DEPARTMENT OF TRANSPORT AND REGIONAL ECONOMICS

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A Discrete Choice Approach for Analysing the Airport Choice for Freighter Operations in Europe

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Abstract

Airport competition is a topic which recently gained interest in transport research. However, many studies about airport competition focus on passengers or passenger operations. Research about airport competition for air cargo is still scarce. This paper contributes to the understanding of this topic by analyzing the airport choice for freighter operations in Europe. It first reveals the choice process that airports follow, as well as the different factors that play a role therein. Furthermore, using a discrete choice experiment, we analyzed six choice factors more in-depth. We collected completed questionnaires from 26 airlines and used the discrete choice data as input for a multinomial logit model. The results show that the presence of passenger operations at an airport is not a significant factor in explaining airlines' choices, which, from an airline's point of view, supports the idea of all-cargo airports and therefore the relocation of cargo operations to non-congested airports. The presence of forwarders, on the other hand, is the most important factor. This shows that, when trying to influence airlines in their airport choice, airports and policy makers also have to consider the preferences of forwarders.

Keywords: air cargo; discrete choice analysis; airport choice; multinomial logit

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1. Introduction

During the last decades, air transport has known a tremendous growth. While from 1975 to 2012 passenger transport, measured in passenger kilometers, has been growing at a yearly average of 5.8%, cargo transport, measured in tonne kilometers, has been growing at a yearly average of 6.2% (calculations based on ICAO data). Because of this strong growth, airports play an ever increasing role in economies around the world. Many economic impact studies of air transport, mostly on country or airport level (see, e.g., Hakfoort et al. (2001) and Kupfer and Lagneaux (2009)), confirm this increasing importance. Moreover, on the global level, the impact of aviation is estimated to be 2.2 trillion dollar (Air Transport Action Group, 2012).

Because airports are very important for economies in the creation of value, attractive and competitive airports are desirable, especially from a government's point of view. As Starkie (2002) points out, the real market power of an airport depends on the market segment and the availability of airports in the proximity. While airport competition and airport market power have already been discussed by numerous authors (see Forsyth et al. (2010) and Starkie (2008) respectively), they have mostly been associated with passenger transport. Concerning the competition for air cargo, very little research has been done so far. However, as air cargo transport is a relatively foot-loose business, airport competition for cargo can be quite fierce, especially in Europe, where main airports can be located within a few hours of driving from each other. Therefore, a good understanding of the airport choice of cargo airlines is needed for airports and governments in order to be able to attract cargo airlines and thus economic activity.

In this contribution, we aim to overcome the shortcomings in research concerning airport choice and the airport competition for cargo. We do so by using a discrete choice experiment to quantify the importance of the factors driving the airport choice for freighter operations. In Section 2, we present the airport choice process as well as the factors that potentially influence the cargo carriers' choices. In Section 3, we describe the setup of the discrete choice experiment, the data collected and the multinomial logit model used for analysis. In Section 4, we present the results of our discrete choice exercise. Finally, we discuss the implications of our results for airports and policy makers.

Although carriers transport cargo in the belly of an aircraft as well as in freighter aircraft, this research focuses on the airport choice for the latter as the airport choice for the belly freight is still very much influenced by passenger operations. Furthermore, this study is aimed at the airport choice of combination carriers specialized in the transport of cargo and passengers, and the airport choice of all-cargo carriers. Integrators such as DHL and FedEx are excluded as their business model is very different from that of the traditional carriers and therefore the factors determining competition between airports are judged differently by integrators and combination or all-cargo carriers. To include the integrators' airport choice would be outside of the scope of the study, which is why only traditional carriers are considered. Finally, only scheduled operations are studied, which, in contrast with non-scheduled or ad-hoc operations, are set up before the specific demand for the operations is known and involve airport decisions that are taken more independently.

2. The airport choice process

A first step towards understanding the way airports and regions compete for scheduled all-cargo services is to outline the process that airlines follow when choosing their airport for cargo operations. In this process, many factors can play a role.

In a previous study by Gardiner (2005a), the airport choice was depicted as a three-stage process: the airline first decides on a region of operation, then analyses the airports in this region based on possible barriers to operate and finally selects an airport based on its individual merits. However, during discussions with airline representatives[2], it became clear that the process is less hierarchical than outlined by Gardiner (2005). The three steps of Gardiner (2005a) make up an important part of the airport choice process, but are not always followed consecutively by the airline. The process of the demand analysis (part of economic analysis), the analysis of possible barriers to operate (restrictive factors) and the final selection based on other operational factors often overlap or are carried out by the airline at the simultaneously. Therefore, these three parts should be considered as phases of the choice process that may overlap in time, rather than as consecutive steps. In parallel, during the whole airport choice process, different financial analyses are executed at various times to check whether serving an airport is also financially viable. The course of the airport choice process as understood after the discussions with airline representatives, is depicted in Figure 1.

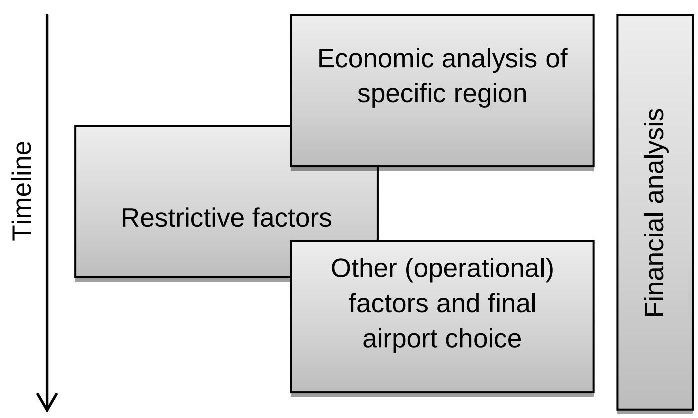


Figure 1 - The airport choice process: findings from discussions with airline representatives

[2] When contacting the airlines, we ensured that they were representative for the different groups of airlines, regarding, for example, geographical origin or type of airline (combination or all-cargo).

2.1 Economic analysis

Generally, the economic analysis is the first phase of the airport choice process. Within some airlines, especially larger ones, the economic analysis is even a constant process. The aim of the economic analysis is to define the market and the possible demand in a certain region. It can include studies on the general economy of the region as well as of its traffic in goods and trade, as they are often seen as catalysts for air transport (Kupfer et al., 2011). The economic analysis can also include revenue and profitability projections, where yield plays an important role, as well as projections of the inbound and outbound expected demand.

