AIR TRAFFIC MODELING BASED ON A LONG MEMORY APPROACH

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ABSTRACT

This paper deals with modeling air traffic data using a long memory class of models that uses fractional integration. Two datasets have been considered: monthly global Revenue Passenger Kilometers and the number of monthly flights in Europe. The objective of this paper is to investigate whether Covid-19 has had a temporary or permanent impact on the air traffic trends. To do so, we investigate the orders integration of the series. Both datasets produced the same results: the trend was mean reverting when considering data before Covid-19, but the shock was so strong and long-lasting, that it produced a change to non-mean-reversion results after Covid-19. That said, if it is desirable to bring the air traffic trend back to its values before Covid-19, it will require intervention on the part of authorities or external factors since the series will not return by themselves to their original long-term projections.

Keywords: Time series; nonstationarity; unit roots; long memory; fractional integration

1. INTRODUCTION

This paper deals with the analysis of air traffic data across time using updated time series techniques that will allow us to determine if shocks in the series will have permanent or transitory effects. There is one big event (the Covid-19 pandemic) that shook the air traffic trend more than others, and we are still perceiving the effects of it today. In fact, it seems, looking at studies on the trend, that Covid-19 was a bigger shock to air traffic than the terrorist attack of 9/11 and the world recession of 2008, causing a 60% drop in the number of international flights on expected figures, in just a few weeks, (Fraherty et al., 2022).

Air traffic can be divided into transport for passengers and cargo. Since the Covid pandemic did not have a direct effect on the movement of freight, we will be concentrating on the trends of passenger transport. The objective of this paper is to analyze the trend in the number of flights and RPK per month in Europe and on a global scale, and to find a model for it, using long memory processes; in particular, we use fractional integration, to see if the shocks are mean reverting or not. This technique seems to be very appropriate for our purpose since with a single parameter (i.e., the order of differentiation of the series) we can determine the nature (transitory or permanent) of the shock, and, if it is mean reverting, the speed of the adjustment to its original trend or long-term projection (Solarin et al., 2021). As far as we know, there are very few studies that use fractional integration in the analysis of air transport data (Barros et al., 2016; Dingari et al., 2019), and none of them use the data used in this application.

We will also examine in detail the most recent shock in the air traffic data, the one produced by the Covid-19 pandemic. While the 9/11 terrorist attacks and the 2008 financial recession were proven to be mean reverting in many air traffic time series (Cunado et al., 2008; Ahmed et al., 2018), we find that the shock produced by Covid is not, since it seems to be more significant and with a longer effect on the series. Some recent studies, in fact, have proved this result, or at least have shown that its effect is very persistent, analyzing specifically the cases of the tourism sector in Spain (Gil-Alana and Poza, 2020) and in Croatia (Payne et al., 2021).

The main contribution of the present paper is to employ updated time series techniques based on fractional integration in the analysis of air transportation data in order to determine if the shocks in the series have transitory or permanent effects. Fractional integration is an appropriate technique for this purpose based on its flexibility which allows us consider cases of series which are nonstationary though with reversion to the mean (Solarin et al., 2021).

The structure of the paper is as follows: Section 2 deals with the literature review on air traffic modeling; Section 3 presents the methodology based on fractional integration; Section 4 displays the dataset examined; Section 5 is devoted to the empirical results, while in Section 6 we discuss the results and main conclusions of the paper.

2. LITERATURE REVIEW

Recent studies regarding the Covid shock in air traffic trends prove that the chance of mean reversion is very probable though usually slow (Gudmundsson, 2021), while others focus on the economic and social consequences of such a drastic drop in air traffic due to the present Covid-19 pandemic (Iacus, 2020).

Some recent studies focus on the other two big events already mentioned that significantly changed the trend of air traffic: the world financial recession of 2008/2009 and subsequent recovery, and the 9/11 terrorist attack, and its effects on monthly arrivals in the US (Gil-Alana et al., 2008), on international air traffic demand (Ito and Lee, 2005), on US domestic flights (Blunk et al., 2006), on US tourists compared to those in Hawaii (Bonham et al., 2006) and on the Spanish air traveling data (Inglada and Rey, 2004).

