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Competition in Multi-Airport Regions: Measuring airport catchments through spatial interaction models

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ABSTRACT

The paper makes use of a novel dataset of the surface access flows of passengers departing from the four main airports surrounding London to construct a spatial interaction model for the region. This model explains the spatial variability in the flows through four separate components being [1] spatial separation between the origin of the flow and the destination airport, [2] the demand characteristics at the origin, [3] the attractiveness of the service offered by the airport, and [4] the presence of intervening opportunities. A spatial econometric approach is taken in the modelling to account for the presence of spatial dependence in the data.

The output of the model reveals a strong distance decay effect, where the level of interaction between origins and airports displays a negative spatial gradient. Each of the four airports dominate passenger flows in their immediate vicinity, with the market in the region being hotly contested in central London. All four components of the model are useful in explaining spatial variation in passenger flows, demonstrating the efficacy of this approach in considering how airports source their demand in a Multi-Airport Region. The performance of the model is superior when considering passenger surface access flows for scheduled flights, while the explanatory power is reduced for flows associated with chartered flights. Having verified the applicability of the model, it is possible for policy makers to utilise the approach to consider such issues of expanding, limiting or reducing capacity at existing airports in the region, establishing new airport facilities, and the effect of population growth on the geographic form of airport demand.

1. Introduction

The aviation market has experienced consistent levels of growth over the past century as more travellers take to the skies. In the last decade, the number of air passengers in the European Union has increased by 52%, with over 1.1 billion journeys conducted in 2019 across member states (EuroStat, 2020). This growth has resulted in, while also being partially driven by, the expansion of airports, with existing providers enlarging their operations and new airports being established. This trend of airport expansion is arguably best illustrated by the rapid development of the Chinese aviation sector, with 40 new commercial airports under construction between 2015 and 2020 (Dong and Ryerson, 2019).

These trends are challenging from a climate policy perspective, as aviation is one of the most rapidly growing emission sectors (Lamb et al., 2021; International Transport Forum, 2021; Lee et al., 2021) and scalable technological solutions to mitigate these emissions are extremely challenging (Åkerman et al., 2021; Committee on Climate Change, 2019; Gössling et al., 2021; Lai et al., 2022). For this reason, experts and environmental organisations have called for a halt to airport expansion (Committee on Climate Change, 2020; Dunne, 2021; Stay Grounded, 2019), because of the role of new airport capacity in accommodating and possibly even inducing demand for air travel (see e.g., Mattioli et al., 2021). Yet many governments, including in the United Kingdom (UK), are committed to investment in airport expansion even if this means missing their own climate targets (Finney and Mattioli, 2019). Aviation has seemingly been granted a ‘free pass’ from climate change regulation in the past, and still benefits from special treatment today.

Global capitals and city clusters are often served by multiple airports which compete for customers. Such circumstances are generally referred

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to as Multi-Airport Regions (MARs), with examples being present around the cities of New York, Tokyo, and Beijing (Derudder et al., 2010). Indeed, the presence of multiple airports is becoming synonymous with conceptions of what it is to be a 'global city' (O'Connor and Fuellhart, 2016), with cities often judged by the quality of their aviation links. Airport competition within MARs is multifaceted, including elements such as the routes offered, the facilities provided, as well as surface access options. The spatial configuration of airports within MARs produces obvious geographical questions such as from where airports source their passengers and in what locations is the competition for passengers between airports fiercest (Fuellhart, 2007; Paliska et al., 2016). However, the lack of revealed preference data concerning observed passenger surface access flows into MARs substantially hinders research in this area, with projects instead falling back on methods to estimate the spatial dispersion of air travel demand within MARs given data on airport passenger volumes and population densities (Loo et al., 2005; Lieshout, 2012; Teixeira and Derudder, 2021).

This paper focuses on this issue of spatial competition in MARs through an assessment of the origin points of travellers. The analysis is situated on the city of London, UK, and the four major airports that surround it. A set of spatial econometric interaction models are specified to explain the geographic spread in the surface access flows coming into each of these airports from across England and Wales. Measurements of distance between the airport and the point of origin, characteristics of the demand at the point of origin, service offer at the airport, and the presence of intervening opportunities are used as explanatory variables. Spatial interaction effects are also utilised to mitigate for biases resulting from spatial autocorrelation. Given the logistic challenge of acquiring the necessary data, the research reported here delivers arguably the most complete evaluation of observed spatial interaction in a MAR to date. The outputs of this analysis provide insights on the geographic reach of each airport, how the aviation market in the London city region can be allocated to each airport, and the factors which affect the spatial structure of the airport catchments.

2. Background

2.1. Multi-airport regions

During the second half of the twentieth century, the commercial aviation sector grew dramatically around the globe. This expansion was motivated by an assemblage of interrelated factors including rapid industrialisation, globalisation, increasing tastes for international tourism as household incomes expanded and paid holiday time increased, airport expansion, the softening of border restrictions, and the expansion of activity spaces and social networks (Graham, 2000; Scott and Gössling, 2015; Schäfer et al., 2009). Deregulation agreements struck in the United States and European Union provided the sector with the agility to respond to these changing conditions and resulted in increasing levels of competition between airlines and airports (Humphreys, 1999). One visible outcome of the increased size of this more competitive sector is the occurrence of MARs. What exactly constitutes a MAR is an issue of debate, though one generally agreed aspect is that MARs involve air passengers having a realistic choice of departure airport to conduct their onward travel.

Certain organic processes have assisted in the growth of MARs. Urbanisation has increased the size of city populations while the installation of high-quality transport corridors has brought neighbouring cities closer together. These processes have resulted in conurbations which encompass multiple cities, such as the city cluster present on the North-East coast of the United States. One outcome of this type of urbanisation is that airports which were initially constructed to serve one city are now accessible to residents in the wider conurbation, providing air passengers with choice on where to depart from (de Neufville, 1995). Situations are also present where MARs surround individual megacities (i.e. cities with a population exceeding 10 million), where considerable transit times from one side of the city to the other can encourage the presence of multiple airports to serve the metropolitan population.

While factors around urbanisation and the integration of city clusters provide a natural explanation for MARs, planned process are also present that describe their formation. A series of commissions were established in the UK from the 1950s onwards to consider how best to provide additional capacity to the aviation sector (Sealy, 1955). Different options were put forward, including expansion of capacity at existing airports or the establishment of new airports to provide an improved regional coverage (Cripps and Foot, 1970). Existing airports found their expansion prospects significantly limited due to urban growth occurring up to their perimeters, making the process of acquiring land to expand into a substantial barrier. Given these challenges, serious consideration was given to identifying suitable locations to construct new airports or to scale up operations at small runways (Farrington, 1984).

These organic and planned process have culminated in MARs that encompass three or more airports being present in the North America, European, South America, and Asian aviation markets (Sun et al., 2017). Airports within such regions may divide the market up by function, with certain airports specialising on specific submarkets such as intercontinental travel (Derudder et al., 2010). Recent estimates put the number of MARs at fifty-three (O'Connor and Fuellhart, 2016), though this is sensitive to the qualification assumptions. This number has been steadily increasing over the past few decades, meaning that the presence of MARs is a sector condition which is likely to persist into the future.