Previous research (see, e.g., Gardiner and Ison (2008)) as well as in-depth interviews showed that above all origin-destination demand (demand from the vicinity of the airport and not generated by transit) is one of the most important factors in the economic analysis. This is especially true for non-hub airports as the airlines are especially concerned about minimizing total flight kilometers and costs when choosing their hubs (Zhang, 2003). The government can play an important role in making a region more attractive for air cargo carriers by stimulating the development of industries that rely on air transport, such as biotech industries.

Another factor which plays an important role in the economic analysis and which is closely related to the origin-destination demand is the presence of forwarders at the airport, as this can be an indication of the market size in the area. Studies by Rodrigue (2012) and Strale and Bouilla (2012), among others, show that forwarders are often clustered around main cargo airports. As a trend towards consolidation of forwarders can be observed and therefore an increase in their market power, forwarders might even become more important in the airport choice in the future.

2.2 Restrictive factors

The restrictive factors that are considered during the airport choice process are often restrictive from an operational point of view. Some of the most cited restrictive factors are the bilateral agreements and traffic rights. Within a region, an airline might not be able to operate from all airports or countries due to traffic right restrictions. Studies by Zhang (2003) and Zhang et al. (2004) show that traffic rights are especially important for the attractiveness of cargo hubs. Such restrictions, however, hinder the airports and regions in their development as well as restrict airlines in their strategies. On the other hand, interviews showed that some airlines do not rely on general bilateral or multilateral agreements for their scheduled operations but rather work on an ad-hoc basis and ask for flight permissions when needed. The government plays an important role in granting these permissions.

Other factors that restrict airlines in using certain airports are noise and night-time restrictions. Noise restrictions especially affect operators that use freighter aircraft, as these aircraft are often older and produce more noise than passenger aircraft. With many airports introducing noise related charges, freighter aircraft provoke higher costs for the airlines. Night-time restrictions are a special case of noise restrictions and specifically concern integrators, as their network operations are based on the nightly transport of packages from airport to airport, mostly via a hub. However, also non-integrated freight operators value night-time slots. In particular on the Asian market, night-time operations at an airport are a must, as the cargo leaves the Asian continent during the night to arrive in Europe the next morning.

At the local level, infrastructure such as warehouse facilities, is of utmost importance for airlines and forwarders (Zhang, 2003). Other necessary infrastructure includes sufficient numbers of ramps, parking spaces, and runways as well as sufficient terminal capacity (Kingsley-Jones, 2000; Page, 2003). Moreover, the infrastructure is expected to fit the need of air cargo and to be maintained and improved or expanded whenever necessary (Berechman and de Wit, 1996; Hall, 2002).

Another factor that is closely related to infrastructure is capacity. As a matter of fact, capacity restrictions may prevent airlines from flying to specific airports (for instance in the case of London Heathrow which operates at almost 100% of its runway capacity).

2.3 Other (operational) factors

The last phase of the airport choice process is the analysis of other (operational) factors and the choice of an airport itself. In this phase, airlines compare different airports located in a specific region which meet their expectations with regard to (the lack of) restrictions, and finally choose the airport they wish to serve.

There are a myriad of factors influencing the airlines in this phase, such as congestion, airport delays, custom clearance times, turnaround time and the market access. Fast and convenient access to the market is especially important when the origin-destination demand of an airport cannot compete with the origin-destination demand of another airport, which is often the case with regional airports. One of the competitive advantages of regional airports is congestion free operations on the air- as well as on the landside, which the main airports often cannot offer anymore. This advantage enables airlines to reach the market from regional airports in the same time as they would via congested main airports that are often closer to the market.

As profit maximization is the ultimate goal of a cargo airline, direct and indirect costs also play an important role in the airlines' decisions. Studies by Berechman and de Wit (1996), among others, reveal that airport charges are important for airlines in their airport choice process. However, also handling and fuel costs, labour costs (next to labour availability) and line-haul costs can play a role.

In their airport choice process, airlines also have to decide whether they want to operate from an airport with passenger operations, competitors and/or partner airlines. To operate from an airport where a partner airline is present can give airlines a competitive advantage due to, for example, the possibility to offer a larger number of destinations from this airport. Operations from the same airport as a competitor, on the other hand, can have disadvantages. Competition in this case might be higher and revenues therefore lower.

Airports usually offer (financial) incentives to attract airlines in order to start services to their airport. However, airlines view incentives as well as airport marketing often only as short-term advantages. In the long run, they consider a good airport reputation and experience with cargo as more important because it reduces uncertainty concerning the quality of collaboration. Sometimes, however, airlines expect incentives to continue and to form a permanent part of their agreement.

Finally, the guarantee for sufficient future capacity, a stable regulatory environment and unfavorable climate conditions such as thick fog, heavy snow or strong winds play a role in the airport choice.

2.4 Financial analysis

During the three main phases of the airport choice process, airlines perform financial analyses at different times to analyze whether the service to a certain region or airport is financially viable in the long run. In the starting phase of the airport choice process, the focus of the financial analysis is on the total revenue of the route, with airlines trying to maximize the revenue derived from the origin-destination demand. At the end of the choice process, the focus is more on the direct operating cost, with airlines selecting specific airports for comparison. At this point, airlines try to minimize landing fees, parking and crew costs, etc.

3. Experimental setup, data and the multinomial logit model

In the previous section, we showed that there are numerous factors that influence airlines in their airport choice. Some factors are directly influenced by policy makers (e.g., regulations) or by airports (e.g., airport charges). Inevitably, airlines have to make trade-offs between those factors in their airport choice. To better understand how policy makers and airports can influence airlines in their airport choice, a deeper understanding of these trade-offs is needed.

In economics, different valuation methods exist that might give policy makers and airports an idea of the value that airlines attach to the different factors. Examples of such valuation methods are hedonic pricing, contingent valuation, rating-based conjoint analysis and discrete choice analysis. The discrete choice approach is the most promising approach as it mimics the choice process best and also enables the researcher to measure the trade-offs that respondents make between the different characteristics of an airport.

Over the years, the number of studies applying the discrete choice approach in air transport research and other areas of transport (see, e.g., Ben-Akiva and Lerman (1985) or Rich et al. (2009)) has increased substantially. However, the focus of most studies has been on the airport or airline choice of passenger airlines or passengers (see, e.g., Ashford and Bencheman (1987); Hess and Polak (2010); Ishii et al. (2009); Martín et al. (2008) and Wen and Lai (2010)), rather than on the airport choice of cargo airlines.