Air traffic has already been studied through time series processes, showing that this methodology is quite efficient. Some examples of the existing works include: forecasts based on a seasonal Box–Jenkins model (SARIMA) (Jungmittag et al., 2016); long memory processes using ARFIMA (Dingari et al., 2019) and fractional integration in dual memory processes (Karlaftis and Vlahogianni, 2009).[1]

Other time series methods have been used in more specific environments of air traffic, and the analysis of these can be useful to observe the methodology employed, which is based, for example, on modeling monthly flows of global air travel passengers (Mao et al., 2015); or on the number of passengers carried by selected routes and a market share comparison (Pitfield, 2008), and on the reversibility of air transport demand based on airfare, fuel prices and price transmission (Wadud, 2015).

Other time series methods which are found to be quite appropriate for modeling air traffic data are the seasonal univariate long memory processes (Gil-Alana, 2005), that employ seasonality in fractionally integrated ARMA (ARFIMA) models. In non-fractional contexts, we can also observe some examples of applications of ARIMA on air modeling in more local studies, such as Chai (2021), investigating Hong Kong's passenger traffic; Al Sultan et al. (2021), forecasting air traffic in Kuwait; Bougas (2013) for the case of Canada; Tsui et al.

[1] Another interesting study is the general forecasting framework proposed in Phillips (1996) in the presence of large shocks in time series.

(2014) for Hong Kong; Oh et al. (2005) for Singapore and Lim and McAleer (2002) in the case of Australia. Fractional integration approaches, on the other hand, have been also employed, being more general than the above-mentioned applications since they allow for non-integer degrees of differentiation (Sutcliffe, 1994). These have been employed for modeling traffic (Liu et al., 1999); for forecasting general tourism demand (Chu et al., 2008), and for forecasting air traffic in Thailand (Chokethaworn et al., 2010).

Focussing more specifically on a similar approach to the one used in this work, Dingari et al. (2019) examined the number of Air India domestic air passengers using ARIMA and ARFIMA models, and their results seem to indicate that the fractional models perform better than the non-fractional ones in terms of forecasting. Our model differs from the one used in Dingari et al. (2019) in the treatment of the error term, that, given the monthly nature of the data, is based on a seasonal autoregressive process.

3. METHODOLOGY

We model air traffic data by using long memory, which seems to be very adequate for the purpose of our analysis. Long memory can be described either in the time domain or in the frequency domain. In the time domain, we say that a covariance stationary process, say {x(t), t = 0, ±1, …} displays this property if the infinite sum of its autocovariances, defined as γ(u) = E[(x(t)- Ex(t)) (x(t+u)- Ex(t))] is infinite, i.e.,

$$\sum_{u=-\infty}^{\infty} | \gamma(u) | = \infty. \qquad (1)$$

Within this category of long memory processes, we have many models, including, for example, the fractional Gaussian noise (fGn) model described in Mandelbrot and Wallis (1965a,b,c) and others. Another one, very common within the time series analysts, is the one based on fractional integration, that means that the number of differences required in a series to render it stationary I(0) may be a fractional number. Thus, we say that a process is fractionally integrated or integrated of order d, and denoted as I(d), if it can be represented as:

$$(1-B)^d x(t) = u(t) , \quad t = 0, \pm 1, \pm 2, \quad \ldots, \qquad (2)$$

where B represents the backshift operator, i.e., Bx(t) = x(t-1) and with the differenced series, u(t), displaying a short memory or integrated of order 0 (I(0)) pattern described by:

$$\sum_{u=-\infty}^{\infty} | \gamma(u) | < \infty. \qquad (3)$$

The differencing parameter d becomes crucial since it indicates the degree of persistence or dependence in the data, as the higher its value is, the higher the level of association is between observations far apart in time. Moreover, it allows us to consider a large degree of flexibility in the dynamic specification of the model, including the specification of the following processes:

i) anti-persistence: $d < 0$,

ii) short memory: $d = 0$,

iii) stationary long memory and mean reversion: $0 < d < 0.5$,

iv) non stationarity and mean reversion: $0.5 \leq d < 1$,

v) unit roots: $d = 1$, and

vi) explosive patterns: $d > 1$.

