Spectral Density Estimation of Load Factor of Flight of Domestic and Cross Border Europe of Airlines that are Members of AEA

by
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Abstract

The airline industry is one of the main components of the global economy. The airline industry has its own unique characteristic that differentiates from other industries. In the airline industry the term load factor defined as the percentage of seats filled by revenue passengers is used to measure of efficiency and the performance of an airline. This study is proposed to fit appropriate panel data econometric model of the load factor of flights of domestic and cross boarder Europe of airlines that are the member of the AEA (Association European Airlines) based on the monthly data from Jan 1991 to Dec 2013. The econometric analysis is done by a profound investigation of the structure of autocorrelation of the load factor. The result showed that the structure of autocorrelation of load factor of the domestic and cross border having both periodic and serial correlations. In such circumstance using ordinal panel data models found to be inappropriate to build realistic econometric model. Therefore, in order to control the periodic autocorrelation structure we advance our analysis by specifying dynamic time effect of the panel data. Further in order to eliminate serial correlation we apply the Prais–Winsten autoregression to fit the model. The fit of the dynamic time effect panel data model using the Prais–Winsten autoregression enable us to forecast the load factor of flights of domestic and cross border Europe of airlines that are a member of the AEA.

Key words: AEA, Load factor, Spectral density estimation, dynamic time effect panel data model.

1. Introduction

Yield, revenue per unit of output sold, is a highly significant metric in the airline industry, but it is by definition just the mathematical outcome of two even more fundamental metrics: output sold and revenue earned. For more than five decades, real yields across the industry as a whole has been in decline and the price stimulus to which this has given rise accounts for a significant portion of the traffic growth achieved during the period (Netessine&Shumsky, 2002). Very broadly, yields will soften when (1) traffic growth is flat or insufficient to absorb output growth (low prices are used to sustain load factors), (2) intense competition lower prices, and yields will harden when (1) load factors are already high and output is growing no faster than traffic, (2) traffic growth is outstripping growth in output and (3) lower competition keeps prices unchanged. The fact that traffic, load factor, and revenue (therefore yield) will each be affected by these type of adjustments illustrates how intimately connected the variables are – all within the context of available output (Talluri&Ryzin, 2001).

1.1 Background

This paper’s main emphasis is the airline industries load factors. The load factor measures the percentage of an airline´s output that has been sold – in effect, a measure of the extent to which supply and demand are balanced at prevailing price points. The achieved load factors for the industry conceal marked variations between different type of airline, with regional carriers at the lower end of the spectrum and charter airlines generally achieving higher load factors than scheduled carriers (Cross, 1997). The average load factor for any individual airline masks variations between different markets and cabins, with economy/coach achieving higher load factors because customers tend to book further in advance and expect lower levels of seat accessibility than is the case in premium cabins; it also conceals pronounced daily, weekly and – in particular – seasonal variations. For example, an monthly annual passenger load factor of, say, 75% will conceal full flights and spilled demand across much of the schedule, especially during peak days, but load factors perhaps as low as 50-60% on off-peak days departures. Load factors are driven to a considerable extent by the following factors. The first driver is the industry’s output decisions relative to demand growth. The output growth must be brought into closer alignment with demand growth. The second driver is pricing. Fare reductions generally stimulate demand and, depending upon what decisions are taken with respect to output, generate higher load factors. The third driver is traffic mix. Historically, the higher the proportion of business travellers carried by an airline, the lower the average seat factor. Due to the random element in demand for business travels (volatile) imply that demand spill will be encountered at a lower average load factor in business and first class cabins (McGill& van Ryzin, 1999). The fourth factor is payment policies. A carrier taking non-refundable payment at the time of reservation is likely to have relatively fewer no-shows and a relatively higher seat factor than on selling a greater portion of tickets on a fully flexible basis. The fifth driver is commercial success. A success of product design, promotions, marketing communications, distributions, and service delivery will clearly influence current load factors. Finally, the sixth driver is revenue management. The effectiveness of a revenue management system in minimising spoilage will influence load factors. Revenue management system capabilities – specifically, the refinement of demand forecasting tools – will contribute significantly (Marriott &Cross, 2000).

Depending on prevailing market conditions, it is often the case that load factor and yield trade off against each other: unless demand is particularly strong and output growth is under firm control, it is likely that rising yield will be associated with downward pressure on load factors. Conversely, falling yield tends to be associated with higher load factors. Hence, airline carriers will generally want to arrive at a capacity plan with target load factors that strike a balance between the costs of turning passengers away and the costs of meeting all

peak demand coming forward and oversupplying the market at other times. Hence, high load factors might sometimes be a “double-edged sword”. Both positive (lower cost per passenger mile) and negative (unacceptable levels of spill) effects are in operation. Moreover, it is much easier from an operational perspective to manage an airline when load factors are at 64% then when they are at 84% (Cross, et al, 2010). A moderate average load factor might be acceptable if the break-even load factor is sufficiently low – as when, for example, a high yield product is being offered. A high average load factor will not necessary be enough to ensure acceptable operating performance if the break-even load factor is high – as when, for example, unit cost is high or yield is low. If average load factor rises whilst yield and unit cost (and therefore the break-even load factor) remain constant, operating performance will improve (and vice versa).
The load factor is therefore a measure of the success or otherwise of an airline´s capacity management efforts. These efforts are hindered by the fact that whilst demand fluctuates in units of single seat-departures in different origin and destination markets and is volatile, supply can only be produced in units equivalent to the capacity of whichever aircraft type is available to operate the flight-legs and routes designed to serve targeted origin and destination markets and is broadly fixed in the short run. Furthermore, the requirements to maintain both high flight completion rate and the integrity of network connections and aircraft and crew assignments might preclude a scheduled passenger carrier from cancelling a significant number of its lightly loaded flights (Bruckner, & Whalen, 2000).

1.2 The Problem

The main objective of this paper is therefore to provide an econometric model that can capture the variations of load factors of the flights of domestic and cross boarder flights of Europe of airlines under the AEA (Association European Airlines) across different geographical regions of the world. The fit of the econometric model will helpful to forecast the load factor of the flights of the airlines under the AEA.
Our first problem is the identification of which econometric model is appropriate to study the load factor of the flights of domestic and cross boarder flights of Europe of airlines under the AEA. The most important stochastic quantitative analysis is regression analysis and time series analysis. Regression analysis is a type of multivariate analysis which applied to the cross-sectional (spatial) data to stochastically measure the impact of exogenous variables (predictors) on the endogenous variable (response variable). Time series analysis is helpful to see the dynamic aspect of the endogenous variable (Pearl, 2000; Granger, 1991).
Time series analysis is incomplete to measure the spatial effect and regression analysis is incomplete to measure the dynamic effect of the endogenous variable. This showed that these two fundamental models are complementary. An econometric model which represents both the combination of regression and time series analysis is called panel data analysis. Therefore, in order to acquire the advantages of time series and regression analysis we employ panel data analysis to build an econometric model of the regional flights of load factor of the airlines under the AEA (Pearl, 2000; Sims, 1980).
Panel data regression equation consists of the special effect and the time effect. Usually these effects can be fixed or random effect according to the test results of the Hausman specification. However, in this study of the Hausman specification test is not sufficient to have a concrete understanding of the effect of time of the load factor (Fitzmaurice, et al, 2004).

One of the major challenges in this econometric analysis of time effect on the load factor of the flights across the different regions is identifying the structure of the autocorrelation of the series (Vassilis, 2008). Typically we think the intensity of the autocorrelations of the time series data is vanishing with lags.However, reality the exact autocorrelation structure of the load factor showing highly seasonal dependence. This makes the autocorrelation structure of the load factor is behaving in complicated manner.

Therefore, in this study we advance the classical panel data analysis by expressing the time effect of the load factor is a dynamic (can be linear or nonlinear) function of parameters which are integrated to geographical flights (Domestic and Cross Boarder Europe). This helps us to control the periodic autocorrelation. Further in order to control the serial autocorrelation we apply the Prais–Winsten recursive autoregression estimation (Prais & Winsten, 1954).

Finding the most suitable mathematical relationships of the dynamic time effect of the load factor and controlling serial correlation is therefore the indispensable task of this study.The best panel data model fit should therefore capture geographical markets, economy/premium cabins and – in particular - seasonal variations. Moreover, well-calibrated forecasts may bring superior new information and techniques to revenue management system capabilities.

2. Review Literature

In December 17, 1903, after four years research and design two scientists named Orville and Wilbur Wright created a flying machine today called air plane. Prior to 1903, people had flown only in gliders and balloons. Since the birth of flight in 1903, air travel has developed as an essential means of transportation for people and cargo around the world (Crouch, 2004). In the history, Leon Delagrange was the first person to fly as a passenger with French pilot Henri Farman from a grazing land outside of Paris in 1908. The first American aircraft passenger flew with Orville Wright at Kitty Hawk in 1909 was Charles Furnas. In January 1, 1914, the first scheduled air service began in Florida, America by an aircraft designed by Glenn Curtiss (Gibbs, 2000).

So many years following the innovation of the first aircraft have conveyed about a revolution in the way people travel. The airline business is a main industry, have faith in millions not only for transportation but also mobilize the research and developments (R&D) of many countries. In 1933, the American aircraft company Boeing produced the first modern passenger airliner called the Boeing 247. In the same year United Air Lines promptly bought 60 of the Boeing 247. The Boeing 247 which accommodates for 10 passengers and flying at a speed of 155 miles per hour is also used for military purpose (Bowers, 1989).

The Douglas Aircraft Company incorporated Boeing's innovations and improved the Boeing 247 and designed the DC-1. The DC-1 had a more powerful engine and accommodates two or more passengers than did the Boeing 247. Most prominently, the airframe was designed so that the casing of the aircraft windbag most of the stress on the plane during flight (Francillon&Douglas, 1979).

