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Externalities in the Aviation Industry

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Chapter 1

Introduction

The aviation industry has been characterized by a sharp growth in recent years, owing mainly to the strong demand of both leisure and business travelers. This spectacular growth in air traffic volumes has its roots in the increase in competition in the airline market that is derived from the deregulation process in the United States, which started in the 1970s, and from the more recent Open Sky agreement, also involving European countries, which started in the early 1990s (Borenstein and Rose, 2014). The deregulatory process has been substantially more difficult in Europe than in the United States because it had been necessary to dismantle several bilateral agreements among European countries, differently from the process in the United States, which affected solely a market composed of domestic operations. In particular, Europe had to replace all bilateral agreements among its countries and replace them by the coordination of a supranational organization such as the European Union over Member States. However, despite the fact that deregulation has brought benefits to passengers in terms of lower fares and a wider choice of new carriers to fly with (Kahn, 1988), such as low-cost carriers, this movement has also introduced new potential sources of market distortion. Given the lack of coordination among regulatory institutions, distorting components have the ability to spread easily among airlines' networks, fostering the difficulties of governments in developing efficient responses to disruptive events such as the recent COVID-19 pandemic or in finding a common international climate agreement. This thesis contributes to the presentation and evaluation of how distortions in the aviation market alter the competitive environment and how correcting policies that do not take them into account properly can end up leading to unexpected outcomes.

Externalities and distorting forces can assumes different forms within the aviation industry. They encompass from competition inefficiencies to environmental damages. Academics devoted much effort over the years to explore the impact of carriers market power in the airline competitive industry. Market power arises in condition where the market depart from be perfect competitive and lacks of enough competing firms. Several reasons can lead to this situation in which incumbent firms are not able to serve the market due to high entry-barriers or due to a monopoly and oligopoly condition. The results of market power is a departure from the efficient fully-competitive output due to fares higher than the social optimum.

Related to output distortions, the Mohring effect (Mohring, 1972) plays an important role in the willingness of passengers to fly. This positive externality consists increasing return to scale in passenger utility due to a higher service frequency. Specifically, an increase in airline operations increase the demand of passengers willing to fly. This implies that to serve the newly generated higher traffic volume, a higher service frequency is required, generating a feedback loop process. The Mohring effect has been extensively studied in the urban transport literature but is missing from aviation related analysis.

Airlines have continuously leveraged on their network structure in order to maximise their profits. Two main paradigms of network configurations establish over the years: the point-to-point and the hub-and-spoke structures. Point-to-point network relies on connecting directly airports served by an airlines. This structure is typical of low-cost carriers. The hub-and-spoke structure relies on an intermediate airport, the hub, which aggregate all the traffic and connects remote airports, the spokes. This network structure leverage on generating high economies of densities through the exploitation of hub airports. The drawbacks of this network structures are that it is more prone to delays given the high level of traffic in hub airports, and that it generates more pollution given the rerouting of flight to the hub airport.

In particular, curbing aviation emissions is considered one of the current main challenge of the industry. Some emission regulation mechanisms have been propose so far, but their effectiveness is not clear yet. Furthermore, these policies are prone to free-riding behaviours, emissions leakages to unregulated countries and to double marginalisation from overlapping mechanisms. These regulatory shortcomings undermine schemes efficiency. Most importantly, these schemes fall shortly in the case of all the aforementioned distortions are not considered in the policy design process and may generated outcomes

far from the expected ones.
The Covid-19 pandemic had represented an exogenous distorting shock that severely affected the entire aviation industry. Specifically, the imposition of lockdown measures by local governments resulted in a collapse of traffic volume, undermine the survivability of airlines, most of them already burden in debts.

By presenting three papers, this thesis aims to investigate the distortions in the competing aviation market and to highlight the principal sources of failure in effectively regulating the industry. The papers presented in this thesis use a wide range of methodologies. The first paper belongs to the econometrics domain with a focus on time series analysis and forecasting practices. The second and third papers bridge optimization algorithms with game-theoretic models, with a focus on finding a solution to complex games.

Chapter 2 presents the first paper of the thesis. This paper provides estimates of the disruptive impact of the COVID-19 outbreak on air transport at the macroregional level. To this end, weekly data on air service volumes are analyzed through an ITS SARIMA model and a counterfactual analysis covering 2016-2020. This paper shows that the real effect of COVID-19 was a reduction greater than 80% in all macroregions of the world in May 2020, and still a decrease of approximately 70% at the end of summer 2020, with the only exception of China and eastern Asia and North America, where the reductions are, respectively, -29% and -54%. Empirical evidence confirms that the impact of the pandemic crisis and subsequent lockdown has been dramatic, much more disruptive than any previous crisis. This paper also finds that the impact is greater for intercontinental connections and for legacy airlines, while low-cost carriers appear to be slightly more resilient. These results confirm that airline economic sustainability is currently at high risk and that the unequal resources of the various countries in subsidizing national airlines could generate a competitive imbalance in the future.

Given the aforementioned situation during the COVID-19 pandemic, Chapter 3 of this thesis models the impact of bailout schemes on the competitive airline market. By blending game theory with operations research practices, this paper develops a Nash single-stage, best-response game. Under this framework, airlines compete at a strategic level by setting airfares, service frequencies, and the size of their fleet. Investigating the European aviation market, served by both legacy and low-cost carriers, this paper assesses how the form of aid offered during the COVID-19 outbreak may lead to changes in market equilibrium outcomes over the coming years. The impact of government bailouts is addressed by identifying changes in social welfare, taking into account passengers, airlines, and governments. The results suggest that the European Commission has likely distorted the competition in aviation markets by allowing Member States to provide different types of rescue packages. In addition, this paper shows that the most efficient solution would have been to coordinate state aid uniquely in the form of loans. Furthermore, the proposed methodology could be applied ex ante as a screening tool to rescue firms in a network-based industry should exogenous shocks be an issue.

Using a similar approach to the one proposed in the previous chapter, Chapter 4 of this thesis presents a game-theoretic model to analyze market equilibria in the presence of environmental policies at national and supranational levels. In a two-stage game, regulators maximize social welfare over their jurisdiction by setting emission charges, whilst airlines compete through frequencies, fares, and fleet choice. Consequently, airlines decide whether to absorb the costs of the environmental charges, pass them on to consumers, replace part of their fleet with new and less polluting and more fuel efficient aircraft, redistribute the inefficient fleet to less regulated itineraries, or adapt their networks. The equilibria outcomes suggest the presence of several distorting forces in the aviation market that can undermine the effectiveness of environmental policies. To assess the robustness of our results, the model is applied to North American and Western European markets under different regulatory configurations, such as a global scope regulation under a single regulator, a regulator duopoly, and a setting characterized by regulators with overlapping jurisdictions. This paper shows that a reduction in the emissions produced comes at the expense of welfare and that the effectiveness of the policy is limited when regulators interact in their own interests in presence of market distortions.

Chapter 5 presents the conclusions summarizing the findings and results of this thesis. This final chapter also provides a discussion of the implications of not properly evaluating distorting forces in defining aviation policies.

Chapter 2

The disruptive impact of COVID-19 on air transportation: An ITS econometric analysis

2.1 Introduction[1]

The air transportation industry has suddenly passed from a positive and flourishing sentiment regarding the industry and its future development to a shocking situation due to the COVID-19 pandemic crisis, that has severely affected the sector. Up to the end of year 2019 forecasts were extremely positive: Airbus (2019) and Boeing (2019) forecast, respectively, +4.3% and +4.6% annual increase in air transportation demand for the period 2019-2038, new aircraft demand reaching about 39,000 and 44,000, confirming the resilience of the industry despite financial, economic, and geopolitical crises (Boeing (2019) points out a +6.7% annual increase in passengers demand since year 2010). Eurocontrol (2019) reports lower annual demand increase in Europe (+1.9% in the period 2019-2040), but shares the same optimistic view.

These positive sentiment was literally destroyed by the COVID-19 pandemic crisis, which started in China in January 2020 and then spread to Europe and all over the world (currently involves 188 countries). Since the beginning of the crisis, the numbers have

[1]This chapter is based on the paper published as Andreana G., Gualini A., Martini G., Porta F., Scotti D., The disruptive impact of COVID-19 on air transportation: An ITS econometric analysis. Research in Transport Economics (2021)

shown that the lockdown adopted in most countries with infections has had dramatic effects in the industry. ICAO (2020) estimates for the full year 2020 an overall reduction ranging from 32% to 59% of seats offered by the airlines, an overall reduction of 1,815 to 3,213 million passengers, and about USD 236 to 416 billion potential reduction of airlines' gross operating revenues (if we take the central value of this range we get that airlines are losing 1 billion USD a day). ICAO considers some scenarios relating to the easing period and the end of the lockdown, i.e., V-shaped, U-shaped, or L-shaped. At the moment it is not possible to say with certainty which of these scenarios is the prevailing one. However, the latter scenario, at least for year 2020 and probably also for 2021, it is very likely to prevail. Hence, it is highly likely that the air transport sector will not quickly return to pre-crisis levels.[2] Furthermore, the greater use of smart-working during the lockdown could lead executives to severely limit business travels in the future, negatively impacting long-distance business flights which represent the most profitable segment of the market.

Despite the above uncertainty about the future, it is now possible to provide estimates of the impact of the COVID-19 crisis and the consequent lockdown on the air transportation activities, and of the recovery taking place in the post-lockdown period. Moreover, using an appropriate econometric method, it is possible to identify the real effect of COVID-19. To this purpose, a simply intertermporal comparison of observed data may be misleading. A proper estimate must rely on the comparison to a conterfactual scenario, i.e., the levels that would have been observed in the absence of COVID-19. It is also interesting to analyze whether the outbreak has had the same impact on the different world's macro-regions, and if full-service carriers (FSCs) and low-cost carriers (LCCs) have been affected in the same way. These are precisely the goals of this paper, namely (1) to estimate the impact of COVID-19 on the air transport sector using a counterfactual analysis, and (2) to identify which macro-regions and airline business models have been most penalized. In this sense, we aim to analyse the real downturn in terms of airlines operations taking into account for industry growth trends across regions. Without controlling for these trends, any comparison with pre-pandemic years results in underestimate of the pandemic impact.

The COVID-19 pandemic is a recent phenomenon. The first official data for China date back to the beginning of January 2020. Towards the end of February 2020, the

[2]IATA (IATA, 2020b) estimates that passenger traffic will not rebound to pre-crisis levels until at least 2023.

pandemic spread to Italy, and within a few weeks across Europe and the world. The resulting lockdown was generally implemented since mid-March, and has forced about 4 billion people into their homes and stopped the vast majority of businesses, including air transportation. After about two months the lockdown was gradually lifted, maintaining more limited restrictions on the movement of people between some countries. This coincided with a general resumption of activities during the summer of 2020. Regarding air transport, the recovery was partial, as will be seen below. In fact, many people have not resumed flying, merely moving within national borders, and business travel is still significantly reduced.

Being the COVID-19 a recent event there are not many contributions in the literature. As far as we know, the majority of the few available studies have analyzed the impact of the air travel ban on the spread of coronavirus. Chinazzi et al. (2020) study the impact of lockdown on the COVID-19 contagion rate in the Wuhan area in China, and find that the restrictions on flights from/to China delayed the progression of the epidemic in that area but it didn't have a big impact in limiting the spread all over the world. Lau et al. (2020) investigate the same issue and find that the air travel ban and the consequent lockdown have led to a significant decrease in the contagion rate, doubling the number of infected people from 2 to 4 days. Gilbert et al. (2020) analyze the vulnerability of African countries to the spread of the COVID-19 outbreak using the volume of air travel departing from China and directed to Africa and find that aviation is a driver of contagion and this exposes some countries more than others. Christidis and Christodoulou (2020) develop a model to measure the risk, in the early months of 2020, of the disease spreading outside China, and identify the countries most affected by the pandemic. The predictive model identifies the passengers from the Hubei region as the main driver to explain the growth of the first COVID-19 cases in many countries.

Some recent contributions have instead investigated the impact of COVID-19 on different dimensions of aviation. Sun et al. (2020) analyze the changes in the global aviation network due to the pandemic, focusing on network metrics, number of O-D pairs, and number of aircraft in operation. They find a stronger impact in the Southern hemisphere and a more marked connectivity reduction in international flights compared to domestic ones, especially in the US. Forsyth et al. (2020) examine the impact of COVID-19 on airports' performances, and highlight that, given the large decrease in passengers and traffic, there is a need for public subsidization. Iacus et al. (2020), using historical data from the

SABRE database, limited to October 2019, elaborate a predictive model of the effects of the lockdown on the economy. Having no actual data on the post lockdown sector, they assume hypothetical scenarios, and show how the lockdown leads to an estimated reduction of world GDP between 1.4% and 1.7% in the worst case scenario. Their estimates are rather low, and also are not aimed only at the air transport sector, which is instead the focus of this work.

Some other contributions have investigated the influence of other exogenous shocks on air transport. Lai and Lu (2005) study the impact of the 11*th* September 2001 terrorist attacks on US air travel demand, and find that both domestic and international air traffic were significantly impacted, but only temporarily. After only one month following the terrorist attack to the Twin Towers, the industry had recovered to pre-shock levels. Other papers have exploited some quasi-natural experiments due to exogenous shocks to identify either the contribution of air transportation to regional growth in the US (Blonigen and Cristea (2015)), or to the international trade volumes in Italy (Brugnoli et al. (2018)).[3] Conti et al. (2019) analyze, instead, the effects of a new European airport regulation on aeronautical charges.[4]

Our contribution differs from the previous ones since it uses the COVID-19 outbreak as an exogenous shock to estimate the impact on air transportation using a single interrupted time series (ITS) model. The ITS model can be adopted when an exogenous shock affects all the population and not only a treatment group (Baicker and Svoronos (2019)), i.e., it is a quasi-experimental design that does not require data on a control group. As other models estimating the effects of a shock (i.e., regression discontinuity design, difference–in–differences model) ITS allows to compare the observed trend to a counterfactual one. However, in a ITS model the counterfactual is estimated using the time series, as shown by Baicker and Svoronos (2019) and Bernal et al. (2017). Hence, differently from Sun et al. (2020), Iacus et al. (2020) and Forsyth et al. (2020), we do not assess the impact of COVID-19 on aviation activity using observed data, but we estimate its causal effect by

[3] Blonigen and Cristea (2015) exploit the U.S. Air Deregulation Act (1978) and show, using data over the 1969-91 period, that a +50% increase in aviation activity generates a +7.4% increase in real GDP over 20 years. Brugnoli et al. (2018) use the *Alitalia*'s de-hubbing from Milan Malpensa airport to estimate an elasticity of aviation activity on international trade up to +0.13%.

[4] Conti et al. (2019) exploit the European airport regulation model introduced in 2009 and adopted by EU member states between 2011 and 2014. This new setting was applied to all airports with more than 5 million passengers per year. Using data for the 2008-2017 period (air airports with less than 5 million annual passenger as a control group), they find that the new regulation led to a reduction of about 2% in airport charges.

comparing the observed trend with a counterfactual, i.e., a trend that would be observed in absence of an exogenous shock. This means that the counterfactual trend is generated by using the data before the exogenous shock (the lockdown) in order to have a projection after it (the post-period trend).[5]

We analyze the effects of COVID-19 and the subsequent lockdown on air transportation by applying a ITS framework with errors following a SARIMA model to a weekly data set from the beginning of 2016 to $8th$ September 2020. The reference date chosen for the lockdown is different among the world macro-regions, and it is identified using the share of grounded scheduled seats due to the travel ban. Consequently, the lockdown started in different weeks of March 2020. This means that our data set can be divided into two sub-samples: several pre-lockdown weeks (ranging between 220 and 222) pre-lockdown weeks and 24-26 post-lockdown weeks. Such a structure, combined to the utilization of a ITS model with SARIMA errors, allows to study the observed trend of the industry for the period before and after the lockdown, and to check the magnitude of the recovery during the Summer 2020.[6]

Regarding aviation activity, we focus on three key supply-side variables of the air transport industry: seats available on scheduled commercial flights around the world, flight frequencies, and total ASKs.[7] The data are extracted from the OAG archive and are grouped by 10 world macro-areas: North America, Western Europe, Eastern Europe, Latin America, Africa, Middle East, Oceania, Central Asia & India, South-East Asia, and Eastern Asia & China.[8] Clearly, it may be interesting to study other supply-side effects due to the lockdown. For instance, many airlines have adopted a cancellation strategy after the lockdown: flights are scheduled (and hence, seats are available), but then are canceled if the load factor is too low. This cancellation policy may further reduce the

[5] ITS requires that two conditions are fulfilled: (1) a sufficiently long time interval before the shock, and (2) the absence of concurrent changes to exogenous shock. We have weekly data for a 4-year period before the lockdown, a sufficiently long time span with repeated seasonal effects. No other shocks have the impact of the lockdown.

[6] As previously mentioned, we have enough information to build a counterfactual scenario representing what it would have occurred in the absence of the COVID-19 outbreak and the subsequent lockdown, during the year 2020. This extends the analysis from a comparison between observed and past data, to an estimate of the "real" loss of traffic – i.e., the decrease in air service volume compared to the predicted (and never observed due to the pandemic crisis) level of air traffic.

[7] Available seat kilometers (ASK) are a key variable in air transportation, given by seats multiplied by flight distance.

[8] The lockdown date for China is $4th$ February 2020, earlier than the other macro-regions, since several countries have imposed travel bans to flights to/from China before adopting themselves the lockdown.

available seats during the recovery period. However, we have no data regarding offered and then canceled seats.

Moreover, the COVID-19 outbreak has also exerted a strong effect on the demand for air transportation. Both business and leisure travels have been dramatically reduced and this may be a long-lasting effect, since the pandemic may have changed the willingness to travel. We can observe some features of the demand side, since we have data regarding the bookings up to June 2020, i.e., the first month of resumption of activity in air transport after the lockdown. Hence, we can only look at some short-run effects regarding the demand side, while the long-run impact on the willingness to travel, and on the interaction with airlines capacity and supply strategies, might be explored when more data will be available.

Last, the lockdown has affected cargo activities. The e-commerce market has exploded because consumers, not being able to go to brick-and-mortar stores, have provided a very strong impulse to online orders using channels such as Amazon, Alibaba, etc. This significant push in demand for products transported by air has mainly turned towards integrators (DHL, Fedex, UPS, etc.). In fact, full-service airlines carry out cargo services mainly using the hold capacity on passenger aircraft. Bombelli (2020) find that integrators capacities surpassed their nominal values in North-East Asia, North America and Europe since March 2020. Suau-Sanchez et al. (2020) argue that the significance of air cargo has been vindicated by the Covid-19 crisis. Shipments of food and medical supplies have been protected by governments to ensure the supply of basic necessities. Li (2020) focus on the China market and confirms that air cargo suffered a less severe depression than passengers during the period December 2019-May 2020. The IATA cargo industry outlook (IATA, 2020a) points out that, despite an extra-utilization, freighters are insufficient. The ongoing capacity crunch continues to be driven by the lack of international passenger traffic. In July 2020, international belly cargo capacity was down by 70.5% on year-on-year base, a modest progress from the peak of the crisis in April (-82.5%). All these contributions highlight that the impact of COVID-19 on full-cargo traffic has been exactly the opposite than the dramatic decrease occurred in passenger activity. However, we do not have data on cargo volumes and focus only on the passenger segment effects, which is, in any case, the most important one in the air transportation sector.

The paper is organized as follows: Section 2.2 presents the econometric model adopted to estimate the effect of the lockdown and the counterfactuals in the absence of the

COVID-19 pandemic crisis. Section 2.3 presents the data and provides a first descriptive analysis of the impacts. Section 2.4 shows the results of the econometric analysis, while Section 2.5 highlights the main evidence achieved. Some further estimates to test the robustness of the results are given in the Appendix at the end of the paper.

2.2 Empirical methods

To estimate the effect of the lockdown on air transport, we use a weekly time series of seats offered on scheduled flights, which consists of 246 observations from 29*th* December 2015 until 8*th* September 2020. We apply a ITS framework with errors following a SARIMA$(p, d, q)(P, D, Q)_s$ model, i.e., the error term takes also into account for autoregressive (AR) and moving average (MA) components, differencing and seasonal effects (Box et al. (2015)).[9]

The ITS SARIMA$(p, d, q)(P, D, Q)_s$ model is defined by the following two equations:

$$y_t = \alpha_0 + \alpha_1 \cdot t + \alpha_2 \cdot L_t + \alpha_3 \cdot t \cdot L_t + \beta \cdot x_t + \eta_t \tag{2.1}$$

$$\begin{aligned}\eta_t = \phi_1 \eta_{t-1} + \ldots + \phi_p \eta_{t-p} + \epsilon_t + \ldots + \theta_1 \epsilon_{t-1} + \ldots + \theta_q \epsilon_{t-q} + \\ + \Phi_1 \eta_{t-s} + \Phi_P \eta_{t-s-P} + \Theta_1 \epsilon_{t-s-1} + \ldots + \Theta_Q \epsilon_{t-s-Q}.\end{aligned} \tag{2.2}$$

In Eq. (2.1) the dependent variable y_t is the weekly number of seats in scheduled flight in a macro-region, while $\alpha_0 + \beta x_t$ represents its baseline level when there is no lockdown. The latter is captured by the variable L_t, which is equal to 1 from the first week of lockdown in each of the 10 macro-regions and 0 before. The lockdown did not start at the same time around the world. Moreover, even within each macro-region, the lockdown started at different dates. To take these differences into account we examined the share of seats no longer available due to the forced cessation of airline activity on the total number of seats offered in a given macro-region in the first week of January 2020. We then assume as the lockdown date in a macro-region the week in which at least 50% of the seats entered into lockdown. The coefficient α_1 is the baseline trend slope (t is the trend) when $L_t = 0$. When the lockdown is implemented the ITS model modifies both the level and the trend slope: the former becomes $\alpha_0 + \alpha_2 + \beta x_t$, the latter $\alpha_1 + \alpha_3$, i.e., α_2 is the post-lockdown change in level, and α_3 is the change in trend slope after the

[9] s indicate the number of time steps for a single seasonal period.

restriction.

The regressor x_t is given by the number of COVID-19 cases recorded in the 10 macro-regions according to the John Hopkins University (JHU) database (Jonh Hopkins University, 2020).[10]. The use of this variable allows to disentangle the effect of imposed restriction from the airline lower supply in the different phases of the pandemic not affected by lockdowns. The cases of people infected with coronavirus start prior to the lockdown date and represent in Eq. (2.1) the independent response, from the decisions of the various national governments, of the air transport sector to the spread of COVID-19. They are included in the model to separate the government block from the spread of the disease. In most macro-regions the trend of cases is not influenced by the lockdown in the period considered, since people confinement take time to show its effect on the contagion rate.[11] The estimated coefficient of the interaction term $T \cdot L_t$, i.e., α_3, is a variable of interest, since it captures the impact of lockdown on the air transportation sector obtained by implementing a ITS design.

We estimate a log-linear model of Eq. (2.1), i.e., the dependent variable is the logarithmic transformation of the response variable. To identify the percentage variation in the volume of seats we can rewrite Eq. (2.1) (dropping the subscript t for simplicity) as follows:

$$\log(y) = \alpha_0 + \alpha_1 \cdot t + \alpha_2 \cdot L + \alpha_3 \cdot t \cdot L + \beta \cdot \log(x) + \eta$$

Our aim is an estimate on the seats volume y; hence we can make the following exponential transformation:

$$e^{\log(y)} = e^{\alpha_0 + \alpha_1 \cdot t + \alpha_2 \cdot L + \alpha_3 \cdot t \cdot L + \beta \cdot \log(x) + \eta},$$

and compute it when $L = 1$:

$$y(L = 1) = e^{\alpha_0 + \alpha_1 \cdot t + \alpha_2 \cdot L + \alpha_3 \cdot t \cdot L + \beta \cdot \log(x) + \eta},$$

and under $L = 0$:

[10] The cases recorded by the JHU database start from 22nd January 2020 in China.

[11] The exception is China that started the lockdown in the Wuhan region on $23rd$ January 2020 and removed it on $8th$ April 2020.

$$y(L=0) = e^{\alpha_0+\alpha_1\cdot t+\beta\cdot\log(x)+\eta}$$

The relative variation is as follows:

$$\frac{y(L=1)-y(L=0)}{y(L=0)} = \frac{e^{\alpha_0+\alpha_1\cdot t+\alpha_2\cdot L+\alpha_3\cdot t\cdot L+\beta\cdot\log(x)+\eta} - e^{\alpha_0+\alpha_1\cdot t+\beta\cdot\log(x)+\eta}}{e^{\alpha_0+\alpha_1\cdot t+\beta\cdot\log(x)+\eta}},$$

which simplifies to:

$$e^{\alpha_2}\cdot e^{\alpha_3\cdot t},$$

so that the percentage variation is $e^{\alpha_2}\cdot e^{\alpha_3\cdot t}\times 100$. By inspection, the impact of lockdown depends on the period t. However, we need also an estimate of what is the trend before and after the lockdown, i.e., what is the impact of time (the trend t) on y. The latter depends if $L=0$ or $L=1$. Hence we need to compute $y(t)$ and $y(t+1)$ when $L=0$ and when $L=1$. Start with $L=0$. We have (for simplicity we assume that $x=0$) the following:

$$y(t)|_{L=0} = e^{\alpha_0+\alpha_1 t}$$

and

$$y(t+1)|_{L=0} = e^{\alpha_0+\alpha_1\cdot(t+1)}$$

so that

$$\frac{y(t+1)|_{L=0} - y(t)|_{L=0}}{y(t)|_{L=0}} = \frac{e^{\alpha_0+\alpha_1\cdot(t+1)} - e^{\alpha_0+\alpha_1 t}}{e^{\alpha_0+\alpha_1 t}}$$

i.e., $e^{\alpha_1}-1$. Let us look now at the trend when $L=1$

$$y(t)|_{L=1} = e^{\alpha_0+\alpha_2+(\alpha_1+\alpha_3)t}$$

and

$$y(t+1)|_{L=1} = e^{\alpha_0+\alpha_2+(\alpha_1+\alpha_3)\cdot(t+1)}$$

so that

$$\frac{y(t+1)|_{L=1} - y(t)|_{L=1}}{y(t)|_{L=1}} = \frac{e^{\alpha_0+\alpha_2+(\alpha_1+\alpha_3)\cdot(t+1)} - e^{\alpha_0+\alpha_2+(\alpha_1+\alpha_3)t}}{e^{\alpha_0+\alpha_2+(\alpha_1+\alpha_3)t}}$$

and we get that it is equal to $e^{\alpha_1+\alpha_3} - 1$. Hence, the percentage impact of the lockdown on the industry is given by $(e^{\alpha_1+\alpha_3} - 1) \cdot 100$. The number of COVID-19 cases is also expressed in logarithm, i.e., the coefficient β is an elasticity. The model in Eqs. (2.1)–(2.2) is estimated 10 times, one regression for each of the 10 investigated macro-regions.

Eq. (2.2) defines the error term η_t temporal structure, a SARIMA$(p, d, q)(P, D, Q)_s$ process with autoregressive order p for the ARIMA component and P for the seasonal one, moving average order q and Q, respectively, and the degree of differencing among periods d and D. The seasonal lag is defined by the parameter s, and in our case is given by 52, i.e., we consider a yearly seasonal effect. The model coefficients are $\phi_1, \ldots, \phi_p$, $\theta_1, \ldots, \theta_q$, $\Phi_1, \ldots, \Phi_P$ and $\Theta_1, \ldots, \Theta_Q$, whereas the innovation error term ϵ_t is assumed to be normally distributed with zero-mean and variance σ^2. The model is estimated with maximum likelihood (Hyndman and Athanasopoulos, 2018).

We need to address some identification problems in order to have unbiased estimates of the coefficients. First, we need to identify the SARIMA model with the best goodness of fit, i.e., to specify the parameters of the autoregressive, and moving average orders, as well as the degree of differencing. We control for this possible mis-specification by using the Hyndman-Khandakar algorithm (Hyndman and Athanasopoulos (2018)) implemented by the `auto.arima()` function in R, that combines unit root tests, minimization of the Akaike Information Criterion (AIC) and MLE to obtain a SARIMA model.[12] Second, we need to check if the residuals from the selected SARIMA model are white noise. Our post-estimation diagnostic analysis involves both a check of the residuals by plotting the autocorrelation function (ACF) and by implementing a portmanteau test, i.e., a Liung-Box test.

Last, we need to estimate the counterfactual time series, to have a complete outcome of the ITS model. The counterfactual time series represents the predicted times series under the hypothesis that the COVID-19 never happened and the lockdown did not take place. The counterfactual time series is obtained by estimating the SARIMA model using the Hyndman-Khandakar algorithm applied to a data set limited to the end of the year 2019, and then computing the forecasts for all weeks up to $8th$ September 2020 as shown

[12]The algorithm minimizes the corrected AIC, given by $AIC + \frac{2(p+q+k+1)(p+q+k+2)}{T-p-q-k-2}$, where k is the parameter for the number of independent variables and T is the maximum time period.

in Box et al. (2015) and in Hyndman and Athanasopoulos (2018). In this way, we control for time varying confounding factors of the dependent variable, since the data for the year 2020 are clearly not representative of a normal trend. Furthermore, we control also for the possible effect of some events that occurred before the COVID-19 outbreak that may modify the counterfactual analysis, such as the grounding of the Boeing 737MAX during the year 2019.

2.3 Data and descriptive analysis

In this Section we describe how we build a data set to estimate the impact of lockdown in air transportation and present some descriptive statistics regarding the observed trends in the 10 macro-regions. The data refer to the total number of seats available on commercial flights scheduled for each week in the following 10 macro-regions: Africa (AF), Central and Southern Asia–AS1 (including India and Pakistan), South Eastern Asia–AS2, Central Eastern Asia–AS3 (including China, Japan and the two Korean republics), Western Europe–EU1, Eastern Europe–EU2, Latin America–LA, Middle East–ME, North America–NA and Oceania–OC. The macro-regions have different characteristics, shown in Table 2.1. Africa (AF) and Central Eastern Asia (AS3) are the largest territories, while South Eastern Asia (AS2) and Eastern Europe (EU2) are the smallest ones. However, the two macro-regions with highest population density are Central and Southern Asia (AS1) and South Eastern Asia (AS2), while Oceania has the smallest population density. The macro-regions have been affected by the COVID-19 outbreak at different times and with different intensities: the largest number of cases in May 2020 is in Western Europe and in North America, while it is in Latin America and North America in September 2020. In May 2020 the share of cases on the macro-region population was varying between 0.01% in Africa, Central and Southern Asia (AS1) and South Eastern Asia (AS2), and 0.3% (Western Europe). In September 2020 the same share varies between 0.07% (Central Eastern Asia–AS3) and 1.95% (Latin America–LA). These data are important since they highlight the role played in the diffusion of the contagion by the different population concentration. In fact, EU1 and NA result, as the richest macro-regions, among the most affected (respectively 0.54% and 1.15% of the population at the beginning of September).

