



**HOW AIR TRANSPORT CONNECTS THE WORLD
A NEW METRIC OF AIR CONNECTIVITY
AND ITS EVOLUTION BETWEEN 1990 AND 2012**

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by

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SUMMARY

Objective

Scheduled air transport services connect airports throughout the world and thereby enable interaction on a global scale. By doing so, they spur globalization (Hummels, 2007) as well as social and economic development (Lakshmanan, 2011). In order to facilitate integration of regions into global value chains, planners, scholars and policymakers therefore need to understand as to how scheduled air transport services link a region to other markets. For this purpose, connectivity metrics have been developed, which measure the degree of connections between airports (Burghouwt, Redondi, 2013). In particular, the ‘connection quality-weighting’ approach (Veldhuis, 1997; Burghouwt, de Wit, 2005) has been used to compute the aggregate quality of all available connections at an airport with regard to their properties in quickly bridging distances. However, such a metric has neither been calibrated on the basis of observed passenger behavior nor been computed for the world’s airports across a multi-decade time series. This paper sets out to develop the first such metric and to discuss global airline network development between 1990 and 2012 from a connectivity perspective.

Methodology

The Global Connectivity Index (GCI) for each airport is computed by summing the connection-quality of each available flight connection weighted by the interaction potential, to which the connection provides access. This requires three levels of analysis. First, on the link-identification level, we identify from OAG flight schedules all scheduled nonstop and onestop connections, which are available to passengers at each airport. Second, on the link-quality level, we compute each connection's frequency and relative connectivity value as compared to (hypothetical) nonstop flights. The relative connectivity value is derived from flight duration and layover time and calibrated through observed routing data for US passengers. Third, on the destination-quality level, we model the interaction potential, to which each worldwide airport provides access. For this purpose, we use gridded wealth-adjusted population data and a distance-decay function.

Results

By computing yearly GCI scores for 1990 to 2012, we analyze the geography of and trends in worldwide connectivity. While we observe significant growth of aggregate connectivity at the world's airports, the growth patterns are heterogeneous with regard to the type of connectivity as well as time and location: First, nonstop connectivity increases significantly and steadily at Asian airports from 1990 to 2012, yet remains relatively unchanged at North American airports and European airports between 2000 and 2012. Economic crises as well as consolidation among legacy carriers, which has been offset by the emergence of newly established Low Cost Carriers, can be considered key contributors to the limited growth in nonstop connectivity in North America and Europe. Second, growth in global onestop connectivity outperforms growth in nonstop connectivity by a factor of ~3.5. Onestop connectivity growth coincides with the extension of global hub-and-spoke networks through increasing cooperation among airlines.

1 Introduction

Air transport connections enable interaction on a global scale, thereby catalyzing globalization (Hummels, 2007) and spurring social and economic development (Lakshmanan, 2011). Consequently, there is a significant societal interest to analyze air transport networks in terms of the connections, which airports offer to potential users in its surrounding regions. In order to appraise air transport-related policy measures such as, for example, airport infrastructure investments or route subsidies, there is a need for planners and policymakers to consider the impact of these measures on air transport connections.

Researchers have evaluated air transport networks and their connections with different approaches as summarized in recent reviews by Zanin and Lillo (2013) and Burghouwt and Redondi (2013). While Zanin and Lillo (2013) focus on analyses of network structure and overall network performance, Burghouwt and Redondi (2013) specifically address the concepts of ‘connectivity’ and ‘centrality’. They define connectivity as the degree of connection between nodes (airports) in a network and centrality as the significance of transfer points in forming indirect connections. In their review, Burghouwt and Redondi (2013) distinguish several metrics, including metrics based on shortest and quickest connection paths (e.g. Shaw, Ivy, 1994; Malighetti et al., 2008; Paleari et al., 2010; Zhang et al., 2010) as well as metrics computed by summing connection quality over all available connections (e.g. Veldhuis, 1997; Burghouwt, de Wit, 2005). However, they do not discuss the relative merits of these metrics. While shortest and quickest paths analyses study overall network quality through optimal connections, ‘connection quality-weighting’ approaches focus on the ‘value’ of each connection as perceived by passengers. The latter approach consider all feasible connections for reaching each available destination and use a set of assumptions to compute the (relative) ‘connectivity value’ of each link. Connectivity values are derived from the relative quality of each connection in terms of passengers’ efforts in traveling on that connection (i.e. flight duration and layover time). Transaction-specific idiosyncrasies such as tastes or fares, which vary among potential passengers and impact on each passenger’s itinerary choice, are not considered since they cannot be aggregated to the route level, yet.

To date, no analysis exists which evaluates ‘quality-weighted’ connectivity and/or centrality at the world’s airports with the help of an empirically calibrated model. Such a model is developed in this paper. We compute these metrics to analyze worldwide connectivity and centrality trends

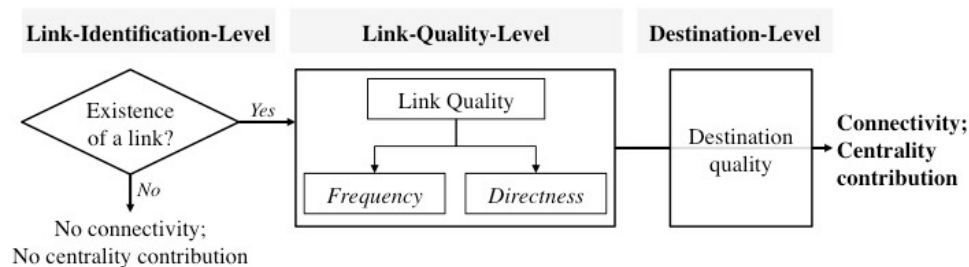
between 1990 and 2012. This period is of particular interest since it includes major changes in the airline industry by means of deregulation and liberalization in different world regions, and the emergence of global airline alliances and new airline business models.

The remainder of this paper proceeds as follows: In Section 2, the building blocks of ‘connection quality-weighted’ connectivity and centrality are outlined. Section 3 develops the connectivity and the centrality metrics. Global and world-region trends in connectivity and centrality between 1990 and 2012 are analyzed in Section 4. Section 5 concludes.

2 Building Blocks of the Model

Following ‘connection quality-weighting’ approaches (Veldhuis, 1997; Burghouwt, de Wit, 2005), we compute connectivity and centrality by assessing the quality of each air travel opportunity. For this purpose, we structure the analysis into three levels (Fig. 1).

Fig. 1.
Building blocks of the connection quality-weighting approach.



First, on the ‘link-identification-level’, we identify each airport’s travel connections to all linked destinations as well as each connection’s transfer point (if applicable). Since air transport is mostly scheduled transport, links are formed through (a series of) scheduled flights. We do not follow analyses of shortest and quickest paths (e.g. Shaw, Ivy, 1994; Malighetti et al., 2008; Paleari et al., 2010; Zhang et al., 2010), but instead identify all connections, which a passenger might consider a feasible travel option. In so doing, we follow our objective to evaluate connectivity and centrality of the entire network as perceived by passengers.

Second, the ‘link-quality-level’ assesses the ‘connectivity value’ of each connection through the efforts to overcome distances with the help of the respective connection. As shown in the itinerary choice literature (Coldren, Koppelman, 2005; Hsiao, Hansen, 2011), a connection’s quality is systematically driven by its frequency and its directness. The additional value of higher

frequencies results from a reduction in waiting time between a passenger's desired departure time and the scheduled departure time. The directness of a flight connection is a function of detours and layovers which both cause disutility to the passenger. As discussed in the introduction, fares are not considered, as fares are not a systematic property of a scheduled connection due to widespread yield management practices leading to transaction-specific fare levels.

Third, the 'destination-level' is used to account for the economic value of a connection in terms of the interaction potential, to which the respective connection provides access. Most analyses of air transport networks (e.g. Shaw, Ivy, 1994, Pailari et al., 2010) do not consider this quality dimension since they intend to evaluate traffic patterns and overall network performance without accounting for destination properties. In order to meet our objective of assessing the quality of each connection from a potential passenger's perspective and in line with the Economic Geography literature (Redding, Venables, 2004; Breinlich, 2006; Redding, 2010), we add a destination quality dimension to the connectivity model. Consequently, our connectivity metric bears some resemblance to a transport-related accessibility metric, which maps the level of potential interaction accessible through transport from a specific location (Geurs, van Wee, 2004).

3 The Model

3.1 The Connectivity Model

The connectivity metric is derived from the building blocks as outlined in Section 2. It extends a connectivity metric developed by Wittman and Swelbar (2014) through adding a global perspective, an itinerary model, an assessment of onestop flights' relative connectivity value and continuous modeling of global destination quality.

To compute the Global Connectivity Index score $GCI_{a,t}$ for an airport a in year t , let \mathcal{A} be the set of world airports, $D_{a,t}$ be the set of all destination airports that can be reached from airport a in year t and $\mathcal{R}_{a,t}$ be the set of all routings which link airport a to its set of destinations $D_{a,t}$ in year t . Assuming the connectivity metric to be the sum of potential destinations' quality weighted by properties of each routing, we yield eq. (1).

$$GCI_{a,t} = \sum_{r \in \mathcal{R}_{a,t}} \alpha_{r,t} f_{r,t} w_{d_r,t} \quad (1)$$

where $\alpha_{r,t}$ maps the directness of routing $r \in \mathcal{R}_{a,t}$, $f_{r,t}$ measures routing r 's frequency in year t and $w_{d_r,t}$ is the destination quality of route r 's final destination airport $d_r \in D_{a,t} \subseteq \mathcal{A}$ in year t . The model is parameterized with the help of four sub-models, which are discussed in the subsequent paragraphs.

3.1.1 Itinerary Model

The Itinerary Model parameterizes the 'link-identification-level' by identifying each departure airport $a \in \mathcal{A}$'s set of valid routings $\mathcal{R}_{a,t}$ in year t . For the identification of $\mathcal{R}_{a,t}$, two routing types are distinguished:

1. Nonstop Routings

A nonstop routing r consists of a single scheduled flight which links departure airport $a_r \in \mathcal{A}$ to destination airport $d_r \in D_{a,t}$ without a stop. It is identified through the tuple $i_r^{nonstop} = (a_r; d_r; airline_r; ta_{r,d_r})$ where $airline_r$ is the operating airline of routing r 's flight and ta_{r,d_r} is routing r 's arrival time at destination airport d_r . The set of airport a 's nonstop routings $\mathcal{R}_{a,t}^{nonstop}$ is derived from flight schedules as published in the Official Airline Guide (OAG). It is obtained by listing all scheduled passenger flights, which depart

airport a during year t .¹ For multi-segment flights (e.g. NZ1 on LHR-LAX-AKL), we treat the first destination airport as being connected through a nonstop routing (e.g. LHR-LAX for LHR or LAX-AKL for LAX) only.

2. Onestop Routings

A onestop routing r links its departure airport $a_r \in \mathcal{A}$ to its destination airport $d_r \in \mathcal{A}$ through two scheduled flights and a transfer at layover airport $l_r \in \mathcal{A}$. It is identified through tuple $i_r^{onestop} = (a_r; l_r; d_r; air.f1_r; air.f2_r; ta_{r,l_r}; td_{r,l_r})$ where $air.f1_r$ and $air.f2_r$ are the operating airlines of routing r 's first and second flight respectively, ta_{r,l_r} is the arrival time of routing r 's first flight at layover airport l_r and td_{r,l_r} is the departure time of routing r 's second flight from layover airport l_r . Identification of an airport a 's set of valid onestop routings $\mathcal{R}_{a,t}^{onestop}$ builds on the set of its nonstop routings $\mathcal{R}_{a,t}^{nonstop}$. For each nonstop flight, we list all connecting flights in airport l_r 's flight schedule to build all potential onestop routings, each mapped by $i_r^{onestop}$. A potential onestop routing is considered a feasible onestop routing $r \in \mathcal{R}_{a,t}^{onestop}$ if the following conditions are met:

- i. Since passengers need sufficient time for a transfer at layover airport l_r , a valid routing must meet $td_{r,l_r} - ta_{r,l_r} \geq 30 \text{ min}$.²
- ii. If flights of routing r are operated by different airlines or if the operating airline does not sell connecting itineraries on a single ticket, passengers will have to buy separate tickets, will have to bear the risk of missing their connection (without monetary compensation) and will have to re-check their baggage. Given this disutility, only onestop routings with two flights operated by a single airline, which sells connecting tickets,³ are considered feasible routings.⁴ Exceptions are routings, which are operated under code-share agreements. Such routings are evaluated as if the itinerary was operated by a single airline (Oum, Park, 1997; Park, 1997). This yields the conditions in eqs. (2).

¹ For this analysis, the OAG data is filtered to include (i.) scheduled passenger flights only and (ii.) to remove multiple listings of a single flight (i.e. codeshare entries).

² We note that minimum layover time can exceed 30 min at numerous airports and longer minimum connection times (MCT) have been assumed in the literature (e.g. Veldhuis, 1997, Paleari et al., 2010). As most passengers transfer at hubs where airlines coordinate incoming and outgoing traffic to offer indirect connectivity (Burghouwt, de Wit, 2005), bias of using a short MCT is smaller than using long MCT.

³ Many European Low Cost Carriers, for example, do not offer connecting tickets. A year-specific list of all airlines, which do not offer connecting flights, is compiled through desktop research. In a first step, we use an heuristic approach so that all airlines, which offer code shares, are assumed to sell transfer connections.

⁴ We note that this approach implicitly assumes a prohibitively high disutility of 'self-help hubbing' (Malighetti et al., 2008).

$$(air.f1_r = air.f2_r \wedge transfer(air.f1_r) = 1) \quad (2a)$$

$$\vee air.f1_r \in \Gamma_{f2_r} \vee air.f2_r \in \Gamma_{f1_r} \quad (2b)$$

where Γ_{f1_r} [Γ_{f2_r}] is the set of airline codes on flight 1 [flight 2] of routing r ⁵ and

$$transfer(a) = \begin{cases} 1 & \text{if airline } a \text{ offers connecting tickets} \\ 0 & \text{else} \end{cases} \quad (3)$$

We assume the set of all routings to consist of the set of nonstop routings and the set of onestop routings ($\mathcal{R}_{a,t} = \mathcal{R}_{a,t}^{nonstop} \cup \mathcal{R}_{a,t}^{onestop}$). Burghouwt and Redondi (2013) suggest that limiting the analysis to nonstop and onestop connections induces negligible bias for short- and medium-haul connections, while some bias might exist for ultra-long-haul journeys ($\geq 8,000$ km). For our model, we regard such potential bias to be negligible for two reasons. First, transfers result in significant additional travel time for taxi, take-off and landings as well as for potential detours. Second, empirical analyses show that waiting time and transfer time cause high disutility to passengers (Veldhuis, 1997; Wardman, 2004). Since our model considers these dimensions of connection quality, it would assign very low connectivity values to itineraries with more than one transfer so that such itineraries would contribute only negligibly to overall connectivity.

3.1.2 Frequency Model

Frequency is considered as a driver of connectivity on the ‘link-quality-level’. Since a routing r is defined through the combination of origin airport $a_r \in \mathcal{A}$, layover airport $l_r \in \mathcal{A}$ (if applicable), destination airport $d_r \in \mathcal{A}$, operating airline(s) and arrival and departure times, we map multiple daily frequencies as different routings.⁶ In an effort to avoid potential seasonality bias caused by computing connectivity scores for a small number of days (e.g. Malighetti et al., 2008; Paleari et al., 2010; Redondi et al., 2011), we run a yearly connectivity analysis.⁷ Therefore, frequency $f_{r,t}$ maps the number of days on which routing r is operated during year t . For onestop routings, both flights have to be operated to consider the routing operational.

⁵ Codeshare information is drawn from OAG schedule data. Each entry’s codeshare set, which is posted in the original OAG schedules, is completed through adding codes from duplicate entries.

⁶ Given the additive nature of the GCI score, this approach is equivalent to an approach which does not use a time-sensitive routing definition and therefore, explicitly considers frequency during the day.

⁷ The data, which is used for this purpose, represent schedules as loaded in the OAG database in December (1990-1998) or January (1999-2012).