In the 1950s major technological innovations of jet aircraft for commercial use was introduced in the global airline industry. In 1970s the technological innovations continued its growth and enabled by the introduction of the development of wide-body "jumbo jets". During this time, airlines were seriously regulated throughout the world (Gradidge& Jennifer, 2006).

Since the mid of 1970s forwards the technological innovation on the aircraft is focused switched on the improvement of more efficient engine, avionics, lighter composite materials and wide-bodied medium-haul aircraft. During this time for example the Boeing 767 and the Airbus A-310 introduce to the aircraft market. At the same time, the tendency on the road to larger aircraft flying at the same speed continued. For instance is the Airbus A-320 familiarized in 1988 which having up to 180 seats. During the 1990s the Boeing 767–200 EQ, Airbus A340 and Boeing 777 were introduced in the aircraft market (Rigas, 2010).

Since the early days of the 21-century the technological developments of the aircraft industry are continued by improving engine (especially fuel consumption) and airframes (reduction of the weight of the aircraft). Both the developments critically contributed to reduction of the operating costs of the aircraft. In 2008 Boeing 787 Dreamliner introduced to service. The aircraft as much as 50 per cent of the main structure, comprising the fuselage and wings, is made of composite materials. In 2010 the Airbus A350 and entering service later, would also have a high composite component (Rigas, 2010).

2.1 The Global airline industry

The global airline industry is responsible for a service to effectively every country in the world, and has played anessential role in the establishment of a global economy. The airline industry by itself is a main economic power of many countries in many directions.For example, the aircraft manufacturing industry is a wide industry which is running through many peripheral industries that cause reduction of the unemployment rate and mobilize the research and developments. On the other hand economic integration of the many countries across the world is highly supported by the airline industry. Therefore, including the expansion of tourism and recreation, the role of air transportation is significant to facilitate the world economy (Belobaba, et al, 2009).

According to Rigas(2010) the airline industry gives the impression of being both cyclical and strappingly subjective to external dynamics. This unsurprisingly means that growth rates can vary enthusiastically from time to time. On the other hand the fundamental trend has been one of consistently virtuous growth in demand but at a diminishing rate. Most industries challenged with sustainable and high growth of demand for their services or products would be spread out in huge profits. However, such marketing phenomena cannot suitable for the airline industry. Scholars explained such situation as the international airline industry is complex, dynamic subject to rapid change and innovation, and marginally profitable. In line for the difficulty of efficient approximating real asset values for airlines with inconsistent depreciation, the rate of return on assets (ROA) cannot be fully applied easily to the airline industry.

In the airline industry pricing refers to by considering various service facilities and capacities, for a set of airline products then procedure of determining tariff levels in an origin-destination market. Revenue management is a consequent the process of determining the number of seats available at each tariff level. This shows the revenue management of the airline is a function of its tariff strategy and the load factor. According to Kellner (2000) the success of the airline is determined by its ability to make unit revenues (Yield.LF) higher than its unit costs (Total Cost/ ASK). Therefore, in addition to minimize the unit cost, the important task of the airline manager is to simultaneously maximize yield and load factor. Alternative evaluation of the profitability of airlines is the operating ratio. The operating ratio is a ratio that demonstrates the efficiency of an airline by matching operating expense to net sales (ICAO, 2013).

2.1.1 The Main Features of the Global airline industry

The main key features of the airline industry are summarized as follows.

Service Industry: Airlines give transportation service for their customers and their properties (Cargo) from one location to another for an agreed price.

Capital Intensive: Airlines essentially needed varieties of expensive and luxurious equipment and facilities. Consequently, the airline industry is a capital-intensive business, demanding big amounts of money to function successfully (Belobaba, et al, 2009).

High Cash Flow: Because airlines possess large fleets of expensive aircraft that depreciate in value over time, they stereotypically produce a significant positive cash flow. Most airlines

use their cash flow (profits plus depreciation) to reimburse debt or purchase new aircraft (John, 2009).
Labor Intensive: Anyairline needed employs of effective army of pilots, mechanics, flight attendants, baggage handlers, security personnel, reservation agents, gate agents, cooks, cleaners, managers, accountants, lawyers, etc. Therefore, the Airlines typically are labor intensive (Belobaba, et al, 2009).
Airline Revenue: The major revenueof the airline industry comes from the transportation of passengers. The minor revenue of the airline is comethe transportation of cargo and the postal service (Chua, et al, 2005).
Airline Costs: The major airline costs are (Flew, Terry 2008; Babikian, et al, 2002; Oum& Yu,1998; Borenstein, 1992): flying operations (costs of such as fuel and pilot salaries); maintenance (both parts and labor); the aircraft and traffic service (mostly the cost of handling and holding passengers, cargo and aircraft on the ground and including such things as the earnings of baggage dispatchers, handlers and airline gate agents; Sales and promotions (including travel agent commissions, reservations and advertising); the passenger service (mostly in-flight service and including such things as food and flight attendant salaries); transport related (delivery trucks and in-flight sales); administrative costs; depreciation and amortization (equipment and plants) and other different labor costs.
Small Profit Margins: Airlines have gotten a net profit of small percentages (Mark & Brian 2006).
Seasonal: The airline business traditionally has been very seasonal (Ľubomír&Hospodka, 2013).

2.1.2 Deregulation and its Impact on the Airline Industry

Prior to the 1978 the airline industry aspect is regulated by the government agency. US economists pointed out a number of studies which supports unregulated intrastate airfares were considerably lower than fares for interstate flights. As a result stress for airline deregulation had been increased for many years. Especially, a series of concrete econometric studies intensified the pressure of deregulation in the mid-1970s (Millbrooke, 2006).
According to U.S. General Accounting Office, (1990), on October 24, 1978 President Jimmy Carter signed the Airline Deregulation Act of the airline industry which was approved by the American Congress. Deregulation of the airline industry beginning in the USA cause to the airline management cost efficiency and effectiveness; operating profitability and competitive behavior.Airline deregulation (liberalization) has now binged to most of the industrialized world, that continuing progression of exceedingly competitive world-wide airline industry (Bamber, et al, 2011)).
Deregulation contributes to extensive development of hub-and-spoke networks. Hubs are strategically and advantageously positioned airports used as transfer points for passengers and cargo moving from one location to another. Airlines implemented hub-and-spoke systems enable to play a part of many market places of the same fleet size (Brueckner, 2004; Kahn, 1988).
Deregulation allows the airline service by introducing new carriers. The entrance of new airlines resulted in extraordinary competition in the airline industry. Consequently, increased and intensified competition produced discount fares. Therefore, the discount fares are the most important result of airline deregulation (IATA, 2008); Poole, & Butler, 1998).
In addition to the discount of fares, schedule is an important dimension of air travelers. Due to deregulation, airlines have been able to function and they can adjust their schedules often, in reaction to market prospects and competitive pressures. Deregulation also generated marketing novelties, the most remarkable existence of frequent flyer programs, which repayment of customers with free tickets and other benefits (Card, 1986).

A computer reservation system is also subsequent result due to deregulation. The computer reservation systems empower airlines and travel agents to efficiently and effectively process the many of the passengers who serve in a wide market area. Deregulation also help for the innovations in the development of code-sharing agreements of airlines. The Code-sharing agreements consent different airlines to compromise better coordinated and well harmonized services to their customers (Winston, 1995).

2.2 Load Factor-Measure of airline performance

Yield management is the assortment of schemes, strategies and tactics airlines use to systematically manage demand for their services and products. Airlines are the most prominent users of yield management systems and also the drivers of innovations. The yield management practice has developed from its roots in airlines to its prominence today as a typical business run through in a wide range of industry areas, including fashion retail, hospitality, energy, and manufacturing (Link, 2004).

A bid price is the highest price that a passenger is agreeable to pay for the air transport service. So, this price is depending on the type of customer at a time. The bid price specifies a fitting together the dynamic network models and the optimal network solution. The performance of dynamic network models is its ability to control the optimal revenues in the market (Kaul, 2009).

Passenger load factor (or every so often simply called load factor) is a measure of the degree of an airline passenger carrying capacity. In other words, load factor is a measure of efficiency and the performance of an airline. Success of high load is supposed indispensable for airline's profitability.International airline literature can be divided into demand structures, fleet, network and revenue modelling, market structures and operating performance (Dender, 2007). As illustrated in the introduction, the paper's main objectives are operating performance focusing on the unit revenue defined as. The load factor is therefore a measure of the extent to which supply and demand are balanced at prevailing price points (Distexhe, &Perelman, 1994).

The percentage of the seats the airline has in service that it must sell at a given yield (or price level) to cover its costs is called break-even load factor. In order to avoid the risks of negative profit, every single airline has a break-even load factor. The cost of the airline is positively and the price of the airline is negatively correlated with the break-even load factor (Flores&Moner, 2007).

The magnitude of the load factor of the given airline directly reflects the competency of that airline. Therefore, it is thought-provoking to examine factors that are potentially affecting the load factor of the airline. Generally, operational factors play significant title role in affecting the load factor of airlines. Specifically, the capacity of the airline, the distance covered by the journey of the airline, tourist, codeshare agreement (is an aviation business arrangement where two or more airlines share the same flight) and market concentration HHI index (a commonly accepted measure of market concentration) are the most important factors that have a positive and significant effect on load factor (Minho, et al, 2007).

The GINI index (a measure the degree of price dispersion, or price inequality in the airline of the same flight) and is discovered as the factor that negatively affects the load factor of the airline. Other important factors that affect the load factor are airport features, performance limitation, flight conditions, seasonally of demand, time of traveller schedule, frequency of flight and dynamic route networks (Minho, et al, 2007; Karagiannis& Kovacevic,2000).

