easyJet® Airlines: Small, Lean, and with Prices that Increase over Time

Oded Koenigsberg
Columbia Business School
Columbia University, New York, NY 10027
ok2018@columbia.edu

Eitan Muller
Leon Recanati Graduate School of Business Administration
Tel Aviv University, Tel Aviv, Israel 69978
muller@post.tau.ac.il

Naufel J. Vilcassim
London Business School
London, England NW1 4SA
nvilcassim@london.edu

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Abstract

easyJet® Airlines, which has emerged as one of Europe’s most successful low-cost, short-haul airlines, has a simple pricing structure. For a given flight, all prices are quoted one-way, a single price prevails at any point, and in general, prices are low early on and increase as the departure date approaches. In this paper, we examine the optimality of this pricing scheme and analyze the factors that determine how the price should change over time by building a model of dynamic pricing that incorporates demand uncertainty.

We find that while a pricing strategy such as easyJet’s is indeed profit-maximizing, the magnitude of the increase in price from the first date of seat sales to the departure time is dependent upon the capacity of available seats between the given city pair, and varies inversely with it.

We examine the issue of last-minute deals by assuming that while consumers have uncertainty with respect to the firm’s capacity and therefore the availability of last minute deals, the firm might not know a-priori if it offers such deals or else randomize its decision to offer such deals. We find that when the firm does not know a-priori if it will offer a last-minute deal, then it discounts both Period 1 and Period 2 prices below the non-constraint optimal price. When the firm knows it will offer a last-minute deal, then Period 1 price is above the non-constraint optimal price, and Period 3 price is below the non-constraint optimal price. However, the higher Period 1 price may act as a signal to consumers, who then wait for the last-minute deal. Thus in both cases, as compared with the two-period game, employing last-minute deals is not optimal for the firm.

We empirically analyze the data for several easyJet flights and find empirical support for our main model assumption and the result of an inverse relationship between the magnitude of the price increase over time and the available seat capacity.

An important strategic implication of our analysis for easyJet is that while its current pricing strategy is optimal given its size, it would not be optimal for the airline to offer such low initial prices were it to add substantial capacity to any given route. This would be a challenge for a firm that has built up expectations among customers as an airline with a great value proposition for those willing to buy early.
1. Introduction

easyJet® Airlines has emerged as one of the most successful low-cost airlines in Europe since its launch in 1995. One key aspect of its marketing strategy is a simple fare structure, where all fares are quoted one-way and a single price is quoted for all seats on a given flight at any point in time without any restrictions being stipulated (such as, requiring a Saturday night stopover). However, the price charged for a seat on a given flight changes over the period between the flight being made available for booking and the date of departure. All easyJet sales are booked directly via either the Web or telephone. The company’s Web site (www.easyJet.com) describes its pricing policy as being “based on supply and demand, and prices usually increase as seats are sold on every flight. So, generally speaking, the earlier you book the cheaper the fare will be.”

In figure 1 (a) and (b) we plot over time the number of seats sold on a given date and the price charged per seat for a flight between Liverpool, England and Alicante, Spain departing on a Monday in the winter of 2003, and another between Stansted (a London airport) and Edinburgh, Scotland departing on a Monday in the Summer of 2003.

Certain distinct patterns emerge from figure 1. We note that seat sales in both cases form a discrete pattern with sales spread over time, but with a burst in sales about two to three weeks after the initial sales for the Liverpool-Alicante flight, while for the Stansted-Edinburgh flight, sales are sparse in the first half of the period, with a sales burst on a certain date, followed by some activity toward the end. Thus, there seems to be some uncertainty in the pattern of demand. Moreover, though in both cases the price charged has a clear upward trend, there is a distinct difference in the magnitude of the change.
**Figure 1a:** Seats sold and prices paid (in British pounds) of a one-way ticket from Liverpool to Alicante (flight date January 27, 2003)

**Figure 1b:** Seats sold and prices paid (in British pounds) of one-way ticket from Stansted to Edinburgh (flight date July 21, 2003)
For the Liverpool-Alicante flight, the price increases by about 2.5 times, from about £40 to £100, whereas the price increase for the Stansted-Edinburgh flight is about 4.5 times, from around £20 to a high of £90.

In this paper, we address the following issues relating to easyJet’s pricing strategy: How should the airline price the seats over time? Is increasing price over time an optimal strategy? How is the pricing strategy influenced by customer heterogeneity? What factors determine the rate at which price increases over time? Does it pay to have last minute deals?

We develop a two-period analytical model of dynamic pricing and determine how prices change over time, given i) the presence of two types of customers who value air travel differently and ii) a level of airline seat capacity. A key factor in our model is the existence of uncertainty in demand for one of the customer groups. We solve for the equilibrium two-period prices in a game in which the airline maximizes profits and customers maximize utility.

We find that the equilibrium prices increase over time for all levels of capacity. In the high-capacity case, the firm practices straightforward price discrimination between the two segments. In the intermediate case, the firm adjusts the level of prices for both segments. That is, it does not serve the business passenger first and use the tourists as a buffer in case it has some excess capacity, but rather restricts the demand of both segments (by raising the appropriate prices) so as to match capacity with expected demand. Only in the low-capacity case does the firm forgo the tourist segment and serve the business segment exclusively.

We also find that when capacity is high, the prices in the two periods are independent of the level of capacity, and thus the difference between the prices in the two periods is independent of the level of capacity. When capacity is low or medium, the levels of prices do
depend on capacity. In addition, the difference between the two prices either remains constant or decreases as capacity increases.

We examine the issue of last-minute deals by assuming that while consumers have uncertainty with respect to the firm’s capacity and therefore the availability of last minute deals, the firm might not know \textit{a-priori} if it offers such deals or else randomize its decision to offer such deals. We find that when the firm does not know \textit{a-priori} whether it will offer a last-minute deal, then it discounts both Period 1 and Period 2 prices below the non-constraint (i.e. the results mentioned previously when last minute deals were not a consideration) optimal price. When the firm knows it will offer a last-minute deal, then Period 1 price is above the non-constraint optimal price, and Period 3 price is below the non-constraint optimal price. However, the higher Period 1 price may act as a signal to consumers, who then wait for the last-minute deal. Thus in both cases, as compared with the two-period game, employing last-minute deals is not an equilibrium.

The empirical results support the main assumption in our model development that there are heterogeneous groups of customers with differing price responses. The empirical results also support the main results or predictions of our model that the seat price increases over time, but the \textit{rate} at which price increases declines as capacity increases, i.e., that there is an inverse relationship between the rate at which price increases over time and the available seat capacity. We further find that price at each point of time is a function of the remaining capacity at that point of time.

The rest of this paper is organized as follows. In the next section, we relate our research to the extant literature on airline pricing. In section 3, we lay out the structure of the model and the underlying assumptions. This is followed by the derivation of our main analytical results in
section 4. We next consider in section 5 the special situation of last-minute deals. In section 6 we describe our empirical analysis to test the validity of the model’s main assumption and to verify whether the prediction of the model of an inverse relationship between price increase and seat capacity holds. In section 7, we conclude by summarizing our results and identifying issues for future research.

