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Working Paper nº 08/09

Persistence on airline accidents

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Working Paper No.08/09
October 2009

ABSTRACT

This paper analyses airline accidents data from 1927-2006. The fractional integration methodology is adopted. It is shown that airline accidents are persistent and (fractionally) cointegrated with airline traffic. Thus, there exists an equilibrium relation between air accidents and airline traffic, with the effect of the shocks to that relationship disappearing in the long run. Policy implications are derived for countering accidents events.

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1. Introduction

Airline accidents are a paramount issue in the contemporary airline industry, since they have a significant impact on the demand for air travel, affecting the finances of the airlines. If travelers believe that an air travel incident is a random event, then they will pay little attention to it, since it does not reveal any further information on air travel safety. However, if they believe that it is not a random event, then air travel is perceived as dangerous and passengers switch for a safer airline or choose an alternative traveling mode. This issue has been examined among others by Rose (1992), Borenstein and Zimmerman (1988), Bosch et al. (1998) and Liu and Zeng (2007).

Research in air travel accidents usually focuses on the impact of the fatal event on the equity value of the air travel, Chance and Ferris (1987), Borenstein and Zimmerman (1988), Mitchell and Maloney (1989) Nethercutt and Stephen (1997), Bosch et al. (1998). Another line of research focuses on the impact of air travel accidents on the demand for air travel, Borenstein and Zimmerman (1988), Liu and Zeng (2007). The present research contributes to the literature by analyzing the persistence of air travel accident events using fractional integration, estimating both univariate and multivariate models that account for the order of integration of the individual variables as well as the order of integration between variables.

The objective of this paper is threefold. Firstly, we examine the special characteristics of airline fatal accident events by performing a descriptive analysis of the data set. Secondly, we examine the univariate behavior of the series in terms of fractional integration to assess whether the series present a persistent pattern over time. Finally, we study how airline accidents are related to traffic volume, and use long range dependence techniques (fractional cointegration) to assess empirically this relationship. Policy implications are derived for countering airline accident events.

The paper is organized as follows; in the next section a literature survey is presented. Then a theoretical model that supports the empirical evidence is presented. Finally, the empirical results are displayed, followed by the discussion and conclusion.

2. Literature Survey

Previous studies on air travel accidents have focused either on the impact of fatal accidents on the equity values of airlines (e.g. Chance and Ferris, 1987; Borenstein and Zimmerman, 1988; Mitchell and Maloney, 1989; Nethercutt and Stephen, 1997; Bosch et al., 1998) or on the impact of fatal accidents on air travel demand, (Borenstein and Zimmerman, 1988, and Liu and Zeng, 2007). The first type of research finds that fatal accidents have a significant negative effect on the stock value of the airline involved in such accidents, but they also find that fatal accidents have no significant impact on the equity values of other airlines. However, Mitchell and Maloney (1989) find that the equity value of the airline involved in a fatal accident falls only if the accident is the fault of the company. If the financial market is perfect, the stock value should have already incorporated the expected responses of the demand. Therefore, their results may suggest that fatal accidents have little impact on the total demand for air travel. Moreover, as pointed out by Bosch et al. (1998), because the rivals of the crash airline may benefit from the fatal accident by attracting more customers from the crash airline and non-rivals may be hurt by the crash, the seeming immunity to the stock value of all non-crash airlines to fatal accidents does not necessarily imply that fatal accidents do not affect the total demand for air travel. Furthermore, examining the effect of plane crashes on different airlines, Nethercutt and Pruitt (1997) group the entire airline industry into 'low cost' airlines and major airlines, while Bosch et al. (1998) categorize non-crash airlines into direct and indirect competitors. If the overall demand for air travel falls after a plane crash, the market value of all airlines should decline.

With regard to air travel demand Borenstein and Zimmerman (1988) has explicitly examined the impact of fatal incidents on the demand for air travel, finding that the demand for the services of crash airlines remained largely unaffected by the fatal incidents prior to deregulation, e.g. that fatal incidents did have a negative, but not statistically significant effect on the demand in the pre-deregulation period. Because their sample has information on 13 accidents in the pre-deregulation period, Borenstein and Zimmerman (1988, p. 927) warned readers about the danger of inferring a systematic demand response for that period. Moreover, Liu and Zeng (2007) analyzing air travel demand in accidents context found that the demand for air travel is likely to fall as the fatality rate increases.

