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16. Abstract

Airport choice is an important air travel-related decision in multiple airport regions. This report proposes the use of a probabilistic choice set multinomial logit (PCMNL) model for airport choice that generalizes the multinomial logit model used in all earlier airport choice studies. This study discusses the properties of the PCMNL model, and applies it to examine airport choice of business travelers residing in the San Francisco Bay Area. Substantive policy implications of the results are discussed. Overall, the results indicate that it is important to analyze the choice (consideration) set formation of travelers. Failure to recognize consideration effects of air travelers can lead to biased model parameters, misleading evaluation of the effects of policy action, and a diminished data fit.

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A Parameterized Consideration Set Model for Airport Choice: An Application to the San Francisco Bay Area

by

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Research Report SWUTC/03/167520-1

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ABSTRACT

Airport choice is an important air travel-related decision in multiple airport regions. This report proposes the use of a probabilistic choice set multinomial logit (PCMNL) model for airport choice that generalizes the multinomial logit model used in all earlier airport choice studies. This study discusses the properties of the PCMNL model, and applies it to examine airport choice of business travelers residing in the San Francisco Bay Area. Substantive policy implications of the results are discussed. Overall, the results indicate that it is important to analyze the choice (consideration) set formation of travelers. Failure to recognize consideration effects of air travelers can lead to biased model parameters, misleading evaluation of the effects of policy action, and a diminished data fit.

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EXECUTIVE SUMMARY

In contrast to the increasing contribution of air travel to urban travel, airport-related travel is still treated in a rather coarse and simplified manner within the urban travel modeling framework of most Metropolitan Planning Organizations in the State and the Country. In particular, airports are identified as "special attractors" and assigned a certain number of trip attractions, without adequate systematic analysis of the spatial and temporal patterns of the trip attractions. It is important for transportation agencies to consider a more systematic approach to analyze and forecast airport-related personal travel, so that improved predictions of traffic characteristics and traffic levels on urban roadways may be achieved. A systematic analysis of airport travel is also important for mobile-source emissions forecasting.

An important choice dimension related to airport travel is the origin departure airport choice in a multiple airport region. A multiple airport region is one in which a passenger living within has the option of departing and/or arriving from more than one airport. Common examples that have been used as regions of study in the past include New York City, the San Francisco Bay Area, Chicago, and the Washington, D.C./Baltimore region. A good understanding of the factors underlying a passenger's origin airport choice in multiple airport regions can enable airport management and airline carriers to attract passengers, upgrade airport facilities and equipment to meet projected air travel demands, and determine airport staffing needs. It can also aid Metropolitan Planning Organizations in forecasting travel demand in the urban region, and in planning transportation networks to/from airports.

The research in this report proposes the use of a probabilistic choice set multinomial logit (PCMNL) model for airport choice that generalizes the multinomial logit model used in all earlier airport choice studies. This study discusses the properties of the PCMNL model, and applies it to examine airport choice of business travelers residing in the San Francisco Bay Area. Substantive policy implications of the results are discussed. Overall, the results indicate that it is important to analyze the choice (consideration) set formation of travelers. Failure to recognize consideration effects of air travelers can lead to biased model parameters, misleading evaluation of the effects of policy action, and a diminished data fit.

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CHAPTER 1. INTRODUCTION

Since airline deregulation in 1978, there has been a dramatic increase in the number of passengers flown per year. Airline deregulation has generated substantial economic benefits for the vast majority of the traveling public. Because of lower fares and better overall level of service, demand for air travel has increased. Within the context of intercity travel, air travel is the fastest growing travel mode in the United States. Notwithstanding the events of September 11, 2001, projections suggest that the number of air travelers in the U.S. will double in this first decade of the 21st century. Further, airports are increasingly serving as freight gateways to facilitate long-distance commodity movement nationally and internationally. As the number of air travelers and amount of air freight movements increase, so will the contribution of airport-related travel to overall urban traffic levels. In addition, increases in person travel and freight lead to higher staffing needs at airport, thus increasing commuting travel to/from airports.

In contrast to the increasing contribution of air travel to urban travel, airport-related travel is still treated in a rather coarse and simplified manner within the urban travel modeling framework of most Metropolitan Planning Organizations in the State and the Country. In particular, airports are identified as "special attractors" and assigned a certain number of trip attractions, without adequate systematic analysis of the spatial and temporal patterns of the trip attractions. It is important for transportation agencies to consider a more systematic approach to analyze and forecast airport-related personal travel, so that improved predictions of traffic characteristics and traffic levels on urban roadways may be achieved. A systematic analysis of airport travel is also important for mobile-source emissions forecasting.

There are several dimensions characterizing air traveler decisions that impact the spatial and temporal distribution of trips to the airport. For residents of an urban area, some of the first decisions regarding inter-urban travel may include whether to travel away from the urban area and to where, the duration of the trip, and the mode for the inter-urban trip (*i.e.*, whether to travel by air, or some other mode). If air is the mode of choice, the relevant decisions include the destination airport, the origin airport in a multi-airport urban area, the desired arrival time at the destination (which impacts the desired flight departure time at the origin), the location and departure time to the origin airport, and the access mode of transport to the airport. In addition to these choices, other air traveler decisions that would be of relevance to air carriers and airport management include air carrier choice, fare class of travel, and method of purchase of tickets[1].

The many dimensions of air travel identified above are clearly inter-related. Ideally, the analyst would prefer a modeling structure that models all these dimensions jointly. But such a joint framework is infeasible in practice, and thus the analyst needs to adopt a sequential structure that may be assumed to reasonably represent the air travel choice process. For one possible choice hierarchy, please refer to Appendix A. This flowchart represents only one possible hierarchy of decisions within the context of air travel. The hierarchy of decision depends on several factors including a passenger's travel purpose and a passenger's sensitivity to variables such as time and cost. For example, if a passenger is extremely price sensitive then he or she might first jointly choose an airline and travel destination based on special deals at the time, and then choose the vacation time period depending on when it is cheapest to fly. In contrast, a passenger traveling on business often has a specific time and day on which he or she must fly, so they choose to fly the airline that offers the most convenient schedule.

An important choice dimension, which precedes most other air travel decisions in the choice framework, is the origin departure airport choice in a multiple airport region. Specifically, a multiple airport region is one in which a passenger living within has the option of departing and/or arriving from more than one airport. Common examples that have been used as regions of study in the past include New York City, the San Francisco Bay Area, Chicago, and the Washington, D.C./Baltimore region. A good understanding of the factors underlying a passenger's origin airport choice in multiple airport regions can enable airport management and airline carriers to attract passengers, upgrade airport facilities and equipment to meet projected air travel demands, and determine airport staffing needs. It can also aid Metropolitan Planning Organizations in forecasting travel demand in the urban region, and in planning transportation networks to/from airports.

Multiple airport regions can be classified into one of two categories. The first of these is a metropolitan area where there is more than one airport, and where the airports all tend to be hubs or large-scale operations offering similar services. The second type is that in which regional airports compete with larger, neighboring airports. The two cases can be analyzed in similar ways, though it is interesting to note that different factors defining a passenger's choice

[1] Refer to Appendix A for a sample hierarchy of choices involved in air travel.

prevail in each scenario. For example, when departing from a regional airport one usually connects through one of the neighboring airports, depending on the destination. Passengers can instead opt to travel to these larger airports by personal vehicle, rail, or bus and travel directly from them. In this case, regional airports lose passengers to the larger airports, but equally importantly, regional airports lose passengers to various other modes including personal vehicle, rail, and bus. Passengers might choose to forego the services of their regional airports, and travel long distances to the larger airports because of factors such as availability of nonstop flights, jet service, or lower ticket prices.

In the first scenario, where multiple airports compete with one another in large, metropolitan areas, these same factors (jet service, ticket prices, etc) may not come into play. For the most part, when dealing with larger airports, the variability of services to destinations is not as apparent, therefore passengers may choose airports based on specific departure times of flights, specific airline availability, or because of airport familiarity. The focus in this study is on the first of the two scenarios, multiple airports in a metropolitan area competing with one another.

The rest of this study is structured as follows. The next section discusses previous work in the area of airport choice. Section 3 presents the model structure. Section 4 discusses the data source and sample formulation procedures. Section 5 describes the empirical results. The final section highlights the important findings of this study.

