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AN ASSESSMENT OF THE POTENTIAL FOR SELF-CONNECTIVITY AT EUROPEAN AIRPORTS IN HOLIDAY MARKETS

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ABSTRACT

In a context of intense airport and airline competition, a few European airports have recently started offering self-connection services to price-sensitive holiday passengers travelling with a combination of tickets where the airline/s involved do not handle the transfer themselves. This paper provides an exploratory analysis of the potential and implications of self-connectivity for European airports and airlines using a case study of air travel routes to holiday destinations in the Mediterranean. With the help of a forecasting model based on a zero-inflated Poisson regression, we identify the airports and airlines that have the highest potential to facilitate self-connections in the selected markets. The results also explore some implications of the widespread development of self-connection services in Europe.

Keywords: Tourist airports; self-connectivity; holiday travel; Poisson regression.

1. INTRODUCTION

In recent years, many low-cost carriers (LCCs) have reacted to the strong competitive environment by adopting strategies traditionally associated to full-service network carriers, such as price bundling, codesharing agreements, and operating connecting flights (Klophaus et al., 2012; Lieshout et al., 2015; Morandi et al., 2015; Fageda et al., 2015). This reveals an interest by low-cost operators to tap into a market they have been neglecting: self-connecting passengers that build their own itineraries by combining multiple tickets and taking care of their own baggage transfer. Recently, a few airports have shown that they wish to cater to the needs of self-connecting passengers as well. For example, London Gatwick and Milano Malpensa started offering self-connection services to passengers travelling with a combination of tickets where the airline/s involved do not handle the transfer themselves (ViaMilano, 2016). In exchange for a fee, self-connecting passengers at Gatwick are offered a baggage transfer service as well as insurance against the risk of missing their onward flight in the event of delays (Gatwick Airport, 2015). Another feature of these self-connectivity platforms is a dedicated booking system that presents self-connecting tickets to the passengers automatically. This improves the "visibility" of these travel options since passengers do not have to put an extra search effort to build their own tickets, as they have to do in booking systems that only show traditional flight connections. Airlines must sign up to participate in self-connecting schemes at each airport and they may do so if the interline connectivity creates economies of traffic density (Starkie, 2007). Airports, on the other hand, can also benefit from increased non-aeronautical revenues linked to the extra connecting passengers (Malighetti et al., 2008).

One of the key targets of self-connection services are price-sensitive holiday passengers[1]. This is evident from the marketing materials of Gatwick and Milano airports, which point at potential cost savings in self-connection itineraries to/from destinations in the Mediterranean. Assuming that leisure passengers are willing to accept travel detours to save in airfares (Fageda et al., 2015; OAG, 2016), and taking into account that intra-European routes are dominated by point-to-point LCC services (Dobruszkes, 2013) with limited traditional connectivity, we hypothesize that there is potential for a more widespread development of self-connection platforms at European airports that cater to passengers in holiday markets.

In this context, we aim to evaluate several aspects of this business opportunity that have not yet received substantial attention in the literature. We focus on 1) identifying the airports and airlines that have the highest potential for self-connectivity, and 2) discuss the barriers and facilitating factors for airports and airlines to support self-connectivity. To that end, we use Market Information Data Tapes (MIDT) for June 2014 that cover routes from Europe to holiday destinations in the Mediterranean. A Quality of Service Index (QSI) methodology, based on coefficients obtained using a zero-inflated Poisson regression, is employed to predict the amount of potential traffic that could be captured by self-connecting travel alternatives identified with a connections builder (CB) algorithm.

Table 1. Examples of self-connecting routes marketed by European airports

GatwickConnects				*ViaMilano*		
Origin	*Destination*	*Regular Connection Cheapest price (travel time)*	*Self-Connection Cheapest price (travel time)*	*Origin*	*Destination*	*Price*
New York	*Larnaca*	*£957 (18 h)*	*£203 (14 h 5 m)*	*Barcelona*	*Rome*	*€131*
Agadir	*Helsinki*	*£378 (21 h 50 m)*	*£152 (9 h 55 m)*	*Budapest*	*Rome*	*€128*
Inverness	*Palma*	*£225 (22 h)*	*£108 (7 h)*	*Budapest*	*Alghero*	*€130*
Madrid	*Reykjavik*	*£237 (9h 10 m)*	*£144 (8h)*	*Budapest*	*Cagliari*	*€139*

Source: Gatwick Airport (September 2015), www.flyviamilano.edu (April 2016)

The rest of this paper is structured as follows: Section 2 reviews the literature and states our contribution. Section 3 introduces the case study, datasets, and methodology. Section 4 presents the results and discusses their main implications. Finally, Section 5 summarizes our findings, addresses the limitations of our model, and proposes new paths for future research.

2. PREVIOUS LITERATURE

While there have been many papers analyzing the connectivity of airline networks (e.g. Veldhuis, 1997; Burghouwt and de Wit, 2005), the phenomenon of self-connectivity was firstly defined by Burghouwt (2007) as "self-help hubbing", while Malighetti et al., (2008) were the first to analyse it in detail. Using data on airline schedules, they concluded that there were many attractive indirect travel options[2] involving self-connections. In particular, they found that two-thirds of the fastest indirect connections within Europe were provided outside the scope of the individual airline alliances. In terms of methodology, we aim to complement their analysis of airline schedules with demand data on actual passenger itineraries (MIDT). This is a novel contribution to the literature on self-connectivity in airline networks. It is a relevant improvement since not all self-connecting travel alternatives will be equally important for the airport and airlines involved. Their importance will depend on factors that can only be measured with demand data: 1) the size of the relevant origin and destination market, i.e. how many passengers do actually want to travel between the two places? 2) how competitive are the other available travel options that passengers have actually taken within the same market?

[1] Indeed, tourism demand is influenced by the cost of travel (Garin-Munoz et al., 2006; Ben-David et al., 2016).

[2] In this paper, we refer to a travel alternative, travel option or travel itinerary as a sequence of flights between the passenger's point of origin and ultimate destination. Most origin and destination markets can be served by multiple travel alternatives, which can be either direct (non-stop) or indirect (involving at least one flight connection).

Connection builders (CB) are typically employed to identify the competitive travel alternatives in air transport markets (Halpern and Graham, 2013). Using data on airline schedules, these algorithms search for all valid flight connections between predefined origin and destination airports. Then, there is need to forecast the demand that each travel itinerary can capture. In that regard, Halpern and Graham (2013) notes that Quality of Service Index (QSI) models have been adopted as industry standard and are widely applied by airports to forecast market shares of new routes. QSI models assign a weighted "score" to each travel alternative based on a set of predictors of passenger choice. The most common demand predictors include fares, frequencies, connecting times, number of stops, travel detours, aircraft type, or departure time[3] (Tembleque-Villalta and Suau-Sanchez, 2015; Narangajavan et al., 2014). Our paper is the first to add self-connectivity to that list of demand predictors. A common criticism of QSI models is that the weights of each predictor usually take arbitrary values (Wei and Hansen, 2006). In order to overcome that limitation, we calibrate the predictor weights using a regression method on the observed passenger behaviour recorded in the MIDT data. In accordance with the observed distributional characteristics of passenger bookings, we model it as count data and employ a Poisson model (Mao et al., 2015).

