OIL PRICE VOLATILITY AND AIRLINES' STOCK RETURNS: EVIDENCE FROM THE GLOBAL AVIATION INDUSTRY

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Abstract. The paper explores the long versus short-term attributes of the airline industry exposure to oil price risk in a macroeconomic framework that emphasizes the interconnections between various risk factors, which is the main contribution to the research in the field. A panel ARDL model and PMG estimator have been applied on monthly data between 2007 and 2020 to investigate the long-term equilibrium relationship between airline companies' stock prices, oil price risk, financial market volatility, currency risk, inflation, and maturity risk. The negative impact of oil price risk on airlines' stock prices is significant, robust, and pervasive, and is coupled with a concerning exposure to the US dollar currency risk. As another contribution, the paper analyses the prospects and challenges of the airline industry in dealing with oil price risk in the post-pandemic world. The results point towards the need of the airline industry to rethink its strategic decisions in the more uncertain and unpredictable post-pandemic world, requiring a more comprehensive approach of the complex and dynamic network of risk exposures and a reconsideration of hedging policies.

Keywords: oil prices, exposure, air transport, ARDL panel, PMG estimator, risk management.

JEL Classification: G32, L93, C33.

Introduction

April 20, 2020 was a wild day in financial markets' history, when WTI futures oil price for May 2020 delivery plunged to a record low of minus $37.63 per barrel and disconnected from its typical long-run equilibrium with Brent and Dubai oil prices (AlMadi & Zhang, 2011; Ji & Fan, 2015). Although it remained positive, the price of Brent oil, the other international oil market benchmark, had fallen almost by 70% from the beginning of 2020 because of the plummeting oil demand caused by the Covid-19 pandemic (U.S. Energy Information

Administration [EIA], 2020). These unusual market conditions were amplified by the oil price war between Saudi Arabia and Russia, as well as the lack of storage space for oil in the United States (Ngai et al., 2020). At the end of 2019, oil held a share of 33.76% in the global direct primary energy consumption and 33.06% when inefficiency factors are applied (Ritchie & Roser, 2020), which makes it the most important resource of the global economy. The impact of oil price fluctuations is varied across industries and companies but is particularly strong on the transport sector and related industries, where fuel costs are significant, along with labor costs, aircraft maintenance and fees paid for airport facilities use. Airline fuel (or jet fuel) is a petroleum derivate, therefore its cost tracks closely the price of crude oil.

The intense connections between governments, corporations, institutions, and citizens in a globalized world, driven by trade, investments, joint projects and collaborations, etc., have radically transformed the role of air transport in the last decades, as the aviation industry – which includes, besides airlines, airports and connected services, air navigation service providers, and the civil aerospace sector that develops and manufactures overhead frames, engines, and equipment (Schlumberger & Wang, 2012) – contributes significantly to the global economy through trade flows, tourism and investment, employment, etc. Air cargo, on its turn, plays an important role in the aviation industry, but its operating environment was increasingly difficult before the pandemic and continues to be so. The recent deterioration in world trade and the rise of protectionism have led to a declining demand for air cargo transportation – in 2019, the demand fell by 3.3% compared to the previous year, which made 2019 the year with the weakest performance since the global financial crisis, but before the pandemic – notably coupled with increasing cost pressures due to uncertainty in fuel prices (International Air Transport Association [IATA], 2020a; Peskett, 2020).

For airlines, fuel represents a significant cost, and the industry has deployed many efforts in the pre-pandemic years to improve fuel use efficiency by replacements of aircraft fleets or by undertaking better operations. As emphasized by Ateş et al. (2018) and Zhang et al. (2017), the highly competitive environment, fluctuations in fuel price and environmental constraints imposed by governments or international organizations, as well as high fixed and variable costs forced airline operators to invest in technological developments, operational improvements or the use of alternative fuel to reduce fuel consumption. IATA adopted in 2008 a bold target of an average improvement in fuel efficiency of 1.5% per year between 2009 and 2020, combined with a cut of 50% in net aviation CO_2 emission by 2050, compared to 2005 (IATA, 2018). The fuel efficiency target has been accomplished until the end of 2019 mainly with the support of engine and aerodynamic efficiency improvements, the use of alternative fuels, better aviation infrastructure, and strategies for mitigating uncertainties (Singh et al., 2018) but challenges lie ahead as the industry will need to "restart" after the pandemic (Suk & Kim, 2021).

Unfortunately, the pandemic has made 2020 the worst year in the airline industry history, with estimated net losses of $118 billion in 2020, and further $38 billion in 2021 (IATA, 2020b). In fact, the pandemic crisis has proven to be a serious wake-up call for the airline industry but the recovery pattern and speed after the pandemic remain unknown. The recovery will take place differently across countries, as it depends on vaccinations against SARS-CoV-2, the condition of the countries' health systems, policy interventions, and many other

factors (Chang et al., 2020; Zhu et al., 2021). In this gloomy framework, airline companies are faced with the stringent need to manage their fuel costs and exposure to oil price risk. We add here the rising levels of debt in the industry by $120 billion in 2020, of which $79 billion were supportive government loans, deferred taxes and loan guarantees during the pandemic that will have to be repaid. Therefore, the pressure on profit margins will be even higher and will add to forecasted higher unit costs and low passenger yields (Pearce, 2020).

