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Regional economic impact of airports

Final report

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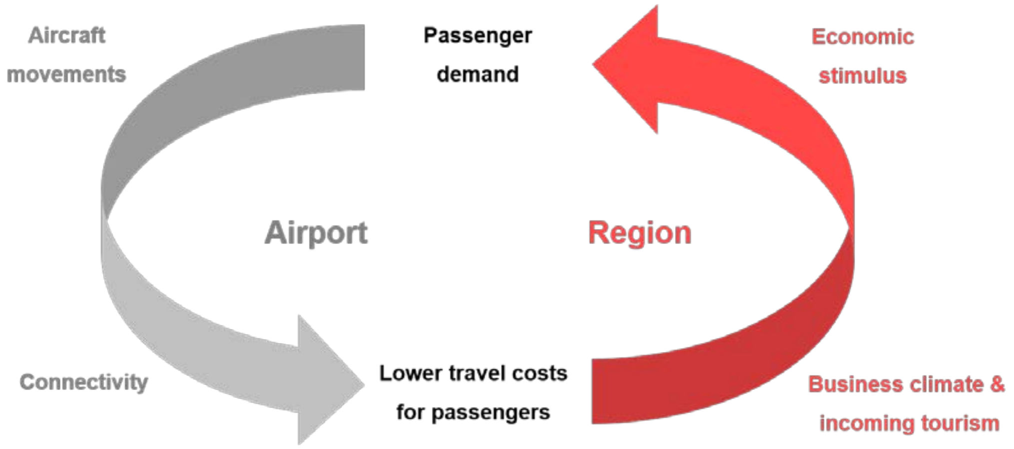
1 Introduction & Objective

This report presents the results of a multivariate analysis regarding the impact of air travel on the local economy. The SEO airport database enables us to assess the regional impacts of air connectivity on GDP and employment within a certain radius around an airport. A fixed effects panel data model is used to determine to what extent change in connectivity affects change in GDP and employment (in knowledge intensive sectors).

Numerous studies have shown the existence of a strong relationship between air travel and economic development. Some of these studies were able to prove that the causality runs in both ways. This results in the so-called 'virtuous circle' of connectivity: economic growth stimulates air passenger demand, which drives air connectivity. An increase in air connectivity leads again to an improved business climate and attracts tourism, which further enhances economic growth.

Figure 1.1 Virtuous circle of connectivity



The main objective of this study is to gain a deeper understanding of the economic impact of airports in Europe upon the local economy. This entailed building several models to assess the impact of factors such as an airport's size, degree of connectivity and traffic composition upon the local economy. In addition, an 'economic impact tool' will be developed, based upon the most appropriate model. This tool will show for individual European airports[1] to what extent it contributes to the national economy as well as to employment. For the development of the economic impact tool we strive to isolate the causal effect from connectivity to economic growth and employment.

1 Results provided for every airport which had scheduled traffic in both 2014 and 2015 and for which there was sufficient data available. The calculator presents results for the airports for which the required regional data is available. A list of these airports is given in Appendix B.

2 Literature review

Numerous studies have been published on estimating the economic impact of air travel. These differ in their methodology, variables, regional granularity and results. To place this piece of work into perspective we briefly discuss the methodology and results from earlier studies in this paragraph.

Table 2.1 provides an overview of (academic) papers and studies investigating the economic impact of air travel. Using various techniques, a positive correspondence between air travel and economic growth or employment was found.

Table 2.1 Literature overview of the economic impact of air travel

Source	Methodology	Result
Ivy, Fik, & Malecki, 1995	Effect of air service connectivity on employment. Three-stage least squares to determine the effect of change in air connectivity on employment and vice versa.	Changes in connectivity have a greater influence on employment levels than changes in employment levels have on connectivity.
Brueckner, 2003	Two-stage least squares using the following instruments: ‘hub’ dummy, ‘proximity to other large airport’ dummy, ‘slot controlled airport’ dummy and ‘leisure destination’ dummy.	10 percent increase in passenger enplanements leads to a 1 percent increase in employment in service-related industries.
Green, 2007	Two-stage least squares using employment and population growth as dependent variables. As instruments, previous decade population growth and runway capacity are used.	A positive and significant relationship is found between air connectivity and population growth, as well as air connectivity and employment.
Poort, 2000	Three-stage least squares using gdp and employment growth as dependent variables.	A 10 percent increase in passenger enplanements leads to a 1.7% GDP growth and a 1.8% growth in service-related employment.
Baker, Merkert, & Kamruzzaman, 2015	Tests the causality between the number of air passengers and aggregate regional income in Australia, using dynamic panel data models.	A bidirectional causal relationship between air transport and economic growth is shown. The significance and magnitude of causal relationships differ over various airport types. The authors claim that financial support to regional airports is a legitimate manner to boost local industries. On the contrary, subsidies may be reduced with little adverse effects on economic growth during strong economic periods.
Allroggen & Malina, 2014	Instrumental variable estimator (LIML) using population, lagged value of passenger movements and lagged values of relative importance of airport as instruments.	While increase in air service at first- and second-tier airports show significantly positive effects on economic output, these marginal output effects are negative for additional air services at third-tier airports.
PWC; Airports Commission, 2013	Instrumental variable estimators using monthly seat capacity and GDP data for the UK, using lagged variables as instruments.	10% increase in seat capacity yields a 1% GDP growth, 4% inbound tourism increase, 1.7% goods import increase and 3.3% goods export increase.
InterVISTAS; ACI EUROPE, 2015	OLS regression of connectivity per Euro GDP on GDP per capita.	10% increase in air connectivity yields a 0.5% GDP increase.

In measuring the effect of air travel on economic growth, endogeneity is a difficult issue. If there is a two-way causality between two variables, econometric estimators are not efficient and unbiased. Most of the papers in Table 2.1 acknowledged this problem. Some use instrumental variables to deal with the problem. In a reaction on the PWC report issued by the Airports Commission, Mackie, Starkie & Graham (2013) address the problem of endogeneity and suggest to eschew a 'literal' interpretation of the estimates.

Baker, Merkert, & Kamruzzaman (2015) also show there is a bi-directional causal relationship between economic growth and air traffic. The authors show that regional airports in Australia are an important catalyst for the regional economy, motivating that local economic development strategies should ensure a strong focus on air transport. Van de Vijver (2014), using heterogeneous Granger causality analysis, concludes that the influence of air transport passenger volume on regional employment in Europe is more marked than the other way around, but that the relationship is heterogeneous and differs by region.

The economic impact of smaller airports is assumed to be less than large airports. Green (2006) only uses the largest 100 US airports in his panel. Malina & Wollersheim (2008) state that for the smallest airports in their data no significant results were found.

In this research we deal with the endogeneity issue by using a lagged connectivity variable. Hence we analyse the effect of a change in connectivity in year t on the region's economy in year $t+1$. It is rather unlikely that economic growth one year ahead causes connectivity growth in the previous year. Allroggen and Malina (2014) also state that lagged variables are exogenous instruments. Hence, the use of lagged variables in a panel data analysis is the preferred method to deal with the endogeneity issue. In the next section we elaborate on the applied methodology.

3 Methodology

The regional economic impact models should be able to show for each airport to what extent the connectivity it provides contributes to the local economy in terms of GDP growth and employment (in knowledge intensive sectors). To be able to do so we need to determine to what extent airport characteristics affect the local economy. We isolate the influence of these airport characteristics by econometric regression analysis.

3.1 Regression model

A regression model shows how independent variables are related to a dependent variable. We develop three different models in order to assess to what extent the independent variables (airport characteristics and socio-economic variables) affect the following dependent variables:

1. GDP per capita[2] around the airport;
2. GDP per capita around the airport, controlling for airport size;
3. Employment in knowledge intensive sectors around the airport.

Based on the coefficients of the airport characteristics we derive the influence of each of the airport characteristics on these dependent variables.

As we are interested in the local economic impact of an airport in terms of GDP per capita and employment (in knowledge intensive sectors), we first need to delineate the geographical area that an airport is likely to affect. According to the EU, airport catchment areas stretch to at least 1 hour or 100 kilometres from the airport.[3] We therefore hypothesize that the economic impact of an airport covers an area up to 100 kilometres from the airport. We use GIS-analysis to derive GDP per capita and employment (in knowledge intensive sectors) in a circle with a radius of 100 kilometres from the airport. Also the socio-economic variables are determined within this radius from each airport using the SEO Airport Catchment Area database. This is a major advantage compared to previous research, as it reduces the so-called *Modifiable Area Unit Problem:* the problem that the size of statistical units and the location of airports within these units influences results.

Panel data model

The dataset consists of airport characteristics and socio-economic variables around the airport over the period 2004-2014. This means that we can estimate a panel data model. Panel data models are used to estimate the effects of *changes* over time. The model explains year-on-year *changes* in the independent variables (airport characteristics and socio-economic variables) on *changes* in the dependent variables (GDP per capita and employment in knowledge intensive sectors).

The advantage of using a panel data model, is that the model uses a specific constant for each airport. This allows one to control for airport-specific characteristics, which are not covered by the

2 A change in population will most likely result in a change in total GDP of a region. Therefore we include population in the model as an independent variable (see section 3.2). As total GDP and population are very strongly correlated we chose GDP per capita as the dependent variable instead of total GDP.

3 'Communication from the Commission – Guidelines on State aid to airports and airlines' April 2014.

other (explanatory) variables in the model. The constant controls for airport characteristics, which do not change over time, such as location. As a result, the estimated effect of connectivity on GDP is not influenced by specific airport related characteristics that do not change over time, and therefore provides unbiased results of the effect on connectivity on economic growth.

The fixed effects panel data model used in this analysis is given by:

$$y_{it} = \alpha_1 + \beta' x_{it-1} + \gamma' z_{it} + u_i + \epsilon \tag{3.1}$$

Where α is the regression constant. The independent variables contain both airport-related and other socio-economic variables which are not related to the airport. β and γ denote the vectors of the regression coefficients for these respective variable types. u_i is the specific constant for airport i, which captures the effect of all time-invariant factors influencing the economy around the respective airport. By applying OLS regression on u_i we can investigate whether these constants are also driven by airport-related factors. This is further described in section 4.2.5. ϵ is the error term.

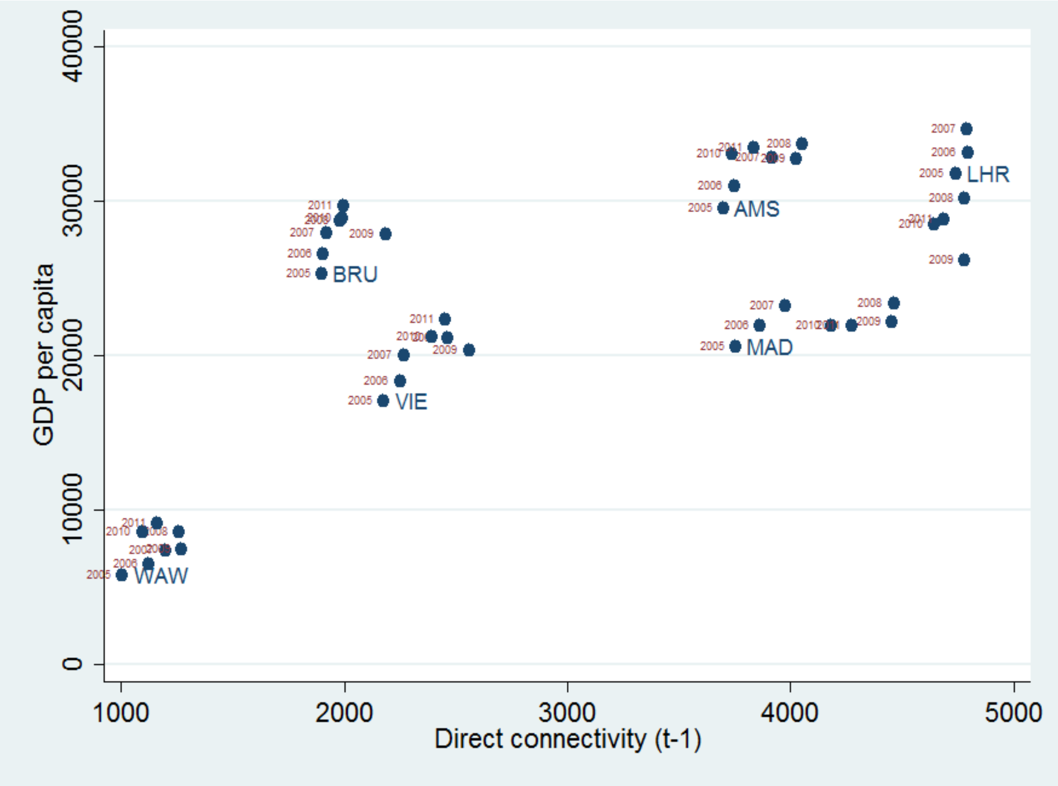
Causality

Airport connectivity may at the same time enhance economic growth and be the result of economic growth. A two-way causal link between GDP per capita and employment (in knowledge intensive sectors) and the airport characteristics may cause endogeneity issues generating flawed results. However, we argue that the dependent and independent variables do not affect one another at the same time. The virtuous circle of connectivity assumes that the effect of air travel on the economy is caused by an improved business climate and tourism catalysed by an increase in air connectivity. Hence a connectivity increase in one year would not lead to an immediate effect on the local economy.

Therefore the airport related variables are included in the model with a one-year lag to estimate the impact of a change in these variables on GDP per capita and employment. Using this approach we isolate the causal effect from air connectivity on GDP. We estimate the correspondence between connectivity growth in year *t* and GDP growth in year *t+1*. It is unlikely that GDP growth in one year causes connectivity growth in an earlier year.

Another common way to prevent causality is to use an instrumental variable estimator. A good instrument would be a variable correlated with air connectivity, but uncorrelated with GDP per capita. As it is extremely challenging finding suitable instruments for connectivity, we prefer to use the lagged variable approach. This approach presents reliable results which are relatively easy to interpret.

Figure 3.1 Development of GDP per capita and direct connectivity one year before for various large European airports



Source: SEO Airport catchment area database

The panel data model estimates the effect of a *change* in certain airport characteristics (such as connectivity) on the *change* of GDP per capita and employment (in knowledge intensive sectors) in the next year for each airport in the panel. Figure 3.1 shows the direct connectivity (with a one-year lag) and GDP per capita for six airports. One can observe that – for separate airports – a higher connectivity level correlates with a higher GDP per capita in the following year. The figures show that each airport is a separate 'cluster' of points. The panel data model estimates separate 'fixed effects' for each of these clusters.

Airport groups

Small airports most likely have a smaller impact on the local economy than larger airports. However the relative and absolute economic impact of a single flight may be higher for small airports than for larger ones. Therefore we shall also estimate separate models for different airport size categories.

We distinguish three groups (see Table 3.1). Group A contains all the airports with up to 100 weekly departing flights. This Group includes a large share of all European airports. However, these airports are responsible for only 8 percent of all direct flights offered from the airports in the sample. Group C contains the largest airports offering over 1,000 departures per week in 2011.

The 40 airports in this Group (6 percent of all European airports) offer 56 percent of all direct flights offered from European airports. [4]

Table 3.1 A small number of airports provides the lion's share of connectivity in Europe

Group name	Direct flights (weekly, summer 2011)*	Average number of passengers (x1000)	Number of airports	Share of direct flights
A	0-100	219	487	8%
B	100-1000	3,329	184	36%
C	1000+	24,137	40	56%
Total			**711**	**100%**

Source: SEO Airport catchment area database.
* The categorisation of the airports was based on the number of weekly direct flights during the summer of 2011. This year was chosen as this is the final year for which socio-economic data was available (also see section 0).

As an indication of the size of an airport in each group, the table presents the average number of passengers in each group. However, as the groups are based on connectivity figures rather than passenger numbers, it is possible that Group A contains airports with more passengers than some airports in Group B. Generally, these are airports with a large share of low cost or charter carriers which operate relatively large aircraft and therefore carry many passengers per unit of connectivity. Besides this, the connectivity index is based on scheduled passenger flights.

3.2 Variables

This section subsequently introduces all dependent and independent variables in our dataset. The data sources used for these variables are presented in section 3.3.