In summary, we advance the literature about self-connectivity in airline networks with the use of MIDT demand data that leads to a more precise determination of the amount and value of the self-connections available at European airports. To that end, we employ methods that are well established in the context of airport route development (QSI and CB), thus helping the implementation of our methods by practitioners in the air transport industry.

3. DATA AND METHODOLOGY

3.1. Case study and datasets

We focus on the air transport routes that originate in the European Economic Area and terminate in a coastal destination in (or around) the Mediterranean region during the first week of June 2014. Data was available from these countries: Morocco, Algeria, Malta, Egypt, Jordan, Israel, Lebanon, Cyprus, Turkey, Greece, Croatia, Italy, France, Monaco, Spain, Gibraltar, and Portugal. All island destinations in these countries are included, even the Atlantic ones (Canaries, Madeira, and Azores). For mainland Spain, France, and Italy, only the airports serving Mediterranean destinations are designed as such (See Appendix A for more details).

Our MIDT dataset includes 3.2 million passenger bookings obtained from the OAG Traffic Analyser. The original sources of information for the MIDT dataset are Global Distributions Systems (GDSs), such as Galileo, Sabre, or Amadeus. Table 2 provides a breakdown of bookings per origin and destination countries. As expected, countries like UK, Italy, and Germany are among the largest generators. Spain, Italy, and Greece are the top traffic attractors on the European side, while Morocco is the top destination on the African side. It is worth highlighting Italy's dual role as origin and destination country, which is related to its unique geography with a large number of Mediterranean airports, including Rome, while also leaving major airports in the North (e.g. Milan), outside of the pool of destinations.

Table 2. Distribution of MIDT passenger bookings per origin and destination country (1st week June 2014)

Origin Country	*bookings*	*Origin Country (cont.)*	*bookings*	*Destination country*	*bookings*
UK	610,964	Poland	26,593	Spain	1,182,721
Italy	509,613	Romania	23,528	Italy	766,121
Germany	417,678	Finland	19,027	Greece	353,872
Spain	408,459	Cyprus	15,577	Portugal	263,274
France	368,574	Hungary	13,743	France	223,846

[3] Travel purpose is also a common predictor. However, due to the selection of routes in our case study (leisure destinations), the distinction between business and leisure is less relevant. Furthermore, recent evidence from Bilotkach et al., (2015) challenges the view that LCC leisure passengers are significantly more price elastic.

Greece	144,927	Croatia	11,353	Morocco	102,550
Belgium	106,454	Luxembourg	8,543	Israel	72,744
Switzerland	96,075	Malta	7,584	Croatia	64,669
Netherlands	95,289	Lithuania	6,704	Algeria	49,408
Portugal	63,361	Bulgaria	6,208	Cyprus	42,342
Ireland	55,384	Slovakia	2,837	Egypt	39,014
Norway	50,497	Latvia	2,536	Malta	38,671
Sweden	46,781	Estonia	2,337	Lebanon	14,733
Denmark	38,388	Iceland	2,304	Jordan	8,636
Austria	34,816	Monaco	644	Gibraltar	3,627
Czech Republic	27,487	Slovenia	566	Monaco	848

Source: MIDT

It is also possible to disaggregate the bookings according to the type of itinerary (Table 3). The vast majority of bookings (91.7%) are for non-stop travel. In spite of that, the amount of connecting passengers is not negligible (266 thousand per week) and represents an attractive segment of demand that airports could develop by facilitating self-connections.

Table 3. Distribution of MIDT passengers in the sample market per type of itinerary (1st week June 2014)

Itinerary	*Bookings*	*%*
Non-stop	2,959,429	91.7%
1-stop	250,940	7.8%
2-stops	16,707	0.5%
Total	3,227,076	

Source: MIDT

Table 4 shows the top ten intermediate hubs in the sample. Rome Fiumicino (FCO) has a dual role as a major traffic generator and Europe's busiest gateway to onward Mediterranean destinations. However, airports located outside the Mediterranean countries, such as Frankfurt or Munich can also leverage their destination mixes to expand their participation in leisure markets by means of indirect connections. Table 4 also shows the top ten airlines according to passenger bookings. As expected, intra-European markets are dominated by LCCs such as Ryanair and Easyjet, which supports the hypothesis that a large number of self-connecting opportunities will be found among these airlines that do not typically operate transfer flights.

Table 4. Top ten airlines and hub airports in the sample (1st week June 2014)

Airport	*Code*	*Departures*	*Connections*	*Ticketing Airline*	*Code*	*Bookings*
Rome Fiumicino	FCO	108,444	36,572	Ryanair	FR	742,839
Frankfurt	FRA	71,923	25,642	Easyjet	U2	359,445
Munich	MUC	66,984	18,896	Vueling	VY	211,895
Madrid Barajas	MAD	105,037	18,268	Alitalia	AZ	134,504
Athens	ATH	70,810	12,622	Air Berlin	AB	127,995
Barcelona	BCN	86,461	11,864	Aegean Airlines	A3	118,023
Paris Charles de Gaulle	CDG	80,727	10,333	Air France	AF	91,849
Zurich	ZRH	37,233	9,483	TAP	TP	76,474
Istanbul Ataturk	IST	9,246	9,246	Lufthansa	LH	70,970
Vienna	VIE	35,231	9,048	Monarch	ZB	70,963

Source: MIDT

We also employ two additional datasets of global flight schedules and airport-specific minimum connecting times (including airline-specific exceptions) valid for the first week of June 2014, obtained from OAG as well.

3.2 Connection Builder

Flight frequency is one of the key predictors of passenger choice. Therefore, we employ a CB method to find all valid itineraries in the selected markets. The parameters of our CB algorithm are summarized in Table 5. For each airport-pair in the MIDT file, a search is made in the schedules dataset for all valid flight combinations from the origin airport to the destination airport (up to a maximum of two stops). No interline restrictions are imposed. For a flight combination to be valid it must meet the published minimum connecting times.

