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

Gianmarco Andreana, Andrea Gualini, Gianmaria Martini, Flavio Porta, Davide Scotti

Università degli Studi di Bergamo, Italy

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ABSTRACT

This paper provides estimates of the destructive impact of the COVID-19 outbreak on air transport at the macro-regional level. To this end, weekly data on the air service volumes are analyzed through an ITS SARIMA model and a counterfactual analysis covering the 2016–2020. We find that the real effect of COVID-19 was a reduction above 80% in all world’s macro-regions in May 2020, and still a decrease of about 70% at the end of the Summer 2020, with the only exception of China and Eastern Asia, and North America, where the reductions are, respectively, −29% and −54%. The empirical evidence confirms that the impact of the pandemic crisis and of the subsequent lockdown has been dramatic, much higher than any previous crisis. We also find that the impact is greater for intercontinental connections and for FSCs, while LCCs 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.

1. Introduction

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, which 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 (it currently involves 188 countries). Since the beginning of the crisis, the numbers have 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 1815 to 3213 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. 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

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 Corresponding author. Department of Management Engineering, Viale Marconi 5, 24044, Dalmine, BG, Italy.
 E-mail addresses: gianmarco.andreana@unibg.it (G. Andreana), andrea.gualini@unibg.it (A. Gualini), gianmaria.martini@unibg.it (G. Martini), flavio.porta@unibg.it (F. Porta), davide.scotti@unibg.it (D. Scotti).
 1 IATA (IATA, 2020) estimates that passenger traffic will not rebound to pre-crisis levels until at least 2023.

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appropriate econometric method, it is possible to identify the real effect of COVID-19. To this purpose, a simply intertemporal comparison of observed data may be misleading. A proper estimate must rely on the comparison to a counterfactual 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.

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 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 they 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, i.e., from 2 to 4 days to restrict on flights from/to China delayed the progression of 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 they 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, i.e., from 2 to 4 days to observe a doubling in the number of infected people. 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 of 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 scenario, 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 11th 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 explored some quasi-natural experiments due to exogenous shocks to identify either the contribution of air transportation to regional growth in the US (Blomgren and Cristea (2015)), or to the international trade volumes in Italy (Brugnoli et al. (2018)). Conti et al. (2019) analyze, instead, the effects of a new European airport regulation on aeronautical charges.

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 an 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 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).  

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) and 24–26 post-lockdown weeks. Such a structure, combined to the utilization of an 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.

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. 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. 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 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. 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 increased. The ongoing capacity crunch continues to be driven by the lockdown. The coefficient \( \alpha_0 \) is the 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 starts 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 \( \alpha_1 \) 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., \( \alpha_2 \) is the post-lockdown change in level, and \( \alpha_3 \) is the change in trend slope after the 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 (John Hopkins University, 2020). The cases of people infected with coronavirus start prior to the lockdown date and represent in Eq. (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. The estimated coefficient of the interaction term \( T L_t \), i.e., \( \alpha_3 \), is a variable of interest, since it captures the impact of lockdown on the air transport sector obtained by implementing a ITS design.

We estimate a log-linear model of Eq. (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. (1) (dropping the subscript \( t \) for simplicity) as follows:

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

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

and compute it when \( L = 1 \):

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

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6 Available seat kilometers (ASK) are a key variable in air transportation, given by seats multiplied by flight distance.
7 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.
8 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. 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 available seats during the recovery period. However, we have no data regarding offered and then canceled seats.
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\]

and compute it when \( L = 1 \):
\[ y(L = 1) = e^{i + a L + b L + c L + d L + \phi(s)} + \epsilon, \]
and under \( L = 0 \):
\[ y(L = 0) = e^{i + a L + b L + c L + d L + \phi(s)} + \epsilon. \]