3.1.3 Directness Valuation Model

The directness valuation model evaluates the quality of a routing in terms of its directness. In previous connectivity analyses that consider routings' connection quality authors have suggested to uniformly value onestop routings at one eighth of the value of a nonstop routing (Emrich, de Harris, 2008; Wittman, Swelbar, 2014). Since onestop routings are heterogeneous with respect to their detour and layover though, we follow Veldhuis (1997) and Burghouwt and de Wit (2005) and derive a relative connectivity value α_r for each routing r . This value is introduced so as to map the relative disutility of onestop routings as compared to (hypothetical) nonstop routings. We do not derive the relative connectivity value from disutility as compared to the quickest path (Redondi et al., 2011) because quickest paths' directness is heterogeneous (Palaria et al., 2010) so that it cannot be used to normalize disutility. As shown in eq. (4), we therefore model α_r as a function $g(\cdot)$ of its detour factor Δ_r .

$$\alpha_r = g(\Delta_r) \quad (4)$$

where the detour factor Δ_r is computed as the ratio of total perceived travel time on routing r as compared to the travel time on a (hypothetical) direct flight between airports a_r and d_r . This yields eq. (5).⁸

$$\Delta_r = \begin{cases} 1 & \forall r \in R_t^{nonstop} \\ \frac{ftime_{a_r, l_r} + ftime_{l_r, d_r} + \vartheta \cdot ltime_r}{ftime_{a_r, d_r}} & \forall r \in R_t^{onestop} \end{cases} \quad (5)$$

where $ftime_{c,d}$ is the duration of a flight between airports c and d , $ltime_r$ is the layover time at airport l_r on route r and ϑ is the relative value of layover time as compared to flight time. The latter is considered because empirical evidence suggests the disutility of in-vehicle time (flight time) to be lower than the disutility of waiting (layover) time (Veldhuis, 1997; Wardman, 2004). Given recent empirical analyses on the value of waiting time for public transport, we assume $\vartheta = 2$ (Abrantes, Wardman, 2011).⁹

For the calculation of Δ_r , routing r 's scheduled layover time is computed as $ltime_r = td_{r, l_r} - ta_{r, l_r}$. In order to use a consistent set of operational assumptions for all flights and to

⁸ Note that $\Delta_r = 1 \quad \forall r \in R_t^{nonstop}$ since there is no layover and no detour for direct flights.

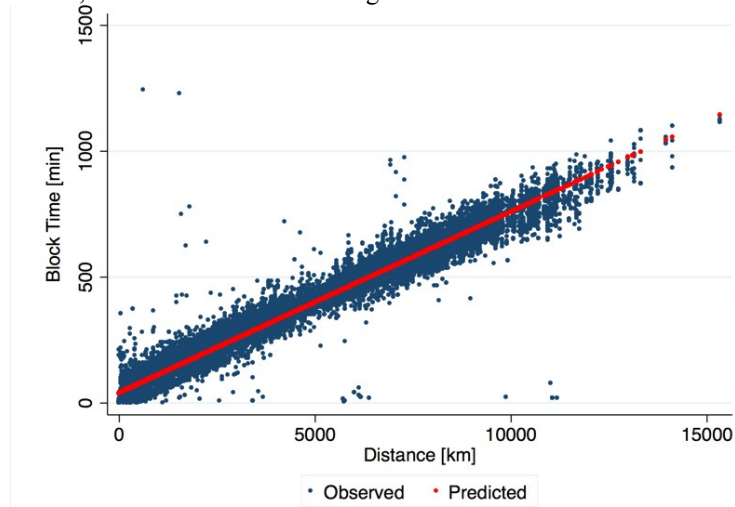
⁹ Veldhuis (1997) assumes $\vartheta = 3$ and Burghouwt and de Wit (2005) use $\vartheta = 2.4$, but none of the analyses derive their values from published empirical literature.

homogenize scheduling behavior of airlines, the duration of nonstop flights is estimated with the help of the linear block-time model in eq. (6).

$$ftime_{a,b} = \beta_0 + \beta_1 \cdot dist_{a,b} \quad (6)$$

This model assumes a flight's block-time (scheduled gate-to-gate duration of a flight) to be a linear function of its great circle distance $dist_{a,b}$ and a fixed block-time component β_0 for taxiing, take-off and landing. The parameters β_0 and β_1 are estimated by using OLS procedures¹⁰ and OAG's block-time data on 27.66m worldwide scheduled nonstop flights in 2008. Great circle distance for each flight is computed by using geographical airport positions from the Open Flights Airport Database. The estimates are reported in Tab. 1. In Fig. 2, a scatterplot of the data and of the block time predictions is presented. The results show a high fit of the model so that the empirically calibrated model can be used to obtain scheduled block-time predictions.

Fig. 2.
Block time, estimated block time and great circle distance.



Tab. 1.
Estimation results for the block-time[#] model.

Parameter	Variable	Estimate
β_0	<i>cons.</i>	39.12*** (0.032)
β_1	$dist_{a,b}$	0.072*** (0.000)
R^2		0.9667
N		27,661,130

Standard errors in parenthesis.

[#] Block-times are reported in minutes.

*** Significant at the 1 % level.

¹⁰ By following this approach, we implicitly assume an 'average flight scenario' for all flights. This scenario does neither account for route-specific impacts of aircraft choice nor for route-specific impacts of congestion or prevailing weather conditions. Thus, flight time differences result from ceteris paribus variations of distance, only.

To compute relative connectivity values α_r , we parameterize function $g(\cdot)$ as follows:

1. We normalize the relative connectivity value of a nonstop connection $r \in R_t^{nonstop}$ to $\alpha_r = 1$. This yields $\alpha_r = g(\Delta_r = 1) = 1$.
2. We assume that a critical detour factor $\widehat{\Delta}$ exists so that $g(\Delta_r) = 0 \quad \forall \Delta_r \geq \widehat{\Delta}$. Thus, a onestop routing r is assigned a relative connectivity value of 0, if passengers are not willing to accept its detour ($\Delta_r > \widehat{\Delta}$).

By using linear interpolation for $1 \leq \Delta_r \leq \widehat{\Delta}$, we yield eq. (7).

$$\alpha_r = \max\left(0, \frac{\widehat{\Delta}}{\widehat{\Delta} - 1} - \frac{1}{\widehat{\Delta} - 1} \cdot \Delta_r\right) \quad (7)$$

Although previous analyses have assumed a maximum detour factor (Veldhuis, 1997; Burghouwt, de Wit, 2005; Redondi et al., 2011), $\widehat{\Delta}$ has not yet been calibrated empirically. For the calibration, this analysis studies Q2-2011 US-domestic ticket data from the DB1B sample on the degree of detour that passengers are willing to bear. For each onestop ticket in the sample, we compute Δ_r by using ticket information and complementary OAG flight schedule data. $\widehat{\Delta}$ is estimated through the 95th percentile¹¹ of the observed Δ_r (Tab. 2). We do not use the observed maximum of Δ_r , since the distribution of observed Δ_r is positively skewed and leptokurtic¹² due to potential outliers and/or unlabeled multi-segment itineraries.

In line with Veldhuis (1997), one might argue that $\widehat{\Delta}$ is a function of (hypothetical) direct flight distance $dist_{a_r, d_r}$ since the maximum acceptable detour in absolute terms might increase with $dist_{a_r, d_r}$, but declines in relative terms. By calculating the 95th percentiles of observed Δ_r for 350-km-intervals of $dist_{a_r, d_r}$ (Tab. 2), we indeed identify a reduction of $\widehat{\Delta}$ with $dist_{a_r, d_r}$. To avoid arbitrary breaks, $\widehat{\Delta}$ conditional on $dist_{a_r, d_r}$ is modeled through linear interpolation of the estimates (Fig. 3). The DB1B sample contains US-domestic tickets only so that 96.3 % of the covered nonstop flights are shorter than 4,200 km. Given visual indications of $\widehat{\Delta}$'s convergence towards a constant value for high $dist_{a_r, d_r}$ (Fig. 3), we assume $\widehat{\Delta}$ to be constant for $dist_{a_r, d_r} \geq 4200$ km.

To validate the directness valuation model, we compute critical layover time and relative connectivity values for connections with a 45 min layover. The results are shown in Tab. 3. We

¹¹ The 92nd and the 97th percentile are considered to assess the sensitivities.

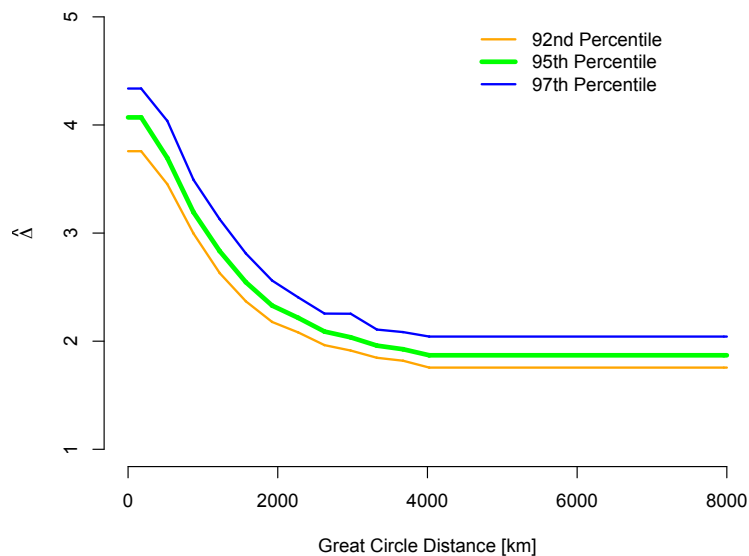
¹² Skewness $v = 6.68$ and kurtosis $\omega = 130.91$.

find that the weights (for a 45 min layover) and critical layover times appear to be within reasonable bounds, which provides evidence for the validity of the directness valuation model.

Tab. 2.
Percentiles of Δ_r in Q2-2011 DB1B tickets.

Distance range		92nd	95th	97th
from [km]	to [km]	Percentile	Percentile	Percentile
0	350	3.757253	4.070018	4.3370387
350	700	3.4519708	3.6936926	4.0369704
700	1050	2.9950553	3.1914789	3.4916569
1050	1400	2.6292191	2.8322571	3.1274016
1400	1750	2.368249	2.544571	2.8105519
1750	2100	2.177788	2.329377	2.560708
2100	2450	2.0806659	2.2152831	2.4047286
2450	2800	1.9633982	2.0890465	2.2553335
2800	3150	1.9133304	2.0356163	2.2538368
3150	3500	1.8464689	1.9590001	2.1074851
3500	3850	1.819149	1.9255417	2.0841169
3850	4200	1.7557251	1.8695927	2.0426838
All distances		3.1266324	3.4331318	3.8511574

Fig. 3.
Maximum relative detour factor.



Tab. 3.
Validation of the directness valuation model

Origin airport	Layover airport	Destination airport	Estimated block time		92nd Percentile $\hat{\Delta}$		95th Percentile $\hat{\Delta}$		97th Percentile $\hat{\Delta}$	
			Nonstop [min]	Onestop [min]	Critical Layover [min]*	Weight with 45 min layover	Critical layover [min]*	Weight with 45 min layover	Critical layover [min]*	Weight with 45 min layover
CDG	MUC	LHR	64	195	18	0.000	27	0.000	37	0.00
CDG	AMS	LHR	64	134	49	0.047	58	0.138	68	0.22
CDG	ARN	LHR	64	294	- **	0.000	- **	0.000	- **	0.00
CDG	FRA	JFK	459	556	125	0.462	151	0.532	191	0.61
CDG	VIE	JFK	459	643	82	0.212	108	0.315	148	0.43
CDG	LHR	JFK	459	502	152	0.617	178	0.667	218	0.72
CDG	ARN	JFK	459	642	82	0.213	108	0.316	148	0.43
CDG	MUC	HKG	730	777	252	0.751	294	0.784	357	0.82
CDG	AUH	HKG	730	889	196	0.548	238	0.607	301	0.67
CDG	JNB	HKG	730	1476	- **	0.000	- **	0.000	7	0.00
CDG	LHR	HKG	730	797	242	0.715	284	0.752	347	0.79
CDG	AMS	IST	200	266	76	0.286	90	0.365	109	0.45
CDG	ARN	IST	200	348	35	0.000	49	0.031	68	0.16
CDG	MUC	IST	200	241	89	0.403	103	0.469	122	0.54
CDG	FCO	IST	200	257	81	0.327	94	0.402	114	0.48
CDG	MAD	IST	200	350	34	0.000	48	0.023	67	0.16
CDG	SIN	SYD	1259	1304	454	0.859	525	0.877	634	0.90
CDG	ICN	SYD	1259	1322	445	0.840	516	0.861	625	0.88
CDG	PEK	SYD	1259	1314	449	0.849	520	0.868	629	0.89
CDG	DXB	SYD	1259	1323	444	0.839	516	0.860	625	0.88
CDG	HKG	SYD	1259	1301	455	0.861	527	0.879	636	0.90
BOS	ATL	MIA	185	257	70	0.240	84	0.326	104	0.42
BOS	ORD	MIA	185	317	40	0.000	54	0.073	74	0.21
BOS	IAH	MIA	185	375	12	0.000	25	0.000	45	0.00
BOS	JFK	MIA	185	226	86	0.383	99	0.453	120	0.53
BOS	ATL	LAX	341	413	93	0.372	112	0.454	142	0.54
BOS	ORD	LAX	341	380	109	0.499	129	0.565	158	0.64
BOS	CLT	LAX	341	408	95	0.390	115	0.470	144	0.56
BOS	JFK	LAX	341	386	106	0.476	126	0.545	155	0.62
BOS	MIA	LAX	341	495	52	0.053	71	0.177	101	0.31
BOS	YYZ	IAH	224	278	83	0.345	97	0.420	116	0.50
BOS	ATL	IAH	224	268	88	0.393	102	0.462	121	0.53
BOS	JFK	IAH	224	264	90	0.409	104	0.477	123	0.55
BOS	SFO	IAH	224	580	- **	0.000	- **	0.000	- **	0.00
BOS	FRA	DUS	451	516	138	0.545	164	0.605	203	0.67
BOS	CDG	DUS	451	505	143	0.577	169	0.632	208	0.69
BOS	LHR	DUS	451	492	150	0.616	176	0.666	215	0.72
BOS	ARN	DUS	451	594	99	0.316	124	0.405	163	0.50
BOS	KEF	DUS	451	517	137	0.543	163	0.603	202	0.67
BOS	FCO	DUS	451	633	79	0.201	105	0.306	144	0.42
BOS	MAD	DUS	451	576	108	0.368	133	0.451	172	0.54

* Layover time which yields $\Delta = \hat{\Delta}$ and $\alpha = 0$. Minimum connecting time and actual schedules are not considered.

** A critical layover time does not exist, since the flights use the maximum allowed additional perceived travel time.

3.1.4 Destination Quality

The destination quality model addresses the ‘destination-level’ by evaluating the level of potential economic interaction to which an airport provides access. Since interaction partners are only partially located at the airport, the model needs to (i.) define the geographical area to which airports provide access and (ii.) identify a metric for interaction potential. As shown in eq. (8), both dimensions are reflected in destination airport d_r ’s quality metric w'_{d_r} , which is defined in line with Accessibility metrics (Paez et al., 2012) and market access metrics in (New) Economic Geography (Redding, 2010).

$$w'_{d_r} = \sum_{g \in G_{d_r}} h(\text{dist}_{d_r, g}) q_g \quad (8)$$

where the set of markets G_{d_r} , to which a destination airport d_r provides access, and the decay function $h(\cdot)$, which is driven by linear distance $\text{dist}_{d_r, g}$ between airport d_r and market g , map the geography of the destination market while q_g measures market g ’s level of potential interaction.