To fill this void in the literature, we performed a discrete choice experiment to model the airport choice of freighter operators. In a first step of the experiment, we identified the potentially most important airport choice factors or attributes and their levels to be used in the experiment. In addition to our literature study described in Section 2, which provided a list of airport attributes, we carried out five exploratory interviews with airlines and airport managers to narrow down the attributes and select attribute levels for the discrete choice experiment. We selected the following six attributes and attribute levels:

Night-time restrictions

1. Night-time flight prohibitions (prohibitions)
2. Limited or very expensive night-time slots (limited)
3. No night-time restrictions (no restrictions)

Airport experience with cargo

1. No experience (no)
2. Limited experience (limited)
3. Extended experience (extended)

Presence of forwarders

1. No forwarders (no)
2. Only major forwarders (major)
3. Broad range of forwarders (broad range)

Presence of passenger airlines

1. No passenger airline operations at airport (no)
2. Only passenger operations of own airline/group or of main passenger airline partner (sibling)
3. Different passenger airline operations from own airline/group as well as other airlines (different)

Airport charges (including handling)

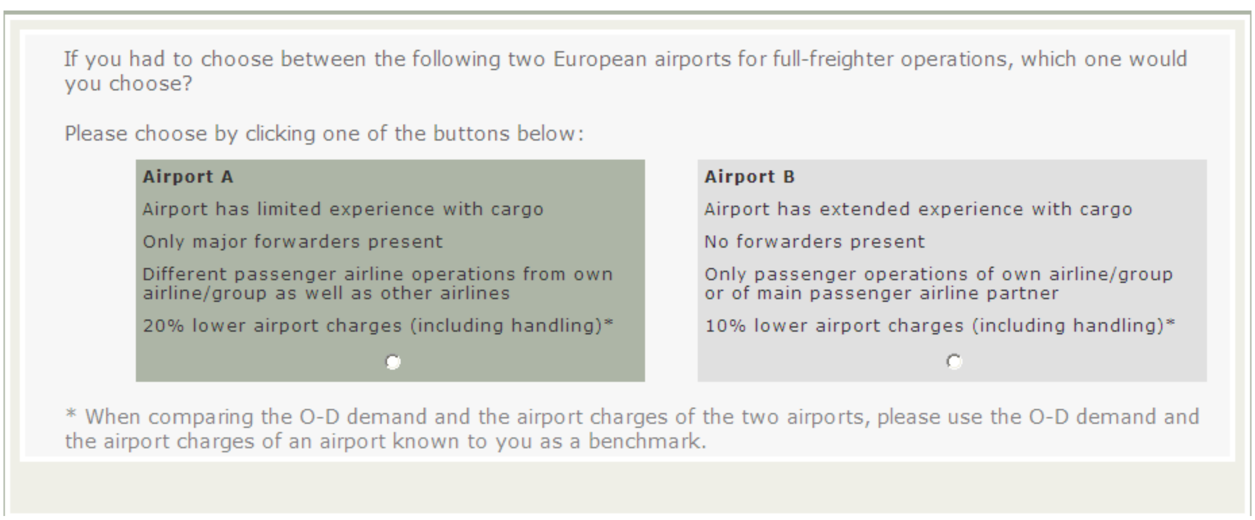
1. 20% higher airport charges (+20%)
2. 10% higher airport charges (+10%)
3. Equal airport charges (equal)
4. 10% lower airport charges (-10%)
5. 20% lower airport charges (-20%)

Origin-destination demand

1. 20% less origin-destination demand (-20%)
2. 10% less origin-destination demand (-10%)
3. Equal origin-destination demand (equal)
4. 10% more origin-destination demand (+10%)
5. 20% more origin-destination demand (+20%)

Due to the difficulty in getting reference data for airport demand and charges that could be used for all airlines, we asked the airlines to compare the airports on demand and charges using a benchmark airport of their choice, with an actual difference of up to 40% between the hypothetical airports. We did not ask the airlines to reveal their benchmark airport with its demand and charges, because this would have led to confidentiality issues with some airlines and therefore to fewer data. Hence, we omitted these types of questions from the questionnaire.

After selecting the six airport attributes for the discrete choice experiment, in a second step, we designed the experiment. We presented each respondent with 20 choice situations or choice sets involving two alternative airports, called profiles. For each choice situation, respondents were asked to indicate the profile they preferred. The alternative airports or profiles are combinations of levels of the attributes. However, to limit the cognitive burden imposed on the respondents, we showed only four of the six attributes in each choice situation. The resulting profiles are called partial profiles (Green (1974); Kessels et al., (2011b, 2012)). Figure 2 shows an example of a choice situation in which airline representatives had to choose between two hypothetical airports A and B, described by four of the six attributes.


If you had to choose between the following two European airports for full-freighter operations, which one would you choose?

Please choose by clicking one of the buttons below:

Airport A	Airport B
Airport has limited experience with cargo	Airport has extended experience with cargo
Only major forwarders present	No forwarders present
Different passenger airline operations from own airline/group as well as other airlines	Only passenger operations of own airline/group or of main passenger airline partner
20% lower airport charges (including handling)*	10% lower airport charges (including handling)*

* When comparing the O-D demand and the airport charges of the two airports, please use the O-D demand and the airport charges of an airport known to you as a benchmark.

Figure 2 - Example of a choice situation used in the airport choice experiment

We expected from literature review and interviews that origin-destination demand could be dominating the airlines' choices. Therefore, we generated two different partial profile designs: one six-attribute design including origin-destination demand and one five-attribute design excluding origin-destination demand. Both designs consist of four different blocks or surveys of ten choice sets and can be consulted in Appendix A. For each respondent, we used one block of ten choice situations from the six-attribute design and one block of ten choice situations from the five-attribute design, so that we presented a total of 20 choice situations to every respondent. This way, we ensured that the experiment also yields information concerning the relative importance of the attributes other than origin-destination demand. We randomized the 20 choice situations for each respondent and made sure the four surveys of 20 choice sets were equally spread over all respondents. Using designs consisting of several surveys results in more precise parameters of the underlying discrete choice model than designs consisting of a single survey (Sándor and Wedel (2005); Kessels et al. (2012)). Furthermore, the partial profile designs take into account prior beliefs about the respondents' preferences. For our experiment, for example, we know that respondents prefer no night-time restrictions at an airport to a limited number of available night-time slots which, in turn, they prefer to night-time flight prohibitions. In Appendix B, we summarize all available information as well as the uncertainty regarding that information in a prior distribution that we used to optimize the designs. The resulting designs are called Bayesian D-optimal designs and are increasingly considered the state of the art for discrete choice experiments (see, e.g., Bliemer et al. (2008); Rose and Bliemer (2009) and Kessels et al. (2011a, 2011c)). One major benefit of Bayesian D-optimal designs is that, using a proper prior distribution, they avoid choice situations in which one profile is completely dominating the other profile(s) on every attribute (Crabbe and Vandebroek (2012)).

