

Airline Price Competition: A Time Series Analysis of 'Low-Cost' Carriers.

D.E.Pitfield

Transport Studies Group

Department of Civil and Building Engineering

Loughborough University

Loughborough

Leicestershire LE11 3TU

UK

E-mail: D.E.Pitfield@lboro.ac.uk

This paper, after providing an introduction to the operating context of low cost carriers in Europe, examines the competitive pricing behaviour of airlines. Data is collected by route for cases where more than one airline is in direct competition. Data on fares is obtained from the internet for two airlines with competing services to Alicante, Prague and Malaga, departing from Nottingham East Midlands Airport in the UK, for the six working weeks up to and including the actual departure. These destinations represent leisure traffic. Two domestic business destinations were also selected to illustrate price competition on business demand where departure times were within a maximum of 20 minutes of each other and a further examination of competing services from London Gatwick (LGW) was made.

Cross Correlation Analysis is used to examine whether, subject to a variety of lags, the prices offered by one airline can be seen to be both correlated with the other price series and to lead it. This provides some insight into the pricing strategy adopted by the competitors.

Autocorrelation Functions (ACFs) and Partial Autocorrelation Functions (PACFs) can also be produced on the prices offered by each airline. These suggest the nature of the ARIMA model that can be fitted to the series and these models can show the degree to which series values are correlated with their own past values and whether a reasonable model could be based on an ARIMA approach.

The relative strength of these two relationships is examined; are prices more closely explained by the competitor's actions or the airlines own past price setting?

Paper presented to the 44th European Congress of the Regional Science Association International, University of Porto, Porto, Portugal, August 25-29, 2004.

1.0 Introduction

The opportunity to analyse airline competition is rare. This is mostly because direct competition itself is rare. One attempt to understand the process of airline competition is to be found in Pitfield (1993) where competition on UK shuttle routes from London Heathrow to Glasgow, Edinburgh and Belfast were examined. Here the attempt to determine the impact of prices, advertising and other competitive factors floundered on the number of fare classes offered on each flight and the lack of information on which passengers had paid which fare. Price elasticity was impossible to determine, even though the airline was aware of and could manage the yield on each aircraft. The different published fare classes were possible due to the conditions imposed on tickets that facilitated price discrimination along with a flexible cabin configuration that allows different classes of passenger to be segregated¹.

In this traditional environment, pricing was certainly linked to aircraft yield and simultaneously to competition, but it was very hard to disentangle the interactions. In these cases pricing, following a traditional model, originally started at given levels for each fare class, where the numbers in each class would be manipulated until a target load factor of about 70 per cent was achieved. At this point, closer to the date of departure, remaining seats could be sold cheaply, for example, through bucket shops.

The advent of the low-cost carrier has seen a different pricing strategy². Here, simplistically, the flight is opened with a low promotional fare that ensures rapid take up of capacity. As capacity and an acceptable load factor are approached³, the yield management process raises the fares immediately prior to departure when available capacity is scarce. This can be seen in the example quoted by Doganis (2001).

Unfortunately, although price information is in the public domain, detailed information on yield is not, so the focus cannot be directly on airline yield management, but some idea of the influence of price competition can be gleaned and that is the aim of this paper. Indeed, it could be argued that price variations are a direct index of variations in yield. Firstly, price data is collected from competing airlines' web-sites for weekdays, 30 days prior to a Saturday departure to three leisure destinations and 30 days prior to a Tuesday departure for the two business destinations. These were chosen on the basis of regular and comparable frequencies offered by both carriers on each weekday. The LGW-Prague data was collected from just after the announcement of the services heralded as a 'price war' to the first day of competing service, a total of 51 observations. The departure time of the flights was also noted. Plots of this data reveal the variation in price over time and hint at the pricing strategy followed by the airlines. Both the influence of changes in the rivals' prices and the time path of fare levels can be seen. A more formal analysis of this requires the use of time series techniques that are more fully described below.

¹ A more recent attempt to examine competition is found in Pels and Rietveld, where services between a pair of cities, but not the same airports, is examined (in press) and Alderighi *et al* (2004).

² Indeed, there is some evidence that traditional carriers have adopted a similar pricing strategy. See *The Sunday Times*, 22 February 2004, London.

2.0 Low Cost Carriers

It is generally thought that the inspiration behind low cost carriers comes from the case of South West (Calder, 2002). It started operations within Texas in 1971, expanding beyond that after US deregulation in 1978. It is now in sixth position in the USA amongst passenger airlines, in terms of passenger-kms. Within the US there are now a dozen or so low cost carriers such as Jetblue, Airtran, Spirit Airlines and Frontier Airlines (see Doganis, 2001 and Internet Travel Directory). Within Europe, Ryanair and easyJet along with Virgin Express and others benefited from the European Union third package from 1993 and their apparent success resulted in British Airways setting up GO in 1998 and KLM, Buzz in 2000⁴. As is shown below in section 3.0, GO's move to Nottingham East Midlands Airport (EMA) resulted in British Midland International (BMI) announcing the launch of low-cost subsidiary bmibaby. Although much of the initial development in Europe has been UK based, a wealth of operations has recently started elsewhere. These include Air Berlin, Air Polonia, Basiq Air, German Wings, Meridiana and Iceland Express. Elsewhere in the world, start-ups have included Virgin Blue in Australia, Air Asia in Malaysia, Freedom Air in New Zealand, Gol in Brazil and Kulula, based at Johannesburg in South Africa.

As the generic name of this category of airlines suggests, a common characteristic is their focus on cost reductions. If we consider the major cost categories incurred by any commercial airline (see Doganis, 1991), then it is obvious that the focus must be directed at labour costs and other factors that influence costs per seat-km flown. There is scope for doing this in terms of turnaround times and aircraft utilisation, aircraft configuration and seat pitch, the use of fewer crew and of secondary and cheaper airports, and direct selling, but less scope in terms of fuel burn and en-route charges. Consequently a variety of approaches have been followed that invoke a varied mixture of these factors (Williams, 2001).

The other focus of these carriers is on the revenue side where, as the fare structures are simple, yield management is easier as there are fewer fare classes and no dilution from interlining or overbooking costs. This is why this paper is concerned with this side of the profit equation. How do these carriers manipulate prices to manage yield and to cater for the impact of competition?

3.0 Data and Methodology

In March 2002, GO, a low-cost carrier subsidiary of British Airways, announced it was to start services from Nottingham East Midlands Airport. This is a regional airport located close to the East Midlands cities of Nottingham, Derby and Leicester (see Figure 1) which, in that year, had a passenger throughput of 3.2 million passengers per annum (mppa). BMI, although operating the majority of its services from London Heathrow (LHR), had its headquarters near EMA and also had some services, of a traditional nature, operating from EMA. Its reaction to the intentions of GO was, apparently coincidentally, to initiate bmibaby services (the announcement also made in March 2002) from EMA and bmibaby now operates from Cardiff, Teesside, London Gatwick and Manchester as well.

³ easyJet achieved a 77% load factor in 2003. Reported in *The Times*, February 7, 2004, London.

⁴ Buzz was sold to Ryanair in 2003.

In May 2002, not long after the above inaugurated services, it was announced that GO was to be sold to easyJet, one of the two relatively long-existing UK based low-cost carriers and after some service changes, it is bmibaby and easyJet that now provide an example of direct competition from EMA to identical destination airports. Direct competition is less in evidence elsewhere as, for example, Ryanair bases the majority of its UK services at Stansted although since April 2004 it operates some services from EMA, whilst easyJet is based at and operates most of its services from another London area airport, Luton.

The destinations that both airlines served in autumn 2003 were Alicante, Barcelona and Malaga, Spain; Edinburgh and Glasgow, Scotland; Faro, Portugal; Geneva, Switzerland and Prague, Czech republic. Indeed, the only route operated by easyJet without competition from bmibaby is to Venice (Marco Polo) whereas bmibaby operates several routes without competition. In addition, it could be argued that competition is more evident if departure times are similar and on that basis Alicante provides a good case study with ten minutes between departures for the two airlines. So this destination was monitored and Prague and Malaga, respectively morning and afternoon departures, were also included in the data gathering exercise. All three were taken to be primarily leisure destinations so that price should be a key factor in determining leisure demand in contrast to usual expectations about demand on business routes. The Edinburgh and Glasgow routes were chosen as return journeys were possible in a day with early morning departures. There is ten minutes separation between scheduled departure times on the Edinburgh route and twenty minutes on Glasgow between the airlines. The LGW-Prague services were examined as they were heralded as 'price wars'.

Internet fares were observed for 30 working days before departure for all three leisure routes at midday for both airlines for departures to all three leisure destinations on Saturday 13th December 2003. A Saturday departure was chosen (as could a Friday departure have been) to cover passengers that were contemplating a leisure break of either a weekend or a longer trip. Internet fares for the domestic routes were collected for the 30 days prior to departure on Tuesday March 16th 2004 and the LGW data was gathered for 51 days prior to the Friday, April 30th departure.

