Drivers of higher connectivity at new regional airports in India and their implications

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Abstract: Limited research has been conducted on the connectivity of smaller regional airports. As a contribution to the existing body of knowledge, we investigate the factors influencing connectivity levels at newly established regional airports in India. To achieve this, we employ data from the Regional Connectivity Scheme (RCS) using a two-stage approach. In the first stage, we evaluate the levels of connectivity at RCS airports. In the second stage, we empirically examine their drivers, where we found some interesting non-intuitive results particularly when analyzing the role of surface transportation. A higher density of rails in the state supports its airport connectivity, while a higher density of roads imposes a negative influence. We also find that the levels of connectivity are higher in RCS airports that are less affected by competition from other airports. The outcome from this research has policy implications and puts forth some new questions for future study.

Keywords: Air connectivity, Regional Connectivity Scheme, New airports, India; NetScan model; Intermodal competition. **JEL Codes:** R40, L93, C31,

1. Introduction

Well-connected transportation infrastructure is commonly associated with economic progress. Multiple studies have established the causal relation of air connectivity with productivity, tourism, employment generation, regional development, FDI, and trade (Chakraborty et al., 2020; IATA, 2020). Air connectivity cuts down travel time, mitigates economic disparity, enhances territorial cohesion and the competitiveness of cities (Das et al., 2020; Cristea, 2023).

However, connectivity to many remote and regional airports is usually not commercially attractive for airline companies.[1] As a result, scheduled operations to such areas are generally limited and minimal (Pauwels et al., 2024). Policy interventions can be more effective if the drivers for the growth of regional airports are known. Research on the topic is limited and this paper attempts to address it.

In this paper, we investigate the factors influencing connectivity levels at newly established regional airports in India. The air connectivity points to traffic flow and hence is a forward-looking proxy to the actual passenger flow (Cheung et al., 2020). In this regard, regional areas with low and negligible connectivity are of concern to the government. Connectivity analysis helps the government to introduce policy measures to augment the air connectivity of such regions. This also helps in the equitable distribution of resources and boosts the local economy (IATA, 2020).

In India, a Route Dispersal Guidelines (RDG) make it mandatory for domestic airlines in India to allocate a fraction of their capacity on the stipulated high-demand trunk routes to the priority areas (Government of India, 2016b). Such measures are partially successful, and the airlines generally connect to limited airports in the priority areas enough to fulfill the norms (Fageda et al., 2018). A new program, the Regional Connectivity Scheme (RCS) was

[1] The airline industry is characterized by density economies that implies that costs are lower in routes that can generate sufficient amount of traffic (Fageda and Flores-Fillol, 2012). This explains that airlines, in the post-deregulation period, have concentrated on profitable routes connecting bigger airports.

introduced in 2016 (Government of India, 2016a). The scheme seeks to increase the aviation foot print pan-India as well as provide connectivity to remote locations (Government of India, 2016a). The operating airlines bid for routes connecting regional airports, designated as un-served and under-served, offering specified seats at a stipulated price and claim subsidy, termed as viability gap funding. The RCS scheme documents define "Un-served airports" as those that have had no flight operations in the last two flight schedules, while "Under-served airports" are characterized by having no more than seven scheduled flights per week in the current schedule. The scheme has been successful in operationalizing regional airports which were not operational for decades (Das et al., 2020). The subsidy is applicable on a route for three years.

Our study is based on the un-served and under-served regional airports which are part of the RCS. We have analyzed the connectivity of these regional airports. The next logical question is, what are the determinants of airport connectivity? This question has got limited attention, unlike the one that finds the determinants for passenger demand (Boonekamp et al., 2018, Pauwels et al. 2024). The focal point has been developing contextually appropriate connectivity metrics and the analyses are usually based on large airports (Calatayud et al., 2016; Zhang et al., 2017; Lin, 2023). There are limited studies on the connectivity of the smaller regional airports and even less on the aspects of determinants of it (Pauwels et al., 2024). We add to previous literature by analyzing the drivers of the connectivity at new regional airports in India. A comprehensive set of factors that may explain airport connectivity at small regional airports are considered, and the econometric analysis provides novel insights on the role of surface transportation and airport competition.

The remainder of this article is organized as follows: The upcoming section provides a concise literature review and introduces four initial research hypotheses. \Section 3 outlines the variables employed in model construction, data sources, and the study's methodology. Sections

4 and 5 detail the connectivity models and introduce the econometric model, respectively. Lastly, Section 6 discusses the findings from the model analysis.

2. Background and Hypotheses

Developing countries with limited resources face greater scrutiny in public spending. Air connectivity is an important determinant to prioritize and introduce subsidy-based schemes. Some of the prevalent schemes for regional and remote connectivity are Essential Air Services (EAS) in the United States, Public Services Obligations (PSO) in the European Region, Remote Area Subsidy Scheme (RASS) in the Australia (Fageda et al, 2018). Similar schemes are also there in China, Russia and Brazil.[2] In India, the Regional Connectivity Scheme (RCS) has been introduced in 2016 (Government of India, 2016a). In 2017, Government of India allocated Rs. 4500 crores for revival and development of 50 airstrips and airports (Economic Times, 2017). Further, the plan is to establish 100 more airports by 2035 (Kuronuma, 2018). In a country with around 100 scheduled operational airports, it is indeed an ambitious plan.

Calatayud et al. (2016) has done a systematic review on the understanding of connectivity and its determinants. In the domain of infrastructure and transport economics, connectivity broadly refers to the infrastructure availability and hence is linked to the capacity of the transport infrastructure (Zhang et al., 2017). Air connectivity is also representative of the future passenger demand. Iyer and Thomas, (2021) have done air traffic demand analysis for the Indian regional airports. The linear regression analysis for passenger demand has just two

[2] The aviation sector is capital intensive and requires prospective planning (Chakraborty et al, 2020). Fageda et al. (2018) have identified four different modes in which governments support regional aviation: (1) route-based policies (2) passenger policies (3) Airline policies, and (4) airport policy. Under the first three modes, routes and population in the target areas are the focus of policy support. For example, fares are capped on the routes connecting regional airports; state-owned airlines fly routes connecting regional airports where other airlines do not show interest. All four groups of policies are directly or indirectly hinged on airports.

significant variables, one of them being a dummy. Certainly, other underlying factors of regional passenger demand have remained unexplored.

