The Sell Up Potential of Airline Demand

by

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B.S., Civil Engineering
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Abstract

Differential pricing of air transportation plays an important role in the current theories of airline seat inventory management. The ability to recognize those passengers willing to "sell up", or pay more for a seat on a given flight is also important, yet it has received little research attention. The proper detection and booking management of these passenger types can allow air carriers to realize higher flight revenues.

This dissertation begins with an overview of airline pricing policies and seat inventory control management practices. Current fare structures and fare class designations are described in detail. Airline demand and consumer utility measures are then presented. Consumer behavior during the booking process, particularly in relation to sell up behavior, is discussed. Price elasticities of demand also play an important role in the prediction of sell up behavior.

An in-depth description of sell up and its measurement follow. Once specific flights have been identified as having sell up potential, a sell up strategy can be implemented. Methods of testing the revenue benefits/costs of a particular sell up strategy were developed and used in an actual airline environment. A study consisting of a preliminary sell up test followed by an expanded study incorporating different sell up strategies was performed. Revenue results of the sell up strategies are presented and the impacts of each policy are discussed. Price elasticities of demand were estimated for individual fare classes. In general, sell up was found to be flight specific and more prevalent in the highest two fare classes (in terms of fare values) while being almost non-existent in lower fare classes.

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Chapter 1

Introduction

The setting is an air carrier's reservation office. The phone rings and is answered by a reservations agent. The potential air traveler on the other end requests a seat on a specific direct morning flight from Boston to Los Angeles:

- Scenario One: This traveler requests a special promotional round-trip fare that was advertised in the newspaper for $199. The reservations agent, after typing the request into his computer screen, finds that the special fare is not available and offers the passenger a fare of $450 on the same flight. The passenger decides to try a competing air carrier who is offering the same promotional fare on a later connecting flight, since he is in no hurry to get to Los Angeles.

- Scenario Two: This traveler also mentions that she noticed the advertisement for the $199 fare from Boston to Los Angeles. The reservations agent is only able to offer this passenger a $450 round trip ticket, as well. The passenger decides to purchase the $450 ticket since her company is paying for it anyway and she has to be in Los Angeles for an afternoon meeting.

Behavioral differences between these two passenger "types" are of great interest to air carriers. In order to maximize airline revenues, it is necessary to try to satisfy both types of consumers. Enough seats must be available at special promotional rates to prevent the Scenario One passenger from traveling on a different air carrier. It is important, however, to restrict the number of these inexpensive seats in order to realize as much revenue as possible from the Scenario Two passenger. Determining just how many seats to reserve for the second type of passenger, who often makes last minute reservations, is a complex and challenging problem.

Price differentiation in air travel plays an important role in current theories of airline seat inventory management. This thesis discusses how to stratify the second type of passenger who is willing to "sell up", or pay more for a seat on a given flight.

There are numerous benefits associated with sell up. It is highly desirable from an air carrier's perspective to have sell up occur. The airline will gain higher revenue from the passenger, and the costs of carrying this passenger will remain the same regardless of which price is paid for a coach ticket. Thus, the potential exists to increase overall revenues without increasing costs. The air carrier is also able to fill an additional seat on a given flight. Not only does the carrier gain in terms of passenger revenues, but the passenger is given an acceptable flight which satisfies his/her travel needs.

It is important to correctly identify those flights which have sell up opportunities. In not recognizing sell up potential, the carrier loses in in terms of flight revenues. An excess of low fare seats will be reserved for Scenario One types of passengers, at the expense of not saving these seats for those passengers willing to pay higher fares. Potential demand for high fare seats will exceed the supply. Incorrect specification of flights as having sell up potential results in re·venue losses for the air carrier, as well. Too many seats will be allowed for Scenario Two types of passengers, with not enough passengers of this type to fill them. Supply of higher fare seats will exceed the demand. A proper balance must be found, where supply equals demand for each fare type.

1.1 Structure of Thesis

The remainder of this thesis is divided into five chapters. Chapter Two begins with a brief history of airline regulation and pricing policies during the time period prior to 1978. Deregulation and its resulting effects on the industry are then highlighted. The use of differential pricing methods in the development of current fare structures follows, along with a discussion of fare class designations. The chapter concludes with a description of current seat inventory management practices.

Chapter Three is an overview of demand and its relation to airline economic theory. Consumers' utility measures for different travel itiner ies are discussed. A description of consumer behavior during the booking process follows along with a summary of options available to a potential air traveler. This chapter concludes with a discussion of price elasticities of demand for air travel.

The concept of sell up is discussed in great detail in Chapter Four. The chapter begins with a description of the benefits of sell up to an air carrier. A brief history of past attempts to predict sell up behavior is presented along with a discussion of how to accurately predict the occurrence of sell up for a given flight. Once flights have been identified as having sell up potential, a sell up strategy can be implemented and tested using the revenue impact test developed. Measurement of price elasticities using the information obtained from a sell up strategy is discussed in the latter section of the chapter.

A sell up strategy developed and tested in an actual reservations environment in the fall of 1989 and spring of 1990 is the subject of Chapter Five. A preliminary sell up study followed by an expanded study incorporating different sell up strategies is described in detail. Revenue impact results, using measures developed in the previous chapter, are presented. Price elasticity measurements are also described.

Chapter Six concludes the thesis by giving an overview of research findings and contributions, as well as a brief discussion of further research directions.

Chapter 2

Airline Pricing Policies and Seat Inventory Management

2.1 A Brief History

In a completely unregulated market, price is determined by the natural forces of the market. Through a bargaining process between a seller (producer of the good) and a buyer (demander of the good), price is determined. In the airline industry, this process would consist of the airline as the seller with seats to be bought by the potential passenger.

As with other modes of transportation, the government regulated the airline industry for decades. The passage of the Civil Aeronautics Act in 1938 placed the Civil Aeronautics Board (with occasional help from Congress and the President of the United States) in charge of shaping the development of air transportation service and the air transport industry. No one could enter into the business of public air transportation unless authorized to do so by the CAB. Traffic between certain city-pairs and even the carriage of certain categories of traffic had to be approved in public hearings. Similarly, airlines could not lawfully terminate services to and from certain city-pairs without CAB approval.

Route authority was not the only area subject to strict regulation. Passenger fares had to be approved as well, and discrimination was prohibited. The Civil Aeronautics Board applied public utility "rate of return on investment" principles in its rate reviews and rate making, and all carriers were required to charge like amounts for like services. The CAB attempted to take all cost variables into account and then averaged the allowable costs into one overall formula. This formula was then used to represent the average industry cost level, and was used as a proxy for efficient operating cost levels under existing technology. The formula was expected to cover all allocated costs as well as a fair return on investment, and was applied to the industry as a whole rather than to individual carriers.

The Civil Aeronautics Board formula did take into account that unit operating costs vary inversely with flight segment length. A term was included to take this into account, and thus, fare per mile decreased with increasing distance. However, cost variation between routes was only reflected by differences in mileage. This resulted in an inflexible fare structure for coach service where identical fares were applied to all equal-distance markets, even though a higher or lower fare might have been more appropriate based on specific cost or marketing considerations. Above-average profits were realized on some routes and below-average profits on other routes. The CAB concluded that the public would be best served by this type of fare structure based on an averaging of profitability, as long as excess profits were not amassed and inefficient operating costs were not incurred.

Since much of the operating cost of a flight is for fuel, labor, and airport usage, the airlines could have gained additional revenue at comparatively little extra cost by offering discounts to passengers who might have not flown at full fare. This strategy was not possible, however, prior to deregulation. Fares were more or less constrained to two price-quality combinations, first class and coach.

Airlines set to differentiate themselves in other ways, due to the lack of pricing flexibility. Powerful drives were made toward product rather than price differentiation. Carriers strove to differentiate their identically priced services by offering varying frequencies, new equipment, alternate seating configurations, and often lavish in-flight and ground services. Fancy meals served on linen and china and piano lounges were not uncommon, as airline carriers competed for an increased market share.

Scheduled air service was characterized by other standard quality of service conditions. Carriers were publicly obligated to perform scheduled service regardless of actual on-board loads. Tickets could be refunded at any time with no cancellation penalty. If prices were lowered, the consumer could have the lower price, but was protected from price increases. These conditions, coupled with a relatively simple fare structure which remained stable over time, led to gross inefficiencies among air carriers.

2.2 The Advent of Deregulation

Airline regulation gradually came to be criticized, despite advances under the regulatory scheme, established with the Civil Aeronautics Act of 1938. The basic economic policies of the Act came under attack in favor of completely unrestricted competitive behavior. Tight government control of entry, exit, pricing and other competitive matters was widely questioned.

With the advent of the 1970s, an intensified push for deregulation of the airline industry began. Large increases in aircraft capacity due to wide-bodied jets, coupled with an economic recession, served to decrease overall load factors. CAB pricing policies were said to lead to airline inefficiencies, higher operating costs and, as a result, higher prices than necessary. The 1973 Arab oil embargo increased fuel costs substantially and airline operating costs soared. Traffic levels were again hurt by the recession, leading to a series of fare increases. The increase in operating costs was not exceeded by an increase in yields. All of this led to widespread speculation as to whether the airlines themselves might be better off without the CAB regulatory procedures.[10]

In July of 1975 a CAB report was issued based on a study of regulatory reform. Its overall conclusions were:

> "... protective entry control, exit control, and public utility-type price regulation under the Federal Aviation Act are not justified by the underlying cost and demand characteristics of commercial air transportation. The industry is naturally competitive, not monopolistic."[12]

The study recommended that route control (entry and exit) and public utility-type price control in the domestic air transportation industry be eliminated within three to five years.

A similar report was issued at about the same time by the Subcommittee on Administrative Practice and Procedure of the U.S. Senate Judiciary Committee. The report's most important message was that fares would and should be lower if a more competitive system were to be allowed. While the Subcommittee acknowledged that the Civil Aeronautics Board had been effective in maintaining reasonable industry profits, technological improvement, and industry growth, the Board's practices had not been effective in promoting low prices. It further stated that it was economically and technologically possible to provide air service at significantly lower prices than those currently available.[13]

The release of these two important studies led to the first deregulation bills sponsored by the Ford Administration in 1975. These bills culminated in the passage of the Airline Deregulation Act of 1978. The overriding theme of this act was to promote competition among airline carriers, which would lead to an increased range of price/service options and increased airline efficiencies. Restrictions on air carrier entry and exit were gradually eliminated over a three year period. Complete abolishment of route restrictions occurred at the end of 1981, and airlines were free to serve or to cease serving any and all domestic routes and cities. The provisions of the Airline Deregulation Act also dealt with domestic fare values. Rate regulation functions were amended to give more weight to the desirability of lower fares and increased pricing and service options, with the gradual phasing out of all pricing regulations. It was hoped that increased competition among air carriers would lead to lower fares.

2.3 Effects of Deregulation

The passage of the Airline Deregulation Act in 1978 was the impetus for a series of widespread changes in the airline industry. Routes served by each carrier, service levels, marketing strategies, operating costs, and pricing policies were radically affected by the advent of deregulation.

A major focal point for these changes has been the greatly increased emphasis on hub-and-spoke network scheduling by airlines. All carriers began to shift their primary emphasis from point-to-point nonstop service to hub-and-spoke patterns. Prior routes that did not incorporate service to/from a hub were abandoned. This new scheduling strategy provides an enormous multiplier effect as to the number of city-pairs a carrier can serve. Cost and operational efficiencies can be realized using this strategy, as maintenance, crew and training facilities can be conveniently located at hub airports. Service improvements favoring larger communities were realized, mostly due to the hub-and-spoke network development. In some cases, small communities received decreased levels of service, particularly with the phasing out of government subsidies for service to these areas. In general, more passengers received improved service than those receiving reduced service.

Marketing strategies began to expand after deregulation, as carriers improved computer reservation systems in hopes of increasing market share. The role of the travel agent increased, and airlines sought to provide innovative services to attract customer loyalties, such as frequent flyer programs. Operating costs decreased overall, as increased competition required carriers to make the most productive use of their resources. Technological advances made during this period served to further increase overall carrier efficiencies.

Deregulation also allowed airlines freedom in their pricing policies, allowing them to lower prices as well as to charge a multiplicity of prices. A selective offering of multiple price-quality combinations had the potential to induce more air travel and increase airline revenues in comparison to what would be realized if all consumers were charged the same price.

2.4 Differential Pricing

After deregulation, a carrier could offer any fare it wanted on any flight. It became possible to offer a wide array of discount fares for the same coach seat on a given flight. Changing fares was facilitated by posting new tariff conditions in a centralized data base to which all carriers and travel agents had access, as opposed to the elaborate previous procedure which required CAB approval. These legal and technological changes transformed the fare structure of the U.S. domestic airline industry into a complex, ever-changing system.

This new freedom in pricing led to the introduction of advance purchase excursion fares (APEX). American Airlines first introduced this type of fare into the U.S. domestic travel market in 1975 with its "super-saver" fares. APEX fares required an advance purchase of a round-trip ticket and a minimum length of stay at the traveler's destination. These fares were offered for standard coach seats and only differed from regular coach fares in their restrictions.

APEX fares were aimed at a different market segment than standard full-fare tickets. A "leisure" traveler, defined as a vacation-type traveler, was more likely to purchase APEX tickets. This type of passenger had a higher likelihood of knowing when he/she wished to travel in advance and was able to meet the advance purchase/minimum stay requirements. Business travelers, on the other hand, were more likely to travel at a last minute's notice. The nature of business travel forced this market segment to buy standard, full-fare tickets. These passengers were more willing to pay a higher fare in order to have the flexibility of making last-minute decisions to or not to travel, without penalty. The restrictions imposed on APEX fares were thus aimed at stimulating the market demand of vacation travelers (by offering lower priced fares), and keeping potential full-fare business travelers from purchasing these lower-priced tickets.

Airlines currently use a variety of methods to "fence out" (i.e. to prevent consumers from purchasing a lower fare than they are willing to pay) full-fare business travelers. The purpose of these "fences" is twofold: (1) To discourage air travelers who would normally pay for the convenience and flexibility of on-demand scheduled air service from taking advantage of low fares, preventing diversion of demand; (2) To allow as many new passengers as possible to enter the market who would not have done so at normal levels, stimulating demand. Examples of these fencing methods include advance booking and payment services, minimum stay restrictions, round-trip conditions, cancellation charges, and unchangeable bookings.[14]

The potential to increase revenues by filling up otherwise empty seats was recognized by airlines after deregulation gave them more freedom in pricing. In the short run, airline operating costs are fairly fixed. Thus, the marginal cost of carrying an additional passenger in a seat that would otherwise be empty is very small and would essentially consist of the cost of reservations, ticketing, baggage handling, and meal service. If revenue received by the additional passenger exceeds the marginal cost of carrying the passenger, a contribution will be made to the fixed cost of the flight.

A selective offering of a multiplicity of price-quantity combinations is often referred to as "differential pricing." This pricing method essentially charges each customer what he or she is willing to pay. The discount fare passenger can be distinguished from the full-fare passenger by charging different prices and applying fences to restrict diversion. Potential benefits of differential pricing include the stimulation of passenger demand, targeted at those who would not otherwise travel, filling seats that would otherwise go empty.

Differential pricing methods are designed to capture different segments of market demand. An extremely price sensitive passenger who is insensitive to time would be willing to conform to restrictions imposed in order to pay the lowest price possible. This passenger type wants the lowest fare available and is able to make travel adjustments as necessary. Vacation travelers often fall into this category. A particularly low fare could induce this passenger type to travel. Conversely, the unavailability of a low fare could cause this passenger to decide against travel. The most common type of passenger is both time and price sensitive. This passenger is somewhat flexible in making travel arrangements and will conform to some restrictions in order to pay a lower price. He/she cannot book far enough in advance in order to pay the lowest fare, but possibly might make re-arrangements if savings are big enough. Passengers who are time sensitive but price insensitive are most commonly the business travelers. This passenger type has to travel at a specific time and is not able to make advance arrangements. Flexibility and last minute seat availability are a necessity for this traveler and he/she is willing to pay a high price for these conveniences.

An example of the benefits of using differential pricing is shown in Figure 2.1. These graphs show the demand for a given flight using a classical linear demand curve. Ticket price P, is plotted against the quantity of seats sold, Q. The first graph shows the revenue potential of a flight offering only one fare value. The airline would set the fare at the point which would generate the highest number of passengers at the greatest fare. Revenue is defined as price times quantity of seats sold. In Graph A, this would result in P = 75 seats sold at a \$75 fare, generating \$5,625 in revenues. If the airline offered four fare classes, as in Graph B, \$8,775 in revenues could be generated from 100 passengers (10 x \$140 + 35 x \$105 + 30 x \$75 + 25 x \$50).

2.5 Current Fare Structures

Airlines that wish to segment demand for their product must design a variety of fare types which will be attractive to different types of travelers. The ideal product from an air carrier's perspective would minimize the diversion of demand, or minimize fence jumping by potential high fare passengers and would stimulate demand for the lower class fare product.

On any particular flight, a variety of fare classes can be offered with different restrictions applying to each fare class, in order to differentiate it from the others. Passenger demand for different fare levels is governed primarily by the rules and restrictions attributed to each fare. Fare classes are established on a market-by-market basis, taking into consideration historical demand levels and competing air carrier's offerings.

The airline industry makes use of a variety of techniques to "fence out" customers from particular fare classes. Advance purchase requirements are the most common restriction and are used in many travel markets. It has been shown that business travelers consider total travel time and travel convenience in making their trip plans, and typically make reservations an average of five days in advance compared with twenty-one days in advance for vacation travelers. Advance purchase requirements serve to prevent the diversion of business travelers to lower classes. Round-trip and minimum stay requirements often segment the market according to trip purpose.

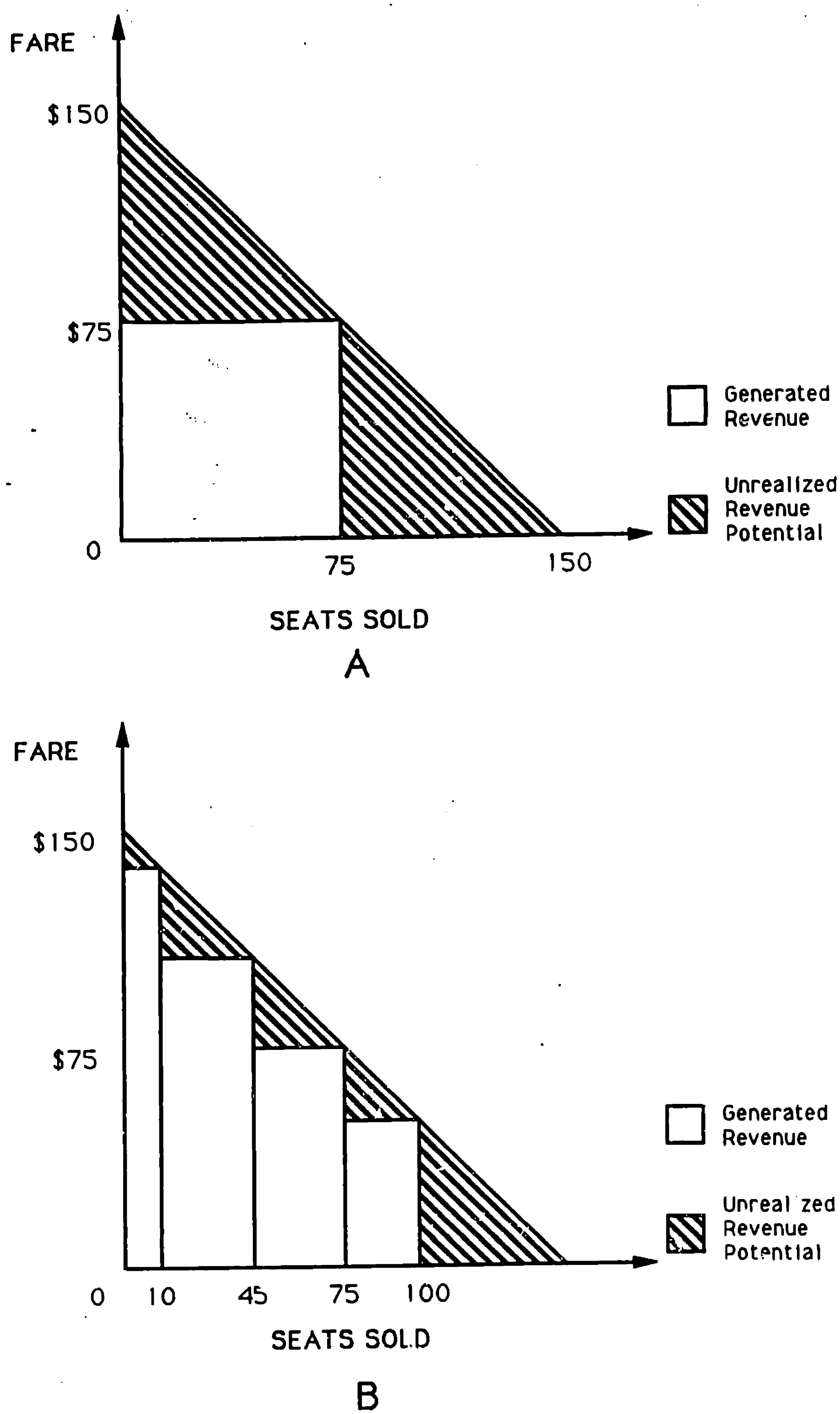


Figure 2.1: Revenue Potential of a Flight Using Different Fare Class Options

Passengers traveling for non-business reasons are more able to adhere to round-trip travel restrictions and are also more likely to stay at their destination longer. Business travelers, on the other hand, are forty percent less likely to travel round-trip, and due to the nature of their travel, stay at their destination for shorter time periods.[15]

The industry has thus found that those consumers willing to conform to round-trip and minimum stay requirements are generally price sensitive non-business travelers. Seven-day minimum travel and Saturday night minimum stay are common examples of travel restrictions used to segment fare classes. Non-stop travel is a convenience valued by business travelers who are time sensitive. A premium is often charged for the convenience of making a non-stop or one-stop trip. Day of week, time of day, and seasonal fluctuations allow air carriers to offer discounts during off-peak hours, days of week, and seasons. These discounts cater to the non-business travel sector. Market demand segmentation is possible when utilizing a combination of these techniques for any given flight.

First class and business class services are priced at a premium above full coach fares. These classes are aimed at price insensitive consumers and offer added amenities such as advanced check-in, upgraded meal service, free unlimited alcoholic beverages, complimentary movies and expanded seating and leg-room. First class is generally priced at up to fifty (50) percent above full coach fare, and is the most extravagant, prestigious class in terms of service. While first class service has been around for decades, the idea of a business class has appeared since deregulation. Business class serves as an intermediate class between first and full fare coach, and is aimed at price insensitive business travelers who desire upgraded service. Premiums for travel in this class are generally only ten (10) percent above full coach fare.

Most full coach (one-way) fares are based on a mileage-based or trip length formula without any restrictions. These fares are aimed at the price insensitive traveler who is often extremely time sensitive and desires flexibility in terms of reservations as well as possible last-minute cancellation ability. Amenities associated with this fare class often include advanced check-in for added convenience.

One-way discount fares are sometimes offered in very competitive markets that have heavy demand for strictly one-way travel. These discounts range from ten (10) to forty (40) percent off the full coach fare and often have up to one week advanced purchase restrictions. In general, consumers desiring one-way travel do not qualify for the weekend minimum stay requirements, which are often imposed upon the more heavily discounted round-trip fares. These passengers often must return to their origin during the same week. An example of this is a business traveler along the Boston-Washington, D.C. corridor who is somewhat price sensitive but wishes to travel within the five-day week period.

Excursion fares are even more deeply discounted and range from forty (40) to sixty (60) percent (or more) off of full coach fares. Various fare levels in this category are offered with increasing levels of restrictions as discount rates increase. Restrictions include advance purchase requirements, minimum stay specifications, cancellation penalties, and specific day of week travel. These fares were designed for passengers who are less time sensitive (i.e. flexible as to time and date of travel) and more price sensitive. Business travelers who wish to extend a trip over a weekend will take advantage of these fares, but they are most often utilized by vacation travelers who are able to plan in advance and be flexible in terms of time of travel.