In addition to available seats in scheduled flights, we also consider the weekly dynamics of flight frequencies and ASKs. Frequencies allow to analyze the effects of lockdown on

	Total			Intra macro-region			Extra macro-region		
Macro-region	Seats	Frequency	ASK	Seats	Frequency	ASK	Seats	Frequency	ASK
AF	-72.8%	-60.8%	-84.6%	-65.8%	-55.0%	-75.7%	-83.7%	-81.8%	-88.9%
AS1	-57.3%	-51.4%	-71.4%	-47.2%	-43.6%	-49.3%	-86.7%	-85.0%	-88.7%
AS2	-70.1%	-65.1%	-81.5%	-63.1%	-59.3%	-65.9%	-91.3%	-91.5%	-91.1%
AS3	-50.2%	-45.2%	-63.7%	-44.5%	-40.8%	-46.2%	-88.8%	-86.3%	-90.1%
EU1	-92.5%	-90.9%	-93.5%	-93.0%	-91.0%	-94.2%	-91.1%	-90.4%	-93.0%
EU2	-79.6%	-78.7%	-79.9%	-69.0%	-70.6%	-65.9%	-86.7%	-85.8%	-84.9%
LA	-83.9%	-72.4%	-89.9%	-81.7%	-69.1%	-85.4%	-92.6%	-91.3%	-94.5%
ME	-67.7%	-61.1%	-81.4%	-46.3%	-43.5%	-50.4%	-85.7%	-82.8%	-87.0%
NA	-67.0%	-63.2%	-76.8%	-63.4%	-61.1%	-67.4%	-92.1%	-91.3%	-92.9%
OC	-88.5%	-80.8%	-91.5%	-88.0%	-79.9%	-91.6%	-90.9%	-89.8%	-91.4%

Table 2.1: Macro regions' characteristics and COVID-19 impact

the intensity of the origin–destination network. ASKs instead show the dynamics relating to the length of the scheduled flights; they allow, for example, to assess whether there has been a greater reduction on short and medium-haul flights than on long-haul ones. These data are taken from the Official Aviation Guide (OAG) Schedule Analyzer database. The number of COVID-19 cases per countries are obtained from the JHU online database. They are aggregated at the macro-region level.

The variations in seats, frequencies and ASKs are observed at two time periods: the week beginning $21st$ April 2020, exactly in the middle of the lockdown time interval (usually it lasted 2 months) and the week beginning $8th$ September 2020, i.e., in the new normal period, with the lockdown ended about 3-4 months earlier and the restart of economic activities, including aviation, but still some restrictions imposed on the people mobility.[13]

Table 2.2 shows the percentage variations of seats, frequency and ASK in the 10 regions in the week starting $21st$ April 2020 compared to the same week in year 2019. Similar patterns are observed for available seats, frequencies and ASKs not only at the global level, but also when looking at sub-samples of traffic flows (i.e., intra and extra-regional ones). The highest reduction in total seats is in EU1 (-92.5%), followed by OC (-88.5%). The smallest reduction is in AS3 (-50.2%) because at the end of April 2020 China had already relaxed the restrictions on the movement of people and economic activities. The reduction in total flight frequencies was lower as compared to what observed in total available seats: again the highest reduction is in EU1 (-90.9%), followed by OC (-80.8%), and the lowest reduction in AS3 (-45.2%). As for ASK, on the other hand, the largest

[13]For instance, in Europe during the summer 2020 people traveling from US by air were required a quarantine period at the arrival in a European country.

reduction are recorded: -93.5% in Western Europe (EU1), and -91.5% in Oceania. North America (NA) has a reduction of -67% in seats, -63.2% in frequency, and -76.8% in ASK.

The middle columns of Table 2.2 shows the reductions to air services within the macro-region. These are greater than the total ones for EU1 only: in all other macro-regions the domestic seats negative variation has been lower than the total one. Looking instead at the three columns to the right of Table 2.2, EU1 is the only macro-region exhibiting a reduction in intercontinental flights lower than the total. The highest reduction is in LA (-92.6%), and all other macro-regions have greater reductions in long-haul flights. Hence, the observed variation in the middle of the lockdown period is extremely high, never observed before worldwide in air transportation and above two-third in all macro-regions, with a strong peak in Western Europe, where the activity has been decreased very close to a complete stop. In general, frequencies have decreased less than seats while ASK have decreased more.

	Total			Intra macro-region			Extra macro-region		
Macro-region	Seats	Frequency	ASK	Seats	Frequency	ASK	Seats	Frequency	ASK
AF	-72.8%	-60.8%	-84.6%	-65.8%	-55.0%	-75.7%	-83.7%	-81.8%	-88.9%
AS1	-57.3%	-51.4%	-71.4%	-47.2%	-43.6%	-49.3%	-86.7%	-85.0%	-88.7%
AS2	-70.1%	-65.1%	-81.5%	-63.1%	-59.3%	-65.9%	-91.3%	-91.5%	-91.1%
AS3	-50.2%	-45.2%	-63.7%	-44.5%	-40.8%	-46.2%	-88.8%	-86.3%	-90.1%
EU1	-92.5%	-90.9%	-93.5%	-93.0%	-91.0%	-94.2%	-91.1%	-90.4%	-93.0%
EU2	-79.6%	-78.7%	-79.9%	-69.0%	-70.6%	-65.9%	-86.7%	-85.8%	-84.9%
LA	-83.9%	-72.4%	-89.9%	-81.7%	-69.1%	-85.4%	-92.6%	-91.3%	-94.5%
ME	-67.7%	-61.1%	-81.4%	-46.3%	-43.5%	-50.4%	-85.7%	-82.8%	-87.0%
NA	-67.0%	-63.2%	-76.8%	-63.4%	-61.1%	-67.4%	-92.1%	-91.3%	-92.9%
OC	-88.5%	-80.8%	-91.5%	-88.0%	-79.9%	-91.6%	-90.9%	-89.8%	-91.4%

Table 2.2: Aviation industry percentage change compared to the same week of the previous year, 21*st* April 2020

As mentioned before, the lockdown ended in almost all macro-regions in May 2020, and since June 2020 the aviation activity restarted, exploiting the summer season for the Northern hemisphere. Hence, we analyze the annual variations in seats, frequencies and ASKs until the beginning of September 2020, shown in Table 2.3.

The post lockdown period shows a recovery in aviation activity in all macro-regions. Regarding total seats, the highest reductions in September 2020 are in Oceania (OC, -74.3%), Latin America (LA, -65.7%) and Africa (AF, -62.9%), with Central Eastern Asia (AS3) having the smallest reduction (in comparison with the same week in the year 2019), i.e., only -21.9%. North America has recovered about half of available seats (-54.2% reduction), as well as Central and Southern Asia (AS1, -55.9%). Western Europe (EU1),

	Total			Intra macro-region			Extra macro-region		
Macro-region	Seats	Frequency	ASKs	Seats	Frequency	ASKs	Seats	Frequency	ASKs
AF	-62.9%	-54.4%	-67.0%	-60.3%	-51.1%	-62.7%	-67.0%	-66.2%	-69.1%
AS1	-55.9%	-51.7%	-60.9%	-51.6%	-47.8%	-51.6%	-68.9%	-68.6%	-68.3%
AS2	-59.6%	-54.9%	-72.8%	-50.7%	-47.7%	-54.6%	-86.2%	-87.0%	-84.1%
AS3	-21.9%	-17.4%	-41.5%	-13.3%	-10.9%	-15.3%	-79.5%	-76.2%	-80.9%
EU1	-59.1%	-57.8%	-65.6%	-56.1%	-55.5%	-55.2%	-69.2%	-68.1%	-74.5%
EU2	-41.8%	-44.0%	-47.7%	-19.4%	-28.8%	-15.2%	-57.0%	-57.5%	-59.9%
LA	-65.7%	-59.7%	-69.3%	-65.6%	-59.0%	-66.5%	-66.1%	-65.4%	-72.7%
ME	-60.4%	-56.1%	-66.1%	-52.1%	-48.5%	-51.5%	-67.1%	-65.0%	-68.7%
NA	-54.2%	-51.8%	-62.2%	-51.6%	-50.5%	-53.2%	-73.2%	-71.4%	-76.6%
OC	-74.3%	-62.5%	-82.8%	-71.7%	-60.5%	-79.1%	-85.5%	-84.6%	-85.4%

Table 2.3: Aviation industry percentage change compared to the same week of the previous year, $8th$ September 2020

Middle East (ME) and South Eastern Asia (AS2) are still suffering a robust reduction, respectively -59.1%, -60.4%, and -59.6%. Eastern Europe (EU2) has only a -41.8%, the second-lowest reduction. If we compare the data between May 2020 (Table 2.2) and September 2020 (Table 2.3), the strongest recovery has been in Europe (EU2 has a +38% of minor reduction, EU1 +33%), and Central Eastern Asia (AS3, +28%). North America has +13% in minor reduction regarding seats, Oceania +14%, Latin America +18%, Africa and South Eastern Asia (AS2) +10%, Middle East +8% and Central Southern Asia (AS1) only +2%. Regarding frequency, the recovery was more modest, but Central Eastern Asia is almost returning to normal figures (-17.4%), while the other macro-regions are still at more than 50% (EU2 -44%). Similarly for ASKs: even in Central Eastern Asia (AS3) the reduction in September 2020 is still consistent (-41.5%). This means that the recovery after the lockdown has been concentrated especially in short and medium-haul flights, and in domestic flights, as shown by the data for intra macro-region and extra macro-region in Table 2.3, with all the figures indicating greater reductions in intercontinental flights. Hence, even in the recovery phase, COVID-19 is harming especially long-haul flights.

Figure 2.1 displays the index number of the total seats in the different regions taking as reference equal to 100 the figure of 29th October 2019. This index number provides a description of the most recent trends and of the impact of lockdown if compared to the situation in the middle of Autumn 2019. The three vertical lines correspond to the starting week of the lockdown period in the corresponding macro-regions. The lockdown date in a macro-region is defined on the basis of the percentage ratio between the ”grounded seats” due to the lockdown (i.e., the difference between the available seats at a specific week and the available seats at the reference week of January 2020) and the total seats offered in that macro-region at the reference week of January 2020. More specifically, we assume that the lockdown period in a macro-region starts during the week when this ratio reaches the level of (at least) 50%. As shown by Table 2.4, this threshold is reached the week beginning 17*th* March 2020 in AF, AS1, EU1, EU2, NA, and ME, the week beginning 24*th* March 2020 in LA and OC, and the week beginning 31*st* March 2020 in AS2 and AS3.

Macro-region	10/03/2020	17/03/2020	24/03/2020	31/03/2020	07/04/2020
AF	2%	65%	87%	100%	100%
AS1	0%	92%	97%	97%	97%
AS2	0%	2%	48%	69%	100%
AS3	0%	16%	18%	93%	93%
EU1	0%	69%	73%	84%	84%
EU2	0%	76%	100%	100%	100%
LA	0%	38%	55%	100%	100%
NA	0%	55%	100%	100%	100%
ME	0%	93%	100%	100%	100%
OC	0%	0%	100%	100%	100%

Table 2.4: Share of grounded seats on January 2020 seats per macro-region

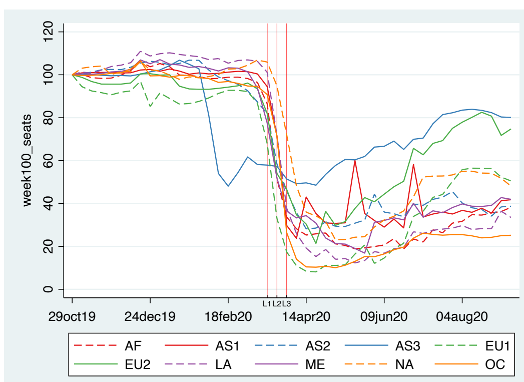


Figure 2.1: Seats index number, base = 100 29*th* October 2019

It is evident, by inspection of Figure 2.1 that in all regions except Central Eastern Asia (AS3) the reduction has been dramatic and has started just a little before than the lockdown date, reaching the bottom at the end of March/beginning of April 2020. In Central Eastern Asia (AS3) the reduction started well before the lockdown, for the ban on aviation imposed in China. Eastern Europe (EU2) has the second strongest recovery with an index quite close to the AS3 one at the end of the observed period. Figure 2.5 and Figure 2.6 in Appendix show, respectively, the frequency index number and the ASK index number. The dynamics are similar to that described for seats.

A further interesting aspect in the analysis of the impact of the lockdown is to investigate its effects on the two prevailing business models in aviation, namely FSCs and LCCs.[14] Table 2.5 shows the different annual percentage variations in available seats, frequency and ASKs between LCCs and FSCs. Regarding seats, LCCs have a minor reduction than FSCs in all macro-regions, with the exception of Central Eastern Asia (AS3), Eastern Europe (EU2), and Oceania. The reduction is much lower especially in Western Europe (EU1), Latin America, Middle East, and North America. The comparison gives mixed indications instead if we look at the frequencies: LCCs have larger reductions than FSCs in some regions while they have lower decreases in South Eastern Asia (AS2), Western Europe, Latin America, and Middle East. Last, the reduction in ASKs is always lower for LCCs, with the exception of Oceania.

	LCCs			FSCs		
Macro-region	Seats	Frequency	ASK	Seats	Frequency	ASK
AF	-63.6%	-62.3%	-61.1%	-68.3%	-56.8%	-72.8%
AS1	-56.1%	-56.1%	-57.8%	-57.5%	-48.0%	-65.7%
AS2	-57.7%	-53.6%	-70.7%	-64.3%	-58.3%	-76.4%
AS3	-28.1%	-24.3%	-43.7%	-23.3%	-19.1%	-43.0%
EU1	-58.6%	-58.7%	-58.1%	-67.4%	-64.3%	-74.4%
EU2	-47.3%	-48.0%	-45.5%	-46.2%	-48.3%	-53.2%
LA	-50.8%	-55.3%	-47.0%	-75.7%	-63.0%	-79.2%
ME	-48.3%	-44.2%	-54.2%	-64.1%	-59.3%	-70.7%
NA	-52.1%	-54.2%	-54.9%	-59.0%	-54.9%	-66.9%
OC	-86.1%	-86.7%	-85.5%	-71.4%	-59.3%	-81.9%

Table 2.5: LCCs vs FSCs percentage change compared to the same week of the previous year, 8*th* September 2020

This descriptive analysis shows a general disruptive effect of the lockdown on supply side air services. Looking at specific macro-regions, such effect is particularly severe in Europe and Oceania, while it has been slightly less intense in other economically advanced areas such as North America and Central-East Asia. In developing areas the impact has been very negative in Africa and Latin America, and a little lighter in Central and South Asia. Last, LCCs seem to have been severely affected by the lockdown too, but to a lesser extent than FSCs. The possible explanations might be lower operating costs and concentration on internal networks, less affected by the bans imposed on long-haul flights.

In the post-lockdown period, Central Eastern Asia is the macro-region with the greatest recovery, while Oceania is the one that lags furthest behind in this regard. Eastern

[14] Macário and Van de Voorde (2010) provide a description of the LCC business model and its differences with the FSC model. Kwoka et al. (2016) find that LCCs charge fares 20% or more below FSCs. We adopt the OAG classification for LCCs.

Europe is also recovering a lot, while Western Europe and North America have a similar pattern, and have reached in the post lockdown period more or less 50% of their supply-side capacity.

COVID-19 outbreak has impacted also the demand side. During March, April, and May 2020 passengers could not travel by flight for the ban on aviation activity. However, our data show that in the post lockdown period passengers did not resume traveling with the same intensity as before. Both the fear of contagion and the strong drive towards smart working have changed the willingness to fly. We can observe these effects by investigating the bookings obtained from OAG Traffic Analyzer, a database providing the data from global distribution systems and an adjusted estimate of the total bookings, including the online ones. We have monthly data, starting from January 2020 and up to June of the same year.[15] We compute the percentage changes in bookings compared to the same month of 2019, reported in Table 2.6.

Macro-region	Jan 2020	Feb 2020	Mar 2020	Apr 2020	May 2020	Jun 2020
AF	5.8%	4.4%	-30.7%	-84.4%	-83.4%	-87.2%
AS1	5.3%	7.8%	-22.9%	-84.0%	-80.6%	-79.6%
AS2	8.7%	-4.8%	-39.0%	-84.3%	-81.3%	-77.5%
AS3	4.2%	-49.3%	-57.7%	-71.9%	-61.9%	-54.1%
EU1	-2.5%	-6.6%	-44.6%	-94.2%	-90.7%	-92.2%
EU2	4.3%	2.3%	-31.6%	-80.7%	-82.1%	-78.9%
LA	1.9%	2.1%	-27.5%	-90.7%	-92.4%	-88.0%
ME	-1.0%	-2.3%	-40.8%	-83.1%	-88.0%	-80.8%
NA	6.6%	11.3%	-36.9%	-90.0%	-87.7%	-78.1%
OC	0.0%	-6.7%	-30.6%	-93.7%	-93.4%	-87.8%

Table 2.6: Percentage changes in bookings per macro-regions compared to the same month of the previous year

All macro-regions have a positive variation in January 2020: North America, for instance, has +6.6% increase in bookings in comparison to January 2020. The only two exceptions are Western Europe (-2.5%) and Middle East (-1%). The lockdown in China and the ban to flights to and from that country explain the 49.3% reduction in AS3 in February 2020, while EU1 continues to lose bookings (-6.6%), as well as Oceania (-6.7%), South Eastern Asia (-4.8%) and Middle East (-2.3%). In March 2020 all macro-regions start to experience a strong reduction in bookings, while April and May 2020 are the months where the huge booking reductions are almost totally explained by the lockdown. In June 2020 the aviation activity restarted. However, bookings are still much lower than

[15] The OAG Traffic Analyzer booking data are adjusted by the data management company and they are delivered with a 3-months delay.

one year before, with the only exception of Central Eastern Asia, where the ticket sales decreased only by 54.1%. This figure is interesting because that part of Asia is where the aviation activity restarted a bit earlier than in the other macro-regions. Hence, it is probably the only region where we can already appreciate that even if the reduction in the available seats was only -34% in June 2020 with respect to the same month one year before, bookings were still much lower, with a reduction of about 54% for the same temporal variation. This means a lower load factor in the post-lockdown period. Figure 2.2 shows the booking dynamics in the different macro-regions.

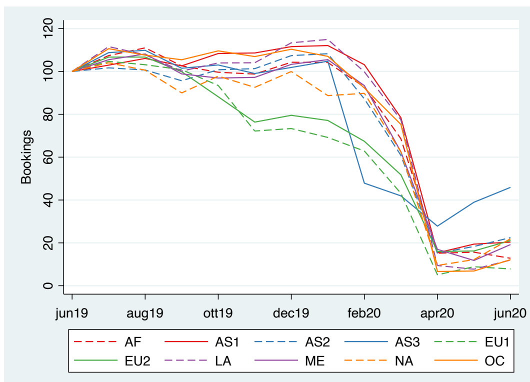


Figure 2.2: Bookings variations in macro-regions, reference month = June 2019

2.4 Econometric results

In this section we estimate the impact of the lockdown in the various macro-regions using the ITS model described in Eqs (2.1)–(2.2). We also generate the counterfactual time series, and we calculate the gap between the observed trend and the counterfactual scenario. The time series of the dependent variable, the logarithm of seats ($lseats$), shown in Figure 2.3, highlights the yearly seasonal pattern, with aa general positive trend interrupted by a huge decrease due to the lockdown (Spring 2020) followed by a recovery (Summer 2020).[16]

[16]The correlation among seats, frequency, and ASK is very high, ranging from 0.95 to 0.98; hence, we limit the econometric analysis presented in the paper to the models having seats as the variable capturing the volume of air transportation service. As mentioned before, the identification of the SARIMA model parameters (i.e., autocorrelation and moving average orders, degree of differencing, and seasonal lag) is performed by implementing the Hyndman-Khandakar algorithm (Hyndman and Athanasopoulos (2018)) in the `auto.arima()` function in R, that minimizes the AIC and selects the best fitting model.

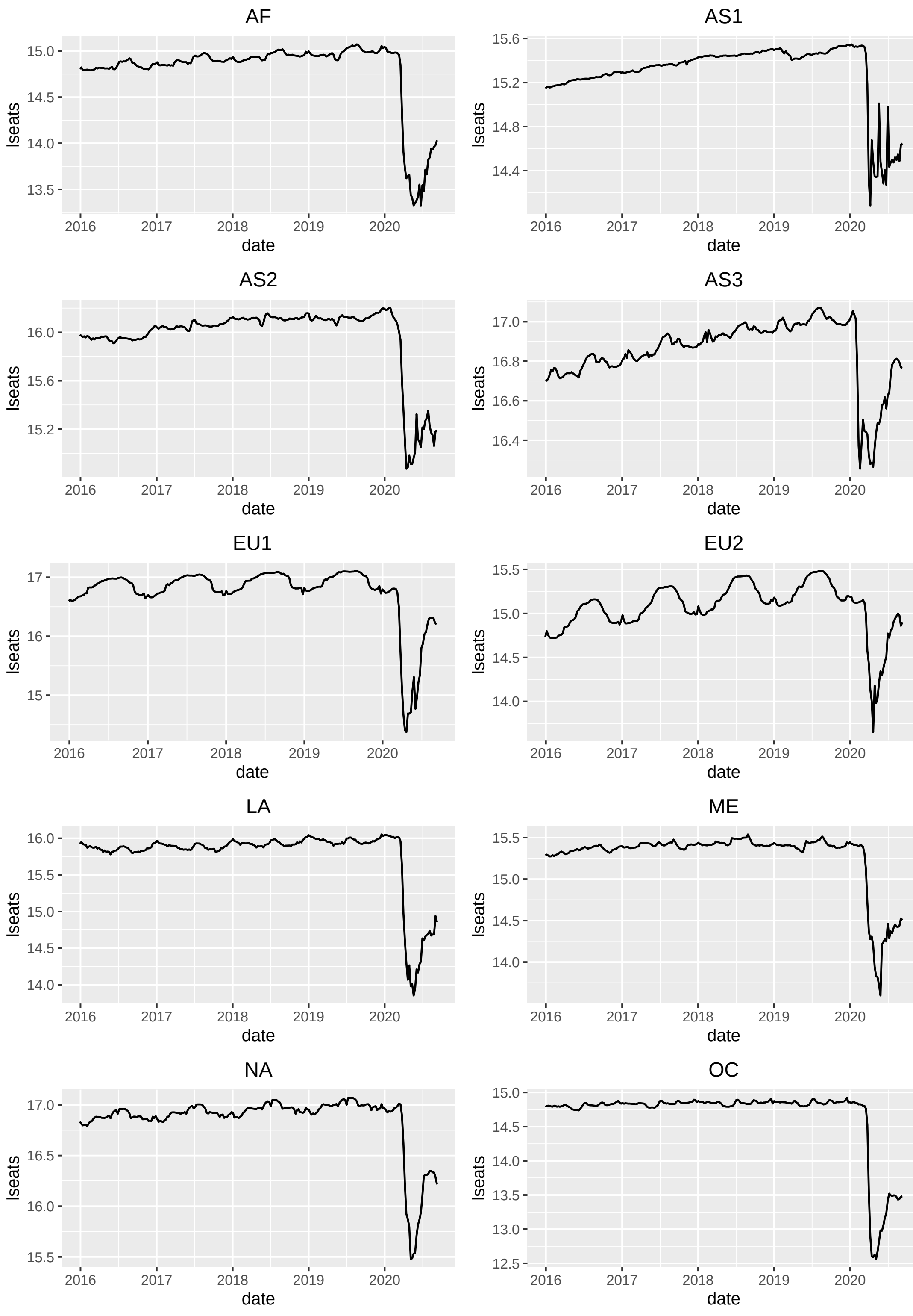


Figure 2.3: Seats time series in the macro-regions

We present two sets of results to appreciate both the lockdown effect and the subsequent partial recovery after it. First, we describe the estimates obtained by considering the sub-sample ending at April 2020; Second, we analyze the results of the ITS model applied to the complete sample ending at the beginning of September 2020. The latter analysis may capture the airlines' reaction to the change in the passengers' willingness to travel only due to COVID-19.

The first set of results relating to the lockdown effect are shown in Table 2.7. The Hyndman-Khandakar algorithm has identified the ARIMA coefficients of the error model in the different macro-regions. The autoregressive seasonal order P is at most 1, the moving average seasonal order Q as well. A certain degree of heterogeneity characterizes the macro-regional combinations of autoregressive and moving average terms.

Concerning the ITS model's coefficients, the estimated trend effect t before the lockdown is positive and significant in almost all macro-regions, and equal to about a $+0.1\%$ weekly percentage increase. A non-significant trend coefficient is observed for Western Europe, Middle East, and Oceania. The estimated coefficient of variable L, capturing the impact of lockdown, is always positive and statistically significant. This coefficient represents the change in the trend level, i.e., $t \cdot L$. This is always negative and statistically significant, and consistent as a magnitude, since it varies between 0.05 (AS3) and 0.53 (OC). The change in slope is drastic, while before the lockdown the slope was just above 0 in all macro-regions.[17] Since the overall estimated effect of lockdown is given by $e^{\alpha_1+\alpha_3}-1$, we obtain that the ban has generated a weekly estimated percentage reduction in available seats varying between -5% (AS3, Central East Asia), and -41% (Oceania). Western Europe and North America have, respectively, -36% and -21%. Latin America has -32%, and Eastern Europe -25%.[18] Therefore, the evidence confirms a general severe impact of the lockdown, especially for Western Europe and Oceania. The estimated coefficient of the COVID-19 cases variable (i.e., *lcase*) is, when significant, always negative with an estimated elasticity (on available seats) between -2% (LA) and -5% (AF).

The results of the ITS model applied to the full sample are shown in Table 2.8. As before, the autoregressive and moving average components are selected using the Hyndman-Khandakar algorithm Hyndman and Athanasopoulos (2018). The estimated coefficients

[17] This means that the statistical model, in fitting the data, adjusts the trend for this important variation of the slope (and, above all, with a change of sign) by increasing the level.

[18] The relatively small weekly percentage reduction in AS3 might be explained by the longer lockdown period in China.

	AF	AS1	AS2	AS3	EU1	EU2	LA	ME	NA	OC
					Dependent variable: *lseats*					
Constant	14.81***	15.25***	15.94***	16.75***	16.82***	14.95***	15.83***	15.39***	16.87***	14.80***
	(1,087.67)	(1,045.23)	(770.95)	(871.97)	(226.94)	(108.17)	(1013.06)	(668.28)	(716.95)	(1898.02)
t	0.001***	0.001***	0.001***	0.001***	0.001	0.002*	0.001***	0.0002	0.001***	-0.0003
	(8.86)	(10.17)	(0.0002)	(7.76)	(1.25)	(2.26)	(6.06)	(1.02)	(3.69)	(3.62)
L	49.95***	48.31***	46.83***	10.88*	98.85***	64.25***	85.69***	50.75***	51.54**	117.81***
	(12.08)	(11.06)	(12.27)	(2.20)	(15.24)	(29.47)	(21.06)	(16.35)	(20.62)	(25.45)
$t \cdot L$	-0.23***	-0.22***	-0.21***	-0.05*	-0.45***	-0.29***	-0.39***	-0.23***	-0.23**	-0.53***
	(-12.07)	(-11.10)	(-12.31)	(-2.23)	(-15.16)	(-29.45)	(-21.10)	(-16.34)	(-20.58)	(-25.40)
lcase	-0.05***	-0.01	-0.04***	-0.04***	-0.03***	-0.01	-0.02***	-0.02***	0.001	-0.04
	(-5.93)	(-1.17)	(-10.39)	(-11.82)	(-3.31)	(-1.29)	(-3.56)	(-5.08)	(0.28)	(-7.20)
					ARIMA error model					
L.AR	1.16***				1.64***	0.94***	1.17***	1.52***	0.75***	0.51***
	(10.20)				(20.41)	(39.73)	(13.33)	(20.77)	(14.16)	(4.10)
L2.AR	-0.94***				-0.78***		-0.53***	-0.97***		
	(-12.88)				(-5.23)		(-6.08)	(-6.96)		
L3.AR					-0.44**			-0.02		
					(-2.77)			(-0.15)		
L4.AR					0.45**			0.27**		
					(2.97)			(2.79)		
L5.AR								0.15		
								(0.09)		
L.MA	0.21^{+}	1.23***	0.98***	0.94***						0.98***
	(1.74)	(22.21)	(32.30)	(10.90)						(8.90)
L2.MA	0.41**	-0.06	0.99***	0.36***						0.31*
	(3.14)	(-0.62)	(27.59)	(3.47)						(2.30)
L3.MA	0.47**	-0.50***	0.90***							-0.55***
	(4.07)	(0.09)	(25.58)							(-5.09)
L4.MA										-0.73***
										(-7.94)
L5.MA										-0.26**
										(-3.09)
					Seasonal effects, $s = 52$					
L.AR	0.50***	-0.11	0.19^{+}		0.51***	0.57***	0.46***			
	(5.66)	(-0.85)	(1.70)		(4.66)	(6.60)	(4.84)			
L.MA					0.52**	0.57**			0.55***	0.49***
					(3.12)	(3.25)			(5.06)	(4.82)
N	182	182	182	182	182	182	182	182	182	182
AIC	-858.84	-617.37	-807.46	-656.56	-680.99	-818.37	-823.07	-847.46	-809.65	-926.71

t statistics in parentheses

$^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2.7: SARIMA ITS model of the lockdown effect in different macro-regions, observations until 21*st* April 2020

for the trend t variable once that the post lockdown period is taken into account are positive and significant in many macro-regions, and equal to about a +0.1% weekly percentage increase. A non-significant trend coefficient is observed for Western Europe, Latin and North America, and Oceania. The change in the level given by the coefficient of the variable L is different across macro-regions. Africa, Central Southern Asia (AS1), and Central Eastern Asia (AS3) have a negative and significant coefficient, while Eastern Europe, Latin and North America, and Oceania have a positive and significant coefficient. No change in the trend level is observed for South Eastern Asia (AS2), Western Europe (EU1), and Middle East. The change in the trend slope is positive and significant in Africa, Central Southern Asia (AS1), and Central Eastern Asia (AS3), while it is negative and significant in Eastern Europe (EU2), Latin America (LA), North America (NA), and Oceania (OC). There is no effect on the trend slope in South Eastern Asia (AS2), Western Europe (EU1), and Middle East (ME). Hence, we have three different groups of aggregate effects on the trend of activity in air transport. First, Africa, Central Southern Asia (AS1) and Central Eastern Asia (AS3) have a decrease in the level due to the initial lockdown shock ($\hat{\alpha}_2$ is negative), and then a positive recovery since their weekly trend has an upward slope ($\hat{\alpha}_3$ is positive). These macro-regions have instead a negative slope with data until April 2020. During Summer 2020 they started a positive weekly trend. The second group is composed by Eastern Europe (EU2), Latin America (LA), North America (NA), and Oceania (OC). They combine a positive $\hat{\alpha}_2$ and a negative $\hat{\alpha}_3$. These estimated coefficients have the same sign of Table 2.7. The magnitude of $\hat{\alpha}_2$ is now much lower while the absolute value of $\hat{\alpha}_3$ is small, i.e., they have also a milder weekly percentage reduction. These combined effects indicate that the recovery initiated in the Summer 2020 was not strong enough to change the trend slope, and that its sharp change due to the lockdown has not been absorbed yet. The third group is composed by South Eastern Asia (AS2), Western Europe (EU1), and Middle East (ME). They have only a positive trend, i.e., $\hat{\alpha}_1 > 0$, and a negative estimated elasticity for the number of COVID cases. In these macro-regions the positive trend before the outbreak has been severely deflected by the spread of the virus, and this effect captures anything else, including the lockdown. $\hat{\alpha}_2$ is nearly 0, as well as $\hat{\alpha}_3$. In April 2020 $\hat{\alpha}_2$ is positive and very high while $\hat{\alpha}_3$ is negative and also quite large. By extending data until September 2020 these two effects are completely absorbed by the COVID-19 cases, with an elasticity varying between -6% and -8% weekly.

