Modelling airport and airline choice behaviour with the use of stated preference survey data

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Abstract

The majority of studies of air travel choice behavior make use of Revealed Preference (RP) data, generally in the form of survey data collected from departing passengers. While the use of RP data has certain methodological advantages over the use of Stated Preference (SP) data, major issues arise because of the often low quality of the data relating to the un-chosen alternatives, in terms of explanatory variables as well as availability. As such, studies using RP survey data often fail to recover a meaningful fare coefficient, and are generally not able to offer a treatment of the effects of airline allegiance. In this paper, we make use of SP data for airport and airline choice collected in the US in 2001. The analysis retrieves significant effects relating to factors such as airfare, access time, flight time and airline and airport allegiance, illustrating the advantages of SP data in this context. Additionally, the analysis explores the use of non-linear transforms of the explanatory variables, as well as the treatment of continuous variations in choice behavior across respondents.

1. Introduction and context

The number of studies using discrete choice models in the analysis of air travel

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choice behavior has increased steadily over recent years, gradually making use of new model structures that allow for an increasingly realistic representation of the complex substitution patterns and taste heterogeneity affecting the choice processes of air travelers. The majority of such research has made use of Revealed Preference (RP) data, generally in the form of survey data collected from departing air passengers. In many of these studies, the absence of adequate and detailed level-of-service information relating to the choices actually faced by respondents leads to an inability to offer a reliable treatment of factors such as air fares, flight availability and airline allegiance. The main aim of this paper is to illustrate how SP data can be used to alleviate these problems. Here it should be noted that the discussion in this paper focuses on the problems arising with RP survey data (e.g. collected from passengers at the airport), and does not look at other sources of RP data, such as bookings data, in which issues with availability do not apply, although problems with auxiliary datasets may still play a role[2].

The biggest advantage of SP data in the present context comes in the form of full information on the choices that respondents were actually faced with. Similarly, the issue of uncertainty with regards to flight availability does not come into play. This is also strongly related to the issue of capacity. Even in the presence of an adequate weighting strategy when using RP survey data, the dummy variables associated with a given airline or a given aircraft type do capture effects of flight availability as a function of capacity. This problem of biased dummy variables does not arise in the case of SP data; a negative estimate for a given airline or aircraft dummy does indeed signal a negative effect on utility associated with that specific airline or aircraft type, where this reasoning is based on the assumption that any SP-design related factors are captured by an appropriate set of constants.

However, another major difference arises between the use of RP and SP data in air travel

[2] For one of the rare applications using bookings data, see Algers and Beser (2001).

research. As discussed for example by Hess & Polak (2006), one of the variables with the greatest explanatory power in RP case studies of air travel choice behavior is flight frequency. Here, it should be noted that, with the possible exception of travelers on very flexible tickets, frequency is not taken into account by travelers in the way it is modeled. Rather, it captures a host of other factors, most notably visibility[3], capacity, and schedule delay between the actual and optimal departure time, on the basis of an assumption of a relatively even spread of departure times. In the case of SP data presenting a choice between individual flights, visibility and capacity need not be taken into account, as described above. And by presenting travelers with a set of actual disaggregate flight options, frequency does not play a role in the description of the alternatives. However, given the use of disaggregate flight options, a treatment of schedule delay becomes possible, given that information is now generally available on the differences between the actual and desired arrival times for each of the flight options. For an in-depth discussion of the issue of flight frequency and schedule delay, in the context of a SP analysis, see Lijesen (2006).

The work presented in this paper follows on from previous work by Adler et al. (2005) on the same data, where that analysis revealed significant effects for a range of variables for which it is often impossible to identify any impact in RP studies, such as air fares, schedule delay and airline and airport allegiance. Aside from using a further segmentation of the leisure segment into holiday and VFR[4] travelers, the study presented in this paper aims to expand on the work by Adler et al. in two main directions.

- Firstly, the main estimation work is preceded by a detailed investigation of the non-linearities in response to changes in explanatory variables, using a preliminary analysis based on Box-Cox transforms.

[3] Flights by an airline with high frequency will carry more weight in booking systems.

The aim of this analysis is to explore the potential for using non-linear transforms for a number of attributes that are generally treated in a linear fashion.

- Secondly, the study aims to explore continuous interactions between taste coefficients and socio-demographic variables. This treatment of deterministic taste heterogeneity, which has clear conceptual advantages over more arbitrary segmentation approaches, does not seem to have found widespread application in air travel research thus far. In fact, it can be argued that this also extends to other areas of transport research, where modelers still rely mainly on the use of segmentations or simple linear interactions in the analysis of deterministic taste heterogeneity. It should also be said that the rise in popularity of mixture models has contributed to this situation, with modelers increasingly relying purely on a random treatment of taste heterogeneity, despite the advantages of the other methods in terms of interpretation.

The remainder of this paper is organized as follows. Section 2 presents a brief review of existing work on the modeling of air travel choice behavior, Section 3 provides a description of the SP data used in the analysis, and Section 4 discusses the specification of the utility functions in the various models. Section 5 presents the results of the estimation process, and Section 6 summarizes the findings of the analysis.