2. Related Literature

Our work ties in to the research literature on airline pricing and to the yield management literature. Yield management is a rich research area that has attracted the interest of both operations management and economics researchers. McGill and van Ryzen (1999) provide a detailed survey that reviews the work on yield (revenue) management. They discuss four areas: forecasting, overbooking, seat inventory control, and pricing. Traditionally, the operations literature on airline yield management concerns itself with seat inventory and capacity planning problems (see, for example, Talluri and van Ryzen 2004; Lautenberg and Stidham 1999; and Belobaba 1987). However, there is also an increasing body of research that considers pricing decisions, such as Talluri and van Ryzen 2004; You 1999; Feng and Gallego 1995; Gallego and van Ryzen 1997 and 1994; and Watherford and Pféiffer 1992. In general, this branch of work focuses on dynamic pricing decisions under a capacity constraint.

Feng and Gallego (1995) look at the optimal timing for changing prices, and show that under mild conditions, it is optimal to decrease prices as flight time approaches. Gallego and van Ryzen (1994) tie together the decisions of pricing and seat allocation and show how price can be used as a tool to shift demand from one customer class to another.
In a recent book chapter, Talluri and van Ryzen (2004) write about the economics of revenue management and focus on pricing decisions.

Our research also draws on the economics literature on airline pricing (see, for examples, Dana 1998 and 1999; Kretsch 1995; Morrison and Winston 1990; Borenstein and Rose 1994). Similar to our work, Dana (1999) looks at a market with two segments: tourist and business. Dana assumes that tourist passengers are consumers with relatively lower “waiting” costs, while business passengers are consumers with relatively higher “waiting” costs, where the cost of waiting is a stochastic variable that defines the cost of flying at the least desirable time. Dana assumes that there are two times to fly, that the peak time can be either one with probability 0.5, and consumers’ preferences are perfectly inversely correlated. Dana presents a stylized model that suggests that yield management may be an efficient equilibrium response to uncertainty regarding the distribution of consumers’ departure time preferences. Dana looks at both monopoly and competitive equilibrium pricing and analyzes the firms’ optimal pricing decisions in each case. Dana shows that under his model assumptions, an increase in the number of tourist passengers actually serve to benefit business passengers. Tourists not only occupy a relative majority of the low-priced seats; they also lower the prices for business passengers. Thus, Dana shows that business passengers are better off with price discrimination.

Finally, our work relates to the marketing literature on pricing under conditions of uncertainty in general and airline pricing in particular. Carpenter and Hanssens (1994) test the optimality of an airline (UTA) pricing strategy and measure the impact of price on the overall size of the market for air travel between Cote d’Ivoire and Paris. They find the optimal prices under capacity constraint and forecast demand for these fares. Carpenter
and Hanssens provide a decision support system that finds the optimal prices, forecasts the market response, and constructs a response model for total volume and fare class share. Based on this analysis, they offer a forecasting model to estimate overall demand for each fare class. Desiraju and Shugan (1999) find that yield management systems (like early discounting, overbooking, and limiting early sales) for capacitated systems are optimal when price-insensitive consumers choose to purchase later than price-sensitive consumers do. Biyalogorsky et al. (1999) find that under some conditions, firms sell more units than their capacity and then cancel (with appropriate compensation) sales made to consumers who pay the list price. Biyalogorsky et al. show that this policy can actually improve both profits and allocation efficiency. In another paper, Biyalogorsky et al. (2003) analyze practices wherein consumers can choose from various service classes (e.g., airlines, hotels, and rail transportation among others), each with limited capacity. They identify the conditions under which the firms find it more profitable to upgrade services.

Another branch of work in marketing and economics that relates to our research is that on advanced purchases (see, for examples, Shugan and Xie 2000; and Gale and Holmes 1992, 1993). Shugan and Xie (2000) discuss the general role of advance pricing, which is not necessarily unique to the airline industry. Under various conditions of intermediary marginal costs, capacity constraint, seller credibility, and risk aversion, they show that advanced selling is an optimal strategy if there is uncertainty on consumer-side valuation. Xie and Shugan (2001), show that the additional profits come from the increase in sales, but not from consumer surplus.
3. Model Development: Tourist and Business Segments

We consider a one-way airline route between two cities, with a monopoly service provider. We assume there are two segments of customers (denoted T for tourists and B for business) and two time-periods (denoted Periods 1 and 2). The tourists’ utility from the travel is uniformly distributed over an interval of (0, α). This utility does not change over time and thus in Period 2, their utility remains at exactly the same level as that of the previous period.

Business consumers arrive in both periods: A fraction γ of the business segment arrives in period 1. Their utility from the travel is distributed uniformly over the interval of (α, α). A fraction (1-γ) of the business segment appears in Period 2. These consumers, however, have uncertainty with respect to their utility. The business passenger learns during Period 2 that with probability θ a business meeting that requires air travel is to be held at the destination city. With probability (1 - θ), this business meeting is not held, and the utility of this executive from the air travel thus equals zero. In order to create a clear-cut segmentation between business and tourists, we assume that the upper bound of the valuation of the business consumer is much higher that that of the tourist, i.e., α < α/2.

Assume there are two periods in which passengers can buy an air ticket. The sequence of events is given in Figure 2 as follows:

**Figure 2**: Sequence of pre-flight events

\[ t = 0 \quad \uparrow \quad t = 1 \quad \uparrow \quad t = 2 \quad \text{time} \]

price 1 announced \[ \uparrow \]
price 2 announced \[ \uparrow \]
consumers buy tickets at either \( t = 1 \) or \( t = 2 \)
There are two events in Period 1: first, the firm announces the price, and then consumers make a decision whether to buy. There are three events in Period 2: first, the firm announces price. Next, uncertainty about the state of the business passengers is resolved. Finally, consumers make a decision whether to buy the ticket. Let $f(x)$ be the density of consumer distribution. As the tourist customers are distributed uniformly in the interval $(0, \alpha)$, the following holds: $\int_{0}^{\alpha} f(x) \, dx = 1$. Thus $f(x) = 1/\alpha$. If the price in Period 1 or 2 is $p$, then the tourists whose utility is larger than the price will buy the tickets. Thus, the proportion of those who buys seats in Period 1 at price $p$ is represented by: $\int_{p}^{\alpha} f(x) \, dx = (\alpha - p) / \alpha$. Similarly, the proportion of business passengers buying tickets at a price of $p$ in Period 2 is represented by:

$$\int_{p}^{\bar{\alpha}} f(x) \, dx = (\bar{\alpha} - p) / (\bar{\alpha} - \alpha)$$

If the number of tourist passengers is denoted by $M_T$, and the number of business passengers by $M_B$, then their respective demands at a price of $p$ are given by $M_T (\alpha - p)/\alpha$, and $M_B (\bar{\alpha} - p) / (\bar{\alpha} - \alpha)$. In order to simplify notations, we normalize the market sizes as follows: $N_T = M_T / \alpha$ and $N_B = M_B / (\bar{\alpha} - \alpha)$. We assume that $M_T > \gamma N_B$ and that $N_T > \gamma N_B$. We shortly show (in section 4.3) that in the reverse case when $\gamma N_B > N_T$ the problem is rather trivial, as the firm would rather sell only to business consumers.