	AF	AS1	AS2	AS3	EU1	EU2	LA	ME	NA	OC
					Dependent variable: *lseats*					
Constant	14.81***	15.20***	15.96***	16.75***	16.83***	14.93***	15.89***	15.36***	16.90***	14.85***
	(388.96)	(948.82)	(435.56)	(148.22)	(141.60)	(141.78)	(79.63)	(984.91)	(258.54)	(96.76)
t	0.001***	0.002***	0.001**	0.0001***	0.0003	0.002*	-0.0002	0.0004**	0.0002	-0.0005
	(3.31)	(12.09)	(3.14)	(11.86)	(0.25)	(2.06)	(-0.15)	(2.88)	(0.43)	(-0.41)
L	-5.70**	-2.45*	-0.32	-5.75***	1.02	11.06**	28.99***	0.3691	13.50**	20.89***
	(-2.76)	(-2.25)	(-0.25)	(-10.97)	(0.14)	(2.71)	(4.15)	(0.22)	(3.19)	(4.40)
$t \cdot L$	0.03**	0.009^{+}	0.0003	0.03***	-0.004	-0.05**	-0.13***	-0.002	-0.06**	-0.09***
	(2.83)	(1.65)	(0.05)	(10.86)	(-0.13)	(-2.72)	(-4.18)	(-0.32)	(-3.17)	(-4.32)
lcase	-0.15***	-0.05***	-0.06***	0.04***	-0.08^{+}	0.01	0.08**	-0.07***	-0.002	-0.03
	(-10.79)	(-3.90)	(-7.06)	(-15.50)	(-1.70)	(0.47)	(3.05)	(-8.39)	(-0.10)	(-1.15)
					ARIMA error model					
L.AR	-0.03	-0.60***	0.85***		1.37***	1.42***	0.44***	1.83***	1.91***	2.07***
	(-0.38)	(-4.26)	(19.53)		(17.47)	(13.17)	(6.14)	(45.86)	(38.96)	(28.15)
L2.AR	0.49***				-0.48***	-0.05	1.30***	-0.88***	-0.94***	-1.61***
	(4.59)				(-4.45)	(-0.30)	(19.25)	(-24.97)	(-20.83)	(-10.15)
L3.AR	0.23*				0.24*	-0.41***	-0.29**			0.60**
	(2.44)				(2.14)	(-5.90)	(2.80)			(3.28)
L4.AR	-0.19**				-0.36**		-0.69***			-0.01
	(-2.62)				(-3.14)		(-10.70)			(-0.05)
L5.AR					0.14^{+}		0.17*			-0.10
					(1.93)		(2.39)			(-1.42)
L.MA	1.22***	1.11***		0.92***		-0.54***	0.91***	-0.90***	-0.61***	
	(30.25)	(7.25)		(14.08)		(-4.81)	(32.71)	(-22.29)	(-6.84)	
L2.MA	0.87***	0.21^{+}		0.43***						
	(11.74)	(1.68)		(6.22)						
L3.MA		-0.22*		-						
		(-2.30)								
L4.MA		0.19*								
		(2.10)								
					Seasonal effects, $s = 52$					
L.AR	0.18				0.23*	0.31**	0.18		0.41***	
	(1.54)				(1.98)	(2.96)	(1.46)		(4.48)	
L.MA										0.30**
										(2.58)
N	246	246	246	246	246	246	246	246	246	246
AIC	-825.55	-504.63	-831.14	-987.32	-509.37	-678.96	-708.95	-690.94	-894.86	-751.30

t statistics in parentheses

$^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2.8: SARIMA ITS model of post-lockdown effect in different macro-regions, observations until $8th$ September 2020

We have performed some diagnostic tests to address the possible identification problems regarding the results shown in Table 2.8. The post-estimation diagnostic analysis consists in plotting the residuals autocorrelation functions and implementing a Liung-Box test. Figure 2.7 in the Appendix shows the residuals plot for two representative macro-regions, Western Europe and North America, together with their histogram plots and the autocorrelation functions (AFC). The distribution is normal and the ACF only in North America has just three spikes outside the 95% confidence interval. The Liung-Box test has a null hypothesis that the errors are independently distributed, and it is shown in Table 2.9.

	AF	AS1	AS2	AS3	EU1	EU2	LA	ME	NA	OC
Q^*	52.6	48.9	84.3	44.9	32.6	51.8	74.9	55.0	62.3	42.8
P-value	0.06	0.13	0.00	0.35	0.72	0.08	0.00	0.08	0.10	0.27
H_0	N.R.	N.R.	R.	N.R.	N.R.	N.R.	R.	N.R.	N.R.	N.R.

Legend: Q^* Liung-Box statistics; N.R. = H_0 not rejected; R. = H_0 rejected

Table 2.9: SARIMA ITS model diagnostic tests

In all macro-regions we do not reject the null hypothesis that errors are independently distributed. The only exceptions are South Eastern Asia (AS2) and Latin America (LA). Hence, for these two macro-regions we estimate an ITS SARIMA model with $d = 1$, i.e., a first difference in time periods. With these settings the Liung-Box test gives $Q^* = 51.45, P = 0.11$ for AS2, and $Q^* = 51.70, P = 0.08$ for LA. The portmanteau test shows that with $d = 1$ errors are independently distributed. Coefficients' results are shown in Table 2.11 in the Appendix. In South Eastern Asia COVID-19 cases are the only variable affecting the trend, while Latin America has a strong negative weekly change in the slope of the trend.

The ITS model makes it possible to derive a counterfactual trend to be compared to the observed data in order to get a more truthful estimate of the quantitative impact of the lockdown. Figure 2.4 presents such a comparison. The green line represents the observed time series, while the red dashed line presents the counterfactual time series. The comparison is carried out for each of the 10 macro-regions. By inspection of Figure 2.4, it is clear that the estimated counterfactual time series is growing in all macro-regions except in Latin America (LA), South Eastern Asia (AS2), and Oceania.

The real effect of lockdown is the difference between the counterfactual and the observed level. This effect can be decomposed into two sub-effects, namely the difference between observed and past data and the difference between past and predicted data in the absence of lockdown. In order to highlight these two components, the computation of the real effect is based on index numbers and is computed as follows in Table 2.10. First, we identify, as a base equal to 100, the week of $29th$ October 2019 (i.e., a period well before any possible confounding effect due to COVID-19). Then, we compute (i) the difference between the observed level and our base and (ii) the difference between our base and the predicted seats at specific weeks of interest. Finally, we obtain the real effect as the sum of these two differences for each macro-region in each week of interest.

In Western Europe the real impact of the lockdown in May 2020 is -101.37 basis points, around further 12 basis points reduction than those observed (i.e., -88.87). In September the real effect is -71.93 points, while the observed series has only a -47.70 reduction. The loss has been about 24 additional points compared to that observed with historical data. In Eastern Europe the impact in May is -84.73, almost 15 points greater than those observed. In September 2020 the real loss is -61.85, about 33 points greater than the observed loss. In North America the real impact in May is -84.89, 9 points greater than that observed; in September the loss is -54.26, 6 points greater than the observed loss. In Latin America there is a real impact in May of -84.24 points, almost equal to that observed; in September the loss is -61.99, just a little less than the observed one (-63.57). In Oceania the actual impact is slightly less than the estimated one: in September the real loss is -72.48, the observed one -74.89. In Africa, the real impact in September is -74.78 points, 11 more than those of the observed historical series. In the Asian continent, the largest estimated impact is in the Middle East, a reduction in September of 69.33 points, about 12 greater than those of the observed time series. The macro-region with the least estimated effect is Central Eastern Asia (which includes China), with -29.42 points in September, about 10 greater than the observed reduction. In Central and South Asia a real impact of -65.68 basis points is estimated in September, about 7 points larger than the observed effect, while in South East Asia the reduction is -63.16 points in September, less than 2 additional points if compared to the observed time series. Once again it is confirmed that the greatest impact was in Europe, but significant differences are also recorded for Central Eastern Asia, North America, Africa, and Middle East. To sum up, the counterfactual analysis shows that air transportation incurred a higher loss in the volumes of activity than that computed using observed data, on average equal to +10%. This evidence confirms that the impact of COVID-19 has been very strong and amplifies the warnings regarding the economic sustainability of the industry.

We have performed a robustness analysis by checking whether the counterfactual anal-

		AF	AS1	AS2	AS3	EU1	EU2	LA	ME	NA	OC
Index counterfactual	7 Apr	102.81	102.77	103.28	106.31	108	104.65	100.98	105.57	107.44	102.5
time series Base = 100	5 May	99.37	103.39	101.08	106	112.5	114.54	98.25	102.97	107.99	93.96
29 Oct. 2019	2 Jun	102.46	104.59	103.57	105.31	119.85	127	99.03	107.97	111.54	94.08
	7 Jul	109.84	105.57	104.36	111.8	123.53	135.331	106.49	109.48	115	104.66
	4 Aug	111.94	106.43	103.71	114.17	122.8	137.13	104.53	111.34	115.13	99.09
	1 Sep	111.05	106.97	101.61	109.75	124.24	133.6	98.41	112.1	106	97.5
Difference between	7 Apr	2.81	2.77	3.28	6.31	8	4.65	0.98	5.57	7.44	2.5
counterfactual and 100	5 May	-0.63	3.39	1.08	6	12.5	14.54	-1.75	2.97	7.99	-6.04
	2 Jun	2.46	4.59	3.57	5.31	19.85	27	-0.97	7.97	11.54	-5.92
	7 Jul	9.84	5.57	4.36	11.8	23.53	35.33	6.49	9.48	15	4.66
	4 Aug	11.94	6.43	3.71	14.17	22.8	37.13	4.53	11.34	15.13	-0.91
	1 Sep	11.05	6.97	1.61	9.75	24.24	33.6	-1.59	12.1	6	-2.5
Index observed	7 Apr	28.25	23.77	35.80	49.25	11.02	34.75	26.01	33.28	48.15	14.05
time series Base = 100	5 May	21.2	30.73	29.38	57.7	11.13	29.82	14.01	21.35	23.1	10.1
29 Oct. 2019	2 Jun	19.95	32.09	44.35	66.3	12.07	40.81	17.57	31.27	29.08	15.2
	4 Aug	31.69	36.81	40.21	83.52	55.8	77.89	29.73	39.81	55.02	25.5
	1 Sep	36.27	41.29	38.45	80.33	52.3	71.75	36.43	42.77	51.74	25.02
Difference between	7 Apr	-71.75	-76.23	-64.2	-50.75	-88.98	-65.25	-73.99	-66.72	-51.85	-85.95
observed and 100	5 May	-78.8	-69.27	-70.62	-42.3	-88.87	-70.18	-85.99	-78.65	-76.90	-89.9
	2 Jun	-80.05	-67.91	-55.65	-33.70	-87.93	-59.19	-82.43	-68.73	-70.92	-84.8
	7 Jul	-77.95	-66.27	-60.84	-29.49	-63.59	-37.30	-73.97	-66.37	-47.65	-73.81
	4 Aug	-68.31	-63.19	-59.79	-16.48	-44.2	-22.11	-70.27	-60.19	-44.98	-74.5
	1 Sep	-63.73	-58.71	-61.55	-19.67	-47.7	-28.25	-63.57	-57.23	-48.26	-74.98
Real lockdown effect	7 Apr	-74.56	-79	-67.48	-57.05	-96.98	-69.90	-74.97	-72.28	-59.29	-88.44
	5 May	-78.17	-72.66	-71.7	-48.29	-101.37	-84.73	-84.24	-81.62	-84.89	-83.86
	2 Jun	-82.51	-72.5	-59.22	-39.01	-107.77	-86.19	-81.47	-76.7	-82.46	-78.87
	7 Jul	-87.79	-71.84	-65.2	-41.29	-87.12	-72.63	-80.45	-75.86	-62.65	-78.47
	4 Aug	-80.25	-69.62	-63.5	-30.65	-67	-59.25	-74.8	-71.53	-60.11	-73.58
	1 Sep	-74.78	-65.68	-63.16	-29.42	-71.93	-61.85	-61.99	-69.33	-54.26	-72.48

Table 2.10: Observed and real impact of lockdown on air transportation

ysis might be affected by the presence of some confounding events that modify substantially the trend before the COVID-19 outbreak. For instance, during 2019 the Boeing 737 MAX was grounded in March 2019 after two crashes with a 346 death toll, due to technical problems. Hence, we have estimated a version of the ITS SARIMA model taking into account for the B737 MAX grounding, including the dummy $737MAX$, equal to 1 since March 2019. The results are shown in Table 2.12 in the Appendix at the end of the paper. The estimated coefficient is never significant with the only exception of AS2 macro-region. In that area the trend had a downward decrease already in 2019. This suggests that the counterfactual analysis for AS2 is slightly overestimated, while the B737 MAX grounding has no effect in all other macro-regions.

The evidence reported in this contribution confirms that the pandemic crisis due to COVID-19 has had a disruptive effect on the air transport sector. The latter is amplified once a more sophisticated counterfactual analysis is implemented. The thriving growth prospects announced by various sources have had to deal with a dramatic downsizing due to an exogenous shock of unimaginable proportions. As we have tried to show, the effects of the lockdown have been severe and even greater than those observed. The differences between the time series in the absence of lockdown (obtained through counterfactual analysis) and the time series of the volumes of air services observed are significant. The resilience that the air transport sector has shown in previous global crises (terrorist attacks, financial crisis, etc.) is being severely tested. The reduction estimated by ICAO of about 80% less passengers in 2020 (ICAO, 2020) could be even greater in some parts of the world, such as in Europe.

2.5 Conclusions

The aim of this work is to quantify the destructive impact that the pandemic crisis caused by COVID-19 has had on air transport worldwide. To do this, a time series ITS SARIMA econometric model is estimated and a counterfactual analysis i performed. This approach allows to measure the impact of the lockdown by comparing the observed trend of sector's business volumes to a counterfactual time series that represents the development trend in the absence of the crisis. In this way it is possible to estimate the real impact of the lockdown, and therefore to correct the measures that various bodies in the sector (e.g., ICAO (2020)) have calculated on the basis only of the observed data.

The empirical evidence confirms that the impact on the air transport sector of the pandemic crisis and of the subsequent lockdown to the economy has been dramatic, and of a size never previously recorded. In all the world's macro-regions the estimated real effect is a reduction in air transportation activity greater than 80% in May 2020 compared with October 2019, and of about 70% in September 2020. The impact has been milder in China and Eastern Asia (-29%) and in North America (-54%). The counterfactual analysis allows to estimate that the real effect of COVID-19 is on average 10% greater than the observed figures.

We also find that the negative effect of COVID-19 is greater for intercontinental connections than for domestic ones, about 22% additional reduction. Moreover, the reduction in available seats has been greater for FSCs than LCCs (about +8%), that appear being more resilient to the crisis. Last, the recovery during Summer 2020 has been moderate and it may be due to a decrease in passengers' willingness to travel, with potential long-lasting effects. Indeed we provide some initial evidence that, after the lockdown, bookings are still very low, and that it likely that airlines will be harmed by lower load factors.

These results suggest that airline sustainability may currently be at high risk. In addition to the lost earnings associated with the forced closure of the connections, there is also the possibility, far from remote, that long-distance flights, which guaranteed the greatest source of earnings especially thanks to business customers, may be drastically reduced in the future.

The air transport sector is under a great pressure running the high risk of heavy losses in year 2020, probably close to the higher range of the forecast formulated by ICAO, that is about USD 350-420 billion. But this estimate must certainly be increased if we consider the entire vertical air transport channel, given that the significant reductions in the volumes of air transportation activities estimated in our work generate immediate losses also to the airport sector, and, due to the likely block of new orders planes by airlines, also for manufacturers, in particular Airbus and Boeing.

These scenarios make public intervention in support of the airlines highly likely, with an entry of national governments into the capital. In this case, a further problem could arise: given that the capacity of public intervention is not the same in all countries, the airlines with economically stronger governments could have an advantage. In this case the industry may face a significant distortion, because the post-lockdown restructuring phase would take place in the absence of that level-playing field conditions that inspire policy makers and international air transport organizations.

In this work it was not possible to estimate the change in the demand for air transportation due to lack of data- Bookings and price data are released by OAG Traffic Analyzer with a 3-months lag; hence, at the moment we have not enough observation to implement an econometric model. Moreover, we could not study the impact on cargo, since data are not available. Regarding our econometric approach, the ITS model can be enriched when more observations regarding the post lockdown period will be available, possibly adding other explanatory variables, such as international trade and e-commerce volumes. These extensions are left for future research.

Appendix

	AS2	LA
Dependent variable: *lseats* first difference		
t	-0.001	0.008
	(-0.21)	(1.10)
L	0.27	96.91***
	(0.09)	(13.46)
$t \cdot L$	-0.002	-0.44***
	(-0.15)	(-7.25)
lcases	-0.03***	-0.004
	(-2.14)	(-0.17)
ARIMA error model		
L.AR	-0.12	-0.46***
	(-0.14)	(-6.42)
L2.AR	0.34	0.72***
	(1.12)	(8.72)
L3.AR	-0.02	0.41***
	(-0.10)	(4.57)
L4.AR		0.02
		(0.21)
L5.AR		0.28***
		(3.81)
L.MA	0.22	0.87***
	(0.26)	(23.45)
L2.MA	-0.15	
	(-0.39)	
Seasonal effects, $s = 52$		
L.AR		0.22**
N	245	245
AIC	-814.43	-726.67
Q^*	51.45	51.70
P-value	0.11	0.08

t statistics in parentheses
** $p < 0.01$, *** $p < 0.001$
Q^* Liung-Box statistics

Table 2.11: SARIMA ITS model with $d = 1$

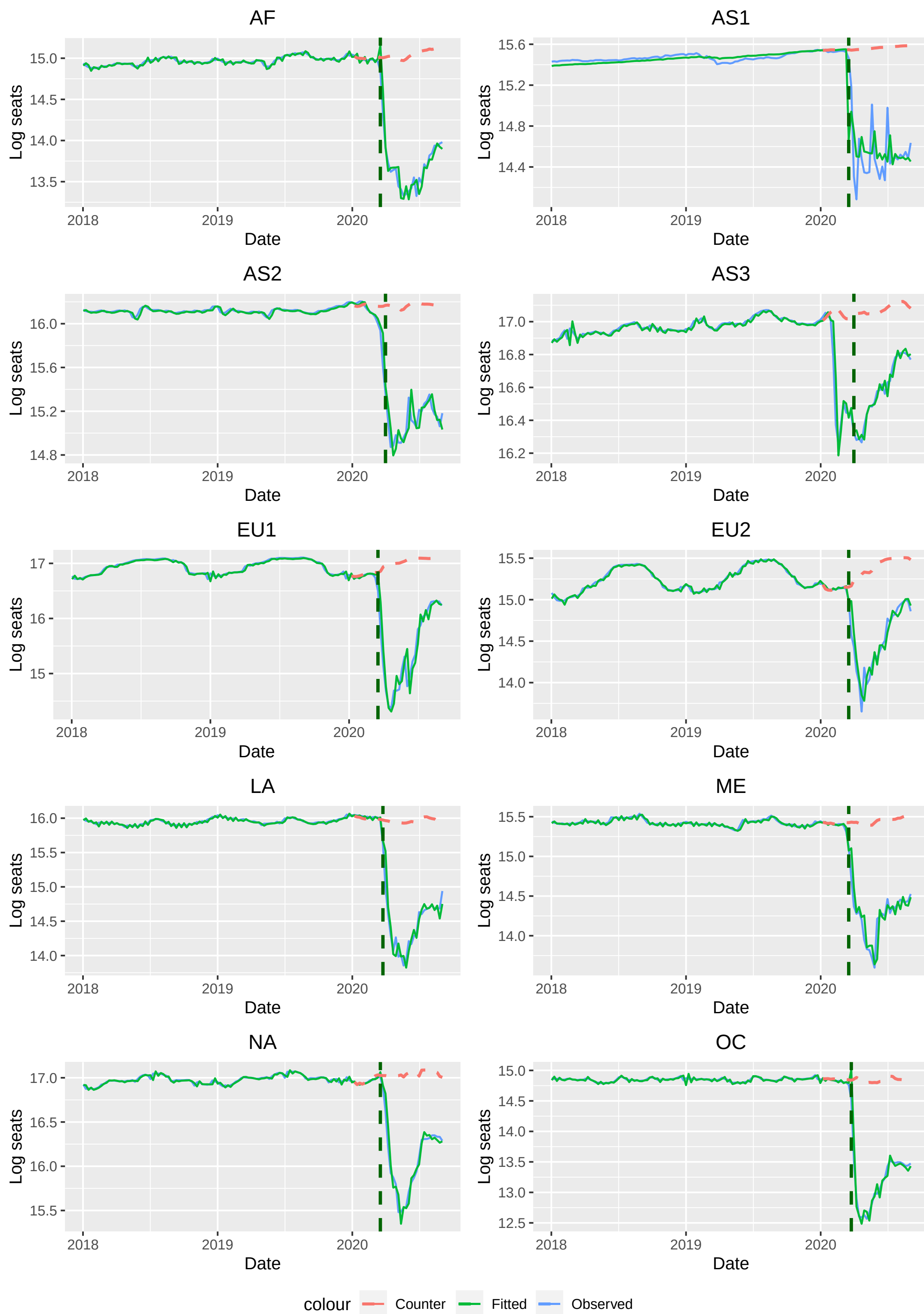


Figure 2.4: Counterfactual analysis: no COVID-19 cases and no subsequent lockdown effect

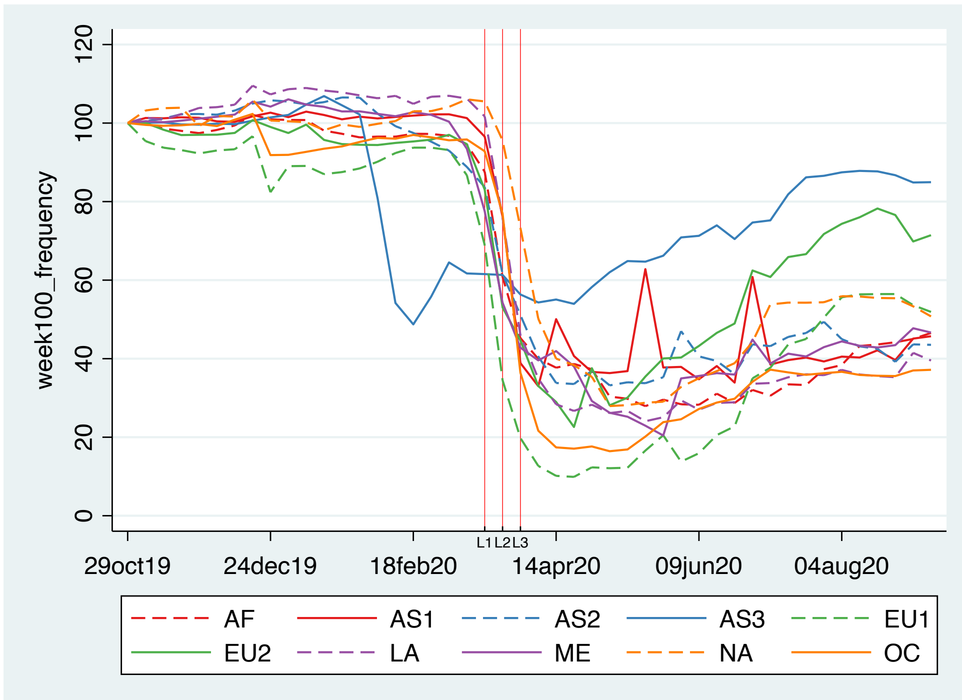


Figure 2.5: Frequency index number, base = 100 29th October 2019

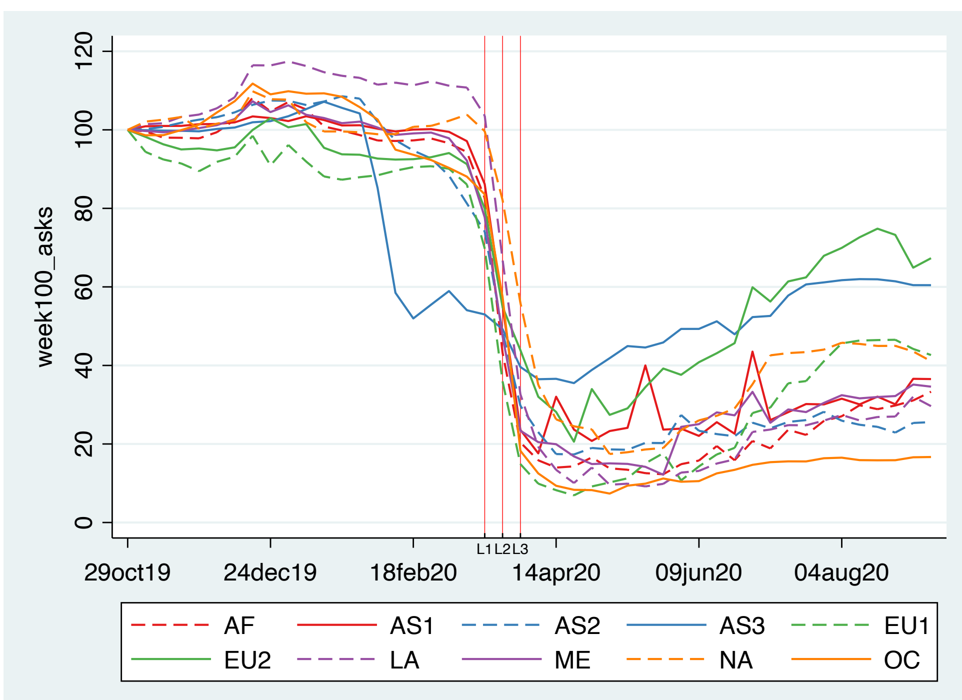


Figure 2.6: ASK index number, base = 100 29th October 2019

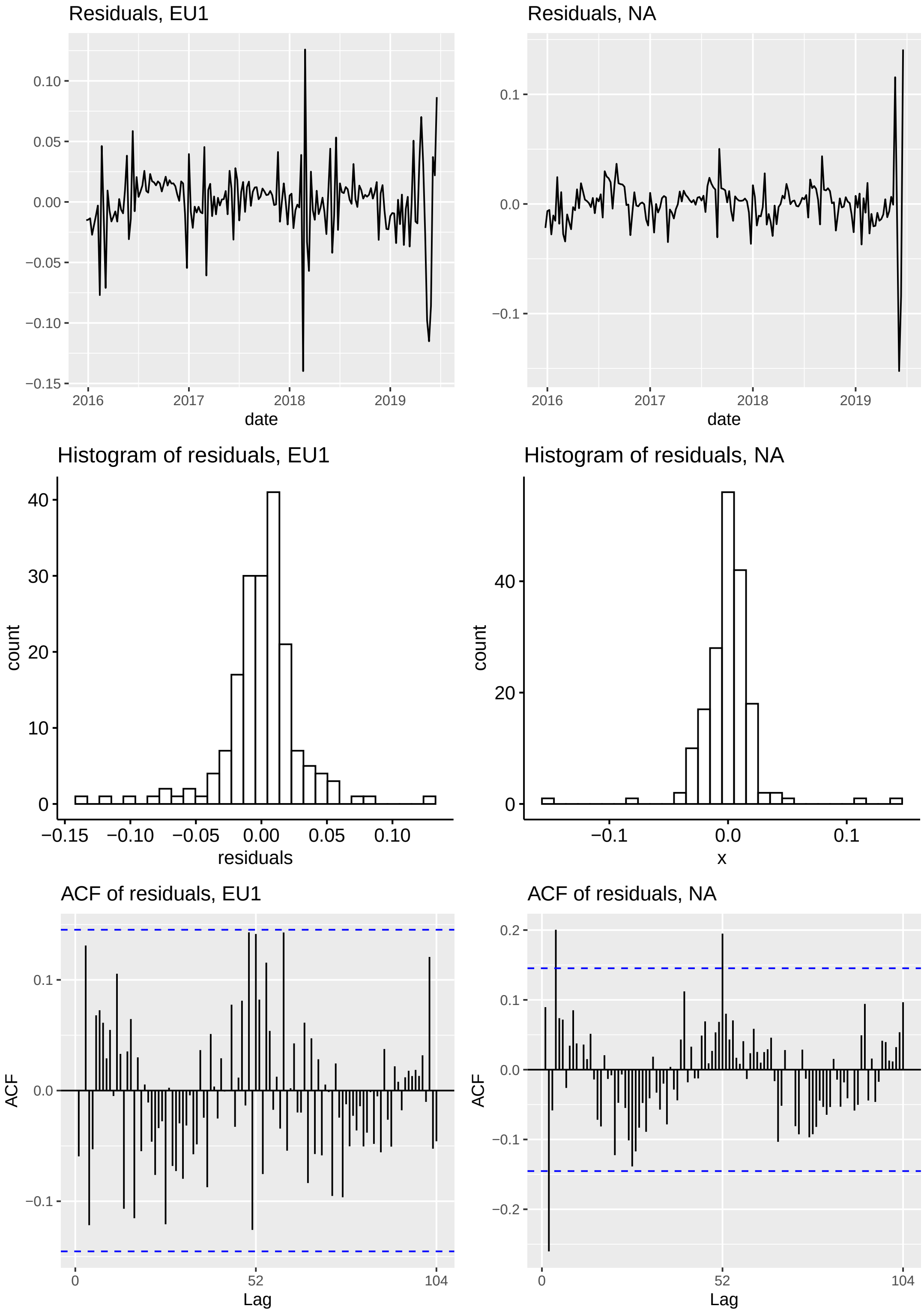


Figure 2.7: Two examples of residuals plot, histogram and ACF

	AF	AS1	AS2	AS3	EU1	EU2	LA	ME	NA	OC
Dependent variable: $lseats$										
Constant	14.82***	15.17***	15.95***	16.83***	16.82***	14.91***	15.88***	15.37***	16.89***	14.84***
	(370.40)	(851.82)	(426.60)	(148.85)	(130.63)	(147.28)	(105.61)	(201.20)	(259.95)	(73.48)
t	0.001*	0.002***	0.001**	0.00004	0.0004	0.002*	0.0001	0.0002	0.0003	−0.0003
	(2.33)	(11.26)	(3.06)	(0.04)	(0.41)	(2.49)	(0.12)	(0.29)	(0.64)	(−0.23)
L	−5.70**	−3.51**	−0.36	−1.39	1.32	10.48**	7.05	3.10	13.45**	20.42***
	(−2.69)	(−3.10)	(−0.28)	(−0.53)	(0.18)	(2.62)	(1.56)	(1.29)	(3.18)	(4.08)
$t \cdot L$	0.03**	0.02**	0.0004	0.01	−0.01	−0.05**	−0.03	−0.01	−0.06**	−0.09***
	(2.76)	(2.72)	(0.08)	(0.47)	(−0.17)	(−2.63)	(−1.60)	(−1.33)	(−3.16)	(−3.99)
$lcase$	−0.15***	−0.08***	−0.06***	0.004	−0.08^{+}	0.01	−0.03	−0.05**	−0.002	−0.02
	(−10.58)	(−5.70)	(−7.23)	(1.27)	(−1.69)	(0.24)	(−0.82)	(−2.70)	(−0.10)	(−0.91)
max	0.04	−0.09**	−0.02	−0.002	−0.04	−0.07	−0.05	−0.01	−0.02	−0.05^{+}
	(1.39)	(−3.11)	(−0.62)	(−0.08)	(−0.58)	(−1.33)	(−1.43)	(−0.21)	(−0.63)	(−1.78)
ARIMA error model										
L.AR	−0.04		0.84***	0.95***	1.38***	1.42***	−0.90***	0.02	1.91***	1.58***
	−(0.49)		(18.98)	(29.95)	(17.59)	(13.04)	(−16.08)	0.23)	(39.45)	(23.23)
L2.AR	0.47***				−0.47***	−0.04	0.72***	0.75***	−0.94***	−0.64***
	(5.65)				(−4.42)	(−0.28)	(8.57)	(9.23)	(−21.14)	(−9.70)
L3.AR	0.26**				0.24*	−0.42***	0.82***			
	(3.08)				(2.15)	(−5.97)	(13.61)			
L4.AR	−0.18**				−0.37**					
	(−2.67)				(−3.19)					
L5.AR					0.14^{+}					
					(1.95)					
L.MA	1.24***	0.33***		0.63***		−0.55***	2.30***	1.09***	−0.61***	0.53***
	(30.10)	(5.85)		(8.13)		(−4.79)	(35.41)	(11.02)	(−6.87)	(7.15)
L2.MA	0.91***			0.24*			2.24***	0.30*		
	(16.03)			(2.40)			(15.03)	(2.24)		
L3.MA				−0.23**			1.43***			
				(−2.91)			(9.88)			
L4.MA							0.53***			
Seasonal effects, s 0 52										
L.AR	0.18				0.24*	0.34**	0.28*		0.41***	
	(1.49)				(2.05)	(3.24)	(2.31)		(4.50)	
L-MA										0.40***
										(3.56)
N	246	246	246	246	246	246	246	246	246	246
AIC	−825.17	−483.57	−829.52	−985.32	−507.70	−678.69	−718.66	−680.15	−893.25	−751.92

t statistics in parentheses

$^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2.12: ITS SARIMA model with Boeing737 MAX grounding