In this paper, we develop econometric models to test hypotheses on likely drivers of airport connectivity. The choice of some of the drivers is reasonably intuitive, while others were discussed in the literature. Our major explanatory variables are indicators of the quality of alternative surface transportation options and variables that may capture competition between airports. Airports may have a larger catchment area if they are close to a dense network of roads. Otherwise, rails may be a competitive option over planes if the journey is not too long. In addition, we may expect that an RCS airport will have lower levels of connectivity if it is affected by competition from hub airports or other nearby airports.

Enhanced ground access makes airports more appealing. With superior road infrastructure surrounding the airport, passengers can reach the airport swiftly and with greater certainty. This, in turn, expands the catchment area of the airports and attracts more airlines to operate from them (Avogadro et al., 2024). Many airports under the RCS are situated in regions with subpar road infrastructure, as one of the scheme's objectives is to provide transport access to residents in these regions.

On the other hand, improved road infrastructure can make road travel more appealing, especially for shorter point-to-point journeys. This is because using the airport would add egress time to the travel times (Das et al. 2022). Therefore, it is crucial to evaluate how airports perform in the presence or absence of good road infrastructure around them. We state the first research hypothesis as follows:

H1: A regional airport in a state with better road-transport infrastructure will have higher connectivity.

Recent studies that compare rail and air transportation often take into account high-speed rail (HSR) (Li et al., 2019). Although HSR is not yet available in India, the average speed of trains has seen a significant increase in recent years. Train travel is viewed as an alternative to air travel, particularly for short to medium distance routes (Wu & Han, 2022). Train stations in India are typically located in the heart of population centres, making the total travel time via train competitive. Furthermore, as passenger train fares receive government subsidies, train travel can be an attractive option for price-conscious leisure travellers (Das et al. 2022). The question arises whether rail can be a viable alternative, and if so, should the government invest in RCS airports at locations with good train access? Therefore, testing the following hypothesis is crucial:

H2: A regional airport in a state with better rail-transport infrastructure will have lower connectivity.

Hub airports play a crucial role in facilitating efficient connections for passengers. The hub-and-spoke network model has emerged as a key strategy for airlines, enabling them to expand their network coverage and attract more passenger demand while utilizing their resources more efficiently. Hub airports allow passengers to travel to a vast array of destinations. These airports are often strategically located in areas with significant economic activity, thereby attracting a large number of travellers (Burghouwt et al., 2009). If hub airports are situated at a considerable distance from regional airports, passengers can reach them more quickly and economically by air. However, if the distance between the hub and regional airports is minimal, passengers may opt for alternative modes of transportation. This is because the total flight time can include not only the transfer time but also the flight access time at regional airports (Cheung et al., 2022). Based on these observations, we propose the following hypothesis

H3: If the distance to the nearest hub airport from a regional airport is more, then the airport will have higher connectivity.

Airports function as two-sided markets, serving two distinct groups: passengers and airlines. These groups are interdependent; the utility of one group increases as the size of the other group expands. For regional airports, demonstrating the potential of the first group, the passengers, seems more intuitive. However, when multiple airports have overlapping catchment areas, passenger demand becomes divided, rendering these airports less appealing to airlines (Bergantino et al., 2021).

Conversely, regional airports in India are primarily generating new demand. They are either providing a faster means of reaching destinations compared to alternative modes of transportation or are opening up new travel markets. For passengers weighing air transport against surface transport, the number of flights becomes a significant attraction factor. In this context, airports serving the same catchment areas can offer complementary capacities (Karanki and Lim, 2023). Airlines, too, can design routes that enhance efficiency and welfare. To discern which of these two arguments holds true, we propose the following hypothesis.

H4: Airports with more competing airports in the neighbourhood will have lower connectivity.

In the following sections, along with the above determinants, we will also measure the effectiveness of the catchment area's population, state income per capita, presence of educational institutions and ease of business as control variables.

3. Study variables and data

The basic approach used in this study was to evaluate the performance and prospect of new airports and then to detect their controlling factors. A vexing problem is the choice of suitable performance metrics. Passenger traffic at a new airport is an outcome that cannot predict the uncertain future demand with reasonable accuracy (Nõmmik and Kukemelk, 2016). We adopt connectivity as the indicator of the immediate prospect of a new airport and correlate the results with those from the passenger traffic.

We first calculate the connectivity values for the regional airports. We adopt two metrics for measuring connectivity at the airport level. The first is the NetScan connectivity scale, which measures how an airport is connected to the rest of the world through direct and indirect flights (Valdhuis, 1997). It places higher weightage to direct flights while penalizing transfer and connection times.

Previous studies on regional aviation have found that aircraft seat capacity and frequency of flights from an airport have a significant positive influence on passenger traffic (Matisziw and Grubesic, 2010). Zhang et al. (2017) modified the NetScan connectivity scale to include the impact of capacity and time required to reach destinations. Both these factors are critical choice criteria for passengers who simultaneously consider surface transport options. We employ this modified NetScan scale (identified as mNetScan model henceforth) as the second connectivity indicator.

Next, we used econometric models to test the hypotheses on drivers of connectivity. In each of the three linear multiple regression models, a connectivity score or the passenger traffic at the airports is taken as the dependent variable. A group of socio-economic and transport infrastructure variables was selected as regressors.

Our sample has data from 39 airports spread across India (Table A1 in the appendix). Before 2016, these airports were termed as ‘under-served’ or ‘un-served’ i.e. with very few air services if any. For instance, under-served airports had seven or fewer flight operations per week in the previous two flight schedules approved by the Directorate General of Civil Aviation (DGCA) of India. After 2016 with the support from the Regional Connectivity Scheme (RCS) of the Government, commercial flight activities were initiated or rejuvenated in these airports (Government of India, 2016a). In the last four years, the scheme has been successful in increasing connectivity in the country (Table 1).