CHAPTER 2. PREVIOUS WORK

2.1 Background

Several earlier studies have examined airport choice in a multiple airport region. Some of these studies have focused on airport choice in isolation, while others have examined airport choice along with other dimensions of air travel. These earlier studies have focused on different urban areas and, sometimes, different population groups (such as business travelers versus leisure travelers and residents versus non-residents). Following is a detailed review of many of the previous studies in the area of airport choice.[2]

2.2 Airport Choice in Isolation

One of the first airport choice models was developed by Skinner (1976). The area of study was the Baltimore-Washington, D.C. region, which includes three major airports (Baltimore, Washington Dulles, and Reagan National). A multinomial logit model was estimated with variables for flight frequency and ground accessibility of each airport. Skinner stratified the passengers into two groups: business and non-business. He concluded that passengers are more sensitive to airport accessibility than to flight frequency.

Harvey (1987) estimated a passenger airport choice model using data from the San Francisco Bay Area. He used a multinomial logit structure with three airport alternatives (San Jose International, San Francisco International, and Oakland International). Passengers were stratified into resident business and resident non-business. Airport access time and flight frequency were found to be significant determinants of airport choice. Harvey's conclusions were that the value of time is lower for non-business travelers while their value of funds is higher relative to business travelers. Another conclusion was that all travelers prefer direct flights to commuter and connecting flights. As for future work, Harvey suggested extending the analysis to include lower-level choices such as access mode in a nested logit framework.

Ashford and Benchemam (1987) estimated a multinomial logit model for airport choice in Central England. The five airport alternatives were Manchester, Birmingham, East Midlands, Luton, and London Heathrow. The passengers were segmented into domestic, international

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[2] For a detailed table of the literature review of previous work within the context of airport choice, please refer to Appendix B.

business, international non-business, and international inclusive tours travelers. The final variables in the model were travel time to the airport and flight frequency for international business and international inclusive tours travelers. Flight frequency, travel time to the airport, and airfare were the final variables in the model for the remaining market segments. Ashford and Benchemam concluded that business travelers are most sensitive to airport access time, and that leisure travelers are most sensitive to both airfare and airport access time relative to the other variables.

Ozoka and Ashford (1987) studied air traveler behavior in Nigeria as a comparison to air traveler behavior in both the United Kingdom and the United States. Passengers traveling from two airports, Enugu and Benn, to one common destination were the focus of the study. The development of a multinomial logit model allowed for the prediction of the effect of a third airport in the area. Variables considered were weekly flight frequency from each airport to the destination, economy class airfare, and airport access travel time. Flight frequency and airfare were found to be insignificant, probably due to the fact that the two airports offered similar flight schedules and airfares to the same destination. Airport access time was found to be significant, implying that any improvements to airport access would greatly influence passengers' choice of airport. The significance of airport access time indicates that airports in Nigeria, much like the rest of the world, do compete with one another.

Innes and Doucet (1990) used a binary logit structure for airport choice in the northern province of New Brunswick, Canada. Their binary structure gave a passenger the choice of flying from the closest airport to them and the second closest. Their region of study was unique because it was the northern part of the province of New Brunswick, Canada, where travelers are faced with the choice of flying out of regional airports, or traveling to another airport where there are not as many restrictions compared to their local airport. Their region of study is a good example of the second type of area that can be analyzed (discussed in section 1): where regional airports compete with neighboring hubs. Original variables were ticket type, who the ticket was paid by, length of stay at destination, type of aircraft, availability of nonstop service, and difference in flying time to destination (again comparing the nearest airport to the next closest). The distance variables were eventually dropped from the model, and Innes and Doucet focused on level of service. They found that type of aircraft plays a significant role in airport choice, and that air travelers are willing to travel long distances in order to have access to jet service. Also, Innes and Doucet found that passengers prefer direct flights to connecting flights.

Thompson and Caves (1993) estimated a multinomial logit model to forecast the potential market share for a new airport in North England that would serve six destinations. Passenger survey data as well as data for flight services (average fares, flight frequency, aircraft type) from 1983 were used to compare the predicted services of Sheffield (the new airport) with those of Birmingham, East Midlands, and Manchester airports. The final variables used in the estimation were access time to the airport, daily flight frequency, and the maximum number of seats available on an aircraft serving a specific destination; passengers were stratified into business and leisure groups. With the assumptions made regarding flight frequency and fare offered from Sheffield airport, Sheffield was projected to take 86% of business travelers (traveling to the six destinations) living within an hour of the airport. Additionally, Thompson and Caves found that individuals living closer to an airport value access time significantly more than any other variable, and are only slightly affected by changes in flight frequency and fare, compared with people living further away who show higher sensitivity to changes in flight frequency and airfare.

Windle and Dresner (1995) estimated a multinomial logit model with weekly flight frequency data and airport access times. They also included a chooser specific variable that indicated how many times during the past year a passenger had used each of the airports. Their analysis was in the Baltimore-Washington, D.C. region, including 30 domestic destinations. As in many previous studies, they found that the level of service variables were significant, and that the choice specific variable was highly significant. The more an individual used an airport, the more likely they were to use it in the future.

2.3 Airport Choice Along With Other Dimensions of Air Travel

In addition to airport choice in isolation, many studies throughout the years have focused on origin airport choice within the context of other air travel choice dimensions. These include, but are not limited to, destination airport, ground access mode to the airport, and airline choice. Following is a summary of some of these studies.

Ndoh, Pitfield, and Caves (1990) compared the multinomial logit (MNL) structure with that of the nested multinomial logit (NMNL) structure to analyze passenger route choice in

Central England. They found that the NMNL model where the selection process is route type, followed by choice of hub airport, and then departure airport, is statistically superior to the MNL model with the alternatives being different routes. Business travelers were found to value access time the most, followed by weekly flight frequency on a direct route in their choice of route. Other significant variables in the model were average journey time, average connection time to hub airport, and weekly available aircraft seats on each route.

Furuichi and Koppelman (1994) studied air travelers' departure airport and destination choice behavior using data from an international air traveler behavior survey administered in Japan in 1989. Their study included passengers traveling on nonstop flights to international destinations from four major airports in Japan. A nested logit structure was used for the choice of departure airport and destination among both business and pleasure passengers. The preferred model specification for business and pleasure travelers was the same; the variables used for airport choice were access time and costs to the airport, line-haul time and cost from an individual's departure airport to their destination, and the relative flight frequency (flights from departure airport to chosen destination to the sum of flights at all other possible departure airports). The variables used in the destination choice model were the log sum variable for access and line-haul service and the log of the trade value (international trade between Japan and destination area).

One finding of this study was that both business and pleasure travelers value access travel cost to the airport more than line-haul travel cost; this finding implies that cost could be valued differently depending on the type of expenditure. Additional findings were that all travelers place a high value on flight frequency, access and line-haul time.

Pels, Nijkamp, and Rietveld (2000, 2001) developed a joint airport-airline choice model for the San Francisco Bay Area using a nested logit structure. Flight frequency and ground access time were found to be significant. They used number of seats in an aircraft as a proxy for comfort, and found this variable to be significant as well. Contrary to previous findings, they found there to be little difference between the estimations for business and leisure travelers. They also found the choice hierarchy of passengers first choosing departure airport, and then choosing airline to be more statistically favorable than the opposite case.

Pels, Nijkamp, and Rietveld (2002) estimated an access mode – airport choice model for the San Francisco Bay Area. A nested logit structure was used, with airport choice at the top level and access mode choice at the lower level being the preferred structure. Resident business and resident non-business travelers from the Bay Area were examined. Access mode choice was a function of access cost and access time, while airport choice was a function of airfare and flight frequency. They found that business travelers have a higher value of time than leisure travelers, and that access time to the airport is one of the most important factors in airport choice.

A common finding in all these studies (airport choice in isolation and airport choice in the context of other air travel dimensions) is that access time to the airport and frequency of service from the airport to the desired destination are the dominant factors affecting airport choice. Several of these studies also suggest that a simple measure of access time to the airport; *i.e.*, auto access time; performs as well as more complex formulations that consider multiple modes and both access time and access cost. In addition, many earlier studies find that airfare is not a significant factor in airport choice for business travelers, though a few studies find airfare to affect airport choice for non-business travelers.

2.4 Choice Set Formation

The current study contributes to the existing body of literature by focusing on airport choice in the San Francisco Bay Urban Area context. An important characteristic of the current study is its recognition that travelers may not consider all the available airports when making the choice of their departure airport. Earlier research on choice set generation has indicated the important impact of consideration effects on consumer choice (see, for example, Roberts and Lattin, 1991; Ben-Akiva and Boccara, 1995; Chiang *et al.*, 1999).

Despite the importance of choice sets, all the airport choice models discussed earlier assume that each traveler makes a choice from the full set of available airports, where an airport is assumed to be available if there is at least one flight (direct or connecting) from the airport to the destination city. Such an assumption is rather untenable because an individual's choice set is likely to depend on the traveler's specific sociodemographic, informational, psychological, and societal contexts as well as subjective criteria associated with individual attitudes/perceptions. For example, an individual may consider a particular airport to be too far away to be even considered, while another individual may consider this distance to be acceptable. Similarly, an individual may eliminate from consideration any airport that does not have airline club lounges, while another may include airports without airline club lounges in her/his choice set. Thus, it is important to recognize that different travelers may, and in general will, consider different sets of alternatives.

