Dissecting preference heterogeneity in consumer stated choices

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ABSTRACT: This paper investigates alternative methods to account for preference heterogeneity in choice experiments. The main interest lies in assessing the different results obtainable when investigating heterogeneity in various ways. This comparison can be performed on the basis of model performance and, more interesting, by evaluating willingness to pay measures. Preference heterogeneity analysis relates to the methods used to search for it. Socioeconomic variables can be interacted with attributes and/or alternative-specific constants. Similarly one can consider different subsets of data (strata variables) and estimate a multinomial logit model for each of them. Heterogeneity in preferences can be investigated by including it in the systematic component of utility or in the stochastic one. Mixed logit and latent class models are examples of the first approach. The former, in its random variable specification, allows for random taste variations assuming a specific distribution of the attribute coefficients over the population and permit to capture additional heterogeneity by consenting parameters to vary across individuals both randomly and systematically with observable variables. In other words it accounts for heterogeneity in the mean and in the variance of the distribution of the random parameters due to individual characteristics. Latent class models capture heterogeneity by considering a discrete underlying distribution of tastes. The small number of mass points are the unobserved segments or behavioral groups within which preferences are assumed homogeneous. The probability of membership in a latent class can be additionally made a function of individual characteristics. Alternatively, heterogeneity can be incorporated in terms of the random component of utility. The covariance heterogeneity model adopts the second approach representing a generalization of the nested logit model and can be used to explain heteroscedastic error structures in the data. It allows the inclusive value parameter to be a function of choice alternative attributes and/or individual characteristics. An alternative method refers to an extension of the multinomial logit model in which the integration of unobserved heterogeneity is performed through random error components distributed according to a tree. An interesting improvement in modeling preference heterogeneity is related to its simultaneous inclusion in both systematic and stochastic parts. A valid example is the inclusion of an error component part in a random coefficient specification of the mixed multinomial logit model. The empirical data used for comparing the various methods tested relates to departure airport choice in a multi-airport region. The area of study includes two regions in central Italy, Marche and Emilia-Romagna, and four airports: Ancona, Rimini, Forlì and Bologna. A fractional factorial experimental design was adopted to construct a four alternative choice set and five hypothetical choice exercises in each questionnaire. The selection of the potentially most important attributes and their relative levels was developed on the basis of previous research.

Key words: heterogeneity, airport choice, stated preferences, discrete choice model.

1. Introduction

The study of airport choice has, in recent years witnessed a resurgence of interest in various areas of the world which is mainly due to the transport intensive growth path adopted world wide and to the relevance of passenger mobility in a knowledge based economy.

Both airport mangers and public decision makers alike need to take critical decisions under stringent budget constraints knowing that alternative policies might produce drastically different results both on airports' profits as well as on local pro-growth policies. Under these circumstances, knowing agents' demand better has an intrinsecally high value.

A novel approach based on stated preference (SP) data has increasingly been adopted by researchers in this field due to the widespread difficulties involved in the use of revealed preference data (Hess et a. 2007) to study airport choice and develop airport specific development policies. In fact, SP data allow for estimating marginal values of different airport characteristics and welfare effects for attribute variations.

A previous study (Marcucci and Gatta, in press) suggests the relevant presence of preference heterogeneity even in a much smaller sample taken from the same geographical area and thus motivating the present work.

Heterogeneity can be captured using different approaches with potentially diverse results and, consequently, with alternative policies implemented.

This paper tests different methods to account for preference heterogeneity in airport choice with the intent of evaluating the sensitivity of the estimated welfare measures to the specific heterogeneity research method chosen by the analyst. In so doing we investigate and compare different types of models that use the *systematic*, *stochastic* as well as *both systematic and stochastic* components of the utility function to account for heterogeneity.

In our case the discrete choice alternatives are the four airports considered: Ancona, Rimini, Forlì, and Bologna which are all located within the same catchment area as Marcucci and Gatta (in press) show.

To the best of our knowledge there is no study in the airport choice literature that has adopted this systematic and thorough research method to investigate heterogeneity.

Hess and Polak (2005) study heterogeneity in airport choice using a Mixed Logit (MMNL) model specification.

Colombo et al. (2009) compare different models and investigate heterogeneity in the context of agricultural economics while posing a lighter emphasis, compared to the present paper, on the use of socio-economic variables to characterise choice heterogeneity.

Greene and Hesher (2007) opt for the intensive use of socio-economic variables to study choice heterogeneity using a MMNL specification.

The present study offers both a detailed and integrated treatment of preference heterogeneity in the specific sector of airport choice while also basing the results on a wide, accurate, updated and original data set for Italy.