Once the data series had been collected and tabulated they were subject to preliminary investigation before the application of time series methods. It is immediately obvious that data for Prague were not going to yield any insights into competition (see Figure 2). Although easyJet varies its price in a manner expected of a low cost carrier managing yield, bmibaby has a constant fare for the first twenty days observed and then lowers it by £7.50 for the last ten days. It could be argued that the airline is so used to managing yield on this route, given all the circumstances, including the presence of competition, that varying price beyond what it has done is unnecessary. Consequently, if the series is differenced, white noise results, suggesting that the original series could have been a random walk which, of course, as the plots reveal, it is not⁵ and neither does the easyJet series reveal any significant spikes in the

⁵ The series should be akin to the representative perambulatory progress of an inebriated individual. The best forecast for a random walk is the previous observation.

autocorrelation function (ACF) of the differenced series. Differencing may be necessary to begin with to ensure stationarity so that the mean and variance are about the same over the length of the series⁶. Indeed, removing any influence of strong frequencies is equivalent to filtering or pre-whitening and this is necessary so that other relationships of interest can be unmasked and clearly seen. In particular, our concern is with the relationship of the series with its own past values that is, the autocorrelation coefficient, which correlates the values of the series with values lagged for one or more periods up to a specified number, and also with the cross correlation which measures the correlation between the two price series at various leads and lags giving us the strength of the correlation and indicating which is the leading indicator.

If the Prague data is surprisingly of little utility, what about the other two leisure routes? For Alicante, it appears that easyJet is fully conversant with fares necessary to optimise yield. For the first 24 days, price is stationary but on day 25 it goes up £10 which it does again on day 26. On day 30, it goes up a further £20 prior to the next day's departure. There is more variation in the fare data for bmibaby (see Figure 3) but after differencing, only significant spikes are seen in this ACF so there seems there will be some difficulty in modelling both fares.

Fortunately, the observations for Malaga are more interesting (see Figure 4) given the observed variation and there are very clear spikes on the ACF for bmibaby indicating that a time series model can be developed. However, this is less clear for easyJet, so at this stage, it seems that fares on two leisure routes may be modelled, albeit with some difficulty, and the ACF and cross correlation function (CCF) determined. Neither is the evidence for Edinburgh or Glasgow clear cut. Guidance on the appropriate form of the ARIMA model for bmibaby is poor whereas autoregressive (AR) models are suggested for the easyJet routes as they are for both services from LGW.

Whereas differencing maybe required before preliminary data analysis using time series methods, to use cross correlation analysis, requires filtered or pre-whitened input series⁷. However, there is no presumption here that one series is explanatory and the other response, where the filtered model of the explanatory series would also be applied to the response series, so it is necessary to undertake double pre-whitening, that is both series are pre-whitened using an Autoregressive Integrated Moving Average (ARIMA) or Box-Jenkins model as no a priori information exists on which series leads or lags the other.

As is usual practice, the form that this model should take can be judged by examining plots of the ACF and the partial autocorrelation function (PACF) for the stationary series.⁸ If the raw series is given by Y_t ,

⁶ Gottman (1981) suggests a rule of thumb for determining stationarity. This is that the square of the ACF will go to zero very rapidly as the number of lags increase and although this isn't a strict criterion, it may be adequate for most practical applications. Another route, but not one followed here, as the data series are not long enough, is to examine the mean, variance and ACF for separate chunks of the observed series.

⁷ This may be achieved simply by differencing if the resultant Box-Ljung Q statistic indicates white noise.

⁸ See any text on ARIMA models, for example, Wei (1994) or Gottman (1981).

then the differenced series is $z_t = Y_t - Y_{t-1}$. An AR model is suggested if there is an exponential decline in the ACF and spikes in the first one or more lags of the PACF, whereas a moving average (MA) process is suggested if there are spikes in the first one or more lags of the ACF and an exponentially declining PACF. A mixed model would show exponential declines in both functions.

An AR (1) process with one parameter can be written as

$$z_t = \theta_1 z_{t-1} + a_t \quad (1)$$

and using the backshift operator, B

$$(1 - \theta_1 B) z_t = a_t \quad (2)$$

An AR (2) process is

$$z_t = \theta_1 z_{t-1} + \theta_2 z_{t-2} + a_t \quad (3)$$

or

$$(1 - \theta_1 B - \theta_2 B^2) z_t = a_t \quad (4)$$

A simple MA(1) process again with one parameter is

$$z_t = a_t - \theta_1 a_{t-1} \quad (5)$$

or

$$z_t = (1 - \theta_1 B) a_t \quad (6)$$

And a MA(2) process is

$$z_t = a_t - \theta_1 a_{t-1} - \theta_2 a_{t-2} \quad (7)$$

or

$$z_t = (1 - \theta_1 B - \theta_2 B^2) a_t \quad (8)$$

A mixed model can be written as either an AR or MA process, for example, for an ARIMA (1,1) model

$$z_t = \theta_1 z_{t-1} + a_t - \lambda a_{t-1} \quad (9)$$

or

$$(1 - \theta_1 B) z_t = (1 - \lambda B) a_t \quad (10)$$

An acceptable model can be judged in part by a variety of indicators and goodness of fit statistics, such as the standard error, the Schwartz Bayesian Criterion (SBC) and the Akaike Information Criterion (AIC), but also by the fact that the properly filtered series produces a white noise residual and this can be judged by looking at the ACF and the Box-Ljung Q statistic⁹. It is this residual, the filtered series that is subject to the CCF analysis, but there is an issue of how best to represent the serial dependence within each of the original series. If the raw data is examined this conflates both stationarity, serial dependence and unexplained components such as interdependence with other series so it may be best to use the derived ARIMA model and look at the serial correlation evident in this.

⁹ On occasion, a constant term might be included in a model to ensure white noise residuals and this can be interpreted as a trend term. However such recourse was not needed and besides, the interpretation of a constant term on differenced data that is stationary seems problematic.

4.0 Results

4.1 Malaga

The plot of the two airlines' fare data is shown in Figure 4. This shows that although easyJet adopts a low cost carrier pricing strategy with clear increases as the date of departure approaches, bmibaby does not. The ACF and PACF are shown in Figure 5 for both airlines on the differenced data¹⁰. It seems likely that bmibaby can be modelled with an AR (1) model such as shown in equation (2) although the prescription for easyJet is less clear. The models derived on the differenced data are AR (1) for bmibaby and MA (1) for easyJet, see equation (6), with a θ_1 of -0.4127 (-2.4222) and -0.2910 (-1.4846) respectively¹¹. The goodness of fit indicators are a standard error of 5.3631 and 6.7295, an AIC of 180.8928 and 193.9609 and a SBC of 182.2601 and 195.3282 respectively for the two airlines¹². These models suggest that the present values of fare are most autocorrelated with the companies past values of fare with a lag of one day and autocorrelation coefficients of 0.899 and 0.650 and are shown in Figure 6. The filtered series so obtained can be subjected to the CCF analysis and this shows that easyJet fares lead bmibaby fares by one day with a correlation coefficient of 0.452 as is shown in Figure 7. It seems that the experienced low-cost operator is being followed by the less experienced, but that in both cases, yield management is more determined by each airlines' previous fares and their impact on load factors than the actions of the competition.

4.2 Alicante

Figure 3 shows the time series plot of fares for the two airlines on this route and the contrary pricing strategies can be observed. However, investigation of the ACF and PACF of the differenced series does not give a clear indication of a suitable model form and experimentation using the models described in equations (1)-(10) does not yield residuals with insignificant ACFs. However, if we consider the original series to be stationary and subject that to ACF and PACF plots (see Figure 8), unambiguous guidance emerges that both should be modelled using an AR (1) specification. This results in white noise residuals. The values of θ_1 of 0.9935 (109.1770) and 0.9962 (120.4950) are obtained, respectively for bmibaby and easyJet, with standard errors, AIC and SBC at 3.9535, 173.1359 and 174.5372 for bmibaby and 4.6654, 183.6742 and 185.0754 for easyJet. The ACF for the fitted models in Figure 9 shows a correlation of 0.375 and 0.535 at lag one but the CCF of the filtered series shows a correlation of 0.808 at lag zero (see Figure 10), that is, neither one series nor the other, lags or leads, but the series are contemporaneously correlated and this is more important than the highest level of autocorrelation in the fitted models, which seems to suggest in this case that competitive forces are most important in price setting.

4.2 Edinburgh and Glasgow

The time sequence plot of fares for the EMA- Edinburgh (EDI) route in Figure 11 show the bmibaby fare stationary at £4.50 for the first 15 days, followed by two days of rising prices to £29.99 which lasted until

¹⁰ An ARIMA model was calibrated on the basis of non-differenced data, but the standard errors etc. were higher than the model reported here.

¹¹ t statistics in brackets.

just a few days before departure, when fares rose again. In the meantime, the easyJet fare remained at a much lower level until the week before departure, when sharp rises took place. It is not obvious from these plots, that there is any cross correlation between the series.

An apparently similar picture is given by the fare data for the EMA-Glasgow (GLA) route in Figure 12. Indeed, the easyJet fare has an identical pattern, staying virtually constant and low for most of the period, rising steeply prior to departure¹³. The bmibaby fare starts at a higher level and then experiences stepped increments at fairly regular intervals. There appears here to be a stronger suggestion of cross correlation.