Customers will decide to purchase the ticket in period $i$ ($i = 1, 2$) if the utility in this period will be positive and higher than the utility of purchasing in the other period. Therefore, the following system represents demand in the two periods:
period 1, \[ D_1 = \begin{cases} N_T (1 - L_T) (\alpha - p_1) + \gamma N_B & \text{if } p_1 < \alpha \\ \gamma N_B (\alpha - p_1) & \text{if } \alpha > p_1 > \alpha \end{cases} \]

period 2, \[ D_2 = (1 - \gamma) N_B \theta (\alpha - p_2) + N_T (\alpha - p_2) L_T \]

$L_T$ is an identity function that equals 1 if the tourist customer purchases the product in Period 2, and zero if s/he purchases the product in Period 1. The condition $L_T = 1$ is that the Period 2 price is lower than the Period 1 price (we assume that there is no discounting factor and that the consumer would rather buy today than wait if the prices in both periods are the same). Thus $L_T$ are represented by:

\[
L_T = \begin{cases} 1 & \text{if } p_2 < p_1 \\ 0 & \text{otherwise} \end{cases}
\]

Without loss of generality, let the marginal cost of supplying the seat be zero. Let the capacity (the number of airline seats) be fixed at $C$. Restrictions on capacity play a dominant role in our analysis, as will be explained later on.

4. Derivation of Equilibrium Prices

From the assumptions specified in the previous section and from the demand system, we can show that the firm should consider three cases. The first case is where capacity is so low that the firm sells only to business consumers. The second case is where capacity is binding but is high enough such that the firm can effectively discriminate, so that it sells to both markets, while the third case is where capacity is high enough and is not effectively binding. A concise summary and a graphical presentation of the pricing results are given in Table 1 and Figure 3 at the end of this section. In order to set the boundary of these cases, define $\beta(C)$ to be:
\[ \beta(C) = \alpha N_f / 2 + N_b [\gamma(\bar{\alpha} - \alpha) + (1 - \gamma)\theta\bar{\alpha}] / 2 - C \]

We will shortly show (in section 4.3) that \( \beta(C) \) is the capacity shortage, i.e., the difference between demand and capacity. Thus when \( \beta(C) > 0 \) indeed the firm faces capacity shortage and when \( \beta(C) < 0 \), the firm has excess capacity.

4.1 Prices and profits with low capacity

When capacity is low, the firm is better off selling exclusively to business consumers, who have higher valuation and thus will pay more. We will shortly show that this case could be divided into two sub-sections: very low and low.

Consider the extreme case when the firm has only one seat available. Obviously, the firm would rather sell it to a business consumer who has higher valuation. As we increase the capacity, this policy is valid until capacity exceeds the optimal selling quantity to the business segment \( C_1 = N_b \bar{\alpha} (\theta + \gamma(1 - \theta))/2 \). It is easy to show that the corresponding price is the monopoly price, \( p = \bar{\alpha}/2 \). Equivalently, this case corresponds to a large capacity shortage, i.e., \( \beta(C) > \alpha (N_f - \gamma N_b)/2 \). Thus the following proposition holds for this low-capacity case (for a proof see the appendix):

**Proposition 1**: With low capacity \( C < C_1 \), optimal prices are given by:

\[ p_1 = p_2 = \bar{\alpha} - \frac{C}{N_b(\theta + \gamma(1 - \theta))} \]  

When \( C_1 < C < C_2 \) the firm charges \( p_1 = p_2 = \bar{\alpha}/2 \).

In order to find out the value of \( C_2 \), note that when the capacity equals \( C_1 \), the firm charges the optimal monopoly price \( p = \bar{\alpha}/2 \) and sells only to the business segment. When the capacity increases further, the firm does not immediately decrease the price in the first
period order to capture more demand from the tourist segment and compensate by increasing price in the second period to the business segment. The firm employs this policy only when the additional revenues from the tourist segment compensates for the loss in revenues from the business segment. Up to this capacity (defined as $C_3$) the firm would keep the price constant at $p = \bar{\alpha}/2$ in both periods and serve only the business segment. We derive the value of $C_3$ in the appendix.

### 4.2 Prices and profits with intermediate capacity

One might have expected that when capacity increases further, the firm continues to sell to the business consumers in the second period at price of $p_2 = \bar{\alpha}/2$ and starts to sell to tourist consumers in the second period in a reduced price as fillers in order to increase utilization. This however, is not the case. In this section we show that the optimal pricing scheme is to increase the price over time so as to discriminate between the two segments when the capacity is intermediate in value, $C_2 < C < C_3$, where $C_3$ is given by $\beta(C_3)=0$.

Thus, this section deals with the case where there is capacity shortage, but it is not exceedingly acute as in the previous case.

The overall optimization problem is represented by:

**Period 2:** Max $p_2 \ (1-\gamma)N_B \ \theta(\bar{\alpha} - p_2)$

Subject to: $C - N_T (\alpha - p_1) - \gamma N_B (\bar{\alpha} - \alpha) - \theta(1-\gamma) N_B (\bar{\alpha} - p_2) > 0$

**Period 1:** Max $p_1 \ [N_T \ (\alpha - p_1) + \gamma N_B (\bar{\alpha} - \alpha)] + \Pi_2$

Subject to: $C - N_T (\alpha - p_1) - \gamma N_B (\bar{\alpha} - \alpha) - \theta(1-\gamma) N_B (\bar{\alpha} - p_2) > 0$ and $\alpha - p_1 > 0$
We define Lagrangian in Period 2 with coefficient $\lambda$, and in Period 1 with coefficients $\delta$ and $\mu$.

$$L_2 = p_2 (1 - \gamma)N_B \theta (\alpha - p_2) + \lambda [C - N_T (\alpha - p_1) - \gamma N_B (\alpha - \bar{\alpha}) - \theta (1 - \gamma)N_B (\alpha - p_2)]$$

$$L_1 = p_1 [N_T (\alpha - p_1) + \gamma N_B (\alpha - \bar{\alpha})] + \Pi_2 + \delta [C - N_T (\alpha - p_1) - \gamma N_B (\alpha - \bar{\alpha}) - \theta (1 - \gamma)N_B (\alpha - p_2)] + \mu (\alpha - p_1)$$

In order to find the sub-game perfect equilibrium, we solve the game backward starting in Period 2, and find out the optimal prices as given in the following proposition:

**Proposition 2:** With intermediate capacity $C_2 < C < C_3$, the optimal prices are represented by

$$p_1 = \frac{\alpha}{2} + \frac{\gamma N_B (\alpha - \bar{\alpha})}{2N_T} + \frac{\beta(C)}{N_T + \theta (1 - \gamma) N_B} \quad \text{and} \quad p_2 = \frac{\alpha}{2} + \frac{\beta(C)}{N_T + \theta (1 - \gamma) N_B}$$

It is clear that the price in Period 2 in this case is also higher than the price of Period 1 since the inequality $N_T > \gamma N_B$ holds. Thus, optimal prices are increasing over time. Note that, because of the constraint on $C$, the term $\beta$ is positive, and thus both prices are higher than the monopoly unconstrained prices. In the next section we derive these latter prices.