The paper is structured as follows. Section 2 describes the main structural characteristics of the models subsequently used. Section 3 illustrates the survey instrument. Section 4 reports the main results obtained and section 5 concludes.

2. Methodology

Random utility maximization and discrete choice modelling assume that an agent's (i) indirect (latent) utility function (U) for a choice alternative (j) is composed of a systematic or observable part (V) and an unobservable one (ε). In other words one can write the indirect utility function of agent i for alternative j as follows:

$$U_i(j) = V_{ij} + \varepsilon_{ij}$$
$$\text{where } V_{ij} = \boldsymbol{\beta}'\mathbf{x}_{ij}$$

In the early '70s McFadden (1973) developed the multinomial logit (MNL) model that along with many interesting and much appreciated advantages (closed form, ease of interpretation, etc.) is also characterised by relevant drawbacks linked to preference homogeneity assumption across respondents. Even if confounded for the scale, the estimated parameter represents the marginal utility of each attribute variation and implies an equal taste for all agents for the given attribute.
The probability of choosing alternative j for agent i at time t is:

$$\text{Prob}(y_{it} = j) = \frac{\exp(\boldsymbol{\beta}'\mathbf{x}_{jit})}{\sum_{q=1}^{J}\exp(\boldsymbol{\beta}'\mathbf{x}_{qit})}$$

A *naïve* way to incorporate preference heterogeneity can be achieved by interacting socio-economic variables with attributes (MNL+SE) or alternatively by estimating different models for subsets of data.
The probability of choosing alternative j for agent i at time t becomes:

$$\text{Prob}(y_{it} = j) = \frac{\exp(\boldsymbol{\beta}'\mathbf{x}_{jit} + \boldsymbol{\beta}_z'\mathbf{x}_{jit}\mathbf{z}_i)}{\sum_{q=1}^{J}\exp(\boldsymbol{\beta}'\mathbf{x}_{qit} + \boldsymbol{\beta}_z'\mathbf{x}_{qit}\mathbf{z}_i)}$$

where $\mathbf{z}_i$ is the vector of socio-economic variables related to agent i.

Discontent with the drawbacks of the MNL led researchers to explore more flexible and sophisticated ways to treat preference heterogeneity and improve the understanding of the factors impacting on agents' choice behaviour and their willingness to pay.

The first two model developments reported below, both incorporate heterogeneity in preferences via the *systematic* component of utility.

One modelling development aimed at overcoming the manifest weakness of the MNL model is the MMNL model whose popularity has grown considerably (McFadden and Train 2000; Train, 1998). Recent developments in simulation methods coupled with the low-cost computational power now available allow the estimation of open-form discrete choice models with relative ease (Train, 2003; Hensher et al. 2005). The MMNL assumes a continuous mixing distribution and represents agents' utility, when choosing over J alternatives, by employing a vector of parameters that describe the individual deviations of preferences from the mean.
The probability of choosing alternative j for agent i at time t is:

$$\text{Prob}(y_{it} = j) = \frac{\exp(\boldsymbol{\beta}_i' \mathbf{x}_{jit})}{\sum_{q=1}^{J} \exp(\boldsymbol{\beta}_i' \mathbf{x}_{qit})}$$

and, in this case, an individual specific parameter can be estimated.
The model can be refined by allowing a systematic heterogeneous component of the means and the variances of the parameter distributions which is dependent on observed choice invariant characteristics so that the parameter k for agent i is represented by:

$$\beta_{ki} = \beta_k + \boldsymbol{\delta}_k' \mathbf{m}_i + \sigma_k \exp(\boldsymbol{\omega}_k' \mathbf{v}_i) \zeta_{ki}$$

where $\mathbf{m}_i$ and $\mathbf{v}_i$ are respectively the vectors of socio-economic variables that measure the heterogeneity around the mean and the variance of random parameter k and $\boldsymbol{\delta}_k'$ and $\boldsymbol{\omega}_k'$ are their relative coefficient to estimate. ζ_{ki} is the random unobserved taste variation, while σ_k is the standard deviation of the distribution of β_{ki}s around the population mean β_k.

The Latent Class (LC) model accounts for heterogeneity (Kamakura and Russell, 1989; Boxall and Adamowicz, 2002) by assuming a discrete mixing distribution of preference parameters and a small number of mass points (C) are interpreted as different groups/segments of agents.