Recent research has shown greater concern about the influence of oil price risk on airlines' financial performance. Thus, Kristjanpoller and Concha (2016) demonstrated that share prices of airlines were affected by WTI pricing behaviour but have detected a stronger impact when WTI prices fell instead of increasing. On the other hand, Yun and Yoon (2019) have shown that the three types of international oil prices (WTI, Brent, and Dubai) had a dissimilar influence on the share prices of South Korean and Chinese airlines, depending on airlines' network of fuel suppliers, prices during trading, as well as the variation in correlations between oil prices and stock markets.

The present study contributes to the literature by an investigation of oil price volatility on the market value and stock returns of passenger and cargo transport airlines at global level, in an econometric framework that distinguishes between short- versus long-term oil price influence on stock returns. Such a delineation of the time span on the link between oil price risk and airline companies' returns is needed as it serves as a perspective on market investors' inclusion (or not) of companies' hedging policies of their exposures to oil price risk in stock valuation. To the best of authors' knowledge, this research represents the first attempt in this direction, evidenced in the next section of the paper. The analysis is based on a sample of 25 public airlines included in the Forbes Global 2000 Ranking of the World's Largest Public Companies, 2019. Another contribution comes from the study of oil price volatility impact on the airline industry in a wider global context, using a set of macroeconomic explanatory variables, such as domestic market stock indexes, exchange rates, inflation rate, maturity risk, and financial market volatility. The consideration of the broader framework where the relationship between oil price risk and airlines' stock returns manifest itself is vital for the latter's proper understanding, as interactions between oil price fluctuations and other macroeconomic phenomena bear upon the former's link to airline companies' performance. Moreover, financial market investors ponder the entire portfolio of risk exposures when valuing companies, including airlines, in the stock market.

Three main research questions are addressed in the study: (i) What is the impact of oil price volatility on the stock returns of global airlines? (ii) Is there a significant difference in this impact over the short versus long run? (iii) Which are the main challenges posed by oil price volatility to the airline industry in the post Covid-19 world? The hypothesis of this study is that oil price volatility has a significant and negative impact on airlines' stock returns, but this impact has particularities when the long versus short-run perspective is considered. Regarding the challenges raised by oil price volatility to airline companies in the post-pandemic world, an inference based on empirical results is that, in a framework that will be more uncertain and unpredictable compared to the before-pandemic years, the industry will need to rethink its operational and financial policies to cope and further develop.

The rest of the paper is organized as follows. Section 1 presents the most important directions in research on the topic, Section 2 introduces the data set and methodology, and Section 3 shows the main findings and discusses their significance. Finally, the last Section summarizes the results and extracts implications for airline companies' management, but also presents research limitations and outlines directions for future research.

1. Research background

The literature concerning the impact of oil prices on the airline industry performance is currently growing. There are fewer studies that investigate the impact of oil price fluctuations on market-based or accounting-measured financial performance of airline companies, but particular concern is observed about a more comprehensive understanding of fuel price fluctuations, the methods driving operational fuel cost efficiency or biofuel development and bioenergy consumption.

According to the cash flow hypothesis developed by Fisher (1930), formalized by Williams (1938), and later applied by Jones and Kaul (1996) to the airline industry, a negative relationship between oil prices and stock returns is expected. The rationale behind this hypothesis relies on the oil role as input for many businesses and industries, which means that any increase in oil prices has the effect of rising production costs, reducing future cash flows, earnings, dividends and, consequently, stock prices and returns. Rising oil prices also create inflation and subsequently generate surges in nominal interest rates. At an empirical level, Sadorsky (1999), and Park and Ratti (2008) showed that the relationship between oil prices and aggregate stock returns is negative. Aggarwal et al. (2012) confirmed that transport companies' stock returns were negatively influenced by the rising of oil prices.

Empirical evidence on the impact of oil price volatility on the airline industry are rather numerous and build on fuel costs as the most important expense of airlines (Rodrigue, 2020). Morrison et al. (2010) assessed how rising fuel prices and volatility affected US airline networks and fleets and showed that increases in fuel prices led to higher fares, lower flight frequency, higher load factor, and more fuel-efficient aircraft. Thus, changes in direct operating costs were forcing airlines to change their allocation of resources. Investigating how changes in oil prices affect Asian economies, Thorbecke (2019) presented evidence that certain industries such as airlines, food, and industrial transport, have been adversely affected by increases in oil prices, but other sectors such as oil and gas production, petrochemicals, and precious metals, benefited from oil prices surge. Killins (2020) investigated the relationship between oil price movements and equity returns of Canadian and US rail and airline companies and concluded that equity returns tend to be negatively affected by rising WTI oil prices. Chao and Hsu (2014) have shown that the optimal loads for different aircraft models change according to fluctuations in fuel prices, and cargo tariffs increase simultaneously due to increased fuel surcharges, thus leading to higher revenues for airline companies. Hence, freight tariffs increase with rise in fuel price due to the corresponding increase in the fuel surcharge, bringing higher total revenues. Albeit declines of fuel costs' share in total airlines' costs from 32.3% in 2012 to 23.7% in 2019 (IATA, 2020) and common oil price risk hedging practices, airline fuel costs substantially impact airlines' profitability – see Figure 1.
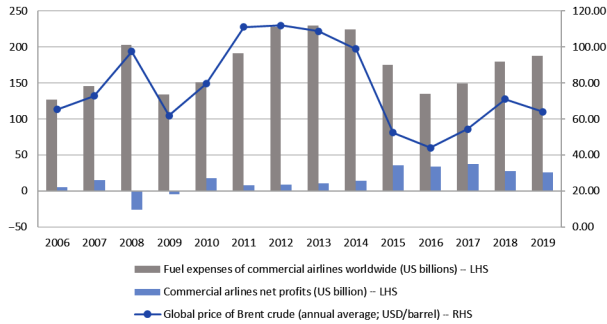
Figure 1. Oil price and airlines' profitability, 2006–2019 (source: authors' work
based on FRED and IATA databases)

Specifically, when the increase in total revenue exceeds the increase in fuel cost, the optimal payload will decrease. Once the impact of fuel price fluctuations on different aspects of air cargo transport has been evidenced, airlines may be able to select different types of aircraft with the best fuel economy for different route distances and cargo volume.