**4.3 Prices and profits with high capacity**

Finally, we analyze the case where the capacity constraint is not binding. In this case we follow the same route as the previous case, *mutatis mutandis*, to come up with:
Proposition 3: With excess capacity $C > C_3$, the optimal prices are represented by

$$p_1 = \frac{\alpha}{2} + \frac{\gamma N_B(\alpha - \alpha)}{2N_T} \quad \text{and} \quad p_2 = \bar{\alpha}/2 .$$

With these prices it is straightforward to compute the overall demand $D$ to be:

$$D = \alpha N_T/2 + N_B[\gamma(\alpha - \alpha) + (1 - \gamma)\theta \bar{\alpha}]/2 .$$

It is now clear that $\beta(C)$ is indeed the difference between demand and capacity ($D - C$), i.e. the capacity shortage.

It is also straightforward to see that $p_1 < p_2$ if (and only if) $N_T > \gamma N_B$. If this constraint is not satisfied then the firm is better of charging $p = \bar{\alpha}/2$ in both periods and serve only the business segment. Since this latter case is almost trivial in its implications, we have assumed throughout the paper that the tourist segment is larger that the business segment appearing in the first period, i.e., $N_T > \gamma N_B$.

The optimal first- and second-period prices for each capacity scenario (low, medium, and high) are summarized in Table 1 and Figure 3:

<table>
<thead>
<tr>
<th>Capacity</th>
<th>Period 1 price</th>
<th>Period 2 price</th>
</tr>
</thead>
<tbody>
<tr>
<td>Very low capacity</td>
<td>$p_1^{vl} = \bar{\alpha} - \frac{C}{N_B(\theta + \gamma(1 - \theta))}$</td>
<td>$p_2^{vl} = p_1^{vl}$</td>
</tr>
<tr>
<td>($C &lt; C_1$)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Low capacity</td>
<td>$p_1^l = \bar{\alpha}/2$</td>
<td>$p_2^l = p_1^l$</td>
</tr>
<tr>
<td>($C_1 &lt; C &lt; C_2$)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Medium capacity</td>
<td>$p_1^m = p_1^l + \beta(C)/N_T + \theta(1 - \gamma)N_B$</td>
<td>$p_2^m = p_2^l + \beta(C)/N_T + \theta(1 - \gamma)N_B$</td>
</tr>
<tr>
<td>($C_2 &lt; C &lt; C_3$)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>High capacity</td>
<td>$p_1^h = \frac{\alpha}{2} + \frac{\gamma N_B(\alpha - \alpha)}{2N_T}$</td>
<td>$p_2^h = \bar{\alpha}/2$</td>
</tr>
<tr>
<td>($C_3 &lt; C$)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Where $\beta$ is the capacity shortage, i.e., $\beta(C) = \alpha N_T/2 + N_B[\gamma(\alpha - \alpha) + (1 - \gamma)\theta \bar{\alpha}]/2 - C$. 

Table 1: (Perfect) equilibrium prices for varying levels of capacity
Figure 3: Equilibrium prices and firm’s policy for varying levels of capacity

We note from Table 1 that the optimal price increases with time (i.e., $p_2 > p_1$) for all levels of capacity, except for the low level where the prices are the same. In the high-capacity case, the firm practices price discrimination between the two segments. In the intermediate case, the firm adjusts the level of prices for both segments. That is, it does not serve the business consumer first and use the tourists as a buffer in case it has some excess capacity, but rather restricts the demand of both segments (by raising the appropriate prices) so as to equate
capacity to expected demand. Only in the low-capacity case, does the firm forgo the tourist segment and serve the business segment exclusively. We also note that when capacity is high, the prices in the two periods are independent of the level of capacity, and thus the difference between the prices in the two periods is independent of the level of capacity as well. When capacity is low or medium, the levels of prices do depend on capacity.

If the capacity $C$ is a strategic decision variable of the firm and it is costly, then the firm would never choose levels of capacity such that $C_1 < C < C_2$ or $C > C_3$ as in these capacity regions, as capacity increases neither the price nor demand change and thus it pays more for capacity while its revenues remain unchanged.

Further, in certain regions of the capacity, we confirm Dana’s result (1999) that the tourist travelers subsidize the business consumers. Thus when $C_2 < C < C_3$ an increase in capacity causes the number of tourists to increase and the price to the business consumers to decrease. However, this is not the case when the capacity is at the point $C_2$. At this point the firm moves from selling only to the business consumers at a relatively low price of $p = \bar{\alpha}/2$ to price discriminating between the two segments by selling to the business at a much higher rate and to tourist at a much lower rate. Thus at this capacity the business consumers suffer from having the tourists join the flight as they pay a higher price.

5. Last-Minute Deals

In actual practice, we do observe last-minute deals that are often offered at a very low price. If the firm decides to engage in such offers, either directly or via a reseller, then it can set a new price so as to attract the lower end of the tourist segment that did not purchase the
tickets in the first period. What we show in this section is that either this policy is not optimal, or it involves a time inconsistency problem on the part of consumers. In addition, if the time inconsistency problem is solved, for example by introducing information asymmetry, then it is clear that this policy is suitable for firms with high capacity. In other words, what we find is that easyJet is behaving optimally in that it increases prices over time, and will continue to behave optimally by increasing prices as long as it remains a small airline. Its policy might not be optimal as soon as it stops being small and lean.

Last-minute deals are often made very close to the actual flight time. For example, in some European airports, one can buy tickets at a greatly reduced price for same-day flights. Thus in actual practice, as well as in our models, last-minute deals are rendered irrelevant for the business segment. If the price in Period 3 (last-minute period) is low, then the firm has to worry about consumers from the tourist segment waiting to buy tickets in Period 3 instead of buying them in Period 1. Indeed, some of them will, but the question is how to fence the higher utility consumers out of this segment. The reason that the high-utility consumers do not wait for last-minute deals is their uncertainty with respect to the existence of such deals. They know that if demand is high enough, the airline will not bother reducing the price. Moreover, if capacity is low relative to demand, then by waiting, they take the risk of finding themselves without a ticket.

First, in order to simplify our three stage model we assume that the business consumers appear only in the second period and thus $\gamma = 0$. We model the uncertainty of the consumers with respect to the capacity with the help of an additional parameter $\beta$. With probability $\beta$, capacity is high and the airline offers last-minute deals, and if capacity is low, then with probability $(1-\beta)$ it does not. In what follows, we offer two possible options on the part of the
airline: It can either randomize with respect to last-minute deals, or it knows with certainty whether it will engage in such practice. As we will see, the option chosen does have an effect on the optimal prices, and consequently on the behavior of the consumers.

