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What is driving the passenger demand on new regional air routes in India: A study using the gravity model

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ABSTRACT

Are there unique determinants of air travel demand for regional routes? Is the passenger mix different for airlines flying these routes in developing countries? This paper attempts to answer these questions through a gravity model that identifies significant factors influencing demand for air travel on new routes connecting regional and remote locations. The data for the analysis is from India, where an ongoing regional connectivity scheme encourages the addition of new air routes to the national network. We estimate a multiple regression model with passenger demand as the response variable. The model tests some new predictors along with the traditional explanatory variables of gravity models. The results show that passengers find the saving in travel time due to the introduction of regional air service most attractive. Rather than the size of the population, the presence of prominent tertiary educational institutions at the origin or destination of a regional route is a more significant determinant of demand. This paper derives policy implications and opens new research questions.

1. Introduction

Setting up and sustaining air transport infrastructure and services are costly. Investing in regional and remote routes carries an immense risk for commercial airlines. Therefore, governments and local bodies usually support such projects through financial and other incentives (Reynolds-Feighan, 1999; Bråthen and Halpern, 2012; Minato and Morimoto, 2012; Gössling et al., 2017; Fageda et al., 2018). In developing countries, competing priorities for governments can be particularly worrisome. The demand for air travel has grown in recent years. Propitious investment in infrastructure and the aviation ecosystem is crucial to avoid bottlenecks. Also, there is often a visible regional imbalance and inequity, and remote areas may be difficult to reach using surface transport (Das et al., 2020). In this context, demand analyses are critical inputs for policymaking, deciding on the quantum of public financing, subsidy, and risk-sharing.

This paper seeks to identify drivers of demand for air travel on new routes, particularly those connecting settlements in regional and remote areas. We take advantage of data from the routes made operational under the Regional Connectivity Scheme (RCS) in India (Government of India, 2016a). Many new regional air routes have been established with the steady operation and reasonable passenger traffic. At the same time, some routes have also failed (Kalita, 2019). This growth in the Indian context needs to be studied to understand the determinants of demand. Stakeholders will face less uncertainty and risk when they know the significant factors affecting the passenger demand. Similar benefits can be expected for many countries that run programs like the RCS (Fageda et al., 2018).

Several studies have analysed demand in air routes, but their focus was on dense routes and American, European, and Australian regions (Gillen and Hazledine, 2015; Albayrak et al., 2020). The emerging economies have received comparatively less attention, although a relevant exception is a study by Button et al. (2019) that examines the effects of institutional reforms on both the demand and supply of air transportation in Sub-Saharan Africa. Also, thin demand routes have not received much attention from researchers; a majority of such routes connect regional and remote airports (Kaemmerle, 1991; Calzada and Fageda, 2019).

In this article, we build a gravity model with a set of factors to determine prominent drivers of demand on routes connecting individual

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airport pairs. The main contribution of this paper is to identify some unique determinants that can have a specific influence on the regional routes. We examine the effects of distance between the airport pair and two distinct socio-economic factors on passenger demand. The unique socio-economic factors tested include whether it is crucial if one of the airports is in a metropolitan city. We also explore the influence of airport cities having prominent tertiary educational institutions.

Our initial model also has variables usually employed in gravity models like population and income at origins and destinations and different distance and travel time measures. Analysis of longitudinal data is more common for such investigations (Gorsche et al., 2007; Valdes, 2015). But data available under the RCS scheme is limited, and we have adopted a cross-sectional study to predict the average demand on regional routes (Boonekamp et al., 2018, Zhou et al. 2018). Due to the nature of explanatory variables considered, the model suffers from multicollinearity. This problem is quite common in passenger demand analyses using the gravity model (Rengaraju and Arasan, 1992; Grosche et al., 2007). To redress this, we propose a supplementary model that can more reliably predict passenger demand.

The main results of the empirical analysis can be summarized as follows. First, the status as an educational hub of origin or destination significantly affects passenger traffic on regional routes. Furthermore, flights to and from existing large airports have a positive influence on demand. Contrary to usual expectations in gravity models (Chen, 2015), we find a positive relationship between surface distance and time between airports and demand.

The structure of the article is as follows. The next section has a brief review of air passenger demand modelling. In section 3, we introduce the data and present the model. In section 4, result analysis and implications are discussed. Limitations and directions for future work are presented in the last section.

2. Drivers of demand on routes linking regional centres

Demand forecasts for a new route can be based on historic passenger data. However, a limitation of familiar sources of information (International Air Transport Association, IATA; Marketing Information Data Tapes, MIDT) is that passenger data for most of the regional and low-cost carriers are general estimates (Nõmmik and Kukemelk, 2016). Thus, the analysis of demand for their routes often lacks generalizability. In contrast, in this paper, actual data is used to estimate demand on regional routes in India.

Methods like aggregate time series and cross-sectional or panel data analysis are used to forecast passenger demand (Ahmadzade, 2010; Wadud, 2013; Priyadarshana and Shamini, 2015; Boonekamp et al., 2018). Gravity models have been widely used in the microanalysis of demand for passenger travel and cargo flow between two cities. Grosche et al. (2007), Wadud (2011), and Chang (2014) have presented a brief review of some important gravity models and listed significant factors identified in them.

Many characteristics of air transportation on regional routes are distinct in contrast to trunk routes, for example, travel purpose and length of haul. Besides, the active participation of governments in these systems affects the price, positioning relative to the competition, and consumer choice. Consequently, forecasting passenger demand has been inconsistent for short-haul regional routes, especially with distance factors (Hazledine, 2009). Short-haul flights have different dynamics as they face stiff competition from other surface modes of transportation and cannot command high fares (Bilotkach et al., 2010).