The ACFs and PACFs for the differenced data for easyJet suggest AR models, whereas the plots for bmibaby suggest differencing alone will produce white noise (see Figure 13 and 14). However, if the ACF of the residuals of the ARIMA model is investigated for significant spikes, it can be shown that it is necessary for an AR (2) model to be applied to easyJet for the Edinburgh route. For Glasgow, a similar model yields white noise residuals for easyJet.

For Edinburgh a cross correlation analysis between the residuals for the two airline models shows no significant correlation. Even if an MA (2) model is imposed on the bmibaby differenced fare data, giving a standard error of 3.123, the conclusion on cross correlation remains the same, however, the dependence of each series on its own past values is significant.

For Glasgow, the cross correlation again shows no significant relationship even if the raw bmibaby data is modelled with an AR(1) model. However, the degree of dependence of both series on their own past values at 0.747 for bmibaby and 0.753 for easyJet is notable.

It is disappointing that these results seem so inconclusive when the business cases selected on the grounds of attraction to domestic business users with similar departure times seemed likely to produce more interesting and conclusive results than the analysis of the leisure market.

4.3 'Price Wars': London Gatwick (LGW) - Prague (PRA)

bmibaby announced in early 2004 that it was to start services from LGW with daily departures to Prague and Cork with its first 'foray' into the south East from April 30th. Seats were on sale from Friday 13th February with one-way internet fares to Prague starting at £19.99, including taxes and charges when booked online.

Within hours of this announcement, easyJet, already present at LGW, announced a service to Prague starting one-week earlier and promised a price war¹⁴. The reaction of bmibaby was to reduce its price to

¹² Where there was poor guidance as to the appropriate model, all the relatively parsimonious models described in equations (1) to (10) were tried and the best chosen according to the goodness of fit indicators.

¹³ It seems the yield management procedure of easyJet is working on its Scottish destinations in unison.

¹⁴ *The Sunday Times*, 15 February 2004, London.

£1 below easyJet's return fare. This resulted in this, in turn, being reduced by a further £10 to £30.98. Airport authorities speculated that the 'war' could spread as both carriers had expressed interest in serving Berlin, Lyons and Stockholm from LGW. Meanwhile British Airways also offered service to Prague from March 28th, albeit at somewhat higher prices.

Consequently, the LGW-PRA route seemed an ideal one to study and data was collected, shortly after the announcements, for weekdays, from 20th February, for a departure on April 30th, when both low cost airlines would offer service. Initially the prices were £48.99 one-way for bmibaby and £91.99 for easyJet. These fares seemed very surprising given the alleged activity in the preceding week, unless the result of this, was a large take up of capacity in the first week. The fare data is shown in Figure 15.

Figure 16 shows the ACF and PACF for both airlines. These plots are based on the non-differenced data. The suggested AR(1) models, shown in Appendix 2, produce white noise residuals and the autocorrelation in the fitted models is shown in Figure 17. Figure 18 shows the cross correlation. It is strong and positive with no lag. It is stronger than the autocorrelation in the fitted models, but it is still difficult to advance a behavioural, economic (such as Cournot) or game theoretic basis for price setting. It appears again that the simultaneous management of yield suggests a correlation in fares offered but that this is somewhat incidental and is not the driving force behind the observations of fares.

5.0 Conclusions

The emergence of the low-cost sector of the airline industry has raised a number of issues that are not well understood. These include their impact on trip generation; trip distribution and the environmental consequences of predominantly road based access trips to the airports at which they offer service. However, an aspect of commercial airline behaviour for which the opportunity of study is rare, is direct price competition. Cases have been examined in this paper where two rival airlines operate from the same origin to a number of identical destinations. The service package they offer consumers is very similar, so their rivalry should be reflected in their fare offerings. Observations suggest that one of the airlines is operating more characteristically as a low-cost carrier than the other. In addition, the relative influence of the competitors' strategy on pricing and yield management and their own past prices can be indicated, using time series methods. This has shown that the influence of past fares is higher than the influence of the competitors fares in one leisure case and these relationships are both significant with the latter indicating one airline is leading the other with a lag of one day in price setting. The other leisure case suggests that the correlation between the series is more important than correlation within the series, but behaviourally this is difficult to interpret with a lag equal to zero. It is difficult to reach firm conclusions on the business routes and further work is intended to explore this area by analysing other such routes. The price war data suggests that fares are correlated but at zero lag. At this point, it seems likely that each airline is pre-occupied by the process of yield management and it is only through this that a competitor's fare offerings indirectly influence their behaviour.

6.0 Postscript

In March, Ryanair announced that it was moving its services from Birmingham to EMA which effectively means that bmibaby will encounter competition, in particular, on the Dublin route. Meanwhile, in early May, easyJet lost over 25 percent of its market value after announcing that it was under severe pressure from 'unprofitable and unrealistic' pricing by airlines across Europe¹⁵. Duo, based at Birmingham, was taken into administration in early May and the reaction to the Civil Aviation Authorities' compensation scheme suggested more potential casualties. Most recently, both bmibaby and easyJet announced the cessation of services from EMA to Barcelona¹⁶.

¹⁵ *The Times*, 5th May 2004, London.

¹⁶ *Nottingham Evening Post*, 15th May 2004.

6.0 References

- Alderighi, M., Cento, A., Nijkamp, P. and Rietveld, P. (2004) The Entry of Low Cost Airlines: Price Competition in the European Airline Market. Work in progress, available from authors.
- Calder, S. (2002), *No Frills: The truth behind the low-cost revolution in the skies*, Virgin Books, London.
- Doganis, R. (1991), *Flying Off Course: The economics of international airlines*, Routledge, London.
- Doganis, R. (2001), *The airline business in the 21st century*. Routledge, London.
- Gottman, J.M. (1981), *Time Series Analysis: A comprehensive introduction for social scientists*, Cambridge University Press. Cambridge.
- Internet Travel Directory website listing low cost airlines at www.itravelnet.com/transport/air/lowcostairlines.html
- Pels, E. and Rietveld, P. (in press), Airline pricing behaviour in the London-Paris market, *Journal of Air Transport Management*.
- Pitfield, D.E. (1993), Predicting air-transport demand, *Environment and Planning A*, 25, 459-466.
- Wei, W.W.S. (1994), *Time Series Analysis: Univariate and Multivariate Methods*, Addison-Wesley, Redwood City, CA.
- Williams, G. (2001), Will Europe's Charter Carriers be replaced by 'No-Frills' Scheduled Airlines? *Journal of Air Transport Management*, 35, 14-25.

Figure 1: A Location Map of Nottingham East Midlands Airport, UK.