This article expands air travel accidents research by examining the relationship between the air travel accidents and the airline traffic or volume in the period from 1927 to 2006 with a fractional integration methodology. None of the above papers investigate unit roots in the series. We find that there is a negative association between the two variables. Thus, while the airline traffic has substantially increased across the years, the number of accidents has been decreasing, which might be explained by technological change, with an increase in security measures, airlines investments in the quality and maintenance of their air fleets across the years. We also find that the airline traffic and the number of accidents are fractionally cointegrated, implying a stable equilibrium relationship between them. However, this relationship is highly persistent, with the effect of the shocks taking a very long time to disappear completely.

3. The Model

The following stylized model is used to show that optimal choices of a profit maximizing representative airline allows us to relate airline accidents with the volume of airline traffic. The model illuminates under what conditions airline accidents are negatively related to the volume of airline traffic.

Let us assume that the number of airline accidents of the representative airline company, A, is a decreasing function of maintenance, u, and the average quality, x, of airline fleet:

$$A(u,x) = \Omega - cxu \, . \qquad (1)$$

Note that $A(u,x) \geq 0$, implying that $\Omega \geq cxu$. According to equation (1), when there is no maintenance, u = 0, and/or the airline fleet is old and/or run down so as that x = 0, then, $A = \Omega$ where Ω is the maximum number of expected airline accidents.

The representative airline's total revenue at time t is proportional to the quality of its fleet x, and decreasing in the industry-wide traffic volume, V. Thus the total revenue takes the form $R(V)x$, where $R'(V)$ <0. The airline faces maintenance costs[1], plus quadratic installation costs, as well as costs associated with any type of accidents [including insurance costs, reputation loss, etc]. The representative airline controls fleet maintenance, u, aiming at maximizing the present value of its profits:

$$\underset{u}{Max} \int \left[px - u\left(1 + \frac{\theta}{2}u\right) - \delta\, A(u,x) \right] e^{-rt} dt$$

subject to the evolution of the quality of airline fleet:

$$\dot{x} = u - bx , \tag{2}$$

where r is the interest rate and fleet quality decays at a constant proportionate rate b. One can think of airline safety regulations as impacting positively on the parameter b, i.e., tougher safety regulation increases b.

Assuming unitary marginal installation costs, □ = 1, and using equation (1), the Hamiltonian function for this problem is:

$$H = px - u - \frac{u^2}{2} - \delta[\Omega - cxu] + \lambda[u - bx] .$$

The first order conditions are:

$$H_u = 0 \Rightarrow -1 - u + \delta cx + \lambda = 0 \Rightarrow \lambda = 1 + u - \delta cx , \tag{3}$$

$$\dot{\lambda} - r\lambda = -H_x \Rightarrow \dot{\lambda} - r\lambda = -[p + \delta cu - \lambda b] . \tag{4}$$

In order to find the steady state equilibrium of this model set equations (2) and (4) equal to zero:

$$\dot{x} = 0 \Rightarrow u = bx , \tag{5}$$

$$\dot{\lambda} = 0 \Rightarrow (r + b)\lambda = p + \delta cu . \tag{6}$$

Using equations (3) and (5) into (6) and solving for u and x, yields the following steady state equilibrium for airline fleet quality and maintenance:

$$x^* = \frac{r + b - p}{\delta c(2b + r) - b(r + b)} , \tag{7}$$

$$u^* = \frac{b(r + b - p)}{\delta c(2b + r) - b(r + b)} . \tag{8}$$

For positive values of optimal quality and maintenance of the airline fleet, it is necessary to impose $r + b > p$ and $\delta c > b$. Recalling that tougher safety regulation increases the parameter b, notice that an increase in b yields an increase in the optimal quality and maintenance of the airline fleet [$\frac{dx^*}{db} > 0; \frac{du^*}{db} > 0$] if $2(\delta c - b) < r$.