2.2. Spatial analysis of multi-airport regions

The diverse processes that have assisted in the formation of MARs produce a number of compelling lines for academic inquiry. Important issues relate to how passengers choose between multiple airports (Pels et al., 2001; Hess and Polak, 2005; Blackstone et al., 2006), the benefits that such situations deliver for the regions (Brueckner 2003; Pagliari and Graham, 2019; Murakami and Kato, 2020), alongside the visible downsides such as encouraging more air travel and the subsequent implications for global emissions and noise pollution (Miyoshi and Mason, 2013; Gössling and Humpe, 2020; Dobruszkes et al., 2021). The spatial configuration of such regions also allows researchers to consider issues around geographic organisation. Three prominent topics have been considered in past work on geographic organisation, covering how easy it is for passengers to travel to airports, the degree to which airports can capture passengers from nearby competitors, and from what distance airports can source passengers.

Given the growing importance of air travel in society, determining which individuals have the ability to utilise the aviation system represents a crucial issue. This stems not only from allowing individuals to participate in global tourism, but also to benefit from core facilities (e.g. healthcare and civic services) that can be concentrated in specific locations and thus inaccessible to the residents of remote areas (Özcan, 2014). Part of the work on this topic of accessibility to the aviation system focuses on the geographic separation between airports and residences. Studies have revealed underserved populations that have limited or no practical system access, as well as those populations that have a wide choice of airports, airlines, and routes to select from. An analysis of the contiguous United States by Matisziw and Grubesic (2010) identifies pockets of relatively poor accessibility to airports located throughout the great plains and western frontier regions. Such circumstances lead to the application of Essential Air Service subsidies to regional airports to support their operations (Park and O'Kelly, 2017), though these policies can often be quite course and lack sensitivity to the different roles that regional airports can serve (e.g. as a feeder into a larger hub or as a means to traverse challenging terrain). While work on airport accessibility tends to take a national approach, a recent project by Sun et al. (2020) demonstrates the ability to scale this up to a global perspective. Their analysis of surface road access to the worldwide airport network uncovers quite stark continental divides, with 90% of the population in the North American and European markets being within 90 minutes of an airport, dropping to just 44% in Southeast Asia. With research showing that proximity to airports is associated with a greater number of flights (Bruderer Enzler, 2017; Kim and Mokhtarian, 2021; Mattioli et al., 2021), access to the aviation system seems to be a primary factor in the expansion of the sector.

For locations that have multiple airports within close proximity, dimensions of competition come into play (Pagliari and Graham, 2020). Passengers may be inclined to bypass their closest airport in order to benefit from the service offered by a rival at a further distance. Such situations could occur when further removed airports offer a better fit for the passenger's requirements (e.g. direct flights, convenient departure times, or increased flight frequencies) or provide ancillary services (e.g. parking, leisure facilities, or hotel accommodation) which meet the passenger's preferences (Kim and Ryerson, 2018). One issue which has increased in prominence as the benefits of deregulation have materialised is price competition. Price sensitive travellers (e.g. those on modest incomes or tourists) can be captured by distant airports which have offer lower air fares (Lian and Rønnevik, 2011). Circumstances such as these generate what is known as market leakage, where airports can attract passengers away from their rivals by providing a more appealing service (Fuellhart, 2007).

Implicit within this topic of market leakage is to concept of airport catchment, which covers the measurement of how far airports can attract passengers from. Drawing from theories of retail geography, studies have considered where the perimeter of airport catchments are (Lieshout, 2012; Suau-Sanchez et al., 2014), the degree to which catchments overlap (Loo et al., 2005), and the temporal variation that is present in catchment size (Teixeira and Derudder, 2021). Often, analysis of market catchments approaches the topic from the perspective of estimation, attempting to calculate the spatial reach of airports given data on surface access options and population placement in the surrounding region. However, there are a few examples of work where revealed passenger data are utilised (i.e. actual observations of flows to an airport). Notable such examples are the work of Heilman (2017), who produced a Huff model to explain spatial variation in the catchments for nine airports in the state of Iowa, and the work of Paliska et al. (2016), who examined passenger airport choice in the upper Adriatic region. The provision of such revealed preference data is crucial in evaluating the performance of statistical models aimed at explaining the spatial form of airport catchments, but acquiring this data can be a difficult task.

2.3. Research gap

Spatial analysis of passenger surface access flows in MARs using revealed preferences is rare given the logistical resources and permissions needed to attain the necessary data. The requirement to conduct widescale surveying of passengers at multiple airports and during different periods of the year generally put revealed preference MAR analysis out of reach of modestly funded academic research, with such data collection exercises demanding either state or industry coordination. This situation has meant that past research in this area has typically relied on stated preferences of airport choice with limited consideration provided to spatial context (Pels et al., 2001; Hess and Polak, 2005) or estimations of airport catchments given data on population distributions (Loo et al., 2005; Suau-Sanchez et al., 2014).

The study reported in this paper overcomes this limitation of revealed preference data availability by gaining access to a restricted dataset managed by an industry regulator. This dataset is derived from extensive airport surveying of passengers departing form the four main airports of London, UK, and culminates in an origin destination matrix which records the surface access flows of departing passenger numbers into each airport. By utilising this restricted data, this study can consider important questions regarding how the regional market can be partitioned between the competing airports and the degree to which passenger flows diminish with distance. This work culminates in the specification of a series of spatial interaction models that can explain the geographic variation observed in the surface access flows. The fidelity in the dataset allows for two different model variants, with one focusing on the departing passenger surface access flows on scheduled services while the other considers chartered flights. This distinction allows the analysis to demonstrate the nuanced perspectives that can be acquired when flow data can be split by a defining feature.

3. Methodology

3.1. Theoretical model of spatial interaction

Airports within a MAR represent destinations which passengers select in order to conduct their air travel. These passengers have a starting point from which their surface access trips commence, generally their household residence. These two pieces of information allow for the specification of an origin-destination matrix which notes the flows that occur from locations at which journeys commence and the airport selected for onward travel.

Origin-destination matrices represent a fundamental building block used in spatial analysis which examine the flows of travellers around a transport system. These matrices act as data inputs to spatial interaction models (SIMs). SIMs can be specified in different ways dependent on the richness of the data that is available and the intended objective of the study (Dennett, 2018). One form of SIMs is applied through multiple linear regression analysis and considers what factors are useful in explaining the variations observed in flow size. The dependent variable in the model represents the flows occurring between origins (i.e. households) and destinations (i.e. airports) in terms of number of passengers. The independent variables cover a set of four components which are hypothesised to affect the magnitude of these flows (LeSage and Fischer, 2016). The first component represents characteristics of the demand such as the demographic profiles of flow origins. The second component focuses on the attractiveness of the destination which is receiving flows. The third component covers the proximity between the origin and the destination of the flows, where interaction is expected to decay with increasing geographic separation. The fourth component is whether intervening opportunities occur between the origin and destination such as the presence of a competitor.