Source: <http://www.multimap.com/>

Figure 2: Fares from EMA to Prague

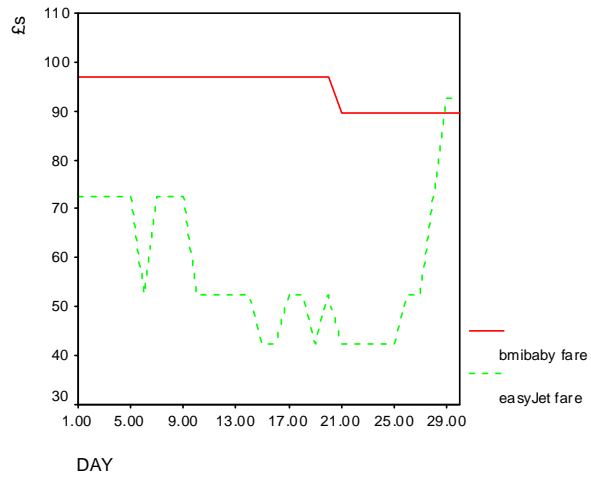


Figure 3: Fares from EMA to Alicante

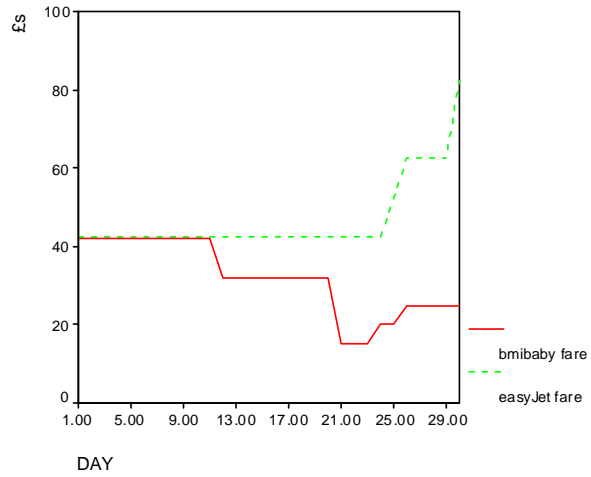


Figure 4: Fares from EMA to Malaga

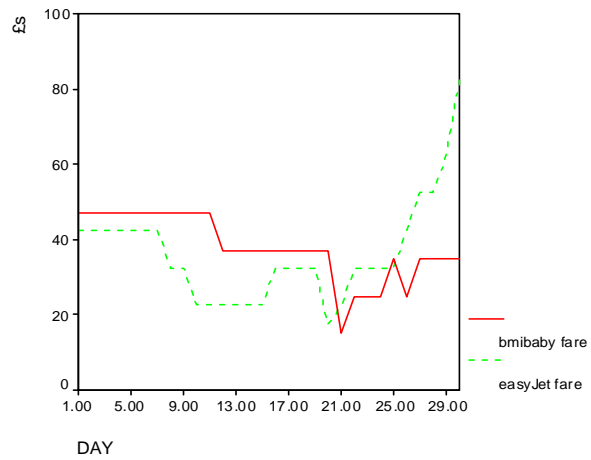


Figure 5: ACF and PACF plots (differenced data) for both airlines: Malaga

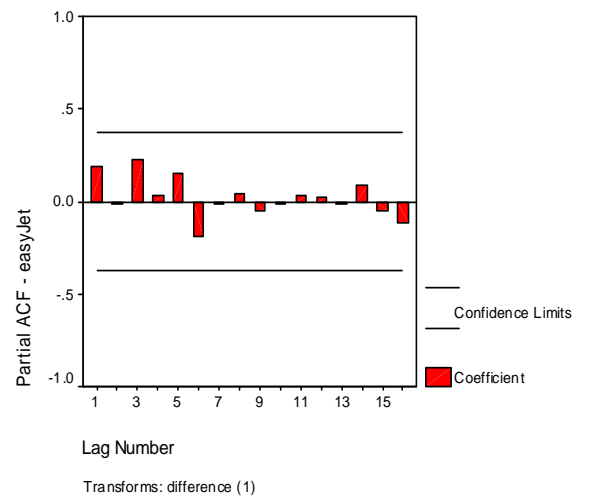
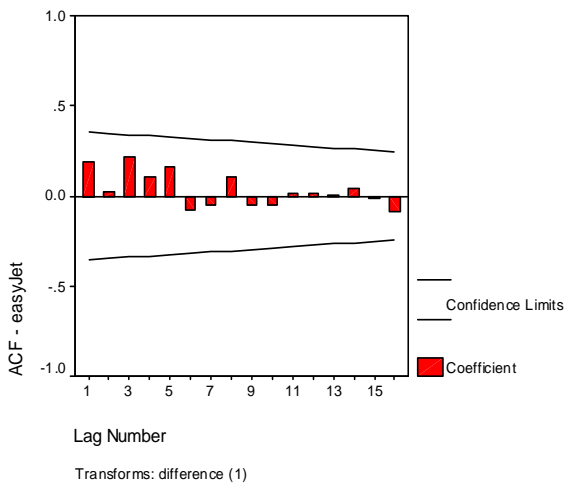
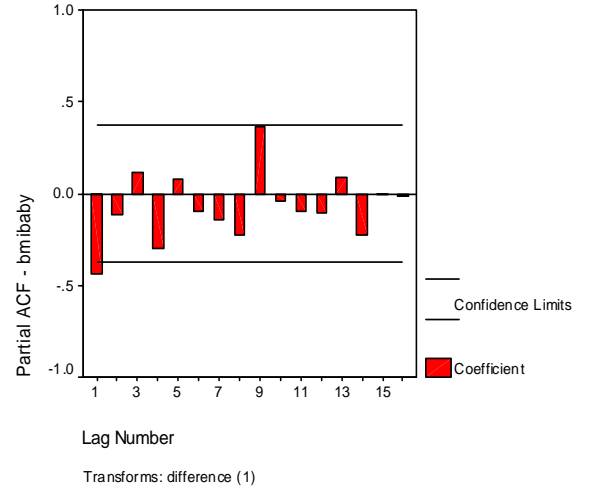
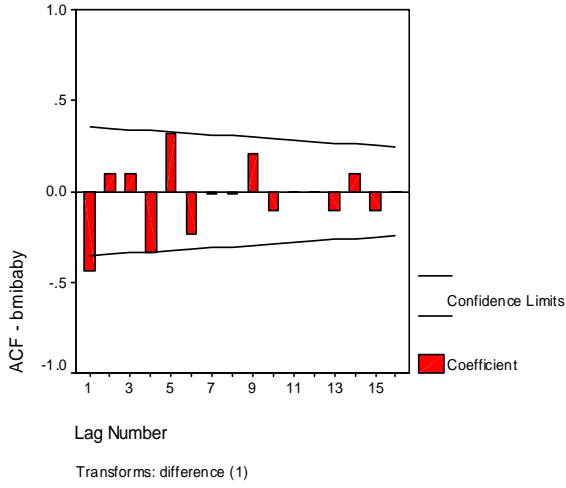


Figure 6: ACF plots for ARIMA models: Malaga

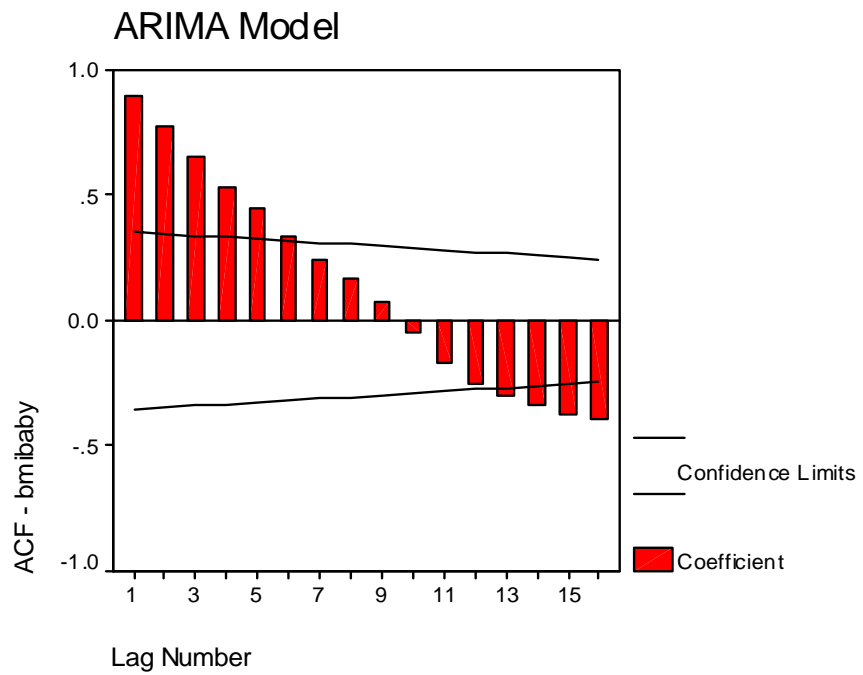
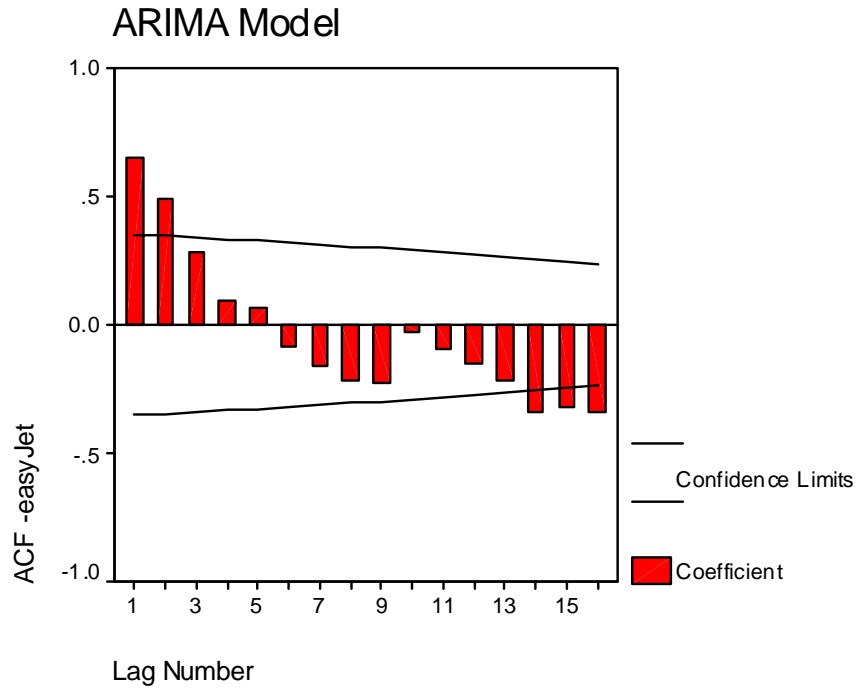