Although most of the empirical literature indicates that oil prices have a negative impact on the transportation sector, Kristjanpoller and Concha (2016) argue that oil prices positively influence prices of airline companies, which supports the theory of market inertia. Thus, bull markets are accompanied by rising asset prices (stocks and commodities), hence increases in oil prices are signals of future economic growth. Chen et al. (2017) also confirmed that oil price volatility and stock market momentum were positively correlated.

Building on the discounted cash flow (DCF) model, Yun and Yoon (2019) concluded that oil prices influence the stock market in three ways. The first consists in changing production costs and expected cash flows, which directly influence companies' value. The second way goes through changes in discount rates; thus, higher oil prices trigger rising prices, resulting in inflation, and further efforts to limit inflation by increasing interest rates result in subsequent increases in the discount rate, with negative effects on the stock market price of companies. The third way brings to the fore increases in commodity prices, which lead to declines in market demand and production.

Because forecasting future oil prices has always been a difficult challenge, research has directed its attention towards the hedging policies and strategies that airlines implemented to protect themselves against oil price volatility. Burghouwt and de Wit (2006) found that fuel price hedging is a strategy to protect against short-term oil price volatility, while the more efficient use of fuel through operational strategies offers significant cost savings over the long-run but does not reduce the industry's oil dependence. Morrell and Swan (2006) also argued that fuel price hedging can bring great value when airlines are close to bankruptcy, when their ability to buy oil derivatives is limited. At the same time, they suggest that variable levels of hedging may be a successful practice of transferring profits from one quarter to another. As one of the first studies that addressed the effect of fuel price hedging on airlines' performance, Carter et al. (2006) showed that fuel price hedging positively influenced US airlines value, mostly through declines in underinvestment costs. Extending the scope to the global airline industry, Berghöfer and Lucey (2014) and Ranasinghe et al. (2021) confirmed that

financial hedging decreased airlines' exposure to oil price risk by improving income predictability. Although hedging oil price risk has no significant effect on profitability and operating costs, an important consequence of hedging was the decrease in EBIT (Earnings before interest and taxes) margin volatility, as indicated by Merkert and Swidan (2019). Contrarily, Wang and Gao (2020) suggest that hedging practices do not positively influence the dynamics or predictability of airline earnings, which is, in the end, one of the most substantial effects that companies look for when engaging in risk management.

2. Data and research methodology

The research objective of this paper is to analyse the impact of oil price risk on the stock returns of global airline companies, by means of panel ARDL modelling. Data of monthly frequency on airlines' stock prices and a set of macroeconomic variables for a period ranging between May 2007 and January 2020 was used. The sample includes 25 listed companies from the Forbes Global 2000 Ranking of the World's Largest Public Companies 2019, based exclusively on data availability. Of these, 20 were specialized in passenger transport and 5 in cargo transportation. The 25 companies originate from 13 countries in North America, Europe, and Asia, with a total market capitalization at the end of 2020 of $504.34 billion (mean market capitalization of $20.17 billion and median of $7.96 billion). Therefore, a balanced panel with N = 25 companies and T = 237 months is used.

The variables included in the panel modelling, some of them used as control variables to surmount the omitted variables bias, are presented in Table 1. Data sources were Bloomberg, Chicago Board of Exchange, Federal Reserve of New York (FRED and Bank of International Settlements (BIS).

Table 1. Panel modelling variables

Variable	Explanation
Companies' stock prices in local currencies	Collected from Bloomberg.
Brent crude oil price (OIL)	Brent prices, WTI and Dubai oil prices are frequently used internationally, but they are highly correlated. Spot oil prices and not futures prices were used, like the previous literature on oil price changes.
Oil market volatility measured by OVX (CBOE Crude Oil ETF Volatility Index)	Estimate of expectations for 30-day volatility in crude oil returns, obtained by applying the "VIX" methodology to oil options. The link between OVX and VIX is of interest, as well as their subsequent influence on airlines' stock prices.
Domestic stock indexes (INDEX) for each origin country of airlines	Included as a measure of market risk and to test whether returns of airlines' stock prices included a risk premium for oil price fluctuations beyond the premium that is already contained in market risk.
Exchange rates	There is significant literature that links crude oil prices and changes in exchange rates (Chen et al. (2016), Yang et al. (2017)).
(i) US dollar per Euro (FX)	The main exchange rate of the international monetary system. Higher/lower values indicate depreciation/appreciation of the US dollar against the Euro.