To be sure, considering the choice set formation process along with the actual choice process is not merely an esoteric econometric issue. Earlier research in the transportation and marketing fields has indicated that failure to properly specify the choice set considered by consumers can lead to biased choice model parameters, a lack of robustness in parameter estimates, and violations of the independence from irrelevant alternatives assumption (see Shocker *et al.*, 1991; Swait, 1984; and Williams and Ortuzar, 1982). On the other hand, the explicit incorporation of consideration effects has both methodological and managerial benefits. Methodologically, the incorporation of consideration effects can lead to a more accurate prediction of the choice process being modeled (see Gensch, 1987; Chiang *et al.*, 1999; and Swait, 2001). Such prediction gains will result in improved forecasting of travel demand to/from airports. Managerially, the recognition of consideration effects can help determine the relative effects of policy relevant variables on consideration and choice, and thus aid in a comprehensive understanding of the impacts of policy actions (discussed in sections 5 and 6). The important point to note here is that regardless of the relative utility of an airport compared to other airports in a traveler's choice set, the airport will not be chosen if it is not first considered (see Andrews and Srinivasan, 1995).

In addition to the methodological issue of modeling the choice set generation process and airport choice from the choice set, the current study also considers the impact of sociodemographic and trip characteristics of the traveler on airport choice. Harvey (1987) is one of the only earlier studies that recognizes demographic impacts, but that study did not find any statistically significant effects of personal characteristics on airport choice.

CHAPTER 3. MODEL STRUCTURE

3.1 Background

The model structure used in this study is based on Manski's (1977) original two-stage choice paradigm, which includes a probabilistic choice set generation model in the first stage followed by the choice of airport from a given choice set.

The first stage uses a probabilistic choice set generation mechanism because the actual choice set of travelers is unobserved to the analyst and, therefore, cannot be determined with certainty by the analyst. Within the class of probabilistic choice set generation models, Swait and Ben-Akiva's (1987a) random constraint-based approach to choice formation is adopted (for a detailed discussion of other approaches to probabilistic choice set generation, see Ben-Akiva and Boccara, 1995). In the random constraint-based approach, an airport is excluded from the choice set if the consideration utility for that airport is lower than some threshold consideration utility level (the reader will note that the consideration of an airport is determined only by the threshold level of that airport, not by any comparisons to the thresholds of other airports). Since the threshold utility level is not observed to the analyst, the exclusion of an airport from the choice set becomes probabilistic. In the current study, the consideration utility is allowed to vary across individuals, so that the consideration probability of each airport varies across individuals. Almost all earlier applications of probabilistic choice set generation have used the same consideration probability across individuals (but see Andrews and Srinivasan, 1995). Swait and Ben-Akiva (1987b) allow the consideration probabilities to vary across individuals, but their parameterized logit captivity (PLC) model constrains consumers to be either captive to a single alternative or to choose from the full set of alternatives. The parameterized choice set model in the current study is more general, and allows consumers to choose from all possible choice set sizes.

The second stage airport choice model, given the choice set, is based on the familiar multinomial logit formulation. At this stage, the utilities of the airports in the choice set are compared directly with each other in a utility maximizing process. The difference in the process at the choice set generation and choice stages enables a change in an attribute associated with an airport to have two separate effects: a consideration effect (*i.e.*, the impact on the consideration set of airports) and a choice effect (*i.e.*, the impact on the choice of an airport, given that the airport is considered by the individual).

3.2 Formulation

The model formulation in this section is developed assuming that all airports are feasible for each traveler (though not all of the airports may be considered by each traveler). This assumption simplifies the presentation and is consistent with the empirical context of the current report, where each airport has at least one direct or connecting flight in the day to each traveler's destination airport.

Let the consideration utility of airport i (i=1,2,…,I) for individual q be U_{qi}. The alternative is included in the choice set if this consideration utility exceeds a certain threshold and is eliminated if not. Since the threshold is not observed to the analyst, it is considered as a random variable. In the current study, this random threshold is assumed to be standard logistically distributed. Then, the probability that alternative i is considered by individual q can be written as:

$$M_{qi} = \frac{1}{1+e^{-\gamma' w_{qi}}}, \qquad (1)$$

where w_{qi} is a column vector of observed attributes for individual q and alternative i (including a constant) and γ is a corresponding column vector of coefficients to be estimated (this coefficient provides the impact of attributes on the consideration probability of alternative i).

Next, assume that the randomly-distributed threshold for each alternative is independent of the threshold values of other alternatives. The overall probability of a choice set c for individual q may then be written as:

$$P_q(c) = \frac{\prod_{i \in c} M_{qi} \prod_{j \notin c} (1 - M_{qj})}{1 - \prod_{i=1}^{I} (1 - M_{qi})}, \qquad (2)$$

where the denominator is a normalization to remove the choice set with no alternatives in it.

The choice of airport from a given choice set can be written, using a multinomial logit formulation, as:

$$P_{qi} \mid c = \frac{e^{\beta' x_{qi}}}{\sum_{j \in c} e^{\beta' x_{qi}}} \text{ if } i \in c$$
$$= 0 \text{ if } i \notin c \,, \tag{3}$$

where x_{qi} is a column vector of exogenous variables and β is a column vector of coefficients indicating the effect of variables at the choice stage.

Finally, the unconditional probability of choice of alternative *i* can be written as follows:

$$P_{qi} = \sum_{c \in G} (P_{qi} \mid c) \cdot P_q(c) \;, \tag{4}$$

where *G* is the set of all nonempty subsets of the master choice set of all airport alternatives. The membership of *G* will include 2^{I-1} elements. For example, in a three airport case, denoted as {A,B,C}, *G* includes the following choice sets: {A}, {B}, {C}, {A,B}, {B,C}, {A,C}, {A,B,C}.

The log-likelihood function for the estimation of the parameters β and γ is:

$$\log \mathcal{L}(\beta,\gamma) = y_{qi} \cdot \log P_{qi}(\beta,\gamma) \,, \tag{5}$$

where y_{qi} is a dummy variable taking the value 1 if individual *q* chooses airport *i* and 0 otherwise. Maximization of the log-likelihood function is accomplished using the GAUSS matrix programming language.

3.3 Properties

The parameterized probabilistic choice set multinomial logit (PCMNL) model structure presented in the previous section nests the multinomial logit structure as a special case. In particular, the probability function of Equation (4) collapses to the MNL model if $M_{qi} = 1$ for all alternatives *i* and all individuals *q* (also note that $M_{qi} \to 1$ when $\gamma' w_{qi} \to +\infty$ for all *i* and *q*). In this situation, $P_q(c) = 0$ for all choice sets *c* that are subsets of the master choice set and $P_q(c) = 1$ for the master choice set, which is equivalent to assuming that all individuals consider all airports.

The disaggregate-level elasticity effects in the PCMNL model can be computed from the probability expression in Equation (4) in a straightforward manner (however, the author is not aware of any earlier study presenting these expressions). In the following presentation of elasticity expressions, the index *q* for individuals is suppressed for notation ease. Let δ_i^c be a dummy variable taking the value 1 if choice set *c* contains airport *i* and 0 otherwise, and let δ_{ij}^c

be another dummy variable taking the value 1 if choice set c contains both airports i and j and 0 otherwise. Also, define B_i as follows:

$$B_i = \sum_{c \in G} \delta_i^c P(c) = \frac{M_i}{1 - \prod_k (1 - M_k)} . \tag{6}$$

Then the self- and cross-elasticities of a change in the m^{th} attribute of an airport $i\,(z_{im})$ that appears at both the consideration stage and choice stage can be written as follows:

$$\begin{aligned} \eta_{z_{im}}^{P_i} &= \left[(1 - B_i)\gamma_m + \frac{1}{P_i} \sum_{c \in G} \left\{ (P_i \mid c)(1 - P_i \mid c) P(c) \beta_m \right\} \right] z_{im} \\ \eta_{z_{im}}^{P_j} &= \left[\left\{ \frac{1}{P_j} \sum_{c \in G} (P_j \mid c) P(c) \cdot \delta_{ij}^c - B_i \right\} \gamma_m + \frac{1}{P_j} \sum_{c \in G} \left\{ (-P_i \mid c)(P_j \mid c) P(c) \beta_m \right\} \right] z_{im} \end{aligned} \tag{7}$$

The expression above comprises two terms. The first term represents the consideration elasticity and captures the impact of a change in z_{im} on the consideration of airport i in the self-elasticity expression and on the consideration of airport j relative to airport i in the cross-elasticity expression. The second term represents the substitution elasticity at the choice stage conditional on the alternative being available in the choice set. Note that for a variable that does not appear in the consideration stage, only the substitution elasticity applies in each of the expressions. On the other hand, for a variable that does not appear at the choice stage, only the consideration elasticity applies. In any case, the cross-elasticity expression is a function of the choice probability for mode j. Thus, the PCMNL model does not exhibit the IIA property of the MNL model. It is also easy to verify that the self- and cross-elasticity expressions collapse to those of the MNL when all airports are considered.