The relative variation is as follows:
\[ \frac{y(L = 1) - y(L = 0)}{y(L = 0)} = \frac{e^{i + a L + b L + c L + d L + \phi(s)} - e^{i + a L + b L + c L + d L + \phi(s)}}{e^{i + a L + b L + c L + d L + \phi(s)}}. \]

which simplifies to:
\[ e^{\eta_1} - e^{\eta_1 t}, \]
so that the percentage variation is \( e^{\eta_1} - e^{\eta_1 t} \cdot 100 \). 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:
\[ y(t)_{L=0} = e^{\eta_1 + a t} \]
and
\[ y(t + 1)_{L=0} = e^{\eta_1 + a t + b (t + 1)} \]
so that
\[ \frac{y(t + 1)_{L=0} - y(t)_{L=0}}{y(t)_{L=0}} = \frac{e^{\eta_1 + a t + b (t + 1)} - e^{\eta_1 + a t}}{e^{\eta_1 + a t}} \]
i.e., \( e^{\eta_1} - 1 \). Let us look now at the trend when \( L = 1 \)
\[ y(t)_{L=1} = e^{\eta_1 + a t + (a_1 + a_2) t} \]
and
\[ y(t + 1)_{L=1} = e^{\eta_1 + a t + (a_1 + a_2) (t + 1)} \]
so that
\[ \frac{y(t + 1)_{L=1} - y(t)_{L=1}}{y(t)_{L=1}} = \frac{e^{\eta_1 + a t + (a_1 + a_2) (t + 1)} - e^{\eta_1 + a t + (a_1 + a_2) t}}{e^{\eta_1 + a t + (a_1 + a_2) t}} \]
and we get that it is equal to \( e^{\eta_1 + a_1} - 1 \). Hence, the percentage impact of the lockdown on the industry is given by \((e^{\eta_1 + a_1} - 1) \cdot 100 \). The number of COVID-19 cases is also expressed in logarithm, i.e., the coefficient \( b \) is an elasticity. The model in Eqs. (1) and (2) is estimated 10 times, one regression for each of the 10 investigated macro-regions.

Eq. (2) defines the error term \( \eta_t \) temporal structure, a SARIMA \((p, d, q) / (P, D, Q)_t \) 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 \( \phi_1, \ldots, \phi_p, \theta_1, \ldots, \theta_q, \Phi_1, \ldots, \Phi_P, \Theta_1, \ldots, \Theta_Q \), whereas the innovation error term \( \epsilon_t \) is assumed to be normally distributed with zero-mean and variance \( \sigma^2 \). The model is estimated with maximum likelihood (Hyndman & 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.\(^{11}\) 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 Ljung-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 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.

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 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 is recorded in Western Europe and in North America in May 2020, while it is recorded 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 0.5% (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 the intensity of the origin–destination network. ASKs instead show the dynamics relating to the

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\(^{11}\) The algorithm minimizes the corrected AIC, given by \( AIC + \frac{2p + q + k + 1}{n} - \frac{1}{n} \), where \( k \) is the parameter for the number of independent variables and \( T \) is the maximum time period.
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. The last is chosen because it is about 3-4 times the lockdown time interval (usually it lasted 2 months), and the week time periods: the week beginning 21st April 2020, exactly in the middle of the lockdown period in the corresponding macro-regions. The lockdown period is extremely high, never observed before worldwide in the same week in year 2019. The three vertical lines correspond to the starting week of lockdown in the main macro-regions taking as reference equal to 100 the figure of 29th October 2019. 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 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), 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) and September 2020 (Table 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 most of 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 traffic in Table 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.

Fig. 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 4, this threshold is reached the week beginning 17th March 2020.

As 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.

