoring, reporting or verification of emissions, and to test the pricing within the carbon market (European Union, 2015). The cap used was mainly based on estimates, as no reliable data on emissions was available. These estimates were an aggregation of the national allocation plans of each Member State, which was approximately 2,096 million tonnes of carbon dioxide equivalent ($MtCO_2e$) in 2005. Allowances were allocated through Member States' national allocation plans, grandfathering/grandparenting[222], on the basis of a benchmark[223] or auctioning. Approximately 90% of the allocated allowances were allocated free of charge (ICAP, 2022). Only CO_2 was considered a GHG and only the Member States of the EU at that time participated in the EU ETS (European Commission, 2015b).[224]

This first phase included, for example, power plants and other incineration[225] plants with a rated thermal input greater than 20 megawatt (MW) (excluding hazardous or municipal waste facilities). Industry, including oil refineries, coke ovens and iron and steel plants with different thresholds was also included. In addition, the production of cement, glass, lime, bricks, ceramics, pulp, paper and cardboard was included in the EU ETS. The aforementioned industrial sites or factories are often grouped together in the literature under the term 'stationary plants' or 'stationary installations' (ICAP, 2022).

Emission reduction units from the Kyoto Protocol mechanisms were allowed to be used to meet the requirements of the EU ETS. There are two such mechanisms. First, there is the Clean Development Mechanism (CDM), where one country with an emission reduction or limitation commitment (so-called Annex B countries) is allowed to set up an emission reduction project in a developing country. These projects can generate and sell certified emission reduction (CER) credits equivalent to one metric tonne of CO_2 (UNFCC, 2022a).[226] Second, there is the Joint Implementation (JI) mechanism. This mechanism

[222]Grandfathering/grandpareting refers to the free allocation of allowances based on historical emissions (ICAP, 2022).

[223]Under the EU ETS, the quantity of allowances for each installation is calculated using benchmarks. These are performance indicators for a specific sector or product that can be used to compare the performance of plants and assess average performance. For this purpose, the average top 10% performers in the sector are used as benchmark (European Union, 2015).

[224]The members of the EU at that time were: Austria, Belgium, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Poland, Portugal, Ireland, Slovakia, Slovenia, Spain, Sweden and the United Kingdom. Romania and Bulgaria joined the EU in 2007.

[225]Process in which something is completely burned (Cambridge Dictionary: `https://dictionary.cambridge.org/dictionary/english/incineration`, visited on 09/29/2022).

[226]An example of such a project is the establishment and operation of a modern mass transit system that ensures high ridership on the Versova-Andheri-Ghatkopar line (known as Blue Line 1) within the rapid transit system of Mumbai in India. In this project, India is the so-called host party and Switzerland is the other participating country (UNFCC, 2006).

is similar to the CDM but involves projects between two Annex B countries (UNFCC, 2022b).[227] These projects can also deliver emission reduction units (ERUs) equivalent to one metric tonne of CO_2 (UNFCC, 2022b). In this first phase it was only allowed to use CERs from the CDM (European Union, 2015).

The second phase fell within the period of the Kyoto Protocol's first commitment period from 1st January 2008 to 31st December 2012 (European Union, 2015).

In this phase, ERUs from the CDM and JI were allowed to be used. These credits could be used up to a certain percentage specified in each country's national allocation plan. Over the entire period from 2008 to 2020, the number of credits used should not exceed 50% of the total reduction below 2005 emission levels achieved by sectors under the EU ETS.[228]

The cap for stationary installations in Phase II was again an aggregation of the national plans of each Member State and started at 2,049 $MtCO_2e$ in 2008 (ICAP, 2022).

At the beginning of this phase Iceland, Norway and Liechtenstein joined the trading scheme, so the whole European Economic Area (EEA) was covered by the EU ETS. From phase II onwards, it was at the discretion of the EU Member States to include N_2O emissions on a voluntary basis.

The allocation was very similar to the one in phase I and allocated through the national allocation plans of the Members States. Approximately 90% of the allowances were allocated for free and approximately 3% were allocated through auctioning.[229]

At the end of this period (2012), CO_2 emissions from the aviation sector were included in the scope of the EU ETS (ICAP, 2022).

The literature refers to Phase III as the learning phase, in which attempts were made to implement the experience gained from the previous two phases. An important part of this was the attempt to harmonize the ETS within the EU. To this end, a general emissions cap for the entire EU and the Market Stability Reserve (MSR) were introduced, which will be discussed in more detail later. Before that, each individual Member State had its own cap. The cap for stationary installations started at 2,084 $MtCO_2e$ in 2013 and was 1,816 $MtCO_2e$ in 2020. The difference results from the annual linear reduction factor of 1.74%,

[227] An example of such a project is the Awapuni landfill gas project, which uses methane previously emitted as a component of landfill gas from the Awapuni landfill in Palmerston North, New Zealand, to generate electricity. In this project, New Zealand is the so-called host party and Austria is the other participating country (UNFCC, 2013).

[228] For further information on the use of international credits under the EU ETS, see European Union (2015).

[229] The source does not provide any further information about the remaining 7% (ICAP, 2022).

which led to an annual reduction of about 38.3 million allowances.[230]

Like Phase II, Phase III corresponded in time to the second period of the Kyoto Protocol, and ERUs from the CDM and JI were allowed to be used as in Phase II. At the beginning of this phase, Croatia was included in the EU ETS and N_2O and $PFCs$ were considered as a GHG (European Union, 2015). In addition, carbon capture and storage installations were covered by the EU ETS. The production of petrochemicals, ammonia, non-ferrous and ferrous metals, gypsum, aluminium, and nitric, adipic and glyoxylic acid (various thresholds) was also included.

88% of the total quantity of allowances was distributed to Member States based on 2005 emissions or average 2005-2007 emissions. 10% were distributed to lower-income EU Member States under the solidarity clause. The remaining 2% were distributed to Member States that had reduced their emissions by at least 20% compared to the Kyoto Protocol base year 1990. In contrast to Phase II, 57% of the allowances were auctioned and the remaining 43% were freely allocated based on the respective benchmarks (ICAP, 2022).[231]

The EU ETS had to contend with a large surplus of allowances in the past due to the 2008 economic crisis. For this reason, the aforementioned MSR was adopted in 2015 and began its operation in January 2019. The intention was to make the system more resilient to future shocks and offset any negative impact of the existing surplus of allowances (European Commission, 2016). The MSR was intended to support the EU ETS's goal of reducing emissions in a cost-effective and economic manner. It was intended to maintain the total number of allowances in circulation at a certain level and to provide a long-term solution to the market imbalance that existed at the time, resulting from the surplus of allowances that had accumulated since 2009 (European Union, 2015). A first short-term measure was the postponement of the auction of 900 million allowances from 2014 to 2016. The auction of these funds was postponed further to 2019-2020, and eventually they were transferred to the MSR. The current MSR upward thresholds are based on the Total Number of Allowances in Circulation (TNAC)[232]. If this exceeds 833 million, 24% of future auctions up to and including 2022 are withheld and placed in the reserve for 12 months. From 2023 onwards, the percentage of allowances retained will be reduced to 12% and the total number of allowances in the reserve will be limited to the previous year's auction volume. All further allowances will be cancelled. If the TNAC is less than the threshold of 400 million allowances, 100 million allowances are transferred from the reserve to the

[230] This implies that the GHG emission from these sectors will be 21% lower in 2020 than 2005 (European Commission, 2016).

[231] The allocation was generalised for Phase III of the EU ETS and was different for different sectors, e.g. industry and energy sector. More information on this topic can be found here: `https://icapcarbonaction.com/index.php?option=com_attach&task=download&id=815`, visited on 04/04/2022.

[232] Quantity of allowances directly available.

market via auctioning (ICAP, 2022). In addition, this increase supports the goal of cutting 40% of EU GHG by 2030 (European Parliament, 2015). In Phase III, Member States used about 75% of their revenues from the EU ETS for climate-related purposes at both national and international level (ICAP, 2022). Phase III is of particular interest here as the dataset to be examined below covers the period through to 2019.

For the so-called current phase (2021-2030), the EU is proposing a 43% reduction in emissions compared to 2005 in its July 2015 proposal (European Commission, 2016). The emissions cap for stationary installations for phase IV started at 1,572 $MtCO_2e$ in 2021 and the yearly linear reduction factor is increased to 2.2% compared to 1.74% in phase III (ICAP, 2022). The allocation of free allowances will be improved by updating the benchmarks to reflect technological progress[233] and the targeted classification of carbon leakage[234] as well as the free allocation depending on the production level will be improved (European Commission, 2016).

The percentage of auctioned and freely allocated allowances in the total quantity of available allowances did not change from phase III to phase IV. In both phases, 57% of the allowances were auctioned and 43% freely allocated. 90% of the auctioned allowances are allocated to Member States based on their share of verified emissions. The remaining 10% of auctioned allowances are distributed among low-income Member States under the solidarity provision. In order to avoid market distortions, auctions are cancelled if the highest bid is significantly below the prevailing secondary market price. The volume of cancelled auctions is distributed among the following four auctions on the same trading platform (ICAP, 2022).

Two new funds have been established to support the industry and power sectors in the transition to a low-carbon economy. The Innovation Fund will expand existing support for innovative technologies in the industry sector. This fund is financed by the sale of at least 450 million allowances and the remaining funds from the NER300[235]. It currently has a funding volume of 1.5 billion Euro (EUR) (1.8 billion USD). The second fund, the Modernisation Fund, supports ten low-income EU countries in modernising their energy systems, improving energy efficiency and promoting the transition to a low-carbon econ-

[233]Product benchmarks within the EU ETS are based on the average GHG performance of the best performing 10% of installations within the EU producing this product or equivalent if data was not available (European Union, 2015).

[234]Carbon leakage is the shifting of carbon dioxide emissions to third countries (in particular) under the EU ETS.

[235]NER300 is a financing programme for low-carbon technologies financed through the sale of 300 million allowances. The sale resulted in a financing volume of approximately 2 billion EUR (2.37 billion USD). The funds were allocated to proposed projects in 2012 and 2014, with the last project coming into effect in 2021 (ICAP, 2022).

omy, e.g. through training and support for the affected workforce. The Modernisation Fund is financed from 2% of the auctioning revenues of all Phase IV allowances.

International credits such as CERs or ERUs may no longer be used within this period of the EU ETS (ICAP, 2022).

In July 2021, the EC announced the 'Fit For 55' package, aiming to reduce the EU's GHG emissions by at least 55% by 2030 compared to 1990 levels and to make the EU climate neutral by 2050. The package contains proposals to achieve these goals by strengthening the existing provisions and extending their scope. Such an extension could be, for example, the inclusion of emissions from the maritime sector in the EU ETS (European Commission, 2021b).[236]

The prices of EUAs in the period between 2005 and 2023 are shown in Figure 5.4. We can see that prices were lowest at the end of Phase I with 0.01 EUR (0.014 USD) per allowance on 30.11.2007 and 17.12.2007.[237] After the start of Phase II, the price recovered and even rose to 29.33 EUR (42.92 USD) per allowance on 01.07.2008, before the global economic crisis of 2007-2008 more than halved the price again with the lowest of 8.20 EUR (11.40 USD) on 12.02.2009. Until the beginning of Phase III, the price of EUAs initially followed a downward trend. At the beginning of the third phase, a slight upward trend can be seen, which turns into a clear upward trend from mid-2017. Only in early 2020 and late 2020/early 2021 this is briefly interrupted by the COVID-19 pandemic with the local bottom points of 15.23 EUR (17.46 USD) per allowance on 18.03.2020 and 23.03 EUR (26.40 USD) per allowance on 28.10.2021. The price of the EUAs continued to rise in the following years and repeatedly reached new highs with 97.51 EUR (111.37 USD) on 08.02.2022 and 97.50 EUR (110.43 USD) on 22.08.2022, although these were always accompanied by lows. After reaching a local high of 96.33 EUR (99.44 USD) on 28.02.2023 the price slowly decreased.

5.1.2 Aviation Industry

In order to include the aviation industry in the EU ETS from 1st January 2012 onwards the European Parliament and the Council adopted a new law in 2008 (Directive,

[236] Further information concerning the 'Fit-For-55 Package' can be found here: `https://www.consilium.europa.eu/en/policies/green-deal/fit-for-55-the-eu-plan-for-a-green-transition/`, visited on 04/20/2022.

[237] Where the literature provided EUR values, these were converted to USD using the average annual exchange rate used in the data set considered in this paper. Either the year of publication of the paper is used as the reference year or, if a reference date exists, the year of that reference date is used.

Figure 5.4: The prices for EUAs are based on primary market and secondary market data from the database Point Carbon (Thomson Reuters). (extension based on Nissen et al. (2020))

2008/101/EC). At the time, it was scheduled to apply to both EU and non-EU airlines operating flights to and from airports in an EU ETS country (European Parliament, 2015).[238]

This excludes some types of flights such as flights of heads of state, military, humanitarian, firefighting and police flights, as well as flights of aircraft that do not exceed a maximum takeoff weight of 5.7 tonnes. Flights by an air transport operator that operates fewer than 243 flights in sequence of three consecutive 4-month periods or produces less than 10,000 tonnes of annual emissions in total are also excluded. In addition, flights between the continental EEA and outermost regions and between two different outermost regions are excluded. Flights within an outermost region are included. For example, flights between Germany and the Canary Islands or between La Réunion and Saint-Martin are excluded. Flights within the Canary Islands, for example from Fuerteventura to Lanzarote, are included. Territories of Member States such as Aruba or Greenland have been excluded for the period 2013-2023 (European Parliament, 2008).[239]

[238] EU and EEA-EFTA (Norway, Iceland, Lichtenstein) countries (European Commission, 2015).

[239] A list detailing which geographical regions are covered by the EU ETS and when can be found here: `https://www.dehst.de/SharedDocs/antworten/EN/Aviation/LV_005_scope.html`, visited on 03/25/2022.

Each aircraft operator is assigned to an EU Member State, which determines the free allowances and monitors compliance. Either the aircraft operator is based in the EU and is assigned to the Member State that issued its license, or it is from outside the EU and is assigned to the Member State to which it attributes the largest amount of emissions.[240]

The cap of the GHG emissions for aircraft operators is derived from historical aviation emissions between 2004 and 2006. Data from the European Organization for the Safety of Air Navigation (EUROCONTROL) and the fuel consumption data provided by the aircraft operators were used for this purpose. In addition, the calculation of the cap took into account the fuel consumption of the auxiliary power units used by aircraft operators at airports to ensure a more holistic approach (European Parliament, 2015). The calculated total annual average was 221.4 $MtCO_2e$, resulting in an upper limit, the so called cap, of 214.8 $MtCO_2e$ for 1st January 2012 until 31st December 2012 and 210.4 $MtCO_2e$ for 1st January 2013 until 31st December 2020 (the end of Phase III) (DEHSt, 2022).[241]

At this point, a distinction has to be made between the already mentioned EUAs and European Union Aviation Allowances (EUAAs). Aviation Allowances (AAs) are special certificates for the aviation industry only, they can only be purchased and used by the airline industry. EUAs can be traded and used to fulfill the obligations within the EU ETS by any participant of the trading scheme (European Parliament, 2015).

As mentioned above, aviation was included in the EU ETS at the end of Phase II. The International Civil Aviation Organization (ICAO) sought a global solution for GHG emissions from international flights, allowing flights to and from non-EEA countries to be temporarily exempted from the EU ETS in November 2012. This was to be applied until the ICAO General Assembly in October 2013. The distribution of the emission allowances is determined based on the *tonne-kilometer*[242] data of each aircraft operator. The benchmark for the aviation sector was calculated as follows

$$\frac{\text{total annual amount of free allowances available (aviation cap)}}{\sum_i \textit{ tonne-kilometer } \text{data from applications of aircraft operator } i}$$

(European Parliament, 2015).

At that time, 85% of the certificates were distributed free of charge to the airlines and 15% were auctioned, which resulted in 0.6797 allowances per 1000 *tonne-kilometer* traveled

[240] An up-to-date list of all aircraft operators with the respective state subject to the EU ETS can be found here: `https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:32021R0662&from=EN`, visited on 03/14/2024.

[241] Cap amounts to 97% and 95% of the total amount of $MtCO_2e$ (DEHSt, 2022).

[242] *tonne-kilometer* is a commonly used unit in the airline industry to measure aviation activity. The passengers and freight carried is multiplied by the total distance traveled (European Parliament, 2015).

during Phase II (DEHSt, 2022).

In Phase III, respectively starting from 2014, the EU legislator (European Parliament, Council of the European Union and European Commission) added a regulation that limited the activities to be covered by the EU ETS to flights between EEA countries to the period between 2013 and 2016 (European Parliament, 2015).[243] Due to this amendments, the cap was adapted accordingly and was set to 32 million allowances, with the calculation unaffected by this change (ICAP, 2022).[244] In Phase III, 82% of the aircrafts operators' emission allowances were freely allocated, which resulted in 0.6422 allowances per 1000 *tonne-kilometers* traveled during Phase III.[245] The remaining 18% of the allowances were divided into 15% auctioned allowances and 3% retained for special reserve, i.e. for new market entrants or fast-growing operators (European Commission, 2015b).[246]

In October 2016, the ICAO agreed upon a global carbon offset and carbon reduction scheme. The aim of the Carbon Offsetting and Reduction Scheme for International Aviation (CORSIA)[247] is to stabilize CO_2 emissions at 2020 levels. After 2020, airlines must offset growth in CO_2 emissions (ICAO, 2016). After reviewing this outcome, it was agreed within the EC to maintain the reduced scope until probably 2024 and to monitor the effectiveness of CORSIA (European Parliament, 2017).

From 2021 onwards (Phase IV), the linear annual reduction factor of 2.2% already applied to stationary installations will also be applied to the emissions cap for aviation. Due to Brexit, the cap for aviation was reduced to 24.5 million allowances annually in 2021 and the EC has proposed legislation to implement CORSIA for flights outside the EEA. The allocation of allowances is the same as in Phase III (ICAP, 2022).

Under the 'Fit For 55' package, the linear annual reduction factor for the aviation industry is to be increased to 4.4% and the free allocation of allowances is to be abolished after 2027 by increasing the percentage of allowances auctioned from 15% to 100% between 2024 and 2027. International aviation is to be integrated through the implementation of CORSIA via the EU ETS (European Commission, 2021b).

[243] Known as 'Stop-the-clock' decision (Decision No. 377/2013/EU) or 'Reduced scope' (DEHSt, 2021).
[244] A detailed overview of the exact cap for air traffic is included in Appendix F Table F.2.
[245] According to the 2019 AR of Lufthansa Group requires 0.870 allowances per 1000 cargo tonne-kilometers, or 870g per cargo tonne-kilometer (Lufthansa Group, 2020).
[246] Fast growing operators are operators increasing their activity by an average of more than 18% annually between 2010 and 2014 (European Parliament, 2015).
[247] Further information on CORSIA can be found in Appendix F.5.

In addition to the EU ETS, there are other national ETSs. These include the Swiss ETS, which has been applied to aviation since 2020 and is linked to the EU ETS since then. Flights from the EEA to Switzerland fall under the EU ETS and flights from Switzerland to the EEA are covered by the Swiss ETS (DEHSt, 2022). Since the United Kingdom (UK) left the EU, the UK is no longer part of the EU ETS. A UK ETS has already been formed and flights from the EEA to the UK are included in the EU ETS. The UK ETS includes flights from the UK to the UK, Gibraltar and the EEA (ICAP, 2022).[248]

Figure 5.5 shows the price development of EUAAs compared to EUAs in the period 2012 to 2019. The period was limited to this, as the data set to be considered in this work extends into 2019. Due to the decision to reduce the scope, no EUAAs were auctioned until 2014 and only for part of 2017, otherwise the prices for EUAAs behave very similarly to those of EUAs (Nissen et al. 2020), which have already been described.

Figure 5.5: The prices for EUA and EUAA are based on primary market data from auctions on the EEX and ICE trading platforms.[249] (extension based on Nissen et al. (2020))

[248] In addition, there are other ETSs outside the EU, but their description is beyond the scope of this paper. For more information on these systems, see `https://icapcarbonaction.com/en/ets-map` (ICAP, 2022).

[249] The straight lines in Figure 5.5 show the delays in auctioning in until 2014 and in 2017.

5.1.3 Environmental impact

There is no general consensus in the literature on which measures are best suited to reduce emissions. Some argue that ETSs and carbon taxes are the most efficient measures to reduce GHG emissions (Crespo and Wang, 2019; Larsson et al., 2019), while others regard them as a first step or complement to addressing aviation's contribution to reducing GHG emissions (Dessens et al., 2014). Regardless of the EU ETS, it is worth noting that the energy intensity of the US aircraft fleet decreased by 70% between 1970 and 2005, or about 3.5% per year (Schäfer et al., 2009). For a later period between 1990 and 2019, CO_2 emissions per RPK were found to decrease by a total of 53% or about 2.6% per year (Airbus Group, 2021).

The following section summarises the different opinions on the environmental impact of the EU ETS and its effectiveness, starting with the proponents. We then address the opposing views and conclude by looking at combinations of options for CO_2 reduction beyond the EU ETS.

Ellerman and Buchner (2008) estimated an annual reduction in emissions of 50 to 100 million tonnes CO_2 ($MtCO_2$), or 2.5% to 5%, compared to a scenario without the EU ETS, based on emissions data from 2005 and 2006. Similar results are reached by Vespermann and Wald (2011). They estimated a decrease of 3.9% in CO_2 emissions from aviation of between 2012 and 2016 and an overall decrease of 7.7% in CO_2 emissions from aviation by 2020 using a simulation based on the then draft of the EU ETS. They conclude that the inclusion of aviation in the EU ETS will initially only lead to small reductions in CO_2 emissions, but that these reductions will increase significantly in the long term, leading to the intended environmental benefits. However, in their opinion, these reductions are still not large enough so as to achieve the underlying policy goal of limiting the overall growth of air traffic. Based on their analysis of the impact of the EU ETS on Lufthansa, Vespermann and Wittmer (2011) agree with Vespermann and Wald (2011) that there will be modest reductions in the first years after its introduction, but a significant reduction in CO_2 emissions in the medium and long term. Ellerman and Buchner's (2008) conclusion is similar. Based on emission data from 2005 and 2006 they estimate annual reductions of 50 to 100 $MtCO_2$ emissions or 2.5% to 5% compared to a scenario without the EU ETS.

Looking back, Bayer and Alkin (2020) note that carbon markets in the EU are effective even when market prices are low. Their study is based on the notion that a carbon market can be effective if it can credibly communicate becoming more stringent in the future. In this case, companies can reduce their emissions even if market prices are low, which is why, according to them, low prices can signal weaker demand for carbon allowances. To

estimate whether the EU ETS has reduced carbon emissions, they estimate counterfactual carbon emissions using a sectoral emissions dataset. Compared to a world without the EU ETS, 11.5% fewer emissions were generated. They also find that the EU ETS saved about 1,200 $MtCO_2$ overall between 2008 and 2016, which is about 3.8% of total emissions in that period (Bayer and Alkin, 2020).

Fageda and Teixidó (2022), using the difference-in-differences method[250] on a sample consisting of all flights within Europe between 2010 and 2016, show that airlines reduced their CO_2 emissions by 4.7% under the EU ETS. An equally large reduction in flights (4.9%) suggests that the reduction in emissions was caused by a reduction in flights rather than, for example, increased aircraft efficiency. However, the reduction in emissions is significant for short-haul flights (10.7%) and LCCs (11%), but not for NLCs.

Within the literature, there are not only different opinions on the effectiveness of the EU ETS, but also on how to measure it. Fuss et al. (2018) distinguish between short-term annual emission targets and long-term cap and the associated decarbonisation of the relevant sectors. According to them, there is evidence that the short-term emission reduction targets have been achieved. However, this could also be due to economic recessions or overlapping instruments rather than a shift in investment towards long-term emission reductions and low-carbon energy.[251] They show that market and government distortions may have lowered the EUA price and affected the intertemporal efficiency of the EU ETS. Moreover they show that the price of the EU ETS is below what would be cost-effective in recent years, which contradicts the findings of Bayer and Alkin (2020) that even in times with low prices carbon markets are effective. Nissen et al. (2020), on the other hand, agree with Bayer and Alkin (2020). Based on data from the EU Transaction Log, they conclude that overall 35% of emissions have been saved since the start of the EU ETS, with the energy sector contributing the most to these reductions. They also find that historical emissions in 2019 are already 35% below 2005 levels, due to the sharp drop in emissions within the EU ETS between 2018 and 2019. They address the price fluctuations of EUAs, whereby these should be seen against the background of the steadily decreasing number of freely allocated emissions and various influences on industrial production. In 2019, the price of EUAs peaked at 29.15 EUR (32.6 USD), while the average price in 2019 was 24.72 EUR (24.6 USD). This in turn underlines the effectiveness of the EU ETS regardless of the price of allowances, as a steady decrease in CO_2 emissions can be observed despite fluctuating prices (Nissen et al., 2020). According to Perino and Willner (2017), this price increase is related to the debate on the reform of the EU ETS and the final decision on it. The expectation is that the number of available allowances would be reduced in the future,

[250] Further information on this method can be found in Roberts and Whited (2013).

[251] Such instruments could be, for example, the EU ETS and a carbon tax at national level.

which, usually leads to an increase in current prices. Other authors argue that the price increase can be explained by the restoration of market confidence in the maintenance of the EU ETS (Sheppard, 2018). Another explanation for the price increase of EUAs could be that the price is formed from short-term demand and supply and that the inclusion of allowances in the MSR leads to a shorter-term market with lower supply (Quemin and Trotgnon, 2021).

Next, we analyse studies on the hypothetical economic impact of including non-European airlines in the EU ETS, although non-European airlines have been excluded from the EU ETS.

For the period from 2012 to 2020, the economic effects of including US airlines in the EU ETS are examined by Malina et al. (2012). They assume a 4% annual increase in fuel and carbon prices and a 1.4% improvement in fuel efficiency, with an emission price of 15 EUR (19.9 USD) per tCO_2 in 2010, and examine four different scenarios. Two of these scenarios, 'Absorb', in which no costs are passed on, and 'Expense', in which only the costs incurred are passed on, do not lead to a clear result. The other two scenarios, 'Business-as-usual' (BaU) and 'Full', where all costs associated with CO_2 allowances, including the opportunity cost of free allowances, are passed on, produce a clear-cut. Malina et al. (2012) conclude that CO_2 emissions would increase by 35% in the BaU scenario, compared to 32% in the 'Full' scenario. They assume that airlines could achieve windfall gains of 2,600 million USD under this scenario due to the grandfathering of allowances. The small reduction in CO_2 emissions between the two scenarios above contrasts with the high abatement costs in aviation compared to other sectors.

According to Hofer et al. (2010), the introduction of a tax on carbon emissions for aviation leads to a reduction in emissions as the use of aircraft decreases. This decline in use may lead to increased use of alternatives such as the car, it puts about a third of the carbon emissions saved by aviation at risk. They were able to conclude that there are differences between short-haul and long-haul markets, where switching to the car is hardly possible. Maximum savings can be achieved by high tax rates for long-haul flights and low tax rates for short-haul flights, as this reduces the extent of substitution of air travel by car travel and the associated car emissions (Hofer et al., 2010). Within the literature, carbon taxes are mentioned as a possible alternative to ETSs. According to Wang et al. (2018), even with rapid gross domestic product (GDP) growth and low oil prices, the introduction of a high carbon tax would reduce CO_2 emissions by 9.7% in the most fuel cost-sensitive Asia-Pacific market and by 6.7% in the less sensitive European market.

Pagoni and Psaraki-Kalouptsidi (2016) follow a similar approach in their measurement of the impact of the EU ETS. They examine the impact of a hypothetical market-based environmental policy on US flights, where airlines have to pay a 'carbon fee' based on their CO_2 emissions. Their analysis suggests moderate changes: With a carbon price between 10 USD and 100 USD per tonne, average ticket prices would increase between 1.18% and 11.77% and average air travel demand would decrease between 2.36% and 20.94%. This would lead to a decrease in CO_2 emissions. They stress that this decrease should not be expected as a proportional reduction in CO_2 emissions as short-haul flights in particular compete with short-haul travel.

Within the literature, there are not only proponents of the effectiveness or benefits of the EU ETS in gerneral or of the inclusion of airlines in the EU ETS. Other studies have shown that under certain circumstances the opposite is true. For example, unilateral GHG emission regulations (e.g. the EU ETS) may lead to an increase in global GHG emissions if connecting flights between hub and spoke airports[252] are shifted from an emission-efficient home network to a less efficient foreign network. Furthermore, this could lead to greater negative impacts on affected than non-affected airlines, potentially leading to biased competition (Yuen and Zhang, 2011).

In their study, Boon et al. (2007) estimate an increase in average emissions of 5.1% per year between 2005 and 2010, 3.9% per year between 2010 and 2015, and 3.1% per year between 2015 and 2020 for flights within the EEA. Similar values (5.2%, 3.9% and 3.3%) are estimated for flights leaving the EEA for the same periods.[253] Against this background, technical, operational and volume options for emission reductions by airlines are identified. These include, for example, new engines for existing aircraft, replacing old aircraft with new ones, changing flight routes, increasing the load factor or reducing the number of *tonne-kilometer* transported. Based on their examination of different variants (BaU, Commission proposal and 100% auctioning, both with 100% pass-through of expenditure) of the policy with different prices per allowance of 15 EUR (18.8 USD) and 45 EUR (56.5 USD), they conclude that the reduction in Revenue Tonne Kilometers (RTKs)[254] for routes within the

[252]Most airlines today have at least one central airport, the so-called 'hub'. Passengers are then routed via this airport on the 'spoke' flights to their actual destinations (Brueckner et al., 1992).

[253]These values were verified against those provided by the European Environment Agency (EEA) for the years 2013-2019. The years 2020 and 2021 were not included due to the Corona pandemic (EEA: `https://www.eea.europa.eu/data-and-maps/dashboards/emissions-trading-viewer-1`, visited on 09/30/2022). This shows that the actual average growth between 2013 and 2015 is 5.18% and between 2015 and 2019 is 7.88%, showing that the estimates of Boon et al. (2007) are not entirely correct.

[254]It measures how much revenue a company generates per tonne of freight transported and corresponds to the revenue generated for transporting one tonne of freight over one kilometre.

EU is slightly smaller than the reduction in CO_2 emissions. From this, they derive an increase in the load factor and fuel efficiency (Boon et al., 2007).

Newell et al. (2014) report that the EU ETS has not been very efficient in the first phase. Certified emissions were well below their cap. As a result, many companies collected allowances and the price dropped significantly, which can also be seen in Figure 5.4. Therefore, the emissions from Phase I were no longer allowed to be used in Phase II.[255] As a result, the prices for derivatives on EUAs were significantly higher in Phase II than in Phase I. Another result of the high number of allowances allocated for free was that utilities passed on the non-existent cost of the free permits to customers (Ellerman et al., 2010). This meant that power plants charged their customers for the free allowances they received. The EC therefore reduced the freely allocated and increased the auctioned allowances. They conclude that the design of carbon markets thrives on experience and that there may be changes within ETSs over the years (Newell et al., 2014).

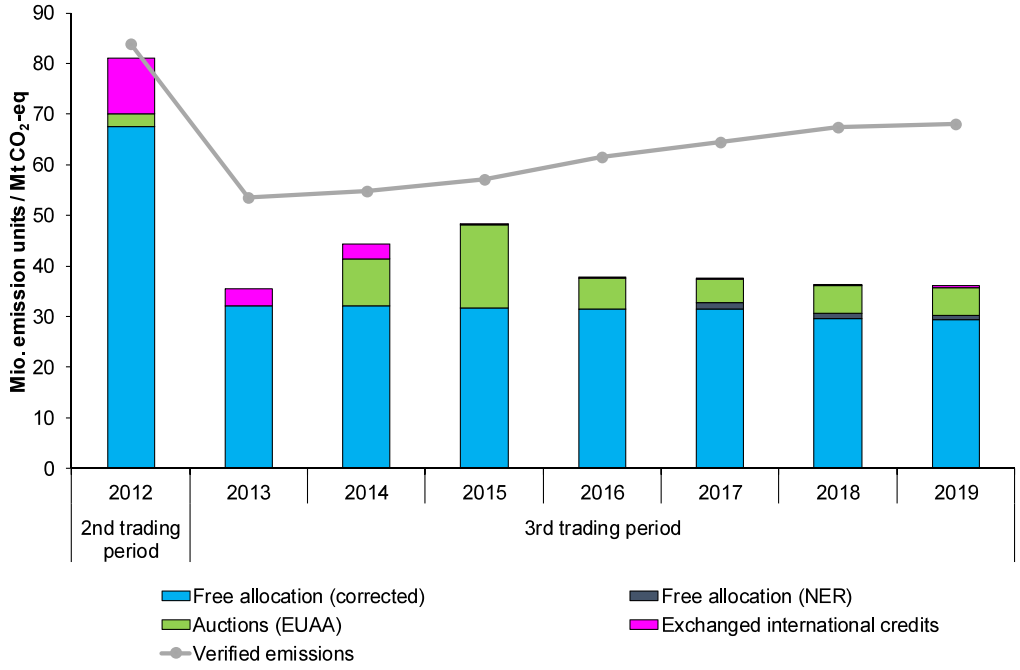
Some authors conclude that there will neither be a reduction in demand growth or carbon emissions nor an improvement in technology in the long term. Anger and Köhler (2010), for example, expect based on their literature review that carbon emissions will not decline due to the small number of emissions from aviation compared to the total number of emissions under the EU ETS and the expected costs after 2012. It is also likely that airlines will pass on the costs of both purchased and freely allocated allowances to customers. Using a dynamic simulation model, the impact of the EU ETS on CO_2 emissions is investigated by Anger (2010). Under different scenarios regarding the price of allowances and 100% cost pass-through, the EU ETS is found to cause a decrease of 0.3% for a low price of 5 EUR (6.6 USD) per tonne and 7.4% for a high price of 40 EUR (53 USD) per tonne in 2020, respectively. The author concludes that this is not high enough to bring about general changes in the aviation sector. Moreover, the competitiveness of the EU is not affected by the inclusion of the aviation industry in the EU ETS.