3.2.1 Dependent variables

As mentioned in the previous chapter we shall develop three models to better understand how certain airport characteristics and socio-economic variables affect the dependent variables GDP per capita, total employment and employment in the knowledge intensive sector around European airports:

- *GDP per capita (log)*: Natural logarithm of the average GDP per capita within 100 kilometres from the airport. GDP per capita is measured in Euros. For countries outside the Euro-zone, GDP per capita is calculated using the exchange rates for 2011 for all years in the data. This way we isolate disturbances caused by changes in exchange rates;
- *Employment (log)*: Natural logarithm of total employment within 100 kilometres from the airport;
- *Employment in knowledge intensive sectors (log)*: Natural logarithm of employment in the knowledge intensive sectors within 100 kilometres from the airport.
- *Employment rate*: Employed people divided by population aged 15-64.

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4 ACI EUROPE categorises its member airports in four categories based on annual passenger numbers. We also grouped airports according to these categories based on their 2011 passenger numbers. However, the number of airports was rather concentrated in category 4 (Cat. I: 10; Cat. II: 22; Cat. III: 33; Cat. IV: 343). Due to the low number of observations model results of the first three categories were unreliable, therefore we stick to the categorisation denoted here.

In the model we use the natural logarithms of these variables, as this will make the interpretation of the regression results easier: coefficients on the natural log scale are relative differences. A coefficient for an independent variable of 0.1 for example means that when the specific variable increases by 10 percent, then the dependent variable will increase by 1 percent.

3.2.2 Independent variables: airport characteristics

It is expected that an increase in the amount of incoming tourists, business travellers and long-haul destinations for instance have an impact on the local economy. However airports are located in different economies, serve different markets and will have different airline clients and passenger profiles. For example, incoming tourism might be enhanced most by low-cost dominated airports, whereas business travellers tend to fly on network carriers from the larger airports. Therefore we include various airport characteristics in the model, which allow us to define the specific impacts of such characteristics.

Airport size
We will be looking at the impact of a *change* in the airport characteristics (and socio-economic) variables on the *change* in GDP per capita and employment. A relative change in connectivity - of say 1 percent - constitutes a much larger absolute increase in capacity at large airports than at small ones. A 1 percent increase in connectivity therefore will have a more pronounced impact on GDP per capita and employment for large airports than for smaller ones.

We use connectivity as a proxy for the size of an airport. Airport connectivity constitutes the direct and indirect connectivity offered from an airport:

- *Airport connectivity (log)*: Natural logarithm of the sum of direct and indirect connectivity offered from the airport;
- *Direct connectivity (log)*: Natural logarithm of the number of direct connections offered from the airport;
- *Indirect connectivity (log)*: Natural logarithm of the number of indirect connections offered from the airport via an intermediate hub airport, weighted by the quality of the connection.[5]

Figure 3.2 provides graphical representation of the different connectivity variables. The various types of connectivity were calculated for the ACI EUROPE Airport Industry Connectivity Report between 2004 and 2014. For more information on the connectivity variables we refer to that report.

All connectivity variables, as well as values derived from the connectivity data (such as the share of long-haul traffic), are weighted for the importance of the destinations. The weighting procedure is described in Box 1. Using weighted connectivity data we correct for the fact that flights to important global cities might contribute more to the region's economy than flights to smaller cities.

[5] Some smaller airports do not offer indirect connectivity as they are not connected to a hub airport by the respective hub carrier or one of its partners. In this case the value for indirect connectivity is zero. As it is not possible to calculate the log of a zero value, we replace the value of indirect connectivity from zero to one and then take the log. The log of one equals zero. This prevents losing many observations. The same approach is used for the log transformation of the other variables which might have a value of zero.

Box 1: Connectivity weighted for destination region

The connectivity values used in the report are weighted for the relative importance of the destination region. Flights are weighted according to the GAWC Global City Ranking (see Appendix C) of the destination. A flight to any of the airports in New York City for example weighs for 1.0, while a flight to Buenos Aires is weighted with a factor of 0.61. The 100 metropolitan areas listed have a value between 1 and 0.25, for other destinations we apply a weighting factor of 0.2.

- *Number of passengers (log):* Natural logarithm of the number of passenger enplanements at the airports.

The various types of connectivity and passenger numbers may be strongly related. Therefore, it may not be possible to include all these variables in a regression model combined, as this would lead to collinearity issues. We look into the correlations between the variables in section 4.1.

Hub function

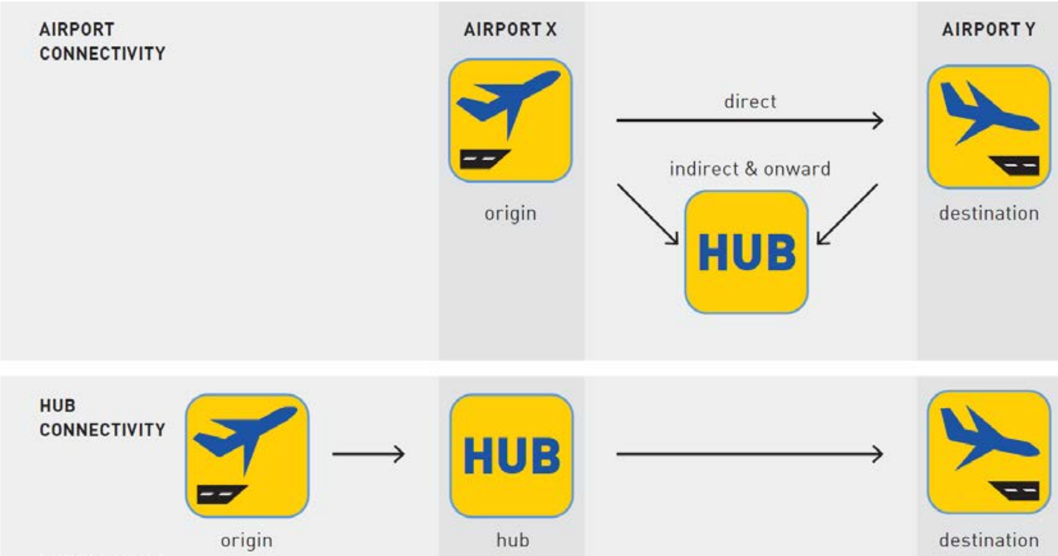
For hub airports a change in connectivity may lead to a different change in GDP per capita and employment than for airports without a hub function. Hub airports are generally large airports, which offer many direct and indirect connections.

Using a hub dummy is not possible in a panel data model as its value will hardly differ over the time period under consideration. An alternative is using hub connectivity[6]. This is a measure for the amount of hub connections offered via an airport by its hub carrier and alliance and codeshare partners, weighted by the quality of those connections (see Figure 3.2). However, this variable is strongly connected to the other connectivity variables, which may lead to multicollinearity. Therefore, we use a derived measure, the airport's feeder value as a proxy for the size of the hub operation of an airport:

- *Feeder value*: The number of hub connections per direct connection. I.e. hub connectivity divided by direct connectivity.

[6] A more detailed explanation of hub connectivity is given in the ACI EUROPE Airport Industry Connectivity Report (2004-2014)

Figure 3.2 Airport connectivity denotes the extent to which airport X is connected to other airports; hub connectivity shows how well airport X provides connections between two other airports



Source: ACI-SEO Airport Industry Connectivity Report

Long-haul connections

Large multinationals with offices all over the world might locate close to an airport, which offers a large network of intercontinental long-haul destinations. It is therefore possible that such airports will have a different impact on the local economy than airports with a small or no intercontinental network (all other things being equal). The share of long-haul connections is therefore included in the model:

- *Share of long-haul*[7] *connections*: Share of direct connectivity to long-haul destinations. Again we did not use the absolute number of long-haul connections as this would be strongly correlated with the other connectivity variables.

Hub airports offer much more long-haul connections than smaller O&D airports. Therefore, the share of long-haul connections may be correlated with the feeder value.

Low cost presence

On the one hand, low cost carriers require less services from suppliers than network carriers, such as caterers and ground handlers. In addition, they carry a large amount of leisure passengers. This means that businesses may depend less upon airports with a large low cost presence and their regional impact may therefore be relatively small. On the other hand airports dominated by low-cost carriers are known for bringing in many tourists, which may facilitate economic growth which otherwise might not have occurred. It is therefore unclear to what extent airports with a large low cost presence have a different impact on the local economy than airports, which are dominated by a network carrier. A separate tourism variable is included (see below) in the model to allow us to separate the impact of low-cost carriers and tourism on the local economy.

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[7] A long-haul flight is defined as a flight between two cities between which the great circle distance exceeds 3,450 kilometres.

To determine the impact of the low-cost carriers we include (one of) the following variables in the model:

- *Share of low-cost connectivity*[8]: Share of direct connectivity provided by low-cost and charter carriers from an airport. We use the share of low-cost connectivity instead of the absolute amount of low-cost connections, because the latter would be strongly correlated with the other connectivity measures, which would result in multicollinearity;
- *Low-cost base*: Dummy for the airports which serve as a base for one or more low-cost carriers;
- *Size of low-cost base*: Number of aircraft stationed by low-cost carriers at their base airports.

Freight

When an airport handles a large amount of freight, we expect that its impact on the local economy might be higher than for an airport without a large freight operation (all other things being equal). Freight is generally handled at the larger hub airports. Larger airports provide more direct connectivity as well as indirect and airport connectivity. Therefore we expect to find a strong correlation between the connectivity variables and the amount of freight handled. To prevent collinearity we therefore do not include the total freight throughput as an independent variable, but the average amount of freight per individual flight:

- *Freight handled per flight (log)*: Natural logarithm of the total amount of freight handled at an airport (in tonnes) divided by the number of direct connections;

Connectivity provided by other airports serving the same catchment area

When a region is served by multiple airports, it is likely that each of those airports affects the economy in the region to a certain extent. When we would look at each of these airports in isolation, we would ascribe the change in local GDP per capita or employment to each of these airports, overestimating the total impacts. Estimating the local economic impact of an airport therefore requires correcting for the impact of all the other airports serving the same catchment area. To prevent overestimation, we include a variable which represents the connectivity provided by all the other airports serving the same catchment area. We include the direct connectivity of all the airports within a 150 kilometre radius from the respective airport. We assume that airports within this range at least partially influence the same catchment area (also see Box 2):

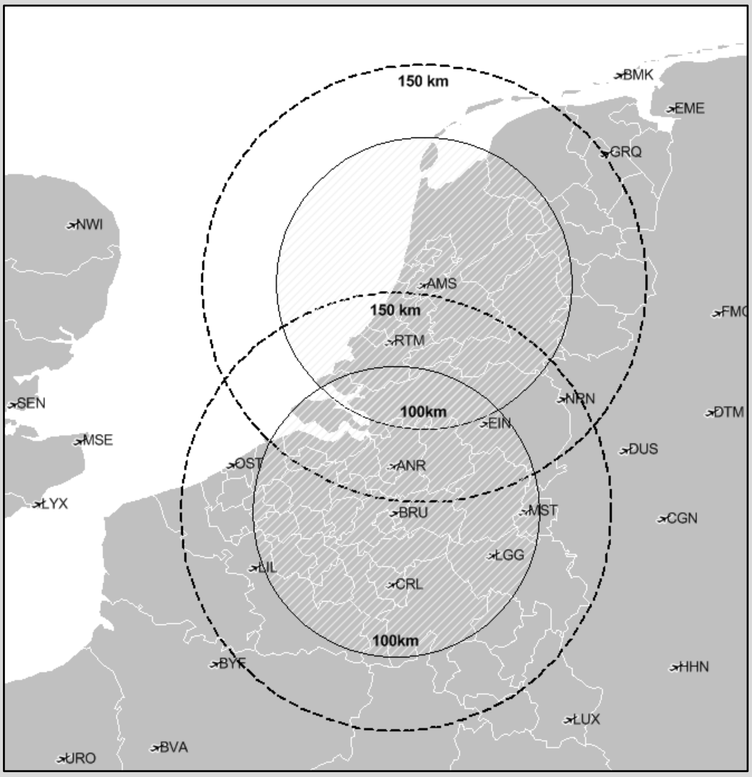
- *Connectivity provided by other airports serving the same catchment area (log)*: The natural logarithm of the sum of the direct connectivity provided by all airports within 150 kilometres of the respective airport. The connectivity provided by other airports is also weighted according to the relative importance of the destination.

8 A list of LCC carriers is given in Appendix D

Box 2: Direct connectivity provided by other airports serving the catchment area

We hypothesise an airport positively influences the economy within a 100 kilometre range. This range could however be influenced by other airports within or just out of this catchment area. Therefore we define a 'other airports' variable as the sum of direct connectivity of airports within a 150 kilometre range.

Figure 3.3 Airports located further than 100 kilometres away still have a large part of overlapping catchment areas



Source: SEO Economic Research

The rationale behind this is best explained by means of a figure. Figure 3.3 shows the 100 kilometre catchment area for Brussels and Amsterdam airports, indicated by the hatched circles. Although Brussels and Amsterdam are located more than 150 kilometres away from each other, still a part of their catchment areas are overlapping. We assume this overlapping part sufficiently small to indicate Amsterdam and Brussels as two airports influencing the same catchment area.

However, looking at Eindhoven Airport (EIN), one can imagine this airport has a large overlapping catchment area with both Brussels and Amsterdam. When only airports within the 100 kilometre catchment area range are included in the 'other airports' variable, the impact of Eindhoven on Schiphol's catchment area - or alternatively - the impact of Schiphol on Eindhoven's catchment area – would not have been taken into account.

3.2.3 Independent variables: Socio-economic variables

As GDP per capita and employment in the areas surrounding an airport are influenced by many other factors than just the airport, we need to account for those other factors. Therefore, the regression models also include various socio-economic variables.

Population

Employment is higher in densely populated urban areas than in less populated rural regions of the same size. GDP per capita might also be related to population. Agglomeration in cities may enhance productivity and therefore GDP per capita. Also, large companies with high productivity are often located in densely populated areas. Therefore population is included in the model as an independent variable. As demographic characteristics such as a higher share of elderly people might bias the results, we also include a variable of population aged 15-64.

- *Population (log)*: The natural logarithm of the number of inhabitants residing within 100 kilometres from the airport.
- *Population aged 15-64 (log)*: The natural logarithm of number of inhabitants within 100 kilometres from the airport, aged 15-64.

Education

We reckon that GDP per capita is higher in regions where the educational level is higher. Employment levels, especially those in the knowledge intensive sectors are also likely to be higher in such regions. As a proxy for the educational level we use the share of the population in tertiary (higher) education:

- *Share of population in tertiary education*: The number of students in tertiary education divided by the total population in the area up to 100 kilometres from the airport. We take the number of students as the share of total population and not the absolute number of students as the latter is highly correlated with population. This would result in multicollinearity issues.

Tourism

Incoming tourism by air is likely to contribute to the local economy of an airport. As data on the number of incoming tourists is not available at the required level of detail, we use the number of available hotel beds within a radius of 100 kilometres from an airport as a proxy:

- *Number of hotel beds per capita (log)*: Natural logarithm of the number of hotel beds per capita within 100 kilometres from the airport. We take the number of hotel beds per capita instead of the total number of hotel beds available, as the latter will be strongly correlated with population.

Employment in knowledge intensive sectors

Knowledge intensive sectors are considered to have higher productivity and persons employed in such sectors are on average likely to contribute more to local GDP than a person employed elsewhere. In other words, GDP per capita is likely to be higher in regions where a large share of the working population is employed in knowledge intensive sectors. When estimating GDP per capita we shall therefore include this variable in the model. When we estimate employment in the knowledge intensive sector this variable is omitted:

- *Share of working population employed in knowledge intensive sectors*: The number of people employed in the knowledge intensive sectors divided by the total number of employed people in the area up to 100 kilometres from the airport.

Year dummies
To correct for economic trends, we include year dummies in the model.

Regional dummies
As year effects might be different in various regions, we performed various analyses crossing the year effects with regional dummies. Results including a dummy-variable for Mediterranean countries are shown in this report. The economic trend in these countries turned out to be significantly different from the average European trend.

Airport-specific constants
The fixed effects model applied in this study includes a dummy variable for all unobserved factors of the airport influencing the GDP per capita and employment (in knowledge intensive sectors) in the surrounding region. These airport-specific constants do not change over time, hence they show the effect of all time invariant factors. This variable can represent the fact that an airport is located in an economically flourishing region, or that the existence of a large hub operation provides wider economic benefits in the surrounding region.

3.3 Data

Estimating the (coefficients in the) regression models, requires data on the dependent variables (GDP per capita and employment (in knowledge intensive sectors)) as well as the independent variables (airport characteristics and socio-economic variables). SEO has constructed an airport catchment area database containing both airport specific variables as well as regional socio-economic variables (GDP, employment, education and tourism).