### Table 1

Macro regions’ characteristics and COVID-19 impact.

| Macro region | area million km² UN | pop 2018 million WPP | pop density inhabit per km² | 1st covid case | # of covid cases 19thMay | % of covid cases 19thMay | # of covid cases 8thSep | % of covid cases 8thSep |
|--------------|---------------------|----------------------|-----------------------------|---------------|-----------------------|------------------------|------------------------|------------------------|
| AF           | 30                  | 1216                 | 40                          | 14thFeb       | 91,060                | 0.01                    | 1,346,866              | 0.1                    |
| AS1          | 9                   | 1884                 | 206                         | 25thJan       | 198,589               | 0.01                    | 5,698,446              | 0.3                    |
| AS2          | 6                   | 670                  | 112                         | 22ndJan       | 70,854                | 0.01                    | 551,904                | 0.08                   |
| AS3          | 29                  | 1734                 | 60                          | 22ndJan       | 411,981               | 0.03                    | 124,7961               | 0.07                   |
| EU1          | 13                  | 502                  | 39                          | 22ndJan       | 1,476,117             | 0.3                     | 2,691,683              | 0.54                   |
| EU2          | 6                   | 238                  | 40                          | 31stJan       | 142,636               | 0.06                    | 725,732                | 0.3                    |
| LA           | 19                  | 422                  | 22                          | 23rdFeb       | 584,862               | 0.14                    | 8,237,309              | 1.95                   |
| ME           | 7                   | 246                  | 35                          | 19thFeb       | 297,582               | 0.12                    | 1,683,388              | 0.68                   |
| NA           | 24                  | 579                  | 24                          | 22ndJan       | 1,617,519             | 0.28                    | 6,678,970              | 1.15                   |
| OC           | 8                   | 38                   | 5                           | 26thJan       | 8601                  | 0.02                    | 29,032                 | 0.08                   |

Legend: WPP, World Population Prospects, the 2019 Revision. United Nations Department of Economic and Social Affairs. Population Division.UN: United Nations Statistics Division; JHU: Johns Hopkins University.
Table 3
Aviation industry percentage change compared to the same week of the previous year, 8th September 2020.

| Macro-region | Total | Intra macro-region | Extra 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% -65.0%     | -56.1%| -55.5% -55.2% | -69.2%| -68.1% -74.5% |
| EU2          | -41.8%| -44.0% -47.7%     | -19.4%| -28.8% -35.2% | -57.0%| -57.5% -59.9% |
| ME           | -65.7%| -59.7% -69.3%     | -65.6%| -59.0% -66.5% | -66.1%| -65.4% -72.7% |
| 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% |

Fig. 1. Seats index number, base = 100 29th October 2019.

Table 4
Share of grounded seats on January 2020 seats per macro-region.

| 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%         | 7%         | 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%       |

in AF, AS1, EU1, EU2, NA, and ME, the week beginning 24th March 2020 in LA and OC, and the week beginning 31st March 2020 in AS2 and AS3.

It is evident by inspection of Fig. 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. Fig. 5 and Fig. 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. Table 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.

This descriptive analysis shows a general disruptive effect of the lockdown on air services supply side. Looking at specific macro-regions, such effect is particularly severe in Europe and Oceania, while it has 

13 Macário and Van de Voorde (2010) provide a description of the LCC business model and its differences with the FSC model. Kwokas et al. (2016) find that LCCs charge fares 20% or more below FSCs. We adopt the OAG classification for LCCs.
lockdown period passengers did not resume traveling with the same frequency as before, with a reduction of about 54%. This figure is interesting because that 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. Fig. 2 shows the booking dynamics in the different macro-regions.

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 (1) and (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 (leats), shown in Fig. 3, highlights the yearly seasonal pattern, with a general positive trend interrupted by a huge decrease due to the lockdown (Spring 2020) followed by a recovery (Summer 2020).  

We present two sets of results to appreciate both the lockdown effect and the subsequent partial recovery. 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 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. First, we estimate the lockdown effect on the booking series for each macro-region. 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.