In the final step of the experimental setup, we developed the questionnaire which consists of three parts. In the first part, we collected information about the respondent and the airline. In the second part, we asked the airline to make choices between hypothetical airports within the framework of the discrete choice exercise. Finally, we asked questions about the airport choice strategy of the airline. Before distributing the questionnaire, we sent the questions to a number of representatives from the air cargo sector for pilot testing. We asked the representatives to fill in the questionnaire and communicate all questions and suggestions concerning the understanding and the relevance of the questions. We then incorporated their suggestions in the final questionnaire.

Between February 2011 and May 2011, we collected a total of 26 completed questionnaires from different airlines. This was done in two ways: through personal interviews and through the internet. Personal interviews give a more in-depth view, especially on the third part of the questionnaire, the airport choice strategy of the airline. Our respondent group of 26 airlines involves more than half of the population of freighter operators with scheduled services to Europe. Because each respondent had to make 20 choices, our dataset contains 520 choices. The 26 respondents involve 11 independent cargo carriers and 15 cargo subsidiaries or cargo divisions of passenger airlines. The positions of the respondents within the carriers suggest that the results are reliable: the majority of the respondents hold a position that makes them a key decision maker in the airport choice decision process. For example, seven respondents are CEOs or directors of the carrier/subsidiary/division, seven respondents are freighter or planning specialists and five respondents are regional managers for Europe.

We used the multinomial logit (MNL) model to analyze the data from the discrete choice experiment. This model is based on random utility theory. The utility that a respondent attaches to alternative *j* (*j* = 1, 2) in choice set *s* (*s* = 1, …, 20) is explained by a systematic and a stochastic component (Hensher et al. 2005):

$$U_{js} = \mathbf{x}'_{js}\boldsymbol{\beta} + \varepsilon_{js},$$

In the systematic component $\mathbf{x}'_{js}\boldsymbol{\beta}$, $\mathbf{x}_{js}$ is a *k* x 1 vector containing the coded attribute levels of alternative *j* in choice set *s*. In our analysis, we initially assumed that all six attributes are categorical, so that our initial model involved *k* = 16 parameters and $\mathbf{x}_{js}$ and $\boldsymbol{\beta}$ are 16 x 1 vectors. The vector $\boldsymbol{\beta}$ is the vector of parameter values indicating the importance of the different attribute levels to the respondents. The stochastic component ε_{js} is the error term capturing the unobserved sources of utility. Under the assumption that the error terms are independently and identically Gumbel distributed, the MNL probability that a respondent chooses alternative *j* in choice set *s* is

$$p_{js} = \frac{\exp\left(\mathbf{x}'_{js}\boldsymbol{\beta}\right)}{\exp\left(\mathbf{x}'_{1s}\boldsymbol{\beta}\right) + \exp\left(\mathbf{x}'_{2s}\boldsymbol{\beta}\right)}.$$

To estimate the parameter vector $\boldsymbol{\beta}$, we used a penalized maximum likelihood approach which maximizes the probability of obtaining the responses from the selected data sample using the Firth bias correction (Firth, 1993, 1995). Kessels et al. (2013) adapted Firth's bias-adjustment method for estimating the MNL model and showed that for a small number of respondents and a reasonably small number of choices per respondent, the Firth bias correction reduces the bias of the asymptotic maximum likelihood estimates. We computed the overall significance and the relative importance of the six attributes by means of likelihood ratio (LR) tests and present the parameter estimates or marginal utility values of the attribute levels. Because we used effects-type coding for the attribute levels, the marginal utility values for all but the last level of each attribute correspond to the elements of the vector $\boldsymbol{\beta}$, while the marginal utility for the last level of each attribute is computed as minus the sum of all other marginal utilities for that attribute. We carried out the entire data analysis using the Choice Modeling platform in the statistical software package JMP, version 10 (SAS Institute, 2010) which uses Firth's penalized maximum likelihood estimation.

4. Modeling results

Table 1 shows the *initial MNL model* that includes all six attributes ranked in order of importance, as well as the *final MNL model* that involves a number of refinements. In the *initial MNL model*, we treated all attributes as categorical using effects-type coding. This enabled us to capture possible nonlinear relationships between the utility of an alternative airport and the attribute levels. In the *final MNL model*, we retained only the significant attributes and used linear coding for the attributes ‘airport charges’ and ‘origin-destination demand’. We did not include a constant term in the models because the experiment involved unlabeled alternatives; that is, we did not label the alternative airports with, for example, the names of real airports (Hensher et al., 2005, p. 372).

For the *initial* and the *final MNL model*, Table 1 shows the parameter estimates or marginal utility values of the attribute levels and the significances of the attributes’ effects from LR tests. For the *initial MNL model*, the LR tests indicate that all attributes are significant at the 0.05 level except for ‘passenger operations’. This means that for scheduled freighter operations, airlines are indifferent between whether an airport has passenger operations or not when choosing which airport to serve. Even when estimating MNL models for all-cargo carriers and combination carriers separately, for both types of airlines, the attribute ‘passenger operations’ remains insignificant. This partly contradicts Gardiner and Ison (2008), who observed that for combination carriers an airport is more attractive when it also has passenger operations. Our result that passenger operations do not influence the attractiveness of an airport also has policy implications because, from an airline point of view, it supports the idea of cargo-only airports. Therefore, when governments have to deal with congestion at a main airport, relocating freighter operations at first glance seems possible. However, since air freight is not only transported in freighters but also in the belly of an aircraft, the viability of an all-cargo airport depends on the total volume of freighter traffic it can attract and whether this will be enough to cover the costs of the airport.

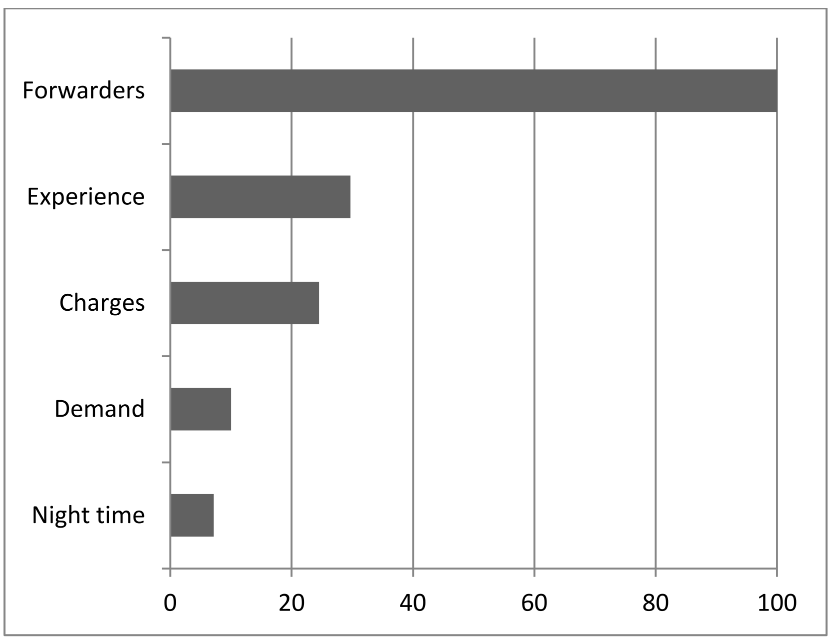
Table 1 - Results of the airport choice MNL modeling

