UNIVERSIDADE CATÓLICA PORTUGUESA

Fuel and Operational Hedging

Evidence from the Airline Industry

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Universidade Católica Portuguesa, Católica Porto Business School
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by

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sob orientação de
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"An investment in knowledge pays the best interest"
Benjamin Franklin

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Resumo

A indústria da aviação é, hoje em dia, caraterizada por uma intensa competição global entre companhias aéreas. Os custos com combustível representam uma parte substancial das despesas operacionais e estão sempre sujeitos à volatilidade do mercado. Tanto a cobertura de risco financeiro como operacional estão ao dispor das companhias aéreas para contrariar a volatilidade e reduzir os custos em combustível. Sendo um dos poucos estudos a incluir companhias aéreas da Europa e da Ásia, esta investigação foca-se em 43 companhias ao longo do período 2007-2017 e conclui que as transportadoras aéreas Europeias têm menor exposição ao risco do preço do combustível, do que as companhias Asiáticas ou Norte-Americanas. Também é realizada uma comparação entre tipos de companhias e é possível concluir que a exposição média ao preço do querosene é maior em companhias-bandeira do que nas de baixo custo. Pensamos que este será o primeiro estudo global a incluir três medidas de cobertura de risco operacional, sendo estes a diversidade da frota, a eficiência de combustível, e a utilização de aviões em *leasing* operacional. Treanor, Carter, Rogers, & Simkins (2013) estudaram estas medidas mas apenas em companhias Norte-Americanas. Usando modelos de efeitos-fixos, os nossos resultados sugerem que a cobertura do risco financeiro acaba por aumentar a exposição. Adicionalmente, as nossas evidências apontam para uma rejeição da hipótese de que a cobertura de risco operacional leva a uma diminuição da exposição ao risco do preço do querosene, em todas as nossas três *proxies*.

Palavras-chave: hedging financeiro, hedging operacional, exposição ao risco, querosene, diversidade da frota, idade da frota, leasing operacional, companhia aérea, indústria da aviação.

Códigos JEL: G32, L93

Abstract

The airline industry is nowadays characterized by an intense competition among carriers around the globe. Jet fuel costs represent a substantial part of airlines' operating expenses and are always subject to the market volatility. Both financial and operational hedging are at the disposal of airlines to offset the volatility and smooth these expenses across the years. Being one of the few studies to include airlines from Europe and Asia, this research focuses in 43 airlines over the period 2007-2017 and finds that European carriers are less exposed to fuel price than Asian or North American airlines. We also test for types of carriers and find evidence that the average fuel exposure is higher on premium airlines, when comparing to low-cost carriers. To our knowledge, this is the first study to include three measures of operational hedging on a global sample of airlines, namely fleet diversity, fuel-efficiency and operating leased aircrafts. Treanor, Carter, Rogers, & Simkins (2013) studied these but only on a sample of North American airlines. Using fixed-effects' models, our results suggest that financial hedging increases fuel risk exposure. Furthermore, our results lead to a rejection of the hypothesis that operational hedging decreases airlines' exposure, on all three proxies we consider.

Keywords: risk management, financial hedging, operational hedging, risk exposure, jet fuel, kerosene, fleet diversity, fleet age, operational leasing, airline industry.

JEL Codes: G32, L93

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Chapter 1
Introduction

The International Air Transport Association (IATA) recently reported that fuel costs accounted for over 18.8% of airlines' operating costs during the year of 2017, enhancing the importance of controlling these costs (IATA, 2018). Higher fuel costs are not fully charged to passengers by means of higher ticket fares, as the airline industry is very competitive, but there is a positive pass-through effect from changes in crude oil prices to airfares (Gayle & Lin, 2017). As so, hedging is a mean through with airlines try putting their efforts on, with the goal of having fuel costs relatively lower than its competitors'.

It is clearly stated in previous studies that current results regarding hedging effectiveness in the aviation industry are inconsistent and there is still a lack of research in this field (Berghöfer & Lucey, 2014; Treanor, Carter, Rogers, & Simkins, 2013). Moreover, Treanor (2008) mentioned that studies on the effectiveness of hedging are biased if they exclude operational hedging. Additionally, the biggest motivation for this study comes up with an enormous passion for the airline industry and its operating challenges.

The main goal of this research is to test whether financial and operational hedging decrease airline companies' jet fuel price risk exposure. This is done using a sample of 43 airlines based on Europe, North America and Asia, throughout a period of 11 years (2007-2017). To our knowledge, this is the first study taking into account fleet fuel-efficiency and operational leasing, two important operational hedges, on a global sample of airlines.

As a representative measure for financial hedging it is computed the next year's percentage of fuel hedged (Berghöfer & Lucey, 2014). Three distinct operating hedges are added to test on its effectiveness on decreasing such fuel exposure. Particularizing, a company's fleet diversity, measured by the number of operating aircraft models (ADI_M) or families (ADI_F), is defined as one of the operational hedges (Berghöfer & Lucey, 2014). Additionally, it is computed the weighted-average of a company's fleet age on every single year, given that there is a negative relationship between a fleet's age and its fuel-efficiency (Treanor et al., 2013). Moreover, the percentage of aircrafts being held in operating leasing contracts is taken into account as the third real option for operational hedging (Treanor et al., 2013). This type of contract allows companies for an easier exchangeability of its rented fleet, manageable in accordance to their demand situation, and balancing the need for more fuel-efficient aircrafts depending on the evolution of jet fuel prices.

Other factors might also impact the exposure of airlines to the fuel price risk, such as the average flight distance or the passenger load factor. It is clear that the higher the number of passengers aboard, the greater dilution of some costs which are incurred regardless of the load factor, such as part of the fuel carried.

We start with a brief literature review on Chapter 2, discussing the rationales for hedging, then going deeper within the airline industry and finally counterposing financial and operational hedging. Chapter 3 presents the characteristics of our data sample, manually introduced in Excel from the readings of 440 annual reports and 10-K fillings, followed by an analysis on the methodology used, presenting the different equations to be regressed and formulating our hypothesis to be tested.

On Chapter 4 we present descriptive statistics, being followed by our results and the discussing of our findings. We estimate a two-step model, the first with the intent to extract jet fuel exposure coefficients. From this, we find a similar percentage of negatively exposed carriers, when comparing to Berghöfer & Lucey (2014). We also get differences statistically significant (at a one percent level) between exposure coefficients between Europe and Asia, as well as between Europe and North America, in line with Berghöfer & Lucey (2014). On the other side, and against Berghöfer & Lucey (2014) findings, we did not get statistically significant differences on the exposure coefficients between North America and Asia.

Our study also contributes to the vast research by testing for the difference on jet fuel exposure between premium and low-cost carriers, on a global scale. Although we could not find significant differences between carriers with a two-sided t-test, we were able to prove, at a 10% significant level on a one-sided test, that premium carriers are more exposed than low-cost carriers.

This study tests several distinct second-step fixed-effects' models with panel data, controlling for airline and year, this way putting jet fuel price exposure under test against several proxies for financial and operational hedging. We do not find evidence that financial or operational hedging decrease airlines' fuel exposure, contrary to Treanor, Simkins, Rogers, & Carter (2014b). In fact, we find evidence that financial hedging increases risk exposure, with five-percent significance. This could be explained by ineffective hedging and sector specificities, validating the policies followed by North American airlines in the past recent years, by decreasing their fuel hedges. Airlines must evaluate if the costs of entering into hedging do not exceed the potential benefits.

Finally, on Chapter 5 we end up presenting the conclusions of our study, followed by some of the limitations a work on this field faces, due to the difficulty and inconsistency of gathering comparable information across annual reports of companies around the Globe, and still providing some ideas for further researches on the impact of hedging in the airline industry.

Chapter 2
Literature Review

In this chapter, we will review and discuss some literature on risk management theories, performing a brief analysis of which is the rationale behind the reason why firms hedge, and if this practice adds value to firms. This is followed by a deeper analysis on specific practices of hedging within the airline industry and ends counterposing both financial and operational hedges airlines have at their disposal.

2.1 Risk Management Theory. Rationales for Hedging.

Under perfect market conditions, firms would have no incentives to hedge with derivative instruments (Modigliani & Miller, 1958). Nonetheless, due to the existence of market imperfections, there may be room and rationale for hedging, in a way of trying to increase the expected value of a firm (Deshmukh & Vogt, 2005).

Froot, Schafstein, & Stein (1993) note that a firm can reduce its variability of cash flows by hedging, ultimately resulting in an increase of firm value. Smith & Stulz (1985) share this opinion, however noticing that hedging will also reallocate wealth from shareholders to bondholders, with prejudice to the first.

Moreover, Smith & Stulz (1985) suggest that hedging can reduce financial distress costs imposed by bond covenants, diminishing the probability of bankruptcy and this way increasing firm value, particularly on larger ones, which present higher distress costs due to its size. These bond covenants have an important risk exposure for the companies, many times linked with accounting ratios, whose volatility should be carefully managed by the enterprise, avoiding bond covenants to become binding. Froot et al. (1993) further improve, considering hedging can be used as a way to increase debt capacity, once having debt in the capital structure is an advantage due to tax shields and also because financial distress is costly.

Besides, Myers (1977) defends that firms with "debt overhang" might have to turn down some investment opportunities, and so, hedging could help reducing distortions, ultimately adding value. On its turn, Froot et al. (1993) extends previous studies by stating that companies which might need external funding and do not hedge, could be obliged to underinvest in some states, due to high costs of external capital, including deadweight costs. The article written by Carter, Rogers, & Simkins (2005) explains that according to the Froot et al. (1993) model, hedging allows companies to decrease their needs of external financing when its cost is higher.

Froot et al. (1993) remember there is a strong evidence stating that investment is sensitive to internal cash flow levels. Indeed, firms will tend to hedge less when they have lower cash flows available, once this traduces itself in lower investment opportunities. On the other side, firms will have an increased desire for hedging when there is a higher correlation between their cash flows and their facility of obtaining external financing.

Tufano (1998) improved in a certain way Froot et al. (1993) model by considering agency costs between shareholders and managers. He explains that when these agency conflicts get high proportions, managers and shareholders may sparkle and take different opinions regarding the optimal hedging policy, ultimately, destroying value.

According to Stulz (1984), managers are the ones who decide the hedging strategy of a firm, and not shareholders. On the other side, the latter are the ones determining managerial compensation, which has a fixed part, plus typically a variable one, tied to the firm's value. Hence, there seems to be an arrangement for a compensation package in a way that shareholders' wealth is maximized as long as managers obtain a level of expected utility sufficiently great to persuade them on working for the shareholders (Stulz, 1984), which is a way of outbalancing managers' risk aversion. Given this, managers would be influenced to reduce the total variance of the firm value, by enforcing hedging contracts.

Froot et al. (1993) finds a weakness on the study computed by Stulz (1984), noticing it relies on the assumption that managers are confronted with substantial costs when "trading in hedging contracts for their own account", because otherwise, they could fine-tune their risks without implying the firm explicitly in hedging events.

Smith & Stulz (1985) develop one more theory of hedging behavior of value-maximizing corporations. Given the structure of the tax code and assuming taxes as a convex function of earnings, hedging can be considered advantageous. Having in mind that hedging will tend to reduce the variability of a pre-tax firm value, the expected value for the corporate tax liability would also be lower. Consequently, and taking in account that hedging costs are relatively small, the expected post-tax firm value shall be higher.

2.2 Does hedging enhance firm value?

There are scarce studies on the impact of hedging on firm value creation, plus there is not a single clear conclusion. For instance, Allayannis & Weston (2001) study the impact of foreign currency derivatives in a sample of 720 U.S.

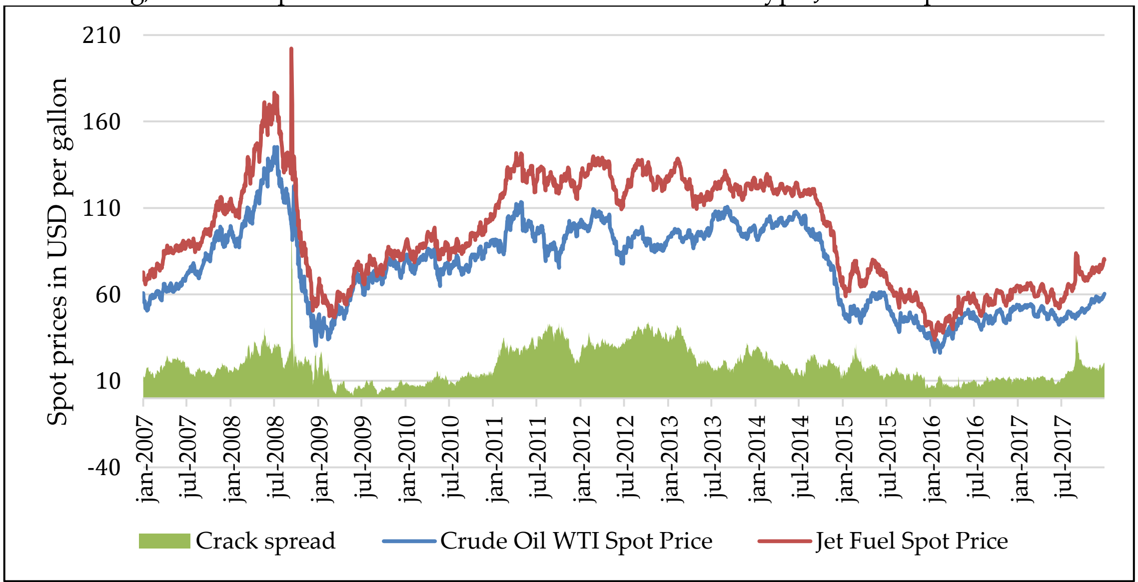
nonfinancial firms for the years of 1990-1995. Taking Tobin's Q as a proxy for the relative market value, they find a positive relation, meaning that hedging improves firm value. Opposing, Jin & Jorion (2006) develop another study, considering a smaller sample of 119 U.S. oil and gas producers for the years of 1998-2001. They observe that hedging decreases a firm's stock price sensitivity to gas and oil prices, however, concluding that hedging does not appear to affect market value, for that particular industry. As a final example, Carter et al. (2006) compute a narrower research, exclusively looking at U.S. airline companies for the years 1992-2003, for assessing the impact of jet fuel hedging on firm value. Their results show that there is a positive relation between jet fuel hedging and airline enterprise value. Additionally, they suggest a "hedging premium" of around 10% exists, being most of this premium due to the interaction of hedging with investment. They claim this is consistent with the statement that the reduction of underinvestment costs turns to be the main consequence and benefit of jet fuel hedging by airlines.

2.3 Hedging in the airline industry

Airlines use financial hedging in a way to manage their exposure to jet fuel prices (Treanor et al., 2014b). Hentschel & Kothari (2001) remember that there is a distinction between hedging, through which return volatility can be reduced, and speculation, which increases volatility and firm risk exposure. Dybvig & Marshall (1997) and Tokic (2012) highlight that concerning fuel hedging, commercial airlines have a long position, by acquiring future or forward contracts. The counterpart, being an oil/fuel company, or simply a trader, has the short position. Their payoffs are symmetrical.

It should be noted that aviation fuel futures are not so frequently traded on the organized exchange-traded futures market, having to be arranged over-thecounter (OTC) alternatives (Berghöfer & Lucey, 2014). OTC derivatives have the ability of being easily customizable, enabling a dynamic hedging strategy. On the other hand, there is a counterparty risk of bankruptcy for both parts involved (Cobbs & Wolf, 2004). As so, airlines rather *cross-hedge* part of their fuel needs with plain vanilla instruments such as swaps, options, forwards and futures on similar commodities (Bessembinder, 1991). The most common underlying commodities used in financial hedging contracts, for jet fuel hedging purposes, are the jet fuel itself, crude oil or even heating oil (Carter, Rogers, & Simkins, 2004). The *crack spread* measures the differential between crude oil spot prices and jet fuel spot prices (Berghöfer & Lucey, 2014). This spread can be observed in the next two figures, one related to Crude oil WTI and other for the Brent Crude oil.

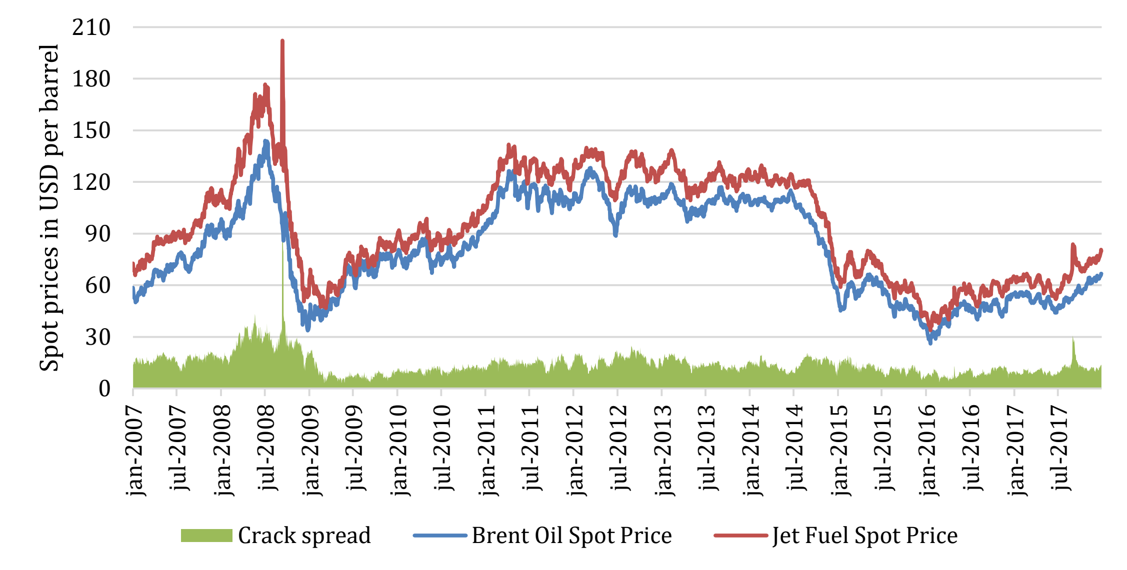
Figure 1: Evolution of the Crude Oil WTI 'crack spread' along the years 2007-2017. Daily values[1] for Cushing, OK WTI Spot Price and U.S. Gulf Coast Kerosene-Type Jet Fuel Spot Price.