Table 5
LCCs vs FSCs percentage change compared to the same week of the previous year, 8th September 2020.

| Macro-region | Seats | Frequency | ASK |
|--------------|-------|-----------|-----|
| AF           | -63.6% | -62.3%    | -61.1% |
| ASI          | -56.1% | -56.1%    | -57.8% |
| AS2          | -57.7% | -53.6%    | -70.7% |
| AS3          | -28.1% | -24.3%    | -43.7% |
| EU1          | -58.6% | -58.7%    | -58.1% |
| EU2          | -47.3% | -48.0%    | -45.5% |
| LA          | -50.8% | -55.3%    | -47.0% |
| ME          | -48.3% | -44.2%    | -54.2% |
| NA          | -52.1% | -54.2%    | -54.9% |
| OC          | -86.1% | -86.7%    | -85.5% |

| Macrosregion | Seats | Frequency | ASK |
|--------------|-------|-----------|-----|
| AF           | -68.3% | -56.8%    | -72.8% |
| ASI          | -57.5% | -48.0%    | -65.7% |
| AS2          | -64.3% | -58.3%    | -76.4% |
| AS3          | -23.3% | -19.1%    | -43.0% |
| EU1          | -67.4% | -64.3%    | -74.4% |
| EU2          | -46.2% | -48.3%    | -53.2% |
| LA          | -75.7% | -63.0%    | -79.2% |
| ME          | -64.1% | -59.3%    | -70.7% |
| NA          | -59.0% | -54.9%    | -66.9% |
| OC          | -71.4% | -59.3%    | -81.9% |

Table 6
Percentage changes in bookings per macro-regions compared to the same month of the previous year.

| 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%  |
| ASI          | 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%  | -57.3%   | -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%     | -2.3%   | -27.5%   | -90.7%   | -92.4%   | -88.0%  |
| ME          | -1.0%    | 2.9%    | -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%  |

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 LCCs’ 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, where Oceania is the one that lags furthest behind in this regard. Eastern 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 due to the ban on aviation activity. However, our data show that in the post lockdown period passengers did not resume traveling with the same frequency 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. We compute the percentage changes in bookings compared to the same month of 2019, reported in Table 6. All macro-regions have a positive variation in January 2020: North America, for instance, has +6.6% increase in bookings. 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 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. Fig. 2 shows the booking dynamics in the different macro-regions.

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.

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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., $\alpha_t-L$. 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.

Western Europe (EU1), and Middle East (ME). They have only a positive trend, i.e., $\hat{\alpha}_3$ is nearly 0, as well as $\hat{\alpha}_3$. In April 2020 $\hat{\alpha}_3$ 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.

We have performed some diagnostic tests to address the possible identification problems regarding the results shown in Table 8. The post-estimation diagnostic analysis consists in plotting the residuals autocorrelation functions and implementing a Ljung-Box test. Fig. 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 Ljung-Box test has a null hypothesis that the errors are independently distributed, and it is shown in Table 9.

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 Ljung-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 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. Fig. 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 Fig. 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 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.

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16 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.

17 The relatively small weekly percentage reduction in AS3 might be explained by the longer lockdown period in China.
Fig. 3. Seats time series in the macro-regions.
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 sus 

tainability of the industry.

We have performed a robustness analysis by checking whether the 
counterfactual analysis might be affected by the presence of some con 
 founding events that modify substantially the trend before the COVID-

19 outbreak. For instance, during 2019 the Boeing 737 MAX was 
grounded 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, 
technical problems. Hence, we have estimated a version of the ITS 
model including the dummy 737 MAX grounding, equal to 1 since March 2019. The results 
are shown in Table 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

### Table 7

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

| Dependent variable | AF | AS1 | AS2 | AS3 | EU1 | EU2 | LA | ME | NA | OC |
|--------------------|-----|-----|-----|-----|-----|-----|----|----|----|----|
| Constant           | 14.81*** | 15.25*** | 15.94*** | 16.75*** | 16.82*** | 14.95*** | 15.83*** | 15.39*** | 16.87*** | 14.80*** |
| t                  | (1087.67) | (1045.23) | (770.95) | (871.97) | (226.94) | (108.17) | (1013.06) | (668.28) | (716.95) | (1898.02) |
| L                  | 49.95*** | 48.31*** | 46.83*** | 10.88* | 98.85*** | 64.25*** | 85.69*** | 50.75*** | 51.54*** | 117.81*** |
| t L                | (12.08) | (11.06) | (12.27) | (2.20) | (15.24) | (29.47) | (21.06) | (16.35) | (20.62) | (25.45) |
| lcase              | −0.05*** | −0.01 | −0.04*** | −0.04*** | −0.03*** | −0.01 | −0.02*** | −0.02*** | 0.001 | −0.04 |

