Modelling the Pass-Through of Airline Operating Costs on Average Fares in the Global Aviation Market

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Abstract

This paper describes the development of a regression model that captures the effect of specific airline operating costs, as well as other key determining factors, on airfare. The model is estimated for a number of world regions. This allows for comparison of the variation in airline cost pass-through within and between regional markets, a topic that has thus far received little focus. Based on the results of model estimation, airfares are found to be the most responsive to changes in fuel cost, and the least elastic to increases in flight-based operating costs. Although similar patterns are found within each of the selected regional markets, the cost pass-through varies significantly across different markets. For example, passengers in Asia-Pacific regions would face higher fare increases than passengers in North America or Europe, given a same percentage increase in fuel costs. Frequently an airline will operate across multiple regional markets and our results have implications for the design of policies to incentivize airlines to reduce aviation emissions. The model described is a core component of the Aviation Integrated Model AIM2015 open source release.

1. Introduction

Global aviation emissions account for 2-3% of total energy-related emissions (Schäfer, et al. 2016). Air transport demand, which accounts for about 10% of passenger-km traveled of all transport modes, is anticipated to continue its strong growth with a rate of 5-6% per year over the next 20 years (Schäfer & Waitz, 2014). Thus, emissions related to aviation driven by the large and still growing demand are projected to increase significantly over current level by 2050, representing up to 22% of global CO_2 emissions (European Parliament, 2015). As a result, the contribution of aviation emissions to climate change has become a growing concern. To limit emissions from air transport with an international scope, in 2016 the UN's International Civil Aviation Organization (ICAO) introduced a market-based program titled Carbon Offsetting and Reduction Scheme for International Aviation (CORSIA). The program, which will come into force in 2021, requires all airlines to purchase carbon offsets to compensate annual increase in their total CO_2 emissions above the 2020 levels (ICAO, 2016).

Market-based measures (MBMs), such as CORSIA, put a price on aircraft emissions in order to incentivize airlines to reduce their emissions with relatively low economic costs. Airlines can adjust to the costs of MBMs through either changes in technology and operations to reduce costs or by modifying airfares to increase revenue. Schäfer, et al. (2016) have demonstrated that reducing aviation emissions via technology and operational changes has potential to significantly reduce emissions. However, the potential pricing responses of airlines to the MBMs-imposed costs in an area that has not received much focus. In order to address this issue, this paper describes the development of a regression model of airfares which captures the operating costs of an airline with higher resolution than previous research. This allows us to answer an important question of this subject: to what extent are airlines able to pass through their operating costs to passengers through airfares, and how does the ability of an airline to pass through costs vary across different world regions?

The question is, however, a challenging one. Although airlines tend to cover the increased cost by increasing airfares, higher fares will result in – depending on the elasticity of demand – lower sales and market shares. As a result, an airline will have to strike a balance between recovering increases in operating cost and ensuring its market share while competing with other airlines. Additionally, fare elasticities to the cost increase may differ between different regional markets, and it will be difficult to design emissions reduction policies that can be adopted globally and at the same time have comparable impacts on passengers. Furthermore, for the regions where aviation emissions are projected to grow most rapidly over the next 20-30 years (Yan, et al. 2014), airline pricing has not been researched in detail and thus is relatively unknown. All of the above indicate that in order to fully understand how airlines pass cost imposed by the MBMs onto passengers through fares, an airfare model that can capture specific airline costs, reflect airline competition, and also have a global coverage is required.

This paper contributes to existing literature mainly in three ways. Firstly, the paper develops an airfare model that explicitly captures airline operating costs as well as other important demand-, competition-, and route-specific factors. This allows us to empirically understand the effects of increasing specific airline operating costs on airfares, in a competitive environment. Notably, this airfare model is also a core component of the updated AIM2015 (Dray, et al. 2017), a state-of-the-art Aviation Integrated Model. Secondly, the fare model is estimated for a number of world regions. Comparison of the different model coefficients provide insight into how the ability of an airline to pass through cost varies within and across different markets. Lastly, through a comparative analysis on different airline cost pass-through rates by cost type and by market, the potential impacts on passengers of a number of market-based emissions reduction measures are discussed.

The next section presents a brief review of existing literature on airfare modelling. Section 3 describes the model specification, with the datasets used and the key operating costs variables discussed in detail. The estimated coefficients are then interpreted and discussed in Section 4, together with their implications to a number of potential market-based emissions reduction policies. Section 5 offers conclusions.

2. Literature Review

There has been extensive literature with respect to modelling airfares, in order to understand the impacts of different factors on airline pricing. Interest in this subject began to emerge when airlines were allowed to set fares after the deregulation of the airline industry in the U.S. in 1978. The effect of competition on airfare has received the most extensive discussion, particularly for the U.S. domestic market. Literature focusing on the competition effects in the U.S. has mainly discussed two important aspects: (i) how fares are affected by market structure (i.e. the level of competition) at both airport and route levels (Borenstein, 1989; Evans and Kessides, 1993; Hofer, et al, 2008; Vowles, 2006; Cho, et al. 2012; Zhang, et al., 2013), and (ii) impact of low cost carriers (LCCs) over domestic fare prices (Dresner, et al., 1996; Morrison, 2001; Goolsbee and Syverson, 2008; Chi and Koo, 2009; Brueckner, et al. 2013).

Previous research on the relationship between airfare and market structure have demonstrated that lower market concentration is often associated with lower fares (Borenstein, 1989; Evans and Kessides, 1993; Hofer, et al, 2008; Vowles, 2006; Cho, et al. 2012; Zhang, et al., 2013). In these studies, the Herfindahl-Hirschman Index (HHI) is commonly used as an indicator of airline concentration at airport- and route levels. Borenstein (1989) found that dominance of major routes and airports by one or two airlines resulted in increases of up to 12% in fares. Vowles (2006) and Zhang, et al. (2013)

examined how airlines determine airfares in hub-to-hub markets, and their results suggest that hub-to-hub markets generally have higher airfares, and the hub hierarchies that distinguishes between 'primary hubs' and 'secondary hubs' also have crucial impacts on fares. Cho, et al. (2012) assessed how fares are affected by the level of competition in multi-airport cities in the US. Using a number of HHIs for airport-, route-, and city-pair concentration, they found that fare reduction due to competition at adjacent airport pairs is significant but markedly smaller than that of added competition in the focal airport-pair market.