The geographic nature of the origin destination matrix data utilised in SIMs can introduce biases to the analysis due to the presence of unobserved spatial linkages (e.g. the occurrence of regional marketing campaigns). This situation is referred to as spatial autocorrelation, whereby spatial dependence is present in a model's error term meaning that they will no longer be independent and identically distributed. If a model has such spatial autocorrelation present, this may have implications for the reliability of the model's parameters (i.e. estimated coefficients and standard errors) if left uncorrected. While some SIM variants do include spatial measurements such as the proximity between origin and destination in conventional gravity models, this often proves insufficient at fully correcting for spatial autocorrelation. To account for this, spatial econometric version of SIMs have been developed (typically referred to as spatial econometric interaction models) which incorporate spatial interaction affects (LeSage and Pace, 2008).

A spatial weights matrix is specified which identifies geographic neighbours and allows for the calculation of spatially lagged variables (i.e. the spatial interaction affects) which are integrated into the SIM as independent variables. Given that structure of this analysis (i.e. many origins to few destinations), an origin-indexed spatial weights matrix based on queen contiguity is utilised. This classifies origins as geographic neighbours if they share either a line or point border with another spatial unit.

Multiple variations of spatial interaction effects can be included in the SIM, covering spatial dependence located at either the flow origin (i.e. spatial lags of the flows coming from neighbouring spatial units), the flow destination (i.e. spatial lags of the flows arriving at neighbouring spatial units), or in the model's error term (i.e. spatial lags of the model residual for either neighbouring origins or destinations). Model diagnostics are available in the form of Lagrange Multiplier tests to determine which model variant to select (Anselin et al., 1996). For the purposes of this analysis, the tests indicated that incorporating spatial interaction effects in the model's error term would provide the most robust results (Fischer and Griffith, 2008).

The structure of spatial econometric interaction models which include spatial dependence in the model error are summarised in Equations (1) and (2).

$$y_{OD} = \beta_O X_O + \beta_D X_D + \beta_{OD} X_{OD} + u_{OD} \tag{1}$$

$$u_{OD} = p_O W_O \, u_O + e_{OD} \tag{2}$$

In Equation (1), y_{OD} represents the variable of interest and records the number of travellers moving between an origin and a destination. The term $\beta_O X_O$ represents the characteristics and model coefficients associated with flow origins while the term $\beta_D X_D$ represent the characteristics and model coefficients associated with flow destinations. Characteristics which cover issues which link flow origins and destinations, being proximity and intervening opportunities, are included in the term $\beta_{OD} X_{OD}$. The model residual, u_{OD}, contains two terms which are expressed in Equation (2). The first of these, $p_O W_O u_O$, is the spatial error component and represents a spatially lagged version of the model's error. An origin-index spatial weights matrix, W_O, is used to calculate the spatial error coefficient, p_O. The last term in the model is e_{OD}, which represents the model residual that is assumed to be independent and identically distributed.

3.2. Case study: London multi-airport region

The region encompassing the South-East of England, East of England, and the Greater London Area has a population of 24.4 million (Office of National Statistics, 2021). Given this sizable local market, the region is served by multiple airports which compete to attract passengers. Of the five largest airports in the UK by passenger number, four are located in this region and encompass Heathrow, Gatwick, Stansted, and Luton airports. Table 1 reports the passenger volumes and air transport movements recorded at these airports alongside their proportion of UK air traffic. Overall, the MAR accounts for 56.66% of all UK air passengers and 40.56% of UK air transport movements, with Heathrow being the most dominant airport of the four.

The location of these airports is displayed in Fig. 1. Heathrow airport is closest to the city of London and is situated within the outer ring road (i.e. M25 motorway) to the west. Gatwick airport is located to the south of the capital towards the English Channel while both Stansted and Luton airports are located north of the capital. These airports have somewhat different market orientations, providing a degree of diversification within the MAR. Heathrow acts as an intercontinental hub airport and serves as a business travel gateway into London. Similarly, Gatwick has sizable transatlantic offerings though also acts as a charter base for travel agents for their package holidays. Stansted and Luton airports have a higher proportion of Low-Cost Carrier operations and cater more to the domestic and European travel markets.

Table 1
Key figures for the airports which comprise the Multi-Airport Region of London for 2008.

Airport	Passengers (PAX)	Air Transport Movements (ATM)	PAX UK %	ATM UK %
Heathrow	66,906,954	473,207	28.43	19.34
Gatwick	34,162,014	256,352	14.52	10.48
Stansted	22,340,375	177,285	9.50	7.24
Luton	10,173,902	85,661	4.32	3.50
UK Total	235,360,813	2,447,096	100	100

3.3. Data sources

To specify the SIMs, data are required on the components set out in equation (1).

The passenger flow data is sourced from the Civil Aviation Authority's annual departing passenger survey of UK airports (Civil Aviation Authority, 2019), which has been in operation since 1968. Passengers are approached in gaterooms and asked to complete the survey which contains 30 questions inclusive of personal characteristics, flight attributes, and surface access features. A stratified random sampling approach is taken with the strata based on carrier, route, and quarter of year. Around 200,000 surveys are conducted per annum, with the number taking place in each airport weighted by passenger volume. The survey includes questions on the origin from which the passenger started their surface access journey which can be used to specify an origin-destination matrix (i.e. residence to airport). Data is recorded for passengers undertaking air travel for both scheduled and chartered services, allowing separate origin-destination matrices to be constructed for these sub-markets. The analysis makes use of data derived from the 2008 departing passenger survey. Given the commercial value of this data, 2008 was the most recent survey wave which the Civil Aviation Authority was willing to provide access to.

The characteristics of the demand at the origins are sourced from the census of the UK (Office of National Statistics, 2001). The demographics of the resident population are incorporated in the model and selected based on those which can be reasonably linked to air travel demand (Mattioli et al., 2021). The number of residents is included as it acts as a proxy for the overall size of the local market (i.e. the number of potential passengers), with the hypothesis being that as local market size increases, passenger flows to airports will tend to increase. The percentage of households without car access is included in the model due to this acting as a prominent mode of surface access, with the hypothesis being that as car access shrinks, passenger flows to airports will tend to decrease. The proportion of residents that have a university level qualification is included in the model to act as a proxy for economic wealth, with the hypothesis being that as education levels increase, passenger flows will tend to increase. The proportion of the residents classified as retired is incorporated in the model due to the occurrence of long-distance travel tending to decline as individuals enter the later stages of life. Finally, the proportion of residents employed in sales-based roles is included in the model to account for the occurrence of business travel, with the hypothesis being that as sales occupations increase, passenger flow to airports will tend to increase.

The attractiveness of the destination data is sourced from the Civil Aviation Authority's (2019) database on airports. Given the purpose of airports, the number of routes provided is used as a proxy for how desirable each of the four London airports is to passengers. The number of routes is disaggregated based on whether they are associated with domestic or international destinations as well as chartered or scheduled services and are summarised in Table 2. The hypothesis here is that as the number of routes increases, the passenger flow to airports will tend to increase.