Source: Own figure, using data from the U.S. Energy Information Administration (2019).

[1] **Source**: http://www.eia.gov/dnav/pet/pet_pri_spt_s1_d.htm - Data obtained on 22/01/2019 for the period 2007-2017.

Figure 2: Evolution of the Brent Crude Oil 'crack spread' along the years 2007-2017. Daily values[2] for Europe Brent Spot Price and U.S. Gulf Coast Kerosene-Type Jet Fuel Spot Price.



Source: Own figure, using data from the U.S. Energy Information Administration (2019).

Carter et al. (2004) state there are two key reasons why companies use different fuels rather than jet fuel itself, for jet fuel hedging purposes. Firstly, simply due to the nature of refining. When the crude oil is processed, the 'top of the barrel' product is gasoline, followed by the middle distillates (heating oil, diesel and kerosene), and then by the 'bottom of the barrel' fuel oil. Knowing that products from the same 'level' of the barrel present similar characteristics, plus, consequently, extremely correlated prices, and being jet fuel mainly pure kerosene with just a few additives, we have that heating oil is one of the chosen by airliners for hedging purposes. They also affirm crude oil prices are highly correlated with kerosene prices, therefore being another option of underlying for hedging. As final reason, the market for jet fuel is not liquid enough to allow for exchange-traded contracts, as already mentioned, reason why airlines prefer trading other similar commodities which are more liquid. However, this choice

[2] **Source**: http://www.eia.gov/dnav/pet/pet_pri_spt_s1_d.htm - Data obtained on 22/01/2019 for the period 2007-2017.

exposes airline companies to 'basis risk'[3], due to the difference between the price of the commodity being hedged and the price of the instrument used to hedge the price risk.

Guay & Kothari (2003) state that financial derivatives are just employed to "fine-tune an overall risk management program that likely includes other means of hedging". Many of the overall risks which non-financial firms face (e.g., operating risks) cannot be dealt with by using standard derivatives contracts.

2.4 Financial versus Operational Hedging

Analogous to some previous studies, both the studies of Allayannis, Ihrig, & Weston (2001) and Treanor et al. (2013) find evidence in the airline industry that operational and financial hedges are complements. However, the latter notices the evidence regarding the effectiveness of financial hedging is mixed: financial fuel derivatives have a positive impact on airlines' value, contrary to fuel contracts, which diminish the value of airlines by locking in the price of fuel. Besides, if an airline solely uses operational hedges, its value is expected to decrease.

Treanor et al. (2013) discuss three types of operational hedges in their studies. First, and commonly to Allayannis & Weston (2001), they account for the diversity of aircrafts in an airline's fleet, which is based on the Hirschman-Herfindahl concentration index. Secondly, they study airlines' fleet's fuel efficiency, which can be estimated by the aircraft's average age. As last type of operational hedging, the authors evaluate the impact of companies which use operating leases on their fleets.

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[3] Basis risk can be defined as the risk that changes in a futures' price over time will not follow accurately the value of the cash position (Figlewski, 1984).

Firms can engage in hedging activities both through derivatives (financial hedging) or by recurring to operational hedges, which are part of the real options a firm owns (Treanor et al., 2013). These authors also mention on their work that the study computed by Allayannis et al. (2001) tests the impact of using financial and operational hedging on firm value. Their results show that there is not a positive relationship between the value of a multinational company and its practice of operational hedging. On the other side, they find that by using both financial and operational hedges, there is a value-enhancing component up to a 16.7% premium facing a firm's market to book ratio.

2.5 Empirical Models

Our main models are inspired in Berghöfer & Lucey (2014), who analyze 64 airlines from Asia, Europe and North America, between 2002 and 2012, testing for the efectiveness of financial hedging, by considering the percentage of next year's fuel hedged, and operational hedging, testing for two different measures of fleet diversity. They reject the hypotheses that financial or operational hedging decrease risk exposure.

Treanor et al. (2013) test whether financial and operational hedging are substitutes or complements, and include two additional operational hedges, fleet fuel efficiency and whether a fleet is held in operating leasing. For their sample of U.S. airlines, throughout the period 1994-2006, they find that financial hedging increases firm value and operational hedging destroys value.

Finally, Treanor et al. (2014b) also study U.S. airlines' exposure to fuel prices for the period 1994-2008, finding that financial and operational hedging strategies are both effective at reducing airlines' exposure.

Chapter 3
Data and Methodology

After reviewing the literature on risk management and hedging, the present chapter has the purpose of identifying the data used on this research, as well as identifying and describing the theoretical model and variables which are going to be used as proxies for testing whether financial and operational hedging can reduce airline companies' jet fuel price risk. We believe this is the first study to include and test three distinct operational hedging measures on a global sample of airlines.

3.1 Data Sample

The period of analysis for this study is comprised between the years 2007 and 2017, considering a sample of 43 airlines based on North America, Europe and Asia as a proxy for the global airline market. Therefore, a panel data is used in the regressions. Due to events such as mergers or withdrawal from publicly listed exchanges, some airlines might not have information available for the whole study period.

The list of companies chosen consists on airlines which are, or at least were quoted, during part of the eleven-year sample, on international exchanges. Airlines from North America are classified with the code 4512 of the Securities and Exchange Commission (SEC) – scheduled air transportation, or also with codes 4522 and 4513, for non-scheduled air transportation and air courier services, respectively. These last two are applied only to Atlas Air Worldwide and Air Transport Services, correspondingly.

Airlines considered on our sample disclose, at least, four annual reports, out of the eleven periods in study. This was defined in order to include Wizz Air, an important European low-cost carrier, which is the only airline counting with four reports. Out of the low cost carriers hereby analyzed, six are based on Europe, one is headed in Asia and four have its headquarters in North America.

Table 1: Overview of the airlines' annual reports / 10-K fillings analyzed, from 2007 to 2017:

	Asia	Europe	North America	**TOTAL**	LCC[4]
Airlines	14	15	14	**43**	11
Periods	144	151	145	**440**	104
Average periods per airline	10.29	10.07	10.36	**10.23**	9.45

Source: Own figure.

On the next page, Table 2 presents an overview of the information manually collected.

[4] LCC – abbreviation for "low cost carrier". LCC's included for Europe are EasyJet, FlyBe Group, Norwegian Air Shuttle, Pegasus Airlines, Ryanair and Wizz Air. North American low-cost carriers are Allegiant Travel, JetBlue Airways, Southwest Airlines and Spirit Airlines. The only Asian LCC is AirAsia.

Table 2: Overview of the data withdrawn from the annual reports and 10-K fillings.

Variable	Nº Obs.	Total Disclosure (%)	Disclosure Europe (%)	Disclosure N. Am. (%)	Disclosure Asia (%)
% Next year fuel hedged	292	66.36	73.51	82.76	42.36
Jet Fuel Costs (% OPEX)	422	95.91	100.00	100.00	87.50
Max. maturity fuel hedges (months)	351	79.77	93.38	82.07	63.19
Underlying commodities	276	62.73	80.79	60.00	46.53
Exchange rate derivatives	424	96.36	100.00	95.17	93.75
Interest rate derivatives	432	98.18	100.00	100.00	94.44
CASK (CASM)[5]	386	87.73	92.72	83.45	86.81
CASK (CASM) ex-fuel	386	87.73	92.72	83.45	86.81
Passenger Load Factor	410	93.18	98.68	84.14	96.53
Revenue Passenger Kms/Miles	365	82.95	76.16	76.55	96.53
Revenue Passengers Carried	352	80.00	82.12	61.38	96.53
Average Flight Distance	357	81.14	82.78	64.14	96.53
CPA[6]	152	34.55	20.53	83.45	0.00

[5] CASK stands for "cost per airline seat-kilometer" and CASM is the "cost per airline seat-mile".

Variable	Nº Obs.	Total Disclosure (%)	Disclosure Europe (%)	Disclosure N. Am. (%)	Disclosure Asia (%)
Fuel derivative instruments	383	87.05	92.05	92.41	76.39
Nº Aircrafts	435	98.86	100.00	100.00	96.53
Nº Models	428	97.27	100.00	100.00	91.67
Nº Families	428	97.27	100.00	100.00	91.67
ADI_M	410	93.18	90.07	100.00	89.58
ADI_F	410	93.18	90.07	100.00	89.58
Fleet Age	334	75.91	82.12	92.41	52.78
% Operational Leasing	364	82.73	84.11	98.62	65.28
Charter	440	100.00	100.00	100.00	100.00
% Turboprop	431	97.95	100.00	100.00	93.75
Total Assets	427	97.05	95.36	98.62	97.22
OPEX[7]	422	95.91	95.36	98.62	93.75
Average	**381**	**86.52**	**88.90**	**89.49**	**81.03**

Source: Own figure.

3.2 Methodology

3.2.1 Financial Hedging

Airlines use financial hedging in a way to manage their exposure to jet fuel prices (Treanor et al., 2014b). Also, jet fuel costs account for an important part of airlines' operating expenses. Therefore, the proxy considered for financial hedging is the percentage of an airline's jet fuel hedged for the following year

[6] CPA stands for Capacity Purchase Agreement.
[7] OPEX stands for Operating Expenses.

(Berghöfer & Lucey, 2014; Treanor et al., 2013; Treanor et al., 2014b). Another aspect of airlines' financial hedging strategic plan is the maximum maturity of derivative instruments used for fuel hedging (Berghöfer & Lucey, 2014), which is also here included.

3.2.2 Operational Hedging

Previous studies with global samples only included one proxy for operational hedging, being the fleet composition (detailed on Chapter 3.2.2.1), as in the case of Berghöfer & Lucey (2014). The inclusion of fleet fuel-efficiency (Chapter 3.2.2.2) and operational leases (Chapter 3.2.2.3) are herewith firstly tested on a global sample.

3.2.2.1 Fleet Composition

Treanor et al. (2013, 2014b) emphasize a diverse fleet provides additional operational flexibility to airlines, once they can adjust their route's supply of seats. Because there is a high cost on abandoning certain markets or routes during periods that are not economically favorable (e.g. high fuel prices), it is great having a real option through which an airline can replace larger aircrafts by smaller ones. Nevertheless, although possessing a diverse fleet has its perks, it also comes with a cost. Besides the need for more spare parts and additional storage for these, there might also be an increase of costs with maintenance, flight crew training and pilots' type-ratings (Berghöfer & Lucey, 2014), in the cases where airlines subsidize these programs.

Similarly to previous studies of Berghöfer & Lucey (2014) and Treanor et al. (2013, 2014b), the proxy for the fleet composition is analogous to the one used by G. Allayannis et al. (2001) as a geographic dispersion measure. Based on the

Hirschman-Herfindahl concentration index, it is computed an aircraft dispersion index (ADI), as entailed next:

$$ADI\_M_i = 1 - \sum_{j=1}^{M} \frac{(No.of\ Aircraft\ model_j)^2}{(Total\ No.of\ aircraft\ _i)^2} \qquad (1)$$

Where M stands for the total number of different models operated on airline i's fleet, and j represents each aircraft model. The ADI index varies from 0 to 1, being one the highest degree of diversity, and zero meaning the airline i is operating one single aircraft model.

An Airbus A319neo, for instance, fits a maximum of 140 seats in 1-class configuration[8], while the A320neo holds space for up to 194 seats[9]. These two aircraft models can serve as substitutes depending on the passengers' demand on a given time, acting as an important operational hedge.

Berghöfer & Lucey (2014) introduce a rational improvement on the ADI calculation, comparing to the previous studies computed by Treanor et al. (2013, 2014b), presenting this way the same index but considering aircraft families.

Additional costs arise more significantly when operating distinct aircraft families, rather than models. Distinct type ratings for cockpit and cabin crew, as well as specific maintenance such as spare parts, as already mentioned above, are usually specific for each aircraft family, and not per model. For instance, pilots who fly the Airbus A320, can also fly the A318, A319 and A321 with the same type rating, not incurring in additional costs for airlines. Flight attendants can also commute within these aircrafts without the need of extra-costs for airlines.

[8] Source: https://www.airbus.com/aircraft/passenger-aircraft/a320-family/a319neo.html consulted on 30/07/2018.
[9] Source: https://www.airbus.com/aircraft/passenger-aircraft/a320-family/a320neo.html consulted on 30/07/2018.

As so, Berghöfer & Lucey (2014) add this new method, by treating all aircraft models of a specific family[10] as a unit, as can be seen next:

$$ADI\_F_i = 1 - \sum_{k=1}^{F} \frac{(No.of\ Aircraft\ family_k)^2}{(Total\ no.of\ aircraft\ _i)^2} \tag{2}$$

Where F stands for the total number of different families operated on airline i's fleet, and k represents each aircraft family. The ADI index varies from 0 to 1, being one the highest degree of diversity, and zero meaning the airline i is operating one single aircraft family.

When the ADI_M_i index is zero, meaning the airline operates just one aircraft model, the ADI_F_i index always turns zero, once it is logically not possible to operate multiple families with just one aircraft model.

The opposite is not necessarily true: if the ADI_F_i takes the value zero, it means the airline operates a single family, but nothing can be concluded *a priori* regarding the ADI_M_i value. The airline might be operating just one type of aircraft, or many more, all belonging to the same family.

The following considerations respect to the way of counting aircraft families and models, which is the basis for the calculation of the aircraft dispersion indexes. In a way to better understand the matter, here follows the explanation of how some specific cases were treated:

a. Freighters are distinguished from passenger/combo aircraft in terms of aircraft types (models), but not regarding families.

[10] Example: the Airbus 320 family includes the following aircraft models: A318, A319, A320 and A321, ranging the maximum seat capacity (considering 1-class configuration) from 100 up to 240 seats. Source: https://www.airbus.com/aircraft/passenger-aircraft/a320-family.html (visited on 30/07/2018).

Example 1: Boeing 777-300 (passenger aircraft) and Boeing 777-F (cargo plane) are two different aircraft types, but belong to a common family (Boeing 777 family).

Example 2: Boeing 767-300F / -300BCF are considered different aircraft types, as the first is a freighter and the second has a passenger-to-freighter conversion possibility. Both belong to the same family (Boeing 767 family).

b. Aircrafts only differing on engine types were considered different models (ex. A320neo and A320ceo). The designation "neo" stands for "new engine option", while the "ceo" means "current engine option". The new engines are more fuel-efficient[11].

c. Same models but different range (ER stands for "extended range").

Example 3: Boeing 777-300 / -300ER are hereby considered as two different types. Although they share a similar fuselage, they can serve different operational needs due to different range spectrums[12]. The difference between these versions is increased tank capacity and wingspan, with the comedown of a slight passenger capacity decrease in the ER version).

Examples of some aircraft families (examples of aircraft models between brackets):

1. **Boeing[13]:**

a. 737 family (737-300, 737-400, 737-700, 737-800, 737-900…)

b. 747 family (747-200, 747-300, 747-400, 747-800…) + Freighter (747-400 Cargo) + Combo (747-400BCF)

c. 757 family (757-200, 757-300…)

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[11] Source: Airbus (https://www.airbus.com/aircraft/passenger-aircraft/a320-family/a320neo.html), visited on 10/02/2019.

[12] Source: Boeing (https://www.boeing.com/commercial/777/), visited on 29/12/2018.

[13] Source: Boeing (https://www.boeing.com), visited on 29/12/2018.

d. 767 family (767-200, 767-200ER, 767-300, 767-400…) + Freighter (767-300F)

e. 777 family (777-200, 777-200LR, 777-200ER, 777-300, 777-300ER…) + Freighter (777-F Cargo)

f. 787 family (787-8, 787-9, 787-10)

2. Airbus[14]:

a. A320 family (A318, A319, A320, A321)

b. A220 family - previously known as Bombardier C-Series - (A220-100, A220-300...)

c. A330 family (A330-200, A330-300, A330-800, A330-900…) + Freighter (A330-200F) + Combo (A330P2F)

d. A340 family (A340-200, A340-300, A340-500, A340-600…)

e. A350 XWB family (A350-900, A350-1000)

f. A380 family (A380-800)

3. Bombardier[15]:

a. CRJ Series – also known as Canadair Jet - (CRJ200, CRJ700, CRJ1000)

b. Q Series - also known as De Havilland Dash 8 - (Q200, Q300, Q400)

4. Embraer[16]:

a. E-Jet Family (175, 170, 190)

b. ERJ-Family (ERJ 140, ERJ 145, ERJ 170, ERJ 135)

c. EMB Brasilia Family (EMB 170, EMB 120)

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[14] Source: Airbus (https://www.airbus.com/aircraft.html), visited on 29/12/2019.
[15] Source: Bombardier (https://www.bombardier.com/en/aerospace/commercial-aircraft.html), visited on 29/12/2019.
[16] Source: Embraer (https://www.embraercommercialaviation.com/our-aircraft/), visited on 29/12/2019.

3.2.2.2 Fleet Fuel Efficiency

Another important factor to take in account is a fleet's fuel efficiency, given that a significant part of airline's operational costs is given by jet fuel costs. Treanor et al. (2013, 2014b) remember that airlines which operate newer fleets are less exposed to fuel price fluctuations, once newer aircrafts are more fuel-efficient. Treanor et al. (2013, 2014b) measure this type of operational hedge by using the natural logarithm of an airline's weighted average fleet age. The fleet age is withdrawn annually from the 10-K reports for the North-American airlines, and from the annual reports for the remaining. When the fleet age is not reported, it is used the adjacent year's value, whenever available.