The other important competition effect discussed is the impact of LCCs on fares. As one critical outcome of deregulation, the emergence of LCCs in the U.S., led by Southwest Airlines, has been researched by a wide body of literature. Dresner et al. (1996) examined the competitive impacts of Southwest's entry to route-level fare prices. Their model showed that the presence of LCCs resulted in 38% lower fares on average at route-level, and when Southwest serves the routes, there was an even more drastic fare reduction. Morrison (2001) found that the existence of Southwest Airline serving neighboring route markets can significantly affect fare prices of legacy carriers at local airport-pair market. Goolsbee and Syverson (2008) further demonstrated that even the threat of Southwest's entry, without its actual presence in a market, can considerably depress fares. More recently, Brueckner, et al. (2013) found that the impact of LCC competition on airfares is substantial in both local airport-pair market (33% reduction in nonstop market and 12% reduction in connecting market) and adjacent airport-pair market.

Airline pricing has been studied for other regional markets too, but by much less literature. In addition, these papers have mainly focused on the phenomenon of LCC competition. The LCC competition started to affect the European airline market since an adoption of LCC model by Ryanair in 1992, and followed by the inauguration of its biggest competitor, easyJet, in 1995 (Malighetti, et al., 2009). Since then, LCCs in Europe have experienced significant growth mainly led by the two airlines (Dobruszkes, 2006). Analogous with the "Southwest Effect" in the U.S., Franke (2004) suggests that Europe has a "Ryanair Effect". Malighetti et al. (2009) also provided analysis of Ryanair's pricing strategies, and found that Ryanair grands fewer discounts on long haul and high-frequency routes. A handful of literature on the LCC effects can also be found for the Chinese domestic airline market. Fu et al. (2015) studied China's first and only LCC, Spring Airlines, and concluded that although Spring has achieved fast growth since its inauguration in 2005, it did not trigger a price war due to regulatory restrictions. Rather, Fu et al. (2015) argue that high speed rail (HSR) services have imposed much more significant competitive pressure than LCCs in China. The findings are supported by Chen (2016), who investigated the competition effects of Spring to legacy carriers China Eastern in Shanghai, and found that there is only a moderate fare reduction of 4%-4.9% from China Eastern after the entry of Spring.

Apart from the airline competition effects, other important factors affecting airfare pricing have been identified in the literature namely passenger demand and delay. Firstly, airfares are found positively correlated with demand if impact of passengers outweighs the possible economies of density effect (Dresner et al, 1996; Cho, et al, 2012), and negatively related if otherwise (Dender, 2007; Chi and Koo, 2009). Brueckner, et al. (1992), who analyzed the relationship between airfares and the hub-and-spoke networks, concluded that given the economies of density, network that connects large cities with higher traffic volume on its spokes has lower cost per passenger therefore lower airfares than smaller networks. Moreover, flight delays can also affect airfares (Forbes, 2008; Cho, et al, 2012; Zou and Hansen, 2014). Forbes (2008) showed that every one-minute increase in delay leads to a \$1.42 reduction in fare. By contrast, Zou and Hansen (2014), who estimated the delay effects separately for nonstop and one-stop routes, concluded that delays will result in higher fares.

Despite the extensive discussion from previous literature on the competition-, demand-, and delay effects on fares, the cost-side effects on airfares have been largely overlooked. In the majority of existing research, distance, fuel price, and aircraft size have been used as proxy variables measuring airline costs (Chi and Koo, 2009; Brueckner, et al, 2013; Zou and Hansen, 2014). However, using these proxy variables cannot reflect any changes in airline operating costs, and therefore it is not possible to quantify the extent to which airlines pass their operating costs onto passengers through fares. As a result, most of the existing fare models, based on the features described above, are not capable of evaluating the economic effects of various policy measures that may lead to fare changes due to changes in operating costs, such as the introduction of the MBMs aimed to limiting aviation CO_2 emissions (ICAO, 2016).

Empirical evidence on airline cost pass-through behavior is to the best of our knowledge limited to a small handful of papers. PWC (2005) regressed changes in annual kerosene prices (with one-year lag) on changes in the UK's annual average airfares, and found that the pass-through rates for LCCs and legacy carriers are 90% and 105%, respectively. However, the models used to obtain these results does not control for any important factors that may affect pass-through behavior, such as market competition and passenger demand. Using a panel data of 18 European airlines from 1990 to 2007, Toru (2011) examined increases of fuel prices resulting from the EU ETS that are passed to airfares, and found that the level of cost pass-through is close to 100%, but only when the high fuel prices triggered capacity changes. Cho, et al. (2012) compute airline operating expenses per passenger mile as an independent variable in their fare model, and they found that every 1 percent increase in the operating cost per mile leads to a 0.82% increase in yield. However, Cho, et al. (2012) do not provide any details about how the operating expenses per mile is computed, and what types of airline costs are included as the expenses.

With the advantages in coefficients interpretation and model prediction, regression analysis has been used in most of the above studies. It is important to note that, airfare modelling is complicated by the potential endogeneity between fare price and demand. Specifically, in airline economics, there is a simultaneity issue between fare and demand, i.e. passenger demand, an explanatory variable in the fare model, is jointly determined with the dependent variable, airfares. As a result, in order to correct for this endogeneity bias, instrumental-variable procedures and simultaneous equations estimation (Woodridge, 2010) have been commonly used in previous airfare modelling.

As reviewed above, the existing literature on airfare modelling has two important gaps. First, previous research has almost exclusively focused on the U.S. domestic airline market, which provide limited insights to other world regions. Second, there have been few empirical studies of the effects of increased operating costs on airfares. Airline cost effects have been commonly measured by proxy variables such as distance, fuel price, and aircraft size in the existing fare models. As a result, these models are not able to quantify variation in airline cost pass-through by market, thus providing little insight to the economic effects of emissions reduction measures that may result in fare changes. The identified gaps motivate this work. In the next section, the fare model developed in this study is discussed in detail.

3. Empirical Model

This section presents the airfare model developed in this research which is also a core component of the AIM2015 model (Dray, et al. 2017). To begin with the datasets used to construct the model variables are described. The specification of the model then follows and we conclude with a detailed discussion of the three key operating-cost variables.