An important qualitative result of this model concerns the impact of traffic volume upon optimal maintenance and quality of the airline fleet. An increase of traffic volume V increases optimal maintenance and quality:

$$\frac{dx^*}{dV} = \frac{-R'(V)}{\delta c(2b+r) - b(r+b)} > 0,$$

$$\frac{du^*}{dV} = \frac{-R'(V)}{\delta c(2b+r) - b(r+b)} > 0.$$

Note that from equation (1), given the optimal values of u^* and x^*, we have the equilibrium number of airline accidents:

$$A(u^*, x^*) = \Omega - cx^*u^*. \qquad (9)$$

It is important to stress that an increase in optimal maintenance or in optimal quality leads to a fall in the equilibrium number of airline accidents:

$$\frac{dA(u^*, x^*)}{dx^*} = -cu^* < 0,$$

$$\frac{dA(u^*, x^*)}{du^*} = -cx^* < 0.$$

Notice that equation (9) using equation (5) can be rewritten as:

$$A(u^*, x^*) = \Omega - cb[x^*]^2. \qquad (10)$$

As a consequence, the number of airline accidents is negatively related to the volume of airline traffic:

$$\frac{dA(u^*, x^*)}{dV} = \frac{dA(u^*, x^*)}{dx^*}\frac{dx^*}{dV} < 0. \qquad (11)$$

The rationale for the negative impact of air traffic volume on airline accidents is as follows: in an increasingly competitive environment, an airline aiming at increasing the number of flights and/or passengers has an incentive to increase fleet maintenance and/or fleet quality, which results in lower number of accidents.

4. Data

A data set from 1927-2006 used in this paper was obtained from two sources: first, the ATA- Air Transport Association of America web site (http://members.airlines.org) that compiles from various publications of Civil Aviation Authority and Federal Aviation Administration and second, the Airsafe.com web site. The data is highly reliable from 1945 to date, but is based in estimations for the period before.

Borenstein and Zimmerman (1988) used monthly data but almost all other authors working in this specific area use annual data. The annual data variables used are, the total number of fatal air accidents, aircraft miles (000000), total number of passengers and airline revenue (mils).[2] The data is presented in Table 1.

INSERT TABLE 1 ABOUT HERE

The average number of total yearly accidents is 43.15 with the minimum 13 accidents in 1984 and the maximum 137 accidents in 1929. The average number of passengers is 533,465, with a minimum of 191 in 1927 and a maximum of 2,128,212 in 2006. These two variables relate inversely, with accidents falling and passengers increasing with time. Air line miles and air line revenues are directly related to the number of passengers.

5. Persistence in Airline Accidents

The analysis of the persistence in time series has important policy implications since the effect of a given shock on a series is different depending on its univariate properties. When a series is stationary and mean reverting (e.g., in the context of I(d) models as those employed here, when d < 0.5), the effect of a given shock on it will have a transitory effect, its effect disappearing fairly rapidly; if the series is nonstationary but mean reverting (0.5 ≤ d < 1) the shock will still be transitory though it will take longer to disappear completely, while it will be permanent if the series is nonstationary with d ≥ 1. While the classical approach to studying the stationarity of the series only allows for the I(1)/I(0) case, in this paper, airline accidents series are allowed to be I(d), where d can be any real number. Thus, it encompasses both the stationary I(0) and the nonstationary I(1) cases. To simplify matters we define an I(d) process in the following way. We say that a covariance stationary process, {ut, t = 0, ±1, …,} is I(0) if the infinite sum of the autocovariances is finite. That is,

$$\sum_{u=-\infty}^{\infty} |\gamma_u| < \infty,$$

where γu = E(ut - Eut)(ut+u - Eut). Thus, it includes the standard white noise, stationary autoregressions (AR), moving average (MA), etc. Then, a process {xt, t = 0, ±1, …,} is said to be I(d) if it requires d-differences to get an I(0) process. That is,

$$(1 - L)^d \, x_t = u_t, \qquad (12)$$

where ut is I(0). Note that the polynomial on the left-hand-side in (12) can be expressed in terms of its Binomial expansion, such that, for all real d,

$$(1-L)^d = \sum_{j=0}^{\infty} \psi_j L^j = \sum_{j=0}^{\infty} \binom{d}{j} (-1)^j L^j = 1 - d\ L + \frac{d\,(d-1)}{2} L^2 - \ldots .$$

Thus, if d is an integer value, xt will be a function of a finite number of past observations, while if d is not an integer, xt depends strongly upon values of the time series in the distant past. Moreover, the higher d is, the higher will be the level of association between the observations. The estimation of the parameter d for the accidents series we analyze here gives us an idea of the persistence of the series, which will be related to traffic. We believe that the disaggregated analysis of airline accidents series may help policy-makers to know how to counteract these events.

The fractional integration approach allows us to identify the level of persistence of a series in a continuous way and therefore overcomes the restrictive view that traditional econometrics identify a series which is either persistent I(1) or non-persistent I(0), but is unable to evaluate the middle term of the persistence level.