Knowing and identifying these potential factors would benefit the airline to make more effective strategic and tactical decisions. These effective strategic and tactical decisions include: staff training, changing the mind-set among airline staff, determining the optimal number of travel agencies and advertisement, changing the airline management practices, optimizing the human resource, and many other related activities (Talluri& Ryzin, 2004).

2.3 Association European Airlines

In 1952, Air France, Royal Dutch Airlines, Sabena and Swissair established a cooperative study group of airline.Immediate of the establishment of the group the British Airways and Scandinavian Airlines joined the group.The joint group of these airlines were responsible for the establishment of the European Airlines Research Bureau (ARB) in 1954 on a permanent basis, in Brussels. In the same year, after the establishment of the ARB, the European Civil Aviation Conference (ECAC) founded in the Strasbourg Conference on the harmonization of air transport in Europe (AEA 2014b, 2013).

The European Civil Aviation Conference (ECAC) inspires air carriers to carry out cooperative and supportive studies designed to promote a methodical development and expansion of air transport in Europe. In process in 1973, the name of the European Airlines Research Bureau changed to the Association European Airlines (AEA, 2013).

The Association of European Airlines (AEA) is a non-profit organisation which works together with the organizations of the European Union (EU) and other interested parties in the air transport value chain to safeguard the sustainable development of the European airline industry in a world-wide marketplace (AEA, 2013).

The Association of European Airlines (AEA) has wide-ranging knowledge and experience of the airline industry. The AEA is a trustworthy contributor to achieve the following key objectives: raise aviation's role in Europe's future; increase the benefit of customers; contribute to better cost-effective regulation; speed up aviation progress towards a single European Sky; decarbonise aviation to protect global environment; safeguard circumstances for fair competition of airlines; and titleholder a global security framework of airlines (AEA, 2013).

According to AEA (2014a) today the Association of European Airlines (AEA) bringing together more than 30 major European airlines listed as: Adria Airways (Slovenia), Aegean Airlines (Greece), Air Baltic (Latvia), Air Berlin (Germany), Air France (France), Air Malta (Malta), Air Serbia (Serbia), Alitalia (Italy), Austrian Airlines (Austria), British Airways (United Kingdom), Belgium Brussels Airlines (Belgium), Cargolux (Luxembourg), Croatia-Airlines (Croatia), Cyprus Airways (Cyprus), Deutsche Lufthansa (Germany), DHL (Germany), Finnair (Finland), Iberia Airlines (Spain), Icelandair (Iceland), KLM (The Netherlands), LOT Polish Airlines (Poland), Luxair (Luxembourg), Meridiana (Italy), Scandinavian Airlines System (Sweden, Norway, Denmark), Swiss (Switzerland), TAP Portugal (Portugal), Tarom (Romania), TNT Airways (Belgium), Turkish Airlines (Turkey), and Ukraine International Airlines (Ukraine).

Here after when we say airlines, we mean that airlines that are members of the AEA until the end of Dec 2013.

3. The Data and Methodology

3.1 The Data

The dataset is from *Association of European Airlines*(www.aea.be)and is downloaded from Research & Statistics(http://www.aea.be/research/traffic/index.html) and AEA Traffic and Capacity Data (AEA, 2014c). The data contains information about Available Seat-Kilometres (ASK), Revenue Passenger-Kilometres (RPK) and Load factor (LF). The data is organised suitable for the objectives set by the panel data model (see next section).

3.1.1 Spatial Effects- The Geographical Codes

DO – Domestic Flights of Europe

Domestic traffic is defined as traffic carried on routes originating and terminating within the boundaries of a State by an air carrier whose principal place of business is in that State, or on routes between the State and territories belonging to it. Note that traffic on domestic stages of international routes is included in the international route group which corresponds to the flight routing in its entirety.

EU - Cross-border flights of Europe

Includes all cross border/ international routes originating and terminating within Europe (including Turkey and Russia up to 55ºE), Azores, Canary Islands, Madeira and Cyprus.

3.2 Methodology

3.2.1 One way Analysis of variance (ANOVA)

One way analysis of variance (ANOVA) is used to see the existences of the mean differences of a certain random variables with a single treatment over its levels. The linear statistical model for ANOVA is given as (Cochran, et al, 1992):

$$y_{ij} = \mu + \alpha_i + \varepsilon_{ij}, \quad i = 1,2,3,....a, \quad j = 1,2,3,....n \qquad (1)$$

where: μ the grand mean, α_i the i^{th} level effect $\varepsilon_{ij} \sim N(0,\sigma^2)$

The method of estimation for the model parameters is using bootstrapping method.

3.2.2 Signal processing

Signal processing is a stochastic process of time series data that formulated as the series of harmonic functions (Hamilton, 1994). Alternatively, we can say signal processing is the spectrum of a time-series or signal is a positive real valued function of a frequency variable associated with a stationary stochastic process. Specifically, the spectrum decomposes the component of a stochastic process into different frequencies present in that process, and helps identify periodicities. The signal processing stochastic model for a discrete variable is given as (Priestley, 1991):

$$y_t = \mu_t^* + \sum_k [a_k \cos(2\pi v_k t) + b_k \sin(2\pi v_k t)] \qquad (2)$$

where: μ_t^* = the mean of the series at a time t.

a_k, b_k are the Fourier transformation coefficients of cosine and sine waves the function.

Mean and Variance of the spectrum of the time series data:

$$E[y_t] = E[\mu_t^*] + E[\sum_k [a_k \cos(2\pi v_k t) + b_k \sin(2\pi v_k t)]]$$

$$= \mu_t^* + \sum_k E[a_k \cos(2\pi v_k t) + b_k \sin(2\pi v_k t)] = \mu_t^* \; (3)$$

$$Var[y_t] = E[[y_t] - E[y_t]]^2$$

$$= E[\mu_t^* + \sum_k [a_k \cos(2\pi v_k t) + b_k \sin(2\pi v_k t)] - \mu_t^*]^2$$

$$\therefore Var[y_t] = E[\sum_k [a_k \cos(2\pi v_k t) + b_k \sin(2\pi v_k t)]]^2 \qquad (4)$$

For simplicity of computation, we assume time as continuous variable (Kammler & David, 2000). Further, we assume that the spectrum extends infinitely $(T \in (-\infty,\infty))$ in time in both directions. Then covariance of the series is given as:

$$Co-\mathrm{var}[y_t, y_{t-\tau}] = \frac{1}{2T}\int_{-T}^{T}(y_t - \mu_t^*)(y_{t-\tau} - \mu_{t-\tau}^*)dt \quad (5)$$

$$= \frac{1}{2T}\int_{-T}^{T}[a_k \cos(2\pi v_k t) + b_k \sin(2\pi v_k t)][a_k \cos(2\pi v_k t-\tau) + b_k \sin(2\pi v_k t-\tau)]dt$$

where: $\tau = 0,1,2,3,....$ is the order of the lag

In order to find the variance we set the $\tau = 0$ on equation 5 so that we have:

$$Var[y_t] = \frac{1}{2T}\int_{-T}^{T}[a_k \cos(2\pi v_k t) + b_k \sin(2\pi v_k t)]^2\,dt \quad (6)$$

3.2.2.1 Estimation of Spectrum density

Non-Parametric- Computer Generated Graphical Method

Spectral density analysis allows us to see the nature of autocorrelation function on the observed time series data in to Fourier space (Boashash, 2003). This creates a good ground to analyse the scope and the nature of autocorrelation structure of the observed time series data. This will help us to choose appropriate econometric model which can eliminate the problem of autocorrelation.

The non-parametric estimation approach of spectral density is transformation of the autocorrelation function of the series in to Fourier series. This will allow us to see the nature of autocorrelation on the series on the Fourier space. The Fourier transformation contains the sum of infinite series of sine and cosine waves of different amplitude. So we plot the density and periodogram over the frequency of the series (Engelberg, 2008).

Parametric Method: The Ljung–Box test

There are a number of parametric methods that detect autocorrelation. However, the Ljung–Box test is preferable for this case because it simultaneously detect the existence and the order of autocorrelation on the time series. Ljung–Box test procedure is given as (Davidson, 2000):

Null Hypothesis H_0: The time series data are independently distributed.

Alternative Hypothesis H_a: The time series data are dependently distributed with autocorrelation structure of order h.

The test statistic of Ljung–Box is given as:

$$Q = n(n+2)\sum_{l=1}^{h}\frac{\hat{\rho}_l^2}{n-l} \quad (7)$$

where*n* is the sample size, $\hat{\rho}_l$ is the sample autocorrelation at lag l, and *h* is the number of lags being tested. The null hypothesis is rejected for α level of significance if:

$$Q > \chi^2_{1-\alpha,h} \quad (8)$$

3.2.3 Panel Data Regression Models

Panel data (also called longitudinal data) is a data that is observed across different cross-sectional (spatial) units over repeated time intervals. Therefore, such data contains information of both spatial effect and time effect of the response variable. Contrasting to cross-sectional data, with longitudinal data we observe subjects over time. Contrasting time series data, with longitudinal data we observe many subjects (Davidson, et al, 1993). This will allow the data to have a broad cross-section of subjects over time allows us to study dynamic, as well as cross-sectional, aspects of a problem. Statistical analysis on panel data is called panel data regression analysis (Hsiao, 2003).