3.1 Data

As mentioned in Section 1, in order to examine airline's cost pass-through behavior across different world regions, this study develops an airfare model that can be used in estimating a number of regional markets. Data for airfares, passenger demand, market shares, flight frequency, and itinerary-specific characteristics are either directly obtained, or constructed from the Sabre Market Intelligence database (Sabre, 2016). Fleet data is obtained from FlightGlobal (2016) and is used to derive aircraft type by segment. Aircraft is categorized into nine different size classes, based on the Sustainable Aviation aircraft categories (Sustainable Aviation, 2015). Flight segment-based operating costs for each aircraft size class are generated by the AIM2015 Direct Operating Cost (DOC) Model by Al Zayat, et al. (2017). En-route and airport landing charges by size class are provided by the RDC airport charges database (RDC, 2017).

This model uses cross-sectional data for the year of 2015. The basic unit of observation in the data, defined as a ‘route’, is the unique combination of an itinerary with maximum three stopovers, i.e. ‘Origin-Connect1-Connect2-Connect3-Destination Airports’. Fares are aggregated across all airlines providing service on a given route, and weighted by passenger numbers so that different observed fares paid by passengers on this route are taken into account by the aggregation procedure. To ensure reliable model estimation, the model data is filtered by the following rules: Routes with annual passengers fewer than 50 or with route share below 0.1 are removed; segments with missing average flight times are excluded; also removed are segments with negative airport landing charges.

Table 1
Route traffic information by region-pair market covered by the dataset.

Region Pair	Total Routes	Total Flight Segments	Total RPK (billions)	Fare per passenger-kilometer
AP-AP	25727	6830	1107.68	0.14
EU-EU	38097	11512	614.84	0.13
NA-NA	51380	4928	603.43	0.13
AP-EU	26642	1035	392.96	0.08
AP-NA	17529	368	303.30	0.09
EU-NA	27388	880	270.57	0.12
AP-ME	5274	683	147.61	0.08
CA-NA	19831	1605	123.59	0.12
AF-EU	13020	991	112.58	0.11
SA-SA	2993	639	98.64	0.13
EU-ME	7373	761	87.65	0.13
EU-SA	6851	136	74.11	0.09
CA-EU	5746	240	73.95	0.08
NA-SA	6179	193	63.52	0.09
ME-NA	3634	107	43.66	0.11
AF-AP	5271	102	38.36	0.08
AF-ME	1952	263	34.62	0.13
AF-NA	4409	40	26.97	0.09
ME-ME	563	292	25.17	0.18
CA-SA	2682	202	22.97	0.11
AF-AF	2454	532	22.30	0.17
CA-CA	1961	572	17.87	0.19
AP-SA	1617	8	15.35	0.09
AP-CA	1112	6	5.27	0.08
ME-SA	444	10	4.10	0.09
AF-SA	532	12	2.10	0.14
CA-ME	244	0	1.31	0.07
AF-CA	189	2	0.59	0.10

To illustrate the coverage of the final dataset, Table 1 presents information on total number of routes, total flight segments between the endpoint regions, total revenue passenger kilometers (RPK, in billions), and average fare per passenger-kilometer (year 2015 USD), on a region-pair basis. Globally, our data covers 1169 airports and 28 different regional markets. For the sake of space constraints, four regional markets with the largest RPK (see Table 1) are selected to analyze in this paper, namely North America to North America (NA-NA), Europe to Europe (EU-EU), Asia Pacific to Asia Pacific (AP-AP), and intercontinental market between Asia Pacific and Europe (AP-EU). The selected regional pairs provide a good representation of markets with different degree of economic development, demand characteristics, and airline market maturity.

Table 2

Desctiptive statistics of model variables for the selected airline markets.

Variable	Mean	Standard deviation	Minimum	Maximum
NA-NA: N = 51,380				
Fare	308.18	84.63	48.02	904.41
FuelCostPerPax	59.4	28.93	6.81	279.28
NonFuelCostPerPax	179.06	39.08	33.33	324.29
NonFuelCostPerFlt	11704.79	7041.74	768.83	56214.75
Passengers	6872.15	36656.27	50	1355143
LegMeanHHI	6678.22	2163.42	1246.47	10000
AirportMeanHHI	2951.26	804.26	1072.12	8897.82
CUIMean16hours	19.31	12.8	0.97	86.61
Freq	1187.47	912.35	2	17734
LoadFactor	0.77	0.08	0.4	1
RouteShare	0.35	0.23	0.1	1
Nlegs	2	0.4	1	4
HubsPass	2.06	0.62	1	4
EU-EU: N = 38,097				
Fare	227.69	80.93	28.85	992.32
FuelCostPerPax	44.92	22.84	3.86	230.53
NonFuelCostPerPax	104.1	39.35	32.21	290.8
NonFuelCostPerFlt	12608.19	7481.8	124.06	79119.75
Passengers	13447.79	47128.3	50	1309872
LegMeanHHI	5737.13	2231.16	1008.98	10000
AirportMeanHHI	2382.11	1077.8	596.99	9979.03
CUIMean16hours	22.77	13.77	1.1	102.19
Freq	716.12	692.42	1	16176
LoadFactor	0.77	0.09	0.4	1
RouteShare	0.51	0.3	0.1	1
Nlegs	1.76	0.5	1	4
HubsPass	1.79	0.65	1	4
AP-AP: N = 25,727				
Fare	384.34	233.11	30.79	2825.99
FuelCostPerPax	83.48	66.14	4.85	481.38
NonFuelCostPerPax	64.64	26.24	21.19	217.35
NonFuelCostPerFlt	21466.6	16472.24	636.85	114421.5
Passengers	31928.1	127851.6	28.85	5956277
LegMeanHHI	4977	2256.8	870.74	10000
AirportMeanHHI	2183.74	1006.59	478.58	9195.06
CUIMean16hours	36.88	18.79	1.5	98.38
Freq	863.8	1033.24	1	32056
LoadFactor	0.77	0.09	0.4	1
RouteShare	0.56	0.32	0.1	1
Nlegs	1.86	0.55	1	4
HubsPass	1.82	0.72	1	4
AP-EU: N = 26,642				
Fare	676.51	306.72	72.86	3003.23
FuelCostPerPax	223.07	98.12	7.33	765.36
NonFuelCostPerPax	94.27	32.55	19.68	250.67
NonFuelCostPerFlt	68673.52	28195.65	1951.51	164584.35
Passengers	1892.83	9803.01	50.00	367533
LegMeanHHI	6017.42	2012.87	1611.31	10000
AirportMeanHHI	2028.58	777.21	493.58	6962.28
CUIMean16hours	41.02	17.53	2.21	101.35
Freq	498.77	368.00	1	5685
LoadFactor	0.78	0.07	0.4	1
RouteShare	0.38	0.25	0.1	1
Nlegs	2.22	0.5	1	4
HubsPass	2.51	0.78	1	5