Nissen et al. (2020) focus on airlines included in the EU ETS and conclude that the total amount of verified emissions from airlines increased by 25% from 2013 to 2019 in contrast to what was already mentioned about the EU ETS in general. In this context, they explicitly mention Ryanair, as it is responsible for the largest share of verified emissions, and Wizz Air, as it shows the strongest growth. Other airlines like Lufthansa or British Airways, on the other hand, have a lower growth in the number of certificates required or even managed to reduce their emissions. In contrast to other sectors, emissions in aviation continue to rise every year due to the ever-growing demand. However, this means that demand for aviation allowances exceeds the number of aviation allowances available each year. Figure

[255] As mentioned in Chapter 5.1, the mechanism has been repeatedly adapted over time.

5.6 shows the composition of the emission allowances. In addition to the decreasing number of allowances freely allocated via the NER and the exchanged international credits, the constant quantity of freely allocated aviation emissions is apparent from this. It illustrates that the quantity of verified aviation allowances has exceeded them every year since 2012 (Nissen et al., 2020). As already mentioned, aviation has so far been allowed to use both types of allowances to comply with the regulation. The difference can therefore be explained by the purchase of EUAs (European Commission, 2020).

Figure 5.6: Demand and supply balance for aviation allowances, 2012-2019 [256] (Nissen et al., 2020)



To further explore different emission reduction targets, for example ICAO's so called '$2\%^{-1}$' target to improve fuel efficiency, Lee et al. (2013) have combined scenarios ranging from 'business-as-usual' to 'maximum feasible reductions' with, for example, operational improvements or different biofuel shares. Only combinations that include an expansion of existing regional market-based mechanisms could achieve this goal by 2050.[257]

[256] The decline in freely allocated emissions from 2012 to 2013 is due to the 'Stop-the-clock' decision; in addition, the allowances for the years 2013 to 2015 were therefore not auctioned until 2015 (Nissen et al., 2020).

[257] Such a combination consists of, for example, technological and operational advances and a regional

Even before the first drafts or the coming into effect of the EU ETS or the Kyoto Protocol, the energy intensity of aviation has been steadily improving. In the period from 1959 to 1995, it was reduced by about 57% through more efficient engines, 22% through aerodynamic improvements, 17% through increased aircraft capacity and 4% through other measures such as enlarged aircraft (Lee at al., 2001). This indicates that beyond the EU ETS or, for example, a carbon tax, there are other ways to minimise the CO_2 emissions of airlines and airplanes. These include for example the use of sustainable aviation fuels (SAFs) as well as improving the efficiency of aircraft technology, air traffic management and operational efficiency (Capoccitti et al., 2010). One possibility for such technological improvements would be, for example, the use of blended-wing aircraft or unducted-profan engines (Lee et al., 2009). Schäfer et al. (2009) assume a 30-50% decrease in CO_2 emissions per passenger kilometers travelled (PKT) of an average new passenger aircraft by the mid-2020s compared to early 2000s fleet emissions. At the fleet level, this decrease should be achieved by 2050, taking into account market growth, the retirement of older aircraft for conversion to cargo and natural fleet turnover.

Another example is the study of the most commonly used aircraft models for short- and long-haul flights by Grampella et al. (2017). They show that incremental technological progress is statistically significant for local and global pollution, with reductions of 1% and 0.1% to 0.3%, respectively. In addition to a fuel-efficient fleet, Miyoshi and Mason (2009) recommend higher load factors and denser cabin configurations to reduce carbon emissions per passenger kilometre.

Sgouridis et al. (2011) examine different measures to reduce CO_2 emissions so that they increase at a lower rate or at the same rate as transport. To find an efficient combination of such measures, they examine a combination of technological and operational efficiency improvements, as well as the use of alternative fuels, demand shifting and carbon pricing. For example, to achieve an 8% reduction in CO_2 emissions, one metric tonne of CO_2 would have to cost 200 USD. They conclude that no single policy is sufficient to achieve this by 2024. Rather, it is concluded that a combination of these improvement options would be needed. This is in line with Nava et al. (2018), who study the competitive effects of airlines' emission reduction efforts under the EU ETS. According to their findings, technological progress alone will not be able to offset emissions from the projected growth of the sector, even in the most optimistic scenario. Chèze et al. (2013) also argue that technological progress alone is not sufficient to offset the negative impact of aviation on the increase of CO_2 emissions in the medium term. In addition to initiatives by airlines and aircraft

market-based mechanism such as the EU ETS (Lee et al., 2013).

manufacturers, CO_2 emissions from aviation should be controlled by policy makers, which is why they advocated the inclusion of aviation in the EU ETS. A similar opinion is held by Becken and Mackey (2017), who point out that carbon offsets are an important part of climate mitigation in aviation, along with technological change and possible demand reductions. They argue that carbon offsets cannot reduce the amount of CO_2 in the atmosphere, so they can only be considered as a complement to the other measures.

The studies summarized so far have focused on ways to reduce CO_2 or measure reductions through the EU ETS, but there are also a small number of other relevant studies.

Liu et al. (2017) examine 12 Chinese airlines from 2007 to 2013 to identify the changes in the performance of the Chinese civil aviation sector and develop a carbon emission performance index. They show that 11.93 % of the improvements in airline carbon emissions are mainly due to technological advances, that there are differences in carbon emission performance between different types of airlines based on the ownership (central, local (both state-owned) and private & joint airlines (non-state-owned), but also a convergence of emission levels, and that route distribution is the most important determinant of emission performance. Ko et al. (2017) use a mathematical model to investigate effective strategies for airlines in terms of aircraft reallocation and route adjustment in the context of carbon constraints in the aviation industry. They find that airlines tend to use more efficient aircraft for short-haul flights and more inefficient aircraft for long-haul flights, thereby reducing the carbon emissions of inefficient aircraft and increasing those of efficient aircraft. A large part of the fuel is consumed during takeoff and landing, which means that fuel consumption is not proportional to distance. Against the backdrop of the EU ETS, they conclude that the number of carbon emissions is reduced, but profit suffers as well, which is why such a change in business operations would only take place with correspondingly high prices of carbon emissions allowances. Otherwise, airlines would simply buy carbon emission allowances at a low price. Sharma et al. (2021) use a fixed effects regression model to examine the three largest US NLCs over the period 2003-2019, identifying fuel cost per gallon, average airfare, EU ETS, average age, load factor and total departures as negative determinants of emissions, with only fuel cost per gallon and average airfare being significant. They can show a positive influence on emissions for total fuel cost, average stage length, aircraft size and RPM, with all variables except total fuel cost being significant. Grote et al. (2014) go one step further, they conclude that even if all available mitigation measures were used, there would be no absolute reduction in CO_2 emissions because the projected increase in demand for air travel is too high.[258] In their opinion,

[258] In 2014, ICAO forecast passenger numbers to increase from 3.3 billion to six billion in 2030 (ICAO, 2014).

this gap could only be closed by reducing the demand for air travel. Even if the indirect reductions through the EU ETS were included in the studies of Larsson et al. (2019), the reduction in carbon emissions would only be 0.8% per year. They do not assume that radical technologies such as fully electrified aircraft will lead to significant reductions in CO_2 emissions in the coming decades. Therefore, they recommend additional measures to achieve a faster impact.

5.1.4 Additional Costs caused by the EU ETS

In the following, we will take a closer look at the additional costs caused by the EU ETS. We will first look at sources that consider the price per allowance, the cost pass-through rate and finally additional cost sources such as fleet renewal.

Vespermann and Wald (2011) estimate the additional costs for 2012 due to emissions to be 0.92% for Air France-KLM, 0.82% for Lufthansa and 2.1% for British Airways, based on the cost structure of the respective airline. They conclude that the additional costs are unlikely to have a material adverse effect on the industry under these circumstances. Vespermann and Wittmer (2011) agree with them. They examine the financial, ecological and managerial influences of the EU ETS on Lufthansa as an example. They demonstrate a weaker influence of allowance prices than kerosene prices on the costs of airlines. Overall, they conclude that costs will increase less than in other industries such as the chemical industry.

Using the example of Italian Airlines for the years 2012 to 2016, Meleo et al. (2016) conclude that the direct costs of the EU ETS and the impact on passengers are quite limited at this stage. However, they predict that costs could increase from 2016 onwards, thus increasing the impact on air fares or revenues. They base their hypothesis on the one hand on the fact that the demand for certificates will increase again in the wake of the recovery after the economic crisis of 2008, and on the other hand on the fact that the surplus of allowances in the aviation sector will be fully absorbed after 2012.

Based on an empirical study of 12 European airlines for the years 2012 to 2014, Cui et al. (2017) examine the private costs of pollution reduction. For the two airlines Lufthansa and Norwegian it is shown that efficient aircraft and the use of biofuels can help to reduce emissions. Ryanair had the highest costs for reducing pollution, compared to the other 11 airlines, where pollution abatement costs show little difference, regardless of whether the effects of the EU ETS were taken into account or not. Furthermore, the comparison of pollution abatement costs before and after 2012 shows that these are higher for most airlines

after 2012. From this, the authors conclude that the regulations already in place have positive effects for most airlines, such as the introduction of newer aircraft. They conclude that controlling emissions could be more effective by linking them to other regulations.

Scheelhaase et al. (2010) examine two selected airlines, one from the US (Continental Airlines) and one from Europe (Lufthansa). In their model-based empirical study, they analyse the potential impact of the EU ETS on competition between European and non-European aircraft operators. They conclude that non-European NLCs with moderate emissions growth between 2006 and 2012 are likely to have a competitive advantage over European NLCs. The EU ETS-specific costs of European carriers will exceed the benefits of hub-and-spoke networks, despite possible improvements. Assuming that the opportunity costs of freely allocated allowances are fully passed on and that the price per allowance on the market is 20 EUR (26.4 USD), they estimate that the price increase for long-haul flights will be a moderate 10 to 13 EUR (13.25 to 17.2 USD) and that demand for long-haul flights will decrease by about 2%.

Considering the two different airline types, Frontier Economics (2006) predicts that with rising costs due to the EU ETS (CO_2 prices of 27-40 EUR (37.0-54.8 USD)) and a price elasticity of demand of -1.5, there will be a 7.5% to 12% decline in demand for LCCs and 2% to 3% for NLCs. NLCs have a large share of price inelastic business travellers. However, not all business travellers are price inelastic, so some may switch from NLCs to LCCs.

In their report on the challenges and implications arising from a stricter EU ETS for aviation, Nelissen et al. (2021) conclude that due to the increasing share of emission allowance auctions and the expected higher CO_2 prices (by up to 120 EUR (141.5 USD)), there could be an increasing cost of up to 10 EUR (11.8 USD) per passenger per flight in the EEA segment. They argue that this could lead to shifts of an unknown proportion of aviation demand and activity to destinations outside the EEA or to routes via hubs outside the EEA, causing a carbon leakage.

To investigate the impact of the EU ETS on passenger demand and ticket prices, Albers et al. (2009) focus on selected routes covered by the EU ETS. In order to do so they compare these routes with routes that use a stopover outside the EU ETS but otherwise have the same origin and destination. In their study they conclude that a price of 20 EUR (27.8 USD) per tonne CO_2 could result in additional costs of between 1.47 EUR (2.0 USD) and 26.79 EUR (37.3 USD) per trip per passenger. This implies that individual airlines could come under pressure on certain routes, but that major route changes are unlikely to occur. In their opinion, the additional costs due to the EU ETS should be seen in relation to other cost factors. The calculated additional surcharge of 20 EUR (27.8 USD)

per passenger on a Lufthansa flight from Singapore to Frankfurt should be considered in relation to the cost of 77 EUR (107.1 USD) per passenger for the current fuel surcharge (Albers et al., 2009).

Another aspect of the aviation industry's inclusion in the EU ETS is that barriers to entry have been raised for new entrants. By allocating allowances free of charge, the established market participants do not pay their full social costs on the one hand, but on the other hand there can be considerable distortions of competition. For this reason, some authors recommend auctioning all certificates, as it is already the practice for energy-intensive plants (Barbot et al., 2014).

Within the literature, yet another way is used to examine the impact of the EU ETS, which is done by a cost pass-through rate. The authors justify this approach by the fact that the airlines try to pass on the rising costs to the passengers (Boon et al. (2007); Scheelhaase and Grimme (2007); Giradet and Spinler (2013) and Wang et al. (2017)). Based on the proposed trading scheme, Boon et al. (2007) conclude in their study that a cost pass-through rate of 47.3% is achieved, also assuming that competition between airlines changes as a result of the introduction of the EU ETS.

Scheelhaase and Grimme (2007) use empirical estimates to examine potential costs and travel demand of four different types of European airlines under three different scenarios for an ETS. The scenarios differ e.g. in the price per allowance, the allocation method or the flights included in the trading scheme. Their research shows that the economic consequences for airlines depend mainly on the design of the trading system. In general, they conclude that the financial impact on airlines included in the trading scheme will be relatively moderate, with NLCs likely to be less affected financially. Furthermore, they point out that the inclusion of aviation in the EU ETS is likely to lead to competitive effects.

Giradet and Spinler (2013) develop a model based on dynamic programming to calculate this surcharge for air travel depending on the costs of kerosene and CO_2. The model shows a significantly higher cost increase for routes with low elasticity than for routes with high elasticity. The cost pass-through of long-haul and short-haul flights results in significantly higher price increases for long-haul flights. This contrasts with the results of Meleo et al. (2016) for Italian airlines. They conclude for the years 2013-2015 that even with a cost pass-through of 100%, the impact on fares and revenues is still limited with a maximum increase of 0.23% for fares and 0.24% for revenues.

Wang et al. (2017) show that besides the EU ETS, there are other emission reduction

measures. The comparison of these and their impact on passengers show that there are not only differences between the individual measures, but also between regions. Due to the high cost pass-through of fuel costs per passenger, emission reduction measures that involve an increase in the airline's fuel costs, such as fuel taxes, would have the greatest impact on passengers. From a regional perspective, passengers in the Asia-Pacific region would be most affected. Measures based on route charges - the EU ETS is classified as such a measure - and landing fees for aircraft would have the smallest impact on passenger prices (Wang et al., 2017).

In addition to the already mentioned possibilities for checking the additional private costs, the possibilities of fleet renewal or technological progress should not be neglected. These can also help to minimise the additional costs caused by GHG emissions. For example, the study by Schäfer et al. (2016) on the cost-effectiveness of CO_2 emission reductions in narrow-body aircraft shows that at least 75% of the potential to reduce CO_2 emissions is associated with negative or zero marginal costs. Airline operating strategies, almost all technology options and all aviation measures are shown to be cost-effective (Schäfer et al., 2016).

It seems a natural thought in terms of operating cost to renew the fleet to reduce fuel consumption and CO_2 emissions. Fleet renewal makes sense in terms of carbon costs, especially if the fleet is renewed after the monitoring period.[259] Airlines could have flown as many kilometres as possible during this period to get more emission credits. However, this strategy requires high investments and a lot of time (Miyoshi, 2014). An economic analysis modelling both the EU ETS and CO_2 emissions shows that the use of more efficient aircraft increases and the use of less efficient aircraft decreases, which leads to the conclusion that more passengers are carried in equilibrium and fewer GHG emissions are produced (Malavolti and Podesta, 2015).

Wei and Hansen (2003) develop an econometric cost function for aircraft operating costs and find that there are economies of scale for both aircraft size and stage length (distance flown). For any given stage length, there is an optimal aircraft size that increases with stage length.

Using the capital cost function per aircraft, Czerny (2015) shows that airlines react differently to fuel price changes. Possible reactions are changes in ticket prices, investments in more fuel-efficient aircraft technology and adjustments in aircraft size. They can demonstrate for both fixed aggregate passenger demand and elastic aggregate passenger

[259] This means using a high emitting fleet during the monitioring period, which in the case of the EU ETS was used to calculate the emission allowance benchmark, and then using a lower emitting fleet to reduce CO_2 emissions (Miyoshi, 2014).

demand that, in particular, an increase in fuel price tends to increase equilibrium aircraft size when it is easier to increase fuel efficiency for larger aircraft. Thus, it can also be shown that airlines tend to use larger aircraft on long-haul routes to take advantage of economies of scale, but also because the cost of fuel in the air increases and the potential for fuel cost savings increases with aircraft size. Another result is that the distributional effects of fuel price changes and emissions levies can work in opposite directions. In particular, if aircraft size in the equilibrium decreases and load factors increase as fuel costs increase, fuel price increases can weaken competition and lead to an increase in the equilibrium profit of airlines (Czerny, 2015). In terms of aircraft size, Brueckner and Abreu (2017) agree with Czerny (2015) that the use of larger aircraft reduces fuel consumption and carbon emissions. They conclude that a reduction in delays would also reduce fuel consumption and carbon emissions. By estimating the impact of fuel prices on airline fuel consumption, they were able to estimate how many emissions could be saved by introducing an optimal emissions levy that increases the price of fuel. The calculated reduction of 2.2% should only be understood as a short-term effect, as aircraft efficiency and size are fixed. Among the larger, long-term effects of such a levy would be a faster shift to fuel-efficient aircraft and a likely increase in aircraft size.

Brueckner and Zhang (2010) use a theoretical model of competing duopoly airlines to examine the impact of emissions charges on fares, service quality, aircraft design and network structure. They show that emission charges increase fares, load factors and aircraft fuel efficiency, reduce flight frequency, while having no impact on aircraft size.

Comparing three types of aircraft (turbopop, regional jet and narrowbody jet), Ryerson and Hansen (2010) show that determining the minimum cost of operating an aircraft is heavily sensitive to fuel prices and passenger costs[260]. They also address other private costs dependent on fuel consumption, such as environmental costs. The consideration of an additional tax, such as the carbon tax, shows that airlines should consider environmental and fuel savings when selecting their fleet. Ryerson and Hansen (2013) set up two operating cost models for jet aircraft in order to model air transport costs and investigate the impact of fuel price on airline operating strategies. The finding suggests that a reduction in fuel consumption and the resulting reduction in emissions can be achieved primarily through up-gauging[261] as well as through new and advanced technologies.

[260] 'Passenger costs include travel time costs (flying time differences and schedule penalties) and the perceived disutility of flying on turboprops (relative to jets).' (Ryerson and Hansen, 2010, p.306)

[261] A technical term in the aviation industry describing the increase in airline capacity by adding to existing aircraft and replacing smaller aircraft with larger ones (National Academies of Science, Engeneering, and Medicine, 2019, p.1),

5.1.5 Other Influences

In addition to studies on the impact of the EU ETS on emissions and marginal costs, the literature includes studies on the impact of the EU ETS or other techniques to reduce CO_2 emissions on e.g. passenger demand, renewable fuel or air fares.

For the period before the inclusion of aviation in the EU ETS 2008 to 2012, Li et al. (2016) examine 22 international airlines in their data envelopment analysis (DEA).[262] Overall, airlines increased their efficiency during this period, with European airlines being significantly more efficient than non-European airlines. These results are independent of whether GHG emissions are weakly or strongly disposed.[263] Chinese airlines stand out in that their overall average efficiency is below the average of the entire sample. For the same period, Cui and Li (2015) empirically analyse 11 international airlines. Based on the average CO_2 emission reduction index per unit of capital, they conclude that high capital efficiency has a significant impact on an airline's energy efficiency, with the average energy efficiency of the four Chinese airlines included being below the average of the whole sample. Similar to Li et al. (2016), Merkert and Hensher (2011) use a two-stage DEA approach to evaluate the operational performance of 27 European airlines between 2000 and 2005. They conclude that both demographics in the airline's home country and membership in an alliance network influence airline efficiency.

Morrell (2009) investigates the impact of using larger aircraft on short-haul and long-haul flights on increasing fuel and emissions efficiency in the European market. The results show an overall positive correlation between aircraft size, fuel efficiency and emissions reduction. On long-haul flights, there seems to be less scope for emissions reduction through aircraft size alone (and even less through higher seat density). The situation is different for short- and medium-haul flights with single-aisle aircraft, where efficiency gains are more likely. Merkert and Hensher (2011) agree with the results and find a positive relationship between aircraft size and, in particular, allocative efficiency and cost efficiency. For this purpose, they evaluate the determinants of 58 passenger airlines' efficiency for the two financial years 2007/2008 and 2008/2009 using a two-stage DEA approach.[264] They find that all three efficiency measures (technical, allocative and cost) are significantly negatively affected by a larger number of aircraft families. Airlines with a small number or only one aircraft family therefore have relatively high efficiency overall. The age of the fleet plays

[262] DEA is a 'data-driven' approach to evaluate the performance of a group of peer units. These units are also called decision-making units (DMUs) and convert multiple inputs into multiple outputs (Cooper et al., 2011).

[263] GHG emissions are considered undesirable outputs here, which is why they are considered under weak and strong disposability.

[264] None of the airlines considered in the sample went into administration.

a minor role in comparison, as a young fleet does not necessarily lead to higher efficiency. Applying a similar approach to data from 49 international airlines in 2005, Barbot et al. (2008) find that LCCs tend to be more technically efficient than NLCs because of their business model. Another conclusion is that airlines from regions with a uniform regulatory structure are more uniform in their productivity. Like Morell (2009), Morrison et al. (2012) study single-aisle aircraft. Using a game-theoretic analysis, they show how manufacturers' incentives to innovate can be altered by subsidies, technology-enhancing regulations, higher effective fuel costs, the threat of new entrants and long-term competitive strategies. They measure the impact of possible technological advances on reducing CO_2 emissions. Improvements to existing aircraft of one type lead to an annual reduction in fuel intensity of 1%, retrofitting an aircraft leads to a one-time improvement in fuel efficiency of up to 15%, and a completely new aircraft can potentially lead to an improvement of 25%. Schäfer et al. (2016) agree that the greatest potential for saving CO_2 lies in technical options for aircraft with about 50% and in air traffic management measures as well as airline operating strategies with 20% each.

Other aspects to consider when using alternatives to conventional kerosene include greater resource constraints, much poorer handling and storage of the fuel, compatibility issues with existing fuel infrastructure or long lead times before a significant market share can be achieved. For this reason, only first-generation biofuels have a chance of achieving a significant market share by 2030.[265] The reduction in GHG emissions from the use of these fuels is likely to be less than 10%. After 2030, second-generation biofuels are expected to lead to a more significant reduction in GHG emissions.[266] A prerequisite for this is that these fuels can be produced at an acceptable cost. Their biggest obstacle will be the land available for growing biomass feedstock (Schäfer et al., 2009).

The opposite conclusion is reached by Strategy& (2022), they showed that even a high share of SAF would not lead to significantly higher costs compared to fossil kerosene.[267] However, LCCs are more affected by the SAF cost premium due to the higher fuel cost share and price-sensitive passengers. Without additional costs for CO_2, a price increase of kerosene is likely, which is why SAF will become increasingly important. In their opinion, the improvement of existing aircraft technology plays an important role, but these

[265] First-generation biofuels for aviation here mean biodiesel or vegetable oils blended with jet fuel (Schäfer et al., 2009).

[266] Second-generation biofuels for aviation here mean biomass-to-liquids (BTL). BTL means the conversion of biomass and municipal solid waste into biofuels, where the conversion uses the entire crop (whatever that may be) as both a feedstock and a source of process energy (Schäfer et al., 2009).

[267] The cost premium for SAF here refers to the comparison of the costs of SAF with those of fossil kerosene (Strategy&, 2022).

improvements will soon reach their technical limits, which is why the use of SAF will also play an important role here.

Using a two-stage least squares method for seven major US airlines, Sibidari et al. (2018) find that an increase in fuel costs reduces total passenger demand. Furthermore, they find that airlines adjust their flight frequency and aircraft size in response to fluctuations in passenger demand and fuel costs. In this context, higher passenger demand is associated with smaller aircraft and higher flight frequencies, while higher fuel costs are associated with larger aircraft and less frequent flights. Givoni and Rietveld (2009) agree with Sibidari et al. (2018) and conclude that airlines increase flight intensity rather than aircraft size when demand is higher. This is in contrast to the results of the three-stage least squares analysis by Pitfield et al. (2012). The econometric results of the British Airways analysis on certain routes between the UK and the US suggest that adjustments in aircraft size are more important than adjustments in frequency as demand increases. Similar to the study by Sibidari et al. (2018), Lu (2009) investigated the impact of environmental costs on passenger demand for the two different airline business models, NLCs and LCCs, using six different European short-haul flights with two city pairs. The conclusion of this study is that Easyjet is more affected by a potential percentage decrease in passenger demand than the two NLCs due to the lower fares of LCCs despite lower environmental costs per passenger.

In contrast, Gössling et al. (2012) conclude in their survey paper that current climate change mitigation measures in the aviation sector are likely to not have an impact on international tourism demand. They conclude that there is no evidence that there would be even a moderate impact on tourism demand in the immediate future due to climate change mitigation measures for international aviation.

Forsyth (2009) looks at the potential impact of climate policy on competition, prices and profitability in the aviation industry. Voluntary offsets, route optimisation, fleet renewal, operational savings at airports, alternative fuels and engine development are mentioned as ways to reduce CO_2. Reducing emissions will increase airline costs, and these costs will be passed on to customers, which in turn will affect demand. Long-haul and short-haul flights are equally affected and competition will not change in the short term. In the long term, individual exits are possible on certain routes in competitive markets, markets with slot restrictions at airports or capacity constraints are not affected, with the remaining airlines being able to raise prices and restore profitability by reducing competition. Forsyth also concludes that free permits could be treated by airlines as purchased permits, thus changing the cost structure of airlines, making the ETS less efficient and

keeping fares below marginal social costs.

Hu et al.(2018) investigate the hedging behaviour of airlines with regard to CO_2 emissions. According to them, operational hedging should be promoted more as it has a positive impact on aircraft emissions compared to financial hedging. Financial hedging can have an additional negative impact on fuel efficiency, as a successful financial fuel hedging strategy encourages airlines to continue using it instead of using more fuel-efficient aircraft and reducing fossil fuel consumption. Policy measures such as a carbon tax or a cap-and-trade system could also make operational improvements more attractive than financial improvements, for example by encouraging the introduction of new technologies. Their theoretical model shows that the introduction of a carbon tax makes financial hedging less attractive and operational hedging more attractive (Hu et al., 2018).

The literature does not only evaluate the EU ETS with regard to how effective it is in reducing CO_2 emissions, but its function as a role model, too. Presten et al. (2012) believe that the EU ETS can be seen as a model or signpost for a global solution and that the true value of this policy may not lie in the effective reduction of CO_2 emissions. Efthymiou and Papatheodorou (2019) conclude that the EU does not have sufficient regulatory powers to impose rules on non-EU countries and airlines. The EU ETS should, in their view, address climate change holistically once ICAO has fully implemented CORSIA in the early 2030s.

5.2 Hypotheses

Hypothesis 1a (H1a): 'The level of aircraft emissions was higher before the aviation industry was included in the EU ETS than afterwards.'
Ellerman and Buchner (2008) estimated an annual reduction in emissions of up to 5% compared to a scenario without the EU ETS. In line with this, Verspermann and Wittmer (2011) and Verspermann and Wald (2011) assume that there will be significant reductions in the medium and long term following the introduction of the EU ETS.

Hypothesis 1b (H1b): 'The intensity of aircraft emissions has increased overall.'
Boon et al. (2007) estimate an increase in emissions from flights within the EEA of up to 5.1% between 2005 and 2010, 3.9% between 2010 and 2015 and 3.1% between 2015 and 2020. Nissen et al. (2020) find an overall increase in verified emissions of 25% between 2013 and 2019, which is due to a higher increase in demand than a decrease in emissions.

Hypothesis 2a (H2a): 'Financial hedging has a negative impact on the level of aircraft emissions.'
According to Hu et al. (2018), financial hedging can also have a negative impact on fuel efficiency and thus indirectly on aircraft emissions. A successful financial fuel hedging strategy can encourage airlines to continue using it instead of using more fuel-efficient aircraft, which can be seen as an operational hedge.

Hypothesis 2b (H2b): 'Operational hedging has a positive impact on the level of aircraft emissions.'
Hu et al. (2018) suggest that operational hedging should be promoted more strongly, as it could potentially have a positive impact on aircraft emissions by using more fuel-efficient aircraft and thus reducing fuel consumption.

5.3 Empirical Analysis

In the following subsection, the univariate and multivariate analysis with CO_2Asm as the dependent variable are presented. In contrast to the previous analyses, the year 2019 can be partially taken into account. If the variable under consideration or the regression model is not or does not contain a variable that is affected by the changes in accounting standards, the year 2019 is taken into account.

5.3.1 Univariate Analysis

Table 5.1 shows the tests for mean differences between airlines that are covered by the EU ETS and those that are not. Except for CO_2Rpm and $S3Em_$, none of these differences are significant. The value of CO_2Rpm is significantly higher (at the 1% level) for airlines not covered by the EU ETS. This could be interpreted to mean that airlines that are covered by the EU ETS emit less CO_2 per passenger mile sold than airlines that are not covered by the EU ETS. The significant difference (at the 5% level) for $S3Em_$ could indicate that airlines not covered by the EU ETS emit less Scope 3 emissions. Due to the otherwise insignificant differences, there are no further indications of differences between airlines that are covered by the EU ETS and those that are not.

Table 5.1: Difference-in-means test of the variables relevant to airlines included the EU ETS ($euetsDm = 1$) and not included ($euetsDm = 0$))

	EU ETS		non-EU ETS		t-Test		
variable	mean	N	mean	N	diff.	SE	N
$CO_2Tl_$	14.744	102	13.300	277	−1.445	1.026	379
CO_2Chg	0.036	87	0.046	241	0.011	0.008	328
CO_2Rpm	193.304	112	223.712	266	30.105***	5.080	378
CO_2Asm	180.908	96	177.966	279	−2.942	3.567	375
$S1Em_$	14.633	63	12.790	255	−1.843	0.984	318
$S2Em_$	0.073	42	0.086	213	0.013	0.007	255
$S3Em_$	3.032	40	1.630	117	−1.402**	0.301	157

p< 0.10 :*, p< 0.05 :**, p< 0.01 :***

Variables ending with '_' are denoted in millions

In Table 5.2, variables related to emissions are compared for airlines covered by the EU ETS before the airline industry was included and afterwards. The differences for $CO_2Tl_$ and CO_2Rpm are not significant. Additionally, the value of $CO_2Tl_$ is higher before aviation was included in the EU ETS, which could be interpreted as a rejection of H1a.

The difference for CO_2Asm is significantly different at the 1% level with the value being higher before the inclusion. This result could as well be interpreted as a rejection of H1b, as it indicates an overall decrease of intensity of emissions emitted by aircraft. Figure 2.36 supports this result as well as it indicates an overall decrease of CO_2Asm for all subgroups besides LCCs.

Table 5.2: Difference-in-means test of the variables relevant to airlines included the EU ETS after they were included in the EU ETS ($timeDm = 1$) and before ($timeDm = 0$))

	after		before		t-Test		
variable	mean	N	mean	N	diff.	SE	N
$CO_2Tl_$	15.2665	62	13.936	40	−1.329	1.816	102
CO_2Chg	0.053	56	0.003	31	−0.050***	0.013	87
CO_2Rpm	185.375	64	203.875	48	18.499	8.849	112
CO_2Asm	170.469	56	195.475	40	25.005***	5.848	96

p< 0.10 :*, p< 0.05 :**, p< 0.01 :***

Variables ending with '_' are denoted in millions

In Table 5.3 the same is done as in Table 5.2 for airlines not covered by the EU ETS. Again the difference of CO_2Asm is significantly (at the 1% level) lower after airlines were included in the EU ETS. In addition the difference of CO_2Rpm is significantly (at the 1% level) lower after the EU ETS was introduced, resulting in a possible rejection of H1b as well. These significant differences could also be due, for example, to higher fuel efficiency in the aviation industry in general. In order to test for such influences, further analyses are included in the multivariate analysis. The difference of $CO_2Tl_$ is again not significantly different with the value before the inclusion being slightly higher.

In Table 5.4, selected financial and operational hedging variables are included for airlines covered by the EU ETS and ones not covered by it.

The variables for the decision to hedge with fuel derivatives and for the extent of hedging are significantly higher (at the 1% level) for airlines covered by the EU ETS, which indicates that airlines covered hedge more and to a greater extent. The same holds for *fxdvDm* and *irdvDm*.

The age of the aircraft fleet, both fleet diversity measures and the dummy *fDiv1AgeDm* are significantly lower for airlines covered by the EU ETS. These results indicate that airlines covered by the EU ETS have a younger and more homogeneous fleet. The variables *acOlcashDm* and *acOlPct* are both significantly higher for airlines covered by the EU ETS,

Table 5.3: Difference-in-means test of the variables relevant to airlines not included the EU ETS after it was established ($timeDm = 1$) and before ($timeDm = 0$))

	after		before		t-Test		
variable	mean	N	mean	N	diff.	SE	N
$CO_2Tl_$	13.243	197	13.438	80	0.195	0.822	277
CO_2Chg	0.050	183	0.034	58	−0.016	0.008	241
CO_2Rpm	213.110	188	249.267	78	36.157***	5.514	266
CO_2Asm	172.689	199	191.095	80	18.407***	3.672	279

p< 0.10 :*, p< 0.05 :**, p< 0.01 :***

Variables ending with '_' are denoted in millions

indicating a higher percentage of aircraft under operating lease and simultaneously a higher cash ratio. The dummy variable for alliance affiliation and both variables for operating leasing are not significantly different.