The probability of choosing alternative j for agent i at time t is the expected value, over classes, of the choice probability within each class.

$$\text{Prob}(y_{it} = j) = P(j \mid c)P(c) = \frac{\exp(\boldsymbol{\beta}_c' \mathbf{x}_{jit})}{\sum_{q=1}^{J} \exp(\boldsymbol{\beta}_c' \mathbf{x}_{qit})} \sum_{c=1}^{C} \left(\frac{\exp(\boldsymbol{\varphi}_c' \mathbf{k}_i)}{\sum_{c=1}^{C} \exp(\boldsymbol{\varphi}_c' \mathbf{k}_i)} \right)$$

The class probabilities can be functions of socio-economic variables $\mathbf{k}_i$.
One can calculate an individual specific parameter β_{ki} through a weighted average of class specific parameters β_k with a posterior estimate of the individual specific class probabilities Q_{ic}^*.

$$\beta_{ki} = \sum_{c=1}^{C} Q_{ic}^* \beta_{kc}$$

Heterogeneity can also be accounted for in the stochastic component of the utility. We investigate both Covariance Heterogeneity (COVHET) and Error Component (EC) model. Both models, in a different way, use the correlation across alternatives present in the data to account for preference heterogeneity.

More in detail EC constitutes a particular specification of a standard MMNL model with no random-coefficients, and can be used to represent error components that create correlations among the utilities for different alternatives. Various correlation patterns and, consequently, substitution patterns can be obtained by an appropriate choice of variables entering the model as error components (Brownstone and Train, 1999).
The probability of choosing alternative j for agent i at time t is:

$$\text{Prob}(y_{it} = j) = \frac{\exp\left[\boldsymbol{\beta}' \mathbf{x}_{jit} + \sum_{m=1}^{M} d_{jm} \theta_m \exp(\boldsymbol{\gamma}_m' \mathbf{e}_i) E_{im} \right]}{\sum_{q=1}^{J} \exp\left[\boldsymbol{\beta}' \mathbf{x}_{qit} + \sum_{m=1}^{M} d_{qm} \theta_m \exp(\boldsymbol{\gamma}_m' \mathbf{e}_i) E_{im} \right]}$$

where $\mathbf{e}_i$ is the vector of socio-economic variables that measure the heterogeneity in the variances of the error components and γ_m' is the relative coefficient. E_{im} is the individual specific random error component which is assumed $\sim N(0,1)$; d_{jm} is the auxiliary variable which takes one if E_{im} appears in the utility function for alternative j; and θ_m is the standard deviation of the error component.

Analogously COVHET (Bhat, 1997), a generalisation of the Nested Logit (NL) model, assumes that the inclusive value for branch b can be expressed as an exponential function of covariates. The model can explain the heteroscedastic error structure present in the data since the inclusive value is a scaling parameter for a common random component in the alternatives within a choice branch.
The probability of choosing alternative j for agent i at time t is calculated by multiplying the probability of choosing alternative j within branch b (MNL) by the probability of choosing branch b which depends on the related inclusive value I_b.

The inclusive value parameter τ_b is assumed to be function of a set of socio-economic variables $\mathbf{i}_i$.

$$\text{Prob}(y_{it} = j) = P(j \mid b)P(b) = \frac{\exp(\boldsymbol{\beta}'\mathbf{x}_{j|b})}{\sum_{q=1}^{J|b}\exp(\boldsymbol{\beta}'\mathbf{x}_{q|b})} \frac{\exp[\tau_b \exp(\boldsymbol{\psi}'\mathbf{i}_i)]I_b}{\sum_{b=1}^{B}\exp[\tau_b \exp(\boldsymbol{\psi}'\mathbf{i}_i)]I_b}$$

Finally, a more comprehensive and exhaustive way to investigate heterogeneity is to simultaneously search for it both in the *systematic* and *stochastic* part of the utility. In other words, one can concurrently use the MMNL model with both specifications (i.e. random parameter and error component) while using socio-economic variables to account for heteroscedasticity. This model (MMNL+EC) searches both for continuous parameter taste heterogeneity as well as for correlation across alternatives.
The probability of choosing alternative j for agent i at time t is now:

$$\text{Prob}(y_{it} = j) = \frac{\exp\left[\boldsymbol{\beta}_i'\mathbf{x}_{jit} + \sum_{m=1}^{M} d_{jm}\theta_m \exp(\boldsymbol{\gamma}_m'\mathbf{e}_i)E_{im}\right]}{\sum_{q=1}^{J}\exp\left[\boldsymbol{\beta}_i'\mathbf{x}_{qit} + \sum_{m=1}^{M} d_{qm}\theta_m \exp(\boldsymbol{\gamma}_m'\mathbf{e}_i)E_{im}\right]}$$

The same notations and properties, previously described for MMNL and EC models, apply.