3.2 Model Specification

An overview formulation is firstly specified in Eq.(1) in order to illustrate the rationale of model specification. The dependent variable in this fare model is passenger class weighted annual average fare (including taxes) at the Origin-Destination airport-pair level, aggregating across all airlines on the same route.

$$(Fare)_{mn} = f(Cost_{mn}, Demand_{mn}, Competition_{mn}, CountryFE_{OD},) \qquad \text{Eq.(1)}$$

Informed by the previous research described in Section 2, several key factors that have been shown to be significant and important to airline pricing are included in this model. These features are grouped into four categories: cost effects, demand effects, competition effects, and origin- and destination country fixed effects. Fare price is determined by supply and demand, where supply is expressed mainly via airline costs, and demand is captured by route-specific O-D passenger numbers, route share, and average load factor. Market competition, in the form of route- and airport HHIs, has been demonstrated to have substantial impacts on fares (Hofer, et al, 2008; Vowles, 2006; Cho, et al. 2012, to name a few) and thus also included in the model. Lastly, the origin and destination country fixed-effects are included in order to capture any possible country-specific effects on airfares, such as taxes imposed on airfares by endpoint countries, as well as the countries' overall economic condition.

$$\begin{aligned}\ln(Fare)_{mn} = {} & \beta_0 + \beta_1 \ln(FuelCostPerPax)_{mn} + \beta_2 \ln(NonFuelCostPerPax)_{mn} \\ & + \beta_3 \ln(NonFuelCostPerFlt)_{mn} + \beta_4 \ln(LegMeanHHI)_{mn} + \beta_5 \ln(AirportMeanHHI)_{mn} \\ & + \beta_6 \ln(CUIMean)_{mn} + \beta_7 \ln(Freq)_{mn} + \beta_8 \ln(Pax)_{mn} + \beta_9 \ln(LoadFactor)_{mn} \\ & + \beta_{10}(RouteShare)_{mn} + \beta_{11}(Nlegs)_{mn} + \beta_{12}(HubsPass)_{m,n,k} + \beta_{13}(OriginCountry) \\ & + \beta_{14}(DestCountry) + \varepsilon_{mn}\end{aligned}$$

Eq. (2)

Following Eq.(1), a regression-based airfare model is specified in Eq.(2), where m, n, and k denote origin airport, destination airport, and connecting airports, respectively, and ε is the error term. Some continuous variables take logarithmic values so that their resulting coefficients represent fare elasticities with respect to these variables. Table 2 provides descriptive statistics for the selected airline markets, from which we can see that the inter-continental market AP-EU has the highest mean value of fare, followed by AP-AP, NA-NA, and EU-EU. In total, the selected regions contain 51,380 (NA-NA), 38,097 (EU-EU), 25,727 (AP-AP) and 26,642 (AP-EU) different routes, respectively. Given that the focus of this paper is on airline cost pass-through in different regional markets, we will discuss the cost variables in more details. The reader is referred to Appendix A for the specific definition of all variables.

3.3 Operating Costs Variables

As discussed in Section 2, in previous research, airline operating costs have been largely captured by proxy variables, such as distance, fuel price, and dummy variables for different aircraft sizes (Chi and Koo, 2009; Brueckner, et al, 2013; Zou and Hansen, 2014). However, changes in specific operating costs cannot be measured by such proxy variables, and therefore it is not possible for previous fare models to quantify airline cost pass-through. As one of the key novelties of this paper, the airfare model explicitly captures airline operating costs by including three route-specific operating cost variables: fuel cost per passenger (FuelCostPerPax), nonfuel cost per passenger (NonFuelCostPerPax), and nonfuel cost per flight (NonFuelCostPerFlt), based on the input from the AIM2015 Direct Operating Cost (DOC) model by Al Zayat, et al. (2017).

Output of the DOC model includes fuel cost, crew cost, maintenance cost, finance cost (interest, depreciation and insurance), and volume-related cost, by aircraft size class. This fare model takes the above aircraft-based cost components as well as en-route and landing charges from the RDC airport charges database (RDC, 2017), and distributes each of these costs to all flights operating on a given flight segment. As such, each scheduled flight is associated with the above operating cost components for a given flight segment. Following this, the total operating cost by cost component is aggregated across all flights operating on the given segment. Fig.1 presents the segment-based total operating costs by cost component, taking flight segment LHR-PEK as an example.