Variable	Explanation
(ii) Nominal effective exchange rates of airlines' home currencies against the currencies of their main trading partners (NEER)	Measure the strength of currencies against their main trading partners (higher values indicate stronger home currencies).
(iii) Real effective exchange rates of airlines' home currencies against the currencies of their main trading partners – REER	Assesses price competitiveness across countries. Higher values indicate a real appreciation of domestic currency and losses in countries' competitive positions against their trading partners.
Consumer price index (CPI) in airlines' home countries	Changes in CPI as measure of inflation may be incorporated by market investors into airlines' returns directly (a negative relationship is usually hypothesized) or through the oil price or exchange rate channel (Orlowski, 2017).
Maturity risk premium on Treasury bonds (YTM)	Difference between yield to maturity on bonds with 10-years maturity and yield on bonds with 1-year maturity for each origin country of the airline company. Fama (1990) and Chen (1991) have demonstrated for a long time the existence of a strong relationship between maturity premiums and business cycles and included maturity risk among the macroeconomic factors that explain changes in stock prices.
Global financial market volatility measured by CBOE's VIX	Real-time market index that represents the expected forward-looking 30-day volatility embedded in the S&P 500 index options prices. VIX is commonly used in empirical research as a measure of global market volatility (see BenSaïda et al. (2018), or Elsayed et al. (2020)).

Brief descriptive statistics of the variables (in logarithmic form) are presented in Table 2.

Table 2. Descriptive statistics (log values of variables) (source: authors' work)

Variable	Mean	Median	Std. Dev.	Skewness	Kurtosis
STOCK	1.558	1.381	0.982	1.330	4.954
OIL	1.875	1.872	0.148	−0.281	2.126
INDEX	3.892	4.002	0.558	−1.670	6.281
FX	0.272	0.272	0.035	−0.421	2.361
NEER	2.008	2.005	0.065	−3.468	25.708
REER	2.009	2.003	0.051	−0.760	5.185
CPI	6.062	1.992	19.944	4.740	23.646
YTM	0.533	0.383	1.525	−6.448	92.815
VIX	1.260	1.232	0.155	0.872	3.716
OVX	1.532	1.516	0.145	0.292	3.295

Panel estimation controls better for heterogeneity among individual cases and the panel Autoregressive Distributed Lag (ARDL) model proposed by Pesaran et al. (1999) and Pesaran

et al. (2001) has been used, given its advantage over vector autoregressive (VAR) models and in the work with variables at different orders of integration, i.e., I(0) or I(1), compared to the cointegration methodology of Johansen (1988) and Engle and Granger (1991) – see, in this respect, Nkoro and Uko (2016), Shrestha and Battha (2018), Philips (2018). Table 3 shows the results of panel unit root tests, which indicate that variables are mostly I(1), but NEER and VIX are I(0); this indicates a higher appropriateness of the panel ARDL model for the data used and analysis carried out in the current study. Moreover, ARDL models perform more efficiently when portraying the long-term relationships between variables compared to more traditional cointegration tests such as Johansen (1991) or Engle and Granger (1987), particularly in heterogeneous panels, as the one used in this paper (smaller number of companies and high number of months).

Table 3. Panel unit root test results (source: authors' work)

Variable	Levin, Lin & Chu		Im, Pesaran and Shin		ADF - Fisher		Level of integration
	Level	First difference	Level	First difference	Level	First difference	
STOCK	0.150	–5.884*	–1.136	–20.862*	66.188	542.687*	I(1)
OIL	–0.009	–27.154*	–3.700*	–21.979*	73.996**	577.493*	I(1)
INDEX	1.631	1.772	–0.234	–17.851*	73.530**	432.902*	I(1)
FX	–0.626	–23.331*	–3.660*	–22.150*	73.401**	583.905*	I(1)
NEER	–2.173**	–16.337*	–2.110**	–20.239*	71.213**	519.150*	I(0)
REER	–2.620*	15.867*	–1.464	–20.858*	58.947	540.263*	I(1)
CPI	2.335	–12.174*	6.133	–22.773*	42.824	612.766*	I(1)
YTM	–0.166	–8.907*	–1.070	–22.255*	54.087	604.488*	I(1)
VIX	–1.945*	–14.632*	–5.183*	–30.460*	97.579*	917.860*	I(0)
OVX	0.414	–14.461*	–5.728*	–28.620*	107.160*	841.187	I(1)

Note: Levin, Lin & Chu test – null: unit root assumes common process; Im, Pesaran & Shin, and ADF – Fisher: null: unit root assumes individual process. *Note*: * and ** indicate statistical significance at 1% and 5% level, respectively.

Building on ARDL models, the Pooled Mean Group model (PMG) has been proposed by Pesaran et al. (1999), which is basically a cointegrated ARDL adjusted to the requirements of panel data sets. One of the distinctive features of PMG resides in its likelihood estimators' ability to estimate long-term and short-term coefficients for the relationship between variables.

The general form of the panel ARDL model is the following:

$$Y_{it} = \sum_{j=1}^{p} \alpha_i Y_{i,t-j} + \sum_{j=0}^{q} \delta_{ij} X_{i,t-j} + \mu_i + \varepsilon_{it}, \tag{1}$$

where Y_{it} is the dependent variable (stock return), $X_{i,t-j}$ is a vector of explanatory variables that are I(0) or I(1) which includes oil price, VIX, OVX and the other macroeconomic vari-

ables (CPI, FX, NEER, REER, YTM), α_i is the coefficient of the lagged dependent variable, δ_{ij} are the $k{\times}1$ coefficient vectors; μ_i is the unit-specific fixed effects; ε_{it} is the error term, $i = 1, \ldots, N; t = 1, .., T; p$ and q (from 1 to n) are the optimal lag orders.