2. Previous work

This section presents a brief review of existing research in the analysis of air travel

[4] Visiting friends or relatives.

choice behavior, focusing on the airport and airline choice dimensions (which are looked at in this paper). More comprehensive reviews are for example given by Basar & Bhat (2004) and Hess & Polak (2006).

The majority of studies of air travel choice behavior look at the choice of airport for passengers departing from multi-airport regions. Recent examples of such studies include the work of Pels et al. (2001), Pels et al. (2003), Basar & Bhat (2004), and Hess & Polak (2006, 2005a,c), who all use data collected in the San Francisco Bay area. These studies make use of various modeling approaches, including Nested Logit (NL), Mixed Multinomial Logit (MMNL), and choice set generation models, and generally account for the additional choices along either the airline or the access-mode dimension. Another example of a recent study of airport choice behavior is given by Hess & Polak (2005b), who look at the combined choice of airport, air-line and access-mode in the Greater London area, using Cross-Nested Logit (CNL) models.

The common point across many RP studies are the difficulties in retrieving significant effects for air fare, along with many other factors that conceivably play a role in choice behavior, such as the membership in frequent flier programs. Aside from being partly linked to the often low quality of auxiliary data, especially for fare information, it can be seen that availability plays a major role. As an example, in the case where a traveler is forced to accept a more expensive ticket as all cheap fares have sold out, an absence of information on availabilities will, from the modeler's perspective, suggest cost-prone choice behavior.

Here, the use of SP data can have certain advantages, since it allows the explicit specification of availability and the attributes of un-chosen alternatives. In addition to the work of Adler et al. (2005), there have been a few other studies using SP data. One example of an application using SP data is given by Bradley (1998), who uses binary logit models in the analysis of the choice of departure airport and route, with data collected from passengers at Schiphol (Amsterdam), Brussels, and Eindhoven airports. The most significant impact on choice behavior is found to be the air fare, where a log-transform was used, and where differences exist across different groups of travelers. Proussaloglou & Koppelman (1999) use a telephone survey resembling a booking process, for passengers from whom information about actual trips had previously been collected. Respondents then made a choice of carrier, flight and fare class for their specific route. The results show negative impacts of fare, especially for leisure travelers, as well as for schedule delay, with positive impacts for frequent flier programs. Similarly, increased market presence of the carrier, and quality of service had positive effects. Algers & Beser (2001) discuss the modeling of the choice of flight and booking class. They acknowledge the limitations of RP data in this context, but also stress that issues with SP bias need to be borne in mind. As such, they propose to use both RP and SP data in the analysis, with the RP data being used to correct the scale of the utility function obtained with the SP data. Finally, Lijesen (2006) makes use of SP data in conjunction with MMNL models to look at the valuations of schedule delay and discusses the impact of these findings in terms of recommendations for airlines' optimal flight schedules.

3. Description of data

The survey data used in this analysis were collected via the internet in May 2001 from a sample of around 600 individuals who had made a paid US domestic air trip within the twelve months prior to the interview taking place (Resource Systems Group Inc., 2003).

The first stage of the survey was an RP exercise, collecting data on the most recent domestic air trip by a respondent, along with socio-demographic information, and information on membership in frequent flier programs. Besides actual level-of-service information for the observed trip, the survey also collected qualitative data, indicating the level of satisfaction with the observed trip, along the airport as well as airline dimension.

On the basis of the characteristics of the observed trip, a number of alternative flight options, in terms of airports and airlines, were compiled, and the respondents were asked to rank them in order of preference. For the airline options, the ranking was performed under the assumption of equal fares, while the ranking of airports was performed independently of the differences in access time. The rankings of airlines and airports thus serve as proxy variables for service quality attributes not included directly in the later model specification.

The SP survey uses a binary choice set, with ten choice situations per individual. In each choice situation, the respondent is faced with a choice between the current observed trip, and an alternative journey option, compiled on the basis of the information collected in the RP part of the survey. These two alternatives are hereafter referred to as the *RP alternative* and the *SP alternative* respectively. A fractional factorial experimental design was used in the generation of the choice situations, and the airports and airlines used in the choice sets for a given individual were selected on the basis of the ranking compiled in the RP survey.

Aside from the actual airline and airport names, from which access times can be inferred, the attributes used to describe the two alternatives in the SP survey include flight time, the number of connections, the air fare, the arrival time (used to calculate schedule delays[5]), the aircraft type, and the on-time performance of the various flights. Access cost was not included in the surveys (in the absence of an actual specification of the mode-choice dimension), and no choice is given between different travel classes; this can be regarded as an upper-level choice, taken before the actual air journey choices.

Frequent flier information: Three dummy variables were included in the base specification, to account for the effects of frequent flier (FF) membership. These were associated with *standard* membership, *elite* membership, and *elite plus* membership.

- **Connections:** The number of connections for a given flight, with three possible levels, 0, 1 and 2. Instead of assuming a linear effect, two separate dummy variables were initially estimated, associated with single and double-connecting flights.

- **Aircraft-type:** Four different types of aircraft were used in the SP survey; turboprop, regional jet, single-aisle jet, and wide-body jet. Appropriate dummy variables were defined, with single-aisle jet used as the base.