3.2.2.3 Operating Leases

As third and last measure of operational hedge by airlines, operating leases comes up with great importance as it allows companies to easily adjust their fleets to market conditions. These are considered in the previous work of Treanor et al. (2013). As cited in this study, Brigham and Ehrhardt (2005) note that by recurring to leasing contracts, companies have more flexibility on switching some aircrafts for others more appropriate given the market conditions, for instance, when seats' demand for certain routes change.

Operating leasing contracts often include option clauses, which give airlines a real option of buying an airplane when the leasing contract ends, and/or to terminate or modify their leasing responsibilities before the contract ending.

In this study, the proxy used for measuring the impact of leasing is the percentage of an airline's fleet that is held on operating leasing, as did Treanor et al. (2013). This percentage is computed as the total number of aircrafts an airline has in operating leasing, divided by the total number of aircrafts which are in operation, whether owned or leased. The leasing data is withdrawn manually from both the 10-K reports for the North-American airlines (when available), and from the annual reports for the remaining.

3.2.3 Regressions

In order to estimate the way airlines might decrease their fuel price exposure, it is computed a two-step procedure, as previously done by other authors (Berghöfer & Lucey, 2014; Treanor et al., 2014b).

3.2.3.1 First-step regression

For the estimation of airlines' yearly exposure coefficients, we have the following equation:

$$R_{i,w} = \alpha_i + \beta_{i,y} R_{MK,w} + \gamma_{i,y} R_{JF,w} + \delta R_{USD,w} + \varepsilon_{i,w} \tag{3}$$

Where:

$R_{i,w}$ is airline i's weekly log stock price return for week w,

$R_{MK,w}$ is the log return for the corresponding market index for week w,

$R_{JF,w}$ is the weekly log change in jet kerosene prices for week w,

$R_{USD,w}$ is the log change in the trade weighted U.S. dollar index for week w,

$\beta_{i,y}$ is the coefficient for the market risk factor for airline i for year y,

$\gamma_{i,y}$ is the coefficient for jet fuel risk factor for airline i for year y, and

$\varepsilon_{i,w}$ designates the error term of airline i on week w.

The dependent variable on this equation is $R_{i,w}$, and the explanatory variables are $R_{MK,w}$, $R_{JF,w}$ and $R_{USD,w}$.

For the estimation of this first equation, weekly stock prices and corresponding market indexes are gathered from *Datastream* in native currency. The same applies to the U.S. Gulf Coast and Singapore jet kerosene spot prices. As computed by Berghöfer & Lucey (2014), Singapore kerosene prices were used for Asian airlines and the Gulf Coast kerosene was attributed to European and North American carriers. Data used for computing $R_{USD,w}$ corresponds to the "Trade Weighted U.S. Dollar Index: Broad, Index Jan 1997=100, Weekly, Not Seasonally Adjusted" and was retrieved from the website of the "Federal Reserve Bank of St. Louis – Economic Research".

3.2.3.2 Second-step regression – Berghöfer & Lucey (2014)

The following step computes the regression of jet fuel yearly risk exposure coefficients, previously obtained in the first step, on a series of operational and financial hedging measures, added of some control variables. The following equations[17] (4) and (5) are exactly the same Berghöfer & Lucey (2014) did, only substituting ADI_M for ADI_F on Equation (5). On Section 3.2.3.3, there are presented own alternative versions for the second-step equation, including other variables, such as two additional measures of operational hedging.

$$\begin{aligned} |\gamma_{i,y}| = \alpha_0 &+ \alpha_1(HDGPER_{i,y}) + \alpha_2(HDGMAT_{i,y}) + \alpha_3(ADI\_M_{i,y}) \\ &+ \alpha_4(LNTA_{i,y}) + \alpha_5(LTDA_{i,y}) + \alpha_6(LNDIS_{i,y}) \\ &+ \alpha_7(LF_{i,y}) + \varepsilon_{i,y} \end{aligned} \tag{4}$$

$$\begin{aligned} |\gamma_{i,y}| = \alpha_0 &+ \alpha_1(HDGPER_{i,y}) + \alpha_2(HDGMAT_{i,y}) + \alpha_3(ADI\_F_{i,y}) \\ &+ \alpha_4(LNTA_{i,y}) + \alpha_5(LTDA_{i,y}) + \alpha_6(LNDIS_{i,y}) \\ &+ \alpha_7(LF_{i,y}) + \varepsilon_{i,y} \end{aligned} \tag{5}$$

[17] Note: Even though the coefficient terms are displayed with the same notation across Equations 4 and 5, their estimation values will be distinct.

Where:

$HDGPER_{i,y}$ is the percentage of next year's fuel requirements hedged by the airline i on the year y,

$HDGMAT_{i,y}$ is the maximum maturity of fuel derivatives, in months, which the airline i has entered into, on year y,

$ADI\_M_{i,y}$ stands for the airline i's aircraft dispersion index on year y, in a particular version which considers the counting of aircraft models,

$LNTA_{i,y}$ is the logarithm of total assets (included to control for firm size) of the airline i on year y,

$LTDA_{i,y}$ is the long-term debt to assets ratio (included to control for firm leverage) of the airline i on year y,

$LNDIS_{i,y}$ is the logarithm of the average flight distance, in kilometers, for the airline i on the year y,

$LF_{i,y}$ is the passenger load factor of the airline i on the year y, and

$\varepsilon_{i,y}$ designates the error term of airline i on year y.

The dependent variable on this equation is the module of $\gamma_{i,y}$, and the explanatory variables are $HDGPER_{i,y}$, $HDGMAT_{i,y}$, $ADI\_M_{i,y}$, $LNTA_{i,y}$, $LTDA_{i,y}$, $LNDIS_{i,y}$ and $LF_{i,y}$.

The jet fuel price risk exposure $\gamma_{i,y}$ is considered in absolute values for the second equation, once it is assumed this exposure to be diminished towards zero with the use of hedging procedures (Berghöfer & Lucey, 2014; Treanor et al., 2014b).

The natural logarithm of total assets (LNTA) is controlling for firm size[18]. Haushalter (2000) concluded from an oil and gas producers' sample that firms

[18] The choice for controlling firm size with the log of total assets is made in accordance with Berghöfer & Lucey (2014), Treanor et al. (2013) and Carter et al. (2006).

with higher total assets have a greater likelihood of hedging, meaning larger firms tend to diminish more their exposure than smaller ones do. Nance, Smith, & Smithson (1993) provide steady findings on the relation between hedging with derivatives and firm size, while assuming that economies of scale could apply to hedging costs, this way existing a positive correlation between enterprise risk management and firm size.

Long-term debt to assets ratio (LTDA) is included to control for firm leverage. Here, the evidence is mixed. Tufano (1998b) verified that exposure has a positive relationship with firm leverage, while studying gold mining firms, and for that reason, Treanor et al. (2014b) include the variable LTDA on their equations, considering it could be applied the same reasoning to the airline industry. Still with the same results, Carter et al. (2006), while studying the U.S. airline industry, observe that firm leverage is negatively correlated with the volume of fuel hedged, and so, airlines with less financial constraints are the ones which hedge the most. On the other side, Haushalter (2000) find a positive relationship between firm leverage and the likelihood of hedging with derivatives, which ultimately means that higher leveraged firms tend to be less exposed to fuel by recurring to hedging.

Long-term debt to assets ratio (LTDA) and the logarithm of total assets (LNTA) are controlling for firm leverage, and size, respectively. Haushalter (2000) concluded from an oil and gas producers' sample that firms with higher total assets and greater financial leverage have a greater likelihood of hedging.

The variable $LNDIS$ is used as control for some operational issues (Berghöfer & Lucey, 2014). As the average sector length increases, airlines have lower possibilities of using undiversified fleets on operation. For instance, EasyJet cannot operate long-haul flights with their aircrafts' configurations. On the other side, Lufthansa has a much more diverse fleet and can operate short, medium and long-haul flights. Another situation regards tankering, which means taking extra-fuel on the inbound flight, for the outbound trip also. This is carried out by airlines when it is not viable to refuel the aircraft at the destination, such as for fuel shortage or high fuel prices at destination. The further the outbound flight, the need for carrying more fuel, and less the opportunity to carry on fuel for the return flight. As discussed by Berghöfer & Lucey (2014), this can be applied to the load factor as well. The greater the number of passengers carried, the lower is the capability of carrying fuel for the outbound flight, given maximum takeoff weight restrictions (commonly known as MTOW).

In the cases where the variable $LNDIS$ cannot be withdrawn directly from the airlines' annual reports or in its 10-K fillings, it can be computed through the following expression (Berghöfer & Lucey, 2014):

$$LNDIS = \ln(\frac{Revenue\ passenger\ kilometers/miles}{Total\ number\ of\ passengers}) \tag{6}$$

Whenever required, if there is no disclosure on the "Revenue passenger kilometers/miles" variable, it can be computed by the following formula[19] (when in miles, we use RPM and ASM, instead of RPK and ASK, respectively):

$$LF = \frac{RPK}{ASK} \Leftrightarrow RPK = LF * ASK \tag{7}$$

Where:

RPK is "Revenue Passenger Kilometers",

ASK is the "Available Seat Kilometers",

[19] Retrieved from Aegean Airlines 2017 annual report. All the distances in miles were then converted in kilometers, in order to make them comparable.

LF is the passenger load factor.

3.2.3.3 Alternative second-step regressions

This section presents some alternative second-step equations, contemplating more variables than Berghöfer & Lucey (2014) regressions. These include new variables controlling for two additional measures of operational hedging, being fleet-fuel efficiency, measured by the average fleet age, and the percentage of fleet held on operating leasing, as well as other control variables.

$$\begin{aligned}|\gamma_{i,y}| = \theta_0 &+ \theta_1(HDGPER_{i,y}) + \theta_2(HDGMAT_{i,y}) + \theta_3(FX\_DER_{i,y}) \\ &+ \theta_4(IR\_DER_{i,y}) + \theta_5(ADI\_M_{i,y}) + \theta_6(LNAGE_{i,y}) \\ &+ \theta_7(OPLEASE_{i,y}) + \theta_8(TURBOPROP_{i,y}) + \theta_9(LF_{i,y}) \\ &+ \theta_{10}(LNDIS_{i,y}) + \theta_{11}(LNTA_{i,y}) + \theta_{12}(CFSAL_{i,y}) + u_{i,y}\end{aligned} \tag{8}$$

Where, besides the variables already explained on Chapter 3.2.3.2:

- $FX\_DER_{i,y}$ is a dummy variable which takes the value 1 if the airline i enters into foreign exchange derivatives in the year y, turning 0 if otherwise,
- $IR\_DER_{i,y}$ is a dummy variable taking the value 1 if the airline i enters into interest rate derivatives in the year y, turning 0 if otherwise,
- $LNAGE_{i,y}$ is the logarithm of the average fleet age, in years, of airline i in the year y,
- $OPLEASE_{i,y}$ stands for the percentage of fleet held in operating leasing of airline i in the year y,
-$TURBOPROP_{i,y}$ is the percentage of turboprop aircrafts on the operating fleet of airline i, in the year y,
- $CFSAL_{i,y}$ is the cash-flow to sales ratio of the airline i in year y, and
- $\varepsilon_{i,y}$ designates the error term of the airline i on year y.

Dummy variables FX_DER and IR_DER are included in a similar way as Treanor et al. (2013) did on their analysis of whether financial and operational hedges are complements of substitutes, while studying the U.S. airline industry. While they create a single dummy, taking the value 1 if an airline uses currency derivatives, interest rate derivatives or has entered into a fuel pass-through agreement, we discard this last agreement due to the difficulty of obtaining such data on European and Asian carriers, and split interest-rate and currency derivatives into two separate dummies. This was not a problem since their correlation is pretty low[20]. Treanor et al. (2013) include this variable to control for relationships among fleets and the use of financial derivatives. These authors concretize, giving the example that airlines flying more international routes have a greater likelihood of entering into fuel and currency derivatives. They consider that the exclusion of this variable would cause bias on the diversity variable (ADI_M or ADI_F).

One of the operational hedges not studied by Berghöfer, is related with a fleet's fuel-efficiency. This is an important hedge and can be easily proxied by the logarithm of the average fleet age (Treanor et al., 2013; Treanor et al., 2014b). In our study, we always consider fleets in operation.

The other operational hedge added in our equations is the percentage of a fleet that is held under operating leasing. This variable was included by Treanor et al. (2013) and measures airlines' ability in response to high fuel prices or demand oscillations, which ultimately could diminish risk exposure.

The variable TURBOPROP is included since smaller aircrafts turbo-propelled cannot be considered substitutes for larger jets, once their range and speed does not allow them to operate the same routes. On the other side, we have regional jets, which even though they are smaller than narrow-body aircrafts, can service most of their routes (Treanor et al., 2014b).

[20] The correlation between IR_DER and FX_DER was ran on Stata and returned a very low value of 0.0172.

Finally, the cash-flow to sales ratio is recommended by Froot et al. (1993) and included by Treanor et al. (2014a) as an inverse proxy for financial constraints. The latter explains that firms with a greater ability for generating cash-flows have less probabilities of facing "binding constraints" in financial investments. Carter et al. (2006) note that the higher a firm's cash-flows, the higher are investment opportunities and the higher the likelihood of hedging. On the other side, Froot et al. (1993) states that firms will tend to hedge less, the higher the correlation between cash-flows and future investment opportunities. On the other side, firms will hedge more if their cash-flows are highly correlated with their ability of raising external finance.

From Equation 8 to Equation 9, the only difference is dropping the variable $CFSAL_{i,y}$.

$$\begin{aligned}|\gamma_{i,y}| = \theta_0 &+ \theta_1(HDGPER_{i,y}) + \theta_2(HDGMAT_{i,y}) + \theta_3(FX\_DER_{i,y}) \\ &+ \theta_4(IR\_DER_{i,y}) + \theta_5(ADI\_M_{i,y}) + \theta_6(LNAGE_{i,y}) \\ &+ \theta_7(OPLEASE_{i,y}) + \theta_8(TURBOPROP_{i,y}) + \theta_9(LF_{i,y}) \\ &+ \theta_{10}(LNDIS_{i,y}) + \theta_{11}(LNTA_{i,y}) + u_{i,y}\end{aligned} \tag{9}$$

Finally, Equation 10 is the same as the previous Equation 9, except for the fleet diversity proxy, having now included ADI_F instead of ADI_M[21].

$$\begin{aligned}|\gamma_{i,y}| = \theta_0 &+ \theta_1(HDGPER_{i,y}) + \theta_2(HDGMAT_{i,y}) + \theta_3(FX\_DER_{i,y}) \\ &+ \theta_4(IR\_DER_{i,y}) + \theta_5(ADI\_F_{i,y}) + \theta_6(LNAGE_{i,y}) \\ &+ \theta_7(OPLEASE_{i,y}) + \theta_8(TURBOPROP_{i,y}) + \theta_9(LF_{i,y}) \\ &+ \theta_{10}(LNDIS_{i,y}) + \theta_{11}(LNTA_{i,y}) + u_{i,y}\end{aligned} \tag{10}$$

[21] Note: Even though the coefficient terms are displayed with the same notation across Equations 8-10, their estimation values will be distinct.

3.2.4 Hypotheses

Based on the literature review present in Chapter 2, and completing with the analysis performed on Chapter 3.2.3.2, here follows our predictions of the coefficient signs for Equation 4, on the table below.

Table 3: Prediction of coefficient signs for the variables used on the estimation of Equations 4-5.

Variables	**Predicted Coefficient Signs**
HDGPER (percentage of next year's fuel hedged)	-
HDGMAT (max. maturity of fuel derivatives – months)	-
ADI_M (aircraft dispersion index – counting for models)	-
ADI_F (aircraft dispersion index – counting for families)	-
LNTA (logarithm of total assets)	-
LTDA (Long-Term Debt to Assets)	?
LNDIST (logarithm of the average flight distance – kms)	+
LF (passenger load factor)	-

Source: Own figure.

Following the same line of thought as in Berghöfer & Lucey (2014), in order to assess the impact of financial and operational hedging in the risk exposure airlines face, the following hypotheses are to be tested:

H1: Airline companies are equally exposed to jet fuel prices regardless the continent where they are based ($\gamma_{EU,y} = \gamma_{NAM,y} = \gamma_{ASIA,y}$).

H2: Financial hedging diminishes airlines' fuel price risk exposure ($\alpha_1 < 0$).

H3: Airlines experience a higher reduction in risk exposure, the wider its fleet diversity ($\alpha_3 < 0$).

H4: Airline companies' fuel exposure increases with higher average flight distances ($\alpha_6 > 0$).

H5: A higher passenger load factor reduces airlines' risk exposure ($\alpha_7 < 0$).

Furthermore, we can also predict the signs for the variables added on Equations 8-10.

Table 4: Prediction of coefficient signs for the variables estimated on Equations 8-10.

Variables	**Predicted Coefficient Signs**
FX_DER (dummy for the use of currency derivatives)	-
IR_DER (dummy for the use of interest rate derivatives)	-
LNAGE (logarithm of the average fleet age in years)	+
OPLEASE (% of fleet held in operating leasing)	-
TURBOPROP (% of turboprop aircrafts on the total fleet)	?
CFSAL (cash-flow to sales ratio)	?

Source: Own figure.

Given the additional variables included in our models, some additional hypotheses can be formulated:

H_6: Airlines' exposure to fuel prices increases with fleet's average age ($\theta_6 > 0$).