Chapter 3

Aiding airlines for the benefit of Whom? An applied game-theoretic approach

3.1 Introduction [1]

This paper investigates how different government support programs provided to airlines during the COVID-19 pandemic affects competition in the European airline industry. The recent Covid-19 pandemic re-opened the necessity to discuss the rescue of financially distressed companies through government state aid. Over the last decades, policymakers have been discussing the challenging decision whether to allow firms to file for bankruptcy or to save them using taxpayers money. The trend over the last few years has tended towards the latter choice (Jackson et al., 2020) when faced with an exogenous shock. Bailing out a firm consists of an ex post measure that acts to provide financial relief to a company that is facing a liquidity crisis in order to accelerate recovery. During national or international emergencies, regulators may be urged to rescue a firm or an entire industry, through the use of public funds. Academics and decision makers have always seen bailouts as unfair aid instruments, resulting from failures in the capital markets that prevent firms from accessing lines of credit. The most frequently adopted fiscal stimuli include the provision of grants, deferral of taxes, loan issuances or government equity

[1]This chapter is based on the joint work with Nicole Adler. The paper has been submitted to the European Journal of Operational Research on Jul 15, 2022 and it is currently under review.

injections. The latter instrument is rarely applied to bail out firms due to the distorting effect induced by government participation as a firm stakeholder (DG Competition, 2008). However, in the specific event that a firm cannot sustain the burden of additional debt, it may rely on equity instruments as a bailout method in place of bankruptcy (Megginson and Fotak, 2021). The government aid scheme should be carefully evaluated and designed to prevent moral hazard behaviours whilst ensuring adequate government remuneration. The bailout of the US auto-industry in 2008 has proven that government intervention could result in an effective stimulus for a distressed industry and that governments may recover the money borrowed (Goolsbee and Krueger, 2015). An optimal bailout policy should be applied systematically to all firms in the industry, preventing large companies from pursuing risky practices protected by the "too big to fail" paradigm (Bianchi, 2016). Despite several crisis over the past decades, including the financial crisis of 2008, an optimal bailout mechanism has not yet been defined. Another crucial aspect when defining bailout policy is to identify only the liquidity constrained firms that will be capable of repaying the aid over time. However, the process of distinguishing such companies is difficult, particularly under the time pressures caused by a sudden crisis.

Recently, several heterogeneous industries have required state support, ranging from the automobile sector to the banking system. Among these distressed industries, the airline sector has shown continuous vulnerability to shocks due to the high debt exposure. Multiple exogenous events have affected the aviation industry: the 9/11 terrorist aggression, the 2008 financial crisis and epidemics such as the recent Covid-19 outbreak. Regulators have the task of weighing the benefits of bailing out airlines and preserving connectivity for the economic and societal benefits with the risks of endangering taxpayer money and distorting competition. This decision process is made more difficult due to the specific characteristics of the airline industry, which include sovereignty, safety and military concerns as well as multiple business models that compete in a subset of markets. Another layer of complexity is imposed by the lack of cooperation among policy makers in civil aviation, leaving each country with the possibility of enacting autonomous measures. These sovereign decisions generate fragmented policies that potentially result in market inefficiencies and competitive distortions both regionally and internationally. For example, over the last decade, there has been much discussion over the policies of the Middle East as compared to the US and Europe (Tretheway and Andriulaitis, 2015).

The Covid-19 pandemic offers a convenient case study to apply and validate our model specification in the context of the European Union. Specifically, the Coronavirus pandemic has disrupted the entire world economy. Governments enforced national lockdowns which severely affected economic activities. As a consequence of these measures, the aviation industry was one of the more severely affected sectors, with thousands of flights cancelled and billions of dollars in lost revenue. Forecasts estimate that the industry will take years to fully recover and reach the traffic levels offered before the outbreak of the virus. In 2020, the entire industry faced an overall loss of profits of more than 80%, from both domestic and international flights (Pearce, 2020), which has been estimated at approximately $ 372 bn in 2020 (ICAO, 2020). Furthermore, prior to the pandemic, most airlines were in distress due to their leveraged financial position. The debt level, higher than market investment grade (ICAO, 2020), discouraged potential investors and reduced access to traditional lines of credit during the pandemic. After the lockdowns were lifted, the demand for air travel has shown slow signs of recovery, for the most part sustained by domestic markets (Andreana et al., 2021). This has highlighted the absence of a sharp rebound in passenger demand, suggesting that a full recovery will take several years. Since the beginning of the pandemic, 34 legacy and low-cost operators have already been hit by bankruptcy (CAPA, 2021). Given the difficulties and bleak projections for the aviation industry, liquidity remains an issue and many carriers face the risk of debt and bankruptcy. European governments, using public resources, re-wrote the rules and adopted several measures to provide financial aid, including grants, loans, recapitalization and tailored hybrid instruments. Although a public bailout of a Member State requires the authorisation of the European Commission, each country decided on the type of financial aid and its size. This characteristic raises concerns that Member States have chosen a financial instrument in order to increase the market power of domestic carriers at the expense of fair competition (de Jong et al., 2019).

3.1.1 Aviation literature

Bankruptcies and government support for distressed airlines have long been a topic of academic interest (Borenstein and Rose, 1995, 2003; Ciliberto and Schenone, 2012a,b). Borenstein and Rose (1995) analyze pricing strategies of airlines under Chapter 11 protection, using an econometric approach. Starting from the industry claim that bankruptcy protected carriers are harmful to the entire industry due to price-cutting behaviours, they prove that the modest price reduction occurs before any government intervention. They show how protected airlines experience a decline in market share, despite the lower fares, induced by declines in demand for distressed carriers which are perceived as lower quality service providers. In Borenstein and Rose (2003), the authors extend the investigation to the impact of airlines filing for Chapter 11 protection on aggregate air service. They find that carriers under protection tend to reduce their operations, which is particularly significant for midsize airports. The possible bankruptcy of an airline with a relatively high share of flights at the airport would result in a severe contraction of air service. Ciliberto and Schenone (2012b), following the previous works of Borenstein and Rose (1995, 2003), explore the impacts induced by a competitor airline facing bankruptcy filing and protection on the industry. The results of their work highlight how network carriers affected by bankruptcy decrease airfares and offered capacity. In addition, Ciliberto and Schenone (2012a), focus on vertical differentiation by investigating the variation in service quality as defined through flight delays, cancellations and aircraft age, for airlines under Chapter 11 protection. They do not find any significant improvement in the quality of the service after a government restructuring.

Airline competition and network strategies have been widely discussed in the operations research literature since the beginning of the 1990s (Hansen, 1990; Hong and Harker, 1992; Dobson and Lederer, 1993; Hendricks et al., 1999; Adler, 2001, 2005; Vaze and Barnhart, 2012; Hansen and Liu, 2015; Adler et al., 2021; Wang et al., 2022). Among these works, Hansen (1990) defines a non-cooperative framework in which airlines compete in frequency, keeping prices fixed, in a hub-and-spoke network. Market share was defined by a discrete choice model that accounts for passenger preferences. A point of quasi-equilibrium was found that resembled the state of the market. Hong and Harker (1992) proposed a two-stage market model that addresses oligopolistic competition. In this framework, airlines compete over flight allocations, fares, itineraries and landing rights, assuming the carriers' networks as given, by developing two models of competition. The first model assumes exogenous slot allocation, whereas the second internalises this decision. Dobson and Lederer (1993) analyze airline competition in terms of airfares and scheduled flight frequencies by developing a two-stage game framework in which the equilibrium is derived considering one type of passenger and symmetric hub-spoke networks. Under the assumption of a fixed plane size and no traffic originating from the hub, they develop a heuristic and find a solution for a small network, proving the feasibility for realistic large-scale implementation. Hendricks et al. (1999) investigate the effects of different behaviours between competing airlines in a hub-and-spoke network, by developing a two-stage game. Under the assumptions of infinite seat capacity and no shared itineraries, they show that aggressive competition results in a monopoly outcome. In this case, the monopolistic airline is driven to develop a hub-spoke network. On the other hand, in a duopoly equilibrium in which both carriers select a hub-spoke structure, neither airline has an advantage over the competitor. Adler (2001, 2005) investigates competition between hub-spoke networks using a two-stage, non-cooperative game. Following this specification, in the first stage airlines select their network and in the second stage, they compete in frequencies and prices, taking into account multiple passenger types. Vaze and Barnhart (2012) develop a game-theoretic competition model for service frequency when airport slots are constrained. They show that, given the airport capacity requirements, a profitable schedule can be obtained while accommodating all passenger demand. Following the modelling formulation proposed in Vaze and Barnhart (2012), Wang et al. (2022) develop an equilibrium programming model to address airline frequency competition under slot-constrained airports and consider balanced flow. They prove that a Nash equilibrium may not always exist in pure strategy but always exists in mixed-strategy equilibrium. By formulating a mixed-strategy programming model, they analyse the impact of different strategies on profits under different scenarios. Hansen and Liu (2015) design two models able to predict competition between two symmetric airlines when they only differ in the structure of how they compete in frequency. By implementing a nested logit specification, they found consistent results between their analytical framework and empirical evidence. To summarize, Adler et al. (2021) propose a comprehensive review of game-theoretic models applied to transportation markets.

The impact of airline decisions on social welfare, when facing competition, has been addressed in several publications (Schipper et al., 2007; Adler et al., 2010). Schipper et al. (2007) simulate the impact of airline competition on social welfare, focusing on the Amsterdam-Maastricht corridor. They develop a two-stage model in which airlines set prices and frequencies. They find welfare gains when low-cost carriers enter a deregulated market, due to lower fares and higher service frequencies. Adler et al. (2010) develop a dynamic game in which airlines compete between themselves and also against high-speed rail operators, in terms of fares and service frequency. They solve the resulting non-linear maximization problem, applied to the European Union context and assess the overall impact on social welfare.

The literature analyzing the impact of the pandemic support mechanisms on airline competition is still scant (Abate et al., 2020; Zhang and Zhang, 2021). Abate et al. (2020) propose an exploratory analysis on the impact of direct government support measures on the airline industry. They describe the different forms of aid available to airlines, examining the effect on air connectivity and the environmental dimension. Their work suggests that government bailout decisions were mainly motivated by connectivity preservation which ignores preexisting policies to limit the impact of aviation environmental externalities. Zhang and Zhang (2021) discuss government interventions on airline bankruptcies, with an application to Virgin Australia. The authors highlight that the preferred funding channel should be the private market, but warn of the potential social costs resulting from the failure to reach such an agreement in the private market.

3.1.2 Bailout mechanisms literature

How to optimally bail out a distressed firm has been long discussed in the academic literature. Most of these studies theoretically investigate the impact of bailout mechanisms specifically on the banking and financial systems (Diamond and Rajan, 2002; Gorton and Huang, 2004; Diamond and Rajan, 2005; Philippon and Skreta, 2012; Bianchi, 2016; Chari and Kehoe, 2016; Wollmann, 2018; Pandolfi, 2022). Diamond and Rajan (2002) warn about the risk associated with a partial rescue of the bank system and how the aggregate liquidity constraints and its excess of demand can lead to a systemic default. Gorton and Huang (2004) develop a theoretic model to include moral hazard behaviour. The results of their model suggest that a well defined government bailout is able to eliminate the moral hazard and obtain an efficient social outcome. Bianchi (2016) finds that the only way to efficiently bailout an industry during a crisis, when hazardous behaviours may arise, is to systemically rescue all the distressed firms in the sector. Adopting a different perspective, Chari and Kehoe (2016) build their work from the intuition that bailouts are the source of inefficiencies rather than a cure for them. They show in their dynamic model that an optimal mechanism can be achieved by allowing governments to exert a more stringent, ex ante authority and commitment.

Liquidity shortage and insolvency can lead to contagion between endangered and healthy firms, increasing the risk of a systemic meltdown. This effect is modelled in Diamond and Rajan (2005). The authors develop an equilibrium model able to incorporate the interaction between insolvency and scarce liquidity as the cause of contagion in the banking system. They show that government intervention, whether in the form of liquidity injection or recapitalization, can prevent a systemic collapse if the institution financed remains solvent. If the rescued bank is not able to ensure enough liquidity, it would trigger an excess of new recapitalization, spreading the contagion across healthy institutions. Adopting an operations research approach, Klages-Mundt and Minca (2022) investigate the optimal intervention to a shock in a specific type of financial network. They apply approximation algorithms to the NP-hard problem of a network subject to an intervention scheme and show that it is possible to bail out a set of firms to obtain the maximal value.

The design of an optimal government mechanism to bail out an industry, considering an outside market, has been addressed in Philippon and Skreta (2012). The results obtained from their theoretical model show the impossibility of improving investment schemes using cost-less interventions and the ability to define an ex ante, optimal intervention by assessing borrowing rates outside the market. They also highlight the irrelevancy of the size of the intervention, the efficiency of debt-like bailout and that there is no linkage between the cost of implementing the intervention and the private market. Wollmann (2018) in his structural model investigates the change in the product offering given an industry shock. Assessing the bailout schemes provided to the auto industry in 2009, he finds that the ability to adjust vehicle production impacts firms operating results substantially. Pandolfi (2022) addresses the design of an optimal rescue mechanism for banks considering the availability of bail-in instruments alongside bailouts. He finds that, in presence of a low moral hazard and liquidation option, the optimal policy is a combination of recapitalization (bail-in) and taxpayers' money from a bailout.

3.1.3 Contribution

Given the limited literature that could shed light on the implications of financial aid packages on competition in network based industries, this research aims to develop an applied game-theoretic model to investigate the equilibrium outcome of the aviation transport market, when competition may be distorted by government bailout mechanisms. Specifically, we develop a single-stage, game-theoretic framework in which governments rescue airlines by offering different forms of financial aid and carriers subsequently compete through a market share model that maximises their best response function. Airline decision variables include service frequency, airfares for business and economy passengers per origin-destination served and the number of aircraft to operate. We solve the game iteratively until we find the transport equilibrium outcome. Then we estimate the social welfare by calculating consumer, producer and government surpluses. Consequently, we investigate the implications of the varying types of bailouts on overall welfare.

To the best of our knowledge, the model presented in this paper is the first to investigate the effect of government bailouts on airline competition adopting a game-theoretic approach. In this sense, our work contributes and enriches the literature on applied game-theoretic methodology. The insights provided by this research and the model we develop could guide policymakers in taking more consistent ex ante decisions by predicting their impact on the entire industry. Moreover, we introduce into the modelling process the strategic decisions for an airline to potentially ground part of its fleet in order to reduce operating expenditures in a period of financial distress. This element of novelty enables an analysis of the competitive interactions that is different from "business as usual". Our results shed light on the competitive implications of the uncoordinated responses enacted by the European Union with respect to the Covid-19 outbreak. Finally, the insights provided by this research could be relevant to other distressed sectors characterized by the presence of multiple, competing firms that interact through a network structure. In particular, this approach could be applied ex ante to a single firm in order to test the effectiveness of potential bailout schemes, independent of the status of the specific industry. Consequently, it is possible to obtain insights on any competitive distortions should the rescue mechanism be targeted to a specific firm instead of a systemic bailout.

The plan of the paper is as follows. Section 3.2 develops the model framework and solution method. In section 3.3 we present the data and numerical results of the model applied to the European aviation market in light of the Covid-19 pandemic. Section 3.4 discusses the conclusions of our work and suggests potential future research directions.

3.2 Methodology

In this section, we develop a single-stage, dynamic, Nash game framework in which the players maximize their profits given their network structure and the decisions of their competitors. We begin by defining the network typology and then specify the utility function of passengers over which we develop a market share model that defines airline competition. Subsequently, we specify the airline cost functions and multiple, potential bailout repayment schemes. We combine these elements into our mathematical formulation and, using a non-linear optimization algorithm, we solve the game iteratively. In Table 3.1 we define the notation used throughout the paper.

Table 3.1: Notation

Sets and Indices	
$\mathcal{A}$:	Set of airlines; indexed by a
$\mathcal{H}$:	Set of flight types (i.e short-haul and long-haul); indexed by h
$\mathcal{K}$:	Set of legs served by airline a in the itinerary from i to j for flight type h; **indexed by** k^h
$\mathcal{N}$:	Set of airports nodes; indexed by i, j
$\mathcal{S}$:	Set of passenger types; indexed by s
Parameters	
B_a:	Net present value of the bailout repayment for airline $a \in \mathcal{A}$
β_{0s}:	Direct connection parameter in the utility function for passenger type $s \in \mathcal{S}$
β_{1s}:	Frequency parameter in the utility function for passenger type $s \in \mathcal{S}$
β_{2s}:	Airfare parameter in the utility function for passenger type $s \in \mathcal{S}$
β_{3s}:	Travel time parameter in the utility function for passenger type $s \in \mathcal{S}$
C_k:	Cost for airline $a \in \mathcal{A}$ to serve leg $k \in \mathcal{K}$ per km flown
c_h:	Conversion parameter in the cost functions for flight type $h \in \mathcal{H}$
d_{ijs}:	Potential Demand between nodes $i \in \mathcal{N}$ and $j \in \mathcal{N}$ for passenger type $s \in \mathcal{S}$
δ_{ija}	$= 1$ if the connection between $i \in \mathcal{N}$ and $j \in \mathcal{N}$ for airline $a \in \mathcal{A}$ is direct, 0 otherwise
ϵ_{ijsa}:	Random component of utility between nodes $i \in \mathcal{K}$ and $j \in \mathcal{K}$ for passenger type $s \in \mathcal{S}$ of airline $a \in \mathcal{A}$
$\bar{f}_h$:	Average utilization frequency for flight type $h \in \mathcal{H}$
GCD_k:	Great Circle Distance of leg $k \in \mathcal{K}$
$MCPF$:	Marginal cost of public funds
ζ:	Interest rate on loan
ϕ:	Taxation on airline profits
r:	Bailout discount rate
η_t:	Interest rate on equity increasing over time t
ρ:	Government remuneration as dividends
S_k:	Number of seats available on leg $k \in \mathcal{K}$
τ_{ija}:	Travel time between $i \in \mathcal{N}$ and $j \in \mathcal{N}$ for airline $a \in \mathcal{A}$
T:	Time period at which the aid is fully repaid
Decision variables	
f_{ka}:	Service frequency on leg $k \in \mathcal{K}$ of airline $a \in \mathcal{A}$
p_{ijsa}:	Fare set on itinerary from $i \in \mathcal{N}$ to $j \in \mathcal{N}$ per passenger type $s \in \mathcal{S}$ of airline $a \in \mathcal{A}$
F_{ha}:	Fleet size deployed for flight type $h \in \mathcal{H}$ by airline $a \in \mathcal{A}$ (i.e. number of narrow and wide-body jets)
Auxiliary variables	
$MS_{ijsa}(f_{ka}, p_{ijsa})$:	Market share from i to j per passenger type $s \in \mathcal{S}$ of airline $a \in \mathcal{A}$ as a function of frequency and airfare
$\psi(F_{ha})$:	Size of aid as a function of fleet size for airline $a \in \mathcal{A}$
V_{ijsa}:	Systematic component of utility between nodes $i \in \mathcal{N}$ to $j \in \mathcal{N}$ per passenger type $s \in \mathcal{S}$ of airline $a \in \mathcal{A}$
z_{ija}:	Minimum frequency over an indirect itinerary from $i \in \mathcal{N}$ to $j \in \mathcal{N}$ for airline $a \in \mathcal{A}$

3.2.1 Network specifications

The network in our model, $G(\mathcal{N}, \mathcal{K})$, is based on a hub-and-spoke structure, which allows carriers to maintain an airport base, namely the hub, and several directly connected airports as spokes, or to operate a point-to-point network between nodes. With respect to supply we make the following four assumptions. We assume that only one type of aircraft is used per arc type k^h, according to long-haul and short-haul flights. Based on the data, the legacy carriers use hub-spoke networks to serve both long and short-haul connections whereas the low cost carriers serve short-haul alone on a fully connected network. Given the limited number of itineraries connecting through two or more stops, we assume that the number of arcs belonging to an itinerary is bounded to a maximum of two for all airlines. Under this network formulation, we model both direct and indirect itineraries. Furthermore, the network structure is assumed to be static in that the airlines' choice of network typology does not change. This assumption prevents airlines from acquiring slots at additional airports to serve new routes, however the solution may lead an airline to stop serving a connection by setting its frequency to zero.

3.2.2 Demand and market share functions

With respect to the demand-side, we define potential passenger demand between origin and destination pairs (i, j) per type of passenger s, namely *business* or *economy*. In our model, travellers select their preferred alternative among carriers based on the assumption of utility maximisation. Following the discrete choice models proposed by McFadden et al. (1973) and developed further in Ben-Akiva and Lerman (1985), we specify the utility function U_{ijsa} as a composition of systematic V_{ijsa} and random ϵ_{ijsa} components. The systematic part of the alternative provided by airline a is defined, according to the type of passenger s, for each origin i and destination j pair depending on the itinerary specifications, as shown in Eq.(3.1).

$$V_{ijsa} = \beta_{0s}\delta_{ija} + \beta_{1s} ln(1 + min\{f_{k^{h'}a}\}) + \beta_{2s}p_{ijsa} + \beta_{3s}\tau_{ija}, \ \ \forall i, j \in \mathcal{N}, \ s \in \mathcal{S}, \tag{3.1}$$

where

$$\mathcal{K}' = \{k^{h'} | k^{h'} \text{ are the legs composing itinerary } i, j \in \mathcal{N}\}$$

In the systematic utility function (Eq.(3.1)), β_{0s}, β_{1s}, β_{2s} and β_{3s} are the parameters of the utility components, δ_{ija} indicates whether the route is connected directly or indirectly by the airline assuming a value of 1 or 0 respectively, p_{ijsa} and $f_{hk'a}$ are the airfare and service frequency, respectively, that carrier a sets per itinerary, and τ_{ija} represents the travel time in minutes for the origin-destination connection. This means that a service frequency $f_{ka} = 1$ implies that airline a operates a single flight on leg k in a month. The use of these four elements in the definition of passenger utility functions captures the most important drivers in the decision process. As highlighted in Hansen (1990), the use of a natural logarithm to represent the utility component associated with frequency accounts for the marginal decrease in value related to additional flights. Furthermore, since the origin and destination airports may be linked through a one-stop connection over a hub, the minimum value of the service frequencies of the set of legs in the itinerary is considered to model the bottleneck effect of a specific leg on the itinerary. The last two components of Eq.(3.1) are the dis-utilities induced by the airfare and by the travel time of airline a on the route connecting i to j. These are the variables most commonly used in the literature on game-theoretic models (Hansen, 1990; Hansen and Liu, 2015; Cadarso et al., 2017). More variables can be added, such as punctuality rate and takeoff and landing times (Garrow, 2016; Mumbower et al., 2014). However, the inclusion of more variables comes at the expense of higher complexity and computational time. The random components of the utility function are assumed to follow a Gumbel distribution and to be independent and identically distributed (i.i.d.).

Given the specification of the passenger utility function, a market share model is calculated as a multinomial logit function (MNL), as shown in Eq.(3.2).

$$MS_{ijsa} = \frac{e^{V_{ijsa}}}{e^{V_0} + \sum\limits_{a' \in \mathcal{A}} e^{V_{ijsa'}}} \tag{3.2}$$

where a' includes the set of all airlines operating directly or indirectly on the route (i, j) and V_0 represents the utility when the passenger does not fly. It is important to note that, given the formulation in Eq. (3.2), the market share values range from 0 to 1. Passengers may decide to not fly if the utility associated with the alternatives offered by the airlines is less than that related to the decision not to fly. The no-fly option choice represents the price elasticity of demand and prevents airlines from setting excessively high airfares. We assume that the no-fly option is characterised by a utility equal to zero. The sum of each market share, given the option to not fly, will be less than or equal to 1. Formally:

$$0 \leq MS_{ijsa} \leq 1, \ \ \forall i, j \in \mathcal{N}, \ s \in \mathcal{S} \tag{3.3}$$

$$\sum_{a' \in \mathcal{A}} MS_{ijsa'} \leq 1, \ \ \forall i, j \in \mathcal{N}, \ s \in \mathcal{S} \tag{3.4}$$

MNL models also present shortcomings. In particular, the independence from irrelevant alternatives (IIA) property requires that the relative choice probabilities between two alternatives is independent from the existence of an additional alternative in the choice set. However, this requirement is generally considered too restrictive for modelling purpose (Cao et al., 2022).

3.2.3 Operating costs

The costs incurred by carriers include both operating and fixed components. Swan and Adler (2006) found that direct operating costs may be expressed as a function of aircraft capacity and great circle distance, GCD_k, between the two airports connected by arc k^h. They propose two equations, one for short-haul flights, mainly operated by narrow-body aircraft, and one for wide-body movements, usually employed in long-haul arc connections. The cost functions are multiplied by two to take into account the round-trip nature of the flights. Moreover, we use a conversion parameter c_h to account for the currency conversion rate (from \$ to €) and update the functions to 2019 cost per available seat kilometre (CASK) values per flight type h. We account for ultra-low-cost carriers by adding an additional equation in which the short-haul operating costs are halved, based on data analyzed in 2019.

$$C_{k^s}^{legacy} = 2(GCD_{k^s} + 722)(S_{k^s} + 104)\$0.019c_h \tag{3.5}$$

$$C_{k^s}^{lcc} = (GCD_{k^s} + 722)(S_{k^s} + 104)\$0.019c_h \tag{3.6}$$

$$C_{k^l} = 2(GCD_{k^l} + 2200)(S_{k^l} + 211)\$0.0115c_h \tag{3.7}$$

where,

$$\mathcal{K}^l = \{k^l | k^l \text{ are the long-haul legs}\}$$

$$\mathcal{K}^s = \{k^s | k^s \text{ are the short-haul legs}\}$$

3.2.4 Bailout repayments

The airline industry had a severe liquidity problem and inability to cover the fixed costs, in line with the fact that they could not continue to provide the service. Given the absence of a stream of revenue, the bailouts provided did not exceed the minimum needed to ensure the viability of airlines and did not go beyond covering fixed costs. However, once the crisis has passed, airlines are left with the debt they must repay. Several types of bailout mechanism could be applied to rescue carriers. Consequently, depending on the type of assistance provided, a different repayment scheme B_a is included in the airline's objective function. We model three repayment schemes, namely grants, loans and equity ownership. In the case of grants, no repayment is required. In the case of loans and equity instruments, the reimbursement from this intervention has been modelled as the net present value of the aid repayment scheme discounted by a rate r. The interest rate ζ on the loan is set according to the repayment date. In the case of government intervention through equities, the remuneration and exit strategies are defined such that the beneficiary of the recapitalization is incentivized to repurchase the shares. This is achieved by setting a level of remuneration for the nominal investment that increases over time at an annual interest rate of η_t and an adequate government remuneration ρ in the form of dividends.[2] Given these characteristics, the net present value function of the bailout repayment scheme assumes one of the following forms:

$$B_a = \begin{cases} 0 & \iff \text{Grant} \\ \sum_{t=1}^{T} \frac{\psi(F_{ha})}{T} \frac{\zeta}{(1+r)^t} & \iff \text{Loan} \\ \sum_{t=1}^{T} \frac{\psi(F_{ha})}{T} \frac{\eta_t}{(1+r)^t} + \frac{\pi\rho}{(1+r)^T} & \iff \text{Equity} \end{cases} \tag{3.8}$$

where $\psi(F_{ha})$ is the size of the aid provided to the airline as a function of the fleet deployed when the airline is rescued through a loan or equity and is assumed to remain constant when a grant is received. Specifically, grants are generally provided to small-scale airlines characterized by a fleet composed of a few aircraft. Hence, any reduction in their fleet size will result in a suspension of most of their operations and a consequent airline default. T is the last period in which the carrier completes the bailout repayment (or defaults). A bankruptcy manifests in the case when the airline is not able to perform any operations and its profits turn negative. The instruments provided by European Commission and modelled in our framework, take into account the uncertainty caused by the pandemic through different repayment time and interest rates. Specifically, loans generally are provided when the duration of the debt is shorter compared to the time needed to

[2] Modelling market fluctuations during the period in which airlines buy back their equities is out of the scope of this research. Consequently, we assume that holding equities of airlines, governments are remunerated only through interest rates and dividends.

fully buyout the shares of a recapitalizations. Equity injections are substantially more expensive than loans but they allow for complex and protracted restructuring process.