In order to discard unrealistic flight combinations (Redondi et al., 2011; Seredyński et al., 2014; Grosche and Klophaus, 2015), we impose a maximum geographic detour for each market (ratio between indirect and non-stop flight distance) based on the real-world itineraries in the MIDT file. To mitigate the influence of outliers, we discard every flight combination found by the CB algorithm that is above the 95% percentile of the market-specific distribution of geographic detour calculated from the itineraries in the MIDT file. With the same objective, an additional constraint is imposed in regards to maximum travel time increase (ratio between total indirect travel time, including flight connections, and non-stop travel time). That limit is established at the 95% percentile in the market-specific distribution of travel time increase. This distribution includes all traditional flight combinations within a one-hour window with respect to the best weekly indirect travel time in each itinerary. The goal is to keep only the self-connecting flight combinations that are competitive in the sense that there is evidence that passengers are willing to accept these geographic detours and travel time increases in traditional flight connections[4].

Table 5. Parameters of the connection builder

1. No interline restrictions
2. Published minimum connecting times must be met
3. Maximum geographic detour per origin-destination market (95% percentile of MIDT itineraries)
4. Maximum travel time increase per origin-destination market (95% percentile of MIDT itineraries)
4a. Based on best weekly traditional connecting time (+ 1 hour) in each individual itinerary

A flight combination is labelled as "self-connecting" if either: 1) both arriving and departure airlines are LCCs (as indicated by ICAO, 2014)[5], or 2) arriving and departure airlines are not part of the same alliance. This broad definition, however, leaves some traditional connections misclassified, such as those provided in virtue of out-of-alliance interlining agreements and also the transfer services provided by LCCs at selected locations. We identify these cases by cross-checking our CB flight combinations against the published minimum connecting times dataset, as it is common that airlines providing these connections file an exception to the airport's default values. The outcome of this stage is a dataset of 469,734 unique itineraries that the CB identified as valid travel alternatives within the selected markets.

3.3 Poisson regression and QSI model

The CB itineraries are combined with the MIDT passenger bookings, returning a dataset of 134,724 consolidated itineraries, 78.24% of which (105,402) did not have any bookings. Our dependent variable is the number of weekly passenger bookings per itinerary (See Table 6). Since bookings only take non-negative integer values, they can be defined as count data (Mao et al., 2015). Poisson regressions are typically used to model count data. However, these models are restrictive in the sense that the Poisson distribution assumes that the conditional mean is equal to the conditional variance. This assumption is not met by our data, which shows clear signs of overdispersion.

Table 6. Descriptive statistics of dependent variable

variable	*n*	*mean*	*variance*	*Zero obs*	*p1*	*p75*	*p90*	*p95*	*p99*	*max*
bookings	134,724	23.27	32,932.26	105,402	0	0	7	30	636	12,936

One way to deal with the high variance is to account for the excessive amount of zero-booking travel itineraries. To that end, we employ a zero-inflated Poisson regression in order to separate between "true zeros" and "excess zeros" (Greene, 1994). This method models two separate

[4] For example, assume that the MIDT indicates that the market from airport A to airport B has 100 passengers, 50 travelling non-stop, 48 indirect via C (geographic detour = 1.2 and travel time increase = 1.4), and 2 travelling indirect via D (geographic detour = 1.5 and travel time increase = 2). Self-connecting travel options for this market will be restricted to a geographic detour of 1.2 and travel time increase of 1.4. If the number of passengers on the "D" itinerary was higher of equal than five, the cut-off values would have been 1.5 and 2, respectively.

[5] This applies to either flight connection in the case of 2-stop itineraries.

data generation processes for each observation, one that generates zero counts and another generating Poisson counts. For travel itinerary i *(Y_i)*, the zero-generating process is chosen with probability φ_i and the Poisson process with probability (1- φ_i):

(1) $\mu_i = \exp(x_i'\beta)$

(2) $P(Y_i = 0|x_i, z_i) = \varphi_i(z_i'\gamma) + \big(1 - \varphi_i(z_i'\gamma)\big)\exp(-\mu_i)$

(3) $P(Y_i = y_i|x_i, z_i) = (1 - \varphi_i(z_i'\gamma))\frac{\mu_i{}^{y_i}\exp(-\mu_i)}{y_i!}$

The φ_i probability is modelled against the characteristics of each observation (z_i) using a logistic function with parameters γ to be estimated. The Poisson process has mean μ_i that is regressed against the characteristics of each observation (x_i) using a log-linear specification with parameters β to be estimated. The mean and variance of the zero-inflated Poisson model are given by:

(4) $E(y_i|x_i, z_i) = \mu_i(1 - \varphi_i)$

(5) $V(y_i|x_i, z_i) = \mu_i(1 - \varphi_i)(1 + \mu_i\varphi_i)$

In order to estimate the model, there is need to define the x and z variables. In accordance with the previous literature, the following predictors of passenger choice are included:

1) Weekly frequencies per itinerary: count data can be treated as the product of an incidence rate (in our case, bookings per individual frequency within each itinerary) and an exposure (frequencies per itinerary). Thus, we define weekly frequencies as exposure variable, with its coefficient restricted to 1. The interpretation of the remaining coefficients is thus made in terms of incidence rate.

2) Seat capacity at market and itinerary level: we separate between non-stop, 1-stop, and 2-stop seats. An indicator of concentration of seat capacity across airlines (the Hirschmann-Herfindhal Index-HHI is calculated as the sum of the airlines' squared capacity shares) and the share of the ticketing airline's seat capacity to total market capacity are included as well in order to control for the effects of market dominance.

3) Number of stops and average airfares: Borrowing from Coldren and Koppelman (2005), we create a set of dummy variables that indicate whether the itinerary is non-stop, 1-stop, or 2-stops in comparison with best available itinerary in each market. For example, we find 1-stop itineraries that operate in markets where non-stop connections are either available or not. This captures the diversity in competitive environments. In regards to prices, due to data restrictions, traditional itineraries are given average fares per type of connection between airport-pair markets (i.e. prices are not airline-specific). Self-connecting travel options are given a sum of the average non-stop prices for each travel segment (as if the flights were bought separately). We also identify the indirect itineraries that present the best average fares in each market and calculate the difference between an itinerary's fare and the best in the market.

4) Travel time increase (TTI): It is expected that itineraries with longer travel times (related to either geographic detour of flight transfers) are less attractive to passengers. The impact of TTI is differentiated according to number of stops.

5) Connectivity: The model accounts for two aspects of airline connectivity that can have an impact in demand. First, the proportion of self-connecting frequencies in the consolidated itinerary. This variable is interpreted as an impedance to informed passengers, i.e. a bad "quality" effect associated to the baggage transfer and risk of missing the onward flight. These passengers may or may not self-connect depending on the other aspects of the itinerary.

Second, inter-terminal connectivity labels those itineraries where a transfer between different terminals is required at any time during the trip.