The various factors influencing demand proposed in the past studies can be divided into two groups: geo-economic and service-related (Kanafani, 1983; Rengaraju and Arasan, 1992; Jorge-Calderón, 1997; Albayrak et al., 2020; Boonekamp et al., 2018). Geo-economic factors, which includes market size, market attributes and geographical factors, are related to the population of the two places, the distance between them, the catchment areas served, the economic position of the two locations – in terms of GDP, trade, investments, tourism, per capita income or purchasing power parity. Other factors have been the percentage of working people, university degree holders, big-city proximity, unemployment rate, exchange rates, travel time ratio between air and alternative transportation modes (Chang, 2012; Wei and Hansen, 2006; Boonekamp et al., 2018 and literature cited).

In most studies, distance comes out as a barrier of demand (Grosche et al., 2007; Boonekamp et al., 2018). As the distance increases, the gravitational pull diminishes. But in regional routes where haul lengths are smaller, longer flights may attract passengers who save travel time over alternate modes. Distance also affects fare elasticity. Therefore, the relationship between distance and demand observed in most studies may not hold good for regional routes.

The service-related factors include the type of aircraft deployed (and corresponding seats), airfare, operations frequency, and departure time. When introducing service on a new regional route, airlines seek to benefit from inducements like government subsidies along with the latent demand for air transportation. With a sustained operation, they can create and grow the market. In this regard, past research has shown that service frequency and aircraft size may positively influences demand (Wei and Hansen, 2006; Matisziw and Grubesic, 2010). However, the relationship between demand and supply is bi-directional as the existence of demand will eventually determine the capacity deployed in the route

This paper estimates a gravity model with a set of factors for a sample of regional routes in India. Special attention is paid to factors specific to regional air routes in a developing country.

3. Data and model

The data for the present study is drawn from the newly introduced routes under the RCS in India. We start the section with a quick description of the program.

3.1. The regional connectivity scheme

During the year April 2018 to March 2019, airlines in India carried 140 million passengers under domestic services (Government of India, 2019b). Passenger traffic had double-digit annual growth over the past decade. Airlines serve 649 city pairs of the country from 189 airports (which includes 58 airports and 15 water aerodromes developed under the regional connectivity scheme) (Government of India, 2019b). Yet these are inadequate considering India has a population of 1.3 billion and it has 100 cities with populations of 400,000 or more (Government of India, 2019a). Furthermore, a small subset of routes accounts for the bulk of passenger traffic. Vast regions of the country have minimal air connectivity. Compared to this, China had 216 airports with scheduled operations in 2016 and plan to have 370 by 2025 (Zhang et al, 2017).

The government of India in 2016 introduced a dedicated program named “Regional Connectivity Scheme” (RCS). The purpose of RCS is to speed up the growth of air transportation and spur regional air connectivity and make it affordable (Government of India, 2016b). Under the scheme, a set of un-served and under-served airports were identified (Government of India, 2016a). Un-served airports are those which do not have operations in the last two schedules. Under-served airports have seven or fewer flight operations per week in the last two flight schedules approved by Directorate General of Civil Aviation (DGCA) of India. RCS expects to achieve its objective by increasing the number of flights on the routes connecting un-served and under-served airports to the national network.

An RCS route is a pair of direct origin–destination (OD) airports with either or both airports falling under the un-served or under-served airport category. A ’valid’ OD pair must connect to at least one regional airport. Under the scheme, affordability is ensured by limiting fare on half of the RCS seats or to a stipulated level, called the RCS fare cap. Subsidies (named Viability Gap Funding or VGF) are awarded to

Table 1
Summary of RCS routes.

Region	Non stable/ new routes		Stable routes		Total routes	
	No of routes	Flights operated	No of routes	Flights operated	No of routes	Flights operated
Southern Region	32	6380	34	20539	66	26919
Northern Region	14	2079	25	12122	39	14201
Western Region	27	4833	20	10466	47	15299
Central Region	17	2482	14	3519	31	6001
Eastern India	15	3025	2	641	17	3666
North East India	16	750	1	514	17	1264
All India routes	**121**	**19549**	**96**	**47801**	**217**	**67350**
Major Metro routes*	48	8566	56	32292	104	40858

Note: RCS flights for the period 28 Aug 2017 to 29 Dec 2020);
* Major Metro routes are included in the all India routes

airlines for half of the RCS seats to compensate for the revenue loss from fare cap and low demand. Each RCS route has a cap on the maximum subsidy. An airline operator can propose to fly on an RCS route and bid for the subsidy on a competitive basis (Das et al., 2020).

Airports Authority of India (AAI) is the implementation agency for the RCS. RCS data about traffic and passengers were sourced from the AAI website (Government of India, 2020a; Government of India, 2020e). We have taken the RCS weekly passenger data for the 52 weeks of 2019. For statistical analysis, we have considered the stable routes only. Table 1 shows the distribution of steady and non-steady routes along with the number of flights operated from six geographic regions of India. The southern, northern, and western regions have more operational routes (Table 1). The eastern and the northeastern region, which comprise economically poor states, have been laggards in introducing new RCS routes. Table 1 shows the distribution of routes with major metro connectivity, i.e., a large metropolitan city viz., Delhi, Mumbai, Bengaluru, Hyderabad, Chennai, or Kolkata, in OD pair. Major metro cities are hubs for business, education, health care, and large government institutions. They are the gateways to international and domestic destinations (Fig. 1).