- **On-time performance (OTP):** For the RP alternative, information was collected on whether the flight was on time or not, while, for the SP alternative, five different levels were used, ranging from 50% to 90% probability of being on time. The high number of levels (7) of the attribute, in conjunction with the low number of observations for some of these levels, led to a decision not to use separate dummy variables for the different levels, but to use a marginal coefficient asso-

[5] The schedule delay is the difference between the stated *optimal* arrival time for a given respondent and the actual *scheduled* arrival time of a given flight option.

ciated with the percentage on-time performance, in conjunction with appropriate non-linear transforms where applicable (see Section 4.2). Here, it should be noted that in real-world choice situations, if at all, on-time performance information will only be available to respondents in the form of aggregate statistics.

- **Inertia variables:** Attempts were made to account for respondent inertia or habit formation with the help of a number of variables. Aside from an alternative specific constant (ASC) for the RP alternative (which admittedly also captures other factors), airport and airline inertia constants were included in the utility of the SP alternative in the case where the RP airport or airline was reused in the SP alternative.
- **Qualitative variables:** Attempts were also made to include qualitative variables in the utility of the RP alternative, such as the level of satisfaction expressed by the respondent in relation to service. None of these variables was found to have a significant effect.

4.2. Non-linearities in marginal utilities

Except for those variables for which a separate coefficient was associated with each possible level, there are no a priori grounds for believing that a linear specification of utility is appropriate.

With this in mind, for each of the three population segments, an analysis was conducted to test for the presence of non-linear responses. In this analysis, Box-Cox transforms were used for access time, flight fare, flight time, on-time performance, and the two schedule delay variables. As such, for attribute *x*, with associated marginal utility coefficient β_x, the term $\beta_x \frac{x^{\theta_x}-1}{\theta_x}$ was included in the utility function, with both β_x and θ_x being estimated freely from the data. On the basis of the results of this Box-Cox analysis (i.e. the value of θ_x), a choice was then made between a linear and a non-linear formulation, where, in the latter, a log-transform was used in the case of decreasing marginal returns, and a power-formulation was used in the case of increasing marginal returns. This approach was made possible by the fact that any estimated values for θ_x were always sufficiently close to appropriate boundary values such as 0 or 1. As such, the Box-Cox transforms are used only in an explanatory role, and are replaced by transforms that can be applied directly at the data level, easing estimation costs especially with a view to a later extension of the models to a mixture framework.

4.3. *Continuous interactions*

While the majority of modeling analyses allow for some interactions between estimated parameters and socio-demographic attributes, these generally come in the form of a segmentation using separate models, or the use of separate coefficients in the same model. Despite having clear advantages in terms of flexibility, albeit at a higher computational cost, the treatment of such interactions in a continuous fashion is relatively rare.

In the SP case study presented in this paper, two groups of continuous interactions were included in the final models, after an extensive specification search, in which interactions between individual attributes and all applicable socio-demographic characteristics were explored. The first interaction looks at the impact of travel-distance (in the form of flight time for the RP alternative) on the marginal utilities of access time, flight fare, on-time performance, and early and late arrival. For a given attribute *x*, the utility was specified as

$$U = \ldots + \beta_x \left(\frac{FD}{\overline{\overline{FD}}} \right)^{\lambda_{FD,x}} x + \ldots \qquad (1)$$

where *FD* gives the RP flight time to the destination for the current respondent, and serves as a proxy for flight-distance, such that the same value of *FD* is used for the utilities of the RP and SP alternative. With negative values for $\lambda_{FD,X}$, the sensitivity decreases with increases in *FD*, with the opposite applying in the case of positive values for $\lambda_{FD,X}$. Finally, the rate of the interaction is determined by the absolute value of $\lambda_{FD,X}$, where a value of 0 indicates a lack of interaction. The division by the mean observed flight time $\overline{FD}$ ensures that β_x gives the marginal utility of changes in attribute *x* at the mean flight-distance in the current population segment, where it can be seen that the chosen normalization has no effect on the estimate of $\lambda_{FD,X}$, or indeed on the model fit.

The same approach was used to account for an interaction between household income and the sensitivity to various attributes such as air fare and access time. As an example, in the case of fare sensitivity, we have:

$$U = \ldots + \beta_{fare}\left(\frac{i}{\bar{i}}\right)^{\lambda_{inc,fare}} fare + \ldots \tag{2}$$

where *i* gives the household income for the current respondent, with $\bar{i}$ giving the mean household income in the appropriate population segment. Here, a negative estimate would be expected for $\lambda_{inc,fare}$, indicating reduced fare-sensitivity with higher income.

Interactions with other factors, such as trip duration, or party size, were not found to be significant.

5. Model results

This section describes the findings of the estimation process. In the current work, only basic

Multinomial Logit (MNL) structures were used. Nesting structures are not applicable given the nature of the choice set, while the use of mixture models, such as MMNL, was avoided with the aim of attempting to explain taste heterogeneity in a deterministic fashion. A separate analysis which made use of MMNL structures showed little additional gains in model fit, with the main advantage coming in a treatment of the repeated choice nature of the SP data. At this point, it should be mentioned that, with the current modeling approach, the repeated choice nature of the data was not taken into account, leading to a purely cross-sectional estimation. Further work is required to determine the effects of this on the reliability of the results. All models presented in this paper were estimated using BIOGEME (Bierlaire 2003).