The database covers all airports in EU28, Norway and Switzerland. The socio-economic variables used were obtained from Eurostat and statistics bureaus of Norway and Switzerland at the most detailed level available, where NUTS-2 was the highest acceptable aggregation level. For some countries data was largely unavailable. These are: Albania, Belarus, Bosnia and Herzegovina, Faroer Islands, Montenegro, Serbia, Russia and Ukraine. As a number of ACI EUROPE members are located in one of these countries we used other data sources to be able to obtain results for all member airports. Section 3.4 describes the applied proxy approach.

Table 3.2 shows for each variable that data source that was used and the time period for which the data was available. Altogether the dataset consists of 513 airports over a sequence of years, adding up to 2916 data points in total. Passenger numbers were unavailable for some more airports, leading to a dataset with 479 airports and 2644 data points.

Table 3.2 Data sources

Variables	Source	Time period
Dependent variables		
GDP per capita	Eurostat: GDP per capita at NUTS-3 level, GIS-analysis the average GDP per capita in the area up to 100 kms from the airport	2004-2011
Employment	Eurostat: Total employment at NUTS-3 or NUTS-2 level, GIS-analysis to determine the employment levels within 100 kms from the airport	2004-2011
Employment in knowledge intensive sectors	Eurostat: Employment in knowledge intensive sectors at NUTS-2 level. GIS-analysis to determine the employment levels in the knowledge intensive sectors within 100 kms from the airport	2004-2013
Independent variables		
Airport connectivity	ACI EUROPE Airport Industry Connectivity Report	2004-2014
Direct connectivity	ACI EUROPE Airport Industry Connectivity Report	2004-2014
Indirect connectivity	ACI EUROPE Airport Industry Connectivity Report	2004-2014
GAWC ranking for weighed connectivity	Custom data for SEO delivered by GAWC	-
Passenger numbers	ACI EUROPE, enhanced with data from Eurostat	2004-2014
Feeder value	Calculated based on direct and hub connectivity values taken from the ACI EUROPE Airport Industry Connectivity Report	2004-2014
Share of low-cost connectivity	Share calculated based on direct connectivity values (see above)	2004-2014
Low-cost base	Desk research: Identified which airports were used by Ryanair, EasyJet, Norwegian, Vueling and WizzAir as bases	2004-2015
Size of low-cost base	Desk research: Identified how much aircraft Ryanair, EasyJet, Norwegian, Vueling and WizzAir stationed at their bases	2004-2014
Share of long-haul connections	Share calculated based on direct connectivity values (see above)	2004-2014
Freight handled per flight	ACI EUROPE	2004-2014
Connectivity provided by other airports serving the same catchment area (log)	Calculated based on direct connectivity values of airports up to 150 kms from the airport under consideration using GIS-analysis	2004-2014
Population	Eurostat, NUTS-3 level, GIS-analysis to determine the population levels within 100 kms from the airport	2004-2011
Share of population in tertiary education	Eurostat: Number of students in tertiary education at NUTS-2 level divided by population (see above), GIS-analysis to determine the amount of students in tertiary education within 100 kms from the airport	2004-2012
Number of hotel beds per capita	Eurostat: Number of available hotel beds at NUTS-3 level divided by population, GIS-analysis to determine the number of available hotel beds within 100 kms from the airport	2004-2011
Share of working population employed in knowledge intensive sectors	Calculated based on total employment and employment in knowledge intensive sectors within 100 kms from the airport (see above)	2004-2011
Year dummies		2004-2014

Notes: GDP per capita data was missing for Switzerland, Norway (2004-2007) and Turkey (2004-2008); at NUTS-3 level. Employment data missing for Norway, Turkey and Switzerland at NUTS-3 level, Employment data missing for Switzerland at NUTS-2 level; Number of hotel beds was missing for Macedonia (from 2008) and Turkey; Number of students in tertiary education missing for certain countries.

As can be seen from the table, the socio-economic variables are available up to 2011. This means that the models are estimated on data, which covers the period from 2004 to 2011. To establish a causal relationship between the airport characteristics and the dependent variables, the airport characteristic variables are included in the model with a one year lag. This means that in fact the data on the socio-economic variables over 2004 is not used.

3.4 Data for other countries

For Albania, Belarus, Bosnia and Herzegovina, Faroer Islands, Montenegro, Serbia, Russia and Ukraine Eurostat statistics are unavailable. To be able to include these airports in the calculator we derived socio-economic statistics from other sources. The model used in the calculator uses population and share of employment in knowledge intensive sectors as independent variables, the other socio-economic variables were not found to be significant. Therefore, we have to find data on GDP, population and employment in knowledge intensive sectors for airports where data is not available.

GDP and population
For Russia regional population and GDP statistics were derived from the Russian Statistics Bureau. For the other countries we used data on a national level as derived from the World Bank.

The Russian regional GDP per capita was found on the website of the Russian Statistics Bureau.[9] Population data per region was derived from the GKS website. Total GDP in rubels were obtained by multiplying the GDP per capita by the population. In line with data for other non-Euro countries, values were converted to Euros by using the 2011 exchange rate to exclude exchange rate effects.

Employment in services versus employment in knowledge intensive sectors
As a proxy variable for countries where employment data is unavailable, we use data on population in service industries provided by the World Bank. This variable shows strong correlation with employment in knowledge intensive sectors (0.77). The share of people employed in service industries tends to be higher than the share employed in knowledge intensive sectors. The ratios of share of employment in knowledge intensive sectors over the share of employment in service industry varies from 0.3 (Moldova) to 0.6 (Norway), with an average of 0.5. As a rule of thumb, we use the share of employment in service industries multiplied by 0.5 as a proxy for the share of employment in knowledge intensive sectors.

[9] www.gks.ru/free_doc/new_site/vvp/dusha98-12.xls

4 Model results

This chapter presents the models that are best able to describe changes in GDP per capita and employment in knowledge intensive sectors from changes in the airport characteristics and socio-economic variables. We found a positive and significant correspondence between air travel and GDP growth within 100 kilometres from the airport. We also found a positive relationship between connectivity and employment in knowledge intensive sectors within a radius of 50 kilometres from the airport.

4.1 Correlations

The correlations between the dependent and independent variables described above are given in Appendix A. It shows that the various types of connectivity are strongly correlated. This does not come as a surprise. The more direct connections are offered from an airport, the more likely it is that some of these consist of connections to a hub airport, which generate onward (indirect) connections beyond the hub. Airport connectivity is the sum of both and is therefore also related to direct and indirect connectivity.

As direct connections are most valuable to consumers and companies, we expect that GDP per capita is strongest related to direct connectivity. Therefore this will be the preferred connectivity variable to include in the model. We shall also test however to what extent the change in total airport connectivity is able to explain changes in GDP per capita and employment (in the knowledge intensive sectors).

The dummy variable for low-cost bases appears to be strongly correlated with the size of low-cost bases in terms of number of stationed aircraft. We shall therefore include only one of these variables in the models. The same holds true for feeder value and share of long haul connectivity.

4.2 GDP per capita

Table 4.1 shows the regression results for three different model specifications, which differ with respect to the connectivity measure used. The airport specific constants that control for the individual airport characteristics are not included in the table. First we estimate aggregate models for all airports combined. In section 4.2.4 we estimate separate models for the different airport groups.

4.2.1 Model 1: Direct connectivity as independent variable

In the first model we use direct connectivity as the independent variable. This model shows a positive and significant relationship between the change in direct connectivity and GDP per capita one year later: a 10 percent increase in direct connectivity leads to a 0.23 percent increase in GDP per capita in the subsequent year.

The coefficient for the share of direct low-cost connectivity and the dummy for low-cost bases both appear to be significant. When an airport becomes a base of a low-cost carrier, GDP per capita in the areas within 100 kilometres from an airport, increases by 0.028 percent one year later. Besides this, when the share of connectivity offered by low cost carriers increases by 10 percent-point, GDP per capita increases by 0.43 percent in the following year.

When a low-cost carrier sets up a base, this generally also means that capacity offered by the low-cost carrier from the airport is expanded. Low-cost carriers are known for stimulating tourist demand to places that were previously not visited frequently by tourists. More capacity into a newly formed base, will therefore enhance tourism to the region.

The coefficients for the share of long-haul direct connectivity and freight handled per flight are not significantly different from zero. This means that we find no additional effects of a relative increase of long-haul connections and freight on GDP per capita. This might be caused by the fact that freight transport as well as long-haul air travel supply is concentrated in a limited number of airports. For long haul destinations, it is possible that the benefits of these connections are spread throughout the network via connecting possibilities, and the impact is therefore not identified solely at those airports that have the direct long-haul connections.

Direct connectivity provided by other airports serving the same catchment area however does show a positive and significant relationship with GDP per capita in the following year: a 10 percent increase in connectivity provided by airports within 150 kilometres of the airport under consideration, leads to a 0.58 percent increase in GDP per capita in the subsequent year. This coefficient is even larger than the coefficient for the airport itself, implying that the economic contribution of all surrounding airports together might be larger than the economic impact of the airport itself. This also suggests that the choice of a catchment area of 100km was a conservative estimate, with the cumulative economic impact of airports up to 150km away being considerable.

GDP per capita is negatively influenced by population. A 1 percent increase in population leads to a 1.43 percent decrease in GDP per capita. Population generally increases in Europe because of the fact that people live longer. The share of employed people decreases which has a negative effect on GDP per capita. When we use population aged between 15 and 64 instead of total population, the corresponding coefficient does not differ significantly from zero. However, including total population as independent variable leads to a better model fit, i.e. higher R^2.

The variables depicting the number of hotel beds and the share of people employed in knowledge intensive sectors appear to be negatively correlated to GDP growth. This is contradictory to our expectations, as one would expect that these indicators would stimulate GDP growth. It might be possible that before the economic crisis projects for new hotels were started, which were realised during the recession. The negative correspondence between the share of people employed in knowledge intensive sectors and GDP growth might be explained by the fact that employment in other sectors was affected more fiercely by the crisis than the knowledge intensive sectors. As a result, the share of employment in knowledge intensive sectors could have increased during the economic downturn.

The year dummies show the effect of the economic situation in the reported year, with respect to the reference year 2005. These all appear to be strongly significant. The effect of the economic crisis in 2009 is visible, the coefficient value has a lower value compared to 2008. This means that the average GDP per capita in 2009 was lower than in 2008.

As Mediterranean countries[10] were affected strongly by the economic crisis, we expected other effects for these countries. This is indeed confirmed by the negative sign of the significant coefficients for these regional dummies. These dummies are significantly smaller than zero in the years 2010 and 2011, during the European debt crisis.

Box 3: Interpretation of model results

When the independent variable has undergone a log transformation the coefficient values should be interpreted as follows: a 1 percent increase in the independent variable yields a x% increase in GDP per capita, where x represents the value in the table. Variables for which the log transformation has not been applied, the interpretation is as follows: a 1 unit increase in the independent variable yields a x% increase in GDP per capita, where x again represents the value in the table. This unit increase is an increase of 1% in case of the independent variables that represent a share, such as the share of low-cost connectivity in total direct connectivity. All year-dummy values are relative with respect to the base year 2005. The dummy value for 2008 for instance means that GDP per capita was 0.153 percent higher than in 2005, all other things equal.

10 Countries identified as Mediterranean countries are: France, Spain, Portugal, Italy, Greece, Turkey, Croatia, Malta and Gibraltar.

Table 4.1 Regression results, GDP per capita. 100 km radius

Independent variables	Model 1	Model 2	Model 3
Direct connectivity (weighted by destination) (t-1)(log)	0.0229***		
Airport connectivity (weighted by destination) (t-1)(log)		0.0245***	
Share of direct connectivity in total connectivity (t-1)		0.0433**	
Number of passengers (t-1)(log)			0.0520***
Share of low-cost connectivity (t-1)	0.0432***	0.0446***	0.0004
Low-cost base (t-1)	0.0279**	0.0279**	0.0233*
Share of long-haul connections (t-1)	-0.0883	-0.0926	-0.1463
Freight handled per flight (t-1)	-0.0001	-0.0001	-0.0002
Connectivity provided by other airports serving the same catchment area (150km) (t-1)(log)	0.0577***	0.0576***	0.0542***
Population (log)	-1.4334***	-1.4335***	-1.1909***
Share of population in tertiary education	0.0032	0.0097	0.1846
Number of hotel beds per capita	-0.4803*	-0.4723*	-0.4435*
Share of working population employed in knowledge intensive sectors	-0.1339**	-0.1343**	-0.0603
Year dummy 2006	0.0651***	0.0649***	0.0637***
Year dummy 2007	0.1259***	0.1255***	0.1209***
Year dummy 2008	0.1532***	0.1525***	0.1486***
Year dummy 2009	0.1268***	0.1257***	0.1203***
Year dummy 2010	0.1866***	0.1856***	0.1833***
Year dummy 2011	0.2257***	0.2245***	0.2219***
Mediterranean * Year dummy 2006	-0.0076	-0.0076	-0.0101
Mediterranean * Year dummy 2007	-0.0111**	-0.0110**	-0.0156**
Mediterranean * Year dummy 2008	-0.0149	-0.0146	-0.0211**
Mediterranean * Year dummy 2009	-0.0137	-0.0132	-0.0244**
Mediterranean * Year dummy 2010	-0.0603***	-0.0602***	-0.0745***
Mediterranean * Year dummy 2011	-0.1005***	-0.1002***	-0.1150***
Constant	19.6473***	19.6011***	17.4020***
Number of observations	2916	2916	2644
Number of groups (airports)	513	513	479
R^2 (within)	0.5825	0.5834	0.6223

Legend: * p<.1; ** p<.05; *** p<.01; standard errors corrected for heteroscedasticity

4.2.2 Model 2: Weighted airport connectivity as independent variable

Model 2 shows the results when airport connectivity – weighted for the importance of the destination (see box 3) – is used as the connectivity variable, instead of direct connectivity. As was the case for direct connectivity, we find a positive correspondence between airport connectivity growth and GDP growth one year later. A 10 percent increase in total weighted airport connectivity leads to a 0.25 percent increase in GDP per capita in the following year.

Besides this, we incorporate the share of direct connectivity in total connectivity. The coefficient for this variable has a positive sign. This implies that the economic impact of an airport increases with the share of direct connections. This supports the hypothesis that consumers prefer direct connections and these direct connections induce economic benefits.

The effects measured in model 1 and 2 are very similar. This is what one would expect given the strong correlation between direct connectivity and airport connectivity.

4.2.3 Model 3: passenger numbers versus connectivity

Model 3 provides results when the number of passenger enplanements are used instead of a connectivity measure. There are some airports for which passenger data is missing, therefore the number of observations is slightly lower. Again, one can observe a positive effect of air travel on GDP growth: a 10 percent increase in passenger enplanements yields a 0.52 percent GDP per capita increase.

This effect is stronger than the effect of air connectivity. This might be caused by the fact that an increase in air travel is not only caused by frequency growth – which is depicted by air connectivity – but also an increase in aircraft size. Especially the presence of low cost carriers, which operate larger aircraft than other intra-European carriers, causes a stronger increase in passenger numbers than in connectivity. This explains why the variable 'share of low cost carrier connectivity' is not significant anymore in the model using passenger numbers as independent variable. This effect is now captured by the passenger number variable.

One other difference is that the coefficient for share of employment in knowledge intensive sectors is no longer significant. The coefficients for the other variables are again similar to those in model 1 and 2.

4.2.4 Separate models for the different airport groups

The models in the previous section assume that a 1 percent increase in direct (and indirect) connectivity has the same local economic impact regardless of whether this 1 percent increase constitutes an absolute increase in connectivity of 1 unit or 100 units. In section 3.2.2 it was pointed out that the relative economic impact of airports may differ by airport size however. We expect that for large airports a change of 1 percent in direct or airport connectivity has a larger impact on GDP per capita in the subsequent year than for smaller airports.

In this section we present the results of model estimations for the different airport groups (see Table 3.1). Various model specifications were tested for the different airport groups. The model specification using passenger numbers as dependent variable appeared to provide the most accurate results. The full model specification is shown in Table 4.2.

Airports of different sizes typically operate in regions which may have very different economies. It was therefore necessary to build a model which considered large, small and medium airports separately. Differentiating between the three groups provides more accurate results.

The results indeed show that the relative impact of an increase in air travel is higher for the largest airports. For none of the airport groups a significant relationship could be found between the change in LCC connectivity (or becoming a LCC base) and the regional economic impact.