3. Survey instrument

The methodology used for data acquisition is based on SP choice experiments describing a potential choice situation among the four airports considered. In SP surveys, respondents are asked to compare a set of alternatives and select the one providing the highest utility. The theoretical basis is represented by the micro-economic theory of choice and by the random utility theory (Louviere et al., 2000).

The interviews were distributed by trained university students as computer aided personal interviews (CAPI). Each interview was composed by five hypothetical choice exercises where respondents were asked to evaluate the four airports and choose one.

The area of study includes two regions in central Italy, Marche and Emilia-Romagna, and four airports: Ancona, Rimini, Forlì and Bologna. This area qualifies as a multi-airport region following the definition by Reeven et al. (2003) and Starkie (2008). A total of 1,419 interviews generating 6,839 observations have been gathered both in the four airports and in the airports' catchment areas.

A choice-based conjoint analysis was planned using a fractional factorial, full profile, experimental design with complete enumeration. The structural variables used were: *AN*, *FO* and *RN* three effects coded airports with Bologna used as a reference; *A_GC* generalized access cost (euro); *P_AIRL* binary variable coded one when representing

the preferred airline company; *F_EURO* ticket cost (euro); *NONSTOP* binary variable coded one when the flight is non-stop from origin to destination; *BAL_M_AV* absolute value of the difference between desired and actual departure time (minutes).

Four auxiliary and five socio-economic variables were also used.

In particular, the auxiliary variables used were: *INERTIA* coded one for the last airport chosen; *FREQ* number of times the agent used each airport in the last year; *NEVER* coded one if the airport was never chosen; *K_AIRP* coded one if the agent asserts he would never depart from a given airport.

The socio-economic variables considered were: *GEN* coded one for male; *AGE* respondents' age; *INC* monthly income; *DOM* coded one for domestic flights; *BUS* coded one for business purpose flights.

4. Results

The primary step of the analysis is represented by the assumption of preference homogeneity. Table 1 reports the results of a MNL model with two specifications. The first includes only the structural variables while the second also accounts for the auxiliary variables previously defined. Both models have all statistically significant coefficients with the expected signs: negative for access and ticket costs and departure delay; positive for preferred airline and non-stop flight. While in the first model the airport brand of Bologna has the highest positive influence on utility in the second it falls down to the last position. The role auxiliary variables, directly linked to the airport, play provides a good explanation. In fact, for Bologna *INERTIA* and *FREQ* (positive impact on utility) assume high values while *NEVER* and *K_AIRP* (negative impact on utility) assume low values when compared to the other airports. We use the second model as reference since its overall explanatory power (RsqAdj = 0.1874) is satisfactory and higher than the model not considering the auxiliary variables effects (RsqAdj=0.1701). The interpretation of the estimated coefficients is not straightforward since not all the attributes are binary coded. When considering the mean part-worth utilities, one finds that *F_EURO* and *A_GC* have the most relevant (negative) impact on utility.

Table 1 – Homogeneity: *MNL* model estimates

Model	MNL basic		MNL reference	
Attribute	Coeff.	t-ratio	Coeff.	t-ratio
AN	-0,5291	-2.27	-0,0408	-1.70
FO	-0,8046	-3.45	-0,0525	-2.20
RN	0,0568	2.52	0,1257	5.31
A_GC	-0,1822	-27.61	-0,0186	-27.83
P_AIRL	0,1103	4.20	0,1144	4.31
F_EURO	-0,0077	-37.93	-0,0079	-38.13
NONSTOP	0,7151	25.98	0,7298	26.18
BAL_M_AV	-0,0019	-17.31	-0,0019	-17.24
FREQ			0.0064	1.77
NEVER			-0.5212	-8.44
K_AIRP			-0.3899	-6.71
INERTIA			0.2903	5.31
Log-likelihood	-7850.290		-7681.959	
Adj.pseudo R^2	0.1701		0.1874	

The analysis of preference heterogeneity, in its simplest version, can be accomplished via a *naïve* procedure. Estimation results of MNL+SE are shown in Table 2. All the reported socio-economic interactions are significant and have been selected after performing a log-likelihood ratio test for the unrestricted versions of the model. The explanatory power of this parsimonious model (RsqAdj = 0.2024) is noticeably higher than the reference one. In the following we highlight some of the main socio-economic interactions that struck our attention. In particular, high income agents or those traveling for business purposes are more sensitive to access cost and less so to ticket cost. A possible explanation of the phenomenon is that access cost has a strong time component which is important for business travelers while their traveling expenses are completely refunded by their companies. Furthermore, as expected, actual delay from desired departure time has a greater negative effects on utility for domestic or business flights.