3.2.5 Mathematical formulation

The competitive airline industry is modelled as a Nash non-cooperative game in which carriers maximise their profits, given other airlines' best response functions, until the iterative solutions of the optimization problems converge to an equilibrium. Each airline's profit function assumes the form of revenue minus cost and the three decision variables are airfares, flights frequencies and the fleet size in the case of a loan or equity bailout. Given the cost function, bailout repayment scheme and multinomial market share model, the non-linear profit function assumes the following form:

$$\underset{p_{ijsa},f_{ka},F_{ha}}{Max}\ \pi_a = \left[\sum_{\substack{i,j\\i\neq j}}\sum_{s} MS_{ijsa}(f_{ka},p_{ijsa})d_{ijs}p_{ijsa} - \sum_{k^h} C_{k^h}(GCD_k,S_{k^h})f_{ka}\right]\frac{(1-\phi)}{(1+r)^T} - B_a(F_{ha}) \tag{3.9}$$

where MS_{ijsa} is the market share for an itinerary connecting i to j for passenger type s operated by the airline, d_{ijs} is the potential demand observed between i and j per passenger type s, S_{k^h} is the aircraft seat capacity on the k^h arc and ϕ is the corporate taxation level on airline profits.

The objective function is subject to the constraints (3.10)-(3.17). All constraints are linear except for (3.10) and (3.13).

$$MS_{ijsa} = \frac{e^{V_{ijsa}(f_{ka},p_{ijsa})}}{e^{V_0} + \sum\limits_{a'\in\mathcal{A}} e^{V_{ijsa'}(f_{ka'},p_{ijsa'})}}\ \ \forall\, i,j\in\mathcal{N},\ s\in\mathcal{S} \tag{3.10}$$

$$z_{ija} \leq f_{\omega' a}\ \ \forall\, i,j\in\mathcal{N},\omega'\in\Omega' \tag{3.11}$$

$$z_{ija} \leq f_{\omega'' a}\ \ \forall\, i,j\in\mathcal{N},\omega''\in\Omega'' \tag{3.12}$$

$$\sum_{i',j' \in \mathcal{N}'} \sum_{s} d_{i'j's} MS_{i'j'sa} \leq S_{k^h} f_{ka}, \;\; \forall \, k^h \in \mathcal{K} \tag{3.13}$$

$$\sum_{k^h} f_{k^h a} \leq \bar{f}_h F_{ha}, \;\; \forall \, h \in \mathcal{H} \tag{3.14}$$

$$f_{ka} \geq 0, \;\; \forall \, k^h \in \mathcal{K} \tag{3.15}$$

$$p_{ijsa} \geq 0, \;\; \forall \, i, j \in \mathcal{N}, \; s \in \mathcal{S} \tag{3.16}$$

$$F_{ha} \geq 0, \;\; \forall \, h \in \mathcal{H} \tag{3.17}$$

where,

$$\mathcal{N}' = \{i', j' | i', j' \text{ are the itineraries passing through arc } k^h\}$$

$$\Omega' = \{\omega' | \omega' \text{ is the first arc of the itinerary } i, j \in \mathcal{N}\}$$

$$\Omega'' = \{\omega'' | \omega'' \text{ is the second arc of the itinerary } i, j \in \mathcal{N}\}$$

Constraint (3.10) defines the market share following the multinominal formulation described in Equation (3.2). Since the passenger utility is not a continuous function due to the presence of a minimum, we overcome this discontinuity by linearising the functions using constraints (3.11)-(3.12). Equation (3.13) represents the constraint of the aircraft capacity. This bound ensures that the demand served by airlines never exceed the seat availability offered on the leg. Equation (3.14) specifies that each airline's service frequency is bounded by their fleet size F_{ha} and the average utilization rate $\bar{f}_h$ according to flight type h. Constraints (3.15)-(3.17) specify the domain of the decision variables. Given the strategic nature of this analysis, we assume that all decision variables are continuous, which is clearly a simplification, that undertaken the purpose of reducing complexity.

The resulting program, despite the linearisation enforced through constraints (3.11)-(3.12), is still highly non-linear in its objective function and constraints. To find a solution to the non-linear programming maximisation problem, a primal dual-interior point algorithm with a filter line search method is applied. This procedure, proposed by Wächter and Biegler (2006) and implemented in the *IPOPT* routine, solves nonlinear programs with double differentiable objectives and constraints. We note that the optimal solution found through this algorithm may converge to a local rather than global optimum. To guarantee the robustness of the results obtained, we perform a sensitivity analysis of the equilibrium solution by initialising the program with different control sequences.

3.2.6 Game-theoretic competition

The mathematical program in Eq.(3.9)-(3.17) is embedded into a single-stage dynamic game, where airlines compete given their network structure. The set of players is represented by all airlines operating in the market. Carriers may decide to stop serving existing connections by setting a frequency equal to zero but are not permitted to change the nodes they serve. The Nash equilibrium is obtained as a result of an iterative algorithm, where the mathematical program is solved sequentially for each player of the game and where the values of the decision variables of each iteration are used as input for the next iteration. A cycle is defined when a solution of the mathematical program has been computed for all airlines. The process ends when a Nash equilibrium is found in which no player has an incentive to deviate from his best response to the other players' strategies. We set an exit threshold of less than 1% between the values of the objective function for each airline in the set of players between two consecutive iterations. The pseudo-code of the solution process is described in Algorithm 1.

In this framework, the focus is entirely devoted to airlines, as they are the only player considered in the game. However, since the service frequency, airfares and itinerary characteristics (directness of the flight and elapsed travel time) determine the travellers' utility, passengers play an indirect role in the game. The government sets the rules of the bailout at the beginning of the game and receives remuneration (or not in the case of grants or should the airline enter bankruptcy if the profits are non positive) according to the scheme chosen.

Algorithm 1 Solve the game

```
Start
Initialise values of competitors' decision variables and their network characteristics
condition ← false
iterator ← 1
Create an empty list candidate to store possible solutions
while condition == false do:
cycle:
    for a in airline do:
        Solve the mathematical program for a using IPOPT
        Store solution in candidate
        Airline a moves to set of competitors while airline a + 1 leaves
    if (iterator > 1) & (candidate[iterator] − candidate[iterator − 1] ≤ threshold) then:
        condition ← true
        solution ← candidate[iterator]
    iterator ← iterator + 1
return solution
Stop
```

3.2.7 Social welfare analysis

To analyse the impacts of airline bailouts on overall social welfare, we define the welfare function as the sum of consumer, producer and government surpluses. Formally, the welfare function is expressed as in Eq.(3.18).

$$W = \sum_{a} \pi_a + \sum_{i,j,s} d_{ijs} ln \left(\frac{1}{\beta_{2a}} e^{\left(\sum_{a'} V_{ijsa'}\right)} \right) + \sum_{a} (\phi \pi_a^{'} + B_a) MCPF \tag{3.18}$$

The first term represents airline profits, the second is the surplus of travellers derived from the logsum of the logit function (Small and Rosen, 1981) and the last term represents the government income from taxation and bailout remuneration. $\pi_a^{'}$ is the airline profit net of bailout repayment and $MCPF$ is the marginal cost of public funds.

3.3 European case study

In this section, we first discuss the bailout scheme structure approved by the European Commission, then the airlines' network topology, the data analysed to set the values of the parameters and finally, the results of the analysis. The structure of the results is based on multiple scenarios in which different European Member States invest in the airlines according to the multiple bailout schemes in order to understand their impact on the new competitive equilibria outcomes.

3.3.1 Bailout schemes during Covid-19

To respond to the severe impact caused by the covid pandemic, governments have provided aid packages that support firms during liquidity shortages. The two main bailout schemes were the CARES Act (116th Congress, 2020) in the US and the Temporary Framework for the European Union (TFEU) (European Commission, 2021). Since our interest is focused on the European aviation market, we describe the TFEU in detail. Airline bailouts approved under this scheme are reported in appendix A according to the Member State. Given the limited resources available to the European Union, the Member States individually chose the support measure and its financial magnitude, following the rules set by the European Commission. The TFEU suggests several ways to bailout firms facing the risk of bankruptcy: providing aid in the form of a direct grant, guarantees or subsidised public loans, equity injection, deferral of taxes, hybrid instruments and state recapitalisation. In this research, we focus on the three most prevalent instruments, namely grants, loans and equity investments.

Direct grants, consisting of a lump sum transfer without any repayment, represent the easiest and fastest support measures for firms. Loan-based instruments are designed with a horizon of a maximum of six years from the date that the financial injection is received. The aid is subject to an increasing interest rate over time, depending on the repayment period as reported in Table 3.2.

Table 3.2: TFEU interest rates on loan

Time since loan received	1 year	2-3 years	4-6 years
Interest rate	0.5%	1.0%	2.0%

Government support in the form of equity or hybrid instruments is undertaken through the purchase of newly issued shares and (re)introduces the State as a firm shareholder. We model only equity-based schemes and do not include hybrid instruments due to their specificity. The interest rate of the equity instrument is increasing over time as shown in

Table 3.3. Under this setting, firms are allowed to buy back their shares from the State at any time, repaying the initial nominal investment plus the relevant annual interest rate and paying dividends only in relation to the State.

Table 3.3: TFEU interest rate on equity

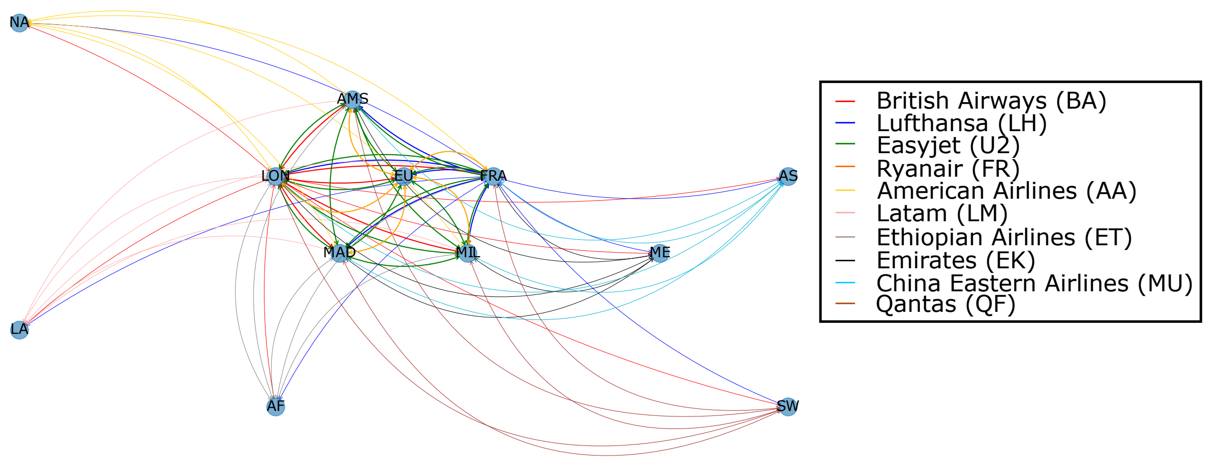
Time since equity received	1 year	2-3 years	4-5 years	6-7 years	8 or more years
Interest rate	4.5%	5.5%	7.0%	9.0%	9.5%

Although the cost of equity is higher than that of the loan, it does provide the airline with a longer time frame to repay the investment. Given the fact that at the beginning of a crisis, there is a lot of uncertainty as to the length of time required to return to business as usual, this is an advantage over the alternative bailout schemes.

3.3.2 Network and Players

The model proposed in Section 3.2 is tested on a real scaled network served by ten competing airlines, over a 12 nodes network, as depicted in Figure 3.1. Four European carriers are modeled including two legacy carriers and two low cost carriers. The remaining six airlines are non-European and fly from their respective hubs to the six European nodes. This is clearly a simplification of the market hence we define all non-European nodes and one European node as "macro-region". A macro-region is defined as a representative agglomerated market capturing the demand from and to the major European cities. In particular, we define six macro-regions outside Europe, *North America, Latin America, Africa, Middle East, Asia* and *Oceania*, and the *Europe* macro-region in order to capture the connections between each of the major European cities and all other possible destinations (origins) within Europe. Table 3.4 summarises the airlines and nodes in the network. Accordingly, both long-haul and short-haul competition is considered. The networks depicted in Figure 3.1 include both hub-and-spoke and point-to-point networks, where adjacent nodes are connected by numbered route arcs. We include British Airways with a hub in London and Lufthansa with a hub in Frankfurt to represent the legacy carriers in the case study. We assume that Ryanair serves all European destinations through the European macro-region and Easyjet serves a fully connected European network, both representing low cost carriers. To locate the node belonging to a macro-region and compute the distance and travel time between the other nodes, we use the region centroid. We note that the network allows both direct and indirect connections between each node pair.

Figure 3.1: 12-node network with 10 competing airlines



For the case study, we selected the largest airlines belonging to the macro-regions and European Member States. The aim is to minimize the size of the game for computational simplicity but ensure a sufficiently rich description of the market that conclusion may be drawn.

3.3.3 Parameters

Here we define values for the parameters used in our model. First we discuss the airlines, subsequently demand and finally the aid packages. We describe the values used for the three bailout types and the time horizon for the repayment.

The distance between two nodes, GCD_k, is computed as the great circle distance between two nodes in kilometers. In a similar fashion we compute the the elapsed travel time in minutes. We assume an average of eight block hours per day for long-haul flights in addition to ground and maintenance operations, which permits one flight on a representative day. Consequently, 30 flights are operated on average in a representative month for a long-haul, wide-body aircraft. In a similar manner, we assume that two short-haul connections are possible, resulting in an average of 60 flights per month for a short-haul, narrow-body aircraft. We define the seat capacity according to two reference aircraft, one for each type of operation. Specifically, we assume that short-haul flights are operated using a Boeing 737 aircraft configured to accommodate 180 seats while long-haul connections are operated using a Boeing 777 accommodating 375 passengers. The conversion

Table 3.4: Cities, macro-regions and carriers in our network

City/Macro-region	Hub carrier (IATA code)	LCC operating (IATA code)
London	British Airways (BA)	Ryanair (FR), Easyjet (U2)
Frankfurt	Lufthansa (LH)	
Amsterdam	-	
Madrid	-	
Milan	-	
Europe	Ryanair (FR)	
North America	American Airlines (AA)	-
Latin America	Latam (LA)	-
Africa	Ethiopian Airlines (ET)	-
Middle East	Emirates (EK)	-
Asia	China Eastern Airlines (MU)	-
Oceania	Qantas (QF)	-

parameter c_h converts the currency in the cost function to Euros and to actualize the parameters in Eq.(3.5)-(3.7) to reflect the CASK values reported in the 2019 airlines' performance reports. In the cost function $c_h = 0.0361$ for short-haul flights and $c_h = 0.0265$ for long-haul flights.

Demand levels are computed using 2019 traffic data from the Official Aviation Guide (OAG). Due to the highly seasonal trend in the pattern of aviation traffic, we calculated the demand as the average number of passengers during the months of February and August, the off-peak and peak month, respectively. Given the predominant nature of flights as round-trips and in order to shorten computational time, demand is assumed to be symmetric between each origin and destination pair. A load factor of 80% is assumed for of both business and economy class passengers for legacy carriers while this value is increased to 90% for LCCs in order to represent the higher load factors that characterize these airlines. The coefficient values in the multinomial logit model are reported in Table 3.5, according to two types of passengers s and whether the flight is continental or intercontinental. Starting from the coefficients published in the aviation literature (Adler et al., 2014a; Birolini et al., 2020) and reported in Appendix B, we calibrate these values by minimizing the error between the model estimates and the observed values in 2019, a period absent of any exogenous shock, in terms of fare, frequency and fleet size.

The magnitude of the aid is a function of the size of the airline. Consequently, the size of the bailout is estimated linearly, through an ordinary least squares (OLS) regression, using airlines' fleet size as a proxy for the carrier size. The regression is presented

Table 3.5: Multinomial logit parameters

	Continental		Intercontinental	
	Economy	Business	Economy	Business
Direct flight (β_{0s})	0.490	0.560	0.460	0.510
Service frequency (β_{1s})	0.610	0.690	0.700	0.773
Air fare (β_{2s})	-0.0252	-0.0096	-0.00182	-0.00072
Travel time (β_{3s})	-0.007	-0.014	-0.0007	-0.0010

Table 3.6: Bailout composition in scenario analysis

	Baserun	Grant-Grant	Loan-Loan	Equity-Equity	Grant-Loan	Grant-Equity	Loan-Equity
British Airways	-	Grant	Loan	Equity	Grant	Grant	Loan
Lufthansa	-	Grant	Loan	Equity	Loan	Equity	Equity
Others	-	Loan	Loan	Loan	Loan	Loan	Loan

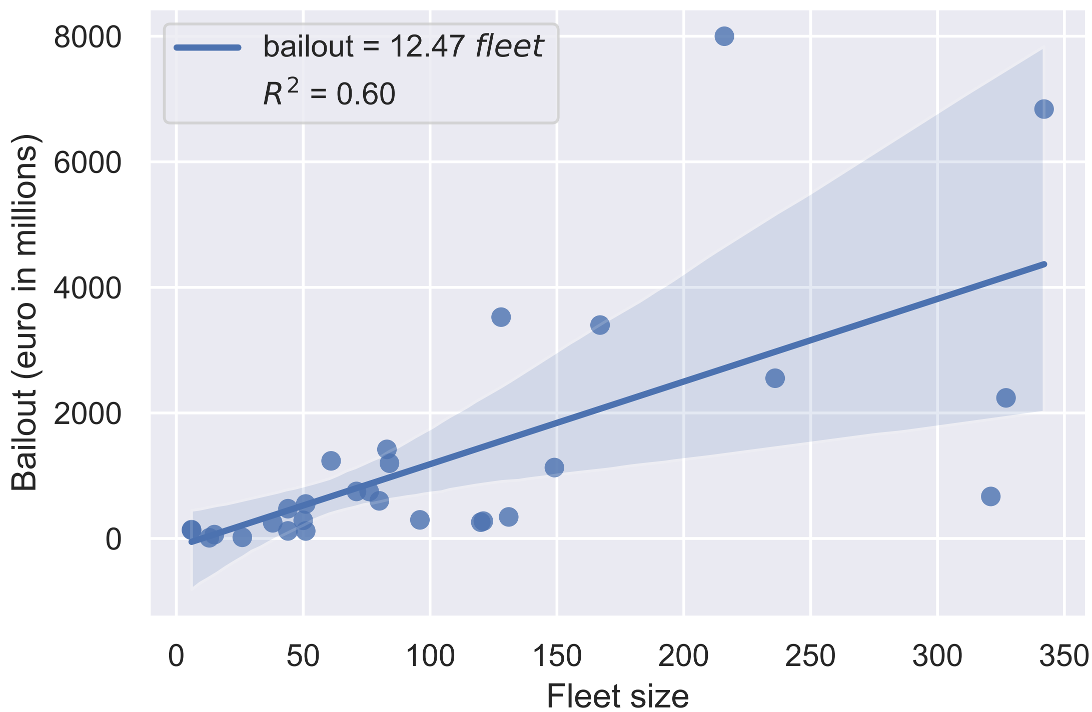
in Figure 3.2 and the specific details in appendix A. The magnitude of the bailouts correspond to an average of € 12.47 million per aircraft[3]. The interest rate for loans, ζ, is set at 2% and for equity, η_t, increasing over time up to 9%, both consistent with the rules of the European Commission (2021). The time horizon T for the analysis is set to six years, in line with most of the industry forecasts (ICAO, 2020; Airbus, 2022). We assume that airline demand will completely recover to pre-Covid-19 levels by 2025 in line with expectations (Airbus, 2022). Corporate taxation on airline profits is assumed to be 20.6% rate, as specified in the OECD (2020) report. The discount rate r of the bailout is defined according to the DG Competition (2008) report, and is set at a 2% level.

3.3.4 Results

We apply our model to seven different scenarios characterized by combinations of bailouts in order to explore the effects of the mix of bailout schemes on airline competition and social welfare. Scenarios are reported in Table 3.6. Without state aid, the European airlines would probably have not survived the pandemic, hence we focus on scenarios in which carriers receive a bailout. Many of the airlines that did not receive bailout either went bankrupt or filed for Chapter 11 protection (Avianca, Latam, Air Italy, Flybe, etc.). The pandemic caused the government to intervene, which in turn forced the airlines to stop operating in most cases. Specifically, we show how the two main European legacy carriers, British Airways (BA) and Lufthansa (LH), compete between themselves and all

[3]We are aware that using only the fleet size as a proxy for the bailout can pose some limitations. However, we aim to keep the model as general as possible and using fleet size we indirectly endogenise bailout magnitude as an airline decision.

Figure 3.2: OLS regression of bailout magnitude on airlines' fleet size



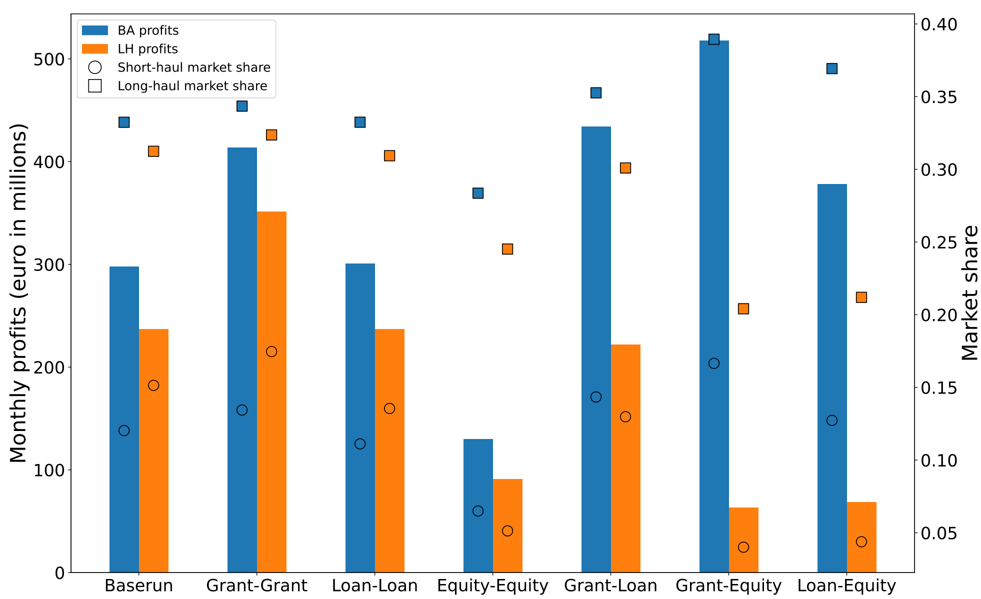
other carriers, under different bailout provisions. LCCs and non-European legacy carriers receive the actual bailout provided across all the scenarios besides the *Baserun*. Figures 3.3 to 3.5 and Table 3.8 present the results in terms of airline profits, airfares, service frequency and fleet size under the different scenarios. The *baserun* scenario validates the model by checking 2019 values in the absence of any type of bailout. Consequently, we analyse all the potential scenarios of different combinations of bailouts. We initialize our algorithm using 50 different randomly generated control sequences and we find consistent results across all cases (Table 3.7).

The scenario in which both legacy European operators receive a bailout through a grant, the *Grant-Grant* case, exhibits an increase in airline profits because the fiscal stimulus is not subject to any repayment mechanism. This scenario resembles the structure of the baserun case and does not alter the competition in the industry since both airlines receive the same type of bailout which is not passed on to the passengers, rather simply increases profits.

Table 3.7: Average *Baserun* values and maximum percentage variation (in brackets) of objective and decision variables of BA in 50 randomly generated control sequences

Profits (€m)	Fares				Frequencies	Fleet	
	Long-haul		Short-haul			Long-haul	Short-haul
	Business	Economy	Business	Economy			
298	3,080	1,595	355	254	463	113	63
(0.0025)	(0.0042)	(0.0001)	(0.0003)	(0.0005)	(0.0005)	(0.0008)	(0.0006)

Figure 3.3: European legacy carriers' monthly profits and market share



The scenario in which both airlines receive a loan, the *Loan-Loan* case, shows that both carriers are slightly less profitable than the Baserun case. This result is caused by a decrease in service frequencies due to the decision to ground part of their fleet in order to reduce operating expenses. Given this decision, the carriers experience a homogeneous decline in their market shares, which the non-European operators serve instead.

In the *Equity-Equity* setting, both European legacy carriers are subject to the buy-back of their shares and repayment of interest to the government. In this scenario, airlines report a severe reduction in profits of more than 60%. To contain costs, the two carriers ground most of their fleet, resulting in a sharp decrease in service frequency. In this scenario, airlines increase fares in both short and long-haul markets. These combined decisions show that airlines tend to focus more on the less competitive long-haul market, giving up market share on intra-continental routes when subjected to severe financial distress. It would appear that loan provision is relatively preferable for both airlines as compared to equity, although this depends on the assumption that the bailouts will be repaid within six years. If this were to prove insufficient, then the more expensive but longer term equity schemes might prove necessary.

The results suggest that government aid in the form of a grant, when the competing legacy carrier is subject to the repayment of a loan, as in the scenario *Grant-Loan*, distorts the competitive outcome. The airline given a loan is penalised compared to the airline receiving a grant, and is forced to reduce expenditures by decreasing the number of flights offered and reducing the size of its fleet. As a result of this distortion, the carrier subject to a loan increases the airfare in both short and long-haul markets in an attempt to increase revenues. The unbalanced bailout setting leads all carriers to acquire market shares at the expense of the airline that receives the loan.

A similar result, but greater in magnitude, is obtained when one of the two European legacy airlines receives a bailout in the form of a grant and the competitor is financed using equity instruments as in the *Grant-Equity* scenario. This combination of bailouts is the most competition distorting, leading to a severe contraction in profits and fleet size and an increase in airfares in the more competitive short-haul market for the carrier subject to the equity burden. The distortion results in the disappearance of the equity-financed carrier from the European short-haul market.

In the scenario *Loan-Equity*, that most closely resembles the British Airways - Lufthansa markets, the carrier receiving a loan takes advantage of the better financial position and

Table 3.8: Percentage variation in average airfares compared to Baserun

	Baserun (€ m)		Grant-Grant (%)		Loan-Loan (%)		Equity-Equity (%)		Grant-Loan (%)		Grant-Equity (%)		Loan-Equity (%)	
Long haul														
	BA	LH	BA	LH	BA	LH	BA	LH	BA	LH	BA	LH	BA	LH
Business	3,080	2,984	1	1	2	2	7	7	2	1	8	2	8	3
Economy	1,595	1,566	1	1	4	4	17	19	2	3	5	17	7	17
Short haul														
	BA	LH	BA	LH	BA	LH	BA	LH	BA	LH	BA	LH	BA	LH
Business	356	341	0	1	11	13	60	84	1	12	5	82	15	82
Economy	254	230	-1	-2	15	20	90	136	-1	20	-2	136	17	136

exploits market power with respect to the recapitalised airline. The partially renationalized airline is forced to ground most of its fleet in order to contain expenditures and decreases service frequency accordingly. As in the previous scenario, the recapitalised airline increases short-haul and long-haul fares. The carrier under greater distress thus continues to compete on the more profitable inter-continental markets, giving up most of the continental operations.

The comparison between European legacy airlines and LCCs, shown in fig 3.5, highlights the impact of the mixed use of bailout schemes on the subsequent competitive equilibria outcome on the intra-European market. This is motivated by the financial burden on the legacy carriers of repaying the bailout, since they were already under competitive pressure before the exogenous pandemic shock. The LCC market share may grow from 40% prior to the pandemic to above 60% in specific scenarios.