The population coefficient is significant and negative for all airport groups. This might be remarkable, as one would assume that an increase of population would also lead to economic growth in a region. However, the dependent variable in the regression is GDP per capita, which has population in the denominator. When population increases and the economic output in the region remains the same, GDP per capita decreases. This particularly happens when an increase in population is caused by births or people living longer rather than migration of working people.

The change of share of employment in knowledge intensive sectors does not have a significant impact on the GDP growth. Within the three airport categories, this share remains relatively stable throughout the study period, and therefore has no significant effect in the panel data regression model.

There seem to be significant year effects for all airport groups. In these effects the economic downturn is clearly visible, given the low coefficient value in 2009. Besides this, we crossed the year dummies with a dummy for Mediterranean countries. These effects show that these countries suffered relatively more in the aftermath of the economic crisis.

Airport Group A

There is a significant positive correspondence between the increase in passenger numbers and regional GDP per capita in the subsequent year, for the regions around airports with less than 100 weekly direct flights. A 10 percent in passengers from these airports leads to a 0.3 percent increase in GDP per capita in the following year.

As one would expect, this effect is smaller than the effect for the larger airports. However, a 10 percent increase in passenger numbers is easier to achieve for smaller airports than for larger airports.

Airports sharing the same catchment area as the analysed airport appear to impact the regional economy as well. The regression result indicates that when the total direct connectivity of the airports within 150 kilometres from the considered airport increases by 10%, the regional GDP per capita in a radius of 100 kilometres around the airport under consideration increases by 0.4% in the next year. This indicates that air travel provided by other airports also provide important economic benefits for the region.

Table 4.2 Regression results for the different airport groups, GDP per capita vs. passenger number, 100km

	Group A	Group B	Group C
number of passengers (t-1) (log)	0.0298***	0.1188***	0.1671**
share of low-cost connectivity (t-1)	0.007	0.0446	0.1228
Low-cost base (t-1)	0.0108	0	0.0239
Connectivity provided by other airports serving the same catchment area (150km) (t-1)(log)	0.0415***	0.0658***	0.0283
population (log)	-0.9932***	-0.6795***	-1.4679**
Share of working population employed in knowledge intensive sectors	0.0758	0.0723	-0.03
Year dummy 2006	0.0542***	0.0419***	0.0644***
Year dummy 2007	0.1123***	0.1015***	0.1162***
Year dummy 2008	0.1471***	0.1205***	0.1417***
Year dummy 2009	0.1091***	0.0626***	0.0959***
Year dummy 2010	0.1736***	0.1257***	0.1587***
Year dummy 2011	0.2044***	0.1575***	0.1956***
Mediterranean * Year dummy 2006	0.003	-0.0012	-0.0105
Mediterranean * Year dummy 2007	-0.0063	-0.0224**	-0.0122
Mediterranean * Year dummy 2008	-0.0164	-0.0357**	-0.009
Mediterranean * Year dummy 2009	-0.0071	-0.0298**	-0.0001
Mediterranean * Year dummy 2010	-0.0720***	-0.0661***	-0.0258
Mediterranean * Year dummy 2011	-0.1114***	-0.1036***	-0.0590*
constant	15.7685***	12.7804***	19.9428***
Number of observations	1947	1120	258
Number of airports	369	183	40
R^2	0.5425	0.6616	0.6237

Legend: * p<.1; ** p<.05; *** p<.01; standard errors corrected for heteroscedasticity

Airport Group B

For the group B airports (up to 1,000 direct flights per week), we also find a positive relationship between passenger numbers and GDP per capita one year later. An increase of 10 percent in passengers leads to a 1.2 percent increase in GDP per capita one year later.

The coefficient of connectivity provided by other airports is also positive and significant. The value is higher than in the model for the smallest airports: A 10 percent increase in this connectivity leads to an increase in GDP per capita of 0.66 percent in the subsequent year. For the group B airports, this coefficient is smaller than the coefficient for connectivity, implying that the economic importance of the airport itself is on average larger than that of all other airports in a 150 kilometre radius around the airport.

Airport Group C

Again a positive and significant correspondence is found between growth in passengers and GDP per capita in the following year. A 10 percent increase in passenger numbers leads to a 1.67 percent increase in GDP per capita. This coefficient is larger than that for the smaller Group A and B airports. This is also what one would expect as a 10 percent passenger increase constitutes a larger absolute increase in passenger numbers for large airports than for smaller ones.

Box 4: Economic impact of a new air service

Notwithstanding the fact that large airports induce stronger economic growth with an equal relative increase in passenger numbers, the economic impact of a new service to a smaller airport might be larger than the same new service at a large airport. A new service causes a stronger relative increase in passenger numbers at a smaller airport.

We illustrate this by assuming an additional half million passengers per annum would be delivered to an airport by a new air service, operating a B737-800 with a 90% load factor making four turnarounds a day (i.e. 8 flights), leaving all other factors unchanged.

- For a Group A airport which had 200.000 passengers per annum, this means a 250% passenger increase. Given the regression coefficient of 0.0289, this theoretical rise in traffic volumes would increase regional GDP per capita in the next year by 7.45%
- For a Group B airport which had 3 million passengers per annum, this means a 16.7% passenger increase. Given the regression coefficient of 0.1188, this theoretical rise in traffic volumes would increase regional GDP per capita in the next year by 1.98%
- For a Group C airport which had 20 million passengers per annum, this means a 2.5% passenger increase. Given the regression coefficient of 0.1671, this theoretical rise in traffic volumes would increase regional GDP per capita in the next year by 0.42%

The absolute impact on GDP also depends on the level of GDP per capita and population density in the area around the airport. A 1 percent increase in GDP per capita therefore results in a stronger increase in total GDP in areas with relatively high levels of GDP per capita and population.

Interestingly, the variable for connectivity provided by other airports is no longer significant. This means that for Europe's largest airports, the economic development in the surrounding area (up to 100 kilometres) is not significantly influenced by neighbouring airports.

Only the Mediterranean dummy for 2011 is significant for the largest set of airports. This might indicate that the economic downturn in these countries has first only impacted the smaller regional airports, while in a later stage the areas around these larger airports suffered as well.

4.2.5 Breakdown of fixed effects over airport and non-airport variables

The estimated model consists of airport-related variables (with coefficient vector β) and other socio-economic variables (with coefficient vector γ).

$$\ln(GDP\ per\ capita_{it}) = \alpha_1 + \beta' x_{i,t-1} + \gamma' z_{it} + u_i + \epsilon_1 \qquad (4.2)$$

The airport's fixed effect (u_i) is a variable which captures the effect of time-invariant factors on the economic strength of the region around the airport. Examples of these effects are the average population size of a region, or the type of an airport (hub airport or LCC airport).

Using standard OLS regression, we also split the fixed effect over airport related and non-airport related variables, with the respective coefficient vectors δ and θ. This enables us to find out whether these airport specific fixed effects are caused by airport-related variables, which do not change over time. These variables should also be taken into account when estimating the economic contribution of an airport. The following model is estimated:

$$u_i = \alpha_2 + \delta' v_i + \theta' w_i + \epsilon_2 \tag{4.2}$$

The regression results are shown in Table 4.3.

Table 4.3 Breakdown of the airport fixed effects over time invariant variables

Regression of airport-specific constants (u_i) on time-invariant variables			
	Group A	**Group B**	**Group C**
average share of direct connectivity served by LCC	0.2107**	0.2533	-0.4611**
airport is LCC base (average of dummies)	-1.5590***	-0.1933*	0.0518
average connectivity offered by airports within 150km (log)	0.1151***	0.0887***	0.0626**
average population around airport (log)	0.8690***	0.5375***	1.2529***
average share of employment in knowledge intensive sectors	4.5077***	4.2148***	3.0552***
constant	-7.9036***	-5.9738***	-12.3851***
Number of airports	369	183	40
R^2	0.9317	0.8268	0.9600

Legend: * p<.1; ** p<.05; *** p<.01

A significant relationship between the fixed effects and the LCC presence at the airport could be found for at least one of the two variables in the model.

For Group A a larger share of LCC connectivity leads to a higher average GDP per capita compared to airports with a lower share of LCC connectivity, all other variables being equal. This could illustrate the fact that LCCs tend to serve secondary airports in underserved regions, for which the additional connectivity stimulates tourism or other economic activity in the region. There is a (strong) negative coefficient for the LCC base dummy, but as there are only 4 LCC base airports in the group of small airports, this variable might capture other characteristics.

For Group B there is a negative sign for the LCC base dummy. This indicates that the average GDP per capita in regions around LCC bases is lower than the GDP per capita around comparable regions which are no LCC bases. Group B contains a large number of LCC base airports, which are mostly on secondary airports further away from the region's economic centre – Stockholm Skavsta, Düsseldorf Weeze – or mainly in tourist areas – Faro, Alicante. The non-LCC base counterparts in Group B are either airports in smaller cities which are frequently served by feeder operations of the large hub carriers – such as Aberdeen, Billund or Leipzig – or have their own small hub operation – Ljubljana, Keflavik, Zagreb – or are small airports close to the city centre – Stockholm Bromma, London City.

The LCC base variable is not significant for the group containing the largest airports, but there is a significant negative correspondence between the share of direct connectivity offered by LCCs and the average economic strength of the region. The airports with a high share of LCC connectivity are for example the airports of Malaga and Mallorca, which are mainly tourist destinations. Other airports with a high share of LCC connectivity are large (O&D) airports in secondary cities. Large hub airports with a relatively low share of LCC connectivity appear to contribute more to the regional economy.

This may shed additional light on the relationship between the share of LCC connectivity and its economic impact. If the increase in LCC connectivity is the result of new traffic that would not otherwise have served a region (as will often be the case at relatively small secondary airports), then the impact is significant and positive. However at larger airports which already have considerable connectivity, it is less likely that any increase in the share of LCC's would be delivered purely by new traffic. Instead there might also be an erosion of the connectivity provided by non-LCC carriers – via competition on existing routes. In such a case, the economic impact of LCC connectivity in these markets may be more ambiguous.

The three non-airport related variables appear to be significant for all three airport groups. Connectivity provided by other airports serving the same catchment area has a stronger positive effect on GDP per capita for the smaller airports. The opposite is the case for the largest airports. The economic contribution in the regions surrounding those airports mainly stems from these airports themselves and not so much from the smaller airports in their vicinity.

4.3 Employment in knowledge intensive sectors

One can also focus on employment in the knowledge intensive sectors. These sectors are important users of aviation, which therefore tend to locate close to an airport with an attractive network. In addition knowledge-intensive sectors tend to be more productive and therefore contribute relatively more to wider economic growth. We were unable to establish a significant relationship between connectivity and employment in the knowledge intensive sectors within 100 kilometres from the airport in the subsequent year. However when we reduced the area to 50 kilometres, we did find positive and significant relationships. This may reflect the fact that knowledge-intensive sectors are more likely to seek very close proximity to the airport, given the need for travel for client meetings, as well as the high value of the time of their more productive employees.

4.3.1 Model 1: Direct connectivity as independent variable

In the first model we use direct connectivity again as the independent connectivity variable. The model specification closely resembles that for GDP per capita. A 10 percent increase in direct connectivity results in a 0.021 percent increase in employment in the knowledge intensive sectors in the area up to 50 kilometres from the airport in the subsequent year.

Table 4.4 Regression results, employment in knowledge intensive sectors within 50 kilometres from the airport

Independent variables	Model 1	Model 2	Model 3
Direct connectivity (weighted) (t-1)(log)	0.0214*		
Airport connectivity (weighted) (t-1)(log)		0.0256**	
Share of direct connectivity in total connectivity (t-1)		0.0991	
Number of passengers (t-1) (log)			0.0115*
Share of low-cost connectivity (t-1)	0.026	0.0214	0.0199
Size of low-cost base (t-1)	-0.0052**	-0.0052**	-0.0050**
Share of long-haul connections (t-1)	0.0592	0.0556	-0.0262
Freight handled per flight (t-1)	0.0001	0.0001	0
Connectivity provided by airports within 100 km (weighted) (t-1)(log)	0.0175*	0.0174*	0.0240**
Population (log)	-0.1308	-0.1468	0.0412
Share of population in tertiary education	1.8707	1.9289	2.1291
Number of hotel beds per capita	0.9586	0.9532	0.9165
Year dummy 2006	0.027	0.0266	0.0262
Year dummy 2007	0.0799***	0.0798***	0.0774**
Year dummy 2008	0.0995***	0.0979***	0.0829***
Year dummy 2009	0.1792***	0.1782***	0.1737***
Year dummy 2010	0.1808***	0.1797***	0.1723***
Year dummy 2011	0.2026***	0.2009***	0.1991***
Mediterranean * Year dummy 2006	0.0223	0.0225	0.0204
Mediterranean * Year dummy 2007	-0.0073	-0.0068	-0.0088
Mediterranean * Year dummy 2008	-0.0182	-0.0156	-0.0065
Mediterranean * Year dummy 2009	0.0256	0.0273	0.0161
Mediterranean * Year dummy 2010	0.0814***	0.0838***	0.0754***
Mediterranean * Year dummy 2011	0.0840***	0.0865***	0.0736**
Constant	4.2969***	4.2986***	3.2512*
Number of observations	2815	2815	2490
Number of groups (airports)	509	509	440
R^2 (within)	0.32	0.32	0.31

Significance levels: * p<0.05; ** p<0.01; *** p<0.001

In this model the dummy for a low-cost base did not appear to be statistically significant. The coefficient for the size of the low-cost base in terms of number of stationed aircraft did prove significant. The sign is negative, meaning that 1 extra low-cost aircraft stationed at a base, results in a 0.005 percent decrease in employment in the knowledge intensive sectors around the airport.

The variable 'connectivity provided by other airports' is defined as the sum of direct connectivity of all airports within a radius of 100 kilometres, instead of 150 kilometres in the earlier models. In this model we decreased the radius as we zoom in on a smaller region around the airport. This region is less impacted by airports located further away.

The direct connectivity provided by airports located within a radius of 100 kilometres, also contributes to employment in the knowledge intensive sectors. A 10 percent increase in direct connectivity provided by surrounding airports leads to a 0.18 percent increase in employment in the knowledge intensive sectors in the subsequent year. The year dummies are all statistically significant, except the year dummy for 2006. This indicates that employment in knowledge intensive sectors on average did not increase between 2005 and 2006 (all other things equal). The year dummies for 2007-2011 are statistically significant and increase over time. This means that employment in the knowledge intensive sectors has increased every year between 2006-2011.

Again, the Mediterranean year dummies for 2010 and 2011 appear to be significant. However, in this analysis their sign is positive, indicating that employment in knowledge intensive sectors has increased relatively more than in other European regions.

4.3.2 Model 2: Airport connectivity as independent variable

Again we test a model which includes airport connectivity as an independent variable. A 10 percent increase in airport connectivity in Model 2 leads to a 0.26 percent increase in employment in the knowledge intensive sectors within 50 kilometres from the airport (model 2b).

As was the case in Model 1, the variables representing the size of the low-cost bases, the direct connectivity provided by airports located within a 50 kilometre radius of the airport under consideration and the year dummies are again statistically significant. The coefficients of these variables are also rather similar to the coefficients of Model 1.

4.3.3 Model 3: Passenger numbers as independent variable

Model 3 shows the results when passenger numbers are used as an indicator for airport activity. The effect of a passenger increase is smaller than the same relative connectivity increase. A 10 percent increase in the number of passengers leads to a 0.12 percent increase in employment in knowledge intensive sectors in the subsequent year.
In contrast with the models for GDP per capita, the impact of an increase in passengers on employment in knowledge intensive sectors is smaller than the impact of a similar increase in connectivity. This could mean that for business-related activity the number of connections is more important than seat capacity or passenger numbers. This is supported by other literature, which states that a large number of connections is a key factor for business activity.

Coefficients of other variables in the model do not differ strongly from those in model 1 and 2. The value of the population coefficient is positive rather than negative in models 1 and 2, however still not significantly different from zero.

4.3.4 Separate models for the different airport groups

Estimating models for the different airport groups proved challenging. We only found a statistically significant relationship between direct connectivity and employment in the knowledge intensive sectors for Groups B and C. These are airports with over 100 direct connections per week.

The models using passenger numbers as independent variable were not found to be significant. This again supports the hypothesis that it is the number of connections (to important economic centres) that stimulates employment in knowledge intensive sectors, rather than an increase in the amount of air passengers.

As pointed out above, companies in the knowledge intensive sectors are important users of aviation and therefore tend to locate close to airports offering attractive networks. Those are by definition the larger airports. Smaller airports offering only a handful of destinations or a vast amount of holiday destinations are less attractive for businesses. A more attractive network of at least 1,000 direct flights per week may therefore be an important factor for companies to base the location of their offices on.