6) Other: The Poisson model is completed with other common predictors of passenger choice, such as aircraft size (calculated as seats per frequency), market length (great circle distance from origin to destination), and departure time (morning: 6am-12pm; afternoon: 12pm-6pm; and evening: 6pm-12am, all times UTC). In addition, we include dummies for countries of origin and destination, as well as the largest hubs and airlines in order to capture any unobserved heterogeneity.

7) Zero-generating process: Excess zeros represent itineraries that were not easily accessible to passengers because of not appearing alongside traditional flight connections in booking systems (they are not "visible") and required an extra search effort. Thus, one can expect self-connecting itineraries to be disproportionately empty of bookings as they may be actually unknown to the air travellers. TTI is the second variable that can explain a disproportionate amount of zero-bookings for travel itineraries.

The estimation output is presented in Table 7. The equation is globally significant and the signs of the coefficients are similar. Marginal effects of the individual variables are provided, which indicate the increase in predicted bookings per itinerary associated to a unit increase in the relevant explanatory variable. These are evaluated are the sample means. The dummy variables related to number of stops have the expected signs, 2-stop itineraries tend to have less passengers per frequency than 1-stop itineraries and the negative impact of indirect travel is exacerbated by the availability of shorter itineraries in the market. In terms of marginal effects, a 1-stop itinerary can be expected to capture between 35 and 39 fewer weekly bookings than a non-stop itinerary. The marginal effect for a 2-stop itinerary is between 76 and 85 fewer weekly bookings. Interestingly, having the lowest fares tends to boost demand only when indirect travel undercuts direct travel. Travel Time Increases generally have the expected negative impact on the number of passengers per itinerary. However, being the fastest 2-stop itinerary boosts demand. Inter-terminal connections are seen as a burden by passengers (marginal effect: -2.08 bookings), and the same applies to self-connections in 1-stop itineraries. Involving a self-connection decreases demand in 21.3 weekly bookings with respect to a traditional 1-stop connection. Surprisingly, self-connectivity seems to boost demand for 2-stop itineraries, which suggests that, in an intra-European context where distances are relatively short, the few 2-stop itineraries taken by passengers (0.5% of total bookings – See Table 3) come as a result of passengers actively searching for these routes to save in airfares (or for other, unexplained reasons). Overall, the marginal effect for self-connections (without separating 1-stop and 2-stop) is negative and significant (-2.9) which is consistent with our expectations. As expected, self-connectivity also increases the probability of an itinerary to capture zero bookings, and the same applies to Travel Time Increase for 2-stop itineraries.

Table 7. Estimation output

Dependent variable: bookings	***zero-inflated Poisson***			
	coeff.	***s.d.***	***prob.***	***Marginal***
Non-stop weekly seat capacity (market)	-0.0000114	2.38E-07	0.000	-0.0002
1-stop weekly seat capacity (market)	-1.04E-06	1.69E-08	0.000	-2.22E-05
2-stops weekly seat capacity (market)	-1.12E-07	4.26E-08	0.009	-2.39E-06
HHI of weekly seat capacity (market)	0.2026337	0.0055259	0.000	4.3268
Share of seat capacity to market capacity (itinerary)	-0.3395394	0.0053488	0.000	-7.2501
Non-stop weekly seat capacity (itinerary)	0.000019	4.71E-07	0.000	0.0004
1-stop weekly seat capacity (itinerary)	-0.0000449	7.34E-07	0.000	-0.0010
2-stops weekly seat capacity (itinerary)	-0.000882	0.0000333	0.000	-0.0188
1-stop itinerary in non-stop market	-1.827484	0.0216595	0.000	-39.0218
1-stop itinerary in non-stop market: Lowest fare	0.0328398	0.0097996	0.001	0.7012
1-stop itinerary in non-stop market: Diff. to lowest fare	-0.008993	0.0045128	0.046	-0.1920
1-stop itinerary in 1-stop market	-1.668231	0.0204645	0.000	-35.6214
1-stop itinerary in 1-stop market: Lowest fare	-0.0556045	0.00839	0.000	-1.1873

1-stop itinerary in 1-stop market: Diff. to lowest fare	-0.0900833	0.0048127	0.000	-1.9235
2-stops itinerary in non-stop market	-4.008253	0.2709896	0.000	-85.5873
2-stops itinerary in non-stop market: Lowest fare	0.2692836	0.1661858	0.105	5.7499
2-stops itinerary in non-stop market: Diff. to lowest fare	-0.0607061	0.0556148	0.275	-1.2962
2-stops itinerary in 1-stop market	-3.602122	0.2278661	0.000	-76.9153
2-stops itinerary in 1-stop market: Lowest fare	-0.5977984	0.0863144	0.000	-12.7647
2-stops itinerary in 1-stop market: Diff. to lowest fare	-0.2221506	0.0356289	0.000	-4.7435
2-stops itinerary in 2-stops market	-3.656345	0.2376258	0.000	-78.0731
2-stops itinerary in 2-stops market: Lowest fare	0.3344464	0.0752663	0.000	7.1414
2-stops itinerary in 2-stops market: Diff. to lowest fare	0.0262828	0.0366443	0.473	0.5612
Travel Time Increase (Itinerary)	-0.2616182	0.0040136	0.000	-5.6510
1-stop itinerary: Lowest TTI	-0.5932619	0.0181459	0.000	-12.6678
1-stop itinerary: Difference to lowest TTI	-0.6167698	0.0142583	0.000	-13.1697
2-stops itinerary: Lowest TTI	0.6825578	0.2200457	0.002	14.5745
2-stops itinerary: Difference to lowest TTI	0.5548282	0.1827161	0.002	11.8471
Inter-terminal connection	-0.097404	0.0062859	0.000	-2.0798
1-stop itinerary: Self-Connection	-0.9955423	0.0085201	0.000	-21.2576
2-stops itinerary: Self-Connection	0.2498127	0.0580707	0.000	5.3342
Morning Departure	-0.0940203	0.0024768	0.000	-2.0076
Afternoon Departure	-0.0805105	0.0026272	0.000	-1.7191
Evening Departure	-0.0938494	0.0036608	0.000	-2.0039
Great circle distance (market)	0.0000125	1.31E-06	0.000	0.0003
Average aircraft size (itinerary)	0.007477	0.0000231	0.000	0.1597
Constant	3.375696	0.0347714	0.000	
ln(total weekly frequencies per itinerary)	1	(exposure)		
+ origin/destination country effects				
+ airline effects				
+ hub effects				
Excess zeros				
1-stop itinerary: Self-Connection	3.202783	0.0267361	0.000	
2-stops itinerary: Self-Connection	2.267641	0.0683318	0.000	
1-stop itinerary: TTI	0.0680469	0.0119891	0.000	
2-stops itinerary: TTI	1.825959	0.0263364	0.000	
Constant	-1.971573	0.0294371	0.000	
Overdispersion				
Alpha				
Observations: 132911 (1813 missing values)		Chisq(125)	1.23E+07	
non-zero: 29319			0.000	