Besides Eq. (1), which captures the long-term relationship between variables, the panel ARDL methodology offers information about the short-term links between the same variables, in the form of a short-term Error Correction Model (ECM), which means that any short-term disequilibrium is an adjustment process towards the long-term equilibrium between the variables. Moreover, in the ECM equation the parameters can vary between units, thus being estimated using the group average estimator for each unit (company). The PMG estimator restricts long-run equilibrium to be homogeneous across individual cases (companies), while allowing for short-term heterogeneity, compared to the MG (Mean Group) estimator that permits heterogeneity in both long-term and short-run relationships. Moreover, the MG estimator is less appropriate for heterogeneous panels and sensitive to outliers and permutations of small models (Asteriou et al., 2021). A homogenous behaviour of airline companies' prices and returns over the long-term is expected, given the significant importance of oil as jet fuel, but a more heterogeneous behaviour over the short-term considering companies' business structures. Nevertheless, the Hausman test has been used to decide between the MG and PMG estimators and the acceptance of the null hypothesis (the difference between PMG and MG estimation is not significant) indicates that PMG is the more efficient and better estimator for the data in this study.

The ECM is captured in Eq. (2):

$$\Delta Y_{it} = \varphi_i \left(Y_{i,t-1} - \beta_i' X_{i,t} \right) + \sum_{j=1}^{p-1} (\alpha_{i,j}^{\star} \Delta Y_{i,t-j}) + \sum_{j=0}^{q-1} (\delta_{i,j}^{\star} \Delta X_{i,t-j}) + \mu_i + e_{it}, \qquad (2)$$

where $\varphi_i = -(1-\alpha_{ij})$ is the speed of adjustment coefficient specific to the group; β_i' is the vector of long-term relationships; $\left(Y_{i,t-1} - \beta_i' X_{i,t} \right)$ is the error correction term (ECM); $\alpha_{i,j}^{\star}$ and $\delta_{i,j}^{\star}$ are the short-term dynamic coefficients; e_{it} is the error term.

Eviews 11 was used to conduct the estimation of the parameters in the models, based on the Akaike Information Criterion (AIC) to determine the optimal lag number. Overall, 16 models with different combinations of the variables have been implemented.

Previous research has used this methodology to investigate the relationship between share prices of financial companies and oil price (Horobet et al., 2019), to analyse the effects of sectoral shifts and capital inflows in Latin American countries (Kumar, 2013), or to study the uncovered interest parity (Afat & Frömmel, 2021).

3. Results and discussion

3.1. Cointegration tests

In the first step of the analysis, the presence of a cointegration (or long-term) relationship among the variables was verified. The Kao (1999) cointegration test has been used, which identifies a cointegrating relationship between variables if a linear combination of at least two non-stationary time series was stationary. The Kao test indicated the presence of a cointe-

grating relationship between the variables considered in the model, regardless of their combination in panel ARDL testing (results are available from the authors). This suggests that a long-run equilibrium between airlines' stock prices, oil price and volatility, market prospects, exchange rates and financial market volatility exists and points towards an integrated approach of risk exposure by airline companies, instead of their management on a one-by-one basis. The results confirm the long-run equilibrium between oil prices, stock prices of transport companies (airlines included), short-term interest rates, and the S&P 500 stock market index identified by Shaeri and Katircioğlu (2018), and the long-time trending relationship between interest rate, exchange rate and fuel price risk exposures for Cathay Pacific Airlines and China Airlines, two major Asian airlines, demonstrated by Yashodha et al. (2016). For what concerns the presence of cointegration between oil prices and macroeconomic variables, the literature abounds in validating it, regardless of country, periods and mix of variables – see, for example, Maghyereh and Al-Kandari (2007), Lardic and Mignon (2008), Rafailidis and Katrakalidis (2014), or Elian and Kisswani (2018).

3.2. Panel ARDL results

Long-run coefficients

Given the evidence of cointegrating relationships between variables, the estimated coefficients in the long-term and short-term panel regressions were further explored. The results for all models are presented in Table 4 (long-term regressions) and Table 5 (short-term regressions). The baseline models are 1 to 3 and they include all types of variables. The difference between the three baseline models comes from the foreign exchange variable used: FX in model 1, NEER in model 2, and REER in model 3. Further, the robustness of estimations was tested and the interrelationships between variables and their impact on estimations were explored. First, VIX was excluded (models 4 to 6), also OVX (models 7 to 9), and only OVX (models 10 to 12) to observe the impact of removing the direct impact of oil price volatility and financial market volatility on the relationship between oil price and airlines prices. Moreover, INDEX was excluded in models 13 to 15 to test whether there is a specific exposure of airlines' prices to oil price, besides the market exposure (considering that oil price risk is a component of market risk). Last, currency rates were excluded (model 16) to verify the robustness of oil price coefficients in the absence of airlines' price exposure to exchange rate risk. The results for long-term coefficients are presented first and then the ones for short-term coefficients.

Oil price (OIL) is the first variable of interest and the results show that the estimated long-term coefficients are negative and statistically significant in 10 out of 16 models. This in line with the expectation that higher oil prices increase airlines' costs, and this translates into lower prices and returns for these companies.

The result confirms the findings of Sadorsky (1999), Park and Ratti (2008), Aggarwal et al. (2012) Yun and Yoon (2019) and Mollick and Amin (2021), who also evidenced the negative impact of oil prices on transport companies' stock returns. Supplementarily, Figure 2 shows the ARCA Global Airline Index (AXGAL) traded on the New York Stock Exchange, which tracks the performance of listed high capitalization and liquid airline companies around the world, against the WTI Crude oil spot price between December 2002 and October 2020.

AXGAL and WTI oil prices have a "love and hate" relationship, illustrated by periods of high negative correlation (2003–2004, 2006–2007, and 2014), but also by times of strong positive correlation (2006, 2016, or 2019). Also, AXGAL volatility mirrors the WTI price volatility in many periods, although their amplitude is different and variable over time.