Contrary to the geographical scope of airport catchment areas for departing passengers, no literature exists, to date, on the geographical scope of regions to which arrival airports provide access. However, it is reasonable to assume that access to regions from an arrival airport is symmetric to airport access for departing passengers. The latter has been analyzed in airport choice studies, which have identified a negative impact of airport access impedance on airport choice (Pels et al. 2001; Bařar, Bhat, 2004; Hess, Polak, 2005; Ishii et al., 2009; Marcucci, Gatta, 2011).¹³ While such evidence underlines the significance of a decay pattern, the functional form of that pattern remains unexplored, since most analyses apply choice models derived from linear or linear-log utility functions. Notable exceptions are Harvey (1987), Hess et al. (2007) and de Luca (2012). Given their results, one might expect the decay function to be inversely s-shaped. Thus, we model the decay pattern through the logistic decay function in eq. (9).

$$h(\text{dist}_{d_r, g}) = \frac{s}{(1 + e^{-x \cdot \text{dist}_{d_r, g} + u})} \quad (9)$$

which is decreasing for $x < 0$ and inversely s-shaped for $u < 0$. For $x < 0$, this pattern implies that markets far-away from an airport d_r do not significantly add to airport d_r ’s destination

¹³ We note that according to airport choice studies, air service-related attributes impact on airport choice. We do not model such attributes, as our analysis investigates the quality of the market, to which destination airports *potentially* provide access.

market quality, since $h(\cdot) \rightarrow 0$ for $dist_{d_r,g} \rightarrow \infty$. To avoid large computational burden, especially in case of using high-resolution market data, without inducing considerable error, we modify $h(\cdot)$ to include a distance threshold \widehat{dist} so that $h(dist_{d_r,g}) = 0$ for $dist_{d_r,g} > \widehat{dist}$. This yields eq. (10).

$$h(dist_{d_r,g}) = \max\left(0, \frac{s}{(1 + e^{-x \cdot dist_{d_r,g} + u})} - v\right) \quad (10)$$

Parameters s , u , v and x are fitted as follows:

1. The decay function is standardized by assuming $h(dist_{d_r,g} = 0) = 1$. Based on this assumption, the scaling parameter s is calculated as shown in eq. (11).

$$s = (1 + e^u)(v + 1) \quad (11)$$

2. Matisziw and Grubestic (2010) consider airports within 257 km as part of a person's airport choice set. By assuming symmetry of airport access and market access, we yield $\widehat{dist} = 257$ km and eq. (12).

$$v = \frac{(1 + e^u)(v + 1)}{1 + e^{-x \cdot 257 + u}} \quad (12)$$

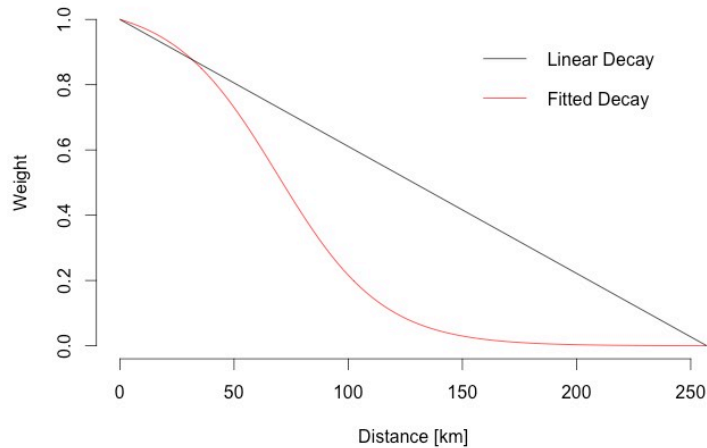
3. We consider the decay function a representation of (scaled) passenger density, so that the share of passengers $paxpct(z_r)$, who travel less than z_r km to airport d_r , at airport d_r is shown in eq. (13).

$$paxpct(z_r) = \frac{\int_0^{z_r} h(dist_{d_r,g}) ddist_{d_r,g}}{\int_0^{\widehat{dist}} h(dist_{d_r,g}) ddist_{d_r,g}} \quad (13)$$

While considering eqs. (10), (11) and (12), we use eq. (13) to compute $paxpct$ for a distance threshold z_r at given u and x . With the help of airport choice data, parameters u and x can now be chosen so as to minimize the sum of squared deviations between observed and estimated passenger shares. For that purpose, we use data from the 2001 Airline Passenger Survey for the San Francisco Bay Area (CRA, 2004) and from the 2003 German Air Traveler Survey (Wilken et al., 2007).¹⁴ This yields $s = 1.0500$, $u = -3.0020$, $v = 0.0003$ and $x = -0.0435$ with an average absolute deviation of estimated and observed passenger shares at 3 percentage points. The resulting decay pattern is plotted in Fig. 4.

¹⁴ From the Airline Passenger Survey for the San Francisco Bay Area, we include data on the share of (weighted) passengers for distance thresholds between 75km and 250 km at a 25 km resolution. In addition, the average share at a 75 km threshold at German airports is considered.

Fig. 4.
Airport access decay pattern.



We note that this analysis sets out to approximate markets, to which airports *potentially* provide access. Thus, it does not model observed passenger behavior, which varies between airports or between destination markets at a specific airport (Wilken et al., 2007; Lieshout 2012). Nevertheless, we regard this approach as advancing previous work since it does neither rely on a subjective definition of a maximum access distance threshold without any decay (Malighetti et al., 2008; Maertens, 2010) nor on subjective definitions of decay not backed by observed passenger behavior (e.g. Bel, Fageda, 2010).

To model the level of potential interaction in market g , gridded global population data adjusted by differences in wealth levels is used.¹⁵ In particular, the analysis is based on the LandScan data¹⁶, which contains global estimates of ambient population at a 30 arc-second resolution for yearly model iterations between 2000 and 2012 (Oak Ridge National Laboratory, 2014). For missing years, population data is obtained by applying yearly country-level population growth rates from the World Bank's World Development Indicators database (World Bank, 2014a) to each grid cell. Wealth differences are considered by normalizing the population in each grid cell with GDP per capita data from the World Development Indicators database for the respective country and year.

For our calculations, we use the standardized destination quality metric $w_{d,r,t}$ in eq. (14).

¹⁵ We do not follow Wittman and Swelbar (2014) or Reynolds-Feighan and McLay (2006) in using traffic data to approximate destination quality since traffic does not reflect the level of *potential interaction* to which a destination airport provides access.

¹⁶ LandScan (2000 through 2012)TM High Resolution global Population Data Set is copyrighted by UT-Battelle, LLC, operator of Oak Ridge National Laboratory under Contract No. DE-AC05-00OR22725 with the United States Department of Energy.

$$w_{d_r,t} = \frac{w'_{d_r,t}}{\max(\{w'_{k,t'} \mid k \in \mathcal{A} \wedge t' = t\})}. \quad (14)$$

This metric can be interpreted as the relative quality of the market, to which airport d_r provides access, in year t as compared to the highest observed destination quality of any airport in year t . Year-2007 results for the LandScan-based destination quality metric are presented in Tab. 4.

Tab. 4.
Results from the destination quality model for the year 2007.

Airport	City	Country	IATA Code	$w_{d_r,t}$	Percentile in Dataset
Tokyo Intl.	Tokyo	Japan	HND	0.949	0.0%
Newark Liberty Intl.	Newark	United States	EWB	0.730	0.2%
John F. Kennedy Intl.	New York	United States	JFK	0.705	0.2%
Heathrow	London	United Kingdom	LHR	0.594	0.5%
Los Angeles Intl.	Los Angeles	United States	LAX	0.512	0.7%
Düsseldorf	Düsseldorf	Germany	DUS	0.501	0.8%
Manchester	Manchester	United Kingdom	MAN	0.445	1.2%
Orly	Paris	France	ORY	0.418	1.6%
Charles De Gaulle	Paris	France	CDG	0.409	1.6%
Schiphol	Amsterdam	Netherlands	AMS	0.360	2.1%
Chicago O'Hare Intl.	Chicago	United States	ORD	0.360	2.1%
Brussels	Brussels	Belgium	BRU	0.359	2.2%
Incheon Intl.	Seoul	South Korea	ICN	0.340	2.5%
Ronald Reagan Washington Natl.	Washington	United States	DCA	0.276	3.2%
Washington Dulles Intl.	Washington	United States	IAD	0.246	4.1%
Hong Kong Intl.	Hong Kong	Hong Kong	HKG	0.221	4.6%
...					
Bahrain Intl.	Bahrain	Bahrain	BAH	0.036	24.9%
Lourdes	Tarbes	France	LDE	0.035	25.1%
...					
Lanzarote	Las Palmas	Spain	ACE	0.006	50.0%
Luxor Intl.	Luxor	Egypt	LXR	0.005	50.2%
...					
Strahan Airport	Strahan	Australia	SRN	0.001	74.9%
Teniente Vidal	Coyhaique	Chile	GXQ	0.001	75.2%
...					

3.2 The Centrality Model

For each airport $l \in \mathcal{A}$, we define the set of onestop routings $\mathcal{R}_{l,t}^{onestop}$ which pass through airport l , so that $l_r = l \forall r \in \mathcal{R}_{l,t}^{onestop}$. Following eq. (1), airport l 's Global Hub Centrality Index score $GHCI_{l,t}$ can be calculated as the sum of destination quality at each destination $d_r \forall r \in \mathcal{R}_{l,t}^{onestop}$ weighted by properties of the respective routing. This yields eq. (15).

$$GHCI_{l,t} = \sum_{r \in \mathcal{R}_{l,t}^{onestop}} \alpha_{r,t} f_{r,t} w_{d_r,t} \quad (15)$$

Applying the methodology from Section 3.1 parameterizes this metric.

3.3 Growth Decomposition of the Metrics

As analytically shown in Appendix A, changes of the GCI metric over time can be decomposed into three partial effects:

1. Network effects

Network effects capture GCI-variation, which results from ceteris paribus changes of air services, i.e. in frequency, layover time or layover airport. We note, that in order to compute these network effects, the GCI decomposition (Appendix A) requires the network-induced changes in connection quality to be weighted by the year-1990 destination quality score. If one wants to map network changes without accounting for destination weights, a related metric, the change in destination-invariant GCI, should be used. This is because the destination-invariant GCI assumes the destination weight to be 1 for all airports.

2. Destination-quality effects

Destination-quality effects are changes in GCI, which result from ceteris paribus variation in destination quality. In a full decomposition of GCI growth, these effects must be calculated by assuming connection quality as derived from the year-1990 network (Appendix A).

3. *Simultaneity effects*

The network effects and the destination-quality effects are *ceteris-paribus* GCI variations, which are computed by using the base-year destination-weights and the base-year network respectively (Appendix A). In turn, simultaneous variation of the network and of destination quality causes impacts beyond the sum of the network effects and the destination quality effects (Appendix A). In the subsequent analysis, we call these additional effects “simultaneity effects”. They are positive, if destinations with growing destination weights receive improved air services, and negative if air services to destinations with growing destination weights are reduced.

4 Results

4.1 *Nonstop Connectivity*

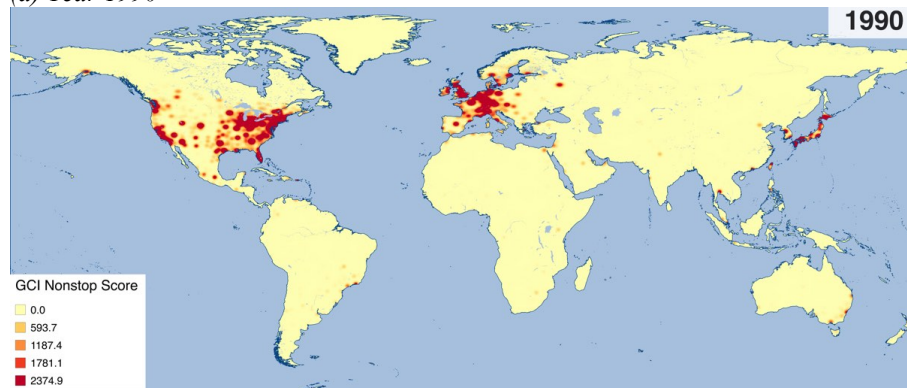
We assess the distribution of global nonstop connectivity among airports first by visualizing the scores.¹⁷ Fig. 5 (a) shows that global year-1990 nonstop connectivity was concentrated in North America, Europe and Japan. In particular, North American airports [European airports; Japanese airports] accounted for 63 % [23 %; 6 %] of global nonstop GCI in 1990. High destination weights in developed countries and well-established nonstop links between airports in these countries partly explain this dominance. However, while the year-1990 distribution of destination-invariant GCI scores (Fig. 6 (b)) is more balanced than the distribution of GCI scores (Fig. 6 (a)), airports in North America, Europe and Japan still accounted for 76.2 % of global destination-invariant nonstop GCI in 1990.¹⁸

¹⁷ The distance decay function outlined in Section 3.1. is applied for assigning each airport’s score to its surrounding region.

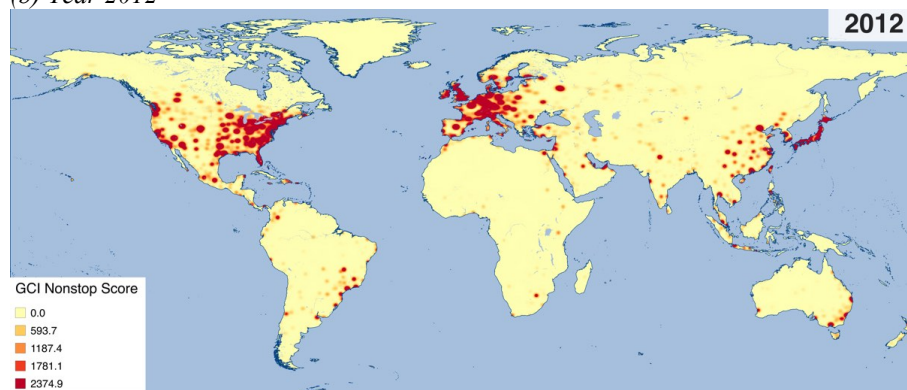
¹⁸ Japan is part of the “East Asia & Central Asia” world region. In 1990, Japanese airports explained 76.2 % [41.8 %] of nonstop GCI [destination-invariant nonstop GCI] in this region.

Fig. 5.
World map of nonstop GCI.

(a) Year 1990



(b) Year 2012

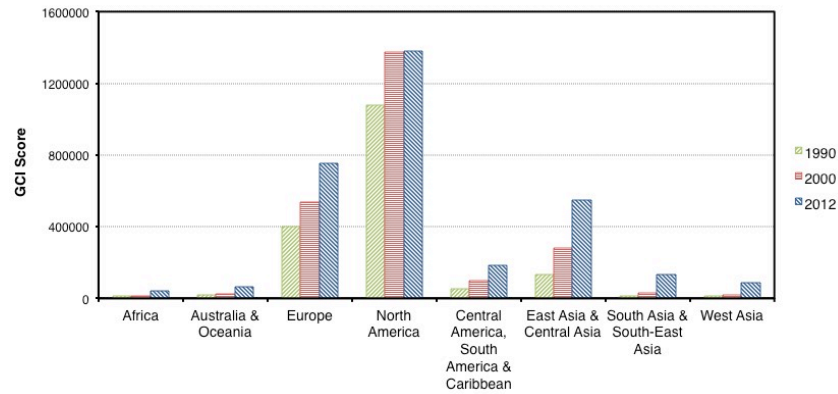


From 1990 to 2012, global aggregate nonstop GCI grew by 86.3 % (Fig. 7). During the 1990s, growth was almost exclusively driven by network effects (96.7 % of growth), whereas between 2000 and 2012, network effects [destination-invariant GCI] declined [increased] by 1.0 % [9.6 %]. At first glance, the results for the destination-invariant GCI for 2000-2012 might seem contradictory to observed increases in air traffic volumes over the same time-period.¹⁹ However, the reported 62 % rise in revenue passenger kilometers for 2000-2012 (Airbus, 2013) can be explained by increases in flight distances (+12.7% (Airbus, 2013)), aircraft capacity (+18.6 % (Airbus, 2013)) and load factors (~71% to ~79% (Airbus, 2014)). The difference between the development of the network effects and destination-invariant GCI is caused by above-average growth in traffic in less-developed world regions which points to the existence of spatial heterogeneity in the connectivity development.

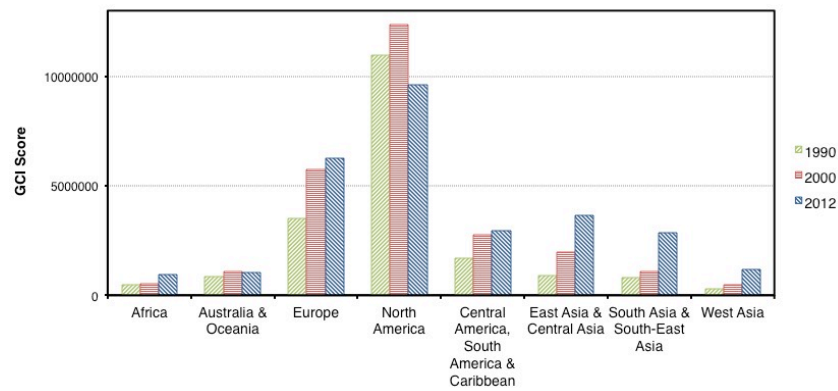
¹⁹ Note that the destination-invariant GCI should be used for the comparison to traffic growth since it is independent of destination weights (Section 3.3).

Fig. 6.
Nonstop connectivity distribution by world region.

a) *Nonstop GCI.*

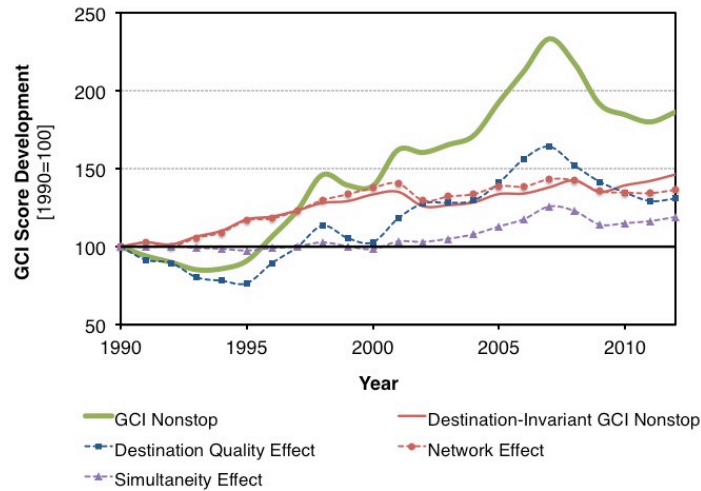


b) *Destination-invariant nonstop GCI.*



To further assess this spatial heterogeneity, we analyze changes in the nonstop connectivity distribution between 1990 and 2012. Although the year-2012 nonstop connectivity distribution was still concentrated to North America, Europe and Japan (43.2 %, 23.6 % and 8.7 % of global nonstop connectivity), the connectivity share of airports in those areas declined from 92.0 % to 75.4 % (Fig 5 (b); Fig. 6 (a)). This was particularly caused by high connectivity growth at (non-Japanese) Asian airports, whereas during the 2000s, the North American network deteriorated and network-related connectivity growth in Europe slowed down (Fig. 6 (b)). Given the heterogeneity in development in North America, Europe and Asia, we discuss nonstop connectivity trends in these regions in more detail.