Table 5.4: Difference-in-means test of selected variables for airlines included in the EU ETS ($euetsDm = 1$) and not included ($euetsDm = 0$)

	EU ETS		non-EU ETS		t-Test		
variable	mean	N	mean	N	diff.	SE	N
fdvDm	0.968	187	0.689	726	−0.279***	0.021	913
fdvPct12m	0.542	167	0.249	624	−0.293***	0.020	791
fxdvDm	0.968	185	0.551	726	−0.417***	0.022	911
irdvDm	0.701	187	0.562	726	−0.139***	0.038	913
acAge	7.920	146	8.814	537	0.894***	0.263	683
acOlcashDm	0.260	146	0.178	454	−0.082**	0.036	600
acOlPct	0.511	146	0.385	454	−0.126***	0.023	600
alliDm	0.513	187	0.446	737	−0.067	0.041	924
fDiv1	0.616	169	0.692	606	0.076***	0.024	775
fDiv2	0.460	169	0.527	606	0.067**	0.025	775
fDiv1AgeDm	0.191	136	0.312	513	0.121***	0.034	649
fDivNet	0.156	169	0.164	606	0.009	0.011	775
olexpRev	0.070	177	0.077	688	0.006	0.005	865
*olexpTl_*	366.679	177	381.085	688	14.406	33.240	865

p< 0.10 :*, p< 0.05 :**, p< 0.01 :***

Variables ending with '_' are denoted in millions

For the variables *acOlcashDm*, *acOlPct*, *plexpRev* and *olexpTl_* the year 2019 is not considered due to the changes in accounting standards concerning operational leasing.

As the differences in the mean value tests could also result from the geographical location of the airlines[268], Table F.5 is included in Appendix F.3. No significant changes can be recognised between the two tables.

5.3.2 Multivariate Analysis

The variable CO_2Asm is used as the dependent variable in the following multivariate analysis to analyse the relationship between the ratio of CO_2 emitted and ASM of the individual airlines to the independent variables of the models. As for the independent variables, all variables included in the dataset and in previous already mentioned studies (see Chapters 3 and 4) were considered. Following the previous procedure, the function *regsubsets* was used to determine the explanatory power of each independent variable and subsets of independent variables. An iterative process based on the previous empirical analyses was then carried out to use the most suitable composition of independent variables for the base model. For subsequent models, variables of particular interest were added as appropriate.

Table 5.5 shows six OLS models with airline fixed effects for airline specific, financial hedging and underinvestment variables. The basic framework consists of the variables *divDm, divYld, cashRto, cashRtoSqr, capAs, mtbRto* and *lf* and is contained in all models. In the first model the coefficient of *capAs* is positive and significant (at the 10% level), while the other coefficients are not significant. The difference between the first two models is that model (2) takes year effects into account. These are taken into account in all further models, as they influence the significance of the coefficients, R^2 increases and the AIC value decreases. The significance of *capAs* is reduced from the 10% level to not significant.

Model (3) includes *fdvDm* in order to test whether the decision to hedge with fuel derivatives influences the amount of CO_2 emitted per ASM. The coefficient of *fdvDm* is negative and significant at the 5% level, which can be interpreted as support for H2a. In addition, the coefficient of *lf* is positive and significant at the 10% level. Compared to this, model (4) includes *fdvPct12m* to test the influence of the extent of hedging with fuel derivatives. The coefficient is negative and significant at the 1% level, implying that the extent of financial fuel hedging influences CO_2Asm negatively, which can be interpreted as support for H2a. The coefficients of *cashRto* and *cashRtoSqr* are both significant at the 10% level, being negative and positive, respectively. Model (5) combines the influence of *fdvDm, fxdvDm* and *irdvDm* in order to check whether the use of more than one type of financial hedging instrument has an influence. Only the coefficient of *irdvDm* is negative

[268] From the airlines covered by the EU ETS all are located within the EU. From the airlines located within Europe only Aeroflot and Cyprus Airways are not covered by the EU ETS.

and significant at the 1% level, which indicates that the use of interest rate derivatives is associated with a negative impact on CO_2 emitted per ASM. Again, the coefficient of *lf* is positive and significant at the 10% level. In addition, the coefficients of *divDm* (negative) and *capAs* (positive) are significant at the 10% level. The negative significance of *irdvDm* and insignificance of *fxdvDm* are not changed when *fdvDm* is excluded in model (6). To summarise, these results can be interpreted as support for H2a: Both the decision to hedge and the extent of the hedge appear to be associated with negative effects. The same seems to hold for the usage of interest rate derivatives.

For robustness reasons, tables containing the same models as in Table 5.5 are included in Appendix F.4, where each table includes one variable connected to financial hedging and where the models are calculated for different geographical regions (AM, AS and EU) and business models[269]. Table F.6 includes the models with *fdvDm*, from which can be seen that the negative and significant (at the 5% level) coefficient is not robust, besides for NLCs only, where the coefficient is negative and significant at the 10% level. The basic framework is generally not robust, as the significances and directions of the influences change for each subset and each added variable.

Table F.7 contains the results for *fdvPct12m*, where the significance of the coefficient is negative and significant at the 1% level only for the whole sample. For the other subsets, the significance is not robust, but the coefficient is still negative, which can be seen as support for H2a. As for *fdvDm*, the basic framework is not robust concerning the directions of the coefficients and its significances.

For the variables *fxdvDm* and *irdvDm* (see Table F.8), the results are robust for American airlines and NLCs. Again, the basic framework is not robust.

The AIC value decreases noticeably for all models that only consider regional subsets or the subset consisting only of LCCs. This raises the question on whether there exist regional strategies.

Table 5.6 includes the same basic model, consisting of *divDm, divYld, cashRto, cashRtoSqr, capAs, mtbRto* and *lf*, as Table 5.5, but the added variables are operational hedging variables. Models including variables connected to operating lease exclude the year 2019, as the accounting standards for operating leases have been changed from the financial year 2019 onward.[270] Model (1) is again the basic model including year dummies and it is not robust to the inclusion of any of the operational hedging variables. Models

[269] Due to the number of observations, the regression could not be successfully performed for all subgroups for all financial or operational hedging variables.

[270] This affects models (3), (4), (7) and (8). For further information see Subsection 2.2.3.

Table 5.5: Airline fixed effects model for variables related to financial hedging

	Dependet variable: CO_2Asm					
	(1)	(2)	(3)	(4)	(5)	(6)
divDm	−3.294	−3.387	−4.143	−1.773	−4.517*	−4.234
	(2.760)	(2.663)	(2.596)	(2.788)	(2.581)	(2.601)
divYld	4.127	−3.603	−5.443	−3.054	−1.127	−0.502
	(25.019)	(21.010)	(21.014)	(18.789)	(22.746)	(22.696)
cashRto	−5.865	−10.785	−13.640	−38.430*	−11.263	−14.131
	(13.515)	(13.935)	(17.975)	(20.637)	(17.628)	(18.354)
cashRtoSqr	6.245	7.978	13.274	23.311*	10.285	11.361
	(6.469)	(6.679)	(11.194)	(12.850)	(10.902)	(11.288)
capAs	40.162*	32.488	34.394	39.424	46.977*	46.770*
	(24.221)	(24.915)	(25.011)	(27.994)	(26.792)	(26.922)
mtbRto	−0.497	−0.428	−0.471	−0.465	−0.435	−0.420
	(0.325)	(0.339)	(0.330)	(0.331)	(0.331)	(0.327)
lf	−30.896	87.256	101.994*	94.174	114.642*	112.407*
	(37.326)	(59.206)	(58.093)	(59.415)	(58.818)	(59.113)
fdvDm			−12.154**		−6.440	
			(5.529)		(5.406)	
fdvPct12m				−20.010***		
				(5.446)		
fxdvDm					1.270	0.356
					(7.136)	(7.072)
irdvDm					−11.319***	−12.906***
					(4.031)	(3.875)
Year dummies	No	Yes	Yes	Yes	Yes	Yes
N	362	362	357	302	357	357
R^2	0.891	0.904	0.905	0.899	0.908	0.907
Adjusted R^2	0.874	0.884	0.885	0.874	0.887	0.887
AIC	3110.239	3092.147	3047.910	2569.849	3042.377	3041.976

*p<0.1; **p<0.05; ***p<0.01
Robust standard errors in parentheses
Variables ending with '_' are denoted in millions

(2) to (4) include *acAge, acOlcashDm* and *acOlPct* as additional variables, for which the coefficients are all insignificant, which can be interpreted as rejection of H2b.

When *alliDm* is added in model (5), the coefficient itself is again not significant, which can be interpreted as a contradiction to H2b. Model (6) includes the two fleet diversity measures, with *fDiv1* having a positive and significant coefficient at the 1% level and *fDiv2* having an insignificant coefficient. This indicates that a more diversified fleet positively influences CO_2Asm and can be interpreted as support for H2b, while more switching costs do not seem to influence the emitted CO_2Asm. The coefficient of *fdv1AgeDm* in model (7) is not significant. Model (8) contains the two variables concerning the amount of operating leasing, with both coefficients being not significant. To summarise, the results for H2b can be interpreted as contradictory, with one exception: fleet diversity appears to have a positive effect on the emissions emitted per ASM. All other operational hedging variables seem to have no impact.

Again for robustness reasons, Appendix F.4 incorporates further tables concerning each operational hedging variable. The basic framework is not robust for the inclusion of operational hedging variables. Table F.9 includes the models for *acAge*, where the coefficient of *acAge* is not significant in any of the models. The same holds for the variables *acOlcashDm* (Table F.10) and *acOlPct* (Table F.11).

The results for *fDiv1* and *fDiv2* (Table F.12) are robust for Asian airlines. For American airlines, both coefficients are significant with the coefficient of *fDvi1* being positive and significant at the 1% level and for *fDiv2* being negative and significant at the 10% level. For European airlines and NLCs, neither one of the coefficients is significant. For *fDiv1AgeDm* in Table F.13, the result is again robust for all subsets, besides that of American airlines, where the coefficient is negative and significant at the 5% level.

The results for *olexpRev* and *olexpTl_* (Table F.14) are robust and not significant for all subsets, besides for Asian airlines only, where the coefficient of *olexpTl_* is positive and significant at the 5% level.

5.3.3 Limitations

The number of observations should be taken into account here, similar to the number of observations for operational hedging. The dataset itself consists of 924 firm years. Due to missing variables, the maximum number of observations of the airline fixed effects model is 362. The minimum of the models is 268, when *acOlcashDm* is included and the year 2019 is excluded due to changes in the accounting standards. When robustness checks are taken into account, the minimum decreases to 61 for the model where *fdvDm* is included

Table 5.6: Airline fixed effects model for variables related to operational hedging

	Dependet variable: CO_2Asm							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
divDm	−3.387	−3.029	−4.494	−4.402	−3.439	−2.536	−3.484	−4.423
	(2.663)	(2.686)	(3.156)	(3.182)	(2.676)	(2.717)	(2.802)	(2.821)
divYld	−3.603	−22.130	38.250	38.904	−3.786	−18.777	−21.626	36.880
	(21.010)	(16.611)	(32.602)	(32.255)	(21.022)	(21.386)	(16.941)	(27.772)
cashRto	−10.785	−22.994	−28.167	−25.748	−11.305	−29.803*	−25.360	0.713
	(13.935)	(22.763)	(23.456)	(23.303)	(14.703)	(15.875)	(23.164)	(14.162)
cashRtoSqr	7.978	20.887	20.435	19.179	8.162	25.509***	20.897	2.290
	(6.679)	(13.835)	(14.173)	(14.096)	(6.881)	(8.720)	(13.915)	(6.534)
capAs	32.488	30.573	27.456	26.351	33.057	16.945	30.025	19.999
	(24.915)	(30.388)	(30.571)	(30.215)	(25.814)	(24.060)	(31.454)	(23.363)
mtbRto	−0.428	−0.456	−0.357	−0.354	−0.425	−0.524	−0.446	−0.459
	(0.339)	(0.339)	(0.394)	(0.406)	(0.341)	(0.348)	(0.340)	(0.440)
lf	87.256	102.190	78.084	66.302	87.754	209.373***	92.166	63.844
	(59.206)	(64.652)	(70.488)	(67.099)	(59.802)	(66.964)	(67.274)	(55.327)
acAge		1.401						
		(1.233)						
acOlcashDm			−2.303					
			(4.319)					
acOlPct				−7.580				
				(12.704)				
alliDm					1.751			
					(7.262)			
fDiv1						147.098***		
						(20.023)		
fDiv2						−19.525		
						(13.636)		
fDiv1AgeDm							−3.147	
							(3.491)	
olexpRev								−57.351
								(46.774)
*olexpTl_*								0.005
								(0.008)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	362	293	268	268	362	325	285	328
R^2	0.904	0.901	0.885	0.885	0.904	0.912	0.899	0.910
Adjusted R^2	0.884	0.876	0.856	0.856	0.883	0.892	0.874	0.888
AIC	3092.147	2505.649	2291.905	2291.913	3094.117	2737.274	2442.635	279.993

*p<0.1; **p<0.05; ***p<0.01
Robust standard errors in parentheses
Variables ending with '_' are denoted in millions

for LCCs only. In addition to the absolute number of observations, it should also be noted that approximately 80% of these observations were made between 2010 and 2019, which should be taken into account as the dataset is unbalanced in terms of the availability of emission information in the early years compared to the later years. It should also be noted that approximately 47% and 45% of European and American airlines provided sufficient data to be included in the models in these analyses, while only about 26% of Asian airlines provided the required data.

Regarding general limitations, these have already been discussed in Subsection 3.3.4 and limitations concerning financial and operational hedging variables have been discussed in Subsections 3.3.4 and 4.3.3.

In view of the problem of omitted trends and unobserved differences when comparing two different groups, a difference-in-difference analysis[271] was considered. The analysis did not yield a single significant variable, which is why these are not discussed or presented in more detail.

The values for R^2 are very high in almost all models, with few to no significant variables. This raises the question of overfitting of the model and multicollinearity. However, the collinearity tables in the appendix do not show any particularly conspicuous values for the variables contained in the models.

The limitations concerning the variable CO_2Asm connected to aircraft emissions should nevertheless be discussed here. The main limitation is the availability. $CO_2Tl_$ is available in 387 firm years (41.84%). 15 of these values were available in the Thomson Reuters Database but neither in the ARs nor SRs. Due to the small number of observations, the results of the statistical tests should be treated with caution. A study over a longer period with more data points would be advisable in order to reach more general conclusions.

One idea for further research would be to combine variables relating to financial and operational hedging. Similar to Chapter 4, conclusions could be drawn as to whether the two hedging methods complement or substitute each other.

[271] More information on the difference-in-differences analysis can be found in Roberts and Whited (2013).

5.4 Results

As far as the author is aware, aircraft emissions have not yet been analysed on the basis of data from ARs or similar reports, which is why no direct reference studies are available to which the results could be compared.

Looking at the results for H1a, the univariate analysis shows that the total amount of CO_2 is not significantly lower following the inclusion of the aviation industry in the EU ETS. This result is independent of whether the airlines included (see Tabe 5.2) or not included (see Table 5.3) in the EU ETS are considered. When analysing total emissions, it should be noted that ASM increased by 104.11% during the observation period, which is associated with an increase in emissions.

Concerning H1b, the univariate analysis as well as Figure 2.36 show that the intensity of emissions decreased during the sample period. For airlines covered by the EU ETS, CO_2Asm is significantly higher before the ETS was introduced and for non EU ETS airlines, CO_2Rpm and CO_2Asm are significantly higher before 2012.

This is on the one hand in contrast to Ellerman and Buchner (2008), Vespermann and Wald (2011) and Vespermann and Wittmer (2011) for the total amount of emissions but in line with the results for the relative amount of emissions, which all estimated an annual reduction of at least 2.5% and up to 5% for airlines covered by the EU ETS. For airlines not covered by the EU ETS the opposite is true, as the total amount of emissions is lower (not significantly) after 2012, which could be a result of generally increased efficiency (Li et al., 2016) or of more efficient aircraft (Morrison et al., 2012).

With regard to H2a, both the results for the decision to hedge and for the extent of hedging can be interpreted as support for H2a, as the coefficients are negative and significant in both cases (see Table 5.5). These results are only robust for the decision to hedge and when only NLCs are considered; in all other cases, the coefficients are negative but not significant. These results are in line with Hu et al. (2018), who suggest a potential negative impact of financial hedging on aircraft emissions.

Concerning operational hedging, the suggested positive influence by Hu et al. (2018) can only be seen in the positive and significant coefficient of *fDiv1* (see Table 5.6), with the results of *fDiv1* being robust for American and Asian airlines only (see Table F.12). The coefficients for the other variables on operational hedging are not significant.

6 CONCLUSION

Jet fuel costs are of great importance to airlines as they account for up to 20% of total operating costs and are highly volatile (Carter et al., 2006).[272] To hedge these costs, airlines have two options: financial hedging, i.e. the use of derivatives on underlying assets that are correlated with jet fuel, or operational hedging, which includes operating a diversified fleet, alliance membership or operating leasing of aircraft. Although all airlines in the sample are exposed to jet fuel price risk, their hedging behaviour varies greatly. Some hedge a relatively constant percentage of their jet fuel consumption over the entire period, others change their hedge ratio over time and still others do not hedge at all, which is why the hedging behaviour of the airlines included in the sample is examined in this paper. In this context, the relation of financial and operational hedging on the CO_2 emissions of airlines is also analysed, as this is of increasing interest to airlines in light of the inclusion of aviation in the EU ETS since 2012 and the introduction of CORSIA.

The sample consists of 78 airlines from 39 countries and covers the period between 2005 and 2019, resulting in 924 firm observations. For a more detailed description of the data, the sample is divided by region (Africa, America, Asia, Europe and Oceania) and by business model (low-cost and network legacy carriers). The dataset is hand-collected. The data collection process itself and the variables are explained in detail for better comprehensibility. In order to exclude outliers, the dataset is winsorised at the 1% and 99% level for the univariate and multivariate analyses. In addition, variables such as leverage are lease-adjusted, as 98.62% of the airlines use operating leases.[273]

The descriptive analysis shows that fuel costs for NLCs are on average 25.7% higher than those of LCCs, even though jet fuel is a frequently traded commodity. The regional differences show that fuel costs for Asian airlines are on average 30.51% higher than for American airlines and 21.17% higher than for European airlines. The fuel consumption of Asian and NLCs is higher than that of European and American airlines or LCCs. The

[272] During the study period, the price fluctuated between 33 and 198 USD per barrel.

[273] Due to the changes in accounting standards from 2019, this percentage is only based on the years 2005 to 2018.

data on the hedging behaviour of the individual airlines depends heavily on the respective ARs, and it is noticeable that American airlines are the most consistent.[274] The average hedge ratio for the next 12 months of the whole sample is 29.05%, with the highest average hedge ratio in 2014 being at 35%. European airlines have the highest average hedge ratio during the whole period with an average of 50.86%, while American airlines have an average of 20.19%, closely followed by Asian airlines with 19.76%. The most frequently used instruments are options and swaps with jet fuel and crude oil as underlyings. The average maturity of these contracts decreases from 22 months in 2005 to 18 months in 2019. Airlines slightly reduce their fleet diversity by decreasing the first measure of fleet diversity, which refers to the number of different aircraft models, by 0.56% and the second measure of switching costs by 15.31%. LCCs have the lowest fleet diversity. The average net measure of fleet diversity increases by 70.72%, which can be interpreted from the comparatively small change from the first to the second fleet diversity measure as meaning that operational flexibility is hardly changed, while increasing conversion costs are accepted. Relative CO_2 emissions compared to ASM decrease during the sample period. Asian airlines record the sharpest decline, but still have the highest values in all sample years.

The multivariate analysis for financial and operational hedging consists of Probit models with random effects and OLS regressions with fixed effects in relation to the dependent variables, whether the decision to hedge and its extent. The multivariate analysis regarding CO_2 emissions consists of OLS regressions with fixed effects regarding the relative CO_2 emissions to ASMs.

The results of the multivariate analysis in relation to financial hedging cannot confirm a positive relationship between leverage and the use of fuel price derivatives. On the contrary, for highly leveraged airlines, the results indicate a non-linear convex relationship between leverage and the use of derivatives, which is in contrast to Purnanandama (2008), who assumes a non-monotonic relationship. An explanation for these results could be that airlines use fuel derivatives as insurance against fluctuating fuel prices regardless of their financial position, or that the share of fuel costs in an airline's operating costs and their volatility is high. In both cases, airlines with low leverage have the financial ability to take derivative positions to hedge their financial position in the future and protect their ability to fulfil pre-agreed purchase commitments (Carter et al., 2006; Pfefferle, 2019). With regard to the underinvestment problem, the results of the multivariate analysis are mixed. Concerning the decision to hedge and its extent, the coefficients of Tobin's Q are

[274] A comparison of the availability of the percentage of fuel consumption hedged for the next 12 months shows that it is available for American airlines in 95.26% of cases and for all others in 74.03%. The SEC amended its reporting requirements for the use of derivatives in 1997 (Jin and Jorion, 2006). In comparison, there are no precise disclosure requirements in Europe for the use of derivatives in annual financial statements (de Ceuster et al., 2000).

not significant on the one hand and positive and significant on the other, which is consistent with the results of Carter et al. (2006). In contrast, the coefficients of the other variables relating to growth opportunities and capital expenditure are not significant. Based on these results and the negative effect of leverage on the amount of jet fuel hedged, Carter et al. (2006) argue that airlines facing higher costs of financial distress ideally choose a lower leverage ratio. Since underinvestment costs are a subset of the costs of financial distress, companies with higher productivity and greater investment opportunities have a higher loss of value in the event of distress (Carter et al., 2006). In line with this, Tobin's Q is less than one in about 27% of firm years, suggesting that airlines with higher leverage and lower Tobin's Q hedge less. Both the decision to hedge and the extent of hedging are positively influenced if interest rate and foreign exchange derivatives are held in addition to the fuel derivatives, whereby the association of the interest rate derivatives is more robust in all robustness tests.

As far as the influence of fleet diversity on the hedging behaviour of airlines is concerned, neither the univariate nor the multivariate analysis can support the hypothesis that fleet diversity and financial fuel hedging are substitutes. Rather it suggests that they complement each other. The fact that operational hedging is more effective in the long term and less restrictive in terms of instruments and that financial hedging is more flexible in the short term suggests that airlines use both (Huchzermeier and Cohen, 1996; Van Mieghem, 2003; Kim et al., 2006). The univariate analysis of operational hedging shows that alliance membership is not a substitute for financial hedging, as there is a significant difference, with hedgers having the higher value. Compared to non-alliance members, alliance members have a lower leverage ratio while having a higher hedge ratio (not significant) and higher probability to hedge, confirming the negative correlation between leverage and hedging. Due to their business model, LCCs are not members of strategic alliances. To further investigate alliance members only, LCCs were not included in a further analysis. The significance of the hedging variables does not change, while the significance of the leverage ratio increases to the 1% level with non-alliance NLCs having the lower value. These results can be supported by the multivariate analysis as the dummy for alliance membership is neither significant for the decision to hedge nor for the extent of hedging. Since alliance NLCs have a higher lease-adjusted interest coverage ratio and a lower lease-adjusted leverage ratio, arguments based on the cost of financial distress could be the explanation for these results in the univariate analysis if the airlines were selected as members of alliances based on their financial security and are more inclined to engage in hedging transactions. This is in line with the findings by Pfefferle (2019). Both the univariate and the multivariate analysis show that the business model has no influence on

hedging behaviour.

The results relating to the inclusion of airlines in the EU ETS indicate that the total amount of CO_2 emitted was not reduced, but the relative value in terms of available seat miles is significantly lower after airlines were included in the EU ETS. This applies to both included and non-included airlines. Financial hedging appears to negatively influence the decision to hedge and the extent for the whole sample and NLCs, while it shows no significant influence for the other subsets. In turn, only the first fleet diversity measure appears to have a positive and significant impact on the emissions in relation to ASM. According to Hu et al. (2018), a successful financial hedging strategy may encourage airlines to continue pursuing them instead of pursuing a more fuel-efficient strategy that can be achieved through operational hedging, which is why they suggested a negative relation between financial hedging and emissions and a positive one for operational hedging.

With the small number of observations in mind and the already mentioned possible study over a longer period, the developments relating to the EU ETS should also be taken into account. According to Ehlers et al. (2022), prices for intra-European flights will increase significantly due to the 'Fit-for-55' package compared to the changes resulting from CORSIA. This may lead to a decline in demand within Europe. For intercontinental connections, on the other hand, passengers could switch to cheaper routes via non-European airports, which would not save CO_2 emissions, but merely shift them (so-called 'carbon leakage') (Ehlers et al., 2022).

In order to analyse the robustness of the results above, the independent variables of the base models were exchanged for various alternative variables. In addition, a merger dummy was used in the robustness analyses to control for growth caused by mergers and acquisitions. Due to the different accounting standards, the regressions were also carried out for samples containing only airlines that prepare their accounts in accordance with IFRS or US GAAP. Regressions relating only to the Americas, Asia and Europe and to the two business models were also included in the robustness analysis.

APPENDIX

A List of abbreviations

AA	Aviation Allowance
AF	Africa
AM	Americas
AR	Annual Report
AS	Asia
ASK	Available Seat Kilometer
ASM	Available Seat Mile
BTL	Biomass-To-Liquids
CO_2	Carbon Dioxide
CO_2e	Carbon Dioxide Equivalent
CDM	Clean Development Mechanism
CER	Certified Emission Reduction
CEO	Chief Executive Officer
CNY	Renminbi Yuan
CORSIA	Carbon Offsetting and Reduction Scheme for International Aviation
CPA	Capacity Purchase Agreement
CSR	Corporate Social Responsibility Report Unit
DEA	Data Envelopment Analysis
DMU	Decision-Making

EDGAR	Electronic Data Gathering Analysis And Retrieval System
EEA	European Economic Area
EEX	European Energy Exchange
ERU	Emission Reduction Units
EU ETS	European Union Emission Trading Scheme
EU	Europe
EUA	EU Emission Allowance
EUAA	EU Aviation Allowance
EU ETS	European Union Emission Trading Scheme
EUR	Euro
FPA	Fuel Pass-Through Agreement
g	gram
GAAP	Generally Accepted Accounting Principles
GBp	Great Britain Pence
GBP	Great Britain Pound
GDP	Gross Domestic Product
GHG	Greenhouse Gas
HHI	Herfindahl Concentration Index
IAG	International Airlines Group
IAS	International Accounting Standard
IATA	International Air Transport Association
ICAO	International Civil Aviation Organization
ICE	Intercontinental Exchange
IFRS	International Financial Reporting Standard
ISIN	International Securities Identification Number
ISO	International Organization for Standardization
IPE	International Petroleum Exchange

JI	Joint Implementation
kg	kilogram
LCC	Low-Cost Carrier
LF	Load Factor
MBM	Market-Based Measure
MSR	Market Stability Reserve
Mt	Million Tonnes
MTB	Market-To-Book
$MtCO_2$	Million Tonnes of Carbon Dioxide
$MtCO_2e$	Million Tonnes of Carbon Dioxide Equivalent
NER	New Entrants Reserve
NLC	Network Legacy Carrier
NM	Nautical Miles
NPV	Net Present Value
NYMEX	New York Mercantile Exchange
NZ	New Zealand
OC	Oceania
PKM	Passenger Kilometer
PKT	Passenger Kilometers Traveled
PV	Present Value
RASM	Revenue per Available Seat Mile
RPK	Revenue Passenger Kilometer
RPM	Revenue Passenger Mile
RTK	Revenue Tonne Kilometer
tCO_2	Tonne of Carbon Dioxide
tCO_2e	Tonne of Carbon Dioxide Equivalent
TNAC	Total Number of Allowances in Circulation

SAF	Sustainable Aviation Fuel
SD	Standard Deviation
SEC	Security and Exchange Commission
SIC	Standard Industrial Classification
SR	Sustainability Report
Std.	Standard
UK	United Kingdom
U.S.	United States of America
USD	United States Dollar
USG	United States Gallon
WTI	West Texas Intermediate
YEN	Japan Yen

B Data Description

B.1 Complete List of Variables included in the Analyses

Table B.1: Complete List of Variables included in the Analyses. (extension based on Pfefferle (2019))

Variable	Label	Description
acAge	Average age of aircraft fleet	Average age of 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 ($acAge_{t-1}$ + 1 + new number of aircraft x 0.5) / *acTl*.
accDate	Accounting date	End of financial reporting period from annual report
accStd	Accounting standard	Accounting standard used
*acChg**	Percentage change in the number of aircraft	Year-on-year percentage changes in the number of aircraft in an airline's operating fleet
acFl	Number of aircraft under finance lease	Number of aircraft under finance lease (=financial lease, capital lease) if reported in the AR
acOl	Number of aircraft under operating lease	Number of aircraft under operating lease if reported in the AR
*acOlcashDm**	Low cash, high operating leased aircraft dummy variable	Dummy, one if the airline's annual cash ratio is below the annual average cash ratio and its annual percentage of aircraft under operating leasing is above the annual sample average.
*acOlPct**	Percentage of operating lease aircraft	Percentage of aircraft in airline's operating fleet under operating leasing, calculated as *acOl* / *acTl*
acOw	Number of owned aircraft	Number of owned aircraft if reported in the AR
acTl	Total number of aircraft	Total number of aircraft in operating fleet 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 text of the AR.
aEmEU	Allocated emissions by the EU	Freely allocated emissions for the airline by the EU (`https://www.eea.europa.eu/data-and-maps/data/european-union-emissions-trading-scheme-17`, visited on 04/15/2020)
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 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.