The distance between origins and destinations is calculated using the OpenRouteService API. This process determines shortest paths between origins and destinations and estimates proximity in both distance and travel time. The use of shortest path algorithms (i.e. network) provides a more realistic method for determining proximity as compared to simpler Euclidean distance approaches. This calculation uses the centroid of the origin spatial unit and the location of the airport and considers road network distances and durations for car travel. The duration of travel time between origins and destinations is incorporated in the model, with the hypothesis being that as travel times increase, the passenger flow to

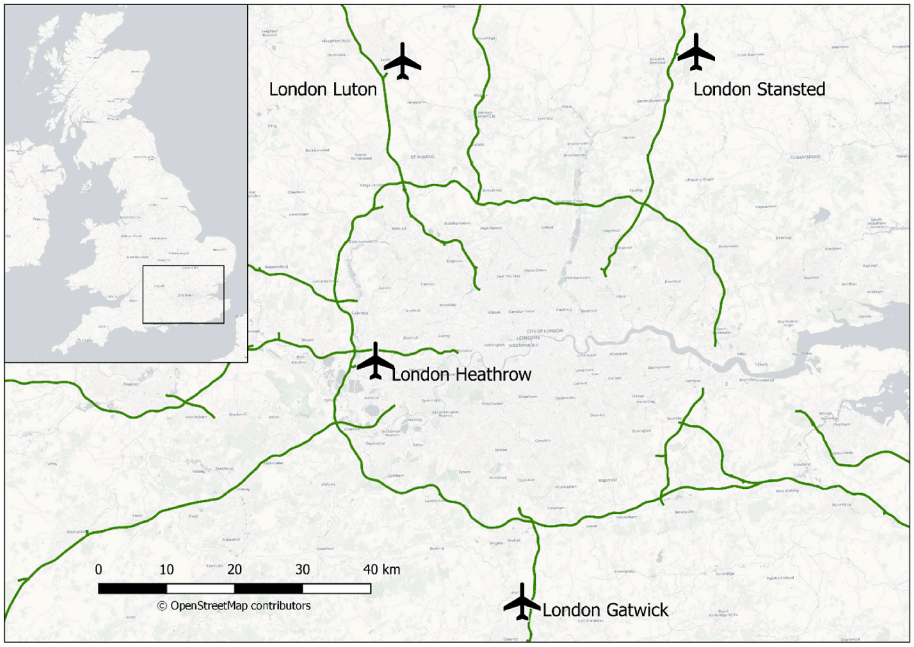


Fig. 1. The Multi-Airport Region surrounding the city of London in the United Kingdom.

Table 2
Breakdown of scheduled and chartered passengers alongside types of routes served within the Multi-Airport Region of London for 2008.

Airport	Scheduled Passengers	Chartered Passengers	Domestic Routes	International Routes	Scheduled Routes	Chartered Routes
Heathrow	66.9 m	0.05 m	11	198	189	11
Gatwick	7.8 m	26.4 m	13	268	201	145
Stansted	21.5 m	0.8 m	8	197	167	46
Luton	9.7 m	0.5 m	12	106	87	34

airports will tend to decrease.

Airport competition is incorporated in the model by the presence of intervening opportunities. This is calculated through a time penalty, which is based on whether one of the four London airports is closer to an origin as compared to the airport in question. For example, if the travel time between an origin and Heathrow is 45 min but the nearest London airport to that origin is Gatwick which is a 30 min journey, a time penalty of 15 min would be calculated. This accounts for whether the passenger flow between and origin and an airport have the possibility of a closer provider within the MAR, with the hypothesis being that as the time penalty increases, passenger flow to an airport will tend to decrease. The calculation of this time penalty is summarised in equation (3).

$$Penalty_{OD} = TravelTime_{OD} - TravelTime_{MIN} \tag{3}$$

Where:

$Penalty_{OD}$ represents the extra time required to travel to an airport when a closer London airport is present

$TravelTime_{OD}$ represents the travel time between an origin and the airport

$TravelTime_{MIN}$ represents the travel time between an origin and the closest London airport

3.4. Spatial resolution

The data included in the analysis is aggregated at the lower-tier local authority level of spatial resolution. This covers a jurisdiction of local government in the UK and represents a common format for government statistical releases. The analysis is constrained to the local authorities which are present within England and Wales and covers 376 spatial units. Given that there are 4 airports considered in the analysis, this leads to an origin-destination matrix with 1,504 cells which represent the passenger flow between possible pairings of local authorities (i.e. origins) and airports (i.e. destinations).

3.5. Statistical analysis

The evaluation of the dataset progresses through three stages.

3.5.1. Stage one: Airport catchment illustration

First, the flows of passengers from each local authority to each of the London airports is illustrated across all of England and Wales through choropleth maps with equal count bins. This step allows the geographic reach of the airports to be considered and their catchment's to be defined. Following this, the MAR is partitioned based on airport dominance. Local authorities located in the East of England, South-East of England, and London are assigned to the airport which they have the greatest level of interaction with. This stage provides insights on the structure of the region in terms of airport prominence and control. To conclude this stage, a distance decay analysis is conducted to demonstrate the spatial gradients of interaction within catchments.

3.5.2. Stage two: Spatial autocorrelation analysis

Second, tests to determine whether spatial autocorrelation is presented within the passenger flow data are conducted. This occurs at both the global level, through the calculation of the Moran's I test, and at the local level, through the application of the Local Indicator of Spatial Association (LISA; Anselin, 1995). This stage of the analysis provides credence to the use of the spatial econometric interaction models while offering additional insights on the geographic structure of interactions with the airports.

3.5.3. Stage three: Spatial interaction models

Third, a set of SIMs are specified using the spatial error model variant and maximum likelihood estimation, whereby a spatial lag of the model residual is incorporated in the SIM as an independent variable to account for the observed spatial autocorrelation. The first set of SIMs uses total flow of passengers from each of the local authorities to the airports as the dependent variable and follows a staged entry procedure for the independent variables. The second set of SIMs disaggregates this total flow of passengers into separate models for chartered and scheduled services. A log-normal approach is taken in the modelling, whereby the dependent variable is transformed into its natural logarithm.

3.6. Limitations

The data used in this research contains a number of implicit constraints which may limit the scope of the results. First, outside of the distinction on scheduled or chartered flights, no characteristics of the passengers are revealed. Due to this, it is not possible to consider if airport catchments alter across such characteristics as mode of surface access or purpose of trip. Second, the aggregation of the data to spatial units makes inferences to individual behaviour challenging. With this in mind, it is safer to consider the results as reflecting the acts of the population rather than specific passengers. Third, the data used is over a decade old which may raise concerns about shelf life. The Civil Aviation Authority also provided the research team with access to the data from the 2000 and 2004 surveys. To consider the temporal stability between these data and the 2008 version, a correlation analysis was conducted and returned coefficients in excess of 0.95. This provides some confidence that the spatial variation in passenger surface access flows to the airports is reasonably stable, with the data being old but not obsolete. Fourth, the analysis omits small-scale airports which are present in the MAR as they do not feature as part of the departing passenger survey. One notable absentee is London City airport, though this facility only accounted for 1.4% of UK passenger volume in 2008.