Figure 7: CCF plot: Malaga

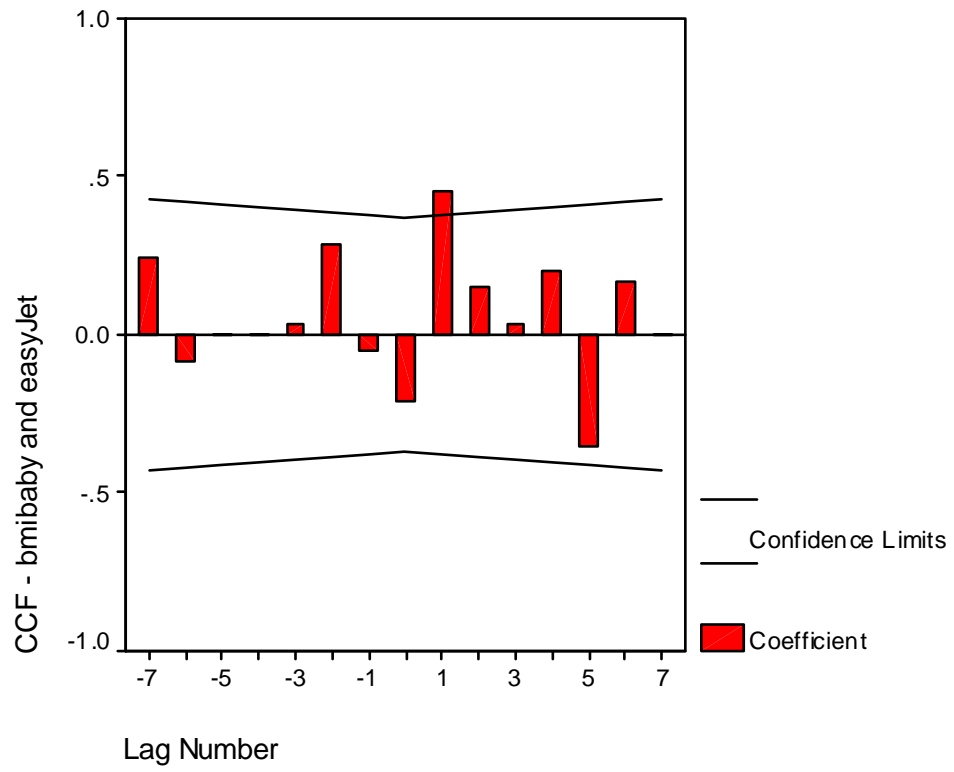


Figure 8: ACF and PACF plots for both airlines: Alicante

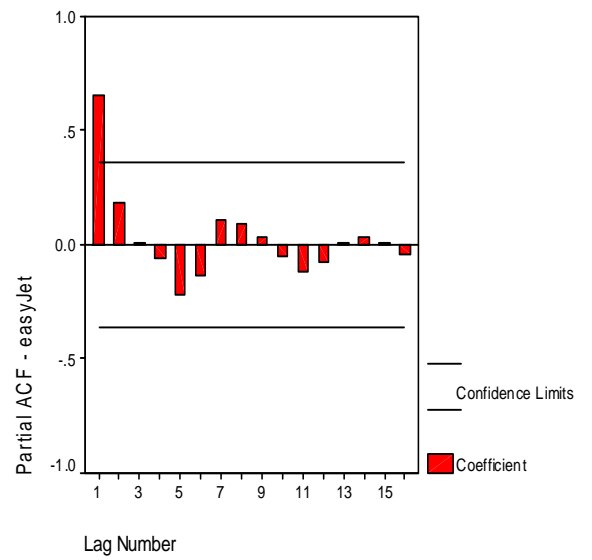
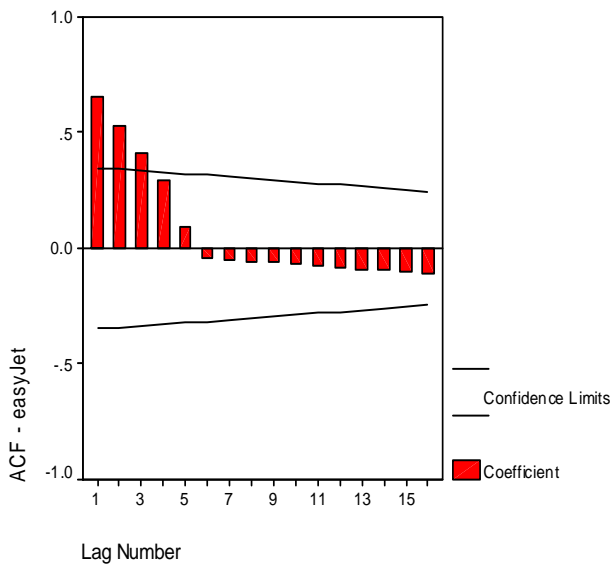
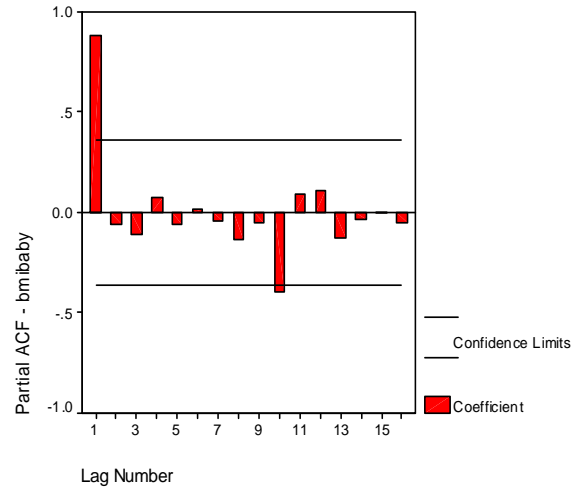
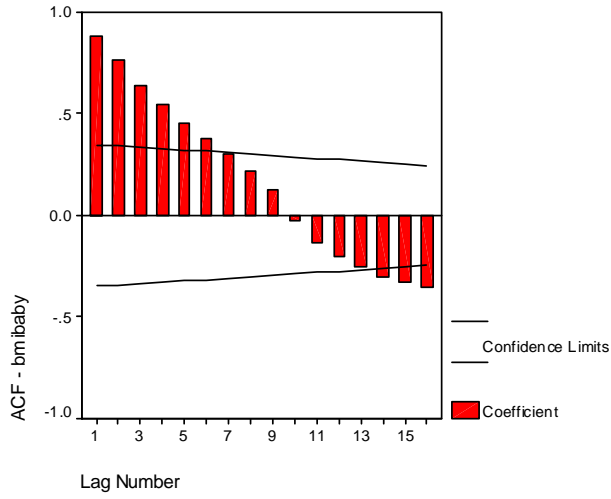


Figure 9: ACF plots for ARIMA models: Alicante

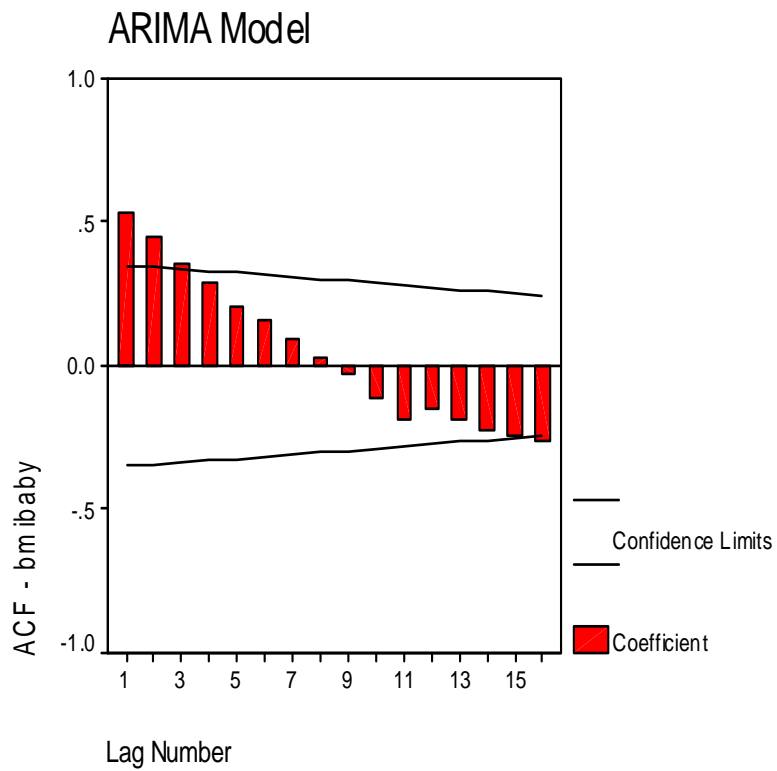
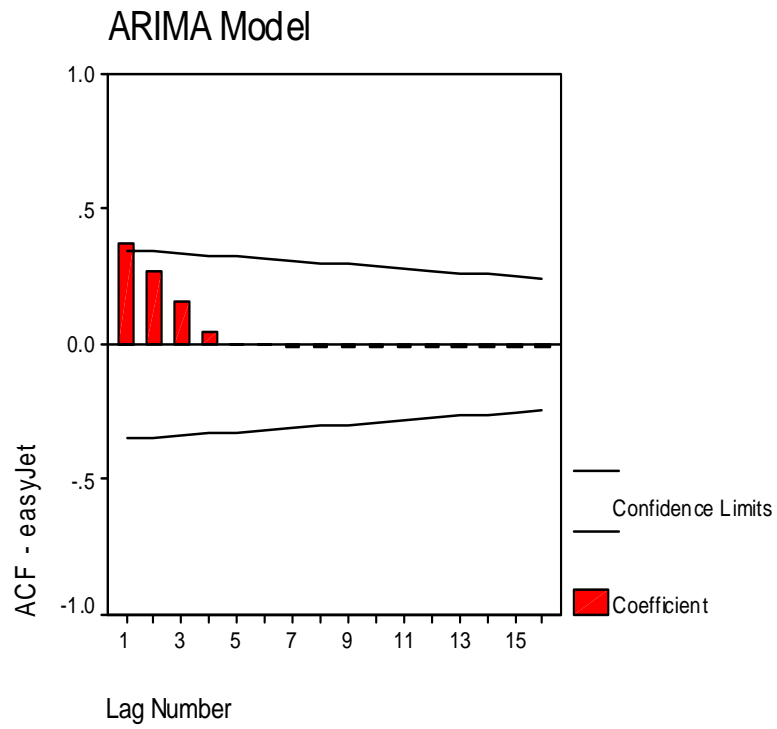


