



Since January 2020 Elsevier has created a COVID-19 resource centre with free information in English and Mandarin on the novel coronavirus COVID-19. The COVID-19 resource centre is hosted on Elsevier Connect, the company's public news and information website.

Elsevier hereby grants permission to make all its COVID-19-related research that is available on the COVID-19 resource centre - including this research content - immediately available in PubMed Central and other publicly funded repositories, such as the WHO COVID database with rights for unrestricted research re-use and analyses in any form or by any means with acknowledgement of the original source. These permissions are granted for free by Elsevier for as long as the COVID-19 resource centre remains active.



Forecasting temporal world recovery in air transport markets in the presence of large economic shocks: The case of COVID-19

S.V. Gudmundsson^{a,*}, M. Cattaneo^b, R. Redondi^b

^a Reykjavik University, 102 Reykjavik, Iceland

^b University of Bergamo Via Pasubio 5b, 24044, Dalmine, Italy

ARTICLE INFO

Keywords:

COVID-19
Recovery time
Passenger demand
Freight demand
Air transport industry

ABSTRACT

This paper estimates the relationship between the strength of economic shocks and temporal recovery in the world air transport industry. Our results show that world recovery of passenger demand to pre-COVID-19 levels is estimated to take 2.4 years (recovery by late-2022), with the most optimistic estimate being 2 years (recovery by mid-2022), and the most pessimistic estimate 6 years (recovery in 2026). Large regional differences are detected, Asia Pacific has the shortest estimated average recovery time 2.2 years, followed by North America 2.5 years and Europe 2.7 years. For air freight the results show a shorter average world recovery time of 2.2 years compared to passenger demand. At the regional level, Europe and Asia Pacific are comparable with average recovery times of 2.2 years while North America is predicted to recover faster in 1.5 years. The results show that the strength of economic shocks of various origins impacts the linear growth of passenger and freight traffic and the temporal recovery of the industry in a predictable transitory way. Hence, the impact of the COVID-19 recession will represent a temporary, although long-lasting, correction to previous growth levels.

1. Introduction

In the first part of 2020, the COVID-19 pandemic had a major impact on the airline industry, much stronger than past disruptive events, such as 9/11 and the 2008 global financial crisis. After a few months from the first infection cases (January–March 2020), lockdown measures were implemented in a few countries (e.g., China and Italy) and then gradual introduction of border closures took place, followed by quarantine restrictions and testing regulations, creating widespread impact on the air transport industry. Only a few months later, facing a worsening situation of almost 46 million infections and 1.2 million deaths by November 2020 (Johns Hopkins University COVID-19 Map), governments declared more restrictive measures to limit the virus contagion, inevitably resulting in a dramatic decline in demand for air transport services, with unprecedented consequences. At the first peak of the pandemic, between March–June 2020, up to 17,000 aircraft sat idle. This massive demand contraction depressed the entire industry, with airports and aircraft constructors facing important cuts in output (e.g., Amankwah-Amoah, 2020; Macilree and Duval, 2020; Serrano and Kazda, 2020; Sun et al., 2020).

Concerned about the ability to withstand a prolonged downturn in

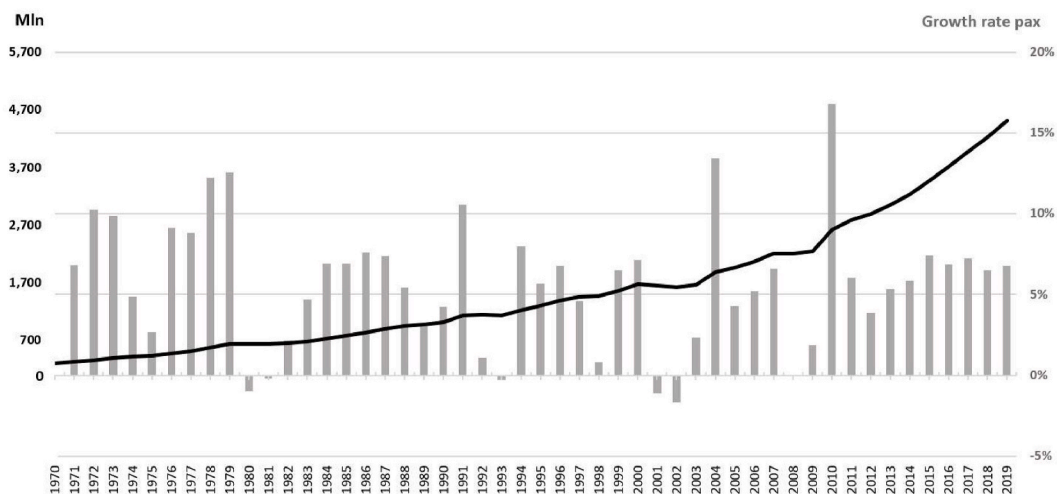
demand, all industry actors have concerns about the duration of the crisis and recovery to past volumes. Although the world is struggling, the lack of knowledge on its severity, breath and duration, calls for analyses aimed at better understanding how recovery, following pandemics, takes place; an essential gauge for governments and the sector when planning strategic and tactical actions putting idle resources back in place.

Despite other “black swan” events in the past, that shocked the aviation industry, airline traffic growth has remained quite stable in the middle-to long-term. However, the current downturn is unprecedented in its depth and fast rebound depends on readily available vaccines for the world population. What has made this epidemic especially tough is the unprecedented global coverage of the virus, the waves of infection, and the development time of vaccines.

This paper aims to forecast temporal recovery of air traffic volumes building on the more general considerations of Doran and Fingleton (2014), who explore the spatio-temporal perspectives on Europe’s economies following economic shocks on growth using the concept of regional resilience suggested by Martin (2012), and Phillips (1996) who advanced the debate on forecasting approaches in the presence of large economic shocks.