	Initial MNL model				Final MNL model			
	Parameter estimate	**L-R ChiSquare**	**DF**	**P-value**	**Parameter estimate**	**L-R ChiSquare**	**DF**	**P-value**
Forwarders								
no	-1.144				-1.161			
major	0.412	91.954	2	<0.0001*	0.413	92.426	2	<0.0001*
broad range	*0.732***				*0.748***			
Experience								
no	-0.412				-0.416			
limited	-0.168	27.625	2	<0.0001*	-0.166	27.442	2	<0.0001*
extended	*0.580***				*0.582***			
Charges								
+20%	-0.535							
+10%	-0.365							
equal	0.011	28.913	4	<0.0001*	-0.029[LC]	28.094	1	<0.0001*
-10%	0.370							
-20%	*0.519***							
Demand								
-20%	-0.578							
-10%	-0.374							
equal	0.007	13.396	4	0.0095*	0.032[LC]	13.308	1	0.0003*
+10%	0.273							
+20%	*0.672***							
Night-time								
prohibitions	-0.275				-0.289			
limited	0.009	6.291	2	0.0430*	0.016	6.609	2	0.0367*
no restrictions	*0.266***				*0.273***			
Passenger								
no	-0.106							
sibling	-0.085	3.761	2	0.1525				
different	*0.191***							

* Significant at 5% level
** Marginal utility values corresponding to the last level of each effects-coded attribute are indicated in italic to stress that they are calculated as minus the sum of all other marginal utility values of that attribute.
[LC] Linear coefficient

The six attributes in Table 1 are ranked in order of importance, where the importance of an attribute is measured by –log(p-value of the LR test). Figure 3 shows the importances of the five attributes in the *final MNL model* relative to the importance of the attribute 'presence of forwarders', which is the most important attribute for the airlines when choosing an airport for freighter operations in Europe. The second most important attribute is the experience of an airport with cargo, which airlines find about three times less important than the presence of forwarders. As mentioned in Section 3, prior to the experiment, we expected origin-destination demand to be the most important attribute of airport choice. Therefore, we constructed one six-attribute choice design including the attribute demand and another five-attribute design excluding it. To assess whether this design strategy had an influence on the importance ranking of the attributes, we estimated two separate MNL models. For one MNL model, we used the observations related to the six-attribute design including demand, and for the other MNL model, we used the observations related to the five-attribute design excluding demand. In both models, we observed that the importance ranking of the different attributes is similar to that from pooling the data and estimating a single MNL model. Therefore, the decision to generate two different choice designs and to pool the associated data for the estimation of a single MNL model did not have an influence on the importance ranking of the attributes.

Figure 3 - Importance of the five attributes in the final MNL model relative to the most important attribute 'presence of forwarders'



For the construction of the *final MNL model*, we excluded the insignificant attribute 'passenger operations', and examined whether the effects of the attributes 'airport charges' and 'origin-destination demand' on an airport's relative utility could be linearized. Figures 4 and 5 show the marginal utilities or parameter estimates obtained from both nonlinear or effects-type coding and linear coding for the attributes 'airport charges' and 'origin-destination demand', respectively. It is clear that assuming linear relationships for the two attributes is perfectly reasonable, and that switching from effects-type coding to linear coding is justified. For these two attributes a LR test indicated that the nonlinear specifications of the attributes did not add to the quality of the MNL model (L-R ChiSquare = 0.88; DF = 6; p-value = 0,99). As a result, the *final MNL model* contains linear parameter estimates for the attributes 'airport charges' and 'origin-destination demand'. A total of 71% (369 out of 520) of the respondents' choices could be predicted correctly using this model.

Figure 4 - Marginal utilities of airport charges, obtained using nonlinear and linear coding

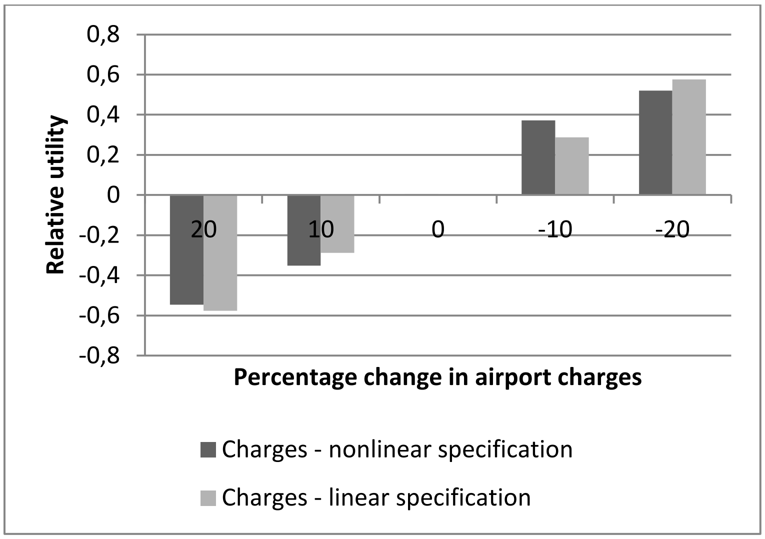
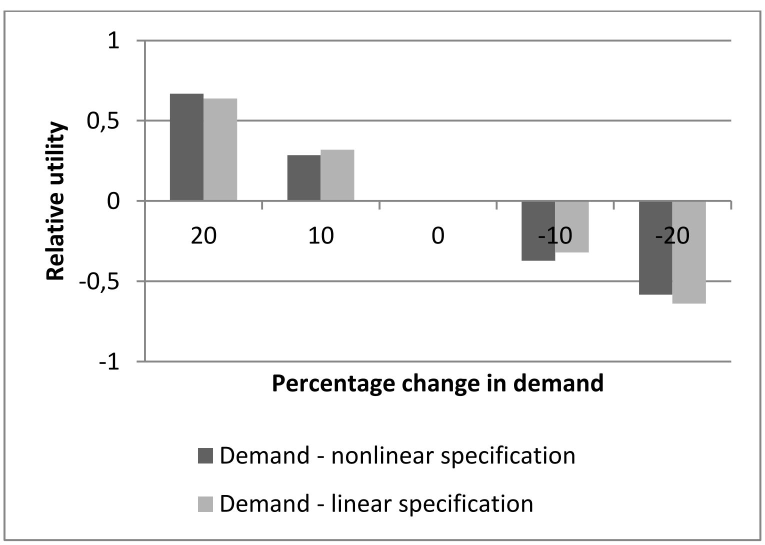