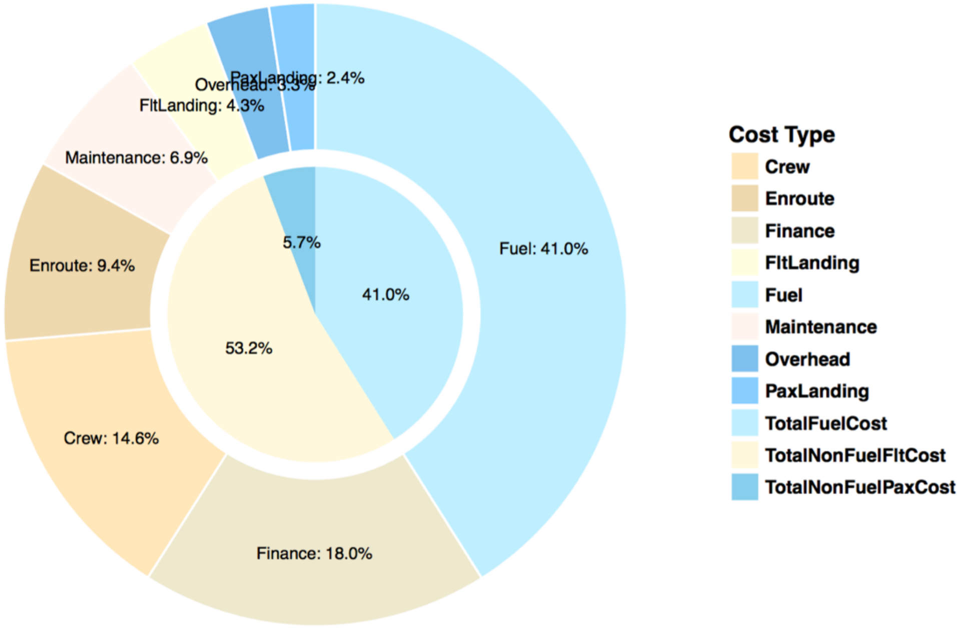

Figure 1
Flight Segment Total Operating Cost Structure Example: LHR-PEK

As Fig.1 shows, these cost components are further grouped into three categories, i.e. Total fuel cost, Total nonfuel passenger cost, and Total nonfuel flight cost, based on their attribute of variance over time as well as whether the cost can be directly distributed to passengers. Specifically, costs are grouped as fuel costs and nonfuel costs because fuel cost is more fluctuated than other cost components over time, and it represents the majority of volatility in airline operating costs. Furthermore, the fuel- and nonfuel-costs are split into per passenger cost and per flight cost, depending on whether their total costs will change with the number of passengers enplaned.

In practice, for each flight, its crew cost, maintenance cost, ownership (or finance) cost, en-route charges, and aircraft landing charges do not change as long as the flight departs to its planned destination. Taking an extreme example, even if a flight is flying empty, the above costs will stay exactly the same as the given flight flying with 100% load factor on the same segment. As a result, these cost components are grouped together and averaged by the total number of flights on the segment, defined as nonfuel cost per flight (NonFuelPerFlt). In contrast, fuel cost, passenger landing charges, and volume-related cost (e.g. meals, in-flight services, etc.), do change with the enplaned passenger numbers. Again, for an empty flight, since there were no meals and in-flight services required, no passenger charges taken by airport, and less fuel consumed due to the lower aircraft taking-off and landing weight, the total costs associated with these components would be much lower than a fully-enplaned flight. We therefore calculate these costs as fuel cost per passenger and nonfuel cost per passenger (i.e. FuelCostPerPax, NonFuelCostPerPax). Finally, as all cost components are computed on the flight-segment basis, the route-specific fuel cost per passenger, non-fuel cost per passenger, and non-fuel cost per flight are the sum of average corresponding costs of all segments covered by a given route.

After understanding how the key operating cost variables are constructed in the fare model, in the next section we will estimate the model for the selected regional markets, and analyze airline cost pass-through behavior through the estimated coefficients.

4. Estimation Results

The previous section described the features used and formulation of our airfare model. This section covers the methodology employed for model estimation and the results obtained. The estimated coefficients of models for NA-NA, EU-EU, AP-AP, and AP-EU regional markets are interpreted and discussed, with a focus on the implications for policies aimed at reducing aviation emissions through MBMs.

4.1 Methodology

As mentioned in Section 2, airfare modelling is complicated by the effects of demand on fares. An endogeneity bias of the demand variable arises due to simultaneity, i.e. demand, as an explanatory variable, is jointly determined with the dependent variable, airfare. Having one or more endogenous variables in the model will result in biased coefficient estimates. Additionally, while the presence of heteroscedasticity does not cause bias or inconsistent estimation, the standard errors and test statistics are no longer valid. To determine the presence of these confounding effects, we conduct two diagnostic tests for the presence of heteroscedasticity and endogeneity in the fare model.

Table 3
Diagnostic tests for heteroscedasticity and endogeneity in the model for the selected airline markets.

Diagnostic test[1]	**NA-NA**	**EU-EU**	**AP-AP**	**AP-EU**
Heteroscedasticity[2]				
Breusch-Pagan test	$F(51,357) = 121.1^{***}$	$F(37,987) = 9.424^{***}$	$F(25,643) = 21.25^{***}$	$F(26,474) = 11.55^{***}$
	[0.001]	[0.001]	[0.001]	[0.001]
Endogeneity[3]				
Passengers	-0.0698^{***}	-0.0529^{***}	-0.0871^{***}	0.0692^{***}
	[0.001]	[0.001]	[0.001]	[0.001]
LegMeanHHI	-0.561^{***}	0.0095	-0.1120^{***}	-0.0218^{*}
	[0.001]	[0.2240]	[0.001]	[0.049]
AirportMeanHHI	0.0106	−0.0062	-0.0776^{***}	0.0614^{***}
	[0.112]	[0.365]	[0.001]	[0.001]
RouteShare	0.0582^{***}	-0.0710^{***}	-0.0562^{***}	0.0359
	[0.001]	[0.001]	[0.001]	[0.076]
Joint F-statistic	228.725^{***}	32.064^{***}	62.96^{***}	21.673^{***}
	[0.001]	[0.001]	[0.001]	[0.001]

*** Significant at the 0.1% level.
** Significant at the 1% level.
* Significant at the 5% level.
[1] p-values are presented in parentheses.
[2] The null hypothesis of homoscedasticity is used.
[3] Paremeter estimates of residual are presented. The joint null hypotheses of exogeneity is used.

To test for the presence of heteroscedasticity, the Breusch-Pagan test (Breusch and Pagan, 1979) is used. The Hausman test (Hausman, 1978) is conducted to test for potential endogenous variables. Each potential endogenous variable is regressed by all exogenous variables and the instrumental variables to obtain the reduced-form residuals. The residuals are then added to the structural equation and tested for their joint significance, using an F-test (Woodridge, 2010). If the joint F statistics are significant at the 5% level, the null hypotheses of exogeneity are rejected.

Testing for potential endogeneity requires valid instrumental variables (IVs). For the passenger variable, we introduce the total number of segments connected with origin and destination airports, respectively, and the great-circle distance between O-D airport pair, all logarithmically transformed, as additional IVs. The total segments connected with endpoint airports are clearly exogenous to route-specific airfares, and they are correlated with O-D demand based on the assumption that the number of flight segments a given airport connected with represents the attractiveness of the airport. There are better opportunities that passengers choose to fly from/to airports connected with more segments. O-D distance is also exogenous, and given that we do not include this variable in our structural equation (see Eq.(2)), it is valid to use O-D distance as an IV to passenger demand. Demand is assumed to be negatively correlated with O-D distance.