3.2. Variables and descriptive statistics

The geo-economic attractiveness factors chosen for our models are defined below. Most of these variables have been part of previous works. We have selected a few more that describe factors relevant to a developing country like India. To maintain data homogeneity in the passenger demand model, we have ignored intermittent, discontinued, and recently launched routes. For uniformity of notations, only direct routes (O – D) have been considered. For easy identification, we have denoted variable names with the extension ‘o’ (resp. ‘d’) to represent the values for the origin airport (resp. destination airport). The variables included in the models are as follows.

Passenger Demand: Most of the routes included in the dataset for regression were operational by late 2018. The data on the number of passengers carried during 2019 was obtained from AAI. The average passenger traffic for the year 2019 is the dependent variable D in the regression models.

Population: The size of populations at the origin and destination are the principal determinants of demand cited in gravity models (Calzada and Fageda, 2012; Gillen and Hazledine, 2015). Population data of the district where the airport is located is taken from the India Census website. However, for Metropolitan cities, the population of urban area agglomeration covering multiple adjoining districts were combined (Government of India, 2019a). The variables are named ‘Population.o’ and ‘Population.d’.

Economic status: With increasing prosperity people tend to prefer a faster and more convenient mode of transportation. More air travel is associated with higher per-capita income (Ishutkina and Hansman, 2008). The variables for income per capita of the state where origin and destination airports are located are named as ‘Incomepc.o’ and ‘Incomepc.d’ respectively (data source: Government of India, 2020b).

Distance and travel time: In spatial interaction models, distance is an essential component. The direct air distance between the origin and destination is a significant determinant of flight duration (Grosche et al., 2007). At the same time, travel time and cost for alternate transport modes depend on surface distance, topography, quality of motorable roads, etc. Variables ‘air.distance’ and ‘surface.distance’ give the air and surface distances, respectively. Due to arduous terrain, water bodies, or sometimes the international borders coming in a direct line between the origin and destination, the surface distance is not always proportional to the air distance. Empirical evidence suggests the influence of the terrain and relative inaccessibility of the destination, by other surface modes, on air travel (Fridström and Thune-Larsen, 1989; Xiao et al., 2013). The travel time by the fastest alternative method on the surface and the corresponding distance was estimated using Google maps. A ratio between the air time and the fastest surface time is included as an explanatory variable, ‘Time.ratio’. Similarly, we have included a ratio between the air and surface distances as an explanatory variable, ‘Distance.ratio’. These two composite variables reduce the problem of multicollinearity in the baseline gravity model proposed below while describing the relative importance of time and distance in predicting travel demand.

Following are the criteria based categorical dummy variables included in the models:

Existing major airports: These are the airports in bigger cities and in metropolis. These airports connect to multiple destinations and many are international gateways. The major airports are identified with the dummy variables ‘Metrocity.o’ and ‘Metrocity.d’.

Tertiary education hubs: RCS connects cities in India having higher educational institutions of national repute. Many among them have seen agglomeration of both public and private funded educational institutions. The criteria adopted for identification was the presence of educational institutions mentioned in international and national rankings (Government of India, 2020d). Airports in educational hubs have been identified with the dummy variables ‘Eduhub.o’ and ‘Eduhub.d’.

The descriptive statistics for all the variables are shown in Table 2 and the correlation matrix is included as Table A1 of the appendix. The Table A1 presents the values of Pearson correlation coefficient. The metric describes the extent of the linear relationship between a pair of variables. It can be deficient when the variables are not continuous.

3.3. Gravity model

Gravity models (Grosche et al., 2007) assume that attributes of individual cities and their spatial interactions can decide the quantum of demand for air travel between them. It organizes the measurable characteristics among them into one equation. A simple formulation is as follows:

$$T_{ij} = \delta \prod A_i^{\alpha_i} A_j^{\alpha_j} d_{ij}^{\beta_{ij}} \quad (1)$$

In Eq. (1), T_{ij} is the passenger volume from city i to city j. A_i and A_j are the vectors of attractiveness factors of the two cities respectively. d_{ij} are measures of spatial relations between i and j like distance and air fare etc. δ, α_i, α_j and β_{ij} are the parameters of the model. To simplify the process of estimation, log-linearised equation (1) is obtained as,