CHAPTER 4. DATA SOURCES

4.1 Primary Data Source

The primary data source for this study is an air passenger survey conducted by the Metropolitan Transportation Commission in the San Francisco Bay Area. This survey was administered to randomly selected travelers in August and October of 1995 at four airports: San Francisco International (SFO), San Jose International (SJC), Oakland International (OAK), and Sonoma County (STS). The full data set included 21,124 samples, and was comprised of twenty-one survey questions. Information collected in the survey included purpose of travel, destination, size of the traveling party, mode of transport to the airport, airline carrier, and flight details. Passengers were also asked how many flights they took from each of the six Bay Area airports during the past twelve months. In addition, sociodemographic attributes of the traveler such as gender and income were obtained[3].

In the current research, the survey responses from the three major Bay Area airports; SFO, SJC, and OAK; are used because of the very low share of travelers using the Sonoma County airport[4]. For ease in data preparation and assembly, the top thirty domestic destinations from these three Bay Area airports are identified from the sample and the airport choice of Bay Area residents to these top destinations are considered[5]. These top thirty destinations are served from each of the three Bay Area airports, either through direct flights and/or connecting flights. Thus, all the three airports are available as potential choices, though not all of them may be considered by travelers (please refer to Figure 1 on the following page for a diagram of the three airports in this study).

The air travel market is segmented, for the purpose of this analysis, into business and non-business trip purposes. To narrow the focus, only business trips are considered in this study. The final business sample comprises 1,918 observations, of which 1,618 observations are used for estimation and the remaining 300 observations are set aside as a validation sample for evaluating the performance of an ordinary multinomial logit (MNL) model and the parameterized probabilistic choice set multinomial logit (PCMNL) model of this report. The sample shares and the market shares in the estimation sample are presented in Table 1.

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[3] For a listing of all questions asked in the survey, refer to Appendix C.
[4] Please refer to Appendix D for a flowchart of the data screening/preparation process.
[5] Please refer to Appendix E for a listing of the thirty destinations used in this study.

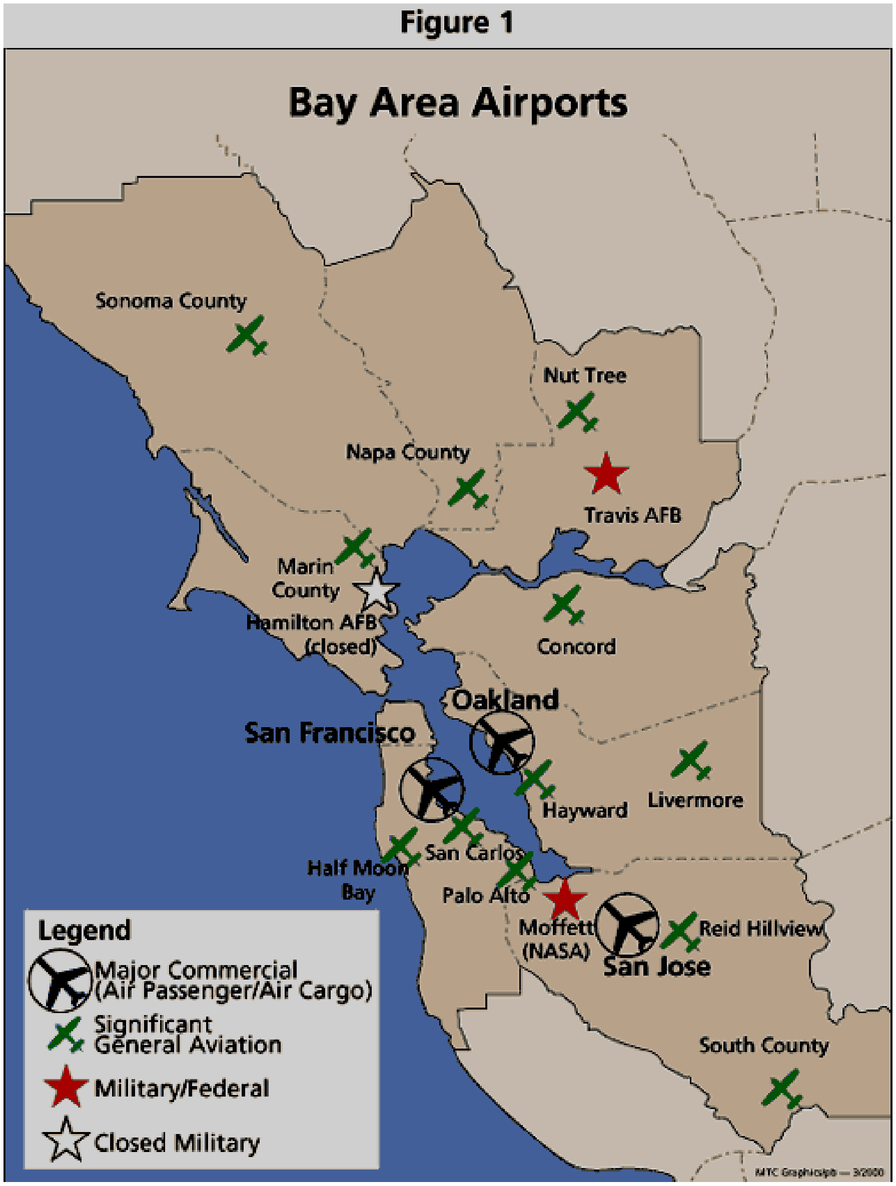

Figure 1. Study Area

Table 1. Estimation Sample Shares, Market Shares, and Weights

Airport	Estimation sample shares	Market shares	Weight[1]
San Francisco International (SFO)	0.2559	0.6248	2.4420
San Jose International (SJC)	0.4932	0.1775	0.3596
Oakland International (OAK)	0.2509	0.1977	0.7882

[1]The weight variable refers to the weight placed on individuals choosing each airport. Thus, for example, each individual in the estimation sample choosing SFO is assigned a weight of 2.4420 during estimation.

As can be observed, there is an over sampling of travelers flying out of San Jose in the airport survey (the actual shares of airport choice in the population are obtained from the Bureau of Transportation Statistics). Since the sample is choice-based with known aggregate shares, the Weighted Exogenous Sample Maximum Likelihood (WESML) method proposed by Manski and Lerman (1977) is employed in estimation. This method weights the log-likelihood value for each individual in Equation (5) by the ratio of the market share of the airport chosen by the individual to the sample share of the airport chosen by the individual (the resulting weights are presented in the final column of Table 1). Maximizing the resulting likelihood function provides consistent estimates of the parameters. The asymptotic covariance matrix of parameters is computed as $H^{-1}\Delta H^{-1}$, where *H* is the hessian and Δ is the cross-product matrix of the gradients (*H* and Δ are evaluated at the estimated parameter values). This provides consistent standard errors of the parameters (Börsch-Supan, 1987).

4.2 Secondary Data Sources

In addition to the air passenger travel survey, three other secondary data sources are used to develop the final sample. The first is a zone-to-zone ground access level of service file, obtained from the Metropolitan Transportation Commission in Oakland. This information is appropriately appended to the sample observations based on the originating zone of departure to the airport and the zone that contains each airport. In the current analysis, level-of-service (time and cost) values corresponding to the highway mode are used, since a majority of the trips to the airport are pursued by a private or rental car[6].

The second secondary data source used in the analysis is the daily flight frequency from each Bay Area airport to the thirty destination airports, obtained from the 1995 Official Airline Guide (Official Airline Guide Market Analysis, 1995)[7]. This information is appended to the sample observations based on the origin-destination airport pair and the day of week of travel. The third source of data is on-time flight statistics for nonstop flights from each airport to each destination, obtained from the Bureau of Transportation Statistics (BTS). These data provide the percentage of late flights, defined as the percentage of flights delayed beyond 15 minutes of the scheduled departure time[8].

The three secondary data sources discussed above provide measures of the quality of service offered by each airport for the traveler's trip.