In this context, it is crucial to know if the value of $d = 1$, since $d < 1$ implies mean reversion while $d \geq 1$ implies lack of it. To see this, note that the polynomial in the left-hand side in Equation (2) can be expressed in its Mc Laurin's form:

$$(1 - B)^d = \sum_{j=0}^{\infty} \binom{d}{j} (-1)^j B^j = 1 - dB + \frac{d(d-1)}{2} B^2 - \cdots, \tag{4}$$

and then, x(t) can be expressed in terms of an infinite Moving Average (MA) process, with the coefficients decaying hyperbolically to zero as long as d is smaller than 1. If $d \geq 1$, this condition does not hold. Thus, if $d = 1$, for example, Equation (1) becomes

$$(1 - B)\, x(t) \;\; = u(t) \;\; , \quad t \; = 0, \; \pm 1, \; \pm 2, \quad \ldots, \tag{5}$$

and noting that

$$\frac{1}{(1-B)} \; = \; 1 + B + B^2 + \; \ldots. \tag{6}$$

Equation (2) can be written as:

$$x(t) = \; u(t) \; + \; u(t-1) \; + \; u(t-2) \; + \; \ldots \tag{7}$$

which proves that shocks keep having permanent effects on the series across time, and the trend is not mean reverting.

After a sudden event that significantly changes the trend in time series, determining if such time series is mean reverting or not requires knowing if the trend will recover automatically or if it will be necessary to employ external factors to bring the trend back to its original values before the shock. It is very important in political and financial situations to find out as soon as possible if the trend is mean reverting, so the competent authorities know if it is necessary to invest in the recovery from the shock or not.

A clear example of this was examined in terms of the arrivals in the US after the terrorist attack of 9/11/2001 (Gil-Alana et al., 2008). It was found in the paper that the estimated differencing parameter d was close to 0.5 for most of the origin locations. Therefore, there was no urgent need to invest in efforts to recover tourism in the US, since it would have gone back to its previous trend sometime in the near future. Another meaningful study regarding the importance of mean reversion focuses on linkages between Central Bank Policy Rates in Africa and other significant bank systems worldwide (Gil-Alana et al., 2020). The analysis proves that many African countries will not be able to undertake independent monetary policies without taking into consideration global policies, since the coefficient of integration was found to be significantly higher than 1.

In order to allow for potential trends in the data, allowing also for seasonality, and based on a fractional integration process, we consider the following model,

$$y(t) = \alpha + \beta\, t + x(t); \;\; (1-B)^d x(t) = u(t), \;\; u(t) = \rho\, u(t-12) + \varepsilon(t) \qquad (8)$$

where y(t) represents the observed data; α and β are unknown coefficients dealing with an intercept and a (linear) time trend; t represents the trend, and ρ is a seasonal AR coefficient such that ε(t) is a white noise process.

4. DATA

Two different datasets have been analyzed, both with monthly samples collected in nearly the same range of years: the number of passengers in Europe and a dataset regarding the global RPK (Revenue Passenger Kilometers).

The monthly global RPK data was collected by ICAO (International Civil Aviation Organization**,** (https://www.icao.int).

RPK stands for Revenue Passenger Kilometers, which is a unit of measurement widely used in aviation; it shows the number of kilometers traveled by paying passengers, and it is calculated as the number of passengers carried multiplied by the total distance traveled. See Figure 1.