**ARIMA error model**

| LAR     | 1.16*** | (10.20) | 1.64*** | (20.41) | 0.94*** | (39.73) | 1.17*** | (13.33) | 1.52*** | (20.77) | 0.75*** | (14.16) | 0.51*** | (4.10) |
| L2.AR   | 0.94*** | (12.88) | −0.78*** | (5.23) | −0.53*** | (6.08) | −0.97*** | (6.96) | 0.97*** | (14.16) | 0.51*** | (4.10) |
| L3.AR   | −0.44** | (2.77) | −0.02 | (0.15) | −0.59** | (0.01) | −0.97*** | (0.01) | 0.51*** | (2.30) | 0.51*** | (2.30) |
| L4.AR   | 0.45** | (2.97) | 0.27** | (2.79) | 0.31** | (2.09) | 0.51*** | (2.09) | 0.51*** | (2.09) | 0.51*** | (2.09) |
| L5.AR   | 0.15 | (0.09) | 0.15 | (0.15) | 0.09*** | (0.09) | 0.96** | (0.09) | 0.96** | (0.09) | 0.96** | (0.09) |
| LMA     | 0.21+ | (1.74) | 1.23*** | (22.21) | 0.98*** | (32.30) | 0.94*** | (10.90) | 0.94*** | (10.90) | 0.94*** | (10.90) |
| L2.MA   | 0.41** | (3.14) | −0.06 | (27.59) | 0.99*** | (3.47) | 0.36*** | (27.59) | 0.36*** | (27.59) | 0.36*** | (27.59) |
| L3.MA   | 0.47** | (4.07) | −0.50*** | (25.58) | 0.90*** | (35.58) | −0.55** | (35.58) | −0.55** | (35.58) | −0.55** | (35.58) |
| L4.MA   | 0.15 | (0.09) | 0.15 | (0.15) | 0.09*** | (0.09) | 0.96** | (0.09) | 0.96** | (0.09) | 0.96** | (0.09) |
| L5.MA   | 0.15 | (0.09) | 0.15 | (0.15) | 0.09*** | (0.09) | 0.96** | (0.09) | 0.96** | (0.09) | 0.96** | (0.09) |

**Seasonal effects, s = 52**

| LAR     | 0.50*** | (5.66) | −0.11 | (1.07) | 0.19+ | (0.85) | 0.51*** | (1.70) | 0.57*** | (1.70) | 0.46*** | (1.70) |
| LMA     | 0.52** | (3.12) | 0.57** | (3.23) | 0.55*** | (3.06) | 0.49*** | (3.06) | 0.49*** | (3.06) | 0.49*** | (3.06) |

| N       | 182 | 182 | 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 |
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.

5. Conclusions

The aim of this work is to quantify the disruptive 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 is performed. This approach allows to measure the impact of the lockdown by comparing the observed trend

| Table 8 |
| SARIMA ITS model of post-lockdown effect in different macro-regions, observations until 8th September 2020. |
| 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*** | 0.002** | -0.0002 | 0.004** | 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) |
| 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

| LAR | -0.03 | -0.60*** | 0.85*** |
| (0.38) | (-4.26) | (19.53) |
| L2.AR | 0.40*** |
| (4.59) |
| L3.AR | 0.23* |
| (2.44) |
| L4.AR | -0.19** |
| (-2.62) |
| L5.AR | 0.14 |
| (1.93) |
| LMA | 1.22*** |
| (30.25) |
| L2.MA | 0.87*** |
| (11.74) |
| L3.MA | -0.22* |
| (-2.30) |
| L4.MA | 0.19* |
| (2.10) |

Seasonal effects, s = 52

| LAR | 0.18 |
| (1.54) |
| LMA | 0.30** |
| (2.58) |

Table 9

SARIMA ITS model diagnostic tests.

| 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 |
| H0 | N.R. | N.R. | R. | N.R. | N.R. | N.R. | R. | N.R. | N.R. | N.R. |

Q*: Ljung-Box statistics; N.R. = H0 not rejected; R. = H0 rejected.
Fig. 4. Counterfactual analysis: no COVID-19 cases and no subsequent lockdown effect.
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 (such as 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 all the world economy has been 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 observations 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 moment we have not enough observations 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 scenario are available.