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Variable	Label	Description
alliOne	Oneworld dummy	Dummy, one if the airline is a member of Oneworld
alliSky	Skyteam dummy	Dummy, one if the airline is a member of Skyteam
alliStar	Star Alliance dummy	Dummy, one if the airline is a member of Star Alliance
asCrt	Current assets	Total current assets as reported in balance sheet
*asmChg**	Percentage change in ASM	Year-on-year percentage changes in the available seat miles
asmTl	Available seat miles (ASM)	Total number of available seat miles per year; either disclosed in the AR or calculated as i) *rpmTl* / *lf* ii) *revTl* / *rasm* iii) the number of flights multiplied with the average stage lenth (*lgtAvg*) iv) *fuelExp* divided by fuel costs per ASM v) *fuelCons* / *fuelConsAsm* vi) available seat kilometers (ASKs) / 1.852
asTl	Total assets	Total assets as reported in balance sheet
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*

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Variable	Label	Description
capAsAdj7	CAPEX scaled by total assets adjusted by operating lease expenses 7	Calculated as *capNetAdj7 / asTlAdj7*
capAsAdj8	CAPEX scaled by total assets adjusted by operating lease expenses 8	Calculated as *capNetAdj8 / asTlAdj8*
capexIn	Capital expenditure (inflow)	Capital expenditure as reported in cash flow statement under cash flow from disinvestment activities (cash inflow) - Excluding: dividends received, financial assets and increase in cash in connection with mergers
*capexNet**	Capital expenditure (net)	Calculated as *capexOut + capexIn* (-) means a net capital expenditure (cash outflow) (+) means an inflow
capexNetAdj1	Capital expenditure (net) adjusted by operating lease expenses 1	Calculated as *capexNet + olexpPv1Chg* (yearly absolute change in *olexPv1)* For missing values, assume that the absolute change equals zero as not to lose to many observations
capexNetAdj5	Capital expenditure (net) adjusted by operating lease expenses 5	Calculated as *capexNet + olexpPv5Chg* (yearly absolute change in *olexPv5)* For missing values, assume that the absolute change equals zero as not to lose to many observations
capexNetAdj6	Capital expenditure (net) adjusted by operating lease expenses 6	Calculated as *capexNet + olexpPv6Chg* (yearly absolute change in *olexPv6)* For missing values, assume that the absolute change equals zero as not to lose to many observations
capexNetAdj7	Capital expenditure (net) adjusted by operating lease expenses 7	Calculated as *capexNet + olexpPv7Chg* (yearly absolute change in *olexPv7)* For missing values, assume that the absolute change equals zero as not to lose to many observations
capexNetAdj8	Capital expenditure (net) adjusted by operating lease expenses 8	Calculated as *capexNet + olexpPv8Chg* (yearly absolute change in *olexPv8)* For missing values, assume that the absolute change equals zero as not to lose to many observations
capexOut	Capital expenditure (outflow)	Capital expenditure as reported in cash flow statement under cash flow from investing activities (cash outflow) - Including: capital expenditure for PPE, investment in joint venture, purchase of non-current assets, tangible and intangible assets, payments for advances for new aircraft, investment in associated firms, increase in lease prepayments, acquisition of equity method investments, increase in equipment purchase deposits, acquisition of subsidiary - Excluding: purchase of financial assets and available-for-sale securities

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Variable	Label	Description
*capRev**	CAPEX to sales ratio	Calculated as *capexNet / revTl*
capRevAdj1	CAPEX to sales ratio adjusted by operating lease expenses 1	Calculated as *capexNetAdj1 / revTl*
capRevAdj5	CAPEX to sales ratio adjusted by operating lease expenses 5	Calculated as *capexNetAdj5 / revTl*
capRevAdj6	CAPEX to sales ratio adjusted by operating lease expenses 6	Calculated as *capexNetAdj6 / revTl*
capRevAdj7	CAPEX to sales ratio adjusted by operating lease expenses 7	Calculated as *capexNetAdj7 / revTl*
capRevAdj8	CAPEX to sales ratio adjusted by operating lease expenses 8	Calculated as *capexNetAdj8 / revTl*
*capSize**	CAPEX scaled by firm size	Calculated as *capexNet / size*
capSizeAdj1	CAPEX scaled by firm size adjusted by operating lease expenses 1	Calculated as *capexNetAdj1 / sizeAdj1*
capSizeAdj5	CAPEX scaled by firm size adjusted by operating lease expenses 5	Calculated as *capexNetAdj5 / sizeAdj5*
capSizeAdj6	CAPEX scaled by firm size adjusted by operating lease expenses 6	Calculated as *capexNetAdj6 / sizeAdj6*
capSizeAdj7	CAPEX scaled by firm size adjusted by operating lease expenses 7	Calculated as *capexNetAdj7 / sizeAdj7*
capSizeAdj8	CAPEX scaled by firm size adjusted by operating lease expenses 8	Calculated as *capexNetAdj8 / sizeAdj8*
cashChg	Change in cash and cash equivalents	Calculated as *cashEq(t+1) - cashEq / cashEq*

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Variable	Label	Description
cashEq	Cash and cash equivalents	Cash and cash equivalents as reported in balance sheet (or in the notes) - Excluding: restricted cash and deposits for lease agreements
cashRev	Cash to sales ratio	Calculated as *cashEq / revTl*
*cashRto**	Cash ratio	Calculated as (*cashEq + mktSec) / liaCrt*
casm	Cost per ASM	Total amount of operating costs per available seat mile as stated in AR or calculated as *opExp / asmTl*
CO_2Tl	Total amount of CO_2 in tonnes	Total amount of CO_2 in tonnes per year either taken from AR, CSR or SR. If not available in one of the mentioned reports is is calculated as - *S1Em + S2Em + S3Em*
CO_2Chg	Percentage change of CO_2 emissions	Calculated as ($CO_2Tl(t)$ - $CO_2Tl(t-1)$) / $CO_2Tl(t-1)$
CO_2Pkm	CO_2 emissions per passenger kilometer	CO_2 emissions per passenger kilometer in gram taken from AR, CSR or SR
CO_2Rpm	CO_2 emissions per revenue passenger kilometers	CO_2 emissions per RPM either taken from AR, CSR, SR or calculated as $CO_2Tl \times 100{,}0000$ / *rpmTl*
CO_2Asm	CO_2 emissions per ASM	CO_2 emissions per ASM calculated as $CO_2Tl \times 100{,}0000$ / *asmTl*
*costDbt**	Cost of debt	Calculated as *rfRate + spreadAvg*
cpaDm	CPA dummy	Dummy, one if variable 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.
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.
ctryEuEts	Country of EU ETS	Country for emissions allocation within the EU ETS
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
divTl	Total amount of dividend payment	Calculated as *shrTl * divShr*
*divYld**	Dividend yield	Calculated as *divShr / shrEnd*

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Variable	Label	Description
*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 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 has negative *eqtyTl* in that reporting period
eqtyTl	Total equity	Book value of total equity as reported in balance sheet
EuaaAP	EU Aviation Allowances Price	Cost per allowance in the allocated country calculated as $\sum$ (allowance price of respective auction x number of allowances sold in respective auction) / # of auctioned allowances for respective year (if e.g. EU and DE were allocated both geographical areas were taken into account)
euEtsDm	EU ETS dummy	Dummy, one if the airline is established in the EEA territory, covered by the EU ETS and/or regularly operates in the EEA territory (if the verified emissions of the airline within the EU ETS represent more than 15% of the total verified emissions of the airline), zero otherwise.
*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 the airline
fDiv1AgeDm	Combined fleet diversity and aircraft age dummy variable	Dummy, one if the airlines' fleet diversity measure is above the annual sample average and simultaneously the age of the airlines' fleet is above the annual sample average
*fDivNet**	Combined fleet diversity measure	Calculated as *fDiv1* - *fDvi2*
fdvAs	Fair value of fuel derivatives (asset)	Fair value of outstanding fuel derivative contracts (asset) as reported in balance sheets (notes), including current and non-current portion
fdvCo	Underlying crude oil dummy	Dummy, one if airline used crude oil as the underlying
fdvCol	Fuel collar dummy	Dummy, one if airline used fuel collar as derivative instrument
fdvDi	Underlying diesel oil dummy	Dummy, one if airline used diesel oil (=gasoil) as underlying

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Variable	Label	Description
fdvDm	Fuel derivative dummy	Dummy, one if the airline had outstanding fuel derivatives at 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, one is assigned. Including: hedge derivatives, derivatives held for trading
fdvFut	Future fuel contract dummy	Dummy, one if the airline used future fuel contracts
fdvFwd	Forward fuel contract dummy	Dummy, one if the airline used forward fuel contracts
fdvHo	Underlying heating oil dummy	Dummy, one the if airline used heating oil as underlying
fdvJf	Underlying jet fuel dummy	Dummy, one if the airline used jet fuel as underlying
fdvLia	Fair value of fuel derivatives (liability)	Fair value of outstanding fuel derivative contracts (liability) as reported in balance sheets (notes)), including current and non-current portion
fdvMtr	Fuel derivatives maturity	Maximum maturity in months of outstanding fuel derivative contracts
fdvMtrChg	Change in fuel derivatives maturity	Year-on-year percentage changes in fuel derivatives maturity
*fdvNet**	Net fair value of fuel derivatives	Net fair value of outstanding fuel derivative contracts, calculated as *fdvAs* – *fdvLia*
fdvNm	Nominal amount of fuel contracts	Total nominal amount of fuel derivative contracts outstanding at year end in USG
fdvOpt	Fuel option dummy	Dummy, one if the airline used fuel options
fdvPct12m	Hedge percentage for next 12 months	Percentage of the next 12 months expected fuel consumption hedged, either reported in- or outside the notes in the AR or calculated as (*fdvNm* x *(12 / fdvMtr*)) / $fuelCons_{t+1}$
fdvPct12mChg	Change in hedge ratio for next 12 months	Year-on-year percentage changes in the hedge ratio for the next 12 months
fdvPct24m	Hedge percentage for the next 13-24 months	Percentage of the next 13 to 24 months expected fuel requirements hedged (excluding the months 1 to 12)
fdvPct36m	Hedge percentage for the next 25-36 months	Percentage of the next 25 to 36 months expected fuel requirements hedged (excluding the months 1 to 24)
fdvPct48m	Hedge percentage for the next 37-48 months	Percentage of the next 37 to 48 months expected fuel requirements hedged (excluding the months 1 to 36)
fdvSpr	Fuel spread dummy	Dummy, one if the airline used fuel spreads (=refining margin swaps)
fdvSwp	Fuel swap dummy	Dummy, one if the airline used fuel swaps

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Variable	Label	Description
fdvUg	Underlying unleaded gasoline dummy	Dummy, one if the airline used unleaded gasoline as underlying
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 by ASMs iii) lagged nominal amount of fuel contracts outstanding (*fdvNm*) divided by the lagged fuel percentage hedged for the expected fuel consumption in the following 12 months (*fdvPct12m*)[275] 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 the text, i.e. 'consumption increased by X%' vi) fuel expense (*fuelExp*) divided by average fuel price per USG vii) *fuelExpAsm* × *asmTl*
*fuelConsAsm**	Fuel consumption per ASM	Calculated as *fuelCons* / *asmTl*
fuelExp	Fuel expenses	Total fuel expenses as reported in income statement (or notes), net of hedging gains or losses
*fuelExpAsm**	Fuel expense per ASM	Calculated as *fuelExp* / *asmTl*
*fuelExpUSG**	Fuel expense per USG consumed	Calculated as *fuelExp* / *fuelCons*
fxdvDm	Foreign exchange derivative dummy	Dummy, one if the airline had outstanding foreign exchange rate derivatives at year end (e.g. cross currency swap)
ibd	Interest bearing debt	Interest bearing debt as reported in balance sheet (or in the notes) - Including: loans, financial leases, bonds, debentures, notes payable Other short and long-term liabilities are only included if the relevant items include 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 1	Calculated as *ibd* + *olexPv1*
ibdAdj2	Interest bearing debt adjusted by operating lease expenses 5	Calculated as *ibd* + *olexPv5*
ibdAdj3	Interest bearing debt adjusted by operating lease expenses 6	Calculated as *ibd* + *olexPv6*

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

Variable	Label	Description
ibdAdj4	Interest bearing debt adjusted by operating lease expenses 7	Calculated as *ibd* + *olexPv7*
ibdAdj5	Interest bearing debt adjusted by operating lease expenses 8	Calculated as *ibd* + *olexPv8*
*incBfeo**	Income before extraordinary items	Calculated as *incNet* - *eoItem*
incNet	Net income	Net income as reported in income statement, after minority interests have been paid and including discontinued operation and extraordinary items
*intAtax**	After-tax interest	Calculated as (1 - *taxSta*) × *intExp*
intAtaxAdj	After-tax interest adjusted by operating lease expenses	Calculated as (1 - *taxSta*) * *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 income statement (or in the notes) - Including: interest payments on finance lease obligations
*intExpAdj**	Adjusted interest expenses	Calculated as *intExp*+1/3 x *olexpTl*
irdvDm	Interest rate derivative dummy	Dummy, one if the airline had outstanding interest rate derivatives at year end (e.g. interest rate swap) Variable rate obligations do not count as interest rate derivatives
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 AR or calculated as *rpmTl* / *asmTl*
lgtAvg	Average length of flight	Average length of one flight (sector length, stage length) as reported in 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 balance sheet
*liaLt**	Long-term liabilities	Calculated as *liaTl* - *liaCrt*
liaLtAdj1	Long-term liabilities adjusted by operating lease expenses	Calculated as *liaTlAdj1* - *liaCrt*
liaLtAdj5	Long-term liabilities adjusted by operating lease expenses	Calculated as *liaTlAdj5* - *liaCrt*

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Variable	Label	Description
liaLtAdj6	Long-term liabilities adjusted by operating lease expenses	Calculated as *liaTlAdj6* - *liaCrt*
liaLtAdj7	Long-term liabilities adjusted by operating lease expenses	Calculated as *liaTlAdj7* - *liaCrt*
liaLtAdj8	Long-term liabilities adjusted by operating lease expenses	Calculated as *liaTlAdj8* - *liaCrt*
liaTl	Total liabilities	Total liabilities as reported in balance sheet, calculate 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 1	Calculated as *liaTl* + *olexpPv1*
liaTlAdj5	Total liabilities adjusted by operating lease expenses 5	Calculated as *liaTl* + *olexpPv5*
liaTlAdj6	Total liabilities adjusted by operating lease expenses 6	Calculated as *liaTl* + *olexpPv6*
liaTlAdj7	Total liabilities adjusted by operating lease expenses 7	Calculated as *liaTl* + *olexpPv7*
liaTlAdj8	Total liabilities adjusted by operating lease expenses 8	Calculated as *liaTl* + *olexpPv8*
*lvrg1**	Leverage ratio 1	Calculated as *ibd* / *asTl*
lvrg1Adj1	Leverage ratio 1 adjusted by operating lease expense 1	Calculated as *ibdAdj1* / *asTlAdj1*
lvrg1Adj1Sqr	Leverage ratio 1 adjusted by operating lease expense 1 squred	Calculated as *lvrg1Adj1* * *lvrg1Adj1*
lvrg1Adj5	Leverage ratio 1 adjusted by operating lease expense 5	Calculated as *ibdAdj5* / *asTlAdj5*
lvrg1Adj6	Leverage ratio 1 adjusted by operating lease expense 6	Calculated as *ibdAdj6* / *asTlAdj6*
lvrg1Adj7	Leverage ratio 1 adjusted by operating lease expense 7	Calculated as *ibdAdj7* / *asTlAdj7*
lvrg1Adj8	Leverage ratio 1 adjusted by operating lease expense 8	Calculated as *ibdAdj8* / *asTlAdj8*
*lvrg1Sqr**	Leverage ratio 1 squared	Calculated as *lvrg1* × *lvrg1*

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Variable	Label	Description
*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*
lvrg2Adj1Sqr	Leverage ratio 2 adjusted by operating lease expenses 1 squared	Calculated as *lvrg2Adj1 * lvrg2Adj1*
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* × *lvrg2*
*lvrg3**	Leverage ratio 3	Calculated as *liaTl / asTl*
lvrg3Adj1	Leverage ratio 3 adjusted by operating lease expenses 1	Calculated as *liaTlAdj1 / asTlAdj1*
lvrg3Adj1Sqr	Leverage ratio 3 adjusted by operating lease expenses 1 squared	Calculated as *lvrg3Adj1 * lvrg3Adj1*
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 7	Calculated as *liaTlAdj7 / asTlAdj7*
lvrg3Adj8	Leverage ratio 3 adjusted by operating lease expenses 8	Calculated as *liaTlAdj8 / asTlAdj8*
*lvrg3Sqr**	Debt ratio 3 squared	Calculated as *lvrg3* × *lvrg3*
*mktCap**	Market capitalization	Calculated as *shrCom* × *shrEnd/xrEnd* + *shrPrfMv*
mktSec	Marketable securities	Marketable securities as reported in balance sheet (or in the 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
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*
*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 x *olexpTl* - Basis for the calculation of variables that end with 'Adj5'
*olexpPv6**	Multiple (6) of annual operating lease expenses	Calculated as 6 x *olexpTl* - Basis for the calculation of variables that end with 'Adj6'
*olexpPv7**	Multiple (7) of annual operating lease expenses	Calculated as 7 x *olexpTl* - Basis for the calculation of variables that end with 'Adj7'
*olexpPv8**	Multiple (8) of annual operating lease expenses	Calculated as 8 x *olexpTl* - Basis for the calculation of variables that end with 'Adj8'
olexpYr1	Future lease payments in year t+1	Operating lease expenses in year t+1 as reported income statement (or notes)
olexpYr2	Future lease payments in year t+2	Operating lease expenses in year t+2 as reported income statement (or notes)
olexpYr3	Future lease payments in year t+3	Operating lease expenses in year t+3 as reported income statement (or notes)
olexpYr4	Future lease payments in year t+4	Operating lease expenses in year t+4 as reported income statement (or notes)
olexpYr5	Future lease payments in year t+5	Operating lease expenses in year t+5 as reported income statement (or notes)

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Variable	Label	Description
olexpYr5b	Future lease payments in year t+6 until t+10	Operating lease expenses in year t+6 until t+10 as reported income statement (or notes)
*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)
opExp	Total operating expenses	Operating expenses as reported in income statement (or in the notes), including fuel expenses
*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 balance sheet (or in the notes) under current assets. Including: receivables from sale of aircrafts, 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 hubs, based on UN 'Composition of macro geographical (continental) regions, geographical sub-regions, and selected economic and other groupings' (United Nations, 2023). The regions are Africa (AF), America (AM), Asia (AS), Europe (EU), and Oceania (OC).
revTl	Total revenues	Total revenue as reported in income statement (or in the notes), including other revenues

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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 Data- stream between 2004 and 2014. Of these only Kuwait, Panama, South Africa, Turkey and United Arab Emirates are included after 2014. The values of South Africa are available from 2015 onward, which is why the described calculation is sufficient. For the other countries other web sources are searched. The calculations for the years 2004 until 2014 can be found in Pfefferle (2019, p. 258-259). - See Appendix B.7 for an exact calculation.
*roa**	Return on assets	Calculated as (*incBfeo* + *intAtax*) / *asTl*
roaAdj1	ROA adjusted by operating lease expenses 1	Calculated as (*incBfeo* + *intAtaxAdj*) / *asTlAdj1*
roaAdj5	ROA adjusted by operating lease expenses 5	Calculated as (*incBfeo* + *intAtaxAdj*) / *asTlAdj5*
roaAdj6	ROA adjusted by operating lease expenses 6	Calculated as (*incBfeo* + *intAtaxAdj*) / *asTlAdj6*
roaAdj7	ROA adjusted by operating lease expenses 7	Calculated as (*incBfeo* + *intAtaxAdj*) / *asTlAdj7*
roaAdj8	ROA adjusted by operating lease expenses 8	Calculated as (*incBfeo* + *intAtaxAdj*) / *asTlAdj8*
rpmTl	Revenue passenger miles	The number of miles on which a passanger is transported, either as reported in AR or calculated as *asmTl* × *lf*.
*rrpm**	Revenue per revenue passenger mile	Revenue per RPM, calculated as *revTl* / *rpmTl* Also referred to as 'the yield' in the airline industry.
S1Em	Scope 1 Emissions	All direct GHG emissions in tonnes either taken from AR, CSR or SR
S2Em	Scope 2 Emissions	Indirect GHG emissions from consumption of purchased electricity, heat or steam in tonnes. Either taken from AR, CSR or SR.
S3Em	Scope 3 Emissions	Other indirect emissions in tonnes, such as the extraction and production of purchased materials and fuels, transport-related activities in vehicles not owned or controlled by the reporting entity, electricity-related activities (e.g. T&D losses) not covered in Scope 2, outsourced activities, waste disposal, etc. Either taken from AR, CSR or SR
shrCom	Ordinary shares outstanding	Total number of ordinary shares (common stock) outstanding taken from AR
shrEnd	Share price at end of the financial year	Share prices are retrieved from Thomson Reuters Eikon - For the financial years not ending 31st December, the period end date share price is used (e.g. for 31st March the share price from 31st March is taken).

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Variable	Label	Description
shrPrf	Preference shares outstanding	Total number of preference shares (preferred stock) outstanding
shrPrfMv	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 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*
spread	Default spread	An airline's individual default spread is taken from the synthetic rating sheets of Damodaran (2002), Damodaran (2016) and Damodaran (2022) and which are based on calculated interest coverage ratios - For the years 2015 until 2019 the table from Damodaran (2019) is used - 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 used
*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 2019 is the average of $spread_t$ and $spread_{t-1}$

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Variable	Label	Description
timeDm	Time Dummy	Dummy, one in the years 2012 to 2019 and zero in the years 2005 to 2011
taxExp	Tax expense	Total tax expenses as reported in income statement (or in the notes), including deferred and current tax expense 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, 2023), 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, 2023).[276]
*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 $(mktCap + liaTlAdj2) / asTlAdj5$
tobQAdj6	Tobin's Q adjusted by operating lease expenses 6	Calculated as $(mktCap + liaTlAdj3) / asTlAdj6$
tobQAdj7	Tobin's Q adjusted by operating lease expenses 7	Calculated as $(mktCap + liaTlAdj4) / asTlAdj7$
tobQAdj8	Tobin's Q adjusted by operating lease expenses 8	Calculated as $(mktCap + liaTlAdj5) / asTlAdj8$
vEmEu	Verified Emissions by EU	Emissions verified for the airline by the EU (`https://www.eea.europa.eu/data-and-maps/data/european-union-emissions-trading-scheme-17`, visited on 04/15/2020)
xrAvg	Average exchange rate	Until 2012: Average end-of-month bid exchange rate USD to local currency over the reporting period from OANDA From 2013: Average end-of-month bid exchange rate USD to local currency over the reporting period from Thomson Reuters Eikon
xrEnd	End of financial year exchange rate	Until 2012: Exchange rate USD to local currency at the end of the reporting period from OANDA From 2013: Exchange rate USD to local currency at the end of the reporting period from Thomson Reuters Eikon

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[276] The OECD data is largely consistent with the KPMG figures. Counterexamples are, for example, the USA and Japan, whereby the values were taken from the OECD source.

Variable	Label	Description
year	Year of analysis	Financial years ending in March are allocated to the previous calender year, otherwise to the current year respective of whether the financial year ended in June, September, October or December.

B.2 Key Business Model Characteristics

Table B.2: Key business model characteristics of Low-cost Carriers and Network Legacy Carriers (based on Nelissen et al., 2021).

	Low-cost Carriers	**Network Legacy Carriers**
Network structure	Point-to-point between various bases and non-base airports	Hub-and-spoke from few hub airports
Geographical scope	Continent of origin and surrounding countries	Worldwide
Fleet structure	Homogenous fleet of just one short-haul aircraft type	Mixed fleet of short-, medium, and long-haul aircraft
Inflight service	Snacks/drinks à la carte at extra cost	Complementary snacks/drinks at least on long-hauls
Travel class(es)	Usually Economy only	Economy, Business; sometimes also Premium Economy and First
Fares	Simple, dynamic one-way based pricing, different fare types (not) containing bundles of additional extra services	Complex pricing based on, e.g. advance booking, length of stay, rebooking options
Emissions	Lower specific emissions	Higher specific emissions

B.3 FastJet PLC

The airline FastJet Limited (FastJet PLC until September 2020), which is registered in the commercial register of the UK, is not included in the dataset due to the disparate corporate structure. For one thing, the currency of the AR (USD) and the currency of the shares, which were listed on the London Stock Exchange (Great Britain pence (GBp)), differ. In addition, the head office was relocated from Gatwick Airport to Johannesburg, South Africa in 2018 due to cost constraints (FastJet PLC, 2017) and operations are limited to Zimbabwe, South Africa and Botswana.

B.4 Exchange Rate Application

Table B.3: Variables with exchange rate applied (extension based on Pfefferle, 2019).

Adjusted by the average month-end exchange rate (*xrAvg*)	**Adjusted by the end-of-fiscal-year exchange rate (*xrEnd*)**
CASM	*asCrt*
depamExp	*asTl*
eoItem	*asCrt*
EUaaAp	*capexNet*
fdvPLeff	*cashEq*
fdvPLineff	*divShr*
fdvPLrcl	*divTl*
fuelExp	*eqtyTl*
incNet	*ibd*
intExp	*liaCrt*
olexpAc	*liaTl*
olexpTl	*mktSec*
opExp	*rvcCrt*
opRev	
revTl	
taxExp	

B.5 Missing Values

Table B.4: Missing values of variables: absolute number of missing firm years and percentage of the total number of firm years (924)

Variable	Missing firm years	% missing
acAge	242	26.16
acOl	284	30.70
acTl	147	15.89
asmTl	94	10.16
divYld	6	0.65
dynHedLtDm	132	14.27
dynHedPfDm	210	22.70
dynHedStDm	132	14.27
fDiv1	150	16.21
fDiv2	150	16.21
fdvDm	12	1.30
fdvMtr	62	6.70
fdvNm	205	22.16
fdvPct12m	109	11.78
fdvPct24m	155	16.76
fdvPct36m	141	15.24
fdvPct48m	139	15.03
fdvPLeff	168	18.16
fdvPLineff	157	16.97
fdvPLrcl	133	14.38
fuelCons	222	24.00
fuelExp	51	5.51
lf	72	7.78
olexpTl	4	0.43
opExp	3	0.32
shrEnd	4	0.43

B.6 Adjusted Variables

Table B.5: Variables adjusted by future operating lease payments (based on Pfefferle (2019))

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*
intExp	$\frac{1}{3} \times olexpTl$	*intExpAdj*
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*
tobQ	*olexpPv1/5-8*	*tobQAdj1/5-8*

B.7 Calculation of the governmont bond yields for certain countries

Kuwait

In line with Pfefferle (2019) the bond yields of the United Arab Emirates (UAE) are employed, as the bond yields for Kuwait are not available.

Panama

The values are taken from the page of the government of Panama for the 10-year government bonds (`https://fpublico.mef.gob.pa/en/curvaderendimiento`, visited 05/09/2023).

Turkey

The values for the turkish government bonds is taken from: `http://www.worldgovernmentbonds.com/bond-historical-data/turkey/10-years/` (visited 05/09/2023).

United Arab Emirates

For 2015, in line with Pfefferle (2019) as for 2013 and 2014, a value of 3.125% is assumed, as no further information is available here. As of 30.04.2016, the values for the abovementioned 10-year government bond (XS1402929746) is available on Thomson Reuters. Therefore, the *rfrate* as of this date is calculated as described in Table 2.15. For 2016, the calculation is based on 9 months only.

B.8 Descriptive Statistics

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

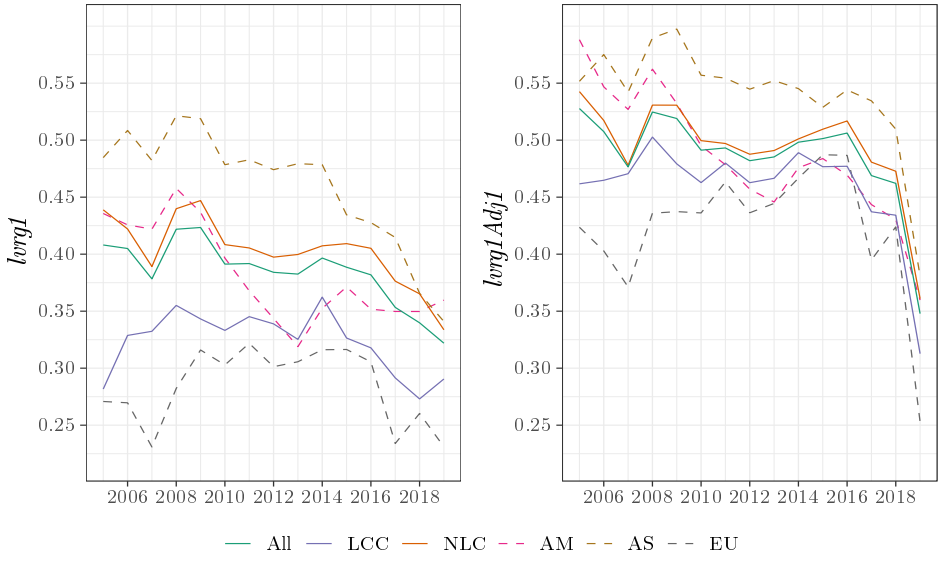


Figure B.2: Time series: unadjusted leverage ratios 2 (*lvrg2*) and lease-adjusted (*lvrg1Adj2*), annual average of all airlines and divided into NLCs, LCCs and regions

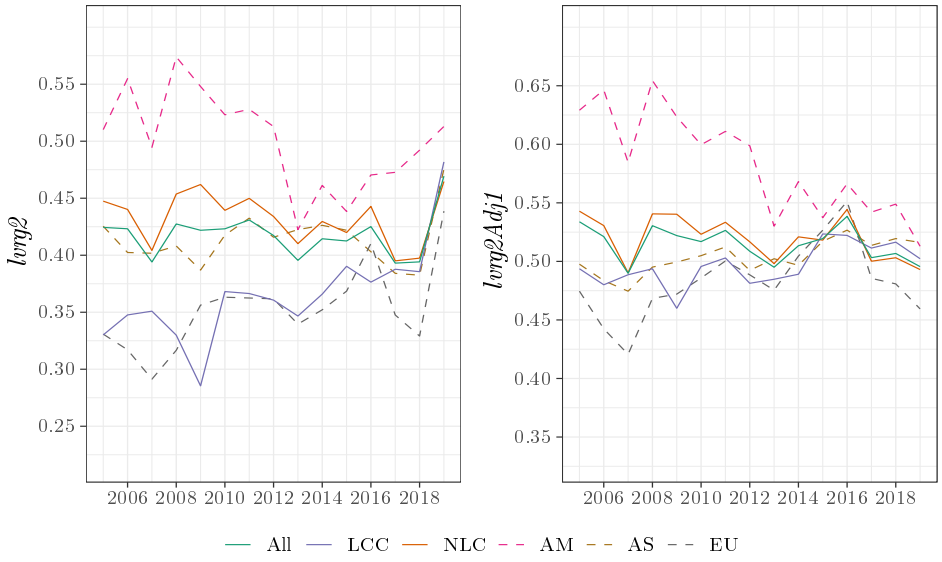


Figure B.3: Time series: unadjusted leverage ratios 3 (*lvrg3*) and lease-adjusted (*lvrg3Adj1*), annual average of all airlines and divided into NLCs, LCCs and regions

Figure B.4: Time series: unadjusted leverage ratios 3 (*lvrg3*) and lease-adjusted (*lvrg3Adj1*), annual average of all airlines and divided into NLCs, LCCs and regions

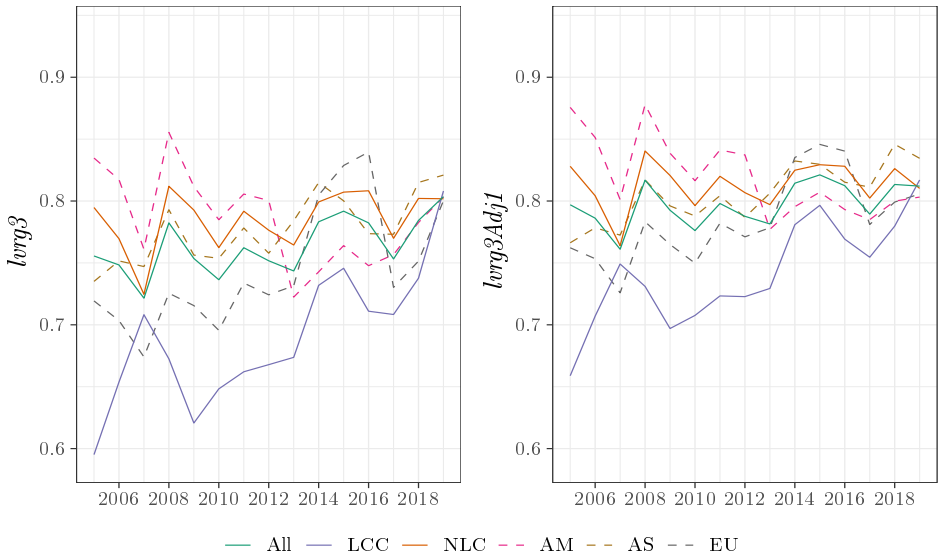


Figure B.5: Time series: lease-adjusted interest coverage ratios (*intCovAdj*), annual average of all airlines and divided into NLCs, LCCs and regions

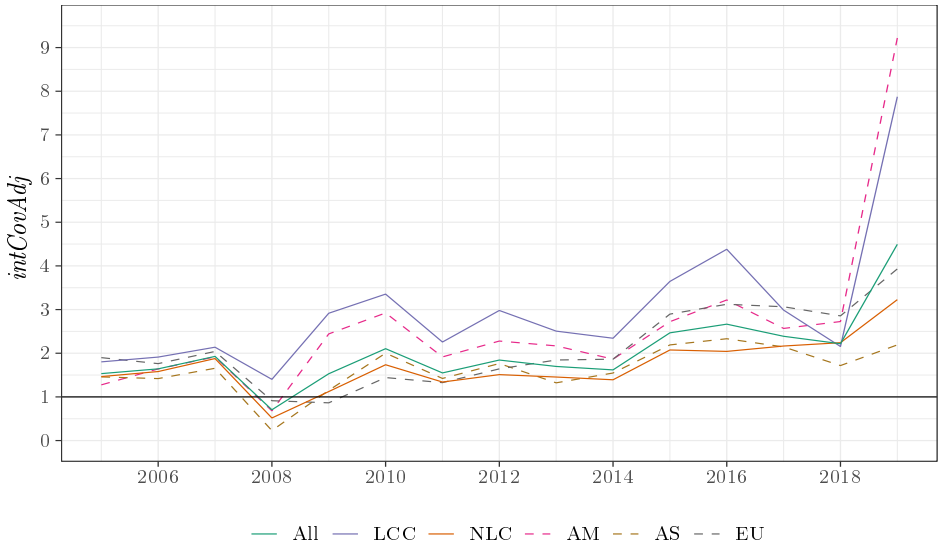


Figure B.6: Time series: lease-adjusted profit margin (*prfMrgAdj*), annual average of all airlines and divided into NLCs, LCCs and regions

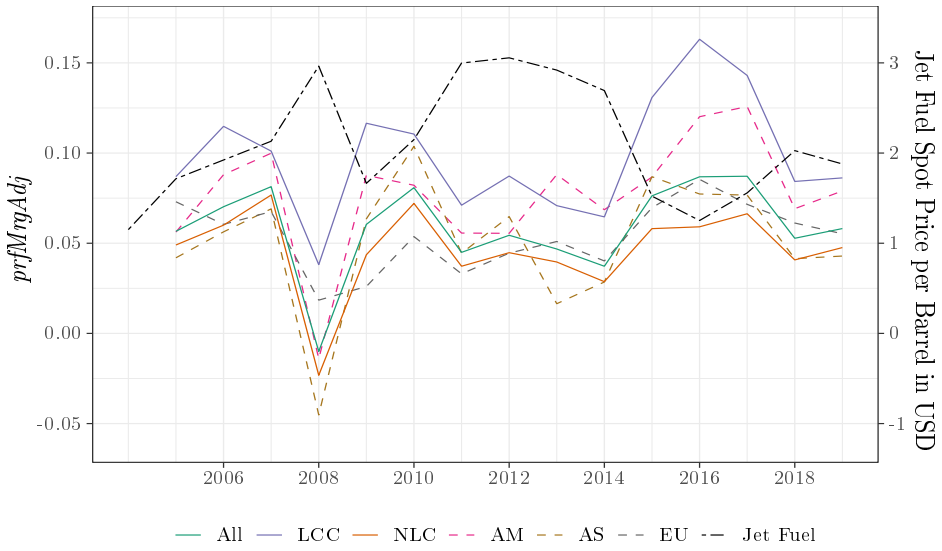


Figure B.8: Cross-sectional (including 2019): cost of debt (*costDbt*) versus lease-adjusted variables (leverage ratio 1 (*lvrg1Adj1*) and leverage ratio 3 (*lvrg3Adj1*), average across years for each airline (weighted by lease-adjusted total assets (*asTlAdj1*))