3.2.3.1 Two-way Fixed Effect Panel data regression model

This model is applied when there is significant effect of both the special and the time effect on the response. The Two-way Fixed Effect panel data regression model is given as (Baltagi, 2008):

$$y_{it} = \eta_i + \lambda_t + \beta_1 x_{1it} + \beta_2 x_{2it} + ... + \beta_l x_{lit} + ... + \beta_k x_{kit} + \varepsilon_{it} \quad (9)$$

$i = 1,2,3,..., n,\ t = 1,2,3,..., T,\ l = 1,2,3,..., k$

Where: y_{it} is the response from cross section i at a time t, η_i is theithspecific spatial effect λ_t is the tth specific time effect, x_{lit} are exogenous imputes of coefficients β_l are the model parameters and $\varepsilon_{it} \sim iid(0, \sigma^2 I_{nT})$ is the random error term of the model

Estimation: Under the complete fulfilment of the Gauss-Markov assumption the estimates from the Least Squares Dummy Variable (LSDV) estimation are the best linear unbiased estimator (BLUE) of the model parameters (Barreto, et al, 2005).

3.2.3.2 Two-way Random Effect Panel data regression model

This model is applied when there is significant effect of both the special and the time effect on the response. The Two-way random effect panel data regression model is given as (Davies & Lahiri,1995):

$$y_{it} = \eta_i + \lambda_t + \beta_1 x_{1it} + \beta_2 x_{2it} + \beta_3 x_{3it} + ... + \beta_k x_{kit} + \varepsilon_{it} \quad (10)$$

$i = 1,2,3,..., n,\ t = 1,2,3,..., T,\ l = 1,2,3,..., k$

Where: y_{it} is the response from cross section i at a time t, $\eta_i \sim iid(E[\eta_i], \sigma_\eta^2)$ is theithspecific spatial effect λ_t $\lambda_t \sim iid(E[\lambda_t], \sigma_\lambda^2)$ is the tth specific time effect, x_{lit} are exogenous imputes of coefficients β_l are the model parameters and $\varepsilon_{it} \sim iid(0, \sigma^2 I_{nT})$ is the random error term of the model.

Estimation: Under the complete fulfilment of the Gauss-Markov-Aitkin assumption the estimates from the Generalized Least Squares (GLS) estimation are the best linear unbiased estimator (BLUE) of the model parameters (Amemiya& Takeshi,1985).

3.2.3.3 Dynamic Time effect two-way Panel data regression model

This model is applied when spatial is significant and the time effect is dynamic. The dynamic panel data regression model is given as (Davies & Lahiri, (2000); Hayashi, Fumio (2000); Luc et al, 2000; Schittkowski, K., 2002; Fahrmeir, et al, 2009; Chan, et al, 2012; Maria & Jim 2014):

$$y_{it} = \eta_i + \lambda_t + \beta_1 x_{1it} + \beta_2 x_{2it} + \beta_3 x_{3it} + ... + \beta_k x_{kit} + \varepsilon_{it} \quad (11)$$

$$\lambda_t = f(t; \varphi_i)$$

$$\varepsilon_{it} = U(\varepsilon_{i,t-1}, \varepsilon_{i,t-2}, ...\varepsilon_{t,t-h}; \rho_{i1}, \rho_{i2}, ..., \rho_{ih}) + v_{it},\ v_{it} \sim iiDN(0, \sigma_v^2)$$

$i = 1,2,3,..., n,\ t = 1,2,3,..., T,\ l = 1,2,3,..., k$

Where: y_{it} is the response from cross section i at a time t, η_i is theithspecific spatial effect λ_t is the tth specific time effect, x_{lit} are exogenous imputes of coefficients β_l. $f(\bullet)$ is any real valued function of time "t" and a vector of parameter $U(\bullet)$ is a linear function of $\varepsilon_{i,t-j}$, ρ_{ij}, $j = 1,2,3,..., h$ and $\varphi = [(\varphi_{11}, \varphi_{12}, ..., \varphi_{1m}), (\varphi_{21}, \varphi_{22}, ..., \varphi_{2m}), ..., (\varphi_{b1}, \varphi_{n2}, ..., \varphi_{nm})]$,

Estimation: Case 1:

If $\lambda_t = f(t; \varphi_i)$ is a linear function then under the complete fulfilment of the Gauss-Markov assumption the estimates from the Least Squares Dummy Variable (LSDV) estimation are the best linear unbiased estimator (BLUE) of the model parameters. Otherwise, under the complete fulfilment of the Gauss-Markov-Aitkin assumption the estimates from the Generalized Least Squares (GLS) estimation are the best linear unbiased estimator (BLUE) of the model parameters (Voinov&.Nikulin (1993); Babaket al, (1999); Thomas, et al (2000); Hsiao (2003)).

Estimation: Case 2:

If $\lambda_t = f(t;\varphi_i)$ is a nonlinear function,then we apply the following estimation procedure to estimate the model parameters (Seber, et al, 1989; Meade & Islam, 1995; Kelley, 1999; Billings, 2013; Wooldridge, 2013).

Let $y_{it} = F(t, X;\theta) + \varepsilon_{it}$ (12)

where

$F(t, X;\theta) = \eta_i + f(t;\varphi_i) + \beta_1 x_{1it} + \beta_2 x_{2it} + \beta_3 x_{3it} + \ldots + \beta_k x_{kit}$,

$\theta = [\theta_1, \theta_2, \theta_3, \ldots, \theta_{n(m+1)+k}] = [\eta_i, \varphi, \beta]$ is the vector of model parameters

Now let's minimize the total sum of the errors as:

$$Min\left[\sum_{i=1}^{n}\sum_{t=1}^{T}[y_{it} - F(t;X;\theta)]^2\right] \tag{13}$$

$$\Rightarrow \frac{\partial}{\partial\theta_s}\left[\sum_{i=1}^{n}\sum_{t=1}^{T}[y_{it} - F(t;X;\theta)]^2\right] = 0, \quad s = 1,2,3,\ldots n(m+1)+k$$

$$\Rightarrow \sum_{i=1}^{n}\sum_{t=1}^{T}[y_{it} - F(t;X;\theta)]\left[\frac{\partial F(t;X;\theta)}{\partial\theta_s}\right] = 0$$

$$\Leftrightarrow \sum_{i=1}^{n}\sum_{t=1}^{T}\left[y_{it}\left[\frac{\partial F(t;X;\theta)}{\partial\theta_s}\right] - F(t;X;\theta)\left[\frac{\partial F(t;X;\theta)}{\partial\theta_s}\right]\right] = 0$$

In order to solve equation 7 we apply the Newton-Raphson recursive algorithm by defining a new function as:

$$G_s(t, X;\theta) = \sum_{i=1}^{n}\sum_{t=1}^{T}\left[y_{it}\left[\frac{\partial F(t;X;\theta)}{\partial\theta_s}\right] - F(t;X;\theta)\left[\frac{\partial F(t;X;\theta)}{\partial\theta_s}\right]\right] \tag{14}$$

$$G = [G_s(t, X;\theta)]_{n(m+1)+k}$$

Now lets drive the Jacobean matrix (Hazewinkel, 2001)from equation 8 as:

$$J_G = \begin{bmatrix} \frac{\partial G_1(t;X;\theta_1)}{\partial\hat{\theta}_1}, \frac{\partial G_1(t;X;\theta_1)}{\partial\hat{\theta}_2} \cdots \frac{\partial G_1(t;X;\theta_1)}{\partial\hat{\theta}_{n(m+1)+k}} \\ \frac{\partial G_2(t;X;\theta_2)}{\partial\hat{\theta}_1}, \frac{\partial G_2(t;X;\theta_2)}{\partial\hat{\theta}_2} \cdots \frac{\partial G_2(t;X;\theta_2)}{\partial\hat{\theta}_{n(m+1)+k}} \\ \vdots \qquad \cdots \qquad \vdots \\ \frac{\partial G_{n(m+1)+k}(t;X;\theta_{n(m+1)+k})}{\partial\hat{\theta}_1}, \ldots \frac{\partial G_{n(m+1)+k}(t;X;\theta_{n(m+1)+k})}{\partial\hat{\theta}_{n(m+1)+k}} \end{bmatrix}_{[n(m+1)+k]x[n(m+1)+k]} \tag{15}$$

Then by inverting the Jacobian matrix (i.e. J_G^{-1}) the Newton-Raphson recursive algorithm to get the numerical solution as the estimates of the model parameters is given as (Ortega & Rheinboldt, 2000; Bonnans, et al, 2006):

$$[\hat{\theta}_s]_{r+1} = [\hat{\theta}_s]_r - [J_G^{-1}][G], \quad r = 1,2,3.... \tag{16}$$

3.2.4 Advanced Model Adequacy Checking

In this section after controlling the periodic autocorrelation by selling the time effect as a function of time, we need to remove the serial correlation. This makes to obtain efficient model parameters. The following steps, therefore, in order to remove serial correlation we use the following algorithm.

Step 1: First estimate the model fit residuals as (Weisberg,1985; Cook, et al, 1982):

$$\hat{\varepsilon}_{it} = y_{it} - F(t; X, \hat{\theta}) \qquad (17)$$

Step 2: Determine the structure of autocorrelation

At this step we use the Brewish-Godfrey test of autocorrelation (Godfrey, 1978). The test procedure is given as:

Step 2.1: Set Hypothesis

Null-Hypothesis (H_0): The error terms are independently distributed

Alternative Hypothesis (H_1): The error terms are serially correlated of order h

Step 2.2: Regress the residual as:

$$\hat{\varepsilon}_{it} = \rho_{i1}\hat{\varepsilon}_{i,t-1} + \rho_2\hat{\varepsilon}_{i,t-2} + ... + \rho_{i,h}\hat{\varepsilon}_{i,t-h} + H(X;\phi) + v_{it} \qquad (18)$$

where: $H(\bullet)$ is a linear function of exogenous imputes that are significant to fit our original panel data model $F(t; X, \hat{\theta})$ and a vector of parameter $\theta = [\theta_1, \theta_2, \theta_3, ..., \theta_{n(m+1)+k}] = [\eta_i, \varphi, \beta]$.