H_7: Airlines' exposure to fuel prices decreases with the percentage of aircrafts held in operating leasing ($\theta_7 < 0$).

H_8: Airlines entering into currency derivatives are more likely to hedge with fuel derivatives, consequently their exposure is expected to decrease ($\theta_3 < 0$).

H_9: Airlines entering into interest rate derivatives are more likely to hedge with fuel derivatives, and so their exposure is expected to decrease ($\theta_4 < 0$).

Given we have a dummy variable in our data for differentiating between premium airlines and LCC, it should be interesting testing for the following hypothesis:

H_{10}: Airline companies are equally exposed to jet fuel prices regardless they are premium or low-cost carriers ($\gamma_{PREMIUM,y} = \gamma_{LCC,y}$).

Chapter 4
Results and Discussion

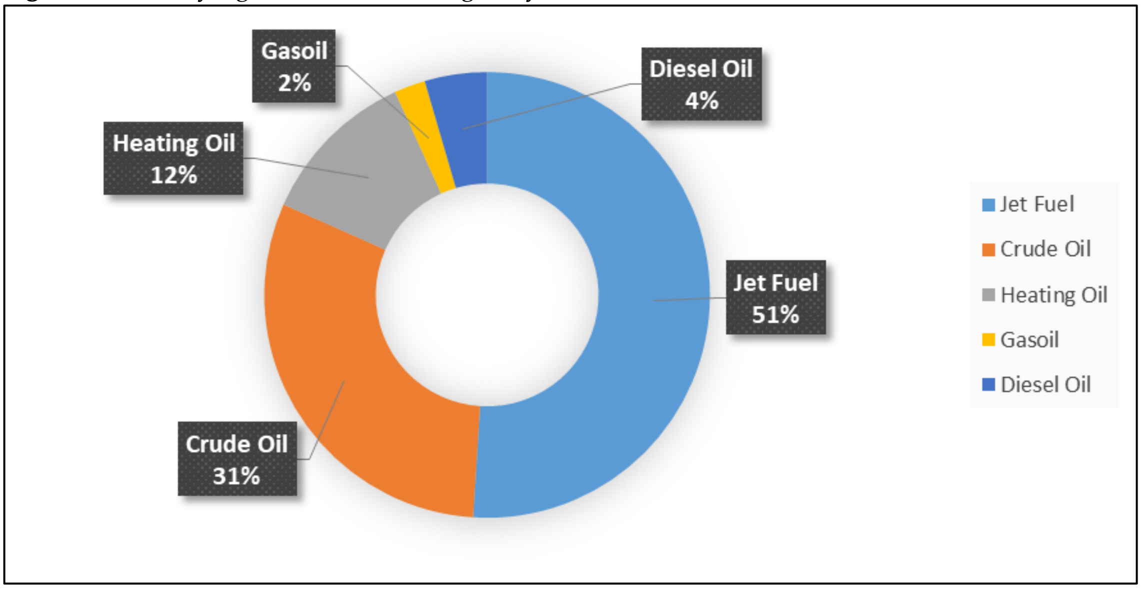
In the present chapter, are presented descriptive statistics for financial and operational hedging variables, as well as statistics regarding passenger load factor. This is followed by the results of the first-step equation, and finalized with the results for several second-step equation versions, the first six replicating Berghöfer & Lucey (2014) and three more formulations we propose.

4.1 Descriptive Statistics

4.1.1 Financial Hedging

Of the total 440 annual reports and 10-K fillings analyzed, 57 had no information regarding the instruments used, 164 did not report the underlying commodity used on fuel hedging, and 89 did not report derivatives' maturities.

Figure 3: Underlying commodities hedged by airlines between 2007 and 2017.



Source: Own figure.
Note: Based on 276 observations.

From the figure above it can be perceived that jet fuel still represents the main commodity used as an underlying, with a global value of 51%, once Berghöfer & Lucey (2014) reported approximately 42% for the period 2002-2012, although with a slightly different sample. The second and third choice for airlines are noticed to be crude oil, with 31 percent, followed by heating oil with 12 percent, maintaining the same ranking of Berghöfer & Lucey (2014). Finally, the two less used underlyings are diesel oil and gasoil, with approximately 4 and 2 percent, respectively.

Table 5: Overview per continent, as well as comparing low-cost carriers against premium airlines, on the underlying commodities, maturities and instruments used over the period 2007-2017. The percentage of periods hedged is also included.

	Europe	**North America**	**Asia**	**Low-cost carriers**	**Premium carriers**
Commodity					
Jet Fuel	95.90%	56.32%	55.22%	84.93%	69.46%
Crude Oil	18.03%	79.31%	46.27%	31.51%	48.77%
Heating Oil	0.00%	52.87%	0.00%	15.07%	17.24%
Gasoil	4.10%	0.00%	5.97%	0.00%	4.43%
Diesel Oil	8.20%	9.20%	0.00%	0.00%	8.87%
Maturity					
Average	22.01	12.15	14.32	16.04	16.92
Median	24.00	12.00	12.00	12.00	12.00
Instrument					
Options	45.32%	55.97%	55.45%	30.39%	59.79%
Swaps	38.85%	40.30%	42.73%	36.27%	41.99%
Collars	19.42%	39.55%	10.00%	25.49%	23.13%
Futures	6.47%	6.72%	0.00%	0.00%	6.41%
Forwards	54.68%	1.49%	1.82%	44.12%	12.46%
% Periods Hedged	97.46%	66.42%	56.52%	81.73%	71.25%

Source: Own figure.

Table 5 allows a wide analysis on multiple aspects of airlines' choices for commodity, maturity and instruments used on fuel hedging.

Both in Europe and Asia, the main choice for underlying asset is jet fuel, with 95.90 percent of European carriers having hedged jet fuel during the years 2007-2017. This value drops to 55.22 percent when mentioning Asian carriers, nevertheless it is still their first choice. Finally, North American airlines do give a first preference to crude oil, with 79.31 percent of the companies choosing this commodity, followed by jet fuel with 56.32 percent and then by heating oil (52.87%).

Hedging with other commodities may sound more appealing to airlines, given the fact there is more liquidity than there is with jet fuel, although it was already mentioned there are also some disadvantages, mainly the exposure to the called 'basis risk', as well as the counterparty risk, when trading in OTC markets (Cobbs & Wolf, 2004).

Still regarding commodities, when comparing low-cost with premium carriers, the evidence remains the same, jet fuel is the main choice for both types of airlines, with crude oil as a second preference and heating oil as third. Gasoil and diesel oil present residual values for premium carriers, and are not even used by low-cost airlines.

The global average percentage of next year's fuel requirements hedged is 33.73 percent for the following 16.68 months, with a median of 12.00 months. Low-cost and premium carriers register average maturities around 16-17 months, and equal a 12-month median. If we compute the same analysis for continents where airlines are based in, European carriers hedge with an average maturity of 22.01 months, much higher than Asian and North American airlines, with 14.32 and 12.15 months, respectively. These last two continents present a median maturity of 12.00 months, half of the 24.00 months' median of European carriers.

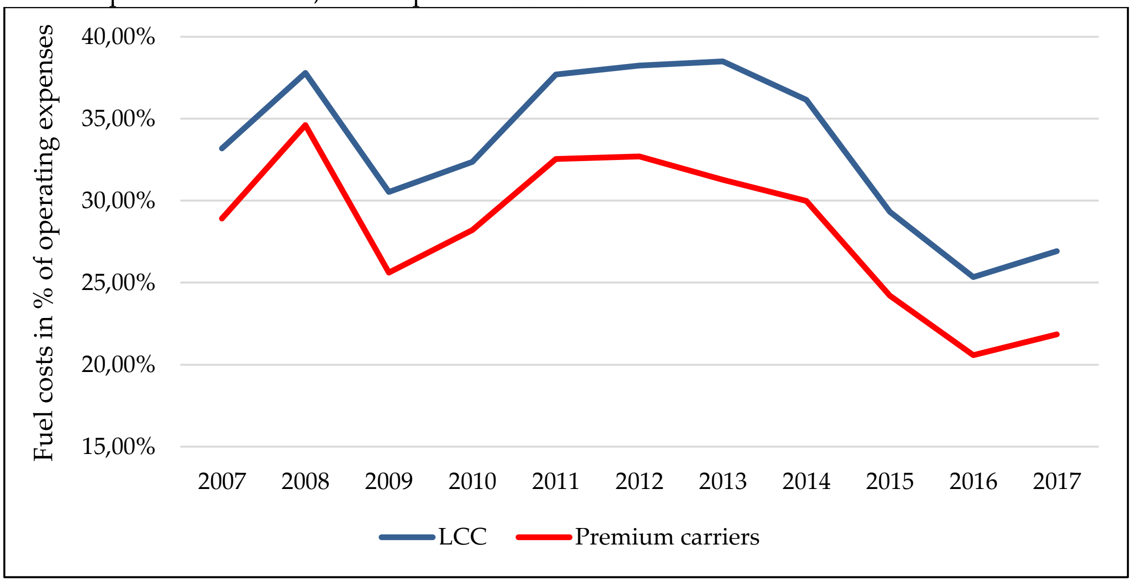
Regarding derivative instruments used, the two main preferences in Europe are forwards and options, respectively, followed by swaps, collars, and then, with a minor expression of 6.47 percent, futures. In North America and Asia, options are the main choice, followed by swaps and collars. Futures and forwards have little expression in these last two continents.

If comparing across types of airlines, low-cost airlines used forwards in 44.12 percent of the years, followed by swaps with 36.27 percent. On the other side, premium carriers preferred options with 59.79 percent, followed by swaps, which accounted for 41.99 percent.

European carriers were the ones hedging the greater percentage of the periods in study (97.46%), tailed by North American and the Asian airlines, which accounted for 66.42 and 56.52 percent, respectively. While comparing between types of airlines, LCC hedge more than premium carriers in around 10 percentual points.

Low-cost carriers are generally characterized by a lower cost structure, while comparing to other carriers. Because fuel costs are more homogenous across airlines, it is logic that jet fuel costs make up a greater percentage of total operating costs on low-cost carriers, as can be observed on the next figure. The share of fuel costs on the total operating expenses decreased from 29.86 to 23.32 percent, between the years 2007 and 2017.

Figure 4: Evolution of the percentage of fuel costs over total operating expenses, between low-cost and premium carriers, for the period 2007-2017.



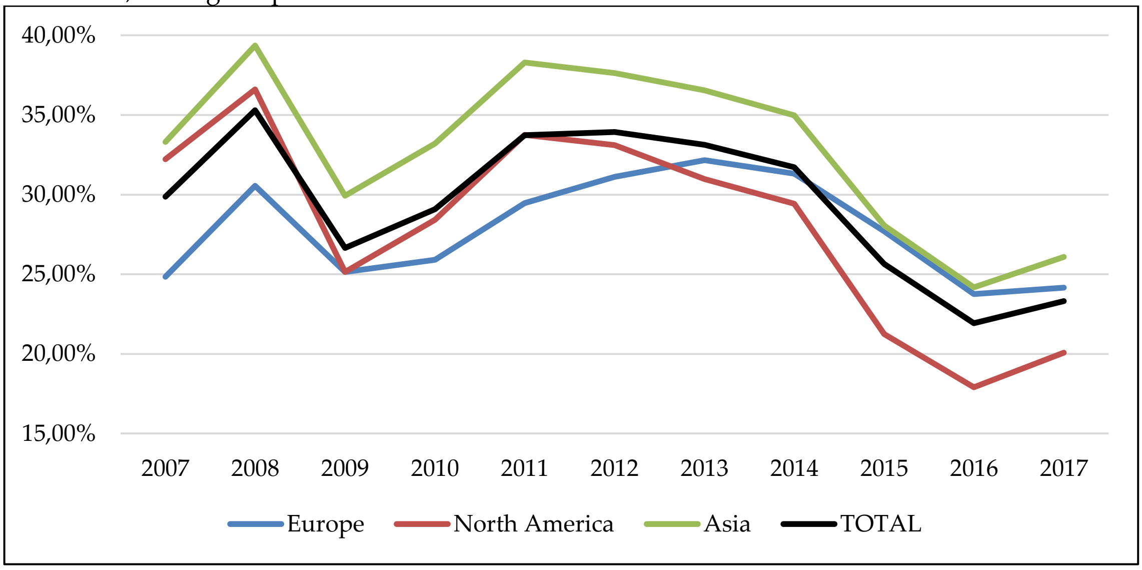
Source: Own figure.

Note: Based on 410 observations of 42 airlines.

As can be seen in Figure 5, during the initial two years of the period analyzed, in parallel with the peak of the financial crisis, it is clear that European airlines had lower relative fuel costs than Asian and North American carriers. From 2011 onwards, it can be observed North American airlines steeped down their fuel cost percentages more than European and Asians, and remained since that time under the global average, represented in the figure by the black line.

Asian carriers have always remained above the average values during the whole eleven-year period. European airlines have been showing values lower than the global average until 2014, year since which they have been slightly above the average percentage of fuel costs on the operating costs.

Figure 5: Evolution of the percentage of fuel costs over total operating expenses, across continents, during the period 2007-2017.



Source: Own figure.
Note: Based on 410 observations of 42 airlines.

4.1.2 Operational Hedging

4.1.2.1 Fleet Diversity

The following table presents the results obtained for aircraft dispersion index (ADI) equations. ADI_M values are considering the diversity of aircraft models, and ADI_F values consider aircraft families.

Table 6: Statistics for fleet diversity, measured by models (ADI_M) and families (ADI_F).

Year	**ADI_M**				**ADI_F**				**ADI_M-ADI-F**
	Europe	**NAm**	**Asia**	**Total**	**Europe**	**NAm**	**Asia**	**Total**	
2007	0.6437	0.6781	0.8198	**0.7099**	0.5425	0.4831	0.7072	**0.5714**	0.1385
2008	0.6479	0.6773	0.8225	**0.7137**	0.5247	0.4965	0.7099	**0.5724**	0.1413
2009	0.6630	0.6626	0.7688	**0.6971**	0.5112	0.4799	0.6592	**0.5471**	0.1500
2010	0.6476	0.6703	0.7392	**0.6859**	0.4863	0.5150	0.6483	**0.5497**	0.1362
2011	0.6225	0.6608	0.7305	**0.6720**	0.4405	0.4887	0.6420	**0.5241**	0.1479
2012	0.6130	0.6660	0.7493	**0.6775**	0.4286	0.4924	0.6683	**0.5314**	0.1461
2013	0.6046	0.6759	0.7376	**0.6710**	0.4454	0.5016	0.6662	**0.5344**	0.1366
2014	0.5676	0.6861	0.7312	**0.6552**	0.4200	0.4872	0.6611	**0.5142**	0.1410
2015	0.5565	0.7093	0.7225	**0.6585**	0.4192	0.5122	0.6561	**0.5231**	0.1354
2016	0.6049	0.7310	0.7280	**0.6828**	0.4544	0.5310	0.6624	**0.5417**	0.1411
2017	0.6021	0.7359	0.7246	**0.6866**	0.4346	0.5388	0.6602	**0.5415**	0.1451
Avg	**0.6120**	**0.6863**	**0.7511**	**0.6820**	**0.4608**	**0.5024**	**0.6669**	**0.5410**	**0.1417**

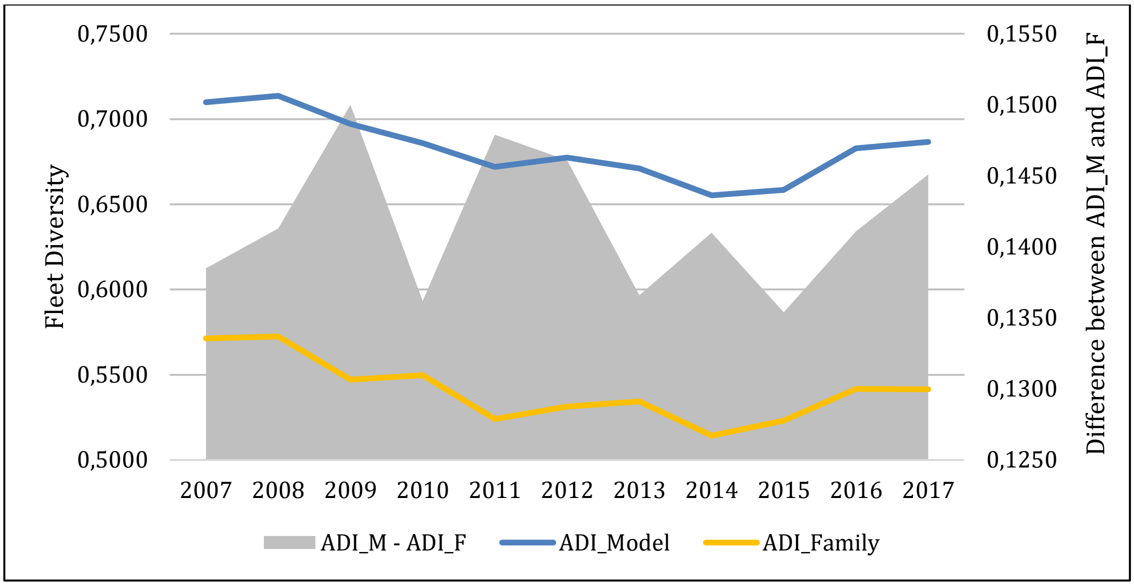
Source: Own figure.
Note: Based on 410 observations.

It was always chosen operating fleets[22] for counting purposes, ignoring parked aircrafts, aircrafts in maintenance or not in service, as well as aircrafts subleased to un-affiliated entities.

The following three figures help to better understand the choices airlines have been conceiving in the past years and its trend.

[22] (Berghöfer & Lucey, 2014) note that the fuel risk airlines are exposed to, is better measured by the operating fleet, rather than entire fleets, which include, for instance, parked aircrafts.