[6] Eighty-six percent of passengers in the estimation sample traveled to the airport by either private or rental car.
[7] These include nonstop flights and flights with a stop but no change in equipment.
[8] The BTS on-time flight statistics are for 1997, and its use in the current analysis assumes the absence of significant changes between 1995 and 1997

CHAPTER 5. EMPIRICAL ANALYSIS

5.1 Variable Specification

The choice of variables for potential inclusion was guided by previous empirical work on airport choice modeling, intuitive arguments regarding the effects of exogenous variables, and data availability considerations. Three broad classes of variables were considered for inclusion: (1) quality of service variables, (2) interactions of sociodemographics with quality of service, and (3) interactions of trip characteristics with quality of service.

The quality of service variables, as discussed earlier, included ground-access level of service variables (time and cost) and air travel level-of-service variables (flight frequency to destination and percentage of late flights). Traveler sociodemographic variables considered in the analysis included the gender, age, and household income of the traveler. Finally, the trip characteristics explored in the specifications included the following dummy variables: (a) an "alone" variable identifying whether or not the individual was traveling alone, (b) a "short trip" variable representing if the traveler was away for fewer than 2 nights or 2 or more nights, (c) a "car used to reach airport" variable indicating whether the traveler used a car (private or rented) to reach the airport, (d) a "weekday" variable indicating if the trip was pursued on a weekday or the weekend, and (e) a "left to airport from work" variable identifying if the traveler left to the airport from work or from a nonwork location.[9] Additionally, although some earlier studies have found nonstop flights to be a significant factor in airport choice, the variable was not included in this study since almost all passengers in the estimation sample flew nonstop flights to their final destination.

In the early stages of this study the significance of an airport loyalty variable was explored in an attempt to capture airport desirability characteristics as well as a measure for airport familiarity. The airport loyalty variable came out to be highly significant, showing that the more a passenger flies out of one airport relative to the other airports in the area, the more likely they are to fly out of this airport again. Although this variable came out to be statistically significant, it was excluded from further estimation because of the fact that airport loyalty is most likely a function of the other variables in the model. Likewise, though the "percentage of late flights" variable came out to be significant, it was excluded from further estimation.

[9] Please refer to Appendix F for a listing of those variables considered.

Preliminary results with respect to this variable indicated that passengers were likely to choose airports with poor on-time flight performance records. The assumption was made that results were opposite from what would have been expected either due to a) inaccurate data since the only on-time flight data available was from 1997, while the air passenger survey was from 1995, or b) the percentage of late flights variable was highly correlated with some other, desirable characteristic of an airport such as size, number of airlines serving the airport, or simply overall airport activity.

Several nonlinear forms for capturing the effect of access time and flight frequency were explored in this analysis. But the simple linear functional form for access time and flight frequency performed as well as the more complex functional forms. The arrival at the final specification was based on a systematic process of eliminating variables found to be insignificant in previous specifications and based on considerations of parsimony in representation.

5.2 Estimation Results

The results of the multinomial logit (MNL) model and the parameterized probabilistic choice set multinomial logit (PCMNL) model are presented in Table 2 and discussed in the subsequent two sections.

Table 2. Estimation Results

Variable	MNL Model		PCMNL Model			
			Consideration Stage		Choice Stage	
	Parameter	t-statistic	Parameter	t-statistic	Parameter	t-statistic
Access time-related variables (access time is in 100s of minutes)						
Access time	-6.964	-13.43	-2.185	-1.91	-7.503	-11.13
Access time x traveling alone	-0.825	-1.76	---	---	-2.169	-3.24
Access time x female	-0.796	-1.92	1.748	2.02	-0.701	-1.11
Access time x weekday travel	---	---	-3.788	-2.89	---	---
Frequency-related variables (frequency is in flights per day divided by 10)						
Frequency	0.411	2.88	3.893	5.83	0.360	2.19
Frequency x traveling alone	0.271	1.87	---	---	0.232	1.40
Frequency x female	-0.173	-1.36	---	---	-0.092	-0.62
Frequency x high income indicator (annual income > 150K)	-0.257	-2.09	---	---	-0.581	-2.85
Frequency x weekday travel	---	---	1.832	2.00	---	---
Airport Constants						
San Francisco International	---	---	3.826	3.08	---	---
San Jose International	-1.998	-12.30	-0.595	-1.90	-1.659	-8.44
Oakland International	-2.162	-17.17	-1.531	-3.14	-1.522	-10.98

5.2.1 The MNL Model Results

The coefficients on the access time variable in the multinomial logit model indicate, as one would expect, that business travelers are averse to traveling long durations to reach an airport. This is particularly the case for individuals traveling alone and women travelers. The coefficients on the frequency variable indicate a preference for airports that have frequent flight service to the traveler's destination. Individuals traveling alone, in particular, place a premium on frequency. This result, along with the higher access time sensitivity of individuals traveling alone, suggests that time is less onerous when traveling in a group (perhaps because of the opportunity to socialize or conduct business when traveling together). The results also indicate the lower sensitivity of women and high-income individuals to frequency of service. The latter result is a little surprising, but may be a reflection of high-income individuals traveling at narrow peak-period time windows of the day, and thus not being sensitive to the frequency of flights over the entire day. Frequency of service does not impact airport choice for high-income women travelers.

5.2.2 The PCMNL Model Results

The PCMNL model includes estimates of the probabilistic choice set generation model as well as the airport choice model. The coefficients at the consideration stage provide estimates of the γ vector in Equation (1). Table 2 shows that the coefficients on the access time and frequency variables at the consideration stage are statistically significant, indicating variation in the consideration of each airport across individuals. In particular, airports that are farther away and/or that have a low frequency of flights are less likely to be considered by individuals. As one would expect, these effects are magnified on weekdays compared to weekends. Additionally, women appear to be more willing than men to consider airports that are distant from their point of departure to the airport.

The coefficient estimates in the choice stage in the PCMNL model have interpretations that are similar to those in the MNL model. However, there are differences in the magnitude of the access time impacts. Specifically, the access time effects at the choice stage are higher than the corresponding MNL estimates. The reason is that airports that are very far away are "removed" from consideration in the PCMNL model. For example, consider an individual with one close airport and two very distant airports, and assume that this individual considers only the close airport. For this individual, access time has no impact (by definition) at the choice stage (the probability of choice of the close airport is one, given that the choice set includes only that airport). Thus, the sensitivity to access time at the choice stage in the PCMNL model is automatically based on data from individuals who have a high probability of consideration of two or more airports, and who are sensitive to access time at the choice stage. The MNL model, on the other hand, includes relatively "captive" individuals in the choice model estimation, despite these individuals not being sensitive to access time. The result is a dilution of the sensitivity to access time in the MNL choice model. The impact of frequency at the choice stage of the PCMNL model is not very different from the MNL model.

The combination of results at the consideration and choice stages shows that access time is less important for women when developing the perception "space" of availability of airports, but is more important for women when choosing an airport from the choice set of available airports.

5.3 Trade-off Between Access Time and Frequency of Service

The coefficients on time and frequency can be used to examine the trade-offs between the two determinants of airport choice. For example, the MNL model indicates that male, low-income, individuals traveling in a group would be willing to travel about 6 minutes [=0.411/(6.964/100)] longer if the frequency of flight service were to be increased by ten flights per day. The corresponding values for other traveler subgroups are provided in Table 3 for both the MNL and PCMNL models. In general, these results indicate that access time is the dominant determinant of airport choice for business travelers, particularly for high-income group travelers. In addition, the PCMNL values indicate that, at the choice stage, access time is an even more dominant determinant than suggested by the MNL model.

The time values of frequency can also be computed for the consideration stage from the PCMNL model. Interestingly, these values are very high. An additional flight per day from an airport has the same impact on consideration utility as 18 less minutes to that airport for male weekend travelers, 90 less minutes for female weekend travelers, 9.5 less minutes for male weekday travelers, and 13.5 less minutes for female weekday travelers. These results show the relatively dominant effect of frequency at the consideration stage, especially on weekends.

Table 3. Time Value of Frequency of Service at Choice Stage

Population Subgroup	MNL	PCMNL[1, 2]
Male, low-income, traveling in a group	5.9	4.8
Male, high-income, traveling in a group	2.3	--
Male, low-income, traveling alone	8.8	6.1
Male, high-income, traveling alone	5.5	≈ 0
Female, low-income, traveling in a group	3.1	3.3
Female, high-income, traveling in a group	≈ 0	--
Female, low-income, traveling alone	5.9	4.8
Female, high-income, traveling alone	2.9	≈ 0

[1]The numbers indicate the additional access time travelers are willing to endure for an increase in ten flights per day to their destination.

[2]A "--" entry indicates that frequency has a negative effect at the choice stage for the corresponding population group. While not intuitive, these negative frequency effects are not significantly different from zero.