Table 2 – Heterogeneity naïve: *MNL plus socio-economic interactions* model estimates

Attribute	Coeff.	t-ratio	Attribute	Coeff.	t-ratio
AN	-0.0560	-2.30	GEN*FREQ	0.0208	2.13
FO	-0.0354	-1.45	GEN*BAL_M_AV	-0.0012	-4.59
RN	0.1696	6.05	AGE*NEVER	-0.0234	-5.33
FREQ	0.0017	0.13	AGE*K_AIRP	0.0190	3.75
NEVER	0.3590	1.99	INC*A_GC	0.7e-06	-2.06
INERTIA	0.2697	4.51	INC*F_EURO	0.5e-06	4.81
K_AIRP	0.3350	1.67	DOM*RN	-0.1021	-2.60
A_GC	-0.0134	-12.42	DOM*INERTIA	-0.2855	-4.60
P_AIRL	0.1132	4.22	DOM*BAL_M_AV	-0.0007	-2.88
F_EURO	-0.0109	-31.42	BUS*FREQ	-0.0212	-1.90
NONSTOP	0.7490	26.53	BUS*INERTIA	0.2696	3.84
BAL_M_AV	-0.0007	-3.01	BUS*A_GC	-0.0071	-4.80
			BUS*F_EURO	0.0032	6.93
			BUS*BAL_M_AV	-0.0007	-2.86
Log-likelihood	-7524.851				
Adj.pseudo R^2	0.2024				

Preference heterogeneity can be examined focusing on the systematic component of utility and assuming a continuous mixing distribution. MMNL model estimates are presented in Table 3.

We investigated several model specifications since we have to: 1) test whether a parameter has to be assumed random or fixed; 2) choose the distribution for random parameters; 3) verify the capability of individual characteristics to explain heterogeneity around the means and the variances of the random parameters. The best results were obtained when considering all random parameters following the “dome” distribution (an appropriate transformation of beta distribution – *2beta(2,2)-1*) taking into account the socio-economic variables with a statistically significant impact on the heterogeneity around the means and the variances of the random parameters. We found four socio-economic variables (*AGE*, *INC*, *DOM*, *BUS*) that impact on the means of specific attributes (*RN*, *NEVER*, *K_AIRP*, *INERTIA*, *A_GC*, *F_EURO*, *BAL_M_AV*) and only two (*AGE*, *BUS*) that have influence on the variances of some attributes (*INERTIA*, *A_GC*, *F_EURO*).

The overall fit increases (RsqAdj = 0,2462) and the expected signs for the various coefficients, notwithstanding the unrestricted dome distribution adopted for the random variables, are, overall, correct.

Table 3 – Heterogeneity on systematic U component: *MMNL* model estimates

Attribute	Coeff.	t-ratio	Attribute	Coeff.	t-ratio
Random parameter means			*Standard deviations of parameter distributions*		
AN	-0.0930	-2.73	sdAN	0.4263	1.44
FO	0.0140	0.41	sdFO	0.0411	0.05
RN	0.1751	4.61	sdRN	0.3386	2.04
FREQ	0.0068	0.92	sdFREQ	0.0078	0.13
NEVER	0.3349	1.41	sdNEVER	0.3192	0.51
K_AIRP	0.1789	0.63	sdK_AIRP	0.1175	0.09
INERTIA	0.9742	11.27	sdINERTIA	3.1011	6.85
A_GC	-0.0229	-8.19	sdA_GC	0.0563	4.87
P_AIRL	0.2294	5.70	sdP_AIRL	1.1768	5.14
F_EURO	-0.0131	-25.92	sdF_EURO	0.0201	11.65
NONSTOP	0.8876	19.34	sdNONSTOP	2.1360	8.92
BAL_M_AV	-0.0034	-9.76	sdBAL_M_AV	0.0198	11.09
Heterogeneity around mean			*Heterogeneity around standard deviation*		
RN | DOM	-0.1439	-2.73	sdINERTIA | AGE	0.0075	2.02
NEVER | AGE	-0.0258	-4.46	sdINERTIA | BUS	-0.0454	-0.54
K_AIRP | AGE	-0.0156	-2.40	sdA_GC | AGE	0.0090	1.95
INERTIA | DOM	-0.2521	-2.47	sdF_EURO | BUS	-0.0624	-0.47
A_GC | INC	-0.0019	-3.04			
A_GC | BUS	-0.0079	-3.33			
F_EURO | BUS	0.0059	8.91			
BAL_M_AV | DOM	-0.0009	-2.78			
BAL_M_AV | BUS	-0.0012	-3.73			
Log-likelihood	-7099.869				
Adj.pseudo R^2	0.2462				

The systematic component of utility can also be investigated assuming a discrete mixing distribution. LC model estimates are presented in Table 4.
The results providing the best fit was achieved by assuming 5 different latent classes. This result was obtained both when using structural variables alone as well as when employing socio-economic variables to determine the probability of belonging to a given class. The latter model produced the best fit (RsqAdj = 0,2586).