INSERT FIGURE 1 ABOUT HERE

First we focus on the total number of air accidents, annually, from 1927 to 2006. The plot of the series is displayed in Figure 1 and we observe it has been decreasing across the years, probably due to the improvements in the aircrafts. Thus, the series could be nonstationary I(1). Conducting tests of fractional integration, the evidence points to values strictly above 0 and close to 1, thereby showing a large degree of persistence.

INSERT TABLE 2 ABOUT HERE

Table 2 displays the estimated values of d for the above series in the following set-up:

$$y_t \;=\; \beta_0 + \beta_1 t \;+\; x_t, \quad t \;=\; 1,\; 2,\; ..., \qquad (13)$$

and (12), i.e.,

$$(1 - L)^d\, x_t \;=\; u_t,$$

where yt is the observed time series (in our case, the total air accidents), d is a real value and ut is an I(0) process. Thus, ut might be a white noise process but also any type of I(0) autocorrelated structure. We estimate d in the above model, using a Whittle function in the frequency domain, for the three standard cases of no regressors, an intercept, and an intercept with a linear trend, assuming that the disturbances ut are both white noise and autocorrelated, in the latter case using the exponential model of Bloomfield (1973). This model uses a non-parametric approach that produces autocorrelations decaying exponential as in the AR case. This method is fairly convenient in the context of fractional integration (See, e.g. Gil-Alana, 2004). Along with the estimates we also produce the 95% confidence intervals for the values of d.3

The results in this table strongly support the view that this series is highly persistent, with values of d constrained between 0.73 and 0.91. Moreover the unit root null hypothesis (d = 1) cannot be rejected in any case at the 5% level. The implications of this result is that shocks are long lasting.4

INSERT FIGURE 2 ABOUT HERE

Next we look at some variables that might be related to the airline traffic. In particular, we examine the number of passengers, the airline miles and the airline revenues for the same period of time as in the previous case, i.e., annually, from 1927 to 2006.5 We note in Figure 2 that the three series display values increasing across time, being clearly nonstationary. Tables 3 – 5 displays the estimates of d along with the 95% intervals for the three series.

INSERT TABLES 3 – 5 ABOUT HERE

We observe that the estimated values of d are higher than 1 in all cases. Starting with the variable "*Passengers*" (Table 3), the order of integration is about 1.34 if we assume white noise disturbances, and it is slightly smaller (1.12) when using the model of Bloomfield for the disturbance term. In the latter case, the unit root hypothesis cannot be rejected. If we focus on the "*Airline miles*" series (Table 4), the estimated d is found to be around 1.10 in all cases, and the unit root is included along all the confidence bands. Finally, for the "*Airline revenues*" (Table 5), d is found to be strictly above 1 in all cases. Thus, we observe a higher degree of dependence in these series compared with the "*Total air accident*" series, however, the fact that the unit root null hypothesis cannot be rejected in some cases for these variables suggests that there might exist a cointegrating relation between the number of accidents and some of the variables referring to airline traffic.

6. The relationship between airline accidents and airline traffic

Given the potential fractional nature of the series under study, in what follows we examine the relationship between accidents and traffic by using new methodological techniques based on fractional cointegration.

Engle and Granger (1987) provided the following definition for cointegration. Given two real numbers d, b, the components of the vector zt are said to be cointegrated of order d, b, and denoted zt ~ CI(d, b) if:

(i) all the components of zt are I(d),

(ii) there exists a vector $\alpha \neq 0$, such that wt = α'zt ~ I(d - b), b > 0.

Here, α and wt are called the cointegrating vector and error respectively. Thus, in a bivariate case, if two processes xt and yt are both I(d), and there exists a linear combination wt = yt – axt that is I(d – b) with b > 0, the two series are then cointegrated. Engle and Granger (1987) offered some intuition behind this crucial concept in modern time series econometrics, suggesting the existence of forces in economics which tend to keep series not too far apart.6

Though the original idea of cointegration, as espoused by Engle and Granger (1987), allows for fractional orders of integration, all the theoretical and empirical work carried out during the 1990s was restricted to the case of integer degrees of differencing, in particular, d = b = 1. Thus, the series are individually I(1) but there exists a linear combination of them which is I(0). Only in recent years, have fractional values also been taken into account. In fact, it is plausible that there exists long-run co-movements between nonstationary series which are not precisely I(1). On the other hand, there is usually no a priori reason for restricting analysis to just I(0) cointegrating errors, as the convergence to equilibrium of any cointegrating relation could be much slower than the adjustment implied by, for example, a finite ARMA cointegrating error.[7]