The regression coefficients are applied to the original CB itineraries in order to obtain QSI scores. Market shares are then calculated as the ratio between the scores of each individual CB itinerary and the sum of the scores of all itineraries in the same origin and destination market. This leads to our baseline scenario. The development scenario is obtained using the same procedure with two key changes: 1) removing the effect of the four self-connection coefficients in the Poisson and zero-generating models, 2) increase the price of self-connecting itineraries in 40 USD per transfer[6]. By removing the two self-connection coefficients from the Poisson equation, the difference in connection "quality" associated to self-connecting travel options, with respect to traditional flight transfers, is removed. We argue that this represents a scenario in which airports provide baggage and insurance services with self-connecting platforms. By removing the two additional self-connection coefficients from the zero-generating equation, the difference in "visibility" between self-connections and traditional connections is removed as well (e.g. by having online booking platforms that automatically show self-connecting options to the passenger and hence, finding them does not require an extra search effort). Our development scenario combines both effects (the quality and visibility gaps are closed). This will lead to a forecast of the amount of self-connection traffic in the event of a widespread development of platforms like the ones in Gatwick or Milano that make the self-connection experience more comparable to traditional connectivity.

4. RESULTS AND DISCUSSION

[6] This is intended to match the price for self-connectivity at Gatwick (GBP 27.50). Alternative prices we also used (from USD 20 to USD 50) without a significant impact on the results.

As seen in Table 8, the baseline scenario indicates that about 1.5% of air travel in European holiday markets is currently self-connecting (approximately 50,000 weekly connections). In the development scenario, self-connectivity is predicted to increase five-fold (approximately 250,000 weekly connections), at the expense of both non-stop travel and traditional connectivity. Overall, the development scenario contemplates a 5% increase in the share of indirect air travel in European holiday markets.

Table 8. Summary of baseline and development scenarios

Baseline (weekly traffic)			*Development (weekly traffic)*		
Itinerary	*Bookings*	*%*	*Itinerary*	*Bookings*	*%*
Non-stop	2,913,200	90.3%	Non-stop	2,779,473	86.1%
Indirect Traditional	264,031	8.2%	Indirect Traditional	198,984	6.2%
Self-Connecting	49,845	1.5%	Self-Connecting	248,619	7.7%
Total	3,227,076		Total	3,227,076	

The predicted amounts of self-connecting traffic for the top-25 airports in the baseline scenario are presented in Table 9. In addition, we also include the actual (MIDT) and predicted amounts of total connectivity (traditional plus self-connectivity) in order to establish the degree of accuracy of our model. The average deviation from the actual connectivity for the selected airports is 15%. In spite of that, the airport rankings according to actual and predicted connectivity are highly consistent (Spearman's rank correlation = 95.9%). The results for the top-25 airports in the development scenario are shown in Table 10.

Given the current schedules in the European air transport network, the airports with the highest potential to benefit from implementing self-connection platforms in European holiday markets are Rome, Barcelona, Munich, Frankfurt, Athens, and Gatwick. The leading position of these airports arises as a result of good indirect connectivity, with respect to competing hubs or direct air travel, in origin and destination markets that are relatively dense with passenger traffic. Furthermore, these airports are characterized by their central location in relation to the European holiday traffic flows. This centrality can be understood in both a geographical sense (e.g. Rome, Athens) and in a topological sense (e.g. airports that serve as gateway between their countries and international holiday destinations). In the baseline scenario, it is clearly seen that airports dominated by of LCCs benefit from a higher amount of self-connecting potential (e.g. Barcelona, Gatwick). However, this is not a necessary requirement as interlining opportunities can also be present in airports with a diverse mix of traditional network airlines from different alliances. In the development scenario, LCC-dominated airports present the highest increases in self-connecting traffic. This reflects negatively on Frankfurt, whose lack of LCC traffic leads to traffic leakage to other hubs with expanded travel options, particularly in comparison with Rome Fiumicino or other hubs in central Europe (Appendix B provides information on the three markets where Frankfurt Airport is predicted to lose the largest amount of indirect traffic in the development scenario).

Tables 9 and 10 also provide several airport-specific indicators that assess the complexity of the implementation of self-connecting platforms. First, we report the proportion of self-connecting bookings that would involve an inter-terminal transfer as a proxy for the increased pressure on passenger mobility or airport baggage handling systems. The rates of inter-terminal transfer are significant for most airports with complex terminal layouts, ranging from 22% at Barcelona to 94% at Paris-CDG, respectively. Thus, they are an important factor to take into account while evaluating the feasibility and timescales of implementation since a large flow of inter-terminal passengers and luggage would need to be incorporated into the terminal operations. The variability across airports, however, suggests that the self-connecting fees charged to the passengers could be different depending on the size and complexity of the airport's terminal layout, with the objective to reflect any differences in operating cost associated to the self-connection. This is a factor that airports without inter-terminal transfers, like Palma de Mallorca, Athens, or Vienna could exploit to achieve a pricing advantage. On the other hand, airports and airlines could also decide to bring the busiest self-connection partners closer together in the terminal to minimize disruption to other passenger flows.

From the airline perspective, there is a clear divide between LCC-dominated and other airports as the first category allows for a higher proportion of inline self-connectivity. This would allow for an initial implementation of these services that is not highly dependent on interline negotiations. For example, 53.4% of feeding passengers (arriving) and 47.1% of onward passengers (departing) could be served by Easyjet at Gatwick (Table 11). While Lufthansa would also dominate both feeding and onward self-connecting traffic at Frankfurt and Munich, it is always dependent on reaching agreements with other airlines. The same applies to the recently announced strategy of Ryanair to start offering connecting services at Barcelona Airport (CAPA, 2016), which, at least in what concerns to intra-European holiday markets, can greatly benefit from interlining. The complexity of these airline negotiations, however, will benefit from a reduction in the number of actors involved. We characterize that by calculating the HHI of the interline traffic flows: the higher the HHI the more concentrated is interline traffic among fewer airlines at a particular location. Our results show that airports like Vienna, Prague, or Copenhagen may benefit from a higher concentration in self-connecting frequencies, and thus simpler negotiations, in comparison with other airports.