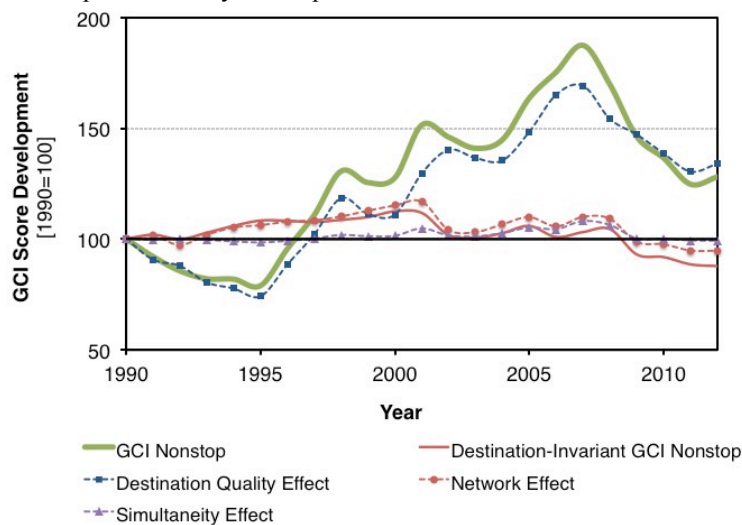
Fig. 7.
Global nonstop connectivity development.



4.1.1 North America

Between 1990 and 2012, the increase in nonstop GCI at North American airports (28.1 %) was lower than global aggregate GCI growth (86.3 %) (Fig. 8). Network effects drove 54.7 % of the North American increase in GCI during the 1990s. In the 2000s, network effects at North American airports decreased by 17.7 %. Since US airports accounted for 95 % of aggregate North American nonstop GCI, we can explain the development in North America with US developments.

Fig. 8.
Nonstop connectivity development in North America.



In the beginning of the 1990s, the US airline industry incurred significant losses (Chan, 2000; Dempsey, 2008). Carriers such as Continental, Pan Am, Midway, Eastern Airlines and TWA filed for bankruptcy (Chan, 2000). However, these bankruptcies did not significantly impact on aggregate connectivity since many services were taken over by competitors (e.g. PanAm) or bankrupt airlines were allowed to continue their operations (Chan, 2000). From the mid 1990s, the industry recovered (Dempsey, 2002; Goetz, Vowles, 2009), which is reflected in positive network effects until the end of the 1990s.

From 2000 to 2002, declining travel demand after the collapse of the dot-com bubble, catalyzed by the attacks on September 11, 2001, rising security concerns and the SARS outbreak (Goetz, Vowles, 2009), led to an 11 % service reduction at North American airports. In spite of schedule reductions, US carriers incurred losses of \$ 35b between 2001 and 2006 (Dempsey, 2008). Furthermore, several legacy carriers (e.g. Delta Airlines, United Airlines, US Airways and Northwest Airlines) filed for bankruptcy (Goetz, Vowles, 2009) and/or underwent reorganization resulting in a reduction of legacy operations by 4.0 % between 2002 and 2007.²⁰ At the same time, US low cost carriers were still profitable (Francis et al., 2006; Goetz, Vowles, 2009), grew their business by 41.7 %²¹ and thereby stabilized the aggregate US network effect.

During the US subprime crisis starting in summer 2007 and the subsequent world financial crisis, a decrease in air travel demand caused airlines to enter another phase of substantial financial losses (Dobruszkes, van Hamme, 2011; Wittman, 2014). As a reaction to decreased demand, US carriers employed “capacity rationalization” (Wittman, 2014) and adjusted schedules by cutting flight services, which lead to a decrease in the North American destination-invariant GCI [the network effect] by 12.1 % [10.7%] from 2008 to 2010. Between 2010 and 2012, the reductions in North American destination-invariant nonstop connectivity [the North American network effect] slowed to 4.4 % [2.9 %], which Wittman (2014) calls a phase of “capacity discipline”.

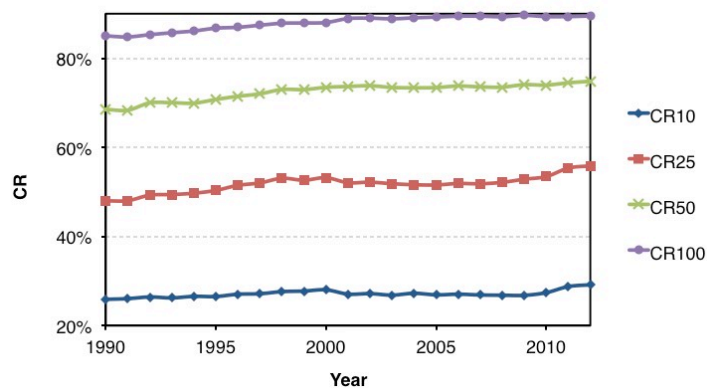
Turning to the connectivity distribution among North American airports, researchers have found the build-up of US hub-and-spoke networks to enhance core-periphery patterns

²⁰ We consider American Airlines, Northwest Airlines, United Airlines, Delta Air Lines, US Airways, Continental, America West Airlines, Midwest Airlines and Alaska Airlines.

²¹ We consider Southwest Airlines, JetBlue, AirTran, Frontier Airlines, Spirit Airlines, Sun Country Airlines, Allegiant Air and Virgin America.

(Goetz, Sutton, 1997). Indeed, the year-1990 distribution of nonstop connectivity among North American airports was highly concentrated on the largest 25 [10] North American airports, which accounted for 48.0 % [25.9 %] of aggregate year-1990 nonstop GCI (Fig. 9). Furthermore, the concentration ratio of the 25 [10] largest airports increased by $\Delta CR_{25} = 7.8$ pp [$\Delta CR_{10} = 3.3$ pp] between 1990 and 2012 (Fig. 9). 30.8 % [54.1 %] of the CR_{25} [CR_{10}] increase was observed between 2010 and 2012. This is consistent with observed network development strategies of US carriers, which have centered traffic at their hubs in these years (Wittman, 2014) and thereby increased the “peripheralization” (Goetz, Sutton, 1997) of secondary and tertiary US airports.

Fig. 9.
Connectivity concentration among US airports.

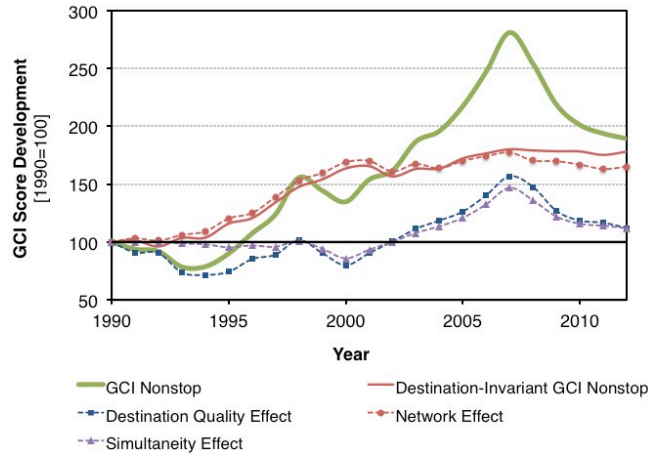


4.1.2 Europe

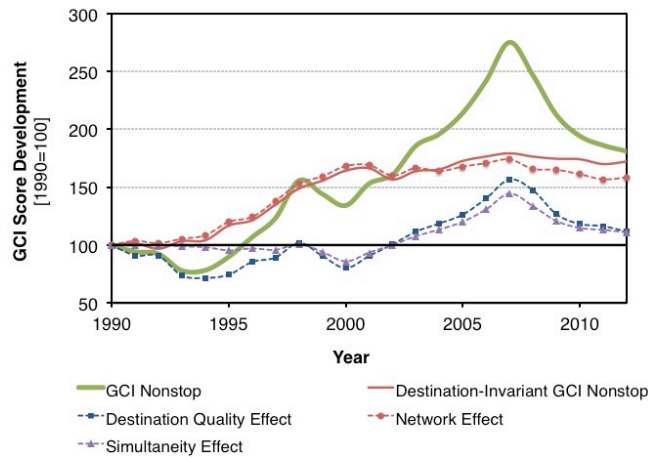
European nonstop GCI grew by 89.7 % from 1990 to 2012, which is similar to global average nonstop GCI growth (86.3 %) (Fig. 10 (a)). The growth between 1990 and 2000 was predominantly fueled by a 69.0 % increase in network effects (Fig. 10 (a)), whereas in the 2000s, destination quality effects largely drove nonstop GCI developments (correlation coefficient: 0.99).

Fig. 10.
Nonstop connectivity development in Europe.

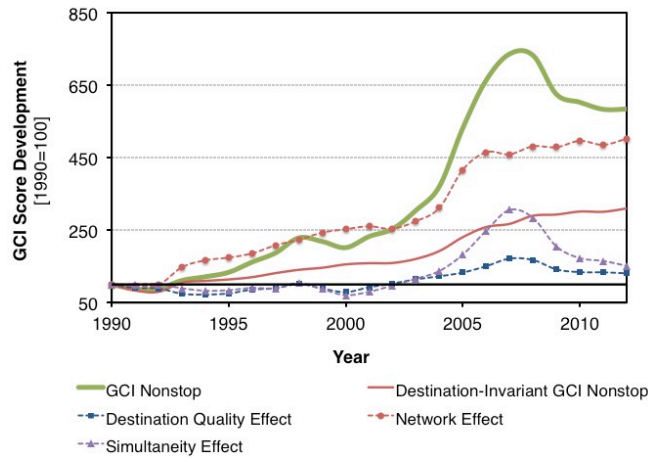
(a) World region "Europe"



(b) EU-15 and Norway



(c) New EU entrants



Between 1987 and 1997, the European air transport market was liberalized. In 1993, capacity control and market access control were abolished with the exception of cabotage rights, which were granted in 1997 (Berechman, de Wit, 1996). Deregulation first affected the EU-15 member states and Norway.²² In these countries, network effects increased by 59.7 % between 1993 and 2000 (Fig. 10 (b)), thereby outperforming the global aggregate nonstop network effects over the same period (30.5 %). Although this growth might partly be explained by economic recovery after the Gulf crisis, market deregulation should be considered a catalyst since new (albeit small) airlines entered the market (Berechman, de Wit, 1996) and above-average growth in intra-European traffic was observed (Burghouwt, Hakfoort, 2001).

In 2004, 10 countries joined the European Union followed by Romania and Bulgaria in 2007. This has resulted in significant aviation growth (Dobruszkes, 2009; Dobruszkes, 2013). While the compound annual growth rate (CAGR) of the nonstop network effect in the new member states averaged 8 % between 1990 and 2003, it increased to 19.2 % between 2003 and 2006 (Fig. 10 (c)). We note that multiple causal relationships, which are catalyzed through EU entry, may cause this, including the deregulation of air transportation in the new member states (Dobruszkes, 2009), additional trade as part of the common European market and increases in income in the new member states (Rapacki, Próchniak, 2009).

Deregulation has also been a catalyst for the emergence of European Low Cost Carriers (LCCs). During the early 1990s, European LCCs first entered the deregulated domestic UK and Irish markets, successively followed by market entries throughout Europe after full market deregulation (Francis et al., 2006; Budd et al., 2014; Fig. 11). Despite a 77 % failure rate among the new carriers (Budd et al., 2014) and two major economic crises, annual LCC traffic growth in the EU-27, Switzerland, Norway and Iceland averaged 18.8 % between 2000 and 2012.²³ This growth explains roughly 57.2 % [72.2 %] of European aggregate destination-invariant GCI growth between 1990 [1995] and 2012²⁴ and

²² We note that Austria, Sweden and Finland became EU members in 1995.

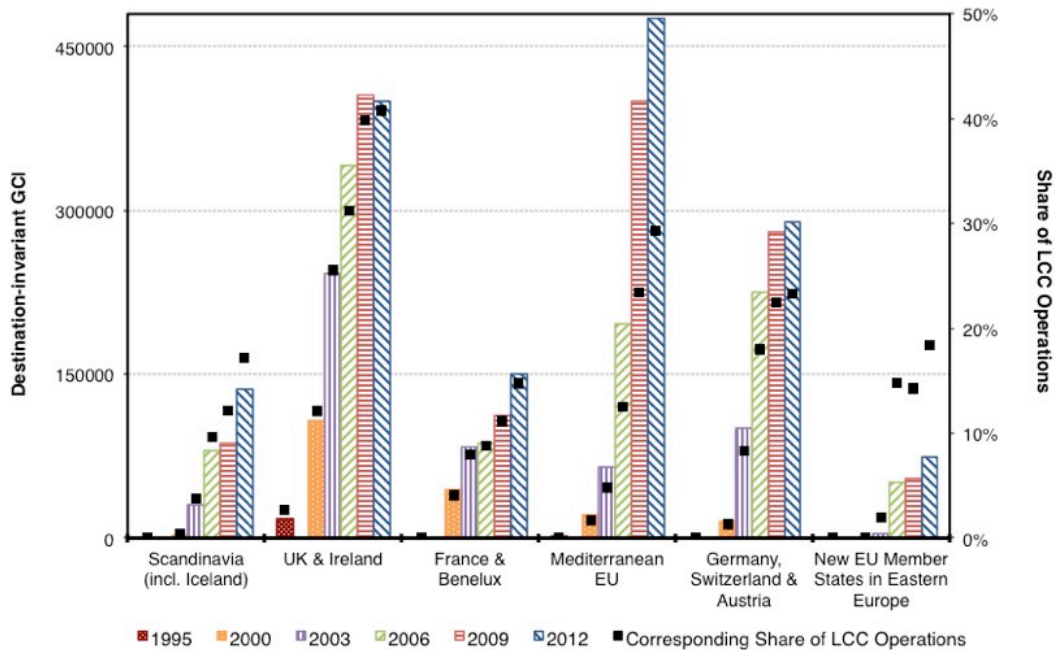
²³ Airlines have been classified as LCCs using information from Budd et al. (2014) and Dobruszkes (2006).

²⁴ In line with our results, Dobruszkes (2013) reports that additional LCC flights explain approximately 70 % of the increase in total number of flights in the EU from 1995 to 2012.

compensates the 18.8 % service reductions of the 20 largest European legacy carriers²⁵ between 2000 and 2012 by a factor of 2. Consequently, LCCs gradually became established market participants and accounted for 25.2 % of destination-invariant GCI at airports in the EU-27, Switzerland, Norway and Iceland by 2012. The highest year-2012 destination-invariant LCC-connectivity was observed in the UK and Ireland (40.8 % market share), the Mediterranean EU countries (29.3 % market share) and the German-speaking countries (23.3 % market share) (Fig. 11). This spatial distribution supports Dobruszkes (2006) and Dobruszkes (2013) who observe a concentration of European LCC traffic in (North-)Western Europe and at (Mediterranean) tourist destinations. With the EU enlargement in 2004 and 2007, the LCCs also built up a significant market presence in Eastern Europe (Dobruszkes, 2009; Budd et al, 2014; Gabor, 2010). Due to their significant size at the time of EU enlargement²⁶, they could quickly enter new markets, thereby increasing their destination-invariant GCI share in the new member states from 2.0 % in 2003 to 14.2 % in 2006 (Fig. 11).

Fig. 11.

Destination-invariant GCI generated by European Low Cost Carriers by origin airport location.



²⁵ Operations at airports in the EU-27, Norway, Iceland and Switzerland are considered only.

²⁶ LCCs claimed roughly 10.1 % of the year-2003 destination-invariant GCI in the EU-15.