In this paper we follow a very simple strategy for testing fractional cointegration. Given the I(1) evidence of the two variables of interest, i.e, the total air accidents and airline traffic (this latter variable measured by any of the three series used in the previous section), we run first the OLS regression of one variable over the other.[8] Here, in the standard cointegrating setting, with d = b = 1, it has been shown (see, e.g., Phillips and Durlauf, 1986) that the OLS estimate of α is n-consistent with non-standard asymptotic distribution, in general. In fractional settings, the properties of OLS could be very different from those in this standard framework. For example, Robinson (1994b) showed the inconsistency of OLS when $d < 0.5$. When the observables are purely nonstationary (i.e., $d \geq 0.5$), consistency is retained, but its rate of convergence and asymptotic distribution depends crucially on d and b. Thus, in what follows we first run the OLS regressions of total air accidents on the variable representing airline traffic. The results are displayed in Table 6.[9]

INSERT TABLE 6 ABOUT HERE

We observe in this table that the coefficients are all statistically significant and the slope coefficient is negative in the three cases, which is consistent with the theoretical model described in Section 3.

Next, we examine the residuals from the cointegrating regressions and estimate the order of integration in the residuals from the cointegrating regressions. In other words, we employ the same methodology as in Engle and Granger (1987) though applied to the fractional case. (See, Gil-Alana, 2003).

In this context, we can use Robinson's (1994a) univariate tests. They have a standard normal null limit distribution and permits us to test any real value d, including thus stationary and nonstationary processes. Then, the non-rejection of the null hypothesis that the order of integration of the estimated residuals is equal to that of the original series (in our case, 1) will imply that the series are not cointegrated. On the other hand, rejections of the null in favour of alternatives with a smaller degree of integration (i.e., d < 1) will give us evidence of fractional cointegration of a certain degree. However, it should be pointed out that, though the asymptotic results in Robinson (1994a) are still valid, given that the residuals used are not actually observed but obtained from minimising the residual variance of the cointegrating regression, in finite samples the residual series might be biased towards stationarity. Thus, we would expect the null to be rejected more often than suggested by the normal size of Robinson's (1994a) tests.[10] Therefore, the empirical size of these tests for cointegration in finite samples has to be obtained using a simulation approach. Montecarlo experiments indicate that they perform better than standard tests, regardless of whether fractional or AR alternatives are considered (see Gil-Alana, 2003; Caporale and Gil-Alana, 2005).

INSERT TABLES 7 – 9 ABOUT HERE

The results report several cases of fractional cointegration. Thus, starting with the variable "*Passenger*", (in Table 7), if the disturbances are white noise and we do not include regressors, the estimated d is about 0.73 and the unit root is rejected in favor of d < 1. For the remaining two cases (with an intercept and/or a linear trend) the estimated d is also found to be smaller than 1 but the unit root is included in the confidence band. However, allowing autocorrelation throughout the model of Bloomfield, d is found to be strictly smaller than 1 for the three cases considered. Thus, it is concluded that there exists a (nonstationary) fractional cointegration relationship between total air accidents and airline passengers, with shocks affecting the long run equilibrium disappearing in the very long run.

For the variable "*Airline miles*" (Table 8) the only evidence of fractional cointegration is found if we do not include regressors for the two cases of white noise and autocorrelated disturbances. However, including an intercept or an intercept with a time trend, the unit root null cannot be rejected at the 5% level.

For the variable "*Airline revenues*" (Table 9) the results are similar to "*Passengers*", and fractional cointegration occurs if u_t is white noise and we do not include regressors, and for the three cases with autocorrelated disturbances.

The fact that in those cases where we find cointegration d is constrained in the interval (0.50, 1) means that the equilibrium relationship is nonstationary though mean reverting, with the effect of the shocks disappearing in the very long run.

7. Discussion

We have shown that in spite of the increasing volume of airline traffic in the last eighty years the total number of airline accidents has been reduced considerably. Possible explanations lie on technological change throughout the improvements in safety and greater competition among airline companies. It is important to stress that greater competition makes airlines to invest in the quality and maintenance of their fleet.