Once the equilibria have been computed for the seven scenarios, we evaluate the passengers, airlines and government surpluses and the overall social welfare, as shown in Equation (3.18). Specifically, we compare the six scenarios in which a bailout is provided to airlines against the Baserun case in the absence of any scheme. We note that during the Covid-19 pandemic, grant stimuli have been provided to small carriers alone and are of a marginal magnitude compared to the loans and equity offered to legacy airlines (appendix A). Due to the onerous nature of this type of aid on taxpayers, we consider it to be an unfeasible mechanism for bailing out large airlines. Table 3.9 presents the variation across the three welfare components as a function of the scenario analyzed. Our analysis suggests that airline surplus increases in all scenarios involving the use of a grant. This is especially visible in the scenario in which both airlines receive a grant, *Grant-Grant*, in which carriers benefit from government intervention and increase their profits by up to 25%. Conversely, airlines are worse of when subject to the repayment of interest on the bailout, particularly when they are subject to the repayment of an equity scheme. In

Figure 3.4: Long-haul fleet (left) and short-haul (right) for the two European legacy carriers

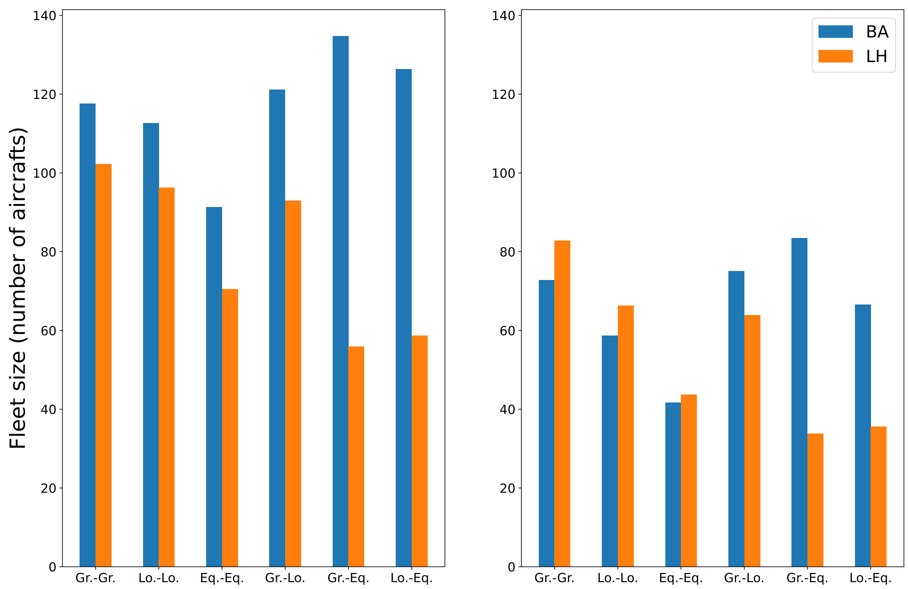


Figure 3.5: Market share of legacy and LCC carriers in the short-haul markets

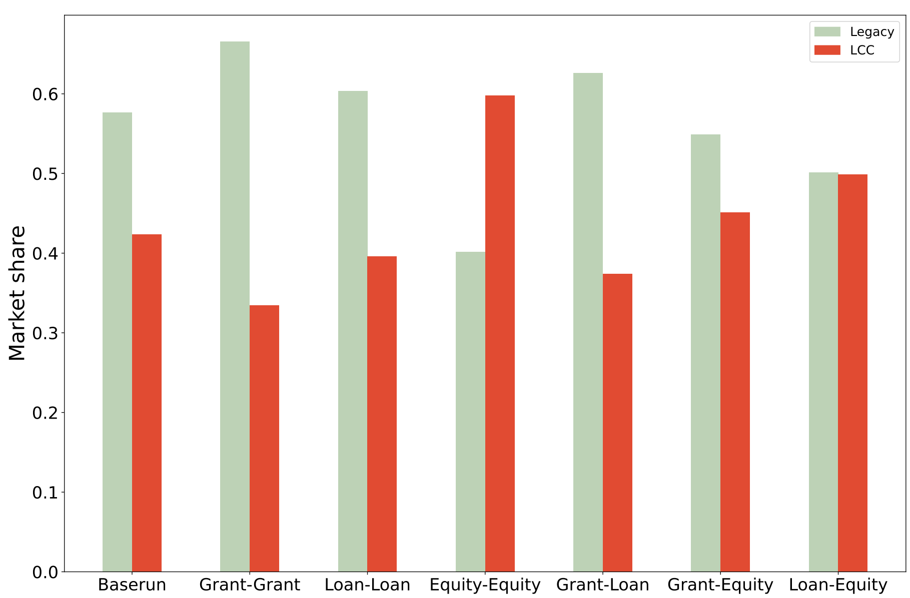


Table 3.9: Variation in the social welfare components

	Baserun (€ m)	Grant-Grant (%)	Loan-Loan (%)	Equity-Equity (%)	Grant-Loan (%)	Grant-Equity (%)	Loan-Equity (%)
Airline surplus	671.86	24.87	-8.49	-55.49	9	-2.06	-21.95
Consumer surplus	3623.71	-16.23	-21.18	-45.57	-19.24	-35.58	-36.88
Government surplus	226.07	-37.79	103.9	300.26	32.36	96.91	174.48
Social welfare	4521.65	-11.2	-13.04	-29.75	-12.46	-23.97	-24.09

the scenario *Equity-Equity*, in which the highest variation occurs, airlines are worse off by 55% compared to the Baserun case. Our results suggest that bailing out carriers with a debt or equity instrument, results in a loss of welfare for passengers too. This downturn in surplus is driven by the increases in airfares and by the reductions in service frequencies, impacting the perceived utility from flying. This reduction is particularly severe in the *Equity-Equity* scenario, suggesting a reduction of 46% in passenger surplus. The government surplus is positive in all the intervention scenarios with the exception of the case when both airline are rescued through a grant (*Grant-Grant*) hence are not subject to any repayment. Notably, our analysis suggests that the most profitable scenario for the government is renationalization of the airline, enabling government participation in airline dividends and financial inflows through the interest rate repayment. This scenario results in a 300% increase in surplus compared to the Baserun case. Our welfare analysis suggests that the most distorting scenario is that in which both airlines are renationalized through equity, reaching a loss in welfare up to 30% compared with the Baserun scenario. However, the airlines are likely to survive thus ensuring the repayment of the taxpayers' bailouts. In summation, our analysis suggests that the optimal intervention, which also ensures a level playing field, may be to provide loans to all carriers. This intervention results in a marginal loss of 13% in social welfare compared to the Baserun scenario and it is mainly driven by the slight contraction in airline profits and passenger surplus. However, these negative variations are compensated by an increase in government surplus from the repayment of bailout interests. Despite the drop in social welfare caused by the failure of an entire industry due to an exogenous shock, governments need to make a decision whether public money should help the industry during the pandemic. This form of insurance balances the substantial risk of private firms with the general public, assuming that the date and duration of the exogenous shock cannot be predicted. Overall, if the general public share the risk of the pandemic, they found they there will better off given that airlines survive and repay the interests on their debt. The results of our model are reflected in what happened in the real world (Darroch et al., 2022).

3.4 Conclusions and future directions

In this research, we develop a game-theoretic model capable of representing the competition between airlines under different government aid packages. In our model formulation, not only do carriers strategically set service frequency and airfares, but they also select the number of aircraft to operate. We apply our model to the recent Covid-19 outbreak in order to assess the potential market distortions induced by state aid. We develop an algorithm that estimates the Nash equilibria across seven scenarios, characterized by different combinations of bailouts.

Our analysis suggests out that the airline industry has been severely affected by the uncoordinated provision of state aid, leading to an unlevel playing field for the European carriers and a likely welfare reduction of approximately 24%. In particular we compare two airlines of similar size prior to the pandemic, and show that unequal bailout policies will likely disrupt the profitability and structure of the two carriers. Successively, results have shown that it is possible to achieve a socially preferable outcome through a coordinated and homogeneous bailout mechanism across the Member States. Our findings are consistent with the results of the analysis of Bianchi (2016). We demonstrate that the European Commission would have been more efficient in requiring all carrier bailouts to be in the form of loans hence limiting the negative effects on social welfare. Furthermore, our analysis suggests that the financial burden of any type of aid on European legacy carriers results in a gain in market share for LCCs operating short-haul flights within Europe. This highlights how the rescue policies enforced autonomously by European Member States may harm their flag carriers, to the advantage of low-cost operators in the European market and of non-European airlines in the long-haul market. As Kahn (1988) and Rose (2012) emphasised, deregulation of the airline industry has been a success in terms of efficiency and competition. The inefficiencies we highlight are the result of the failures drawing from additional government interventions.

Future directions for research consist of several options since this paper represents the first attempt to model the bailout in the airline industry in a competitive game-theoretic network environment. It could be interesting to evaluate the effects that government involvement, as an airline shareholder, may have on carrier decisions to act in the country's interest, departing from the assumed profit maximisation strategy paradigm. It would also be interesting to address the impact of bailouts on the strategic behaviour of carriers within alliances and the possible reshaping of interline and codeshare agreements. Another interesting research question would be to assess the impact of the market equilibrium on the aviation supply chain, including airports and air navigation service providers.

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Appendix A

Government support for airlines in Europe

Country	Airline	Aid size (€ m)	Type of aid
Austria	Austrian Airlines	450	Grant and Loan
Austria	Condor	550	Loan
Belgium	Brussels Airlines	290	Loan
Croatia	Croatia Airlines	11.7	Grant
Estonia	Nordica	30	Equity
Latvia	Air Baltic	250	Equity
Finland	Finnair	1,237	Equity
France	Air France	8,000	Loan and Equity
France	Corsair	141	Grant
Germany	Lufthansa	6,840	Loan and Equity
Germany	TUI	3,526	Loan
Greece	Aegean	120	Grant
Italy	Alitalia	297	Grant
Netherland	KLM	3,400	Loan
Norway	Norwegian	277	Loan
Norway	Wideroe	121	Loan
Poland	Lot	750	Loan and Equity
Portugal	SATA	133	Loan
Portugal	TAP	1,200	Loan
Romania	Blue Air	62	Loan
Romania	TAROM	19.3	Loan
Spain	Air Europa	475	Not confirmed
Spain	Iberia	750	Loan
Spain	Vueling	260	Loan
Sweden, Denmark	SAS	1,130	Equity
Switzerland	Swiss (Lufthansa)	1,420	Loan
UK	British Airways	2,553	Loan
UK	Easyjet	2,240	Loan
UK	Ryanair	670	Loan
UK	Wizz air	344	Loan

Source: self collected from European Commission (2021)

Appendix B

Logit coefficients used in other studies as starting point for model calibration

Birolini et al (2020)			
Selected variables	All	Medium-haul	Long-haul
Frequency	0.011	0.0104	0.0111
Price (IV)	-0.0159	-0.0171	-0.0012
Flight time	-0.0054	-0.0113	-0.004
Type of service	2.5921	2.232	2.4272
Inclusive value	0.6971	0.8307	0.7516

Adler et al (2014)				
Selected variables	European routes		International routes	
	Business	Leisure	Business	Leisure
ln (log frequency)	0.5220	0.4005	0.4176	0.1602
Total price	-0.0018	-0.0043	-0.0003	-0.0018
Total trip time	-0.15	-0.053	-0.0050	-0.0018

Chapter 4

Competing on emissions charges

4.1 Introduction [1]

Despite the increased understanding in recent years of the negative impacts derived from emissions produced by industries, an effective and globally accepted emissions curbing mechanism has not yet been implemented. Many governments developed unilateral emissions reduction schemes, often in the form of taxes or cap-and-trade policies, to regulate emissions production and to reduce the negative effects of climate change. However, the lack of coordination among countries' policymakers generates sub-optimal outcomes. A clear example is given by the presence of multiple, overlapping policies to address aviation emissions, such as the European Emissions Trading Scheme (EU-ETS) applied alongside Member States' ticket taxes and the Carbon Offsetting and Reduction Scheme for International Aviation (CORSIA). Another source of inefficiency arising from the lack of coordination between countries manifests itself in the form of emissions leakage from heavily regulated countries to those jurisdictions or sectors in which schemes are less strict or non-existent (Baylis et al., 2013; Nordhaus, 2015; Perino et al., 2019). Furthermore, other market failures such as firms' market power will result in a departure from the standard first-best formulation in which government intervention can address negative externalities by imposing a Pigouvian tax, even in the presence of perfect coordination between regulators (Pels and Verhoef, 2004).

This calls for a game-theoretic framework to analyse how non-cooperative regulators at different administrative levels will set environmental policies strategically and how firms

[1] This chapter is based on the joint work with Nicole Adler and Gerben de Jong.

will subsequently react to these mechanisms. Given the complexity and numerous forces in the aviation industry, there is a need to represent a realistic framework capable of including these exogenous components. We will focus on the case of airline environmental regulation because the concerns about the impact of aviation emissions are rapidly growing in policymakers' interest and the fragmentation in the aviation environmental regulatory setting offers the right context to be analysed using a game-theoretic approach.

Among the different sectors, the transport industry is one of the largest sources of pollution, accounting for approximately 37% of the carbon produced. Within the transportation domain, the aviation industry currently produces 5% of the worldwide anthropogenic carbon dioxide (CO_2) emissions, and this is expected to continue to increase by 2050 if air transport continues to grow following this trend (Lee et al., 2021; Kwan and Rutherford, 2015). In the absence of global environmental regulation, decision-makers at the local, national and supra-national levels have mandated various environmental policies in an attempt to control aviation emissions (Larsson et al., 2019). However, the extent and environmental efficiency of these measures differ significantly between countries. Furthermore, since airlines operate globally, policy makers need information on how airlines respond to different (sometimes overlapping) policies, to ensure that their interventions balance the carbon footprint of aviation with its wider economic and connectivity benefits.

To mitigate the aviation environmental footprint two market-based policies are currently in place: the EU-ETS and the Carbon Offsetting and Reduction Scheme for International Aviation (CORSIA), proposed by the International Civil Aviation Organisation (ICAO). The initial scope of the ETS required all airlines serving airports in the European Economic Area (EEA) to acquire emission allowances, but flights to and from the non-EEA were excluded after facing substantial opposition (Leggett et al., 2012). CORSIA was developed with the goal of compensating aviation emissions and reaching carbon neutral growth starting from 2020 on international routes, but is currently still in its voluntary pilot phase. Under this global policy, carriers can commit to compensating the tons of carbon they produce through emission abatement projects. In addition to these market-based policies, some EU member states have implemented ticket taxes (Faber and Huigen, 2018). These taxes usually do not differentiate between the emission efficiency of aircraft and therefore provide limited incentives for airlines to replace their fleets or change their operations, although they may affect network decisions (e.g., destinations and frequencies). Finally, at the most local level, around 60% of the airports in Europe levy environmental charges to foster airlines to acquire quieter and lower-emission aircraft (European Commission, 2017; EASA, 2019). With some exceptions (Sweden), these charges focus on local pollutants and do not consider global climate impacts.

The literature on environmental emission charges and pollution curb mechanisms has grown largely in the last decades (Marron and Toder, 2014; Nordhaus, 2015, 2018; Stiglitz, 2019). Marron and Toder (2014) give insight into how a carbon tax should be implemented and administered to work efficiently, focusing on the optimal usage of generated revenues. In his paper on Climate Clubs, Nordhaus (2015) examines the conditions that allow the existence of cooperation among countries in curbing emissions, avoiding free-riding. The results of his work show the non-existence of a climate coalition without sanctions on international trade. In his consequent paper, Nordhaus (2018) proposes a model to assess the uncertainties related to climate change and take them into account in policy implementations. He shows that by introducing uncertainty into existing emissions curb mechanisms, at the current abatement level it would be impossible to meet the $2°C$ temperature increase target in 2050 as ratified in the Paris Agreement. Stiglitz (2019) revises the implications of the Stern-Stiglitz report by considering also redistributional, innovation, and uncertainty concerns. He shows that the non-discriminating carbon price estimated in the report, despite not considering the aforementioned concerns, will still result in a welfare increase if applied in defining environmental policy. Timilsina (2022) provides a comprehensive literature review of studies on carbon charges since the 1970s by classifying the literature by the adopted methodology.

Sgouridis et al. (2011) analyse the impact of five different emission policies on civil aviation. Through simulations, they found that none of the five policies can maintain the demand level while reducing the emissions on its own, but an overall positive effect is reached if the policies are combined. Kahn and Nickelsburg (2016) address the impact of fuel prices on the composition and utilisation of the airline fleet in an empirical way. They document that in periods when real jet fuel prices are higher, airlines substitute miles flown to more fuel-efficient aircraft, scrap older fuel-inefficient planes earlier and fly all aircraft at a lower speed. The study by Oesingmann (2022) assesses the effect of ETS on aviation demand. Using a Poisson pseudo-maximum likelihood framework in conjunction with a gravity model, the author found no significant effect of EU ETS in dampening demand and reducing emissions. The author also controls for the effect of additional aviation taxation and found a negative impact on the passenger demand. Fageda and Teixido-

Figueras (2020) explore the effects of EU ETS on aviation supply assessing the impact of carbon pricing on the aviation industry considering several countries. They found that EU ETS can reduce the expansion of air traffic in terms of service frequency and drives airlines toward operating through aircraft with higher capacity. In a recent paper, de Jong (2022) investigates how the EU-ETS instigates airlines fleet replacement and the consequent net environmental benefits. Using a survival analysis approach, he shows that the incomplete implementation of the EU ETS (only on intra-European routes) leads to the positive effects of a fleet upgrade for smaller, short-haul aircraft being compensated by a longer utilisation of the more bigger and more polluting long-haul aircraft, generating an additional form of carbon leakage.

Game-theoretic competition among airlines has been addressed in several works since the early 1990s in terms of theoretical and computational contributions (Hansen, 1990; Hong and Harker, 1992; Dobson and Lederer, 1993; Hendricks et al., 1999; Adler, 2005; Adler et al., 2010; Vaze and Barnhart, 2012; Adler et al., 2014b). Among these works, the study by Hansen (1990) defines a non-cooperative game where airlines compete in service frequency within a hub-and-spoke network. Passengers' preferences allow for deriving market shares by using a discrete choice model. A market-resembling point of quasi-equilibrium is found. Dobson and Lederer (1993) develops a two-stage game framework in which the equilibrium is derived considering only one type of passenger and symmetric hub-spoke networks, in a context where airlines choose airfares and service frequency. Under the assumption of a fixed plane size and no traffic originating from the hub, they develop a heuristic and found a solution for a small size problem. Adler (2005) studies competition between hub-spoke networks using a non-cooperative two-stage game setting. In this framework, airlines select which destinations to serve in the first stage, while, in the second stage, they compete in service frequency and airfares. Adler et al. (2010) and Adler et al. (2014b) include a nested-logit model, based on discrete choice formulations, to define market shares for the airlines competing in the game, starting from passengers' demand and assess the competition between airlines and other transport modes.

Due to growing interest in aviation-related emission mitigation measures, an increasing body of literature addresses the impact on airline competition resulting from the implementation of environmental policies aimed at reducing aviation emissions. The potential emission savings and competitive effects of these policies have so far been studied without considering airline responses, rather than assuming that airline fleets and networks remain fixed. Yuen and Zhang (2011) explore the effects on competition induced by unilateral greenhouse gas regulations. By developing a two-stage model, they show that emissions regulations affect more domestic carriers than foreign ones and can result in an environmentally inefficient network structure. The work proposed by Brueckner and Zhang (2010) sheds light on the implication of an aeronautical charge on competing airlines as a duopoly, taking into account travellers' preferences, airline characteristics, and network structure. They found that an environmental charge has a positive effect on overall welfare, making airlines seek more fuel-efficient aircraft and redistributing their fleet, fares, and network more efficiently. Vespermann and Wald (2011) analyse the impacts derived from the inclusion of the aviation industry in the European ETS mechanism. By adopting a simulation approach, they show that emissions mitigation and competition distortion are mainly driven by the price of carbon allowances. Sheu and Li (2014) proposed a game-theoretic analysis to investigate the impact on airline competition in a duopoly when EU ETS carbon allowances and the possibility of long-term environmental efficiency investments are introduced. They find equilibrium strategies, both analytically and numerically, in a symmetric duopoly environment for different allowances and investment scenarios. Zheng et al. (2019) define a theoretical framework to investigate the propensity that airlines have to collude and form cartels to purchase carbon offsets. They allow for two types of market-based mechanisms, legally binding and non-binding, and found that airlines are more willing to collude in offset purchases under the latter mechanism.

Competition between transport regulators is an area that has not been explored extensively in the literature. Most of the papers in the literature are related to regulatory competition in terms of congestion pricing. Pels and Verhoef (2004) explore the impact of congestion charges at two airports located in different countries. Using a stylised analytical model, they proved that applying directly a Pigouvian tax is detrimental to welfare and that an optimal congestion policy requires addressing airlines' market power first. They test their model by taking into account both coordinated and competing regulators, which aim to maximise their network welfare by setting a congestion toll. In the coordinate regulators' case, they show that, given airlines' market power exceeding the congestion effect, the optimal toll assumes a negative value for a subsidy to maximise welfare. Differently, in the uncoordinated scenario, the regulator enters a tax competition raising charges above the congestion produced, resulting in an overall welfare loss. Similarly, Silva et al. (2014) analyse airline competition when tolls per passenger and per route congestion are taken into account. Specifically, they model congestion tolls as the result of competition between welfare-maximising regulators. They found that the socially optimal welfare allocation can be different from the regulated one due to market inefficiencies. Moreover, they prove this efficiency gap for both the first and second-best structures. The review of the literature done in De Borger and Proost (2012) offers an overview of the papers that address the competition of horizontal and vertical regulators in the transport sector.

The aviation industry is severely pervaded by market distortions that interfere with an efficient output. Brueckner (2002) explore how the market power can lead to sub-optimal congestion correction policies, resulting in a welfare reduction. The exploitation of the structure of the airline network, that is, hub-and-spoke and point-to-point operations, can distort an optimal allocation (Brueckner et al., 1992; Borenstein, 1989). Brueckner et al. (1992) in their paper investigates how economies of densities resulting from a hub-and-spoke concentration affect airlines fares. They prove that this network structure leads to lower fares for the spokes served from the hub. In addition to this variation in the fares at the destination points, Borenstein (1989) shows that the airlines that dominate a hub exert market power by increasing the prices for passengers departing from these airports. Another distortion playing an important role is the Mohring effect (Mohring, 1972). This phenomenon, prevalent in the urban transport sphere, has not been extensively addressed in the aviation literature. The Mohring effect happens when an increase in service frequency increases also travellers' utility. Consequently, the demand increases, requiring an even higher frequency to serve it, generating a positive feedback effect. Distortions can also arise from carbon leakage across regions (Perino et al., 2019; Carbone, 2013). This effect will redirect most pollutant operations toward less-regulated jurisdictions and undermine the effectiveness of carbon policies.

The contribution of this paper is to develop a game-theoretic model that helps to assess the impact of environmental policies on the aviation industry, taking into account both airline and regulatory competition. Specifically, our model considers how airlines respond to policies instigated by multiple, non-cooperative policymakers at different administrative levels that set rules according to their objectives. More in-depth, our model gives the possibility to analyse and understand policy implications deriving from the competition of multiple regulators and comparing them to the implementation of a global scope policy. Furthermore, we investigate how overlapping policies imposed by different regulators interact with each other and their combined effect on welfare. We identify the case in which a carbon charge may result effectively and those in which the implementation of such a policy would fail due to the divergence in regulator objectives. To the best of our knowledge, this game represents a novelty in the (air) transportation literature.

Table 4.1: Literature

	Type of competition	Network structure	Airlines entry/exit	Environment	Demand function	Analytical/ Numerical	Regulators competition	Aircraft version environmentally efficient
Borenstein (1989)	Price	HS	No	No	Exogenous	Empirical	No	No
Hansen (1990)	Price/Freq.	HS/FC	No	No	ML	Numerical	No	No
Brueckner et al (1992)	Price	HS	No	No	Exogenous	Empirical	No	No
Hong & Harker (1992)	Price/Freq.	FC	No	No	ML	Numerical	No	No
Dobson & Lederer (1993)	Price	HS	No	No	ML	Numerical	No	No
Hendricks et al (1999)	Price	HS	Entry	No	Linear	Analytical	No	No
Brueckner (2002)	Price/Freq.	-	No	No	-	Analytical	No	No
Pels & Verhoef (2004)	Freq./Tax	FC	No	No	Linear	Analytical	Yes	No
Adler (2005)	Price/Freq.	HS	Exit	No	ML	Numerical	No	No
Adler et al (2010)	Price/Freq.	HS	Exit	Yes	NL	Numerical	No	No
Brueckner & Zhang (2010)	Price/Freq./Eff./Load	HS/FC	No	Yes	Linear	Analytical	No	Yes
Yuen & Zhang (2011)	Freq./Tax	HS	No	Yes	Linear	Analytical	Yes	No
Vespermann & Wald (2011)	-	-	No	Yes	Endogenous	Numerical	No	Yes
Vaze & Barnhart (2012)	Freq.	HS	No	No	S-curve	Numerical	No	No
Silva et al (2014)	Freq./Pax./Size/Tax.	HS	No	No	Linear	Analytical	Yes	No
Adler et al (2014)	Price/Freq./Size	HS/FC	No	No	NL	Numerical	No	No
Sheu & Li (2014)	Price	-	No	Yes	Linear	Analytical	No	No
Zheng et al (2019)	Freq./Allowances	-	No	Yes	Linear	Analytical	No	No
Our paper	Price/Freq./Tax	HS/FC	Exit	Yes	ML	Numerical	Yes	Yes

The remainder of this paper is structured as follows. In section 4.2 we formally define our model with all the elements that characterise it. In section 4.3 we present an application of our model to a representative global network. Concluding remarks are provided in section 4.4.

4.2 Methodology

In this section, we define our game-theoretic model as a two-stage Nash game with perfect information. The set of players in the first stage is characterised by the different regulators composed of the governments of the countries in which airlines are based and/or supranational decision-makers, i.e. ICAO and EU. In the first stage, each regulatory body aims to maximise the social welfare of the area of its interest by deciding the level of environmental taxation applied. By setting a higher environmental tax, the regulator can reduce (global) environmental damages, but this may come at the costs of (local) consumer and producer surplus. Consequently, regulators compete on the entire level of emissions produced considering how much they are susceptible to the environmental damage resulting from these emissions. In the second stage, airlines compete with each other in price and service frequency through their best response functions, pursuing profit maximisation. To respond to changes in the climate policies environment, airlines can scrap inefficient aircraft and replace them with more environmentally friendly ones, fly their high-emission aircraft less, reallocate their high-emission aircraft to routes with less environmental taxation or reduce frequencies on regulated routes.

Table (4.2) summarises the notation used throughout the paper.

Table 4.2: Notation

Sets and Indices	
$\mathcal{A}$:	Set of airlines; indexed by a
$\mathcal{H}$:	Set of the type of flight (i.e. Short and long haul flight); indexed by h
$\mathcal{K}$:	Set of all legs in the network; indexed by k
$\mathcal{N}$:	Set of airports nodes; indexed by i, j
$\mathcal{R}$:	Set of regulators; indexed by r
$\mathcal{T}$:	Set of passenger types; indexed by t
$\mathcal{V}$:	Set of aircraft versions; indexed by v
Parameters	
β_{0t}:	Direct connection parameter in the utility function for passenger type t choosing airline a
β_{1t}:	Frequency parameter in the utility function for passenger type t choosing airline a
β_{2t}:	Price parameter in the utility function for passenger type t choosing airline a
β_{3t}:	Time parameter in the utility function for passenger type t choosing airline a
C_{ka}:	Cost for airline a to serve leg k
d_{ijt}:	Demand between nodes i and j for passenger type t
δ_{ija}	1 if the connection between i and j operated by a is direct, 0 otherwise
ϵ_{ijta}:	Random component of utility between nodes i and j for passenger type t and airline a
$\bar{f}_h$:	Average utilization of aircraft in the time period by type of flight h
γ_k:	Great circle distance of leg k
s_{kv}:	Seats available on flights served by a on leg k per aircraft version v
ϕ_{hv}:	Fuel consumption of aircraft version v for aircraft type h
ψ:	Fuel price in dollar per ton of kerosene
o_{hv}:	Ownership cost for aircraft type h version v
co_2:	Conversion factor between fuel consumption and co_2 produced
$opcs$:	Share of operating costs without fuel and ownership costs
ρ_{hv}:	Initial purchase price of an aircraft of type h version v
σ_{hv}:	Salvage value of an aircraft of type h version v at the end of the time period
i:	Interest rate
n:	Time periods
ξ:	social cost of carbon
Decision variables	
θ_r:	Fuel tax imposed by regulator r
f_{ka}:	Service frequency on leg k for airline a
p_{ijta}:	Fare set for itinerary from i to j and passenger type t for airline a
x_{hva}:	Number of aircraft owned of type h version v for airline a
Auxiliary variables	
$m_{ijta}(f_{ka}, p_{ijta})$:	Market share of airline a for itinerary from i to j and passenger type t
V_{ijta}:	Systematic component of utility between nodes i to j per passenger type t of airline a
z_{ija}:	Minimum frequency over an indirect itinerary from i to j for airline a

4.2.1 Network design

We define a hub-and-spoke network, $G(\mathcal{N}, \mathcal{K})$, in which each carrier has a hub base in its home country. Each airport represents a node of the network belonging to the set $\mathcal{N}$. The hubs are connected to the spokes through ordered legs within the set $\mathcal{K}$, allowing indirect connections between the spokes passing through the hub airport. In the current setting, airlines do not cooperate with code-sharing behaviours or interlining practises.

Given the network configuration, airlines are subject to different levels of climate policies imposed by regulators. Specifically, we aim to analyse different regulatory settings allowing for both a multi-regulator competitive environment and a single-regulator monopolistic setting. Given the network of our model, regulators set a carbon tax on each ton of CO_2 generated by a flight departing from an airport under their authority, taking into account the variant of the aircraft (i.e., emission efficiency) so as to incentivise the usage of more efficient aircraft.

The sets belonging to the influence area of a specific regulator are defined as:

$$\mathcal{N}^r = \{i^r, j^r | i^r, j^r \in \mathcal{N}, i^r \text{ and } j^r \text{ are nodes in the area regulated by } r\}$$

$$\mathcal{A}^r = \{a^r | a^r \in \mathcal{A}, a^r \text{ is an airline based in the area regulated by } r\}$$

$$\mathcal{K}^r = \{k^r | k^r \in \mathcal{K}, k^r \text{ is a network leg served by an airline based in an area regulated by } r\}$$

4.2.2 First stage

In the first stage, regulators aim to maximise the social welfare of the area under their influence. Welfare is defined over four main components: passenger surplus, producer profits, environmental damages and governmental income from environmental taxation. Formally, the social welfare function is defined as follows

$$\begin{aligned} \underset{\theta_r}{Max}\, SW_r = & \sum_{i^r jt} d_{i^r jt} \frac{1}{-\beta_{2t}} ln \left(e^{V_0 + \sum_a V_{i^r jta}(f^*_{kva}, p^*_{i^r jta})} \right) \\ & + \sum_{a^r \in \mathcal{A}^r} \pi_{a^r} \left(f^*_{k^r va^r}, p^*_{ijta^r}, x^*_{hva^r}, \theta_r \right) \\ & + \sum_{k^r va} \varepsilon_{k^r v} f^*_{k^r va} \theta_r - \eta_r \sum_{kva} \varepsilon_{kv} \xi f^*_{kva} \end{aligned} \tag{4.1}$$

s.t.

$$-\infty < \theta_r < +\infty \;\; \forall\, r \in \mathcal{R} \tag{4.2}$$

where

$$\varepsilon_{kv} = \gamma_k \phi_{hv} co_2$$

is the ton of CO_2 produced on a flight leg k by a specific version of aircraft v.

In Eq.(4.1) the first element represents the consumer surplus, expressed as the log-sum of the utility of passengers departing from regulator jurisdiction [2], and the second is the profit generated by airlines based in the regulator area, the third is the income from the carbon charge imposed on CO_2 generated on the regulated legs, and the last element expresses the share η_r of the overall social cost of emissions that affect the regulator. The decision variable for the regulatory entity is the value θ_r to charge for each ton of carbon originating from a flight departing from its jurisdiction, taking into account the airline's responses to carbon charges in the second stage. Eq.(4.2) express the domain of the carbon charge. In the case of a negative value, the charge assumes the form of a subsidy to airlines.

4.2.3 Regulators competition

Regulators compete to maximise their social welfare taking into account environmental damage. The aviation industry of each regulator contributes to the total amount of emissions produced. However, not all regions are affected in the same way by emissions. Specifically, we allow for different degrees of risk exposure through the η_r parameter. In this way, regulators that are interested in their region's climate damage have the incentive to free-ride on the emissions reduction achieved by the actions of regulators of more climate-vulnerable regions. All CO_2 emissions generated by civil aviation bear a social cost common to all regulatory bodies, namely the social cost of carbon and represented by the parameter ξ. This social cost is homogeneous between regions given the global impact of carbon emissions on the environment. Consequently, regional regulators not only take

[2] Given that the consumer surplus is computed considering only passengers departing from airports in regulator jurisdiction, consumer surplus of trans-Atlantic passenger is accounted half for each regulator if we assume roundtrip flights.

into account damage to their regions, but they also influence other regions' climate damage through their decisions. In our game, regulators can trade off environmental externalities with their region passengers' surplus and carriers' profits by deciding the level of taxation on CO_2 in their jurisdiction. In this way, the regulator's decision is strictly connected to other regulators' actions and forming competition at a regulatory level. The results of this first-stage competition are inherited in the second stage by the competing airlines.