Figure 2. ARCA Global Airline Index and WTI Crude oil spot price, 2002–2020.
WTI Spot – left axis; AXGAL – right (source: authors' work)

At the same time, the statistically significant coefficients are present even when INDEX is considered, which means that exposure to oil prices is significant for airline companies and market investors include it in stock prices and returns beyond the consideration of market risk. Moreover, the exposure to oil prices is significant when financial market volatility (VIX) and oil price volatility (OVX) are also included in the model, indicating a very robust and consistent link between airline companies' stock prices and oil market. This result is complemented by the statistically significant and negative coefficients for VIX and OVX in nine out of ten models that included these variables, which confirm that stock prices and returns of airline companies are negatively affected by surges in global financial market volatility but also in oil market volatility. The significant impact of oil price shocks on major US carriers was also demonstrated by Hsu (2017), while Nandha et al. (2013) evidenced that airline stocks were prone to the joint effects of oil volatility and oil regimes induced by global significant events. Considering the pandemic as a significant shock on financial markets and economies, Salisu et al. (2020) also proved that oil and stock markets experienced more prolonged impacts of own and cross shocks during the pandemic than before, thus emphasizing the relevance of financial market volatility on oil price volatility and, further, on companies' stock returns.

Besides the long-term consistent link between oil prices and oil market volatility, on the one hand, and stock prices and return, on the other hand, airline companies' share prices are positively influenced by growing markets, and negatively influenced by declining markets. This is observable through the positive 13 out of 13 estimated coefficients for INDEX, which suggest strong airline companies' exposure to market risks. This is in line with the results of Kristjanpoller and Concha (2016) and Chen et al. (2017) that advance the concept of "market inertia" which drives companies stock returns depending on overall market conditions, regardless of the specific attributes that may generate risk exposures. The same consistent

Table 4. Long-term coefficients of panel ARDL estimation (source: authors' work)

Model	Regressors									SE	LL
	INDEX	OIL	VIX	OVX	FX	NEER	REER	CPI	YTM		
1	0.989*	–3.866*	–0.434*	–0.666	14.110	–	–	0.001	0.028	0.045	7104.04
2	1.113*	–0.509*	–0.313**	–0.718*	–	0.134	–	0.006	0.030	0.045	7102.47
3	1.496*	–0.388*	–0.208	–0.582*	–	–	1.133*	0.005	0.169*	0.045	7104.31
4	1.069*	–1.686	–	–1.002*	4.339	–	–	0.002	0.025	0.045	7065.61
5	1.441*	–0.472*	–	–0.790*	–	0.844**	–	0.007	0.148*	0.045	7069.17
6	1.579*	–0.412*	–	–0.669*	–	–	1.369*	0.007	0.170*	0.045	7071.06
7	1.161*	1.094	–	–	–5.169**	–	–	–0.418*	0.068*	0.046	7037.35
8	1.146*	–0.079	–	–	–	0.335	–	–0.476*	0.072*	0.046	7039.77
9	1.160*	–0.077	–	–	–	–	0.434	–0.476*	0.077*	0.046	7039.19
10	1.350*	–6.007**	–0.841*	–	24.195**	–	–	–0.010	0.180*	0.045	7083.79
11	1.492*	–0.186	–0.668*	–	–	0.524	–	–0.002	0.193*	0.045	7079.37
12	1.658*	–0.166	–0.515*	–	–	–	1.327*	0.000	0.223*	0.045	7080.95
13	–	–14.273*	–1.452*	–0.486*	57.748*	–	–	–0.008	0.039**	0.048	6711.49
14	–	–0.846*	–1.246*	–0.872*	–	–0.597	–	0.002	0.021	0.049	6708.14
15	–	–0.875*	–1.282*	–0.880*	–	–	–0.849	0.000	0.025	0.049	6706.43
16	1.338*	–0.537*	–0.354**	–0.691*	–	–	–	–0.004	0.130*	0.045	7078.51

Note: * and ** indicate statistical significance at 1% and 5% level, respectively. SE and LL designate standard error and log likelihood.

exposure of airlines' stocks to market risk is also evidenced in the studies conducted by Goh and Rasli (2014) on Asian low-cost and traditional airlines, by Flouris and Walker (2005) on Canadian carriers, or by Turner and Morrell (2003) on a sample of global airlines.

Results for exchange rates show only positive statistically significant coefficients, regardless of the type of exchange rate used, but with different importance across the types of exchange rates. For the USD/EUR exchange, there are 3 out of 5 statistically significant coefficients, but only 1 in five for NEER. Nevertheless, their sign indicates that airline companies benefit from the appreciation of the Euro against the US dollar and from depreciations of the US dollar against the Euro, but also from overall nominal depreciations of their domestic currencies against their most important trading partners (NEER). Therefore, a weak US dollar is good news for the airline industry, but also domestic currencies' depreciations. This contradicts Loudon (2004) on the lack of exposure to currency risk of airlines from Australia and New Zealand, but this research considered a panel of global airline companies. On the other hand, the findings confirm the study of Tai (2008) that reveal the impact of USD/JPY movements on US industries, including airlines, and show that currency risk is priced in stock returns. Overall, the results indicate that airline companies confront themselves with currency risk, particularly the ones with high shares of sales and/or debt denominated in foreign currencies or who source most of their supplies (such as jet fuel) in foreign currencies (Merkert & Swidan, 2019). Similarly, Huse and Oliveira (2012) show that Brazilian real's depreciation against the US dollar in 1999 and 2002 negatively impacted Brazilian airlines, and the aggravating factors were the pricing of fuel, leasing, and maintenance costs denominated in US dollars. Besides different samples and periods of analysis, the different results may also be the consequence of business transformations in the airline industry, which could have changed the exposure profile of these companies. Still, the presence of a joint exposure of the airline industry to oil price risk and US dollar currency risk, given that oil prices are globally set in US dollars, should direct financial managers towards a consolidated dynamic risk management approach in the already established Enterprise Risk Management (ERM) framework. Moreover, the significant exposure of the airline industry to changes in the external price competitiveness of companies' home countries asks for an integrated micro- and macroeconomic consolidation and understanding of more complex business risks that influence each other. Recently, Jain et al. (2020) proposed a dynamic risk management strategy focused on an adapted and flexible risk management decision system, able to detect the significant risks, to assess the business risk appetite and to quickly decide, that helps companies navigate an unpredictable business environment where change is the order of the day.