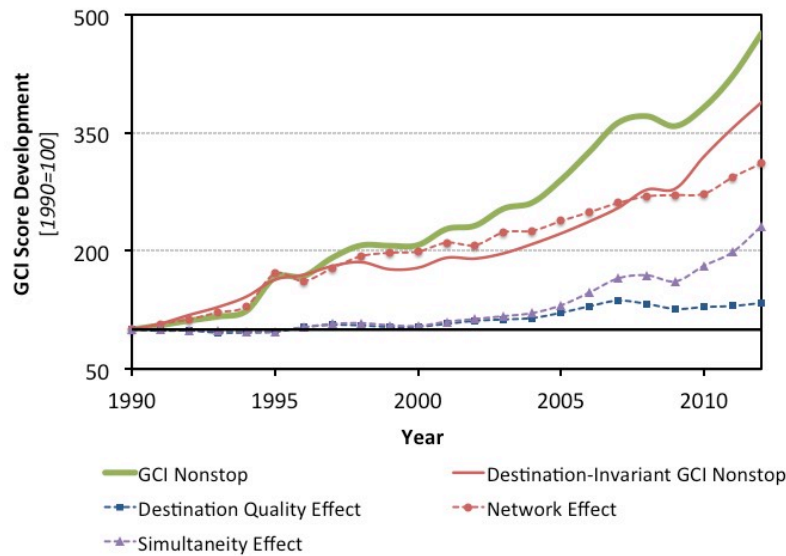
The observed growth of European LCCs during the early 2000s and the traffic decline of European legacy carriers are responsible for the divergence of the destination-invariant GCI from the network effects as depicted in Fig. 10 (a). This is because as compared to legacy carriers, LCCs serve more remote (secondary) airports (Francis et al., 2006), which have 13.2 % lower average destination weights than European airports served by the 15 largest European legacy carriers.²⁷ In turn, the LCC growth resulted in additional connectivity at airports, which received little or no service by the legacy carriers (Burghouwt, Hakfoort, 2001; Fan, 2006; Suau-Sanchez, Burghouwt, 2011).

4.1.3 Asia

The largest relative growth in nonstop connectivity scores among the world-regions was observed at Asian airports where, driven to a large extent by network effects (56.1 % of the Asian 1990-2012 nonstop GCI growth), nonstop GCI increased by 376.1 % from 1990 to 2012 (Fig. 12). In turn, 41.2 % of the global aggregate nonstop GCI increases were recorded at Asian airports. The Asian development differs from the European and North American as network effects are steadier. Network deteriorations are only observed in two years, as compared to 11 years in North America and 6 years in Europe. In particular, Asian air transportation was not significantly hit by the Gulf crisis in the beginning of the 1990s (Rimmer, 2000; Fig. 12) and network deterioration first appeared during the Asian crisis towards the end of the 1990s (Chin et al., 1999; Bowen, 2000, Rimmer, 2000). Due to Asian carriers being relatively financially healthy (Lawton, Solomko, 2005), carriers were able to quickly recover from the crisis, before the 9/11 attacks led to service reductions (2001-2002) and the SARS outbreak slowed network growth (2003-2004) (Fig. 12; Lawton, Solomko, 2005). Fueled by increasing liberalization of air transportation in Asian countries (Forsyth et al., 2006) and the emergence of Asian Low Cost Carriers (Hooper, 2005; Lawton, Solomko, 2005), network effects recovered, and, with the exception of a one-year slowdown in growth during the world financial crises in 2009, high growth rates prevailed until 2012 (Fig. 12; Dobruszkes, van Hamme, 2011).

²⁷ Average destination weights are calculated for destination airports located in the EU-27 states, Norway, Iceland and Switzerland. The average is weighted by flight frequency.

Fig. 12.
Nonstop connectivity development in Asia.



A geographical decomposition of the Asian 1990-2012 nonstop GCI growth reveals that Chinese and Japanese airports accounted for more than half of the absolute Asian increase in nonstop GCI.

- In 1990, Japanese airports explained 63.0 % [6.0 %] of Asian [global] nonstop GCI, and could therefore be considered the dominant air transport market in Asia. From 1990 to 2012, the nonstop GCI in Japan increased by 170.9 % - almost twice as much as the global average growth (89.7 %). Network effects caused 96.3 % of the GCI increase at Japanese airports. This increase occurred in conjunction with gradual deregulation of the Japanese air transport market during the 1990s, with full deregulation of airfares happening in the early 2000s (Yamauchi, Ito, 1996; Yamaguchi, 2007; Murakami, 2011).
- Connectivity generated at Chinese airports increased unprecedentedly in the years 1990-2012. While in 1990, only 1.6 % [0.2 %] of Asian [global] aggregate nonstop GCI was accessible to passengers at Chinese airports²⁸, the GCI score increased by 5856.9 % between 1990 and 2012 (Fig. 13). As a consequence, Chinese airports accounted for 20.0 % [4.8 %] of the year-2012 Asian [global] aggregate nonstop GCI. Network effects (1688.0 %), potentially driven by growing passenger demand

²⁸ Hongkong and Macau are not considered.

and by the transformation of the Chinese airline industry from an entity under military control into a business (Zhang, 1998; Zhang, Round, 2008; Shaw et al., 2009; Wang et al., 2011), were a significant source of this increase. Furthermore, network improvements in China coincided with significant destination quality growth, so that rising simultaneity effects were observed (Fig. 13). These effects indicate that services to locations, which have substantially grown in destination quality since 1990, have significantly increased. Given the high growth rates of the Chinese economy, the simultaneity effects can, in turn, be interpreted as an indication of considerable service growth in the Chinese domestic market.

Fig. 13.
Nonstop connectivity development in China.

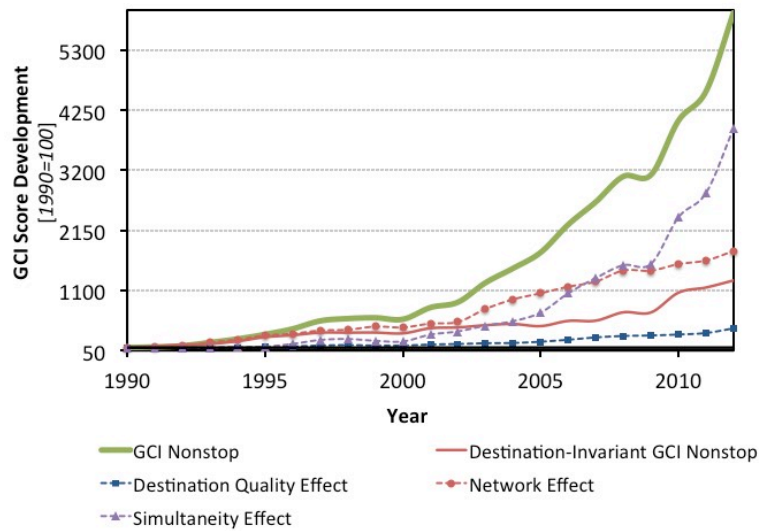
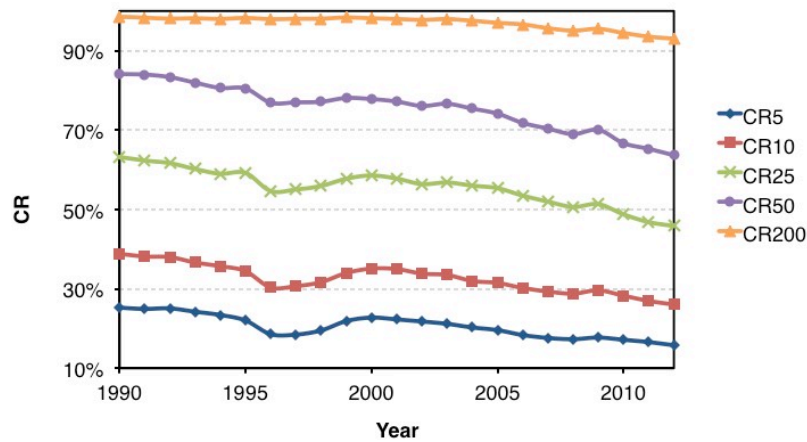


Fig. 14.
GCI concentration rates in Asia.



Compared to 1990, when Asian nonstop GCI was concentrated at Japanese airports, nonstop GCI scores dispersed over time and the concentration rates of nonstop GCI among Asian airports declined (Fig. 14). While connectivity growth has occurred at existing airports, we also observe a 63.1 % increase in the number of airports, which receive regular scheduled air services²⁹ between 1990 and 2012 (Tab. 5). This increase in the number of airports with regular service can be assumed to have been facilitated through demand growth for air travel in Asia. Furthermore, the growth coincides with supply-side developments such as the emergence of Asian LCCs (Francis et al., 2006), more liberal international air service agreements, that open up access to additional airports for international routes and/or multiple carriers, (Hooper, 1997; Bowen, 2000; Hooper, 2005; Lawton, Solomko, 2005; Forsyth et al., 2006) and the development of new airport infrastructure (Yamaguchi, 2007).

Tab. 5.
Airport count by airport size class in Asia.

Airport size [daily flights]		Number of airports		
from	to	1990	2000	2012
2	20	388	451	550
21	50	33	64	90
51	100	22	17	42
101	200	6	20	31
201	400	1	5	15
401		0	0	6
		450	557	734

4.2 Onestop Connectivity and Onestop Centrality

4.2.1 The Connectivity Perspective

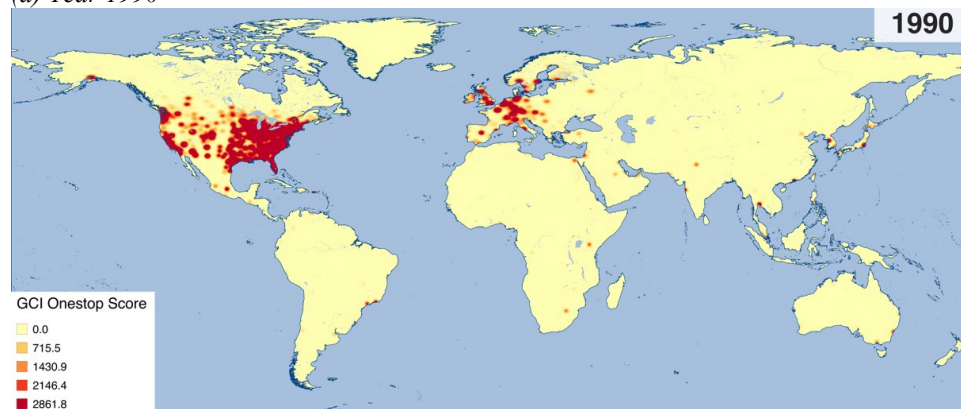
The results from Fig. 15 (a) suggest that the year-1990 onestop GCI was concentrated at North American airports, which, indeed, accounted for 85.9 % of global onestop GCI, whereas airports in Europe accounted for 8.7 % only (Fig. 17 (a)). The North American dominance in the year-1990 onestop GCI is still observed if destination-weights are factored out (North American share in global aggregate destination-invariant onestop GCI 87.4 %) (Fig. 17 (b)). Thus, one may conclude that North American airports were served through extensive hub and spoke networks already in 1990 (Berechman, de Wit,

²⁹ “Regular” is defined here as two or more departures per day on average

1996; Borenstein, 1992). In such networks, frequent flights to hub airports facilitate high-frequency services to many onward destinations (Kanafani, Ghobrial, 1985; Alderighi et al., 2007), thereby creating high onestop connectivity at each spoke airport. This effect is especially high if (1) hub locations are chosen so as to attract passengers to the indirect routings (Dempsey, 1991; O’Kelly, 1998) and (2) flight schedules at the hubs are designed to avoid excessive waiting time during layovers (Kanafani, Ghobrial, 1985; Burghouwt, de Wit, 2005). While US carriers designed their year-1990 networks in that regard, European carriers operated centralized, but temporally rather uncoordinated networks (Burghouwt, de Wit, 2005) so that European aggregate year-1990 onestop GCI was relatively low.

Fig. 15.
World map of global onestop connectivity scores.

(a) Year 1990



(b) Year 2012

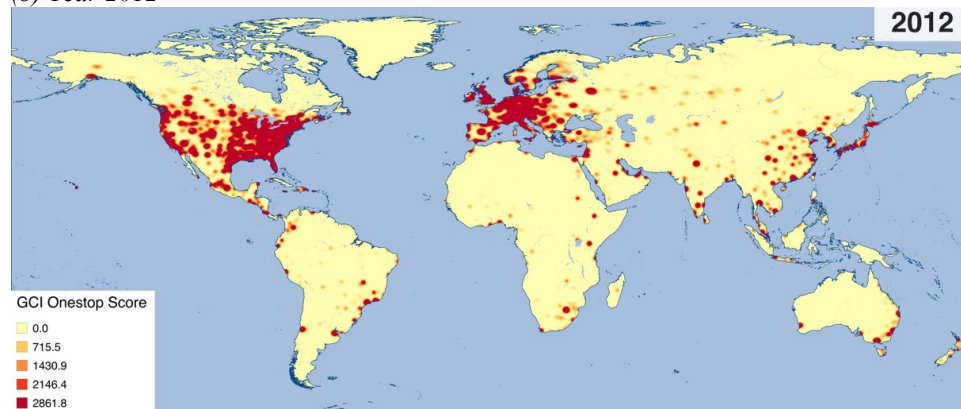
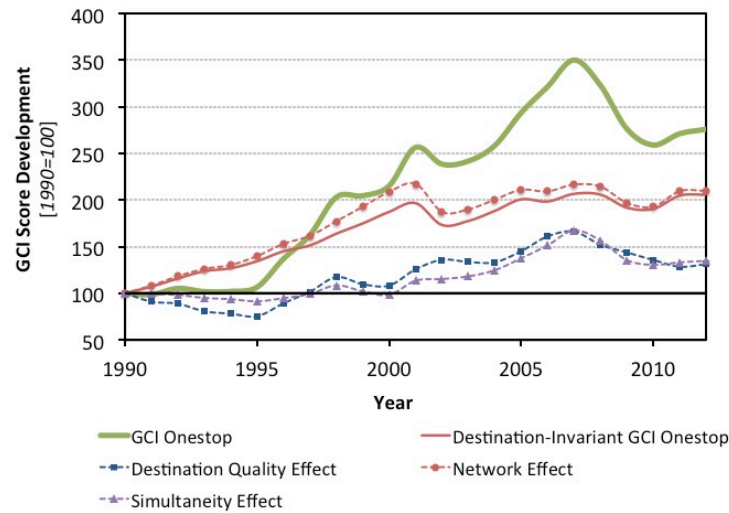


Fig. 16.
Onestop connectivity development 1990-2012.



Between 1990 and 2012, global onestop GCI grew by 175.8 % and thereby outperformed growth in nonstop connectivity by a factor of roughly 3.5. The development can be subdivided into two phases.

Phase 1: 1990-2000

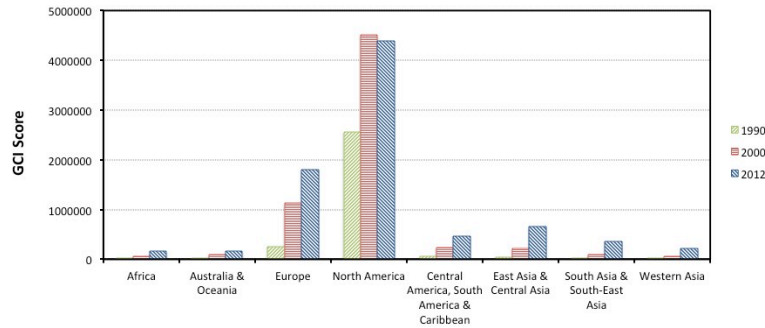
From 1990 to 2000, network effects explained 94.4 % of the 115.2 % global onestop GCI growth (Fig. 16). The increase in network effects coincided with expanding cooperation among carriers. In particular, carriers started offering their customers “seamless” global network coverage by selling tickets of onward flights, which are operated by partnering airlines, but carry the ticketing carrier’s code (“codeshares”) (Chan, 2000; Gudmundsson, Rhoades, 2001; Fan et al., 2001). Such collaborations first emerged during the late 1980s and their number grew significantly during the 1990s (Oum, Park, 1997; Chan, 2000; Gudmundsson, Rhoades, 2001). The foundation of global airline alliances such as Star Alliance (1997), Qualiflyer (1998),³⁰ oneworld (1999) and SkyTeam (2000) marked the peak of that trend. An estimate of the significance of cooperation in creating onestop connectivity can be obtained by computing the codeshare-induced onestop GCI³¹. The results underline the significance of inter-airline cooperation for the growth of global onestop GCI during the 1990s (Tab. 6).

³⁰ Qualiflyer was disintegrated in 2001.