Special promotional fares are often offered in highly competitive markets as a carrier's attempt to increase market share, or as a way to entice potential travelers (stimulate demand). These fares are often deeply discounted up to eighty (80) percent off of full coach fares. The introduction of these fares often induces "fare wars" among carriers, where price battles between airlines rage as a result of their attempts to remain competitive. The relative ease of changing fares in the deregulated airline industry has served to exacerbate fare wars. A complicated, often incomprehensible fare structure has resulted.

Different fare values and their corresponding restrictions are grouped into fare classes in the reservations sytem, for the purpose of controlling booking levels and accepting reservations. A specific fare product is a fare level and the restrictions imposed on the purchase of the ticket (if any). For example, a "HWE7P50" fare product is a "H" class ticket to be used for weekend travel ("W"), excursion product ("E"), seven day in advance purchase ("7"), with a fifty percent of the ticket price cancellation penalty ("P50"). Several fare products could belong to one particular fare class. An example of a major airline's fare products for the Boston Washington market, offered in March of 1990 is shown in Table 2.1.

In general, fare classes are specified by a particular letter code and correspond to a specific seating area of the plane. The letter "F" is commonly used to designate first class, and the letter "C" is often used for business class designations. Coach fare classes are generally more complicated, with the industry standard being "Y" designated for full fare coach, while all discounted seats may be specified as "B","M","H","Q","K", and "L" classes, in descending value. This fare class structure will be used throughout this thesis, but is just one example of a coach fare class specification. Fare class structures can differ between air carriers. All passengers purchasing seats in coach class ("Y" through "L" classes) will sit in the same coach section of the plane. Service characteristics differ only in the number of restrictions imposed on the fare classes, with "Y" class representing the completely unrestricted full fare coach fare, "B" class as a somewhat restricted, slightly discounted excursion fare, through "L" class, representing a highly restricted, deeply discounted promotional fare.

2.6 Seat Inventory Control

The potential benefits of filling otherwise empty seats with low-fare passengers that an airline would otherwise not have carried must be weighed against the possibility of displacing potential higher-fare paying passengers that would have been otherwise carried. The problem is further complicated by numerous flights operated by an airline during the course of a given time period, of which any one or combination of two or more could be used to carry a passenger to his/her destination. The existence of a multitude of fare classes for each flight and fluctuating levels of demand over time also makes the problem a difficult one to manage.

Seat inventory control addresses the issue of balancing the number of bookings in each fare class with the goal of maximizing total passenger revenues. By offering more seats at lower fares, an airline can capture extra passengers that would otherwise not have traveled. Too many seats at low fares will result in diversion of potential higher fare passengers to lower fares, lowering overall revenues. An airline is able to influence total yields, or the average revenue traveled per passenger mile, by applying effective seat inventory control techniques on a flight-by-flight basis, thus potentially increasing overall revenues.

Effective yield management, or revenue management, includes not only seat inventory control, but pricing techniques as well. However, fare classes are often

AIRLINE FARE PRODUCTS

FARE CODE	% DISCOUNT FROM FULL FARE COACH	ROUND TRIP FARE	ONE WAY FARE	CLASS DESIGNATION RESTRICTIONS
KXE14NR	-63%	$227		K-CLASS SERVICE #1, #2, #4, #6
QXE14NR	-59%	$248		Q-CLASS SERVICE #1, #2, #4, #6
KWE14NR	-56%	$268		K-CLASS SERVICE #1, #3, #4, #6
HXE7P50	-52%	$289		H-CLASS SERVICE #1, #2, #5, #7
QWE14NR	-52%	$289		Q-CLASS SERVICE #1, #3, #4, #6
MXE7P50	-49%	$310		M-CLASS SERVICE #1, #2, #5, #7
HWE7P50	-45%	$331		H-CLASS SERVICE #1, #3, #5, 7
MWE7P50	-42%	$352		M-CLASS SERVICE #1, #3, #5, 7
M9A3	-40%	$362	$181	M-CLASS SERVICE #8, #9
YN	-19%	$488	$244	Y-CLASS SERVICE #10
Y	--	$606	$303	Y-CLASS SERVICE
FN	5%	$638	$319	FIRST CLASS #10
C	7%	$648	$323	BUSINESS CLASS
F	50%	$906	$453	FIRST CLASS

RESTRICTION CODES:

#1	ROUND-TRIP TRAVEL ONLY
#2	TRAVEL 12 NOON MONDAY THROUGH 12 NOON THURSDAY
#3	TRAVEL 12:01P THURSDAY THROUGH 11:59P MONDAY
#4	NON-REFUNDABLE TICKET
#5	50% OF TICKET PRICE PENALTY FOR CHANGES IN TRAVEL PLANS
#6	14-DAY ADVANCE PURCHASE
#7	7-DAY ADVANCE PURCHASE
#8	3-DAY ADVANCE PURCHASE
#9	FARE APPLIES ON ONLY CERTAIN CITY PAIRS
#10	NIGHT FLIGHTS ONLY

Table 2.1: A Major Airline's Fare Products for the BOS-WAS Market; March 1990

set according to competitor's offerings in similar markets. It is the view of many managers in the airline industry, including the president of American Airlines, that the "most important aspect of fare competition is not absolute fare levels but the art of managing the mix of fares on a given airplane."[5] Seat inventory control is thus the aspect of revenue management that the airline has complete control over, with the potential to increase revenues on a flight-by-flight basis.

In seeking the best mix of passengers, the air carrier must be able to structure and manage its reservations system more effectively, setting appropriate limits governing the number of passengers in each fare class for a given flight. Different price/route combinations can then be evaluated with the goal of determining the best mix in terms of overall revenue. A computer-based system with an efficient revenue optimization model is necessary to meet the reservation monitoring objective.

On any given flight, operating costs are relatively fixed, and the marginal cost of carrying another passenger is small. Seat inventory control assumes the task of maximizing total revenues, which in turn serves to maximize overall profits for a flight. Thus, a model must be developed where the objective function is to maximize total revenues on a given flight subject to the limitations imposed by the flight capacity, schedule constraints, and the reservation system's ability. The type of aircraft for a specific flight is determined in advance, and thus the number of seats in the coach cabin can be determined. Schedules are posted in advance, and in most cases even fare classes can be assumed relatively fixed in the short term. The output from this model would be the optimal number of seats to make available in each fare class in the coach cabin in order to maximize revenues.

Proper yield management can be beneficial both from the standpoint of the passenger and the air carrier. The passenger is able to select from a variety of price/service options and yield management techniques are such that the price of a seat on a given day is dictated by demand. This demand-based pricing concept makes it possible for an airline to provide passengers with a level of service that would not otherwise be financially possible. The airline is able to generate higher revenues by allocating seats to different fare classes than by only using one fare class. Often, flights that would otherwise be unable to fully cover operating costs, are able to operate profitably, by using yield management techniques.

Demand for seats on a flight is extremely dynamic. Some forecast of demand levels is necessary in order to properly utilize a seat inventory control model. Using historical booking patterns, demand by fare class can be determined. Day of week, weekly, and seasonal fluctuations in demand must be accounted for in the forecasting process, as well as unusual situations such as holidays and regional special events. This information must be stored in the reservations system for use as inputs to the seat inventory control model.

Demand must also be monitored throughout the booking process as the number of requests changes due to cancellations and new reservations. Initial booking limits will be set for each fare class on a flight departure basis. Actual bookings relative to these limits must be monitored, and limits must be adjusted as bookings are accepted.

The complexity of this process is enormous. Booking limits must not only be set for each flight for local (non-connecting) traffic, but passengers with different origin-destination itineraries who utilize a flight as a connection must also be taken into account. In effect, decisions must be made on whether to allocate a seat to a local passenger or a connecting passenger in terms of maximizing flight revenues. With the development of the hub-and-spoke network system, the number of connecting passengers has increased substantially. A given flight leg can be used to serve as many as forty possible flight destinations. With as many as seven fare classes offered for each origin-destination market this creates two-hundred and eighty different potential fare classes per destination on a single flight leg!

Proper designation of booking limits per fare class on a given flight is an extremely important issue and a challenging problem faced by air carriers in today's deregulated environment. The potential to substantially increase revenues using seat inventory control methods has greatly increased the importance of revenue management. The process by which to allocate these limits is constantly being improved and modified in an effort to truly optimize revenues.

Chapter 3

Airline Demand and Booking Patterns

3.1 Air Transport Demand

Air transportation demand analysis relates the demand for air transportation to the socioeconomic activities that generate it. Its main purpose is to achieve an understanding of the determinants of demand and the manner in which they interact and affect the evolution of traffic volumes.[7]

Demand for transportation in general is unique in that it is a derived demand. Actual transit required by travel is not desirable, but is a means of being at certain locations at certain times. This need is derived from the desire to undertake certain patterns of activities. To understand the demand for air travel, it is necessary to understand the basic human desires for various activity patterns. From this understanding, one can derive the demand for travel to certain locations.

Air travel demand is a function of socioeconomic variables and system supply, or level of service variables. Two types of models exist for predicting transportation demand. A macro-model is useful in forecasting overall activity levels in air transportation, and deals with systemwide measures of air travel. A micro-model of air travel demand is more concerned with specific traffic flows, and can be used as a planning tool. The micro-model's results are often used as an input for a seat inventory management system, providing estimates of demand by fare class. The most common type of model in microanalysis is by origin and destination, often called a city-pair model. In general, a typical micro-model would follow the general formulation:

$$T = T(L, S) \tag{3.1}$$

where T = a measure of traffic

L = a vector of socioeconomic activity levels that determine the demand for air travel

S = a vector of transportation supply variables

The choice of L, the socioeconomic variables for city-pair models, must include several demographic measures. Population of the area served by an airport must be considered. A market area containing a large number of people is generally better for air travel than one with only a small population. However, population size alone is not often enough to predict air travel demand. Industrial structure gives a good indication of the types of air travel demanded. A structure based mainly on agricultural production would have a lesser potential for business travel than a structure with an emphasis on manufacturing. Employment statistics are also important and must include occupation type as well as disposable income measures on a per-capita basis. These variables will be very important in influencing leisure air travel potential. Other factors influencing leisure travel can be the age structure of the population and family structures. If an origin-destination pair is dominated by passengers traveling to or from other points (connecting passengers), socioeconomic data for these passengers must also be included in the model. This increases the complexity of the modeling procedure.

Supply variables S, can be specified in greater detail since the characteristics of the air transportation system connecting any two city-pairs is generally known. Level of air fares on a route are crucial variables, particularly for leisure travelers, where price elasticities tend to be high. Air fares of competing carriers will also play an important role in instances of high price elasticities. Travel time is an important consideration and represents the time costs of air travel. This variable will obviously play an important role in business travel demand, where time elasticities tend to be high. Frequency of service variables are used to measure trip convenience. The more flights available, the more convenient are departure and arrival times likely to be. Trip reliability measures are often included in terms of space availability, schedule reliability, and trip safety. Fares and characteristics of competing modes of transport must be taken into account on short-haul routes. Other possible level of service attributes include flight schedules, routings, and equipment types.

The importance of proper demand analysis to air carriers cannot be understated. Its use in forecasting future traffic volumes affects fleet acquisitions[1], scheduling, and route determination. The role demand forecasting plays in the seat inventory management process is of utmost importance. Precise forecasts of bookings yield better inputs into the seat inventory optimization procedure, which results in an improved allocation of seats among fare classes.

[1] In 1989, the price of a Boeing 767-300 was approximately 53 million dollars. One can easily see how important accurate forecasting methods are to the prediction of future fleet requirements.

3.2 Consumer Behavior

A model which effectively describes passenger demand for air travel is based on the theory of consumer decision-making. The behavior of a large number of individuals expressed in terms of aggregate quantities such as the market demand for an airline product is frequently of interest. This aggregate behavior is the result of individual decisions. The modeling of individual behavior is the basis of all models which predict aggregate behavior. Individuals face different choice situations and have varying tastes. While the goal is to ultimately predict aggregate demand, it is important to first treat the differences in decision-making processes among individuals. The term "individual" can be defined as any group that behaves as a single unit in making transportation decisions. For simplicity, the term *consumer* is often used here to denote a single decision-making unit.

The decision maker's environment determines what is often called the *universal set* of alternatives. A subset of this universal set, the *choice set*, is what the consumer considers on an individual level.[4] Any choice set is made from a nonempty set of alternatives. The choice set contains the alternatives that are feasible to the decision maker and those that are known during the decision process. In the airline reservations process, a choice set would consist of all flight itineraries acceptable to a particular consumer. Each alternative is discontinuous from the other alternatives in the choice set.

In general, a consumer with a desired travel itinerary will have a variety of air travel options from which to choose. The passenger will demand travel from his or her origin to a specific destination D_{ik}, which will be satisfied with a departure flight i, on a specific air carrier, k. In many cases, this passenger will also demand travel from the destination back to the origin in the form of a return flight R_{jk}, on flight j, traveling on carrier k. Each travel "package", or itinerary will be offered to the consumer at a certain fare class level L_{mk}, in fare class m, on carrier(s) k, which consists of the price and restrictions that come with a ticket purchase. Thus, a typical item within a consumer's choice set for a round-trip travel itinerary would appear as follows:

$$I_n = F(D_{ik}, R_{jk}, L_{mk}) \tag{3.2}$$

where I_n represents itinerary n.[2] The choice set itself for a consumer would consist of one or more alternatives. An N numbered choice set would follow the general formulation:

$$(I_1, I_2, \ldots, I_N) \tag{3.3}$$

For example, if a consumer was interested in traveling round-trip from Boston to San Francisco on the evening of February 9, returning on the evening of February 12, the choice set would consist of those flights with seats available during the two requested time periods which satisfy the individuals' constraints. Assuming that three travel itineraries fulfill the consumer's travel criterion the choice set would consist of the three different travel options. The characteristics of these three alternatives are listed in Table 3.1, ıd the choice set would appear as follows:

$$(I_1, I_2, I_3)$$

Each option would consist of the following:

$$\begin{aligned} I_1 &= F((D_{378,A;34,A}), R_{983,A}, L_{H,A}) \\ I_2 &= F(D_{123,B}, R_{269,B}, L_{K,B}) \\ I_3 &= F(D_{976,C}, R_{237,D}, L_{Q,C;Q,D}) \end{aligned}$$

Thus, itinerary one, I_1, begins with a departure on Flight 378 on Airline A connecting with Flight 34 on the same carrier. The return flight is on Flight 983 on Airline A, and the passenger would be booked in a Class H fare package. Itinerary two, I_2 consists of a departure on Flight 123 on Airline B, a return on Flight 269 on Airline B and the fare package is a Class K. The third itinerary I_3 consists of a departure on Flight 976 on Airline C returning on Flight 237 on Airline D, booked in Class Q.

A decision rule is necessary if two or more alternatives are available. This decision rule describes the cognitive process used by the decision maker to evaluate the information available in order to reach a specific choice. Utility measures can be a way of modeling individuals' choice. One can define a single objective function expressing the attractiveness of an alternative in terms of its attributes. This index of attractiveness is often referred to as *utility*, a measure that the decision maker attempts to maximize through his or her choice.

Economists have always assumed that individuals make those choices that are the most favorable to them. It is well known from the classical economists that:

> "An object can have no value unless it has utility. No one will give anything for an article unless it yields him (or her) satisfaction."[16]

It is recognized that individuals seldom take actions that are counter to their own best interests.

Since utility is used as a term for overall satisfaction, it is clear that this measure is affected by a variety of factors. The characteristics of a commodity or a combination of commodities are the same for all consumers. The personal element in consumer choice arises in the differences between collections of characteristics, depending upon individual preferences. Thus, the commodity does not give utility to the consumer, but it possesses characteristics, and these characteristics give rise to utility. In general, a commodity will possess more than one characteristic and many characteristics will be shared by more than one commodity.[8] The attractiveness of an alternative to a consumer is evaluated in terms of a vector of attribute values.

In comparing different attributes, the decision maker uses the notion of trade-offs in order to make an optimal decision. For example, it may be necessary for a consumer to pay a higher price for a travel itinerary, if this consumer desires a non-stop flight. The value that the consumer places on time will be the determinant of whether the higher price is paid. In contrast, a passenger wishing to obtain a highly discounted fare may be willing to make one or more connections in the itinerary, depending upon the passenger's value of time. Trade-offs between price and time will be made in either case. Relative importance of each characteristic to a consumer will vary according to individual tastes.

It must be noted that travel is not taken for the sake of travel itself. The purpose of travel, in most cases, is to be at a particular place at a specific time. This makes transportation demand, or specifically air transport demand unique, because the potential benefits associated with it are the benefits of arriving at a particular place at a particular time, and then returning to one's destination. The transport process does not impose much utility, but the end result (arrival at a specific destination) gives utility to the passenger. The trip imposes costs in terms of the passenger's time, as well as monetary costs, which can be referred to as the negative utility, or *disutility* of travel. In this case, instead of maximizing utility, the consumer is assumed to minimize disutility. The end result is the same.[9]

For the previous example of a potential air travel consumer making a decision between three different options, the characteristics of each itinerary (shown in Table 3.1) are reduced into three disutility values, $U(I_1), U(I_2)$, and $U(I_3)$. The traveler will select the flight with the lowest disutility, or the flight with the minimum generalized costs.

The disutilities of air travel are numerous, but can be grouped into three distinct groups:

1. *Monetary Cost*, M_i, refers to the actual price paid for travel. These values will vary widely, depending upon the fare class purchased. As shown in Chapter 2, a first class ticket can cost as much as one and one-half times the price of a standard coach class ticket. On the other hand, a deeply discounted special promotional fare can be reduced as much as eighty percent from the price of a standard coach fare. This attribute of a trip will be of more importance to those travelers who are highly price sensitive. Leisure travelers, in particular, will rank this characteristic highly on their list of important characteristics.

2. *Travel Time*, T_i, refers to the total time of travel. This characteristic can include a variety of factors. Actual departure and arrival times will play an important role in the consumer's decision-making process. Another important factor that can be included in this category is whether the trip will be a non-stop flight, one-stop or multiple-stop flight, or whether a connecting flight will be necessary. The disutility of travel increases with an increasing number of stops and connections from origin to destination because of necessary waiting and transfer times which increase the total time of travel. The possibility of unscheduled delays is increased with the number of stops and connections, as

well. Other factors which can be included into the travel time category include airport access and egress time (travel time to and from an airport), waiting time, and processing time. The travel time characteristic will be of greater importance to those travelers who are highly time sensitive. Business travelers most frequently fall into this category, and will place travel time on the top of their list of important attributes to consider.

3. *Convenience Attributes*, C_i, refer to the convenience, or in some cases the inconvenience of traveling on a particular travel itinerary. In certain higher fare classes, these variables are positively valued by the consumer (thus giving a negative disutility). An example of this would be first class travel, which allows the passenger to be pampered and travel in a more comfortable atmosphere. In general, reservations can be made without advance notice, and cancellations can be made without penalty. Discounted coach fare classes carry negatively valued convenience attributes which give disutility to a travel itinerary. These fare classes carry certain restrictions, or rules and penalties imposed on certain fare classes in order to "fence" out passengers who would be willing to pay a higher price to travel. Examples of these, as discussed in Chapter 2, are advanced purchase restrictions, cancellation fees, minimum stay requirements, and specific travel time restrictions. Some fare classes, such as first class, business class, and full fare coach classes, have no restrictions. Highly discounted coach class tickets have many restrictions imposed upon them, which give a high disutility to these fare classes terms of convenience. The number of stops on a given flight and the number of connections to be made can also be grouped into this category. As the number of stops and connections increases, the convenience to the passenger decreases. Other characteristics which can

be grouped into this category include trip reliability (on-time departure and arrival records), trip safety measures, and the convenience of travel-making arrangements.

Thus, a negative utility function, or a disutility function can be formulated for each travel itinerary, I_n, including each attribute which influences a passenger's choice. If we choose to express this choice in terms of minimizing disutility, rather that maximizing utility, the function can be expressed in terms of a *generalized cost* function:

$$U(I_i) = U(M_i, T_i, C_i) \tag{3.4}$$

The cost function thus gives a positive value to all negatively valued attributes (or disutilities), and is expressed in terms of the three main groupings of attributes described previously, monetary costs, M_i, time costs T_i, and convenience costs (or inconveniences), C_i. An example of different itinerary attributes for round-trip travel from Boston to San Francisco is shown in Table 3.1. Each itinerary can be differentiated in terms of its attributes, and the consumer will use an individual generalized cost function to determine which combination of these attributes best suits his or her preferences.

The objective is thus to choose the travel itinerary which minimizes the generalized cost to the consumer,

$$minimize U(I_i) = U(M_i, T_i, C_i)$$

or, to choose the alternative with the minimum cost by minimizing the objective function:

$$min[U(I_1), U(I_2), \ldots, U(I_n)] \tag{3.5}$$

ITINERARY		M_i	T_i	C_i
I_1 :	$(D_{378,A;34,A}, R_{983,A}, L_{H,A})$	\$350.00	8 hours	One-stop 14-Day Advance Purchase Non-Refundable
I_2 :	$(D_{123,B}, R_{269,B}, L_{K,B})$	\$500.00	6 hours	Non-Stop
I_3 :	$(D_{976,C}, R_{237,D}, L_{Q,C;Q,D})$	\$450.00	6 hours	Non-Stop 7-Day Advance Purchase

Table 3.1: Passenger Choice Set for Round-Trip Travel from BOS to SFO

In terms of travel itineraries, the consumer will have the following general cost function:

$$X_i = X(I_1, I_2, \ldots, I_n) \tag{3.6}$$

As stated before, I_n represents a consumer's choice set for a round-trip travel itinerary and is a function of the price and restrictions with a specific fare class level:

$$I_n = F(D_{ik}, R_{jk}, L_{mk})$$

Restrictions are imposed such that within the choice set:

$$I_i = \begin{cases} 1 & \text{if Itinerary i is chosen,} \\ 0 & \text{otherwise;} \end{cases}$$

Only one itinerary is generally chosen by the consumer:

$$I_1 I_2 = I_1 I_3 = I_2 I_3 =, \ldots, = 0 \tag{3.7}$$

Under these restrictions the general cost function can have only a finite possible number of values,

$$(X(1,0,\ldots,0), X(0,1,\ldots,0), \ldots, X(0,0,\ldots,1))$$

For the example used previously, where the consumer has three unique travel itineraries from which to choose, a generalized cost function expressed in terms of the attributes of the alternatives is as follows:

$$\begin{aligned} U(I_1) &= U(M_1, T_1, C_1) \\ U(I_2) &= U(M_2, T_2, C_2) \\ U(I_3) &= U(M_3, T_3, C_3) \end{aligned}$$

The function $U(I_i)$, which maps the attributes values to a generalized cost scale, is an ordinal generalized cost function.[4] Itinerary 1, for example will be chosen if and only if

$$U(I_1) - U(I_2) < 0$$

and

$$U(I_1) - U(I_3) < 0$$

The alternative I_1 will be chosen because the generalized cost:

$$U(I_1) < U(I_2)$$

and

$$U(I_1) < U(I_3)$$

$U(I_1)$ represents the minimum generalized cost, or minimum disutility to the consumer.