Let \( x \) be the tourist with the highest utility that will purchase the ticket in Period 3 at the price of \( p_3 \). What we do next is to find the values of \( x, p_1, p_2, \) and \( p_3 \) that will constitute an equilibrium to the new game. We begin at Period 3 where the profits are represented by:

\[
\pi_3 = M_T (x - p_3) p_3 / \alpha
\]

Maximization with respect to the price yields that

\[
p_3 = x/2, \text{ and } \pi_3 = \frac{M_T x^2}{4\alpha}.
\]

In Period 2, the expected profits depend on the business segment and the expected Period 3 profits. We define \( \delta \) as an indicator parameter that is equal to 1 if the firm decision whether to introduce Period 3 prices is unknown to the firm prior to Period 3, and that \( \delta \) is equal to \( 1/\beta \) if the firm knows with certainty that it will provide a ”last-minute deal.” Thus, Period 2 profits can be represented as:

\[
\pi_2 = p_2 \frac{M_b \theta (\bar{\alpha} - p_3)}{\bar{\alpha} - \alpha} + \delta \beta \pi_3
\]

First-order conditions imply that the price in Period 2 is represented by:

\[
p_2 = \bar{\alpha} / 2, \text{ and the profits are represented by } \pi_2 = \frac{M_b \theta \bar{\alpha}^2}{4(\bar{\alpha} - \alpha)} + \delta \beta \frac{M_T x^2}{4\alpha}.
\]

In Period 1, profits are represented by:

\[
\pi_1 = \frac{M_T p_1 (\alpha - x)}{\alpha} + \frac{M_b \theta \bar{\alpha}^2}{4(\bar{\alpha} - \alpha)} + \delta \beta \frac{M_T x^2}{4\alpha}.
\]
We now use the fact that \( x \) is the marginal consumer for whom the utility from purchasing the ticket in Period 1 is exactly equal to the utility from waiting and buying the ticket in Period 3. This fact yields the following equation for \( x \):

\[
x - p_1 = \beta (x - p_3).
\]

Substituting \( p_3 = x/2 \) and solving for \( x \) yield:

\[
x = \frac{2p_1}{2 - \beta}
\]

Substitute this expression for \( x \) in the profit function \( \pi_1 \) yield:

\[
\pi_1 = \frac{M_r p_1 (\alpha - \frac{M_r}{2p_1})}{\alpha (\alpha - \alpha) + \delta \beta \frac{M_r}{\alpha} \frac{p_1^2}{(2 - \beta)^2}}
\]

When the firm does not know if it will introduce a last-minute deal (\( \delta = 1 \)), the first-order condition for optimality yields the following solution for \( p_1 \):

\[
p_1^a = \frac{\alpha (2 - \beta)^2}{2(4 - 3\beta)}
\]

and

\[
p_3^a = \frac{\alpha (2 - \beta)}{2(4 - 3\beta)}.
\]

It is easy to see that \( p_1^a > p_3^a \) and that \( p_1^a < \frac{\alpha}{2} \) as \( p_1^a = \frac{\alpha}{2} \frac{\beta^2 - \beta}{4 - 3\beta} < 0 \).

When the firm knows that it will introduce a last-minute deal (\( \delta = \frac{1}{\beta} \)), the first-order condition for optimality yields the following solution for \( p_1 \):

\[
p_1^b = \frac{\alpha (2 - \beta)^2}{2(3 - 2\beta)}
\]

and

\[
p_3^b = \frac{\alpha (2 - \beta)}{2(3 - 2\beta)}.
\]

It is easy to see that \( p_1^b > p_3^b \) and that \( p_1^b > \frac{\alpha}{2} \) as \( p_1^b - \frac{\alpha}{2} = \frac{\alpha (1 - \beta)^2}{2(3 - 2\beta)} > 0 \).

**Proposition 4:** a. When the firm does not know whether it will offer a last-minute deal (\( \delta = 1 \)), then it discounts both Period 1 and Period 3 prices below the non-constraint optimal price, i.e., \( \frac{\alpha}{2} > p_1^a > p_3^a \). In this case, as compared with the two-period game, employing last-minute deals is not optimal for the firm.

b) When the firm knows it will offer a last-minute deal (\( \delta = \frac{1}{\beta} \)), then Period 1 price is above the non-constraint optimal price, and Period 3 price is below the non-constraint optimal price, that is: \( p_1^b > \frac{\alpha}{2} > p_3^b \).
With incomplete but symmetric information (Proposition 4a), when the firm offers a last-minute deal, it charges the tourist consumers two discrete prices, both of which are below $\alpha/2$. Note from Table 1 that with $\gamma = 0$, $p_1^h = \alpha/2$ and thus these two prices are lower than the optimal price for the tourist segment. Therefore, the firm sells to more consumers in the tourist segment and generates lower-than-optimal profits. The reason for this sub-optimal behavior is the commitment to a price reduction in Period 3. When such a commitment is made, some strategic consumers with marginal valuations above price would choose to wait to obtain the ticket at a lower price, thereby forcing the firm to reduce prices further in Period 1.

With asymmetric information (Proposition 4b), the optimal policy is to offer last minute deal. The reason that it is indeed optimal is that the firm succeeds in discriminating between two classes within the tourist segment, based on their valuation. This discrimination, however, is possible only under the existence of uncertainty of consumers. Those with high valuation will not care to wait for the super last minute deal as they have uncertainty with respect to the capacity of the firm. The low valuation tourist will indeed wait, knowing that the flight might be sold out, and buy at the last minute if tickets are still available.

There are cases under which this uncertainty is resolved, and thus this policy break down. We next discuss two such cases. In this paper, we model a single flight. In this case, this policy of offering last minute deal is optimal. However, in case that the game is repeated and the consumers update their expectation, the consecutive appearance of last minute deals will resolve their uncertainty. In this case, when $\beta=0$, all tourist consumers will wait and purchase tickets at the last minute. In addition, suppose that consumers can compare the last minute deal policy to a two periods policy (with out a last minute deal). In this case the fact
that the first period price is above $\alpha/2$, removes uncertainty and consumers will wait and purchase tickets at the last minute.

One can ask the question whether the airline should price to sell all the remaining seats in period 3. The answer clearly depends on the capacity. Proposition 4b was solved under the assumption of unconstraint capacity. The demand of this case can be shown to be

$$D = \frac{N_{\beta} \alpha}{2} + \frac{N_{\gamma} \alpha (4 - 3\beta)}{2(3 - 2\beta)}.$$  

The firm will sell all the remaining seats if (and only if) the capacity is lower than this demand, $D$.