Step 2.3: Calculate the coefficient of determination of regression equation 11

$$R^2_{\hat{\varepsilon}} = 1 - \frac{SSE_{\hat{\varepsilon}}}{SST_{\hat{\varepsilon}}} \qquad (19)$$

where: $SSE_{\hat{\varepsilon}}$ is the sum of squares of the error and $SST_{\hat{\varepsilon}}$ is the total sum of squares.

Step 2.4: Calculate the Brewish-Godfrey test statistic

$$BL = nR^2_{\hat{\varepsilon}} \sim \chi^2_h \qquad (20)$$

Step 2.5: Decision: Reject H_0 if

$$BL = nR^2_{\hat{\varepsilon}} > \chi^2_{h,\alpha} \qquad (21)$$

Step 3: If we do not reject our null-hypothesis we take the model fit is free from the problem of autocorrelation. Otherwise, if we reject our null-hypothesis we apply the Prais–Winsten transformation as (Davies &Lahiri, 1995; Verbeek, 2004; Frees, 2004; Amemiya,1985; Prais & Winsten,1954; Wooldridge, 2008; Wooldridge, 2013):

$$\sqrt{1-\hat{\rho}_i^2}\, y_{it} = \sqrt{1-\hat{\rho}_i^2}\, F(t, X; \hat{\theta}) + \sqrt{1-\hat{\rho}_i^2}\, \varepsilon_{it} \qquad (22)$$

where: $\hat{\rho}_i = \dfrac{\sum_{t=2}^{n} \hat{\varepsilon}_{it}\hat{\varepsilon}_{i,t-1}}{\sum_{t=1}^{n} \hat{\varepsilon}^2_{it}}$

Step 5: Apply the principle of from equation 8 of equation 11

Step 6: Repeat from Step 1 to Step 5 unless the Brewish-Godfrey test of autocorrelation confirms that there is no serial correlation on the random error terms.

4. Results and Discussions

4.1 Assessment of the regional characteristics of Load Factor

Before we fit the panel data model it is essential to analyse the relationship of the load factor of the flights of both the domestic and cross country of Europeof the airlines with respect of the available seat-kilometres (ASK) and revenue passenger-kilometres (RPK).

The bootstrap estimates of the results of the revenue passenger-kilometres (RPK) and available seat-kilometres (ASK) of the domestic and cross border flights of Europe are given in Table 1. From the Table we observe that the estimates of the mean revenue passenger-kilometres (RPK in million) of the domestic and cross border of Europe are 3,936.89 and 11,632.11 respectively. Furthermore, the estimates of the mean available seat-kilometres (ASK in million) of the domestic and cross country of Europe are 5,895.59and 17,519.27respectively. The result confirmed that both in revenue passenger-kilometres (RPK) and available seat-kilometres (ASK) the cross boarder flights are higher than the domestic ones.

Conferring to the result from Table 2, the average cross border flights have 7,695.222revenue passenger-kilometres (RPK in million) and 11,623.677available seat-kilometres (ASK in million) than the domestic flights. However, the result from Table 2, confirmed that the load factor of the domestic flights is 1.85 % higher than the cross boarder flights.

Observation of Figure 1 and Figure 2 showed that there exist significant positive linear relationships between the revenue passenger-kilometres and available seat-kilometresfor both domestic and cross border flights. This is showing that, generally these airlines have a good coordination to balance the demand and their air transport supply. Nevertheless, in order to have a deep insight about the managerial performance of these airlines we have to analyse the results from Figure 3 and Figure 4.

From Figure 3we observe that there is a no important (since the coefficient of determination is only 16.2%) linear relationship between load factor and revenue passenger-kilometres in the domestic flights of Europe. However, there exists a significant positive linear correlation between load factor andrevenue passenger-kilometres of the cross boarder flights Europe. In addition the linear relationship of load factor and revenue passenger-kilometres of the cross border flights with coefficient of determination of 80.7% is given as:

$$LF = 45.47 + 0.00166 RPK(in \quad million)$$

This result confirmed that these airlines have a better demand management for the cross border flights than the domestic flights.

From Figure 4we observe that there is a no important (since the coefficient of determination is only 2.1%) linear relationship between load factor and available seat-kilometres in the domestic flights of Europe. However, there exist a significant positive linear correlation between load factor andAvailable Seat-Kilometres (ASK) of the cross boarder flights Europe. In addition the linear relationship of load factor and available seat-kilometres of the cross border flights with coefficient of determination of 66.4% is given as:

$$LF = 41.11 + 0.00135 ASK(in \quad million)$$

This result confirmed that these airlines have a better capacity management for the cross border flights than the domestic flights.

4.2 Assessment of the structure of Autocorrelation of Load Factor

In time series econometric analysis it is always a challenge to get the exact autocorrelation structure of the series. One of the powerful methods of identifying the structure of autocorrelation function is the spectral density analysis. The non-parametric spectral density and analysis gives us graphical information about how the autocorrelation function behaves in the Fourier space.

One of the graphical methods is the response of periodogram of the autocorrelation function of the frequency of the time series observation. This method is extremely sensitive the optimal autocorrelation structure of the series. The other method is the response of density of the autocorrelation function of the frequency of the time series observation. This method is sensitive to the weighted autocorrelation structure of the series. Therefore, both plots have important information about the structure autocorrelation of load factor.

The result of the spectral density estimation and the Ljung–Box test of the load factor of the domestic and cross border Europe flights of the airlines under AEA is given in Table 3. The interpretation of Table 3 is given as follows:

Autocorrelation structure of load factor of the Domestic Flights of Europe

The non-parametric plot of the periodogram and spectral density of the load factor of the domestic flights of Europe suggest that there exists strong periodic autocorrelation which is observed after jumping a certain period of months. The repeated yearly plot of load factor of the domestic flights of Europe over months showed that there are strong periodic pattern with small variance from year to year.

In the repeated yearly plot of load factor over months, we observe that there is one important pattern. The smallest load factor is observed in January then it started grow until July then declining until December.

The plot of the periodogram and spectral density suggest that the load factor distribution of flight is strongly serially correlated up to a certain month lags. Furthermore, the parametric test of the Ljung-Box test suggests that there exist significant serial correlation of order 17 months and dissipated after 18^{th} month.

Autocorrelation structure of load factor of the Flights of Cross-border Europe

The non-parametric plot of the periodogram and spectral density of the load factor of flights of cross border Europe suggest that there exists strong periodic autocorrelation which is observed after jumping a certain period of months. The repeated yearly plot of load factor of the flights of Cross-border Europe over months showed that there is strong periodic pattern.

In the repeated yearly plot of load factor over months, we observe that there is one important pattern. The smallest load factor is observed in November, December and January then started to grow until July, August and September then declining until November.

The plot of the periodogram and spectral density suggest that the load factor distribution of flight is strongly serially correlated up to a certain month lags. Furthermore, the parametric test of the Ljung-Box test suggests that there exist significant serial correlation of order 15 months and dissipated after 16^{th}month.

4.3. Fitting the Dynamic Time Effect Panel Data Regression Model

The analysis of section 4.1 we identified that both in revenue passenger kilometre and available seat kilometre the cross border flights are higher than the domestic flights of Europe. Besides the average load factor of the domestic flights is higher that the cross border of Europe. This confirms that inclusion of spatial effects to the fit of the panel data model controls such important variability.

The analysis of section 4.1 we identified that the characteristics of load factor behave differently for the flights of the domestic and cross border Europe.The load factor is significantly correlated with both the revenue passenger kilometre and available seat kilometre for the cross boarder flights of Europe. However, there is no important linear correlation with both the revenue passenger kilometre and available seat kilometre for domestic flights of Europe. Therefore, using these variables (both RPK and ASK) as a common exogenous impute to predict the load factor becomes inappropriate.

The analysis on the structure of autocorrelation in section 4.2, we identified that both periodic and serial correlations exist on the load factor. The structure of autocorrelation is different for both domestic and cross border flights of Europe. This is showing that the time effect on the load is not simply fixed or random effect; rather it is dynamic and uniquely associated with the regional flights.

Therefore, the appropriate model that we will fit to analyse the load factor of the flights of airlines is the dynamic time effect two way panel data regression model.The fit of the

dynamic time effect two way panel data regression model of the load factor of the domestic and cross border flights is given in Table 4.
The significance of the time function harmonic component suggests that the load factor is seasonal by its nature.Generally, the fit of the model suggests that the load factor is improving (growing) with time for both domestic and cross border flights. Specifically, the spatial effect of the load factor of the domestic flights(70.01%) is greater than the spatial effect of cross border flights(60.65 %). However, the significance of the cubed polynomial showed that, in the long run the load factor of the cross border flights will exceed the domestic flights.
In Figure 5 (left side) we see that the comparison of the actual and the predicted values of the load factor. From the Figure we determine that the fit of the dynamic time effect two way panel data regression modelis found to be robust and realistic to forecast the load factor of the domestic and cross border flights of Europe. Furthermore, in Figure 5 (right side) we give the plots of the monthly forecasted valuesof the load factor with upper and lower 95% prediction intervals for 2014.