The Airports Authority of India (AAI) publishes the weekly RCS flight data (Government of India, 2020a). We conducted the connectivity analysis for regional airports using this data for the period 27th January 2020 to 1st March 2020. RCS flight operations with fixed-winged aircraft only were considered. The rationale for taking this period is that February 2020 was the last full month of operation before domestic flights got disrupted due to the COVID-19 pandemic. For passenger traffic analysis, we aggregated data from two financial years 2019-2020 and 2020-2021.

In India, the COVID-19 flight disruptions started in the month of March 2020 and there was a complete closure of scheduled domestic flights from 25th March 2020 (Government of India. (2020c). The domestic operations restarted in a phased manner from 25th May 2020. We have taken a 5-week period of 28th September 2020 to 1st November 2020 for comparison with the post COVID-19 status. October 2020 saw significant growth after the flights were restarted. However, the domestic operation was still down by 58 % year on year (Bloomberg Quint, 2020). In the October 2020 period, one airport *Jagdalpur* commenced RCS operations and ten existing RCS airports operating in February 2020 were not operating RCS flights. In the North East region of India, one of the priority areas, under the RCS only three under-served airports were operational in February 2020 and only two of them in October 2020. The data also shows that the routes under RCS are operated by either Regional airlines or low-cost carriers (LCC).

Airports	Type	India Regions					Grand Total
		Eastern	North-eastern	Northern	Southern	Western	
Existing (36)	Metro	1	0	1	3	1	6
	State Capitals	2	4	6	1	2	15
	Rest	0	0	7	5	3	15
RCS (53)	RCS Underserved	1	4	6	4	4	19
	RCS Unserved	2	1	18	6	7	34
Grand Total		6	9	38	19	17	89

Table 1: Airports having flights operations under the RCS as on November 2020

Notes: 1. Six metro airports (New Delhi, Mumbai, Chennai, Hyderabad, Bengaluru, and Kolkata) are major metropolitan cities as well as state capitals and providing international gateways. 2. One RCS under-served airport in each of North-eastern, Southern and Western region are State Capitals. 3. Two RCS un-served airports in Western region are Water Aerodromes. 4. Five RCS un-served airports in Northern region are Heliports. 5. Categorization of un-served and under-served is based on the criteria while initiating RCS at that airport. 6. Some of the airports are not operating RCS flights at present.

The determinants chosen include the most commonly used parameters in similar studies as well as those new ones that can possibly influence regional air transportation. The following explanatory variables are in the models.

Alternative surface transportation: Regional air travel has close competition with the surface modes of travel. Hence, we have defined a couple of variables to measure the various accessibility options available through surface modes as an influencer of air connectivity.

The surface options available to the population have a strong impact on the regional air connectivity (Allroggen and Malina, 2014). To verify this, we take the density of the length of the national highways and railway tracks in the states where RCS airports are present. We have labeled the variables *state.road* and *state.rail* for the length of road and railway tracks per square kilometer of the state area. The road length data has been sourced from the Ministry of Road website (Government of India, 2021a). The railway length data has been sourced from (Government of India, 2021b). The state land area data has been taken from (Statistics Times, 2021).

Airport competition: The hub airports are the gateways to international destinations as well as provide end to end connectivity. Intuitively, the hub airport will get preference if the time to reach it using surface transport is within an acceptable limit. The vicinity of a hub airport can be disadvantageous to a small regional airport unless the former suffer congestion (Burghouwt et al. 2009). With this premise, we take the time to reach the hub airport (*hub.time*) as an indicator of the regional airport's connectivity. If an area has more choices of airports, the demand gets distributed. In India, a distance of 400 km can be covered within seven to eight hours by surface travel. In many cases, it can be an overnight train journey. We, therefore, take the count of the operational airports within 400 km surface distance from the regional airport as the variable *aptin400*. *Google maps* is the source for the data for both variables named above.

Population: Population has been widely linked to both connectivity and passenger demand (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 (Government of India, 2019a). For *Hindon* airport, which is in the National Capital Region and easily accessible over a greater area, we have taken the aggregated urban area population.

Economic factors: With increasing prosperity, there is an inclination to using a faster and more convenient mode of transportation. More air travel is associated with people with higher per-capita income (Ishutkina and Hansman, 2008). The income per capita of the state where the airport is located is an explanatory variable in the models (data source: Government of India, 2020b).

Initiation of commercial air service requires considerable infrastructure development. A complimentary business eco-system grows simultaneously with the airport. Participation of the local government and a supportive regulatory environment are vital enablers of growth (Baker et al, 2015; Zhang and Graham, 2020). The econometric models proposed below have the *ease of doing business index* (EDBI) as an explanatory variable. Economists at the World Bank created the index and it includes parameters on construction permits, access to electricity, enforcement of contracts, etc. (Leal Rodríguez and Sanchís Pedregosa, 2019). A high EDBI score indicates that the settings are more suitable for starting and operating businesses (Canare, 2018). The Reserve Bank of India publishes EDBI for all the states of India (Reserve Bank of India, 2019). The latest scores for RCS airport states are listed under the variable *easebus*.

Educational hubs: Most of the regional airports connect cities in India having educational institutions of national repute. With the rising aspiration of the middle class towards higher education, many public and private funded educational institutions have emerged. The criteria adopted for identification was the presence of premier educational institutions. These institutions figure in various international and national rankings (Government of India, 2020d). Cities with RCS airports having top-ranked higher educational institutes are identified with the dummy variables *edu*.

Passenger Demand: We study the correlation between passenger demand and connectivity at the regional airports, and we also evaluate the impact of determinants mentioned above on the passenger traffic at the airport. The variable *passavg* is the average passenger flow of two years at the RCS airports. The data was sourced from the AAI website (Airports Authority of India, 2021). The descriptive statistics of the variables calculated as on May 2021 are in Table 2.