Table 1 about here

5.1. MNL model for business travelers

The findings from the analysis using the 1,190 observations collected from business travelers are summarized in Table 1. Only parameters estimated in the final model are shown here, with any normalized or excluded parameters not listed explicitly.

The analysis revealed effects for all the main continuous variables, including access time, air fare, flight time, and early and late arrival. Except for the early arrival penalty (*BSDE* is only significant at the 89% level), the analysis showed that the use of a log-transform leads to significant gains in model performance, suggesting decreasing marginal returns for the associated attributes. The use of a log-transform for the air fare attribute could be seen as controversial, given the notion that *a dollar is a dollar,* and has the same value independently of the base cost. However, it can equally well be argued that the sensitivity to air fare changes works on a proportional scale, such that an increase by $10 at a base fare of $100 has a bigger impact than an equivalent increase at a base fare of $1,000.

The results further show positive effects of improvements in on-time performance. Initial results showed a reduced sensitivity to on-time performance on longer flights, but this resulted in problems with significance for the actual on-time performance coefficient. Efforts to use a power formulation[6] for the on-time performance attribute (allowing for a much stronger *dislike* of very late flights) led to minor gains in model performance, which were however offset by significant drops in parameter significance for the marginal utility coefficient. Similar problems were encountered when using separate coefficients for the seven different levels of on-time performance. As such, the effect was specified to be linear.

In terms of interactions, the estimates additionally suggest a reduced sensitivity to early arrival on longer flights, as well as reduced fare-sensitivity with higher income, where the interaction parameter is significant at the 89% level.

The final part of this discussion looks at the findings for dummy variables. Here, a significant positive ASC was found to be associated with the current alternative, capturing inertia as well as a host of other effects. The estimation further shows a strong effect of frequent flier membership on the utility of an alternative, where, due to insignificant differences, a common factor was used for elite and elite plus membership, where the estimates show this to be over twice as large as for standard frequent flier membership. The fact that none of the airline dummy variables (linked to ranking) was found to be significant suggests that, for business travelers, airline allegiance is primarily limited to membership in frequent flier programs. In terms of

[6] With an attribute x and associated marginal utility coefficient β_x, the contribution to the utility function would be given by $\beta_\chi \chi^\lambda$ *instead of* by $\beta_\chi \chi$, where values smaller and larger than 1 would indicate decreasing

airport allegiance, a significant effect could only be associated with the second and top-ranked airports, where the former one was significant only at the 81% level.

The estimated dummy variables for flights with one and two connections were indistinguishable, leading to the use of a common factor, where this can in part be seen as a result of the low incidence of flights with double connections in the data. The final set of dummy variables, associated with aircraft type, show that single-aisle jets are clearly preferred over turboprop planes and regional jets, while the negative effect associated with wide-body jets is not statistically significant above the 78% level.

Table 2 about here

5.2. MNL model for holiday travelers

The findings from the analysis using the 1,840 observations collected from holiday travelers are summarized in Table 2, which again only shows parameters included in the final model.

As in the case of business travelers, the analysis revealed significant effects of access time, air fare and flight time, where a log-transform was again found to be appropriate for all three attributes. The first difference with the business models arises in the treatment for schedule delay, where the use of linear effects was found to be preferable, and where, given the small differences between the effects for early and late arrival, a common coefficient was used (significant at the 88% level).

The results again show positive effects of improvements in on-time performance, where the associated interaction term suggests that holiday travelers' sensitivity to on-time

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and increasing marginal returns respectively.

performance increases with flight-distance, although the associated effect is significant only at the 91% level. This can be explained for example by the notion that holiday flights are often pushed to the edges of the off-peak periods, where sensitivity to on-time performance may indeed be greater, and especially so for very long flights.

Other interactions again show a reduced fare-sensitivity with higher income, although the confidence level for the associated term is very low. The interaction terms also show that, for holiday travelers, fare sensitivity increases with flight-distance. It is important to put this into context by remembering that a log-transform is also used on the fare attribute. As such, the results simply suggest that, at a given fare level, increases are valued more negatively in the case of longer flights. A possible explanation for this could be the higher secondary costs associated with longer flights in the case of holiday travelers; such trips are generally more costly overall (e.g. longer duration), leading to a greater desire for savings when it comes to air fares.

As in the model for business travelers, the ASC associated with the RP alternative is again positive, and highly significant. However, some important differences arise for the remaining dummy variables. The first observation that can be made is that, as expected, frequent flier benefits play a much smaller role in this segment of the population, where it was only possible to estimate a common dummy variable for all levels of membership, which in addition only attains a very low level of statistical significance. On the other hand, a significant positive effect is associated with the top-ranked airline. Positive effects are also associated with the second and third-ranked airlines, where these are less important and also only significant at lower confidence levels, with the differences between the two dummy variables not being significant. Additionally, positive effects, of decreasing importance as well as statistical significance, are associated with the three top-ranked airports.