The period of the data collected extends from July 2012 to December 2021, resulting in 114 observations. The data, as expected, show seasonal peaks during the months of July, August and December, and a sudden drop in the number of RPK. It is easy to understand that this drop corresponds with the start of the sanitary emergency period, in April 2020, due to the Covid-19 pandemic. (See, Figure 1 below). Another factor which is noticeable from the analysis of this dataset is that it reveals a growth in air traffic, proving that this industry keeps improving and getting bigger year by year.

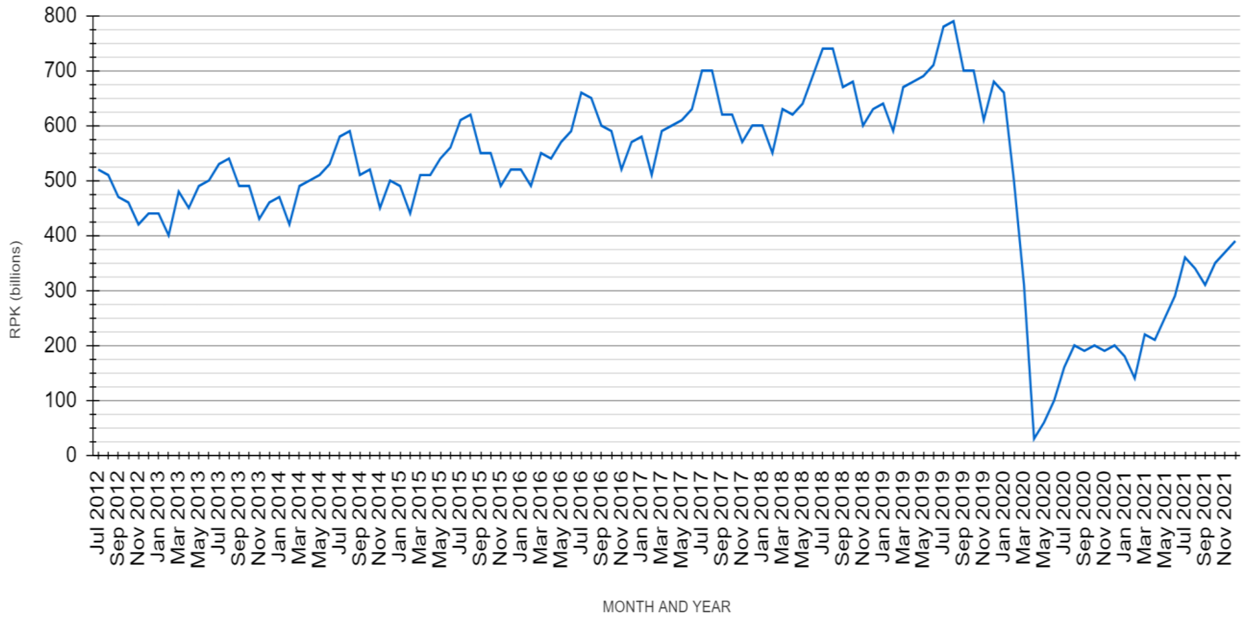

Figure. 1 Monthly global RPK starting from July 2012 to December 2021

The monthly number of passengers carried by EU flights was sourced from the Eurostat database, the accessible-to-all database for all European concerns, including politics, economics, demographics and geography. This data starts in January 2009 and continues to July 2021, resulting in 151 observations, (see Figure 2), and it shows the same trend and seasonality as the global monthly RPK data, proving European air travel follows the global trend, though on a smaller scale.[2]

[2] European air travel stands for the entirety of flights within the European Union, so flights from EU countries to EU countries. This includes domestic flights as well.