We base our analysis on the assumption of two segments that differ in their valuations over-time. We find that the firm’s optimal policy under these assumptions is to charge a relatively low price in Period 1, and to increase the price in Period 2, and not to offer a period 3 price. If the firm decision regarding whether to offer the service in period 3 or not is exogenous, then the firm decreases the price below the first period price. We further show that this price change is a function of seating capacity.

At first glance our result appears to differ from some previous findings (for example Xie and Shugan 2001). They find that under high (but not unlimited) capacity, advance (high) pricing at a premium to the spot price is an optimal strategy, and that the firm generates more revenues from the increased demand (consumers buy at a price that equals their expected value and that may exceed their true value).

There are two major assumptions in the models that derive this difference. First, Shugan and Xie assume that consumers in each of the two market segments have the same valuation for the service. Our work, however, assumes that each segment has its own continuous distribution function for the valuation of the product, which may change over time. Second, we assume that the business segment has clearly higher future valuation and therefore, the firm
finds it optimal to charge non-decreasing prices. In the next section, we show empirically that our assumption that there are two segments in the market is consistent with the easyJet market and that prices are changed as a function of capacity.

6. Empirical Analysis

For our empirical analysis, we have data on 23 easyJet flights between six different European city pairs during the year 2003. Some of these flights are in the winter and others in the summer. The flights depart on two different days of the week – Monday and Sunday. For each flight we have data from the first day on which the seats were available to the traveling public up to the date of departure. The duration ranged from 63 days for a flight between Liverpool, England and Alicante, Spain to a maximum of 211 days for a flight between East Midlands, England and Barcelona, Spain. For each flight, we also have data on the number of seats sold per day (if any) and the price at which each was sold. Additionally, we also have data on the total available easyJet seat capacity between each city pair.

The first phase of analysis is to test the validity of the assumption that there exist two segments (and possibly a third segment in the case of last-minute deals) of customers with differing price responses. Since the data suggest that customers arrive at discrete points in time (see figure 1), a latent class Poisson regression model would be an appropriate way to model that, see Wedel et al. (1993).

---

1 Data pertaining to one flight had to be deleted, resulting in 23 usable observations.
2 The Negative Binomial (NB) distribution has also been used in previous research to model the aggregate demand for airline seats as it overcomes some of the well-known limitations of a Poisson model. We note that an aggregate NB model for demand can be derived by assuming that demand is Poisson at the individual level and accounting for heterogeneity over individuals using a gamma distribution. In our analysis, we model demand at the individual level using a Poisson model, but account for heterogeneity using a latent class approach, which can be also interpreted as providing a finite approximation to any mixing distribution, such as the gamma. Therefore, the demand model we use is quite flexible.
We thus take the following model to data. The probability that in any given period ‘y’ customers arrive to buy tickets at a price ‘p’ is represented by:

\[ P(Y = y / p, \beta, \theta) = \sum_{j=1}^{L} \theta_j \lambda_j^y \exp(-\lambda_j)/y! \]

where \( \lambda_j = \lambda_{j0} \exp(\beta_j p) \) and \( \sum_{j=1}^{L} \theta_j = 1 \)

In the above equation, ‘\( \theta_j \)’ is the probability that the arriving customer belongs to the latent class or segment \( j = 1,2,\ldots,L \). We estimate the parameters of the latent class Poisson regression model using maximum likelihood methods. As the number of segments is unknown, we keep incrementally adding segments until there is no improvement in the fit of the model as measured by the Bayesian Information Criterion (BIC), i.e., we keep increasing the number of segments from 1,2,3… and so on until the BIC value is minimized (see Chintagunta, Jain, and Vilcassim 1991).

**Table 2:** Bayesian Information Criterion for the 23 flights

<table>
<thead>
<tr>
<th>Flight Number</th>
<th>BIC Values</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1-segment</td>
<td>2-segment</td>
<td>3-segment</td>
</tr>
<tr>
<td>1</td>
<td>225.1</td>
<td>140.0</td>
<td>131.4</td>
</tr>
<tr>
<td>2</td>
<td>135.6</td>
<td>102.3</td>
<td>104.1</td>
</tr>
<tr>
<td>3</td>
<td>228.5</td>
<td>168.2</td>
<td>168.4</td>
</tr>
<tr>
<td>4</td>
<td>245.2</td>
<td>184.8</td>
<td>161.9</td>
</tr>
<tr>
<td>5</td>
<td>244.2</td>
<td>106.4</td>
<td>101.9</td>
</tr>
<tr>
<td>6</td>
<td>159.3</td>
<td>94.5</td>
<td>92.7</td>
</tr>
<tr>
<td>7</td>
<td>243.7</td>
<td>192.4</td>
<td>186.3</td>
</tr>
<tr>
<td>8</td>
<td>202.2</td>
<td>149.9</td>
<td>146.7</td>
</tr>
<tr>
<td>9</td>
<td>118.4</td>
<td>90.2</td>
<td>95.2</td>
</tr>
<tr>
<td>10</td>
<td>267.5</td>
<td>146.5</td>
<td>135.1</td>
</tr>
<tr>
<td>11</td>
<td>266.0</td>
<td>186.6</td>
<td>161.0</td>
</tr>
<tr>
<td>12</td>
<td>220.6</td>
<td>166.1</td>
<td>172.8</td>
</tr>
<tr>
<td>13</td>
<td>212.7</td>
<td>117.6</td>
<td>87.3</td>
</tr>
<tr>
<td>14</td>
<td>245.9</td>
<td>132.9</td>
<td>125.8</td>
</tr>
<tr>
<td>15</td>
<td>197.2</td>
<td>166.9</td>
<td>161.8</td>
</tr>
<tr>
<td>16</td>
<td>173.3</td>
<td>153.5</td>
<td>160.4</td>
</tr>
<tr>
<td>17</td>
<td>95.1</td>
<td>75.0</td>
<td>79.6</td>
</tr>
</tbody>
</table>
The results of the estimation for the 23 flights are given in table 2. We note from table 2, that the fit of the Poisson regression model improves considerably when going from one segment to two segments in all cases. For 11 out of the 23 flights, the two-segment solution fits the data better than the three-segment solution, while a three-segment solution provides a better fit for the remaining flights. Thus, there is empirical support for model assumption of two or three segments of customers.

We next examine whether the main results of our analytical model—that optimal ticket price increases with time, but the rate at which the price changes depends on the level of seat capacity—are supported by the data. Additionally, whether this is a direct or inverse relationship depends on the proportion of business to tourist passengers. It should be noted that what is of practical interest is the case wherein the airline capacity is at medium or high levels, more than the low-capacity case.

For each time period (Time$_{it}$, a week in this case), and for each flight (23 flights in all), we estimate the following regression model for the price variable (Price$_{it}$, $i=1,2,3,...,23$).

\[ \text{Price}_{it} = \alpha + \beta_1 \text{Time}_{it} + \epsilon_{it} \]

Our hypothesis is that the parameters ‘$\beta_i$’ are positive, and in addition, they will depend on the level of capacity ‘$C_i$’ in that market. Thus, we let:

\[ \beta_i = \nu + \eta * C_i + \delta \text{ Summer Dummy } + \lambda \text{ Sunday Dummy } + \mu_i \]
where Summer_Dummy = \{1 if the flight is in the summer, and 0 in the winter\} and

Sunday_Dummy = \{1 if the flight is on a Sunday and 0 on Monday\} are two control variables that we introduce because they could affect the rate at which price changes.