In the decision process, the consumer will first explicitly formulate preferences for all possible combinations of attributes. He or she will then identify all of the alternatives open, which are listed in Table 3.1, and will characterize each alternative in terms of its attributes. In this case, three alternative round-trip itineraries are acceptable to the consumer and have been identified in terms of their level of service attributes: monetary cost, travel time, and convenience attributes. The decision process follows from the definition of disutility. The consumer will choose the alternative that has the lowest disutility as determined by his/her expressed preferences. Trade-offs will be made between different attributes. When the consumer chooses itinerary one, I_1, the general cost function will appear as X (1, 0, 0). I_1 in this example consists of a departure flight with a connection $D_{378,A;34,A}$, a return flight $R_{983,A}$, at a fare level $L_{H,A}$. In this case,

$$I_3 \sqsupset I_2 \sqsupset I_1$$

or, itinerary one is preferred to itinerary two, which is preferred to itinerary three. This consumer obviously places a high value on monetary cost and is willing to make trade-offs in terms of travel time and convenience attributes in order to save money. Thus, although

$$T_1 > T_2 > T_3$$

and

$$M_1 < M_2 < M_3$$

the lower monetary cost of itinerary one overrides its higher travel time for this price elastic passenger. A more time sensitive consumer would select itineraries two or three. To this passenger, travel time would be of greater importance than the monetary costs, and tradeoffs would be made in order to obtain a shorter travel time.

3.3 Passenger Choice Options

Predicting human behavior is a challenging task. People are complex and their preferences and decision-making behaviors are different and constantly changing. It is necessary to understand this behavior in order to adequately predict future travel. Any model for explaining consumer behavior must consider: (1) what alternative choices consumers perceive; (2) what consequences these alternatives they consider important, and; (3) how they make their choices among the preferred alternatives.[9]

The decisions that a potential air traveler faces are first whether to make a trip, where to make a trip, at what time to make a trip, what route to take, and on what air carrier on which to travel. These decisions are highly interrelated. Some are fixed, depending upon trip purpose. For example, a business traveler would have the "whether", "where", and often the "time" fixed. A vacation traveler would be more flexible; all of the options are often open and sometimes determined simultaneously. In choosing among different alternatives, a passenger is influenced by his or her socioeconomic background and, most importantly, the level of service attributes of a trip.

Once a passenger decides to potentially make a trip and has some idea as to where he or she wants to go, outside help is necessary. In order to make a reservation, the consumer must make contact directly with a specific airline or travel agent. Although passengers can purchase tickets directly from an airline, most tickets today are purchased through travel agents. Agencies have been used even more by the public since deregulation, due to the increased number of flights being offered and to the extremely complex and often confusing fare structure that has ensued. According to one estimate, about 74 percent of the total revenues of U.S. airlines come from tickets bought through agents.[11]

In a reservations framework, whether with a travel agent or a specific air carrier, the passenger will make a request for travel. Some passengers will request specific flight numbers on a carrier, while others will simply give their desired destination and times of travel. Extremely price elastic travelers may simply give a price range as their only criterion of choice. In any case, if the consumer's request is satisfied, a seat on a specific flight at a fare class level will be assigned to the passenger in the form of a reservation. For example, a specific flight itinerary will be reserved for a passenger in the form similar to (D_{1A}, R_{2A}, L_{KA}), a departure flight, D_{1A}, a return flight R_{2A}, at a fare class level L_{KA}. These seats will be decremented from the booking limits set through seat inventory control methods. For example, if Class K on Flight 1 on Airline A has a booking limit of 25 seats, a reservation made in this class will decrement the available inventory to 24 seats.

What happens if a consumer's initial request is not satisfied? That is, upon selecting a particular flight/fare class option, suppose the request is refused due to a limited number of seats. The request could be denied due to limitations on the departure flight, the return flight, or on a specific fare class level on either flight. If a potential passenger's initial request is denied, an attempt will be made to offer another itinerary which matches the original itinerary as closely as possible. It is to the original airline's benefit if this "second-best" itinerary includes travel on their airline, in which case no revenue will be lost. On the other hand, the new itinerary could incorporate travel on another carrier, which would represent a revenue loss to the airline. From this, one can see why actions taken by passengers who are denied a specific flight itinerary are of concern to air carriers today.

Depending on the purpose of travel, several options are available to consumers who are denied a requested flight itinerary. If a potential passenger's choice set (I_N) contains more than one option, the passenger will choose the next best itinerary. One possible option to the passenger would be the choice of the same departure flight and return flight at a higher fare class (D_{1A}, R_{2A}, L_{QA}), where the price of a "Q" class ticket exceeds that of an "L" class ticket. In this instance, the passenger would be paying a higher value for the same departure and arrival flights. A price inelastic, time sensitive business traveler would be most likely to make this kind of a shift from a lower fare class (in this case "K" class) to a higher fare class ("Q" class). Conversely, a price elastic "leisure" traveler would be less likely to make this shift. A shift such as this is often called a *vertical shift*, and is defined as a shift up in fare classes on the same flight(s).

Another option could be chosen with perhaps a different return flight on the same airline, with the same departure flight initially requested, (D_{3A}, R_{2A}, L_{KA}). Depending upon the number of options within a consumer's choice set incorporating travel on the initially requested air carrier, the list could continue indefinitely. If this shift occurs on the same airline (i.e. the passenger chooses a different return flight on the same air carrier), the airline continues to receive the passenger's revenue. In this case, a *horizontal shift* occurs, or a shift to a different flight(s) on the same airline. This occurrence does not hurt the airline; passenger revenue is not lost.

Not every passenger will choose an itinerary which incorporates travel on the same carrier. There is a possibility that the next best itinerary in a passenger's choice set will consist of the following: (D_{4B}, R_{5B}, L_{LB}). In this case, the traveler has decided to make reservations on Carrier B, resulting in a reservation loss to Carrier A. This represents a *booking loss* to the airline and is what air carriers try to minimize. A booking loss is defined as a shift to a flight on another airline, incurring a loss in passenger revenue. Booking losses can also be incurred if a passenger decides not to travel at all, which also represents a revenue loss. The decision not to travel could occur if a passenger only had one itinerary in his or her choice set, or if all of the itineraries in a passenger's choice set were unavailable.

What causes these shifts to be made in terms of a consumer's generalized cost function, or disutility function? As stated previously, every individual has a unique generalized cost function, which explicitly gives a potential passenger's preferences in terms of trip attributes. The individual hopes to minimize this function, and therefore minimize the total disutility of travel. When choosing between different travel itineraries, a consumer is able to rank each itinerary in terms of order of preference in accordance with the attributes each itinerary possesses. In an airline reservations framework, upon being denied an initial request a passenger is often given several options from which to choose. These choices could incorporate potential vertical or horizontal shifts, or booking losses to the initial carrier if options are included incorporating travel on different air carriers. The option of not traveling at all is also a possibility, and can be included in the choice set.

Table 3.2 lists the three additional options made available to a passenger who is initially denied a request for travel on I_1. The passenger will make the next choice using the following rule:

$$min[U(I_i) - U(I_1)]$$

such that

$$U(I_i) < Z$$

or minimize the difference in generalized costs (minimize disutility) between itinerary one and the next best alternative. The variable Z represents the disutility of not traveling. Thus, the passenger attempts to choose the next best travel itinerary, making sure that the disutility of this itinerary is less than the disutility of not making the trip.

ITINERARY		UTILITY	PASSENGER CHOICE SHIFT
I_1 :	(D_{1A}, R_{2A}, L_{KA})	$U(I_1)$	—
I_2 :	(D_{1A}, R_{2A}, L_{QA})	$U(I_2)$	Vertical Shift, v
I_3 :	(D_{3A}, R_{2A}, L_{KA})	$U(I_3)$	Horizontal Shift, h
I_4 :	(D_{4B}, R_{5B}, L_{LB})	$U(I_4)$	Booking Loss, l
I_5 :	Not to Travel	Z	Booking Loss, l

Table 3.2: Example of Alternative Itineraries Offered to a Passenger

A passenger making a *vertical shift* would quantify, in terms of generalized costs:

$$U(I_2) - U(I_1) = min[U(I_2) - U(I_1), U(I_3) - U(I_1), U(I_4) - U(I_1), Z - U(I_1)]$$

Similarly, a *horizontal shift* will be made if

$$U(I_3) - U(I_1)$$

is the minimum difference in generalized cost to the passenger. A *booking loss* will be incurred if either

$$U(I_4) - U(I_1)$$

or

$$Z - U(I_1)$$

are the smallest differences in generalized costs.

Airlines are naturally interested in the proportion of passengers that, upon being refused their initial request for a travel itinerary, will choose another itinerary which incorporates travel on the same airline. This proportion has been referred to as the *recapture rate* by American Airlines, and is defined as the "likelihood that a customer whose initial reservation request is refused, makes a subsequent request on the same airline, and there is space available to satisfy this request."[1] Air carriers realize the impact that recapture has on all aspects of seat inventory control. Refused reservation requests could result in reduced airline revenues if passengers decide to travel on other carriers or not to travel at all.

In general, three possible alternatives exist to a passenger who is initially denied a request:

1. The passenger can choose the same travel itinerary at a higher fare class, or perform a *vertical shift, v.*

This option is often referred to as *sell up*, which refers to a passenger purchasing a higher fare class ticket on the same travel itinerary originally requested.

2. The passenger can choose from a different travel itinerary on the same airline, which is defined as a *horizontal shift, h.*

Both options one and two are included in the concept of recapture rate, RR, because they incorporate shifts within the same air carrier. In addition to shifts which improve the airline's recapture rate, another option exists to passengers:

3. The passenger can choose from a different travel itinerary on a different air carrier or decide not to travel at all, which results in a *booking loss, l* to the airline.

Air carriers hope to minimize the occurrence of this alternative because of its detrimental impact on passenger revenues.[2]

The percentage of total passengers that are originally denied a request who choose a particular alternative can be expressed in terms of *probabilities*. Thus, each alternative can be expressed as follows:

$P(v)$ The probability of a vertical shift, or the *sell up probability* if the passenger is initially denied a request.

$P(h)$ The probability of a horizontal shift if the passenger's original request is denied.

$P(l)$ The probability of a booking loss if the passenger is initially denied a request.

In terms of recapture rate, or recapture probability, $P(r)$:

$$P(r) = P(v) + P(h) \tag{3.8}$$

Also, once a passenger is denied his or her original request,

$$P(v) + P(h) + P(l) = 1 \tag{3.9}$$

which states that the passenger has three and only three alternatives when this occurs. Figure 3.1 incorporates these probabilities with the previous example used in Table 3.2 in the form of a flow chart, detailing various passenger choice options.

The above listed probabilities are of great importance to airlines. In order to maximize total revenues, an air carrier's objective function is to minimize the number of booking losses, which represent a loss in revenue to a carrier or, conversely, to maximize the number of recaptured passengers. By minimizing booking losses, the airline seeks to decrease the number of passengers being diverted to travel on other carriers. In maximizing the recapture probability, or vertical and horizontal passenger shifts, the air carrier seeks to retain passenger revenues when initial passenger requests are denied. Methods of measuring these probabilities and improving total air carrier revenues will be discussed further in Chapter 4.

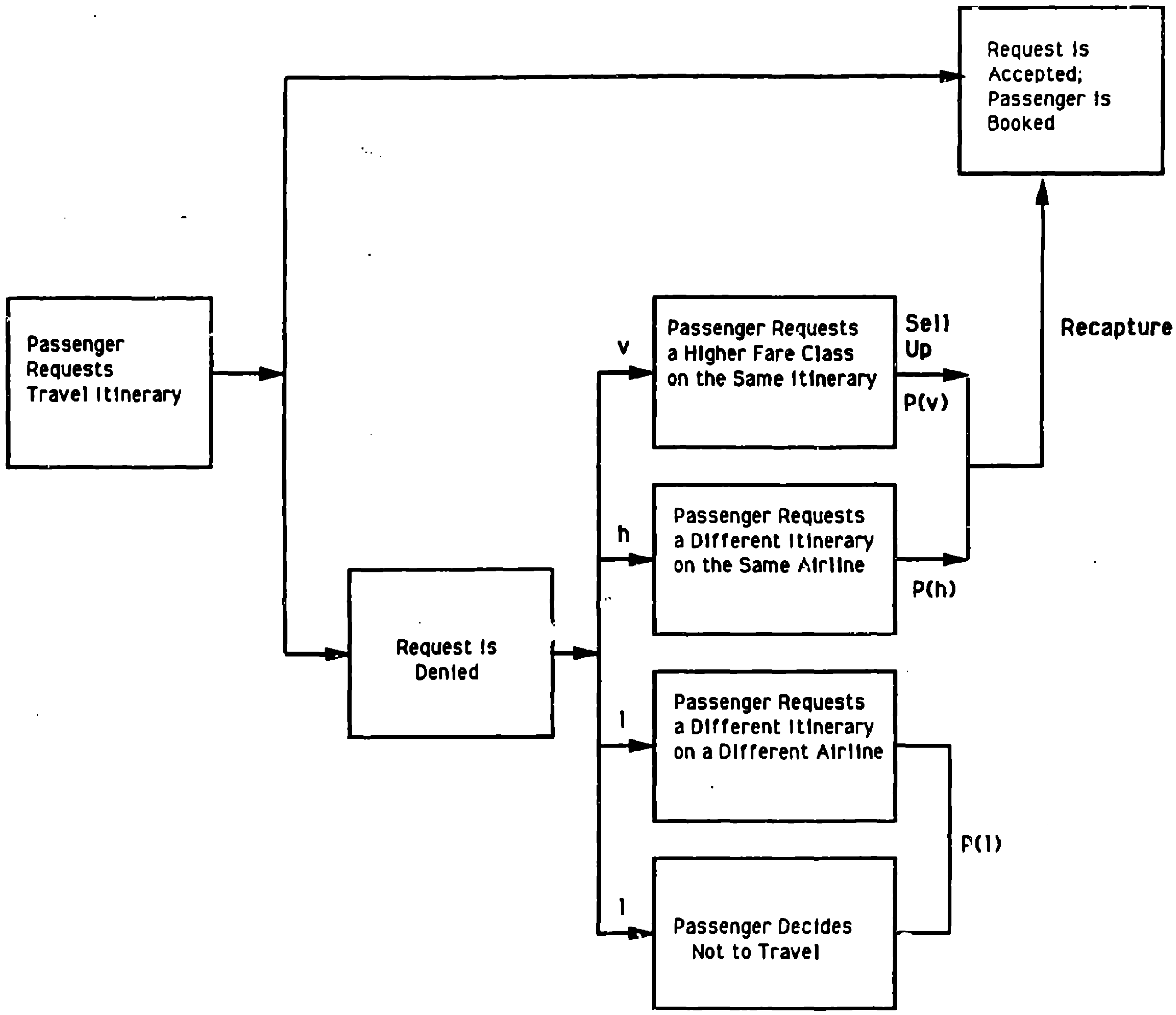


Figure 3.1: Passenger Choice Options

3.4 Elasticity of Demand

Sensitivity to different itinerary attributes can be related to consumer demand using elasticity values. Elasticities are used by economists to summarize how the changes in one variable of a demand function will affect demand for a product. For example, it might be of interest to measure how the change in the price of an item affects the quantity demanded. This is probably the most important application of the concept of elasticity and is referred to as the *price elasticity of demand.* Changes in the price of a good will lead to changes in the quantity demanded, and the price elasticity of demand is intended to measure this response. Formally, demand for air travel, D, depends upon many variables including the monetary cost of a ticket, M:

$$D = f(M, \ldots) \tag{3.10}$$

where the dots in the equation indicate the other variables that demand for air travel depend on. The elasticity of demand with respect to price is defined as[2]:

$$e_{D,M} = \frac{\Delta D}{\Delta M}\frac{M}{D} \tag{3.11}$$

This elasticity value tells us how D changes with respect to a percentage change in M. In most cases, $\Delta D/\Delta M$ is negative. This is explained by the fact that M and D are most likely to move in opposite directions. As the price of a product increases, demand for the product usually decreases. Thus, $e_{D,M}$ will usually be negative. For example, a value of $e_{D,M}$ of -1 would mean that a 1% rise in price would lead to a 1% decline in the quantity demanded.

If $e_{D,M}$ is less than negative one, a price increase is met by a more than proportionate demand decrease. Passengers who are highly price sensitive would exhibit

[2]This is actually the definition of a specific type of elasticity, an *arc elasticity*

this type of behavior and are referred to as *price elastic.* Demand is elastic if a given percentag change in price results in a larger percentage change in the number of passengers carried. Conversely, if $e_{D,M}$ is greater than negative one (and less than zero), quantity demanded will increase proportionally less than price increases. Air travelers who are more price insensitive will have this demand characteristic and are referred to as *price inelastic.* A given percentage change in price is accompanied by a relatively smaller change in the number of passengers carried.

Another way of determining elasticity is to see what happens to total revenue as a result of a price change. If demand is elastic, an increase in price will result in a decrease in total revenues, because the sharp decline in the number of passengers carried will not be offset by the increase in fare per passenger. The opposite will occur for inelastic demand, with an increase in total revenues resulting from a price increase.

Determinants of the elasticity of demand with respect to price are many. Business travelers tend to be less responsive to price changes than leisure travelers, and thus have more inelastic demand curves. These passengers are often on expense accounts and, due to the nature of their travel, are unable to make their reservations far in advance. Time of travel is much more important to them than the price of a ticket. In contrast, vacation travelers have a much more elastic demand curve for opposite reasons. Schedules are much more flexible with this type of passenger, and less importance is placed on time than price. The more competition from other carriers, the more price elastic is the demand observed by a single carrier. If there are three carriers offering similar flights to the same city within twenty minutes of one another and one carrier offers a lower fare, a passenger is more than likely going to fly the low-priced carrier.

Chapter 4

Measurement of Potential Sell Up Benefits

4.1 A Description of Sell Up

All aspects of seat inventory control are impacted by the reduction in revenues when a reservation is refused. The benefits associated with accommodating a passenger whose initial reservation request is denied are many; not only does the carrier gain in terms of passenger revenues, but the passenger is given an acceptable itinerary that suits his or her travel needs.

Sell Up refers to the *vertical shift* portion of recapture, and occurs when passengers purchase a ticket at a higher fare class level on the same travel itinerary originally requested. This phenomenon is highly desirable from an air carrier's perspective. The airline gains higher revenue from the passenger and the costs of carrying this passenger remain at the same level regardless of which fare class is purchased (in the coach cabin). The carrier is also able to fill an additional seat on a given flight. Thus, the airline increases its profits by the amount of the difference in the two fare class values.

For example, if the value of the original fare class requested is F_L, and the variable costs of carrying an incremental passenger is C, total profits, or contribution to fixed costs to the carrier in carrying an "L" class passenger would be:

$$Profit = \Pi_L = F_L - C \tag{4.1}$$

If seats are unavailable in "L" class, and the passenger is willing to purchase a ticket on the same flight itinerary at the higher fare class "K", the profit gained by the carrier becomes:

$$\Pi_K = F_K - C \tag{4.2}$$

Costs of carrying the passenger, C, remain the same regardless of which fare class in the coach cabin is purchased. The difference in profits to the carrier resulting from the sell up into "K" class is:

$$\Pi_K - \Pi_L = F_K - F_L = \Delta F_{KL} \tag{4.3}$$

Thus, the increase in profit to the airline is simply the difference in the fare class values, or the difference between "L" and "K" class fares.

The benefits to an airline of achieving sell up are obvious. The ability to increase revenues without affecting costs is a simple way to increase overall airline profits. How prevalent is sell up? Does it occur in every market? If not, which markets have a high occurrence of sell up and why? These are some of the questions to be addressed in this chapter and the chapters that follow.

4.2 Predicting the Occurrence of Sell Up

The larger the passenger choice set, the more difficult it is to predict sell up potential. One way of measuring sell up potential would be through the direct survey of passengers. Hypothetical situations could be presented to passengers surveyed, for instance, in a given airport. As an example, passengers would be asked what their course of action would be if their current itinerary package were not available (i.e. sold out). A variety of options would be presented to the persons surveyed, in the form of different travel itineraries. Each itinerary would, in effect, represent either a vertical shift, horizontal shift, or a booking loss to the original air carrier. The proportion of those passengers stating they would be willing to pay a higher price for the same travel itinerary would be the proportion of passengers willing to "sell up".

The Air Transport Committee of the Canadian Transport Commission (CTC), as part of an investigation of low priced air fares, performed a direct passenger survey of domestic (Canadian) scheduled air passengers using deeply discounted fares. The survey was conducted at Toronto and Vancouver airports over a three-week period in August of 1982. Passengers were asked (on a survey form) what their course of action would be if their current type of discount fare had not been available to them. Various alternative options were presented to the passengers surveyed, including the purchase of a higher priced ticket (a vertical or a horizontal shift), air travel to another destination (either a horizontal shift or a booking loss to an air carrier), travel on another mode of transportation, and the option of not traveling at all (the latter two of which would represent booking losses). The purpose of this survey was to explore the impact of deeply-discounted, weakly constrained air fare products from the point of view of traffic diversion and stimulation. It must be noted, however, that this survey incorporated travel on several carriers, and was not done for the purpose of measuring vertical shifts on a specific air carrier. The results of this study yielded stimulation/diversion rates for the three-week survey period.[6]

While the relative cost of performing such a survey would be low, its accuracy can be questioned. Passenger responses to such a survey are likely to be different from actual behavior. While the CTC survey yielded stimulation/diversion rates for different fare types, it would be difficult to incorporate this type of survey to include the measure of vertical shifts. To do so, one would have to find a way to present alternative available flight itineraries to a passenger, in order for the passenger to formulate a choice set and make a decision among itinerary/fare class packages. Reliable estimates of sell up are unlikely to come from this type of a survey.

Perhaps the most accurate way to estimate the proportion of passengers accepting vertical shifts would be to directly monitor reservation calls. In doing so, an airline could directly observe passenger behavior as alternate itineraries are presented, given that the passenger is denied an initial request. The proportion of those passengers accepting vertical shifts could be tabulated in a fairly accurate way.

Unfortunately, this method would require much time and effort to be expended observing and monitoring phone lines. A significant amount of elapsed time would be required for data collection due to the relatively low frequency of sell up opportunities. The costs of performing this type of study would be high in terms of the labor required to effectively monitor reservation calls. This method could also prove to be unreliable. Passengers frequently make a reservation in a higher fare class on their desired itinerary (accepting a vertical shift), only to seek lower fares on other carriers (resulting in a booking loss to the original carrier). It is possible for a passenger to make reservations on several air carriers, ultimately choosing the itinerary which best suits his/her travel needs. The existence of wait lists[1] serves to further complicate the matter of monitoring reservation calls.

[1] A "wait list" for a given flight/fare class package, where the passenger is given a reservation if cancellations occur from passengers already booked on the flight.

American Airlines conducted a pilot study at one of their reservation offices to observe what they refer to as " recapture behavior".[1] Recall that recapture behavior is defined by American as the likelihood that a customer whose initial reservation is refused makes a subsequent request on the same airline. It was their belief that recapture can be estimated by redistributing demand from a closed or canceled flight. This study did not give passengers the opportunity to perform vertical shifts; the simulation involved the closing of entire flights rather than the closing of specific fare classes on a given flight. Therefore, passengers were not given the option of purchasing a ticket in a higher fare class for the same flight itinerary.

American Airlines' study was performed on an extremely small scale. To reduce the time required to collect data through call monitoring, recapture opportunities were created by simulating the closings of flights. A consumer who made a call to the designated reservation office would first choose a preferred flight (or the preferred itinerary in his or her choice set). The consumer would then be informed that the flight was closed and would be hypothetically "wait-listed", or put on a waiting list for the flight. Alternate flight offerings were then given to the consumer. The consumer's desired choices were recorded. The option of booking on the initial preferred flight was then ultimately given to the consumer.

While only thirty sample calls were monitored, the results were somewhat consistent. In general, consumers were extremely flexible in terms of departure time and much more sensitive to changes in fares. Seventy percent of those surveyed were flexible up to four hours around the desired departure time, and thirty percent were flexible within one or two days of the desired departure time.[1] It is difficult to conclude that the consumers surveyed by American Airlines were a good, representative sample of airline passengers due to the small sample size. Any specific inferences about the rate of recapture cannot be made from the results of the pilot study. The fact that consumers were more flexible relative to travel times indicates that those surveyed *in this study* were less time-sensitive than price-sensitive.