Additionally, this model also treats the market concentration variables as endogenous. As discussed in Section 2, in previous research (Borenstein, 1989; Hofer, et al, 2008; Cho, et al. 2012), the Herfindahl-Hirschman Index (HHI) often appears as an indicator of market concentration at various levels. HHIs are computed as the sum of the squared market shares of airlines operating in a relevant market. From Eq.(2), this model includes both route- and airport HHIs (see Appendix A). We consider these variables endogenous because an airline's market share, which are input to the calculation for HHIs, is expected to be a function of the price it charges (Borenstein, 1989; Brueckner, et al., 2013). IV used for identifying LegMeanHHI is the average number of competing airlines (with at least 5% share) of all flight segments that the given route uses. The selection of this IV is motivated by Koopmans and Lieshout (2016), who showed that there is a high correlation between HHIs and the number of effective competitors in the relevant market. Moreover, the logic of using this IV is also supported by Borenstein (1989). Following a similar rationale, IVs for the AirportMeanHHI is the number of competitors (with at least 5% share) at endpoint-airport markets.

Lastly, the RouteShare variable, defined as the share of total O-D passengers on this city-pair using a given route, is also treat as endogenous. This is because the route share is a function of O-D demand, which is simultaneously determined with average O-D fare. One possible IV for route share is the total number of routes available between a given O-D city pair. In our model, an O-D city pair market can be linked by both non-stop and various connecting routes (if available). When at least one endpoint city has multi-airport system, the adjacent routes are also taken into account. Share of each route between a given city pair is clearly affected by the total routes available between two cities, and the route count is also largely exogenous to fares on a given route.

Table 3 presents the results of the diagnostic tests for heteroscedasticity and endogeneity in the model, for the selected airline markets. It can be seen that the null hypotheses of homoscedasticity and exogeneity can be rejected at the .1% level by the Breusch-Pagan test and the Hausman test, respectively, indicating the Ordinary Least Squares (OLS) estimation will be biased, inconsistent, and no longer efficient. Note that, in the Hausman test, even though using separate *t* statistics, the coefficients of some reduced-form residuals are statistically insignificant in Table 4, this does not mean that the null hypotheses of exogeneity for these variables should be accepted, as long as their joint *F* statistic is significant (Woodridge, 2010). As a result, we can conclude from the Hausman test that all the four variables should be treat as endogenous in the model.

As a consequence, the model is estimated using a feasible generalized two-stage least squares (FG2SLS)[1] procedure to correct for the heteroscedasticity and endogeneity bias (McFadden, 1999; Woodridge, 2010). The estimation procedures are: (1) estimate OLS residuals from the reduced-form equation; (2) regress the log of the squared residuals by all the exogenous variables (including the IVs); (3) estimate the error variance from the fitted values in step (2); (4) apply 2SLS with the dependent variable, the explanatory variables, and all the IVs divided by the estimated error variance.

Next, the estimated model coefficients for the selected airline markets will be interpreted and discussed in details.

4.2 Model Results and Discussion

Table 4 presents the estimated coefficients for the selected NA-NA, EU-EU, AP-AP, and AP-EU markets, respectively.

Overall, most of the coefficients estimated by FG2SLS have the expected signs and are statistically significant at the 5% significance level. Additionally, the fairly large values for the first stage F-statistics of the added IVs suggest that the chosen IVs are sufficiently strong. The model for the AP-AP market has the best coefficient of determination among the four models, with a R^2 value at 0.85 indicating that it explains a significant proportion of the variance in airfares. This is followed by the AP-EU model with an R^2 of 0.72. NA-NA and EU-EU have very close R^2 statistics at about 0.56. The operating cost variables (FuelCostPerPax, NonFuelCostPerPax, and NonFuelCostPerFlt), which are the focus of this study, have positive and significant coefficients in all markets, demonstrating that airlines do pass operating cost increase to passengers through higher airfares. More importantly, the coefficients tend to vary in magnitude depending on the specific type of costs that airlines pass through and the particular regional market they operate in.

Based on the estimated coefficients, this paper focuses on comparing fare elasticities to specific airline costs from two critical aspects: (i) how the pass-through rates of fuel cost per passenger, nonfuel cost per passenger, and nonfuel cost per flight differ within a given regional market, and (ii) how the cost pass-through rates for the same cost type vary across different regional markets.

Taking into account the standard errors of in the estimated coefficients, the conditional mean of fare elasticities with respect to fuel cost increase are estimated to be between 0.29-0.31 in NA-NA, 0.28-0.32 in EU-EU, 0.52-0.55 in AP-AP, and 0.25-0.30 in AP-EU

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[1] Alternatively, a simultaneous equation system may be estimated with each endogenous variable specified, as the dependent variable of one equation (Woodridge, 2010). However, the goal of this research is to examine the impacts of the interested variables on airfares, and therefore we use the single equation for estimation.

with 95% confidence intervals. Fares are found to be less elastic to changes in nonfuel cost per passenger. For each 10% increase in NonFuelCostPerPax, the average increases in the mean of airfares are by 1.9%-2.3% in NA-NA, 0.8%-1.1% in EU-EU, 1.1%-1.6% in AP-AP, and 1.1%-1.5% in AP-EU, respectively. The elasticities of airfares with respect to changes in nonfuel cost per flight in the four regional markets are estimated to be 0.06-0.07 in NA-NA, 0.08-0.11 in EU-EU, 0.07-0.10 in AP-AP, and 0.08-0.13 in AP-EU, respectively.

Table 4
Feasible Generalised Two-stage Least Square (FG2SLS)[a]estimation results for the selected airline markets.