Figure 5 - Marginal utilities of demand, obtained using nonlinear and linear coding



Finally, Table 1 shows that the parameter estimates for the attributes ‘forwarder’, ‘experience’ and ‘night-time’ in the *final MNL model* do not differ much from those in the *initial MNL model*. The signs of the parameter estimates are as expected. For example, they are negative for night-time flight prohibitions and the absence of forwarders at an airport, and positive for no night-time restrictions and extended experience with cargo. It can be seen that the largest difference in relative utility is realized between having no forwarders at an airport and having only the major forwarders. This means that an airport with no forwarders at the site is much less attractive than an airport with the major forwarders only. Second in magnitude comes the difference in relative utility between limited experience with cargo and extended experience with cargo. Furthermore, the difference in relative utility between limited experience with cargo and no experience with cargo is rather small, showing that airlines do not make a clear distinction between airports with limited experience with cargo and airports with no such experience.

5. Conclusion

Although airport competition has recently received increased attention in air transport research, competition for air freight is a topic that has not been thoroughly analyzed yet. To fill this void in the literature, this contribution focuses on the competition for air freight, and more specifically on the airport choice for scheduled freighter operations.

This contribution first outlines the choice process which airlines deploy in choosing their airports for freighter operations. In this process, airlines consider a myriad of factors on which policy makers and airports sometimes only have limited influence. Although the causality of economic development and the provision of transport infrastructure is still largely circumstantial, Button and Yuan (2013) showed that air freight services can positively influence regional development. Therefore, by attracting new freighter services, policy makers can stimulate economic development. One of the factors that policy makers can influence is the origin-destination demand. Governments can stimulate the development of industries that rely on air transport, such as biotech industries, to make a region more attractive for cargo operations. Furthermore, they can provide a stable regulatory environment for the airlines as well as a framework for night-time flights, which make a region more attractive to airlines. The latter, however, also has to be balanced with the needs of other stakeholders, such as nearby communities.

The second part of this contribution concerns a more in-depth analysis of a smaller set of airport choice. While previous studies analyzed only costs or distance as factors (see, e.g., O’Kelly (1986), Dennis (1994) or Wantanabe et al. (2009)) or relied on ratings of factors (see Gardiner et al. (2005b)) we approached this problem by conducting a discrete choice experiment. We performed the experiment to measure the trade-offs that airlines make when choosing between alternative airports. We collected stated preference data from 26 airlines and used the discrete choice data as input for a multinomial logit model. Our results showed that the presence of passenger operations is not a significant factor in the airport choice for scheduled freighter operations. This partly contradicts previous studies (see Gardiner and Ison (2008)) where passenger operations turned out to be very important for combination carriers. This suggests that all-cargo traffic not only has been gaining market share in the air freight market, but that there might be, to a certain extent, some decoupling between all-cargo traffic and cargo traffic transported on passenger flights. This could be an argument for governments to further investigate the possibility of all-cargo airports in order to decrease the pressure on the capacity of major airports. Currently, some regional airports in Europe, such as Liège Airport, succeed in developing their business relying mostly on air cargo. However, governments have to keep in mind that the viability of an all-cargo airport also depends on the total volume of freighter traffic it can attract and whether this will be enough to cover the cost of the airport.

Some authors attribute the increase of competition for freight amongst airports to the shift in market power towards large international forwarders (see, e.g., Andriulaitis (2010)). The consolidation and growth in the forwarding business during the last decades increased the forwarders' market power and therefore their ability to influence a cargo carrier in their airport decision. The results of our discrete choice experiment provide support for this line of reasoning. The estimated model clearly showed the importance of the forwarders' presence in the airport choice. The absence of forwarders on an airport has a major negative impact on an airport's attractiveness, whereas the presence of a broad range of forwarders adds significantly to it. Therefore, when aiming to guide airlines in their airport choice decisions, policy makers also have to consider the influence of forwarders.

The results of our discrete choice experiment contribute to a better understanding of the airport choice for scheduled freighter operations and the competition for air cargo between airports. The results show an aggregated picture, where no difference between airlines is made. However, the airport choice of an all-cargo airline might be different from the airport choice of the cargo division/subsidiary of a combination carrier. That is why, in future research, additional variables reflecting the differences between the airlines should be introduced in the model. Furthermore, as the presence of forwarders turned out to be the most important airport choice attribute, more research should be carried out further down the supply chain, more specifically on how forwarders choose their airports and which attributes influence their decisions.

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Appendix A. Bayesian D-optimal partial profile designs for the airport choice experiment

The discrete choice experiment involved four surveys of 20 choice situations. Each survey was taken by six or seven respondents. We created the four surveys by constructing two partial profile designs involving four surveys of 10 choice situations and combining the surveys from the two designs in a pairwise fashion, one survey from each design. We chose this design approach because we suspected that origin-destination demand would dominate the airlines' choices. Therefore, one design includes the attribute origin-destination demand, and the other design does not. For each of the four surveys, we randomized all 20 questions.

Tables A.1 and A.2 show the two designs with alternative airports in the different choice situations, including and excluding the demand attribute, respectively. Asterisks indicate attributes not used in the choice situations, which are all described by four attributes. The last line of each table indicates how often each attribute appears in the choice situations of a design. The five-level attributes, 'charges' and 'demand', are used more often than the three-level attributes.