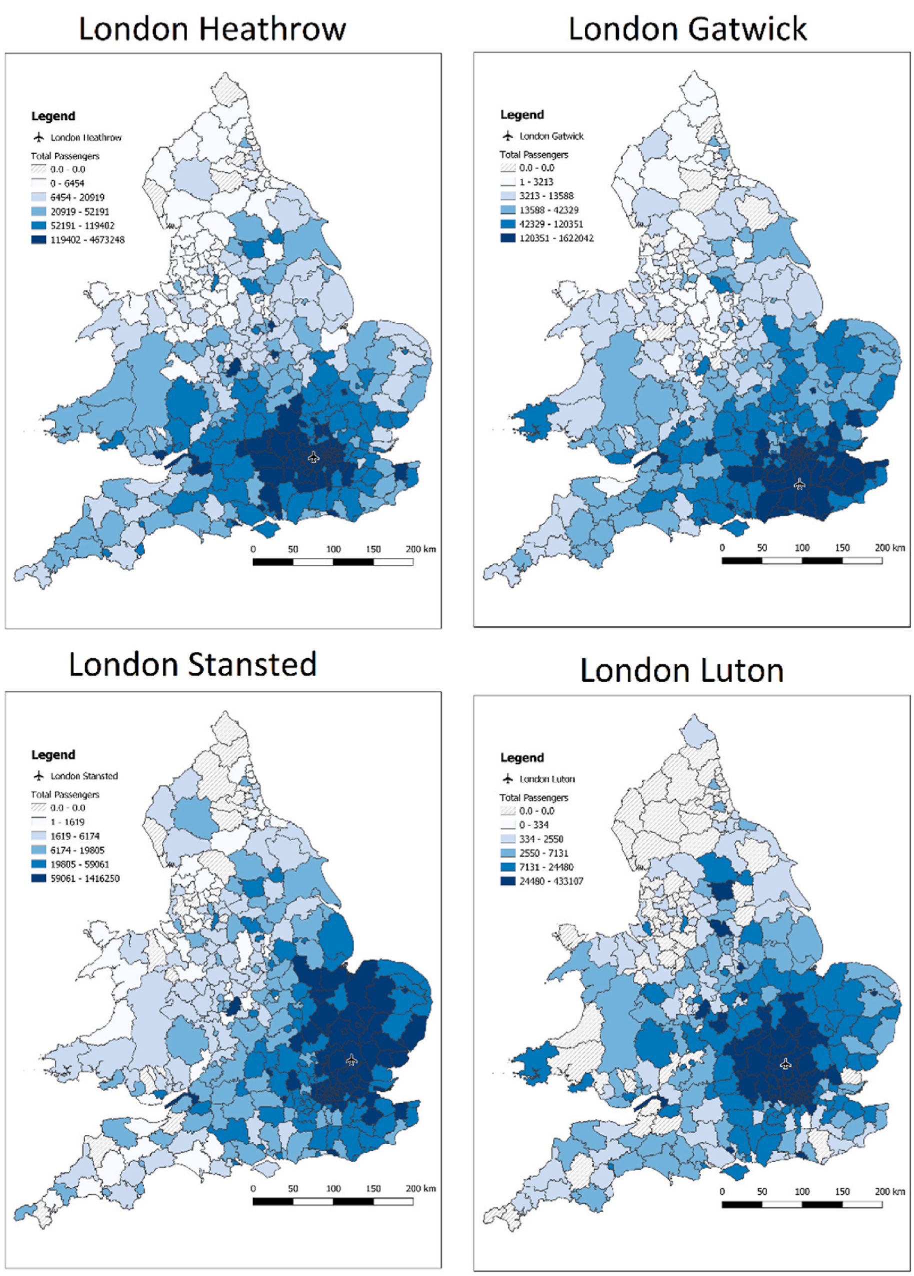


Fig. 2. Catchment areas for the four London airports represented by total number of passengers flowing from local authorities to airports.

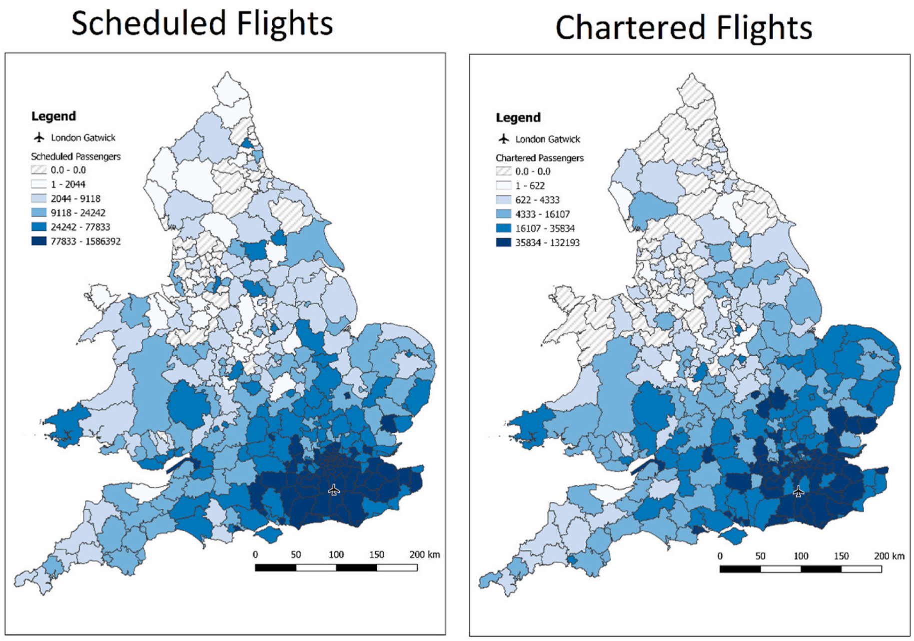


Fig. 3. Catchment areas for Gatwick Airport disaggregated by [left panel] scheduled and [right panel] chartered flight passenger flows.

4. Results

4.1. Airport catchments

The catchments for each of the four London airports are displayed in Fig. 2 for total number of passenger flows. In all instances, larger flows of passengers are observed from the local authorities in London, the South-East of England, and the East of England. Passenger flows into the airports extend to cover most of England and Wales, with only two local authorities displaying no interaction with any of the airports. What these catchment visualisations demonstrate is the substantial reach of the MAR. Passengers are willing to travel considerable distances and bypass multiple closer airports to access the services offered by the MAR.

Fig. 3 disaggregates total passenger flows into those associated with scheduled or chartered services departing from Gatwick airport (the only airport in the MAR with a sizable charter market). This disaggregation of Gatwick's catchment by service type reveals both similarities and differences. The broad trend of sourcing most passengers from the South-East and London is retained, though the chartered flight catchment is slightly fragmented and extends more prominently into the East of England. The most obvious difference is that the scheduled flight catchment for Gatwick extends further north of London, with passengers bypassing the nearer airports of Stansted and Luton. This could reflect passenger taking transatlantic flights, which do not have direct routes present from the airports in the north of the MAR.

From the visualisation of passenger flows to the individual airports in the MAR, it is clear that a considerable degree of overlap occurs, where passengers from a given local authority are selecting from all four airports for their onward journeys. Fig. 4 considers how the region can be partitioned amongst the airports. In the top panel, local authorities in the region are assigned based on which airport has the greatest number of passenger volume. The outcome of this assignment is that the region is split into reasonably even quadrants, though the area allocated to London Luton is slightly smaller than the other airports.