5. Conclusions and Recommendations

5.1 Conclusions

This study applied advanced econometric analysis on the load factor of flights of domestic and cross boarder Europe of airlines that are a member of the AEA. The econometric analysis can help us to conclude the following points.
The mean revenue passenger-kilometres of the domestic and cross border of Europe are 3,936.89 and 11,632.11 respectively. Likewise, the mean available seat-kilometres of the domestic and cross country of Europe are 5,895.59 and 17,519.27 respectively. Therefore, both in revenue passenger-kilometres and available seat-kilometres the cross boarder flights are higher than the domestic ones. However, the average load factor of the domestic flights is 1.85 % higher than the cross boarder flights. The primary reason for the domestic flights have higher load factor that the cross boarder flights of Europe is due to the domestic flights have by far lower available seat kilometres than the cross border flights.
The load factor for cross border flights of Europe is significantly and positively correlated with both the revenue passenger-kilometres and available seat-kilometres. While correlation of the load factor of the domestic flights of Europe with both the revenue passenger-kilometres and available seat-kilometres is insignificant. This showed the airlines have a better demand and capacity management in the cross border flights than the domestic flights.
The load factors of both domestic and cross boarder flights have periodic (season to season) correlations. The smallest load factor of the domestic flights is observed in January then it started grow until July then declining until December. The smallest load factor of cross boarder flights is observed in November, December and January then started to grow until July, August and September then declining until November. Furthermore, the load factors of both domestic and cross boarder flights have serial (month to month) correlations. The load factors of domestic and cross border flights have order of 17 and 15 months respectively. This showed that the load factor of domestic flights is more stable than the cross boarder flights.
The overall autocorrelation structure pointed us the appropriate and realistic forecasting model to the load factor of the domestic and cross border flights is the dynamic time effect two way panel data regression model. The fit of the dynamic time effect two way panel data regression model showed that in the long run, the load factor of the cross border flights will exceed the domestic flights. By using the fitted model the paper contributed the monthly forecasted values of the load factor with upper and lower 95% prediction intervals for 2014.

5.2 Recommendations and Policy Implications

This paper has applied profound Econometric analysis of the load factor of flights of domestic and cross boarder of Europe of the airlines that are members of the Association European Airlines (AEA). These domino effects of the study have important managerial implications. The econometric analyses help us to give the following recommendations.

Firstly, the fit of the load factor using the dynamic time effect panel data model is found more robust and realistic. Therefore, the Association European Airlines (AEA) use (inform to use its airlines) the model for prediction of the load factor of distribution of the domestic and cross boarder of flights Europe. In this regard it is recommended that the association applies the model to regional flights of its airlines across the globe to have a more precise forecasting tool of the load factor.

Secondly, in the airline industry, in addition to decreasing the airlines cost the profitability of the given airline is dependent on the joint maximization of yield and load factor. In this aspect, in order to push up the load factor and the yield simultaneously, and to produce strategic decisions about the profitability of these airlines, the Association European Airlines (AEA) is recommended to do further analysis of the load factor by considering individual airlines (spatial effects) into the dynamic time effect panel data model. The outcome of such analysis will give rigours information about the load factor of each the airline. Consequently, the AEA will have quantitative input for its airlines how to restructure the yield management, network design, etc. of the airlines with respect of their specific flights over the time periods.

Thirdly, our econometric analysis identified that the reaction of the airlines to adopt the demand is found generally good for both domestic and cross border flights. However, when we deeply investigate the performance it is found that the demand and capacity management of these airlines is better in the cross border flights than the domestic flights. Furthermore, we identified that the load factor of the cross border flights of the airlines growing more rapidly than the domestic flights. Therefore, it is recommended that the Association European Airlines (AEA) will identify the airlines showed weak performance of the demand and capacity management in the domestic flights to improve their status.

Fourth, as many scholars mentioned the airline industry is seasonal. This means the revenue generated from transporting passengers and cargo is dependent on the time periods. In this paper we found that the load factor of the flights of domestic and cross border Europe is seasonal. This implied that stabilizing the load factor is still not achieved by the airlines. Therefore, it is recommended that the AEA (advise to use its airlines) continuously works with how to improve the load factor of the airlines.

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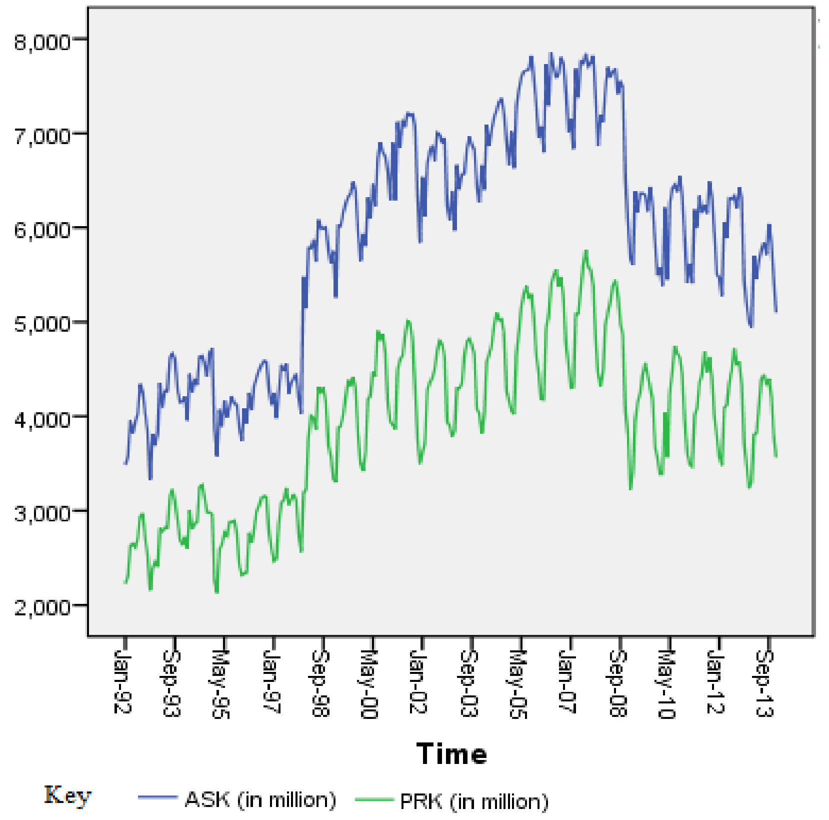
Table 1: Estimates of the Revenue Passenger Kilometre (RPK in million) and Available Seat Kilometre (ASK in million) over geographical code

Geographical Code	Estimates of Revenue Passenger Kilometre (RPK in million)						Estimates of Available Seat Kilometre (ASK in million)					
	Statistic	Estimates	Bias	Std. Error	95% Confidence Interval		Statistic	Estimates	Bias	Std. Error	95% Confidence Interval	
					Lower	Upper					Lower	Upper
Domestic Flights	Mean	3,936.89	3.02	54.35	3,838.41	4,050.08	Mean	5,895.59	-0.852	75.68	5,739.66	6,040.57
	Std. Dev	881.50	-3.29	28.16	821.84	935.21	Std. Dev	1,224.98	-1.73	37.212	1,150.33	1,299.46
	Std. Error	54.25					Std. Error	75.39				
Cross Border Flights	Mean	11,632.11	-3.13	258.35	11112.27	1,2125.85	Mean	17,519.27	14.07	272.6	17,015.25	18,091.02
	Std. Dev	4,144.79	-9.89	148.87	3,849.33	4,407.68	Std. Dev	4,549.63	-19.7	147.71	4,235.96	4,832.41
	Std. Error	249.49					Std. Error	273.86				
Estimation Method	Bootstrap results are based on 1000 bootstrap samples											

Table 2: Comparison of Available Seat Kilometre (ASK in million), Revenue Passenger Kilometre (RPK in million) and Load factor (in %)of Cross Border and Domestic flights

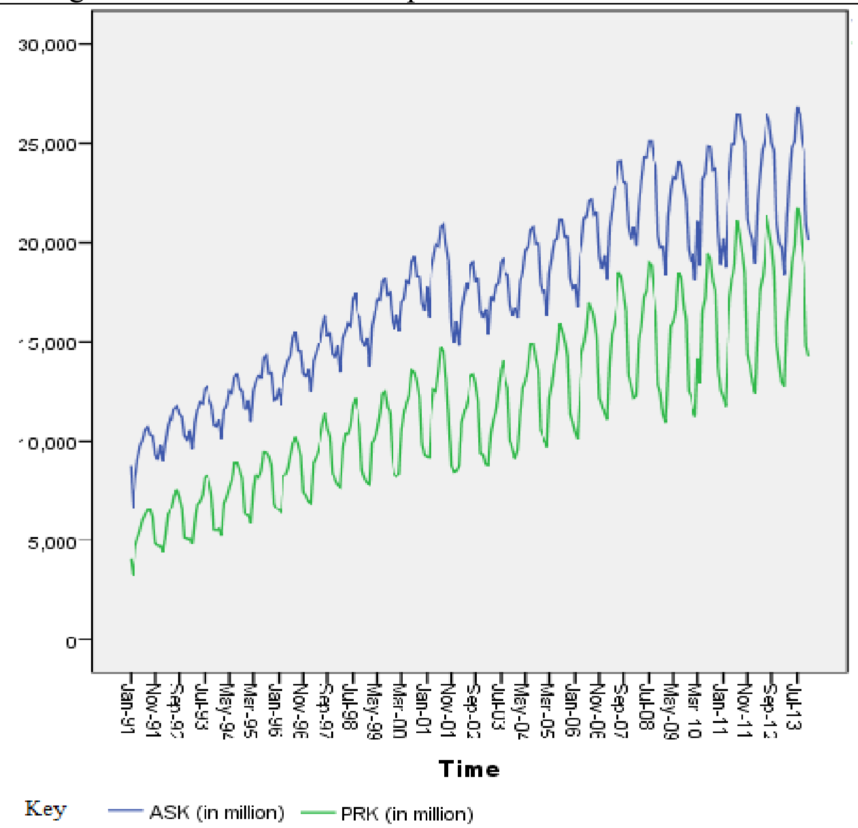
Variables	Comparison of flights	Mean Difference	Std. Error Difference	t-cal	Sig. (2-tailed)	95% Confidence Interval	
						Lower	Upper
ASK (in million)	Cross Border Vs. Domestic Flights	11,623.677	289.5660	40.1417	0.0000	11054.8585	12192.4955
RPK (in million)	Cross Border Vs. Domestic Flights	7,695.222	260.5634	29.53301	0.0000	7183.3754	8207.0681
LF (in million)	Domestic Vs. Cross Border Flights	1.85408	.53419	3.470859	0.0010	0.80054	2.85387
Estimation Method	Bootstrap results are based on 1000 bootstrap samples						