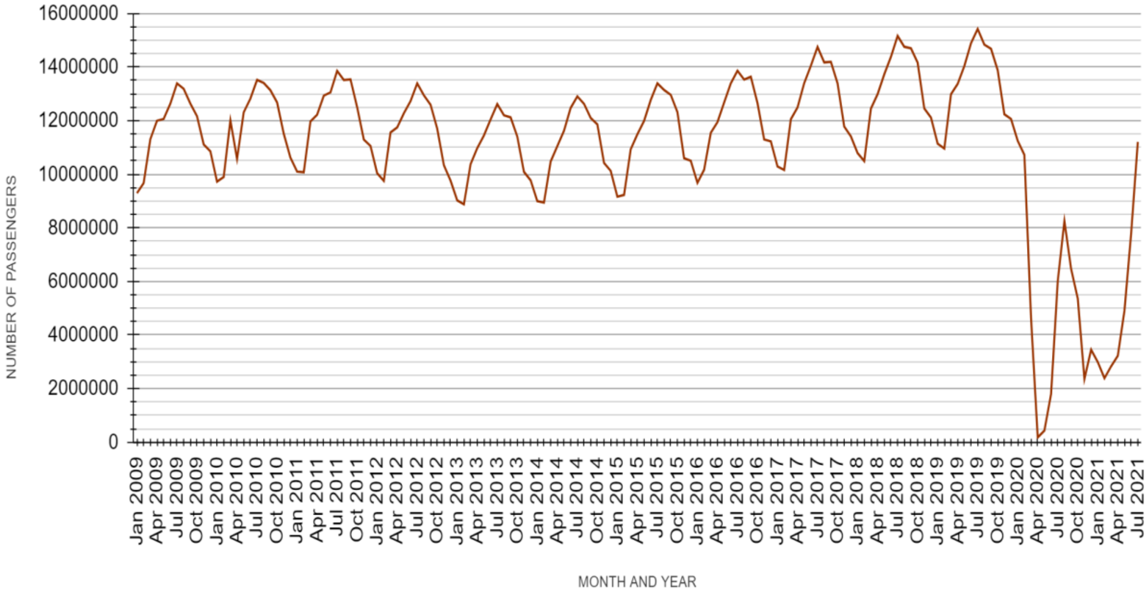

Figure 2. Monthly number of passengers carried by EU flights from January 2009 to July 2021

Descriptive statistics of the two series are reported in Table 1, containing statistical values, such as maximum and minimum values, range, mean, mode (when applicable), median and standard deviation.

Table 1: Descriptive statistics of RPK

SERIES	RPK	N. PASSENGERS IN EUROPE
NUMBER OF SAMPLES	114	151
MAXIMUM VALUE	790	15423290
MINIMUM VALUE	30	174964
RANGE	760	15248326
MEAN VALUE	503.5	11146685.3
MODE	490	---
MEDIAN	520	11944207
STANDARD DEVIATION	162.3	2978578,8

The seasonality of the trend can be studied through a deterministic approach or by using a stochastic method, whether the effect we want to model is fixed across the years, or is changing over time. In this case, we choose the stochastic approach since the trend presents some differences from year to year. In addition, there are two stochastic models to choose from: the autoregressive process and the seasonal unit root process, which is used, like first differences, when the seasonal component of the time series seems nonstationary, for example if the seasonal effect increases with time.

For this study we use an autoregressive stochastic model and for simplicity, we consider a monthly seasonal AR process, which is described by the last equality in Equation (8), where ρ is the only not null coefficient of the AR(12) model.[3]

5. EMPIRICAL RESULTS AND DISCUSSION

To examine if the Covid-19 pandemic has produced any effect on the degree of persistence of the series, the first thing we do is to consider a sample ending in December 2019, that is, only a few months before the start of the pandemic. Table 2 reports the estimates of d in the above equation under three potential scenarios: i) with no deterministic terms, that is, imposing a priori that α and β are both equal to zero; ii) including only an intercept, i.e., with β = 0; and iii) including both the intercept and a linear time trend. The values in bold in Table 2 refer to the selected specification according to these three specifications. Along with the estimates of d we also include the 95% confidence bands for the values of d. Panel i) refers to the original data, while Panel ii) displays the results for the logged values. Table 3 displays the estimated coefficients of the selected model for each series.