Variable	Description	Range	Mean	Std. Dev	Source
passavg	Logarithm of average passenger traffic	135, 6634.50	1502.10	1491.71	Airports Authority of India (AAI)
netscan	NetScan connectivity value (computed score)	11.07, 266.41	72.92	67.87	Author calculation
mnetscan	modified NetScan connectivity value (computed score)	2, 148.90	42.44	43.11	Author calculation
lnpop	Logarithm of Population	10.86, 16.82	14.44	1.10	Census website
lnpcsi	Logarithm of per capita state income (Indian rupees)	11.11, 12.30	11.89	0.39	MOSPI Website
edu	Education dummy	0, 1	0.31	0.47	Author calculation based on MoE data
lnhub.time	Time to reach nearest hub airport (hours)	4.61, 6.67	5.91	0.45	Author calculation using Google maps
aptin400	Number of airports within 400 km of surface distance	1, 11	6.54	2.48	Author calculation using Google maps

state.road	Density of national highway in the State (km per square km)	0.03, 0.11	0.05	0.02	Ministry of Road
state.rail	Density Railway track in the State (km per square km)	0, 0.48	0.05	0.07	Ministry of railways
easebus	Ease of doing business score of the state (computed score)	0.10, 98.30	80.91	27.10	RBI Website
MOSPI: Ministry of Statistics and Program Implementation; MoE: Ministry of Education; Last access date: 30 May 2021					

Table 2: Descriptive statistics of the variables

4. Connectivity model

The first of the two connectivity models tested below is the much favoured NetScan model (Veldhuis 1997). NetScan model is equally recognized among practitioners and academic researchers for measuring the performance of an airport (Burghouwt et al, 2009; Burghouwt and Redondi et al, 2013). It can capture two important dimensions of the connectivity performance of regional airports. First, it measures the number of destinations reachable from the airport through direct and one-stop flights. Second, it evaluates the quality of connections as many regional routes use smaller aircraft with lower maximum speed. It is likely that the travel time on some routes, especially for one-stop flights, can be higher than the threshold value of passengers to prefer an alternative.

In the NetScan Model, the connectivity performance of an airport is stated as a numeric value called ‘Connectivity Units (CNUs’)’. This value is computed based on flight frequencies, travel time and necessity of travel (Veldhuis, 1997). The total flying time taken from origin to destination is denoted by the variable FLT. The transfer time in hours at the hub is denoted by TRF and the service is denoted by number of flights operated as NOP. The method of calculating the connectivity unit, CNU as cited in Burghouwt et al, 2009 is as follows.

The nonstop (direct) travel time in hours is computed as:

$$\text{NST} = \frac{(40+0.068 \times Great\ Circle\ Distance\ in\ km)}{60} \qquad (1)$$

The maximum perceived travel time in hours is computed as:

$$\text{MXT} = (3\text{-}0.075 \times \text{NST}) \times \text{NST} \quad \ldots \quad (2)$$

The perceived travel time in hours is computed as:

$$\text{PTT} = \text{FLT} + (3 - 0.075 \times \text{NST}) \times \text{TRF} \quad \ldots \quad (3)$$

The Quality index is computed as: $$\text{QLX} = 1 - \frac{(\text{PTT} - \text{NST})}{(\text{MXT} - \text{NST})} \quad \ldots \quad (4)$$

Number of Connectivity units $$\text{CNU} = \text{QLX} \times \text{NOP} \quad \ldots \quad (5)$$

NetScan recognizes the intrinsic capability of a regional airport by giving higher weightage to direct connections. India has six metro airports at Delhi, Mumbai, Kolkata, Hyderabad, Bengaluru, and Chennai. Along with Ahmedabad, these airports for major hubs. The regional airports are the new spokes to the established hubs and other major airports in the domestic network (Figure 1). The role of regional airports as minor hubs is minimal. Intuitively, the higher the number of connections, the greater is the connectivity of the airport.

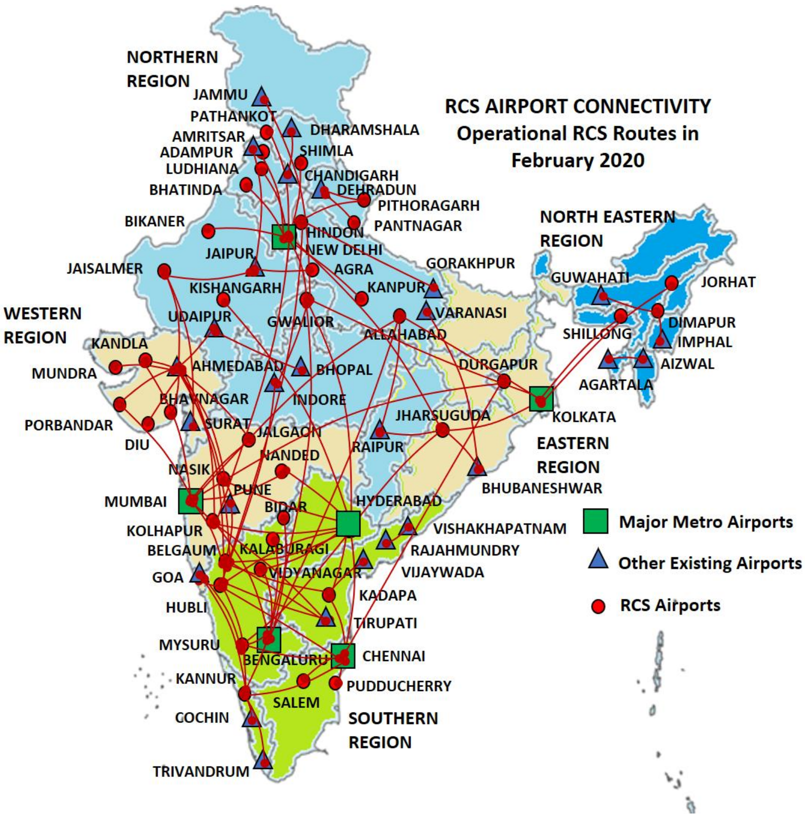

Fig 1. RCS operational routes in February 2020

NetScan model has been modified and extended several times to incorporate newer aspects of connectivity and to new contexts (Boonekamp and Burghouwt, 2017; Zhang et al, 2017). Zhang et al. (2017) adapted the model for a study of connectivity of Chinese airports. This method is also adopted by Zhang et al. (2022) and the cited papers therein. This method incorporates both capacity discount factor and service factor in terms of travel time. We briefly describe the method for calculating the scores. Let, $Seat_0$ be the maximum aircraft seat capacity in the network. A flight between airport *i* to airport *j* is assigned an index *k*, then it's capacity $D_{Cap_{ijk}}$ is computed as,

$$D_{Cap_{ijk}} = \sqrt{\frac{Seat_{ijk}}{Seat_0}} \qquad \ldots \qquad (6)$$

Here frequency gets more weightage in comparison to the number of seats. For example, two flights with hundred seats each get more weightage than one flight with two hundred seats. The model also takes into account the time taken for direct flying of k^{th} flight, from airport *i* to airport *j*, computed as the time difference between the landing and take-off time as $= T_{landing_{ijk}} - T_{takeoff_{ijk}}$ and the check-in time as $t_{airport_{ijk}}$. It also attributes a penalty P_T for the transit time $t_{transit_{ijk}}$ incurred at intermediate airports. Based on the timings, the perceived time duration is computed as,

$$Duration_{Adjusted_{ijk}} = T_{landing_{ijk}} - T_{takeoff_{ijk}} + P_T \times t_{transit_{ijk}} + t_{airport_{ijk}} \qquad (7)$$