A large scale study of this type with simulated *class* closings as opposed to flight closings could be extremely effective in the measurement of sell up potential. It would be necessary to monitor different types of markets, both those with a high proportion of business travelers and a high proportion of leisure travelers. Acquiring a good passenger mix would yield a more representative sample of overall market demand and its relation to recapture rates, or the probability of sell up, depending upon which statistic is desired.

Unfortunately, this type of survey cannot be performed in a travel agency environment and could only be done from an airline's reservation department. Flight availability displays are generally biased towards the airline in question when reservation requests are made directly to a specific carrier. Any estimates of the recapture rate using surveys performed solely in an individual carrier's reservation department would most likely be too large. If it is difficult to accurately predict sell up behavior using passenger surveys, what other methods of predicting this occurrence exist?

The issue of passenger choice shifts was incorporated into a seat inventory management model developed by Peter Belobaba in his doctoral thesis[2], published in 1987. Belobaba developed a model in conjunction with Western Airlines, referred to as the Expected Marginal Seat Revenue Model (EMSR Model). The model consists of a revenue optimization procedure which is used to set and revise fare class booking limits for future flights, by departure. It attempts to maximize flight revenues by determining the optimal number of seats to be authorized for sale in each individual fare class. These seats are "nested", or structured such that a high revenue fare request (e.g. "Y" Class), will not be refused as long as any seats remain in the lower fare classes. Inputs to this model are historical demand data, average fares, and current bookings.

The EMSR model was extended to include the possibility of vertical choice shifts in the booking process. Only the probability of vertical choice shifts, $P(v)$, or the sell up probability, was considered in the model which manages seat inventory on a single flight leg. While horizontal shifts, $P(h)$, are often of interest to an airline in terms of keeping passengers within the carrier, in order to simplify matters, only revenues on an individual flight basis were considered. Thus, the model was formulated on a micro (individual flight) rather than a macro (total carrier) revenue basis. Vertical shifts from one fare class to the next highest fare class were assumed to be the only shifts that occur. A vertical shift of two or more fare classes was therefore considered unlikely.

Output from the EMSR model is the optimal number of seats to be protected for the use of the highest fare class, and in turn for each successively lower fare class in a nested manner. If the potential for sell up exists, there is a probability that a passenger who is refused a seat in one fare class will request a seat in the next higher fare class. For example, if "B" Class is directly below "Y" Class in terms of relative cost, the probability $P_B(v)$ is the probability that a passenger will vertically shift to the next higher fare class, "Y" Class, upon being denied a seat in "B" Class. Probability values would exist for each successively lower fare class, $P_M(v)$, $P_H(v)$, $P_Q(v)$, $P_K(v)$, and $P_L(v)$, in order of descending relative cost. In his thesis, Belobaba addressed how these probabilities can be incorporated into the EMSR model in order to take into account the potential for revenue in a fare class if the class below it is closed.[2]

Including vertical shift probability values into the EMSR model serves to increase the protection levels for each of the higher fare classes. Each lower fare class will have its booking limit value decrease by the incremental level of protection required to account for the possibility of vertical choice shifts. The relative magnitude of this increase in seats protected for the higher fare classes depends on the magnitude of the probability value; if $P_B(v)$ is high, then the number of seats to be protected for "Y" class will increase by a larger amount than if $P(v)_B$ is low. This shows the importance of the estimation of the $P_i(v)$ values.

Unfortunately, the model actually tested at Western Airlines was a basic version of the EMSR model, which did not incorporate the probability of vertical shifts into its formulation. The effectiveness of this proposed version of the model incorporating sell up probabilities has yet to be tested.

One of the difficulties involved with implementing such a model into an actual reservations system lies in the estimation of the $P_i(v)$ values. How can one obtain accurate estimates of these probability values? Historical booking data can be used to estimate $P_i(v)$ values by observing past instances of sell up behavior. The best that can be done, however, is the inference of these sell up probabilities; their true values cannot be determined.

Sell up probability values will be different on a flight by flight basis. In order to increase sell up opportunities, it is important to identify those flights with high sell up potential. Some flights will have a high occurrence of sell up; others will not have any instance of it. Sell up potential is founded in consumer choice theory. Each passenger has his/her own sell up potential for a given flight itinerary, independent of overall flight demand. In general, however, sell up will be prevalent on high demand flights. On these flight itineraries, a passenger is more likely to be denied an initial itinerary/fare class request. Thus, while an individual's sell up potential is unaffected by overall demand for a flight, the necessity to perform some type of a shift increases with increasing flight demand. Those flights with historically high demand levels should therefore have a higher overall sell up potential than those that typically experience lower demand levels. Sell up probabilities will fluctuate on a seasonal, monthly, weekly, and daily basis due to fluctuations in demand. Peak travel periods such as major holidays will have a higher potential for sell up than off-season travel times. Similarly, heavily traveled days of week such as Monday flights in a predominantly business travel market will have more of a sell up potential than a day such as Saturday, which usually experiences low levels of demand for business travel.

It is possible for a passenger to shift two or more fare classes, instead of just one fare class, as assumed previously. Thus, if "M" class is sold out, it is possible for a consumer to purchase a "Y" class ticket instead of shifting only one fare class and purchasing a "B" class ticket. Possible explanations for this occurrence could be the dislike of the restrictions imposed on "B" class tickets, the ability to potentially upgrade to business or first class with a "Y" class ticket, or simply because "B" class is sold out.

In general, a larger probability exists for sell up in fare classes of a higher revenue value. This can be explained by the passenger types which purchase different fare class tickets. Business travelers, who are normally less price sensitive and more time sensitive, would be the most likely to accept a vertical shift. In doing so, they are able to travel on the same flight initially requested, but will be paying a higher price. These travelers are more apt to purchase tickets in higher fare classes due to the nature of their travel.[2] In contrast, leisure travelers are less likely to sell up due to their high price sensitivity and flexibility in terms of time of travel. These passengers are more likely to accept horizontal shifts or represent booking losses to the air carrier in their search for the lowest possible fares. Leisure travelers typically purchase tickets in lower fare classes due to this price sensitivity. Thus, it can be hypothesized that:

$$P_B(v) > P_M(v) > P_H(v) > P_Q(v) > P_K(v) > P_L(v) \tag{4.4}$$

because passengers requesting tickets in higher fare classes are more likely to sell up. Markets which have a large proportion of business travelers often generate a higher probability for sell up in the higher fare classes than leisure markets due to this phenomena.

Highly competitive markets have a lower sell up potential compared to those markets which are dominated by one or a few carriers. The reasoning behind this statement is simple; if a fare class is closed to a consumer and many other options exist (as in a highly competitive market), the chance of that consumer shifting to a different flight itinerary is high. The probability of a vertical shift in a competitive market is low due to the numerous other itinerary options available to a passenger. If the market is dominated by one carrier or relatively few carriers, the passenger will be more likely to perform a vertical shift if the initially requested itinerary is unavailable, simply because not as many other options exist.

In summary, when trying to identify flights with high sell up potential, the following general guidelines can be followed:

1. The flight should experience historically high demand levels.

[2] For a more in depth discussion on the tendencies of different types of travelers, see Chapter 2.

2. A larger proportion of business travelers increases the probability of sell up.

3. A large amount of competition from other carriers serves to decrease sell up potential. Thus, the carrier in question should be a fairly dominant carrier in the flight's market.

Note that it is not necessary for all of these guidelines to be fulfilled in order for a market to have sell up potential. The above statements simply represent a summary of general criteria for identifying sell up potential on a market basis.

4.3 Revenue Impact Measurements

Once flights that have the potential for sell up have been identified, a sell up policy, or strategy can be implemented into the reservations system. This sell up policy would serve to induce vertical choice shifts, with the intent of increasing overall flight revenues. Before implementing such a strategy, it is important to test what kind of an impact the sell up policy will have on passenger bookings and most importantly, overall flight revenues.

To test the effects of a potential sell up policy, a *revenue impact test* can be performed on those flights targeted to have a sell up strategy implemented. This impact test compares the overall flight revenues of two types of flights in the same market, a sell up flight, s, and a control flight, c. The sell up flight(s), s, is the flight for which the proposed sell up policy will be implemented. The control flight(s), c, will be managed using ordinary seat inventory control methods described in Section 2.6. This flight will be used as a comparison to test the revenue impact of the sell up strategy. The two flights types must exhibit as many similarities as possible.

For example, it is essential that both traverse the same origin and destination pair. Other similarities must exist, such as the same flight number across different days of the week, or the same flight number and day of week across different weeks. In any case, in order to minimize revenue differences due to fluctuations in demand across different flights, the sell up flight and the control flight must contain as many idenitical characteristics as possible.

The idea of using a control flight is akin to the case control method used in many medical studies. The idea is to pair two individuals with "identical" characteristics who only differ in a single relevant variable. The revenue impact test attempts to do this in using a sell up flight and a control flight, with the only difference between the two being the seat inventory control procedure used. It must be noted, however, that as in the case control method, stochastic variability in demand between the sell up flight and the control flight will occur since the flights are drawn from random samples. Revenue impact measurements described in this section will attempt to minimize these differences. It is possible, however, for variations in demand not due to the sell up strategy to exist between the two comparison flights. These demand variations could influence revenue results.

In general, the revenue earned R^k_m, on a particular flight k, in fare class m, will be:

$$R^k_m = f_m \sum_{j=J}^{0} b^k_{mj} \tag{4.5}$$

where f_m represents the fare value in class m, and b^k_{mj} represents bookings accepted in class m, day j prior to departure, on flight k. J is the first day that a reservation is booked in class m (e.g. if the first reservation to be booked in "M" Class is sixty days prior to departure, $J = 60$), and these bookings will continue to Day 0, which is the day the flight departs. Thus, the revenue earned by class is the fare value of the class multiplied by the total daily revenue bookings received in that class.

Total revenue for a flight, R^k_{tot}, can be expressed as a sum of the revenues earned by class:

$$R^k_{tot} = \sum_{m=1}^{M} R^k_m = \sum_{m=1}^{M} (f_m \sum_{j=J}^{0} b^k_{mj}) \tag{4.6}$$

To test the *revenue impact difference*, ΔR between two flights, where k is equal to either s, the sell up flight or c, the control flight,

$$\begin{aligned} \Delta R_{tot} &= R^s_{tot} - R^c_{tot} && (4.7) \\ &= \sum_{m=1}^{M} (R^s_m - R^c_m) && (4.8) \\ &= \sum_{m=1}^{M} (f_m \sum_{j=J}^{0} (b^s_{mj} - b^c_{mj})) && (4.9) \end{aligned}$$

Thus, the total revenue difference between the sell up flight and the control flight is the difference between the revenue values of each flight. The revenue impact, ΔR, can be expressed on a class by class basis if necessary. If the sell up policy is successful and produces an improvement in overall flight revenues, positive benefits will be incurred, and ΔR_{tot} will be greater than zero. In contrast, if the policy yields negative benefits, the value of ΔR_{tot}, will be less than zero. To sum, if

$$R^s_{tot} > R^c_{tot} \tag{4.10}$$

then the sell up strategy has been effective in that it has improved flight revenues. On the other hand, if

$$R^s_{tot} < R^c_{tot} \tag{4.11}$$

flight revenues decreased with the implementation of the sell up policy.

An example of a potential sell up strategy would be to close "M" class seven days prior to the sell up flight's departure. Passengers requesting reservations in

"M" class from Day 7 to Day 0 would be denied this option and would have the opportunity to sell up into either "B" class or "Y" class, in ascending fare value order. It is assumed that lower fare classes ("H", "Q", "K", and "L" classes) are closed[3] to the passenger due to advance purchase restrictions (or due to a nested reservations system). Seat inventory management on the control flight would be performed as usual with no premature class closings.

In order to test the impact of this particular sell up policy, an *incremental revenue test* can be performed. This test would measure the revenue impact difference between the sell up flight and the control flight. Differences in flight revenues would only be measured from Day 7 ($j = 7$) to Day 0 ($j = 0$), since this is the time period during which the sell up strategy is to be implemented. Revenue impact is measured for Classes "M", "B", and "Y" only. Any lower valued fare classes are considered closed at Day 7 due to restrictions and it is assumed that these classes' revenues will not be affected by the proposed sell up policy. Sell up is thus considered for vertical shifts between Class "M" and Class "B" and also between Class "M" and Class "Y" (a shift of two fare classes).

The revenue impact difference, ΔR for this particular flight would be:

$$\begin{aligned} \Delta R &= f_Y \sum_{j=7}^{0} (b^s_{Yj} - b^c_{Yj}) + \\ & \quad f_B \sum_{j=7}^{0} (b^s_{Bj} - b^c_{Bj}) + \\ & \quad f_M \sum_{j=7}^{0} (b^s_{Mj} - b^c_{Mj}) \end{aligned} \tag{4.12}$$

Revenue impact difference is thus the sum of the revenue impact differences for Classes "Y", "B", and "M", which are the classes affected by the sell up strategy.

[3] "Closed" denotes that no additional reservations may be accepted in this fare class

The first and second terms of the above equation will most likely be positively valued due to sell up from Class "M" to Classes "Y" and "B". The third term will probably be negative due to the loss in bookings experienced when prematurely closing out Class "M" of the sell up flight. The question then becomes whether the positive benefits gained by sell up in "Y" and "B" classes will outweigh the negative benefits incurred when prematurely closing "M" class of the sell up flight. If

$$f_Y \sum_{j=7}^{0} (b^s_{Yj} - b^c_{Yj}) + f_B \sum_{j=7}^{0} (b^s_{Bj} - b^c_{Bj}) > f_M \sum_{j=7}^{0} (b^s_{Mj} - b^c_{Mj}) \tag{4.13}$$

then

$$\Delta R > 0$$

and the sell up flight has yielded more revenue than the control flight. Conversely, if

$$f_Y \sum_{j=7}^{0} (b^s_{Yj} - b^c_{Yj}) + f_B \sum_{j=7}^{0} (b^s_{Bj} - b^c_{Bj}) < f_M \sum_{j=7}^{0} (b^s_{Mj} - b^c_{Mj}) \tag{4.14}$$

then

$$\Delta R < 0$$

and the sell up flight has lost revenue in comparison with the control flight.

The revenue impact difference can be generalized for any given sell up policy as follows:

$$\Delta R = \sum_{m=v}^{M} (f_m \sum_{j=t}^{0} (b^s_{mj} - b^c_{mj})) \tag{4.15}$$

where v is the lowest fare class that is affected by the sell up policy and t is the first day that the sell up policy is implemented. In the previous example, Class v would be equated to Class "M" because the sell up strategy affected Classes "M" and higher. Day t in this case is Day 7, the day that Class "M" was closed. Of course stochastic fluctuations in demand across flights must be taken into account between the sell up flight(s) and the control flight(s).

The costs of implementing a sell up policy must also be considered. In some cases, the overall difference in revenue, ΔR may be positively valued, but of a small magnitude. A small improvement in flight revenues may be attributed to an outside cause (such as demand fluctuations) other than the sell up policy. Also, if ΔR is of a small magnitude, this slight increase in flight revenues due to a sell up policy may not offset the costs of implementing such a policy.

4.4 Revenue Slope Changes

To test the incremental revenue between the two types of flights on a class by class basis, a *daily incremental revenue test* can be performed. This test measures the net change in revenues for a flight on a daily basis. The daily change in revenue in class m evaluated at day j is denoted as:

$$\Delta R^s_{mj} = R^s_{mj} - R^s_{m,j-1} \tag{4.16}$$

where the change in revenue is equal to the difference of the revenue values between day j and day $j-1$ for class m.[4]

The *revenue slope change* can be determined in a similar fashion, where RS^s_{mj} is the revenue slope change associated with class m on day j of the sell up flight:

$$RS^s_{mj} = \frac{R^s_{mj} - R^s_{m,j-1}}{R^s_{,j-1} - R^s_{m,j-2}} = \frac{\Delta R^s_{mj}}{\Delta R^s_{m,j-1}} \tag{4.17}$$

Revenue slope is thus the ratio of the net change in revenues from day j to day $j-1$ to the net change in revenues from day $j-1$ to day $j-2$. If this value is greater

[4] Recall that $R^c_{mj} = f_m \sum_j b_{mj}$.

than one, the revenue for a particular fare class is increasing at an increasing rate. A value less than one for RS^s_{mj} would indicate fare class m revenues increasing at a decreasing rate.

The revenue slope change concept can be used in terms of bookings by class as well:

$$BS^s_{mj} = \frac{\sum_j b^s_{mj} - \sum_j b^s_{m,j-1}}{\sum_j b^s_{m,j-1} - \sum_j b^s_{m,j-2}} = \frac{\Delta b^s_{mj}}{\Delta b^s_{m,j-1}} \tag{4.18}$$

where BS^s_{mj} is the booking slope change associated with class m on day j for the sell up flight. Daily booking values are substituted for revenue values in Equation 4.17. If $BS^s_{mj} > 1.0$, the bookings for class m are increasing at an increasing rate. In contrast if $BS^s_{mj} < 1.0$, bookings are increasing at a decreasing rate.

A successful sell up strategy might incorporate slope changes as a method of evaluating sell up performance. In this way, revenue growth or booking patterns would be constantly monitored. A revenue slope change greater than one would indicate that the sell up strategy is proving to be successful on a net revenue basis, assuming that revenues are increasing at an increasing rate due to sell up. Low revenue slope change values would serve as a warning signal to re-set booking limits in order to generate higher revenues in classes which are closed due to a sell up strategy.

An optimal sell up model would restrict the number of seats in fare classes known to generate sell up without completely closing out any fare class. In this way, if a flight experiences uncharacteristically low demand levels, it will still be possible for some bookings to be made in these fare classes. A model that continuously monitors slope changes during the booking process could adjust booking limits accordingly. This would serve to prevent revenue losses due to premature class closings, should demand levels be lower than expected.

4.5 Price Elasticity Measurements

In general, passengers in each market segment will have different preferences. The relative importance different travelers will place on fare values will vary according to trip purpose, times of day, days of week, and weeks of the year. In this section, we will concentrate on different traveler types for a given flight.

The idea of price elasticities, can be related to the concept of sell up. The price inelasticity of passengers requesting tickets in higher-priced fare classes results in a larger probability of sell up. Business travelers who typically purchase tickets in these fare classes are willing to pay more for a seat on a given flight. Highly price elastic leisure travelers are less willing to sell up. This passenger generally purchases tickets in lower fare classes due to price sensitivity. Just as Equation 4.4 relates sell up probabilities $P_m(v)$ for a given fare class m, an assumption can be made that elasticities for a given fare value f_m, e_{D,f_m}, are related as follows:

$$0 > e_{D,f_Y} > e_{D,f_B} > e_{D,f_M} > e_{D,f_H} > e_{D,f_Q} > e_{D,f_K} > e_{D,f_L} \tag{4.19}$$

Since sell up probabilities increase with increasing fare class values, it can be assumed that fare class elasticities also increase (become less negatively valued) with increasing fare class values, due to the relation of sell up probabilities to the elasticity concept. Thus, the elasticity of demand with respect to price in fare class "Y", e_{D,f_Y}, should be less than the elasticity of demand with respect to price in fare class "B", e_{D,f_B}, and so on, with "L" class having the most negative elasticity value. Intuitively, this makes sense because passengers requesting tickets in higher fare classes are more price inelastic than passengers in lower fare classes. Also, elasticities of demand with respect to price are generally less than zero. Price and demand generally move in opposite directions. As the price of a product increases, demand for the product usually decreases.

It is possible to measure passengers' elasticity values for a given set of sell up flights, s, and control flights, c, described in the previous section. Using average fare values and booking rates prior to departure, elasticity of demand with respect to price for a given fare class, e_{D,f_m} can be determined. These elasticity values will vary across markets, flight numbers and time of departure.

When a specific fare class is closed due to the imposition of a sell up strategy, passengers requesting tickets in this fare class m, are denied their requests. In essence, the price of an originally requested seat is being increased to f_{m+1}, or the next highest fare class value because the lower fare class value f_m is no longer available. An elasticity value can be obtained, evaluating the change in demand (or bookings) with a change in price. In order to measure this, it is necessary to have a sell up flight s, in which a sell up strategy is implemented to prematurely close down a specific fare class(es), as well as a a control flight c. Those willing to "sell up" into fare class $m+1$ must be isolated in order to evaluate the price elasticity of fare class m.

In general, arc price elasticity of demand for a particular fare class m can be expressed as:

$$e_{D,f_m} = \frac{\Delta b}{\Delta f_m} \frac{f_i}{b_i} \tag{4.20}$$

Elasticity evaluated at point (f_i, b_i) is the resulting change in demand or bookings, Δb, divided by the change in fare class value incurred Δf, multiplied by a ratio of fare value to demand at a specific point i.

The value of Δf is the difference in fare value between class m and class $m+1$:

$$\Delta f = f_{m+1} - f_m \tag{4.21}$$

The variable Δb is defined as:

$$\Delta b = b_2 - b_1 = \left[\sum_{j=J}^{0} (b^s_{m+1,j} - b^c_{m+1,j}) \right] - \left[\sum_{j=J}^{0} b^c_{mj} \right] \tag{4.22}$$

The first term b_2, is the net change in bookings in class $m+1$ after Day J (which is when class m is closed) between the sell up flight s and the control flight c. This value gives the number of passengers who, once denied an initial request in class m, purchased a ticket in class $m+1$. It is used as a measure of those passengers willing to perform a vertical shift, or those willing to sell up. Term b_1 is used to represent the number of passengers from the sell up flight who would have booked in class m, had it remained open (as it did in the control flight).

Typically,

$$b_2 - b_1 < 0 \tag{4.23}$$

because this term is a proxy for the the net change in passengers due to an increase in price, which is almost always less than zero. Thus, the value e_{D,f_m} is negatively valued, as expected.

Terms f_i and b_i are the points at which the elasticity is evaluated, and can be one of many (f_i, b_i) combinations. The point (f_m, b_1) will be used in this thesis, and price elasticity of demand for a specific fare class m is as follows:

$$e_{D,f_m} = \frac{[\sum_{j=J}^{0}(b^s_{m+1,j} - b^c_{m+1,j})] - [\sum_{j=J}^{0}(b^c_{mj})]}{(f_{m+1} - f_m)} \cdot \frac{f_m}{\sum_{j=J}^{0}(b^c_{mj})} \tag{4.24}$$

It is possible for one elasticity measure to be related to more than one fare class. If a sell up strategy, for example, involves closing out Class "H" at Day 14, it is assumed that sell up will occur from "H" class to "M" class. The price elasticity of demand for "H" class will try to estimate the change in "H" class passengers due to a change in the price of "H" class, which is essentially an increase to the price of a ticket in "M" class. For the purposes of this thesis, the elasticity measure for this strategy will be denoted as e_{D,f_H}, but is measured by using information from both "H" and "M" classes.

Price elasticity values by fare class can be used as an indication of whether a particular sell up strategy will be successful. Fare classes associated with inelastic price elasticitites ($-1.0 < e_{D,f_m} < 0.0$) will have a higher probability of sell up occurring. For example, an "H" class elasticity of -0.5 indicates that passengers from "H" class have a strong probability of selling up to "M" class due to passengers' price insensitivities. Elastic price elasticities ($e_{D,f_m} < -1.0$) imply a weak probability for sell up. A "K" class elasticity of -2.5 should be associated with a low sell up probability from "K" class to "Q" class, as a result of travelers' price sensitivities.

The estimation of price elasticities for air travel is extremely complex. It is difficult to come up with standard price elasticity values by fare class because values will fluctuate across markets, flights, and time. With the implementation of a sell up strategy, it is possible to measure price elasticity values for certain fare classes, depending upon what type of strategy is implemented. The following chapter will attempt to estimate price elasticities for certain fare classes, on a flight by flight basis.

Chapter 5

Assessment of Sell Up

Having developed a method of measuring the *revenue impact* of sell up, we will now examine the application of a sell up strategy in an actual airline environment. The impact of this strategy will be measured and an overall assessment of the potential benefits and costs of sell up will be made.