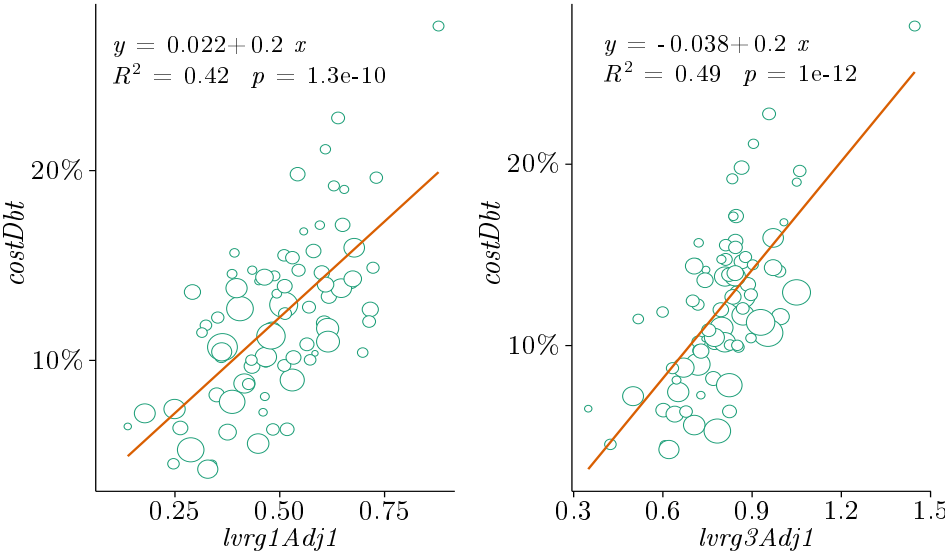


Figure B.7: Time series: unadjusted (*capRev*) and lease-adjusted CAPEX to sales ratio (*capRevAdj1*[277]), annual average of all airlines and divided into NLCs, LCCs and regions

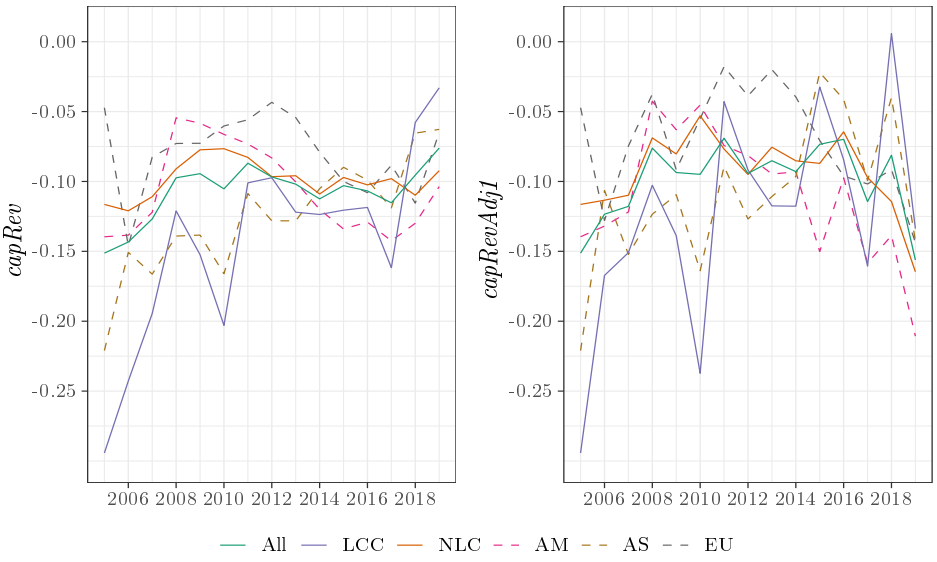


Figure B.9: Time series: unadjusted (*capAs*) and lease-adjusted CAPEX to total assets ratio (*capAsAdj1*[278]), annual average of all airlines and divided into NLCs, LCCs and regions

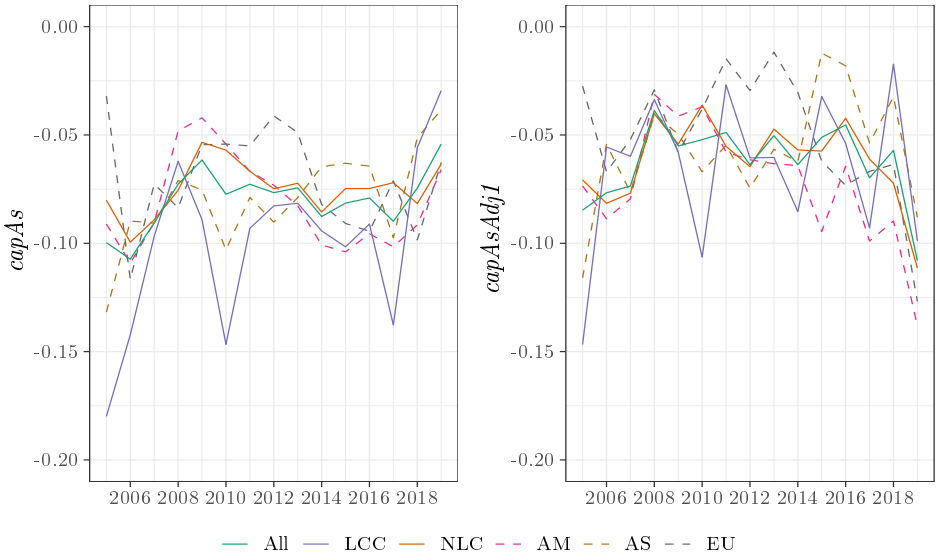
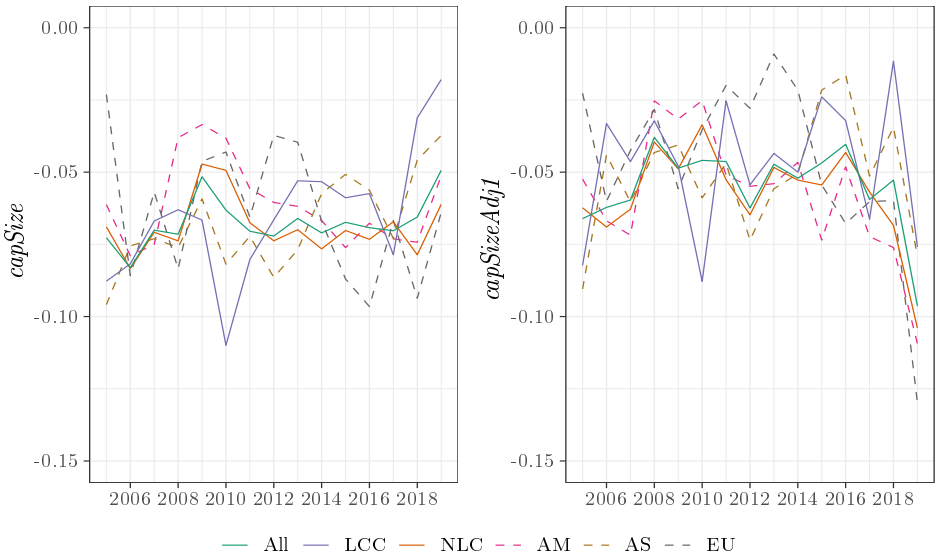


Figure B.10: Time series: unadjusted (*capSize*) and lease-adjusted CAPEX to firm size ratio (*capSizeAdj1*[279]), annual average of all airlines and divided into NLCs, LCCs and regions



[278] *capRevAdj1* is calculated by *capexNetAdj1/asTlAdj1*
[279] *capRevAdj1* is calculated by *capexNetAdj1/size*

Figure B.11: Time series: cash ratio (*cashRto*), annual average of all airlines and divided into NLCs, LCCs and regions

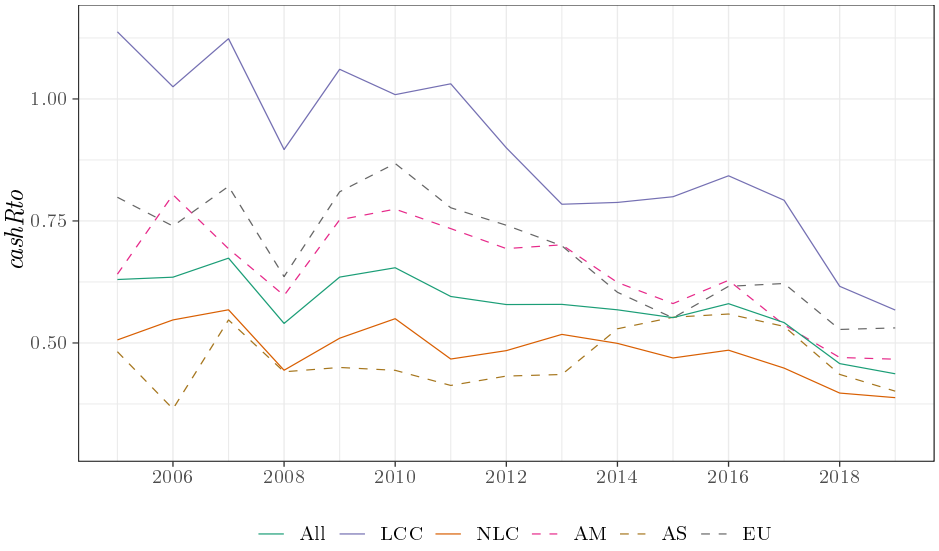


Figure B.12: Time series: quick ratio (*qckRto*), annual average of all airlines and divided into NLCs, LCCs and regions

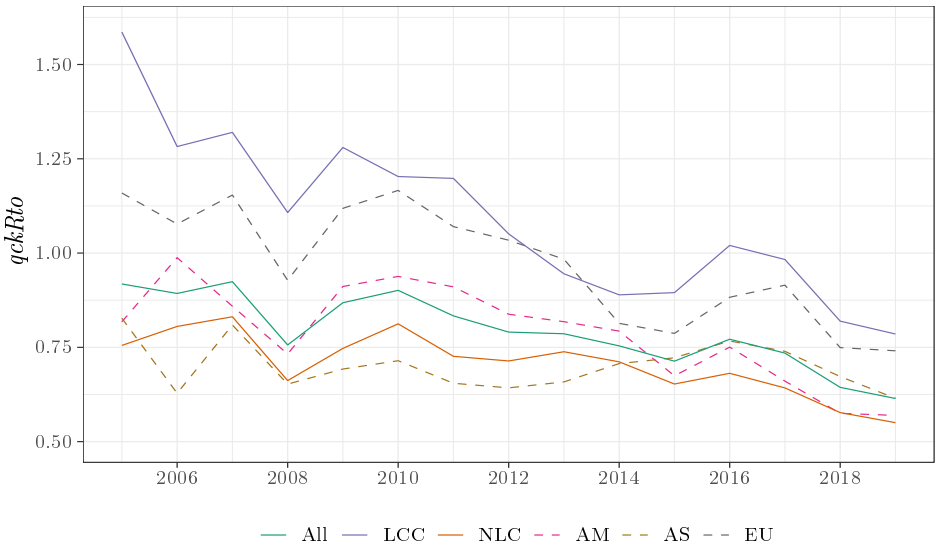


Figure B.13: Time series: current ratio (*crtRto*), annual average of all airlines and divided into NLCs, LCCs and regions

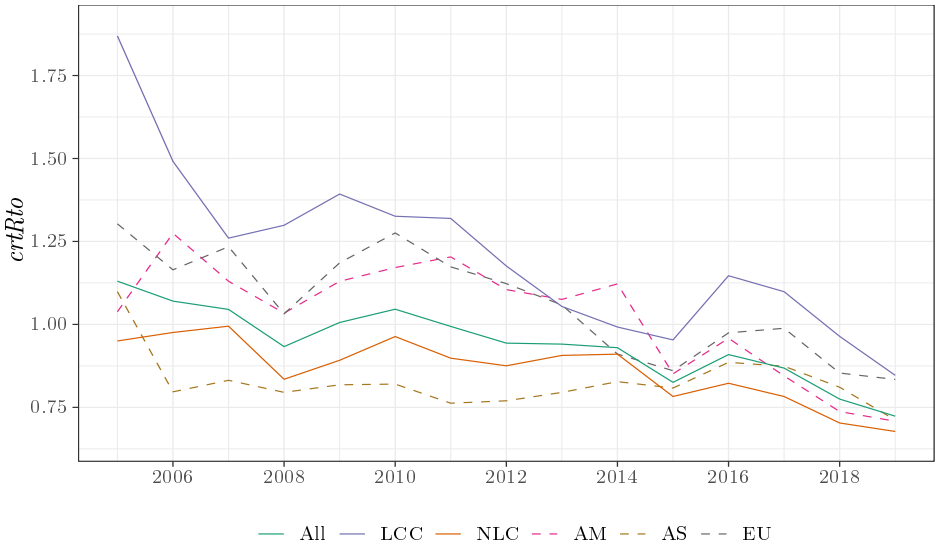


Figure B.14: Time series: unadjusted (*tobQ*) and lease-adjusted Tobin's Q (*tobQAdj1*), annual average of all airlines and divided into NLCs, LCCs and regions

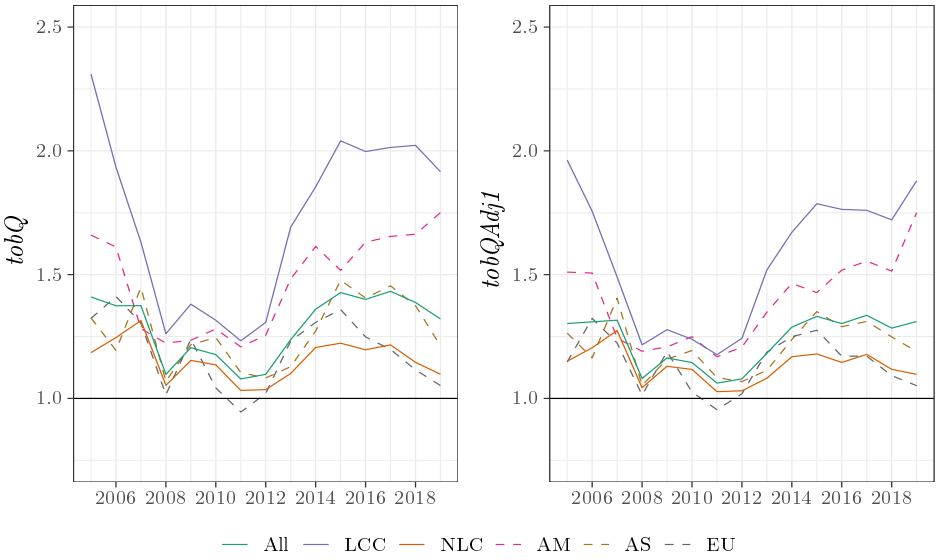


Figure B.15: Time series: alliance membership (*alliDm*) in percentage of total sample scaled by *asmTl*, divided into alliance members, Oneworld, Star Alliance and SkyTeam

Figure B.16: Time series: percentage of aircraft under operating lease within the fleet (*acOlPct*), annual average of all airlines and divided into LCC, NLC as well as AM, AS and EU

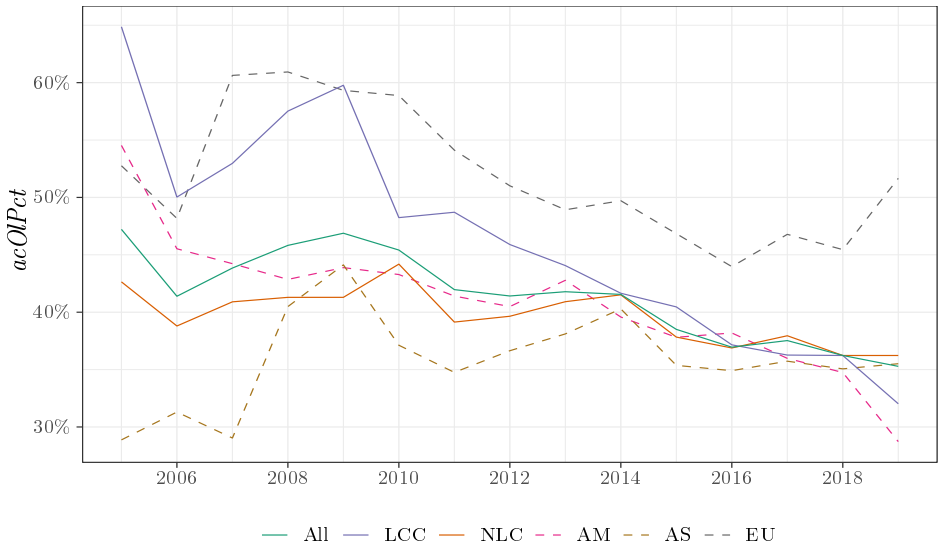


Figure B.17: Cross-sectional: correlation between the variables percentage of operating lease aircraft (*acPlOct*) and percentage change in *acOlPct* with hedge ratios for the next 12 months (*fdvPct12m*), average across years for each airline (weighted by lease-adjusted total assets (*asTlAdj1*)) with year 2019

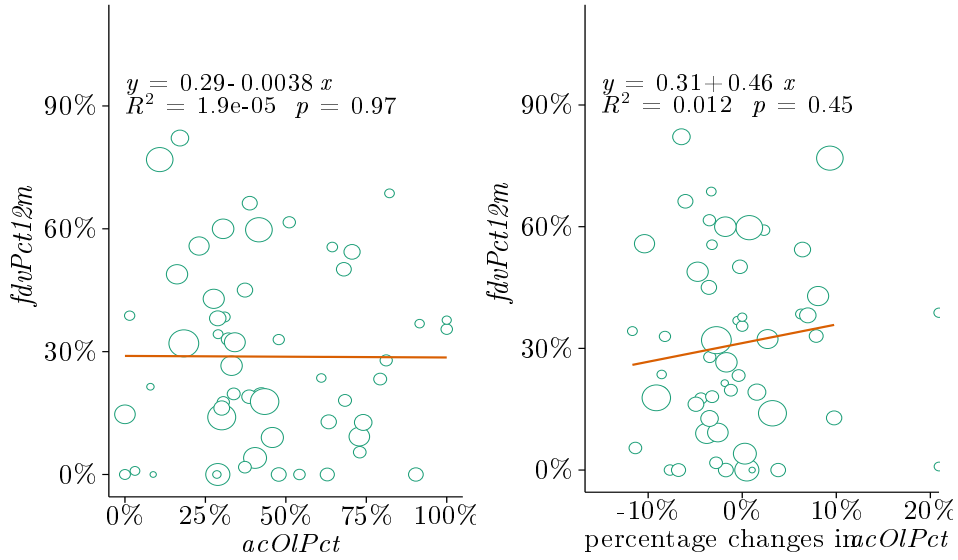


Figure B.18: Cross-sectional: correlation between binary variable for low cash ratio and high percentage of aircraft under operating lease (*acOlcashDm*) and hedge ratios for the next 12 months (*fdvPct12m*), average across years for each airline (weighted by lease-adjusted total assets (*asTlAdj1*)) with year 2019

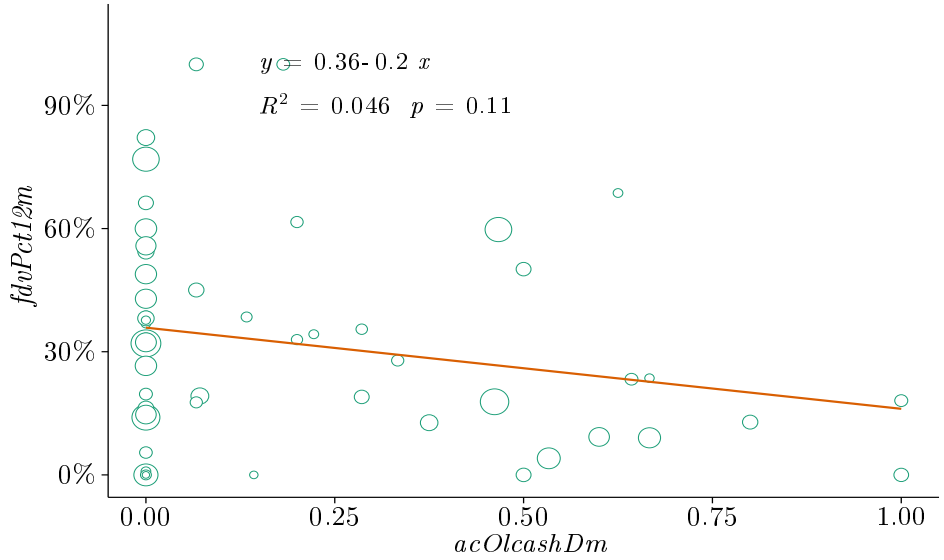


Figure B.19: Time series: present value of operating lease expenses (*olexpPv1*) scaled by lease-adjusted total assets (*asTlAdj1*), annual average of all airlines and divided into NLCs, LCCs and regions

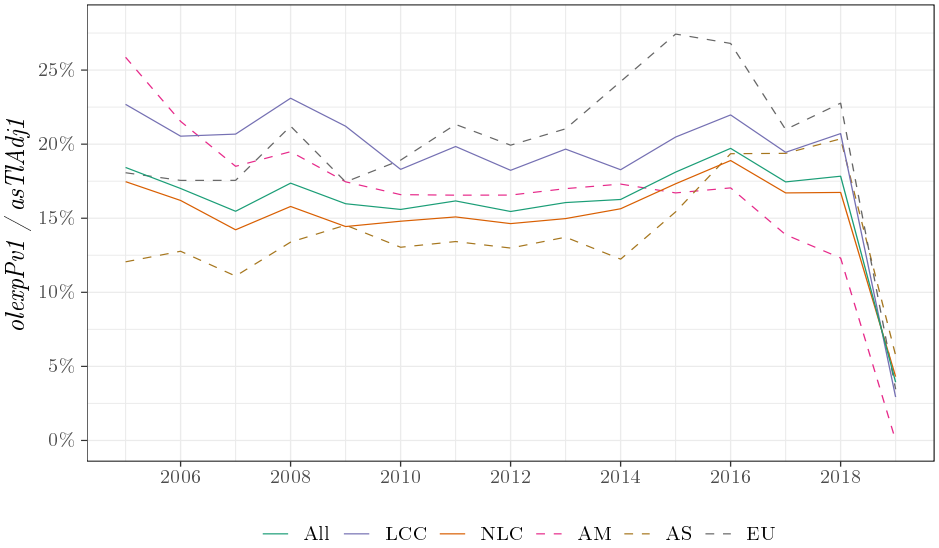


Figure B.20: Time series: present values of operating lease expenses (*olexpPv5*) scaled by lease-adjusted total assets (*asTlAdj5*), annual average of all airlines and divided into NLCs, LCCs and regions

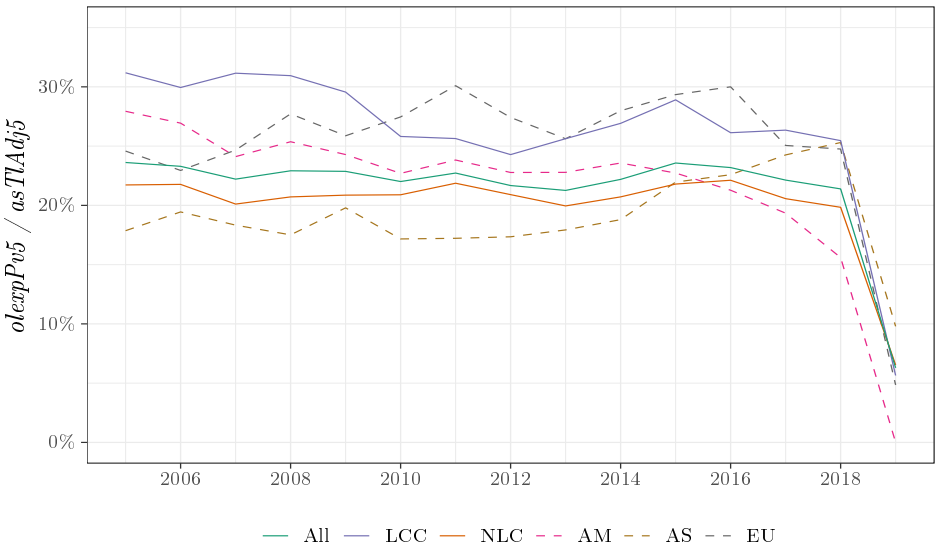


Figure B.21: Time series: present values of operating lease expenses (*olexpPv6*) scaled by lease-adjusted total assets (*asTlAdj6*), annual average of all airlines and divided into NLCs, LCCs and regions

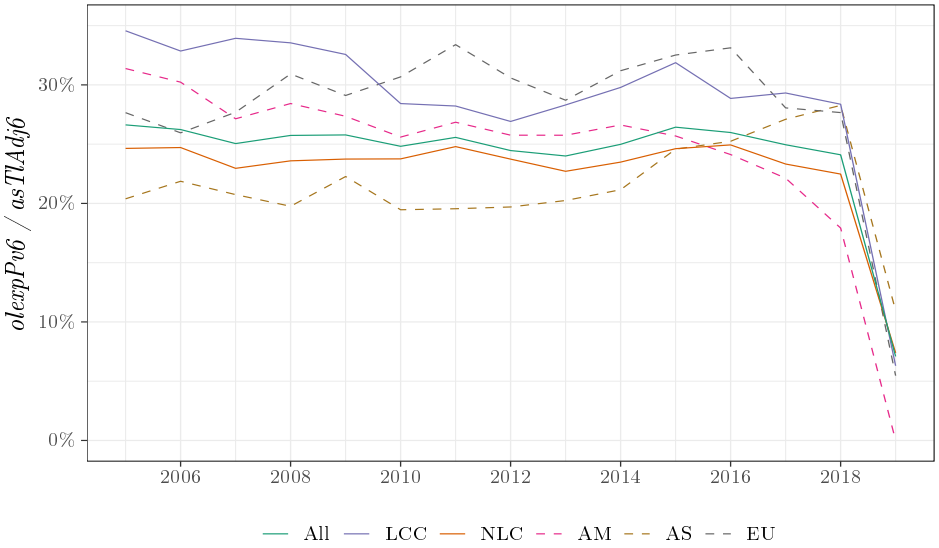


Figure B.22: Time series: present values of operating lease expenses (*olexpPv7*) scaled by lease-adjusted total assets (*asTlAdj7*), annual average of all airlines and divided into NLCs, LCCs and regions

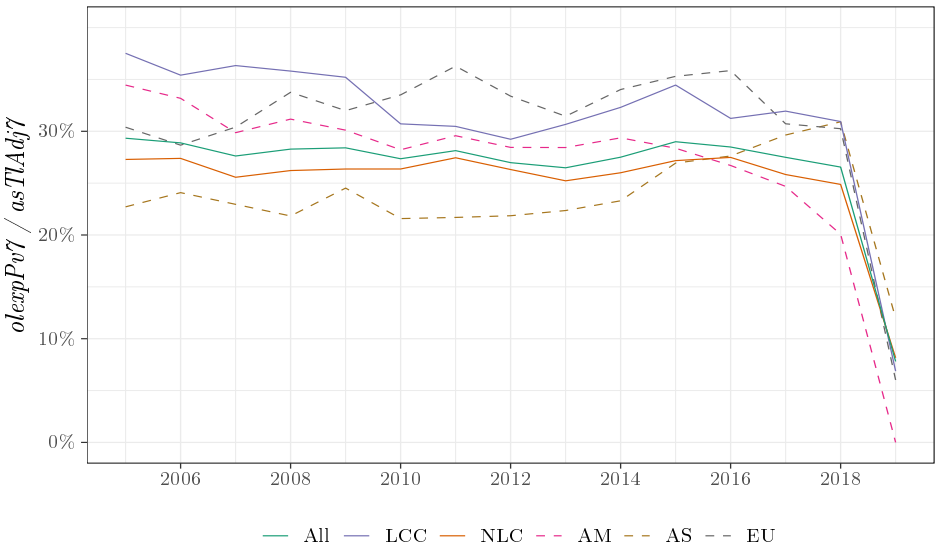


Figure B.23: Time series: present values of operating lease expenses (*olexpPv8*) scaled by lease-adjusted total assets (*asTlAdj8*), annual average of all airlines and divided into NLCs, LCCs and regions

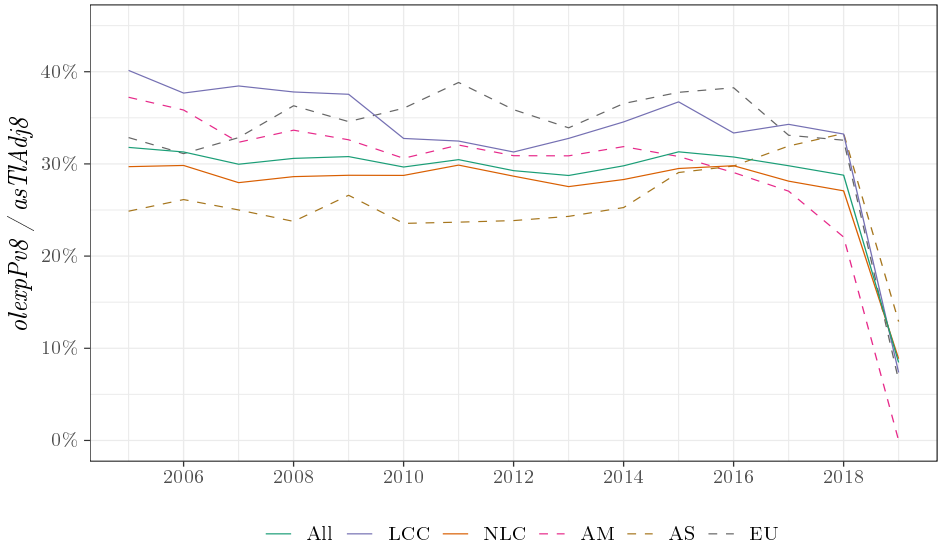
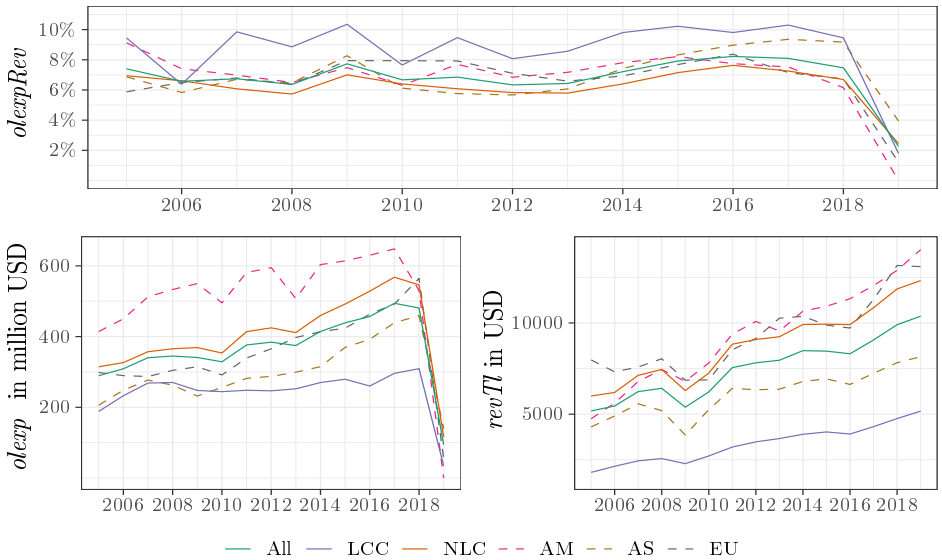


Figure B.24: Time series: operating lease expenses scaled by revenues (*olexpRev*), total operating lease expenses *olexpTl* and total revenues (*revTl*), annual average of all airlines and divided into LCC, NLC as well as AM, AS and EU[280]



[280] *olexpRev* > 0.5 excluded, 12 observations excluded

C Description Data Analysis in R

1. Data Description

   a) Description via plot

   b) *summary* function is a generic function used to produce result summaries of the results of various model fitting functions. The function invokes particular methods, which depend on the class of the first argument.

2. Univariate and Multivariate Analysis

   a) Winsorization of the data at [0.01,0.99] (*winsorize* function from *DescTools* package)

   b) Univariate Analysis

      i. two-sided T-test of relevant variables in different groups (*t.test* function from *stats* package, *t.test*: Performs one and two sample t-tests on vectors of data. Use *two.sided* for alternative and *var.equals* = *FALSE*, as otherwise it would be assumed that the two groups have the same variance.)

   c) Multivariate Analysis

      i. Probit model with random effects (*pglm* function from *pglm* package; *pglm* is used to estimate panel models by maximum likelihood of glm (binomial and Poisson) and 'glm-like' models (Negbin and ordered).)

      ii. Firm fixed effects model (*felm* function from *lfe* package) with robust standard errors (check with Hausman Test (*phtest*) if fixed effects are sensible); *felm* is used to fit linear models with multiple group fixed effects, similarly to *lm* (Fitting Linear Models).