When investigating the long-term coefficients for REER, which captures the influence of changes in price competitiveness of a currency against its major trading partners, there are 3 out of 5 statistically significant coefficients, with a positive sign. This suggests that airlines benefit from decreases in price competitiveness of their origin countries' currencies against their trading partners. Similarly, real appreciations of their domestic currencies are good news for the airline industry. At first sight, this is a surprising result, but it may be easily explained by the global nature of the industry but also by a perceived stronger domestic economy by market investors, which benefits all companies, not only airlines. At the same time, this result deserves to be further investigated.

Changes in prices, included in the model through CPI, do not seem to significantly influence airlines' stock prices, as only in 3 out of 16 models the estimated coefficients are statistically significant. Still, they are all negative, indicating that airlines' stock prices are negatively affected by increasing prices. Genc et al. (2006) indirectly confirmed the lack of airlines' exposure to price increases, as they found that inflation does not have significant effects on airlines' profitability, in a study of 19 US airlines between 1999 and 2003.

Lastly, maturity risk (YTM) is an important risk factor, as in 10 out of 16 models the estimated coefficients are statistically significant. Their positive sign is in line with the findings of Fama and French (1989), or Fraser (1995), who have shown that positive term spreads (i.e., higher interest rates for longer maturities compared to shorter maturities) explain stock market returns and the state of the economy is influencing equilibrium returns in both bonds and stock markets.

Short-term coefficients

The next step is to examine the short-term estimated coefficients with the help of the Error Correction Model (ECM). An advantage of panel ARDL models is their ability to reveal the long and short-term properties of the relationship between variables and any short-term disequilibrium is considered an adjustment process towards the long-term equilibrium. Table 5 presents the short-term coefficients and the ECM term.

All ECM coefficients are negative and statistically significant at 1% level, which confirms the long-term link between the variables identified by the long-run tests. The coefficients range between –0.043 and –0.058, with an average of –0.046 across the 16 models. Thus, over the short-term, 4.6% of the deviation from the long-term equilibrium is corrected, on average, within a month.

Moreover, most coefficients are statistically significant at 1% or 5% level and their signs are consistent across models. Negative coefficients are encountered for OIL, VIX, OVX, and YTM, suggesting negative short-term adjustments to the long-term relationship, while positive coefficients were identified for INDEX, FX, NEER and REER, indicating positive short-term adjustments. The only variable that does not present statistically significant short-term coefficients is CPI, but this is in line with the general lack of significance of price increases for airlines' stock prices evidenced by the long-term equations.

Conclusions

This study explored the impact of oil price and oil price volatility on the performance of the largest publicly traded airline companies after the global financial crisis in a methodological framework that delineates long-term and short-term attributes of this impact, which is, to the authors' knowledge, the first research attempt in the field.

The results show a long-term equilibrium relationship between airline companies' stock prices, oil price and oil price volatility, financial market volatility, currency risk, inflation, and maturity risk. The most interesting result is the pervasive and significant negative exposure of airline companies' stock prices and returns to oil price and oil price volatility, which goes beyond their exposure to market risks, embedded in stock market indexes, and to financial

page 298 A. Horobet et al. Oil price volatility and airlines' stock returns: evidence from the global aviation...

Table 5. Short-term coefficients of panel ARDL estimation (source: authors' work)

Model	ECM(-1)	D(INDEX)	D(OIL)	D(VIX)	D(OVX)	D(FX)	D(NEER)	D(REER)	D(CPI)	D(YTM)	C
1	−0.050*	0.899*	−0.926*	−0.033**	−0.012	2.977**	–	–	−0.087	−0.019**	0.132*
2	−0.058*	0.927*	−0.203*	−0.031**	−0.016	–	0.524*	–	−0.305	−0.022*	−0.035*
3	−0.048*	0.913*	−0.197*	−0.034**	−0.020	–	–	0.452**	−0.520	−0.025*	−0.229*
4	−0.049*	0.981*	−0.956*	–	−0.021	3.134*	–	–	−0.123	−0.021**	0.041*
5	−0.047*	0.974*	−0.195*	–	−0.032*	–	0.487**	–	−0.346	−0.026*	−0.179*
6	−0.048*	0.975*	−0.192*	–	−0.035*	–	–	0.435**	−0.549	−0.026*	−0.270*
7	−0.054*	1.048*	−1.029*	–	–	3.627*	–	–	−0.061	−0.023*	−0.143*
8	−0.054*	1.063*	−0.152*	–	–	–	0.464**	–	−0.263	−0.026*	−0.127*
9	−0.053*	1.070*	−0.149*	–	–	–	–	0.449**	−0.413	−0.026*	−0.138*
10	−0.043*	0.888*	−0.934*	−0.033**	–	3.099*	–	–	−0.028	−0.019*	0.087*
11	−0.044*	0.926*	−0.180*	−0.132**	–	–	0.456**	–	−0.259	−0.022**	−0.184*
12	−0.444*	0.928*	−0.175*	−0.035**	–	–	–	0.397**	−0.466	−0.024*	−0.298*
13	−0.051*	–	−0.553	−0.102*	−0.035*	1.605	–	–	0.183	−0.021	0.778*
14	−0.047*	–	−0.180*	−0.105*	−0.027**	–	0.126	–	0.042	−0.025**	0.343*
15	−0.047*	–	−0.175*	−0.104*	−0.027**	–	–	0.122	−0.044	−0.024	0.365*
16	−0.046*	0.886*	−0.196*	−0.035**	−0.017	–	–	–	−0.253	−0.023*	−0.057*
Average						−0.046					