5.1 Description of Test Methodology and Results

A successful sell up policy has the potential to increase airline revenues without substantially increasing operating costs, thus increasing overall airline profits. The question becomes how to accurately predict markets/flights with high sell up potential. Within those flights with sell up opportunities, a decision must be made as to what type of sell up policy to impose.

Under a research agreement with Delta Air Lines, a sell up strategy was developed and tested in the fall of 1989 and the spring of 1990 on a select group of flights. The purpose of the study was to address the issue of passenger choice shifts during the booking process. As shown in Chapter 3, the unavailability of a desired flight and fare class to a consumer can lead to:

1. A vertical choice shift, or a shift to a higher fare class on the same flight.

2. A horizontal choice shift, or a shift to a different flight on the same air carrier.

3. A booking loss to the airline, or a decision to travel on another carrier, another mode type, or not to travel at all.

The prevalence of sell up, or specifically vertical choice shifts, was studied and an assessment was made on the overall revenue impact of the sell up policy implemented.

5.1.1 Preliminary Study

A small scale preliminary study was performed on a select group of flights to initially determine the impact of sell up. Ten flight markets were selected for the study. All flights chosen experienced historically high demand levels. Expected demand levels for each flight number were high enough to cause fare class booking limits to be reached in one or more fare classes.

A test week was designated for the study and two days of departure for each flight were chosen as test flights. The test flights were similar in that both traversed the same origin-destination pair and had the same flight number across different days of the week. The identification of flight pairs valid for comparison was done by choosing days of week which experienced similar historical demand levels. Two *actions to be taken* were distributed among the test flights:

- AUTOMATED CONTROL
- SINGLE POINT SELL UP

The *single point sell up* flights were those flights in which the sell up policy was imposed. For the purposes of this preliminary study, a uniform policy was implemented on all test flights in this category. The sell up policy was as follows:

- Close "K" Class at Day 21
- Close "H" Class at Day 14

Thus, passengers requesting reservations in "K" class from Day 21 to Day 0 were denied the option and would have the potential to sell up into a higher fare class. Similarly, passengers requesting a reservation in "H" class from Day 7 to Day 0 would also be denied the opportunity. For a description of the fare class structures used in this thesis, see Section 2.5.

Seat inventory control on the *automated control* flights was performed as usual using the carrier's automated optimization system. No premature class closings were imposed on these flights. This category of flights was to be used in the revenue impact measurements for the purpose of testing the revenue effect of the sell up policy.

Actions to be taken were distributed evenly among the two groups. Thus, a proportionate amount of each day of week received each treatment type. All ten flights to be tested received each of the treatments, resulting in a total of twenty flights to be examined.

Daily reports were made on the booking histories of all flights. Once the test flights departed, a complete booking history for the flight was made available. An example of this can be seen in Table 5.1. Total bookings by fare class for each

HISTORICAL BOOKING DATA
CITY PAIR: MCI / ATL

DAYS PRIOR	SEATS BOOKED YB	BB	MB	HB	QB	KB	LB	TOT BKD
0	23	11	7	12	12	34	6	105
1	20	11	7	12	12	34	6	102
2	20	12	7	13	12	34	5	103
3	17	11	7	14	12	33	5	99
4	12	10	7	15	15	33	5	97
5	6	8	7	15	15	33	5	89
6	6	9	6	14	15	33	5	88
7	6	9	6	14	15	33	5	88
8	6	9	6	14	15	33	5	88
9	6	9	6	13	15	33	5	87
10	5	9	8	11	15	33	5	86
11	5	8	8	14	16	33	5	89
12	5	8	5	12	16	33	5	84
13	5	9	3	12	16	33	5	83
14	5	9	3	12	16	33	5	83
15	5	9	2	12	15	33	5	81
16	6	6	1	12	14	33	5	77
17	6	6	1	13	12	33	5	76
18	3	6	1	13	11	33	5	72
19	3	5	1	10	11	33	5	68
20	2	5	1	8	10	28	5	59
21	2	5	1	8	9	28	5	58
22	2	5	1	8	9	28	5	58
23	2	5	0	8	[illegible]	28	6	57
24	3	3	0	8	[illegible]	26	6	54
25	3	4	0	8	6	25	6	52
26	3	3	0	8	6	24	6	50
27	3	3	0	7	6	24	6	49
28	3	3	0	7	6	24	6	49
29	3	3	0	7	6	24	5	48
30	3	3	0	7	6	23	5	47

Table 5.1: Booking History for a Departed Flight, Day 30 to Day 0

departed flight can be extracted for any selected range of days prior to departure. In this case, data is listed from Day 30 to Day 0 (or departure date) for a flight from Kansas City (MCI) to Atlanta (ATL). For example, it can be determined that from Day 21 to Day 0 in "Y" class, a net gain of 21 bookings was realized. It is impossible to tell the actual number of bookings accepted and canceled within this period, however. Only the net gain or loss in bookings can be determined from this information.

5.1.2 Preliminary Test Results

Out of the ten flight numbers tested, four had to be eliminated due to large group reservations made early in the booking process or unexpectedly low demand levels. This left six valid flight comparisons in which to measure the impact of the sell up strategy.

Table 5.2 lists the six valid flight comparisons. For each flight pair listed, the fare class mix of passengers and the percentage difference in flight revenues (single point sell up over automated control) are shown. The passenger mix is the number of coach class bookings at Day 0.

The *% Difference from Control* value reflects the difference in total coach class revenues of the single point sell up flight over the automated control flight. Thus, a positive value indicates that the sell up flight had a higher total revenue value than the control flight. Conversely, a negative percentage difference reflects that the sell up flight had a lower total revenue value. For example, the ATLBOS single point sell up flight yielded 29 percent lower coach class revenues than the automated control flight. Actual revenue values have been omitted for reasons of data confidentiality.

MARKET	ACTION TAKEN	Y	B	M	H	Q	K	L	TOTAL	% DIFF.FROM CONTROL
LGAATL	AUTOMATED CONTROL	92	23	7	24	15	7	27	195	
	SINGLE POINT SELLUP	91	24	14	16	14	5	9	173	-4.36%
ATLBOS	AUTOMATED CONTROL	69	40	22	40	17	49	19	256	
	SINGLE POINT SELLUP	44	34	26	15	24	15	24	182	-29.30%
LAXSFO	AUTOMATED CONTROL	5	1	33	5	40	0	19	103	
	SINGLE POINT SELLUP	9	0	12	0	8	0	6	35	-58.59%
STLATL	AUTOMATED CONTROL	36	0	4	37	10	28	24	139	
	SINGLE POINT SELLUP	55	10	9	6	11	11	46	148	18.21%
ONTATL	AUTOMATED CONTROL	59	25	7	45	24	62	41	263	
	SINGLE POINT SELLUP	47	26	17	17	13	32	36	188	-24.03%
MCIATL	AUTOMATED CONTROL	17	9	6	11	32	20	12	107	
	SINGLE POINT SELLUP	12	10	19	4	10	8	9	72	-24.82%

Table 5.2: Preliminary Sell Up Test Results

It can be seen from Table 5.2 that only one flight pair exhibits a positive percentage difference value, indicating that only one sell up flight yielded higher coach class revenues than the corresponding control flight. To further assess the revenue impact of the sell up policy, a revenue impact test was performed on each of the six flight pairs. The *incremental revenue test*, described in Section 4.3, measures the revenue impact difference between the sell up flight and the control flight. In this test case, differences in flight revenues would only be measured from Day 21 to Day 0, since this is the time period during which the sell up strategy was implemented. Revenue impact is only measured for Classes "H", "M", "Q", and "K", the only classes assumed to be affected by the sell up policy. Sell up of more than one fare class was not considered in this case.

The incremental revenue impact test is important because it serves to screen out any differences in booking levels between the sell up flight and the control flight prior to the implementation of the sell up test. The *difference* in bookings after the sell up test is implemented is the basis of the incremental revenue test. This test is thus a more relevant measure of revenue differences due to the imposition of the sell up policy.

The revenue impact difference, ΔR, for this set of preliminary test flights would be:

$$\begin{aligned}\Delta R \;=\; & f_M \sum_{j=14}^{0} (b^s_{Mj} - b^c_{Mj}) + f_H \sum_{j=14}^{0} (b^s_{Hj} - b^c_{Hj}) + \\ & f_Q \sum_{j=21}^{0} (b^s_{Qj} - b^c_{Qj}) + f_K \sum_{j=21}^{0} (b^s_{Kj} - b^c_{Kj}) \end{aligned} \tag{5.1}$$

Revenue impact difference is thus the sum of the revenue impact differences for Classes "M" and "H" from Day 14 to Day 0, because the sell up policy closed class "H" at Day 14 to try to induce sell up into Class "M". Also included is the sum of the revenue impact differences between Classes "Q" and "K" from Day 21 to Day 0, because "K" class was closed at Day 21 in order to induce sell up into "Q" class.

Results of the incremental revenue test, performed on Classes "M", "H", "Q", and "K" were fairly consistent in that on all six pairs of test flights, the revenue impact of the sell up policy was negative. The automated control flights thus yielded higher incremental revenues than the single point sell up flights using equation 5.1, ticket fare values, and daily booking information.

Table 5.3 shows the results of the incremental revenue test for the LGAATL and the MCIATL markets. The net *change in bookings* is the difference in bookings between the time the sell up strategy affected a specific class and Day 0. For example in the LGAATL market, the change in bookings for "H" class is the difference in

MARKET	ACTION TAKEN	REVENUE IMPACT M	H	Q	K	TOTAL REVENUE IMPACT M THROUGH K
LGAATL	AUTOMATED CONTROL	$528	$2,389	$2,115	$0	$5,032
	SINGLE POINT SELL UP	$1,584	$0	$0	$0	$1,584
		$1,056	($2,389)	($2,115)	$0	($3,448)
MCIATL	AUTOMATED CONTROL	$1,248	$748	$2,695	$812	$5,502
	SINGLE POINT SELL UP	$3,744	$299	$476	$232	$4,751
		$2,496	($449)	($2,219)	($580)	($752)

Table 5.3: Preliminary Sell Up Test: Incremental Revenue Impact Results

bookings from Day 14 to Day 0. The *revenue impact* is the change in bookings multiplied by the average posted fare value for the class. The total revenue impact value is listed in the final column below the individual revenue impact values for the sell up and control flights.

In general, sell up was more prevalent from Class "H" to Class "M" than from Class "Q" to Class "K". Two examples of this can be seen from the revenue difference values on a class by class basis, listed in Table 5.3. For example, the MCIATL flight had a negative revenue difference value for "Q" class, but a positive revenue difference value for "M" class. Sell up occurred in this market in the higher fare class, but was not apparent in the case of the lower fare classes. Negative values for "K" and "H" classes are to be expected due to the premature closings of these classes (at Day 21 and Day 14, respectively).

It is necessary to realize the importance of judging sell up from an incremental revenue basis as opposed to just looking at the increase in bookings incurred. This can be seen when looking at results from the LGAATL flight. While some sell up exists from Class "H" to Class "M", the revenue gained does not offset the revenue lost by prematurely closing "H" class at Day 14. Thus, while it can be said that sell up exists on this flight from Class "H" to Class "M", in this case, sell up has not been beneficial in terms of flight revenues. In contrast, the MCIATL market shows a beneficial case of sell up from "H" class to "M" class. The revenue gained in "M" class does offset the revenue lost by prematurely closing "H" class. Total revenue impact was still negative for this flight, however, due to the negative impacts of the sell up strategy for Classes "K" and "Q".

Appendix A contains graphs of the daily booking information for Classes "M", "H", "Q", and "K" of the LGAATL and MCIATL markets. The predominance of sell up from Class "H" to Class "M" can be seen in both markets. For example, in the LGAATL market it can be seen that sell up has occurred in "M" class from Day 14 to Day 0, judging from the differences in bookings between the sell up flight and the control flight. On the other hand, no sell up is apparent in "Q" class between bookings in the sell up flight and the control flight from Day 21 to Day 0. Graphs of Classes "H" and "K" reveal how the sell up policy served to restrict bookings in these classes. For example, the MCIATL flight's "H" class graph shows a pronounced difference between bookings for the sell up flight versus those of the control flight. These additional bookings were made between Day 21 and Day 0, when "H" class of the sell up flight was closed out. Revenue difference values for this flight pair in "H" class also reflect this loss.

From this preliminary study, it can be concluded that:

1. Any sell up policy should be initiated on a flight by flight basis. Sell up does not exist on all flights.

2. Arbitrary sell up (Close "K" class on Day 21, "H" class on Day 14) had an overall negative revenue impact (i.e. revenue gained through sell up was less than revenue lost by closing "K" and "H" classes prematurely).

3. It is important to judge sell up potential on a net revenue impact basis, rather than on the basis of incremental bookings.

4. Sell up appears to be more prevalent in higher fare classes, as presumed in Chapter 4.

5.1.3 Expanded Study

A large scale sell up test was developed to further study the impact of sell up. In this case, eleven flight markets, or origin-destination pairs were selected. Again, all of these flight markets experienced historically high demand levels. Two flights a day in each market were selected on the basis of having expected demand levels high enough to cause fare class booking limits to be reached in one or more fare classes.

Two test weeks were designated for the study. Two days of departure a week for each flight were chosen as test flights, for a total of forty-four flights a week to be included in the study, or eighty-eight departures total for the two week period. Once again, actions to be taken were as follows:

- AUTOMATED CONTROL
- SINGLE POINT SELL UP

MARKET	FLIGHT	WEEK	DAY OF WEEK	ACTION TAKEN
ATLBOS	A	1	Tuesday	AUTOMATED CONTROL
		1	Wednesday	SINGLE POINT SELL UP
		2	Tuesday	SINGLE POINT SELL UP
		2	Wednesday	AUTOMATED CONTROL
	B	1	Tuesday	SINGLE POINT SELL UP
		1	Wednesday	AUTOMATED CONTROL
		2	Tuesday	AUTOMATED CONTROL
		2	Wednesday	SINGLE POINT SELL UP

Table 5.4: Example of Actions to be Taken, Two Week Study

Actions were distributed evenly across flight numbers, days of week, and across the two week period. An example of how these actions to be taken were distributed can be seen in Table 5.4 for a given flight market, Atlanta-Boston. From this, one can see that it is possible to compare test results (of the sell up flight versus the control flight) from the same flight number across the same week (Flight A, Week 1, Tuesday vs. Flight A, Week 1 Wednesday) or the same flight number and day of week across weeks (Flight A, Week 1, Tuesday vs. Flight A, Week 2, Tuesday). Comparisons of different flight numbers across the same day (Flight A, Week 1, Tuesday vs. Flight B, Week 1, Tuesday) were found to be unreliable due to varying fluctuations in demand across flight numbers. With this expanded study, it was possible to obtain a larger-scale comparison of sell up flight results versus control flight results.

As in the preliminary study, the single point sell up flights are those flights in which the sell up strategy was imposed. In this case, a sell up policy was developed for each individual market, tailored according to historical demand levels for the market. When and in what classes in which to impose sell up was determined on

GROUP	MARKET	SELL UP ACTION FARE CLASS	DAY CLOSED
I	ATLBOS	K,L	42
	BOSATL	H	14
		B	7
II	ATLLAX	K,L	21
	LGAATL	H	14
	ATLDCA	B	7
	DFWATL		
	ATLGSP		
	GSPATL		
III	LGAFLL	K,L	21
	ATLMLB	H	7
	MLBATL		

Table 5.5: Sell Up Policies Developed on an Individual Market Basis

an individual market basis. Table 5.5 lists each of the eleven test markets and the corresponding sell up strategies imposed on the single point sell up flights. Similar demand histories resulted in the formulation of three different sell up policies, and three market "groups".

For example, in the ATLBOS market, a high demand market with a large number of business passengers, the sell up policy involved closing "K" and "L" classes six weeks in advance to induce sell up to "Q" class, closing "H" class at Day 14 to force sell up into "M" class, and closing "B" class at Day 7 in order to induce sell up into "Y" class. In contrast, the LGAFLL market is dominated by vacation travelers, and thus the sell up strategy only incorporated prematurely closing the lower fare Classes "L", "K", and "H", at Day 21 for the first two classes, and Day 7 for the latter fare class.

5.1.4 Expanded Study Results

Table 5.6 highlights revenue results of the expanded study incorporating eleven markets and forty-four total flights. The table serves as a comparison of the single point sell up flight to the automated control flight in terms of flight revenues. Appendix B documents booking results of the expanded study, showing the fare class mix of passengers in coach class.

The *% Difference Same Week* value compares the coach class revenue value of the sell up flight with the control flight of the same week. For example, in the ATLBOS market, a comparison is made between the automated control Flight A, Week 1 with the single point sell up Flight A, Week 1. In this case, the sell up flight had twenty-two percent lower coach class revenues than the control flight. The *% Difference Across Weeks* value compares revenue values of the single point sell up flight with the automated control flight across different weeks. For the ATLBOS market a comparison is made between Flight A, Week 1 which yielded nineteen percent lower coach revenues than the sell up Flight A, Week 2. Thus, a positive percentage value in these two columns would indicate that the sell up flight had a higher coach class revenue value than the control flight, with a negative percentage value indicating that the sell up flight had a lower revenue value. Again, comparisons were not made across different flight numbers due to fluctuations in demand.

It is apparent from Table 5.6 that relatively few flight pairs exhibit positive percentage differences, when compared in the same week or across weeks. Fourteen out of a possible forty-four percentage difference values for the same week comparison are positive, indicating higher revenue values for the sell up flight than the control flight. Twelve out of forty-four percentage difference values for the across

MARKET	FLIGHT	DEP. WEEK	ACTION TAKEN	% DIFF SAME WEEK	% DIFF ACROSS WEEKS
ATLBOS	A	1	AUTOMATED CONTROL		
		1	SINGLE POINT SELLUP	-22.06%	-19.12%
		2	SINGLE POINT SELLUP	-51.05%	-52.82%
		2	AUTOMATED CONTROL		
	B	1	SINGLE POINT SELLUP	-9.46%	12.40%
		1	AUTOMATED CONTROL		
		2	AUTOMATED CONTROL		
		2	SINGLE POINT SELLUP	16.51%	-6.15%
ATLLAX	A	1	AUTOMATED CONTROL		
		1	SINGLE POINT SELLUP	5.47%	-0.24%
		2	SINGLE POINT SELLUP	16.67%	23.36%
		2	AUTOMATED CONTROL		
	B	1	SINGLE POINT SELLUP	-41.06%	-28.32%
		1	AUTOMATED CONTROL		
		2	AUTOMATED CONTROL		
		2	SINGLE POINT SELLUP	-19.70%	-33.98%
LGAATL	A	1	SINGLE POINT SELLUP	-7.03%	12.99%
		1	AUTOMATED CONTROL		
		2	AUTOMATED CONTROL		
		2	SINGLE POINT SELLUP	123.91%	84.25%
	B	1	AUTOMATED CONTROL		
		1	SINGLE POINT SELLUP	27.00%	-3.99%
		2	SINGLE POINT SELLUP	-30.41%	-7.95%
		2	AUTOMATED CONTROL		
MLBATL	A	1	AUTOMATED CONTROL		
		1	SINGLE POINT SELLUP	-33.09%	-38.27%
		2	SINGLE POINT SELLUP	-0.79%	7.53%
		2	AUTOMATED CONTROL		
	B	1	SINGLE POINT SELLUP	-16.34%	-40.15%
		1	AUTOMATED CONTROL		
		2	AUTOMATED CONTROL		
		2	SINGLE POINT SELLUP	-36.69%	-11.51%
DFWATL	A	1	SINGLE POINT SELLUP	-38.84%	-9.63%
		1	AUTOMATED CONTROL		
		2	AUTOMATED CONTROL		
		2	SINGLE POINT SELLUP	26.63%	-14.30%
	B	1	AUTOMATED CONTROL		
		1	SINGLE POINT SELLUP	-22.93%	-36.76%
		2	SINGLE POINT SELLUP	-29.20%	-13.72%
		2	AUTOMATED CONTROL		
LGAFLL	A	1	AUTOMATED CONTROL		
		1	SINGLE POINT SELLUP	-35.80%	-20.62%
		2	SINGLE POINT SELLUP	2.55%	-17.06%
		2	AUTOMATED CONTROL		
	B	1	SINGLE POINT SELLUP	-43.93%	-6.25%
		1	AUTOMATED CONTROL		
		2	AUTOMATED CONTROL		
		2	SINGLE POINT SELLUP	46.94%	-12.11%
ATLGSP	A	1	SINGLE POINT SELLUP	-18.28%	-18.42%
		1	AUTOMATED CONTROL		
		2	AUTOMATED CONTROL		
		2	SINGLE POINT SELLUP	7.32%	7.51%
	B	1	AUTOMATED CONTROL		
		1	SINGLE POINT SELLUP	-7.61%	-11.00%
		2	SINGLE POINT SELLUP	14.87%	19.25%
		2	AUTOMATED CONTROL		
BOSATL	A	1	AUTOMATED CONTROL		
		1	SINGLE POINT SELLUP	-25.40%	-17.38%
		2	SINGLE POINT SELLUP	-33.41%	-39.88%
		2	AUTOMATED CONTROL		
	B	1	SINGLE POINT SELLUP	-39.39%	-24.94%
		1	AUTOMATED CONTROL		
		2	AUTOMATED CONTROL		
		2	SINGLE POINT SELLUP	63.42%	31.96%
GSPATL	A	1	SINGLE POINT SELLUP	-9.14%	33.66%
		1	AUTOMATED CONTROL		
		2	AUTOMATED CONTROL		
		2	SINGLE POINT SELLUP	104.19%	38.82%
	B	1	AUTOMATED CONTROL		
		1	SINGLE POINT SELLUP	2.63%	-13.33%
		2	SINGLE POINT SELLUP	-38.49%	-27.17%
		2	AUTOMATED CONTROL		
ATLMLB	A	1	AUTOMATED CONTROL		
		1	SINGLE POINT SELLUP	-39.75%	-51.53%
		2	SINGLE POINT SELLUP	-39.94%	-25.35%
		2	AUTOMATED CONTROL		
	B	1	SINGLE POINT SELLUP	-39.38%	-45.55%
		1	AUTOMATED CONTROL		
		2	AUTOMATED CONTROL		
		2	SINGLE POINT SELLUP	-0.03%	12.05%
ATLDCA	A	1	SINGLE POINT SELLUP	-10.96%	-13.62%
		1	AUTOMATED CONTROL		
		2	AUTOMATED CONTROL		
		2	SINGLE POINT SELLUP	6.73%	10.02%
	B	1	AUTOMATED CONTROL		
		1	SINGLE POINT SELLUP	-22.38%	-10.70%
		2	SINGLE POINT SELLUP	-14.80%	-18.66%
		2	AUTOMATED CONTROL		

Table 5.6: Expanded Sell Up Test Results

week comparison are positive percentages. In general, the automated control flights outperformed the single point sell up flights on a total coach class revenue basis.

Revenue impact tests were performed on a flight by flight basis to further assess sell up impact. The incremental revenue test, as in the preliminary study, allows one to compare flight revenues during the period the sell up policy was implemented, screening out differences in booking levels not due to sell up. Since the test incorporated flights over a two week period, the revenue impact difference, ΔR, was determined a bit differently. Also, since the sell up policies implemented varied on a group basis, the calculation of ΔR varied. For the markets in Group I, ΔR was determined as follows:

$$\begin{aligned}
\Delta R \;=\; & f_Y \sum_{j=7}^{0} (b^{s1}_{Yj} + b^{s2}_{Yj} - b^{c1}_{Yj} - b^{c2}_{Yj}) + f_B \sum_{j=7}^{0} (b^{s1}_{Bj} + b^{s2}_{Bj} - b^{c1}_{Bj} - b^{c2}_{Bj}) + \\
& f_M \sum_{j=14}^{0} (b^{s1}_{Mj} + b^{s2}_{Mj} - b^{c1}_{Mj} - b^{c2}_{Mj}) + f_H \sum_{j=14}^{0} (b^{s1}_{Hj} + b^{s2}_{Hj} - b^{c1}_{Hj} - b^{c2}_{Hj}) + \\
& f_Q \sum_{j=42}^{0} (b^{s1}_{Qj} + b^{s2}_{Qj} - b^{c1}_{Qj} - b^{c2}_{Qj}) + f_K \sum_{j=42}^{0} (b^{s1}_{Kj} + b^{s2}_{Kj} - b^{c1}_{Kj} - b^{c2}_{Kj}) + \\
& f_L \sum_{j=42}^{0} (b^{s1}_{Lj} + b^{s2}_{Lj} - b^{c1}_{Lj} - b^{c2}_{Lj}) \qquad (5.2)
\end{aligned}$$

Revenue impact is the sum of the revenue impact differences in Classes "Y" and "B" from Day 7 to Day 0, Classes "M" and "H" from Day 14 to Day 0, and Classes "Q", "K" and "L" from Day 42 to Day 0. Revenue comparisons were made between all four flights in the two week period, for a given flight number. For example, in the ATLBOS market, Flight A, total revenue impact is the sum of the individual revenue impact for the sell up flights Weeks 1 and 2 minus that of the control flights Weeks 1 and 2.