Figure 10: CCF plot: Alicante

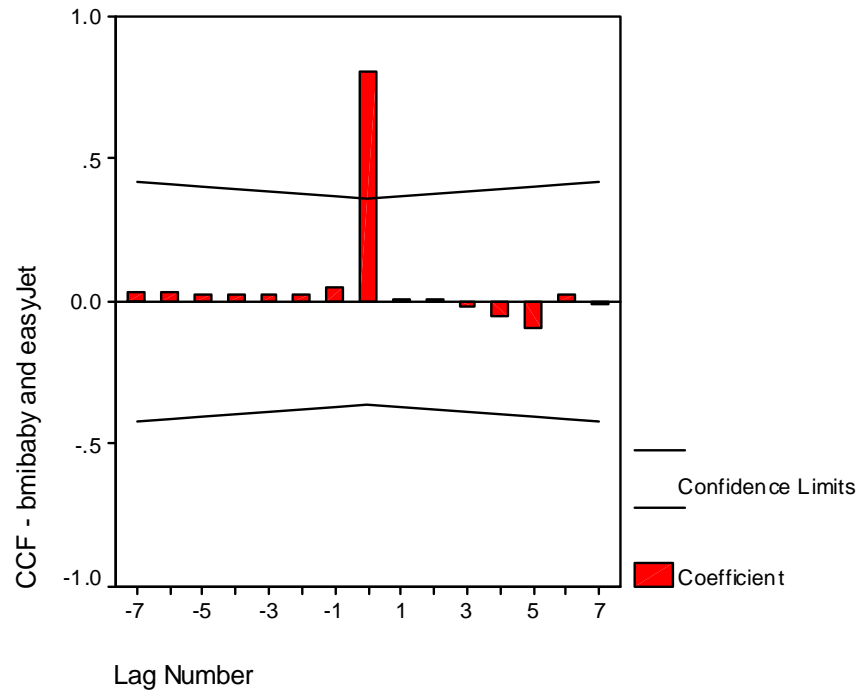


Figure 11: Fares from EMA to Edinburgh

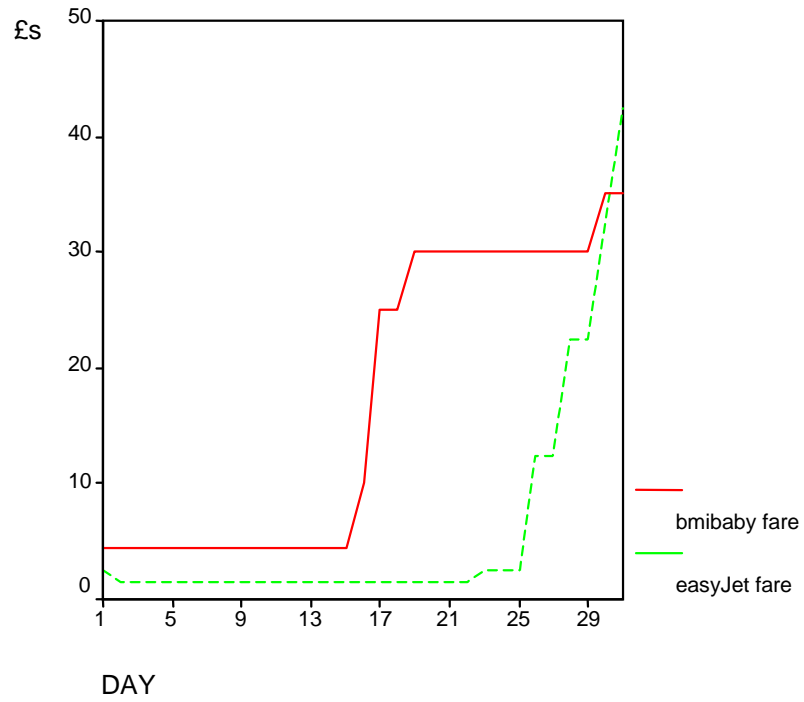


Figure 12: Fares from EMA to Glasgow

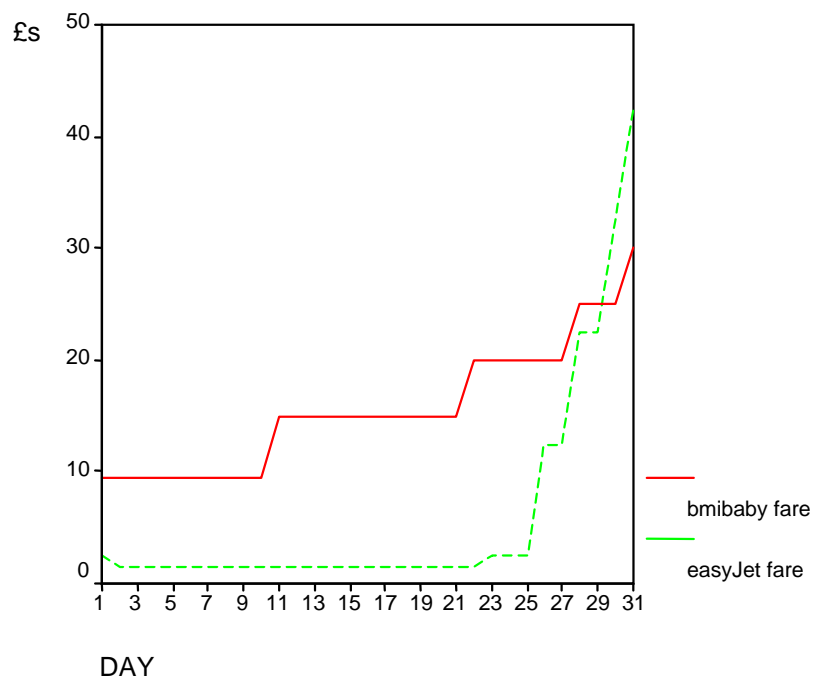


Figure 13: ACF and PACF plots (differenced data) for both airlines: Edinburgh

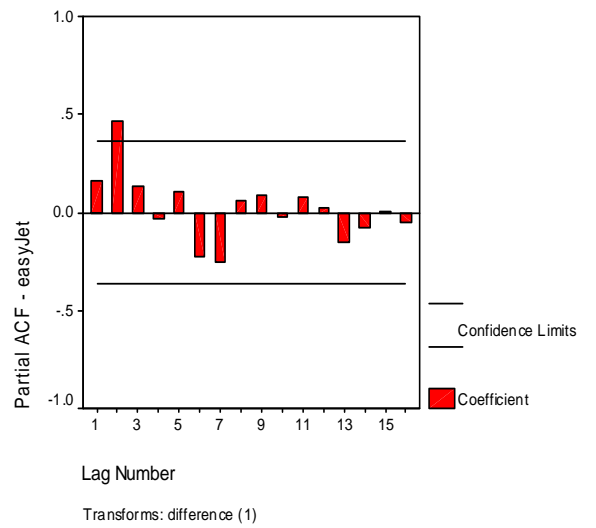
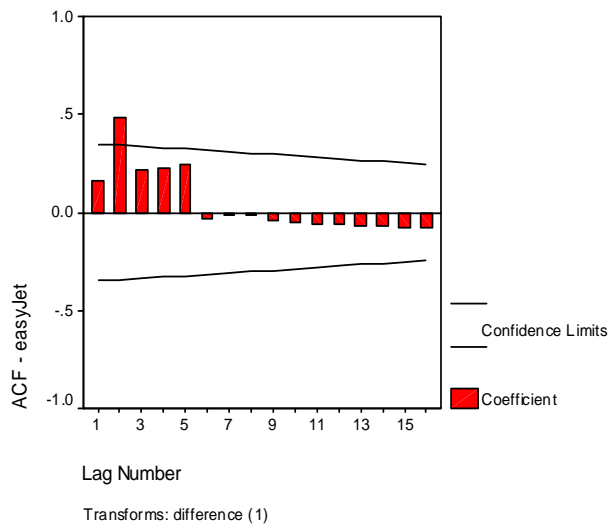
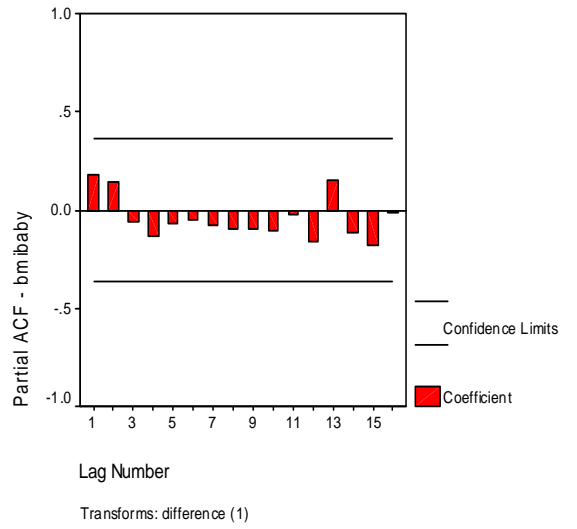
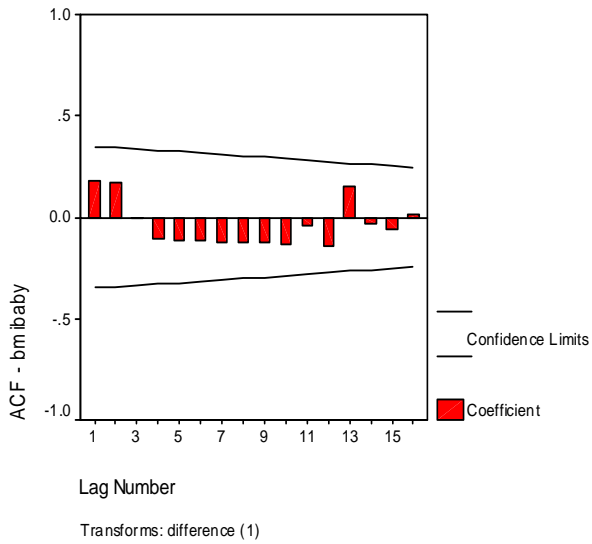