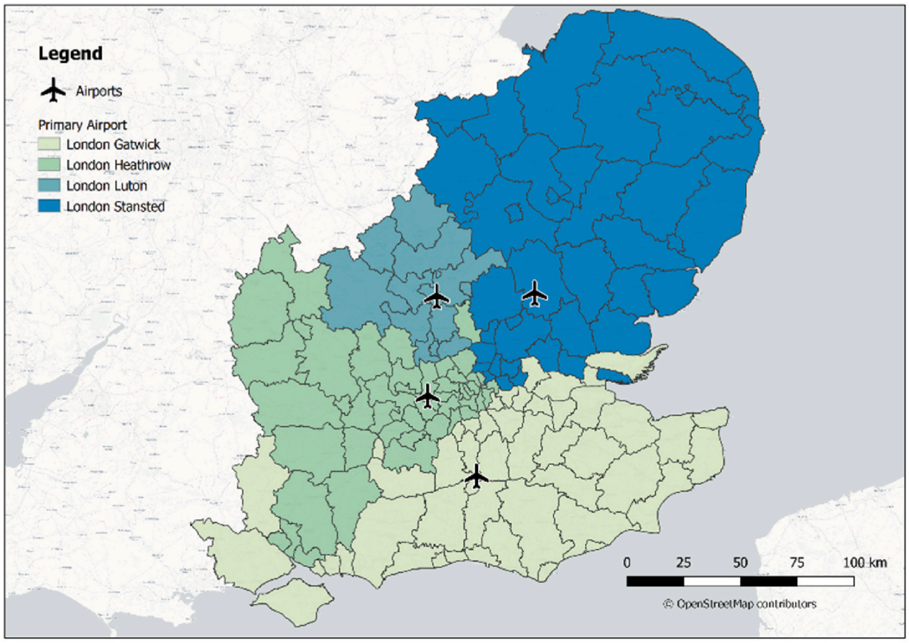
While producing a neat split of the MAR by primary airport, this approach can mask some of the areas in which competition between airports for passengers is fiercest. To bring this issue to light, the bottom panel assigns local authorities as core markets to airports if that airport accounts for over 50% of all passenger volume while identifying contested markets in local authorities where no airport has more than 40% of the passenger volume. This reveals a more complex picture on both fronts. In terms of core markets, Luton Airport has a markedly small area of dominance, only controlling more than 50% of passenger volumes in three local authorities in near proximity to the airport. Conversely, London Stansted and Gatwick airports have core markets that extend over much of the East and South-East of England respectively. In terms of contested markets, the boroughs of central London display relatively high rates of flow to multiple airports. This indicates that in these locations, passengers are most fickle and have a greater tendency to select the airport which provides the best offer given their travel requirements.

To provide a clear view on how levels of interaction between origins and airports is affected by distance, Fig. 5 displays the relationship between passenger volumes and travel times. A strong distance decay effect is visible, with interaction falling as travel times increase. The rate of decline is acute in close proximity to the airports, and then softens as distances increase. This effect seems particularly pronounced for passengers on scheduled services, while being more muted for chartered services. This observation could be motivated by the increased sensitivity that business travellers have for airport access times (Brooke et al., 1994), while leisure passengers who are travelling on chartered services for holiday purposes have lower values of time.

4.2. Spatial autocorrelation analysis

The Moran's I test, which measures the relationship between a variable and its spatial lag, is reported in Fig. 6 [left panel] for passenger flows from local authorities to Heathrow airport (the same analysis for the other airports delivered very similar results and is not reported here for the sake of brevity). The test returns a significant coefficient ($I = 0.537$, p-value <0.001), indicating that spatial autocorrelation is present for passenger flows to airports. This implies that the size of passenger flows which are observed in any given local authority are associated with the magnitude observed in neighbouring local authorities.

The LISA analysis is reported in Fig. 6 [right panel] and offers additional detail regarding where the spatial organisation in passenger flows is occurring. Hotspot regions (i.e. high-high) are shaded deep red and are concentrated around London and the South-East. Conversely, coldspot regions are shaded deep blue and are present primarily in the North-East and North-West, though also extending partially into



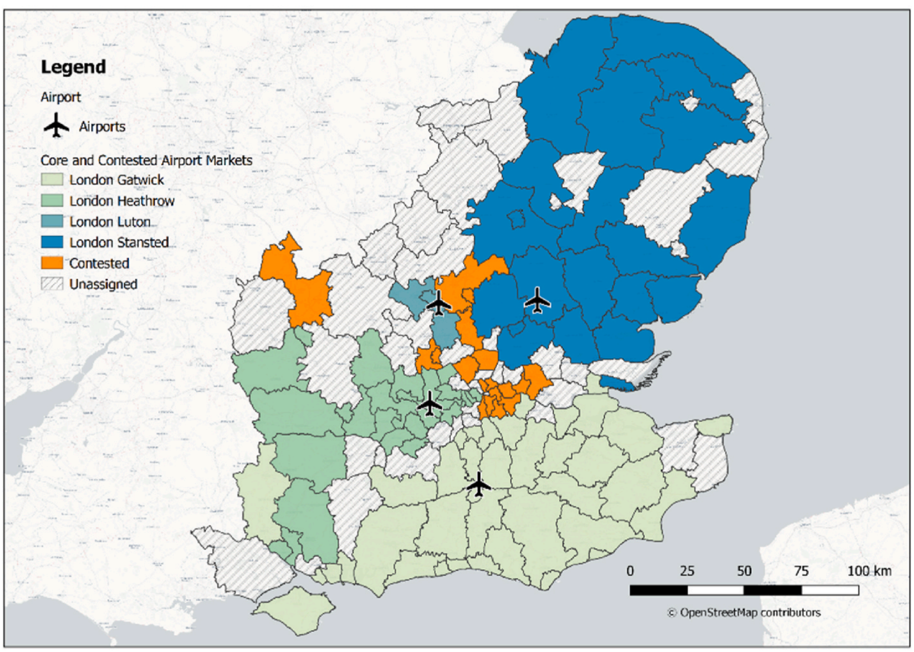


Fig. 4. The Multi-Airport Region catchments in terms of [top panel] primary airport and [bottom panel] core and contested markets.

Yorkshire and the Midlands. Interestingly, a band of local authorities which display no significant degree of spatial association is present between these hotspot and coldspot regions. This may suggest the presence of an intervening space whereby the attractiveness of this MAR to passengers is offset by the distance they are from it (i.e. the two forces balance each other out).

A number of high-low areas are also identified, with certain cities in the Midlands (e.g. Nottingham) and Yorkshire (e.g. Leeds) displaying significantly higher passenger volumes than their neighbouring local authorities. This could be motivated by the relatively superior transport links from such cities to London (i.e. direct rail links) which improves surface access to the airports. In addition, the South-West of England (e.g. Cornwall) contains areas classified high-low. One plausible explanation of this is the paucity of large airports serving this part of England which may encourage passengers to travel to London airports for their onward journeys.