D Financial Hedging

D.1 Statistical Studies

Table D.1: List of studies relevant for financial distress

Reference	Sample	Model	Dependent Variable	Independent Variable	Significance
Adam (2002)	92 North American gold mining firms (1989-1999)	Heckman-Two-Step-Estimator (only second step reported)	Fixed future income stream	Operating Net Cash Flow Financing Net Cash Flow	not significant not significant
		Binomial Probit (Cragg Model)	Ratio of a firm's fixed future income over next year's investment expenditure (Hedge Dummy)	Profit Margin Dividend Dummy Credit Rating Dummy Leverage Aggressive Financial Policy Dummy (if (firm's leverage ratio > industry median & quick ratio < industry median); one; zero) Conservative Financial Policy Dummy (if (firm's leverage ratio < industry median & quick ratio > industry median; one; zero)	not significant not significant negatively significant (at 5% level) (in one out of four models) not significant not significant negatively significant (at 10% level) (in one out of two models)
		Truncated Model (Cragg Model)	Ratio of a firm's fixed future income over next year's investment expenditure (Extent of Hedging)	Profit Margin Dividend Dummy Credit Rating Dummy Leverage Aggressive Financial Policy Dummy (if (firm's leverage ratio > industry median & quick ratio < industry median); one; zero) Conservative Financial Policy Dummy (if (firm's leverage ratio < industry median & quick ratio > industry median; one; zero)	not significant not significant negatively significant (at 5% level) (in one out of four models) not significant not significant not significant
Adam et al. (2017)	93 North American gold mining firms (1989-1999)	Heckman-Two-Step-Estimator	Hedging Dummy	Dividend Dummy Leverage	negatively significant (at 5% level) not significant
			Hedge Ratio	Dividend Dummy	negatively significant (at 1% level)
Allayannis and Ofek (2001)	378 S&P 500 nonfinancial firms (1993)	Binomial Probit (Cragg Model)	FX Hedging Dummy	Dividend Yield Leverage ROA	not significant negatively significant (at 5% level) not significant
		Conditional Regression (Cragg Model)	Total notional of FX derivatives scaled by total assets	Dividend Yield Leverage ROA	not signifikant not signifikant not signifikant

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Reference	Sample	Model	Dependent Variable	Independent Variable	Significance
Bartram et al. (2009)	7,319 nonfinancial firms from 50 countries (80% of global market capitalization)	Single equation Probit model	Hedging Dummy	Leverage Interest Coverage Ratio (3-year average) Dividend Dummy Gross Profit Margin	positively significant (at 1% level) negatively significant (at 10% level) positively significant (at 1% level) positively significant (at 1% level)
		Simultaneously estimated multivariate Probit model	Hedge Dummy (FX, IR and CP)	Leverage Interest Coverage Ratio (3-year average) Dividend Dummy Gross Profit Margin	positively significant (at 5,1,1% level) negatively significant (at 5,5,1% level) positively significant (at 1% level) positively significant (at 1% level), not significant, not significant
Carter et al. (2006)	29 U.S. airlines (1992-2003)	Random Effects Tobit	Percent of next years's fuel requirements hedged	LT Debt-to-Assets Ratio Credit Rating	not significant negatively significant (at 1% level)
				LT Debt-to-Assets Ratio (adjusted for lease) Credit Rating	negatively significant (at 5 level) negatively significant (at 1% level)
		Random Effects Logit	Fuel Hedging Dummy	LT Debt-to-Assets Ratio Credit Rating	not significant not significant
Dionne and Triki (2013)	36 North American gold mining firms (1993-1999) (Ted Reeve)	Random Effects Tobit	Delta percentage for a given quater (fraction of planned gold production that is being hedged over the next three years)	LT Debt (BV) to MV Cash Costs ($US/oz) (operating cost of producing one ounce of gold, excluding all non-cash items such as depreciation, amortization, and other financial costs)	positively significant (at 1% level) positively significant (at 1% level)
Gay and Nam (1998)	325 derivatives-using and 161 non-derivatives-using firms (year-end 1995)	Tobit	Notional amount of derivative holdings (IR, FX, COM) scaled by total assets	Debt Ratio (3-year avergae) Interest Coverage Ratio (3-year average) Convertible Debt to MV Preferred Stock to MV	positively significant (at 1% level) not significant not significant not significant
			Notional amount of derivative holdings (IR, FX, COM) scaled by total assets	Debt Ratio (3-year avergae) Interest Coverage Ratio (3-year average) Convertible Debt to MV Preferred Stock to MV Low Cash - High Growth Dummy	positively significant (at 1% level) not significant not significant not significant positively significant at (1\% and 10\% level), not significant in three other cases
Gay et al. (2011)	1541 non-financial U.S. firms (1992-1996), 1341 non-financial U.S. firms (2002-2004)	Probit	Notional amount of derivatives holdings scaled by total assets	Industry-adjusted Leverage (difference between leverage estimate and median industry leverage estimate)	Whole sample, 1992-1996 & 2002-2004: not significant
		Tobit	Derivative Dummy	Industry-adjusted Leverage (difference between leverage estimate and median industry leverage estimate)	Whole sample, 1992-1996 & 2002-2004: not significant
Géczy et al. (1997)	372 industrial firms from Fortune's 1991 list of the 500 U.S. industrial corportaions with the highest sales for fiscal year 1990	Logit	FX Hedging Dummy	LT Debt Ratio	not significant

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Reference	Sample	Model	Dependent Variable	Independent Variable	Significance
Graham and Rogers (2002)	442 nonfinancial U.S. firms facing ex ante currency and/or interest rate risk (fiscal years ending from March until December 1995)	Tobit	Net derivativs scaled by bookvalue of assets	Debt Ratio Floating Rate Debt-to-Assets	positively significant (at 1% level) not significant
Guay and Kothari (2003)	234 large non-financial corporations using derivatives (Compustat (1995))	Regression (no further specification)	Total notional of derivatives scaled by total assets	Debt (BV) to Total Assets (MV) 3yr. Avg. Absolute chg. in annual (Cash from Operating Activities/Assets)	not significant not significant
Haushalter (2000)	Survey data from CFO's of 100 U.S. oil and gas producers (1992-1994)	Tobit	Fraction of production hedged	Dividend Payout Ratio Credit Rating Debt Ratio Debt Constraint Location of Production	not significant negatively significant (at 5-10% level) positively significant (at 1-5% level) positively significant (at 5% level) positively significant (at 1% level)
		Binomial Probit (Cragg Model)	Hedging Dummy	Dividend Payout Ratio Debt Ratio Location of Production	not significant not significant positively significant (at 1% level)
	Survey data from CFO's of 100 U.S. oil and gas producers (1992-1994) (only hedgers are considered)	Conditional Regression (Cragg Model)	Fraction of production hedged	Dividend Payout Ratio Debt Ratio Location of Production	negatively significant (at 1-5% level) positively significant (at 1% level) positively significant (at 1% level)
Judge (2006)	441 non-financial UK companies (1995)	Logit	Hedging Dummy	Gross Gearing Industry-adjusted Gross Gearing Net Gearing Interest Coverage Ratio Net Interest Receivable Dummy Credit Rating (Qui Score (measure of likelihood of firm failure in next 12 months))	positively significant (at 1% level) positively significant (at 1% level) positively significant (at 10% level) negatively significant (at 1% level) negatively significant (at 1% level) negatively significant (at 1% level)
			Hedging Dummy (derivatives only)	Gross Gearing Industry-adjusted Gross Gearing Net Gearing Interest Coverage Ratio Net Interest Receivable Dummy Credit Rating (Qui Score (measure of likelihood of firm failure in next 12 months))	positively significant (at 5% level) not significant not significant not significant not significant negatively significant (at 1% level)
Lin and Chang (2009)	69 airline companies (from 32 countries) from 1995-3005	Tobit	Percent of next years's fuel requirements hedged	Dividend Dummy LT Debt-to-Assets Ratio	not significant positively significant (at 10% level)
		Logit	Hedging Dummy	Dividend Dummy LT Debt-to-Assets Ratio	not significant not significant
Nance et al. (1993)	Survey data of 169 Fortune 500 and S&P 400 firms (1986)	Logit	Hedge Dummy	Interest Coverage Ratio (3 year average) Debt / Value Preferred Stock / Value Dividend Yield	not significant not significant not significant positively signifikant (at 1% level)
Nguyen and Faff (2002)	239 (1999), 230 (2000) non-banking firms listed on the Australien Stock Exchange	Logit	Hedging Dummy (forwards, futures, swaps and/or options)	Leverage Dividend Yield	positively significant (at 1% level) not significant

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Reference	Sample	Model	Dependent Variable	Independent Variable	Significance
		Tobit	Hedging Dummy (use of any derivatives)	Leverage Dividend Yield	positively significant (at 1% level) positively significant (at 1% level)
Rampini et al. (2014)	23 U.S. airlines (1996-2009)	Tobit	Total notional amount of derivatives scaled by firm size	Net Worth to Assets (BV) Net Worth to Assets (MV) Net Worth (BV) Net Worth (MV) Credit rating Change in Net Worth to Assets (BV) Change in Net Worth to Assets (MV) Change in Net Worth (BV) Change in Net Worth (MV) Change in Credit Rating	not significant not significant positively significant (at 1% level) positively significant (at 1% level) positively significant (at 1% level) not significant positively significant (at 10% level) not significant positively significant (at 5% level) positively significant (at 1% level)
Spanò (2007)	443 UK non-financial companies (1999-2000)	Probit	Hedging Dummy	Debt Ratio LT Debt scaled by Total Debt Dividend Yield	not significant not significant positively significant (at 10% level)
	169 UK non-financial companies (1999-2000) (hedgers)	OLS	Fair value of currency hedging position scaled by market value	Debt Ratio LT Debt scaled by Total Debt Dividend Yield	not significant not significant not significant
Sprcic and Sevic (2012)	157 Croatian non-financial firms (2005) (data from annual reports, notes to financial statements and own survey)	Logit	Hedging Dummy	Credit Rating Dummy	positively significant (at 5% level)
	189 Slovenian non-financial firms (2005) (data from annual reports, notes to financial statements and own survey)	Logit	Hedging Dummy	Credit Rating Dummy	not significant
Swidan and Merkert (2019)	80 global airlines for 4 fiscal years (2010/2011 to 2013/2014)	Random Effects GLS	Jet Fuel Hedging Status	LT Debt to Equity	not significant
Treanor et al. (2013)	US airline industry 1994-2006	Tobit	Percent of next years's fuel requirements hedged	LT Debt Ratio Dividend Yield	not significant not significant
		Logit	Hedging Dummy	LT Debt Ratio Dividend Yield	not significant not significant

Table D.2: List of studies relevant for the underinvestment problem

Reference	Sample	Model	Dependent Variable	Independent Variable	Significance
Adam (2002)	92 North American gold mining firms (1989-1999)	Heckman-Two-Step-Estimator (only second step reported)	Fixed future income stream	Investment Expenditures Change in Cash Position (excluding hedging) Net Cash Holdings	positively signifikant (at 5% level) not significant not significant
		Binomial Probit (Cragg's Model)	Ratio of a firm's fixed future income over next year's investment expenditure (Hedge Dummy)	MTB Quick Ratio	negatively significant (at 1-5% level) negatively significant (at 1-5% level), not significant
		Truncated Model (Cragg's Model)	Ratio of a firm's fixed future income over next year's investment expenditure (Extent of Hedging)	MTB Quick Ratio	negatively significant (at 1-5% level) negatively significant (at 5% level), not significant
Adam et al. (2017)	93 North American gold mining firms (1989-1999)	Heckman-Two-Step-Estimator	Hedging Dummy	MTB Quick Ratio	negatively significant (at 1% level) negatively significant (at 10% level)
			Hedge Ratio	MTB Quick Ratio	not significant negatively significant (at 1% level)
Allayannis and Ofek (2001)	378 S&P 500 nonfinancial firms (1993)	Binomial Probit (Cragg Model)	FX Hedging Dummy	R&D expenditures / sales MTB	positively significant (at 5% level) not significant
		Conditional Regression (Cragg Model)	Total notional of FX derivatives scaled by total assets	R&D expenditures / sales MTB	not significant not significant
Bartram et al. (2009)	7,319 nonfinancial firms from 50 countries (80% of global market capitalization)	Single equation Probit model	Hedging Dummy	Quick Ratio MTB MTB * Leverage	negatively significant (at 1% level) negatively significant (at 1% level) positively significant (at 5% level)
		Simultaneously estimated multivariate Probit model	Hedge Dummy (FX, IR and CP)	Quick Ratio MTB MTB * Leverage	negatively significant (at 1,1% level), not significant negatively significant (at 5% level), negatively significant (at 1% level), not significant not significant, positively significant (at 1% level), not significant
Carter et al. (2006)	29 U.S. airlines (1992-2003)	Random Effects Tobit	Percent of next years's fuel requirements hedged	Capital Expenditures-to-Sales Tobin's Q Cash Flow-to-Sales Cash-to-Sales	not significant positively significant (at 5% level) positively significant (at 1% level) not significant
				Capital Expenditures-to-Sales (adjusted for lease) Tobin's Q (adjusted for lease) Cash Flow-to-Sales Cash-to-Sales	not significant positively significant (at 1% level) not significant not significant
		Random Effects Logit	Fuel Hedging Dummy	Capital Expenditures-to-Sales Tobin's Q Cash Flow-to-Sales Cash-to-Sales	not significant not significant positively significant (at 10% level) not significant

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Reference	Sample	Model	Dependent Variable	Independent Variable	Significance
Dionne and Triki (2013)	36 North American gold mining firms (1993-1999) (Ted Reeve)	Random Effects Tobit	Delta percentage for a given quater (fraction of planned gold production that is being hedged over the next three years)	Acquisitions scaled by MV Quick Ratio	not significant negatively significant (at 5% level)
Gay and Nam (1998)	325 derivatives-using and 161 non-derivatives-using firms (year-end 1995)	Tobit	Notional amount of derivative holdings (IR, FX, COM) scaled by total assets	Cumulative Abnormal Return R&D Expenses Tobin's Q MTB PE Ratio	positively significant (at 5% level) positively significant (at 5% level) positively significant (at 5% level) positively significant (at 5% level) positively significant (at 1% level)
	137 derivatives-using and non-derivatives-using firms (year-end 1995) (only firms using only interest rate derivatives are considered)	Tobit	Notional amount of derivative holdings (IR, FX, COM) scaled by total assets	Cumulative Abnormal Return R&D Expenses Tobin's Q MTB PE Ratio Low Cash - High Growth Dummy	not significant not significant not significant not significant not significant positively significant (at 1% level in one out of five cases)
Gay et al. (2011)	1541 non-financial U.S. firms (1992-1996), 1341 non-financial U.S. firms (2002-2004)	Probit	Notional amount of derivatives holdings scaled by total assets	BTM Quick Ratio	Whole sample not significant negatively significant (at 1% level)
				BTM Quick Ratio	1992-1996 not significant negatively significant (at 10% level)
				BTM Quick Ratio	2002-2004 not significant negatively significant (at 10% level)
		Tobit	Derivative Dummy	BTM Quick Ratio	Whole sample not significant negatively significant (at 1% level)
				BTM Quick Ratio	1992-1996 not significant positively significant (at 1% level)
				BTM Quick Ratio	2002-2004 not significant not significant
Géczy et al. (1997)	372 industrial firms from Fortune's 1991 list of the 500 U.S. industrial corportaions with the highest sales for fiscal year 1990	Logit	FX Hedging Dummy	BTM LT Debt Ratio * (1/BTM) R&D Expenses to Sales LT Debt Ratio * R&D Expenses to Sales Quick Ratio	not significant positively significant (at 10% level) positively significant (at 1% level) not significant not significant
Graham and Rogers (2002)	442 nonfinancial U.S. firms facing ex ante currency and/or interest rate risk (fiscal years ending from March until December 1995)	Tobit	Net derivativs scaled by bookvalue of assets	Debt Ratio * MTB R&D-to-assets BTM (Equity) Negative Equity (BV) Dummy	positively significant (at 5% level) negatively significant (at 5% level) positively significant (at 1% level) negatively significant (at 1% level)

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Reference	Sample	Model	Dependent Variable	Independent Variable	Significance
Guay and Kothari (2003)	234 large non-financial corporations using derivatives (Compustat (1995))	Regression (no further specification)	Total notional of derivatives scaled by total assets	MTB 3yr. Avg. [(Cash + Marketable Securities)/Assets]	positively significant (at 10% level) positively significant (at 10% level)
Haushalter (2000)	Survey data from CFO's of 100 U.S. oil and gas producers (1992-1994)	Tobit	Fraction of production hedged	Investment Expenditures / MV Total Assets Cash Ratio	positively significant (at 5% level) (not significant in two out of three cases) not significant
		Binomial Probit (Cragg Model)	Hedging Dummy	Investment Expenditures / MV Total Assets Cash Ratio	not significant not significant
	Survey data from CFO's of 100 U.S. oil and gas producers (1992-1994) (only hedgers are considered)	Conditional Regression (Cragg Model)	Fraction of production hedged	Investment Expenditures / MV Total Assets Cash Ratio	not significant not significant
Judge (2006)	441 non-financial UK companies (1995)	Logit	Hedging Dummy	Cash Ratio	negatively significant (at 1-10% level)
			Hedging Dummy (derivatives only)	Cash Ratio	not significant
Lin and Chang (2009)	69 airline companies (from 32 countries) from 1995-3005	Tobit	Percent of next years's fuel requirements hedged	Capital Expenditures-to-Sales Tobin's Q Cash Flow-to-Sales Cash-to-Sales	not significant not significant not significant not significant
		Logit	Hedging Dummy	Capital Expenditures-to-Sales Tobin's Q Cash Flow-to-Sales Cash-to-Sales	not significant not significant not significant not significant
Mian (1996)	3,022 non-financial firms (1992)	Logit	Hedge Dummy	MTB	negatively significant (at 1% level)
Nance et al. (1993)	Survey data of 169 Fortune 500 and S&P 400 firms (1986)	Logit	Hedging Dummy (forwards, futures, swaps and/or options)	R&D / Value BTM	positively significant (at 5-21% level) (in 48 regressions) not significant
Nguyen and Faff (2002)	239 (1999), 230 (2000) non-banking firms listed on the Australien Stock Exchange	Logit	Hedging Dummy (use of any derivatives)	MTB Current Ratio Cash Ratio	not significant not significant negatively significant (at 1% level)
		Tobit	Total notional amount of derivatives scaled by firm size	MTB Current Ratio Cash Ratio	negatively significant (at 10% level) not significant not significant
Spanð (2007)	443 UK non-financial companies (1999-2000)	Probit	Hedging Dummy	Tobin's Q R&D Expenditure Dummy Cash Ratio	not significant positively significant (at 1% level) negatively significant (at 5% level)
	169 UK non-financial companies (1999-2000) (hedgers)	OLS	Fair value of currency hedging position scaled by market value	Tobin's Q R&D Expenditure Dummy Cash Ratio	not significant not significant not significant

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Reference	Sample	Model	Dependent Variable	Independent Variable	Significance
Sprcic and Sevic (2012)	157 Croatian non-financial firms (2005) (data from annual reports, notes to financial statements and own survey)	Logit	Hedging Dummy	Investment Expenditures-to-Assets Quick Ratio	positively significant (at 5% level) not significant
	189 Slovenian non-financial firms (2005) (data from annual reports, notes to financial statements and own survey)	Logit	Hedging Dummy	Investment Expenditures-to-Assets Quick Ratio	negatively significant (at 10% level) not significant
Swidan and Merkert (2019)	80 global airlines for 4 fiscal years (2010/2011 to 2013/2014)	Random Effects GLS	Jet Fuel Hedging Status	Quick Ratio	positively significant (at 10% level)
Treanor et al. (2013)	US airline industry 1994-2006	Tobit	Percent of next years's fuel requirements hedged	Cash Flow to Sales Cash to Sales Log(Tobin's Q) Capital Expenditures to Sales	not significant not significant positively significant (at 10%level) not significant
		Logit	Hedging Dummy	Cash Flow to Sales Cash to Sales Log(Tobin's Q) Capital Expenditures to Sales	positively significant (at 5% level) not significant positively significant (at 10%level) not significant
Tufano (1996)	48 U.S. Gold Mining Companies (1990-1993)	Tobit	Percent of next years's fuel requirements hedged	Exploration Activities (Exploration Expenditures and Expenses scaled by Firm Value) Acquisition Activities (Dollar Value attempted Acquisitions attemped over prior 3 years scaled by Firm Value) Quick Ratio (3-year average)	negatively significant (at 5 & 10% level) not significant negatively significant (at 5% level, when largest outlier excluded)

D.2 Correlation Matrices

Table D.3: Correlation Matrix of variables relevant for financial hedging and financial distress without 2019

	fdvPct12m	*fdvDm*	*fdvMtr*	*divDm*	*divRto*	*divYld*	*eqtyDm*	*intCovAdj*	*lvrg1Adj1*	*lvrg3Adj1*	*prfMrgAdj*	*roaAdj1*
fdvPct12m	1.00											
fdvDm	0.68	1.00										
fdvMtr	0.39	0.10	1.00									
divDm	0.03	-0.06	0.23	1.00								
divRto	0.04	0.03	0.07	0.33	1.00							
divYld	0.07	0.04	0.06	0.56	0.32	1.00						
eqtyDm	-0.14	-0.13	-0.12	-0.26	-0.09	-0.15	1.00					
intCovAdj	0.07	-0.02	0.18	0.33	0.11	0.25	-0.22	1.00				
lvrg1Adj1	-0.36	-0.3	-0.28	-0.35	-0.16	-0.3	0.36	-0.48	1.00			
lvrg3Adj1	-0.16	-0.12	-0.22	-0.41	-0.21	-0.32	0.65	-0.47	0.72	1.00		
prfMrgAdj	-0.01	-0.05	0.05	0.35	0.15	0.27	-0.37	0.54	-0.35	-0.55	1.00	
roaAdj1	-0.02	-0.09	0.05	0.34	0.12	0.25	-0.35	0.58	-0.39	-0.51	0.9	1.00

Table D.4: Correlation Matrix of variables relevant for financial hedging and the underinvestment problem

	fdvPct12m	*fdvDm*	*fdvMtr*	*acChg*	*capAsAdj1*	*capRevAdj1*	*capSizeAdj1*	*cashRev*	*cashRto*	*crtRto*	*mtbRto*	*peRto*	*qckRto*	*tobQAdj1*
fdvPct12m	1.00													
fdvDm	0.68	1.00												
fdvMtr	0.39	0.10	1.00											
acChg	0.00	-0.02	-0.05	1.00										
capAsAdj1	-0.03	0.04	-0.12	0.00	1.00									
capRevAdj1	-0.02	0.05	-0.1	-0.09	0.9	1.00								
capSizeAdj1	-0.03	0.03	-0.13	0.02	0.95	0.86	1.00							
cashRev	0.08	0.05	-0.04	0.15	-0.02	-0.13	-0.01	1.00						
cashRto	0.17	0.12	0.03	0.12	-0.01	-0.04	0.00	0.65	1.00					
crtRto	0.16	0.08	0.03	0.14	-0.06	-0.08	-0.04	0.51	0.87	1.00				
mtbRto	0.03	0.05	-0.03	0.1	-0.04	-0.04	0.03	0.08	0.14	0.11	1.00			
peRto	-0.01	0.01	0.03	-0.03	0.01	0.04	0.02	0.02	0.00	0.01	0.04	1.00		
qckRto	0.2	0.13	0.03	0.15	-0.02	-0.05	0.00	0.6	0.94	0.93	0.13	0.02	1.00	
tobQAdj1	-0.05	-0.08	-0.03	0.08	-0.02	-0.01	0.13	0.03	0.14	0.1	0.15	0.05	0.13	1.00

D.3 Alternative Difference in Means Tests

Table D.5: Difference-in-means test of the variables relevant to financial distress for hedgers with low ($\leq$ mean of *fdvPct12m*) and hedgers with high hedge ratios ($>$ mean of *fdvPct12m*)

	high ratios		low ratios		t-Test		
variable	mean	N	mean	N	diff.	SE	N
divDm	0.473	336	0.448	411	−0.026	0.037	747
divRto	0.185	336	0.129	411	−0.056	0.040	747
divYld	0.017	336	0.013	409	−0.003	0.002	745
intCov	9.049	336	8.412	410	−0.638	1.968	746
intCovAdj	1.940	336	1.823	412	−0.118	0.149	748
lvrg1	0.319	336	0.439	412	0.120***	0.013	748
lvrg1Adj1	0.430	336	0.547	410	0.117***	0.012	746
lvrg2	0.390	336	0.432	412	0.043***	0.013	748
lvrg2Adj1	0.490	336	0.538	410	0.048***	0.011	746
lvrg3	0.724	336	0.791	412	0.068***	0.016	748
lvrg3Adj1	0.763	336	0.826	410	0.063***	0.014	746
prfMrg	0.040	336	0.044	412	0.004	0.006	748
prfMrgAdj	0.056	336	0.063	410	0.007	0.006	746
roa	0.029	336	0.033	412	0.004	0.005	748
roaAdj1	0.037	336	0.041	409	0.004	0.004	745

p< 0.10 :*, p< 0.05 :**, p< 0.01 :***

Table D.6: Difference-in-means test of the variables relevant to the underinvestment problem for hedgers with low ($\leq$ mean of *fdvPct12m*) and hedgers with high hedge ratios ($>$ mean of *fdvPct12m*)

	high ratios		low ratios		t-Test		
variable	mean	N	mean	N	diff.	SE	N
achChg	0.068	302	0.086	287	0.025	0.014	589
capAs	-0.079	336	-0.086	412	−0.006	0.006	748
capAsAdj1	-0.060	336	-0.059	409	0.0003	0.006	745
capAsAdj5	-0.056	336	-0.052	410	0.004	0.006	746
capRev	-0.105	336	-0.115	412	−0.009	0.010	748
capRevAdj1	-0.092	336	-0.100	411	−0.008	0.012	747
capSize	-0.070	336	-0.069	410	0.001	0.005	746
capSizeAdj1	-0.054	336	-0.051	407	0.002	0.005	743
cashRev	0.158	336	0.141	412	−0.017	0.011	748
cashRto	0.665	336	0.529	412	−0.137***	0.034	748
crtRto	1.034	336	0.898	412	−0.136***	0.040	748
mtbRto	1.613	336	1.589	410	−0.025	0.223	746
peRto	8.213	336	12.554	409	4.341	8.936	745
qckRto	0.903	336	0.731	412	−0.172***	0.037	748
tobQ	1.219	336	1.341	410	0.122***	0.044	746
tobQAdj1	1.176	336	1.262	408	0.086**	0.034	744

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

D.4 Alternative Random Effects Probit Models

Table D.7: Random effects probit models for different financial hedging variables based on different samples

	Dependent variable: *fdvDm*						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
lvrg1Adj1	−5.694**	−6.301**	−6.301**	−5.535*	−2.943	−4.828	−40.787
	(2.777)	(2.946)	(2.946)	(2.858)	(2.818)	(3.380)	(32.723)
lvrg1Adj1Sqr	3.050	3.371	3.371	3.004	0.972	2.508	32.948
	(2.328)	(2.428)	(2.428)	(2.381)	(2.416)	(2.770)	(26.970)
intCovAdj	−0.266***	−0.265***	−0.265***	−0.264***	−0.251***	−0.148*	−1.783
	(0.060)	(0.061)	(0.061)	(0.061)	(0.071)	(0.085)	(1.441)
tobQAdj1	0.138	0.166	0.166	0.119	0.108	0.050	0.994
	(0.224)	(0.229)	(0.229)	(0.225)	(0.258)	(0.246)	(1.475)
cashRto	1.866***	1.689***	1.689***	1.908***	1.937***	0.273	19.394*
	(0.550)	(0.539)	(0.539)	(0.548)	(0.572)	(0.703)	(10.317)
cashRtoSqr	−0.665***	−0.627***	−0.627***	−0.674***	−0.695***	−0.338	−7.569**
	(0.207)	(0.201)	(0.201)	(0.208)	(0.218)	(0.236)	(3.745)
irdvDm	1.324***	1.359***	1.359***	1.294***	1.077***	1.247***	2.912***
	(0.307)	(0.284)	(0.284)	(0.346)	(0.273)	(0.358)	(1.048)
fxdvDm	0.921***	0.968***	0.968***	0.913***	1.209***	1.260***	−1.143
	(0.267)	(0.260)	(0.260)	(0.291)	(0.295)	(0.300)	(1.266)
cpaDm			11.210				
			(344.441)				
mrgDm				0.282			
				(0.485)			
(Intercept)	1.681*	1.829*	1.829*	1.639*	0.997	2.436**	7.724
	(0.860)	(0.962)	(0.962)	(0.864)	(0.886)	(1.221)	(7.425)
Specification	None	CPA excl.	*cpaDm*	*mrgDm*	Allegiant excl.	IFRS	US GAAP
AIC	481.734	460.940	482.512	482.696	470.244	247.411	115.938
N	851	826	851	851	838	428	177

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$
Standard errors in parentheses

D.5 Alternative Airline Fixed Effects Models

Table D.8: Airline fixed effects model with underinvestment problem variables

	Dependent variable: *fdvPct12m*					
	(1)	(2)	(3)	(4)	(5)	(6)
lvrg1Adj1	−0.181	−0.180	−0.168	−0.168	−0.407	−0.972**
	(0.243)	(0.245)	(0.242)	(0.276)	(0.362)	(0.377)
lvrg1Adj1Sqr	0.067	0.068	0.051	0.052	0.180	0.897***
	(0.233)	(0.235)	(0.233)	(0.256)	(0.335)	(0.344)
intCovAdj	−0.015***	−0.015***	−0.015***	−0.017***	0.003	−0.021***
	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.006)
peRto	−0.0001*	−0.0001*	−0.0001*	−0.0001*	−0.00002	−0.0001***
	(0.00004)	(0.00004)	(0.00004)	(0.00004)	(0.0002)	(0.00002)
crtRto	−0.072	−0.074	−0.071	−0.074*	−0.073	0.173**
	(0.044)	(0.045)	(0.044)	(0.045)	(0.064)	(0.071)
crtRtoSqr	0.021*	0.022*	0.021*	0.021*	0.002	−0.037**
	(0.012)	(0.012)	(0.012)	(0.012)	(0.014)	(0.018)
irdvDm	0.095***	0.098***	0.095***	0.094***	0.097**	0.072***
	(0.020)	(0.021)	(0.020)	(0.020)	(0.040)	(0.021)
fxdvDm	0.031*	0.031*	0.034*	0.033*	0.030	0.056**
	(0.017)	(0.017)	(0.017)	(0.018)	(0.027)	(0.027)
mrgDm			−0.037			
			(0.025)			
Specification	None	CPA excl.	*mrgDm*	Allegiant excl.	IFRS	US GAAP
N	742	717	742	729	362	177
R^2	0.767	0.714	0.767	0.763	0.769	0.849
Adjusted R^2	0.738	0.679	0.738	0.734	0.736	0.825
AIC	−604.686	−558.964	−604.242	−581.707	−294.307	−165.970

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$
Robust standard errors in parentheses

E Operational Hedging

E.1 Statistical Studies

Table E.1: List of studies relevant for operational hedging

Reference	Sample	Model	Dependent Variable	Independent Variable	Significance
Adam (2002)	92 North American gold mining firms (1989-1999)	Heckman-Two-Step-Estimator (only second step reported)	Ratio of a firm's fixed future income over next year's investment expenditure (Hedge Dummy)	Herfindahl index (asset segments) Herfindahl index (metals production)	not significant positively signifikant (at 1-5% level)
		Binomial Probit (Cragg Model)	Ratio of a firm's fixed future income over next year's investment expenditure (Hedge Dummy)	Herfindahl index (asset segments) Herfindahl index (metals production)	not significant positively signifikant (at 5% level) (in one out of four cases)
		Truncated Model (Cragg Model)	Ratio of a firm's fixed future income over next year's investment expenditure (Extent of Hedging)	Herfindahl index (asset segments) Herfindahl index (metals production)	positively signifikant (at 1-5% level) not significant
Carter et al. (2006)	29 U.S. airlines (1992-2003)	Random effects Tobit	Percentage of next years's fuel requirements hedged	Fuel pass-through indicator	negatively significant (at 1% level)
		Random effects Logit	Fuel Hedging Dummy	Fuel pass-through indicator	negatively significant (at 5% level)
Dionne and Triki (2013)	36 North American gold mining firms (1993-1999) (Ted Reeve)	Random Effect Tobit regression	Delta percentage for a given quater (fraction of planned gold production that is being hedged over the next three years)	Dummy US	not significant
Dionne and Triki (2013)	36 North American gold mining firms (1993-1999) (Ted Reeve)	Random Effect Tobit regression	Delta percentage for a given quater (fraction of planned gold production that is being hedged over the next three years)	Dummy US	not significant
Gay et al. (2011)	1541 non-financial U.S. firms (1992-1996), 1341 non-financial U.S. firms (2002-2004)	Probit regression	Derivative Dummy	Number of segments	Whole sample & 1993-1996 positively significant (at 5% level)
				Number of segments	2002-2004 not significant
		Tobit Regression	Derivative Dummy	Number of segments	Whole sample, 1992-1996 & 2002-2004 not significant
Guay and Kothari (2003)	234 large non-financial corporations using derivatives (Compustat (1995))	Regression (no further specification)	Total notional of derivatives scaled by total assets	Segment diversification Geographic diversification	positively significant (at 5% level) positively significant (at 5% level)

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Reference	Sample	Model	Dependent Variable	Independent Variable	Significance
Haushalter (2000)	Survey data from CFO's of 100 U.S. oil and gas producers (1992-1994)	Tobit Regression	Fraction of production hedged	Oil and gas production sales/ Total revenues	not significant
		Binomial Probit (Cragg Model)	Hedging Dummy	Oil and gas production sales/ Total revenues	not significant
	Survey data from CFO's of 100 U.S. oil and gas producers (1992-1994) (only hedgers are considered)	Conditional Regression (Cragg Model)	Fraction of production hedged	Oil and gas production sales/ Total revenues	positively significant (at 5% level) (in one of four cases)
Lin and Chang (2009)	69 airline companies (from 32 countries) from 1995-3005	Tobit regression	Percentage rate of next years's fuel hedging requirments	Fuel pass-through indicator	negatively significant (at 5% level)
		Logit regression	Hedging Dummy	Fuel pass-through indicator	negatively significant (at 1% level)
Spanò (2007)	443 UK non-financial companies (1999-2000)	Probit regression	Hedging Dummy	Dummy for multinationality	not significant
	69 UK non-financial companies (1999-2000) (hedgers)	OLS regression	Fair value of currency hedging position scaled by market value	Dummy for multinationality	not significant
Swidan and Merkert (2019)	80 global airlines for 4 fiscal years (2010/2011 to 2013/2014)	Random Effects GLS	Jet Fuel Hedging Status	Fleet Size Fleet Average Age	not significant positively significant (at 5% level)
Treanor et al. (2013)	US airline industry 1994-2006	Tobit regression	Percentage of next years's fuel requirment hedged	Fleet Diversity Age Leased Fleet REG (regional airline)	positively significant (at 10% level) not significant not significant negatively signifikant (at 5% level)
		Logit	Hedging Dummy	Fleet Diversity Age Leased Fleet REG (regional airline)	positively significant (at 10% level) not significant not significant negatively signifikant (at 1% level)
Tufano (1996)	48 U.S. Gold Mining Companies (1990-1993)	Tobit Regression	Percentage of estimated production sold effectively short through financial contracts (of the next three calendar years)	Diversificantion (percentage of non-mining assets)	not significant

E.2 Correlation Matrix

Table E.2: Correlation matrix of variables relevant for operational hedging

	fdvPct12m	*fdvDm*	*fdvMtr*	*acAge*	*acOlcashDm*	*acOlPct*	*alliDm*	*fDiv1*	*fDiv2*	*fDivNet*	*fDiv1AgeDm*	*olexpRev*	*olexpTl_*
fdvPct12m	1.00												
fdvDm	0.53	1.00											
fdvMtr	0.35	0.10	1.00										
acAge	-0.09	-0.11	-0.01	1.00									
acOlcashDm	-0.14	-0.02	-0.17	-0.12	1.00								
acOlPct	-0.01	0.12	-0.21	-0.41	0.43	1.00							
alliDm	0.01	0.19	0.00	0.20	0.00	-0.1	1.00						
fDiv1	0.00	0.12	0.03	0.34	0.02	-0.14	0.64	1.00					
fDiv2	0.03	0.13	0.01	0.34	0.02	-0.2	0.66	0.88	1.00				
fDivNet	-0.06	-0.04	0.04	-0.09	0.00	0.16	-0.21	0.00	-0.47	1.00			
fDiv1AgeDm	-0.09	-0.11	-0.07	-0.35	0.11	0.01	0.22	0.33	0.28	0.01	1.00		
olexpRev	-0.08	-0.11	-0.18	-0.27	0.16	0.41	-0.23	-0.11	-0.21	0.26	-0.01	1.00	
*olexpTl_*	-0.07	0.01	0.06	0.16	0.14	0.06	0.43	0.38	0.33	0.01	0.01	0.16	1.00

Variables with '_' are denoted in millions

E.3 Alternative Difference in Means Tests

Table E.3: Difference-in-means test of the variables relevant to operational hedging for hedgers with high (> mean of *fdvPct12m*) and low hedge ratios (≤ mean of *fdvPct12m*)

	high ratios		low ratios		t-Test		
variable	mean	N	mean	N	diff.	SE	N
acAge	8.500	284	8.840	278	0.348	0.271	562
acOlcashDm	0.156	276	0.240	279	0.084**	0.029	555
acOlPct	0.416	276	0.422	279	0.006	0.020	555
alliDm	0.494	338	0.420	410	−0.075**	0.037	748
fDiv1	0.704	332	0.635	319	−0.069***	0.019	651
fDiv2	0.552	332	0.468	319	−0.084***	0.021	651
fDiv1AgeDm	0.268	280	0.308	263	0.040	0.033	543
fDivNet	0.153	332	0.167	319	0.015	0.010	651
olexpRev	0.067	338	0.080	408	0.013***	0.005	746
*olexpTl_*	356.000	338	402.000	408	45.600	30.600	746

p< 0.10 :*, p< 0.05 :**, p< 0.01 :***

Variables ending with '_' are denoted in millions.