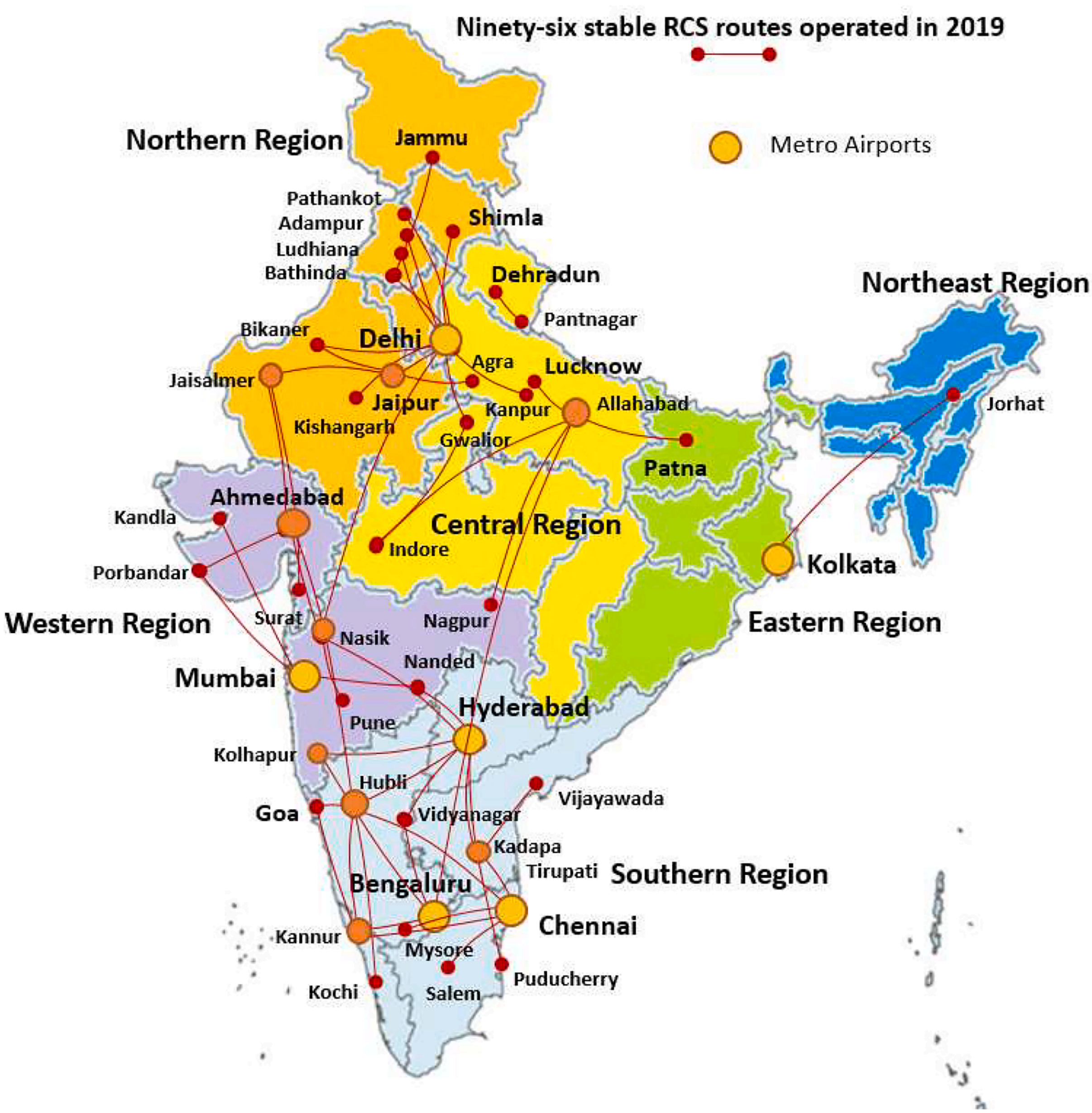

Fig. 1. Six regions of India with steady RCS routes operational in all the quarters of 2019.

$$\ln(T_{ij}) = \ln(\delta) + \alpha_i \ln(A_i) + \alpha_j \ln(A_j) + \beta_{ij} \ln(d_{ij}) \quad (2)$$

We include all the variables defined above in (2) to get a baseline model. Variables other than the dummy variables were log transformed.

$$\begin{aligned} D = {} & \alpha_0 + \alpha_1 \text{Population.o} + \alpha_2 \text{Population.d} + \alpha_3 \text{Incomepc.o} \\ & + \alpha_4 \text{Incomepc.d} + \alpha_5 \text{Metrocity.o} + \alpha_6 \text{Metrocity.d} \\ & + \alpha_7 \text{Eduhub.o} + \alpha_8 \text{Eduhub.d} + \alpha_9 \text{Surface.distance} \end{aligned} \quad (3)$$

Notable associations exist between variables. Multicollinearity is a common problem with gravity models that have many socio-economic regressors. We have presented the baseline model for ordinary least squares (OLS) estimation despite this shortcoming to conform to the spirit of this modelling approach. Later we address the multicollinearity created by associations through transformations. The baseline model also benefits from knowing that multicollinearity can inflate the standard errors in OLS estimates while their expected values do not change. Many past studies have ignored multicollinearity in their analysis (Rengaraju and Arasan, 1992; Grosche et al., 2007; Hazledine, 2009).

Next, we implement a stepwise regression for variable selection. We observe the reduction in the number of predictors and the quantum of deterioration in model performance. Based on the results, we have proposed a new estimation model (in the next section). For the sake of controlling endogeneity and higher multicollinearity, we have not selected an important determinants of passenger demand, viz. fare. Airlines adopt a dynamic pricing scheme for selling seats. The fare, therefore, is dependent on both supply and demand. However, under the RCS, airlines are constrained to sell nearly half of the seats at a pre-determined fare. The pre-determined rate is based on the air distance slab. Moreover, on almost all routes, one airline operator has a monopoly under the scheme. Therefore, until airlines are given pricing power, the air distance of OD pair imitates fare.

3.4. Results

Table 3 presents the estimation results for the base model (named Model-0 given as eq. (3)). The studentized Breush-Pagan (B-P) and Non-Constant Error Variance (NCV test) were conducted on the models to test the presence of heteroscedasticity. The test results ruled out that

Table 2
Definition of variables and their summary statistics.