Note: * and ** indicate statistical significance at 1% and 5% level, respectively.

market volatility. Furthermore, the airline industry is a cyclical industry, as signalled by the significant positive link to market indexes and the positive exposure to maturity risks. A concerning finding is the coupling of oil price risk exposure to the USD/EUR exchange rate, particularly when considering the negative exposure sign, which means that the depreciating trend of the Euro after the global financial crisis has harmed the industry's performance, but once a reversal trend will appear it will negatively impact airlines' profits. On the other hand, airline companies' exposure to their domestic currency exchange rate risk is minor, which is not surprising given the global nature of their businesses and the diversity of currencies used.

Given the global profile of the airline industry, the prospects of the industry returning to low levels of traffic and more active interventions from governments, similar to the 1970s, are rather high; but this might be an optimistic story, as airlines will also face with people's reluctance towards flying in an environment that is considered less safe. Even when recovery will occur, the revenues of airline companies will be under strain, considering the need to reduce ticket prices to stimulate demand for travel in a more uncertain world than the pre-pandemic one. Additionally, on-board sales restrictions that will remain in place for some time will affect airlines' revenues (particularly in the case of low-cost companies), thus causing more concern about companies' profitability and shareholders' returns. Besides, the high level of debt in the industry, fuelled by the financial support received during the pandemic, will also increase the pressure on profit margins and cash flows. Furthermore, the costs to comply with the assumed CO_2 emission targets and environmental protection are not meagre – they are estimated at $1.3 trillion. However, this massive investment effort will also lead to declines in fuel costs estimated at 225 US dollars for every ton of CO_2 emitted, which is a strong incentive towards these investments, according to IATA reports.

In this intricate framework, managing the exposure to oil price and its volatility is essential for companies' operational and financial planning, as part of the recovery process. The presence of a pervasive exposure to oil price risk shows, interestingly, that market investors do not incorporate into their valuation airline companies' hedging policies. Furthermore, oil price risk is a component of a complex network of risks that affect the industry that need to be addressed conjointly in the post-pandemic world. Airlines should devise strategies to adapt to future challenges, given the devastating effects the pandemic crisis has had on industry beyond traffic levels. In many areas of activity, the demand has increased largely due to the shift to work and consumption from home, which has stimulated the demand for fuel to power delivery trucks, cargo ships and freight trains. Although the demand for oil is still lower than its pre-pandemic levels, the progress of the vaccination campaign brings hopes for a faster-than-expected economic recovery. The oil price volatility will continue to have an impact on fuel costs, as well as the availability of financing and investment for airlines. Hence, the innovation and adoption of alternative fuels by the airline industry could be a successful alternative to oil price uncertainty.

The research presented in this paper is not free from limits. First, it used only a small sample of airlines, but they are the largest publicly traded companies with a true global scope, which makes the results relevant for the entire industry. Second, since this analysis used market data (i.e., companies' stock prices), it excluded information about non-listed companies in the airline industry. Including them is a needed future step; however, the methodological approach and research scope will have to change to consider variables that accommodate

with the nature of the data that is not market-based. Third, cargo transport companies have more diversified operations than passenger air transport companies, which, at first sight, might alter the results; however, the entire transportation sector is highly dependent on oil prices as fuel is a consistent component of their costs. Fourth, an indirect test of oil price volatility in the model was performed, using an oil price volatility index (OVX), instead of using heteroskedasticity-based specifications to model oil price risk. Fifth, the tests observed only linear relationships between variables, but asymmetric and general non-linear links might also be present. Both the exploration of heteroskedastic specifications and non-linear relationships between variables are intentions for future research. Likewise, further investigations on airline companies' hedging policies to oil price risk, but also currency risk, and their inclusion by market investors into stock valuations are needed. In addition, the interplay between oil price risk, macroeconomic and business-related variables in the airline industry deserves to be studied, as it may offer interesting insights into companies' managerial policies and the constraints they are confronted with when making strategic decisions such as innovating, investing in new aircraft or in improved operations, opening new routes or exiting existing ones. The post-pandemic world will offer the ground for studying these decisions, as airline companies, and not only, are forced to rethink their businesses to cope with a more complex and unreliable environment.

Author contributions

AH, MLEZ and LB conceptualized the study and were responsible for overall design and econometric data analysis. DGD was responsible for data collection and interpretation of results. All authors wrote the first draft of the article. AH and LB wrote the final version of the manuscript.

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