Table 2. Estimates of the differencing parameter with data ending at December 2019

Series	No deterministic terms	With an intercept	With an intercept and a linear time trend
i) Original data			
Number of passengers carried in EU flights	0.98 (0.85, 1.15)	**0.52 (0.46, 0.64)**	0.56 (0.46, 0.72)
Global Revenue Passenger Kilometers	0.86 (0.68, 1.13)	0.70 (0.60, 0.86)	**0.56 (0.17, 0.84)**
ii) Logged data			

3 Testing for seasonal unit roots, using various tests (Dickey et al., 1984; Hylleberg et al., 2001), the results reject the null of nonstationarity in favour of stationary seasonality.

Number of passengers carried in EU flights	0.98 (0.86, 1.12)	**0.51 (0.44, 0.67)**	0.60 (0.48, 0.76)
Global Revenue Passenger Kilometers	0.95 (0.81, 1.14)	0.70 (0.60, 0.85)	**0.54 (0.09, 0.82)**

The values in parenthesis are the 95% confidence intervals for the non-rejection values of d. In bold, the selected specification for each series is selected.

Table 3. Estimate coefficients of the selected models in Table 2

Series	D (95% interval)	Intercept (tvalue)	Time trend (tvalue)	Seasonal AR coefficient
i) Original data				
Number of passengers carried in EU flights	0.52 (0.46, 0.64)	1110302 (16.68)	---	0.943
Global Revenue Passenger Kilometers	0.56 (0.17, 0.84)	480.381 (13.63)	2.362 (2.74)	0.945
ii) Logged data				
Number of passengers carried in EU flights	0.51 (0.44, 0.67)	16.216 (287.79)	---	0.942
Global Revenue Passenger Kilometers	0.54 (0.09, 0.82)	6.1727 (101.18)	2.892 (115.62)	0.944

In parenthesis, in column 2, the 95% interval for the estimated value of d. In columns 3 and 4 the corresponding t-values.

The first thing we observe in Table 2 is that the time trend is found to be statistically insignificant for the EU data using both original and logged values, while it is significant (and positive, see Table 3) for the global data. If we focus now on the estimates of d, we observe that they are constrained between 0 and 1 in the four series, supporting the hypothesis of fractional integration and long memory characteristics. Using the original data, the estimates of d are 0.52 for the EU data and 0.56 for the global revenues respectively, and they are slightly smaller (0.51 and 0.54) with the logged values. In any case, the estimates are significantly smaller than 1, supporting thus the hypothesis of mean reversion and transitory shocks. In addition, seasonality seems to play an important role, with the seasonal AR coefficient being close to 1 in the four series (see last column in Table 3).

Table 4. Estimates of the differencing parameter with data ending at the end of the sample

Series	No deterministic terms	With an intercept	With an intercept and a linear time trend
i) Original data			
Number of passengers carried in EU flights	1.35 (1.21, 1.53)	**1.41 (1.21, 1.65)**	1.41 (1.21, 1.64)
Global Revenue Passenger Kilometers	1.10 (0.95, 1.30)	**1.30 (1.10, 1.56)**	1.30 (1.10, 1.56)
ii) Logged data			
Number of passengers carried in EU flights	1.01 (0.90, 1.15)	**0.93 (0.68, 1.27)**	0.93 (0.68, 1.25)
Global Revenue Passenger Kilometers	0.97 (0.85, 1.13)	**0.88 (0.71, 1.12)**	0.88 (0.71, 1.12)

The values in parenthesis are the 95% confidence intervals for the non-rejection values of d. In bold, the selected specification for each series is selected.

Table 5. Estimate coefficients of the selected models in Table 3

Series	D (95% interval)	Intercept (tvalue)	Time trend (tvalue)	Seasonal AR coefficient
i) Original data				
Number of passengers carried in EU flights	1.41 (1.21, 1.65)	9.036 (8.65)	---	0.450
Global Revenue Passenger Kilometers	1.30 (1.10, 1.56)	525.74 (9.82)	---	0.544
ii) Logged data				
Number of passengers carried in EU flights	0.93 (0.68, 1.27)	16.055 (46.58)	---	0.091
Global Revenue Passenger Kilometers	0.88 (0.71, 1.12)	6.242 (24.44)	---	0.078

In parenthesis, in column 2, the 95% interval for the estimated value of d. In columns 3 and 4 the corresponding t-values.