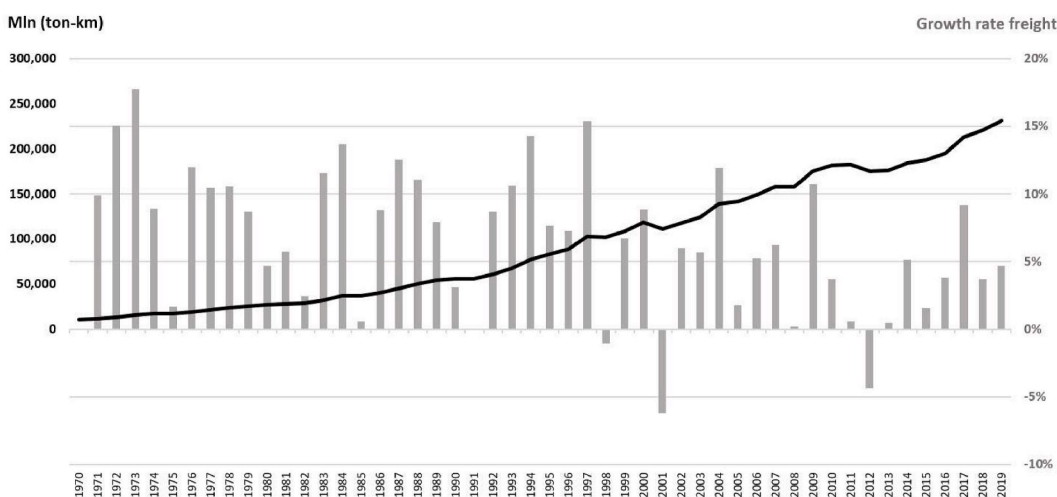
* Corresponding author.

E-mail address: sveinng@ru.is (S.V. Gudmundsson).



Source: World Bank data.

Fig. 1. World growth in air transport passengers (1970–2019).



Source: World Bank data.

Fig. 2. World growth in air freight (1970–2019).

We also rely on Friedman’s (1969, p. 273) plucking model was an important early contribution, which held that “a large contraction in output tends to be followed on the average by a large business expansion”, later complemented by the work of Bordo and Haubrich (2017, p. 536), who found that the measure of “time required to return output to the pre-crisis level, confounds the depth of the recession with the strength of recovery”, necessitating the separation of the notions of recession depth and recovery strength. To address this latter issue, it is necessary to employ a time-series forecasting approach that explicitly accounts for both the regulatory restrictions imposed by the pandemic circumstances and the traditional relationship linking air transport activities and economic development.

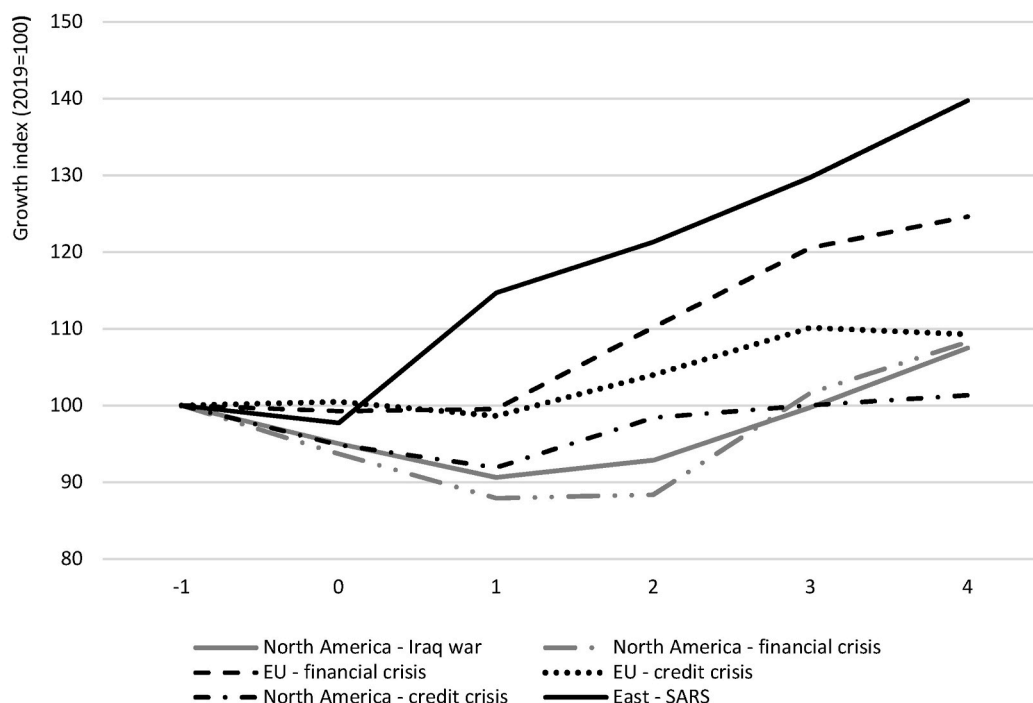
Furthermore, conflicting research results exists on the question if economic shocks cause a transitory or permanent impact on growth trends. Nelson and Plosser (1982) argue that trends change frequently in macro-economic time series, while Perron (1989), Rappoport and Reichlin (1989), and Balke and Formby (1991), came to the opposite conclusion. Thus, predictive analysis on traffic recovery must focus on global and macro-regional level recovery to investigate if major recession represent a temporary or permanent correction to previous growth levels.

The paper is organized as follows. Section 2 reviews the literature on air transport recovery. Section 3 describes the data and the methodology, while Section 4 the empirical analysis. Section 5 concludes.