Table A.1 – Six-attribute partial profile design including the 'demand' attribute

Survey	Choice Set	Night-time	Experience	Forwarders	Passenger	Charges	Demand
1 1	1 1	* *	* *	major broad range	no sibling	+20% -20%	+20% -10%
1 1	2 2	* *	extended limited	* *	different no	equal -20%	equal -20%
1 1	3 3	* *	limited extended	* *	different sibling	+10% -20%	+20% +10%
1 1	4 4	* *	no extended	broad range major	* *	-10% equal	+10% -10%
1 1	5 5	* *	no limited	broad range major	* *	-20% equal	+20% +10%
1 1	6 6	prohibitions no restrictions	* *	* *	no sibling	-10% +20%	-10% -20%
1 1	7 7	no restrictions limited	limited no	* *	* *	+20% equal	equal +10%
1 1	8 8	no restrictions limited	limited no	* *	* *	+20% +10%	-10% equal
1 1	9 9	prohibitions no restrictions	extended no	* *	* *	+10% -10%	+10% -10%

1 1	10 10	no restrictions limited	no limited	* *	* *	-20% equal	equal -20%
2 2	1 1	* *	limited extended	* *	sibling different	+20% -10%	+10% -20%
2 2	2 2	* *	limited extended	broad range major	* *	equal -10%	equal +10%
2 2	3 3	* *	no limited	major no	different no	+20% +10%	* *
2 2	4 4	limited no restrictions	* *	* *	sibling different	-10% equal	equal -20%
2 2	5 5	limited no restrictions	* *	* *	no different	-20% -10%	equal +10%
2 2	6 6	limited no restrictions	* *	no broad range	* *	-20% -10%	+20% equal
2 2	7 7	limited no restrictions	* *	broad range no	* *	+20% +10%	-10% +20%
2 2	8 8	no restrictions limited	* *	major no	* *	-20% +20%	-20% +10%
2 2	9 9	no restrictions limited	limited extended	* *	* *	-20% -10%	+10% +20%
2 2	10 10	prohibitions no restrictions	limited no	major no	* *	-20% equal	* *
3 3	1 1	* *	* *	no major	no sibling	equal +10%	equal -20%
3 3	2 2	* *	* *	broad range no	no different	+20% -20%	-20% -10%
3 3	3 3	* *	limited no	* *	sibling no	-10% +20%	-20% +20%
3 3	4 4	no restrictions prohibitions	* *	broad range major	* *	+10% -20%	-10% +20%
3 3	5 5	limited prohibitions	* *	broad range major	different sibling	* *	+10% +20%
3 3	6 6	limited prohibitions	* *	major no	no sibling	* *	-20% +20%
3 3	7 7	prohibitions no restrictions	* *	broad range no	different no	+10% -10%	* *
3 3	8 8	prohibitions limited	* *	broad range no	no different	equal +20%	* *
3 3	9 9	prohibitions limited	extended limited	* *	no sibling	+20% equal	* *
3 3	10 10	no restrictions prohibitions	extended limited	* *	no different	equal -10%	* *

4 4	1 1	* *	* *	major no	sibling different	+10% -20%	-10% -20%
4 4	2 2	* *	extended no	broad range major	* *	+20% +10%	-10% +10%
4 4	3 3	* *	no extended	broad range no	* *	equal +10%	+20% equal
4 4	4 4	* *	limited extended	major no	different sibling	* *	equal -10%
4 4	5 5	* *	limited extended	no broad range	no different	-10% +10%	* *
4 4	6 6	prohibitions limited	* *	* *	sibling no	equal +10%	equal -10%
4 4	7 7	prohibitions limited	extended limited	* *	sibling different	* *	-20% -10%
4 4	8 8	prohibitions limited	extended no	* *	no sibling	* *	+10% +20%
4 4	9 9	limited prohibitions	extended no	no major	* *	* *	-20% -10%
4 4	10 10	prohibitions no restrictions	limited no	broad range major	* *	* *	+20% equal
Frequency		24	24	23	23	33	33

Table A.2 – Five-attribute partial profile design excluding the 'demand' attribute

Survey	Choice Set	Night-time	Experience	Forwarders	Passenger	Charges
1 1	1 1	* *	extended limited	broad range major	no different	+10% equal
1 1	2 2	* *	extended limited	broad range major	sibling no	+20% +10%
1 1	3 3	* *	extended no	broad range major	sibling different	+10% -20%
1 1	4 4	prohibitions limited	* *	broad range no	different sibling	+10% +20%
1 1	5 5	no restrictions prohibitions	* *	no broad range	different sibling	+10% -10%
1 1	6 6	prohibitions no restrictions	* *	broad range major	different sibling	-20% equal
1 1	7 7	limited no restrictions	extended limited	* *	different no	-20% +10%
1 1	8 8	limited prohibitions	extended limited	* *	no different	-20% -10%
1 1	9 9	no restrictions limited	extended no	* *	no sibling	+20% -10%
1 1	10 10	limited no restrictions	limited no	major no	* *	+10% -20%
2 2	1 1	* *	limited extended	broad range major	no sibling	-10% +20%
2 2	2 2	* *	extended limited	broad range major	no different	equal -10%
2 2	3 3	no restrictions limited	* *	no major	sibling no	+20% equal
2 2	4 4	limited prohibitions	* *	no major	different no	-20% equal
2 2	5 5	limited prohibitions	no extended	* *	no different	equal -10%
2 2	6 6	no restrictions prohibitions	no limited	* *	sibling no	-10% +20%
2 2	7 7	no restrictions limited	limited extended	* *	sibling different	-10% equal
2 2	8 8	no restrictions limited	no extended	broad range major	* *	-20% +20%
2 2	9 9	no restrictions limited	no limited	major broad range	* *	-20% -10%

2 2	10 10	prohibitions no restrictions	no limited	broad range no	* *	equal +20%
3 3	1 1	* *	no limited	major no	different sibling	+10% -20%
3 3	2 2	* *	limited extended	no major	no sibling	equal +10%
3 3	3 3	prohibitions limited	* *	broad range no	different no	equal +10%
3 3	4 4	prohibitions limited	* *	major no	no different	-20% equal
3 3	5 5	prohibitions no restrictions	* *	major no	sibling different	+20% +10%
3 3	6 6	limited no restrictions	* *	broad range major	different no	+20% -10%
3 3	7 7	limited no restrictions	no limited	* *	no different	-10% +10%
3 3	8 8	no restrictions prohibitions	no limited	no major	* *	equal +20%
3 3	9 9	prohibitions no restrictions	extended no	no broad range	* *	-20% +20%
3 3	10 10	prohibitions limited	extended no	no broad range	* *	-20% +20%
4 4	1 1	* *	limited extended	broad range major	sibling no	+10% -10%
4 4	2 2	* *	limited no	broad range major	no sibling	+20% +10%
4 4	3 3	* *	limited extended	major no	different sibling	-20% -10%
4 4	4 4	limited no restrictions	* *	no major	no sibling	-10% equal
4 4	5 5	no restrictions limited	extended limited	* *	different sibling	-10% -20%
4 4	6 6	prohibitions limited	limited extended	* *	sibling different	-20% -10%
4 4	7 7	no restrictions limited	no limited	* *	no sibling	+20% equal
4 4	8 8	no restrictions limited	limited no	no broad range	* *	equal +10%
4 4	9 9	prohibitions no restrictions	extended no	no broad range	* *	+10% +20%
4 4	10 10	prohibitions limited	extended no	no major	* *	equal -20%
Frequency		30	30	30	30	40

Appendix B. Multivariate normal prior parameter distributions used to construct the Bayesian D-optimal partial profile designs for the airport choice experiment

This appendix describes the prior parameter distributions used for constructing the two Bayesian D-optimal partial profile designs for the airport choice experiment, shown in Appendix A.