Figure 6: Evolution of fleet diversity across the years 2007-2017, measured by models and families.



Source: Own figure.
Note: Based on 410 observations, from which 104 are of low-cost carriers.

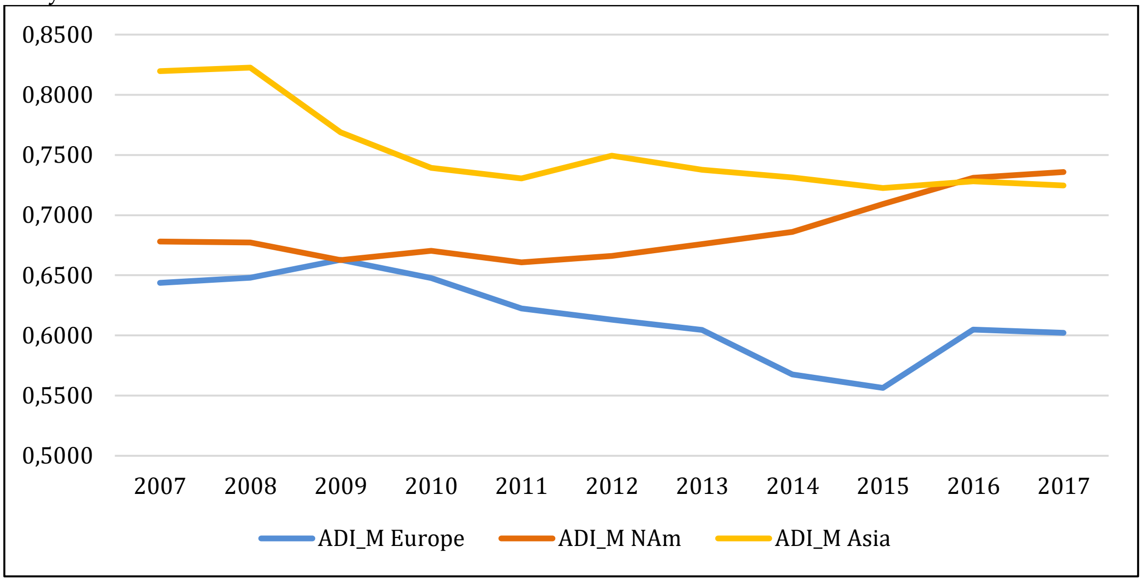
It is possible to understand there has been a decrease in the fleet diversity, especially from 2007 until 2014, but still true when comparing both ends of the period in analysis. This evidence is clear whether we are evaluating the number of aircraft families used or even the number of models. The tendency to reduce diversity may be associated with the need to cutting costs, such as trainings for pilots and cabin crew, as well as with spare parts.

Nevertheless, not every continent-base seems to be following the same tendency. European carriers have decreased their fleet diversity on 6.5 percent (ADI_M) or 19.9 percent (ADI_F). On the other side of the Atlantic, North American airlines experienced an increase of 8.5 percent (ADI_M) or 11.5 percent (ADI_F). Finally, Asian carriers kept the European tendency and diminished its fleet diversity by 11.6 percent (ADI_M) or 5.2 percent (ADI_F).

These results are consistent with the results obtained by Berghöfer & Lucey (2014) for the period 2002-2012, except for one difference. While their study verified a decrease on the ADI_F for North American airlines, this present study finds an opposite result for 2007-2017. However, still regarding North

American companies, both our works find an increase on the ADI_M value. It should also be noted the airlines' sample is not the exactly the same within these two studies, and the periods in analysis also differ, as their study was between 2002 and 2012.

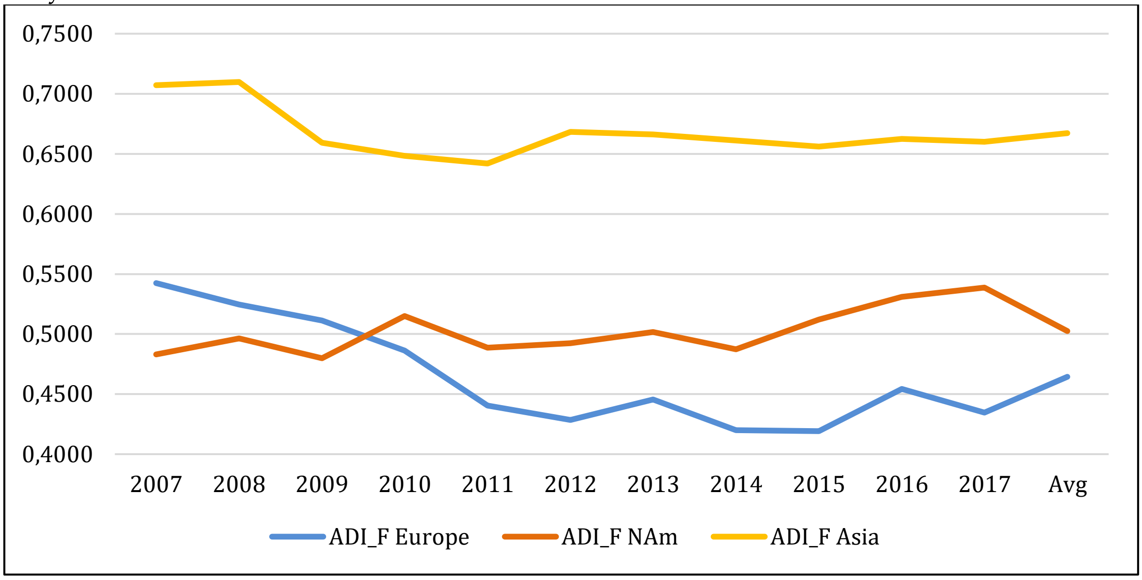
Figure 7: Overview of fleet diversity, measured by ADI_M, over the different continents, across the years 2007-2017.



Source: Own figure.
Note: Based on 410 observations, from which 104 are of low-cost carriers.

From the figure above it is possible to conclude that the fleet diversity, measured by the number of aircraft models, has decreased approximately 6.5 percent for European carriers, from 2007 until 2017. Asian airlines followed the same path and diminished its diversity by 11.6 percent. On the opposite side, North American carriers increased its fleet diversity by 8.5 percent.

Figure 8: Overview of fleet diversity, measured by ADI_F, over the different continents, across the years 2007-2017.



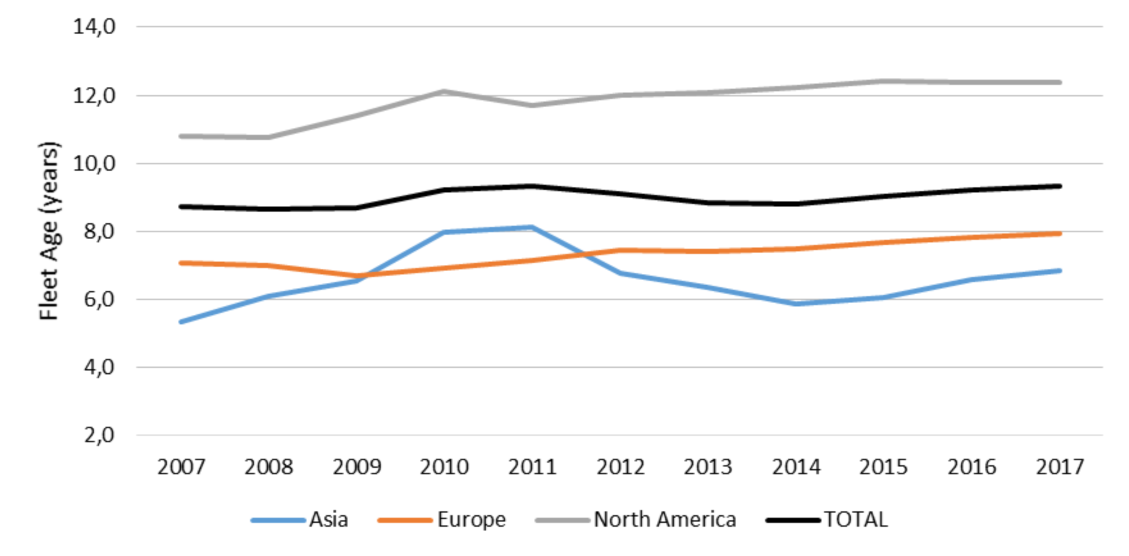
Source: Own figure.
Note: Based on 410 observations, from which 104 are of low-cost carriers.

From the figure above it is possible to conclude that the fleet diversity, measured by the number of aircraft families, has decreased approximately 19.9 percent in Europe, from 2007 until 2017. Asian carriers followed the same tendency and decreased diversity in 6.6 percent. On the other side, North American airlines increased its fleet diversity by 11.5 percent. Still, the diversity of families operated by Asian airlines is much higher than on the other continents, during the whole period in analysis.

4.1.2.2 Fleet Fuel Efficiency

The following graphs provide some interesting statistics regarding the average age of airlines' fleets.

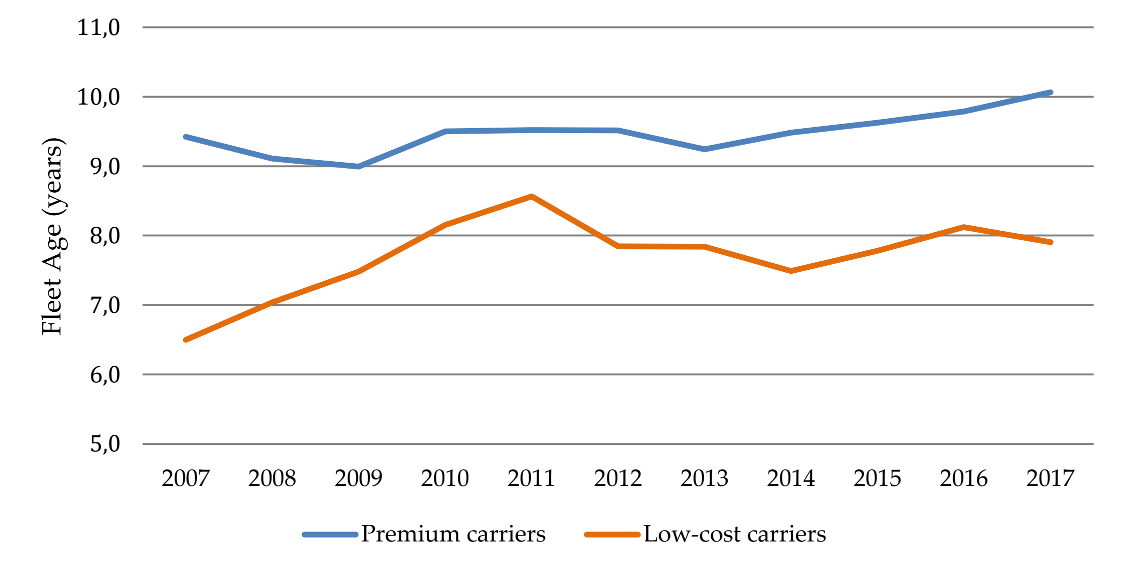
Figure 9: Evolution of airlines' average fleet age per continent, for the years 2007-2017.



Source: Own figure.
Note: Based on 334 observations.

The figure above clearly shows North American carriers have much older fleets than Asian or European ones. On all three cases, there has been an increase of age while comparing both ends of the period analyzed. Asian airlines are the ones with the lower average age in 2007, being 5.3 years, while comparing to the European average of 7.1 or the immensely higher North American average of 10.8 years. From 2009 until around mid-2011, European airlines had its fleet age under the Asian carriers, nevertheless, both their values remained the whole period under the global average, which can be explained by the great differences to North America. Still to notice, as of 2017, the average fleet age was of 6.8 years for Asian carriers, 7.9 for European and 12.4 for North American airlines. At this time, the global average was 9.3 years.

Figure 10: Comparison fleet age between premium and low-cost carriers, for the years 2007-2017.



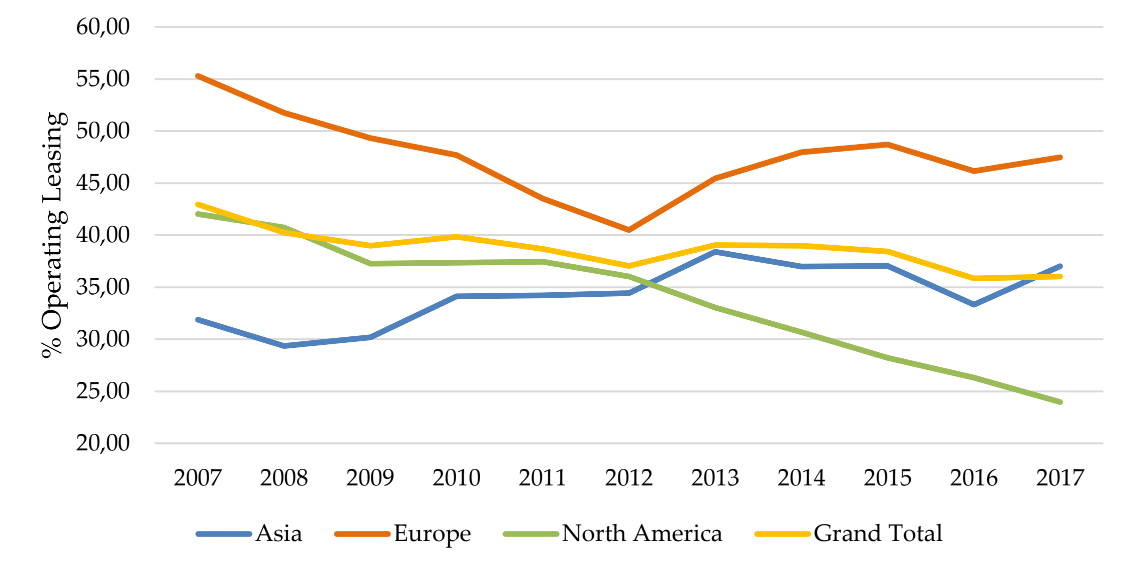
Source: Own figure.
Note: Based on 334 observations.

It is interesting to observe in the graph above that low-cost carriers have, in fact, a lower average fleet age than premium carriers. This difference was much more substantial in the beginning of the period, in 2007, when the average age for low-costs was 7.9 years and premium carriers registered 10.1 years, but during the whole period the differential is clear. In 2017, the average age difference between types of carriers was of 2.2 years.

4.1.2.3 Operating Leases

The following two figures provide an overview over airlines' preferences for operating leases on their total operating fleets, whether owned or not.

Figure 11: Evolution of fleets' percentages held under operating leasing, per continent and across the years 2007-2017.



Source: Own figure.
Note: Based on 364 observations.

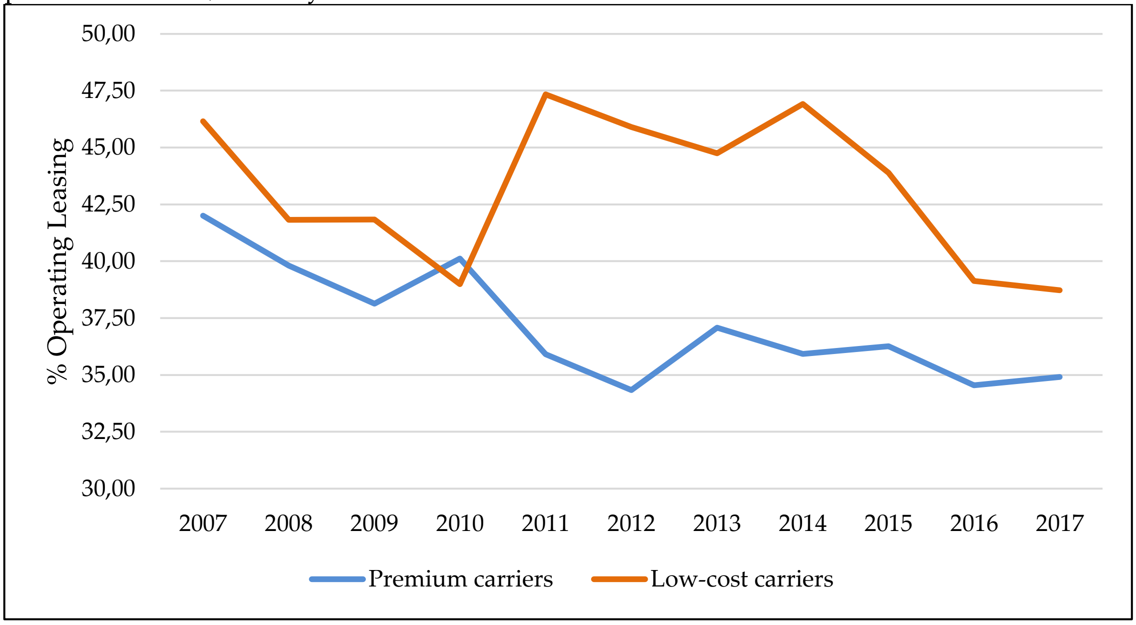
The graph above shows the tendency and the practices adopted by airlines across continents throughout the years. During the period studied, European carriers are the ones with the higher preference for operating leasing, with 55.30% of the total fleet in 2007, then converging more with Asian and European carriers until around 2012, but still ahead of them until 2017. Asian airlines increased its operating leasing percentage in 5.14 percentual points between 2007 and 2017.

On the other side, both European and North American carriers showed a decrease between both ends. The latter had 42.04 percent of its aircrafts under operating leasing in 2007 and finished 2017 with a huge drop throughout the 11-year period, 18.06 less percentual points, resulting on 23.98 percent of its fleet under operating leasing. Finally, European airlines noticed a decrease of

7.82 percentual points, ending 2017 with 47.48 percent of its fleet under operating leasing.

The global average ended up in 36.04 percent, after dropping 6.94 percentual points since 2007.