4.3. Spatial econometric interaction models

Table 3 displays the results of the SIMs which have total passenger flow between local authorities and the four London airports as the dependent variable. A staged entry process is followed, whereby the variables associated with the different components of the SIM (outlined in equation (1)) are entered separately (models 1 through 4) followed by an integrated model which includes all the independent variables (model 5). The highest Variance Inflation Factor calculated for the independent variables is 2.16, which indicates the SIMs are not unduly affected by multicollinearity. The residual for each of the models is tested for spatial autocorrelation, with no significant Moran's – I being returned. This implies that the spatial interaction affect included in the

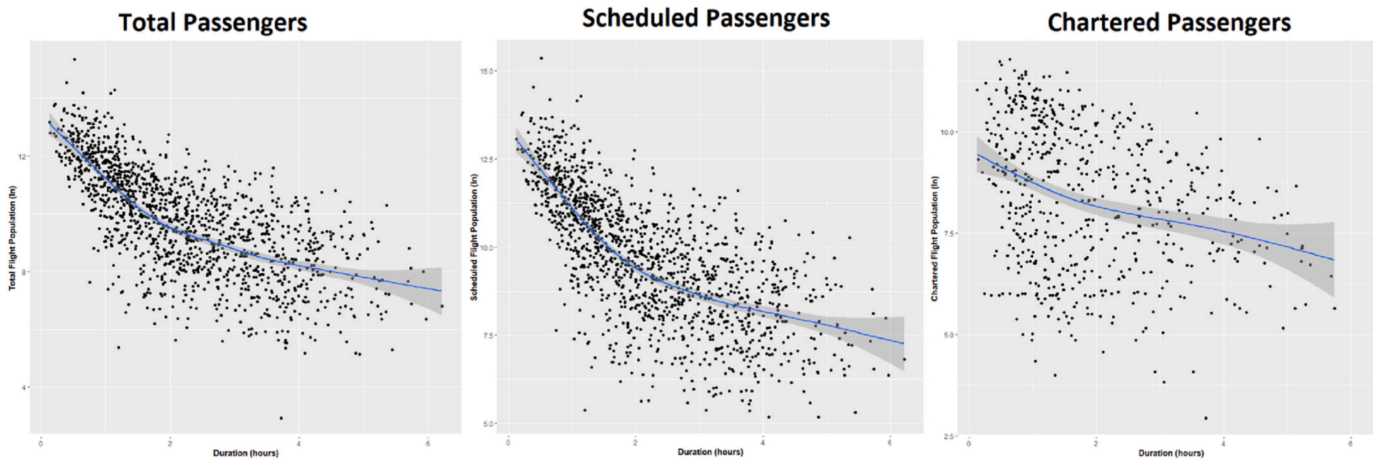


Fig. 5. Distance decay analysis of how passenger volumes diminish with increased travel times between point of origin and destination airport for [left panel] total passengers, [middle panel] scheduled flight passengers, and [right panel] chartered flight passengers.

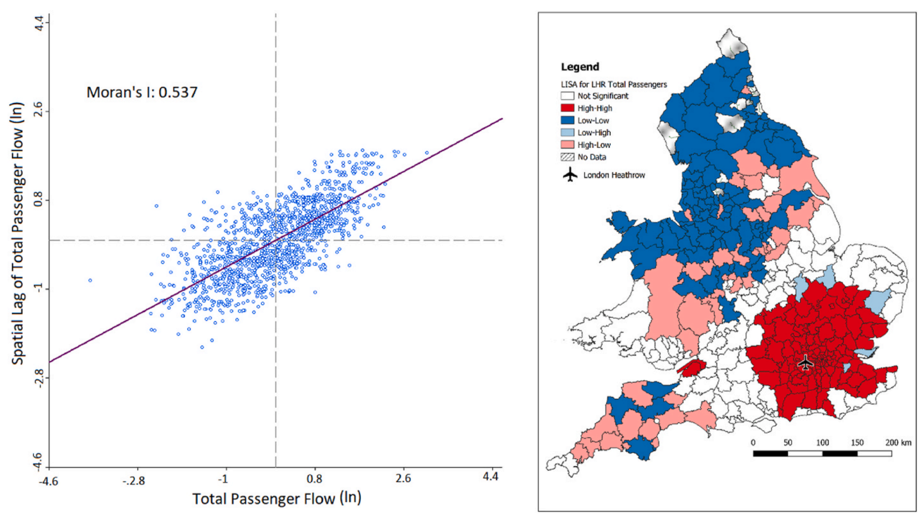


Fig. 6. Spatial autocorrelation analysis reporting the [left panel] Moran's I coefficient and [right panel] Local Indicator of Spatial Association.

SIMs has accounted for the spatial autocorrelation observed in the dependent variable. In terms of performance, the integrated model has the best explanatory power and is capable of accounting for 80% of the variation in surface access flows. Interestingly, the model fit of the individual components (i.e. models 1 through 4) are quite similar, indicating that each component is comparable in terms of its performance.

The origin characteristics included in the model, which relate to the population characteristics of the origin local authorities for the passenger flows, mostly follow expectations. The number of residents in a local authority positively affects (Beta: 0.045) the total passenger flow to an airport, which reflects the impact of local market size. Similarly, the proportion of the population in a sales-based role boosts passenger flow (Beta: 0.140), which could be motivated by the conduct of business trips to meet clients. The presence of individuals that hold a university degree is positively linked with passenger flow (Beta: 0.071). This variable acts as a proxy for wealth given the close overlap between level of education and earnings. With air travel often reflecting discretionary trips, it is unsurprising to see higher passenger flows from areas that are likely to have greater earnings. The presence of retired households holds an insignificant coefficient in the model, implying that local authorities with a high proportion of population from older age groups are no more or less likely to utilise the MAR.

The final socioeconomic characteristic considered in the model is the proportion of households that do not have access to a car. As car travel is the primary mode of access to London airports with the exception of Heathrow (Civil Aviation Authority, 2016), the expectation is that areas with low levels of car availability will be associated with smaller passenger flows. The opposite result is observed, with the proportion of no car households displaying a positive effect in the model (Beta: 0.027). One plausible explanation for this observation is that areas with low levels of car availability are likely to have high levels of access to public transport networks. Given that the MAR airports are well connected to these networks, this result could be picking up the impact of public transport accessibility on passenger flow. Another plausible explanation is that of a 'rebound effect' whereby urban households without cars tend to spend the resulting savings on more air travel, as suggested by Ottelin et al. (2014).

The quantity of routes provided by an airport is playing a significant role, but seems to be pulling the model in different directions. The number of domestic routes provided by an airport (i.e. departing to other airports in the UK) holds a negative coefficient (Beta: 0.170). This could be motivated by domestic routes within the MAR acting to redirect connecting passengers to regional airports. For airports that offer a high number of domestic routes, passengers from far afield may not have to make long-distance surface access journeys to the MAR, instead using their regional airports to connect into the MAR's international route network. The number of international routes provided by an airport displays a positive coefficient in the model (Beta: 0.018), suggesting that

Table 3
Results of the Spatial Econometric Interaction Models for total passenger flow between local authorities and the four London airports.