4.2.4 Market share model

We assume that passengers are utility maximisers in selecting the airline and itinerary for their travel. According to McFadden (1974) utility can be decomposed into a systematic element, V_{ijsa} and a random one, ϵ_{ijsa}, as follows:

$$U_{ijta} = V_{ijta} + \epsilon_{ijta}, \ \ \forall i, j \in \mathcal{N}, \ t \in \mathcal{T}, \ a \in \mathcal{A} \tag{4.3}$$

The systematic component is defined as follows:

$$\begin{aligned} V_{ijta} = \beta_{0t}\delta_{ija} + \beta_{1t} ln \left(1 + \min_{k^* \in \mathcal{K}^*} (f_{k^*a})\right) + \beta_{2t} p_{ijta} + \beta_{3t} \tau_{ija}, \\ \forall i, j \in \mathcal{N}, \ t \in \mathcal{T}, \ a \in \mathcal{A} \end{aligned} \tag{4.4}$$

where δ_{ija} is the component of utility associated with a direct connection, the second term represents the utility of a higher service frequency, the third element is the disutility of paying the ticket fare, and the last represents the loss of utility generated by the travel time τ_{ija}. As Hansen (1990) suggested in his work, the use of frequency logarithms is suitable to represent the decreasing return of utility of a higher service frequency. This element represents the Mohring in the utility function. effect Moreover, we use the minimum frequency among all the legs composing an itinerary to select the frequency that acts as the bottleneck of the full route. Moreover, we define the set of legs belonging to an itinerary and the set of regulators with jurisdiction on a node as:

$$\mathcal{K}^* = \{k^* | k^* \in \mathcal{K} \text{ is a network leg belonging to itinerary } i, j \text{ for airline } a\}$$

The random component is assumed to be independently and identically distributed according to a Gumbel distribution. Consequently, demand can be split between airlines into their market shares through a multinomial logit model (MNL):

$$m_{ijta} = \frac{e^{V_{ijta}}}{e^{V_0} + \sum_{a' \in \mathcal{A}} e^{V_{ijta'}}}, \ \ \forall i, j \in \mathcal{N}, \ t \in \mathcal{T}, \ a \in \mathcal{A} \tag{4.5}$$

where the term V_0 is the utility associated with the outside option from fly, specific for each market.

4.2.5 Airline operating costs

According to Swan and Adler (2006), the direct operating cost of the airline can be defined through a cost function that differentiates between long- and short-haul flights. We modify this function to unravel the components of fuel, ownership, and remaining operating costs. The reason why we do this process is two-fold. First, by separating fuel costs, we can better tailor the cost functions to represent more accurately the increased share of fuel costs in the airline operating costs by using recent fuel prices. Secondly, we also need to separate ownership costs because they depend on the number of aircraft deployed, which is a decision variable for the airline. Thus, we define ownership costs directly in the objective function of the airline. We actualise the costs at the 2019 values to take into account the increase in inflation and the variation in operating costs in recent years and to convert the value of the function from the dollar to the euro. Furthermore, we account for low-cost carriers by assuming that they face half of the operating costs incurred by legacy airlines.

$$C_{kv} = \begin{cases} [\psi \phi_{hv} \gamma_k + opcs(\gamma_k + 722)(s_{kv} + 104)\$0.019 & \text{if } \ k \in \mathcal{K}^s \\ [\psi \phi_{hv} \gamma_k + opcs(\gamma_k + 2200)(s_{kv} + 211)\$0.0115 & \text{if } \ k \in \mathcal{K}^l \end{cases} \tag{4.6}$$

where

$$\mathcal{K}^s = \{k^s | k^s \in \mathcal{K} \text{ are the short-haul legs served}\}$$

$$\mathcal{K}^l = \{k^l | k^l \in \mathcal{K} \text{ are the long-haul legs served}\}$$

The first element of Eq.(4.6) specifies the cost of fuel. This is a major component of airline operating costs representing around 30% of costs (IATA, 2019). It is computed considering the distance of the flight γ_k, the fuel consumption ϕ_{hv} of the flight according to its type and the version of the aircraft, and the price of a ton of fuel ψ based on the

2019 values. The second term of the function represents the operating costs, excluding fuel and ownership costs. We compute this element by weighing the function by the share of the cost components they address in Swan and Adler (2006) and excluding ownership and fuel costs. Under this definition, the operating costs of each flight solely depend on the characteristics of the leg and the specific version of the aircraft used.

4.2.6 Ownership costs

The monthly cost of owning an aircraft is approximated by the equivalent annual capital costs divided by the number of months per year:

$$o_{hv} = \frac{(\rho_{hv} - \sigma_{hv})\left(\frac{i(1+i)^n}{(1+i)^n-1}\right) + \sigma_{hv} i}{12} \tag{4.7}$$

where ρ is the initial purchase price of an aircraft; σ is the salvage value at the end of the n-year time period; and i is the interest rate. We select four (most) commonly used aircraft models as reference models for the different types of aircraft in our game (see Table 4.4).[3] The purchase prices of these aircrafts are based on the average list prices published on the websites of aircraft manufacturers (Airbus, 2018; Boeing 2022). Salvage values are derived by assuming straight-line depreciation in 30 years, with a service life of 20 years – that is, the salvage value is equal to one third of the purchase price. We assume an interest rate i of 10%. We further assume a discount factor on the purchase price of an aircraft. The offering of a discount on the retail price of the aircraft to airlines is a common practise in the aviation industry. However, this is airline private information and is the result of a negotiation process between airlines and aircraft manufacturers.

4.2.7 Second stage

In the second stage, airlines aim to maximise profits given the environmental charges imposed by regulators at different geographical levels. Each airline strategically sets the service frequency of each version of the aircraft f_{kva} on the leg of the network, the fares p_{ijta} on the routes between an origin and destination and selects the optimal number and version of the aircraft x_{hva} to operate their chosen flight network. Given this setting, the objective function for airlines can be modelled in the following way:

[3] Using competing models does not lead to materially different capital cost values.

$$
\begin{aligned}
\underset{p_{ijta}, f_{kva}, x_{hva}}{Max} \quad \pi_a = & \sum_{\substack{i,j,t \\ i \neq j}} d_{ijta} m_{ijta} p_{ijta} - \sum_{k,v} C_{kv} f_{kva} \\
& - \sum_{k^r, v} \varepsilon_{k^r v} \theta_r f_{k^r va} - \sum_{h,v} o_{hv} x_{hva}
\end{aligned} \tag{4.8}
$$

where m_{ijsa} is the market share function specified in (4.5) and represents the share of demand served by a specific airline for each pair of cities and type of passengers, C_{kv} represents the operating costs, defined in Eq.(4.6), incurred by the airline to serve a specific leg, o_{hv} is the monthly ownership cost of the version of the type of aircraft h v and x_{hv} is the number of aircraft of type h and version v that the carrier decided to operate on its network. Airlines can decide whether to internalise regulator charges or pass them on to passengers by increasing airfares and/or adapting accordingly to service frequency and fleet mix.

The second-stage problem is subject to constraints (4.9)–(4.16).

$$
m_{ijta} = \frac{e^{V_{ijta}(f_{kva}, p_{ijta})}}{e^{V_0} + \sum_{a' \in \mathcal{A}} e^{V_{ijta'}(f_{kva'}, p_{ijta'})}}, \;\; \forall\, i, j \in \mathcal{N}, \; t \in \mathcal{T}, \; a \in \mathcal{A} \tag{4.9}
$$

$$
z_{ija} \leq f_{\omega' va} \;\; \forall\, i, j \in \mathcal{N}, \omega' \in \Omega' \tag{4.10}
$$

$$
z_{ija} \leq f_{\omega'' va} \;\; \forall\, i, j \in \mathcal{N}, \omega'' \in \Omega'' \tag{4.11}
$$

$$
\sum_{i^\circ, j^\circ, t} d_{i^\circ j^\circ t} m_{i^\circ j^\circ ta} \leq \sum_{v} s_{kv} f_{kva} \;\; \forall\, k \in \mathcal{K} \tag{4.12}
$$

$$
\sum_{k^h} f_{k^h va} \leq \bar{f}_h x_{hva} \;\; \forall\, h \in \mathcal{H}, \; v \in \mathcal{V} \tag{4.13}
$$

$$
f_{kva} \geq 0, \;\; \forall\, k \in \mathcal{K}, \; v \in \mathcal{V} \tag{4.14}
$$

$$
p_{ijta} \geq 0, \;\; \forall\, i, j \in \mathcal{N}, \; t \in \mathcal{T} \tag{4.15}
$$

$$
x_{hva} \geq 0, \;\; \forall\, h \in \mathcal{H}, \; v \in \mathcal{V} \tag{4.16}
$$

where,

$$
\mathcal{N}^\circ = \{i^\circ, j^\circ | i^\circ, j^\circ \text{ are the itineraries passing through arc } k\}
$$

$$
\Omega' = \{\omega' | \omega' \text{ is the first arc of the itinerary } i, j \in \mathcal{N}\}
$$

$$\Omega'' = \{\omega'' | \omega'' \text{ is the second arc of the itinerary } i, j \in \mathcal{N}\}$$

Eq. (4.9) specifies the multinominal logit model as the market share function in the objective function of the airline. Constraints (4.10) and (4.11) represent a linearisation of the minimum frequency of indirect flights in the utility function in Eq. (4.4). These constraints are needed to avoid discontinuities in the market share function during the solution process. Eq. (4.12) is the capacity constraint and ensures that the demand served by an airline meets the availability of seats offered on the specific leg considering all possible itineraries offered by the airline and using the leg. Constraint (4.13) restricts the number of flights operated to be less than the average service frequency, differentiating between long- and short-haul flights. Constraints (4.14) to (4.16) represent the lower bounds for the decision variables.

4.2.8 Game-theoretic competition and algorithm

The competition framework for regulators and airlines is structured as an extensive game with complete and perfect information (Osborne and Rubinstein, 1994). In this model, the players make strategic decisions sequentially in two stages. This framework allows players to define their strategies in the stage in which they are required to play an action, relaxing the restriction of selecting strategies only in the initial phase of the game. This allows second-stage players to decide their strategy in response to the decisions of first-stage players. The players p of the game are regulators, in terms of the first stage and all the airlines in the second stage. Formally, the set of players is $\mathcal{P} = \{\mathcal{R}, \mathcal{A}\}$. The game is defined over a set of histories, where each element of the history is an action. The set of histories is Φ and every action after a non-terminal history φ belongs to the set of actions $\Lambda(\varphi) = \{\lambda : (\varphi, \lambda) \in \Phi\}$. The actions of the regulators, in the first stage, are represented by the environmental charges imposed on airlines, while, in the second stage, the airlines react by choosing service frequency, ticket fares and the number of new and old versions of aircraft to deploy.[4] At each non-terminal history is assigned a player through a function $P(\cdot)$, where $P(\varphi)$ is the player after the history φ. The last element is the preference relationship ($\succsim_{player}$) over payoffs for each player, which in our case are social welfare for the regulators and profits for the airlines. The entire game is defined as

[4] While airlines network is assumed as fixed in the game, airlines can indirectly decide to stop operating a connection by choosing a frequency of zero. This allows carriers to endogenously decide whether to continue serving a market or not.

$\Gamma = \langle \mathcal{P}, \Phi, P, (\succsim_{player}) \rangle$.

It is possible to solve this two-stage simultaneous game using a Kuhn-Zermelo type of backward induction algorithm (Schwalbe and Walker, 2001), as described in Alg. (2). The algorithm starts by initialising the values for the first and second stages. Successively, the algorithm computes the sub-game perfect Nash equilibrium (SPNE) for the second stage by solving the mathematical program for all airlines in the set of airlines $\mathcal{A}$, which we refer to as a cycle. Once the SPNE has been computed in the second stage, the algorithm solves the problem in the first stage for all regulators in the set $\mathcal{R}$. Specifically, after each first-stage computation, a new cycle needs to be computed with the updated values for the charges. When an SPNE is found at each stage, the equilibrium of the game is reached. Following the consistent approach used in Adler et al. (2022) our algorithm performs a space search for a point grid around each iteration optimal solution. This means that we compute the second stage solution for all the points around the initial guess and we select the strategic decision that is maximising the regulator's social welfare. Repeating this approach iteratively and consistently shrinking the grid radius every time the best response for the regulators is found.

It is important to note that, even if the existence of an SPNE is assured in the extensive games with perfect information by the Kuhn theorem Kuhn (1953), due to the high non-linearity of the objective functions it is not possible to ensure that the solution found is a global optimum. Consequently, the robustness of the results is tested by selecting different starting points and sequences of players within each specific set of players.

Another important aspect to highlight is that, although passengers are not well defined players in our game, their decisions are pivotal to airline objectives in the second stage of the game. In particular, airlines compete to obtain a higher market share of passengers in the markets they serve to increase their revenues. Hence, the market share function indirectly endogenizes passengers' decision of which flight alternative to choose.

4.3 Case study

We validate our model on a representative network considering two world regions, namely North America and Europe. The nodes that compose the network are depicted in Fig. (4.1). Specifically, our network is made up of 22 nodes, divided equally between the two regions. This network configuration allows for domestic flights within a region and

Algorithm 2 Solve the two-stage game (pseudo code)

```
Start
initialise values of competitors' decision variables and their network characteristics,
for both regulators and airlines
while first stage solution > optimal threshold do:
    while first stage solution is not a best response for all regulators do:
        for each regulator do:
            create point grid around previous first stage solution
            for each point in the grid do:
                while second stage solution not a best response for airlines do:
                    for each airline do:
                        solve the mathematical program using IPOPT
                    assess whether the second stage solution is a best response for all
                    airlines
                return second stage solution
            return second stage solution for each point
            select the point that maximizes welfare
        return first stage solution for each regulator
    shrink the grid radius
return first and second stage solutions
Stop
```

trans-Atlantic connections between the two regions. Nodes in our network are selected to represent 9% of the monthly demand within the two regions and the trans-Atlantic (TRA) market. Moreover, the average distances between nodes are in line with the actual ones (i.e., EU: 1250 km, NA: 2076 km, TRA: 6959 km). Trans-Atlantic connections are operated by legacy carriers operating through their hubs. We define six hub airports, one for each airline, assigned equally between Europe and North America. Specifically, we select Frankfurt, London, and Paris as European hubs for Lufthansa, British Airways, and Air France, respectively. Similarly, Toronto, New York, and Atlanta are the North American hubs for Air Canada, American Airlines, and Delta. Low-cost carriers operate point-to-point within the regions. We identify SouthWest, Spirit, and JetBlue as North American LCCs while Ryanair, Easyjet, and WizzAir are their European counterparts.

We define three regulators, two of them exerting authority on a single region and a global one with jurisdiction over both regions. Given the round-trip assumption of flights, regional connections are subject twice to regulator charges, while to trans-Atlantic connections, both regulator charges are applied. Furthermore, in the scenario in which the global regulator is introduced, all operations are also subject to his charge. We assume a social cost of carbon ξ equal to 200 EUR, according to the latest IPCC reports (Pörtner et al., 2022).

Figure 4.1: Selected nodes in North America and Western Europe.

4.3.1 Data

We retrieve data on 2019 passengers' demand, airlines' ticket fares, service frequencies, and aircraft type from the Official Aviation Guide (OAG). The monthly demand is reported in Table (4.3) for business and economy passengers and according to the different regions. By choosing 2019 as the reference year, we avoid distortion induced by the Covid-19 pandemic. To move from actual to potential demand, we increase the value of the traffic by 20%. We identify four variants of aircraft, two for short-haul flights and two for long-haul ones. The aircraft purchase and salvage values, retrieved from manufacturer websites, are reported in Table (4.4). We assume a discount factor of 25% on the retail price. Since the magnitude of the discount is private information of manufacturers and specific to each airline, we select this discount level as half of the maximum discount level applied by Airbus[5].

The coefficients used in the multinomial logit model are reported in Table (4.5). We calibrate utility parameters startinin the caseg from estimates in the literature (Adler et al., 2010), in order to replicate actual 2019 results in the baseline scenario described in

[5]The discount values applied by Airbus are computed by comparing annual report information on aircraft prices and quantity sold, with the operating revenues.

Table 4.3: Monthly demand, two-way

	Business	Economy	Tot.
EU	295,062	4,681,656	4,976,716
NA	354,987	5,504,787	5,859,774
Trans-Atl.	66,405	397,356	463,761
Tot.	716,453	10,583,798	11,300,251

Table 4.4: Aircraft purchase and salvage values

h, v	ρ (\$ M)	σ (\$ M)	Reference model	Fuel (ton/km)	Seats (LCC)
short, old	100	33.33	A320ceo	4	180 (189)
short, new	110	36.30	A320neo	3	180 (189)
long, old	345	113.85	B777	8	350 (-)
long, new	370	122.10	A350	7	350 (-)

the following section (Sec.(4.3.2)). The outside option is normalised to 0.4 for European domestic consumers, to -2.8 for North American passengers, and to 1.3 for trans-Atlantic flights. These values reflect well-known patterns, such as a higher price sensitivity for leisure, a greater value for frequency and directness for business, etc. including some references to well-known studies (Berry and Jia, 2010).

Table 4.5: Logit coefficients

	European		North American		Trans-Atlantic	
	Business	Economy	Business	Economy	Business	Economy
Directness (β_0)	0.5600	0.4900	0.5600	0.4900	0.5100	0.4600
Frequency	0.9660	0.8540	0.9660	0.8540	1.0820	0.9700
Price	-0.0154	-0.0508	-0.0110	-0.0363	-0.0008	-0.0018
Travel time	-0.0140	-0.0070	-0.014	-0.0070	-0.0010	-0.0007
Outside option	0.4		-2.8		1.3	

4.3.2 Results

The mathematical program resulting from the game belongs to general non-linear programming problems. We use the *IPOPT* solver (Wächter and Biegler (2006)) to find the second stage equilibrium. To find an equilibrium in the first stage, we rely on our space search algorithm described in the previous section.

Baseline scenario

After having defined the regulatory mechanisms, we compare the results obtained from our model with the outcomes of a counterfactual scenario. We define a *Baseline* scenario in the absence of any charge in the North American region and a carbon charge $\theta_{EU} = 22$ applied to all intra-European flights. This scenario aims to replicate the 2019 values taking into account also a European carbon charge to replicate the scope of the EU-ETS scheme. Using this scenario, we validate our model and the parameterisation used. Specifically, we compare Cost per Available Seat Kilometer (CASK), Revenue per Available Seat Kilometer (RASK) and passengers carried with the real word values obtained from airlines' annual reports and OAG data. Validation results are reported in Table (4.7). Our model produces estimates that are close to the real-world ones for both legacy and low-cost carriers, thus validating our modelling approach.[6] Results from the baseline case, reported in Table (4.6), show that, despite the higher demand in North America, the European market generates a greater surplus for passengers and its airlines than the American one. This discrepancy between the two regions is due to the disutility faced by American passengers who pay a higher ticket fare than European travellers and have a regional network characterized by longer distances. Thus, higher fares are the result of the higher operating costs in North America and the presence of fewer alternatives, resulting in passengers locked in by the airline system and paying more than Europeans. The averages for the fares and service frequencies are reported in the Appendix (4.11). Given the higher demand in North America, both LCCs and legacy carriers operate more flights in this region compared to European ones. As a result of higher fares and higher demand, American carriers are more profitable than European ones, despite the higher operating costs incurred by American airlines. North American operations result in emissions that are more than double those generated by European movements. However, since we assumed that the impacts of emission are equally distributed between the two regions, the difference in environmental damage between the two regions is zero. As such, our baseline suggests that North Americans have been free-riding on the EU (and the EU ETS) in 2019. In the *baseline* scenario, our model predicts that 80% of the potential market is served while the remaining 20% of the passengers decide not to fly, consistent

[6] Small discrepancies between our estimates and the actual values are due to the difficulty in replicating, in a single model and a representative network, different cost structures used by regular and low-cost carriers.

with the increase in potential demand.

Table 4.6: Baseline scenario

	Baseline		
	EU	NA	Δ NA-EU
θ_r (€)	22	0	-22
Government surplus (€ M)	8	0	-8
Emissions (€ M)	-110	-110	0
Consumer surplus (€ M)	942	683	-259
Producer surplus (€ M)	102	139	37
Welfare (€ M)	942	712	-231

Table 4.7: Validation (real world values in brackets)

	CASK (€c)	RASK (€c)	Demand, two-way (pax. M)		
			EU	NA	TRA
EU legacy	7.2 (7.1)	9.1 (7.7)			
NA legacy	6.4 (6.4)	7.9 (8.7)			
EU LCC	4.2 (4.3)	5.3 (4.8)	4.7 (4.7)	5.7 (4.9)	0.5 (0.4)
NA LCC	5.3 (5.9)	6.2 (6.5)			

Competing regulators

We now define a scenario in which two regulators, based in different regions, compete by setting emission charges on each flight departing from their jurisdiction. We assume that one regulator sets charges for all departing flights from North America, and similarly, one regulator charges all departing operations from Europe. We name this scenario *2REG*. Given the round-trip assumption of each flight, operations within a region are charged twice by the same regulator; instead, trans-Atlantic flights are subject to both regulators' charges, one per direction. The results of our model for this scenario are reported in Table (4.8). We observe that competing regulators decide to free-ride on each other, resulting in charges that are much lower than the social cost of carbon. In this way, regulators protect the surplus of both passengers and carriers under their jurisdiction. This effect is dominating the other forces in our game and prevent regulators from starting a tax war in an attempt to extract surplus from the opponent region trans-Atlantic passengers. This outcome is particularly visible due to the discrepancy between the amount charged by the European and the North American regions. Specifically, the price elasticity of the demand for European passenger is lower than the one of North-American passenger. As Barnett (1980) shows, in presence of market power, the optimal charge will be lower than the social cost imposed by the externality given the distortion in output level. In fact, the more the demand is inelastic, the more the charge would be close to the Pigouvian tax. Since European passengers show a more inelastic demand, Europe is charging consistently more than North America. In addition, airlines are able to increase the share of fuel efficient aircraft in their fleet, resulting in a reduction of the social cost. This results in an increase of the effectiveness of carbon charges in a market already affected by distorting forces. In fact, the results from this competing regulators case closely reflect the actual charges imposed by the Europeans (EU ETS price of 22) and the North Americans (zero) in the real world in 2019. For the American regulator, a higher charge would be welfare detrimental given the higher operating cost of regional carriers and the lower surplus of passengers resulting from higher fares. In Europe, where airfares and distances are lower and there are more alternatives to fly, the regulator is much more eager to set a higher charge. The gain of regulators from charges is visible in the government surplus of the respective region, which increases compared to the *baseline* scenario. As a consequence of the implementation of the policies, airlines respond by slightly increasing airfares and moderately reducing service frequency (4.13). This small reduction in frequencies also generates a small contraction in the carbon emission generated across the entire network. Overall welfare is in line with the one in the *baseline* scenario, highlighting how the implementation of a corrective policy in the presence of the possibility of free-riding results in an ineffective way of addressing a negative externality.

Table 4.8: Two-regulator scenario

	Baseline		2 REG		Δ	
	EU	NA	EU	NA	EU	NA
θ_r (€)	22	0	38	4	16	4
Government surplus (€ M)	8	0	14	3	6	3
Emissions (€ M)	-110	-110	-109	-109	1	1
Consumer surplus (€ M)	942	683	936	678	-6	-4
Producer surplus (€ M)	102	139	101	139	-1	-0
Welfare (€ M)	942	712	943	711	0	-1

Single regulator

The second scenario we explore is the one in which a single entity regulates both regions. In this setting, a global regulator defines a single charge per ton of CO_2 generated that applies to all flights. We name this scenario *1 REG* and our model results are reported in Table (4.9). Given the presence of a single regulator, in this setting, there is no possibility of free-riding on other regulators, since the single regulator is fully responsible for all generated emissions ($\eta_r = 1$). The results of our model show that the optimal charge set by the regulator is much lower compared to the expected Pigouvian tax, which should compensate solely for the CO_2 produced. This result is in line with the standard economics literature. In fact, this value is lower than the social cost of carbon due to the market power of airlines and the Mohring effect. Market power arises in the presence of an airline dominant position that allows the carrier to increase prices while still capturing a significant share of passengers. As a consequence of higher fares imposed by airlines market power. The Mohring effect generates a more than proportional increase in utility given an increase in service frequencies, resulting in a feedback effect increasing passenger demand. The economic literature predicts that these combined effects should call for a charge lower than the Pigouvian tax. It is particularly important to note that, in our framework, a regulator is not able to discriminate between itineraries and the charge is the same for all operations. The absence of this discrimination element may result in a suboptimal charge setting. As a result of this global scope policy, we observe a slight departure from the *baseline* scenario. Specifically, as a consequence of this marginal global charge, we do not observe changes in airlines' strategies (4.12). Specifically, fares, fleet composition and service frequency resemble the value obtain in the *baseline* scenario throughout all markets in airlines network. With regard to the environment, the imposition of a charge also on the North American market leads to a small reduction in the emission generated. We observe that social welfare remains unchanged. The charge imposed by the world regulator lies between the two set by those set by competing regulators. This implies that even a coordinated mechanism which adopts solely a carbon tax equal across regions is not necessarily welfare improving. Specifically, the regional regulator can address the heterogeneity of passenger preferences and climate vulnerability of their region with a tailored carbon charge. These results highlight how even in the absence of free riding and carbon leakage, market distortions lead to ineffective environmental policies in the case regulators have a carbon charge as the sole instrument to reduce emissions.

Table 4.9: Single regulator scenario

	Baseline			1 REG	Δ
	EU	NA	Sum	REG	
θ_r (€)	22	0	22	8	-14
Government surplus (€ M)	8	0	8	10	1
Emissions (€ M)	-110	-110	-220	-219	1
Consumer surplus (€ M)	942	683	1,624	1,623	-2
Producer surplus (€ M)	102	139	241	241	-0
Welfare (€ M)	942	712	1,654	1,655	0

Overlapping policies

The last scenario we explore is the one in which our model is applied to a context in which three competing regulators, one per region plus a global scope regulator with jurisdiction over the entire network. We named this scenario *Overlapping* given the overlap in scope of the policies, and we report the results in Table (4.10). More in detail, the third regulator is fully responsible for all carbon generated, the producer surplus of all airlines, and is interested in the consumer surplus of all passengers in the network. All the revenues collected by the world regulator are redistributed to the two regions' regulators according to the flights departing from the region. Henceforth, regional regulators take into account the extra revenues from the world regulator in their objectives. More specifically, regional regulators now take into account also the redistribution of world regulator revenues in the third term of Eq.(4.1). Under this setting all flights are subject to the charge imposed by the global regulator on top of the one applied by each region regulator, resulting in double taxation. Similarly to the two competing regulators scenario, in this case charges also assume a value close to the *baseline* scenario and substantially far from the expected Pigouvian taxation reflecting the social cost of carbon. As in the *2REG* scenario, also in this case we observe a reduction in the level of emissions generated thanks to the introduction of a third regulator. However, the magnitude of this reduction is marginal. This combined effect outweighs the negative externalities imposed by carbon emissions. Regarding airlines, our results show a moderate increase in airfares and a slight contraction in service frequencies compared to the counterfactual scenario (4.14). The moderate charges imposed on airlines have a small effect on the fleet replacement rate of the older version of aircraft deployed by airlines. These results seems to follow the case of the two competing regulators. Fares, frequencies and fleet mix are in line with the *baseline* case in both regional and trans-Atlantic markets.The outcomes of this scenario are the result of both free-riding behaviours combined with regulator protectionism consumer and producer surplus. These distortions at the regulatory level have the effect of undermining the effectiveness of environmental policies.

Table 4.10: Overlapping policies scenario with global scope charge

	Baseline		Overlapping		
	EU	NA	EU	NA	WR
θ_r (€)	22	0	28	2	2
Government surplus (€ M)	8	0	12	3	-
Emissions (€ M)	-110	-110	-110	-110	-
Consumer surplus (€ M)	942	683	929	646	-
Producer surplus (€ M)	102	139	100	135	-
Welfare (€ M)	942	712	931	675	-

4.4 conclusions and future directions

In this paper, we develop a two-stage model capable of representing competition between regulators and airlines under different emission charges. In our model formulation, regulators compete by strategically selecting the carbon emissions charge that maximises their welfare, taking into account passengers, carriers, and environmental impact. As a consequence of the carbon charge, carriers strategically set the service frequency, airfares, and the number and version of the aircraft to operate. We apply our model to the different scenarios to assess the implications of regulators' competition and cooperation. More in dept, we shed light on the implication of addressing environmental externality in an economically distorted market, such as the aviation industry. Specifically, we develop an algorithm that estimates the Nash equilibria of a two-stage game across scenarios, characterised by different combinations of regulatory settings.

By comparing scenarios with a 2019 baseline case, we assess the impacts of the different regulators' interactions on welfare and the environment. Our analysis suggests that imposing an environmentally optimal carbon charge on the aviation industry can lead to unexpected and welfare-detrimental outcomes. Specifically, we have assessed that the carbon charge imposed by a single regulator results in a level that is well below the social impact of emissions. This environmental sub-optimal result is driven by the existence of severe market distortions affecting the outcome of the emission curbing policy. We further show that when regulators are free to set their charges, they enter into a welfare-detrimental free-riding competition and regional surplus protectionism, which undermine the effectiveness of the mechanism. We find similar outcomes in the scenario with three competing regulators in which a global-scope policy overlaps with the two regional ones. The outcomes we present in our paper are the result of several distorting forces in the aviation industry. More in depth, our results find theoretical evidence also in the literature related to different aviation externalities (Brueckner, 2002; Pels and Verhoef, 2004; Silva et al., 2014) and offer an explanation behind the reasons for the absence of an international cooperative carbon policy.

Future directions for research consist of several options since this paper represents the first attempt to model environmental regulators' competition in the airline industry in a competitive game-theoretic network environment. Some of the assumptions we made can be relaxed in future work. An interesting extension of our model would be to allow regulators to price discriminate at the route level by setting a specific charge for each connection. However, this will result in a much more complex model that can easily turn out to be intractable. A further extension of our model can include an extra layer of players characterised by profit-maximising airports, turning the model into a three-stage game where local airports act as a middle layer between regulators and airlines. Finally, we focus our paper on carbon emissions. However, our model can also be extended to consider local externalities, such as heavy pollutants and aircraft noise.