Relative to the unit root, we show that there is a high level of persistence in total air accidents series, concluding that shocks in this series are persistent and long lasting. Moreover, variables assumed to be related to air travel accidents (passengers, airline miles and airline revenues) also reveal a high level of persistence, being nonstationary I(1). Based on this result, it is hypothesized that the series are cointegrated and this hypothesis cannot be rejected from a fractional viewpoint. Therefore, it is concluded that there exists a (nonstationary) fractional cointegration relationship between the total airline accidents and the airline passengers, airline miles and airline revenues, with shocks affecting the long run equilibrium disappearing in the very long run. Moreover, this relation is negative, which might be due to the fact that air travel is becoming safer and greater competition in the airline industry.

What is the policy implication of this result? According to the theoretical model, competition among airlines makes them invest in the quality of their fleets, and in their maintenance[11], increasing safety. So airline competition should be stimulated. In the same vein, the model shows that safety regulation of airlines is also important. Therefore, toughening and enforcing safety regulation is of paramount importance to make sure there will be fewer air accidents. For example, the March 2006 ban of certain air travel companies from the European skies is a policy along these lines. The list of air accidents displayed in Airsafe.com web page is also a way to pressure air companies into adopting safety procedures.

More research is needed to confirm the present result. In particular, some new developed methods for fractional cointegration have been proposed by Hualde and Robinson (2006), Chen and Hurvich (2006), Johansen (2006) and others. The implementation of some of these methods in our data will be examined in future papers.

8. Conclusion

This paper has analysed the persistence in airline accidents from 1927 to 2006 using long range dependence techniques based on fractional integration and cointegration methods. It is shown that there is a high level of persistence in air total accidents series, signifying that shocks in this series are persistent and long lasting. Air travel characteristics (number of passengers, airline miles and airline revenues) also reveal a high level of persistence, being nonstationary I(1). Based on this result, it is hypothesized that the series are cointegrated and this hypothesis cannot be rejected from a fractional viewpoint. Therefore, it is concluded that there exists a (nonstationary) fractional cointegration relationship between the total airline accidents and the airline passengers, airline miles and airline revenues, with shocks affecting the long run equilibrium disappearing in the very long run. Moreover, this relation is negative, which might be a consequence of greater competition among airlines and technological improvements in safety and security in the airline services. Policy implications are derived.

Footnotes

1. See Thompson (1968) and Brosh et al. (1975) for optimal maintenance models.

2. Though the analysis was conducted based on nominal revenues, very similar conclusions to those reported in the paper were obtained when using this variable in real terms.

3. The estimated values of d and the associated confidence bands were computed using Robinson's (1994a) tests. See, e.g., Gil-Alana and Robinson (1997) for an implementation of this procedure.

4. We also employed Sowell's (1992) maximum likelihood estimation procedure in the time domain for different ARMA-type disturbances and the results were completely in line with those reported in the paper.

5. Additional variables such as the number of departures were also employed obtaining identical results as with the variables used in the paper.

6. In a general multivariate setting, a more general definition of cointegration than the one given by Engle and Granger (1987) is possible, allowing for a multivariate process with components having different orders of integration. See, e.g., Johansen (1996), Flôres and Szafarz (1996), Robinson and Yajima (2002), Robinson and Marinucci (2003), etc.

7. See Gil-Alana and Hualde (2008) for a review of recent developments in fractional integration and cointegration.

8. We also tested the equality of the orders of integration for each pair of variables using an adaptation of Robinson and Yajima's (2002) statistic with log-periodogram estimation and different trimming and bandwidth numbers, and evidence of equal orders

of integration were obtained in the majority of the cases. The only exception was in case of the "*ariline revenues*" series for some bandwidth numbers.

9. A problem with this estimate is that it may suffer from second-order bias in finite samples. In that respect, other estimates such as the fully-modified proposed by Kim and Phillips (2000) or the frequency-domain one proposed by Robinson and Hualde (2003) may be preferred. Using the latter one the results were fairly similar to those reported here in Table 5.

10. Note that a similar problem is faced in Engle and Granger's (1987) methodology for the standard case of cointegration.