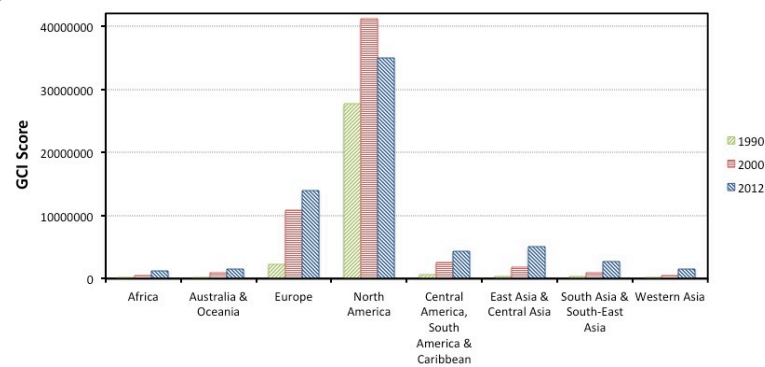
³¹ The codeshare-induced onestop GCI is the difference between the onestop GCI and a onestop GCI metric, which allows for intra-airline transfers only (if applicable for the airline).

Fig. 17.
Onestop connectivity distribution by world region.

(a) Onestop GCI



(b) Destination-invariant onestop GCI



The largest absolute 1990-2000 increases in onestop GCI were observed at North American airports (57.3 % of the absolute 1990-2000 onestop growth) and European airports (25.6 % of the absolute 1990-2000 onestop growth) (Fig. 17 (a)). In particular, the onestop GCI CAGR at European airports (15.9 %) outperformed the CAGR at North American airports (5.9 %), so that European airports significantly caught up on their North American counterparts in terms of onestop connectivity. Overall, the share of European airports in global onestop GCI increased from 8.7 % in 1990 to 17.7 % in 2000 (Fig. 17 (a)). This growth coincides with the reorganization of European airline networks. While North American airlines had already operated established hub-and-spoke networks back in 1990, European legacy carriers significantly optimized their networks during the 1990s by further consolidating their (long-haul) operations at their hubs (Burghouwt, Hakfoort, 2001; Burghouwt et al., 2003) and improving temporal coordination of their schedules (Burghouwt, de Wit, 2005).

In total, airports in wealthy regions in Europe and North America received 82.9 % of the 1990-2000 onestop GCI growth. Thus, one may conclude that during the first phase of hub-and-spoke network development, those networks predominantly enhanced links among wealthy regions. In turn, the (destination-weighted) network effects outperformed destination-invariant GCI growth between 1990 and 2000 (Fig. 16). Furthermore, this result supports Bowen (2002) who finds higher air traffic connectivity improvements in wealthy countries than at poor and peripheral locations during the late 1980s and early 1990s.

Tab. 6.
Share and growth rate of codeshare-induced onestop GCI.

	Share of codeshare-induced onestop GCI						CAGR of aggregate codeshare-induced onestop GCI				
	1993	1997	2000	2004	2008	2012	1993-1997	1997-2000	2000-2004	2004-2008	2008-2012
Africa	2.9%	18.7%	31.1%	32.8%	34.4%	34.8%	98.0%	41.8%	14.8%	15.3%	0.3%
Australia & Oceania	10.6%	17.5%	46.6%	35.7%	38.7%	51.1%	58.8%	65.5%	-4.4%	12.1%	10.6%
Europe	1.3%	23.4%	34.2%	41.0%	48.3%	52.2%	156.3%	31.3%	11.1%	14.0%	-1.5%
North America	0.9%	9.6%	22.2%	38.6%	39.9%	45.8%	99.7%	42.3%	18.8%	3.2%	-3.0%
Central America, South America & Caribbean	1.1%	11.1%	28.9%	32.6%	32.4%	33.3%	112.8%	61.0%	11.7%	11.2%	-0.9%
East Asia & Central Asia	0.8%	8.2%	25.4%	33.1%	41.1%	45.3%	117.3%	68.8%	17.1%	24.1%	6.0%
South Asia & South-East Asia	0.3%	18.0%	32.3%	34.6%	36.7%	36.5%	249.5%	33.6%	17.3%	18.7%	3.1%
West Asia	1.2%	13.9%	24.2%	30.1%	38.5%	37.6%	124.6%	42.7%	13.9%	26.6%	5.8%
Global	1.0%	12.0%	25.3%	38.3%	41.2%	45.7%	110.9%	40.8%	16.1%	7.7%	-1.3%

Phase 2: 2000-2012

Between 2000 and 2012, the network effects declined twice (13.8 % (2001-2002); 11.0 % (2007-2010)), but subsequent recoveries led to an almost constant level in 2012 as compared to 2000. While economic crises following the 9/11 attacks and the collapse of the US subprime market explain short-term variations (Section 4.1), significant spatial heterogeneities in the development patterns exist (Fig. 17).

- At North American airports, a 21.1 % [15.0 %] decline in the onestop network effects [destination-invariant GCI] was observed between 2000 and 2012 (Fig. 17 (b)). This is because the legacy carriers, which operate hub-and-spoke networks (Franke, 2004; Dempsey, 2002), reduced their services, whereas the LCCs, which offer fewer indirect connections (Franke, 2004; Gillen, Lall, 2004), grew (Section 4.1.1). We also find that the absolute growth in codeshare-induced GCI offset 88.6 % of the decline

in onestop intra-airline-transfer GCI, and that the codeshare-induced GCI share increased from 22.2 % in 2000 to 45.8 % in 2012 (Tab. 6). Thus, one may conclude that North American carriers were able to stabilize aggregate onestop connectivity in times of “capacity rationalization” and “capacity discipline” by partially substituting intra-airline-transfer offerings with inter-airline-transfer offerings through codeshares.

- At European airports, growth of onestop connectivity slowed as compared to 1990-2000. In particular, the network effect CAGR fell from 16.7 % (1990-2000) to 1.1 % (2000-2012). At EU-15 airports, EU legacy carriers significantly reduced their services (Section 4.1.2). The resulting *ceteris-paribus* decrease in onestop connectivity, however, was offset by growth of codeshare-induced GCI so that the share of codeshare-induced GCI rose from 2000 to 2012 (Tab. 6). We note that at airports in the new EU member states, onestop GCI grew by 89.3 % from 2000 to 2012 and almost all of this growth (96.3 %) was observed in the aftermath of the EU enlargement.
- The largest 2000-2012 GCI growth was observed in Asia and Africa, which accounted for 53.3 % of the 2000-2012 global onestop GCI increase (Fig. 17). Network effects (CAGR between 5.5 % (Africa) and 8.2 % (South & Southeast Asia)) were significant contributors to this trend, explaining between 57.7 % (Africa) and 65.6 % (East & Central Asia) of the 2000-2012 onestop GCI increase in the respective region.

Overall, the onestop connectivity trends resulted in a spatial deconcentration of global onestop connectivity (Fig. 15 (b)). In particular, the share of onestop GCI at North American airports dropped from 85.9 % in 1990 to 53.5 % in 2012, whereas the onestop GCI share of European airports increased from 8.7 % in 1990 to 17.7 % [21.9 %] in 2000 [2012] and the Asian onestop connectivity share rose from 5.7 % [2.8 %] to 14.9 % between 2000 [1990] and 2012. Thus, a shift of onestop connectivity growth from prosperous western countries (1990-2000) into emerging markets (2000-2012) was

observed and caused the destination-invariant GCI to catch-up on the (destination-weighted) network effects during the 2000s (Fig. 17).

In terms of the world's poorest countries³², we find that while they had a less than proportionate share in onestop GCI growth between 1990-2000 (onestop GCI CAGR of these countries 6.1%, global average: 8.0%), onestop GCI growth from 2000-2012 outperforms the global average (CAGR 15.0% vs. 2.1%). This might indicate that the “marginalization” of poor countries within airline networks described by Bowen (2002), has ended – at least in terms of onestop connectivity.

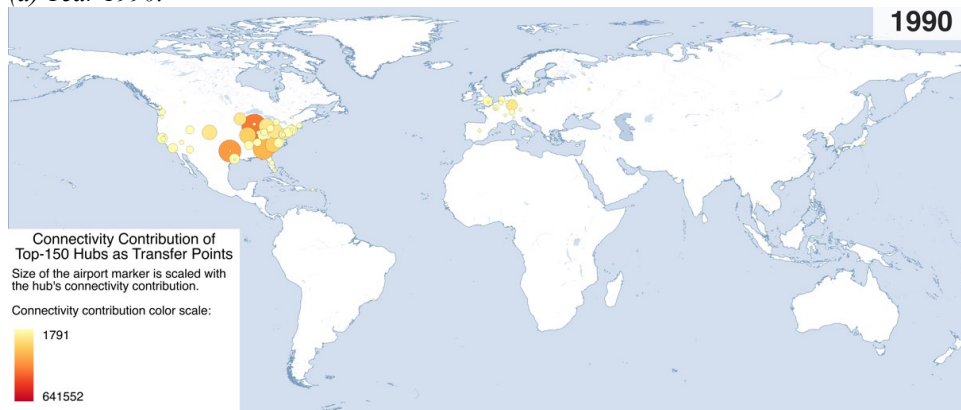
4.2.2 *The Centrality Perspective*

We now turn to the centrality perspective, i.e. the contribution of transfer airports to the generation of connectivity. In 1990, 87.4 % of global onestop connectivity was facilitated through hub operations at North American airports (Fig. 18 (a)), which can be explained by coordinated hub-and-spoke networks already being available to passengers in North America, whereas hub-and-spoke networks were less extensive in other parts of the world (Section 4.2). Furthermore, the GHCI was concentrated at the Top-5 [10] hub airports, which accounted for 38.7 % [56.5 %] of the global GHCI score (Fig. 18). The most important hubs outside North America were Frankfurt and London Heathrow, which together explained roughly one third of the aggregate non-North American GHCI, but only achieved 33.1 % and 22.4 % of the average GHCI score at Top-5 North American hubs, respectively.

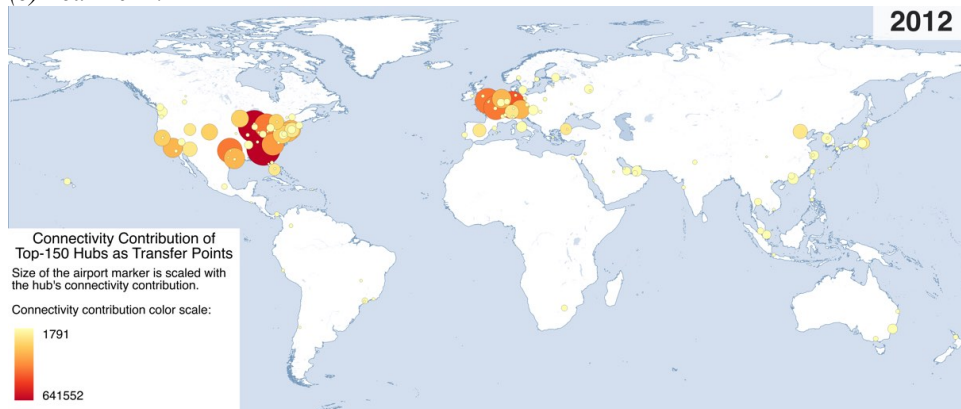
³² We consider the 34 countries with the lowest per-capita income as defined by the World Bank (2014b).

Fig. 18.
World map of Top-150 Hubs.

(a) Year 1990.

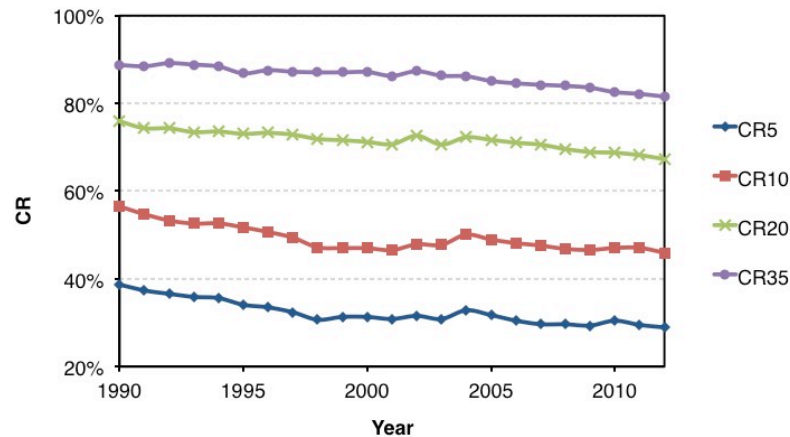


(b) Year 2012.



Between 1990 and 2000, 93.6 % of the GHCI growth occurred at airports in North America and Europe. In particular, the strong centrality growth of European airports caused the centrality share of European airports [North American airports] to increase [decrease] from 10.0 % [87.4 %] in 1990 to 20.1 % [75.3 %] in 2000. Since European legacy carriers drove this trend by improving temporal schedule coordination in their centralized networks (Burghouwt, Hakfoort, 2001; Burghouwt, de Wit, 2005), the five most central European hubs in 1990 received the largest absolute growth in centrality (68.4 % of the 1990-2000 GHCI growth at European airports). In turn, European hubs significantly caught up to their American counterparts in terms of centrality so that the global centrality concentration rate of the 5 [10] largest global hubs fell from 38.7 % [56.5 %] in 1990 to 28.9 % [45.9 %] in 2000 (Fig. 19).

Fig. 19.
Concentration rates of global hub centrality.



After 2000, the growth of hub centrality scores remained strong at European airports (50.5 % of global 2000-2012 growth) and accelerated at Asian airports (43.1 % of global 2000-2012 growth), whereas the centrality score remained almost constant in North America.

- In Europe, the three largest hubs, Frankfurt, London Heathrow and Paris CDG, accounted for 64.9 % of the 2000-2012 GHCI growth and in 2012, explained 51.4 % of the European year-2012 GHCI (Fig. 18 (b)). In addition, the extension of Lufthansa's second hub at Munich airport (Albers et al., 2005) caused an 11.6 % increase in European GHCI and led to Munich Airport becoming the fifth most central European airport.
- In Asia, hub centrality more than quintupled between 2000 and 2012. The largest growth was observed at Chinese airports (34.5 % of Asian GHCI growth), Japanese and South Korean airports (18.7 % of Asian GHCI growth), airports in the United Arab Emirates and Qatar (14.7 % of Asian GHCI growth) and Turkish airports (8.6 % of Asian GHCI growth). The growth contribution of airports in the United Arab Emirates and Qatar is particularly noteworthy, since it is driven by the market entry and expansion of Middle East Carriers (Qatar, Etihad, Emirates), which use the geographical position of their home airports to connect world-regions with one-transfer hub-and-spoke networks (Vespermann et al., 2008; O'Connell, 2011). As a consequence, we find their home airports (Doha, Abu Dhabi, Dubai) to develop from regional hubs for Africa, Western Asia and South Asia & Southeast Asia to hubs for

journeys into all world regions (Tab. 7). In particular, we observe significant year-2012 centrality of the three hubs under consideration in South Asia & Southeast Asia, West Asia, Africa and Australia & Oceania. This results from the Middle East carriers' network structures, which were particularly focused on these regions (Vespermann et al., 2008; Hooper et al., 2011; Grimme, 2011). We note that the relative centrality of the three hubs with regard to North America and Europe remains low in 2012 (Tab. 7) due to limited frequencies to these regions from Middle Eastern hubs, relatively long layovers and low destination weights for routes with reasonable detour factors (e.g. South and Southeast Asia) (Grimme et al., 2011).

Tab. 7.

Onestop connectivity ranking and onestop connectivity share facilitated through Dubai Airport, Doha Airport and Abu Dhabi Airport by world region of origin airport.

		2000		2012	
		<i>GHCI</i>	<i>Destination-invariant</i>	<i>GHCI</i>	<i>Destination-invariant</i>
Africa	DXB	39 (0.1%)	35 (0.2%)	6 (5.6%)	7 (5.1%)
	DOH	71 (0.0%)	57 (0.1%)	10 (2.3%)	10 (2.6%)
	AUH	78 (0.0%)	47 (0.1%)	26 (0.7%)	23 (0.8%)
Australia & Oceania	DXB	-	-	8 (3.1%)	7 (3.4%)
	DOH	-	-	18 (0.7%)	24 (0.7%)
	AUH	-	-	16 (0.9%)	18 (0.9%)
Europe	DXB	119 (0.0%)	89 (0.0%)	32 (0.4%)	24 (0.7%)
	DOH	206 (0.0%)	164 (0.0%)	44 (0.3%)	31 (0.6%)
	AUH	193 (0.0%)	154 (0.0%)	64 (0.1%)	48 (0.2%)
North America	DXB	372 (0.0%)	393 (0.0%)	89 (0.0%)	55 (0.1%)
	DOH	-	-	105 (0.0%)	71 (0.1%)
	AUH	-	-	141 (0.0%)	91 (0.0%)
Central America, South America & Caribbean	DXB	-	-	45 (0.2%)	45 (0.2%)
	DOH	-	-	51 (0.1%)	58 (0.1%)
	AUH	-	-	-	-
East Asia & Central Asia	DXB	116 (0.0%)	127 (0.0%)	53 (0.2%)	44 (0.5%)
	DOH	-	-	51 (0.2%)	47 (0.4%)
	AUH	134 (0.0%)	181 (0.0%)	81 (0.1%)	75 (0.1%)
South Asia & South-East Asia	DXB	18 (1.2%)	21 (0.9%)	2 (7.6%)	3 (6.1%)
	DOH	36 (0.2%)	47 (0.3%)	8 (4.5%)	8 (4.3%)
	AUH	41 (0.1%)	48 (0.3%)	15 (1.9%)	22 (1.4%)
Western Asia	DXB	26 (0.5%)	18 (1.0%)	5 (4.3%)	5 (4.5%)
	DOH	28 (0.4%)	20 (0.9%)	4 (4.6%)	4 (5.5%)
	AUH	31 (0.3%)	24 (0.8%)	13 (2.2%)	15 (2.0%)

Onestop connectivity share through a transfer at the respective hub in the respective origin region given in parentheses.