The table shows that a 10 percent increase in direct connectivity from Group C airports, leads to a 1.5 percent increase in employment in the knowledge intensive sectors within a radius of 50 kilometres from the airport in the following year. For the Group B airports, the same increase in direct connectivity yields a 0.45 percent increase in employment in knowledge intensive sectors.

For the Group B airports only the year dummies were statistically significant, besides the direct connectivity variable. For the Group C airports, the share of long-haul connectivity is also significant. The sign of this coefficient is negative, indicating that an increase in the share of long haul connectivity yields a decrease in employment in knowledge intensive sectors. A possible explanation is that at the largest airports the number of short-haul connections has grown relatively stronger than long-haul connections, resulting in a decrease in the share of long-haul connections.

Table 4.5 Regression results for the different airport groups, employment in knowledge intensive sectors within 50 kilometres from the airport

	Airport group		
Independent variables	**Group A**	**Group B**	**Group C**
Direct connectivity (weighted) (t-1)(log)	0.015	0.0448*	0.1512*
Share of low-cost connectivity (t-1)	0.0231	0.0944	-0.1329
Size of low-cost base (t-1)	-0.0252**	-0.0055	-0.0018
Share of long-haul connections (t-1)	0.1966	0.3497	-0.4273*
Freight handled per flight (t-1)	0.0002	0.0013	-0.0091
Connectivity provided by other airports within 100km (t-1)(log)	0.0203	0.0134	0
Population (log)	-0.1132	-0.034	0.4248
Share of population in tertiary education	2.5266	0.0615	-1.0408
Number of hotel beds per capita	3.3168**	-0.3435	0.1445
Year dummy 2006	0.0339	0.0141	0.0172
Year dummy 2007	0.0955*	0.0501***	0.0497***
Year dummy 2008	0.1136***	0.0672***	0.0586**
Year dummy 2009	0.1816***	0.1620***	0.1552***
Year dummy 2010	0.1767***	0.1721***	0.1727***
Year dummy 2011	0.2013***	0.1832***	0.1959***
Mediterranean * Year dummy 2005	(omitted)	-0.0408**	0.0056
Mediterranean * Year dummy 2006	0.0018	(omitted)	0.0184
Mediterranean * Year dummy 2007	-0.0375	-0.0092	0.0165
Mediterranean * Year dummy 2008	-0.0399	-0.0354*	0.0024
Mediterranean * Year dummy 2009	0.0723*	-0.0801	0.003
Mediterranean * Year dummy 2010	0.1105***	0.0058	(omitted)
Mediterranean * Year dummy 2011	0.1013*	0.0141	0.0003
Constant	3.4069*	4.3147*	1.6108
Number of observations	1675	906	234
Number of groups (airports)	325	148	36
R^2 (within)	0.3802	0.2438	0.8319

Significance levels: * p<0.05; ** p<0.01; *** p<0.001

5 Application to the ACI EUROPE Economic Impact calculator

The results of the model described earlier are used to estimate the regional economic impact of individual airports. The Economic Impact Calculator presents results on the airport's relative and total GDP contribution, as well as the contribution to the GDP per capita in the surrounding regions. Besides this, the national catalytic GDP and employment impacts calculated by InterVISTAS (2015) are allocated to individual airports, controlling for the fact that an airport can have an impact on the local economy of a neighbouring country.

5.1 Estimating an airport's regional economic impact

In this section we use the model results from chapter 4 to estimate the regional economic impact in terms of GDP per capita and employment in knowledge intensive sectors for each ACI EUROPE member airport. The models in chapter 4 contain both airport related variables and non-airport related (socio-economic) variables. The regional economic contribution of an airport depends on the extent to which the airport related variables affect GDP per capita ad employment in the knowledge intensive sectors.

First we estimate for each airport GDP per capita and employment in the knowledge intensive sectors, by using the models from chapter 4 per airport category and populate those with real-life data about the airport and the surrounding region. Next we determine what share of GDP per capita can be attributed to the airport related variables (e.g. pax numbers, share of LCC-related connectivity). For each airport group we only attribute effects of airport related variables (with a significance level over 5%) to the economic impact of an airport. Subsequently the total share of the individual airport-related variables is applied to the actual GDP per capita of the surrounding region to obtain the airports contribution in the GDP per capita of the region. Finally the airports contribution in the region's GDP per capita is multiplied by the population to obtain the airport's total contribution in the region's GDP.

To estimate the regional economic impact in 2014, we determined the relative passenger growth between 2010 and 2013. All other factors were assumed to remain constant in 2014 compared to 2011. The coefficient corresponding to the logarithm of the passenger numbers in the fixed effects model is interpreted as elasticity. Hence, the relative increase in passenger numbers is multiplied by this coefficient to estimate the GDP growth between 2011 and 2014 attributed to the passenger increase at the respective airport.

The applied methodology is shown by means of a numerical example. For a technical description we refer to Appendix E.

Box 5: Numerical example: the economic impact of Rome Fiumicino

Variable	Value
GDP per capita (2011)	30,453.59 (log = 10.3239)
Pax 2010	36,227,778 (log = 17.4053)
Share LCC 2010	13.80%
Airport is LCC base (2010)	1
Direct cnx airports within 150km (2010)	125.85 (log = 4.8430)
Population (x 1000)	5,403.43 (log = 8.5948)
Share employment in knowledge intensive sectors	41.23%
Average share of direct LCC cnx	15.38%
Airport is LCC base (average of dummies)	0.5455
Average cnx offered by airports within 150km (log)	4.8805
Average population around the airport (log)	8.5516
Average share of employment in knowledge intensive sectors	39.15%

The estimated logarithm of the GDP is given by:

$$\begin{aligned}\ln(GDP\ per\ capita_{2011}) \\ &= 19.94 + \mathbf{0.1671} * \mathbf{17.4053} + 0.1228 * 0.1380 + 0.0239 * 1 + 0.0283 \\ &* 4.8430 - 1.4679 * 8.5948 - 0.0300 * 0.4123 + 0.1956 - 0.0590 + u_i\end{aligned}$$

The fixed effect of Rome Fiumicino u_i is given by:

$$\begin{aligned}u_i = -12.3851 - \mathbf{0.4611} * \mathbf{0.1538} + 0.0518 * 0.5455 + 0.0625 * 4.8805 + 1.2529 * 8.5516 \\ + 3.055 * 0.3915 + \epsilon\end{aligned}$$

Hence the estimated GDP equals $e^{10.3251} = 30489$, which is very close to the actual GDP per capita around Rome, which is 30454.

Only the statistically significant airport related variables are used to estimate the proportional impact of the airport on the regional GDP. For Group C this is the passenger number variable and the average share of LCC connectivity, which are printed in bold in the above formulas. These two variables add up to a value of 2.8373. The relative contribution of these to variables is given by:

$$\frac{\frac{e^{2.8373}}{e^{10.3251}}}{\frac{e^{2.8373}}{e^{10.3251}} + \frac{e^{7.4878}}{e^{10.3251}}} = 0.947\%$$

We apply this factor to the actual GDP per capita in the region, which results in the GDP contribution of the airport is 0.947%*30454 = €288.33 per capita, or €288.33*5403430 = €1.55 billion.

In the final step the results are converted to 2013 price level. The results for all airports are updated according to the inflation rates in the Euro zone. The inflation rate was 2.5% in 2012 and 1.4% in 2013, therefore the GDP impacts are increased by 102.5%*101.4%=103.9%. This results in an impact of €299.67 per capita or a total impact of €1.62 billion for Rome Fiumicino.

Between 2010 and 2013 the total number of passengers for Rome Fiumicino has decreased by 0.17%. Hence, the estimated economic impact for 2014 decreases by 0.0017*0.1671 =0.03%. This yields an estimated economic impact per capita of Rome Fiumicino in 2014 is €299.67 * (1-0.03%) = €299.59.

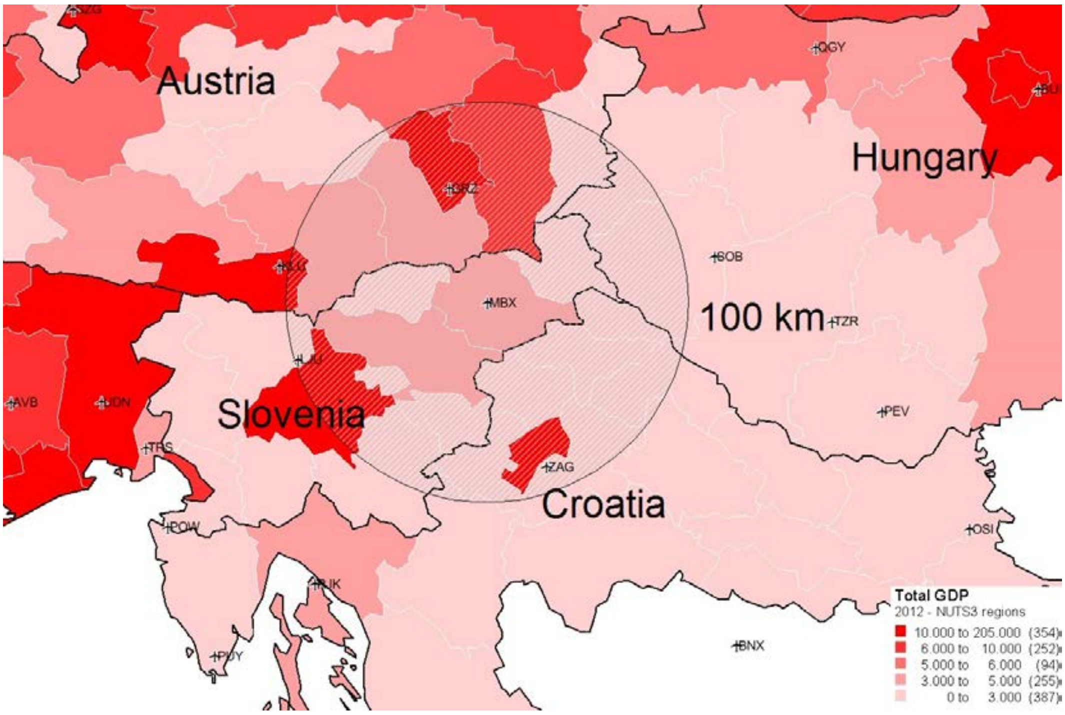
5.2 Estimating effects in neighbouring countries

There are numerous examples of airports where the 100 kilometre catchment area stretches over more than one country. The regional economic impact of such airports may therefore strike down in different countries. Using additional GIS analysis we estimate the distribution of this economic impact over the different countries.

Using buffer analysis we can calculate the total GDP in a radius of 100 kilometres around the airport. When the 100 kilometre range stretches over more than one country we can determine the share of each country in the total GDP in the 100 km radius. We assume that the total economic impact of the airport is distributed over the various countries accordingly.

To further explain this methodology we use Maribor airport as an example. The 100 km catchment area of the Slovenian airport covers parts of Slovenia, Austria, Croatia and Hungary (see Figure 5.1). The total GDP within the 100 kilometre catchment area is added up for each country. According to these figures we can estimate the share of GDP in the airport's catchment area. The economic impact of Maribor airport is distributed according to these shares, which are shown in Table 5.1.

Figure 5.1 The 100 km catchment area of Maribor Airport stretches over four countries



Source: SEO Airport Database

Table 5.1 The largest share of total GDP in the catchment area of Maribor is located in Austria

Country	Total GDP in 100 km catchment area of MBX (Eur. million)	Share of total
Slovenia	21,505	29%
Croatia	20,558	27%
Austria	31,368	42%
Hungary	1,896	3%

Note: Numbers may not add up to 100% due to rounding.
Source: SEO Airport Database.

5.3 Allocation of catalytic impacts on country level over individual airports

InterVISTAS (2015) has estimated the catalytic impacts and employment effects generated by air travel at country level. In this report we estimated the regional economic impact of each ACI EUROPE member airport in a radius of 100 kilometres around the airport. Using the GIS-methodology explained in the previous section, we estimated the total economic impact of each of these airports in each country. Hence we are able to calculate the share of each individual airport in the impact of all airports providing air travel services to the respective country. These shares may in turn be used to allocate the catalytic impacts estimated by InterVISTAS over the individual airports.

As an example we allocate the economic impact of airports for Switzerland over various airports. Table 5.2 shows the airports providing air travel services to this country. These include airports from Switzerland, but also Italy, France and Germany. The total catalytic impacts and employment figures for Switzerland as a whole – as estimated by InterVISTAS – can be allocated amongst individual airports according to the percentages shown in the table.

Table 5.2 Airports from Switzerland, France, Germany and Italy provide air travel services to Switzerland

Airport	Country	Contribution to Switzerland
Zurich (ZRH)	Switzerland	63.9%
Geneva (GVA)	Switzerland	14.5%
Basel/Mulhouse (BSL)	Switzerland/France	6.9%
Milan Malpensa (MXP)	Italy	4.9%
Friedrichshafen (FDH)	Germany	4.0%
Lyon St. Exupéry (LYS)	France	3.8%
Bern (BRN)	Switzerland	0.5%
Milan Bergamo (BGY)	Italy	0.4%
Milan Linate (LIN)	Italy	0.4%
Annecy (NCY)	France	0.1%
Lugano (LUG)	Switzerland	0.1%
Turin (TRN)	Italy	0.1%

Note: Numbers may not add up to 100% due to rounding.
Source: SEO Airport Database.

6 Conclusions

We were able to establish positive and significant causal relationships between airport characteristics and GDP per capita as well as employment in the knowledge intensive sectors. The relative economic impact of an increase in passengers appeared to be stronger for the larger airports.

6.1 Models used in the calculator

The regional economic impact of airports differs substantially between airports of different size (in terms of passenger numbers). Therefore different models were estimated for various airport size categories. These models were used in the calculator.

6.2 GDP per capita

We found positive and statistically significant relationships between airport capacity and GDP per capita in the area up to 100 kilometres from the airport in the subsequent year. The models using passenger numbers as the capacity indicator yielded the best relationships. Therefore we suggest using these models for explaining GDP per capita growth.

Passengers
At larger airports (Group C) a 10 percent increase in passengers leads to a 1.7 percent increase in GDP per capita in the next year. The same percentage increase at a medium-sized airport (Group B) produces a 1.2 percent GDP per capita increase. At the smaller airports (Group A) the same percentage increase in passengers results in an increase of 0.3 percent of next year's GDP per capita. However, large percentage increases in passenger traffic are more attainable and common at smaller airports than at larger airports. On the other hand, larger airports may be located in areas with higher levels of GDP per capita and population density, which means that a 1 percent increase in GDP per capita results in larger absolute increases in GDP than in areas where GDP per capita and population density are smaller.

Low cost carriers
Share of low cost carrier connectivity: The impact of the share of low cost carrier connectivity is statistically insignificant when considering the different sizes of airports. However, when considering the breakdown of airport fixed effects over time invariant variables we do find statistically significant effects. These results denote the effect of having a high share of LCC connectivity on the average strength of the economy around the airport. The coefficient of the share of low cost carrier connectivity is statistically significant and positive (+0.21) for the smallest airports. For the largest airports a higher share of LCC connectivity has a negative impact on the economic strength (-0.46). This may shed additional light on the way LCC traffic impacts the economy. For smaller airports they might provide air travel supply which would not be present otherwise, while at larger airports they might replace traffic which would otherwise be served by non-LCC traffic.

Low-cost carrier base: In the models for different airport sizes, the variable indicating an airport becoming a LCC base is also statistically insignificant. In the analysis of the airport fixed effects we find a negative correspondence between being a LCC base and the economic strength of a region for medium sized airports (Group B). The result indicates that the average GDP around a LCC base is lower than around a non-LCC base airport for medium sized airports. This is caused by the fact that the LCC base airports in this category are more remotely located than the non-LCC bases in the same category. In these remote areas the average GDP per capita tends to be lower than in more densely populated regions.

These results suggest that while overall the low cost carrier traffic has a positive impact on GDP per capita, the relationship is not unambiguously positive, and is likely to apply only in certain circumstances, e.g. where the low cost carriers are providing air services where these services would otherwise not exist.

Direct connectivity provided by other airports in the catchment area
Other airports located within 150 kilometres of small- (Group A) and medium-sized (Group B) airports provide an additional economic impact. A 10% increase in direct connectivity provided by these 'other' airports leads to an increase of GDP per capita of 0.66% for airports in Group B and 0.42% for Group C airports. For the largest airports (Group C), we did not find an additional economic contribution for the airports located within a 150 kilometre range. The largest airports seem to have a stronger effect on the regional economy than any surrounding airports, allowing them to impact the catchment areas of other smaller airports up to 150km away, while at the same time not being affected by the presence of those same smaller airports themselves.