11. We can include training of air personnel in security and safety issues as part of the airlines maintenance policies.

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Figure 1: Total air accidents

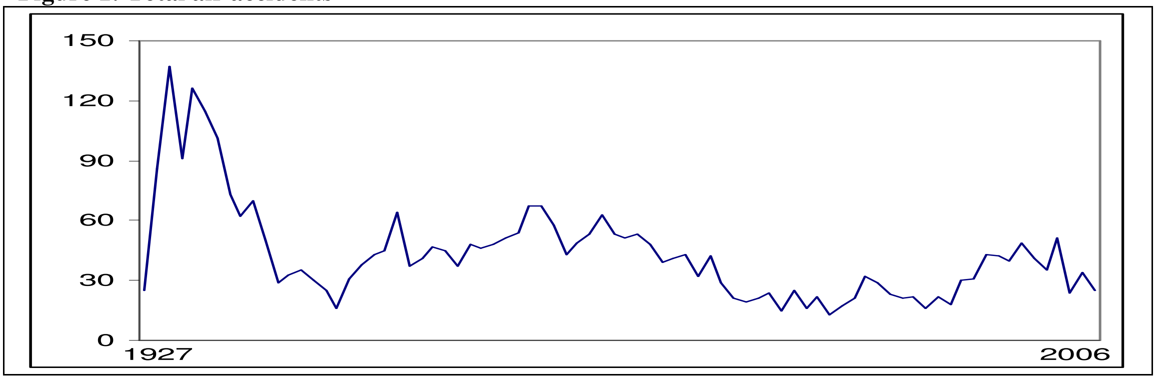

Figure 2: Total number of passengers, airline miles and airline revenues

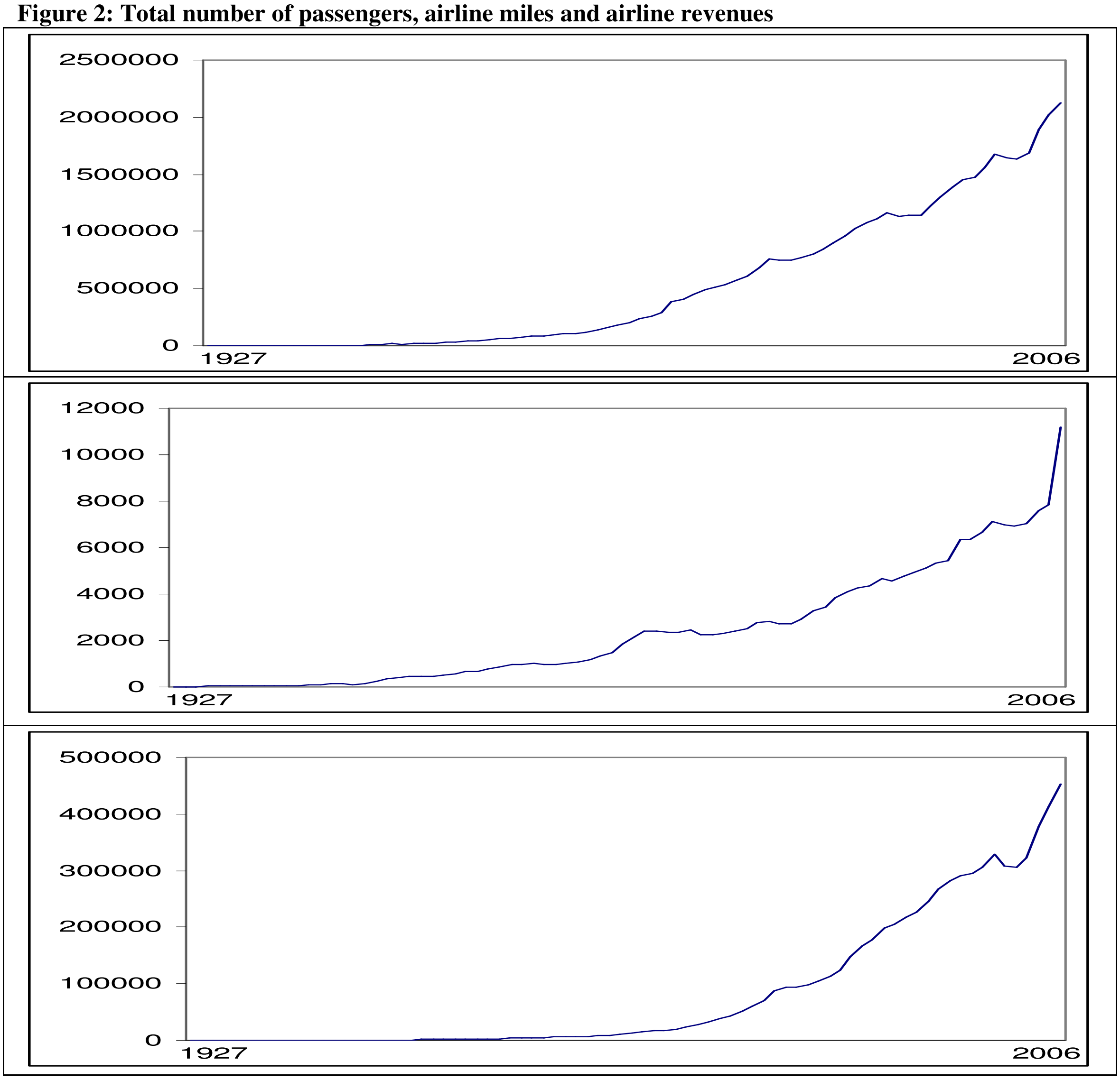

Table 1: Descriptive data

	Mean	Std. Dev.	Minimum value (year)	Maximum value (year)
TAA	43.15	24.186	13 (1984)	137 (1929)
P	533465	605212.392	191 (1927)	2128212 (2006)
AM	2410.36	2469.08	6 (1927)	11200 (2006)
AR	84574.80	121275.30	10 (1927)	452400 (2006)

The sample runs from 1927 to 2006. TAA = Total Airline Accidents; P = Passengers; AM = Airline Miles, and AR =Airline Revenues.

Table 2: Estimates of d for the Total Airline Accident series (Y_t)

	No regressors	An intercept	A linear time trend
White noise	0.91 [0.77, 1.10]	0.76 [0.62, 1.02]	0.73 [0.56, 1.02]
Bloomfield (Autoc.)	0.78 [0.51, 1.30]	0.80 [0.49, 1.26]	0.79 [0.50, 1.26]

In brackets the 95% confidence band of non-rejection values of d.

Table 3: Estimates of d for the Passenger series

	No regressors	An intercept	A linear time trend
White noise	1.34 [1.22, 1.56]	1.34 [1.22, 1.56]	1.33 [1.21, 1.56]
Bloomfield (Autoc.)	1.12 [0.99, 1.31]	1.12 [0.99, 1.31]	1.12 [0.99, 1.31]

Table 4: Estimates of d for the Airline Miles series

	No regressors	An intercept	A linear time trend
White noise	1.10 [0.86, 1.96]	1.13 [0.90, 1.96]	1.13 [0.90, 1.96]