Figure 1: Time Series Plot of Available Seat Kilometre (ASK in million) and Revenue Passenger Kilometre (RPK in million) of domestic flights of Europe



$$RPK = -148.965 + 0.693 ASK \qquad R^2\ Linear = 0.928$$

Figure 2: Time Series Plot of Available Seat Kilometre (ASK in million) and Revenue Passenger Kilometre (RPK in million) of flights of cross boarder Europe



$$RPK = -3{,}967.659 + 0.890 ASK \quad R^2\ Linear \quad = 0.955$$

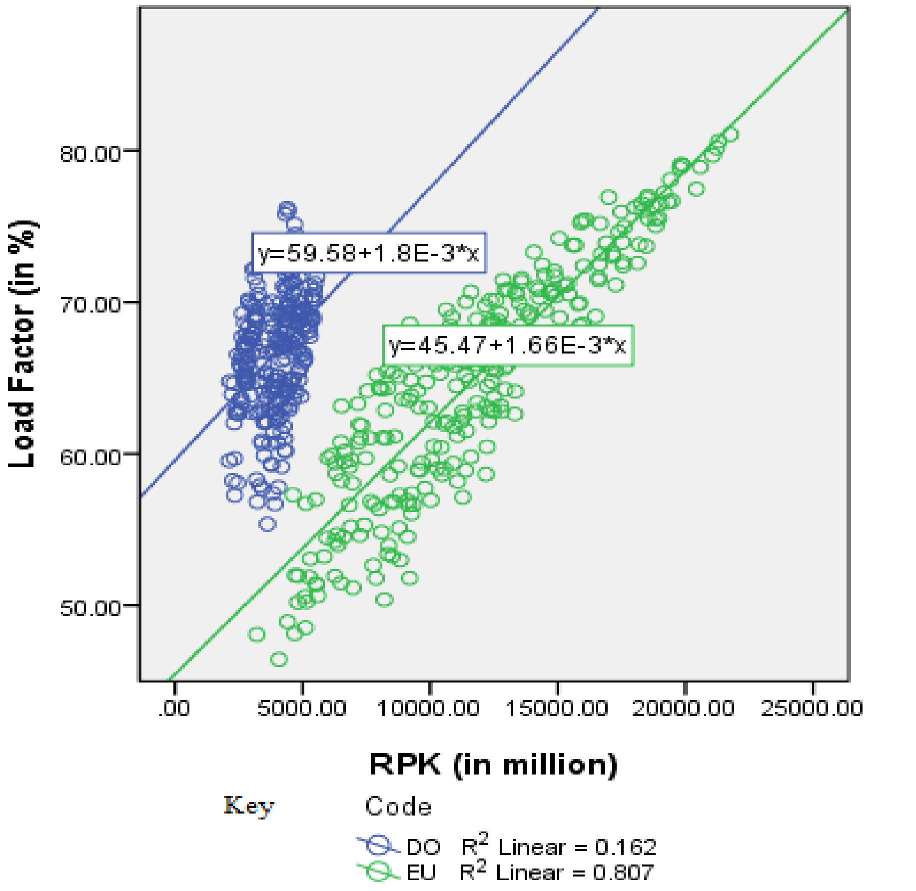
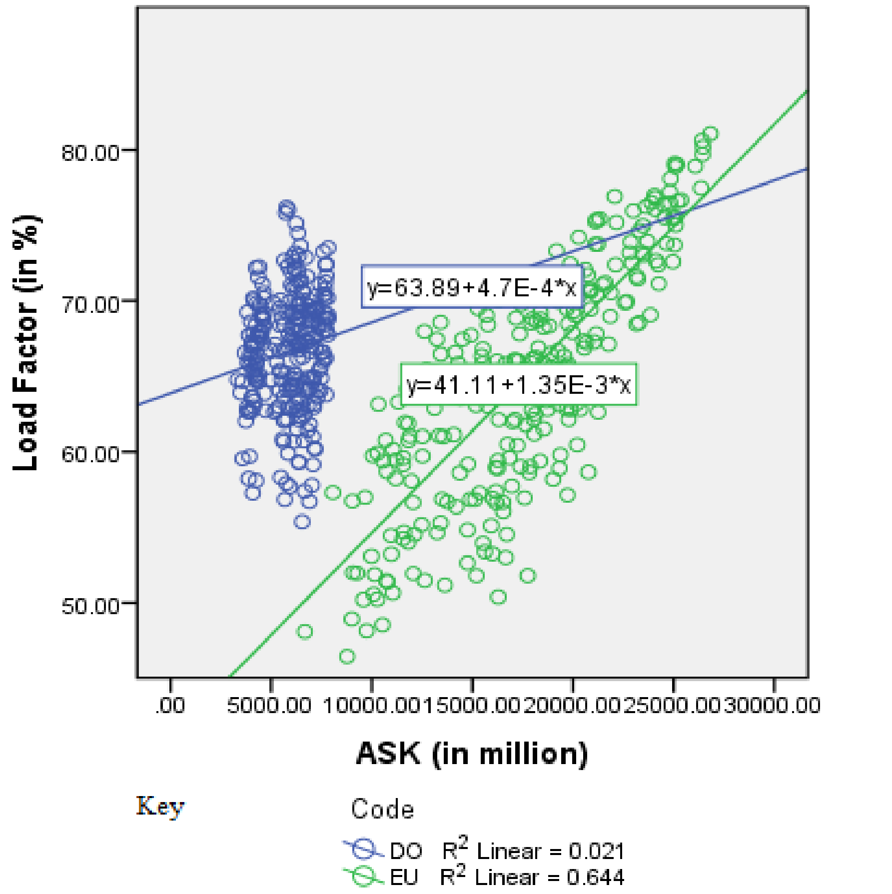
Figure 3: Scatter Plot of Load Factor (in %) versus Revenue passenger Kilometre(RPK in million)	Figure 4: Scatter Plot of Load Factor (in %) versus Available Seat Kilometre (ASK in million)
	

Table 3: The structure of autocorrelation of load factor of domestic and cross boarder Europe flights of airlines under the AEA

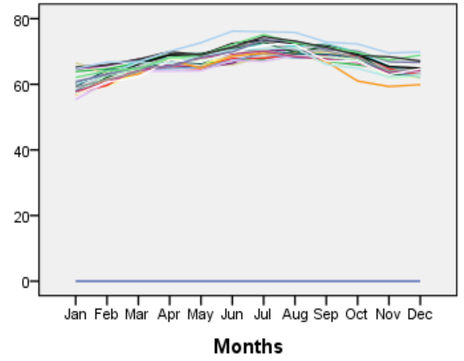
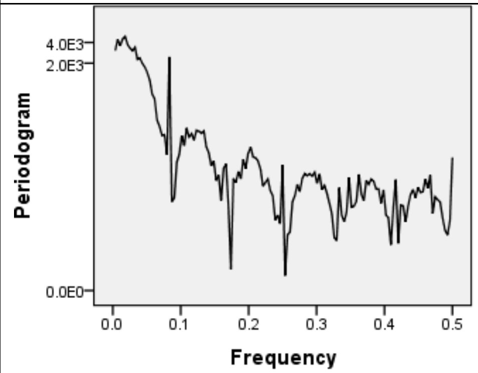
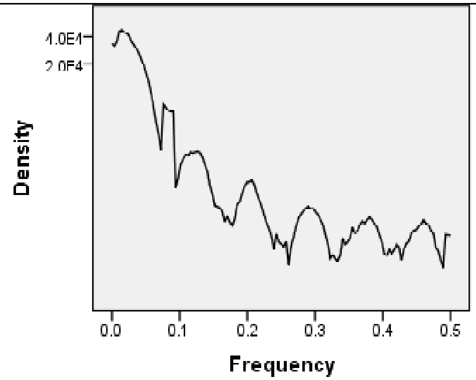
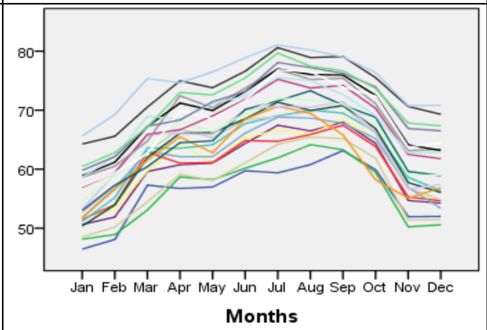
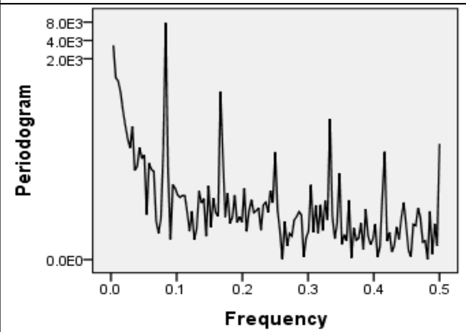
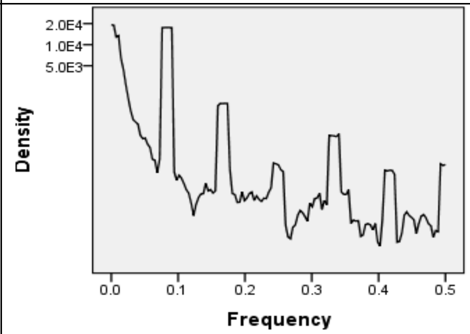
Regions	Monthly distributions of load factor across regions over time	Autocorrelation structure of load factor using Periodogram	Autocorrelation structure of load factor using Density	Ljung-Box Q		
				Chi-Sq	DF	Sig.
Domestic Flights of Europe				44.343	17	.000
Cross Border Flights of Europe				315.90	15	0.000
Key	1991, 1992, 1993, 1994, 1995, 1996, 1997, 1998, 1999, 2000, 2001, 2002, 2003, 2004, 2005, 2006, 2007, 2008, 2009, 2010, 2011, 2012, 2013					