Variable	Symbol	Mean	Std. dev.	Min	Max.
Average passenger demand	D	57.53	29.52	10.98	157.30
Population in the origin district	Population.o	6423953	5922986	585449	20352983
Population in the destination district	Population.d	6407968	5933934	585449	20352983
Income per-capita at origin	Incomepc.o	186061	86467	43822	458304
Income per-capita at destination	Incomepc.d	189143	87813	43822	458304
Origin is an educational hub	Eduhub.o	0.64	0.48	0	1
Destination is an educational hub	Eduhub.d	0.63	0.49	0	1
Origin is an existing large airport	Metrocity.o	0.49	0.50	0	1
Destination is an existing large airport	Metrocity.d	0.49	0.50	0	1
Air-distance	Air.distance	437.61	231.07	135	1419
Surface distance	Surface.distance	555. 89	300.31	185	1725
Ratio of airtime and fastest land time	Time.ratio	0.137	0.0353	0.0699	0.2222
Ratio of air distance and surface distance	Distance.ratio	0.9625	0.0145	0.8978	0.9813

possibility (Model-0: B-P test, p-value = 0.8961; NCV-test, p = 0.4163). An inspection of the scatter plot of standardized residuals against standardized estimates of the dependent variable exhibited a nearly random pattern. The overall explanatory power of this hedonic model is moderate, with an adjusted R-squared value of 0.4603.

There are six significant variables at $p < 0.05$ level, and Incomepc.d is significant at $p < 0.1$. The size of the populations at the origin or the destination is not among them. The influence of surface distance is positive. The income per capita of origin and destination states are positively correlated with demand. As expected, the model suffers from multicollinearity. The two dummy variables on metropolitan airports have substantial Variance Inflation Factor (VIF) scores (see Table A2 in the appendix). We implemented the stepwise regression method to obtain a subset of significant variables with acceptable VIF scores. The resultant best-fit model retains five from the original set of significant variables while dropping the dummy of metropolitan airports. The adjusted-R^2 value dropped a little to 0.4432. The regression coefficient of surface distance is the highest, followed by the educational hub variables indicating that they can influence the dependent variables more than the others. The VIFs for all the variables are within an acceptable range.

We estimated the Model-0 in equation (3) again but replaced Surface.distance with Air.distance. The results were similar as above, while the adjusted-R^2 dropped to 0.4101. Again Air.distance came out as among the most important predictors. Introducing Air.distance in Model-0 will add to the problem of multicollinearity (Pearson correlation coefficient 0.98, $p < 0.05$). One way to address multicollinearity in a multiple regression model is by an appropriate transformation of variables. We introduce two new variables to encapsulate the benefit to a passenger from introducing a new air route. A ratio between the air time and the fastest surface time is included as an explanatory variable, 'Time.ratio'. Similarly, we have included a ratio between the air and surface distances: 'Distance.ratio'. The estimation model now has the following form (Model 1).

$$\begin{aligned} D = {} & \alpha_0 + \alpha_1 \text{Population.o} + \alpha_2 \text{Population.d} + \alpha_3 \text{Incomepc.o} \\ & + \alpha_4 \text{Incomepc.d} + \alpha_5 \text{Metrocity.o} + \alpha_6 \text{Metrocity.d} \\ & + \alpha_7 \text{Eduhub.o} + \alpha_8 \text{Eduhub.d} + \alpha_9 \text{Time.ratio} + \alpha_{10} \text{Distance.ratio} \end{aligned} \tag{4}$$

The estimation and regression diagnostics result from Model 1 is presented in Table 4. The adjusted-R squared value now moderates to 0.3835. There are seven variables significant at $p < 0.05$. However, the major metropolitan city dummy variables still manifest high VIFs. The best fit model, however, takes care of this issue as the two variables get dropped. The best fit model has an adjusted R squared value of 0.361 with six variables significant at $p < 0.05$. All the variables have VIFs<2.

Time.ratio and distance.ratio are significant and have negative coefficients. Between the two time.ratio has a more considerable influence on passenger demand. If the reduction in travel time from surface to air mode is high (lower value of the ratio), more consumers get attracted to air travel. The status of origin or destination as a tertiary education hub positively influences the volume of passenger traffic. These are the four variables tested for the first time as a determinant of demand for regional air travel. In the next section, we further discuss these results.

4. Discussion

The purpose of demand models is to find the relationship between the socio-economic characteristics of travellers and the infrastructural and technical characteristics of the transportation system. Potent relationships are hinged to context and vary in a subtle as well as diametrically as the new transportation systems are studied. Research of

Table 3
Regression results for the baseline model (Model 0).

Variables	Model 0			Best fit Model 0		
	Estimates	Std. Error	t-value	Estimates	Std. Error	t-value
(Intercept)	−5.9241 ***	1.539	−3.849	−5.01183 ***	1.40866	−3.558
Population.o	0.06256	0.04851	1.29	0.07508	0.04611	1.629
Population.d	0.02835	0.04731	0.599			
Incomepc.o	0.22564 **	0.08513	2.651	0.20425 *	0.08308	2.459
Incomepc.d	0.15682 ˆ	0.08362	1.876	0.16719 *	0.08145	2.053
Eduhub.o	0.23093 *	0.09564	2.414	0.21947 *	0.0922	2.38
Eduhub.d	0.24617 *	0.09886	2.49	0.28517 **	0.09321	3.06
Metrocity.o	0.52084 *	0.24491	2.127			
Metrocity.d	0.53054 *	0.24465	2.169			
Surface.distance	0.49462 ***	0.07307	6.769	0.48804 ***	0.07399	6.596
Adjusted R^2	0.4603			0.4432		
F-statistic	10 on 9 and 86 DF, p-value: 2.321e-10			13.61 on 6 and 89 DF, p-value: 6.698e-11		
studentized Breusch-Pagan test	4.223, df = 9, p-value = 0.8961			4.1776, df = 6, p-value = 0.6527		
Non-constant Variance Score Test	Chisquare = 0.6606242, Df = 1, p = 0.41634			Chisquare = 0.2322189, Df = 1, p = 0.62988		
Estimates significant at ˆ p < 0.1, * p < 0.05, ** p < 0.001, *** p < 0.0001						

Table 4
Regression results for the Model 1.