5.4 Substantive Policy Implications

The relative effects discussed above provide useful information about the effects of access time and frequency on choice in the MNL model, and separately on consideration and choice in the PCMNL model. However, these effects do not provide a measure of the absolute magnitude of impacts. Further, in the PCMNL model, the overall effects of access time and frequency are not directly discernible from the coefficients at the consideration and choice stages.

To examine the overall effects of access time and frequency, we now compute the aggregate self- and cross-elasticities. These aggregate elasticities provide the proportional change in the expected market shares of each airport in response to a uniform percentage improvement in access time and frequency across all individuals. The aggregate self- and cross-elasticities can be obtained from the disaggregate-level elasticities presented in Equation (7). Table 4 shows the elasticity effects for the MNL and PCMNL models.

Several common conclusions may be drawn from the elasticities of the MNL and PCMNL models. First, in the overall, access time is a more important determinant of airport choice than is air service frequency. This is consistent with several earlier studies on airport choice. Second, the self-elasticities indicate that Oakland International is best positioned to improve its market share through improvements in its quality of service (note the higher self-elasticity effects for Oakland compared to the self-elasticity effects of the other two airports). Third, San Francisco International has tremendous "clout" in the market, since it can easily negate attempts by other airports to draw away share by making its own marginal service improvements (see the much higher cross-elasticities corresponding to improvements in SFO's quality of service compared to the cross-elasticities corresponding to improvement in the quality of service of other airports).

Table 4. Elasticity Effects of Quality of Service Improvements

Improvement in Quality of Service	Elasticity Impact on Market Share					
	MNL Model			PCMNL Model		
	SFO	SJC	OAK	SFO	SJC	OAK
San Francisco International (SFO)						
Decrease in travel time	1.313	-1.597	-2.715	0.870	-1.150	-1.709
Increase in air frequency	0.277	-0.393	-0.524	0.169	-0.237	-0.322
San Jose International (SJC)						
Decrease in travel time	-0.220	1.111	-0.301	-0.205	0.971	-0.223
Increase in air frequency	-0.054	0.227	-0.034	-0.096	0.400	-0.056
Oakland International (OAK)						
Decrease in travel time	-0.566	-0.306	2.063	-0.431	-0.251	1.582
Increase in air frequency	-0.114	-0.053	0.409	-0.152	-0.079	0.549

The substantive policy implications from the MNL and PCMNL models, while similar in some ways, are also quite different in others. First, compared to the MNL model, the PCMNL model indicates substantially lower self- and cross-elasticities corresponding to access time. If the PCMNL model is a more appropriate model (as we will clearly demonstrate in the next section), use of the MNL model would overestimate the potential gain in an airport's market share due to an improvement in access time to that airport and would overestimate the reduction in market share of other airports due to such an access time improvement. Second, the PCMNL model shows higher self- and cross-elasticities corresponding to improvement in air frequency from San Jose and Oakland airports. This can be attributed to the strong impact of air frequency on consideration of an airport in the PCMNL model, as discussed in the previous section. The reason why such an effect does not extend to San Francisco is that San Francisco already has a very high consideration level in the market. In fact, the overall consideration level can be estimated from the parameter estimates in Table 2. Defining S_i as the share of individuals who consider airport *i* when making a choice, we can write:

$$S_i = \frac{\sum_q w_q \sum_{c \in G} \delta_i^c P_q(c)}{Q}, \tag{8}$$

where w_q is the weight for individual *q*, *Q* is the total number of individuals in the sample, and other quantities are as defined earlier. The estimated values of airport consideration are 99.4% for SFO, 77.2% for SJC, and 70.7% for OAK. Clearly, there is little room to increase the consideration level of SFO, which is the reason for the low self- and cross-elasticities corresponding to air service frequency improvement for SFO.

To summarize, the substantive implications for policy analysis from the MNL and PCMNL models are different in the current empirical context. These differences suggest the need to apply formal statistical tests to determine the structure that is most consistent with the data. This is the focus of the next section.

5.5 Measures of Data Fit

The fit of the MNL and PCMNL models is evaluated in both the estimation sample and a validation sample. In the estimation sample, the standard measures of fit, including the log-likelihood at convergence and the adjusted likelihood ratio index are computed. The adjusted likelihood ratio index is defined with respect to the log-likelihood at market shares:

$$\bar{\rho}^2 = 1 - \frac{\mathcal{L}(\hat{\beta}) - M}{\mathcal{L}(c)}, \qquad (9)$$

where $\mathcal{L}(\hat{\beta})$ and $\mathcal{L}(c)$ are the log-likelihood functions at convergence and at market shares, respectively, and M is the number of parameters estimated in the model (besides the alternative specific constants of the choice model). In addition, the average probability of correct prediction is computed. The average probability of correct prediction is computed as $Q^{-1}\sum_q w_q \sum_i y_{qi}\hat{P}_{qi}$, where $\hat{P}_{qi}$ is the estimated probability of individual q choosing airport i at the convergent values. The results for the estimation sample are presented in the second main column of Table 5. The adjusted likelihood ratio index and the average probability of correct prediction clearly favor the PCMNL model (see the last two rows of the table). A formal statistical nested likelihood ratio test between the convergent log-likelihood values of the two models indicates a value of 400.0, which is larger than the corresponding chi-squared value with 8 degrees of freedom at any reasonable level of significance.

The performance of the MNL and PCMNL models is also evaluated on a holdout (validation) sample to verify that the results obtained from the estimation sample are not an artifact of overfitting. Three hundred observations are set aside for validation such that the shares in the validation sample are close to the actual market shares (this allows the direct application of the estimated model results to the validation sample, without the need to adjust the airport-specific constants). Two measures of fit are computed in the validation sample. The first is the predictive adjusted likelihood ratio index, which is computed by calculating the predictive log-likelihood function value at the parameter estimates obtained from estimation. The second is the average probability of correct prediction, also computed at the parameter values obtained from estimation. These disaggregate measures of fit are presented in the last two rows of the third main column in Table 5. As can be observed, there is a drop in the adjusted likelihood ratio index from the estimation sample for both the MNL and PCMNL models. But the PCMNL model still provides a value that is higher than the MNL model. The average probability of correct prediction in the validation sample also reflects this superior fit of the PCMNL model. In summary, the PCMNL clearly outperforms the MNL model from a statistical standpoint.

Table 5. Measures of Fit in Estimation and Validation Sample

Summary Statistic	Estimation Sample		Validation Sample	
	MNL	PCMNL	MNL	PCMNL
Log-likelihood at zero	-1777.55	-1777.55	-329.58	-329.58
Log-likelihood at market shares	-1490.40	-1490.40	-275.69	-275.69
Log-likelihood at convergence (estimation) / Predictive log-likelihood (validation)	-897.50	-697.04	-174.74	-151.15
Number of parameters[1]	7	15	7	15
Number of observations	1618	1618	300	300
Adjusted likelihood ratio index (estimation) / Predictive adjusted ratio index (validation)	0.393	0.522	0.340	0.397
Average probability of correct prediction	0.662	0.749	0.665	0.729

[1]The number of parameters refers to the parameter on the exogenous variables; it does not include the alternative-specific constants in the MNL model and the alternative-specific constants at the choice stage of the PCMNL model

Another more informal, but intuitive, way to compare the two models is to compute the estimated distribution of consideration sets across resident air travelers in the Bay Area. This can be computed as $Q^{-1}\left[\sum_q w_q \hat{P}_q(c)\right]$, where $\hat{P}_q(c)$ is the predicted probability from the PCMNL model of individual *q* having the consideration set *c*. The resulting distribution, providing the percentage of individuals with each of the seven possible choice sets, is as follows: SFO only (23.50%), SJC only (0.22%), OAK only (0.12%), SFO and SJC (13.46%), SJC and OAK (0.07%), SFO and OAK (9.83%), and all airports (52.80%). These results indicate that about half of all travelers do not choose from the universal choice set of all the three airports. However, the MNL model assumes that all travelers choose from the universal choice set. Another interesting observation is that about a quarter of all travelers consider only SFO. In summary, these results again highlight the clout of SFO in the consideration perception map of Bay Area air travelers.

CHAPTER 6. SUMMARY AND CONCLUSIONS

This report proposes the use of a probabilistic choice set multinomial logit model (PCMNL) for airport choice analysis that generalizes the commonly used multinomial logit (MNL) model. The PCMNL model takes the form of a random constraint-based approach to choice formation in which an airport is excluded from the choice set if the consideration utility of that airport is lower than a threshold utility level. The choice of airport from a given choice set is based on the usual MNL structure. The properties of the PCMNL model are discussed, including the presentation and interpretation of elasticity expressions.