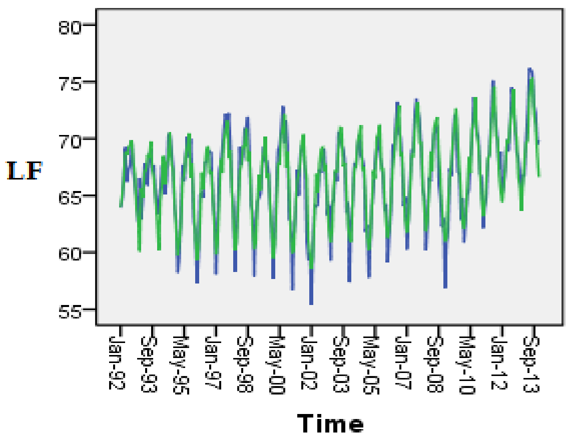
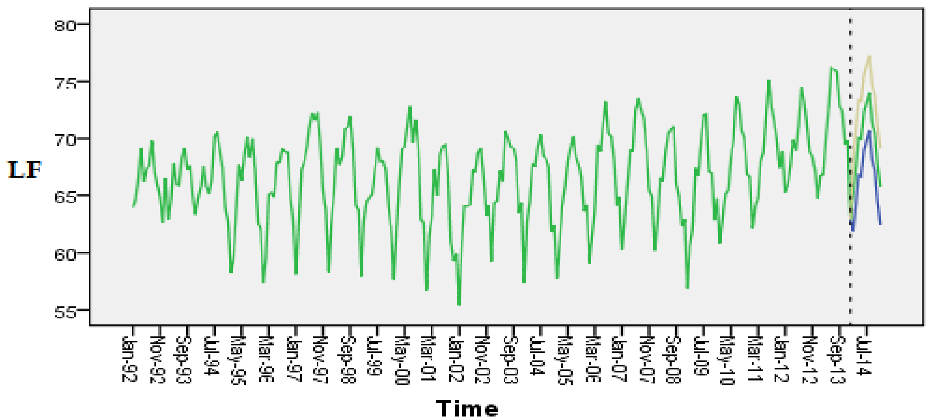
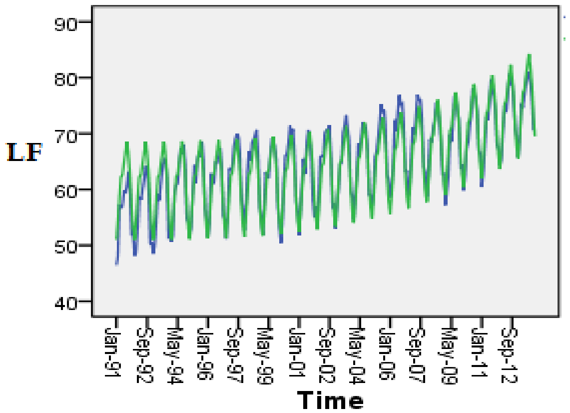
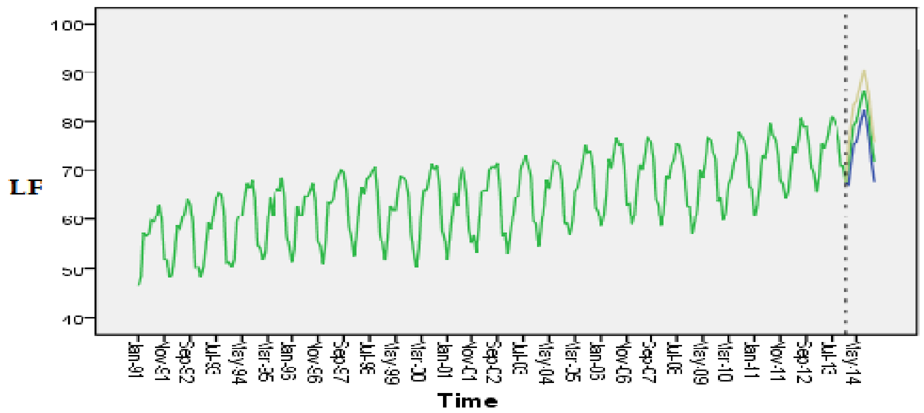
Table 3: The fits of dynamic time effect two way panel data regression model of load factor of domestic and cross border flights of Europe

Parameter Estimates	Spatially integrated Dynamic Time Effects	Estimates	Std Error	t-cal	Approx Sig.	Model S.E	Month	Forecasting of Load factor of 2014 (in %)		
									95% Prediction Interval	
								Expected	LB	UP
Rho (AR1)		0.52596	0.05414	9.71445	0.00000		Jan	62.97555	59.69048	66.26063
Time function Coefficients	t	0.02989	0.00567	5.27210	0.00000		Feb	65.15267	61.86760	68.43775
	$\ln(t)$	-1.58953	0.43320	-3.66923	0.00030	1.66973	Mar	67.42164	64.13657	70.70672
	$Sin(\omega_2 t)$	-0.64336	0.12880	-4.99499	0.00000		Apr	70.08880	66.80373	73.37388
	$Sin(\omega_3 t)$	-0.37554	0.16806	-2.23457	0.02632		May	69.96331	66.67823	73.24838
	$Sin(\omega_6 t)$	-2.55438	0.24096	-10.60100	0.00000		Jun	72.24851	68.96343	75.53358
	$Cos(\omega_1 t)$	0.40723	0.06744	6.03816	0.00000		Jul	73.20196	69.91688	76.48703
	$Cos(\omega_2 t)$	0.31712	0.12874	2.46328	0.01443		Aug	73.95869	70.67361	77.24376
	$Cos(\omega_3 t)$	-0.62849	0.16762	-3.74943	0.00022		Sep	71.38772	68.10265	74.67280
	$Cos(\omega_6 t)$	-3.60355	0.23957	-15.04190	0.00000		Oct	70.41949	67.13442	73.70457
Spatial Effect of Domestic Flights of Europe		70.01087	1.39757	50.09470	0.00000		Nov	67.70716	64.42209	70.99224
							Dec	67.70716	62.53499	69.10514

Table 3 Continued

Parameter Estimates	Spatially integrated Dynamic Time Effects	Estimates	Std Error	t-cal	Approx Sig.	Model S.E	Month	Forecasting of Load factor of 2014 (in %)		
								Expected	95% Prediction Interval	
									LB	UP
Rho (AR1)		0.60266	0.04880	12.34929	0.00000	2.08231	Jan	67.61567	63.51956	71.71177
Time function Coefficients	$Sin(\omega_2 t)$	-0.43466	0.15197	-2.86013	0.00457		Feb	71.36272	67.26662	75.45883
	$Sin(\omega_3 t)$	-0.49577	0.20354	-2.43576	0.01552		Mar	75.60042	71.50431	79.69653
	$Sin(\omega_6 t)$	-4.13576	0.31410	-13.16700	0.00000		Apr	79.40927	75.31316	83.50537
	$Cos(\omega_1 t)$	0.34008	0.07832	4.34234	0.00002		May	79.89951	75.80341	83.99562
	$Cos(\omega_2 t)$	0.32398	0.15198	2.13179	0.03394		Jun	82.32718	78.23108	86.42329
	$Cos(\omega_3 t)$	-2.02934	0.20314	-9.99008	0.00000		Jul	84.41854	80.32244	88.51465
	$Cos(\omega_6 t)$	-6.17512	0.31229	-19.77356	0.00000		Aug	86.45922	82.36311	90.55533
	t^3	$7.81 x10^{-7}$	$5.16 x10^{-8}$	15.14532	0.00000		Sep	84.12061	80.02450	88.21671
Spatial Effect of Cross boarder flights of Europe		60.65079	0.41780	145.16631	0.00000		Oct	80.87545	76.77935	84.97156
Where: $t = 12$ *(Current year-1991)+Current month* and $\omega_i = \frac{\pi}{i}, i = 1,2,3....$ are the periods							Nov	75.34288	71.24677	79.43898
							Dec	71.76682	67.67071	75.86293

Figure 5: The comparison of fit of dynamic time effect two way panel data regression model with the actual value

<table>
<tr><td>Flights</td><td>Comparison of f itted and actual value</td><td>Forecasting Power</td><td>Forecasting</td></tr>
<tr><td>Domestic Flights of Europe</td><td>
</td><td>Very Good</td><td>
</td></tr>
<tr><td>Cross Border Flights of Europe</td><td>
</td><td>Excellent</td><td>
</td></tr>
<tr><td>Key</td><td>Actual value Predicted Value</td><td></td><td>Predicted Value Upper Prediction Interval Lower Prediction Interval</td></tr>
</table>