Figure 12: Comparison of fleet percentage under operating leasing between low-cost and premium carriers, for the years 2007-2017.



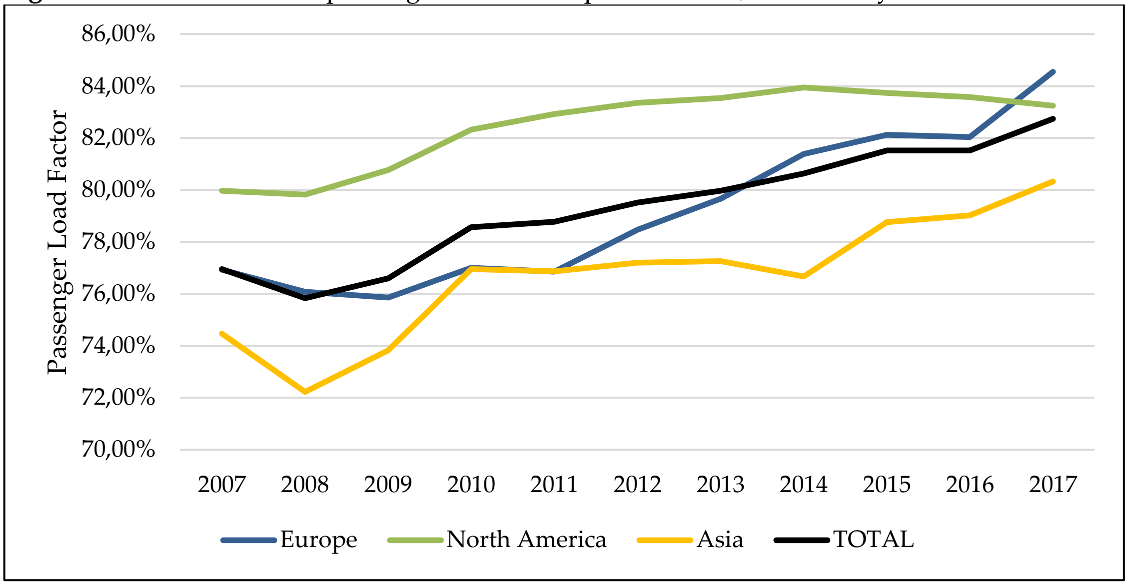
Source: Own figure.
Note: Based on 364 observations.

The figure above notices some differences between types of carriers. From 2007 until 2010, values are similar and end up converging in 2010. From this year onwards, the gap increases, and starts closing in again around 2014. Nevertheless, and except for the year of 2010, premium carriers had always registered a lower percentage of its fleet under operating leasing, when comparing to low-cost carriers, in the same period.

4.1.3 Load Factor

By analyzing the evolution of the passenger load factor on carriers around the globe, one can get a very interesting perspective on such an important key-aspect as is the load factor on aviation, which reflects the global economy.

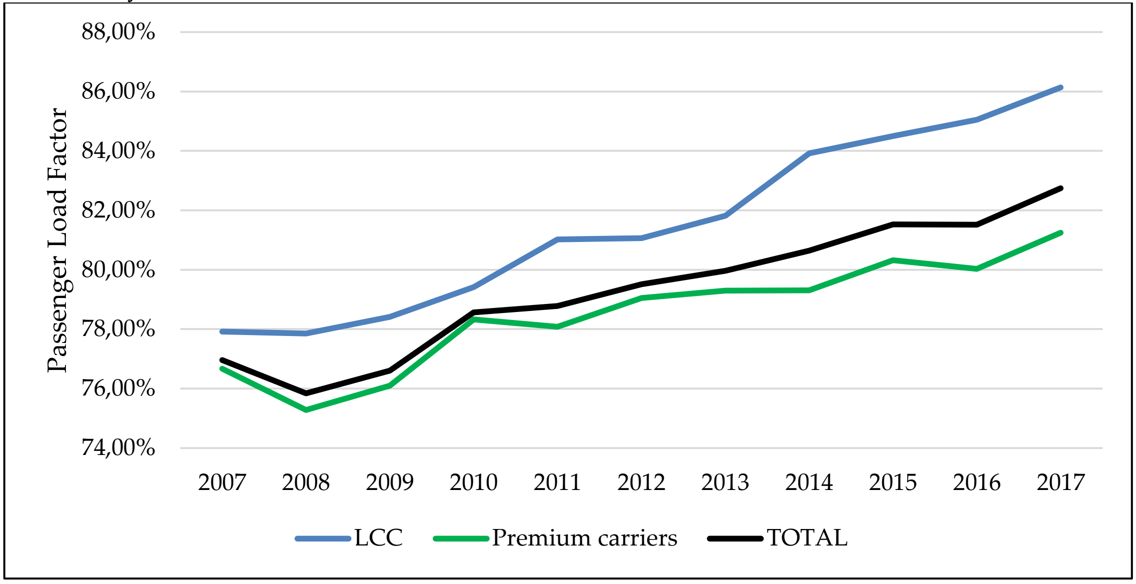
Figure 13: Evolution of the passenger load factor per continent, across the years 2007-2017.



Source: Own figure.
Note: Based on 410 observations, of which 104 are of low-cost carriers.

European airlines had the higher escalation in load factor during the period 2007-2017, with an increase of around 7.6 percentual points. Asian carriers follow the trend with an increase of 5.9 percentual points, and North American airlines are the ones with the lightest variation, with a rise of approximately 3.3 percentual points. Globally speaking, the increase is of 5.8 percentual points, or 7.5 percent.

Figure 14: Evolution of the passenger load factor between premium and low-cost carriers, across the years 2007-2017.



Source: Own figure.
Note: Based on 410 observations, of which 104 are of low-cost carriers.

The graph above allows to conclude that *low-cost carriers* felt the biggest increase on passenger load factor, along the years in analysis, with a variation of 10.6 percentual points. Premium carriers, on its side, did not record such a steep climb, and notice an increase of 4.6 percentual points.

It can also be mentioned that the highest value for load factor was hit by Ryanair on 2017 with 95.0%, an European *LCC* which has maintained an average aircraft load of 85.9% over the period in analysis. Nevertheless, its *low-cost* competitors WizzAir and EasyJet maintained higher average load factors, with 89.1 and 88.4 percent, respectively.

On the other side, the lowest value was recorded by FlyBe Group on 2010, being also the company with the worst average load factor (67.8%). Along with this airline, the bottom three are completed with All Nippon Airways (67.9%) and Japan Airlines (71.8%).

4.2 Results

In the current section, we will present the results obtained on the estimation of both first and second-step equations, followed by a critical analysis and subsequent discussion of the proposed hypotheses to test.

4.2.1 First-step equation

The following two tables present summary statistics for jet fuel exposure coefficients obtained after regressing the first-step equation (3). Afterwards, in order to decide whether the previously formulated hypothesis (H_1) that airline companies are equally exposed to jet fuel prices regardless the continent where they are based ($\gamma_{EU,y} = \gamma_{NAM,y} = \gamma_{ASIA,y}$) is valid or not, we present the results for a mean-comparison test.

Table 7 reports the summary for jet fuel exposure coefficients. We can name high-exposed airlines to the ones more negatively exposed, and low-exposed to the ones more positively exposed (Berghöfer & Lucey, 2014). Of the 315 observations withdrawn from the estimation of Equation (3), 93 belong to European carriers, 122 to North American and 100 to Asian airlines. The global average exposure coefficient is (-0.1483) and the median stands on (-0.1138). Comparing with the previous results of Berghöfer & Lucey (2014), they register a mean coefficient of (-0.131) for the period 2002-2012 with a slightly different set of global airlines, and a median of -0.091, both lower than our findings. Our standard errors are though very similar, with a value of 0.2261, comparing to Berghöfer & Lucey (2014) value of 0.223. Interestingly, they also find a minimum exposure coefficient of (-1.794), while our lowest value is of (-1.1264).

Table 7: Summary statistics of jet fuel exposure coefficients.

	TOTAL	EUROPE	NORTH AMERICA	ASIA	PREMIUM	LCC
Observations	**315**	93	122	100	215	100
Mean γ	**-0.1483**	-0.0548	-0.1934	-0.1802	-0.1649	-0.1126
Median γ	**-0.1138**	-0.0477	-0.1652	-0.1556	-0.1310	-0.0857
Standard error γ	**0.2261**	0.2155	0.2174	0.2466	0.2283	0.2213
Minimum γ	**-1.1264**	-0.8761	-1.1264	-1.0858	-1.1264	-0.8364
Maximum γ	**1.8071**	0.8175	1.8071	0.2279	1.8071	0.8175
% Negative γ	**72.06%**	61.29%	77.05%	76.00%	73.49%	69.00%
% Significant at 10%	**30.16%**	22.58%	38.52%	27.00%	32.09%	26.00%
Number γ significantly different from 0						
10% level	**62**	9	37	16	48	14
5% level	**40**	5	24	11	33	7
Number γ significantly less than 0						
10% level	**85**	16	42	27	61	24
5% level	**57**	8	33	16	44	13
Number γ significantly greater than 0						
10% level	**10**	5	5	0	8	2
5% level	**5**	1	4	0	4	1

Source: Own figure.
Note: Based on 315 observations of 32 airlines. Jet fuel exposure coefficients are estimated using Equation (3): $R_{i,w} = \alpha_i + \beta_{i,y}R_{MK,w} + \gamma_{i,y}R_{JF,w} + \delta R_{USD,w} + \varepsilon_{i,w}$.

In our findings, a great majority of airlines register negative exposure coefficients, in concrete, 72.06 percent. Treanor et al. (2014b) have similar results with 72% of negative exposure coefficients[23], plus Berghöfer & Lucey (2014) recorded 67.86 percent of negative coefficients.

From this estimation, we get around 30.16 percent significant coefficients at a 10% level, similar to Berghöfer & Lucey (2014) value of 32.88 percent. Treanor et al. (2014b) got around 39.42 percent[24] significant at 10%.

Further, regarding comparison between low-cost and premium carriers, both our results and Berghöfer & Lucey (2014) come to a similar conclusion that premium airlines have a much higher average and median exposure than LCC. The percentage of negative coefficients is not very distinct between types of carriers on both studies. On our study, the percentage significant at 10% is slightly higher on premium carriers, while Berghöfer & Lucey (2014) has more significant values on LCC. Treanor et al. (2014b) do not distinguish between types of carriers.

On Table 8, there is an extended overview on the individual fuel exposure coefficients, with details per company. Additionally, it is shown on the side the percentage of fuel hedged for the following year.

[23] Stephen D Treanor et al. (2014b) study a sample of 27 U.S. Airlines for the period 1994-2008.
[24] Manually calculated, with data from the authors' Table 2 – Panel B.

Table 8: Detailed statistics of airlines' jet fuel price exposure and financial hedging engagement.

Airline	Mean	Median	SE	Min	Max	% Neg	% Significant at 10% level (one-side test)	% of next year fuel hedged
Aegean	-0.0838	-0.0596	0.2142	-0.4457	0.0552	81.82%	9.09%	33.23%
AF-KLM	-0.2442	-0.1069	0.2162	-0.8761	0.0630	81.82%	36.36%	57.36%
EasyJet	-0.1314	-0.0938	0.2151	-0.3738	0.0814	90.91%	27.27%	71.27%
Finnair	0.0769	0.0419	0.2120	-0.2190	0.3760	36.36%	27.27%	64.23%
FlyBe Group	0.1072	0.0473	0.2360	-0.3519	0.8175	37.50%	25.00%	69.78%
Lufthansa	-0.1215	-0.0565	0.2129	-0.5347	0.1349	63.64%	18.18%	72.92%
Norwegian	-0.0799	-0.0142	0.2253	-0.3405	0.1461	45.45%	27.27%	25.67%
Pegasus	0.1134	0.0261	0.2275	-0.0750	0.6245	40.00%	20.00%	30.06%
Ryanair	-0.0293	-0.0672	0.2091	-0.2523	0.1890	54.55%	9.09%	82.45%
Wizz Air	0.0747	0.0548	0.1538	-0.0256	0.1950	33.33%	0.00%	62.00%
Subtotal Europe	**-0.0548**	**-0.0477**	**0.2155**	**-0.8761**	**0.8175**	**61.29%**	**22.58%**	**59.74%**
Air Canada	-0.0984	-0.1115	0.2211	-1.0083	0.5909	54.55%	54.55%	19.64%
A.T. Services	0.1778	0.0470	0.2168	-0.2890	1.8071	36.36%	18.18%	0.00%
Alaska Air	-0.2946	-0.1651	0.2168	-0.8283	-0.0338	100.00%	36.36%	45.55%
Allegiant T.	-0.1666	-0.0977	0.2168	-0.6988	0.1980	72.73%	36.36%	0.18%
Amer. Airl.	-0.1739	-0.1739	0.1708	-0.5060	0.0930	80.00%	40.00%	16.27%
Atlas Air	0.0236	-0.0107	0.2168	-0.4894	0.4426	54.55%	18.18%	0.00%
Delta Airl.	-0.3174	-0.2443	0.2233	-0.8882	-0.0485	100.00%	36.36%	37.00%
Hawaiian	-0.3512	-0.3461	0.2168	-0.6978	0.0166	90.91%	54.55%	37.28%
JetBlue	-0.3700	-0.4350	0.2168	-0.8364	0.0092	90.91%	63.64%	15.27%
Southwest	-0.1855	-0.1516	0.2168	-0.5256	0.0580	90.91%	9.09%	49.00%
Spirit Airl.	-0.0439	-0.0005	0.2426	-0.6053	0.4083	57.14%	28.57%	7.14%
United Cont.	-0.4556	-0.4181	0.2168	-1.1264	0.0609	90.91%	63.64%	19.67%
Subtotal N. America	**-0.1908**	**-0.1573**	**0.2173**	**-1.1264**	**1.8071**	**77.05%**	**38.52%**	**19.02%**
Air China	-0.2400	-0.1928	0.2367	-0.8970	0.0646	90.91%	45.45%	0.00%
AirAsia	-0.1826	-0.1703	0.2405	-0.4123	0.0270	81.82%	18.18%	26.71%
China East.	-0.1312	-0.1310	0.2367	-0.6897	0.2005	63.64%	27.27%	0.00%
China South.	-0.2456	-0.2015	0.2367	-0.6724	0.0754	90.91%	45.45%	0.00%
Eva Air	0.0014	0.0110	0.2396	-0.1261	0.0652	40.00%	0.00%	0.00%

Airline	Mean	Median	SE	Min	Max	% Neg	% Significant at 10% level (one-side test)	% of next year fuel hedged
Garuda Ind.	-0.0552	0.0150	0.2669	-0.3179	0.2038	42.86%	0.00%	0.00%
Japan Airl.	-0.2144	-0.2262	0.3493	-0.5191	0.0480	83.33%	16.67%	71.00%
Jet Airways	-0.3122	-0.2598	0.2335	-1.0858	0.2279	81.82%	45.45%	0.00%
Singapore A.	-0.0965	-0.0446	0.2426	-0.2582	0.0391	81.82%	9.09%	29.50%
Thai Air.	-0.2791	-0.3031	0.2364	-0.8969	0.0223	90.91%	45.45%	45.75%
Subtotal Asia	**-0.1844**	**-0.1595**	**0.2458**	**-1.0858**	**0.2279**	**74.44%**	**27.00%**	**13.84%**
TOTAL	**-0.1522**	**-0.1246**	**0.2268**	**-1.1264**	**1.8071**	**72.06%**	**30.16%**	**32.43%**

Source: Own figure.
Note: Based on 315 observations of 32 airlines. Jet fuel exposure coefficients are estimated using Equation (3): $R_{i,w} = \alpha_i + \beta_{i,y} R_{MK,w} + \gamma_{i,y} R_{JF,w} + \delta R_{USD,w} + \varepsilon_{i,w}$.

The following table shows the results obtained for testing the validity of H_1.

Table 9: Results of a mean-comparison t-test for exposure coefficients between regions.

Difference in regional exposure coefficients	T-statistic between regions (two-sided)	
Europe – Asia	3.7228	***
North America – Asia	-0.3235	
Europe – North America	3.4023	***

Source: Own figure.
Note: *** denote p-values <0.01, ** denote p-values <0.05 and * denote p-values <0.10.

Using Stata, it was computed a mean-comparison t-test, in order to find out if the exposure to fuel prices is identical across continents (H_1). Being the null hypothesis a zero-difference between means, the results allow us concluding that for the sample here analyzed, the exposure for European and Asian carriers should be distinct, once a t-statistic of 3.7228 allows for the rejection of H_0. Therefore, our H_1 that airline companies are equally exposed to jet fuel prices regardless the continent where they are based ($\gamma_{EU,y} = \gamma_{NAM,y} = \gamma_{ASIA,y}$) can be rejected, going along with the results of Berghöfer & Lucey (2014).