- No scheduled service.

- In North America, the concentration rate of the 10 largest hubs increased from 61.3 % in 2000 to 67.7 % in 2012. This process was driven by restructuring of US legacy carriers during the 2000s (Wittman, 2014), which, inter alia, led the carriers to strengthen their main hubs, i.e. Atlanta (Delta), Charlotte (US Airways), Newark (United) and Philadelphia (US Airways), and to de-hub secondary hubs such as Dallas Fort Worth (Delta), St. Louis (TWA / American Airlines), Pittsburgh (US Airways) and Cincinnati (Delta).

Overall, significant GHCI scores were created at airports in all world regions between 1990 and 2012 (Fig. 18). However, the world's most significant hubs in 2012 were still located in North America and Europe and airports in these regions explain 85.5 % of global aggregate year-2012 GHCI. In addition, we find evidence that the 4 hubs with the highest GHCI score in each world-region account for 39 % to 89 % of the GHCI score in each world region (Fig. 18 (b); Tab. 8), which we explain with economies of scale and density (Brueckner, Spiller, 1994) of centralized hub-and-spoke networks. We note that hubs with the highest centrality in a region may not have the highest contributions to onestop connectivity of a region (Tab. 8). This is because highly valued connections (short detour, short layover and/or high destination weight) may pass through hubs, which are located outside of the respective region (e.g. Redondi et al. 2011).

Tab. 8.

Top-4 central hubs in and for each world region.

	Top-4 central hub in the region				Top-4 central hubs for the region			
	1	2	3	4	1	2	3	4
Africa	JNB (57%)	CAI (17%)	CMN (7%)	NBO (4%)	CDG (14%)	LHR (13%)	JNB (13%)	FRA (9%)
Australia & Oceania	SYD (54%)	MEL (14%)	AKL (14%)	BNE (10%)	SYD (26%)	LAX (14%)	AKL (8%)	SIN (7%)
Europe	FRA (19%)	LHR (17%)	CDG (15%)	AMS (10%)	FRA (15%)	CDG (11%)	LHR (11%)	MUC (9%)
North America	ATL (13%)	ORD (12%)	DFW (7%)	DTW (7%)	ATL (12%)	ORD (11%)	DFW (7%)	DTW (7%)
Central America, South America & Caribbean	GRU (19%)	MEX (17%)	PTY (12%)	BOG (8%)	MIA (11%)	ATL (10%)	IAH (10%)	DFW (7%)
East Asia & Central Asia	PEK (20%)	NRT (13%)	HKG (11%)	ICN (10%)	PEK (13%)	HND (6%)	NRT (5%)	ORD (5%)
South Asia & South-East Asia	SIN (29%)	BKK (20%)	KUL (16%)	DEL (8%)	LHR (9%)	DXB (8%)	FRA (7%)	HKG (6%)
Western Asia	IST (34%)	DXB (29%)	DOH (18%)	AUH (8%)	IST (18%)	LHR (13%)	FRA (8%)	DOH (5%)

Centrality share given in parenthesis

5 Conclusion

In this paper, we have proposed a new connectivity and centrality model that sets out to assess the quantity and quality of nonstop and onestop air transport services from the perspective of (potential) passengers. By computing the metric for 1990 to 2012, we have analyzed both the geography of, and trends in global air services. In turn, this paper is the first to describe the effects of airline deregulation, airline network structures, cooperation among airlines, market entry of Low Cost Carriers and Middle East carriers and economic crises on connectivity in a consistent framework. Since the societal value of air transportation depends on its quality in bridging distances quickly, we regard the connectivity perspective as particularly insightful.

The contribution of this paper is threefold. First, it extends existing connectivity models as summarized by Burghouwt and Redondi (2013). In particular, our approach builds on the “connection quality-weighting” model (Veldhuis, 1997; Burghouwt, de Wit, 2005; Burghouwt, Veldhuis, 2006) rather than shortest- or quickest-path models (e.g. Malighetti et al., 2008; Paleari et al., 2010; Zhang et al., 2010), which allows us to compute connection quality as perceived by passengers at each airport. While the assessment of connection quality previously relied on assumptions about maximum detour, our approach estimates these patterns empirically. In line with the accessibility approach (Geurs, van Wee, 2004; Paez et al., 2012), we further extend the connection quality assessment by considering the economic interaction potential to which each destination airport provides access.

Second, this paper is the first to use a connectivity model for describing the impacts of global 1990-2012 aviation market developments on connectivity. While analyses of network structures and performance (Burghouwt, Hakfoort, 2001; Bowen, 2002; Reynolds-Feighan, 2007; Paleari et al., 2010; Wang et al., 2011; Lin, 2012) as well as market developments following airline deregulation (Borenstein, 1992; Dempsey, 2002; Goetz, Sutton, 1997; Chan, 2000), the emergence of new airline business models (Dobruszkes, 2006, 2009, 2013; Fan, 2006; Francis et al., 2006; Hooper et al., 2011; Budd et al., 2014;) and economic crises (Rimmer, 2000; Alderighi, Cento, 2004; Wittman, 2014) have been conducted, a consistent framework for global supply-side

market analyses from the connectivity perspective has not been applied, to date. As shown by Suau-Sanchez and Burghouwt (2012), the development of such an approach is particularly important given the increasing significance of indirect connections, which require network analyses to simultaneously model network geography and temporal schedule coordination.

Third, the application of our connectivity metric can advance air transport-related research. The methodology proposed for connection quality weighting might be used to study, for example, competition among hub airports or among different routings (Hansen, 1990; Redondi et al., 2011). In line with Grubestic and Matisziw (2011), Grubestic and Wei (2012) and Matisziw et al. (2012), one might also apply the connectivity model to evaluate the effectiveness and efficiency of the US Essential Air Service Program or the European Public Service Obligations. It could also be used to assess the impact of airport incentive schemes (Malina et al., 2012; Allroggen et al., 2013) from a societal perspective. Furthermore, analyses of the economic growth and employment effects of aviation (e.g. Brueckner, 2003; Percoco, 2010; Allroggen, Malina, 2014) would benefit from incorporating a connectivity metric, since the metric reflects the degree of access to other regions facilitated through air transport services.

We close by noting that future extensions of the connectivity model could deal with transaction-specific heterogeneities such as airfares, airline service levels and passenger preferences, as they impact on individually perceived connectivity. In order to do so, one would need to empirically analyze the trade-off between these heterogeneities and the degree of connectedness, as well as to develop an approach for the aggregation of individual preferences. In addition, future work could be directed towards identifying causal drivers of connectivity to complement our descriptive analysis. This would entail the development of suitable empirical identification strategies for these drivers.

Acknowledgement

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APPENDIX

Appendix A: Decomposition of GCI Growth

The growth rate $\gamma_{a,t,t-\delta}$ of the GCI score for an airport a between base-year $t - \delta$ and year t is calculated as outlined in eq. (A-1):

$$\gamma_{a,t,t-\delta} = \frac{GCI_{a,t} - GCI_{a,t-\delta}}{GCI_{a,t-\delta}} = \frac{\sum_{r \in \{\mathcal{R}_{a,t} \cup \mathcal{R}_{a,t-\delta}\}} (\alpha_{r,t} f_{r,t} w_{d,r,t} - \alpha_{r,t-\delta} f_{r,t-\delta} w_{d,r,t-\delta})}{GCI_{a,t-\delta}} \quad (A-1)$$

For routings r , which are operated in year t or year $t - \delta$ only, we assume eqs. (A-2).

$$f_{r,t} = 0 \quad \forall r \in \mathcal{R}_{a,t-\delta} \setminus \mathcal{R}_{a,t} \quad (A-2a)$$

$$f_{r,t-\delta} = 0 \quad \forall r \in \mathcal{R}_{a,t} \setminus \mathcal{R}_{a,t-\delta} \quad (A-2b)$$

For each route r , we now derive the absolute change of its GCI-contribution $\Delta GCI_{r,a,t,t-\delta}$ as shown in eq. (A-3).

$$\Delta GCI_{r,a,t,t-\delta} = \alpha_{r,t} f_{r,t} w_{d,r,t} - \alpha_{r,t-\delta} f_{r,t-\delta} w_{d,r,t-\delta} \quad (A-3)$$

Furthermore, we rewrite $\alpha_{r,t}$, $f_{r,t}$ and $w_{d,r,t}$ as outlined in eqs. (A-4).

$$\alpha_{r,t} = \alpha_{r,t-\delta} + \Delta \alpha_{r,t,t-\delta} \quad (A-4a)$$

$$f_{r,t} = f_{r,t-\delta} + \Delta f_{r,t,t-\delta} \quad (A-4b)$$

$$w_{d,r,t} = w_{d,r,t-\delta} + \Delta w_{d,r,t,t-\delta} \quad (A-4c)$$

where $\Delta \alpha_{r,t,t-\delta}$, $\Delta f_{r,t,t-\delta}$ and $\Delta w_{d,r,t,t-\delta}$ are the absolute changes of α , f and w respectively between base-year $t - \delta$ and year t . Substitution of eqs. (A-4) into eq. (A-3) yields eq. (A-5).

$$\begin{aligned} \Delta GCI_{r,a,t,t-\delta} = & w_{d,r,t-\delta} (\alpha_{r,t-\delta} \Delta f_{r,t,t-\delta} + f_{r,t-\delta} \Delta \alpha_{r,t,t-\delta} + \Delta \alpha_{r,t-\delta} \Delta f_{r,t,t-\delta}) \\ & + \alpha_{r,t-\delta} f_{r,t-\delta} \Delta w_{d,r,t,t-\delta} \end{aligned} \quad (A-5)$$

$$+\Delta w_{d_r,t-\delta}(\alpha_{r,t-\delta}\Delta f_{r,t,t-\delta} + f_{r,t-\delta}\Delta\alpha_{r,t,t-\delta} + \Delta\alpha_{r,t-\delta}\Delta f_{r,t,t-\delta})$$

In eq. (A-5), we identify the destination-quality-neutral absolute growth $\rho_{r,t,t-b}$ of route r 's GCI contribution which is caused by a ceteris paribus variation of the network between base-year $t - \delta$ and year t . It is shown in eq. (A-6).

$$\rho_{r,t,t-b} = \alpha_{r,t-\delta}\Delta f_{r,t,t-\delta} + f_{r,t-\delta}\Delta\alpha_{r,t,t-\delta} + \Delta\alpha_{r,t-\delta}\Delta f_{r,t,t-\delta} \quad (A-6)$$

Eq. (A-5) is now rewritten as presented in eq. (A-7).

$$\Delta GCI_{r,a,t,t-b} = w_{d_r,t-\delta}\rho_{r,t,t-\delta} + \alpha_{r,t-\delta}f_{r,t-\delta}\Delta w_{d_r,t,t-\delta} + \Delta w_{d_r,t-\delta}\rho_{r,t,t-\delta} \quad (A-7)$$

From eqs. (A-7) and (A-1), we derive eq. (A-8).

$$\begin{aligned} \gamma_{a,t,t-\delta} = & \frac{\sum_{r \in \{\mathcal{R}_{a,t} \cup \mathcal{R}_{a,t-\delta}\}} w_{d_r,t-\delta} \rho_{r,t,t-\delta}}{GCI_{a,t-\delta}} + \frac{\sum_{r \in \{\mathcal{R}_{a,t} \cup \mathcal{R}_{a,t-\delta}\}} \alpha_{r,t-\delta} f_{r,t-\delta} \Delta w_{d_r,t,t-\delta}}{GCI_{a,t-\delta}} + \\ & \frac{\sum_{r \in \{\mathcal{R}_{a,t} \cup \mathcal{R}_{a,t-\delta}\}} \Delta w_{d_r,t-\delta} \rho_{r,t,t-\delta}}{GCI_{a,t-\delta}} \end{aligned} \quad (A-8)$$

GCI-growth rates are subsequently decomposed as follows:

1. Network effects

Network-related GCI effects result from ceteris paribus changes of the network.

$$v_{a,t,t-\delta} = \frac{\sum_{r \in \{\mathcal{R}_{a,t} \cup \mathcal{R}_{a,t-\delta}\}} w_{d_r,t-\delta} \rho_{r,t,t-\delta}}{GCI_{a,t-\delta}}$$

maps the network-related GCI growth rate $v_{a,t,t-\delta}$ at airport a between base-year $t - \delta$ and year t . For our analysis, we compute $v_{a,t,1990}$ from the difference of year t 's GCI scores with constant year-1990-destination quality weights³³ and the year-1990 scores divided by the year-1990 scores.

2. Destination-quality effects

Destination quality-related GCI effects result from ceteris paribus changes of

$$\text{destination quality. } \theta_{a,t,t-\delta} = \frac{\sum_{r \in \{\mathcal{R}_{a,t} \cup \mathcal{R}_{a,t-\delta}\}} \alpha_{r,t-\delta} f_{r,t-\delta} \Delta w_{d_r,t,t-\delta}}{GCI_{a,t-\delta}}$$

represents the destination quality-related GCI growth rate $\theta_{a,t,t-\delta}$ at airport a between year $t - \delta$ and year t . In our analysis, we calculate $\theta_{a,t,1990}$ from the difference of the

³³ For each year t , this score is computed by assuming the network of year t and the destination quality weights for year 1990. Computation is conducted by airport.

constant year-1990-network GCI scores for year t ³⁴ and the year-1990 GCI scores divided by the year-1990 GCI scores.

3. *Simultaneity effects*

Simultaneity effects are the additional GCI effects of simultaneous variation of the network and destination quality. The interaction-related GCI growth rate for airport a , base-year $t - \delta$ and year t is defined by

$$l_{a,t,t-\delta} = \frac{\sum_{r \in \{\mathcal{R}_{a,t} \cup \mathcal{R}_{a,t-\delta}\}} \Delta w_{dr,t-\delta} \rho_{r,t,t-\delta}}{GCI_{a,t-\delta}}. \text{ According to eq. (A-8), we calculate}$$

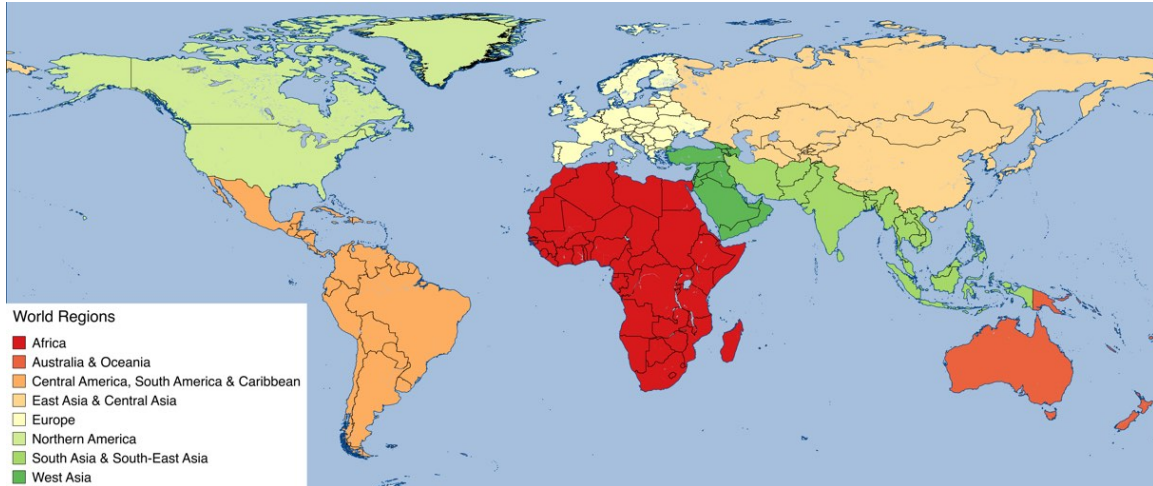
$$l_{a,t,1990} = \gamma_{a,t,1990} - \theta_{a,t,1990} - \nu_{a,t,1990}.$$

Appendix B: Definition of World Regions

The world regions are defined in Fig. B-1.

Fig. B-1.

Map of world regions.



³⁴ For each year t , this score is computed by assuming the year-1990 network and the destination quality weights for year t . Computation is conducted by airport.