2. Literature review

In past studies, the state of air travel demand after recessions has been widely investigated to understand the duration of value destruction within the industry after significant downturns. Research has shown that air passenger and freight growth respond differently to economic shocks, with the former showing greater response to post-shock economic growth (Chi and Baek, 2013). Furthermore, observing changes in revenue passenger kilometres (RPK) and gross domestic product (GDP) demonstrates that RPK changes are larger in both directions (positive and negative) on average than GDP changes (ICAO, 2013). Economic fluctuations are indeed known to be absorbed by the air transport industry in an amplified and lagged way mainly due to the timing and the pattern of (capacity) investments (Chin and Tay, 2001; Holloway, 1998).

To give further weight to these findings, Pearce (2012) found that air transport recovery following the recession of 2008–2009 was robust and



Source: World Bank data. Note: index set at 100 one year prior to crisis; -1 = pre-crisis year; 0 = crisis year.

Fig. 3. Impact of past crisis on the air transport growth index (2019 = 100).

international air travel and air freight came back to pre-recession levels in less than 18 months from the lowest level. Similarly, [Fuellhart et al. \(2016\)](#) found that long-term adjustments in the airline industry following economic-shocks occurred in a geographically coherent manner. The research cited so far suggests that the airline industry is particularly robust to economic-shocks and showing strong “bounce-back” characteristics.

The “bounce-back” or “rubber-band” effect following recessions ([Wynne and Balke, 1993](#), p. 1) “contains a certain amount of intuitive appeal but seems to have been subject to few empirical tests.” According to Wynne and Balke, the earliest work to test this hypothesis was [Moore \(1961\)](#) who found that the level from which the recovery starts, significantly impacts recovery strength in its early stages. Following up on this work, Wynne and Balke empirically showed that the peak-to-trough decline in output during recession time is correlated to the subsequent growth in the short-run recovery phase. They also documented that the average Pre-World War II contraction was 21.2 months, followed by an average expansion period of 28.9 months, while the Post-World War II contraction period was 10.7 months followed by a much longer expansion period of 49.9 months. Another similar empirical test was performed by [Bordo and Haubrich \(2012\)](#), who found that recessions associated with financial crises are generally followed by rapid recoveries.

In contrast, [Bonham et al. \(2006\)](#), researching into the 9/11 recession on U.S. and Hawaiian tourism, reported the presence of large regional differences in recovery rates, evidenced by mainland U.S. tourism levels lagging well behind Hawaiian tourism that received a growth boost due to the diversion of U.S. passengers to Hawaii in lieu of traveling abroad. Thus, economic shocks on air transport may affect world regions and within regions growth differently.

These macro results for U.S. tourism demand were supported by [Ito and Lee \(2005\)](#) assessing the impact of 9/11 on U.S. airline demand, finding a 30% transitory demand shock and a 7.4% negative demand from pre-9/11 levels carried on over several years, and not explained by

other factors.

In the backdrop of what has been discussed so far this paper predicts how the world’s air transport growth recovers across the world. First, we ask if economic shocks to air transport have transitory or permanent impact on growth trends and to which extent a “bounce-back” effect will take place. Second, we question whether some world regions differ in terms of temporal strength of growth recovery.

Toward this aim, we examine the reaction of air travel to previous economic shocks to model the regional temporal recovery trend. We examine first the post-recession path of growth relative to what might be expected, given previous trends, and then predict temporal recovery following COVID-19.

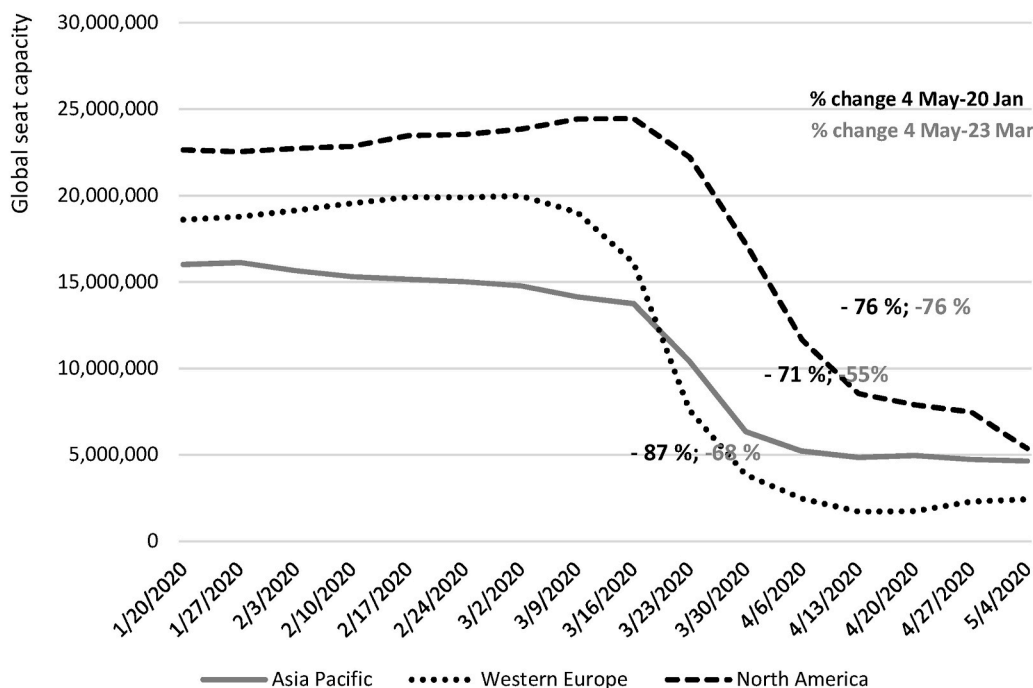
3. Data

For the scope of our research we gathered longitudinal data on domestic and international air passengers and air freight (million ton-km) in the period 1970 to 2019¹ from the World Bank collection of Development Indicators.² [Figs. 1 and 2](#) show volumes and growth rates for passengers and freight.