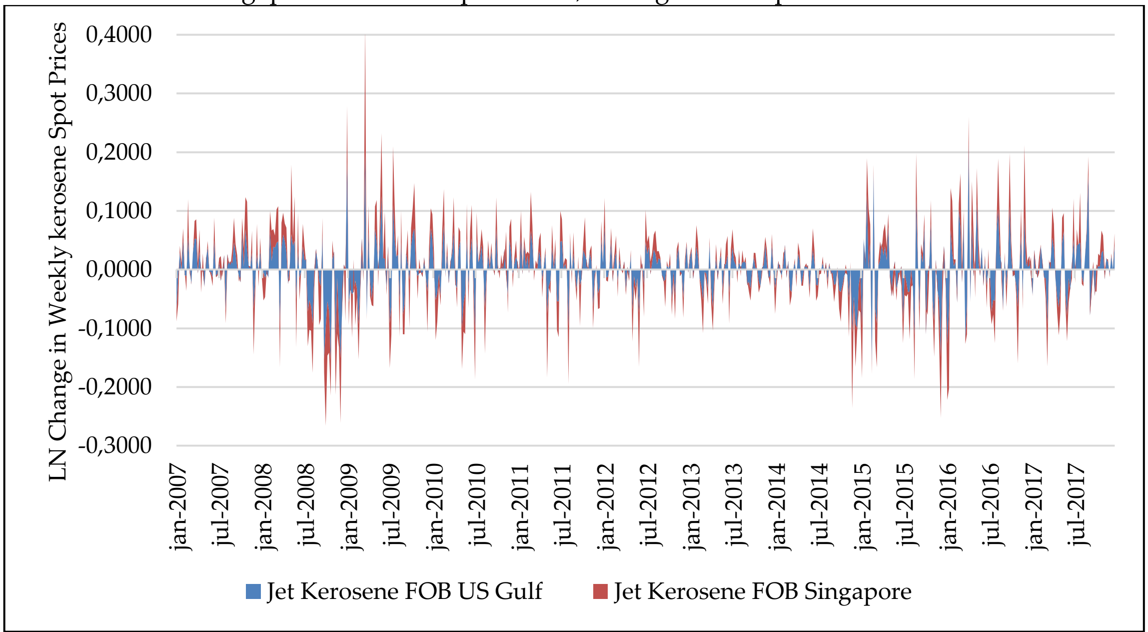
Similarly, there is a 1%-level significantly different exposure between Europe and North America, given by a t-statistic of 3.4023, reinforcing the rejection of H_1.

It is also possible to conclude that both Asian and North American carriers are more negatively exposed than European airlines, confirming again the results of Berghöfer & Lucey (2014).

On the other side, we could not find differences on exposure levels between North America and Asia, contrary to the findings of Berghöfer & Lucey (2014), even though Asian airlines' exposure was estimated with Singapore kerosene prices and North American carriers were estimated with Gulf Coast kerosene.

In Figure 15, it is possible to notice that although US Gulf Coast price changes seem to be more contained, both usually vary on the same direction, during the period analyzed.

Figure 15: Graphical representation of the magnitudes of weekly changes on US Gulf Coast Kerosene versus Singapore Kerosene Spot Prices, throughout the period of 2007 until 2017.



Source: Own figure.
Note: Based on 573 observations per each of the two US Gulf Coast Kerosene and Singapore Kerosene Spot Prices. Data retrieved from *Datastream*.

Using Stata, it was computed another mean-comparison t-test, this time in order to find out if the exposure to fuel prices is identical between premium and low-cost carriers (H_{10}). The null hypothesis is a zero-difference between means. If we pursue a two-sided test as we did for testing the exposure across continents, the results do not show there is a significant difference between types of carriers, once the p-value (0.1158) is slightly above the minimum 10%-level of significance needed to reject the null hypothesis. Nevertheless, if considering a one-sided t-test on the left, we can conclude that premium carriers are more exposed than low cost carriers, once a t-statistic of -1.5785 allows for the rejection of H_{10}.

Table 10: Results of a mean-comparison t-test for exposure coefficients between types of carriers.

Difference in carriers' exposure coefficients	T-statistic between regions (two-sided)
Premium carriers – Low cost carriers	-1.5785

Source: Own figure.
Note: *** denote p-values <0.01, ** denote p-values <0.05 and * denote p-values <0.10.

4.2.2 Second-step equation - Berghöfer

Table 11 presents the summary statistics for the dependent and independent variables used to regress Models 2-3 and 5-6, replicating the same regressed by Berghöfer & Lucey (2014).

Table 11: Summary of descriptive statistics for the data used on estimating Equations 4 and 5.

Variables	Mean	Median	Std. Dev.	Min	Max
ABS_FUELEXP	0.2261	0.1546	0.2210	0.0005	1.0858
HDGPER	0.3622	0.3500	0.3069	0.0000	0.9500
HDGMAT	15.9273	12.0000	13.5896	0.0000	60.0000
ADI_M	0.5975	0.6242	0.3063	0.0000	0.9506
ADI_F	0.4653	0.5575	0.3364	0.0000	0.8759
LNTA	15.9507	15.8991	1.2402	12.9932	18.1869
LTDA	0.2401	0.2346	0.1389	0.0102	0.6882
LNDIST	7.4630	7.4580	0.3576	6.5530	8.4288
LF	0.8158	0.8160	0.0515	0.6600	0.9500

Source: Own figure.
Note: Based on 165 observations. ABS_FUELEXP stands for the absolute value of the variable γ.

The median airline in the cleaned sample has, in the median year, a jet fuel price risk exposure of 0.1546, in absolute value, and has hedged 35 percent of its next year fuel requirements with a median maturity of 12 months. This adds to a median fleet models' diversity index of 0.6242 and of 0.5575 when measured by families. The median airline still has a flight distance of approximately 1,734 kilometers, flies with a passenger load factor of 81.60 percent, has around 8,033 million USD on total assets and its long-term debt to assets ratio is 23.46 percent.

Additionally, a matrix of correlations was ran on Stata, in order to evaluate if the variables tested were not highly correlated with each other. Gujarati (2003) suggests a good rule of thumb on this, by analyzing if the "pair-wise or zero-order correlation coefficient between two regressors" is high (over 0.8), then multicollinearity is a severe problem.

As here analyzed for all six equations, multicollinearity is not a problem. Table 12 includes a correlation matrix, which serves Models 1-3 (using ADI_M), and Models 4-6 (using ADI_F).

Table 12: Correlation matrix for the independent variables estimated on Models 1-6.

	HDGPER	HDGMAT	ADI_M	ADI_F	LNTA	LTDA	LNDIST	LF
HDGPER	1.0000							
HDGMAT	0.5569***	1.0000						
ADI_M	-0.0725	0.1973**	1.0000					
ADI_F	-0.0927	0.0562	0.8909***	1.0000				
LNTA	0.1994	0.2237***	0.3221***	0.3194***	1.0000			
LTDA	-0.1467*	-0.2019***	0.1533**	0.3410***	0.1610**	1.0000		
LNDIST	-0.0031	0.1820**	0.6333***	0.6856***	0.3572***	0.2764***	1.0000	
LF	0.1708**	-0.0553	-0.3354***	-0.3281***	0.1897**	-0.3235***	-0.0638	1.0000

Source: Own figure.
Note: *** denote p-values <0.01, ** denote p-values <0.05 and * denote p-values <0.10.

Apart from the correlation between ADI_M and ADI_F, it is possible to observe on the previous table that there are no correlations higher, in absolute value, than 0.80, value of reference for Gujarati (2003) for the existence of multicollinearity problems. Nevertheless, these two ADI indexes are never used together in the same equation, being one a substitute for the other, so there seems to be no multicollinearity problems.

On Table 13, we show the results for the Models computed by Berghöfer & Lucey (2014). It should be noticed that our results are for the time period of 2007-2017, while Berghöfer & Lucey (2014) study between 2002-2012. Both samples are of airlines from Asia, Europe and North America, although slightly distinct.

All models, except for the OLS estimations, which are included for comparison purposes only, include year and firm dummies, not reported. Models 1-2 and 4-5 present heteroscedastic robust standard-errors. Models 3 and 6 are clustered for airlines, controlling for heteroscedasticity and autocorrelation (Berghöfer & Lucey, 2014).

Fixed effects' models can measure for airline-specific variations in exposure that are not captured by the variables itself, and so, they are a suitable option model (Tufano, 1998c). The preference for fixed effect models has the advantage of being always consistent, despite the downturn of increasing standard-errors in such small samples. Nevertheless, studies within the airline industry cannot withdraw much bigger samples due to the great difficulty on obtaining consistent information across continents and along distant past years. Plus, most of the data has to be manually gathered from annual reports or 10-K fillings.

Table 13: Estimation results for the same equations computed by Berghöfer & Lucey (2014).

	Models					
	Using ADI_M			Using ADI_F		
	OLS	Fixed Effects	Fixed Effects/ Cluster	OLS	Fixed Effects	Fixed Effects/ Cluster
Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
HDGPER	-0.1205** (-2.31)	0.1421 (1.44)	0.1421* (1.75)	-0.1319*** (-2.61)	0.1475 (1.53)	0.1475* (1.86)
HDGMAT	0.0013 (1.10)	-0.0010 (-0.47)	-0.0010 (-0.42)	0.0019 (1.62)	-0.0008 (-0.38)	-0.0008 (-0.34)
ADI_M	0.1360* (1.84)	-0.1315 (-0.63)	-0.1315 (-0.63)			
ADI_F				0.1883*** (2.71)	-0.0796 (-0.43)	-0.0796 (-0.45)
LNTA	-0.0186 (-1.26)	-0.0723 (-1.00)	-0.0723 (-0.94)	-0.0204 (-1.40)	-0.0723 (-0.93)	-0.0723 (-0.83)
LTDA	0.5337*** (3.61)	0.2458 (0.94)	0.2458 (0.71)	0.4772*** (3.33)	0.2570 (0.96)	0.2570 (0.70)
LNDIST	-0.0566 (-0.99)	-0.2112 (-1.28)	-0.2112 (-1.43)	-0.0996 (-1.63)	-0.1964 (-1.27)	-0.1964 (-1.43)
LF	0.9601*** (2.73)	0.9468 (1.50)	0.9468** (2.38)	1.0528*** (3.11)	1.0175* (1.67)	1.0175** (2.57)
R-squared	0.1189	0.7279	0.7279	0.1368	0.7277	0.7277
Overall F-Test	3.2100***			3.8400***		

Source: Own figure.

Note: All Models include a constant term and are based on 165 observations of 23 airlines. Values for Models 1-3 are the results of the estimation of Equation (4): $|\gamma_{i,y}| = \alpha_0 + \alpha_1(HDGPER_{i,y}) + \alpha_2(HDGMAT_{i,y}) + \alpha_3\left(ADI_{M\,i,y}\right) + \alpha_4(LNTA_{i,y}) + \alpha_5(LTDA_{i,y}) + \alpha_6(LNDIS_{i,y}) + \alpha_7(LF_{i,y}) + \varepsilon_{i,y}$.

Values for Models 4-6 are the results of the estimation of Equation (5): $|\gamma_{i,y}| = \alpha_0 + \alpha_1(HDGPER_{i,y}) + \alpha_2(HDGMAT_{i,y}) + \alpha_3\left(ADI_{F\,i,y}\right) + \alpha_4(LNTA_{i,y}) + \alpha_5(LTDA_{i,y}) + \alpha_6(LNDIS_{i,y}) + \alpha_7(LF_{i,y}) + \varepsilon_{i,y}$.

T-statistics are presented between brackets.

*** denote p-values <0.01, ** denote p-values <0.05 and * denote p-values <0.10.

While looking at the results of the fixed-effects' regressions, one might notice high R-squared but not many significant *t* ratios. Gujarati (2003) states that if these R-squared were higher than 0.80, we could probably be facing a "classic symptom of multicollinearity", but given the observed R-squared are smaller than 0.80, and the previously computed matrixes does not present high correlations, then our models should be valid.

According to our hypothesis H_2, financial hedging decreases airlines' fuel price risk exposure. The results for Models 2 and 5 seem to suggest there is no impact on exposure, as our coefficient estimations for the variable HDGPER are not significant. On the other side, using a cluster on airline, capturing specific firm variations, we get statistically significant results at the 10% level, on Models 3 and 6, with coefficients of 0.1421 and 0.1475, respectively. The signal of our coefficient for HDGPER was predicted to be negative though, once it is expected that financial hedging through derivatives should decrease firms' exposure. Our findings actually show that financial hedging actually increased airlines' fuel exposure. Berghöfer & Lucey (2014) got positive but not statistically significant coefficients on the variable HDGPER.

Regarding the coefficients estimated for HDGMAT, we conclude that the maturity of hedging does not seem to impact on exposure levels, along with the findings of Berghöfer & Lucey (2014).

The third hypothesis we test is H_3, that airlines decrease their risk exposure, the wider its fleet diversity. In Models 2-3 we test this using the ADI_M index and in Models 5-6 we use ADI_F. Our coefficient signs are negative, according to predictions, but they are not significant at a 10% level. So, we end up concluding that fleet diversity, whether measured by models or families, seems not to have impact on risk exposure. Berghöfer & Lucey (2014) also did not get statistically significant results on the same regressions, except for a positive coefficient on ADI_M (their ADI_1), significant at 10%, on the equivalent of our

Model 3, suggesting an increase in fleet diversity could actually increase exposure. This could be explained by the fact that, although there is a benefit of more flexibility by possessing a diverse fleet, there are also additional costs such as on spare parts and maintenance.

Our results also do not provide support for H_4, that longer flight distances increase fuel price exposure. Considering Models 2-3 and 5-6, we get negative non-significant coefficients for LNDIST, with t-statistics between -1.27 and -1.43. Along with the results of Berghöfer & Lucey (2014), we conclude there is no major impact of the average flight distance on risk exposure.

According to our hypothesis H_5, a higher load factor would decrease risk exposure. Our results are significant on Model 5, with a 90% confidence level, and on Models 3 and 6 with a significance level of 5%. Nevertheless, contrary to our predictions, we got positive coefficients, which seem to make no common sense, once aircrafts with higher load factors have more coverage of certain fixed costs, and so, their exposure to fuel prices should diminish. Berghöfer & Lucey (2014) had negative but not significant coefficients for the variable LF, on their equivalents to our Models 2-3 and 5-6.

By analyzing the coefficients for the variable LNTA, our results do not show that firm size has an impact on exposure. Though, our coefficients are similar to the ones got by Berghöfer & Lucey (2014). For instance, comparing our Model 3 with their equivalent, we get a coefficient of (-0.0723), while they get (-0.0660). Nevertheless, our results are not significant at a 10% level, and Berghöfer and Lucey (2014) study was able to conclude, at a 1% level on the same Model, that the larger an airline, the greater the effect on exposure reduction.

Neither one of the previous fixed-effects' models showed us that financial hedging, measured by the percentage of next year's fuel hedged, or operational hedging, measured only by fleet diversity, decrease in fact airlines' fuel price risk exposure.

4.2.3 Alternative second-step equations

This section presents alternative second-step equations, contemplating more variables than Berghöfer & Lucey (2014) regressions, and trying to measure also the impact of two other measures of operational hedging: fleet-fuel efficiency, measured by the average fleet age, and the percentage of fleet held on operating leasing, to assess airlines' flexibility in response to higher fuel prices or demand fluctuations, which ultimately could diminish risk exposure.

The following table presents the summary statistics for the dependent and independent variables used to regress our Models 8-10.

Table 14: Summary of descriptive statistics for the data used on estimating Equations 8-10.

Variables	Mean	Median	Std. Dev.	Min	Max
ABS_FUELEXP	0.2249	0.1543	0.2171	0.0005	1.0083
HDGPER	0.4177	0.4350	0.3018	0.0000	0.9500
HDGMAT	18.8438	18.0000	13.7139	0.0000	60.0000
FX_DER	0.7344	1.0000	0.4434	0.0000	1.0000
IR_DER	0.7188	1.0000	0.4514	0.0000	1.0000
ADI_M	0.6451	0.6921	0.2905	0.0000	0.9506
ADI_F	0.5021	0.6499	0.3318	0.0000	0.8759
LNAGE	2.0815	2.1972	0.4613	0.9933	3.1491
OPLEASE	0.3321	0.2823	0.2241	0.0000	1.0000
TURBOPROP	0.0445	0.0000	0.0792	0.0000	0.2943
LF	0.8254	0.8200	0.0411	0.7120	0.9500
LNDIST	7.4995	7.5307	0.3336	6.8477	8.4288
LNTA	16.2588	16.4170	1.1409	13.7440	18.1869
CFSAL	11.3228	10.1950	7.1168	-5.0300	28.1600

Source: Own figure.
Note: Based on 128 observations. ABS_FUELEXP stands for the absolute value of the variable γ.

The median airline in the sample has, in the median year, a jet fuel price risk exposure of 0.1543, in absolute value, has hedged 43.50 percent of its next year fuel requirements with a median maturity of 18 months, and also entered into currency and interest rate derivatives. In addition, the same median airline registers a fleet models' diversity index of 0.6921 and of 0.6499 when measured by families. This airline has a fleet with around 9 years of age, from which 28.23 percent are held in operating leasing, and none is a turboprop. The median flight distance is of approximately 1,864 kilometers[25] and its aircrafts fly with a median passenger load factor of 82.00 percent. Finally, this airline has around 13,484 million USD[26] on total assets and its cash-flow to sales ratio is of 10.1950.

A new matrix of correlations was ran on Stata, in order to evaluate if the variables tested were not highly correlated with each other, and can be found on Appendix 1. From its analysis, and apart from the correlation between ADI_M and ADI_F, we do not observe correlations higher, in absolute value, than 0.80, value of reference for Gujarati (2003) for the existence of multicollinearity problems. However, these two ADI indexes are never used together in the same equation, being one a substitute for the other, therefore there are no multicollinearity problems.

On the following page, the results for our three own Models are discriminated in Table 15.

[25] From the obtained value of LNDIST=7.3507, we get that the median flight distance is approximately equal to $e^{7.3507}$=1,864 kilometers.
[26] Given the value of LNTA=16.4170, we get that the value of total assets is approximately equal to $e^{16.4170}$=13,484 million USD.

Table 15: Estimation results of Models 7-9, based on equations 8-10, respectively.