6.3 Employment in knowledge intensive sectors

We focus on employment in the knowledge intensive sectors as these are important users of aviation. Companies in these sectors tend to locate close to an airport with an attractive network. We did not find a significant relationship between connectivity or passenger numbers and knowledge intensive employment within an area of 100km around the airport. This is likely to reflect the close proximity to air links that these industries require, as well as their tendency to 'cluster' in more geographically concentrated areas.

We did find positive and significant relationships between connectivity and employment in these sectors within 50 kilometres from the airport in the following year. For the models explaining employment in knowledge intensive sectors, direct connectivity performed best as the capacity indicator. Therefore we suggest this model in estimating the effects on growth in knowledge-intensive sectors. In this section we present the observed correspondences between air connectivity and employment in knowledge intensive sectors for the different airport size categories.

Connectivity
In the models for the three airport groups separately we found a positive relationship for the two largest airport groups. The effect of a 10 percent increase in direct connectivity leads to a 0.45% and 1.51% increase in knowledge-intensive employment, for Groups B and C, respectively. In line with the results found for GDP per capita, the relative impact of a connectivity increase at a larger

airport is higher than for smaller airports. On the other hand, a large relative connectivity increase is easier to obtain for smaller airports.

Passengers
Unlike the relationship with GDP per capita, the relationship between employment in knowledge intensive sectors and passengers was not found to be significant. This may reflect the sector's need for a wider number of connections rather than a large volume of seat capacity.

Size of low-cost carrier base
In the models differentiated by airport size, no significant correspondence was found between the size of a LCC base and employment in knowledge intensive sectors.

Direct connectivity provided by other airports in the catchment area
In the models differentiated by airport size, the correspondence between connectivity provided by other airports and employment in knowledge intensive sectors was not found to be significant. This again shows that employment effects are more 'clustered' around the airport, causing no significant effects from airports located further away.

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Appendix A Correlation matrix

	GDP per capita (log)	Employment (log)	Employment in knowledge intensive sectors (log)	Weighted direct connectivity (t-1) (log)	Weighted indirect connectivity (t-1) (log)	Weighted airport connectivity (t-1) (log)	Feedervalue (t-1)	Share of direct connections (t-1)	Share of low-cost connectivity (t-1)	Low-cost base (dummy)(t-1)	Size of low-cost base (t-1)	Share of long-haul connections (t-1)	Freight handled per flight	Connectivity provided by other airports within 150 km (t-1)	Population (log)	Share of population in tertiary education	Hotel beds per capita	Share of working population employed in knowledge intensive sectors
GDP per capita (log)	1.00																	
Employment (log)	0.04	1.00																
Employment in knowledge intensive sectors (log)	0.18	0.96	1.00															
Weighted direct connectivity (t-1) (log)	0.22	0.46	0.47	1.00														
Weighted indirect connectivity (t-1) (log)	0.08	0.41	0.40	0.82	1.00													
Weighted airport connectivity (t-1) (log)	0.19	0.48	0.48	0.96	0.92	1.00												
Feedervalue (t-1)	0.15	0.23	0.25	0.45	0.36	0.43	1.00											
Share of direct connections (t-1)	0.07	-0.25	-0.21	-0.34	-0.79	-0.57	-0.16	1.00										
Share of low-cost connectivity (t-1)	0.03	0.28	0.29	0.08	-0.13	-0.02	-0.10	0.35	1.00									
Low-cost base (dummy)(t-1)	0.10	0.27	0.29	0.38	0.22	0.32	0.07	0.03	0.38	1.00								
Size of low-cost base (t-1)	0.12	0.24	0.26	0.29	0.14	0.24	0.07	0.08	0.29	0.60	1.00							
Share of long-haul connections (t-1)	0.14	0.21	0.23	0.43	0.35	0.41	0.68	-0.16	-0.04	0.18	0.17	1.00						
Freight handled per flight	0.04	0.08	0.09	-0.06	-0.07	-0.06	0.02	0.05	0.10	-0.01	-0.01	0.12	1.00					
Connectivity provided by other airports within 150 km (t-1)	0.38	0.54	0.59	0.14	0.04	0.12	0.02	0.06	0.24	0.16	0.18	0.06	0.08	1.00				
Population (log)	0.03	0.97	0.94	0.47	0.42	0.49	0.22	-0.25	0.29	0.27	0.23	0.22	0.08	0.53	1.00			
Share of population in tertiary education	0.04	-0.19	-0.12	-0.10	-0.10	-0.08	0.00	0.03	-0.03	0.01	-0.04	-0.02	-0.04	-0.24	-0.22	1.00		
Hotel beds per capita	0.02	-0.37	-0.39	-0.08	-0.08	-0.10	-0.07	0.11	-0.03	-0.09	-0.07	-0.06	-0.03	-0.05	-0.35	-0.04	1.00	
Share of working population employed in knowledge intensive sectors	0.69	0.01	0.16	0.17	-0.02	0.11	0.13	0.16	0.05	0.18	0.18	0.15	0.04	0.19	0.02	0.21	-0.23	1.00

Appendix B Airports present in the calculator

AAL	Aalborg Airport	Denmark
AAQ	Anapa	Russia
AAR	Aarhus Tirstrup Airport	Denmark
ABC	Albacete	Spain
ABZ	Aberdeen (GB)	United Kingdom
ACE	Lanzarote	Spain
ACH	Altenrhein	Switzerland
ACI	Alderney	Channel Islands
ADA	Adana	Turkey
ADB	Izmir Adnan Menderes Apt	Turkey
ADF	Adiyaman	Turkey
AER	Sochi	Russia
AES	Alesund	Norway
AEY	Akureyri	Iceland
AGF	Agen	France
AGH	Angelholm/Helsingborg Angelholm Apt	Sweden
AGP	Malaga Airport	Spain
AGQ	Agrinio	Greece
AHO	Alghero	Italy
AJA	Ajaccio	France
AJI	Agri	Turkey
AJR	Arvidsjaur	Sweden
ALC	Alicante	Spain
ALF	Alta	Norway
ALL	Albenga Italy	Italy
AMS	Amsterdam	Netherlands
ANE	Angers Marce Airport	France
ANG	Angoulême	France
ANR	Antwerp	Belgium
ANX	Andenes	Norway
AOC	Altenburg Germany	Germany
AOI	Ancona	Italy
AOK	Karpathos	Greece
AOT	Aosta Italy	Italy
ARH	Arkhangelsk	Russia
ARN	Stockholm Arlanda Apt	Sweden
ARW	Arad	Romania
ASF	Astrakhan	Russia
ASR	Kayseri	Turkey
ATH	Athens (GR)	Greece
AUR	Aurillac	France
AVN	Avignon Caumont Airport	France
AXD	Alexandroupolis	Greece
AYT	Antalya	Turkey
BAL	Batman	Turkey
BAX	Barnaul	Russia
BAY	Baia Mare	Romania
BBU	Bucharest Baneasa	Romania
BCM	Bacau	Romania
BCN	Barcelona Apt	Spain
BDS	Brindisi	Italy
BDU	Bardufoss	Norway
BEB	Benbecula	United Kingdom
BEG	Belgrade	Serbia
BES	Brest (FR)	France
BFS	Belfast International Apt	United Kingdom
BGO	Bergen	Norway
BGY	Milan Bergamo/orio al Serio Apt	Italy
BHD	Belfast George Best City Apt	United Kingdom
BHX	Birmingham Airport	United Kingdom
BIA	Bastia	France
BIO	Bilbao	Spain
BIQ	Biarritz	France
BJF	Batsfjord	Norway
BJV	Bodrum Milas Airport	Turkey
BJZ	Badajoz	Spain
BLE	Borlange/Falun	Sweden
BLK	Blackpool	United Kingdom
BLL	Billund	Denmark
BLQ	Bologna Guglielmo Marconi	Italy
BMA	Stockholm Bromma Apt	Sweden
BMK	Borkum Germany	Germany
BNN	Bronnoysund	Norway
BNX	Banja Luka	Bosnia-Hercegovina
BOD	Bordeaux Merignac Apt	France
BOH	Bournemouth	United Kingdom
BOJ	Burgas	Bulgaria
BOO	Bodo	Norway
BQG	Bogorodskoye	Russia
BRE	Bremen	Germany
BRI	Bari	Italy
BRN	Berne Belp	Switzerland
BRQ	Brno	Czech Republic
BRR	Barra	United Kingdom
BRS	Bristol (GB) 00	United Kingdom
BRU	Brussels Airport	Belgium
BRV	Bremerhaven Germany	Germany
BSL	Basel	Switzerland
BTS	Bratislava	Slovakia
BUD	Budapest	Hungary
BUS	Batumi	Georgia
BVA	Paris Beauvais-Tille Airport	France
BVE	Brive-La-Gaillarde	France
BVG	Berlevag	Norway
BWE	Braunschweig/Wolfsburg	Germany
BWK	Brac	Croatia
BWO		Russia
BYF	Albert Picardie	France
BYJ	Beja Airport	Portugal
BZG	Bydgoszcz	Poland
BZI	Balikesir Airport	Turkey
BZK	Bryansk	Russia
BZO	Bolzano/Bozen	Italy
BZR	Beziers	France
CAG	Cagliari	Italy
CAL	Campbeltown	United Kingdom
CCF	Carcassonne	France
CDG	Paris Charles de Gaulle Apt	France
CEE	Cherepovets	Russia
CEG	Chester	United Kingdom
CEK	Chelyabinsk	Russia
CEQ	Cannes-Mandelieu	France
CER	Cherbourg	France
CFE	Clermont-Ferrand	France
CFN	Donegal	Ireland
CFR	Caen	France
CFU	Kerkyra	Greece
CGN	Cologne/Bonn Apt	Germany
CHQ	Chania	Greece
CHR	Chateauroux	France
CIA	Rome Ciampino Apt	Italy
CKZ	Canakkale	Turkey
CLJ	Cluj-Napoca	Romania
CLY	Calvi	France
CMF	Chambery/Aix-Les-Bains	France
CND	Constanta	Romania
CNL		Denmark

CPH	Copenhagen Kastrup Apt	Denmark
CRA	Craiova	Romania
CRL	Brussels S. Charleroi Airport	Belgium
CRV	Crotone	Italy
CSH	Solovetsky	Russia
CSY	Cheboksary	Russia
CTA	Catania	Italy
CUF	Cuneo	Italy
CVU	Corvo Island	Portugal
CWC	Chernovtsy Ukraine	Ukraine
CWL	Cardiff (GB) 00	United Kingdom
DBV	Dubrovnik	Croatia
DCM	Castres	France
DEB	Debrecen	Hungary
DIJ	Dijon	France
DIY	Diyarbakir	Turkey
DLE	Dole	France
DLM	Dalaman	Turkey
DME	Moscow Domodedovo Apt	Russia
DND	Dundee	United Kingdom
DNK	Dnipropetrovsk	Ukraine
DNR	Dinard/St-Malo	France
DNZ	Denizli	Turkey
DOK	Donetsk Ukraine	Ukraine
DRS	Dresden	Germany
DSA	Doncaster/Sheffield	United Kingdom
DTM	Dortmund	Germany
DUB	Dublin	Ireland
DUS	Duesseldorf International Airport	Germany
EAS	San Sebastian	Spain
EBA	Elba Island	Italy
EBJ	Esbjerg Airport	Denmark
EBU	St-etienne	France
EDI	Edinburgh	United Kingdom
EDO	Edremit	Turkey
EFL	Kefallinia	Greece
EGC	Bergerac	France
EGO	Belgorod	Russia
EGS	Egilsstadir	Iceland
EIK	Eisk Russian Fed.	Russia
EIN	Eindhoven Airport	Netherlands
EMA	Nottingham East Midlands Airport	United Kingdom
EME	Emden Germany	Germany
ENF	Enontekio	Finland
EOI	Eday	United Kingdom
EPL	Epinal	France
EPU	Parnu Estonia	Estonia
ERC	Erzincan	Turkey
ERF	Erfurt	Germany
ERZ	Erzurum	Turkey
ESB	Ankara Esenboga Apt	Turkey
ESL	Elista	Russia
ETH	Eilat	Israel
ETZ	Metz/Nancy Lorraine	France
EVE	Harstad-Narvik	Norway
EVG	Sveg	Sweden
EXT	Exeter (GB) 00	United Kingdom
EZS	Elazig	Turkey
FAB	Farnborough	United Kingdom
FAE	Faroe Islands	Faroer Islands
FAO	Faro	Portugal
FCO	Rome Fiumicino Apt	Italy
FDE	Forde	Norway
FDH	Friedrichshafen	Germany
FIE	Fair Isle	United Kingdom
FKB	Karlsruhe/Baden-Baden Baden Airpark	Germany
FLR	Florence Peretola Apt	Italy
FLW	Flores Island	Portugal
FMM	Memmingen	Germany
FMO	Muenster/Osnabrueck	Germany
FNC	Funchal	Portugal
FNI	Nimes	France
FOA	Foula	United Kingdom
FOG	Foggia	Italy
FRA	Frankfurt International Apt	Germany
FRL	Forli Italy	Italy
FRO	Floro	Norway
FSC	Figari	France
FUE	Fuerteventura	Spain
GCI	Guernsey	Channel Islands
GDN	Gdansk	Poland
GDZ	Gelendzhik	Russia
GEV	Gallivare	Sweden
GIB	Gibraltar	Gibraltar
GKD	Çanakkale Gökçeada Airport	Turkey
GLA	Glasgow International Airport	United Kingdom
GME	Gomel	Belarus
GMZ	San Sebastian/Gomera	Spain
GNA	Grodno	Belarus
GNB	Lyon Grenoble-St Geoirs Apt	France
GNY	Sanliurfa	Turkey
GOA	Genoa	Italy
GOJ	Nizhny Novgorod	Russia
GOT	Goteborg Landvetter Apt	Sweden
GPA	Patrai	Greece
GRO	Girona	Spain
GRQ	Groningen	Netherlands
GRV	Grozny	Russia
GRW	Graciosa Island	Portugal
GRX	Granada	Spain
GRY	Grimsey Iceland	Iceland
GRZ	Graz	Austria
GSE	Goteborg City Apt	Sweden
GVA	Geneva	Switzerland
GWT	Westerland	Germany
GWY	Galway Ireland	Ireland
GZP	Gazipasa	Turkey
GZT	Gaziantep	Turkey
HAA	Hasvik	Norway
HAD	Halmstad	Sweden
HAJ	Hannover	Germany
HAM	Hamburg Airport	Germany
HAU	Haugesund	Norway
HDF	Heringsdorf	Germany
HEI	Heide-Buesum Germany	Germany
HEL	Helsinki-Vantaa	Finland
HEM	Helsinki-Malmi	Finland
HER	Irakleion	Greece
HFA	Haifa Israel	Israel
HFS	Hagfors	Sweden
HFT	Hammerfest	Norway
HGL	Helgoland Germany	Germany
HHN	Frankfurt Hahn Airport	Germany
HLF	Hultsfred Sweden	Sweden
HMV	Hemavan/Tarnaby	Sweden
HOQ	Hof Germany	Germany
HOR	Horta	Portugal
HOV	Orsta/Volda	Norway
HRK	Kharkiv	Ukraine
HSK	Monflorite	Spain
HTA	Chita	Russia
HTY	Hatay	Turkey
HUY	Humberside	United Kingdom
HVG	Honningsvag	Norway
IAS	Iasi	Romania
IBZ	Ibiza	Spain
IDY	Ile D'Yeu France	France
IEG	Zielona Gora Poland	Poland
IEV	Kiev Zhuliany Intl Apt	Ukraine
IFJ	Isafjordur	Iceland
IFO	Ivano-Frankivsk	Ukraine
IGD	Igdir	Turkey
IGT	Magas	Russia
IIA		Ireland
IJK	Izhevsk	Russia
ILD	Lleida	Spain
ILY	Islay	United Kingdom
ILZ	Zilina Slovakia	Slovakia
INI	Nis	Serbia
INN	Innsbruck	Austria
INQ		Ireland