With, the great circle distance between the two airports $Distance_{ij}$ along with the computed perceived time duration, the velocity of the flight *k* between airport *i* to airport *j* is computed as,

$$Velocity_{ijk} = \frac{Distance_{ij}}{Duration_{Adjusted_{ijk}}} \qquad \ldots \qquad (8)$$

The benchmark velocity, $Velocity_0$ is set to a higher velocity, viz. 900 km/h, to arrive at concave function of velocity discount factor,

$$D_{Vel_{ijk}} = \sqrt{\frac{Velocity_{ijk}}{Velocity_0}} \quad \ldots \quad (9)$$

The flight *k* thus contributes to the connectivity as,

$$Connectivity_{ijk} = D_{Cap_{ijk}} \times D_{Vel_{ijk}} \quad \ldots \quad (10)$$

Summing up all the flights between the airport *i* to airport *j* gives the unidirectional route connectivity as,

$$Connectivity_{ij} = \sum_k Connectivity_{ijk} \quad \ldots \quad (11)$$

The airport connectivity unit is calculated as the sum of bi-directional connectivity,

$$Connectivity_i = \sum_{j,k}\left(Connectivity_{ijk} + Connectivity_{jik}\right) \quad \ldots \quad (12)$$

The airport connectivity scores are computed using the two models for the airports in India operating RCS flights. The scores during the period covering February 2020 and October 2020 in ranked order for RCS airports are in Appendix Table A1. The connectivity scores of the regional airports from the two methods are highly correlated (correlation coefficient = 0.95). The top and the bottom-ranked airports in both the methods are nearly identical. The erstwhile un-served airports have done better, picking up more top slots relative to formerly under-served airports.

However, there is a subtle difference in the position of few airports between the two methods. This difference exists as the NetScan model does not consider the capacity of flow between the two airports e.g. *Jorhat*, in North-Eastern India is connected to *Kolkata* by an Airbus A320 aircraft with 185 seats covering a longer distance. On the other hand, *Pithoragarh* is connected to *Hindon* and *Dehradun* with a ten-seater Super King B350 aircraft. In the NetScan model, *Pithoragarh* is ranked higher in comparison to *Jorhat*. The mNetScan model considers the capacity flow and the ranking of *Pithoragarh* is lower than *Jorhat*.

While comparing the scores rankings between pre and post COVID-19 periods, we find that most of the top-ranked RCS airports were able to retain their positions. Table 3 shows the operations data for the top fifteen RCS airports. The RCS airports have flights operated by only one of the Low-Cost Carriers (LCCs). Though there is an exclusivity clause in the RCS route bidding system, multiple carriers can be allowed if they do not demand any subsidy on a route.

RCS Airports		Five week period covering Feb 2020			Five week period covering Oct 2020			
Airport Code	**Airport Name**	**LCC Sectors (Airlines)**	**Regional Sectors (Airlines)**	**Total Sector (Airlines)**	**LCC Sectors (Airlines)**	**Regional Sectors (Airlines)**	**Total Sector (Airlines)**	**Maintained Ranking within Top 15**
IXG	Belgaum	2 (1)	8 (3)	10 (4)	2 (1)	8 (3)	10 (4)	In both method
CNN	Kannur	6 (1)	-	6 (1)	6 (1)	-	6 (1)	In both method
HBX	Hubli	5 (1)	3 (2)	8 (3)	2 (1)	1 (1)	3 (2)	In both method
JRG	Jharsuguda	3 (1)	3 (1)	6 (2)	3 (1)	3 (1)	6 (2)	In both method
MYQ	Mysuru	-	5 (2)	5 (2)	0	6 (2)	6 (2)	In both method
GWL	Gwalior	4 (1)	2 (1)	6 (2)	3 (1)	0	3 (1)	In both method
IXD	Allahabad	4 (1)	-	4 (1)	5 (1)	0	5 (1)	In both method
KLH	Kolhapur	2 (1)	3 (2)	5 (3)	1 (1)	3 (2)	4 (3)	In both method
ISK	Nasik	-	4 (2)	4 (2)	-	4 (2)	4 (2)	In both method
JSA	Jaisalmer	3 (1)	1 (1)	4 (2)	1 (1)	1 (1)	2 (2)	No
CDP	Kadapa	-	4 (1)	4 (1)	-	3 (1)	3 (1)	In both method
KQH	Kishangarh	3 (1)	-	3 (1)	3 (1)	2 (1)	5 (2)	In both method
IXY	Kandla	1 (1)	2 (2)	3 (3)	-	2 (1)	2 (1)	In both method
RDP	Durgapur	2 (1)	-	2 (1)	2 (1)	-	2 (1)	In one method
VDX	Hindon	1 (1)	2 (2)	3 (3)	-	1 (1)	1 (1)	No

Table 3: Top fifteen RCS Airports by connectivity in February 2020 and their distribution of sector operated and carrier. (Figure in bracket shows the number of carriers operating)