Table 3: Regression results - price vs. capacity

The results of the regression are given in table 3. We see from table 3 that in the Price vs. Time regression, 20 out of the 23 slope coefficients (\(\beta_i\)) are positive, and their
overall mean is positive (1.061). This supports our result that the optimal prices increase over time. We also note from table 3 that the coefficient of the capacity variable is significantly different from zero, implying, as per our analytical model, that we are dealing with the situation of intermediate capacity. This result is certainly reasonable for an airline like easyJet, as opposed to say, British Airways, which can be considered to have high capacity. When we examine the sign of the coefficient of the capacity variable, it is negative, implying that as capacity increases, the rate at which price changes decreases.

Another way to look at the relationship between price and capacity is to regress price against remaining capacity. Recall from the maximization problem for the intermediate capacity case (section 4.2) that in Period 2, the firm maximizes profits subject to the remaining capacity constraint and the main result was that the price is a declining function of the remaining capacity (see Table 1). Therefore, for each time period ($Time_{jt}$, a week in this case), and for each pair of cities (six pairs), we estimate the following six regression models for each city pair (four flights per city for five city pairs, and three flights per city pair for a single flight for the remaining capacity variable ($RemCap_{jt}$, $j=1,2, \ldots, J$)).

$$Price_{jt} = \alpha + \gamma_j RemCap_{jt} + \delta Summer_{jt} Dummy + \lambda Sunday_{jt} Dummy + \xi_{jt}$$

Our hypothesis is that the parameters $'\gamma_j'$ are negative.
Table 4: Regression results: price vs. remaining capacity

<table>
<thead>
<tr>
<th>Route</th>
<th>No. of flights</th>
<th>$\gamma$ - Effect of remaining capacity on price (standard error)</th>
<th>R Square</th>
</tr>
</thead>
<tbody>
<tr>
<td>London (Stansted) –</td>
<td>4</td>
<td>-0.316 (0.026)</td>
<td>75.4%</td>
</tr>
<tr>
<td>Edinburgh</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>East Midlands -</td>
<td>4</td>
<td>-0.155 (0.011)</td>
<td>74.6%</td>
</tr>
<tr>
<td>Edinburgh</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>London (Stansted) -</td>
<td>4</td>
<td>-0.128 (0.023)</td>
<td>85.8%</td>
</tr>
<tr>
<td>Rome (Ciampino)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>East Midlands -</td>
<td>4</td>
<td>-0.25 (0.029)</td>
<td>87.7%</td>
</tr>
<tr>
<td>Barcelona</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Liverpool -</td>
<td>4</td>
<td>-0.137 (0.098)</td>
<td>65.2%</td>
</tr>
<tr>
<td>Alicante</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>London (Luton) -</td>
<td>3</td>
<td>-0.145 (0.041)</td>
<td>49.6%</td>
</tr>
<tr>
<td>Malaga</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

The results of the regression are given in table 4. We see from table 4 that in the price vs. remaining capacity, all of the slope coefficients ($\gamma_j$) are negative with an overall mean of -0.189. This supports our result that the optimal prices decrease with the remaining capacity.

Overall therefore, the empirical evidence is consistent with our main analytical results on how optimal price varies with time, and how the change in price from one period to another varies with the level of capacity.

**7. Conclusions and Extensions**

In this paper we have shown that the pricing strategy of easyJet that starts with a low per-seat price and then increases it over time up to the time of departure is indeed an optimal strategy. In addition, we showed analytically that the change in price depends on the airline’s overall seat capacity between the given city pair.
We were able to support the findings of our analytical model with an empirical analysis of several easyJet flight data. We showed empirically that the assumption of the existence of two segments is consistent with the data, as is the main prediction that as capacity increases, the change in price over time decreases. In other words, the greater capacity, the larger the pre-ordering discount will be. We further find that price at each point of time is a function of the remaining capacity at that point of time.

We also examined the phenomenon of last minute discounting by introducing a third period into the analysis in which the firm finds itself with unsold seats. What we found is that, as compared with the two-period game, employing last-minute deals is not optimal for the firm due to time consistency issues and consumers’ rationality. However, in practice we observe last minute deals. One explanation might be consumers’ difficulties in understanding the price signals. An alternative explanation could be the myopic nature of the firm’s decisions makers.

A direct implication of our results is the following. We have shown that when the airline prices (or permits resellers to price) last-minute deals, it should heavily discount pre-orders, and this discounting should be heavier than the case in which the firm does not allow for last-minute seat-clearing pricing. As shown in the examples and the empirical section, easyJet’s pre-order discount is quite deep: A ticket that sells at less than £20 (about $30) two months before the flight jumps to £130 (about $200) a couple of days before the flight.

However, large airlines that allow for last-minute clearing prices do not employ such deep pre-order discounts (for example, one does not observe such deep discounting with an airline like British Airways). Our results suggest that these “flat” pricing schemes, coupled with last-minute deals, are not optimal. Thus, a key strategic issue for an airline like easyJet is that were it to grow and add capacity to any route and become like a “large airline”, the firm
should avoid the temptation to offer last minute deals. easyJet has become successful precisely by developing a strong value proposition among customers that translates into “I can get a great deal by buying seats early on.” If changing that perception turns out to be a challenge, then it may be prudent for easyJet to be extremely cautious about adding capacity on any given route.

An interesting route to extend our study is the impact of competition on easyJet’s dynamic pricing strategy. Some other airlines (for example, Ryanair\(^3\)) also operate as low-cost, short-haul carriers with similarly low prices offered early on to customers, while at the same time long-haul flag carriers such as British Airways also have short-haul flights, but with different pricing arrangements. Knowing whether the two-tiered pricing arrangements can be sustained in such a competitive equilibrium is potentially an interesting research question with important policy implications.

To summarize, our analysis has shed some interesting insights into the pricing strategy of one Europe’s most successful low-cost, short-haul airlines. The pricing scheme used by easyJet of starting with very low prices and then increasing them over time is indeed optimal, and exploits heterogeneity in customer price sensitivity, given easyJet’s current size in the European market. Were easyJet to grow and become larger, then its current strategy might no longer be optimal. This poses an interesting challenge for the airline of whether to retain its current size and strong value proposition, or become a larger airline with a new value proposition that the market may not readily accept.