	NA-NA		**EU-EU**		**AP-AP**		**AP-EU**	
Variables	**Coef.**	**Std.Error**	**Coef.**	**Std.Error**	**Coef.**	**Std.Error**	**Coef.**	**Std.Error**
ln(FuelCostPerPax)	0.297^{***}	0.005	0.300^{***}	0.008	0.533^{***}	0.008	0.278^{***}	0.018
ln(NonFuelCostPerPax)	0.214^{***}	0.011	0.093^{***}	0.008	0.142^{***}	0.015	0.130^{***}	0.012
ln(NonFuelCostPerFlt)	0.065^{***}	0.005	0.092^{***}	0.007	0.088^{***}	0.008	0.107^{***}	0.015
ln(LegMeanHHI)[1]	0.132^{***}	0.003	0.059^{***}	0.004	0.011^{*}	0.005	0.032^{***}	0.007
ln(AirportMeanHHI)[1]	0.069^{***}	0.005	-0.018^{***}	0.005	0.043^{***}	0.006	-0.035^{***}	0.011
ln(CUIMean16hours)	-0.020^{***}	0.003	0.006^{*}	0.003	0.055^{***}	0.004	0.064^{***}	0.007
ln(Freq)	-0.032^{***}	0.002	0.033^{***}	0.005	-0.063^{***}	0.006	0.095^{***}	0.005
ln(Pax)[1]	0.008^{*}	0.003	-0.027^{***}	0.006	0.044^{***}	0.007	-0.081^{***}	0.008
LoadFactor	0.366^{***}	0.012	0.254^{***}	0.018	0.617^{***}	0.018	0.142^{***}	0.030
RouteShare[1]	0.135^{***}	0.010	0.140^{***}	0.008	0.056^{***}	0.007	0.041^{*}	0.017
Nlegs2	-0.090^{***}	0.012	-0.046^{*}	0.026	0.074	0.038	-0.442^{***}	0.031
Nlegs3	-0.142^{***}	0.017	-0.071^{*}	0.036	-0.022	0.046	-0.668^{***}	0.042
Nlegs4	-0.113^{*}	0.050	0.070	0.049	-0.180^{*}	0.069	-0.760^{**}	0.045
HubsPass1	0.129^{***}	0.002	0.032^{***}	0.004	0.047^{***}	0.004	0.048^{***}	0.006
HubsPass2	0.183^{***}	0.003	0.080^{***}	0.006	0.090^{***}	0.007	0.075^{***}	0.007
HubsPass3	0.241^{***}	0.013	0.063^{*}	0.027	0.186^{**}	0.029	0.059^{***}	0.010
HubsPass4							0.001	0.031
Constant	1.105^{***}	0.076	2.111^{***}	0.083	1.151^{***}	0.120	3.487^{***}	0.165
Number of obs.	51,380		38,097		25,727		26,642	
R^2	0.560		0.550		0.849		0.722	
First stage partial F-stat								
ln(Pax)[1]	797.0		383.91		244.40		430.16	
ln(LegMeanHHI)[1]	13820.2		13033.21		7396.97		6885.92	
ln(AirportMeanHHI)[1]	9089.3		7012.03		3649.36		3439.61	
RouteShare[1]	1318.1		3365.41		2203.07		2387.26	

*** Significant at the 0.1% level.
** Significant at the 1% level.
* Significant at the 5% level.
[a] Origin- and Destination-country fixed effects not reported.
[1] The endogeinous variables in the model.

The estimated coefficients above provide some interesting insights. Within each of the four markets, the effect of increasing fuel cost on fares significantly outweigh the effects of increasing nonfuel costs by a same percentage. It indicates that airlines are the most responsive to fuel cost changes, which is possibly because of the great fluctuations of fuel price over the past 15 years (Koopmans and Lieshout, 2016). Furthermore, for nonfuel costs within each market, fares are generally more elastic to changes in nonfuel per passenger cost than nonfuel per flight cost, except in EU-EU, where the estimated coefficients of the two nonfuel costs are not statistically significantly different within error bounds (both between 0.08 and 0.11). This pattern suggests that, within NA-NA, AP-AP, and AP-EU markets, increasing nonfuel per passenger cost has larger impacts on airfares than increasing nonfuel per flight cost by a same percentage.

The differences in elasticities of airfare to the three operating costs within a market have important policy implications for aviation emissions reduction. The highest cost pass-through rates from FuelCostPerPax suggest that, for all regional markets under the study, emissions reduction policies that can result in airline fuel cost increase, such as fuel taxes, will have the greatest impact on passengers. Depending on the elasticity of air travel demand to airfares in a given market, such policy measures would discourage demand the most due to the increases in fare prices, thus leading to lower CO_2 emissions from aviation. However, it will also impose negative impacts to the development of the entire airline industry within the region.

Alternatively, a relatively moderate option on limiting aviation emissions, with the least cost burden passed onto passengers, could be to increase airline's nonfuel per flight cost, given the lowest estimated cost pass-through. Nonfuel per flight cost consists of crew cost, maintenance cost, ownership cost, en-route charges, and aircraft landing charges (see Fig.2). This suggests that a potential approach for reducing aviation emissions that has the least impact on airfares experienced by passengers would be based on airline enroute charges and aircraft landing charges where airlines absorb a higher proportion of cost than seen in fuel costs. Consistent with our findings, the airline industry has already started to limit aviation emissions based on this option, through the existing or forthcoming market-based measures (ICAO, 2013, 2016). As mentioned in Section 1, since CORSIA requires carbon-offset credits for the total annual increase in aviation emissions beyond a 2020 baseline, it is equivalent to putting additional price to airline enroute charges, yet with an international scope. The EU Emissions Trading Scheme (EU ETS) employs a very similar approach but at a regional scale, where airlines are allowed to trade emission permits among different industries, under a total emission 'cap' (European Commission, 2016). By contrast, carbon tax, as a different form of the MBMs, is already a part of the overall airport landing charges (e.g. emission-charges or environment-related charges) in some airports (IATA, 2016).

Turning to the second critical aspect in this analysis: how the cost pass-through rates vary in different regions, we further compare the variation of cost pass-through across the four airline markets.

As discussed earlier, changes in fuel cost per passenger have the greatest impact on fares in all the four markets. However, coefficients of FuelCostPerPax between the markets suggest that the extent to which changes in fuel cost affect fares is different by market. Airfares in AP-AP are the most elastic to fuel cost changes (with an estimated elasticity between 0.52 and 0.55) among the four regions, while the elasticity of fare in AP-EU (0.25-0.30) shows only about half of this effect. NA-NA and EU-EU markets have coefficients that are not statistically significantly different within error bounds, with NA-NA at 0.29-0.31 and EU-EU at 0.28-0.32. Note that the estimated elasticities in NA-NA and EU-EU are very close to the estimation of 0.3 fare elasticity to fuel price by Dray, et al (2009) for the U.S. airline system. The regional variation in fuel cost pass-through implies that policy measures such as fuel taxes have different impacts to airline pricing across regional markets. For example, passengers in AP-AP will face more increases in fare price than any other market under the study. As a result, MBMs that place an additional price on fuel would be considered a more aggressive option in AP-AP than in other regional markets. This could have implications for airlines based on their different exposures to world regions.