For the six-attribute design including origin-destination demand in Table A.1, the prior distribution is a 16-variate normal distribution, and for the five-attribute design excluding origin-destination demand in Table A.2, the prior distribution is a 12-variate normal distribution. To construct the designs and the initial choice model, we assumed all attributes are categorical. Therefore, the total number of parameters equals the sum of the numbers of levels of all attributes minus the number of attributes. As explained in the main text, this enabled us to capture possible nonlinear effects of the attributes on the perceived utility of an airport.

We modeled the attribute levels using effects-type coding. This means that the levels of every 3-level attribute are coded as [1 0], [0 1] and [-1 -1], and the levels of every 5-level attribute are coded as [1 0 0 0], [0 1 0 0], [0 0 1 0], [0 0 0 1] and [-1 -1 -1 -1]. This is important for specifying the prior parameter distributions when constructing the choice designs as well as for interpreting the parameter estimates when analyzing the data from the experiment.

To construct the six-attribute Bayesian D-optimal partial profile design including origin-destination demand, we used the 16-variate normal prior distribution $N\left(\boldsymbol{\beta}\middle|\boldsymbol{\beta}_0,\boldsymbol{\Sigma}_0\right)$, with prior mean vector

$$\boldsymbol{\beta}_0=\left[-0.7,0.2,-0.7,0.2,-0.6,0.2,0,0,-0.5,-0.25,0,0.25,-0.8,-0.4,0,0.4\right]'$$

and prior variance-covariance matrix

$$\boldsymbol{\Sigma}_0=\begin{bmatrix}
0.09 & -0.045 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0\\
-0.045 & 0.09 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0\\
0 & 0 & 0.09 & -0.045 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0\\
0 & 0 & -0.045 & 0.09 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0\\
0 & 0 & 0 & 0 & 0.09 & -0.045 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0\\
0 & 0 & 0 & 0 & -0.045 & 0.09 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0\\
0 & 0 & 0 & 0 & 0 & 0 & 0.09 & -0.045 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0\\
0 & 0 & 0 & 0 & 0 & 0 & -0.045 & 0.09 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0\\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.09 & -0.0225 & -0.0225 & -0.0225 & 0 & 0 & 0 & 0\\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & -0.0225 & 0.09 & -0.0225 & -0.0225 & 0 & 0 & 0 & 0\\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & -0.0225 & -0.0225 & 0.09 & -0.0225 & 0 & 0 & 0 & 0\\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & -0.0225 & -0.0225 & -0.0225 & 0.09 & 0 & 0 & 0 & 0\\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.09 & -0.0225 & -0.0225 & -0.0225\\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & -0.0225 & 0.09 & -0.0225 & -0.0225\\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & -0.0225 & -0.0225 & 0.09 & -0.0225\\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & -0.0225 & -0.0225 & -0.0225 & 0.09
\end{bmatrix}.$$

To construct the five-attribute Bayesian D-optimal partial profile design excluding origin-destination demand, we used a 12-variate normal distribution with the same values for the prior mean vector and prior variance-covariance matrix as the 16-variate distribution described above, except for the values for the last four dimensions, which concern the demand attribute. Below, we therefore limit ourselves to a discussion of the 16-dimensional prior mean vector and prior variance-covariance matrix.

The 16-dimensional prior mean vector $\boldsymbol{\beta}_0$ should be interpreted as follows. The vector's first two elements correspond to the prior utility values of the first two levels of the attribute 'night-time restrictions'. The next two elements correspond to the prior utility values of the first two levels of the attribute 'airport experience with cargo'. The next two sets of two elements correspond to the prior utility values of the first two levels of the attributes 'presence of forwarders' and 'presence of passenger airlines'. Finally, the last two sets of four elements correspond to the prior utility values of the first four levels of the attributes 'airport charges' and 'origin-destination demand'.

The prior mean vector $\boldsymbol{\beta}_0$ does not explicitly contain the utility values for the last level of the attributes. Because of the effects-type coding of the attribute levels, the implied utility of an attribute's last level equals minus the sum of all other utility values of that attribute. For example, the implied utility value for no night-time restrictions is 0.5, indicating that an airport with no night-time restrictions is very attractive for an airline.

The prior distribution also expresses our beliefs that airlines do not favor an airport which has night-time flight prohibitions in place, which has no experience with cargo, which has no forwarders, which has high charges or has low origin-destination demand. This is expressed by the fact that the first element for each of the corresponding attributes in $\boldsymbol{\beta}_0$ has the smallest value. The other elements for each attribute have increasing values, indicating that the attractiveness of an airport increases with the level of each attribute.

When designing the experiment, we expected 'origin-destination demand' to be the most important attribute and potentially dominating the airlines' choices. Therefore, we made sure that this attribute was assigned the largest absolute value in the prior mean $\boldsymbol{\beta}_0$, namely 0.8. Similarly, we expected the two attributes 'night-time restrictions' and 'experience with cargo' to be about equally important in a tied second rank, so that we made sure that these attributes were assigned the second largest absolute value in the prior mean $\boldsymbol{\beta}_0$, namely 0.7. The attributes 'presence of forwarders' and 'airport charges' further make up the prior importance ranking with absolute mean values of 0.6 and 0.5, respectively. For the attribute 'presence of passenger airlines', we had no prior information about the airlines' preferences. This means that prior to the discrete choice experiment, we did not know whether an airline prefers an airport without passenger operations or an airport with, for example, different passenger airlines. That is why we specified zero utility values for the first two levels of this attribute. The implied utility value for the last level of the attribute is then also zero.

For the prior variance-covariance matrix $\mathbf{\Sigma}_0$, we specified 16 variances that express our uncertainty about the prior utility values contained in the prior mean vector $\boldsymbol{\beta}_0$. The variances are all equal to 0.09, because this preserves the natural rank order of the levels of most attributes. This means that the difference between two consecutive prior utility values for an attribute is usually larger than or equal to the standard deviation of 0.3. We also specified negative covariances between the utility values corresponding to a single attribute. If L_i denotes the number of levels of attribute i, we computed these covariances using a correlation coefficient of $-1/(L_i - 1)$. As explained by Kessels et al. (2008), this ensures that the variances of all prior utility values corresponding to a given attribute are the same, meaning that the variance associated with the implied utility of the last level of each attribute also equals 0.09.