To enrich our forecasting specification, we used data on GDP (current value) based on constant local currency (World Bank and OECD national account data) in the period 1970–2018 defined as the sum of gross value added by all resident producers in the economy plus any product taxes and minus any subsidies not included in the value of the products. Data for the year 2019 are drawn from WTO statistics. The inflation adjusted oil price (in \$/Barrel) data were also included in our

¹ Air traffic data for 2019 are computed based on the past 5-year average growth rates.

² Data and estimates are provided by International Civil Aviation Organization, Civil Aviation Statistics of the World and ICAO staff estimates.



Source: OAG data.

Fig. 4. The COVID-19 effect on global flight seat capacity.

projection model based on inflation data statistics.³

To “train” the forecasting model, our simulation analysis considers the air traffic 2020 estimates (see the methodological section for details on the specific effects of the COVID-19 pandemic) for passengers and freight made available by the International Civil Aviation Organization (ICAO, 2020) and the International Air Transport Association (IATA), respectively. Eventually, our forecasting model employs the forecast estimates of the macroeconomic dimensions at a global level and in the various regions as inputs. These estimates were drawn from WTO forecasts (WTO, 2020), to examine the impacts of different scenarios on macroeconomic outcomes through a Dynamic Computable General Equilibrium global model consistent with the literature on past outbreaks (e.g., McKibbin and Fernando, 2020; McKibbin and Wilcoxon 1999, 2013; Lee and McKibbin 2004).

4. Methodology

We aim to estimate recovering periods for passengers and freight, distinguishing world and major regional markets: Asia-Pacific, Europe, and North-America.

For each output variable, we applied multivariate Auto Regressive Integrated Moving Average - ARIMAX models with structural changes to obtain forecast based on past history, GDPs and oil prices. Time series based-ARIMA models have been employed to evaluate the presence of large shocks in forecasting (Phillips, 1996) and have been largely employed to predict traffic flows in the air transportation system, either in their simple form or integrated with other prediction approaches (e.g., Grubb and Mason, 2001; Lim and McAleer, 2002; Chen et al., 2009; Tsui et al., 2014; Jungmittag 2016; Xu et al., 2019). The specific ARIMA model employed is an ARIMA (1,1,1) complemented with other times series as inputs, namely an ARIMAX model, defined as follows:

$$\Delta \ln(y_t) = \alpha + \beta \cdot \Delta \ln(GDP_t) + \theta \Delta \ln(OIL_t) + \xi \cdot EVENT_t + \lambda \cdot \Delta \ln(y_{t-1}) + \epsilon_{t-1} + \epsilon_t \tag{1}$$

where $\Delta \ln(y_t) = \ln(y_t) - \ln(y_{t-1})$ is the difference between the natural logarithm of the output variable (passengers or freight volumes) between two consecutive years; $\Delta \ln(GDP_t) = \ln(GDP_t) - \ln(GDP_{t-1})$ is the difference between the natural logarithm of the Gross Domestic Products (GDP) between two consecutive years; $\Delta \ln(OIL_t) = \ln(OIL_t) - \ln(OIL_{t-1})$ is the difference of the natural logarithm of inflation inflated oil prices (OIL) between two consecutive years; $EVENT_t$ is a dummy variable that is equal to 1 if a disruptive event (e.g., 09/11 and the related recession, SARS, 2008 credit crisis, etc.) occurred in year t , and 0 otherwise. This variable accounts for the structural change in the ARIMAX model, estimated on past aviation crises.

This model is suitable to predict non-stationary output variables, as its mean average (MA) component (by the coefficient θ) accounts for the rebounding effect observed after past crises. However, the COV.

ID-19 crisis is different from past downturns for several reasons. First, the scale of the drop is unprecedented. Estimations for the decrease in world passengers in 2020 vary from 40% to 70% with respect to 2019. In comparison, following the 9/11 event, the world passenger market suffered a drop by only 1.13% and 1.68% for the years 2000 and 2001 respectively. Second, the recovery from past shocks (see Fig. 3) has been relatively fast, with on-average traffic rebounding to its previous levels in 1–2 years.

Another complication is that the COVID-19 is impacting air transport much more than the GDP (see Fig. 4), which will drop only by 10%–15% in 2020 (McKibbin and Fernando, 2020). The main reasons are related to the curtailing of international air transport, the closure of airports, and future limitations impacting airlines and airports. Some of these influences may differ from country to country especially when traffic starts to rebound, but they will not only impact passengers but also freight, as a sizable part of freight is hauled as belly cargo on passenger flights. Furthermore, limitations on passengers and freight traffic are dependent on vaccines, expected to appear for general use in 2021,

³ Source: <https://inflationdata.com>.

could take several months⁴ up to a year to be widely distributed on a world basis. Until then, aviation demand might be limited for reasons of reduced passenger confidence, especially in the case of leisure destinations, or responsible authorities may even require passengers to be vaccinated before being accepted on flights. Thus, the historic relation between aviation output and GDP,⁵ and between aviation output and oil prices, might not hold for the next few years, or until the medical crisis is solved.

As a result, we modelled the drop in aviation output (passengers or freight) using two different components:

1. *The COVID-19 component* represents specific restrictions on aviation (almost total closures over many months in some countries), the blocking of international traffic and any future restrictions of aircraft and airport operations. This component also includes the drop in demand due to reduced travel confidence. We assume that this drop will be recovered after a vaccine will be introduced and distributed to the world population (2021–2022).
2. *The socio-economic component* represents the relationship between aviation output and the development of the economy, in terms of GDP and oil prices. This component accounts for what the aviation output would be if the GDP and oil price dependence trends were as in previous periods. This component is modelled as the ARIMAX process of equation [1], and future trends dependent on GDP and oil price. It represents the potential aviation output if a vaccine is found, and the primary drop recovered.