Continuing with comparison of nonfuel cost pass-through between different markets, we find that changes in nonfuel per passenger cost in NA-NA have an effect more than twice that of EU-EU. Taking standard error into account, NA-NA has fare elasticity to NonFuelCostPerPax between 0.19 and 0.23, while the elasticity in EU-EU is only 0.08-0.11. Additionally, AP-AP and AP-EU have almost statistically identical coefficients for nonfuel per passenger cost at 0.11-0.16 (AP-AP) and 0.11-0.15 (AP-EU), respectively. In contrast, fare elasticities to nonfuel per flight cost show relatively less variation across different markets, ranging from the lowest value in NA-NA (0.06-0.07) to the highest value in AP-EU (0.08-0.13). This adds another important implication for regulators to, among other cost types, focus on using MBMs to affect flight-based operating costs. The relatively low variation of the per-flight cost pass-through indicates that it is more feasible for such MBMs to be implemented at a cross-regional scale.

As discussed earlier, from the comparison of cost pass-through within each market, we learn that increases in nonfuel per flight cost will have the smallest impact on passengers. Thus, emissions reduction policies that focused on flight-based cost will have the least effect on the passenger demand growth of air transportation within a given region. From the cross-regional comparison we further find that such policy measures are also the most feasible option to be adopted globally. Unlike options that aim to increase the other two types of operating costs, which will result in significantly unbalanced fare increases across regions (AP-AP most affected under fuel cost increase, and NA-NA most affected under nonfuel per passenger cost increase), MBMs that aim to increase the nonfuel per flight cost will bring relatively balanced price increases among different regions, and thus is most likely to be accepted by the global aviation community.

5. Conclusion

This research develops an airfare model that captures specific airline operating costs as well as other key determining factors that have been found important and significant in previous fare models. By estimating the fare model for a number of world regions, we are able to compare the variation of cost pass-through within and across regional markets. Based on the estimated cost pass-through rates, policy implications on aviation emissions reduction are also discussed in detail.

Four regional markets were selected for analysis: NA-NA, EU-EU, AP-AP, and AP-EU. A comparison analysis for the cost pass-through within and between regions shows that AP-AP has the highest fare elasticity (between 0.52 and 0.55) with respect to fuel cost increase, while AP-EU, which is the least elastic to fuel cost changes, has only about half of this effect (0.25-0.30). NA-NA and EU-EU markets have statistically close coefficients within error bounds, with NA-NA at 0.29-0.31 and EU-EU at 0.28-0.32. By contrast, increases in nonfuel per flight cost will have the least impacts on passengers, as well as the least variation in cost pass-through across markets, ranging from the lowest value in NA-NA (0.06-0.07) to the highest value in AP-EU (0.08-0.13).

Based on the estimated coefficients, the implications for policy measures on aviation emissions reduction are discussed. Given the highest cost pass-through rates of fuel cost per passenger, emissions reduction measures that can result in airline fuel cost increase, such as fuel taxes, will have the greatest impact on passengers, particularly the passengers in AP-AP. However, such policies would reduce emissions at the expense of lower demand. Alternatively, a relatively moderate option on limiting aviation emissions, with the least cost burden passed onto passengers, could be to increase airline's nonfuel per flight cost. Consistent with our findings, such MBMs are already in place in different forms. For example, extra costs on aircraft landing charges are imposed by some airports via emissions charges; additionally, the EU ETS and the upcoming CORSIA, through requiring airlines to submit emissions credits for their annual emissions, are considered equivalent to putting extra cost to airline enroute charges. Our findings suggest that these MBMs are also more likely to be implemented at the global scale because such policies would bring relatively balanced price increases among different regions, given the least variation of nonfuel per flight cost pass-through.

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Appendix A: Definition of Model Variables

1. **FuelPerCostPax:** The sum of average fuel costs per passenger of all segments used on the given itinerary.
2. **NonFuelCostPerPax:** Nonfuel costs that are charged per-passenger (i.e. airport passenger charges, volume-related charges). NonfuelCostPerPax is the sum of average passenger-based nonfuel cost per passenger of all segments used on the given itinerary.
3. **NonFuelCostPerFlt:** Nonfuel costs that are charged per-aircraft (i.e. crew salaries, maintenance cost, finance cost, en-route cost, and aircraft landing cost). NonfuelCostPerFlt is the sum of average aircraft-based nonfuel cost per flight of all segments used on the given itinerary.
4. **CUIMean:** The mean of airport capacity utilisation of origin and destination airports. CUI is calculated as average hourly aircraft total movements in 16 hours divided by the declared airport capacity.
5. **AirportMeanHHI:** The mean of the HHIs at origin and destination airport. Market share used in calculating AirportHHI is defined as airline's total departing passengers divided by the total passengers at the origin airport (group by origin airport), and ariline's total arriving passengers divided by the total passengers at the destination airport (group by destination airport).
6. **LegMeanHHI:** Geometric mean of the HHIs on all segments used by the itinerary. The LegHHI measures airline market share as the ratio of airline demand on m-n over the total demand of city pair i-j which m-n belongs to. This LegHHI thus takes competition from adjacent routes (multi-airport system) into account.
7. **Freq:** Annual total flight frequency of a given route.
8. **Passengers:** Annual total number of passengers on the route at O-D airport pair level.
9. **LoadFactor:** Geometric mean of average load factors of all segments on the route.
10. **RouteShare:** Ratio of O-D passengers on a given route over total O-D passengers between the O-D city pair.
11. **Nlegs:** Number of flight segments used by a given route.
12. **HubsPass:** Categorical variable measuring total number of hub airports that the given itinerary passes by, including origin hub, connecting hub(s), and destination hubs.
13. **OriginCountry:** Origin country fixed-effects.
14. **DestCountry:** Destination country fixed-effects.