Figure 14: ACF and PACF plots (differenced data) for both airlines: Glasgow

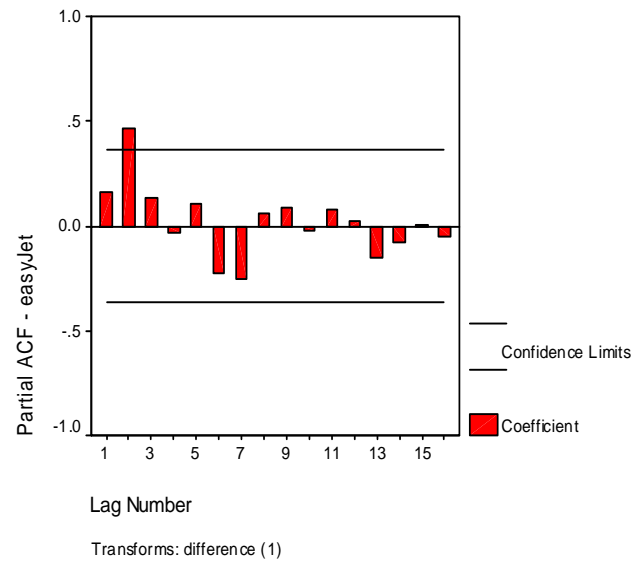
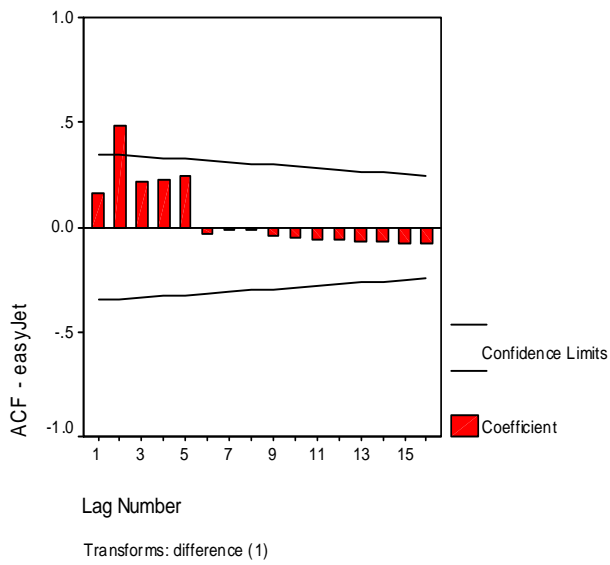
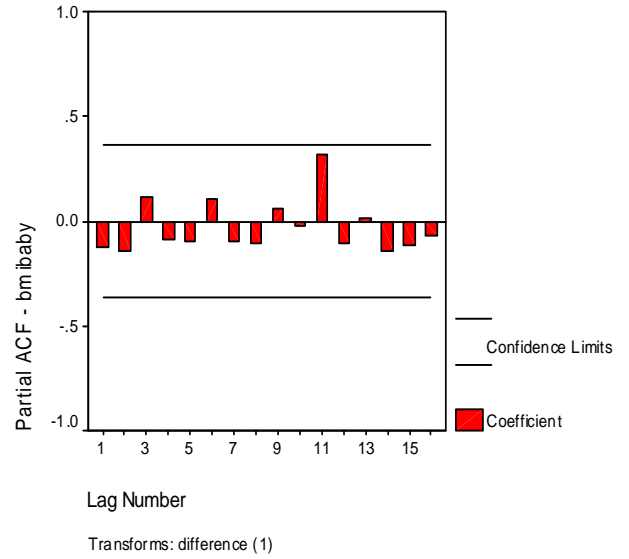
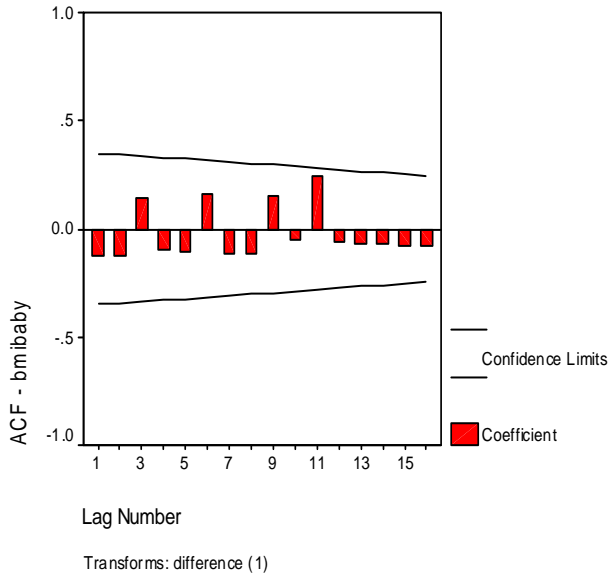