INV	Inverness	United Kingdom
IOA	Ioannina	Greece
IOM	Isle of Man	Isle of Man
IOR		Ireland
ISC	Isles of Scilly St Mary's Apt	United Kingdom
ISE	Isparta	Turkey
IST	Istanbul Ataturk Airport	Turkey
IVL	Ivalo	Finland
IWA	Ivanovo	Russia
JER	Jersey	Channel Islands
JIK	Ikaria Island	Greece
JKG	Jonkoping	Sweden
JKH	Chios	Greece
JKL	Kalymnos Island	Greece
JMK	Mykonos	Greece
JNX	Naxos Is	Greece
JOE	Joensuu	Finland
JOK	Yoshkar-Ola	Russia
JRS	Jerusalem	Israel
JSH	Siteia	Greece
JSI	Skiathos	Greece
JSY	Syros Island	Greece
JTR	Thira	Greece
JTY	Astypalaia Island	Greece
JYV	Jyvaskyla	Finland
KAJ	Kajaani	Finland
KAO	Kuusamo	Finland
KAU	Kauhava	Finland
KBP	Kiev Borispol Intl Apt	Ukraine
KCM	Kahramanmaras	Turkey
KCO	Kocaeli	Turkey
KDL	Kardla	Estonia
KEF	Reykjavik Keflavik International Apt	Iceland
KEL	Kiel Germany	Germany
KEM	Kemi/Tornio	Finland
KEV	Halli	Finland
KGD	Kaliningrad	Russia
KGS	Kos	Greece
KID	Kristianstad	Sweden
KIR	Kerry	Ireland
KIT	Kythira	Greece
KIV	Chisinau	Moldova
KKN	Kirkenes	Norway
KLR	Kalmar	Sweden
KLU	Klagenfurt	Austria
KLV	Karlovy Vary	Czech Republic
KLX	Kalamata	Greece
KMW		Russia
KOI	Kirkwall	United Kingdom
KOK	Kokkola/Pietarsaari	Finland
KRF	Kramfors/Solleftea	Sweden
KRK	Krakow	Poland
KRN	Kiruna	Sweden
KRP	Karup	Denmark
KRR	Krasnodar	Russia
KRS	Kristiansand Kjevik Airport	Norway
KSC	Kosice	Slovakia
KSD	Karlstad	Sweden
KSF	Kassel Calden	Germany
KSJ	Kasos Island	Greece
KSO	Kastoria	Greece
KSU	Kristiansund	Norway
KSY	Kars	Turkey
KSZ	Kotlas Russian Fed.	Russia
KTT	Kittila	Finland
KTW	Katowice	Poland
KUF	Samara	Russia
KUN	Kaunas	Lithuania
KUO	Kuopio	Finland
KUT	Kutaisi	Georgia
KVA	Kavala	Greece
KVX	Kirov	Russia
KWG	Krivoy Rog Ukraine	Ukraine
KYA	Konya	Turkey
KZI	Kozani	Greece
KZN	Kazan	Russia
KZS	Megisti	Greece
LAI	Lannion	France
LBA	Leeds Bradford	United Kingdom
LBC	Hamburg Luebeck-Blankensee Airport	Germany
LBG	Paris-Le Bourget	France
LCA	Larnaca	Cyprus
LCG	A Coruna	Spain
LCJ	Lodz	Poland
LCY	London City Apt	United Kingdom
LDE	Lourdes/Tarbes	France
LDG	Leshukonskoye Russian Fed.	Russia
LDY	Derry	United Kingdom
LED	St Petersburg Pulkovo Apt	Russia
LEH	Le Havre	France
LEI	Almeria	Spain
LEJ	Leipzig/Halle	Germany
LEN	Leon	Spain
LEQ	Land's End	United Kingdom
LGG	Liege Apt	Belgium
LGW	London Gatwick Apt	United Kingdom
LHR	London Heathrow Apt	United Kingdom
LIG	Limoges	France
LIL	Lille Lesquin Airport	France
LIN	Milan Linate Apt	Italy
LIS	Lisbon	Portugal
LJU	Ljubljana	Slovenia
LKL	Lakselv	Norway
LKN	Leknes	Norway
LLA	Lulea	Sweden
LMP	Lampedusa	Italy
LNZ	Linz Blue Danube	Austria
LPA	Gran Canaria	Spain
LPI	Linkoping	Sweden
LPK	Lipetsk	Russia
LPL	Liverpool	United Kingdom
LPP	Lappeenranta	Finland
LPX	Liepaya Latvia	Latvia
LPY	Le Puy	France
LRH	La Rochelle	France
LRS	Leros	Greece
LRT	Lorient	France
LSI	Shetland Islands Sumburgh Apt	United Kingdom
LTN	London Luton Apt	United Kingdom
LTT	Saint-Tropez Airport	France
LUG	Lugano	Switzerland
LUX	Luxembourg	Luxembourg
LUZ	Lublin	Poland
LWK	Shetland Islands Lerwick/Tingwall Apt	United Kingdom
LWO	Lviv	Ukraine
LXS	Limnos	Greece
LYC	Lycksele	Sweden
LYN	Lyon-Bron	France
LYR	Longyearbyen	Norway
LYS	Lyon St-exupery Apt	France
LYX	Lydd	United Kingdom
MAD	Madrid Adolfo Suarez-Barajas Apt	Spain
MAH	Menorca	Spain
MAN	Manchester (GB)	United Kingdom
MBX	Maribor	Slovenia
MCM	Monaco	Monaco
MCX	Makhachkala	Russia
MEH	Mehamn	Norway
MHG	Mannheim	Germany
MHP	Minsk International Apt 1	Belarus
MHQ	Mariehamn	Finland
MJF	Mosjoen	Norway
MJT	Mytilini	Greece
MJV	Murcia	Spain
MLA	Malta	Malta
MLN	Melilla	Spain
MLO	Milos	Greece
MLX	Malatya	Turkey
MME	Durham	United Kingdom

MMK	Murmansk	Russia	PEX	Pechora Russian Fed.	Russia
MMX	Malmo Airport	Sweden	PEZ	Penza	Russia
MOL	Molde	Norway	PFO	Paphos	Cyprus
MPL	Montpellier Mediterranee Apt	France	PGF	Perpignan	France
MPW	Mariupol Ukraine	Ukraine	PIK	Glasgow Prestwick Apt	United Kingdom
MQF	Magnitogorsk	Russia	PIS	Poitiers Biard Airport	France
MQM	Mardin	Turkey	PKV	Pskov Russian Fed.	Russia
MQN	Mo I Rana	Norway	PLH	Plymouth England UK	United Kingdom
MRS	Marseille Provence Apt	France	PLQ	Klaipeda/Palanga	Lithuania
MRV	Mineralnye Vody	Russia	PMF	Milan Parma Apt	Italy
MSQ	Minsk International Apt 2	Belarus	PMI	Palma de Mallorca	Spain
MSR	Mus	Turkey	PMO	Palermo	Italy
MST	Maastricht/Aachen	Netherlands	PNA	Pamplona	Spain
MUC	Munich International Airport	Germany	PNL	Pantelleria	Italy
MVQ	Mogilev Belarus	Belarus	POR	Pori	Finland
MXP	Milan Malpensa Apt	Italy	POX	Paris Pontoise-Cormeilles Apt	France
MXX	Mora	Sweden	POZ	Poznan	Poland
MZH	Amasya	Turkey	PPW	Papa Westray	United Kingdom
NAL	Nalchik	Russia	PRG	Prague Ruzyne	Czech Republic
NAP	Naples Capodichino Apt	Italy	PRN	Pristina	Kosovo
NAV	Nevsehir	Turkey	PSA	Pisa	Italy
NBC	Nizhnekamsk	Russia	PSR	Pescara	Italy
NCE	Nice	France	PSV	Papa Stour	United Kingdom
NCL	Newcastle	United Kingdom	PUF	Pau	France
NCY	Annecy	France	PUY	Pula	Croatia
NDY	Sanday	United Kingdom	PVK	Preveza/Lefkada	Greece
NNM	Naryan-Mar	Russia	PXO	Porto Santo	Portugal
NNR		Ireland	PYR	Andravida	Greece
NOC	Knock	Ireland	QGY		Hungary
NQT		United Kingdom	QPA		Italy
NQY	Newquay	United Kingdom	QSA	Sabadell	Spain
NRK	Norrkoping	Sweden	QSR	Salerno Italy	Italy
NRL	North Ronaldsay	United Kingdom	QYR	Troyes en Champagne	France
NRN	Duesseldorf Weeze Airport	Germany	RDZ	Rodez	France
NTE	Nantes Atlantique Airport	France	REG	Reggio Di Calabria	Italy
NUE	Nuremberg	Germany	REN	Orenburg	Russia
NVK	Narvik	Norway	RET	Rost	Norway
NWI	Norwich	United Kingdom	REU	Reus	Spain
NYO	Stockholm Skavsta Airport	Sweden	RGS	Burgos	Spain
ODB	Cordoba	Spain	RHE	Reims-Epernay	France
ODE	Odense Airport	Denmark	RHO	Rhodes	Greece
ODS	Odesa	Ukraine	RIX	Riga	Latvia
OER	Ornskoldsvik	Sweden	RJK	Rijeka	Croatia
OGZ	Vladikavkaz	Russia	RJL	Logrono	Spain
OHD	Ohrid	Macedonia	RKE	Roskilde	Denmark
OLA	Orland Norway	Norway	RKV	Reykjavik Apt	Iceland
OLB	Olbia	Italy	RLG	Rostock	Germany
OMO	Mostar	Bosnia-Hercegovina	RMI	Rimini	Italy
OMR	Oradea	Romania	RNB	Ronneby/Karlskrona	Sweden
OPO	Porto	Portugal	RNN	Bornholm	Denmark
ORB	Orebro	Sweden	RNS	Rennes St Jacques Airport	France
ORK	Cork	Ireland	ROV	Rostov	Russia
ORY	Paris Orly Apt	France	RPN	Rosh-Pina Galilee Israel	Israel
OSD	Are/ostersund	Sweden	RRS	Roros	Norway
OSI	Osijek	Croatia	RTM	Rotterdam Apt	Netherlands
OSK	Oskarshamn Sweden	Sweden	RTW	Saratov	Russia
OSL	Oslo Gardermoen Airport	Norway	RVK	Rorvik	Norway
OSR	Ostrava	Czech Republic	RVN	Rovaniemi	Finland
OST	Oostende/Brugge	Belgium	RWN	Rovno Ukraine	Ukraine
OSW	Orsk	Russia	RYB		Russia
OSY	Namsos	Norway	RYG	Oslo Moss-rygge Airport	Norway
OTP	Bucharest Henri Coanda Apt	Romania	RZE	Rzeszow	Poland
OUK	Out Skerries	United Kingdom	SAW	Istanbul Sabiha Gokcen Apt	Turkey
OUL	Oulu	Finland	SBZ	Sibiu	Romania
OVB	Novosibirsk	Russia	SCN	Saarbruecken Airport	Germany
OVD	Asturias	Spain	SCQ	Santiago de Compostela	Spain
OZH	Zaporizhia	Ukraine	SCV	Suceava Romania	Romania
PAD	Paderborn/Lippstadt	Germany	SCW	Syktyvkar	Russia
PAS	Paros	Greece	SDL	Sundsvall/Harnosand	Sweden
PDL	Ponta Delgada	Portugal	SDN	Sandane	Norway
PDV	Plovdiv	Bulgaria	SDR	Santander	Spain
PED	Pardubice	Czech Republic	SDV	Tel Aviv-Yafo Sde Dov	Israel
PEE	Perm	Russia	SEN	London Southend Apt	United Kingdom
PEG	Perugia	Italy	SFT	Skelleftea	Sweden
PES	Petrozavodsk	Russia	SGD	Sonderborg Airport	Denmark
PEV	Pecs Hungary	Hungary	SIP	Simferopol	Ukraine

SIR	Sion	Switzerland	TRE	Tiree	United Kingdom
SJJ	Sarajevo	Bosnia-Hercegovina	TRF	Oslo Sandefjord-Torp Arpt	Norway
SJY	Seinajoki	Finland	TRN	Turin Caselle Airport	Italy
SJZ	Sao Jorge Island	Portugal	TRS	Trieste	Italy
SKE	Skien	Norway	TSF	Venice Treviso/Sant'Angelo Apt	Italy
SKG	Thessaloniki	Greece	TSR	Timisoara	Romania
SKN	Stokmarknes	Norway	TTB	Tortoli Italy	Italy
SKP	Skopje	Macedonia	TUF	Tours Val de Loire Airport	France
SKU	Skyros	Greece	TXL	Berlin Tegel Apt	Germany
SKX	Saransk	Russia	TYF	Torsby	Sweden
SLD	Sliac	Slovakia	TZX	Trabzon	Turkey
SLM	Salamanca	Spain	UCT	Ukhta	Russia
SMA	Santa Maria Island	Portugal	UDJ	Uzhhorod	Ukraine
SMI	Samos	Greece	UFA	Ufa	Russia
SNN	Shannon	Ireland	UIP	Quimper	France
SNR	St-Nazaire	France	ULV	Ulyanovsk (RU) 00	Russia
SOB	Balaton	Hungary	ULY	Ulyanovsk (RU) 00	Russia
SOF	Sofia	Bulgaria	UME	Umea	Sweden
SOG	Sogndal	Norway	URE	Kuressaare	Estonia
SOJ	Sorkjosen	Norway	URO	Rouen	France
SOU	Southampton	United Kingdom	URS	Kursk	Russia
SOY	Stronsay	United Kingdom	USK	Usinsk	Russia
SPC	Santa Cruz de la Palma	Spain	USQ	Usak	Turkey
SPJ	Sparti	Greece	UTI	Utti	Finland
SPU	Split	Croatia	UUA	Bugulma	Russia
SQO	Storuman(Gunnarn) Sweden	Sweden	VAA	Vaasa	Finland
SRP	Stord	Norway	VAN	Van	Turkey
SSJ	Sandnessjoen	Norway	VAR	Varna	Bulgaria
STN	London Stansted Apt	United Kingdom	VAS	Sivas	Turkey
STR	Stuttgart Airport	Germany	VAW	Vardo	Norway
STW	Stavropol	Russia	VBS	Verona Brescia/Montichiari Airport	Italy
SUF	Lamezia Terme	Italy			
SUJ	Satu Mare	Romania	VBY	Visby	Sweden
SVG	Stavanger	Norway	VCE	Venice Marco Polo Apt	Italy
SVJ	Svolvaer	Norway	VDB	Fagernes	Norway
SVL	Savonlinna	Finland	VDE	Valverde	Spain
SVO	Moscow Sheremetyevo International Apt	Russia	VDS	Vadso	Norway
			VGO	Vigo	Spain
SVQ	Sevilla Airport	Spain	VHM	Vilhelmina	Sweden
SVX	Yekaterinburg	Russia	VIE	Vienna International	Austria
SXB	Strasbourg	France	VIT	Vitoria	Spain
SXF	Berlin Schoenefeld Apt	Germany	VKO	Moscow Vnukovo International Apt	Russia
SXL	Sligo Ireland	Ireland			
SXZ	Siirt	Turkey	VLC	Valencia Airport	Spain
SYY	Stornoway	United Kingdom	VLL	Valladolid	Spain
SZF	Carsamba	Turkey	VLY	Anglesey	United Kingdom
SZG	Salzburg W A Mozart	Austria	VNE	Vannes	France
SZZ	Szczecin	Poland	VNO	Vilnius	Lithuania
TAT	Poprad	Slovakia	VNT	Ventspils Latvia	Latvia
TAY	Tartu	Estonia	VOG	Volgograd	Russia
TBS	Tbilisi	Georgia	VOL	Volos	Greece
TCE	Tulcea	Romania	VOZ	Voronezh	Russia
TEQ	Tekirdag	Turkey	VPN	Vopnafjordur Iceland	Iceland
TER	Terceira	Portugal	VRK	Varkaus	Finland
TFN	Tenerife Norte	Spain	VRN	Verona Villafranca Airport	Italy
TFS	Tenerife Sur Apt	Spain	VRY	Vaeroy	Norway
TGD	Podgorica	Montenegro	VSG	Lugansk Ukraine	Ukraine
TGK	Taganrog	Russia	VST	Stockholm Vasteras Apt	Sweden
TGM	Tirgu Mures	Romania	VVO	Vladivostok	Russia
THN	Trollhattan/Vanersborg	Sweden	VXO	Vaxjo	Sweden
THO	Thorshofn Iceland	Iceland	WAT	Waterford	Ireland
TIA	Tirana	Albania	WAW	Warsaw	Poland
TIV	Tivat	Montenegro	WIC	Wick	United Kingdom
TJK	Tokat	Turkey	WMI	Warsaw Modlin	Poland
TKU	Turku	Finland	WRO	Wroclaw	Poland
TLL	Tallinn	Estonia	WRY	Westray	United Kingdom
TLN	Toulon/Hyeres	France	XRY	Jerez	Spain
TLS	Toulouse	France	YEI	Bursa	Turkey
TLV	Tel Aviv-yafo Ben Gurion International	Israel	ZAD	Zadar	Croatia
			ZAG	Zagreb	Croatia
TMP	Tampere	Finland	ZAZ	Zaragoza Airport	Spain
TOF	Tomsk	Russia	ZRH	Zurich Airport	Switzerland
TOJ	Madrid Torrejon	Spain	ZTH	Zakinthos Island	Greece
TOS	Tromso	Norway			
TPS	Trapani	Italy			
TRD	Trondheim Vaernes Airport	Norway			