The PCMNL model is applied to examine the airport choice of business travelers residing in the San Francisco Bay Area. Several important conclusions may be drawn from the empirical analysis. First, as found in earlier studies, access time to the airport and flight frequency are the two primary determinants of airport choice. However, unlike earlier studies, this study indicates variation in sensitivity to these two variables based on traveler demographics and trip characteristics. Specifically, individuals traveling alone and women travelers are more sensitive to access time, and individuals traveling alone are also more sensitive to flight frequency. Further, women and high-income travelers are not very sensitive to flight frequency. In addition, the results from the consideration stage of the PCMNL model indicate that access time and flight frequency affect the consideration of an airport.

A second important conclusion of this study is that the access time parameter estimates of the MNL model and the choice stage of the PCMNL model are quite different. This is because the MNL model arbitrarily assumes that all airports are available to all individuals. A comparison of the relative trade-off between access time and frequency from the two models suggests the dominance of access time at the choice stage, particularly in the PCMNL model. However, the PCMNL model also indicates that, in forming perceptions of the availability of airports, flight frequency is the dominating factor. Interestingly, access time is less important to women (relative to men) when forming the perception space of available airports, but is more important to women when choosing an airport from the set of available airports. These results have implications for the design of promotional marketing strategies. For instance, an airport attempting to increase market share by improving access time to its terminals might consider targeting informational campaigns within its traditional catchment area of travelers (*i.e.*, areas in close proximity to the airport) and by targeting women travelers (at airports, or by targeting firms/occupations which are women-dominated). On the other hand, information campaigns regarding frequency improvements are better positioned in areas that are not within the traditional catchment area (*i.e.*, in areas that are distant from the airport) and are likely to be more productive if targeted toward weekend travelers. Clearly, only the PCMNL model is able to offer such comprehensive insights into the effects of variables.

A third conclusion that may be drawn from this study is that the substantive elasticity effects from the MNL and PCMNL models indicate that access time is the most important factor in the choice of an airport. Also, in the San Francisco Bay Area market, San Francisco International has tremendous clout, since it can easily compensate for service improvements at other airports by making marginal improvements in its own service. Between the MNL and the PCMNL model, the PCMNL model predicts a lower overall impact of access time, indicating that the use of the MNL model overestimates the potential gain in airport market share due to an improvement in access time to that airport. On the other hand, the PCMNL model predicts a higher overall impact of flight frequency, suggesting an underestimation of the net gains from improving frequency by the MNL model.

Lastly, the PCMNL model clearly outperforms the MNL model in statistical evaluation of data fit in both an estimation sample and a validation sample.

In summary, the application of the PCMNL model to airport choice suggests that it is important to model consideration sets of air travelers. Failure to recognize consideration effects can lead to biased model parameters, misleading evaluations of the effects of policy actions, as well as a considerably diminished data fit.

One future extension of this study would be to examine airport travel characteristics using more recent data. The author originally planned to use an air traveler survey conducted by the Metropolitan Transportation Commission in the fall of 2001, but surveying halted due to the events of September 11, 2001. Once the newest survey is completed and released to the public, and similar studies are conducted using the data, it would be interesting to compare results from the current study with those done with post-September 11th data.

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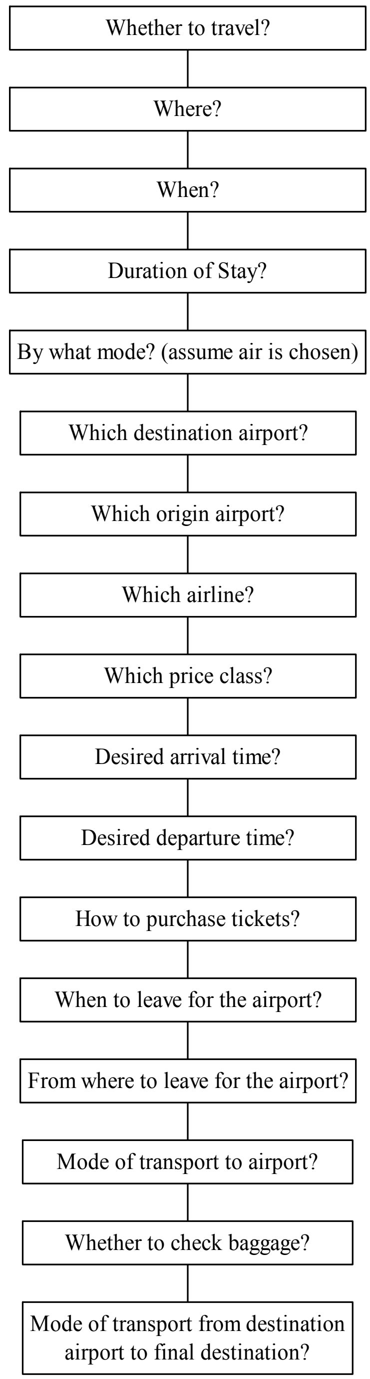
APPENDIX A. Sample of Choices Involved in Air Travel



APPENDIX B. Literature Review Table

Study	Author	Year	Dimensions	Model Structure	Empirical Context
Airport Choice: An Empirical Study	Robert E. Skinner, Jr.	1976	Airport Choice	MNL Model	Baltimore-Washington region with three airport alternatives: Reagan, Dulles, Baltimore
Airport Choice in a Multiple Airport Region	Greig Harvey	1987	Airport choice	MNL Model	San Francisco Bay Area with three airport alternatives: San Francisco, San Jose, Oakland
Passengers' Choice of Airport: An Application of the Multinomial Logit Model	Norman Ashford, Messaoud Benchemam	1987	Airport Choice	MNL Model	Central England with five airport alternatives: Manchester, Birmingham, East Midlands, Luton, Heathrow
Air Transportation Passenger Route Choice: A Nested Multinomial Logit Analysis	Ngoe N. Ndoh, David E. Pitfield, Robert E. Caves	1990	Route (direct vs. connecting flights), hub airport, and departure airport choice	NMNL Model	England with four airport alternatives: East Midlands, Birmingham, Manchester, Liverpool
Effects of Access Distance and Level of Service on Airport Choice	J. David Innes, Donald H. Doucet	1990	Airport Choice	Binary Logit Model	New Brunswick, Canada with three airport alternatives: Charlo, Chatham, St. Leonard
Application of Disaggregate Modeling in Aviation Systems Planning in Nigeria: A Case Study	Angus Ifeanyi Ozoka, Norman Ashford	1989	Airport Choice	MNL Model	Nigeria with two airport alternatives: Enugu, Benn
The Projected Market Share for a New Small Airport in the North of England	Amanda Thompson and Robert Caves	1993	Airport choice	MNL Model	Northern England with three airport alternatives: East Midlands, Manchester, Birmingham
An Analysis of Air Travelers' Departure Airport and Destination Choice Behavior	Masahiko Furuichi, Frank Koppelman	1994	Departure airport and destination choice	NMNL Model	Japan with four airport alternatives: Narita, Osaka, Nagoya, Fukuoka
Airport Choice in Multiple-Airport Regions	Robert Windle, Martin Dresner	1995	Airport Choice	MNL Model	Baltimore-Washington, D.C. region with three airport alternatives: Reagan, Dulles, Baltimore
Airport and Airline Competition for Passengers Departing from a Large Metropolitan Area	Eric Pels, Peter Nijkamp, Piet Rietveld	2000	Airport and airline choice	NMNL Model	San Francisco Bay Area with airport alternatives: San Francisco, San Jose, Oakland,
Airport and Airline Choice in the a Multiple Airport Region: An Empirical Analysis for the San Francisco Bay Area	Eric Pels, Peter Nijkamp, Piet Rietveld	2001	Airport and airline choice	NMNL Model	San Francisco Bay Area with four airport alternatives: San Francisco, San Jose, Oakland, Sonoma County
Airport and access mode choice in the Bay Area	Eric Pels, Peter Nijkamp, Piet Rietveld	2002	Airport and airport access mode choice	NMNL Model	Three airport choices: San Francisco, San Jose, Oakland

APPENDIX B. Literature Review Table (continued)