Table 4 – Heterogeneity on systematic U component: *LC* model estimates

	Class 1	Class 2	Class 3	Class 4	Class 5
Attribute	Coeff (t-ratio)	Coeff (t-ratio)	Coeff (t-ratio)	Coeff (t-ratio)	Coeff (t-ratio)
AN	-0.3357(-2.5)	-0.1993(-3.9)	0.1616(0.8)	-0.0103(-0.3)	0.0102(0.2)
FO	-0.0798(-0.7)	-0.0322(-0.6)	0.2086(0.7)	0.0395(1.4)	0.0580(1.0)
RN	0.2942(2.4)	0.4994(10.5)	-0.6814(-2.4)	0.0077(0.3)	-0.0875(-1.5)
FREQ	0.0347(1.5)	-0.0220(-3.5)	-0.0926(-3.9)	0.0087(2.2)	-0.0371(-2.3)
NEVER	-0.4860(-1.6)	-0.5931(-4.8)	-0.7263(-1.3)	-0.6700(-9.3)	-0.4660(-3.2)
INERTIA	0.4350(2.0)	0.9903(10.4)	6.3420(9.7)	-0.1532(-2.9)	0.1835(1.7)
K_AIRP	-0.4982(-1.8)	-0.5175(-4.6)	-0.4145(-0.7)	-0.3282(-4.7)	-0.4961(-3.5)
A_GC	-0.0245(-6.8)	-0.0550(-31.4)	-0.0439(-5.4)	-0.0163(-19.9)	-0.0124(-7.9)
P_AIRL	0.0602(0.6)	0.2876(5.2)	0.2422(1.0)	0.1327(4.1)	0.1125(1.7)
F_EURO	-0.0203(-10.7)	-0.0062(-14.6)	0.0136(5.1)	-0.0034(-14.0)	-0.0267(-36.6)
NONSTOP	3.4523(11.9)	0.1237(2.1)	0.8405(3.1)	0.9271(26.9)	0.1091(1.6)
BAL_M_AV	0.0005(0.8)	0.0004(1.7)	-0.0042(-3.7)	-0.0052(-33.5)	-0.0009(-3.4)
Socio-economic in class probability model					
Constant	-0.1002(-0.3)	-0.9013(-2.2)	-4.1909(-6.0)	-1.0865(-2.9)	0
GEN	-0.0117(-0.1)	-0.0852(-0.3)	0.2437(0.7)	0.6506(3.0)	0
AGE	-0.0164(-1.5)	-0.0089(-0.8)	0.0301(2.1)	0.0028(0.3)	0
INC	0.2473(3.0)	0.2997(3.8)	0.1781(1.7)	0.2761(4.0)	0
BUS	-0.3677(-1.3)	0.6432(2.3)	1.5661(3.8)	0.6355(2.7)	0
Log-likelihelihood	-6939.215				
Adj.pseudo R^2	0.2586				

No formal test was performed to verify if the various coefficients for the structural and auxiliary variables are statistically different for the five classes. Not all coefficients are statistically different from zero and the same variable might impact differently on utility for the different classes. A good example is the *NONSTOP* variable. *INC* is the only socio-economic variable that have a statistically significant effect on utility for all classes.
Using individual specific probabilities of belonging to a specific class and multiplying it for the parameter estimate for each class, we construct a kernel density of posterior individual estimates.

Alternative approaches incorporate heterogeneity in preferences via the stochastic component of utility. This can be accomplished through the EC model whose estimates are reported in Table 5.
Various correlation patterns between alternatives were tested. The best structure we found, in terms of fit, suggests that three error components should be incorporated into the utility functions: one for Ancona; one for Bologna; and one common for Forlì and Rimini. This structure correctly represents the geographic situation analysed. In fact, both Bologna and Ancona are at the margin of the area considered whereas both Forlì and Rimini are more barycentric. The standard deviation of the first two latent random effects are statistically significant. Furthermore, any socio-economic characteristics are found to have a significant impact on the standard deviations of the error components. However, the overall contribution of the latent random effects is not substantial (RsqAdj = 0,1873).