Table 9. Top-25 airports according to self-connectivity in baseline scenario

Airport	*Code*	*Baseline (weekly traffic)*						
		Connections (MIDT)	*Connections (predicted)*	*Self-Connections*	*% of conn.*	*Inline*	*HHI*	*Inter-terminal*
Rome Fiumicino	FCO	36,572	37,284	8,185	22.0%	2.8%	0.026	72.1%
London Gatwick	LGW	4,049	4,385	2,605	59.4%	24.3%	0.083	46.4%
Barcelona	BCN	11,864	16,667	2,379	14.3%	4.9%	0.043	22.2%
Munich	MUC	18,896	22,722	1,985	8.7%	0.0%	0.039	78.1%
Athens	ATH	12,622	16,058	1,833	11.4%	0.3%	0.043	0.0%
Madrid Barajas	MAD	18,268	20,356	1,541	7.6%	10.5%	0.037	68.5%
Frankfurt	FRA	25,642	32,353	1,497	4.6%	0.0%	0.030	61.2%
Paris Orly	ORY	4,622	5,034	1,284	25.5%	1.9%	0.038	51.8%
Paris CDG	CDG	10,333	8,838	1,103	12.5%	1.7%	0.025	93.9%
Palma de Mallorca	PMI	4,265	4,825	1,030	21.3%	5.3%	0.022	0.0%
Nice	NCE	855	1,395	963	69.1%	3.0%	0.075	41.1%
Vienna	VIE	9,048	11,716	957	8.2%	0.0%	0.189	0.0%
Amsterdam	AMS	8,594	10,373	949	9.2%	0.7%	0.047	0.0%
Brussels	BRU	5,165	5,309	903	17.0%	0.7%	0.019	0.0%
Geneva	GVA	1,287	1,997	836	41.8%	24.9%	0.084	0.4%
Copenhagen	CPH	4,785	4,731	800	16.9%	5.1%	0.086	84.0%
Marseille Provence	MRS	1,301	1,013	784	77.4%	3.8%	0.062	85.1%
Lisbon	LIS	8,148	8,029	753	9.4%	1.7%	0.068	23.2%
Milan Malpensa	MXP	654	1,383	751	54.3%	28.0%	0.072	33.0%
Zurich	ZRH	9,483	11,457	681	5.9%	0.0%	0.036	0.0%
Manchester	MAN	1,463	708	650	91.8%	2.5%	0.029	69.6%
Dusseldorf	DUS	4,491	5,297	603	11.4%	0.0%	0.056	0.0%
Prague Ruzyne	PRG	1,037	1,211	553	45.7%	7.6%	0.108	37.5%
London Heathrow	LHR	5,143	4,465	518	11.6%	0.0%	0.056	68.2%
Lyon St-Exupery	LYS	1,867	2,633	502	19.1%	6.2%	0.042	75.4%

Table 10. Top-25 airports according to self-connectivity in development scenario

Airport	*Code*	*Increase in connecting passengers (%)*	*Development (weekly traffic)*					
			Connections	*Self-Connections*	*% of conn.*	*Inline*	*HHI*	*Inter-terminal*
Rome Fiumicino	FCO	59.25%	59,374	37,515	63.2%	2.2%	0.031	69.9%
Barcelona	BCN	39.03%	23,173	13,480	58.2%	3.8%	0.042	22.8%
London Gatwick	LGW	185.13%	12,503	11,365	90.9%	23.7%	0.090	47.3%
Munich	MUC	17.75%	26,755	10,911	40.8%	0.1%	0.044	78.9%
Frankfurt	FRA	-3.66%	31,168	8,384	26.9%	0.0%	0.029	65.2%
Madrid Barajas	MAD	10.59%	22,510	8,242	36.6%	6.4%	0.031	68.1%
Athens	ATH	12.04%	17,992	7,746	43.1%	0.8%	0.047	0.0%
Palma de Mallorca	PMI	95.91%	9,452	6,354	67.2%	3.9%	0.020	0.0%

Paris CDG	CDG	35.08%	11,938	6,348	53.2%	2.5%	0.030	93.8%
Paris Orly	ORY	70.33%	8,575	5,494	64.1%	3.5%	0.034	54.2%
Geneva	GVA	198.82%	5,967	5,105	85.5%	23.7%	0.078	0.4%
Vienna	VIE	11.94%	13,115	4,932	37.6%	0.0%	0.124	0.0%
Amsterdam	AMS	12.85%	11,705	4,655	39.8%	0.8%	0.042	0.0%
Brussels	BRU	49.72%	7,949	4,634	58.3%	0.8%	0.022	0.0%
Zurich	ZRH	10.89%	12,705	4,350	34.2%	0.0%	0.038	0.0%
Copenhagen	CPH	50.93%	7,140	4,128	57.8%	3.0%	0.136	83.3%
Milan Malpensa	MXP	226.65%	4,518	4,034	89.3%	23.2%	0.053	33.8%
Dusseldorf	DUS	30.10%	6,891	3,626	52.6%	0.0%	0.065	0.0%
Lisbon	LIS	10.77%	8,894	3,490	39.2%	1.2%	0.073	25.7%
Nice	NCE	160.69%	3,635	3,294	90.6%	7.5%	0.046	41.1%
Prague Ruzyne	PRG	170.17%	3,273	2,839	86.7%	4.0%	0.073	42.4%
Marseille Provence	MRS	173.59%	2,771	2,591	93.5%	3.7%	0.051	81.9%
Manchester	MAN	237.98%	2,393	2,346	98.0%	5.1%	0.018	58.4%
London Heathrow	LHR	14.97%	5,134	2,324	45.3%	0.0%	0.049	77.9%
Lyon St-Exupery	LYS	54.08%	4,058	2,225	54.8%	7.9%	0.032	77.6%

Table 11. Top-3 largest feed and onward airlines at selected airports (development scenario)

Hub	*Rome Fiumicino*		*Barcelona*		*Munich*		*London Gatwick*		*Frankfurt*	
Feed	Easyjet	21.71%	Vueling	28.18%	Lufthansa	35.51%	Easyjet	53.40%	Lufthansa	43.80%
	Alitalia	17.12%	Ryanair	19.61%	Air Berlin	24.74%	Norwegian	20.11%	British Awys	6.76%
	Vueling	8.13%	Easyjet	10.61%	British Awys	3.51%	British Awys	9.61%	Air Berlin	5.72%
Onward	Alitalia	48.72%	Vueling	43.40%	Lufthansa	29.43%	Easyjet	47.10%	Lufthansa	30.49%
	Vueling	10.54%	Ryanair	23.27%	Air Berlin	16.63%	British Awys	16.84%	Condor	12.59%
	Ryanair	9.40%	Air Europa	11.45%	Vueling	9.16%	Monarch	10.27%	Air Berlin	8.24%