Author(s) ***continued***	**Market Segment Examined**	**Variables Considered**	**Final Variables in Model(s)**	**Important Results**
Robert E. Skinner, Jr., 1976	Business and nonbusiness travelers	Air carrier level of service measures, ground accessibility measures	Weekday flight frequency, airport access utility	Improvements in airport access are the most effective means of capturing more passengers
Greig Harvey, 1987	Resident business and resident nonbusiness travelers	Airport access time, relative and direct flight frequency	Airport access time, flight frequency	Airport access time and flight frequency provide good approximation of airport choice in the Bay Area. Beyond a threshold level, additional direct flights to a destination do not make an airport more attractive.
Norman Ashford, Messaoud Benchemam, 1987	Domestic, international business, international leisure, international inclusive tours travelers	Travel time to airport, number of flights per day, air fare	Travel time and flight frequency for business and inclusive tours, all three variables for remaining market segments	Business travelers most sensitive to airport access time, while leisure travelers are most sensitive to air fare and airport access time.
Ngoe N. Ndoh, David E. Pitfield, Robert E. Caves, 1990	Business travelers	Airport access time, average journey time, average connection time to hub, number of seats	Access time, journey time, connection time to hub, number of seats, flight frequency	Business travelers value access time the most over any other variable
J. David Innes, Donald H. Doucet, 1990	-----	Ticket type, length of stay, who paid for the ticket, trip purpose, aircraft type, flying time, (direct vs. nonstop)	Same as those considered	Type of aircraft plays significant role in airport choice (air travelers are willing to travel far for access to jet service). Passengers prefer direct flights versus connecting, and shorter flight routes.
Angus Ifeanyi Ozoka, Norman Ashford, 1989	-----	Airport access time, flight frequency, air fare	Airport access travel time	Improving ground access to airport is the best (and possibly only) means of increasing an airport's market share in Nigeria. The catchment area concept does not apply; airports compete.
Amanda Thompson and Robert Caves, 1992	Business and nonbusiness travelers	Airport access time, flight frequency, air fare, number of seats	Airport access time, flight frequency, air fare	Those departing from origins closer to the airport are more sensitive to access time than those living further away.

Masahiko Furuichi, Frank Koppelman, 1994	Business and pleasure travelers	Airport access travel time and cost, line-haul travel time and cost, relative flight frequency	Airport access travel time and cost, line-haul travel time and cost, relative flight frequency	Access travel cost valued more highly than line-haul travel cost. Both business and pleasure travelers have very high values of access and line-haul time, as well as flight frequency.
Robert Windle, Martin Dresner, 1995	Resident business, resident nonbusiness, nonresident business, nonresident nonbusiness	Airport access time, weekly flight frequency, airport experience	Airport access time, weekly flight frequency, airport experience	Airport access time and flight frequency significant. Airport experience comes out to be significant, but could be proxy for omitted variables.
Eric Pels, Peter Nijkamp, Piet Rietveld, 2001	Resident business and resident leisure travelers	Flight frequency, airport access time, air fare	Flight frequency, airport access time	Passengers first choose departure airport, then choose airline is statistically favorable to the opposite. Little difference between business and leisure travelers.
Eric Pels, Peter Nijkamp, Piet Rietveld, 2002	Resident business, resident leisure, summer and fall	Airport distance and access time, average fare, daily flight frequency	Air fare, flight frequency, access time	Access time most significant variable in airport choice

APPENDIX C. Questions in the MTC Air Passenger Survey
(questions that were asked at all four airports, in both summer and fall)

- Residence status (Bay Area[10] resident or visitor)
- Final airport destination, including all flights
- Main trip purpose
- Number of people in the party
- Number of vehicles the party used to get to the airport
- Number of people in the vehicle in which the respondent traveled
- Number of pieces of luggage the party checked
- Mode of transportation used to get to the airport
- Among those who took a private car, how they would have traveled if the car had not been available
- Among those who took a rental car, the company they rented it from
- Among those who took transit, how they got to the transit stop or station
- Mode of transportation used to get from the airport to the Bay Area destination the last time the respondent flew into the airport
- Origin of departure for the airport
- Type of origin the respondent departed from
- Number of people who came into the terminal to see the respondent off

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[1]The Bay Area was defined as the nine greater San Francisco Bay Area counties: Alameda, Contra Costa, Marin, Napa, San Francisco, San Mateo, Santa Clara, Solano, and Sonoma.

- Length of time prior to flight departure time that the respondent arrived at the airport
- Trip length (in nights away from home)
- Extent to which the respondent could have used another airport
- Individual who decided to use the departure airport
- Number of times the respondent had flown out of each of six area airports in the twelve months preceding the survey
- Zip Code of the respondent's residence
- Number of people in the respondent's household
- Respondent's household income before taxes in 1994
- Respondent's gender (by observation)
- Date of interview, airline, flight number, departure time, and interview time (by observation)

APPENDIX D. Data Screening Process

Full Sample = 21,124 cases

↓

Focus only on residents
Sample = 9,510 cases

↓

Focus on three airports: SFO, SJC, OAK (delete Sonoma County airport)
Sample = 9,476

↓

Focus on top 30 domestic destinations for resident travelers
Sample = 7,336

↓

Try to fill in observations missing critical elements
(date, flight departure time, number of connections can all be entered based on flight number and other variables)

↓

Remove observations missing critical items that cannot be filled

↓

Add flight frequency variable, BTS on-time statistics, access times and costs to airport

↓

Focus only on people who said they had the choice of flying from another airport
Sample = 3,795 surveys

↙ ↘

Business trip
Sample = 1,918 surveys

Non-Business trip
Sample = 1,877 surveys

Business trip ↙ ↘

Estimation
Sample = 1,618 surveys

↓

Create weight variable

Validation
Sample = 300 surveys

↓

Create weight variable

↘ ↙

Base Market Share Models to check if weightings are accurate

APPENDIX E. Top Thirty Domestic Destinations

	City	Airport Code	Estimation Sample		Validation Sample	
			Frequency	%	Frequency	%
1	LOS ANGELES, CA	LAX	248	15%	49	16%
2	SAN DIEGO, CA	SAN	148	9%	22	7%
3	BURBANK, CA	BUR	135	8%	22	7%
4	ORANGE COUNTY, CA	SNA	134	8%	11	4%
5	SEATTLE, WA	SEA	84	5%	18	6%
6	PORTLAND, OR	PDX	78	5%	21	7%
7	LAS VEGAS, NV	LAS	70	4%	11	4%
8	ONTARIO, CA	ONT	70	4%	7	2%
9	DALLAS, FT. WORTH,TX	DFW	60	4%	7	2%
10	PHOENIX, AZ	PHX	59	4%	16	5%
11	DENVER, CO	DEN	54	3%	11	4%
12	CHICAGO, IL(O'HARE)	ORD	51	3%	9	3%
13	RENO, NV	RNO	50	3%	7	2%
14	AUSTIN, TX	AUS	48	3%	3	1%
15	SALT LAKE CITY, UT	SLC	45	3%	13	4%
16	BOSTON, MA	BOS	39	2%	15	5%
17	ATLANTA, GA	ATL	31	2%	8	3%
18	NEW YORK, NY(JFK)	JFK	30	2%	7	2%
19	WASHINGTON,DC(DULLES)	IAD	27	2%	5	2%
20	ALBUQUERQUE, NM	ABQ	25	2%	3	1%
21	NEWARK-NEW YORK, NJ	EWR	23	1%	8	3%
22	HOUSTON, TX(INTERCON)	IAH	23	1%	3	1%
23	BOISE, ID	BOI	19	1%	3	1%
24	MINNEANAPOLIS/ST.PAUL	MSP	18	1%	4	1%
25	COLORADO SPRINGS, CO	COS	15	1%	1	0%
26	SPOKANE, WA	GEG	9	1%	1	0%
27	HONOLULU, HI	HNL	9	1%	4	1%
28	TUCSON, AZ	TUS	8	0%	2	1%
29	ORLANDO, FL	ORL	6	0%	8	3%
30	KAHULULI, HI	OGG	2	0%	1	0%
	Total		1618	100%	300	100%

APPENDIX F. Variables Used to Come to a Preferred Specification

Variable	Description
Alt. Specific Constants	
SFO	Constant specific to SFO
SJC	Constant specific to SJC
OAK	Constant specific to OAK
Flight Frequency	Daily flight frequency
Distance	Distance to airport from origin point
Access time	Access time to airport from point of origin
Access cost	Access cost to airport from point of origin
On-time Statistics	Percentage of late flights, specific to each O-D pair
Airport Loyalty	Proportion of flights from each airport over a 12 month period[11]
Weight	Weighting variable representing 1995 airport market shares
Income	Total 1994 household income
Market Segmentation Variables	
Peak	Passenger is traveling during a peak period[12]
Alone	Passenger is traveling alone
Short trip	Trip lasting 0 or 1 night
High income	Income > $150,000 per year
Car	Drove either a private or rental car to airport
Weekday	Flight is on a weekday
Summer	Flight is in summer
Nonstop	Flight is a nonstop flight
Female	Passenger is female
Work	Passenger left straight from work for the airport

[11] Loyalty Factor = $\frac{\#\, flights, airport_n, 1 year}{\sum allflightsfromBayArea, 1 year}$

[12] Passengers traveling during peak periods are those whose scheduled flight departure times are either 6AM - 9:59AM or 4PM - 8:59PM