Variables	Model 1			Best fit Model 1		
	Estimates	Std. Error	t-value	Estimates	Std. Error	t-value
(Intercept)	0.6683	2.77501	0.241	0.69628	2.82421	0.247
Population.o	0.12075 *	0.05188	2.328	0.13208 **	0.04964	2.661
Population.d	0.09678 ˆ	0.05264	1.839	0.11075 *	0.05047	2.194
Incomepc.o	0.24737 **	0.09102	2.718	0.23686 *	0.09043	2.619
Incomepc.d	0.1389	0.08959	1.55	0.13726	0.08899	1.542
Eduhub.o	0.27906 **	0.10256	2.721	0.28436 **	0.10139	2.805
Eduhub.d	0.3096 **	0.10548	2.935	0.32356 **	0.10431	3.102
Metrocity.o	0.56974 *	0.26274	2.168			
Metrocity.d	0.58979 *	0.26254	2.246			
Time.ratio	−5.02559 ***	1.06275	−4.729	−4.80778 ***	1.07752	−4.462
Distance.ratio	−5.1298 ˆ	2.68542	−1.91	−4.86236 ˆ	2.72968	−1.781
Adjusted R^2	0.3835			0.361		
F-statistic	6.911 on 10 and 85 DF, p-value: 8.076e-08			7.708 on 8 and 87 DF, p-value: 9.318e-08		
studentized Breusch-Pagan test	5.5699, df = 10, p-value = 0.85			5.5077, df = 8, p-value = 0.7022		
Non-constant Variance Score Test	Chisquare = 0.7339, Df = 1, p = 0.3916			Chisquare = 0.3988, Df = 1, p = 0.5277		
Estimates significant at ˆ $p < 0.1$, * $p < 0.05$, ** $p < 0.001$, *** $p < 0.0001$						

new and low demand transportation systems often reveal hitherto unknown and interesting relationships. The results of the previous section have identified new determinants with a nudge to revisit established ones.

4.1. Population and income

Some of the regions on RCS routes have a large population. Though sizable passenger traffic is observed from them, it is below expectation. In India, the population density varies extensively across geography. There are multiple strata within each population, and each one of them does not use air transportation equally. Unlike business travel, air travel for personal and leisure purposes is self-financed by travellers. Assuming air travel is costlier than state-subsidized trains and buses, travellers with higher disposable income are more likely to prefer air travel. Valdes (2015) found higher-income elasticities for demand growth in middle-income countries in comparison to advanced economies. The income per capita is among the significant variables in our study. In provinces where the size of the population and the economic status are not positively correlated, airports in their Tier-2 and Tier-3 cities are yet to see great demand.

The central and east of India states, e.g., Uttar Pradesh, Bihar, Madhya Pradesh, West Bengal, are among the most populous, while their economic indicators are in the bottom quartile (Government of India, 2020b). Passenger demand for flights to airports in these states is lower than those in high-income states viz, Maharashtra and Kerala. But this analysis has a limitation. The construct income per capita is an aggregate measure and does not explain the groups and income distribution.

4.2. Distance and time

Availability of alternatives makes demand analysis of short-haul travel more complex. The importance of schedule frequency and egress time increases. In the regression results, the surface distance variable is positively correlated with air-travel demand. In India as in most other countries distance to the regional and remote destination on the surface can be substantially higher. Therefore, the surface distance between airports has a bigger influence than aerial distance. The effects of surface distance and surface time are similar but the later has slightly higher elasticity.

For a short surface distance of 200 km or less, air travel offers minimal utility. Surface travel also gives freedom and convenience of travel schedule. At times it also integrates last-mile access between the origin and the destination. However, this likelihood of substitution diminishes with increase in the distance when air travel can offer reasonable savings in travel time.

In India, the spread of highways across the length and breadth of the country is limited and not uniform. Narrow highways and the presence of intermediary towns with local traffic hinders faster movement. Distance is also a proxy for the cost. Together with the high price of gasoline due to taxes, surface transportation may not always be economical. Generally, flying time is negatively related to demand as the spatial attraction diminishes with an increase in distance. In our data, the mean surface distance is 556 km (Table 2). For regional routes, demand for air transportation is higher for longer distances and this demand is expected to grow further in future.

4.3. Airport cities with tertiary education institutions

RCS routes connecting educational hubs have significantly higher passenger demand. Surprisingly this does not happen with industrial townships and tourist destinations. RCS may not yet be attractive to business travelers, who prefer certainty over the cost of travel (Hunak et al., 2020; Zhang, 2011). Since flight frequency is limited to just one per day in most sectors, schedules have higher uncertainties. Still, many routes have been sustaining a reasonably high load factor (Fig. A1). This brings to the fore the question, who are the early adopters of regional air transportation in India?

India introduced economic liberalization during the early 1990s that ushered in growth. Over the next two decades, the world experienced the information technology (IT) revolution, and India was a beneficiary. Expansion of the service sector, especially of the IT and business process outsourcing businesses, has been disproportionately higher than the manufacturing and agriculture sectors (Government of India, 2020c). Jobs were available in plenty but required specific educational credentials in their aspirants. The agriculture sector is still the largest provider of employment. However, with the availability of better technology, there is less human labour demand.