Appendix C Weights metropolitan regions

airport	metropolitan region	GNC
JFK	New York-Newark-Bridgeport CSA	1.00
EWR	New York-Newark-Bridgeport CSA	1.00
LGA	New York-Newark-Bridgeport CSA	1.00
ISP	New York-Newark-Bridgeport CSA	1.00
SWF	New York-Newark-Bridgeport CSA	1.00
HVN	New York-Newark-Bridgeport CSA	1.00
HPN	New York-Newark-Bridgeport CSA	1.00
LHR	London Metropolitan Area	0.99
LGW	London Metropolitan Area	0.99
STN	London Metropolitan Area	0.99
LTN	London Metropolitan Area	0.99
LCY	London Metropolitan Area	0.99
CAN	Pearl River Delta	0.83
HKG	Pearl River Delta	0.83
SZX	Pearl River Delta	0.83
ZUH	Pearl River Delta	0.83
MFM	Pearl River Delta	0.83
CDG	Ile de France	0.76
ORY	Ile de France	0.76
LBG	Ile de France	0.76
HND	Greater Tokyo Area	0.73
NRT	Greater Tokyo Area	0.73
SIN	Singapore Extended Metropolitan Region	0.73
XSP	Singapore Extended Metropolitan Region	0.73
PVG	Yangtze River Delta	0.72
SHA	Yangtze River Delta	0.72
NKG	Yangtze River Delta	0.72
HGH	Yangtze River Delta	0.72
WUX	Yangtze River Delta	0.72
NGB	Yangtze River Delta	0.72
NTG	Yangtze River Delta	0.72
CZX	Yangtze River Delta	0.72
HSN	Yangtze River Delta	0.72
BWU	Sydney Metropolitan Area	0.72
SYD	Sydney Metropolitan Area	0.72
PEK	Greater Beijing Region	0.70
NAY	Greater Beijing Region	0.70
TSN	Greater Beijing Region	0.70
MXP	Milan Metropolitan Area	0.67
LIN	Milan Metropolitan Area	0.67
BGY	Milan Metropolitan Area	0.67
MAD	Madrid Metropolitan Area	0.66
TOJ	Madrid Metropolitan Area	0.66
ICN	Seoul National Capital Area	0.64
GMP	Seoul National Capital Area	0.64
BRU	Flemish Diamond	0.63
ANR	Flemish Diamond	0.63
DME	Greater Moscow	0.63
SVO	Greater Moscow	0.63
VNO	Greater Moscow	0.63
YYZ	Greater Toronto Area	0.63
YTZ	Greater Toronto Area	0.63
YKZ	Greater Toronto Area	0.63
YZD	Greater Toronto Area	0.63
YOO	Greater Toronto Area	0.63
YHM	Greater Toronto Area	0.63
AMS	Deltametropolis	0.62
RTM	Deltametropolis	0.62
BOM	Mumbai Metropolitan Area	0.61
EZE	Greater Buenos Aires	0.61
AEP	Greater Buenos Aires	0.61
FDO	Greater Buenos Aires	0.61
SZB	Kuala Lumpur Metropolitan Area (KLMA)	0.60
KUL	Kuala Lumpur Metropolitan Area (KLMA)	0.60
VIE	Vienna-Bratislava Metropolitan Area	0.58
BTS	Vienna-Bratislava Metropolitan Area	0.58
WAW	Warsaw Metropolitan Area	0.56
CGH	Greater Sao Paulo	0.56
VCP	Greater Sao Paulo	0.56
GRU	Greater Sao Paulo	0.56
ZRH	European Metropolitan Region of Zurich (EMRZ)	0.56
MEX	Mexico City Metropolitan Area	0.56
TLC	Mexico City Metropolitan Area	0.56
HLP	Jakarta Metropolitan Area	0.56
CGK	Jakarta Metropolitan Area	0.56
DMK	Bangkok Metropolitan Area	0.55
BKK	Bangkok Metropolitan Area	0.55
DUB	Greater Dublin Area	0.55
TSA	Greater Taipei	0.55
TPE	Greater Taipei	0.55
FCO	Rome Metropolitan Area	0.54
CIA	Rome Metropolitan Area	0.54
SAW	Istanbul Metropolitan Region	0.53
IST	Istanbul Metropolitan Region	0.53
RFD	Chicago-Naperville-Michigan City CSA	0.53
MDW	Chicago-Naperville-Michigan City CSA	0.53
ORD	Chicago-Naperville-Michigan City CSA	0.53
LIS	Lisbon Metropolitan Area	0.52
HHN	Frankfurt-Main Region	0.51
FRA	Frankfurt-Main Region	0.51
BMA	Stockholm-Mälar Metropolitan Region	0.50
ARN	Stockholm-Mälar Metropolitan Region	0.50
NYO	Stockholm-Mälar Metropolitan Region	0.50
VST	Stockholm-Mälar Metropolitan Region	0.50
BUD	Budapest Agglomeration	0.49
PRG	Prague Metropolitan Area	0.49
ATH	Attica Basin (Athens/Piraeus Metropolitan Region)	0.49
CCS	Caracas Metropolitan Region	0.47
AKL	Auckland Metropolitan Area	0.47
STI	Santiago Metropolitan Region	0.47
OAK	San Francisco-San Jose-Oakland CSA (SF Bay Area)	0.46
SFO	San Francisco-San Jose-Oakland CSA (SF Bay Area)	0.46
SYQ	San Francisco-San Jose-Oakland CSA (SF Bay Area)	0.46
SJC	San Francisco-San Jose-Oakland CSA (SF Bay Area)	0.46
DCA	Washington-Baltimore-Northern Virginia CSA	0.44
BWI	Washington-Baltimore-Northern Virginia CSA	0.44
IAD	Washington-Baltimore-Northern Virginia CSA	0.44
MEL	Melbourne Metropolitan Area	0.44
AVV	Melbourne Metropolitan Area	0.44
MEB	Melbourne Metropolitan Area	0.44
LAX	Los Angeles-Long Beach-Riverside CSA	0.43
BCN	Barcelona Metropolitan Region	0.43
HLA	Tshwane Metropolitan Area (Johannesburg-Pretoria)	0.43
JNB	Tshwane Metropolitan Area (Johannesburg-Pretoria)	0.43
MNL	Metro Manila	0.42
ATL	Atlanta-Sandy Springs-Gainesville CSA	0.42
BOG	Metropolitan Area of Bogota	0.42
DEL	Delhi National Capital Region (India)	0.42
TLV	Gush Dan (Tel Aviv & Central Israël)	0.41
SDV	Gush Dan (Tel Aviv & Central Israël)	0.41
OTP	Bucharest Metropolitan Area	0.40
HEL	Helsinki Metropolitan Area	0.40
DXB	Dubai-Sjarjah Metropolitan Region	0.40
SHJ	Dubai-Sjarjah Metropolitan Region	0.40
TXL	Berlin-Brandeburg Metropolitan Area	0.40
THF	Berlin-Brandeburg Metropolitan Area	0.40
SXF	Berlin-Brandeburg Metropolitan Area	0.40

OSL	Greater Oslo Region	0.40	MVD	Montevideo	0.31
TRF	Greater Oslo Region	0.40	SDU	Greater Rio de Janeiro	0.31
RYG	Greater Oslo Region	0.40	GIG	Greater Rio de Janeiro	0.31
DUS	Rhine-Ruhr-Megaplex	0.39	YUL	Grand Montréal	0.30
DTM	Rhine-Ruhr-Megaplex	0.39	YHU	Grand Montréal	0.30
CGN	Rhine-Ruhr-Megaplex	0.39	NBO	Nairobi Metropolitan Area	0.30
NRN	Rhine-Ruhr-Megaplex	0.39	WIL	Nairobi Metropolitan Area	0.30
CPH	Oresund region	0.39	SGN	Ho Chi Minh City Metropolitan Area	0.30
MMX	Oresund region	0.39	PTY	Panama City Metropolitan Area	0.29
RUH	Riyadh	0.38	PAC	Panama City Metropolitan Area	0.29
GVA	Franco-Vaud-Geneva Metropolitan Area	0.38	MAA	Chennai Metropolitan Area	0.29
HAM	Metropolregion Hamburg	0.37	CMN	Greater Casablanca Region	0.28
LBC	Metropolregion Hamburg	0.37	MAN	Manchester-Liverpool-Leeds-Sheffield	0.28
XFW	Metropolregion Hamburg	0.37	LPL	Manchester-Liverpool-Leeds-Sheffield	0.28
CAI	Greater Cairo	0.37	LBA	Manchester-Liverpool-Leeds-Sheffield	0.28
BLR	Greater Bangalore	0.36	BLK	Manchester-Liverpool-Leeds-Sheffield	0.28
JED	Jeddah	0.36	BNE	Brisbane Metropolitan Area	0.28
LUX	Luxemburg Cross-Border Metropolitan Area	0.35	DEN	Denver-Aurora-Boulder CSA	0.28
AGB	Munich Metropolitan Region	0.35	STR	Stuttgart Metropolitan Region	0.28
MUC	Munich Metropolitan Region	0.35	YVR	Greater Vancouver Regional District	0.28
KWI	Kuwait Metropolitan Area	0.35	YXX	Greater Vancouver Regional District	0.28
DFW	Dallas-Fort Worth Metroplex	0.35	UIO	Metropolitan District of Quito	0.27
DAL	Dallas-Fort Worth Metroplex	0.35	ZAG	Zagreb Metropolitan Area	0.27
BOS	Boston-Worcester-Manchester CSA	0.34	CPT	Cape Town Metropolitan Area	0.26
PVD	Boston-Worcester-Manchester CSA	0.34	GUA	Guatemala City Metropolitanb Area	0.26
MHT	Boston-Worcester-Manchester CSA	0.34	MSP	Minneapolis-St.Paul-St. Cloud CSA	0.26
IEV	Kiev Metropolitan Area	0.34	SJO	San José Metropolitan Area (Costa Rica)	0.26
KBP	Kiev Metropolitan Area	0.34	LJU	Ljubljana Urban Region	0.26
MIA	South Florida Metropolitan Area	0.34	STD	Metropolitan Santo Domingo	0.26
FLL	South Florida Metropolitan Area	0.34	GLA	Glasgow-Edinburgh	0.25
LIM	Lima Metropolitana	0.33	EDI	Glasgow-Edinburgh	0.25
HOU	Houston-Baytown Huntsville CSA	0.32	PIK	Glasgow-Edinburgh	0.25
IAH	Houston-Baytown Huntsville CSA	0.32	BFI	Seattle Metropolitan Area	0.25
SOF	Urban Region of Sofia	0.32	SEA	Seattle Metropolitan Area	0.25
BEY	Beirut Metropolitan Area	0.32	LKE	Seattle Metropolitan Area	0.25
NIC	Nicosia	0.32		All others	0.20
KHI	Karachi Metropolitan Area	0.31			

Appendix D List of LCC carriers

Carrier name	Carrier code
Aerolinea Principal	5P
Air One	AP
Air Transat	TS
Aircompany Khors	KO
Ajet Aviation	ZU
Allegiant Air	G4
Almasria Universal Airlin	UJ
AMC Airlines	YJ
AMSTERDAM AIRLINES	AAN
Arkefly	OR
Astra Airlines	A2
Atlas Blue	8A
Axis Lines	O8
Balkan Holidays Air	BGH
Blue Air	0B
Blue Wings	QW
bmibaby	WW
Centralwings	C0
Clickair	XG
Condor Flugdienst	DE
Corendon Airlines	CAI
Corendon Dutch Airlines	CND
Corsair Intl	SS
Czech Connect Airlines	CQ
dba	DI
easyJet	U2
easyJet Switzerland	DS
Edelweiss Air	WK
First Choice Airways	FCA
First Choice Airways	DP
flyglobespan	Y2
FlyNordic	LF
germanwings	4U
GIRjet	8G
Hapagfly	HF
Helvetic Airways	2L
Hola Airlines	H5
Intersky	3L
Jazeera Airways	J9
Jeju Airlines	7C
Jet2.com	LS
Jet4you	8J
Jetairfly	JAF
JetX	GX
Lauda Air Italy	L4
Livingston	LM
LTU International Airways	LT
Lydd Air	LYD
Martinair Holland	MP
Monarch Airlines	ZB
Monarch Charter	MON
MyAir	8I
MyTravelLite	VZ
Norwegian Air Shuttle	DY
Pegasus Airlines	H9
PublicCharters	P1
Ryanair	FR
SafariLink	F2
Sayakhat Air Company	W7
Scoot	TZ
Sky Express	XW
SkyEurope	NE
Sterling	NB
Sterling Blue	DM
Sun Country Airlines	SY
Sunny Airways	SUW
Taban Air	HH
Tara Air	TB
Thomas Cook Airlines	TCX
Thomson Airways	TOM
Tiger Airways Australia	TT
Tonlesap Airlines	K9
Transavia.com	HV
TRIP Linhas Aereas	T4
TUIfly	X3
Viking Airlines	4P
Virgin America	VX
Virgin Express	TV
Volare S.P.A.	VE
Vueling Airlines	VY
Wataniya Airways	KW
White Coloured by You	WI
Wizz Air	W6
Wizz Air Bulgaria	8Z
Wizz Air Ukraine	WAU
Yamal Airlines	YC
Zoom Airlines	Z4
Zoom Airlines (UK)	ZX

Appendix E Technical model description

Using panel data regression analysis a model which estimates the GDP per capita in a radius of 100 kilometres around the airport was derived. Separate models were estimated, for small, medium-sized and large airports.

The model contains both airport related variables (denoted by x) and non-airport related (socio-economic) variables (denoted by z):

$$\ln(GDP\ per\ capita_{it}) = \alpha_1 + \beta' x_{i,t-1} + \gamma' z_{it} + u_i + \epsilon \tag{E.3}$$

Where β and γ denote the coefficient vectors for respectively airport related and non-airport related variables. u_i is an airport-specific constant which captures the 'fixed effects' of the level of GDP per capita around the airport. This airport-specific constant can capture either airport-related variables v_i (such as the type of airport or the average size of an airport), or non-airport related variables w_i (for example if the airport is located in a densely populated area) that do not vary over time. By an additional OLS regression analysis we isolate airport-related variables from these fixed effect constants:

$$u_i = \alpha_2 + \delta' v_i + \theta' w_i + \epsilon \tag{E.4}$$

Where δ_l are the airport related coefficients and θ_m the non-airport related coefficients. Our objective is to estimate the share of GDP per capita attributable to an airport in a certain year. As follows from (E.1) and (E.2), the natural logarithm of GDP is a linear combination of airport-related variables (A) and other variables (B), such that:

$$\ln(GDP\ per\ capita) = A + B \tag{E.5}$$

Where:

$$A = \beta' x_{i,t-1} + \delta' v_i \tag{E.6}$$

$$B = \gamma' z_{it} + \theta' w_i + \alpha_1 + \alpha_2 + \epsilon \tag{E.7}$$

Now we are interested in the share of A in the GDP per capita around the airport. Taking the exponent in the left and right hand of equation (3), we obtain:

$$GDP = e^{(A+B)} = e^A \cdot e^B \tag{E.8}$$

The share of A in $e^{(A+B)}$, (S_A) is determined by:

$$S_A = \frac{\frac{e^A}{e^{A+B}}}{\left(\frac{e^A}{e^{A+B}} + \frac{e^B}{e^{A+B}}\right)} \tag{E.9}$$

Which can be rewritten as:

$$S_A = \frac{e^{-B}}{e^{-B} + e^{-A}} \tag{E.10}$$

For a given airport *i* we know the GDP per capita in a certain year. The contribution of this airport to the regional GDP is obtained by multiplying the GDP per capita by S_A. The total GDP effect in the region is obtained by multiplying the airport's contribution on GDP per capita by the total population around the airport.