Unlike in the model for business travelers, the effect associated with flights with two connections is significantly larger than for flights with a single connection, and the scale of the difference (factor of 3) supports the decision not to use a linear effect, but to use two separate dummy variables. Finally, for the aircraft-type dummies, the results suggest that holiday travelers do not distinguish between single-aisle jets, regional jets, and turboprop planes, with the only aircraft dummy with a modestly significant value being that for wide-body aircraft, which are seemingly given a slight preference over single-aisle jets.

Table 3 about here

5.3. MNL model for VFR travelers

The findings from the analysis using the 2,860 observations collected from VFR travelers are summarized in Table 3, which again only shows parameters included in the final model.

An important difference arises immediately when comparing the results for VFR travelers to those for business and holiday travelers. Indeed, while access time and flight fare again enter the utility function under a log-transform, the specification search indicated that it is preferable to treat flight time in a linear fashion. Early and late arrival penalties are treated separately in this model, and both enter the utility in a linear form, where the penalty associated with late arrival is lower, and attains a very low level of statistical significance.

Three non-linear interactions could be retrieved from the data. As in the case of holiday travelers, these again show heightened fare sensitivity on longer flights, along with reduced fare sensitivity with higher income, where this is however only significant at the 82% level. Finally, unlike in the other two models, it was possible to retrieve a relationship between flight-distance and access time sensitivity, showing lower sensitivity to access time on longer flights, which would support a decision to shift long-haul flights to outlying airports, where the issue of point-to-point passengers on the required feeder-flights would however need to be addressed separately.

As in the two other population segments, the ASC associated with the RP alternative is again positive and highly significant. However, in this segment, it was not possible to estimate a significant effect associated with frequent flier programs, while the dummy variables associated with the two most preferred airlines are positive and significant at high levels of confidence. The results also indicate that airport allegiance plays a role, where there is however essentially no difference between the estimates of the dummies associated with the two top-ranked airports. Finally, unlike in the other two population segments, it was also possible to identify a significant positive effect associated with the airport closest to the passenger's ground-level origin.

A common effect was again used for flights with single and double connections, while, in terms of aircraft-type, the difference between single-aisle jets and regional jets is significant only at the 87% level, where the results further indicate a significant dislike for turboprop flights, and a significant preference for wide-body jets over single-aisle jets.

5.4. Comparison of results across population segments

The description of the MNL model fitting exercises has already highlighted a number of differences between the specifications used in the three population segments. As such, it has been shown that frequent flier benefits matter more to business travelers, while simple airline preference plays a bigger role for leisure travelers. Other differences arise in the treatment of schedule delays; here, a common non-linear (decreasing) effect is used for holiday travelers, while for VFR travelers, the effect is linear, but the penalty associated with early arrival is larger than that associated with late arrival. For business travelers, SDL is treated in a non-linear fashion, while SDE is treated linearly, but the sensitivity to it decreases on longer flights. A difference also arises in the case of flight time, which is treated linearly for VFR travelers, while a log-transform is used for business and holiday travelers.

A number of other differences also arise in the treatment of interactions between attributes, where the results show higher fare sensitivity on longer flights for holiday and VFR travelers, with no interaction in the case of business travelers. Also, while holiday travelers are more sensitive to on-time performance on longer flights, there is no distance effect on the sensitivity to on-time performance for business and VFR travelers. In all segments, the results suggest reduced fare-sensitivity with higher income, although the interaction parameter never attains a high level of statistical significance. Finally, the results indicate decreased sensitivity to access time on longer flights only in the case of VFR travelers.

These differences in model specification need to be borne in mind when comparing the substantive results across the three population segments. The calculation of the trade-offs, and hence the comparison of results across groups, is further complicated by the high number of non-linear terms in the utility functions, where the simple ratio between coefficients is no longer applicable. Indeed, in such cases, the value of the trade-off depends on the current choice-situation. As such, in the case of trade-offs where the variable in the numerator enters under a log-transform, the ratio of coefficients needs to be multiplied by the inverse of this attribute. In the case where the concerned attribute is contained in the denominator, the ratio is multiplied by the actual value of the attribute. Appropriate population-level values can be calculated by simple averaging. However, in the case where both attributes enter the utility function under a log-transform, it is preferable to use a mean of ratios approach rather than a ratio of means approach. As such, the ratio of coefficients is multiplied by the average ratio of the two attributes over individuals, as opposed to the ratio of the average values of the two attributes. In the presence of non-perfectly correlated attributes, this approach potentially avoids significant levels of bias in the calculation of trade-offs. The situation becomes more complicated again in the case of coefficients interacting continuously with income or flight-distance, where any trade-off involving such coefficients will vary across individuals as a function of the associated attribute.