Given the uncertainty for the future development of the crisis, our analyses are based on yearly data rather than monthly data, as the former are more stable to predict. We therefore limited our objective to identify the years in which the traffic recovery would take place for different traffic segments, and for the major geographical markets.

To forecast the output variables, we applied the following procedure:

1. For each output variable y_t , we estimate the ARIMAX model of equation (1) and specifically predict the output for future years by considering the assumptions about future GDPs and oil price trends.
2. Based on the difference between the most recent aviation output forecast for 2020 (IATA, 2020), and the related ARIMAX estimation, as reported in the previous step, we estimate the drop in output related to the specific COVID-19 event $\Delta COVID_t$; this component is assumed to be recovered between 2021 and 2022.
3. The final estimation of the aviation output at time t , \hat{y}_t is as follows: for t from 2020 to 2022, we consider the two components of demand described before: $\hat{y}_t = y_t - \Delta COVID_t$; for t from 2023 to 2026, we only consider the “socio-economic” demand level related to the ARIMAX model, as the drop in demand related to the specific COVID-19 emergency is assumed to be recovered: $\hat{y}_t = y_t$.
4. Given the estimation of the aviation output from 2020 to 2021, \hat{y}_t , we compute the recovery period as the earliest year \hat{t} in which the output becomes higher than or equal to the pre-COVID 2019 traffic level: $\min(\hat{t}): \hat{y}_t \geq y_{2019}$

Finally, forecast intervals are estimated by applying the procedure above, and by bootstrapping the existing assumptions on the 2020 drop in aviation output (from 40 to 70 per cent), on GDP (see McKibbin and Fernando, 2020) and the oil price estimations for the period 2020 to

⁴ See for example: How Long Will a Vaccine Really Take? The New York Times, 30th April 2020.

⁵ The relationship between air traffic and GDP has long been investigated in the literature both by contributions aimed at estimating demand generation (e.g., Birolini et al., 2020; Boonekamp et al., 2018) and those focused in examining the causal relationship between air transport and economic growth (e.g., Hakim and Merkert, 2016; Marazzo et al., 2010).

Table 1
Estimated recovery times for world air passenger and freight traffic.

Year	World Passengers			World Freight		
	Recovery time	Scenarios		Recovery time	Scenarios	
		(no of years)	(no)		(%)	(no of years)
2020	0	0	0.0%	0	0	0.0%
2021	1	0	0.0%	1	25	0.3%
2022	2	6631	66.5%	2	7979	79.8%
2023	3	2740	27.5%	3	1996	20.0%
2024	4	439	4.4%	4	0	0.0%
2025	5	154	1.55%	5	0	0.0%
2026	6	36	0.36%	6	0	0.0%
Average	2.43	Tot:		2.20	Tot:	
Recovery time		10,000			10,000	

2025. For each prediction we repeat the analysis 10k times, and build confidence bands for every output variable.

5. Results

This section presents the results of the prediction analysis aimed at consistently providing practical estimates of recovery times for both air passengers and freight in relation to the deterioration of domestic demand and the closure of national borders. Predictions evaluate how severely the COVID-19 pandemic will affect air transport at an aggregated global level and whether consistent differences are detected in recovery dynamics across macro regions (Asia-Pacific, Europe and North America).

Estimates of recovery times reported in Table 1 show that air transport recovery will take on average 2.4 years starting from 2020. The simulation analysis highlight that in most of the cases the passenger demand levels of 2019 will be reached between 2022 (66.5% of the cases) and 2023 (27.5% of the cases). In other words, the predicted recovery time is the longest on record for the industry in a best-case scenario. However, in the worst-case scenario the demand recovery goes beyond 2024 (6.3% of the cases).

The impact on the world air cargo industry shows less prediction uncertainty and on average faster recovery times. While air cargo has been disrupted by the contraction of passenger aircraft utilization (the belly component) and a decrease in airport operations, the sector is expected to recover faster than the passenger counterpart. This supports the findings of Chi and Baek (2013), who found that SARS and 9/11 had adverse short- and long-term effects on air passenger demand but less impact on air freight demand. In fact, some segments of air cargo operations have surged to meet essential supplies to tackle the COVID-19 pandemic and to meet increased online trade demand in many business sectors. On the one side, carriers have converted otherwise idle passenger aircraft to carry cargo (e.g., Delta, Qatar Airways); and on the other side, major dedicated air freight integrators have intensified their activities to fill the void left by belly capacity.

Table 1 demonstrates that on average air freight demand will recover in 2.2 years at a global level and that this prediction suffers from less uncertainty compared to the passenger estimates. According to the simulations, air freight recovery would occur between 2022 and 2023, while in the most optimistic case it might take place in a little over 1 year (second part of 2021).