Table 5 – Heterogeneity on stochastic U component: *EC* model estimates

Attribute	Coeff.	t-ratio	Attribute	Coeff.	t-ratio
Non-random parameter means			*Standard deviations of latent random effects*		
AN	-0.0607	-1.50	sdE01(Ancona)	0.4952	1.98
FO	-0.0277	-0.94	sdE02(Bologna)	0.5855	2.71
RN	0.1540	5.02	sdE03(Forlì; Rimini)	0.1772	0.41
FREQ	0.0071	1.83			
NEVER	-0.5401	-8.37			
K_AIRP	-0.4032	-6.78			
INERTIA	0.3004	6.62			
A_GC	-0.0194	-22.59			
P_AIRL	0.1196	4.27			
F_EURO	-0.0083	-28.10			
NONSTOP	0.7577	22.32			
BAL_M_AV	-0.0021	-16.05			
Log-likelihood	-7679.620				
Adj.pseudo R^2	0.1873				

Heterogeneity in the stochastic component of utility can be studied using a COVHET model. The results are provided in Table 6.
In particular we use a two-level nesting structure similar to that of the previous model. Forlì and Rimini are grouped into one branch while Ancona and Bologna are degenerate ones. *BUS* is the only socio-economic variable affecting the scale parameters and denoting that error variances in the conditional choice model are not systematically related to differences in individuals' characteristics. The overall fit of the model (RsqAdj = 0,1874).

Table 6 – Heterogeneity on stochastic U component: *COVHET* model estimates

Attribute	Coeff.	t-ratio	Attribute	Coeff.	t-ratio
Non-random parameter means			*Inclusive Value parameters*		
AN	-0.0330	-0.38	IV(Ancona)	1.0097	16.76
FO	-0.0290	-0.48	IV(Bologna)	0.9761	16.44
RN	0.1535	2.56	IV(Forlì; Rimini)	1.0042	14.20
FREQ	0.0075	1.86			
NEVER	-0.5315	-8.18	*Socio-economic variables in IV parameters*		
K_AIRP	-0.3974	-6.64	BUS	-0.1085	-2.58
INERTIA	0.2947	6.42			
A_GC	-0.0193	-20.86			
P_AIRL	0.1202	4.27			
F_EURO	-0.0084	-25.52			
NONSTOP	0.7634	20.82			
BAL_M_AV	-0.0021	-15.37			
Log-likelihood	-7677.663				
Adj.pseudo R^2	0.1874				

To account for heterogeneity in both systematic and stochastic utility components one may use a model which considers simultaneously individual parameters as well as error components. The MMNL+EC estimates are reported in Table 7.
We use the same specifications for both MMNL and EC models. Not surprisingly, since what we have previously noted, the explanatory power of the model (RsqAdj = 0,2460) is equivalent to the MMNL showing, for these data, that heterogeneity is high in the systematic component and low in the stochastic one.

Table 7 – Heterogeneity on both systematic and stochastic U component: *MMNL+EC* model estimates

Attribute	Coeff.	t-ratio	Attribute	Coeff.	t-ratio
Random parameter means			*Standard deviations of parameter distributions*		
AN	-0.0986	-2.76	sdAN	0.3129	0.61
FO	0.0150	0.43	sdFO	0.0470	0.05
RN	0.1767	4.59	sdRN	0.3381	1.79
FREQ	0.0059	0.66	sdFREQ	0.0044	0.04
NEVER	0.3554	1.45	sdNEVER	0.2532	0.31
K_AIRP	0.1928	0.68	sdK_AIRP	0.2013	0.19
INERTIA	0.9805	11.13	sdINERTIA	3.0949	6.80
A_GC	-0.0230	-8.19	sdA_GC	0.0568	4.86
P_AIRL	0.2317	5.73	sdP_AIRL	1.1933	5.24
F_EURO	-0.0131	-25.84	sdF_EURO	0.0202	11.67
NONSTOP	0.8929	19.19	sdNONSTOP	2.1418	8.86
BAL_M_AV	-0.0034	-9.77	sdBAL_M_AV	0.0199	11.09
Heterogeneity around mean			*Heterogeneity around standard deviation*		
RN | DOM	-0.1435	-2.70	sdINERTIA | AGE	0.0076	2.03
NEVER | AGE	-0.0261	-4.46	sdINERTIA | BUS	-0.0462	-0.55
K_AIRP | AGE	-0.0157	-2.37	sdA_GC | AGE	0.0089	1.93
INERTIA | DOM	-0.2556	-2.48	sdF_EURO | BUS	-0.0643	-0.48
A_GC | INC	-0.0019	-3.04			
A_GC | BUS	-0.0078	-3.29	*Standard deviations of latent random effects*		
F_EURO | BUS	0.0059	8.95	sdE01(Ancona)	0.2763	1.31
BAL_M_AV | DOM	-0.0009	-2.75	sdE02(Bologna)	0.0078	0.01
BAL_M_AV | BUS	-0.0012	-3.73	sdE03(Forlì; Rimini)	0.1483	0.60
Log-likelihood	-7099.182				
Adj.pseudo R^2	0.2460				