The results, however, change completely once the data are extended until December 2021. They are reported across Tables 4 and 5. First, the time trend that was previously significant in case of the global revenues now becomes statistically insignificant. Moreover, we observe a significant increase in the value of d. Thus, the estimates are now significantly higher than 1 in both series with the original data (1.41 for EU data and 1.30 for global revenues) while the unit root null hypothesis (i.e., d = 1) cannot be rejected with their corresponding logged values. Thus, the former property of mean reversion has disappeared once the Covid-19 pandemic has been taken into account. Finally, the characteristic of seasonality has reduced in importance, becoming insignificant when the logged values are used. These results are consistent with other studies that also investigated the effects of the Covid-19 pandemic on tourism series such as Gil-Alana and Poza (2020) and Payne et al. (2021).

Looking at these results it seems that there is a clear difference between the shock provoked by the 9/11 terrorist attacks and the Covid-19 pandemic: following the observation of one academic colleague belonging to this journal, in the former shock, the passenger demand needed to return to the system, but the passengers were "*alive*" but simply "*unwilling to fly*" until they felt safe and comfortable to fly again. In the case of Covid-19, as sad and as morbid as it is, the passengers are now "*dead*" and "*unable to fly*" now or in the future. It is very sad, but a fact. Thus, it would be very interesting to look at the number of people that died because of Covid-19 in certain markets (e.g., the US, EU, etc.) to look that demand profile as a function of age, and to see if that portion of the demand is "*forever lost*" due to Covid-19. In spite of the difficulty for this time of analysis, work in this direction is now in progress.

6. CONCLUSIONS

In this article we have examined the air traffic data on a global and an European scale by using long memory methods. Specifically, we use fractional integration since it is a technique that allows us to investigate the nature of exogenous shocks in the data.

The Global and European air traffic trends were first analyzed using data starting from July 2012, in the global case, and from January 2009, in the European case, both until December 2019, to see how the series evolved before the pandemic. There were slight differences between the two trends, the Global one, for example, had not only a significant intercept coefficient but also a significant time trend, meaning that the trend was growing over time.[4] The European trend presented significance only in the intercept coefficient. It appears, though, that they were both mean reverting since the orders of integration of the series were significantly smaller than 1 in the two series. The results were robust to the use of logged values.

Repeating the computation with the data extended until December 2021, the results were quite different. Both trends, European and Global, only have relevant intercept coefficients, and most importantly, they no longer are mean reverting, meaning that the shock

[4] A significant time trend coefficient has been usually related with technological progress.

induced by the sanitary crisis was so persistent over time that it produced a complete change in the trends, and became a permanent shock.

Among the limitations of the present work we can mention its linear structure. Other forms of long memory processes, including for example, seasonality (seasonal fractional integration (Gil-Alana and Robinson, 2001) or cyclicity (Gil-Alana, 2001) can be employed in these and in other air traffic data. Along similar lines, non-linear structures still within a long memory model, such as those based on the Chebyshev polynomials and proposed in Cuestas and Gil-Alana (2016), Fourier functions in time (Gil-Alana and Yaya, 2021) or neural networks (Yaya et al., 2021) can be adopted. These methods describe cyclical structures and can be taken as alternative approaches to the potential presence of breaks in the data (Bierens, 1997), approximating them in a much smoother way. Also, it might be interesting to determine the change in the degree of persistence just after the irruption of the Covid-19 pandemic and see how it has evolved observation by observation until the end of the sample. Work in all these directions is now under progress.

CONFLICT OF INTEREST

The authors do not have any conflict of interest with other entities or researchers.

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