	Model 1	Model 2	Model 3	Model 4	Model 5
Constant	7.056**	9.492**	12.210**	10.452**	7.211**
	(0.656)	(0.416)	(0.173)	(0.247)	(0.510)
Residents (number)	0.045**				0.045**
	(0.005)				(0.003)
No Car Household (%)	0.025**				0.027**
	(0.007)				(0.005)
Retired (%)	−0.055*				0.022
	(0.022)				(0.016)
Sales Occupation (%)	0.116**				0.140**
	(0.043)				(0.030)
University Degree (%)	0.069**				0.071**
	(0.009)				(0.006)
Domestic Routes (number)		−0.210**			−0.170**
		(0.059)			(0.041)
International Routes (number)		0.015**			0.018**
		(0.002)			(0.001)
Travel Duration (hours)			−1.066**		−0.837**
			(0.061)		(0.092)
Time Penalty (hours)				−1.154**	−1.037**
				(0.088)	(0.112)
Spatial Interaction Effect (p)	0.855**	0.880**	0.698**	0.868**	0.817**
	(0.024)	(0.021)	(0.039)	(0.023)	(0.028)
Model Fit					
R^2	0.601	0.589	0.576	0.571	0.802
AIC	4376.51	4420.01	4411.85	4471.01	3414.14

*: p-value <0.05, **: p-value <0.01.
Standard Errors in parentheses below coefficients.

a more diverse offshore travel offer by an airport boosts demand. The greater the travel time between the local authority and the airport, the lower the passenger flow (Beta −0.837). This confirms the friction of distance affect for airports, whereby the level of interaction diminishes as spatial separation increases. The presence of intervening opportunities, which is measured by the time penalty of travel between a local authority and an airport in reference to the nearest London airport, also has a negative effect in the model (Beta: 1.037). This indicates that traveller flow between a local authority and airport is reduced if there is a closer airport in the MAR to that local authority (i.e. the intervening opportunity).

Table 4
Results of the Spatial Econometric Interaction Models for passenger flow between local authorities and the four London airports separated by [1] scheduled flight passengers and [2] charactered flight passengers.

	Scheduled	Chartered
Constant	5.823**	5.953**
	(0.447)	(0.705)
Residents (number)	0.044**	0.023**
	(0.003)	(0.005)
No Car Household (%)	0.030**	−0.007
	(0.005)	(0.007)
Retired (%)	−0.027	0.006
	(0.016)	(0.026)
Sales Occupation (%)	0.145**	0.149**
	(0.029)	(0.050)
University Degree (%)	0.076**	0.015
	(0.006)	(0.010)
Routes (number)	0.015**	0.028**
	(0.0004)	(0.0008)
Travel Duration (hours)	−0.792**	−0.734**
	(0.089)	(0.092)
Time Penalty (hours)	−1.001**	−1.031**
	(0.106)	(0.157)
Spatial Interaction Effect (p)	0.816**	0.519**
	(0.028)	(0.056)
Model Fit		
R^2	0.811	0.688
AIC	3277.52	1655.12

*: p-value <0.05, **: p-value <0.01.
Standard Errors in parentheses below coefficients.

Table 4 presents the results of the SIMs which disaggregate passenger flows based on scheduled or chartered flights. The two SIMs share a number of similarities, with the variables measuring the number of scheduled or chartered routes, the travel time to the airport, and the time penalty to closer airports all displaying significant coefficients of comparable size. The main differences between the models occur in the socioeconomic characteristics of the local authorities from which the flows are originating. In the scheduled flight SIM, the proportion of households without car access as well as the percentage of the population with a university degree show significant coefficients while these variables prove to be insignificant in the chartered flight SIM. This suggests that the characteristics of the origin are not as useful in explaining variation in passenger flows for chartered services, with the other components of the SIM holding relatively higher importance. A reasonable interpretation of this finding could be due to the nature of the flights. As chartered fights are primarily serving holiday travellers, it can be inferred that this represents a more ubiquitous purpose for air travel which is not as affected by the demographics of the travellers. At a broader level, the differences identified in this stage of the analysis showcase the subtleties that are typically masked when flow data is not split by a defining feature. Other defining features could also be worthwhile to examine in future work, such as whether surface access flows to MARs are different across passenger type (e.g. leisure or business) or final destination (e.g. regional or intercontinental).

5. Discussion and conclusions

Airports, like many largescale facilities, have associated catchment areas from which they source their passengers. The acquisition of data on the surface access flow of passengers between origins and airports allows for these catchments to be measured and for models to be constructed which explains the spatial structure of aviation markets. Conducting such research on regions which are served by multiple airports provides further insights on how the dominion of airports can be assigned. Through the specification of a set of spatial interaction models, this paper sheds light on this issue of geographic competition in the MAR surrounding London.

The results of the analysis indicate that passenger volume is affected by all the components of the SIMs. The travel time between local authorities and airports is a prominent component in the model. This confirms with expectations, given the universality of distance decay effects when accessing facilities. The presence of intervening opportunities, which is measured by the time penalty to travel to one airport as compared to the closest London airport, also plays a central role in the SIMs. What this suggests is that travellers do prefer to use their closest airport in this region where possible, and that passenger flows will diminish when closer options are available. The number of routes provided by an airport displays a consistent affect across all model variants, implying that airports can expand their catchments by offering a more diverse set of international travel opportunities. Including the number of residents within local authorities represents the most important demand factor in the models, with socioeconomic characteristics covering car availability, level of education, and employment status also playing a role.

Outside of the academic interest in modelling spatial interactions with airports, what are the practical uses and insights of this analysis? One way in which planners can make use of such models is to consider the impact of constructing a new airport within a MAR. Explanatory SIMs (such as those presented in this paper) can be altered without much difficulty to offer such predictions and figure out how passenger volumes at existing airports will be diverted to a newly built facility. Evaluating different options to increase airport capacity in and around London has been a topic of inquiry for the past fifty years and SIMs can be leveraged to provide market intelligence to these discussions (Sealy, 1955; Cripps and Foot, 1970; Farrington, 1984). At the same time, the current context is one where governments are called to limit net airport expansion (Committee on Climate Change, 2020) if they are to meet their climate change targets. As such, it might be interesting to use models similar to the ones presented here to explore scenarios where airport capacity is limited, reduced, or re-allocated between airports. Such analysis could reveal not only the emissions implications stemming from such policy measures, but also which geographical areas and population groups would be most affected in terms of reduced or 'suppressed' demand. A third use of such models is to estimate how population growth patterns in a MAR will affect passenger volumes. The South-East of England and London in particular have been growing in terms of residents for the last twenty years (Simpson et al., 2020). It is possible to combine the spatial forecasts of such growth patterns with the results of the SIMs to predict the magnitude of passenger flows in the future.

Over the past decade, airports in the MAR have partnered with local authorities to improve public transport surface access options to their facilities through the implementation of airport master plans. This investment is usually justified as a means to encourage travellers out of their cars in order to reduce road congestion surrounding airports and lessen the impact on the environment (Budd et al., 2011). However, the findings of the SIMs hint at a possible downside of such investment. A strong distance decay affect is observed in the analysis, with passenger volume dropping substantially for scheduled flights as nearness from the airport recedes. By investing in public transport, airports and local authorities are shrinking the perceived distance between passenger residences and their facilities and, arguable, encouraging more air travel to occur. The resulting induced demand for air travel might more than offset the emission reductions from modal shift for access and egress travel. A different spin on this issue is that improved surface access to the MAR encourages passengers from further afield to travel there on public transport rather than taking connecting flights from regional airports or driving in a private car. With this in mind, the net result in terms of emissions is somewhat ambiguous but could provide an interesting topic for further study.

Author statement

Craig Morton: Conceptualisation, Methodology, Formal analysis, Writing - Original Draft. Guilio Mattioli: Conceptualisation, Writing - Review & Editing.

Declaration of competing interest

None.

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