In the present analysis, the comparison was limited to two mains sets of trade-offs, looking at the willingness to accept increases in fare and access time respectively, in return for *improvements* in other determinants of choice. All attributes were included in the calculation of trade-offs, with the exception of the flight time variable. This is mainly motivated by the fact that the calculation of such trade-offs is hampered by the use of the RP flight time attribute as a proxy for flight-distance in the utility for both RP and SP alternatives, leading to a requirement for a different calculation of the trade-off in the case of the RP alternative, where an additional *correction-term* is required. Here, it is hoped that future work can make use of the actual flight-distance attribute, as opposed to relying on a proxy variable. It should also be noted that trade-offs involving aircraft-type were only calculated in the case of willingness-to-pay indicators, where the benefits of looking at the willingness to accept access time increases in return for flying on a specific aircraft are limited. Finally, in each case, the trade-offs are presented for the average flight-distance and household income in that population-segment, such that $\left(\frac{i_n}{\bar{i}}\right)^{\lambda_{inc,fare}}$ and $\left(\frac{FD}{\overline{\overline{FD}}}\right)^{\lambda_{FD,y}}$ become equal to 1.

The results are summarized in Table 4 for the willingness-to-pay indicators, and Table 5 for the willingness to accept increases in access time. In each case, several coefficients used in the trade-offs were not significant at the 95% level, as pointed out in Sections 5.1, 5.2 and 5.3, and this is indicated appropriately in the presentation of the trade-offs.

The results show important differences between the three model groups, and while there are strong similarities between the two non-business segments for several of the trade-offs, the use of separate models is justified by the differences in other trade-offs, and the differences in the optimal specification, as discussed in Sections 5.2 and 5.3.

Consistent with a priori expectations, the results show a much greater willingness to accept higher fares in return for shorter access times for business travelers than for holiday or VFR travelers, by a factor of just over 2. Given the use of an air fare coefficient as opposed to an access cost coefficient in the calculation of the ratio, this trade-off does not correspond to a standard VTTS measure, which looks at the relative sensitivity to time and cost on a single part of the journey, such as the access leg. Nevertheless, the estimates give an indication of the monetary values of reductions in access time. In fact, the high values, especially for business travelers, are broadly consistent with previous research which actually used an access cost coefficient in the calculation of the trade-off. For example, Pels et al. (2003) report values of between $1.97/min and $2.90/min for business travelers in the SF-bay area. These high values, when compared to other contexts, can potentially be explained by a variety of factors, including the lower frequency of air trips (as opposed to other travel, e.g. commuting), the greater inflexibility in terms of timing, and the severe financial penalty incurred by arriving at the airport late, and missing the flight. As such, it can be argued that travelers associate a longer access-journey with a higher risk of missing their flight.

Table 4 about here

The models also indicate a higher willingness by business travelers to pay for reductions in schedule delay and for improved on-time performance. Interestingly, the models suggest that, except for holiday travelers, respondents are more sensitive to early than to late arrival, a finding that should however be put into context given the small differences, and high associated standard-errors.

Table 5 about here

Perhaps the most striking difference between population groups comes in the willingness of business travelers to pay $125 to fly on an airline where they hold an elite frequent-flier account. Even though this figure decreases to $49 in the case of standard membership, the figures are still much higher than for holiday travelers, while no such effects could be identified for VFR travelers. In these latter two groups, the results however show a certain willingness to pay a premium for flying on either of the top-ranked airlines. These results are broadly consistent (albeit showing slightly higher values, which can partly explained by inflation) with those of Proussaloglou & Koppelman (1999), who show a higher willingness to pay such a premium in the case of business travelers than in the case of leisure travelers. As such, the premium for standard membership is $21 in the case of business travelers, compared to $7 in the case of leisure travelers. These values increase in the case of the program in which they participate most actively, with valuations between $52 and $72 for business travelers, compared to between $18 and $26 for leisure travelers.

For schedule delay, the results show a higher sensitivity to late than to early arrival (except for holiday travelers), where the differences are however rather small. The still rather high sensitivity to early arrival suggests that travelers do prefer to spend additional time at home rather than getting to their destination ahead of their desired arrival time, a concept that makes sense especially for business travelers.

The results also show a willingness to pay higher fares for flying out of one of the top-ranked airports, where this willingness is especially high for the top-ranked airport in the case of business travelers, while VFR travelers are also willing to pay an additional premium of $28 to fly out of the airport closest to their home. In terms of paying a premium for direct flights, the results again suggest a higher willingness for business travelers, although the different treatment in the case of holiday travelers results in a higher value for the trade-off in the case of flights with 2 connections in this group. A difference arises between the three population groups in the trade-offs looking at the willingness to pay for flying on a specific type of aircraft, where the differences in the *most-valued* type of aircraft led to a different base-type.

The findings for the trade-offs looking at the willingness to accept increases in access time do, overall, show a lower willingness for business travelers than for holiday and VFR travelers, which is to be expected. The main exception again comes in the case of frequent-flier benefits, where the results suggest that business travelers are willing to fly out of more distant airports in return for flying on an airline whose frequent-flier program they are a member of. Some of the findings, especially in the two leisure groups, show very high values for the trade-offs. Here, the limitations of an approach looking at simple ratios between coefficients should be kept in mind, while also noting that real-world choice set formation would not allow for the inclusion of airports located more than a few hours from a respondent's home.