4.5 Appendix

Table 4.11: Average airline prices and frequencies in the *baseline* scenario

	Airline	Price s-h. lei.	Price s-h. bus.	Price l-h. lei.	Price l-h. bus.	Freq. s-h	Freq. l-h
	Legacy						
	LH	75	136	773	1,532	101	24
EU	BA	71	130	787	1,644	158	39
	AF	73	133	788	1,625	149	41
	AC	144	250	781	1,590	125	30
NA	AA	140	240	812	1,700	172	41
	DL	138	253	752	1,495	74	17
	LCC						
U2	50	111	-	-	149	-	
EU	FR	50	111	-	-	149	-
	WZ	50	111	-	-	149	-
	WN	114	215	-	-	195	-
NA	NK	114	215	-	-	195	-
	B6	114	215	-	-	195	-

Table 4.12: Average airline prices and frequencies in the *1REG* scenario

	Airline	Price s-h. lei.	Price s-h. bus.	Price l-h. lei.	Price l-h. bus.	Freq. s-h	Freq. l-h
	Legacy						
	LH	75	135	772	1,531	102	24
EU	BA	71	130	786	1,643	159	39
	AF	72	132	786	1,625	150	41
	AC	144	251	781	1,590	124	30
NA	AA	140	242	812	1,700	172	41
	DL	139	255	752	1,495	74	17
	LCC						
	U2	49	110	-	-	148	-
EU	FR	49	110	-	-	148	-
	WZ	49	110	-	-	148	-
	WN	114	216	-	-	194	-
NA	NK	114	216	-	-	194	-
	B6	114	216	-	-	194	-

Table 4.13: Average airline prices and frequencies in the *2REG* scenario

	Airline	Price s-h. lei.	Price s-h. bus.	Price l-h. lei.	Price l-h. bus.	Freq. s-h	Freq. l-h
	Legacy						
	LH	76	137	777	1,536	101	24
EU	BA	72	131	790	1,647	158	39
	AF	73	134	791	1,629	149	41
	AC	144	250	782	1,591	124	30
NA	AA	140	241	812	1,700	171	40
	DL	138	254	754	1,496	73	17
	LCC						
	U2	51	111	-	-	147	-
EU	FR	51	111	-	-	147	-
	WZ	51	111	-	-	147	
	WN	114	216	-	-	194	-
NA	NK	114	216	-	-	198	-
	B6	114	216	-	-	194	-

Table 4.14: Average airline prices and frequencies in the *Over* scenario

		Airline	Price s-h. lei.	Price s-h. bus.	Price l-h. lei.	Price l-h. bus.	Freq. s-h	Freq. l-h
		Legacy						
		LH	77	139	803	1,564	104	25
	EU	BA	73	133	813	1,675	166	40
Corsia		AF	75	136	816	1,658	156	42
		AC	148	259	794	1,604	124	30
	NA	AA	145	251	817	1,702	170	40
		DL	143	263	779	1,523	75	15
		LCC						
		U2	53	114	-	-	155	-
	EU	FR	53	114	-	-	155	-
Corsia		WZ	53	114	-	-	155	-
		WN	118	220	-	-	207	-
	NA	NK	118	220	-	-	200	-
		B6	118	220	-	-	200	-

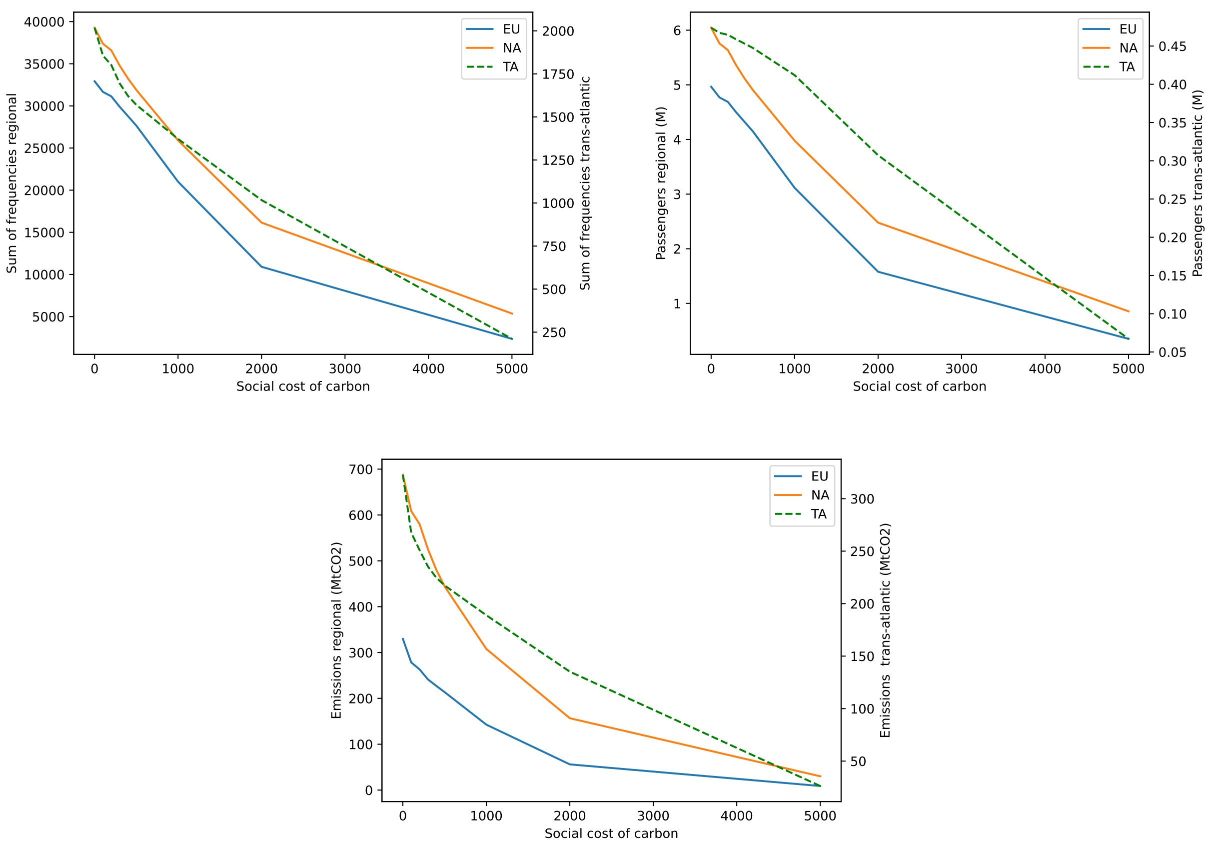

Figure 4.2: Sensitivity analysis over the social cost of carbon

Chapter 5

Conclusions

This thesis analyzes competition at a different level in the presence of market distortions in the aviation industry. In particular, the thesis focuses on the distortion introduced in the airline market by the COVID-19 pandemic and on the implications of environmental policies implemented by competing regulators in a distorted aviation market.

Chapter 2 explores the disruptive impact that the COVID-19 pandemic had on the air transport industry. The empirical analysis uses a time-series ITS SARIMA econometric approach to estimate pandemic effects and compare the results to a counterfactual scenario in the absence of any distortion. This approach allows to disentangle the specific distorting effect imposed by the lockdown. Empirical results show that the real impact on the air transport sector of the pandemic in all macroregions of the world reached a level greater than 80% in May 2020 before the pandemic occurs and about 70% in September 2020. Thanks to a counterfactual analysis, the results highlight that the actual impact of the pandemic is on average greater than the reported observations. Specifically, this effect is predominant in intercontinental operations. Furthermore, the contraction in operations is larger for legacy carriers than for low-cost ones. The results of Chapter 2 highlight that airline survivability can be severely endangered during the pandemic. The airline industry calls for government intervention to support the heavy losses experienced. Given the asymmetric provision of public funds, airlines supported by economically strong governments may have a competitive advantage. This new source of distortion may undermine the level playing field in the aviation industry.

In Chapter 3 competition between airlines under different government bailout programs is analyzed by adopting a game-theoretic approach. Following the results of Chapter 2, the model is applied to the COVID-19 outbreak to assess potential distortions motivated by the asymmetric bailout provision. The results of the model are the outcome of seven scenario analyzes in which a Nash equilibrium is found for different combinations of state aid. As the main result of this analysis, evidence is found that the airline sector has been severely distorted by the uncoordinated provision of bailouts. In particular, by applying a counterfactual analysis, the proposed model compares the impact on major airline competition of government aids with a reference case in absence of any distortion. The analysis shows that various bailout programs disrupt the profitability and operations of carriers. More specifically, results show the presence of an uneven playing field for European airlines and a welfare contraction for society. Consequently, evidence is shown of the existence of a socially preferable outcome. The most efficient outcome is achieved through a coordinated and homogeneous government aid package across all European Member States. These results are also strongly supported by evidence in the literature. Furthermore, results suggest that low-cost carriers will benefit from the financial burden on European legacy airlines, expanding their market share in the intra-European region at the expense of European flag carriers. As the main takeaway of this paper, the uncoordinated provision of state aid by the European Commission during the COVID-19 pandemic may have distorted the aviation market, causing backlash against European flag carriers. The results suggest that a coordinated provision of bailouts in the form of loans across all Member States would have limited the negative impacts on social welfare.

By expanding the model proposed in Chapter 3, Chapter 4 explores regulatory competition alongside the interaction of airlines when different charges are applied to the production of carbon emissions. The paper develops a two-stage game which allows regulators to compete on the environment as a public good by setting an emission charge for their jurisdiction pursuing welfare maximization. Consequently, airlines compete to maximize their profits, given the emission charges imposed by regulators in the first stage. The proposed algorithm finds a Nash equilibrium for different regulator configurations, allowing to explore different policy interactions. As a consequence of this multiple configurations framework, the paper sheds light on how free-riding behaviors combined with the distortions pervading the aviation industry may undermine the effectiveness of emissions reduction mechanisms. By comparing scenarios with a counterfactual case before the COVID-19 pandemic, the analysis highlights that defining an environmentally optimal carbon policy in a distorted industry, such as the aviation sector, may result in suboptimal welfare outcomes. To prove the robustness of these findings, the model has been applied to three different regulator configurations. In the case where the charge is imposed by a single regulator in the absence of free-riding possibilities, the results show that the charge is lower than the social cost of carbon. This departure from the expected Pigouvian taxation highlights how the charge also corrects for distortions typical of the aviation industry, such as market power and the Morhing effect. Therefore, a possible reduction in emissions comes at the expense of a consumer and producer surplus. Furthermore, the model is applied to a scenario in which two regulators compete in welfare maximization and have the possibility of free-riding on each other. Results show that a regulator will free-ride on the opponent one if he can protect the consumer and producer surplus of its region, undermining the effectiveness of the environmental policy. Similar outcomes also characterized the case of competing regulators with a global scope overlapping policy. The outcomes of this paper offer a possible explanation of the reasons for the absence of agreement in defining an efficient and effective carbon policy among international institutions.

In the end, regulatory authorities are required with defining a policy setting that preserve competition among airlines both in domestic and on international connections avoiding detrimental outcome on the welfare of the entire society. When implementing such setting, regulators should be aware of the whole spectrum of industry distortions. This means to take into account of both negative and positive externalities, such as environmental impacts, and of different industry conditions like carriers market power position or asymmetric government support. This thesis helps towards a better understanding of the latter of these imperfections, but it is important to stress that policy makers needs to be informed about these other imperfections as well. This thesis highlights the importance for policy makers wishing to shape effective air policies and for carriers seeking to operate efficient international operations to keep up with changing dynamics and changes that affect air competition in a deregulated international markets. The results described in this thesis provide possible directions that are relevant to accomplish this difficult challenge.

Bibliography

116th Congress (2020). CARES Act. https://www.congress.gov/116/bills/s3548/BILLS-116s3548is.pdf [Accessed: 2022-01-13].

Abate, M., Christidis, P., and Purwanto, A. J. (2020). Government support to airlines in the aftermath of the COVID-19 pandemic. *Journal of Air Transport Management*, 89:101931.

Adler, N. (2001). Competition in a deregulated air transportation market. *European Journal of Operational Research*, 129(2):337–345.

Adler, N. (2005). Hub-Spoke Network Choice Under Competition with an Application to Western Europe. *Transportation Science*, 39(1):58–72.

Adler, N., Brudner, A., and Proost, S. (2021). A review of transport market modeling using game-theoretic principles. *European Journal of Operational Research*, 291(3):808–829.

Adler, N., Fu, X., Oum, T. H., and Yu, C. (2014a). Air transport liberalization and airport slot allocation: The case of the northeast asian transport market. *Transportation Research Part A: Policy and Practice*, 62:3–19.

Adler, N., Fu, X., Oum, T. H., and Yu, C. (2014b). Air transport liberalization and airport slot allocation: The case of the Northeast Asian transport market. *Transportation Research Part A: Policy and Practice*, 62:3–19.

Adler, N., Hanany, E., and Proost, S. (2022). Competition in congested service networks with application to air traffic control provision in europe. *Management Science*, 68:2751–2784.

Adler, N., Pels, E., and Nash, C. (2010). High-speed rail and air transport competition: Game engineering as tool for cost-benefit analysis. *Transportation Research Part B: Methodological*, 44(7):812–833.

Airbus (2019). Airbus global market forecast 2019-2038. *Airbus Market Forecast*.

Airbus (2022). Airbus global market forecast 2021-2040. https://www.airbus.com/sites/g/files/jlcbta136/files/2021-11/Airbus-Global-Market-Forecast-2021-2040.pdf [Accessed: 2022-04-25].

Andreana, G., Gualini, A., Martini, G., Porta, F., and Scotti, D. (2021). The disruptive impact of covid-19 on air transportation: An its econometric analysis. *Research in Transportation Economics*, 90:101042.

Baicker, K. and Svoronos, T. (2019). Testing the validity of the single interrupted time series design. Technical report, National Bureau of Economic Research.

Barnett, A. H. (1980). The pigouvian tax rule under monopoly. *The American Economic Review*, 70(5):1037–1041.

Baylis, K., Fullerton, D., and Karney, D. H. (2013). Leakage, welfare, and cost-effectiveness of carbon policy. *American Economic Review*, 103:332–337.

Ben-Akiva, M. E. and Lerman, S. R. (1985). *Discrete choice analysis: theory and application to travel demand*, volume 9. MIT press.

Bernal, J. L., Cummins, S., and Gasparrini, A. (2017). Interrupted time series regression for the evaluation of public health interventions: a tutorial. *International journal of epidemiology*, 46(1):348–355.

Berry, S. and Jia, P. (2010). Tracing the woes: An empirical analysis of the airline industry. *American Economic Journal: Microeconomics*, 2(3):1–43.

Bianchi, J. (2016). Efficient Bailouts? *American Economic Review*, 106(12):3607–3659.

Birolini, S., Cattaneo, M., Malighetti, P., and Morlotti, C. (2020). Integrated origin-based demand modeling for air transportation. *Transportation Research Part E: Logistics and Transportation Review*, 142(June):102050.

Blonigen, B. A. and Cristea, A. D. (2015). Air service and urban growth: Evidence from a quasi-natural policy experiment. *Journal of Urban Economics*, 86:128–146.

Boeing (2019). Commercial market outlook 2019-2038. *Boeing Commercial.*

Bombelli, A. (2020). Integrators' global networks: A topology analysis with insights into the effect of the covid-19 pandemic. *Journal of Transport Geography*, 87:102815.

Borenstein, S. (1989). Hubs and high fares: dominance and market power in the us airline industry. *The RAND Journal of Economics*, pages 344–365.

Borenstein, S. and Rose, N. L. (1995). Bankruptcy and Pricing Behavior in U.S. Airline Markets. *The American Economic Review*, 85(2):397–402.

Borenstein, S. and Rose, N. L. (2003). The impact of bankruptcy on airline service levels. *American Economic Review*, 93(2):415–419.

Borenstein, S. and Rose, N. L. (2014). How airline markets work... or do they? regulatory reform in the airline industry. In *Economic regulation and its reform: What have we learned?*, pages 63–135. University of Chicago Press.

Box, G., Jenkins, G., Reinsel, G., and Ljung, G. (2015). Time series analysis: Forecasting and control. hoboken, nj 07030-5774.

Brueckner, J. K. (2002). Airport congestion when carriers have market power. *American Economic Review*, 92(5):1357–1375.

Brueckner, J. K., Dyer, N. J., and Spiller, P. T. (1992). Fare determination in airline hub-and-spoke networks. *The RAND Journal of Economics*, pages 309–333.

Brueckner, J. K. and Zhang, A. (2010). Airline emission charges: Effects on airfares, service quality, and aircraft design. *Transportation Research Part B: Methodological*, 44(8-9):960–971.

Brugnoli, A., Dal Bianco, A., Martini, G., and Scotti, D. (2018). The impact of air transportation on trade flows: A natural experiment on causality applied to italy. *Transportation Research Part A: Policy and Practice*, 112:95–107.

Cadarso, L., Vaze, V., Barnhart, C., and Marín, Á. (2017). Integrated airline scheduling: considering competition effects and the entry of the high speed rail. *Transportation Science*, 51(1):132–154.

Cao, Y., Kleywegt, A. J., and Wang, H. (2022). Network revenue management under a spiked multinomial logit choice model. *Operations Research*, 70(4):2237–2253.

CAPA (2021). Only a few airlines collapsed in 2020. https://centreforaviation.com/analysis/reports/only-a-few-airlines-collapsed-in-2020-550663 [Accessed: 2022-04-20].

Carbone, J. C. (2013). Linking numerical and analytical models of carbon leakage. *American Economic Review*, 103(3):326–31.

Chari, V. V. and Kehoe, P. J. (2016). Bailouts, Time Inconsistency, and Optimal Regulation: A Macroeconomic View. *American Economic Review*, 106(9):2458–2493.

Chinazzi, M., Davis, J. T., Ajelli, M., Gioannini, C., Litvinova, M., Merler, S., y Piontti, A. P., Mu, K., Rossi, L., Sun, K., et al. (2020). The effect of travel restrictions on the spread of the 2019 novel coronavirus (covid-19) outbreak. *Science*, 368(6489):395–400.

Christidis, P. and Christodoulou, A. (2020). The predictive capacity of air travel patterns during the global spread of the covid-19 pandemic: Risk, uncertainty and randomness. *International Journal of Environmental Research and Public Health*, 17(10):3356.

Ciliberto, F. and Schenone, C. (2012a). Are the bankrupt skies the friendliest? *Journal of Corporate Finance*, 18(5):1217–1231.

Ciliberto, F. and Schenone, C. (2012b). Bankruptcy and product-market competition: Evidence from the airline industry. *International Journal of Industrial Organization*, 30(6):564–577.

Conti, M., Ferrara, A. R., and Ferraresi, M. (2019). Did the eu airport charges directive lead to lower aeronautical charges? empirical evidence from a diff-in-diff research design. *Economics of Transportation*, 17:24–39.

Darroch, Gordon Georgiadis, P., Mathurin, P., and Campbell, C. (2022). Billion-dollar debt mountain poses invisible threat to airlines. *Financial Times*.

De Borger, B. and Proost, S. (2012). Transport policy competition between governments: A selective survey of the literature. *Economics of Transportation*, 1(1-2):35–48.

de Jong, G. (2022). Emission pricing and capital replacement: Evidence from aircraft fleet renewal. *Tinbergen Institute*.

de Jong, G., Behrens, C., van Herk, H., and Verhoef, E. (2019). Domestic Market Power in the International Airline Industry. *Transportation Science*, 53(3):trsc.2018.0863.

DG Competition (2008). Official Journal of the European Union. https://eur-lex.europa.eu/legal-content/EN/TXT/HTML/?uri=OJ:C:2008:014:FULL&from=MT [Accessed: 2021-12-15].

Diamond, D. W. and Rajan, R. G. (2002). Bank Bailouts and Aggregate Liquidity. *American Economic Review*, 92(2):38–41.

Diamond, D. W. and Rajan, R. G. (2005). Liquidity Shortages and Banking Crises. *The Journal of Finance*, 60(2):615–647.

Dobson, G. and Lederer, P. J. (1993). Airline Scheduling and Routing in a Hub-and-Spoke System. *Transportation Science*, 27(3):281–297.

EASA (2019). European aviation environmental report 2019.

Eurocontrol (2019). European aviation in 2040: Challenges of growth. *Brussels: EUROCONTROL*.

European Commission (2017). Support study to the Ex-post evaluation of Directive 2009/12/EC on Airport Charges.

European Commission (2021). Temporary framework for state aid measures to support the economy in the current covid-19 outbreak. *Official Journal of the European Union*.

Faber, J. and Huigen, T. (2018). A study on aviation ticket taxes.

Fageda, X. and Teixido-Figueras, J. J. (2020). Pricing Carbon in the Aviation Sector: Supply Effects of the European Emissions Trading System. *SSRN Electronic Journal*, pages 1–45.

Forsyth, P., Guiomard, C., and Niemeier, H.-M. (2020). Covid- 19, the collapse in passenger demand and airport charges. *Journal of Air Transport Management*.

Garrow, L. A. (2016). *Discrete choice modelling and air travel demand: theory and applications*. Routledge.

Gilbert, M., Pullano, G., Pinotti, F., Valdano, E., Poletto, C., Boëlle, P.-Y., d'Ortenzio, E., Yazdanpanah, Y., Eholie, S. P., Altmann, M., et al. (2020). Preparedness and vulnerability of african countries against importations of covid-19: a modelling study. *The Lancet*, 395(10227):871–877.

Goolsbee, A. D. and Krueger, A. B. (2015). A Retrospective Look at Rescuing and Restructuring General Motors and Chrysler. *Journal of Economic Perspectives*, 29(2):3–24.

Gorton, G. and Huang, L. (2004). Liquidity, Efficiency, and Bank Bailouts. *American Economic Review*, 94(3):455–483.

Hansen, M. (1990). Airline competition in a hub-dominated environment: An application of noncooperative game theory. *Transportation Research Part B: Methodological*, 24(1):27–43.

Hansen, M. and Liu, Y. (2015). Airline competition and market frequency: A comparison of the s-curve and schedule delay models. *Transportation Research Part B: Methodological*, 78:301–317.

Hendricks, K., Piccione, M., and Tan, G. (1999). Equilibria in Networks. *Econometrica*, 67(6):1407–1434.

Hong, S. and Harker, P. T. (1992). Air traffic network equilibrium: Toward frequency, price and slot priority analysis. *Transportation Research Part B: Methodological*, 26(4):307–323.

Hyndman, R. J. and Athanasopoulos, G. (2018). *Forecasting: principles and practice*. OTexts.

Iacus, S. M., Natale, F., Santamaria, C., Spyratos, S., and Vespe, M. (2020). Estimating and projecting air passenger traffic during the covid-19 coronavirus outbreak and its socio-economic impact. *Safety Science*, page 104791.

IATA (2019). Fuel Fact Sheet. https://www.iata.org/contentassets/25e5377cf53c4e48bbaa49d252f3ab03/fact-sheet-fuel.pdf [Accessed: 2022-11-07].

IATA (2020a). Air cargo market analysis, july 2020.

IATA (2020b). Don't make a slow recovery more difficult with quarantine measures.

ICAO (2020). Effect of novel coronavirus (covid-19) on civil aviation: Economic impact analysis. *ICAO Uniting Aviation*.

Jackson, T., Brickley, J., Smith, C., Hughes, C., Tabas, J., and Zupan, M. (2020). University of Rochester Roundtable on Bankruptcy vs. Bailouts: The Case of General Motors and the U.S. Auto Industry. *Journal of Applied Corporate Finance*, 32(1):58–79.

Jonh Hopkins University (2020). John hopkins university coronavirus research centre.

Kahn, A. E. (1988). Surprises of Airline Deregulation. *The American Economic Review*, 78(2):316–322.

Kahn, M. and Nickelsburg, J. (2016). An Economic Analysis of U.S Airline Fuel Economy Dynamics from 1991 to 2015. Technical report, National Bureau of Economic Research, Cambridge, MA.

Klages-Mundt, A. and Minca, A. (2022). Optimal intervention in economic networks using influence maximization methods. *European Journal of Operational Research*, 300(3):1136–1148.

Kuhn, H. (1953). Extensive games and the problem of information, contributions to the theory of games ii. *Annals of Mathematics Studies*, 28:193–216.

Kwan, I. and Rutherford, D. (2015). Assessment of U.S. domestic airline fuel efficiency since 2010. *Transportation Research Record*, 2501:1–8.

Kwoka, J., Hearle, K., and Alepin, P. (2016). From the fringe to the forefront: Low cost carriers and airline price determination. *Review of Industrial Organization*, 48(3):247–268.

Lai, S. L. and Lu, W.-L. (2005). Impact analysis of september 11 on air travel demand in the usa. *Journal of Air Transport Management*, 11(6):455–458.

Larsson, J., Elofsson, A., Sterner, T., and AAkerman, J. (2019). International and national climate policies for aviation: a review. *Climate Policy*, 19(6):787–799.

Lau, H., Khosrawipour, V., Kocbach, P., Mikolajczyk, A., Schubert, J., Bania, J., and Khosrawipour, T. (2020). The positive impact of lockdown in wuhan on containing the covid-19 outbreak in china. *Journal of travel medicine*.

Lee, D. S., Fahey, D., Skowron, A., Allen, M., Burkhardt, U., Chen, Q., Doherty, S., Freeman, S., Forster, P., Fuglestvedt, J., et al. (2021). The contribution of global aviation to anthropogenic climate forcing for 2000 to 2018. *Atmospheric Environment*, 244:117834.

Leggett, J. A., Elias, B., and Shedd, D. T. (2012). Aviation and the European Union's emission trading scheme. *The European Union's Emissions Trading Scheme: Climate and Aviation Considerations*, pages 29–81.

Li, T. (2020). A swot analysis of china's air cargo sector in the context of covid-19 pandemic. *Journal of Air Transport Management*, 88:101875.

Macário, R. and Van de Voorde, E. (2010). Low-cost airlines: strategies and reaction patterns. In *Critical Issues in Air Transport Economics and Business*, pages 61–84. Routledge.

Marron, D. B. and Toder, E. J. (2014). Tax policy issues in designing a carbon tax. *American Economic Review*, 104(5):563–568.

McFadden, D. (1974). The measurement of urban travel demand. *Journal of Public Economics*, 3(4):303–328.

McFadden, D. et al. (1973). Conditional logit analysis of qualitative choice behavior.

Megginson, W. and Fotak, V. (2021). Government equity investments in coronavirus bailouts: Why, how, when? *Journal of Law, Finance, and Accounting*, 6(1):1–49.

Mohring, H. (1972). Optimization and scale economies in urban bus transportation. *The American Economic Review*, 62(4):591–604.

Mumbower, S., Garrow, L. A., and Higgins, M. J. (2014). Estimating flight-level price elasticities using online airline data: A first step toward integrating pricing, demand, and revenue optimization. *Transportation Research Part A: Policy and Practice*, 66:196–212.

Nordhaus, W. (2015). Climate Clubs: Overcoming Free-riding in International Climate Policy. *American Economic Review*, 105(4):1339–1370.

Nordhaus, W. (2018). Projections and Uncertainties about Climate Change in an Era of Minimal Climate Policies. *American Economic Journal: Economic Policy*, 10(3):333–360.

OECD (2020). Corporate tax statistics: Second edition. *Tax-Policy*.

Oesingmann, K. (2022). The effect of the European Emissions Trading System (EU ETS) on aviation demand: An empirical comparison with the impact of ticket taxes. *Energy Policy*, 160(March 2020):112657.

Osborne, M. J. and Rubinstein, A. (1994). *A course in game theory*. MIT press.

Pandolfi, L. (2022). Bail-in and Bailout: Friends or Foes? *Management Science*, 68(2):1450–1468.

Pearce, B. (2020). Most air travel markets remain weak. *IATA Economics*.

Pels, E. and Verhoef, E. T. (2004). The economics of airport congestion pricing. *Journal of Urban Economics*, 55(2):257–277.

Perino, G., Ritz, R. A., Van Benthem, A., et al. (2019). Understanding overlapping policies: Internal carbon leakage and the punctured waterbed. *National Bureau of Economic Research*.

Philippon, T. and Skreta, V. (2012). Optimal Interventions in Markets with Adverse Selection. *American Economic Review*, 102(1):1–28.

Pörtner, H.-O., Roberts, D. C., Adams, H., Adler, C., Aldunce, P., Ali, E., Begum, R. A., Betts, R., Kerr, R. B., Biesbroek, R., et al. (2022). Climate change 2022: Impacts, adaptation and vulnerability. *IPCC Sixth Assessment Report*.

Rose, N. L. (2012). After Airline Deregulation and Alfred E. Kahn. *American Economic Review*, 102(3):376–380.

Schipper, Y., Nijkamp, P., and Rietveld, P. (2007). Deregulation and welfare in airline markets: An analysis of frequency equilibria. *European Journal of Operational Research*, 178(1):194–206.

Schwalbe, U. and Walker, P. (2001). Zermelo and the early history of game theory. *Games and economic behavior*, 34(1):123–137.

Sgouridis, S., Bonnefoy, P. A., and Hansman, R. J. (2011). Air transportation in a carbon constrained world: Long-term dynamics of policies and strategies for mitigating the carbon footprint of commercial aviation. *Transportation Research Part A: Policy and Practice*, 45(10):1077–1091.

Sheu, J.-B. and Li, F. (2014). Market Competition and Greening Transportation of Airlines Under the Emission Trading Scheme: A Case of Duopoly Market. *Transportation Science*, 48(4):684–694.

Silva, H. E., Verhoef, E. T., and Van Den Berg, V. A. (2014). Airline route structure competition and network policy. *Transportation Research Part B: Methodological*, 67:320–343.

Small, K. A. and Rosen, H. S. (1981). Applied welfare economics with discrete choice models. *Econometrica: Journal of the Econometric Society*, pages 105–130.

Stiglitz, J. E. (2019). Addressing climate change through price and non-price interventions. *European Economic Review*, 119:594–612.

Suau-Sanchez, P., Voltes-Dorta, A., and Cugueró-Escofet, N. (2020). An early assessment of the impact of covid-19 on air transport: Just another crisis or the end of aviation as we know it? *Journal of Transport Geography*.

Sun, X., Wandelt, S., and Zhang, A. (2020). How did covid-19 impact air transportation? a first peek through the lens of complex networks. *Journal of Air Transport Management*, page 101928.

Swan, W. M. and Adler, N. (2006). Aircraft trip cost parameters: A function of stage length and seat capacity. *Transportation Research Part E: Logistics and Transportation Review*, 42(2):105–115.

Timilsina, G. R. (2022). Carbon taxes. *Journal of Economic Literature*, 60(4):1456–1502.

Tretheway, M. and Andriulaitis, R. (2015). What do we mean by a level playing field in international aviation? *Transport Policy*, 43:96–103.

Vaze, V. and Barnhart, C. (2012). Modeling Airline Frequency Competition for Airport Congestion Mitigation. *Transportation Science*, 46(4):512–535.

Vespermann, J. and Wald, A. (2011). Much ado about nothing? - An analysis of economic impacts and ecologic effects of the EU-emission trading scheme in the aviation industry. *Transportation Research Part A: Policy and Practice*, 45(10):1066–1076.

Wächter, A. and Biegler, L. T. (2006). On the implementation of an interior-point filter line-search algorithm for large-scale nonlinear programming. *Mathematical Programming*, 106(1):25–57.

Wang, C.-H., Zhang, W., Dai, Y., and Lee, Y.-C. (2022). Frequency competition among airlines on coordinated airports network. *European Journal of Operational Research*, 297(2):484–495.

Wollmann, T. G. (2018). Trucks without Bailouts: Equilibrium Product Characteristics for Commercial Vehicles. *American Economic Review*, 108(6):1364–1406.

Yuen, A. C. and Zhang, A. (2011). Unilateral regulation and greenhouse gas emissions: The case of the Airline Industry. *Transportation Research Part D: Transport and Environment*, 16(7):540–546.

Zhang, Y. and Zhang, A. (2021). COVID-19 and bailout policy: The case of Virgin Australia. *Transport Policy*, 114(September):174–181.

Zheng, S., Ge, Y. E., Fu, X., and Jiang, C. (2019). Voluntary carbon offset and airline alliance. *Transportation Research Part B: Methodological*, 123:110–126.