5. Econometric model

We estimate a model of airport connectivity with data on a group of variables identified in section 3. The model will investigate the quantum of influence of the socio-economic and transport-infrastructure factors have on connectivity performance. We further estimate the relationship of these variables with the passenger traffic at the regional airports. The models are as follows:

$$\text{Connectivity} = \alpha + \beta_1 \text{lnhub.time} + \beta_2 \text{aptin400} + \beta_3 \text{state.road} + \beta_4 \text{state.rail} + \beta_5 \text{lnpop} + \beta_6 \text{lnpcsi} + \beta_7 \text{edu} + \beta_8 \text{easebus} \quad \ldots \quad (13)$$

$$\text{passavg} = \alpha + \beta_1 \text{lnhub.time} + \beta_2 \text{aptin400} + \beta_3 \text{state.road} + \beta_4 \text{state.rail} + \beta_5 \text{lnpop} + \beta_6 \text{lnpcsi} + \beta_7 \text{edu} + \beta_8 \text{easebus} \quad \ldots \quad (14)$$

We have formed the two baseline models using the connectivity scores. The regression results of the baseline models, one using the NetScan connectivity scores and another using the mNetScan connectivity scores are studied. Table 4 tabulates the results from the regression analysis. The adjusted R squared value for the NetScan model comes out to be 0.399. All the explanatory variables are significant at $p < 0.05$ level (t test). The adjusted R squared value for the mNetScan model comes out to be significantly more at 0.5364. For this model too all the regressors are significant at $p < 0.05$ level (t test).

	Connectivity scores using NetScan model		Connectivity scores using mNetScan model	
Variables	Estimates	t-value	Estimates	t-value
(Intercept)	-1898.50***	-4.05	-1058.01***	-4.05
lnhub.time	99.43***	3.81	66.94***	4.60
aptin400	-10.57*	-2.54	-6.02*	-2.59
state.road	-2024.60*	-2.40	-1674.91**	-3.56
state.rail	463.88*	2.53	317.14**	3.10
Lnpop	43.76***	3.89	28.96***	4.62
Lnpcsi	80.57**	2.94	36.08*	2.36
Edu	48.13*	2.18	41.37**	3.35
Easebus	-0.95*	-2.04	-0.62*	-2.40
	Adjusted R^2 = 0.399 F-statistic: 4.154 on 8 and 30 DF, p-value: 0.001956		Adjusted R^2 = 0.5364 F-statistic: 6.496 on 8 and 30 DF, p-value: 0.0000657	
Estimates significant at ^ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$				

Table 4: Regression result with connectivity units using the NetScan and mNetScan models as the dependent variable

Next, we estimated the model for the average passenger using the same set of independent variables. The regression results are tabulated in Table 5. The adjusted R squared value comes out to be 0.3525. The two variables viz. airports within 400 kilometer radius and rail infrastructure in the state are not significant predictors of passenger traffic at the RCS airports ($p > 0.5$). The Variance Inflation Factor (VIF) of variables in all the models is below 2.5 (Table A3) indicating the possible absence of multicollinearity.

	Regression with Dependent variable as average passenger from the airport	
Variables	Estimates	t-value
(Intercept)	-40500.27***	-3.79
lnhub.time	2415.84***	4.06
aptin400	-147.36	-1.55
state.road	-49852.44*	-2.59
state.rail	7797.18^	1.86
lnpop	963.21***	3.76
lnpcsi	1568.01*	2.50
edu	1087.62*	2.16
easebus	-26.85*	-2.53
Adjusted R^2 = 0.3525, F-statistic: 3.586 on 8 and 30 DF, p-value: 0.004948		
Estimates significant at ^ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$		

Table 5: Regression result with average passenger as the dependent variable

6. Analysis and Implication

The connectivity scores and model estimation reveal an interesting pattern. The spatial distribution of more connected regional airports is concentrated to only one region. This area's surface transportation infrastructure and economic prowess are comparable to states in northern and western India. Still, the airports in the later states do not perform well. States that lack transport infrastructure, the primary focus of the RCS, have not offered substantial improvement in connectivity to their population. The relationships revealed in the econometric models can offer some explanation. The results from the model (13) for both the connectivity scales are similar. The econometric model for passenger traffic (14) shows that some factors found significant determinants for connectivity do not remain so here.

Surface transport options

H1: A regional Airport in a state with better road-transport infrastructure will have higher connectivity. (Not supported)

H2: A regional airport in a state with better rail-transport infrastructure will have lower connectivity. (Not supported)

We found that better road transportation infrastructure negatively impacts connectivity and passenger demand ($p < .01$ and $p < .05$, respectively). The result is counterintuitive, as motor vehicles are commonly used to reach airports. Airports become accessible to a larger geographic area when a network of motorable roads can service them. Instead, our study reveals, the reverse is happening in the case of RCS airports. One explanation is that the passengers in states with high national highway density might prefer directly using a relatively distant major airport. Personal transportation using good road connectivity offers the same convenience with add-on flexibility in travel timing. Thus, major airports might be cannibalizing the demand for RCS airports. Indeed, effective road transportation offers stronger competition to regional air transport.

Rail transport has come out to be significant in the modified NetScan at $p < 0.001$ and at $p < 0.05$ in the NetScan connectivity model. Railways are generally viewed as competitors for air travel. A recent study in China confirmed that high-speed railways (HSR) have a detrimental effect on air connectivity (Li et al., 2019). Indian railways hold a disproportionately large share of the long-distance domestic travel market. Due to faster locomotives and the modernization of coaches, travel times have been reduced, and journeys have become more comfortable. In addition, Indian railways is a government monopoly, and it offers the cheapest transport mode. Express trains have limited stops. Their ingress and egress hop can be similar to taking a flight from an airport. The absence of a good railway network can also be due to the presence of arduous and hilly terrain and areas with a sparing population with less demand for transportation. Both the reasons are barriers to regional air travel as well. Therefore, it is surprising that the connectivity and passenger demand at RCS airports are growing in tandem with rail connectivity. High rail density is an indicator of manifested and latent demand. In

India, demand exceeds capacity on important routes. Airlines may have used this data as input in their bidding strategies for routes. As expected, passenger demand has followed the connectivity scores.