Fig. 5 highlights the difference between passengers (Fig. 5a) and freight (Fig. 5b) in terms of average recovery time and the 5th and 95th percentile confidence levels. The pattern presented highlights how the demand to the aviation industry is more prolonged for passengers than for freight. The air passenger contraction is on average about 60% compared to 10% for freight. In addition, passenger growth has more unpredictable recovery times based on the range in the confidence band percentiles. Overall, the simulation analysis shows that in the most

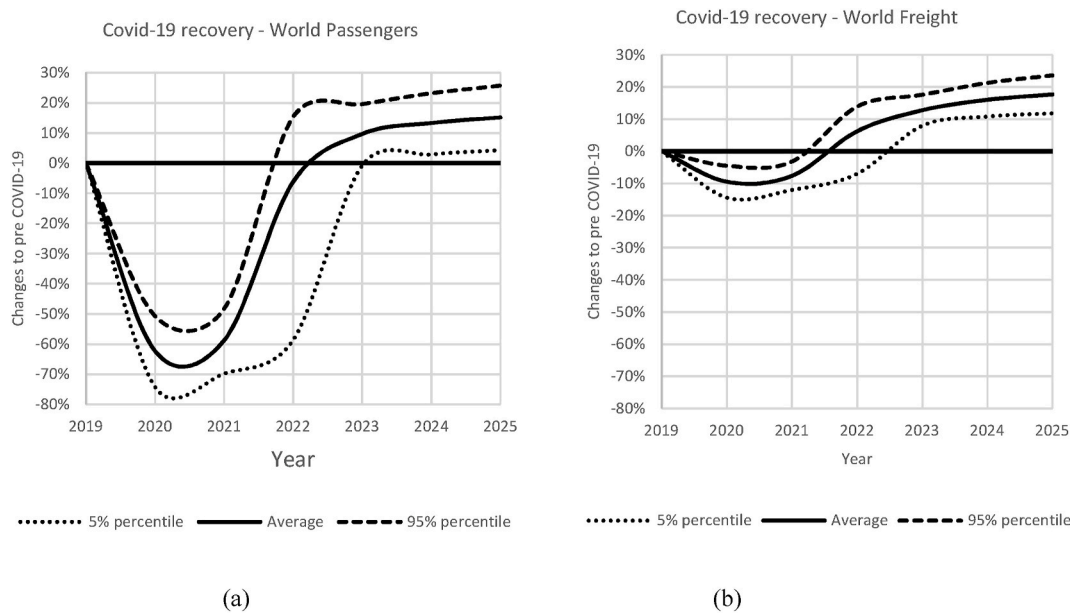


Fig. 5. Distribution of recovery times for air passenger and air freight.

pessimistic scenarios, air transport demand will recover from the COVID-19 pandemic within 6 years (2026).

While average estimated recovery times for passengers are longer than those related to freight, passenger traffic seems to bounce back more forcefully after the shock than freight.

The coefficient of model [1] related to the Moving Average (MA) part of the ARIMAX model— θ , provides a way to measure and compare the bounce-back effects between passengers and freight. In particular, when $\theta < 0$, traffic tends to recover speedily from past shocks. In fact, if past traffic underperforms expectations, and the error terms of previous year ε_{t-1} is negative as during a shock, the model forecasts an extra growth for the current year ($\theta \cdot \varepsilon_{t-1} > 0$), other things being equal. This extra growth comes on top of the expected effect due to the recovery of GDP, considered as an independent variable in the model.

To verify if the bounce-back effect from past shock is greater for passenger than for freight, we tested the statistical significance of the difference between the coefficients θ estimated separately for passengers and freight by applying equation [1]. Especially for passenger traffic, θ is equal to -0.7540 (with a standard error equal to 0.4586) so confirming the presence of a bounce-back effect from past shocks. In the case of freight, θ is equal to 0.8549 (standard error equal to 0.1783), a weaker bounce-back effect from past shocks than passengers. Employing a Z-test⁶ to verify whether the difference between the coefficients θ computed for passengers and freight is statistically significant, we found that the θ coefficient for passengers is significantly lower than for freight, with a statistical significance of 1%. So, the bounce-back effect from past shocks is significantly greater for passenger traffic hinting at the previously fast recoveries of passenger traffic after the Iraq war in 1994 and the credit crisis in 2010 (see Figs. 1 and 3). The forecast reported in Fig. 5, shows a more forceful recovery in case of passengers, reflecting the estimations of the ARIMAX models.

While evaluating global air transport economic trends and shifts provides important insights on how the aviation sector as a whole will be affected by the COVID-19 pandemic, the analysis across different world regions improves the understanding of geographically different recovery paths. In fact, these differences may rest on countries' specific institutional setting and economic structure, determining their readiness for action and resilience in periods of crisis (Martin, 2012). Since the

beginning of the propagation of the virus countries have indeed employed different measures to limit the spread of COVID-19 and different approaches to support their local economies (McKibbin and Fernando, 2020), all pointing to different economic recovery trajectories over the next few years.

However, the stimulus packages introduced in different countries and regions are reflected in GDP expectations for 2020 and in the years that follow. Higher support from governments would reduce the drop in GDP and therefore affect our model estimates in terms of recovery times for the aviation industry to some extent, although the human factor still weights more heavily on the drop for passenger demand than the GDP until the world population has been vaccinated.

The specific recovery patterns of different regions would also depend on several specific market characteristics.⁷ To cope with the virus emergency most countries introduced restrictive measures on air travel. Those measures tend to impact more on international markets than on domestic markets. Our model integrates these effects by considering as an input the steep drop in the 2020 aviation output. As a result, the regions with a higher share of domestic traffic would have relatively less-severe shocks and in turn quicker recoveries, other things being equal.

Table 2 illustrates how recovery patterns differ across Asia Pacific, Europe and North America. On average, Asia Pacific reports the shortest estimated recovery time (2.2 years), followed by North America (2.5) and Europe (2.7). While the simulation highlights a maximum value of 4 years for North America and the Asia Pacific in the pessimistic scenario, Europe might need 6 years to recover. Similarly, to Asia Pacific, Europe's estimate is affected by a higher degree of uncertainty compared to North America's forecast, exemplified by the greater range between the 5th and the 95th percentiles. The Asia Pacific region would be faster to recover passengers after the outbreak, which is in line with the timing of the first epicenter as well as the relaxation of lockdowns compared to other world regions.

Regarding air freight, all the macro regions show a shorter recovery

⁶ See Clogg et al. (1995) for an overview.