During 2001–2011, the population of India grew by 17.6% (Government of India, 2019a), which was incidentally less than the previous decade. The high growth rate ensured the availability of a large pool of youth for employment, touted as the country's demographic dividend. Most of these new jobs were available at select locations and in cities. Training and education for these jobs were also available away from natal places, leading to sizeable domestic migration, especially among the youth in the country (Smith and Gergan, 2015).

In developing countries, higher and technical education options are not widespread. Some places have seen an agglomeration of educational institutions (Basant and Chandra, 2007). Therefore, the migration of the youth can happen in two stages. First, youth migrate to seek academic credentials and then to the locations where new jobs are available (Boyden, 2013). Non-affluent families support migration as diversification of risk and the expectation of upward mobility in the social hierarchy (Smith and Gergan, 2015). Such migrations have increased the disposable income of the population and stimulated travel demand. Non-business travel should be more sensitive to cost, but the cap on RCS fare has given a boost to leisure and family air travel. It can be seen in (Fig. A1) that passenger demand increases during the vacation and college opening months.

4.4. *Attraction of big cities*

The study emphasizes the importance of accessibility to the big cities in regional transportation. This result is on the expected lines. The utilization of alternative modes like railways and roads is very high. It is not unlikely to find these modes over-crowded. Moreover, the new airports connect to only a few destinations. The existing larger airports offer more connections and links to national as well as international networks. Most of them also provide the opportunity for inter-modal switches. LCCs have also leveraged these routes, foregoing subsidy, to strategically connect the big cities to bag additional slots at Tier 1 airports.

5. Implications

The stated objective of the RCS is twofold - to expand the aviation footprint in India and connect remote areas to the national network. In the last three years, it has been able to add a significant number of domestic routes. However, the performance of RCS has not been homogeneous (Das et al., 2020). The root cause of this variation should be identified and then addressed. The determinants of demand identified in this article are important indicators for such analysis.

The findings of the study support established theory while revealing new relationships. Regional air transportation faces close competition from other modes of travel. Less frequent service can discourage passenger intending to switch. Most of the RCS routes operate once in a day. In case of a flight cancellation, due technical, weather or other issues, the only option left is surface transportation. Passengers with onward connections can be apprehensive of such risk.

However, RCS connects to many remote regions of India. These places are difficult to reach through surface modes. Air-travel is usually a better alternative, which utilizes both human and natural resources efficiently (Bråthen and Halpern, 2012). For isolated or remote regions, airports are essential infrastructures like a school or a hospital (Amoroso and Caruso, 2010). Absence of threshold demand for commercial operation prevents mainstream airlines from expanding operations in the remote regions. Many airports in remote regions included in RCS have not seen stable operation of commercial service. Improvement in air transportation to remote regions needs a distinct strategy.

Cities with the presence of reputed educational institutes have provided more customers for RCS flights. India has witnessed fast economic growth. The majority of India's population belongs to the age group of 15–59. The economy is in a position to tap the demographic dividend (Joe et al., 2018). It has already registered as the fastest-growing aviation market. However, the growth has been restricted to a few metropolitan airports. More extensive support needs to be provided to cities with a higher potential for growth. Demand can also be stimulated by augmenting the infrastructure around regional airports.

Business travellers can be a major and stable source of revenue for airlines once their participation grows. For that to happen, the quality of service needs to be improved. Speed, frequency and convenient connections are important quality parameters for attracting business travellers.

These are still early days for the RCS. Therefore, the findings of the article are early indicators. Routes awarded during the first round of bidding would be completing three years of operations during the year 2020. Routes which have achieved commercial success would become self-sustaining. Such routes will now be open for competition. Market forces will determine the capacity as well as the fare. However, for most of the routes to remote locations, there is a need for a policy rethink.

This research provides some helpful input for policymaking. Schemes like the RCS seek to alleviate the economic condition of poorer regions. Past studies have found evidence of its success (Baker et al., 2015; Chow et al., 2021), yet many areas require sustained and prolonged support from the governments. Some new routes may not see immediate passenger interest, which is the case in many highly populous states of India but also in remote areas where air transportation provides essential services. Governments can help with more targeted subsidy schemes.

It also comes out that reduction in travel time is a prominent influencer of demand for air travel. Regional routes can be made more attractive by reducing the travel time even further. Essential infrastructure development can make last-mile connectivity to and from airports faster and movement inside the airports quicker.

This research has some limitations. The RCS scheme was launched recently, and unavailability of multi-year data, we could not conduct a panel data analysis with the gravity model. Such research would be more appropriate to capture the time dynamics of relationships between the variables. Another method could be to measure the choice behaviour of passengers through consumer surveys.

CRediT authorship contribution statement

Amit Kumar Das: Conceptualization, Data curation, Formal analysis, Investigation. **Amit Kumar Bardhan:** Conceptualization, Data curation, Formal analysis, Investigation. **Xavier Fageda:** Conceptualization, Data curation, Formal analysis, Investigation.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