Time to reach Hub airport

H3: If the distance to the nearest hub airport from a regional airport is more, then the airport will have higher connectivity. (Supported)

In both the connectivity and passenger demand models, the time to reach the nearest Hub airport has come out as a significant variable ($p < 0.001$). The farther the regional airport is from the Hub airport, the more is its connectivity. The Hub airports are located in major metropolitan cities and offer a gateway to many domestic and international destinations. Consequently, passengers would prefer directly flying to the destination rather than taking a connecting flight from an RCS airport. The RCS airports in the South, *Belgaum*, and *Hubli* are near the other RCS airports, including the existing airport *Goa*. However, they both manifest very high connectivity scores. The most plausible explanation is that these airports are over 400 km from the three nearest major hub airports, viz., *Mumbai*, *Bengaluru*, and *Hyderabad*. Hence, passengers would prefer accessing the hub airport from the closest RCS airport. The acceptance of hypothesis H3 is in line with earlier results.

Airports in the vicinity

H4: Airport with more competing airports in the neighbourhood will have lower connectivity. (Supported)

Grosche et al. (2007) in their demand forecast model for European airports, have evaluated the impact of competing airports present in the vicinity. We observe a similar phenomenon. It is observed that RCS airports face competition from other regional and major airports. If the number of airports within a radius of 400 km of an RCS airport is high, the connectivity gets significantly affected. In the north, there is a cluster of RCS airports in closer vicinity, viz.

Adampur, *Ludhiana*, *Shimla*, *Bhatinda*, and *Pathankot* all gathering low connectivity scores. These airports are close to hubs and other existing airports like *New Delhi*, *Amritsar*, *Chandigarh*, and *Jammu*.

Similarly, a major airport and hub, *Ahmedabad*, in the west has impacted the RCS airports in *Gujarat* viz. *Kandla*, *Porbandar*, *Mundra*, *Bhavnagar*, and *Diu*. Interestingly RCS airports in close vicinity, *Belgaum* and *Hubli* discussed in the last section, have maintained effective connectivity in the pre-COVID. However, it can be seen that post-COVID *Belgaum* maintained its connectivity ranking, whereas *Hubli* has dropped down significantly, pointing to consolidation. Interestingly, the impact on passenger demand is not significant. Therefore, it might imply that some airports have better than estimated potential, and new routes, if added, can be sustained.

Control Variables

The population has been widely recognized as a significant determinant for connectivity and passenger demand. We observe this for RCS airports too. These airports are situated in tier-2 and tier-3 cities with nearly one million or higher populations. We also find income per capita as a significant determinant for both models. Research in the past has found a correlation between economic status and preference for air travel (Boonekamp et al., 2018, Nõmmik and Kukemelk, 2016). States in the south, north, and west of India have higher income per capita income. It seems airlines have used estimation of latent demand while bidding for a route. As a result, there is an uneven distribution of flights across regions. The passenger demand data supports the use of these criteria.

India has seen phenomenal growth in the service sector, especially in the Information Technology (IT) and Information Technology Services (ITS) industry. These industries offer immense employment potential but require a skilled workforce. Consequently, demand for higher education has received great impetus. The aspiration of the middle-class population is leading to more investments in education. RCS airports, viz., *Hubli*, *Mysuru*, *Gwalior*, and *Allahabad*, have higher connectivity. The presence of premier educational institutes is creating an ecosystem for boosting air connectivity.

The ease of business has come out significant in all the models ($p < 0.05$). To our surprise, the regression coefficients are negative in all three models. *Gujarat* is a highly developed state in west India with a high EDBI score. Many RCS airports are operating from this state. However, as discussed in the earlier sections, their connectivity scores are surprisingly low. Similarly, *Andhra Pradesh* state in south India is consistently ranked top in EDBI score. However, the only RCS airport, *Kadapa*, is not among the top ten airports. In contrast, *Odisha* state in east India has a comparatively lower EDBI score. The second airport of the state, *Jharsuguda*, is an RCS airport ranking high on connectivity. We can offer the following explanations. There still exists a considerable disparity in the economic status of the different states in the country. Some states have made massive progress over the previous decades. Other laggard states have initiated economic reforms and offering a supportive regulatory and infrastructural environment to facilitate new business. Such states report high EDBI scores. Regional airports have gestation time between set up and growth. Hence the benefits of ease of business would fructify after a period.

7. Conclusion

We have examined the underlying factors behind the regional un-served and under-served airport connectivity. The connectivity models, viz. NetScan and the modified NetScan can be explained by an identical set of factors, leading to confidence in the regression analysis. We obtain essential insights linked to the RCS's success and the sustainability of future airport operations through the factors leading to connectivity scores. Understanding the connectivity helps in aligning policy decisions by the government, especially for the priority areas.

However, the strategy and prescription for augmenting connectivity need to be dealt with on a case basis at many locations.

We find that RCS airports less affected by competition from other airports have higher levels of connectivity. In a similar vein, a poorer density of roads benefit RCS airports as it can make worse for passengers to travel to more distant airports. In contrast, the connectivity of RCS airports is higher in states with a higher density of rails so that some hidden factors may spur both demand of air and rail travel. As expected, the levels of airport connectivity are higher in airports located in more populated and richer states and where cities have top-ranked higher educational institutes. Contrary to our expectations, the ease of business is not a positive factor driving the connectivity of RCS airports.

The connectivity study also clearly distinguishes a small group of airports that have majorly benefitted under the scheme. The majority of the airports have minimal connectivity at this stage. One of the interesting aspects that have come out is that a couple of un-served airports have garnered better connectivity than erstwhile under-served airports. This points to latent, untapped demand.

The presence of LCCs has certainly boosted multi-fold connectivity at some of the airports. However, all conditions remaining the same, for sustainable air connectivity to a regional airport, it is imperative to seek active participation of the LCC carriers. LCC carriers operate bigger aircraft and have better economies of scale compared to regional airlines. However, in remote locations where the demand is low, and surface transportation is not congenial, regional airlines remain the only bet to maintain basic connectivity.

The regional bias has also been noticed with the northern and southern regions majorly benefiting in terms of connectivity. This research also confirms that the airline network is indeed a small network and it tends to cluster around some power centers. Most of the regional airports are connected to top metro airports or the state capitals. No under-served or un-served regional airport is connected to another un-served or under-served regional airport.