The sell up strategy for markets in Group II varied from that in Group I only by the day that Classes "K" and "L" were closed (Day 21 instead of Day 42). Thus, Equation 5.2 would change only in that $j = 42$ would be replaced by a $j = 21$. For those flights falling into Group III:

$$\begin{aligned}
\Delta R \;=\;& f_Y \sum_{j=7}^{0} (b^{s1}_{Mj} + b^{s2}_{Mj} - b^{c1}_{Mj} - b^{c2}_{Mj}) + f_H \sum_{j=7}^{0} (b^{s1}_{Hj} + b^{s2}_{Hj} - b^{c1}_{Hj} - b^{c2}_{Hj}) + \\
& f_Q \sum_{j=21}^{0} (b^{s1}_{Qj} + b^{s2}_{Qj} - b^{c1}_{Qj} - b^{c2}_{Qj}) + f_K \sum_{j=21}^{0} (b^{s1}_{Kj} + b^{s2}_{Kj} - b^{c1}_{Kj} - b^{c2}_{Kj}) + \\
& f_L \sum_{j=21}^{0} (b^{s1}_{Lj} + b^{s2}_{Lj} - b^{c1}_{Lj} - b^{c2}_{Lj}) \qquad (5.3)
\end{aligned}$$

Since this sell up policy only includes prematurely closing Classes "H", "K" and "L", the incremental revenue for Classes "B" and "Y" was not determined.

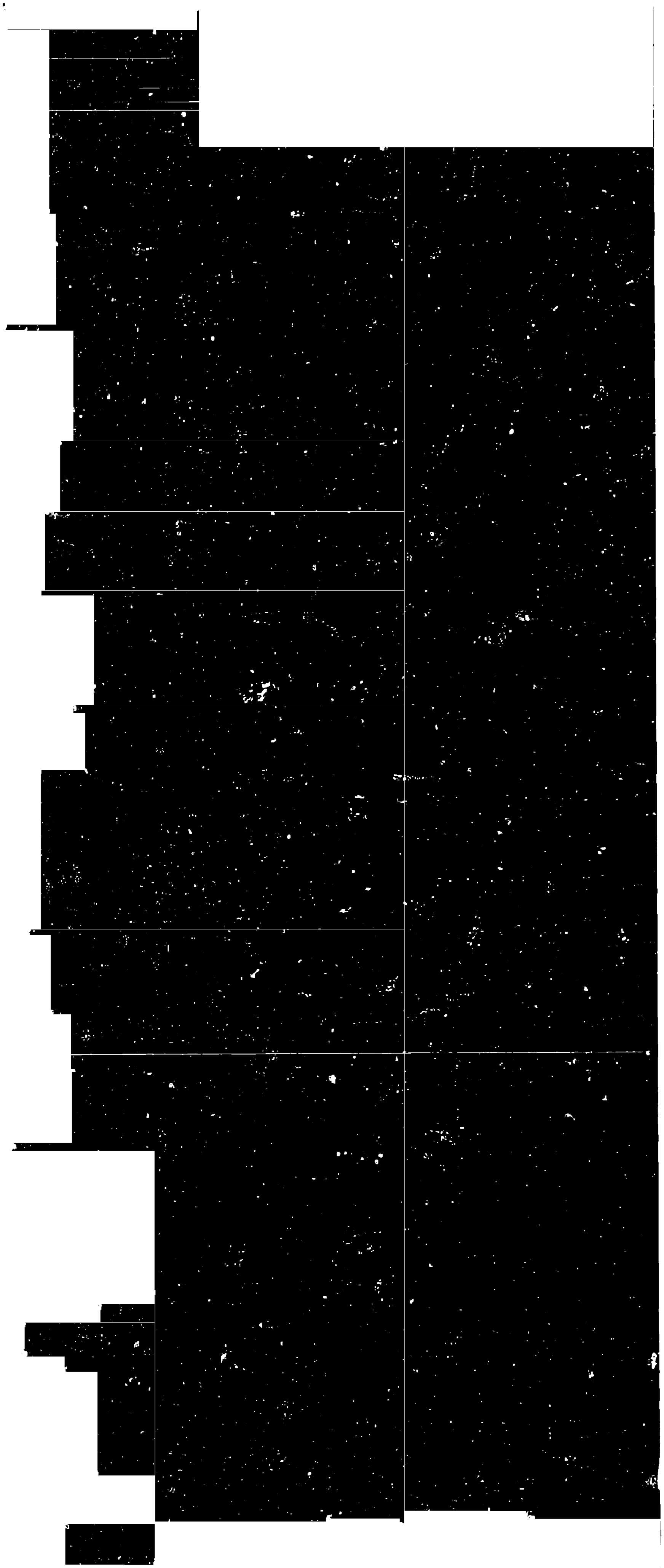
Table 5.7 lists a few examples of the incremental revenue test on a class by class basis as well as the total revenue impact values for a select group of flights. The net *Change in Bookings* was determined on an individual class level, depending upon when the class was affected by the sell up actions. For example, ATLBOS Flight B in Week 1, had a net change of 51 bookings in "Y" class from Day 7 to Day 0. In some cases, the net change in bookings is negative, which means that the number of cancellations made during the specific time period measured (which are negatively valued) offset the number of bookings (positively valued) for the class. *Revenue Impact* for a specific fare class is the change in bookings multiplied by the average posted fare value for the class. If a negative value is realized for the change in bookings variable, then the revenue impact is assumed to be zero. The above example had a revenue impact of $15,543 in Class "Y". Total Revenue Impact for a specific class is the sum of the revenue impact of the two sell up flights minus the sum of the revenue impact of the two control flights. If this value is positive, then sell up has had a positive impact in the specific class. In contrast, if this revenue value is negative, sell up has had an adverse effect on the class. In the ATLBOS example.

CHANGE IN M	CHANGE IN H	CHANGE IN Q	CHANGE IN K	CHANGE IN L	Y	B	REVENUE IMPACT M	H	Q	K	L	TOTAL REVENUE IMPACT L THROUGH Y
-5	-1	16	-2	-7	$15,453	$0	$0	$0	$2,288	$0	$0	$17,741
3	8	11	22	14	$11,817	$0	$555	$1,240	$1,573	$2,750	$1,288	$19,223
2	13	12	9	16	$9,696	$0	$370	$2,015	$1,716	$1,125	$1,472	$16,394
-2	-2	22	-6	-1	$9,090	$0	$0	$0	$3,146	$0	$0	$12,236
					$3,030	$0	($925)	($3,255)	$2,145	($3,875)	($2,760)	($5,640)

CHANGE IN M	CHANGE IN H	CHANGE IN Q	CHANGE IN K	CHANGE IN L	Y	B	REVENUE IMPACT M	H	Q	K	L	REVENUE IMPACT L THROUGH Y
-1	0	3	-6	-1	$10,880	$0	$0	$0	$477	$0	$0	$11,357
0	12	18	25	10	$10,608	$0	$0	$1,836	$2,862	$3,100	$980	$19,386
0	20	11	13	14	$9,248	$468	$0	$3,060	$1,749	$1,612	$1,372	$17,509
2	-1	3	-7	-6	$10,336	$0	$422	$0	$477	$0	$0	$11,235
					$1,360	($468)	$422	($4,896)	($3,657)	($4,712)	($2,352)	($14,303)

CHANGE IN M	CHANGE IN H	CHANGE IN Q	CHANGE IN K	CHANGE IN L	Y	B	REVENUE IMPACT M	H	Q	K	L	REVENUE IMPACT H THROUGH Y
14	0	12	0	-17	--	--	$2,408	$0	$1,968	$0	$0	$4,376
2	10	14	-5	-1	--	--	$344	$1,640	$2,296	$0	$0	$4,280
1	8	39	5	8	--	--	$172	$1,312	$6,396	$640	$744	$9,264
12	-3	23	-10	-3	--	--	$2,064	$0	$3,772	$0	$0	$5,836
							$3,956	($2,952)	($2,952)	($640)	($744)	($3,332)

ncremental Revenue Impact Results



MARKET	FLIGHT NUMBER	WEEK OF DEPARTURE	ACTION TAKEN
ATLBOS	B	1	SELL UP
		1	CONTROL
		2	CONTROL
		2	SELL UP

MARKET	FLIGHT NUMBER	WEEK OF DEPARTURE	ACTION TAKEN
DFWATL	A	1	SELL UP
		1	CONTROL
		2	CONTROL
		2	SELL UP

MARKET	FLIGHT NUMBER	WEEK OF DEPARTURE	ACTION TAKEN
LGAFLL	B	1	SELL UP
		1	CONTROL
		2	CONTROL
		2	SELL UP

Table 5.7: Expan

the total revenue impact for "Y" class was $3,030, and sell up had a positive impact on "Y" class for Flight B.

The revenue impact of a specific sell up strategy can be measured using Total Revenue Impact values. For example, the impact of closing "B" class in the ATLBOS market at Day 7 can be calculated by adding up the Total Revenue Impact of "Y" and "B" classes. In the case of Flight B, this value is $3,030. One could say that sell up from "B" to "Y" classes was successful on a revenue basis for this flight.

Total Revenue Impact of all classes is the sum of the revenue impact differences in all classes affected by a specific sell up policy. For the ATLBOS market, which uses the Group I sell up strategy, this is the sum of the revenue impact differences for Classes "Y" through "L". The total revenue impact for Flight B in this case is -$5.640. Thus while sell up from "B" class to "Y" class was positively valued, the sell up strategy as a whole was not successful in terms of revenue impact, due to the lack of sell up in the lower fare classes.

The Total Revenue Impact of all classes value was positive for only two out of the twenty-two flight numbers surveyed. In general, sell up appeared to be most successful from "B" class to "Y" class. This can be seen in Table 5.8, which isolates the revenue impact of these two classes. Revenue impact was positive for ten out of the twenty-two flights, when "Y" and "B" classes were considered alone. Sell up was less successful in the lower fare classes ("H" class to "M" Class as well as "L" and "K" classes to "Q" class). When considering the revenue impact of "H" and "M" classes alone, two out of the twenty-two flights had a positive revenue impact. None of the flights surveyed had a positive revenue impact with respect to "L", "K" and "Q" classes only.

REVENUE IMPACT MEASUREMENTS
Y AND B FARE CLASSES

MARKET	FLIGHT	Y CLASS REVENUE IMPACT	B CLASS REVENUE IMPACT	TOTAL
ATLBOS	A	($4,545)	($234)	($4,779)
	B	$3,030	$0	$3,030
ATLLAX	A	$2,352	($3,641)	($1,289)
	B	($4,704)	$0	($4,704)
LGAATL	A	$16,038	($723)	$15,315
	B	($4,752)	$0	($4,752)
MLBATL	A	$1,442	($3,800)	($2,358)
	B	$0	($608)	($608)
DFWATL	A	$1,360	($468)	$892
	B	($2,176)	($1,170)	($3,346)
LGAFLL	A	$2,064	($3,444)	($1,380)
	B	$3,956	($2,952)	$1,004
ATLGSP	A	$0	($1,200)	($1,200)
	B	$6,291	($1,680)	$4,611
BOSATL	A	$302	$0	$302
	B	$3,322	($2,270)	$1,052
ATLMLB	A	$1,188	($3,634)	($2,446)
	B	$396	($2,212)	($1,816)
GSPATL	A	$10,992	$233	$11,225
	B	($3,893)	($1,864)	($5,757)
ATLDCA	A	$3,264	$0	$3,264
	B	$5,508	($1,120)	$4,388

Table 5.8: Revenue Impact Results for "Y" and "B" Classes Only

Appendix C contains graphs of the daily booking information for a select group of flight/fare class combinations. The first two graphs are of "Y" and "B" class bookings for ATLGSP Flight B. These graphs typify what happened in those markets which exhibited successful sell up from Class "B" to "Y". Bookings in Class "Y" for the sell up flights increase substantially after Day 7, which is when "B" class was closed. Prematurely closing "B" class did not have an adverse effect on the sell up flights' booking levels, as can be seen by the second graph.

Graphs of "Y" class booking histories for the GSPATL market follow. Flight A is a good example of sell up to "Y" class, with both weeks of sell up flights indicating a jump in bookings from Day 7 to Day 0. Flight B indicates relatively little sell up in "Y" class when comparing the sell up flights to the control flights. These graphs indicate the possibility of having sell up exist for one flight and not for another in the same market.

The following two graphs are of ATLDCA Flight B, indicating an example of the nonexistence of sell up from Class "H" to Class "M". Most test flights exhibited this type of behavior in relation to "H" and "M" classes. It can be seen in the graph of "M" class bookings, that relatively few increases in bookings occur from Day 14 to Day 0 for the sell up flights in comparison to the control flights. Bookings in "H" class for this particular flight indicate low booking levels for the sell up flights in comparison to the control flights, whose bookings increased substantially from Day 14 to Day 0. In general, bookings in "H" class were low for the sell up flights, and this loss was not overcome by an increase of bookings in "M" class, due to the lack of sell up behavior from "H" to "M" classes.

The final two graphs indicate "typical" booking behavior for "Q" and "K" classes, represented by BOSATL Flight A. No sell up is indicated from Day 42 to Day 0 in "Q" class for the sell up flights. Booking levels for "K" class sell up flights are low, due to their premature closing at Day 42. As in the preliminary study, sell up was not prevalent in these lower fare classes.

One can conclude the following from the expanded sell up study:

1. Sell up is flight specific. It is possible for one flight to exhibit sell up behavior and another flight in the *same* market to show no indication of sell up.

2. The sell up strategies tested in this study had an overall negative revenue impact (revenue gained through sell up was less than revenue lost by prematurely closing out specific fare classes).

3. Comparisons of flights within the same week and across weeks yielded relatively the same negative sell up impact results.

4. Some positive indication of sell up was shown from "B" class to "Y" class. In general, lower fare classes showed little or no positive sell up impact.

5.2 Price Elasticity Measurements

Section 4.4 describes how price elasticity measures can be obtained from a sell up test similar to the study described in this section. When a sell up strategy prematurely closes a fare class, the price of a ticket in that class is essentially being increased from f_m to f_{m+1}. Elasticity of demand with respect to price can be related to sell up if a measure can be obtained of the change in demand (or bookings) after the fare class is closed (change in price).[1]

[1] Recall that elasticity of demand with respect to the price of particular fare class is expressed as:

$$e_{D,f_m} = \frac{\Delta b}{\Delta f_m} \cdot \frac{f_i}{b_i} \tag{5.4}$$

Using the change in bookings values listed in the incremental revenue tests of Table 5.7, a proxy for the net change in passengers due to an increase in price can be obtained (Δb). The measure Δf_m is simply the measure of the difference in fare class values between class m and class $m+1$.

For example, DFWATL Flight A's fare and booking values for sell up from Class "H" to "M" are as follows:

$$b_1 = 32 \qquad b_2 = 2$$

$$f_1 = \$153 \quad f_2 = \$211$$

Term b_1 represents the number of passengers who would have booked in Class "H" of the sell up flight, had it remained open. It can be approximated by the sum of the change in bookings for the control flight in Class "H". The term b_2 is the net change in bookings in Class "M" after Day 14 (which is when Class "H" was closed) between the sell up flight and the control flights.

Elasticity of demand with respect to price for this flight in "H" class, e_{D,f_H} becomes:

$$e_{D,f_H} = \frac{(2-32)}{(211-153)}\frac{32}{153} = -2.47 \tag{5.5}$$

This value indicates a negatively valued elasticity measure, as expected. Elasticity for "H" class of this flight is highly elastic, which indicates a weak probability for sell up, due to price sensitivities of passengers requesting this fare class. This is consistent with the findings of the revenue impact tests, which indicated relatively little or no sell up from "H" to "M" classes.

Due to the nature of the sell up strategy imposed, it was only possible to theoretically calculate three elasticity measures, e_{D,f_B}, e_{D,f_H}, and $e_{D,f_{K,L}}$ for Groups I and Groups II, and only the latter two elasticity measures for Group III. Bookings in "B" class were extremely low, making it difficult to extract the Δb values for e_{D,f_B}. In general, reasonable elasticity measures were only obtained in relation to "H" and "K,L" classes. These values are listed in Table 5.9. Elasticity for "K,L" class (which for the purposes of these calculations will be denoted as one class) was determined by combining bookings in "K" and "L" classes, to obtain b_1 and forming a weighted average of fare values for these two classes in order to come up with a standard composite f_1 value.

Elasticity measures for "H" and "K,L" classes are extremely price elastic. This result coincides with the revenue impact results obtained in the previous section, which indicated the nonexistence of sell up in these classes. It is unfortunate that reliable measures of "B" class elasticity could not be obtained. It can be speculated that these elasticities would be between negative one and zero (inelastic) for those flights which sell up to "Y" class was successful, and more elastic (less than negative one) for those flights in which sell up to "Y" class was unsuccessful on a revenue basis.

The elasticity values highlighted in Table 5.9 are uniform in that all are highly elastic. The values vary, however, on a flight by flight basis. For example, in the GSPATL market, Flight A and Flight B's elasticities for Class "K,L" differ by an extremely large amount. The low number of bookings in some classes, particularly for the sell up flights, leads one to wonder about the accuracy of these elasticity measures.

In many cases, elasticity values for Class "H" are more negatively valued than those for Class "K,L", which violates the assumption made in Equation 4.19. This does not make intuitive sense and can be attributed in part to lower booking levels in Classes "M" and "H" than in Classes "Q" and "K,L". While the elasticity measures in Table 5.9 are somewhat unreliable due to booking levels, all are consistent in that they are valued less than negative one and extremely elastic, as expected.

Elasticity values could be extremely useful to an air carrier to aid in identifying specific markets/flights/fare classes with sell up potential. From this study one can conclude:

1. Elasticity measures are flight specific, which reinforces the need for sell up strategies to be tailored to specific flights.

2. It can be speculated that elasticity of demand with respect to price in "B" class is inelastic for some flights, judging from the results of the revenue impact tests, but elastic for other flights.

3. Elasticity of demand with respect to price in "H" and "Q" classes is highly elastic for all flights tested.

MARKET	FLIGHT	e_{D,f_H}	$e_{D,f_{K,L}}$
ATLBOS	A	-6.0	-2.5
	B	-3.9	-2.4
ATLLAX	A	-3.3	-1.6
	B	-3.0	-4.0
LGAATL	A	-5.1	-3.7
	B	-4.4	-3.3
MLBATL	A	-2.2	-1.6
	B	-2.8	-2.8
DFWATL	A	-2.5	-2.5
	B	-2.5	-3.0
LGAFLL	A	-8.8	-1.7
	B	-5.7	-4.4
ATLGSP	A	—	-6.1
	B	-7.2	-5.4
BOSATL	A	-5.2	-9.8
	B	-4.7	-5.8
ATLMLB	A	-3.4	-7.9
	B	-2.9	-1.4
GSPATL	A	-7.3	-2.9
	B	-6.5	-10.5
ATLDCA	A	-6.6	-8.7
	B	-7.2	-12.3

Table 5.9: Price Elasticity Measures for "H" and "K,L" Classes

Chapter 6

Conclusions

6.1 Research Findings

This thesis has concentrated on the issue of passenger choice shifts in the airline reservations and booking process. In particular, the focus has been on the existence and impact of sell up, or vertical choice shifts. Sell up strategies were developed and tested in an actual airline environment in order to make an assessment of the potential benefits and costs of sell up.

Vertical choice shifts made during the booking process are extremely beneficial to an air carrier in terms of flight revenues. By "selling up", a passenger is paying more for a given seat on the same flight originally requested. The question becomes whether the revenue gained by those who sell up is greater than the revenue lost by those passengers who decide to explore other flight itineraries. If the revenue gained offsets the revenue lost, then a sell up strategy has been beneficial to a flight's revenues.

Sell up potential does not exist in all markets or even on all flights in a given market in which sell up has been identified. In general, flights with historically high demand levels will have more instances of sell up. In these markets, a passenger is more likely to be denied an initial request and given the opportunity to sell up. A large probability for sell up exists in fare classes of a higher revenue value. Business travelers, who are more likely to purchase tickets in higher fare classes have a higher likelihood of selling up due to the nature of their travel. Leisure travelers, who are more price elastic, will be less likely to sell up. Finally, highly competitive flight markets will have a lower sell up potential than those which are dominated by only one or relatively few carriers. Markets which are highly competitive give many travel options to a passenger, decreasing potential for sell up. In order to take advantage of sell up opportunities, a carrier should be a fairly dominant carrier in a flight market.

A selection of test flights in an actual airline environment was made. Sell up strategies were developed to close down two or more fare classes prematurely in order to induce sell up behavior. Flights incorporating the sell up strategies were compared to control flights on a revenue basis in order to test the impact of the strategies.

On an overall revenue basis, sell up flights were outperformed by the control flights. Sell up strategies as a whole proved to be unsuccessful in terms of coach class revenues.

It is important to judge sell up impact on the basis of incremental revenues rather than on an incremental booking basis. This thesis placed a great emphasis on the revenue impact test, which served to screen out differences in booking levels between sell up flights and control flights prior to the implementation of the sell up strategy. Using this test, sell up was found to be almost nonexistent in lower fare classes. The only fare classes which showed some positive indication of sell up were from "B" class to "Y" class, which constitute the two highest fare classes in terms of fare values. Thus, sell up behavior was most prevalent in the upper fare classes.

Sell up was shown to be very flight specific. It was possible for sell up to exist for one flight/fare class and not to exist for another flight in the same fare class of the same city pair. Sell up strategies must be developed on a flight-by-flight basis, taking into account fluctuations in demands.

Price elasticity measures obtained from sell up booking information also proved to be flight specific. It was shown that price elasticity of demand for passengers in lower fare classes is extremely elastic, as expected. Although reliable estimates were not obtained due to low booking levels, it was speculated that price elasticities in upper fare classes ("B" and "Y" classes) are inelastic, for certain flights, due to positive sell up impacts from "B" class to "Y" class.

The following criteria should be met in the development of a successful sell up strategy:

1. The policy should be developed on a flight by flight basis, taking into account that sell up is flight specific.
2. Booking limits should be restricted in upper fare classes only, in order to impose sell up in the higher fare classes.
3. Booking limit restrictions should not be made in lower fare classes, due to lack of sell up behavior in these classes.

6.2 Directions for Further Research

More extensive research on sell up opportunities in the airline industry is needed before sell up can be included in the seat inventory control process. The first step lies in the ability to properly identify those flight/fare class combinations which have a high probability for sell up. This thesis has shown that, in general, sell up exists in higher fare classes and is relatively nonexistent in lower fare classes. The thesis also indicated that sell up in higher fare classes is not prevalent on all flights.

A tool to properly identify those flights with sell up potential would be beneficial to airlines. One way of doing so would be to estimate a reliable set of sell up probability values $P_i(v)$ (probability of a vertical shift), on a fare class/flight specific basis. These values would be based on historical booking data, adjusted for seasonality.