However, one trade-off involving access time is of major interest, especially in the context of the increased use by low-cost carriers of outlying airports, namely the willingness to accept increases in access time in return for reductions in air fares. Here the high willingness, especially in the two leisure groups, can help to at least partly explain the success of such operators in being able to draw travelers away from network carriers and centrally-located airports to more regional bases, with often poor ground-level access facilities. From a methodological point of view, this trade-off shows the importance of using the *correct* calculation for the multiplier inside the trade-off (mean of ratios instead of ratio of means). Indeed, the non-linearities in the ratio between the access time and fare attributes mean that the willingness to accept increases in fare in return for reductions in access time is in this case not the same as the willingness to accept increases in access time in return for reductions in fare.

At this stage, it should however also be noted that some of the trade-offs presented in this section are very high; this could potentially be a reflection of the well-established notion that in SP studies, there is a tendency for respondents to exaggerate their responsiveness to changes in attributes (e.g. Louviere et al. 2000, Ortiizar 2000). While it can be argued that a good SP-design can at least partly address this problem, it should nevertheless be acknowledged that the findings presented here are potentially vulnerable to such exaggeration, for example in the case of willingness-to-pay indicators.

6. Summary and Conclusions

This paper has described a study of air travel choice behavior making use of SP data collected in the US in May 2001.

In common with many previous studies (see for example Hess & Polak 2005b), the analysis presented in this paper has highlighted the important role that ground-level distance plays in airport-choice behavior. However, while, in RP studies, it has often not been possible to retrieve a significant and meaningful effect of changes in air fares, the results from this SP study have shown air fare to be the variable with the most explanatory power, across the three population segments used in the analysis. This result is consistent with intuition, and highlights a certain advantage of SP data in this context, given that reliable information is available on the choices that respondents were actually faced with. Additionally, in the context of SP data, data protection issues in relation to frequent flier programs do not apply. As such, while impacts of airline allegiance can often not be identified in RP case studies, the SP analysis presented in this paper has revealed significant effects in response to membership in frequent-flier programs, as well as general airline-preference. Although these results do suggest a certain advantage for SP data in the analysis of air travel choice behavior, these advantages need to be put into context by remembering the usual limitations affecting this type of data (e.g. Louviere et al. 2000). This in turn suggests that an important avenue for further research in air travel comes in the use of a combination of RP and SP data, as discussed by Algers & Beser (2001).

Aside from illustrating the potential advantages of SP data, the study described in this paper has also achieved several other aims. One of the main innovations in the context of air travel is the use of a continuous treatment of the interactions between socio-demographic attributes and the sensitivity to travel-attributes. The improvements in performance obtained with this approach were significant[7], and the approach has clear theoretical advantages in terms of flexibility over more basic methods, such as a simple segmentation into different income-classes.

Another important topic addressed in this paper is the way in which attributes enter the utility function. Although the use of log-transforms for some of the attributes, such as flight frequency, has now become commonplace, other attributes, such as air fare and access time, are in general still being treated in a linear fashion in air travel. The estimation work described in this paper has shown this to be inappropriate in the present case, consistent with the results obtained by Hess & Polak (2005b). Aside from simply comparing the use of a log-transform to a linear approach, the work described in this paper made use of Box-Cox transforms in a preliminary analysis. Although no incidence of such cases was discovered in the present analysis, the use of this approach can also alert the modeler to the presence of variables with increasing marginal returns, something that is not possible when simply comparing the results of a linear and a log-linear approach.

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[7] More detailed results are available from the author on request.

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Table 1
Estimation results for MNL model for business travelers

N=1,190	est.	t-ratio
$^{\beta}$*LN*(*access time*)	-0.3725	-3.20
$^{\beta}$*LN*(*fare*)	-3.5344	-13.80
$^{\beta}$*LN*(*flight time*)	-1.6279	-6.27
$^{\beta}$*LN*(*SDL*)	-0.1390	-2.74
$^{\beta}$*SDE*	-0.0019	-1.61
$^{\beta}$*OT P*	0.0088	3.66
$^{\delta}$*current*	0.5979	4.21
$^{\delta}$*F F standard*	0.4168	2.37
$^{\delta}$*F F* (*elite and elite plus*)	1.0628	2.60
$^{\delta}$*top- ranked airport*	0.7062	3.68
$^{\delta}2^{nd}$*-ranked airport*	0.2593	1.31
$^{\delta}$*connecting flight*	-0.3747	-2.39
$^{\delta}$*wide-body*	-0.2534	-1.22
$^{\delta}$*regional jet*	-0.6748	-3.49
$^{\delta}$*turboprop*	-0.8227	-3.73
$^{\lambda}$*distance, SDE*	-1.5941	-3.09
$^{\lambda}$*income, LN*(*fare*)	-0.1456	-1.61
Parameters	19	
Final log-likelihood	-395.14	
Adjusted p^2	0.5003	