E.4 Alternative Random Effects Probit Models

Table E.4: Alternative random effects probit models with operational hedging variables, without *irdvDm* and *fxdvDm*

	Dependet variable: *fdvDm*									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
lvrg1Adj1	−4.219	−5.328**	−4.476	−5.385**	−6.420**	−3.845	−3.211	−5.536*	−5.650	−5.108
	(2.754)	(2.714)	(2.792)	(2.714)	(2.618)	(3.331)	(3.532)	(3.099)	(3.878)	(4.103)
lvrg1Adj1Sqr	2.948	3.924	3.231	3.311	3.739*	3.001	2.223	3.388	3.054	3.235
	(2.591)	(2.584)	(2.599)	(2.479)	(2.198)	(2.892)	(3.001)	(2.506)	(3.296)	(3.504)
intCovAdj	−0.252***	−0.244***	−0.254***	−0.244***	−0.272***	−0.187***	−0.209***	−0.248***	−0.272***	−0.264***
	(0.060)	(0.063)	(0.061)	(0.060)	(0.070)	(0.061)	(0.060)	(0.060)	(0.070)	(0.088)
tobQAdj1	0.068	0.118	0.077	0.255	0.134	−0.049	−0.027	0.063	0.600*	0.260
	(0.213)	(0.217)	(0.213)	(0.221)	(0.199)	(0.214)	(0.209)	(0.214)	(0.327)	(0.316)
cashRto	2.472***	2.381***	2.535***	1.405***	2.454***	3.417***	3.708***	2.491***	2.826***	3.205***
	(0.629)	(0.744)	(0.599)	(0.541)	(0.579)	(0.667)	(0.720)	(0.553)	(0.628)	(0.750)
cashRtoSqr	−0.840***	−0.893***	−0.858***	−0.676***	−1.010***	−1.138***	−1.159***	−0.902***	−1.032***	−1.088***
	(0.228)	(0.238)	(0.222)	(0.225)	(0.266)	(0.263)	(0.268)	(0.219)	(0.249)	(0.265)
fDiv1	1.440**	1.550**	1.291*							
	(0.722)	(0.680)	(0.686)							
alliDm			0.211	0.257						
			(0.271)	(0.228)						
*olexpTl_*					−0.001***					
					(0.000)					
acOlPct						0.971*				
						(0.538)				
acOlcashDm							0.652**			
							(0.294)			
lccDm								−0.678**		
								(0.343)		
acAge									−0.076*	
									(0.044)	
fDiv1AgeDm										−0.250
										(0.291)
(Intercept)	1.960**	1.979*	1.996**	3.241***	3.592***	1.670	1.561	2.738***	3.018**	2.412**
	(0.928)	(1.098)	(0.950)	(0.910)	(0.868)	(1.053)	(1.131)	(1.024)	(1.365)	(1.225)
Year dummies	No	Yes	No	No	No	No	No	No		
N	719	719	719	853	852	596	596	853	635	602
AIC	417.133	428.458	418.519	504.929	494.319	345.411	343.332	505.857	383.159	353.372

*p<0.1; **p<0.05; ***p<0.01
Standard errors in parentheses
Variables ending with '_' are denoted in millions

Table E.5: Alternative random effects probit models inclusive *fDiv1* with different sample restrictions

	Dependent variable: *fdvDm*				
	(1)	(2)	(3)	(4)	(5)
lvrg1Adj1	−7.087*	−8.531**	−7.123	−3.525	−6.602
	(4.187)	(3.818)	(4.471)	(3.492)	(4.277)
lvrg1Adj1Sqr	4.825	5.808*	4.870	2.059	4.632
	(3.522)	(3.273)	(3.719)	(3.143)	(3.543)
intCovAdj	−0.265***	−0.269***	−0.264***	−0.225***	−0.131
	(0.064)	(0.064)	(0.065)	(0.072)	(0.092)
tobQAdj1	0.056	0.064	0.051	0.142	−0.028
	(0.245)	(0.240)	(0.246)	(0.247)	(0.260)
cashRto	2.582***	2.420***	2.578***	1.952***	1.134
	(0.625)	(0.639)	(0.631)	(0.638)	(1.042)
cashRtoSqr	−0.798***	−0.775***	−0.797***	−0.605***	−0.499*
	(0.215)	(0.221)	(0.216)	(0.206)	(0.263)
irdvDm	1.463***	1.389***	1.458***	1.293***	1.301**
	(0.393)	(0.333)	(0.409)	(0.379)	(0.518)
fxdvDm	0.895***	0.938***	0.889***	1.066***	1.551***
	(0.273)	(0.268)	(0.276)	(0.352)	(0.450)
fDiv1	1.120*	0.986	1.113*	1.269	1.048
	(0.588)	(0.608)	(0.597)	(0.794)	(0.897)
mrgDm			0.077		
			(0.512)		
(Intercept)	1.097	1.684	1.115	0.169	1.528
	(1.529)	(1.336)	(1.666)	(1.139)	(1.739)
Specifications		excl. CPA		excl. Allegiant Air	IFRS only
N	717	692	717	704	351
AIC	383.711	377.630	385.688	372.241	190.595

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$
Standard errors in parentheses

Table E.6: Alternative random effects probit models inclusive *olexpTl_* with different sample restrictions

	Dependent variable: *fdvDm*				
	(1)	(2)	(3)	(4)	(5)
lvrg1Adj1	−6.796**	−6.865**	−6.783**	−1.532	−8.642**
	(2.958)	(2.956)	(2.928)	(2.971)	(4.037)
lvrg1Adj1Sqr	3.849	3.794	3.906	−0.193	5.806*
	(2.596)	(2.617)	(2.577)	(2.648)	(3.218)
intCovAdj	−0.291***	−0.287***	−0.288***	−0.249***	−0.170*
	(0.067)	(0.065)	(0.066)	(0.087)	(0.102)
tobQAdj1	0.070	0.076	0.057	0.152	−0.235
	(0.232)	(0.233)	(0.231)	(0.237)	(0.224)
cashRto	1.864***	1.761***	1.873***	1.925***	−0.015
	(0.509)	(0.513)	(0.508)	(0.518)	(0.844)
cashRtoSqr	−0.699***	−0.672***	−0.700***	−0.671***	−0.644**
	(0.213)	(0.209)	(0.212)	(0.206)	(0.306)
irdvDm	1.321***	1.323***	1.314***	1.314***	2.247***
	(0.278)	(0.276)	(0.277)	(0.299)	(0.551)
fxdvDm	1.137***	1.155***	1.119***	1.294***	1.525***
	(0.251)	(0.257)	(0.250)	(0.284)	(0.332)
*olexpTl_*	−0.001***	−0.001***	−0.001***	−0.001***	−0.004***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
mrgDm			0.266		
			(0.482)		
(Intercept)	2.706***	2.671***	2.691***	0.870	5.398***
	(0.929)	(0.924)	(0.917)	(0.979)	(1.590)
Specifications		excl. CPA		excl. Allegiant Air	IFRS only
N	719	694	850	706	351
AIC	463.486	457.606	465.172	450.199	232.275

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$
Standard errors in parentheses
Variables with '_' are denoted in millions

Table E.7: Alternative random effects probit models inclusive *acOlPct* with different sample restrictions

	Dependent variable: *fdvDm*				
	(1)	(2)	(3)	(4)	(5)
lvrg1Adj1	−4.635	−5.487	−4.658	−0.419	−3.807
	(3.903)	(3.665)	(3.902)	(4.114)	(5.630)
lvrg1Adj1Sqr	3.051	3.584	3.150	−0.074	2.397
	(3.298)	(3.144)	(3.301)	(3.478)	(4.421)
intCovAdj	−0.196***	−0.203***	−0.195***	−0.139*	−0.132
	(0.071)	(0.070)	(0.072)	(0.082)	(0.097)
tobQAdj1	−0.090	−0.063	−0.098	−0.097	−0.045
	(0.242)	(0.235)	(0.240)	(0.243)	(0.260)
cashRto	1.842***	1.739***	1.860***	1.812***	0.501
	(0.628)	(0.634)	(0.632)	(0.612)	(0.966)
cashRtoSqr	−0.686***	−0.660***	−0.689***	−0.643***	−0.360
	(0.229)	(0.224)	(0.230)	(0.222)	(0.258)
irdvDm	1.671***	1.670***	1.662***	1.723***	1.439**
	(0.426)	(0.412)	(0.424)	(0.450)	(0.566)
fxdvDm	0.797*	0.915***	0.779*	1.125**	1.281***
	(0.454)	(0.345)	(0.462)	(0.438)	(0.456)
acOlPct	1.058	0.910	1.026	0.614	0.411
	(0.863)	(0.626)	(0.895)	(0.675)	(0.806)
mrgDm			0.253		
			(0.569)		
(Intercept)	1.422	1.596	1.415	0.096	1.523
	(1.215)	(1.172)	(1.214)	(1.292)	(1.862)
Specifications		excl. CPA		excl. Allegiant Air	IFRS only
N	719	694	850	706	351
AIC	319.972	314.795	321.766	306.366	181.336

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$
Standard errors in parentheses

Table E.8: Alternative random effects probit models inclusive *acOlcashDm* with different sample restrictions

	Dependent variable: *fdvDm*				
	(1)	(2)	(3)	(4)	(5)
lvrg1Adj1	−4.403	−4.925	−4.445	−0.338	−4.798
	(3.685)	(3.623)	(3.683)	(4.058)	(5.653)
lvrg1Adj1Sqr	2.660	2.967	2.766	−0.316	2.850
	(3.187)	(3.128)	(3.200)	(3.446)	(4.396)
intCovAdj	−0.209***	−0.211***	−0.208***	−0.139*	−0.141
	(0.066)	(0.067)	(0.066)	(0.077)	(0.094)
tobQAdj1	−0.117	−0.095	−0.122	−0.105	−0.070
	(0.222)	(0.226)	(0.221)	(0.231)	(0.254)
cashRto	2.236***	2.174***	2.243***	2.154***	0.754
	(0.629)	(0.635)	(0.631)	(0.610)	(0.884)
cashRtoSqr	−0.746***	−0.731***	−0.747***	−0.706***	−0.422
	(0.229)	(0.227)	(0.228)	(0.226)	(0.257)
irdvDm	1.809***	1.762***	1.802***	1.749***	1.607***
	(0.446)	(0.430)	(0.449)	(0.434)	(0.599)
fxdvDm	0.844***	0.872***	0.825**	1.020***	1.125**
	(0.325)	(0.314)	(0.328)	(0.351)	(0.466)
acOlcashDm	0.725**	0.741**	0.711**	0.620*	0.648
	(0.322)	(0.323)	(0.326)	(0.332)	(0.451)
mrgDm			0.231		
			(0.572)		
(Intercept)	1.419	1.509	1.411	0.094	1.862
	(1.167)	(1.144)	(1.166)	(1.270)	(1.907)
Specifications		excl. CPA		excl. Allegiant Air	IFRS only
N	596	571	596	583	291
AIC	317.276	311.641	319.106	303.575	179.390

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$
Standard errors in parentheses

Table E.9: Alternative random effects probit models inclusive *acAge* with different sample restrictions

	Dependent variable: *fdvDm*				
	(1)	(2)	(3)	(4)	(5)
lvrg1Adj1	−6.934*	−7.296*	−7.294*	−1.838	−13.101*
	(4.034)	(3.979)	(4.070)	(4.858)	(7.243)
lvrg1Adj1Sqr	3.718	3.808	4.064	−0.055	8.693
	(3.377)	(3.337)	(3.413)	(3.995)	(5.497)
intCovAdj	−0.287***	−0.292***	−0.293***	−0.250***	−0.158
	(0.078)	(0.079)	(0.078)	(0.086)	(0.113)
tobQAdj1	0.566*	0.542	0.583*	0.556	0.298
	(0.326)	(0.340)	(0.326)	(0.368)	(0.372)
cashRto	2.513***	2.221***	2.627***	1.953**	1.901**
	(0.650)	(0.735)	(0.673)	(0.882)	(0.943)
cashRtoSqr	−0.902***	−0.810***	−0.935***	−0.683**	−0.763***
	(0.254)	(0.256)	(0.262)	(0.293)	(0.280)
irdvDm	1.113***	1.159***	1.119***	1.114***	0.676
	(0.316)	(0.332)	(0.332)	(0.344)	(0.422)
fxdvDm	0.689***	0.751***	0.630**	0.930**	0.987**
	(0.264)	(0.288)	(0.267)	(0.392)	(0.389)
acAge	−0.051	−0.039	−0.048	−0.006	−0.011
	(0.049)	(0.054)	(0.048)	(0.054)	(0.058)
mrgDm			1.466*		
			(0.852)		
(Intercept)	2.669*	2.558*	2.678*	0.747	4.233
	(1.468)	(1.519)	(1.467)	(1.696)	(2.588)
Specifications		excl. CPA		excl. Allegiant Air	IFRS only
N	633	608	633	620	312
AIC	358.775	353.311	356.331	348.301	169.062

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$
Standard errors in parentheses

Table E.10: Alternative random effects probit models inclusive *fDiv1AgeDm* with different sample restrictions

	Dependent variable: *fdvDm*				
	(1)	(2)	(3)	(4)	(5)
lvrg1Adj1	−6.800*	−7.601*	−7.413*	−1.667	−10.656
	(4.115)	(4.014)	(4.158)	(4.729)	(8.111)
lvrg1Adj1Sqr	3.986	4.733	4.846	0.174	7.326
	(3.570)	(3.434)	(3.636)	(4.029)	(5.999)
intCovAdj	−0.277***	−0.296***	−0.284***	−0.224**	−0.115
	(0.077)	(0.095)	(0.082)	(0.088)	(0.139)
tobQAdj1	0.235	0.190	0.224	0.137	0.034
	(0.288)	(0.313)	(0.289)	(0.337)	(0.311)
cashRto	2.933***	2.412***	2.861***	1.890***	1.963*
	(0.828)	(0.737)	(0.787)	(0.732)	(1.055)
cashRtoSqr	−0.994***	−0.853***	−0.970***	−0.696***	−0.783***
	(0.303)	(0.252)	(0.278)	(0.250)	(0.304)
irdvDm	1.444***	1.366***	1.324***	1.500***	1.299
	(0.396)	(0.345)	(0.366)	(0.428)	(0.803)
fxdvDm	0.776**	0.851***	0.696**	1.058**	1.159**
	(0.338)	(0.325)	(0.335)	(0.433)	(0.467)
fDiv1AgeDm	−0.475	−0.618*	−0.545	−0.674**	−0.835*
	(0.346)	(0.325)	(0.377)	(0.317)	(0.472)
mrgDm			6.290		
			(1596.924)		
(Intercept)	2.204*	2.396*	2.305*	1.020	3.617
	(1.336)	(1.307)	(1.337)	(1.460)	(2.783)
Specifications		excl. CPA		excl. Allegiant Air	IFRS only
N	600	575	600	587	292
AIC	324.501	318.369	321.523	313.861	146.229

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$
Standard errors in parentheses

E.5 Alternative Airline Fixed Effects Models

Table E.11: Alternative airline fixed effects model with operational hedging variables without *irdvDm* and *fxdvDm*

	Dependet variable: *fdvPct12m*								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
lvrg1Adj1	−0.136	−0.056	−0.118	−0.098	−0.081	−0.052	−0.081	−0.098	−0.161
	(0.329)	(0.330)	(0.335)	(0.248)	(0.244)	(0.356)	(0.356)	(0.323)	(0.349)
lvrg1Adj1Sqr	0.076	−0.019	0.059	0.036	0.019	−0.020	−0.012	0.068	0.108
	(0.336)	(0.336)	(0.343)	(0.236)	(0.230)	(0.372)	(0.370)	(0.334)	(0.365)
intCovAdj	−0.015***	−0.014***	−0.015***	−0.015***	−0.016***	−0.015***	−0.014***	−0.006	−0.007
	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)
peRto	−0.0001*	−0.0001	−0.0001*	−0.0001	−0.0001	−0.0001***	−0.0001***	−0.0001**	−0.0001**
	(0.00004)	(0.00004)	(0.00004)	(0.00004)	(0.00004)	(0.00003)	(0.00002)	(0.00003)	(0.00003)
crtRto	−0.056	−0.060	−0.052	−0.042	−0.054	0.016	0.009	0.012	0.005
	(0.050)	(0.051)	(0.050)	(0.043)	(0.043)	(0.051)	(0.052)	(0.047)	(0.052)
crtRtoSqr	0.017	0.018	0.017	0.014	0.016	−0.012	−0.012	−0.014	−0.013
	(0.012)	(0.012)	(0.012)	(0.012)	(0.011)	(0.012)	(0.013)	(0.012)	(0.013)
fDiv1	0.167	0.177	0.180						
	(0.133)	(0.132)	(0.134)						
alliDm			0.033	0.021					
			(0.042)	(0.041)					
*olexpTl_*					−0.0001**				
					(0.00003)				
acOlPct						−0.104			
						(0.069)			
acOlcashDm							−0.005		
							(0.019)		
acAge								0.001	
								(0.005)	
fDiv1AgeDm									0.019
									(0.023)
Year dummies	No	Yes	No	No	No	No	No	No	No
N	648	648	648	744	743	552	552	560	541
R^2	0.723	0.731	0.723	0.759	0.760	0.756	0.755	0.764	0.758
Adjusted R^2	0.687	0.690	0.687	0.730	0.731	0.725	0.724	0.731	0.725
AIC	−428.356	−421.438	−427.304	−585.297	−588.177	−410.289	−407.953	−446.666	−420.863

*p<0.1; **p<0.05; ***p<0.01
Robust standard errors in parentheses
Variables ending with '_' are denoted in millions

Table E.12: Alternative airline fixed effects models for *fDiv1* with different sample restrictions

	Dependent variable: *fdvPct12m*					
	(1)	(2)	(3)	(4)	(5)	(6)
lvrg1Adj1	−0.241	−0.243	−0.214	−0.173	−0.474	−0.877**
	(0.354)	(0.357)	(0.352)	(0.408)	(0.528)	(0.383)
lvrg1Adj1Sqr	0.121	0.123	0.092	0.062	0.212	0.776**
	(0.366)	(0.372)	(0.365)	(0.404)	(0.528)	(0.343)
intCovAdj	−0.016***	−0.016***	−0.016***	−0.017***	0.002	−0.019***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.007)
peRto	−0.0001*	−0.0001*	−0.0001*	−0.0001*	−0.00001	−0.0001***
	(0.00005)	(0.00005)	(0.00005)	(0.00005)	(0.0002)	(0.00002)
crtRto	−0.080	−0.083	−0.080	−0.087	−0.087	0.168**
	(0.054)	(0.057)	(0.055)	(0.055)	(0.081)	(0.071)
crtRtoSqr	0.024*	0.024*	0.024*	0.025*	0.002	−0.040**
	(0.014)	(0.014)	(0.014)	(0.014)	(0.018)	(0.018)
irdvDm	0.112***	0.116***	0.113***	0.111***	0.128***	0.060***
	(0.023)	(0.024)	(0.023)	(0.023)	(0.047)	(0.023)
fxdvDm	0.036	0.036	0.039*	0.040*	0.045	0.078**
	(0.023)	(0.023)	(0.023)	(0.023)	(0.037)	(0.034)
fDiv1	0.141	0.135	0.152	0.169	0.040	−0.247
	(0.147)	(0.153)	(0.148)	(0.164)	(0.179)	(0.162)
mrgDm			−0.046			
			(0.029)			
Specifications		excl. CPA		excl. Allegiant Air	IFRS only	US GAAP only
N	646	621	646	633	319	177
R^2	0.734	0.670	0.735	0.727	0.742	0.851
Adjusted R^2	0.699	0.626	0.699	0.691	0.701	0.826
AIC	−447.833	−404.696	−447.762	−426.703	−232.188	−166.127

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$
Robust standard errors in parentheses

Table E.13: Alternative airline fixed effects models for *alliDm* with different sample restrictions

	Dependent variable: *fdvPct12m*				
	(1)	(2)	(3)	(4)	(5)
lvrg1Adj1	−0.229	−0.231	−0.201	−0.156	−0.477
	(0.360)	(0.364)	(0.359)	(0.416)	(0.526)
lvrg1Adj1Sqr	0.112	0.113	0.082	0.049	0.211
	(0.373)	(0.378)	(0.372)	(0.412)	(0.524)
intCovAdj	−0.016***	−0.016***	−0.016***	−0.017***	0.001
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
peRto	−0.0001**	−0.0001**	−0.0001*	−0.0001**	−0.00001
	(0.00005)	(0.00005)	(0.00005)	(0.00005)	(0.0002)
crtRto	−0.077	−0.080	−0.076	−0.084	−0.092
	(0.054)	(0.057)	(0.055)	(0.055)	(0.080)
crtRtoSqr	0.023*	0.024*	0.023*	0.024*	0.003
	(0.014)	(0.014)	(0.014)	(0.014)	(0.017)
irdvDm	0.111***	0.115***	0.112***	0.110***	0.128***
	(0.023)	(0.024)	(0.023)	(0.023)	(0.047)
fxdvDm	0.035	0.034	0.038	0.038	0.047
	(0.023)	(0.023)	(0.023)	(0.023)	(0.037)
fDiv1	0.152	0.146	0.165	0.182	0.023
	(0.148)	(0.155)	(0.149)	(0.166)	(0.177)
alliDm	0.026	0.025	0.028	0.027	−0.021
	(0.043)	(0.043)	(0.043)	(0.043)	(0.065)
mrgDm			−0.047		
			(0.030)		
Specifications		excl. CPA		excl. Allegiant Air	IFRS only
N	646	621	646	633	319
R^2	0.734	0.670	0.735	0.727	0.742
Adjusted R^2	0.699	0.625	0.699	0.691	0.700
AIC	−446.418	−403.226	−446.426	−425.336	−230.437

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$
Robust standard errors in parentheses

Table E.14: Alternative airline fixed effects models for *acOlPct* with different sample restrictions

	Dependent variable: *fdvPct12m*					
	(1)	(2)	(3)	(4)	(5)	(6)
lvrg1Adj1	−0.174	−0.201	−0.158	−0.124	−0.401	−0.944**
	(0.349)	(0.354)	(0.347)	(0.410)	(0.565)	(0.377)
lvrg1Adj1Sqr	0.046	0.063	0.023	0.001	0.137	0.880**
	(0.367)	(0.374)	(0.366)	(0.413)	(0.567)	(0.344)
intCovAdj	−0.015***	−0.015***	−0.015***	−0.016***	0.003	−0.021***
	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.006)
peRto	−0.0001***	−0.0001***	−0.0001***	−0.0001***	−0.00003	−0.0001***
	(0.00003)	(0.00003)	(0.00003)	(0.00003)	(0.0002)	(0.00002)
crtRto	0.006	0.006	0.008	0.001	−0.076	0.176**
	(0.049)	(0.054)	(0.050)	(0.051)	(0.088)	(0.074)
crtRtoSqr	−0.010	−0.013	−0.011	−0.009	0.002	−0.037*
	(0.012)	(0.014)	(0.012)	(0.013)	(0.018)	(0.019)
irdvDm	0.116***	0.122***	0.118***	0.114***	0.146***	0.070***
	(0.025)	(0.026)	(0.025)	(0.025)	(0.054)	(0.021)
fxdvDm	0.042*	0.041*	0.045**	0.046*	0.077*	0.051*
	(0.022)	(0.022)	(0.023)	(0.024)	(0.043)	(0.029)
acOlPct	−0.077	−0.070	−0.065	−0.085	−0.100	−0.036
	(0.068)	(0.069)	(0.069)	(0.068)	(0.116)	(0.083)
mrgDm			−0.046			
			(0.030)			
Specifications		excl. CPA		excl. Allegiant Air	IFRS only	US GAAP only
N	552	527	552	539	272	177
R^2	0.766	0.701	0.767	0.759	0.733	0.849
Adjusted R^2	0.736	0.662	0.736	0.728	0.690	0.824
AIC	−430.766	−386.601	−430.750	−408.274	−166.402	−164.101

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$
Robust standard errors in parentheses

Table E.15: Alternative airline fixed effects models for *acOlcashDm* with different sample restrictions

	Dependent variable: *fdvPct12m*					
	(1)	(2)	(3)	(4)	(5)	(6)
lvrg1Adj1	−0.199	−0.224	−0.177	−0.165	−0.390	−0.986***
	(0.350)	(0.355)	(0.348)	(0.410)	(0.565)	(0.377)
lvrg1Adj1Sqr	0.056	0.072	0.030	0.025	0.106	0.924***
	(0.367)	(0.374)	(0.366)	(0.412)	(0.557)	(0.343)
intCovAdj	−0.014***	−0.014***	−0.014***	−0.015***	0.005	−0.021***
	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.006)
peRto	−0.0001***	−0.0001***	−0.0001***	−0.0001***	−0.00004	−0.0001***
	(0.00003)	(0.00003)	(0.00003)	(0.00003)	(0.0002)	(0.00002)
crtRto	−0.001	0.001	0.002	−0.006	−0.084	0.173**
	(0.050)	(0.055)	(0.050)	(0.052)	(0.090)	(0.070)
crtRtoSqr	−0.011	−0.014	−0.011	−0.010	0.002	−0.038**
	(0.012)	(0.014)	(0.012)	(0.013)	(0.019)	(0.018)
irdvDm	0.119***	0.125***	0.120***	0.118***	0.150***	0.073***
	(0.024)	(0.025)	(0.024)	(0.024)	(0.053)	(0.021)
fxdvDm	0.041*	0.040*	0.045**	0.045*	0.062	0.053*
	(0.022)	(0.022)	(0.023)	(0.024)	(0.042)	(0.028)
acOlcashDm	−0.007	−0.005	−0.006	−0.009	0.012	−0.032
	(0.018)	(0.019)	(0.018)	(0.018)	(0.025)	(0.028)
mrgDm			−0.050*			
			(0.029)			
Specifications		excl. CPA		excl. Allegiant Air	IFRS only	US GAAP only
N	552	527	552	539	272	177
R^2	0.766	0.701	0.767	0.759	0.733	0.850
Adjusted R^2	0.735	0.661	0.736	0.727	0.689	0.825
AIC	−429.510	−385.951	−429.843	−406.850	−165.578	−165.180

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$
Robust standard errors in parentheses

Table E.16: Alternative airline fixed effects models for *acAge* with different sample restrictions

	Dependent variable: *fdvPct12m*					
	(1)	(2)	(3)	(4)	(5)	(6)
lvrg1Adj1	−0.119	−0.141	−0.101	−0.004	0.155	−1.017***
	(0.333)	(0.338)	(0.332)	(0.395)	(0.590)	(0.377)
lvrg1Adj1Sqr	0.048	0.060	0.028	−0.045	−0.244	1.020***
	(0.351)	(0.356)	(0.352)	(0.397)	(0.595)	(0.356)
intCovAdj	−0.009*	−0.009*	−0.009*	−0.009	0.003	−0.021***
	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)
peRto	−0.0001**	−0.0001**	−0.0001**	−0.0001**	0.00002	−0.0001***
	(0.00003)	(0.00003)	(0.00003)	(0.00003)	(0.0002)	(0.00002)
crtRto	−0.005	−0.004	−0.004	−0.013	−0.066	0.185**
	(0.046)	(0.050)	(0.046)	(0.048)	(0.099)	(0.072)
crtRtoSqr	−0.010	−0.013	−0.010	−0.008	−0.001	−0.037**
	(0.012)	(0.014)	(0.012)	(0.012)	(0.021)	(0.018)
irdvDm	0.081***	0.085***	0.082***	0.080***	0.087**	0.074***
	(0.021)	(0.022)	(0.021)	(0.021)	(0.043)	(0.021)
fxdvDm	0.065***	0.064***	0.067***	0.073***	0.122**	0.054**
	(0.022)	(0.023)	(0.023)	(0.024)	(0.050)	(0.027)
acAge	0.003	0.004	0.003	0.004	0.010	0.006
	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.007)
mrgDm			−0.029			
			(0.030)			
Specifications		excl. CPA		excl. Allegiant Air	IFRS only	US GAAP only
N	558	533	558	545	272	177
R^2	0.774	0.708	0.775	0.768	0.733	0.849
Adjusted R^2	0.742	0.666	0.742	0.734	0.687	0.824
AIC	−464.185	−418.286	−462.923	−440.938	−193.131	−164.549

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$
Robust standard errors in parentheses

Table E.17: Alternative airline fixed effects models for *fDiv1AgeDm* with different sample restrictions

	Dependent variable: *fdvPct12m*					
	(1)	(2)	(3)	(4)	(5)	(6)
lvrg1Adj1	−0.235	−0.261	−0.213	−0.136	−0.145	−0.962**
	(0.363)	(0.369)	(0.363)	(0.433)	(0.592)	(0.381)
lvrg1Adj1Sqr	0.130	0.146	0.107	0.047	−0.032	0.893**
	(0.384)	(0.392)	(0.385)	(0.437)	(0.599)	(0.346)
intCovAdj	−0.009*	−0.009*	−0.009*	−0.009	0.005	−0.021***
	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)
peRto	−0.0001**	−0.0001**	−0.0001**	−0.0001**	0.00004	−0.0001***
	(0.00003)	(0.00004)	(0.00003)	(0.00003)	(0.0002)	(0.00002)
crtRto	−0.005	−0.006	−0.004	−0.014	−0.079	0.178**
	(0.052)	(0.057)	(0.052)	(0.054)	(0.099)	(0.072)
crtRtoSqr	−0.011	−0.015	−0.012	−0.010	−0.002	−0.038**
	(0.013)	(0.015)	(0.013)	(0.013)	(0.021)	(0.019)
irdvDm	0.095***	0.101***	0.096***	0.094***	0.112**	0.070***
	(0.021)	(0.022)	(0.021)	(0.021)	(0.045)	(0.021)
fxdvDm	0.072***	0.071***	0.074***	0.080***	0.110**	0.056**
	(0.024)	(0.024)	(0.024)	(0.026)	(0.049)	(0.027)
fDiv1AgeDm	−0.013	−0.016	−0.010	−0.015	−0.035	−0.018
	(0.021)	(0.022)	(0.022)	(0.021)	(0.031)	(0.025)
mrgDm			−0.031			
			(0.033)			
Specifications		excl. CPA		excl. Allegiant Air	IFRS only	US GAAP only
N	539	514	539	526	266	177
R^2	0.770	0.702	0.771	0.763	0.738	0.849
Adjusted R^2	0.737	0.658	0.737	0.728	0.692	0.824
AIC	−441.749	−396.560	−440.502	−418.487	−191.625	−164.097

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$
Robust standard errors in parentheses

Table E.18: Alternative airline fixed effects models with squared *olexpTl_* and *acOlPct*

	Dependent variable: *fdvPct12m*			
	(1)	(2)	(3)	(4)
lvrg1Adj1	−0.154	−0.159	−0.174	−0.091
	(0.242)	(0.243)	(0.349)	(0.350)
lvrg1Adj1Sqr	0.042	0.049	0.046	−0.013
	(0.231)	(0.232)	(0.367)	(0.368)
intCovAdj	−0.016***	−0.014***	−0.015***	−0.017***
	(0.004)	(0.005)	(0.004)	(0.004)
peRto	−0.0001*	−0.0001*	−0.0001***	−0.0001***
	(0.00004)	(0.00004)	(0.00003)	(0.00003)
crtRto	−0.081*	−0.075*	0.006	0.007
	(0.044)	(0.044)	(0.049)	(0.049)
crtRtoSqr	0.023*	0.021*	−0.010	−0.011
	(0.012)	(0.012)	(0.012)	(0.012)
irdvDm	0.093***	0.085***	0.116***	0.109***
	(0.020)	(0.021)	(0.025)	(0.026)
fxdvDm	0.031*	0.025	0.042*	0.042*
	(0.017)	(0.017)	(0.022)	(0.023)
*olexpTl_*	−0.0001**	0.00005		
	(0.00003)	(0.0001)		
*olexpTlSqr_*		−0.00000*		
		(0.00000)		
acOlPct			−0.077	−0.405**
			(0.068)	(0.199)
acOlPctSqr				0.314*
				(0.179)
N	741	741	552	552
R^2	0.768	0.769	0.766	0.768
Adjusted R^2	0.739	0.740	0.736	0.737
AIC -605.095	−606.065	−430.766	−432.125	

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$
Robust standard errors in parentheses
Variables with '_' are denoted in millions

F EU ETS

F.1 Litarature Review

Table F.1: Key features of the EU ETS for Phase I until Phase III (based on European Union, 2015).