Finally, to gain a richer understanding of the different implications when modelling heterogeneity in distinct ways, we derive the mean of the WTP for the structural variables according to the seven models showed up to here. They are compared in Table 8.
The models are ranked, from the best (LC) to the worst (EC), according to their explanatory power by using, for non-nested models, the test proposed by Ben-Akiva and Swait (1986).
We use *A_GC* as the monetary variable. Whenever we obtain individual parameter estimates from a model, we first calculate an individual WTP based on the ratio of the individual coefficients for both numerator and denominator and then average for the sampled agents. For mean parameter estimates we simply compute the ratio between coefficients.

In the last column we consider an "average model" reporting the means of the WTP based on the values associated with the various models. Findings suggest that agents are willing to pay 48.12€ for having a non-stop flight and 6.69€ for travelling with the preferred airline while are willing to accept 7.74€ for an hour of delay with respect to the desired departure time. Interestingly, the WTP for *F_EURO* (0.56€) can be considered as an exchange rate between two monetary attributes revealing that agents are more prone to pay for flight tickets than to spend money to access the airport.
However, taking into account WTP measures for all models we obtain the following ranges: [39.06 - 72.51] for *NONSTOP*; [6.15 – 8.13] for *P_AIRL*; [6.13 - 11.39] for *BAL_M_AV*; [0.42 - 0.90] for *F_EURO*. Percentage deviations with respect to the values calculated as an average of all those obtained with the various models are reported. On average, LC is the closest (5%) to the average followed by MNL+SE (12%), while MMNL is the model with the widest overall variance of the estimated ranges (45%). Evidence shows that the latter tends to overestimate the mean WTP, while MNL tends to underestimate them. Thus, preference heterogeneity seems to be better explained at a segment level than at an individual one when looking at the systematic utility component. Given differences among the various models used to search for heterogeneity, provided the impact they have on WTP, one should conduct multiple attempts to locate the most robust estimates. The results obtained are data specific and no general indications can be drawn. Caution is needed when searching for heterogeneity since results can much depend on the search method used.

Table 8 – Comparison of willingness to pay estimates according to various models

Model Attribute	LC	MMNL	MMNL+EC	MNL+se	MNL	COVHET	EC	Average
				Mean values				
P_AIRL	-6.31	-8.13	-7.50	-6.35	-6.15	-6.23	-6.16	-6.69
F_EURO	0.58	0.90	0.68	0.48	0.42	0.43	0.43	0.56
NONSTOP	-47.66	-72.51	-56.76	-42.00	-39.24	-39.60	-39.06	-48.12
BAL_M_AV	6.95	11.39	10.32	6.45	6.13	6.44	6.49	7.74
				Percentage deviations from mean values of the average model				
P_AIRL	-6%	22%	12%	-5%	-8%	-7%	-8%	-
F_EURO	3%	60%	21%	-14%	-24%	-23%	-24%	-
NONSTOP	-1%	51%	18%	-13%	-18%	-18%	-19%	-
BAL_M_AV	-10%	47%	33%	-17%	-21%	-17%	-16%	-
Average	5%	45%	21%	12%	18%	16%	17%	-

5. Conclusions

This paper inserted in the airport choice literature stream provides, using an original, high-quality and detailed SP dataset, evidence that model results and methods to search for heterogeneity are not independent one from the other. The differences in the methods employed to investigate heterogeneity can produce substantial differences also suggesting that different policy implications might ensue.

Given the relevant amount of resources needed to implement and support airport construction, maintenance and development it is of crucial importance to know as much as possible about potential and effective demand. Our results signal that relevant potential biases in policy selection can depend on the search method adopted to investigate heterogeneity. In particular, for our dataset the main components of heterogeneity seem to reside in the systematic part of utility rather that in the stochastic one. The use of socio-economic variables tend to improve the overall model fit even if they never provide dramatic improvements. The LC model provided the best fit assuming the presence of five different latent classes.

Future research will centre on policy simulations for the various airports considered so to test the impact of different policy mixes for the various airports considered with the intent of defining alternative marketing strategies to be adopted by local policy makers or airport marketing managers.

From a more methodological and technical perspective we would like to apply and test bayesian flexible techniques to estimate MMNL models (Scaccia and Marcucci, in press).

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