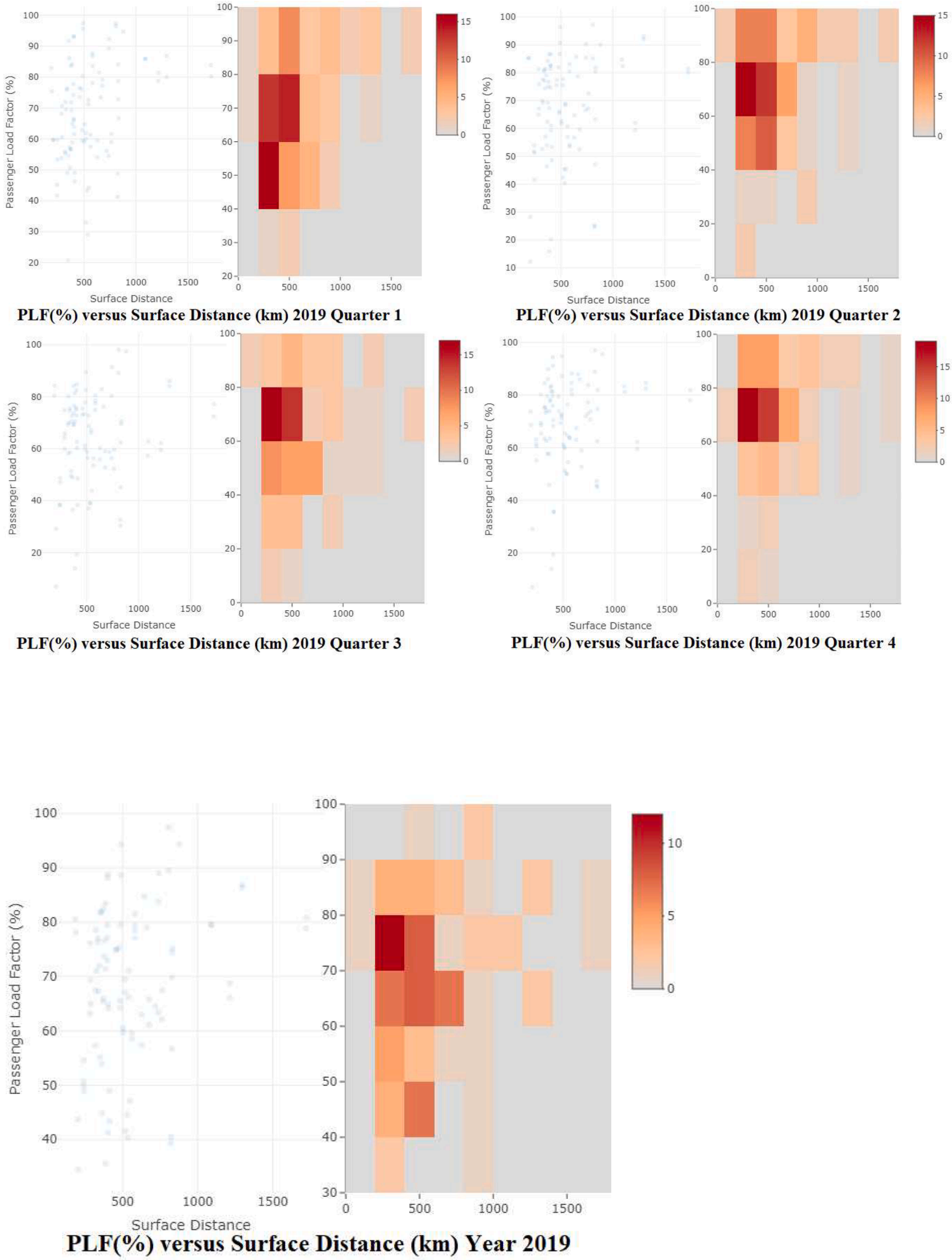

Fig. A1. PLF (%) versus Surface Distance Heat Map, quarterly as well as consolidated year.

Table A1
Correlation matrix.

Sr. No.	Variables	1	2	3	4	5	6	7	8	9	10	11	12	13
1	**D**	1												
2	**Population.o**	0.19	1											
3	**Population.d**	0.06	**−0.37**	1										
4	**Incomepc.o**	0.18	**0.24**	**−0.28**	1									
5	**Incomepc.d**	0.11	**−0.27**	**0.24**	**0.27**	1								
6	**Metrocity.o**	0.08	**0.63**	**−0.6**	**0.33**	**−0.34**	1							
7	**Metrocity.d**	−0.03	**−0.6**	**0.63**	**−0.35**	**0.33**	**−0.96**	1						
8	**Eduhub.o**	0.19	**0.51**	**−0.46**	0.1	**−0.37**	**0.61**	**−0.6**	1					
9	**Eduhub.d**	0.11	**−0.49**	**0.54**	**−0.4**	0.11	**−0.62**	**0.63**	**−0.5**	1				
10	**air.distance**	**0.56**	0.12	0.09	−0.05	−0.07	0.01	−0.01	0.14	0.13	1			
11	**surface.distance**	**0.59**	0.11	0.04	−0.04	−0.06	0.02	−0.02	0.13	0.11	**0.98**	1		
12	**Time.ratio**	**−0.44**	−0.02	0.12	0.02	0.06	−0.06	0.08	−0.15	−0.04	**−0.68**	**−0.73**	1	
13	**Distance.ratio**	−0.12	0.1	**0.25**	−0.06	−0.07	−0.01	0.05	0.04	0.1	0.18	−0.02	0.19	1

N = 96. Correlations significant at $p < 0.05$ are printed in bold.

Table A2
Variance inflation factors for the four models.

VIF	Population. o	Population. d	Incomepc. o	Incomepc. d	Metrocity. o	Metrocity. d	Eduhub. o	Eduhub. d	Surface. distance	Time. ratio	Distance. ratio
Model 0	1.8306	1.8131	1.4989	1.4621	**13.62358**	**13.595248**	1.926187	2.082082	1.085297		
Model 0 Best fit	1.602647		1.383696	1.344875			1.735002	1.793928	1.07867		
Model 1	1.832	1.964	1.500	1.469	**13.727**	**13.706**	1.939	2.075		1.108	1.189
Model 1 Best fit	1.619	1.742	1.428	1.399			1.828	1.958		1.099	1.185

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