	Models		
Variables	**Fixed Effects / Cluster (7)**	**Fixed Effects (8)**	**Fixed Effects (9)**
HDGPER	0.1907**	0.2178**	0.1816*
	(2.27)	(2.41)	(1.91)
HDGMAT	0.0005	0.0004	0.0007
	(0.17)	(0.16)	(0.27)
FX_DER	-0.0019	0.0127	0.0253
	(-0.02)	(-0.10)	(0.21)
IR_DER	0.1231	0.1292**	0.1287**
	(1.60)	(2.08)	(2.03)
ADI_M	0.3133	0.2771	
	(0.80)	(0.82)	
ADI_F			-0.1323
			(-0.39)
LNAGE	-0.2232**	-0.2297**	-0.2080**
	(-2.33)	(-2.17)	(-1.98)
OPLEASE	-0.2470	-0.2532	-0.2491
	(-0.61)	(-0.73)	(-0.67)
TURBOPROP	-0.0905	-0.2101	-0.1529
	(-0.12)	(-0.29)	(-0.20)
LF	0.5863	0.7655	0.6076
	(0.63)	(1.01)	(0.80)
LNDIST	0.1259	0.1014	0.0905
	(1.24)	(0.50)	(0.45)
LNTA	-0.0645	-0.1022	-0.0849
	(-0.56)	(-0.92)	(-0.75)
CFSAL	-0.0073**		
	(-2.12)		
R-squared	0.7770	0.7727	0.7721

Source: Own figure.

Note: All Models include a constant term and are based on 128 observations of 19 airlines. Model (7) results from the estimation of Equation (8):

$$\begin{aligned}|\gamma_{i,y}| = {} & \theta_0 + \theta_1(HDGPER_{i,y}) + \theta_2(HDGMAT_{i,y}) + \theta_3(FX\_DER_{i,y}) + \theta_4(IR\_DER_{i,y}) + \theta_5(ADI\_M_{i,y}) \\ & + \theta_6(LNAGE_{i,y}) + \theta_7(OPLEASE_{i,y}) + \theta_8(TURBOPROP_{i,y}) + \theta_9(LF_{i,y}) \\ & + \theta_{10}(LNDIS_{i,y}) + \theta_{11}(LNTA_{i,y}) + \theta_{12}(CFSL_{i,y}) + u_{i,y}\end{aligned}$$

Model (8) is the result of the estimation of Equation (9):

$$\begin{aligned}|\gamma_{i,y}| = {} & \theta_0 + \theta_1(HDGPER_{i,y}) + \theta_2(HDGMAT_{i,y}) + \theta_3(FX\_DER_{i,y}) + \theta_4(IR\_DER_{i,y}) + \theta_5(ADI\_M_{i,y}) \\ & + \theta_6(LNAGE_{i,y}) + \theta_7(OPLEASE_{i,y}) + \theta_8(TURBOPROP_{i,y}) + \theta_9(LF_{i,y}) \\ & + \theta_{10}(LNDIS_{i,y}) + \theta_{11}(LNTA_{i,y}) + u_{i,y}\end{aligned}$$

Model (9) results from the estimation of Equation (10):

$$\begin{aligned}|\gamma_{i,y}| = {} & \theta_0 + \theta_1(HDGPER_{i,y}) + \theta_2(HDGMAT_{i,y}) + \theta_3(FX\_DER_{i,y}) + \theta_4(IR\_DER_{i,y}) + \theta_5(ADI\_F_{i,y}) \\ & + \theta_6(LNAGE_{i,y}) + \theta_7(OPLEASE_{i,y}) + \theta_8(TURBOPROP_{i,y}) + \theta_9(LF_{i,y}) \\ & + \theta_{10}(LNDIS_{i,y}) + \theta_{11}(LNTA_{i,y}) + u_{i,y}\end{aligned}$$

T-statistics are presented between brackets.
*** denote p-values <0.01, ** denote p-values <0.05 and * denote p-values <0.10.

All the three models presented in Table 13 include year and firm dummies, not reported. Model 7 is clustered for airlines, controlling for heteroscedasticity and autocorrelation. Models 8 and 9 present heteroscedastic robust standard-errors.

Our hypothesis H_2 states that financial hedging diminishes airlines' fuel price risk exposure. According to Model 9, the estimated coefficient for HDGPER are positive (0.1816) and statistically significant at the 10% level, suggesting that financial hedging increases fuel exposure. As previously mentioned, our predictions would be a negative coefficient, but based on our sample, we reject H_2 on all three cases. It can also be observed that the coefficients for HDGPER are positive and statistically significant at a 5% level on Models 7 and 8, enhancing our conclusions.

Regarding the coefficients estimated for HDGMAT on all three models, we conclude that the maturity of hedging is not by itself a relevant variable to impact on exposure levels.

Our third hypothesis, H_3, states that a more diverse fleet would decrease risk exposure. The estimated coefficients for ADI_M are positive on Models 7 and 8, but not significant, allowing us to reject H_3, not being observed any reduction of exposure by altering fleet diversity, when measured by models. The same hypothesis was tested on Model 9, but substituting ADI_M by ADI_F. Results were also not significant, although we observed an opposite signal on our coefficient for ADI_F (-0.1323). Treanor et al. (2014b) concluded that an average U.S. airline would be 2.3% less exposed to jet fuel prices if their fleet diversity (measured by ADI_M) increased by one percentage point.

The fourth hypothesis tested is H_4, that higher average flight distances increase fuel exposure. Our results in all three models lead us rejecting our hypothesis, once the estimated coefficients are not significant at 10%. This way, we conclude there is not an impact of the average flight distance on fuel price exposure.

According to our fifth hypothesis, H_5, a higher load factor reduced exposure. Our results of Models 7-9 lead us to reject this hypothesis, concluding that there is no significant impact of the load factor on fuel price exposure.

The sixth hypothesis, H_6, tells that exposure to fuel prices increases with a fleet's average age. Our results for the coefficient of the variable LNAGE are significant at 5% on all three models. Nevertheless, the estimated coefficients are negative on all models (e.g. -0.2232 on Model 7). According to our results, we should conclude that the higher a fleet's age, the smaller exposure an airline is facing. In particular and according to our Model 7, for instance, by increasing fleet age by one year, there would be a decrease of approximately 11.89% in the jet fuel exposure coefficient[27]. This is contradictory and against the findings of

[27] The 11.89% increase is calculated by multiplying the coefficient on the fleet age variable (-0.2232) by the difference of logarithms of 8.8568 (average fleet age in our sample) and 7.8568 (average fleet age less 1 year), then divided by the average airline fuel exposure coefficient of 0.2249.

Treanor et al. (2014b), who concluded that a reduction of one year on a fleet's age would reduce jet fuel exposure on about eleven percent.

Our seventh hypothesis, H_7, pretended to test whether operational leases would help decreasing risk exposure. From Models 7-9, we come up with negative and non-significant coefficients, this way, concluding the percentage of fleets held in operating leasing do not impact on risk exposure.

The hypothesis H_8 mentions that airlines entering into currency derivatives should be less exposed to fuel prices, giving it would be more likely for these carriers to hedge fuel, as well. Based on our results, we do not reject the null hypothesis that there is no impact on risk exposure.

According to hypothesis H_9, airlines entering into interest rate derivatives should have its fuel exposure diminished, once it would be likely they would also hedge fuel. Our results are significant at a 5% level on Models 8 and 9, but coefficient signs are positive, therefore concluding that airlines hedging interest rates would also have more fuel price risk exposure.

Finally, the estimated coefficient for the cash-flow to sales ratio on Model 7 resulted negative (-0.0073) and significant at a 5% level.

Chapter 5
Conclusions, Limitations and Further Research

In the present chapter, we state the conclusions of our regressions, draw some of the difficulties a research in this particular field has, and, finally, end with some proposals of further research in the industry.

5.1 Conclusions

The airline industry is constantly being characterized by a growing competition among carriers around the globe, especially between premium and low-cost carriers, and for the need to rationalize costs and manage operations as efficiently as possible, to keep up with the fast pace. Jet fuel costs are a substantial part of airlines' operating costs and accounted for over 18.8% of these, in 2017 (IATA, 2018). Jet kerosene and other similar commodities also hedged by airlines are always subject to the market volatility, difficulting airlines' capability to steady results. Both financial and operational hedging are at the disposal of airlines to decrease volatility and smooth these expenses across time. Our study focused on 14 Asian, 15 European and 14 North American airlines, over the period 2007-2017, and meant to test whether financial and operational hedging could decrease airline companies' jet fuel price risk exposure. To our knowledge, this is one of the few studies to include airlines from Europe and Asia, and should be the first one to include three distinct operational hedges on a global sample of airlines.

As a representative measure for financial hedging we computed the next year's percentage of fuel hedged (Berghöfer & Lucey, 2014). As for operational hedges, this study takes into account fleet diversity and the percentage of aircrafts held in operating leasing, once they provide airlines with the real option of adjusting their capacity according to fuel prices and possible fluctuations on demand for seats. In particular, we measured fleet diversity by two ways, the number of operating aircraft models (ADI_M) or families (ADI_F), such as Berghöfer & Lucey (2014). These two aircraft dispersion indexes (ADI) are based on the Hirschman-Herfindahl concentration index.

Additionally, we include a measure of fuel-efficiency, proxied by the logarithm of average annual fleet ages. This is important because newer aircrafts are more fuel-efficient and therefore help reducing airlines' fuel price risk exposure.

We find similar fuel exposure levels to the findings of Berghöfer & Lucey (2014), mainly while comparing the percentage of negatively exposed airlines. Our results allowed us to find significant differences, at a one-percent level, on the average exposure coefficients between Europe and Asia, as well as Europe with North America, extending the findings of Berghöfer & Lucey (2014) on a more recent sample. European airlines are less exposed than Asian or North American carriers. Nevertheless, contrary to their results, we could not find significant differences when comparing North America and Asia.

This work contributes to the extension of previous research by testing for differences on the average jet fuel exposure coefficients between low-cost and premium carriers, on a worldwide scale. Even though we could not find significant differences between types of carriers while performing a two-sided t-test, we were able to prove, with 90 percent confidence level, on a one-sided test, that on average, premium carriers are more exposed to fuel prices than low-cost carriers.

We opted for fixed effects' models, since these can measure for airline-specific variations in exposure that are not captured by the variables itself (Tufano, 1998c), and have the advantage of being always consistent. As so, we estimated a total of seven fixed effects' equations, four replicating Berghöfer & Lucey (2014) and three other computed on our own. From all these, and regarding financial hedging effectiveness, we got five statistically significant coefficients, three of which at a level of 10 percent, and two at a 5 percent level. Contrary to the findings of Treanor et al. (2014b) for the U.S. airline industry between 1994 and 2008, and to our predicted coefficient sign for HDGPER, we got a positive coefficient, concluding that financial hedging actually increased airlines' fuel price risk exposure, between 2007 and 2017. Berghöfer & Lucey (2014) did not get significant coefficients on this.

Regarding operational hedging, our findings do not show an impact of fleet diversity on risk exposure, whether estimating by ADI_M or ADI_F, once our coefficients were not significant. Nevertheless, its impact is contradictory on previous studies. Measuring by ADI_M, Berghöfer concludes that an increase of a one percentage point in fleet diversity would actually increase exposure coefficient on 1.83 percent. On the other side, Treanor et al. (2014b) have that the same increase in fleet diversity would lead to a reduction of the same exposure coefficient in about 11.0 percent.

As a second measure of operational hedging, our evidence for fleet's fuel-efficiency is statistically significant at a 5% on Models 7-9, but contradictory, once our evidence would suggest that older aircrafts decrease fuel exposure. The third measure of operational hedging is the percentage of aircrafts in operating leasing. According to our results, we got negative coefficients as rationally predicted, but they are not significant at the 10 percent level.

Our findings also do not find evidence that a higher load factor or shorter flights help decreasing airlines' fuel risk exposure. In fact, two of our fixed-effects' regressions suggest, with a 5% significance level, that a higher load factor would increase fuel exposure, which is not rational.

Summing up, we did not find strong evidences that fuel risk exposure can be diminished by entering into financial or operational hedges. In fact, our results for the period 2007-2017 suggest financial hedging has had a negative impact on carriers, increasing their exposure. This could be explained by ineffective hedging and sector specificities, validating the policies followed by North American carriers in recent years, by decreasing their fuel hedges. Namely, the average percentage of next year's fuel hedged by North American carriers decreased from 20.15% to 14.09%, from 2007 to 2017. Airlines should always carefully assess internally if the costs of entering into hedging do not exceed the potential benefits, whether regarding financial or operational hedges. As concluded by Guay & Kothari (2003), and concerning airlines using both operational and financial hedging, the latter is just used to fine-tune a risk management program in its whole.

5.2 Limitations

In order to compute a high number of descriptive statistics and regress several equations, the database for this work was manually built on an enormous Excel sheet database: 68 columns per 476 rows, with a total of 32,368 cells. From this total, 6,188 were retrieved from *Datastream*, and the remaining 26,180 were manually imputed during approximately three months, by consulting a total of 440 annual reports/10-K fillings available for the companies/periods chosen.

The lacking of a global annual report template makes the analysis difficult to conceive, not to mention on the great variance on the quality of reports, even within the European continent. The easiest continent to analyze was North

America, as expected, since 10-K fillings are standardized, and that is the reason why the majority of studies is only based on American companies.

Occasionally, there were inconsistencies on values reported within the same report. Example of Aegean Airlines' annual report of 2017: on its page 27, the total group fleet disclosed is of 60 aircrafts. However, on page 8, they report an operating group fleet of 58 aircrafts.

Companies across different countries have, sometimes, distinct fiscal years, and so, we had to adapt them in order to provide the best comparability possible. Sometimes it was also difficult to understand fleet's disclosure, since companies do not always clearly specify what is part of the airline itself or what is being disclosed as part of their group. The same happened for other details regarding financial or operational hedging.

Regarding financial hedging, it happens many times companies disclosing their policies regarding several types of derivative instruments or underlyings they are allowed to use, and not mentioning what did they use on a particular year.

5.3 Further Research

Current findings on hedging effectiveness in the aviation industry are inconsistent and there is still a lack of research in this field.

It would be interesting to see throughout the following years if the application of the IFRS 16 will have an impact on the airlines' choices between financial/operating leasing. This new standard requires lessees to recognize the majority of its leases on their balance sheets, not keeping them off-balance sheet, as it was the case of the operating leases.

Figure 16: Impact of the IFRS 16 standards on the balance sheet.

Balance sheet impact*

	IAS 17		IFRS 16
	Finance leases	Operating leases	All leases
Assets		—	
Liabilities	$$$$	—	$$$$
Off balance sheet rights / obligations	—	$$$$	—

* IASB - IFRS 16 Effects analysis

Source: EY[28].

Figure 17: Impact of the IFRS 16 standards on the income statement.

Income statement impact*

	IAS 17		IFRS16
	Finance leases	Operating leases	All leases
Revenue	$$$$	$$$$	$$$$
Operating costs (excluding depreciation and amortisation)	—	Single lease expense	—
EBITDA		—	
Depreciation and amortisation	Depreciation	—	Depreciation
Operating profit			
Finance costs	Interest		Interest
Profit before tax			

* IASB - IFRS 16 Effects analysis

Source: EY[29].

An extension of current researches could also be done by applying most of the studies onto global samples of airlines, at least, from Europe, Asia and North America, given the great majority is only focused on the latter, due to the great availability of information. For instance, an analysis of whether financial and operational hedging are substitutes or complements should be interesting to perform on a global sample of airlines. Airlines based on South America,

[28] Figure available on https://www.ey.com/Publication/vwLUAssets/ey-leases-a-summary-of-ifrs-16/$FILE/ey-leases-a-summary-of-ifrs-16.pdf) , and consulted on 19/01/2019.

[29] Figure available on https://www.ey.com/Publication/vwLUAssets/ey-leases-a-summary-of-ifrs-16/$FILE/ey-leases-a-summary-of-ifrs-16.pdf) , and consulted on 19/01/2019.

Middle East and Africa are not included in our study due to the difficulty of obtaining relevant data. A possible expansion of samples across new continents, including Oceania as well, and wider time windows would help to enforce findings in this industry.

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Appendix

Appendix 1: Correlation matrix for the independent variables estimated on Models 7-9.

	HDGPER	HDGMAT	FX_DER	IR_DER	ADI_M	ADI_F	LNAGE	OPLEASE	TURBOPROP	LF	LNDIST	LNTA	CFSAL
HDGPER	1.0000												
HDGMAT	0.4666***	1.0000											
FX_DER	0.4138***	0.0760	1.0000										
IR_DER	0.2438***	0.1569*	0.0172	1.0000									
ADI_M	-0.2769***	0.1095	0.1229	0.0811	1.0000								
ADI_F	-0.2539***	-0.0199	0.2379***	0.0834	0.8776***	1.0000							
LNAGE	-0.1809**	0.0749	0.0261	-0.0696	0.6302***	0.5667***	1.0000						
OPLEASE	-0.0441	0.0109	-0.0128	-0.1912**	-0.0668	-0.1465*	-0.3748***	1.0000					
TURBOPROP	-0.0769	0.0005	0.3081***	0.1906**	0.3769***	0.3970***	0.3348***	0.0771	1.0000				
LF	0.1328	-0.2773***	0.0778	-0.3830***	-0.4340***	-0.4097***	-0.1176	0.0738	-0.1710*	1.0000			
LNDIST	-0.1439	0.1645*	0.0423	-0.0044	0.6566***	0.6967***	0.3724***	-0.0724	0.0138	-0.2496***	1.0000		
LNTA	-0.0100	0.0497	-0.0736	0.1745**	0.2388***	0.2287***	0.2237**	-0.5757***	-0.2296***	-0.0054	0.2144**	1.0000	
CFSAL	-0.1693*	-0.3572***	-0.1532*	-0.1486*	-0.4004***	-0.3945***	-0.0690	-0.1708*	-0.2835***	0.2883***	-0.2558***	0.0990	1.0000

Source: Own figure.
Note: *** denote p-values <0.01, ** denote p-values <0.05 and * denote p-values <0.10.