Tables 12 and 13 rank the airlines' potential for self-connections in the baseline and development scenarios, respectively. Unsurprisingly, results indicate that LCCs like Easyjet, Ryanair, and Vueling present the highest potential to benefit from self-connectivity in intra-European holiday markets[7], having a relatively balanced participation as feeding and onward carriers. However, there is also room for traditional carriers, with the primary role determined by the geographic location of the airline's main base. While Air France, British Airways, SAS, and Lufthansa can play a primarily feeding role, Alitalia should be able to leverage its prime position at Rome to serve onward traffic to destinations in the Mediterranean. Similarly to the airport case, the development of self-connectivity seems to affect Lufthansa negatively due to the competition for other airlines and hubs (Appendix B). Finally, Table 14 provides an overall view of potential airline self-connecting relationships in the development scenario. It is interesting to find examples of intra-LCC, inter-LCC, traditional-LCC and traditional-traditional interlining flows among the busiest ones in the holiday markets. Results show that Ryanair would have the largest amount of inline self-connections (34.2%) following by Easyjet (20.4%). Inter-LCC collaboration can also be beneficial: Easyjet could potentially serve the largest proportion of onward seats for the passengers fed by Norwegian. The possibility of collaboration between traditional carriers and LCCs is illustrated by the reciprocal traffic flows between Alitalia and Vueling or between Lufthansa and Air Berlin. Finally, self-connecting opportunities can also be offered across airline alliances, e.g. British Airways (feeding) and Alitalia (onward), though, in this case, the roles are not reciprocal. The diversity in airline partnerships suggested by this exploratory analysis suggests that there is indeed an interesting potential for this type of traffic (hidden in the complexity of airline schedules), as the passengers' desire to cut airfares makes then step beyond the boundaries of traditional connectivity to create links between airlines that have never collaborated before.

Table 12. Top-25 airlines according to self-connectivity in baseline scenario

Airline	*Code*	*Baseline (weekly traffic)*				
		Connecting	*Self-connect*	*% conn.*	*Feed (%)*	*Onward (%)*
Easyjet	U2	11,551	11,551	100%	60.9%	39.1%
Ryanair	FR	10,376	10,376	100%	41.6%	58.4%
Alitalia	AZ	64,266	6,871	11%	25.0%	75.0%

[7] Note that Vueling's connecting services at Barcelona are not considered self-connections.

Vueling	VY	34,513	6,493	19%	35.3%	64.7%
Lufthansa	LH	88,920	3,362	4%	63.8%	36.2%
Air France	AF	27,824	3,105	11%	73.4%	26.6%
Air Berlin	AB	27,808	2,942	11%	53.7%	46.3%
Norwegian	DY	13,528	2,811	21%	67.1%	32.9%
Aegean	A3	35,091	2,589	7%	33.8%	66.2%
British Awys	BA	14,343	2,423	17%	75.9%	24.1%
TAP Portugal	TP	21,533	2,366	11%	34.9%	65.1%
germanwings	4U	7,562	1,883	25%	73.8%	26.2%
SAS	SK	18,484	1,873	10%	90.3%	9.7%
Air Europa	UX	11,357	1,610	14%	45.7%	54.3%
Iberia	IB	33,203	1,541	5%	50.7%	49.3%
Meridian	IG	1,725	1,504	87%	38.3%	61.7%
KLM	KL	17,052	1,357	8%	84.8%	15.2%
Royal Air Maroc	AT	7,259	1,299	18%	0.9%	99.1%
Aer Lingus	EI	3,022	1,211	40%	95.6%	4.4%
Air Malta	KM	1,449	1,054	73%	29.9%	70.1%
Swiss/Crossair	LX	19,208	1,012	5%	67.9%	32.1%
Condor Flugdienst	DE	1,547	937	61%	26.5%	73.5%
Austrian Airlines	OS	15,553	923	6%	72.5%	27.5%
NIKI	HG	5,748	916	16%	38.1%	61.9%
El Al Israel	LY	1,111	909	82%	5.0%	95.0%

Table 13. Top-25 airlines according to self-connectivity in development scenario

Airline	*Code*	*Increase in connecting passengers (%)*	*Development (weekly traffic)*				
			Connecting	*Self-connect*	*% conn.*	*Feed (%)*	*Onward (%)*
Easyjet	U2	447.7%	63,258	63,258	100.0%	63.8%	36.2%
Ryanair	FR	355.8%	47,288	47,288	100.0%	44.0%	56.0%
Vueling	VY	66.8%	57,557	38,882	67.6%	33.7%	66.3%
Alitalia	AZ	20.2%	77,251	34,005	44.0%	23.9%	76.1%
Lufthansa	LH	-4.7%	84,730	20,407	24.1%	68.0%	32.0%
Air Berlin	AB	38.5%	38,510	20,019	52.0%	54.6%	45.4%
Air France	AF	27.3%	35,406	16,027	45.3%	72.5%	27.5%
Norwegian	DY	74.4%	23,592	15,388	65.2%	62.3%	37.7%
Aegean	A3	4.0%	36,500	12,910	35.4%	29.5%	70.5%
British Awys	BA	47.6%	21,166	12,758	60.3%	77.9%	22.1%
germanwings	4U	122.5%	16,822	12,515	74.4%	73.3%	26.7%
TAP Portugal	TP	16.9%	25,167	10,791	42.9%	28.3%	71.7%
SAS	SK	24.2%	22,952	10,508	45.8%	89.6%	10.4%
Iberia	IB	2.1%	33,901	9,648	28.5%	48.3%	51.7%
Air Europa	UX	46.0%	16,586	9,454	57.0%	45.8%	54.2%
Meridian	IG	352.2%	7,803	7,626	97.7%	33.4%	66.6%
KLM	KL	13.3%	19,312	7,258	37.6%	87.0%	13.0%
Swiss/Crossair	LX	10.4%	21,201	6,701	31.6%	68.6%	31.4%
El Al Israel	LY	463.0%	6,256	6,116	97.7%	3.0%	97.0%
Royal Air Maroc	AT	41.7%	10,288	5,606	54.5%	1.1%	98.9%
Condor Flugdienst	DE	247.2%	5,372	5,022	93.5%	34.4%	65.6%
Austrian Airlines	OS	5.0%	16,326	4,964	30.4%	72.2%	27.8%
Air Malta	KM	240.2%	4,931	4,673	94.8%	16.6%	83.4%
Brussels Airlines	SN	30.8%	9,576	4,567	47.7%	81.2%	18.8%
NIKI	HG	38.3%	7,949	4,557	57.3%	46.0%	54.0%

Table 14. Top-10 onward airlines for the busiest feeding airlines (development scenario): all markets