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 observations 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 scenario are available.
period will be available, possibly adding other explanatory variables, such as international trade and e-commerce volumes. These extensions are left for future research.

CRediT authorship contribution statement

Gianmarco Andreana: Writing – review & editing, Empirical Method, Estimation, Reviewing and Editing. Andrea Gualini: Writing – review & editing, Visualization, Empirical Method, Data Mining, Reviewing and Editing, Data Visualization. Gianmaria Martini: Supervision, Estimation, Writing – original draft, preparation. Flavio Porta: Writing – review & editing, Visualization, Data mining, Estimation, Literature review, Reviewing and Editing, Data Visualization. Davide Scotti: Writing – review & editing, Literature review, Reviewing and Editing.

Appendix

Fig. 5. Frequency index number, base = 100 29th October 2019.

Fig. 6. ASK index number, base = 100 29th October 2019.
Fig. 7. Two examples of residuals plot, histogram and ACF.
Table 11
SARIMA ITS model with $d = 1$

|             | 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) |
| lseats      | -0.03*** | -0.004 |
|             | (-2.14) | (-0.17) |

**ARIMA error model**

|             |     |    |
|-------------|-----|----|
| LAR         | -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**, $s = 52$

|             |     |    |
|-------------|-----|----|
| LAR         | 0.22** |        |
|             | (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

$Q^*$ Ljung-Box statistics.

Table 12
ITS SARIMA model with Boeing737 MAX grounding

|     | 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*** | 0.0004  | 0.0004  | 0.002*  | 0.0001  | 0.0002  | 0.0003  | 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** | -2.51** | -0.36   | -1.39   | 1.32    | 10.48** | 7.05    | 3.10    | 13.45** | 20.42*** |
|         | (-3.10) | (-2.81)  | (-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)  |
| lseats  | -0.15** | -0.08*** | -0.06*** | 0.004  | -0.08** | 0.01    | -0.03   | 0.05**  | 0.002   | 0.002    |
|         | (-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)  | (-2.11) | (-0.62) | (-0.08) | (-0.58) | (-1.33) | (-1.43) | (-0.21) | (-0.63) | (-1.78)  |

**ARIMA error model**

|     |     |     |     |     |     |     |     |     |    |
| LAR | -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) | (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*** | -0.37** | -3.19  |       |         |       |       |       |
|     | (2.67) |         |         |        |       |         |       |       |       |
| 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)  |        |         |       |       |       |

(continued on next page)
Table 12 (continued)

|     | AF | AS1 | AS2 | AS3 | EU1 | EU2 | LA | ME | NA | OC |
|-----|----|-----|-----|-----|-----|-----|----|----|----|----|
| 1.3 MA |   |     |     | 0.23** |     |     | 1.43*** |     |     |     |
|     |    |     |     | (2.91) |     |     | (9.88) |     |     |     |
| 1.4 MA |   |     |     | 0.53*** |     |     |     |     |     |     |

Seasonal effects, $\tau \approx 0.52$

|     |     |     |     |     |     |     |     |     |     |     |
| LAR | 0.18 |     |     | 0.24* |     |     | 0.28* |     |     |     |
|     | (1.49) |     |     | (2.05) |     |     | (2.31) |     |     |     |
| L-MA |     |     |     | 0.41*** |     |     | (4.50) |     |     |     |

|     |     |     |     |     |     |     |     |     |     |     |
| 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.

$+ p < 0.1, \ * p < 0.05, \ ** p < 0.01, \ *** p < 0.001$

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