⁷ The specific demand- and supply-based characteristics of the different regions are accounted for in the ARIMAX model, either by the estimation of the model parameters based on past shock recoveries, or by the input variables considered (the initial size of the shock in terms of aviation output and GDP in 2020, and expectations for GDPs and oil prices in the following years).

Table 2
Estimates for world air passenger and freight recovery (2019–2026).

Market	Estimated recovery times (years)			Confidence bands for recovery		
	Min	Average	Max	5% percentile	Average	95% percentile
<i>Passengers</i>						
Europe	2.0	2.7	6.0	1.7%	11.4%	21.0%
North America	2.0	2.5	4.0	7.5%	11.0%	14.6%
Asia Pacific	2.0	2.2	4.0	8.4%	18.5%	29.6%
World	2.0	2.4	6.0	4.3%	15.2%	25.7%
<i>Freight</i>						
Europe	1.0	2.2	3.0	11.2%	14.7%	18.3%
North America	1.0	1.5	3.0	11.9%	17.6%	23.4%
Asia Pacific	1.0	2.2	3.0	11.8%	16.9%	22.4%
World	1.0	2.2	3.0	11.8%	17.7%	23.6%

time compared to air passengers. North America shows the shortest recovery time, 1.5 years, while Europe and Asia-Pacific are highly comparable when considering average recovery times (2.20 vs. 2.19 years). Our forecasting approach indeed accounts for the current expectations on macroeconomic tendencies, which already integrate the effects of ongoing recovery patterns occurring in different countries. In fact, when looking at the last available estimates for freight,⁸ North America is already reducing the drop in 2020, compared with other regions, due to the strength of its internal market.

6. Conclusion

The impact of the COVID-19 pandemic on global aviation has been dramatic in 2020. Lockdown measures, mobility restrictions and quarantines have severely hit the sector, causing major contraction of activities at leading airlines and airports around the world and dramatically raising the potential risk of bankruptcy for air transport related businesses. This tremendous slump has made planning processes harder to design and enforce, thus urgently necessitating the development of forecasts to provide the various players with the necessary tools to correct strategies and re-orientate their businesses.

Aimed at estimating the recovery pattern of the whole sector by specifically tackling the unconventional features of the current disruption compared with past events (the COVID-19 and the socio-economic component) our analysis indicates that air transport recovery will take on average 2.4 and 2.2 years for air passenger and freight, respectively. However, despite the faster recovery of freight traffic compared to passengers, the latter seems to bounce back more forcefully after major economic shocks.

Recovery times are also found to vary across geographical regions given the different pre-shock levels and timing of contagion and the various restrictive measures employed by governments. Given these features, passenger traffic in the Asia Pacific is found to react faster, while Europe and North America follow closely. In terms of freight demand, North America shows a quicker recovery, given the strength of its internal market, followed by the Asia Pacific and Europe. However, on average, while both passenger and freight traffic is estimated to recover to past volumes by 2023, estimation variance is significant, especially for passengers. In the most pessimistic scenarios, the recovery time for passenger demand goes beyond 2024 (in 6.3% of the cases).

In contrast to the literature dealing with macro-economic response to

exogenous catalysts, which suggests that recessions tend to embody permanently within economies (e.g., Cerra and Saxena, 2008; Doran and Fingleton, 2014), our findings suggest that even after pandemic lockdowns, output shocks in air transport do not have permanent effects on demand. This finding is supported by a stream of research focusing both on the air transport industry and the economy in general (Balke and Fomby, 1991; Pearce, 2012; Perron, 1989; Rappoport and Reichlin, 1989; Wynne and Balke, 1993), showing that economies and the air transport industry, in particular, bounce-back to similar levels following a major shock in a rather predictable way. Although the situation is still evolving and new scenarios may arise, our evidence highlights that the COVID-19 recession will make temporal correction to previous growth levels thus being transitory opposed to permanent for the air transport industry. This of course does not imply that the aviation industry would not be affected by a major internal transformation, including a wave of consolidations, the failure of weaker airlines, and a change in market structure. Albeit any transformation of the sector would strive to preserve business survival and invigorate growth in the background of accelerated social transformation to e-societies and environmental sustainability.

Source: World Bank data. Note: index set at 100 one year prior to crisis; -1 = pre-crisis year; 0 = crisis year.