	Phase I (2005-2007)	**Phase II (2008-2012)**	**Phase III (2013-2020)**
Geography	EU27	EU27, Norway, Iceland Liechtenstein	EU27, Norway, Iceland Liechtenstein, Coroatia
Sectors	Power Stations and other combustion plants $\geq$ 20MW Oil refineries Coke ovens Iron and steel plants Cement clinker Glass, Lime Bricks Ceramics Pulp Paper and board	Same as Phase I plus Aviation (from 1st January 2012)	Same as Phase I plus Aviation[281] Aluminium products Petrochemicals Ammonia products Nitric, adipic and glyoxylic acid production CO_2 capture, transport in pipelines and geological storage of CO_2
GHGs	CO_2	CO_2, N_2O (via opt-in)	CO_2, N_2O, PFC (from aluminium production)
Cap	2058 $MtCO_2$	1859 $MtCO_2$	2084 $MtCO_2$ in 2013, decreasing in a linear way by 38 $MtCO_2$ per year
Eligible trading units	EUAs	EUAs, CERs, ERUs (**Not eligible:** Credits from forestry, and large hydropower projects.)	EUAs, CERs, ERUs (**Not eligible:** CERs and ERUs from forestry, HFC, N_2O or large hydropower projects. Note: CERs from projects registered after 2012 must be from Least Developed Countries.)

[281] Since 2013, the number of aviation allowances in circulation has been determined using a bottom-up approach based on free allocation. The free allocation is calculated on the basis of the activity-based benchmark of operators' activities in the EEA. Based on this figure, 85% is allocated free of charge, including a special reserve for fast-growing aircraft operators and new entrants, and the remaining 15% is auctioned. These figures also include international emission allowances exchanged under the EU ETS (European Commission, 2021).

Table F.2: EU ETS emission caps for stationary installations and aviation, 2013 - 2020 (European Commission, 2021).

Year	Annual cap (stationary installations)	Annual aviation allowances put into circulation
2013	2,084,301,856	32,455,296
2014	2,046,037,610	41,866,834
2015	2,007,773,364	50,669,024
2016	1,969,509,118	38,879,316
2017	1,931,244,873	38,711,651
2018	1,892,980,627	38,909,585
2019	1,854,716,381	38,830,950
2020	1,816,452,135	42,803,537

F.2 Correlation Matrix

Table F.3: Correlation Matrix of variables relevant for the EU ETS

	*aEmEU_*	*CO_2Tl_*	*CO_2Chg*	*CO_2Rpm*	*CO_2Asm*	*EuaaAP_*	*euetsDm*	*S1Em_*	*S2Em_*	*S3Em_*	*vEmEU_*
*aEmEU_*	1.00										
*CO_2Tl_*	0.25	1.00									
CO_2Chg	-0.04	0.02	1.00								
CO_2Rpm	-0.06	0.19	-0.04	1.00							
CO_2Asm	0.00	0.24	-0.02	0.93	1.00						
*EuaaAP_*	0.00	0.06	0.04	-0.03	0.02	1.00					
euetsDm	0.50	0.06	-0.06	-0.16	0.07	-0.03	1.00				
*S1Em_*	0.32	0.99	0.02	0.15	0.19	0.03	0.06	1.00			
*S2Em_*	0.17	0.82	-0.06	0.04	0.05	-0.06	-0.04	0.84	1.00		
*S3Em_*	0.31	0.73	0.33	0.15	0.23	0.16	0.18	0.64	0.50	1.00	
*vEmEU_*	0.83	0.26	0.03	-0.02	0.05	0.04	0.67	0.32	0.08	0.50	1.00

Variables with '_' are denoted in millions

F.3 Alternative Difference in Means Tests

Table F.4: Difference-in-means test of the variables relevant to airlines within the EU (*reg* = EU) and not within the EU (otherwise))

	EU ETS		non-EU ETS		t-Test		
variable	mean	N	mean	N	diff.	SE	N
$CO_2Tl_$	14.406	109	13.399	270	−1.007	0.962	379
CO_2Chg	0.042	93	0.044	235	0.002	0.008	328
CO_2Rpm	191.006	119	2225.721	259	34.715***	4.836	378
CO_2Asm	176.790	103	179.450	272	2.660	3.511	375
*S1Em_*	14.117	70	12.884	248	−1.234	0.911	318
*S2Em_*	0.073	42	0.086	213	0.013	0.007	255
*S3Em_*	3.032	40	1.630	117	−1.402**	0.287	157

p< 0.10 :*, p< 0.05 :**, p< 0.01 :***

Variables ending with '_' are denoted in millions

Table F.5: Difference-in-means test of selected variables for airlines within the EU (*reg* = EU) and not (*reg* ≠ EU)

	EU		Non-EU		t-Test		
variable	mean	N	mean	N	diff.	SE	N
fdvPct12m	0.507	182	0.252	609	−0.255***	0.021	791
fdvDm	0.919	209	0.695	704	−0.224***	0.026	913
fxdvDm	0.918	207	0.553	704	−0.365***	0.027	911
irdvDm	0.656	209	0.571	704	−0.084**	0.038	913
acAge	7.891	163	8.853	520	0.962***	0.262	683
acOlcashDm	0.260	146	0.178	454	−0.082**	0.036	600
acOlPct	0.511	146	0.385	454	−0.126***	0.023	600
alliDm	0.526	209	0.441	715	−0.086	0.039	924
fDiv1	0.636	184	0.687	591	0.051**	0.023	775
fDiv2	0.483	184	0.522	591	0.038	0.024	775
fDiv1AgeDm	0.245	151	0.299	498	0.054	0.034	649
fDivNet	0.152	184	0.166	591	0.013	0.010	775
olexpRev	0.070	177	0.077	688	0.006	0.005	865
*olexpTl_*	366.679	177	381.045	688	14.406	33.240	865

p< 0.10 :*, p< 0.05 :**, p< 0.01 :***; Variables ending with '_' are denoted in millions.

For the variables *acOlcashDm*, *acOlPct*, *plexpRev* and *olexpTl_* the year 2019 is not considered due to the changes in accounting standards concerning operational leasing.

F.4 Alternative Fixed Effects Models

Table F.6: Alternative airline fixed effects model for variables related to financial hedging, *fdvDm*

	Dependent variable: CO_2Asm					
	(1)	(2)	(3)	(4)	(5)	(6)
divDm	−4.143	−6.190	0.937	−13.634**	−4.802*	−4.134
	(2.596)	(5.090)	(4.707)	(6.387)	(2.750)	(5.726)
divYld	−5.443	47.631	−19.561	107.422	37.379	−54.557***
	(21.014)	(44.667)	(21.808)	(75.001)	(30.943)	(17.678)
cashRto	−13.640	−32.476	−1.755	−58.463	−30.609	2.293
	(17.975)	(36.138)	(25.859)	(45.589)	(25.141)	(16.996)
cashRtoSqr	13.274	13.284	12.072	33.919	32.038*	0.150
	(11.194)	(25.415)	(17.819)	(22.899)	(17.554)	(9.223)
capAs	34.394	103.913***	7.472	4.500	12.679	−14.034
	(25.011)	(36.127)	(27.072)	(56.825)	(24.940)	(35.992)
mtbRto	−0.471	−0.718*	−1.609	−0.108	−0.666*	−0.974
	(0.330)	(0.368)	(3.002)	(0.636)	(0.381)	(0.594)
lf	101.994*	−133.385*	196.487**	194.470	189.525**	−311.418**
	(58.093)	(68.638)	(85.567)	(183.417)	(74.837)	(131.774)
fdvDm	−12.154**	−9.616	−6.483	2.121	−11.621*	−4.083
	(5.529)	(6.915)	(6.396)	(9.121)	(6.625)	(4.774)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Region		AM	AS	EU		
Business Model					NLC	LCC
N	357	123	110	103	296	61
R^2	0.905	0.769	0.956	0.851	0.893	0.965
Adjusted R^2	0.885	0.676	0.936	0.780	0.869	0.965
AIC	3047.910	1055.707	891.378	943.228	2541.873	458.651

*p<0.1; **p<0.05; ***p<0.01
Robust standard errors in parentheses
Variables ending with '_' are denoted in millions

Table F.7: Alternative airline fixed effects model for variables related to financial hedging, *fdvPct12m*

	Dependent variable: CO_2Asm				
	(1)	(2)	(3)	(4)	(5)
divDm	−1.773	−6.187	3.614	−13.056*	−1.735
	(2.788)	(4.932)	(2.973)	(6.651)	(2.918)
divYld	−3.054	24.040	3.967	107.380	50.413
	(18.789)	(46.018)	(19.724)	(83.938)	(35.815)
cashRto	−38.430*	−61.736	−41.345	−73.781	−62.052**
	(20.637)	(45.363)	(28.306)	(49.218)	(29.209)
cashRtoSqr	23.311*	34.675	31.628	37.254	47.941**
	(12.850)	(33.365)	(21.030)	(23.915)	(20.670)
capAs	39.424	105.467***	8.294	3.223	6.754
	(27.994)	(36.854)	(22.899)	(62.679)	(27.916)
mtbRto	−0.465	−0.635*	0.300	−0.383	−0.593
	(0.331)	(0.358)	(2.320)	(0.678)	(0.384)
lf	94.174	−125.018*	183.704**	169.445	176.338**
	(59.415)	(69.800)	(71.447)	(186.324)	(79.038)
fdvPct12m	−20.010***	−5.679	−18.557	−13.170	−13.410
	(5.446)	(5.527)	(13.118)	(17.935)	(8.309)
Year dummies	Yes	Yes	Yes	Yes	Yes
Region		AM	AS	EU	
Business Model					NLC
N	302	120	95	84	244
R^2	0.899	0.762	0.967	0.866	0.886
Adjusted R^2	0.874	0.663	0.949	0.786	0.856
AIC	2569.849	1035.043	731.523	766.042	2087.853

*p<0.1; **p<0.05; ***p<0.01
Robust standard errors in parentheses
Variables ending with '_' are denoted in millions

Table F.8: Alternative airline fixed effects model for variables related to financial hedging, *fxdvDm* and *irdvDm*

	Dependent variable: CO_2Asm			
	(1)	(2)	(3)	(4)
divDm	−4.234	−6.178	−13.056*	−1.735
	(2.601)	(4.422)	(6.651)	(2.918)
divYld	−0.502	70.634	107.380	50.413
	(22.696)	(53.552)	(83.938)	(35.815)
cashRto	−14.131	2.932	−73.781	−62.052**
	(18.354)	(40.380)	(49.218)	(29.209)
cashRtoSqr	11.361	−5.431	37.254	47.941**
	(11.288)	(27.264)	(23.915)	(20.670)
capAs	46.770*	144.096***	3.223	6.754
	(26.922)	(37.017)	(62.679)	(27.916)
mtbRto	−0.420	−0.763*	−0.383	−0.593
	(0.327)	(0.386)	(0.678)	(0.384)
lf	112.407*	−40.118	169.445	176.338**
	(59.113)	(79.791)	(186.324)	(79.038)
fxdvDm	0.356	3.585	−4.623	−1.203
	(7.072)	(10.197)	(14.678)	(7.650)
irdvDm	−12.906***	−24.316***	−13.404	−13.457***
	(3.875)	(7.653)	(11.174)	(4.012)
Year dummies	Yes	Yes	Yes	Yes
Region		AM	EU	
Business Model				NLC
N	357	123	103	296
R^2	0.907	0.801	0.855	0.896
Adjusted R^2	0.887	0.718	0.783	0.872
AIC	3041.976	1039.535	942.346	2535.478

*p<0.1; **p<0.05; ***p<0.01
Robust standard errors in parentheses
Variables ending with '_' are denoted in millions

Table F.9: Alternative airline fixed effects model for variables related to operational hedging, $acAge$

	Dependent variable: CO_2Asm			
	(1)	(2)	(3)	(4)
$divDm$	−3.029	−4.262	−13.679**	−2.636
	(2.686)	(4.559)	(5.847)	(3.127)
$divYld$	−22.130	38.995	45.104	29.777
	(16.611)	(46.992)	(90.479)	(43.307)
$cashRto$	−22.994	−47.460	−48.827	−52.130
	(22.763)	(36.193)	(49.656)	(34.265)
$cashRtoSqr$	20.887	19.937	30.313	55.253**
	(13.835)	(26.039)	(25.846)	(25.482)
$capAs$	30.573	87.790**	29.717	−10.782
	(30.388)	(37.130)	(55.545)	(31.093)
$mtbRto$	−0.456	−0.699*	−0.304	−0.628*
	(0.339)	(0.371)	(0.609)	(0.377)
lf	102.190	−153.001**	309.188	259.979***
	(64.652)	(74.245)	(204.821)	(86.965)
$acAge$	1.401	0.676	0.448	−0.631
	(1.233)	(1.773)	(2.235)	(1.280)
Year dummies	Yes	Yes	Yes	Yes
Region		AM	EU	
Business Model				NLC
N	293	123	91	232
R^2	0.901	0.764	0.873	0.894
Adjusted R^2	0.876	0.670	0.806	0.865
AIC	2505.649	1058.215	814.253	199.393

*p<0.1; **p<0.05; ***p<0.01
Robust standard errors in parentheses
Variables ending with '_' are denoted in millions

Table F.10: Alternative airline fixed effects model for variables related to operational hedging, *acOlcashDm*

	Dependent variable: CO_2Asm				
	(1)	(2)	(3)	(4)	(5)
divDm	−4.494	−6.080	5.208	−15.524**	−3.975
	(3.156)	(5.441)	(4.678)	(6.900)	(3.189)
divYld	38.250	−1.849	56.290	123.600*	44.932
	(32.602)	(51.667)	(57.976)	(71.376)	(34.875)
cashRto	−28.167	−29.736	−110.905***	−46.086	−57.394
	(23.456)	(40.218)	(41.098)	(48.710)	(36.438)
cashRtoSqr	20.435	4.670	79.575***	27.591	51.363**
	(14.173)	(26.159)	(26.259)	(24.877)	(25.417)
capAs	27.456	118.364***	43.633	−21.688	−13.631
	(30.571)	(36.898)	(43.603)	(45.410)	(27.836)
mtbRto	−0.357	−0.539	3.844	−0.585	−0.486
	(0.394)	(0.430)	(3.556)	(1.146)	(0.470)
lf	78.084	−100.141	318.912***	59.141	191.522**
	(70.488)	(88.376)	(97.935)	(170.507)	(88.215)
acOlcashDm	−2.303	−9.905	2.271	2.300	1.304
	(4.319)	(7.344)	(6.507)	(7.347)	(4.726)
Year dummies	Yes	Yes	Yes	Yes	Yes
Region		AM	AS	EU	
Business Model					NLC
N	268	112	73	83	215
R^2	0.885	0.753	0.965	0.878	0.874
Adjusted R^2	0.856	0.643	0.941	0.803	0.839
AIC	2291.905	960.389	571.463	748.141	1846.509

*p<0.1; **p<0.05; ***p<0.01
Robust standard errors in parentheses
Variables ending with '_' are denoted in millions

Table F.11: Alternative airline fixed effects model for variables related to operational hedging, *acOlPct*

	Dependent variable: CO_2Asm				
	(1)	(2)	(3)	(4)	(5)
divDm	−4.402	−5.954	5.258	−15.868**	−3.741
	(3.182)	(5.585)	(4.768)	(6.652)	(3.206)
divYld	38.904	52.221	51.991	130.040*	47.116
	(32.255)	(47.652)	(59.255)	(72.115)	(33.939)
cashRto	−25.748	−13.813	−110.465**	−57.516	−63.338
	(23.303)	(38.928)	(41.544)	(56.548)	(38.309)
cashRtoSqr	19.179	−3.275	80.716***	32.602	56.278**
	(14.096)	(27.104)	(26.627)	(27.797)	(26.842)
capAs	26.351	117.835***	38.757	−31.020	−14.269
	(30.215)	(37.840)	(39.326)	(54.397)	(27.693)
mtbRto	−0.354	−0.608	3.830	−0.515	−0.537
	(0.406)	(0.442)	(3.579)	(1.067)	(0.477)
lf	66.302	−142.119*	327.625***	66.370	222.741**
	(67.099)	(75.397)	(103.127)	(172.436)	(89.750)
acOlPct	−7.580	11.867	8.353	14.054	21.615
	(12.704)	(17.952)	(25.075)	(36.375)	(13.931)
Year dummies	Yes	Yes	Yes	Yes	Yes
Region		AM	AS	EU	
Business Model					NLC
N	268	112	73	83	215
R^2	0.885	0.748	0.965	0.878	0.876
Adjusted R^2	0.856	0.636	0.941	0.803	0.841
AIC	2291.319	962.560	571.437	748.072	1844.231

*p<0.1; **p<0.05; ***p<0.01
Robust standard errors in parentheses
Variables ending with '_' are denoted in millions

Table F.12: Alternative airline fixed effects model for variables related to operational hedging, *fDiv1* and *fDiv2*

	Dependent variable: CO_2Asm				
	(1)	(2)	(3)	(4)	(5)
divDm	−2.536	−1.101	5.448	−16.226**	−2.957
	(2.717)	(4.587)	(5.673)	(7.206)	(2.851)
divYld	−18.777	41.852	−46.700*	78.236	25.268
	(21.386)	(55.502)	(25.953)	(77.938)	(33.893)
cashRto	−29.803*	−59.364	−24.936	−52.702	−53.085*
	(15.875)	(36.669)	(21.261)	(52.841)	(30.333)
cashRtoSqr	25.509***	34.639	24.071**	37.267	46.579**
	(8.720)	(24.495)	(11.690)	(25.970)	(21.428)
capAs	16.945	62.958*	15.131	12.080	2.362
	(24.060)	(37.584)	(38.099)	(55.634)	(30.057)
mtbRto	−0.524	−0.688*	−3.719	−0.098	−0.666*
	(0.348)	(0.377)	(3.004)	(0.753)	(0.387)
lf	209.373***	93.775	286.617***	211.723	252.782***
	(66.964)	(130.152)	(97.487)	(186.943)	(88.542)
fDiv1	147.098***	145.598***	213.372**	54.547	81.612
	(20.023)	(31.717)	(80.823)	(58.585)	(62.947)
fDiv2	−19.525	−33.847*	−33.607	−63.014	−0.987
	(13.636)	(19.569)	(33.733)	(46.747)	(25.468)
Year dummies	Yes	Yes	Yes	Yes	Yes
Region		AM	AS	EU	
Business Model					NLC
N	325	123	101	91	261
R^2	0.912	0.799	0.961	0.873	0.891
Adjusted R^2	0.892	0.715	0.939	0.800	0.864
AIC	2737.274	1040.648	819.059	821.672	2237.709

*p<0.1; **p<0.05; ***p<0.01
Robust standard errors in parentheses
Variables ending with '_' are denoted in millions

Table F.13: Alternative airline fixed effects model for variables related to operational hedging, *fDiv1AgeDm*

	Dependent variable: CO_2Asm			
	(1)	(2)	(3)	(4)
divDm	−3.484	−6.000	−13.185**	−2.534
	(2.802)	(5.048)	(6.171)	(3.187)
divYld	−21.626	37.467	44.727	22.162
	(16.941)	(45.575)	(95.408)	(44.029)
cashRto	−25.360	−42.192	−58.544	−55.726
	(23.164)	(38.747)	(49.123)	(34.469)
cashRtoSqr	20.897	15.838	35.007	56.762**
	(13.915)	(27.145)	(26.337)	(25.725)
capAs	30.025	87.988**	22.940	−10.992
	(31.454)	(35.601)	(53.675)	(30.791)
mtbRto	−0.446	−0.706*	−0.458	−0.640*
	(0.340)	(0.376)	(0.636)	(0.387)
lf	92.166	−157.331**	328.662	241.261***
	(67.274)	(71.360)	(216.369)	(91.186)
fDiv1AgeDm	−3.147	−11.676**	−0.790	−1.070
	(3.491)	(5.222)	(8.374)	(3.037)
Year dummies	Yes	Yes	Yes	Yes
Region		AM	EU	
Business Model				NLC
N	285	123	86	224
R^2	0.899	0.768	0.868	0.893
Adjusted R^2	0.874	0.674	0.792	0.862
AIC	2442.635	1056.460	773.998	1929.159

*p<0.1; **p<0.05; ***p<0.01
Robust standard errors in parentheses
Variables ending with '_' are denoted in millions

Table F.14: Alternative airline fixed effects model for variables related to operational hedging, *olexpRev* and *olexpTl_*

	Dependent variable: CO_2Asm				
	(1)	(2)	(3)	(4)	(5)
divDm	−4.423	−5.294	7.552**	−14.284*	−3.439
	(2.821)	(5.564)	(3.034)	(7.184)	(2.905)
divYld	36.880	25.250	63.689	122.090	52.748*
	(27.772)	(43.309)	(44.246)	(81.240)	(30.347)
cashRto	0.713	−50.120	11.698	−42.917	−26.204
	(14.162)	(38.255)	(20.918)	(56.154)	(27.731)
cashRtoSqr	2.290	22.586	6.850	25.275	30.446
	(6.534)	(24.789)	(11.997)	(24.943)	(19.050)
capAs	19.999	121.804***	−20.193	−48.519	−5.775
	(23.363)	(38.717)	(21.088)	(47.554)	(21.281)
mtbRto	−0.459	−0.416	4.939**	−0.275	−0.590
	(0.440)	(0.487)	(2.176)	(0.992)	(0.521)
lf	63.844	−169.299***	195.860**	10.432	131.926*
	(55.327)	(63.396)	(74.490)	(157.867)	(70.585)
olexpRev	−57.351	−66.261	−211.695	−180.939	141.579
	(46.774)	(44.243)	(156.713)	(325.122)	(129.982)
*olexpTl_*	0.005	−0.009	0.033**	0.019	0.002
	(0.008)	(0.013)	(0.013)	(0.021)	(0.010)
Year dummies	Yes	Yes	Yes	Yes	Yes
Region		AM	AS	EU	
Business Model					NLC
N	328	112	103	94	269
R^2	0.910	0.755	0.972	0.857	0.899
Adjusted R^2	0.888	0.643	0.958	0.783	0.873
AIC	2793.6631	961.129	799.718	861.104	230.781

*p<0.1; **p<0.05; ***p<0.01
Robust standard errors in parentheses
Variables ending with '_' are denoted in millions

F.5 CORSIA

The Carbon Offsetting and Reduction Scheme for International Aviation (CORSIA) plays a subordinate role within this work, as the data set only includes the years between 2005 and 2019. Nevertheless, this section provides a brief overview in order to be able to provide context for the EU ETS and general development of CO_2 emissions caused by aviation.

Like the EU ETS, CORSIA emerged from the Kyoto Protocol. Article 2 calls on ICAO to develop ways to control emissions from international aviation (UNFCCC, 1997).
CORSIA is a global offsetting mechanism that applies to all international flights, whereby a flight is considered international if it takes off in one country and lands in another. Airlines are required to buy or cancel emission units to offset the increase in CO_2 emissions compared to the average annual emissions of 2019 and 2020.[282] This is to achieve carbon-neutral growth in international aviation from 2020 onwards. Because of the COVID-19 pandemic, it was decided that only 2019 would be used as the new baseline for the 2021-2023 period (ICAO, 2020). To calculate this value, all operators that emit more than 10,000 tCO_2 per year on international flights have to report all emissions from their international flights since 1st January 2019. This includes all those operators administered by states that have not volunteered. Exempt from this are operations with aircraft that have a Maximum Take Off Mass (MTOM) of less than or equal to 5,700 kg. Airlines that have not exceeded the 10,000 tCO_2 threshold in the past but exceed it in a given year must monitor, report and verify (MRV) their emissions to the administrating authority and comply with CORSIA's MRV requirements from 1st January of the following year.

CORSIA is divided into different phases similar to the EU ETS, as shown in Figure F.25. In the pilot phase and Phase I, only flights between countries that have volunteered to participate are considered. Each of these flights is subject to the compensation requirements, including international flights operated by airlines not based in a voluntarily participating state. Nevertheless, CO_2 emissions of all international flights, including exempted flights, are monitored, verified and reported annually.

From 2027 (Phase II) on, all international flights between two countries, including those that have not volunteered, will be included in the offset requirements. This excludes coun-

[282] 'CORSIA eligable emissions units' are determined by the ICAO Council and a list is available here: `ttps://www.icao.int/environmental-protection/CORSIA/Pages/CORSIA-Emissions-Units.aspx`, visited on 02/28/2022.

tries that are either Least Developed Countries[283], Small Island Developing States[284] or Landlocked Developing States[285] as wel as countries that accounted for less than 0.5% of total RTKs from international aviation in 2018. In addition flights for medical, humanitarian, firefighting, military or governmental reasons are exempted. Apart from this, the exempted countries can decide on their participation at the beginning of each year, they only have to notify this by 30$^{\text{th}}$ June of the previous year.

Figure F.25: CORSIA timeline

The calculation of the offset requirement will evolve over time from a purely sectoral approach to a combination of a sectoral component and an individual component.

The sectoral component ($SC_{i,t}$) depends on the total CO_2 emissions of the operators ($TE_{i,t}$) and the 'growth factor' of the sector (SGF_t). This percentage is the same for all operators and is calculated by dividing the total increase in CO_2 emissions of all operators ($TESP_t - AESP_0$) by the total CO_2 emissions of the pairs of states subject to offsetting in a given year ($TESP_t$). The exact calculation is shown below.

[283]Least Developed Countries (LDCs) are a category of states that, for structural, historical and also geographical reasons, are considered to be at a severe disadvantage in their development process (UN, 2022c). A current list of all LDCs can be found here: `https://www.un.org/en/conferences/least-developed-countries`, vistied on 08/02/2022.

[284]Small Island Developing States (SIDS) are a special group of both UN Member States and non-UN members of the United Nations Regional Commissions. They are particularly vulnerable in social, economic and environmental terms. SIDS are located in three geographical regions: the Caribbean, the Pacific and Atlantic Oceans, the Indian Ocean and the South China Sea (AIS) (UN, 2022c). A current list of all SIDS can be found here: `https://www.un.org/ohrlls/content/list-sids`, visited on 08/02/2022.

[285]Landlocked Developing States or Landlocked Developing Countries (LLDCs) continue to face serious obstacles to overall socio-economic development due to lack of territorial access to the sea, isolation from world markets and high transit costs (UN, 2022a). A current list of all LLDCs can be found here: `https://www.un.org/ohrlls/content/list-lldcs`, visited on 08/02/2022.

$$SC_{i,t} = TE_{i,t} \times SGF_t = TE_{i,t} \times \frac{(TESP_t - AESP_0)}{TESP_t},$$

where

$SC_{i,t}$ = sectoral component of operator i in year t,

$TE_{i,t}$ = total emissions emitted by operator i in year t,

SGF_t = sectoral growth factor in year t,

$TESP_t$ = total CO_2 emitted by all operators on state-pairs subject to offsetting requirements in t,

$AESP_0$ = 2019 or 2019-2020 average emissions for the same state-pairs as mentioned earlier.

The individual component for each operator in the respective year ($IC_{i,t}$) depends on the individual emissions on state-pairs subject to the offsetting requirements ($IESP_{i,t}$) and its emissions for the same state-pairs in the baseline ($AESP_0$) and is calculated as follows:

$$IC_{i,t} = IESP_{i,t} - AESP_0,$$

where

$IC_{i,t}$ = individual component of operator i in year t,

$IESP_{i,t}$ = individual emissions of operator i on state-pairs subject to offsetting requirements in year t.

The overall offsetting requirements of each operator in the respective year ($OR_{i,t}$) are then calculated by multiplying each component with the corresponding weight (SW_t and IW_t), which can be found in Table F.15. The exact calculation is shown below.

$$OR_{i,t} = SW_t \times SC_{i,t} + IW_t \times IC_{i,t},$$

where

$OR_{i,t}$ = overall offsetting requirements of each operator i in year t,

SW_t = sectoral weight in year t,

IW_t = individual weight in year t.

Table F.16 lists the main differences between CORSIA and the current EU ETS framework. Here, the difference under 'Cap/Baseline' is striking. The aim of both policies is to

Table F.15: Weights of CORSIA for different phases

	Pilot Phase	**First Phase**	**Second Phase**		
	2021-2023	2024-2026	2027-2029	2030-2032	2033-2035
SECTORAL	100%	100%	100%	Up to 80%	Up to 30%
INDIVIDUAL	0%	0%	0%	At least 20%	At least 70%

reduce emissions. The EU ETS uses an annually decreasing baseline. If participants are above this baseline, they must buy additional allowances. CORSIA uses the emissions of 2019 or 2019/2020 as a constant baseline and only emissions exceeding this baseline need to be offset.

Table F.16: CORSIA vs EU ETS - key differences of the two approaches (Nelissen et al., 2021).

		CORSIA	**EU ETS**
Fundamental differences	Methodology	Baseline and Offsetting	Cap and Trade
	Environmental integrity	Dependent on offset unit quality standards and enforcement	Not critical, overall cap is fixed
	Need for verification by authorities	Both at emitter and at offsetting project level	Only at emitter level
Differences in current implementation and application (coverage and baseline)	Cap/Baseline	Avg. 2019/2020 emissions; no further reduction envisaged *(until 2023: 2019 emissions)*	95% of avg. 2004-2006 emissions; stepwise further reduction of cap through linear reduction factor of 2.2% from 2021 onwards
	Scope	International routes between participating states; fixed-wing only	Intra-EEA including domestic flights to Switzerland (derogation for flights to/from third countries until 2023); fixed-wing and rotorcraft
	Affected carriers	All airlines operating on covered routes, unless exceptions apply	

Further elaboration on the design of the system and itself would have been beyond the scope of this paper, but can be found in ICAO (2016), International Air Transport Association (IATA) (2019a) or Nelissen et al. (2021), which are also the main sources for section 2.3.1, unless otherwise stated.

Even before the pilot phase of CORSIA began, the question was raised as to how the overall climate impact of aviation could be integrated into climate protection at the international level and what could be the economic consequences (Scheelhaase et al., (2015)). The results of Scheelhaase et al. (2015) show that a global trading system would be the best solution from both an economic and an ecological perspective. Scheelhaase et al. (2015) conclude that the costs and the impact on competition could be kept relatively low and at the same time the environmental benefits would be substantial. A further study of Scheelhaase et al. (2018) on the compatibility of the EU ETS and CORSIA shows that a combination of the 'Stop-the-clock' scope of the EU ETS from 2020 and CORSIA would deliver the best results. This combination would bring international and intra-EEA flights under one CO_2 reduction scheme. But since only international flights are considered under CORSIA, airlines with predominantly domestic traffic would have a competitive advantage over airlines with predominantly international traffic. Another difference mentioned between the two trading schemes is that CORISA is an offset scheme, only emissions that exceed the 2020 threshold on the respective route have to be compensated. Under the EU ETS, all CO_2 emissions exceeding 95% of the 2004-2006 average CO_2 emissions must be offset, although as mentioned earlier, this number continues to decrease through the linear reduction factor (Scheelhaase et al., 2018).

Chao et al. (2019) conclude that a CORSIA-type policy could contribute to carbon emission reductions. They find that the level of US airline carbon emissions in 2050 is significantly negatively correlated with fuel price, carbon price growth rate, and airline fuel price risk, and positively correlated with GDP growth rate, under both a no domestic emissions scenario and a CORSIA-like emissions scenario. In order to represent the choices of the different actors, a combined model for aviation operations and sustainable fuels is used. Both a life cycle assessment and a Monte Carlo simulation are used to assess the consumption of the sustainable fuels and the resulting emissions under the two policy scenarios.

In addition to the empirical analysis mentioned above, Sharma et al. (2021) simulate the carbon emissions of the airlines considered until 2035 under four scenarios (status quo, pessimistic, optimistic and realistic). This shows that CORSIA alone will not bring about sufficient emission reductions. Further technological innovations in fuel and fuel-efficient fleets are needed to further reduce emissions per flight. Larsson et al. (2019) share that view and recommend, as also mentioned above for the EU ETS, additional measures in the case of CORSIA to achieve a faster impact. Concerning passenger fares, Wang et al.

(2017) argue that measures based on enroute charges, CORSIA classified as such measures, would have the least impact on passenger fares.

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