References

- Abrantes, P.A.L., Wardman, M.R., 2011. Meta-analysis of UK values of travel time: an update. *Transportation Research Part A* 45, 1-17.
- Airbus, 2013. Global market forecast. Future journeys, 2013-2032.
- Airbus, 2014. Global market forecast. Flying on demand, 2014-2033.
- Albers, S., Koch, B., Ruff, C., 2005. Strategic alliances between airlines and airports: theoretical assessment and practical evidence. *Journal of Air Transport Management* 11, 49-58.
- Alderighi, M., Cento, A., 2004. European airlines conduct after September 11. *Journal of Air Transport Management* 10, 97-107.
- Alderighi, M., Cento, A., Nijkamp, P., Rietveld, R., 2007. Assessment of new hub-and-spoke and point-to-point airline network configurations. *Transport Reviews* 27, 529-549.
- Allroggen, F., Malina, R., Lenz, A.K., 2013. Which factors impact on the presence of incentives for route and traffic development? Econometric evidence from European airports. *Transportation Research Part E* 60, 49-61.
- Allroggen, F., Malina, R., 2014. Do the regional growth effects of air transport differ among airports? *Journal of Air Transport Management* 37, 1-4.
- Başar, G., Bhat, C., 2004. A parameterized consideration set model for airport choice: an application to the San Francisco Bay Area. *Transportation Research Part B* 38, 889-904.
- Bel, G., Fageda, X., 2010. Privatization, regulation and airport pricing: an empirical analysis for Europe. *Journal of Regulatory Economics* 37, 142-161.
- Berechman, J., de Wit, J., 1996. An analysis of the effects of European aviation deregulation on an airline's network structure and choice of primary West European hub airport. *Journal of Transport Economics & Policy* 30, 251-274.
- Borenstein, S., 1992. The evolution of U.S. airline competition. *Journal of Economic Perspectives* 6, 45-73.
- Bowen, J., 2000. Airline hubs in Southeast Asia: national economic development and nodal accessibility. *Journal of Transport Geography* 8, 25-41.
- Bowen, J., 2002. Network change, deregulation and access in the global airline industry. *Economic Geography* 78, 425-439.
- Breinlich, H. (2006): The spatial income structure in the European Union: what role for Economic Geography? *Journal of Economic Geography* 6, 593-617.
- Brueckner, J.K., Spiller, P.T., 1994. Economies of traffic density in the deregulated airline industry. *Journal of Law and Economics* 37, 379-415.
- Brueckner, J.K., 2003. Airline traffic and urban economic development. *Urban Studies* 40, 1455-1469.

- Budd, L., Francis, G., Humphreys, I., Ison, S., 2014. Grounded: characterizing the market exit of European low cost airlines. *Journal of Air Transport Management* 34, 75-85.
- Burghouwt, G., Hakfoort, J., 2001. The evolution of the European aviation network, 1990-1998. *Journal of Air Transport Management* 7, 311-318.
- Burghouwt, G., Hakfoort, J., van Eck, J.R., 2003. The spatial configuration of airline networks in Europe. *Journal of Air Transport Management* 9, 309-323.
- Burghouwt, G., de Wit, J., 2005. Temporal configurations of European airline networks. *Journal of Air Transport Management* 11, 185-198.
- Burghouwt, G., Veldhuis, J., 2006. The competitive position of hub airports in the transatlantic market. *Journal of Air Transportation* 11, 106-130.
- Burghouwt, G., Redondi, R., 2013. Connectivity in air transport networks. An assessment of models and applications. *Journal of Transport Economics & Policy* 47, 35-53.
- Chan, D., 2000. The development of the airline industry from 1978 to 1998. A strategic global overview. *The Journal of Management Development* 19, 489-514.
- Chin, A., Hooper, P., Oum, T.H., 1999. The impacts of the Asian economic crisis on Asian airlines: short-run responses and long-run effects. *Journal of Air Transport Management* 5, 87-96.
- Coldren, G.M., Koppelman, F.S., 2005. Modeling the competition among air-travel itinerary shares: GEV model development. *Transportation Research Part A* 39, 345-365.
- CRA, 2004. Air Passengers from the bay area's airports, 2001 and 2002. Volume 1: Overview and Methods. Final Report prepared for the Metropolitan Transportation Commission.
- De Luca, S., 2012. Modelling airport choice behaviour for direct flights, connecting flights and different travel plans. *Journal of Transport Geography* 22, 148-163.
- Dempsey, P.S., 1991. The disintegration of the U.S. airline industry. *Transportation Law Journal* 20, 9-46.
- Dempsey, P.S., 2002. Predation, competition & antitrust law: turbulence in the airline industry. *Journal of Air Law and Commerce* 67, 685-840.
- Dempsey, P.S., 2008. The financial performance of the airline industry post-deregulation. *Houston Law Review* 45, 421-485.
- Dobruszkes, F., 2006. An analysis of European low-cost airlines and their networks. *Journal of Transport Geography* 14, 249-264.
- Dobruszkes, F., 2009. New Europe, new low-cost air services. *Journal of Transport Geography* 17, 423-432.
- Dobruszkes, F., 2013. The geography of European low-cost airline networks: a contemporary analysis. *Journal of Transport Geography* 28, 75-88.

- Dobruszkes, F., van Hamme, G., 2011. The impact of the current economic crisis on the geography of air traffic volumes: an empirical analysis. *Journal of Transport Geography* 19, 1387-1398.
- Emrich, R.M., de Harris, F.H., 2008. Share shift and airport substitution in origin-destination markets with low-cost entrants. *International Journal of Revenue Management* 2, 109-122.
- Fan, T., Vigeant-Langlois, L., Geissler, C., Bosler, B., Wilmking, J., 2001. Evolution of global airline strategic alliance and consolidation in the twenty-first century. *Journal of Air Transport Management* 7, 349-360.
- Fan, T., 2006. Improvements in intra-European inter-city flight connectivity: 1996-2004. *Journal of Transport Geography* 14, 273-286.
- Forsyth, P., King, J., Rodolfo, C.L., 2006. Open Skies in ASEAN. *Journal of Air Transport Management* 12, 143-152.
- Francis, G., Humphreys, I., Ison, S. Aicken, M., 2006. Where next for low cost airlines? A spatial and temporal comparative study. *Journal of Transport Geography* 14, 83-94.
- Franke, M., 2004. Competition between network carriers and low-cost carriers. Retreat battle or breakthrough to a new level of efficiency? *Journal of Air Transport Management* 10, 15-21.
- Gabor, D., 2010. Low-cost airlines in Europe: Network Structures After the Enlargement of the European Union. *Geographica Pannonica* 14, 49-58
- Geurs, K.T., van Wee, B., 2004. Accessibility evaluation of land-use and transport strategies: review and research options. *Journal of Transport Geography* 12, 127-140.
- Gillen, D., Lall, A., 2004. Competitive advantage of low-cost carriers: some implications for airports. *Journal of Air Transport Management* 10, 41-50.
- Goetz, A.R., Sutton, C.J., 1997. The geography of deregulation in the US airline industry. *Annals of the Association of American Geographers* 87, 238-263.
- Goetz, A.R., Vowles, T.M., 2009. The good, the bad and the ugly: 30 years of US airline deregulation. *Journal Transport Geography* 17, 251-263.
- Gudmundsson, S.V., Rhoades, D.L., 2001. Airline alliance survival analysis: topology, strategy and duration. *Transport Policy* 8, 209-218.
- Grimme, W., 2011. The growth of Arabian airlines from a German perspective. A study on the impact of new air services to Asia. *Journal of Air Transport Management* 17, 333-338.
- Grubestic, T.H., Matisziw, T.C., 2011. A spatial analysis of air transport access and the essential air service program in the United States. *Journal of Transport Geography* 19, 93-105.
- Grubestic, T.H., Wei, F., 2012. Evaluating the efficiency of the Essential Air Service program in the United States. *Transportation Research Part A* 46, 1562-1573.
- Hansen, M., 1990. Airline competition in a hub-dominated environment: an application of noncooperative game theory. *Transportation Research Part B* 24, 27-43.

- Harvey, G., 1987. Airport Choice in a multiple airport region. *Transportation Research Part A* 21, 439-449.
- Hess, S., Polak, J.W., 2005. Mixed logit modelling of airport choice in multi-airport regions. *Journal of Air Transport Management* 11, 59-68.
- Hess, S., Adler, T., Polak, J.W., 2007. Modelling airport and airline choice behaviour with the use of stated preference survey data. *Transportation Research Part E* 43, 221-233.
- Hooper, P., 1997. Liberalizing competition in domestic airline markets in Asia. The problematic interface between domestic and international regulatory policies. *Transportation Research Part E* 33, 197-209.
- Hooper, P., 2005. The environment for Southeast Asia's new and evolving airlines. *Journal of Air Transport Management* 11, 335-347.
- Hooper, P., Walker, S., Moore, C., Al Zubaidi, Z., 2011. The development of the Gulf region's air transport networks. The first century. *Journal of Air Transport Management* 17, 325-332.
- Hsiao, C.Y., Hansen, M., 2011. A passenger demand model for air transportation in a hub-and-spoke network. *Transportation Research Part E* 47, 1112-1125.
- Hummels, D., 2007. Transportation costs and international trade in the second era of globalization. *Journal of Economic Perspectives* 21, 131-154.
- Ishii, J., Sunyoung, S., van Dender, K., 2009. Air travel choices in multi-airport markets. *Journal of Urban Economics* 65, 216-227.
- Kanafani, A., Ghobrial, A.A., 1985. Airline hubbing. Some implications for airport economics. *Transportation Research Part A* 1, 15-27.
- Lakshmanan, T.R. (2011): The broader economic consequences of transport infrastructure investments. *Journal of Transport Geography* 19, 1-12.
- Lawton, T.C., Solomko, S., 2005. When being the lowest cost is not enough: building a successful low-fare airline business model in Asia. *Journal of Air Transport Management* 11, 355-362.
- Lieshout, R., 2012. Measuring the size of an airport's catchment area. *Journal of Transport Geography* 25, 27-34.
- Lin, J., 2012. Network analysis of China's aviation system, statistical and spatial structure. *Journal of Transport Geography* 22, 109-117.
- Maertens, S., 2010. Drivers of long-haul flight supply at secondary airports in Europe. *Journal of Air Transport Management* 16, 239-243.
- Malina, R., Albers, S., Kroll, N. (2012): Airport incentive programs, A European perspective. *Transport Reviews* 32, 435-453.
- Malighetti, P., Palesi, S., Redondi, R., 2008. Connectivity of the European airport network: 'Self-help hubbing' and business implications. *Journal of Air Transport Management* 14, 53-65.

- Marcucci, E., Gatta, V., 2011. Regional airport choice: consumer behaviour and policy implications. *Journal of Transport Geography* 19, 70-84.
- Matisziw, T.C., Grubestic, T.H., 2010. Evaluating locational accessibility to the US air transportation system. *Transportation Research Part A* 44, 710-722.
- Matisziw, T.C., Lee, C.L., Grubestic, T.H., 2012. An analysis of essential air service structure and performance. *Journal of Air Transport Management* 18, 5-11.
- Murakami, H., 2011. Empirical analysis of inter-firm rivalry between Japanese full-service and low-cost carriers. *Pacific Economic Review* 16, 103-119.
- Oak Ridge National Laboratory, 2014. LandScan Documentation. Available Online: http://web.ornl.gov/sci/landscan/landscan_documentation.shtml.
- O'Connell, J.F., 2011. The rise of the Arabian Gulf carriers. An insight into the business model of Emirates Airlines. *Journal of Air Transport Management* 17, 339-346.
- O'Kelly, M.E., 1998. A geographer's analysis of hub-and-spoke networks. *Journal of Transport Geography* 6, 171-186.
- Oum, T.H., Park, J.H., 1997. Airline alliances: current status, policy issues and future directions. *Journal of Air Transport Management* 3, 133-144.
- Páez, A., Scott, D.M., Morency, C., 2012. Measuring accessibility: positive and normative implementations of various accessibility indicators. *Journal of Transport Geography* 25, 141-153.
- Paleari, S., Redondi, R., Malighetti, P., 2010. A comparative study of airport connectivity in China, Europe and US: which network provides the best service to passengers? *Transportation Research Part E* 46, 198-210.
- Park, J.H., 1997. The effects of airline alliances on markets and economic welfare. *Transportation Research Part E* 33, 181-195.
- Pels, E., Nijkamp, P., Rietveld, P., 2001. Airport and airline choice in a multiple airport region: an empirical analysis for the San Francisco Bay Area. *Regional Studies* 35, 1-9.
- Percoco, M., 2010. Airport activity and local development. Evidence from Italy. *Urban Studies* 47, 2427-2443.
- Rapacki, R., Próchniak, M., 2009. The EU enlargement and economic growth in the CEE new member countries. *Economic Papers* 367. The European Commission, Brussels.
- Redding, S., Venables, A.J., 2004. Economic geography and international inequality. *Journal of International Economics* 62, 53-82.
- Redding, S.J., 2010. The empirics of New Economic Geography. *Journal of Regional Science* 50, 297-311.
- Redondi, R., Malighetti, P., Paleari, S., 2011. Hub competition and travel times in the world-wide airport network. *Journal of Transport Geography* 19, 1260-1271.

- Reynolds-Feighan, A., McLay, P., 2006. Accessibility and attractiveness of European airports: a simple small community perspective. *Journal of Air Transport Management* 12, 313-323.
- Reynolds-Feighan, A.J., 2007. Competing networks, spatial and industrial concentration in the US airline industry. *Spatial Economic Analysis* 2, 237-257.
- Rimmer, P.J., 2000. Effects of the Asian crisis on the geography of Southeast Asia's air traffic. *Journal of Transport Geography* 8, 83-97.
- Shaw, S.L., Ivy, R.J., 1994. Airline mergers and their effects on network structure. *Journal of Transport Geography* 2, 234-246.
- Shaw, S.L., Lu, F., Chen, J., Zhou, C., 2009. China's airline consolidation and its effects on domestic airline networks and competition. *Journal of Transport Geography* 17, 293-305.
- Suau-Sanchez, P., Burghouwt, G., 2011. The geography of the Spanish airport system: spatial concentration and deconcentration patterns in seat capacity distribution, 2001-2008. *Journal of Transport Geography* 19, 244-254.
- Suau-Sanchez, P., Burghouwt, G., 2012. Connectivity levels and the competitive position of Spanish airports and Iberia's network rationalization strategy, 2001-2007. *Journal of Air Transport Management* 18, 47-53.
- Veldhuis, J., 1997. The competitive position of airline networks. *Journal of Air Transport Management* 3, 181-188.
- Vespermann, J., Wald, A., Gleich, R., 2008. Aviation growth in the Middle East. Impacts on incumbent players and potential strategic reactions. *Journal of Transport Geography* 16, 388-394.
- Wang, J., Mo, H., Wang, F., Jin, F., 2011. Exploring the network structure and nodal centrality of China's air transport network: a complex network approach. *Journal of Transport Geography* 19, 712-721.
- Wardman, M., 2004. Public transport values of time. *Transport Policy* 11, 363-377.
- Wilken, D., Berster, P., Gelhausen, M., 2007. Airport choice in Germany: new empirical evidence of the 2003 German air traveller survey. *Journal of Airport Management* 1, 165-179.
- Wittman, M.D., 2014. The effects of capacity discipline on smaller U.S. airports: trends in service, connectivity and fares. MIT MS Thesis, Cambridge.
- Wittman, M.D., Swelbar, W.S., 2014. Capacity discipline and the consolidation of airport connectivity in the United States. *Transportation Research Record: Journal of the Transportation Research Board* 2449, 72-78.
- World Bank, 2014a. World Development Indicators 2014. Washington, DC. doi: 10.1596/978-1-4648-0163-1.
- World Bank, 2014b. World Bank Analytical Classifications. Available online: <http://siteresources.worldbank.org/DATASTATISTICS/Resources/OGHIST.xls>

- Yamauchi, H., Ito, T. 1996. Air transport policy in Japan. Working Paper No. 124, Center on Japanese Economy and Business, Columbia Business School.
- Yamaguchi, K., 2007. Inter-regional air transport accessibility and macro-economic performance in Japan. *Transportation Research Part E* 43, 247-258.
- Zanin, M., Lillo, F., 2013. Modelling the air transport with complex networks. A short review. *The European Physics Journal - Special Topics* 215, 5-21.
- Zhang, A., 1998. Industrial reform and air transport development in China. *Journal of Air Transport Management* 4, 155-164.
- Zhang, Y., Round, D.K., 2008. China's airline deregulation since 1997 and the driving forces behind the 2002 airline consolidations. *Journal of Air Transport Management* 14, 130-142.
- Zhang, J., Cao, X.B., Du, W.B., Cai, K.Q., 2010. Evolution of Chinese airport network. *Physica A* 389, 3922-3931.