Once a reliable set of probability estimators is obtained, the estimators can be incorporated into a seat inventory control model. Without $P_i(v)$ values, a seat inventory control model would find the optimal number of seats to be protected for each fare class without taking into account sell up opportunities. Including $P_i(v)$ values would serve to protect more seats for the higher fare classes, in which sell up is more prevalent. The problem lies in obtaining a reliable set of probability values. Trying to estimate one for each fare class/flight combination would result in an unreasonably large number of probability estimators.

Sell up opportunities could also be detected using elasticity estimators, similar to the elasticity measures obtained in Section 5.2. Flight/fare class combinations with inelastic price elasticities would have a higher probability of sell up. Once again, the difficulty lies in the estimation of these values on a flight specific basis. Also, due to fluctuations in demand, their reliability can be questioned.

A more general method of identifying flights with sell up potential would be to somehow formulate a flight specific competitive index. This index would take into account market share values for each flight in a city-pair market. Every flight would have an index which would indicate how much competition exists from other carriers for the specific flight. Those flights which have a large amount of competition would obviously have a lower sell up potential, since many other options would exist to a potential passenger. However, those flights which have relatively little competition from other carriers would naturally have a higher sell up potential. This method is less complex than $P_i(v)$ estimation or elasticity measurements because it is only flight specific, not fare class specific. It could be incorporated into a seat inventory control model as an effective way of identifying *flights* with sell up potential.

Obviously, much research and testing is necessary in order to obtain an "optimal" model which identifies sell up potential. This thesis has attempted to clarify the "where" and "when" of the problem. Guidelines have been established for identifying flights with high sell up potential and fare classes with a high prevalence of sell up behavior. The solution lies in the determination of the "how".

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[13] Reprinted in 41 Journal of Air Law and Commerce 607 (1975).

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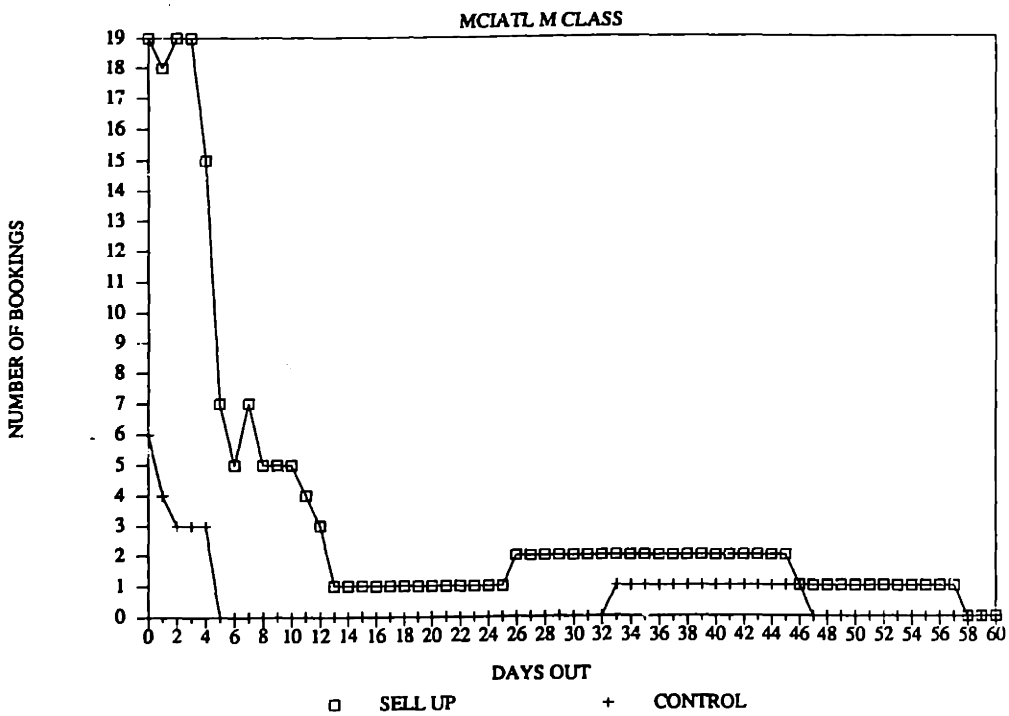
Appendix A

Graphs of Daily Booking Information; Preliminary Study

BOOKING INFORMATION



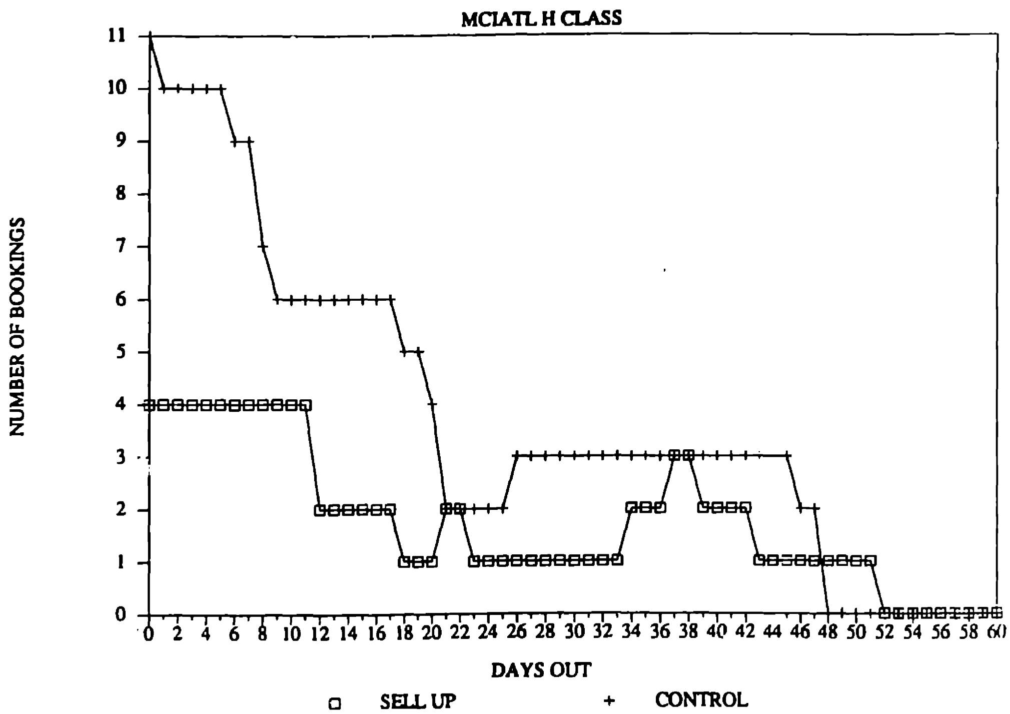
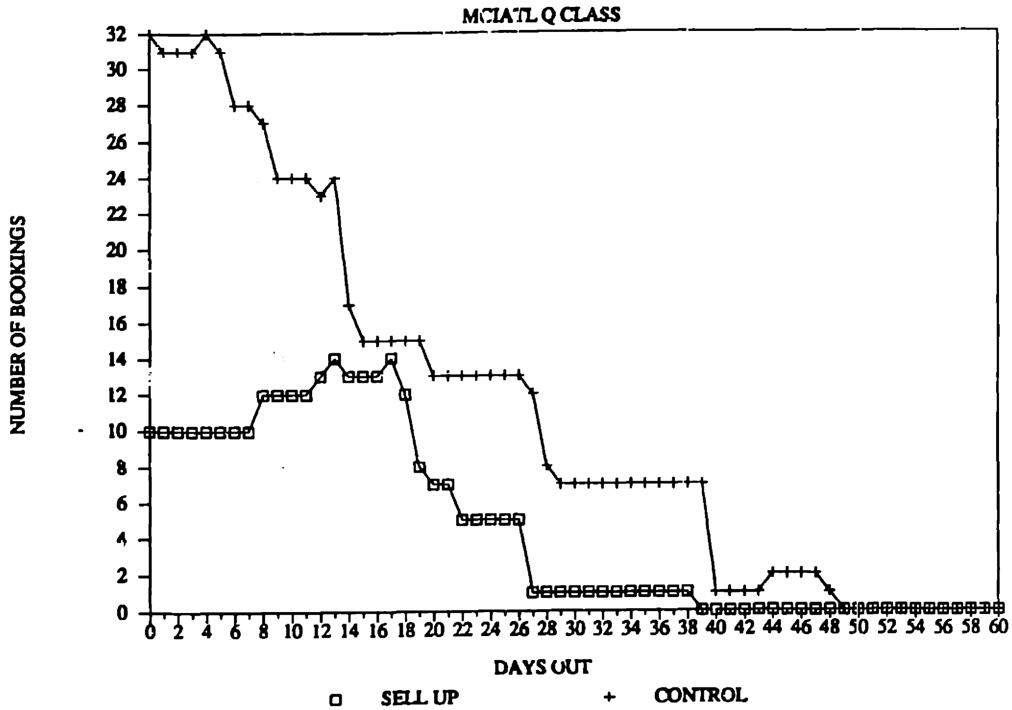


Figure A.1: MCIATL "M", "H" Classes

BOOKING INFORMATION



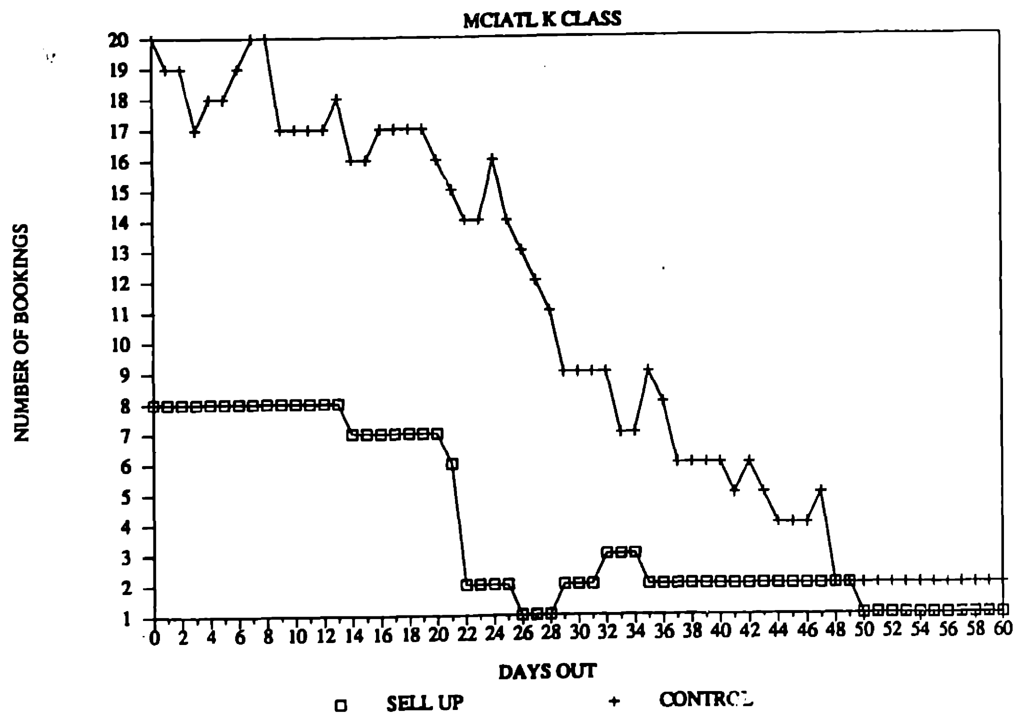
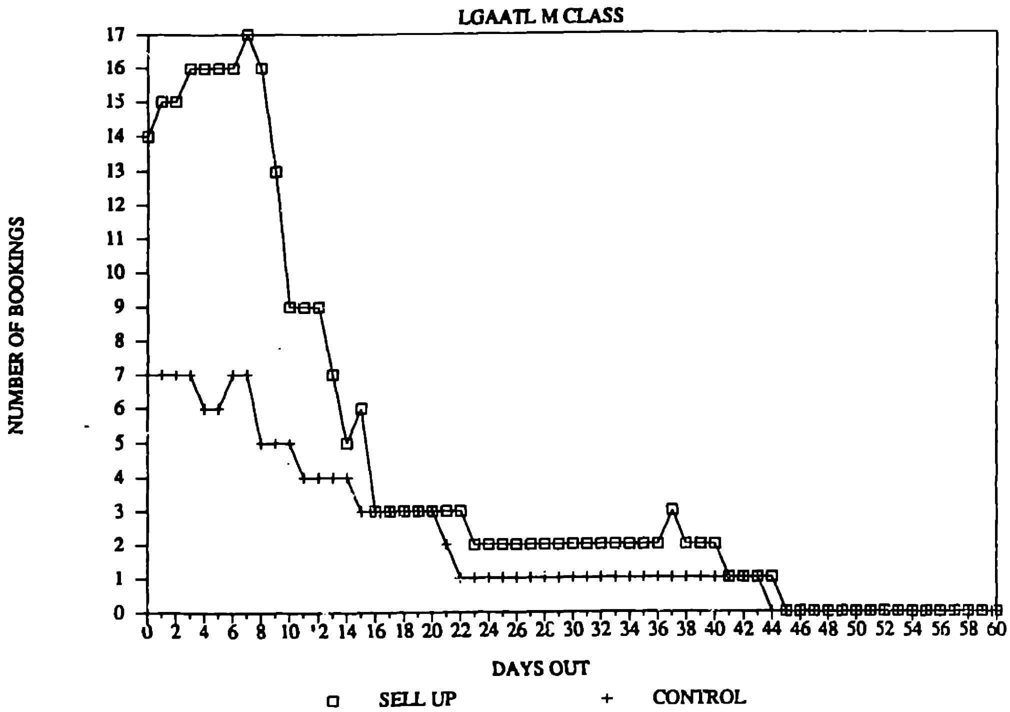


Figure A.2: MCIATL "Q", "K" Classes

BOOKING INFORMATION



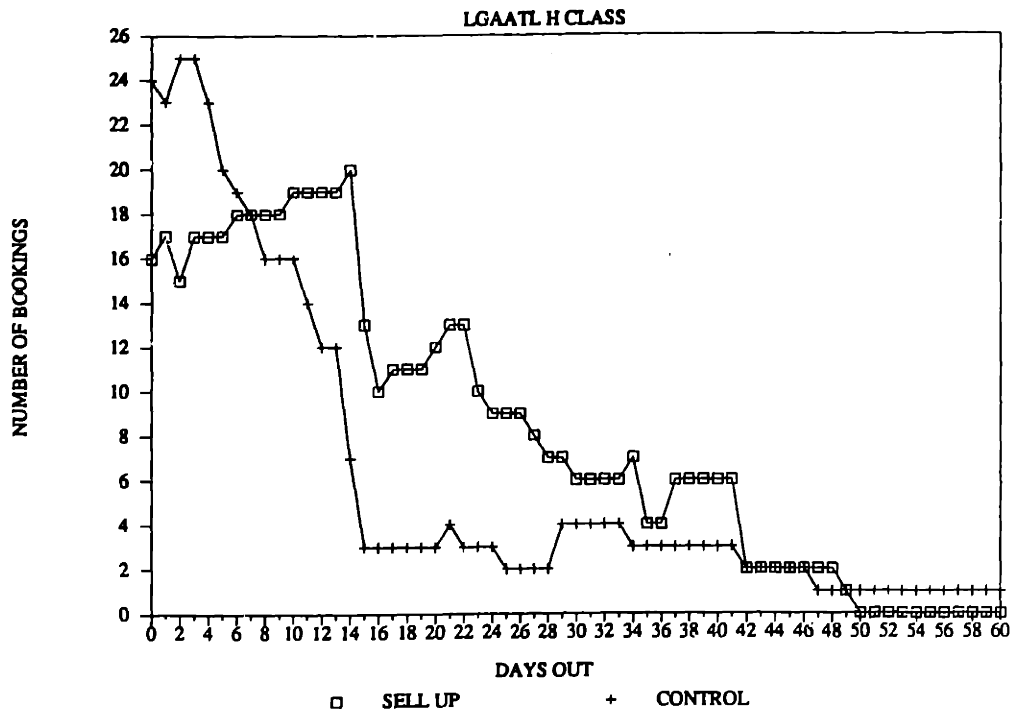
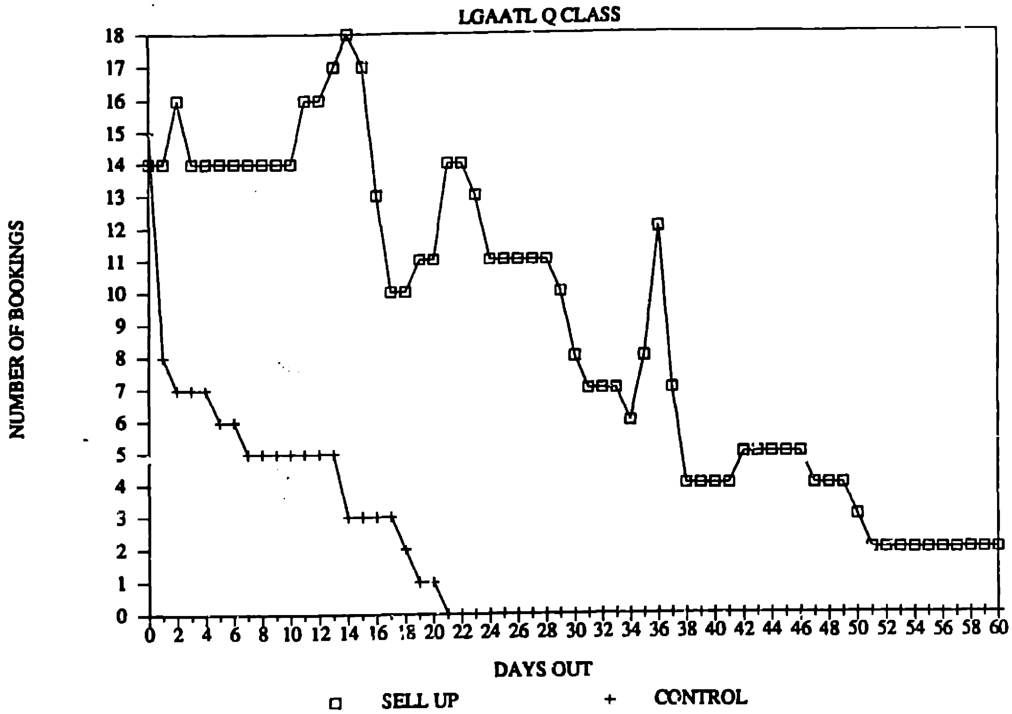


Figure A.3: LGAATL "M", "H" Classes

BOOKING INFORMATION



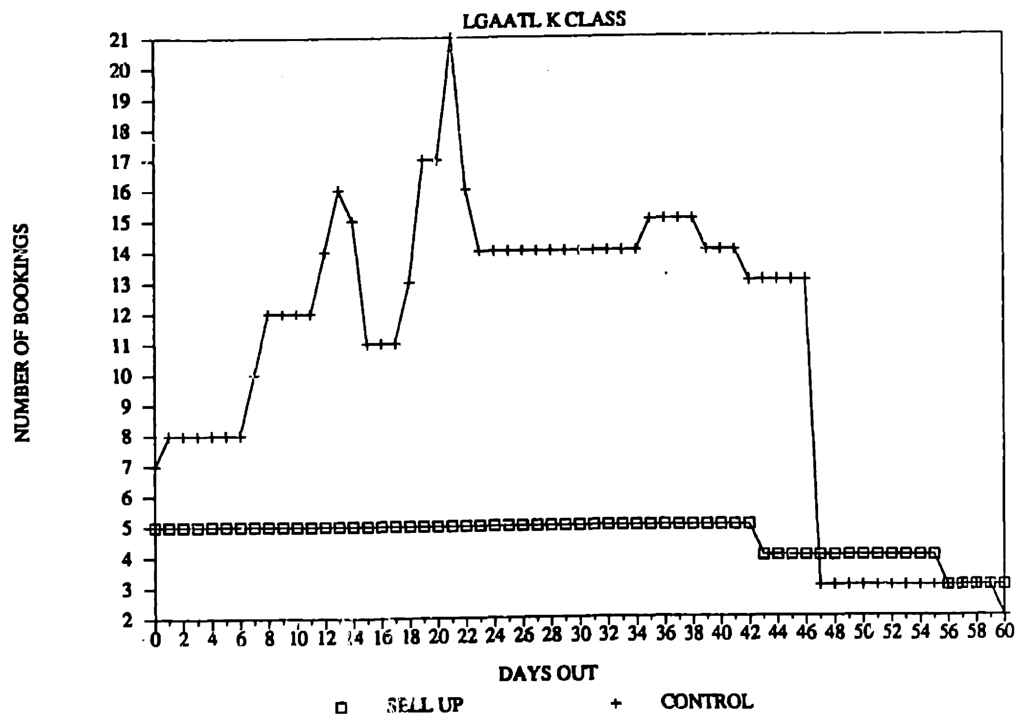


Figure A.4: LGAATL "Q", "K" Classes

Appendix B

Booking Information; Expanded Study

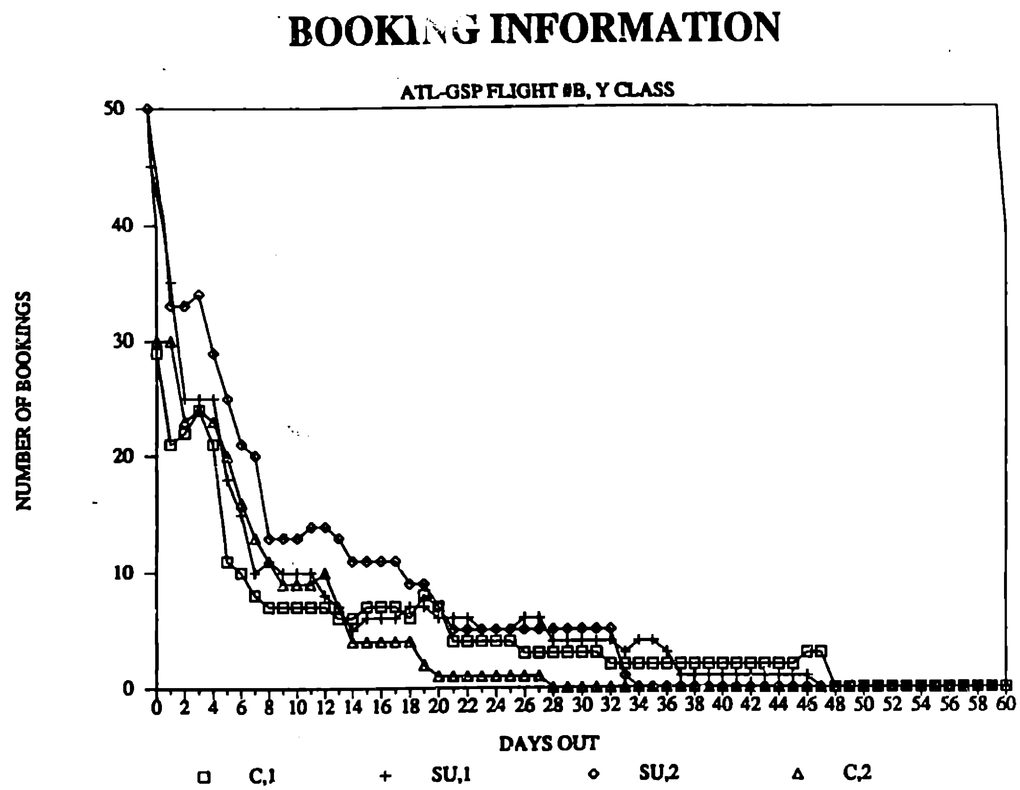
MARKET	FLIGHT	DEP. WEEK	ACTION TAKEN	COACH BOOKINGS BY CLASS Y	B	M	H	Q	K	L	TOTAL
ATLGSP	A	1	SINGLE POINT SELLUP	42	4	3	4	5	16	2	76
		1	AUTOMATED CONTROL	46	9	6	3	15	13	9	101
		2	AUTOMATED CONTROL	49	8	0	7	12	17	6	99
		2	SINGLE POINT SELLUP	61	7	6	1	7	11	4	97
	B	1	AUTOMATED CONTROL	29	5	6	16	4	8	16	84
		1	SINGLE POINT SELLUP	45	1	0	5	3	3	2	59
		2	SINGLE POINT SELLUP	50	2	6	7	4	11	3	83
		2	AUTOMATED CONTROL	30	4	8	10	12	12	8	84
BOSATL	A	1	AUTOMATED CONTROL	40	18	39	18	29	44	5	193
		1	SINGLE POINT SELLUP	56	10	18	2	9	16	0	111
		2	SINGLE POINT SELLUP	37	10	10	3	11	33	0	104
		2	AUTOMATED CONTROL	33	8	27	24	31	44	5	172
	B	1	SINGLE POINT SELLUP	47	11	10	2	7	13	3	93
		1	AUTOMATED CONTROL	69	18	13	24	25	11	1	161
		2	AUTOMATED CONTROL	60	16	12	13	11	11	5	128
		2	SINGLE POINT SELLUP	115	3	8	11	15	17	0	169
GSPATL	A	1	SINGLE POINT SELLUP	44	2	6	4	4	1	3	64
		1	AUTOMATED CONTROL	34	4	7	14	7	11	7	84
		2	AUTOMATED CONTROL	25	1	6	3	10	3	4	52
		2	SINGLE POINT SELLUP	76	3	4	0	6	4	0	93
	B	1	AUTOMATED CONTROL	43	6	1	21	10	5	9	95
		1	SINGLE POINT SELLUP	59	2	4	2	5	7	4	83
		2	SINGLE POINT SELLUP	41	6	4	2	3	6	1	63
		2	AUTOMATED CONTROL	62	6	6	8	10	8	2	102
ATLHLB	A	1	AUTOMATED CONTROL	12	0	4	18	6	18	20	78
		1	SINGLE POINT SELLUP	11	3	6	3	8	8	2	41
		2	SINGLE POINT SELLUP	14	0	2	7	3	20	7	53
		2	AUTOMATED CONTROL	19	4	3	19	14	25	9	93
	B	1	SINGLE POINT SELLUP	8	3	5	8	7	3	8	42
		1	AUTOMATED CONTROL	13	7	0	19	5	18	17	79
		2	AUTOMATED CONTROL	16	0	0	15	12	9	30	82
		2	SINGLE POINT SELLUP	24	6	1	7	7	16	18	79
ATLDCA	A	1	SINGLE POINT SELLUP	37	0	3	4	5	8	6	63
		1	AUTOMATED CONTROL	26	2	3	12	14	21	4	82
		2	AUTOMATED CONTROL	26	3	2	13	15	21	7	87
		2	SINGLE POINT SELLUP	43	6	1	1	16	15	5	87
	B	1	AUTOMATED CONTROL	70	11	8	18	35	21	12	175
		1	SINGLE POINT SELLUP	72	14	14	2	9	13	4	128
		2	SINGLE POINT SELLUP	90	6	3	4	10	3	2	118
		2	AUTOMATED CONTROL	74	12	5	20	29	19	3	162