---

\(^3\) Recently Ryanair reported large losses which were attributed to its expansion that was much faster than easyJet’s cautious expansion (Done, 2004)
References


Appendix: Proof of Propositions 1 and 2

The general optimization problem is represented by:

**Period 2:** \(
\text{Max } p_2 \ (1 - \gamma) N_B \ \theta (\overline{\alpha} - p_2)
\)

Subject to: \(C - N_T (\alpha - p_1) - \gamma N_B (\overline{\alpha} - \alpha) - \theta (1 - \gamma) N_B (\overline{\alpha} - p_2) > 0\)

**Period 1:** \(
\text{Max } p_1 [N_T (\alpha - p_1) + \gamma N_B (\overline{\alpha} - \alpha)] + \Pi_2
\)

Subject to: \(C - N_T (\alpha - p_1) - \gamma N_B (\overline{\alpha} - \alpha) - \theta (1 - \gamma) N_B (\overline{\alpha} - p_2) > 0\) and \(\alpha - p_1 > 0\)

Thus we can define Lagrangian in Period 2 with coefficient \(\lambda\), and in Period 1 with coefficients \(\delta\) and \(\mu\).

\[
L_2 = p_2 \ (1 - \gamma) N_B \ \theta (\overline{\alpha} - p_2) + \lambda [C - N_T (\alpha - p_1) - \gamma N_B (\overline{\alpha} - \alpha) - \theta (1 - \gamma) N_B (\overline{\alpha} - p_2)]
\]

\[
L_1 = p_1 [N_T (\alpha - p_1) + \gamma N_B (\overline{\alpha} - \alpha)] + \Pi_2 + \delta [C - N_T (\alpha - p_1) - \gamma N_B (\overline{\alpha} - \alpha) - \theta (1 - \gamma) N_B (\overline{\alpha} - p_2)] + \mu (\alpha - p_1)
\]

In order to find the sub-game perfect equilibrium, we solve the game backwards:

\[
\frac{\partial L_2}{\partial p_2} = (1 - \gamma) N_B \ \theta (\overline{\alpha} - 2 p_2) + \lambda (1 - \gamma) \theta N_B = 0
\]

Since in this intermediate case the constraint is binding, then \(\lambda > 0\) and thus

\[
C - N_T (\alpha - p_1) - \gamma N_B (\overline{\alpha} - \alpha) - \theta (1 - \gamma) N_B (\overline{\alpha} - p_2) = 0
\]

Therefore the price is represented by:

\[
p_2 = \overline{\alpha} + \frac{N_T (\alpha - p_1) + \gamma N_B (\overline{\alpha} - \alpha) - C}{\theta N_B (1 - \gamma)}
\]

Substituting this price into the Lagrangian of Period 1 yields the following:

\[
L_1 = p_1 [N_T (\alpha - p_1) + \gamma N_B (\overline{\alpha} - \alpha)] - \frac{[N_T (\alpha - p_1) + \gamma N_B (\overline{\alpha} - \alpha) - C][N_T (\alpha - p_1) + \gamma N_B (\overline{\alpha} - \alpha) + (1 - \gamma) \theta N_B \overline{\alpha} - C]}{\theta N_B (1 - \gamma)} + \mu (\alpha - p_1)
\]

Differentiating the Lagrangian with respect to \(p_1\) and equating to zero yields the optimal solution for \(p_1\). It is straightforward to check that if \(C > N_B \overline{\alpha} / 2 (\theta + \gamma (1 - \theta))\), then \(\alpha - p_1 > 0\), thus \(\mu = 0\), and the optimal price in the first period is represented by:

\[
p_1 = \frac{\overline{\alpha}}{2} + \frac{\gamma N_B (\overline{\alpha} - \alpha)}{2 N_T} + \frac{\beta(C)}{N_T + \theta (1 - \gamma) N_B},
\]

where \(\beta(C)\) is the capacity shortage, i.e., \(\beta(C) = \alpha N_T / 2 + N_B [\gamma (\overline{\alpha} - \alpha) + (1 - \gamma) \theta \overline{\alpha}] / 2 - C\).
Substituting this expression into the equation for \( p_2 \) yields:

\[
p_2 = \frac{\alpha}{2} + \frac{\beta(C)}{N_T + \theta (1 - \gamma) N_B}.
\]

If, however, \( C = N_B (\theta + \gamma (1 - \theta)) \alpha / 2 \), then \( \mu > 0 \), and the constraint is binding, i.e., \( \alpha - p_1 = 0 \). It follows that \( p_1 \geq \alpha \). Substituting this expression into the expression for \( p_2 \) yields the following optimal second price period for the low capacity case:

\[
p_2 = \alpha - \frac{C}{N_B (\theta + \gamma (1 - \theta))}.
\]

Note that when \( C = N_B (\theta + \gamma (1 - \theta)) \alpha / 2 \), the firm sells to all the business consumers at price \( p_2 = \alpha / 2 \). This generates the optimal unconstraint profits from the business segment. However, when the capacity exceeds that threshold, the firm continues to charge the competitive business price \( p_2 = \alpha / 2 \) until capacity is large enough such that the benefit revenues from the additional tourist consumers exceeds the loss from deviating from the optimal price for the business consumers segment.

The loss in selling to the business consumers is given by:

\[
p_1 N_B [\gamma + \theta (1 - \gamma)] - \gamma N_B (\alpha - \alpha) p_1^m - (1 - \gamma) \theta N_B (\alpha - \alpha^m) p_2^m.
\]

The revenues from selling to the tourist segment are given by:

\[
p_1^m N_T (\alpha - p_2^m).
\]

Equating these two equation yields the threshold capacity level:

\[
C_2 = \frac{N_T \alpha + N_T N_B [\alpha (\gamma + \theta - \gamma \theta) - \gamma \alpha] - \sqrt{[N_T (N_T - \gamma N_B) [N_T \alpha^2 - \gamma N_B (\alpha - \alpha)^2] [N_T + N_B \theta (1 - \gamma)]]}}{2 N_T},
\]

such that for any \( \alpha \), \( \alpha \) is the firm charges \( p_1 = p_2 = \alpha / 2 \) and for any

\[
C_2 < C \text{ the firm charges } p_1 = \alpha + \frac{\gamma N_B (\alpha - \alpha)}{2 N_T} + \frac{\beta(C)}{N_T + \theta (1 - \gamma) N_B}
\]

\[
\text{and } p_2 = \frac{\alpha}{2} + \frac{\beta(C)}{N_T + \theta (1 - \gamma) N_B}.
\]

Note, that \( \alpha N_T / 2 + N_B [\gamma (\alpha - \alpha) + (1 - \gamma) \theta \alpha] / 2 > C_2 \) for

\[
N_T \alpha^2 \geq \gamma N_B (\alpha - \alpha)^2 \text{ and that } \frac{\alpha}{2} (\theta + \gamma (1 - \theta)] < C_2 \text{ when}
\]

\[
N_T N_B \gamma - N_T \alpha^2 + \sqrt{[N_T (N_T - \gamma N_B) [N_T \alpha^2 - \gamma N_B (\alpha - \alpha)^2] [N_T + N_B \theta (1 - \gamma)]]} > 0.
\]

If this condition is not satisfied the firm moves directly from policy of low capacity to policy of intermediary capacity.