References

- Amankwah-Amoah, J., 2020. Note: mayday, mayday, mayday! Responding to environmental shocks: insights on global airlines' responses to COVID-19. *Transport. Res. E Logist. Transport. Rev.* 143, 102098.
- Balke, N.S., Formby, T.B., 1991. Shifting trends, segmented trends, and infrequent permanent shocks. *Journal of Monetary Economics* 28 (1), 61–85.
- Biolini, S., Cattaneo, M., Malighetti, P., Morlotti, C., 2020. Integrated origin-based demand modeling for air transportation. *Transport. Res. E Logist. Transport. Rev.* 142, 102050.
- Bonham, C., Edmonds, C., Mak, J., 2006. The impact of 9/11 and other terrible global events on tourism in the United States and Hawaii. *J. Trav. Res.* 45 (1), 99–110.
- Boonekamp, T., Zuidberg, J., Burghouwt, G., 2018. Determinants of air travel demand: the role of low-cost carriers, ethnic links and aviation-dependent employment. *Transport. Res. Pol. Pract.* 112, 18–28.
- Bordo, M.D., Haubrich, J.G., 2017. Deep recessions, fast recoveries, and financial crises: evidence from the American record. *Econ. Inq.* 55 (1), 527–541.
- Cerra, V., Saxena, S.C., 2008. Growth dynamics: the myth of economic recovery. *Am. Econ. Rev.* 98 (1), 439–457.
- Chen, C.F., Chang, Y.H., Chang, Y.W., 2009. Seasonal ARIMA forecasting of inbound air travel arrivals to Taiwan. *Transportmetrica* 5 (2), 125–140.
- Chi, J., Baek, J., 2013. Dynamic relationship between air transport demand and economic growth in the United States: a new look. *Transport Pol.* 29, 257–260.
- Chin, A.T., Tay, J.H., 2001. Developments in air transport: implications on investment decisions, profitability and survival of Asian airlines. *J. Air Transport. Manag.* 7 (5), 319–330.
- Clogg, C.C., Petkova, E., Haritou, A., 1995. Statistical methods for comparing regression coefficients between models. *Am. J. Sociol.* 100 (5), 1261–1293.
- Doran, J., Fingleton, B., 2014. Economic shocks and growth: spatio-temporal perspectives on Europe's economies in a time of crisis. *Pap. Reg. Sci.* 93, 137–165.
- Friedman, M., 1969. The optimum quantity of money. In: Friedman, M (Ed.), *The optimum quantity of money and other essays*. Aldine, Chicago, IL, pp. 1–50.
- Fuellhart, K., Ooms, K., Derudder, B., O'Connor, K., 2016. Patterns of US air transport across the economic unevenness of 2003–2013. *J. Maps* 12 (5), 1253–1257.
- Grubb, H., Mason, A., 2001. Long lead-time forecasting of UK air passengers by Holt–Winters methods with damped trend. *Int. J. Forecast.* 17 (1), 71–82.
- Hakim, M.M., Merkert, R., 2016. The causal relationship between air transport and economic growth: empirical evidence from South Asia. *J. Transport Geogr.* 56, 120–127.
- Holloway, S., 1998. *Changing Planes: Strategic Choice, Implementation, and Outcome*, vol. 2 (Ashgate Pub Limited).
- ICAO, 2013. World aviation and the world economy. Available: https://www.icao.int/sustainability/pages/facts-figures_world_economy_data.aspx ICAO.
- Ito, H., Lee, D., 2005. Comparing the impact of the September 11th terrorist attacks on international airline demand. *Int. J. Econ. Bus.* 12 (2), 225–249.
- Jungmittag, A., 2016. Combination of forecasts across estimation windows: an application to air travel demand. *J. Forecast.* 35 (4), 373–380.
- Lee, J.W., McKibbin, W.J., 2004. Globalization and disease: the case of SARS. *Asian Econ. Pap.* 3 (1), 113–131.
- Lim, C., McAleer, M., 2002. Time series forecasts of international travel demand for Australia. *Tourism Management* 23 (4), 389–396.
- Macilree, J., Duval, D.T., 2020. Aeropolitics in a post-COVID-19 world. *J. Air Transport. Manag.* 88, 101864.

⁸ <https://www.iata.org/en/iata-repository/publications/economic-reports/air-freight-monthly-analysis-august-2020/>.

- Marazzo, M., Scherre, R., Fernandes, E., 2010. Air transport demand and economic growth in Brazil: a time series analysis. *Transport. Res. E Logist. Transport. Rev.* 46 (2), 261–269.
- Martin, R., 2012. Regional economic resilience, hysteresis and recessionary shocks. *Journal of Economic Geography* 12 (1), 1–32.
- McKibbin, W.J., Fernando, R., 2020. The Global Macroeconomic Impacts of COVID-19: Seven Scenarios.
- McKibbin, W.J., Wilcoxon, P.J., 1999. The theoretical and empirical structure of the G-Cubed model. *Econ. Modell.* 16 (1), 123–148.
- McKibbin, W., Wilcoxon, P., 2013. A Global Approach to Energy and the Environment: the G-Cubed Model. *Handbook of CGE Modeling*, Chapter 17, pp. 995–1068. North Holland.
- Moore, G.H., 1961. Leading and confirming indicators of general business changes. In: *Business Cycle Indicators*, 1. Princeton University Press, Princeton, pp. 45–109.
- Nelson, C.R., Plosser, C.R., 1982. Trends and random walks in macroeconomic time series: some evidence and implications. *Journal of monetary economics* 10 (2), 139–162.
- Pearce, B., 2012. The state of air transport markets and the airline industry after the great recession. *J. Air Transport. Manag.* 21, 3–9.
- Perron, P., 1989. The great crash, the oil price shock, and the unit root hypothesis. *Econometrica* 57 (6), 1361–1401.
- Phillips, R.F., 1996. Forecasting in the presence of large shocks. *J. Econ. Dynam. Contr.* 20 (9–10), 1581–1608.
- Rappoport, P., Reichlin, L., 1989. Segmented trends and non-stationary time series. *The Economic Journal* 99, 168–177.
- Serrano, F., Kazda, A., 2020. The future of airport post COVID-19. *J. Air Transport. Manag.* 89, 101900.
- Sun, X., Wandelt, S., Zhang, A., 2020. How did COVID-19 impact air transportation? A first peek through the lens of complex networks. *J. Air Transport. Manag.* 89, 101928.
- Tsui, W.H.K., Balli, H.O., Gilbert, A., Gow, H., 2014. Forecasting of Hong Kong airport's passenger throughput. *Tourism Manag.* 42, 62–76.
- WTO, 2020. *Methodology for the WTO trade forecast*. Economic research and statistics division. World trade organization, April 8. Available: https://www.wto.org/english/news_e/pres20_e/methodpr855_e.pdf.
- Wynne, M.A., Balke, N.S., 1993. *Recessions and Recoveries*. Federal Reserve Bank of Dallas, Economic Review, First Quarter, pp. 1–18.
- Xu, S., Chan, H.K., Zhang, T., 2019. Forecasting the demand of the aviation industry using hybrid time series SARIMA-SVR approach. *Transport. Res. E Logist. Transport. Rev.* 122, 169–18.