Table 2
Estimation results for MNL model for holiday travellers

N=1,840	est.	t-ratio
$^{\beta}$*LN(access time)*	-0.3488	-3.49
$^{\beta}$*LN(fare)*	-5.0039	-19.25
$^{\beta}$*LN(flight time)*	-1.9602	-6.76
$^{\beta}$*SD*	-0.0008	-1.57
$^{\beta}$*OT P*	0.0122	5.86
$^{\delta}$*current*	0.9379	6.97
$^{\delta}$*F F*	0.1983	0.99
$^{\delta}$*top- ranked airport*	0.9354	4.22
$^{\delta}$*2nd-ranked airport*	0.7179	3.11
$^{\delta}$*3rd-ranked airport*	0.3213	1.29
$^{\delta}$*top- ranked airline*	0.4346	2.51
$^{\delta}$*2nd-ranked airline*	0.3148	1.69
$^{\delta}$*3rd-ranked airline*	0.3482	1.88
$^{\delta}$*single connection*	-0.3398	-2.33
$^{\delta}$*double connection*	-1.0783	-4.18
$^{\delta}$*wide-body*	0.2330	1.36
$^{\delta}$*regional jet*	0.0228	0.14
$^{\delta}$*turboprop*	-0.0310	-0.14
$^{\lambda}$*distance, LN (fare)*	0.1431	2.27
$^{\lambda}$*distance, OTP*	0.2631	1.71
$^{\lambda}$*income, LN(fare)*	-0.0430	-0.75
Parameters	21	
Final log-likelihood	-532.42	
Adjusted p^2	0.5661	

Table 3
Estimation results for MNL model for VFR travellers

N=2,860	est.	t-ratio
$^{\beta}$*LN(access time)*	-0.3602	-3.96
$^{\beta}$*LN(fare)*	-4.7477	-23.84
$^{\beta}$*flight time*	-0.0086	-8.96
$^{\beta}$*SDE*	-0.0012	-3.25
$^{\beta}$*SDL*	-0.0007	-0.87
$^{\beta}$*OT P*	0.0105	6.09
$^{\delta}$*current*	0.4345	3.70
$^{\delta}$*top- ranked airport*	1.0506	4.93
$^{\delta}$*2^{nd}-ranked airport*	1.0299	5.32
$^{\delta}$*3^{rd}-ranked airport*	0.4880	2.39
$^{\delta}$*closest to home*	0.5281	3.10
$^{\delta}$*top- ranked airline*	0.3971	3.37
$^{\delta}$*2^{nd}-ranked airline*	0.2879	2.17
$^{\delta}$*3^{rd}-ranked airline*	0.0900	0.60
$^{\delta}$*conecting flight*	-0.3578	-3.15
$^{\delta}$*wide-body*	0.5248	3.28
$^{\delta}$*regional jet*	-0.1995	-1.50
$^{\delta}$*turboprop*	-0.3351	-2.03
$^{\lambda}$*distance, LN (access time)*	-0.4877	-1.91
$^{\lambda}$*distance, LN(fare)*	0.1915	3.44
$^{\lambda}$*income, LN(fare)*	-0.0531	-1.34
Parameters	21	
Final log-likelihood	-829.732	
Adjusted p^2	0.5709	

Table 4
MNL trade-offs, part 1: willingness to pay ($)

	Business	*Holiday*	*VFR*
Reduction in access time (1 hour)	75.40	35.80	35.48
Reduction in SDE (1 hour)	13.27$^{(*)}$		3.68
		2.61$^{(*)}$	
Reduction in SDL (1 hour)	11.08		2.25$^{(*)}$
On-time (+10%)	10.39	7.02	5.57
FF elite or elite-plus vs none	125.24		-
		11.44$^{(*)}$	
FF standard vs none	49.12		-
Top airline vs worst	-	25.07	21.06
2^{nd} airline vs worst	-	18.16$^{(*)}$	15.27
3^{rd} airline vs worst	-	20.09$^{(*)}$	4.77$^{(*)}$
Top airport vs worst	83.22	53.97	55.73
2^{nd} airport vs worst	30.56$^{(*)}$	41.42	54.63
3^{rd} airport vs worst	-	18.54$^{(*)}$	25.89
Airport closest to home	-	-	28.02
No connection vs one connection		19.60	
	44.15		18.98
No connection vs two connections		62.21	
Jet vs wide-body	29.86$^{(*)}$	-	-
Jet vs regional jet	79.51	-	10.59$^{(*)}$
Jet vs turboprop	96.94	1.79$^{(*)}$	17.77
Wide-body vs jet	-	13.45$^{(*)}$	27.84
Regional jet vs jet	-	1.31$^{(*)}$	-

(*) Coefficient used in numerator of trade-off not significant at 95% level

Table 5

MNL trade-offs, part 2: willingness to accept increases in access time (min)

	Business	*Holiday*	*VFR*
Reductions in fare ($1)	2.14	4.61	4.57
Reduction in SDE (1 hour)	17.38(*)		12.24
		8.25(*)	
Reduction in SDL (1 hour)	17.00		7.49(*)
On-time (+10%)	13.60	22.16	18.53
FF elite or elite-plus vs none	163.97		-
		36.10(*)	
FF standard vs none	64.31		-
Top airline vs worst	-	79.11	70.08
2nd airline vs worst	-	57.31(*)	50.81
3rd airline vs worst	-	63.40(*)	15.88(*)
Top airport vs worst	108.96	170.29	185.43
2nd airport vs worst	40.01(*)	130.69	181.78
3rd airport vs worst	-	58.49(*)	86.14
No connection vs one connection		61.86	
	57.81		63.15
No connection vs two connections		196.29	63.15

* Coefficient used in numerator of trade-offs not significant at 95% level