Table B.1: Expanded Study, Coach Class Bookings

MARKET	FLIGHT	DEP. WEEK	ACTION TAKEN	Y	B	M	H	Q	K	L	TOTAL
				COACH BOOKINGS BY CLASS							
ATLBOS	A	1	AUTOMATED CONTROL	35	0	13	18	11	37	41	155
		1	SINGLE POINT SELLUP	33	0	10	3	10	27	3	86
		2	SINGLE POINT SELLUP	20	7	5	5	4	17	1	59
		2	AUTOMATED CONTROL	34	4	6	22	11	48	29	154
	B	1	SINGLE POINT SELLUP	95	14	24	8	27	23	15	206
		1	AUTOMATED CONTROL	96	15	30	14	18	44	40	257
		2	AUTOMATED CONTROL	65	18	19	24	21	57	20	224
		2	SINGLE POINT SELLUP	54	7	55	6	31	42	3	198
ATLLAX	A	1	AUTOMATED CONTROL	47	18	28	12	16	22	17	160
		1	SINGLE POINT SELLUP	39	11	39	8	24	15	3	139
		2	SINGLE POINT SELLUP	67	13	36	2	7	34	4	163
		2	AUTOMATED CONTROL	61	32	14	20	26	25	21	199
	B	1	SINGLE POINT SELLUP	39	1	5	5	5	28	34	117
		1	AUTOMATED CONTROL	45	8	6	32	40	37	37	205
		2	AUTOMATED CONTROL	50	7	5	19	19	26	32	158
		2	SINGLE POINT SELLUP	36	9	4	6	29	24	10	118
LGAATL	A	1	SINGLE POINT SELLUP	42	1	3	4	0	6	6	62
		1	AUTOMATED CONTROL	34	7	5	18	3	8	3	78
		2	AUTOMATED CONTROL	21	3	6	9	14	11	9	73
		2	SINGLE POINT SELLUP	79	13	5	8	3	23	4	135
	B	1	AUTOMATED CONTROL	89	4	2	15	5	16	9	140
		1	SINGLE POINT SELLUP	113	6	4	3	5	38	3	172
		2	SINGLE POINT SELLUP	82	5	6	8	5	9	0	115
		2	AUTOMATED CONTROL	113	6	5	18	8	27	17	194
MLBATL	A	1	AUTOMATED CONTROL	11	1	1	20	15	12	28	88
		1	SINGLE POINT SELLUP	9	2	0	9	13	8	4	45
		2	SINGLE POINT SELLUP	13	0	12	5	1	13	10	54
		2	AUTOMATED CONTROL	10	2	4	20	4	25	28	93
	B	1	SINGLE POINT SELLUP	13	1	2	2	1	8	7	34
		1	AUTOMATED CONTROL	17	1	1	1	7	6	6	39
		2	AUTOMATED CONTROL	23	1	1	7	9	6	16	63
		2	SINGLE POINT SELLUP	13	4	0	1	12	5	5	40
DFWATL	A	1	SINGLE POINT SELLUP	61	2	2	0	5	26	14	110
		1	AUTOMATED CONTROL	77	12	2	20	20	58	15	204
		2	AUTOMATED CONTROL	52	11	0	22	12	35	21	153
		2	SINGLE POINT SELLUP	78	1	3	1	6	53	10	152
	B	1	AUTOMATED CONTROL	87	5	3	52	29	37	42	255
		1	SINGLE POINT SELLUP	70	1	5	13	9	63	11	172
		2	SINGLE POINT SELLUP	92	4	10	7	11	34	21	179
		2	AUTOMATED CONTROL	116	14	13	26	29	46	17	261
LGAFLL	A	1	AUTOMATED CONTROL	6	1	1	25	30	42	130	235
		1	SINGLE POINT SELLUP	9	0	7	13	15	8	58	110
		2	SINGLE POINT SELLUP	14	0	10	3	14	28	80	149
		2	AUTOMATED CONTROL	12	0	0	12	31	23	163	241
	B	1	SINGLE POINT SELLUP	22	3	14	5	12	15	59	130
		1	AUTOMATED CONTROL	36	1	12	27	32	33	24	165
		2	AUTOMATED CONTROL	11	1	3	8	42	33	46	144
		2	SINGLE POINT SELLUP	23	0	19	11	29	39	13	134

Appendix C

Graphs of Daily Booking Information; Expanded Study



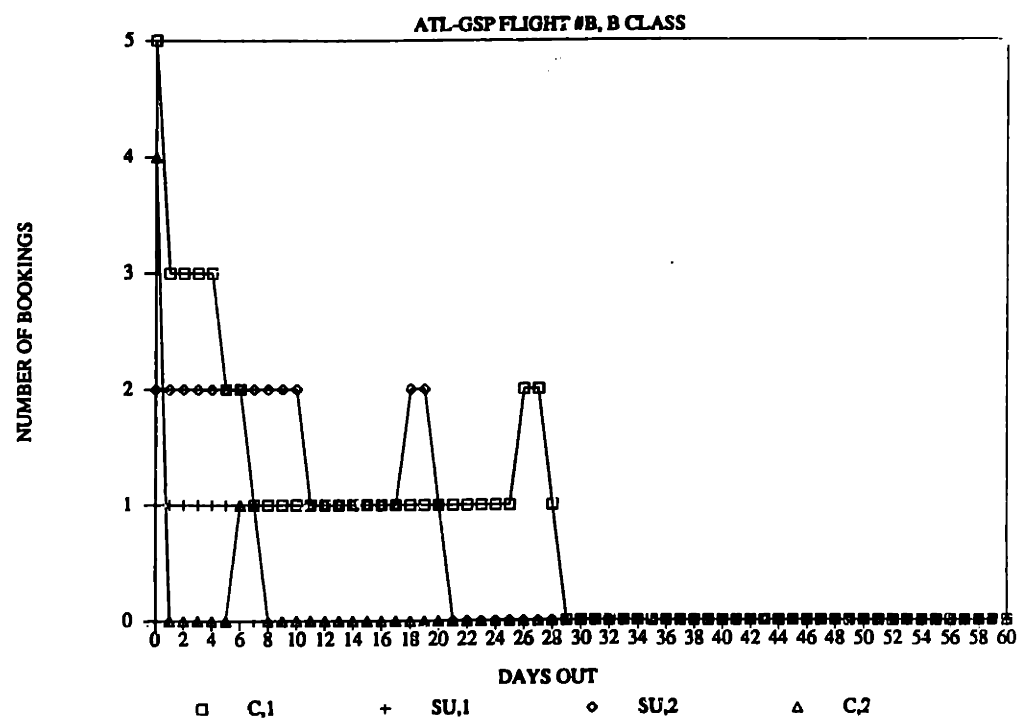
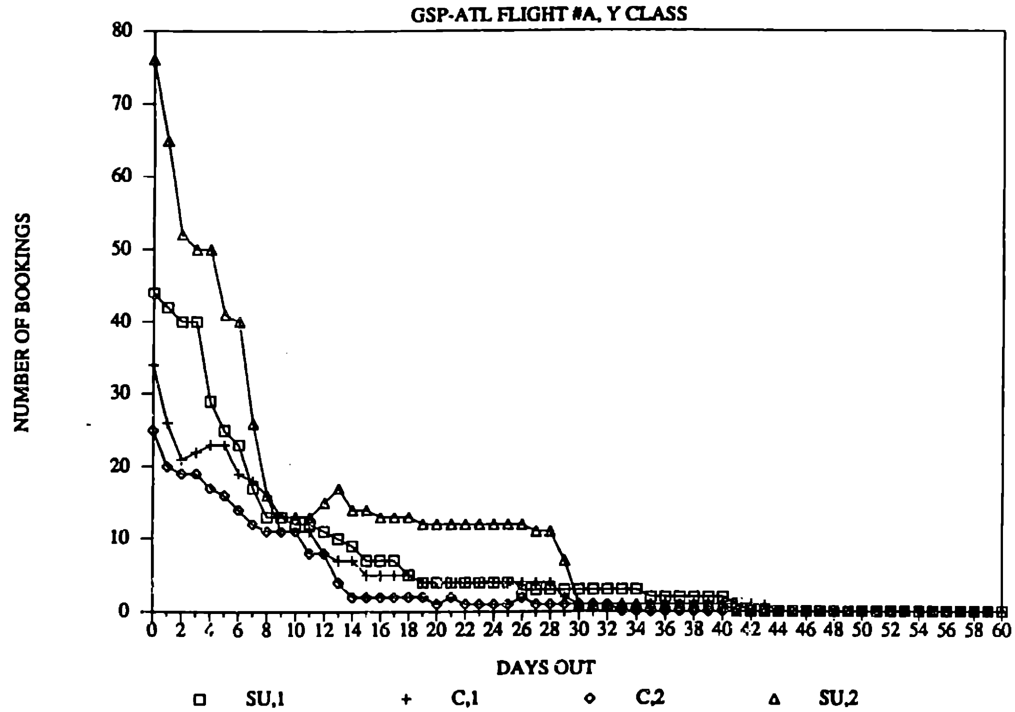


Figure C.1: ATLGSP "Y", "B" Classes, Flight B

BOOKING INFORMATION



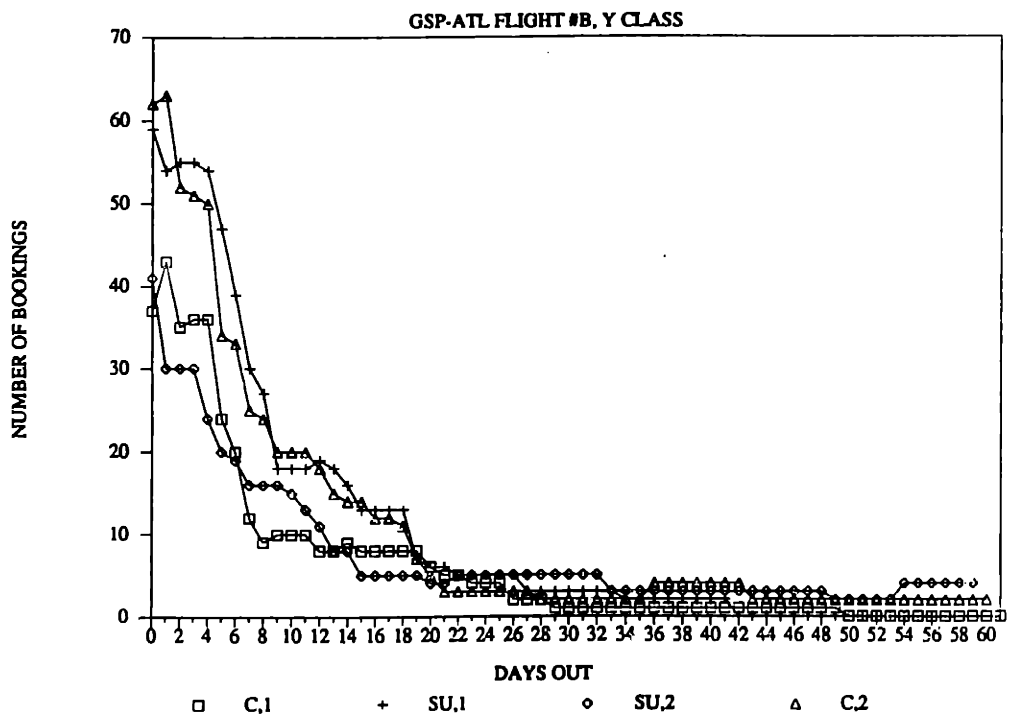
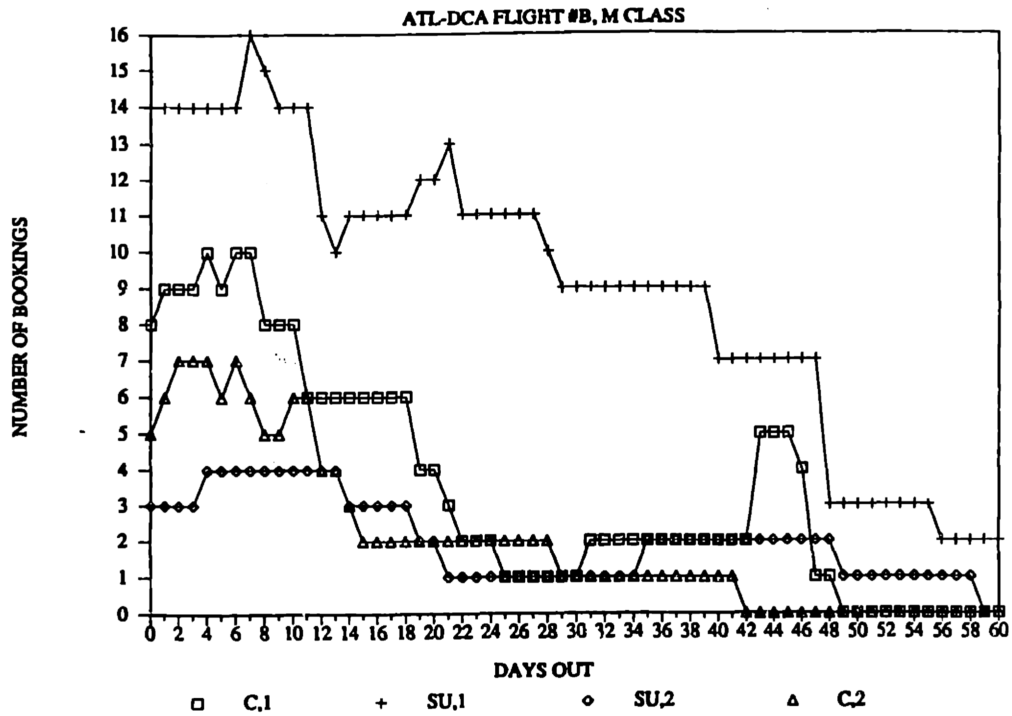


Figure C.2: GSPATL "Y" Class, Flights A, B



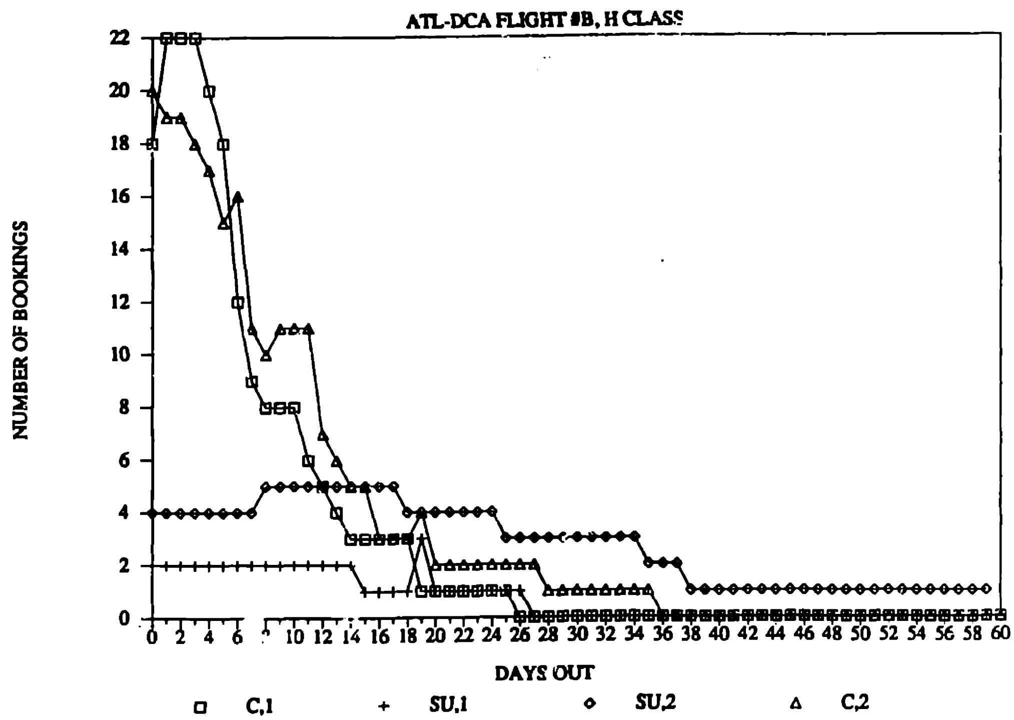
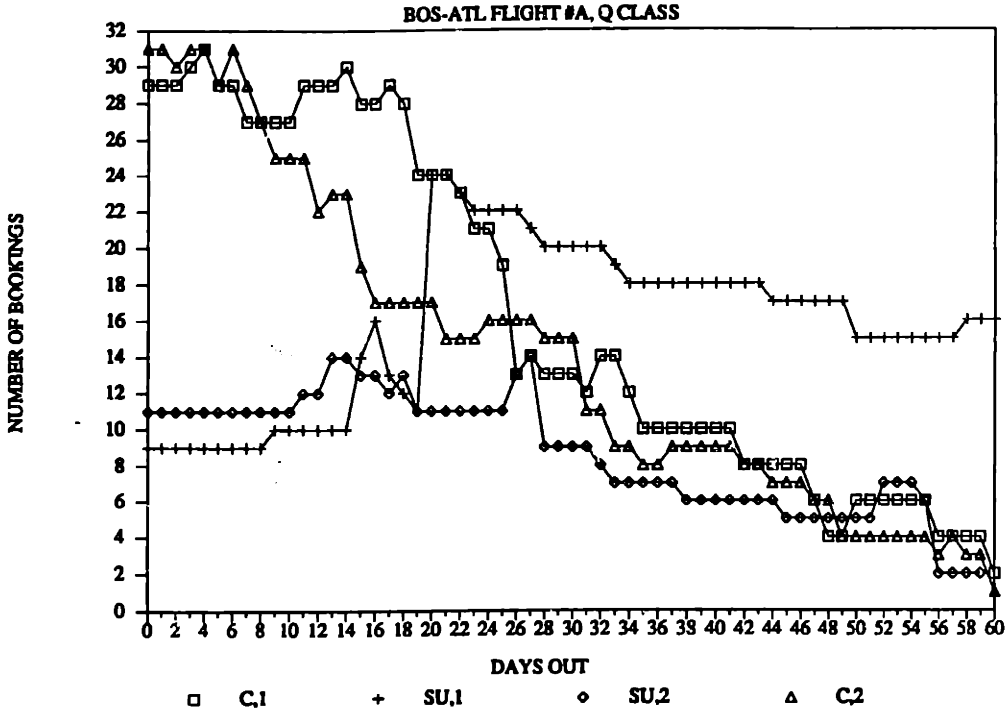


Figure C.3: ATLDCA "M", "H" Classes, Flight B

BOOK...G INFORMATION



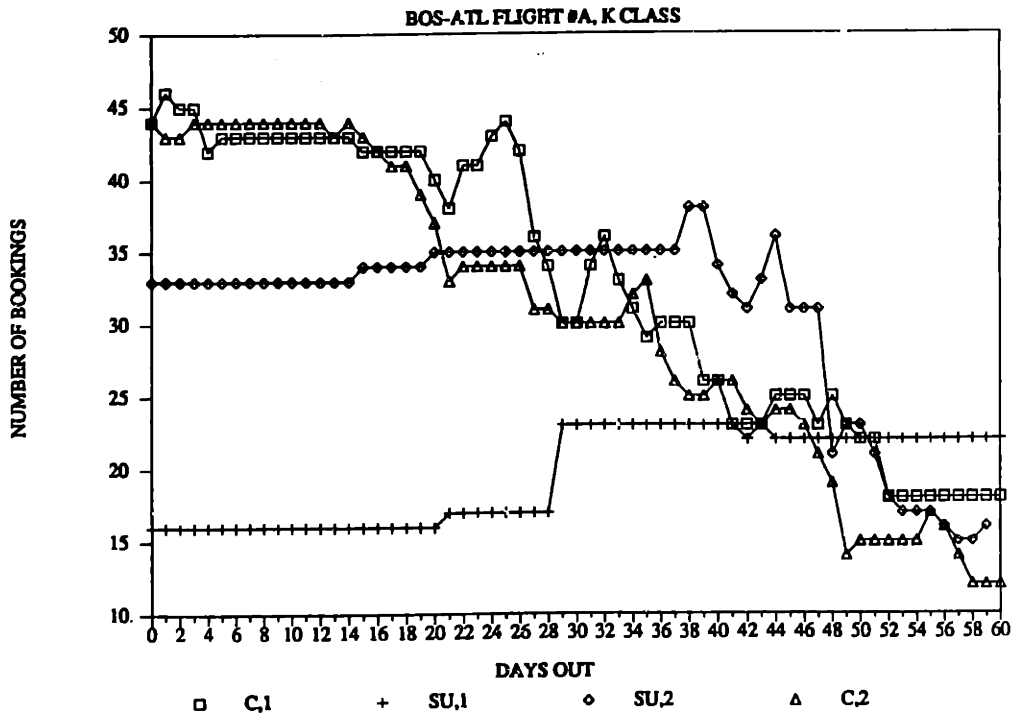


Figure C.4: BOSATL "Q", "K" Classes, Flight A