Bloomfield (Autoc.)	1.10 [0.82, 2.00]	1.10 [0.82, 2.01]	1.09 [0.82, 2.05]

Table 5: Estimates of d for the Airline Revenues series

	No regressors	An intercept	A linear time trend
White noise	1.45 [1.30, 1.69]	1.45 [1.30, 1.69]	1.45 [1.30, 1.69]
Bloomfield (Autoc.)	1.23 [1.06, 1.52]	1.24 [1.07, 1.53]	1.24 [1.07, 1.53]

Table 6: Estimates of the OLS coefficients in the cointegrating regressions

	α (t-values in parenthesis)	Β (t-values in parenthesis)
Passengers	52.3741 (16.115)	-0.0000173 (-4.292)
Airline miles	52.7436 (15.274)	-0.0039801 (-3.977)
Airline revenues	49.0254 (15.864)	-0.0000694 (-3.323)

Table 7: Estimates of d in the cointegrating regression using Passenger

	No regressors	An intercept	A linear time trend
White noise	**0.73 [0.59, 0.91]**	0.77 [0.58, 1.03]	0.77 [0.58, 1.03]
Bloomfield (Autoc.)	**0.67 [0.33, 0.98]**	**0.64 [0.32, 0.96]**	**0.64 [0.32, 0.96]**

Table 8: Estimates of d in the cointegrating regression using Airline miles

	No regressors	An intercept	A linear time trend
White noise	**0.73 [0.60, 0.92]**	0.79 [0.60, 1.07]	0.79 [0.59, 1.07]
Bloomfield (Autoc.)	**0.72 [0.38, 0.99]**	0.74 [0.37, 1.04]	0.74 [0.36, 1.03]

Table 9: Estimates of d in the cointegrating regression using Airline revenues

	No regressors	An intercept	A linear time trend
White noise	**0.74 [0.61, 0.93]**	0.77 [0.59, 1.04]	0.77 [0.59, 1.04]
Bloomfield (Autoc.)	**0.68 [0.35, 0.94]**	**0.69 [0.35, 0.96]**	**0.69 [0.35, 0.95]**