Figure 15: Fares from LGW to Prague

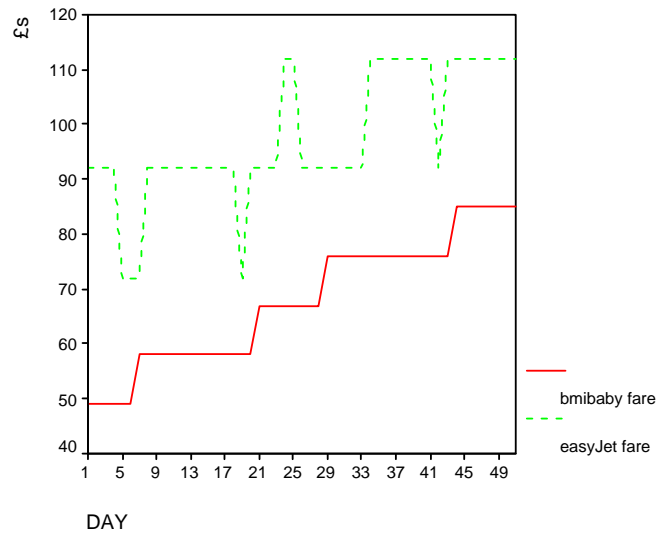


Figure 16: ACF and PACF plots for both airlines. LGW-PRA

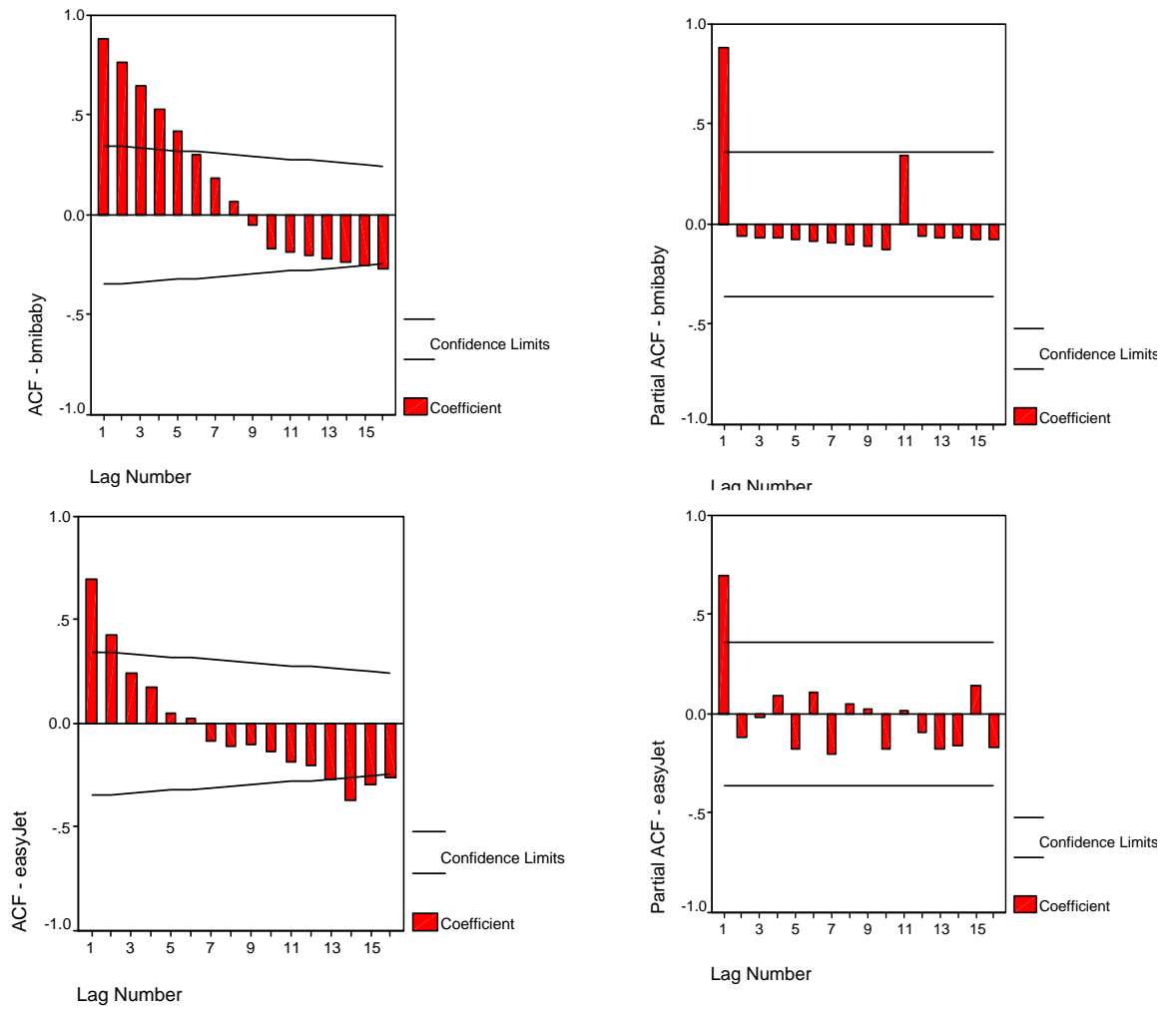


Figure 17: ACF plots for ARIMA Models. LGW-PRA

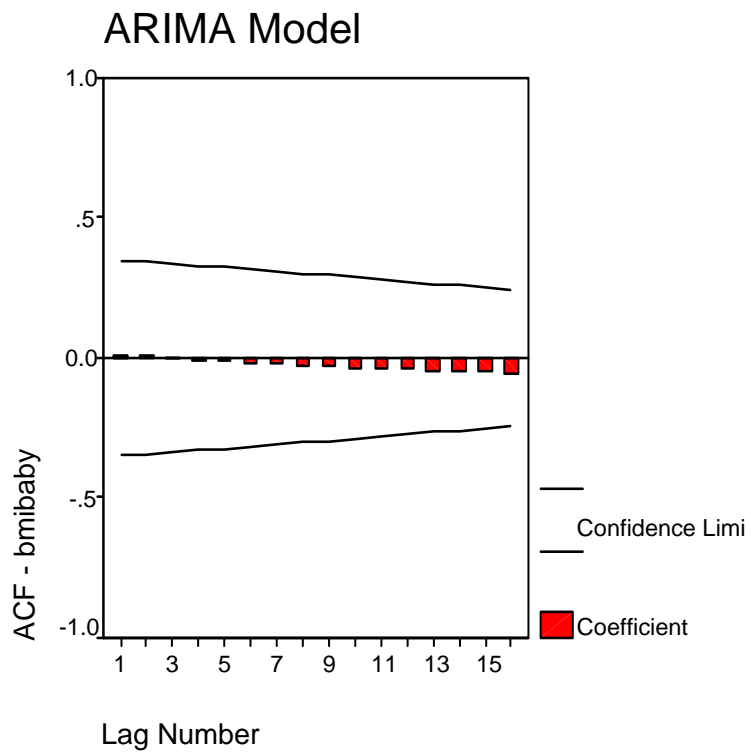
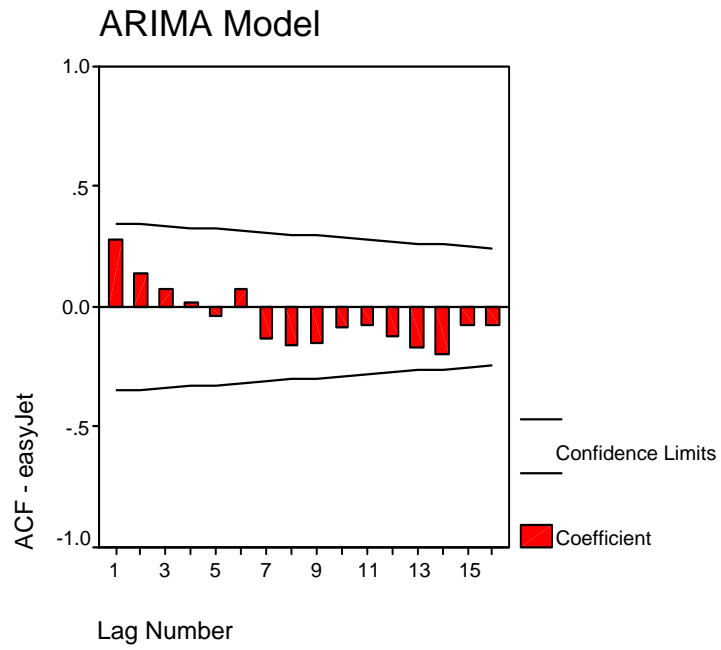
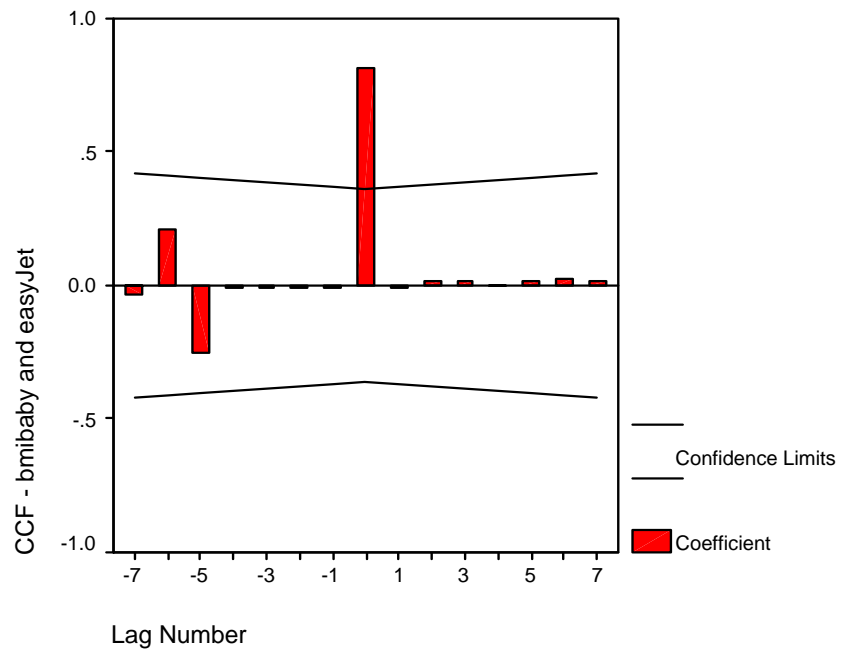


Figure 18: CCF plot. LGW-PRA



Appendix 1:ARIMA results for EMA-EDI and EMA-GLA.

Edinburgh

| | Coefficients | | SE | SBC | AIC | Autocorrelation in Fitted Model |
|--------------------------------|----------------------|----------------------|-------|---------|---------|---------------------------------|
| | θ_1 | θ_2 | | | | |
| easyJet (first differences) | 0.2822 (1.8329) | 0.5465 (2.7915) | 2.745 | 151.664 | 148.862 | 0.753 |
| bmibaby (first differences) | -0.1890 (-1.0233) | -0.2407 (-1.2456) | 3.123 | 158.402 | 155.560 | 0.905 |

Glasgow

| | | | | | | |
|--------------------------------|--------------------|--------------------|-------|---------|---------|-------|
| easyJet (first differences) | 0.2822 (1.8329) | 0.5465 (2.7915) | 2.745 | 151.664 | 148.862 | 0.753 |
| bmibaby | 0.9968 (79.051) | | 1.898 | 135.438 | 134.004 | 0.747 |

t statistics in brackets

Appendix 2:ARIMA results for LGW-PRA

| | Coefficients | SE | SBC | AIC | Autocorrelation in Fitted Model |
|----------------|-----------------------------------|-------|---------|---------|---------------------------------|
| easyJet | θ_1 0.9905 (65.3210) | 9.676 | 227.817 | 226.416 | 0.276 |
| bmibaby | 0.9989 (4429.061) | 1.415 | 117.826 | 116.425 | 0.010 |

t statistics in brackets