Feeding	*Easyjet*		*Lufthansa*		*Ryanair*		*Vueling*		*Alitalia*	
Onward (% self-connections)	Easyjet	20.4%	Air Berlin	20.9%	Ryanair	34.2%	Alitalia	19.5%	Vueling	20.0%
	Alitalia	15.0%	Vueling	11.3%	Vueling	13.4%	Ryanair	16.6%	Ryanair	15.9%
	Vueling	8.0%	Alitalia	11.1%	Alitalia	11.8%	Vueling	9.7%	Easyjet	10.4%
	Ryanair	6.4%	Condor	10.7%	Aegean	4.0%	Air Europa	8.2%	Meridiana	9.7%
	TAP Portugal	4.8%	TUIfly	7.7%	TAP Portugal	4.0%	Iberia	6.5%	Aegean	8.1%
	Aegean	4.4%	El Al Israel	4.3%	Easyjet	4.0%	TAP Portugal	6.0%	Livingston Air	4.6%
	Air France	3.0%	Ryanair	4.3%	Iberia	3.9%	Binter Canarias	4.1%	El Al Israel	4.4%
	Royal Air Maroc	2.8%	Air Malta	3.9%	Air Europa	3.8%	Easyjet	4.0%	Egyptair	4.2%
	British Awys	2.8%	Easyjet	3.0%	Binter Canarias	3.1%	Aegean	2.6%	TAP Portugal	3.7%
	El Al Israel	2.4%	Royal Air Maroc	2.5%	Meridiana	1.4%	El Al Israel	2.6%	Air Malta	3.0%
Feeding	*Air France*		*Air Berlin*		*Norwegian*		*Aegean*		*British Awys*	
Onwa rd (% s	Easyjet	15.0%	Lufthansa	19.6%	Easyjet	16.6%	Alitalia	22.3%	Alitalia	13.9%
	Vueling	9.3%	Vueling	11.1%	Vueling	11.0%	Ryanair	19.0%	Easyjet	12.3%

Royal Air Maroc	8.7%	Germanwings	9.6%	Alitalia	10.2%	Easyjet	12.5%	Lufthansa	5.9%
Air Algerie	7.7%	Aegean	6.4%	SAS	8.4%	Cyprus Awys	11.0%	Ryanair	5.7%
Aegean	7.3%	Condor	6.2%	Ryanair	6.1%	Vueling	5.4%	Aegean	5.5%
Ryanair	6.3%	Ryanair	6.0%	Norwegian	4.3%	Middle East	5.0%	TAP Portugal	4.3%
Air Corsica	6.1%	Alitalia	4.8%	British Awys	4.2%	El Al Israel	4.7%	Vueling	3.7%
El Al Israel	4.2%	TUIfly	4.2%	Aegean	3.8%	Royal Jordanian	2.6%	Air France	3.6%
Aigle Azur	3.9%	Austrian	3.2%	SmartWings	3.3%	Air France	2.2%	Egyptair	3.6%
TAP Portugal	3.7%	Air Europa	2.9%	Monarch	3.0%	Sky Express	1.9%	Air Malta	3.3%

5. SUMMARY, LIMITATIONS, AND FUTURE RESEARCH

This paper analyses the potential for self-connectivity in European holiday air transport markets using MIDT data from June 2014. Our empirical strategy is based on a QSI model calibrated with a zero-inflated Poisson regression. Our baseline scenario estimates that about 1.5% of passenger bookings in European holiday markets are currently self-connecting. A development scenario suggests that this proportion could increase by approximately five times if self-connecting travel achieves the same quality than traditional connections and it becomes visible in booking platforms. The airports with the highest potential to benefit from self-connection platforms in European holiday markets are Rome, Barcelona, Munich, Frankfurt, Athens, and Gatwick. These airports are characterized by their central location in relation to the European holiday traffic flows. In general, LCC-dominated airports benefit from larger increases in self-connecting traffic in the development scenario.

We also investigate potential barriers to the implementation of self-connecting platforms. First, the rates of inter-terminal self-connections are significant for most airports and hence, they are an important factor to take into account while evaluating the feasibility and timescales of implementation due to the increased pressure on baggage handling systems. From the airline perspective, LCC-dominated airports present a higher share of inline self-connectivity. This would allow for an initial implementation of these services that is not dependent on interline negotiations. Results also indicate that LCCs like Easyjet, Ryanair, and Vueling have the highest potential to benefit from self-connectivity in intra-European holiday markets, with Ryanair having the largest proportion of inline connections. However, there is also room for traditional carriers to partner with LCCs or other traditional carriers. While Air France, British Airways, and Lufthansa can play a primarily feeding role, Alitalia can leverage its prime position at Rome to serve onward traffic to destinations in the Mediterranean.

This research, however, has a few limitations. First, the estimation process can benefit for higher-quality price information. This would allow for a better characterization on the impact of reduced fares on passenger demand and also to obtain an estimation on potential cost savings for passengers and revenue implications for airlines. Any generation of new demand as a result of the availability of new frequencies in previously unserved markets is not modelled either. Finally, further research may want to consider expanding this approach to other markets. The recent development of low-cost long-haul routes (e.g. Norwegian routes to North America) may create opportunities for LCCs to tap into intercontinental markets and expand their scope of competition against traditional network carriers.

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APPENDIX A. Tourist airports in mainland Spain, Italy, and France

Country	*Code*	*Airport*	*Country*	*Code*	*Airport*
France	MRS	Marseille Provence	Italy	BDS	Brindisi
France	NCE	Nice	Italy	REG	Reggio Di Calabria
France	MPL	Montpellier Mediterranee	Italy	RMI	Rimini
France	PGF	Perpignan	Italy	TSF	Venice Treviso/Sant'angelo
France	TLN	Toulon/Hyeres	Italy	VIF	Vieste
France	BZR	Beziers	Spain	AGP	Malaga
Italy	BRI	Bari	Spain	ALC	Alicante
Italy	FCO	Rome Fiumicino	Spain	BCN	Barcelona
Italy	NAP	Naples Capodichino	Spain	IBZ	Ibiza
Italy	PSA	Pisa	Spain	PMI	Palma de Mallorca
Italy	SUF	Lamezia Terme	Spain	VLC	Valencia (ES)
Italy	TRS	Trieste	Spain	GRO	Girona
Italy	VCE	Venice Marco Polo	Spain	LEI	Almeria
Italy	CIA	Rome Ciampino	Spain	MJV	Murcia
Italy	GOA	Genoa	Spain	MAH	Menorca
Italy	PSR	Pescara	Spain	REU	Reus
Italy	AOI	Ancona			

APPENDIX B. Passenger leakage out of Frankfurt airport in selected routes

Market		*Hub*	*Market Share*	
Origin	*Destination*		*Baseline*	*Development*
Copenhagen	Malta	Frankfurt	62.1%	25.0%
		Rome Fiumicino	3.6%	12.3%
Helsinki	Malta	Frankfurt	43.4%	17.2%
		Rome Fiumicino	6.3%	19.1%
Stutgart	Malta	Frankfurt	71.8%	34.8%
		Vienna	15.1%	23.9%
		Zurich	4.1%	20.7%