The RCS routes are allocated for three years with concessions. If the demand picks up, the route can be left to market forces. However, there would be routes that may not be sustainable in the future without proper fiscal support. Both the regional and federal governments need a slew of measures to build up an ecosystem for aviation's sustenance and positive growth. Some of the measures could be to build up drivers for the demand like tourism, higher education institutions, cargo hubs, or night stop and maintenance facilities for aircraft maintenance.

The COVID-19 pandemic had a significant impact on air travel demand, causing it to plummet dramatically. However, the industry has gradually recovered, and demand now exceeds pre-pandemic levels. This recovery has been largely driven by a surge in leisure travel. Studies on passenger choice have indicated a preference shift from shared to private modes of transportation (Singh et al., 2022). This shift could have implications for the relative demand between air travel and road travel. Nevertheless, as normalcy has further restored over the past two years, passenger behavior may have shifted yet again. It will be important to analyze new data to understand the latest travel patterns and preferences.

Over the past two years, the Indian passenger aviation sector has grappled with several key challenges. Chief among these have been shortages of aircraft and pilots. The commercial airline industry has also experienced significant consolidation, with mergers and some carriers ceasing operations. Compounding these supply-side issues, the surge in passenger demand has driven fares higher. On some regional connectivity scheme (RCS) routes, the steep increase in airfares has prompted the government to relax the exclusivity granted to the first airline operating on a particular route. Under the new rules, if the passenger load factor (PLF) exceeds 85% for four consecutive quarters, the exclusive flying rights on the RCS route will be withdrawn, opening it up to competition. This dynamic environment poses considerable complexity for commercial airlines in identifying and launching new RCS routes. Future research should look deeper into these challenges and their implications for regional airport connectivity across the country.

Acknowledgement

The authors are thankful to the reviewers. Their insightful comments and suggestions have significantly enhanced the quality of the paper.

This work is partially supported by a grant from SERB-DST, India (MTR/2021/000390) to the first author.

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Appendix

RCS Airports					Five-week period covering February 2020			Five-week period covering October 2020		
Sr. No	**Airport Name**	**India Region**	**Classification**	**Date of Operationalisation under RCS**	**No of Pax (No of Flight)**	**NetScan Ranking**	**Modified NetScan Ranking**	**No of Pax (No of Flight)**	**NetScan Ranking**	**Modified NetScan Ranking**
1	Belgaum	Southern	Underserved	1 May 2019	14767 (280)	1	1	9323 (239)	1	1
2	Kannur	Southern	Unserved	25 Jan 2019	16611 (280)	2	3	4646 (140)	4	5
3	Hubli	Southern	Underserved	14 May 2018	16926 (249)	3	2	1523 (44)	15	14
4	Jharsuguda	Eastern	Unserved	22 Sep 2018	12803 (198)	4	5	9269 (190)	2	3
5	Mysuru	Southern	Unserved	2 Sep 2017	8180 (173)	5	8	4114 (179)	3	4
6	Gwalior	Northern	Underserved	31 May 2017	8197 (161)	6	6	3423 (60)	12	9
7	Allahabad	Northern	Underserved	14 Jun 2018	15828 (140)	7	4	13013 (134)	5	2
8	Kolhapur	Western	Unserved	8 Apr 2018	7278 (153)	8	9	3658 (103)	8	7
9	Nasik	Western	Unserved	23 Dec 2017	6854 (135)	9	12	2702 (136)	6	6
10	Jaisalmer	Northern	Unserved	29 Oct 2017	6615 (129)	10	10	848 (34)	22	17
11	Kadapa	Southern	Underserved	27 Apr 2017	5929 (103)	11	13	2000 (59)	11	13
12	Kishangarh	Northern	Unserved	8 Oct 2018	7022 (99)	12	11	4174 (95)	7	8
13	Kandla	Western	Unserved	1 Jul 2017	5219 (93)	13	14	991 (48)	13	15
14	Durgapur	Eastern	Underserved	25 Jun 2019	9634 (70)	14	7	4707 (30)	17	10
15	Hindon	Northern	Unserved	11 Oct 2019	2269 (70)	15	15	438 (12)	29	26
16	Vidyanagar	Southern	Unserved	21 Sep 2017	3559 (69)	16	18	995 (31)	19	22
17	Nanded	Western	Unserved	27 Apr 2017	3888 (68)	17	17	719 (15)	26	27
18	Kalaburagi	Southern	Unserved	22 Nov 2019	2632 (56)	18	19	3217 (69)	9	11
19	Dimapur	North Eastern	Unserved	7 Dec 2019	1619 (49)	19	25	901 (40)	14	21
20	Pithoragarh	Northern	Unserved	17 Jan 2019	379 (43)	20	32	0 (0)	32	32
21	Jalgaon	Western	Unserved	23 Dec 2017	2388 (49)	21	22	489 (17)	24	29
22	Adampur	Northern	Unserved	1 May 2018	2534 (34)	22	27	0 (0)	32	32
23	Puducherry	Southern	Underserved	16 Aug 2017	2442 (35)	23	21	0 (0)	32	32
24	Bikaner	Northern	Unserved	26 Sep 2017	1997 (35)	24	26	1167 (34)	18	18
25	Porbandar	Western	Underserved	10 Jul 2017	1960 (35)	25	20	653 (31)	20	19

26	Salem	Southern	Unserved	25 Mar 2018	1887 (35)	26	28	740 (31)	21	23
27	Shillong	North Eastern	Underserved	26 Apr 2018	1813 (35)	27	24	0 (0)	32	32
28	Jorhat	North Eastern	Underserved	1 Aug 2018	5058 (35)	28	16	1378 (15)	28	20
29	Kanpur	Northern	Unserved	3 Jul 2018	2737 (34)	29	23	2326 (34)	23	16
30	Mundra	Western	Unserved	17 Feb 2018	126 (21)	30	36	0 (0)	32	32
31	Bidar	Southern	Unserved	2 Jul 2020	1486 (23)	31	29	650 (16)	25	25
32	Pantnagar	Northern	Underserved	4 Jan 2019	640 (17)	32	34	608 (35)	16	24
33	Ludhiana	Northern	Unserved	2 Sep 2017	864 (20)	33	30	176 (10)	30	30
34	Diu	Western	Underserved	24 Feb 2018	123 (18)	34	38	0 (0)	32	32
35	Shimla	Northern	Unserved	27 April 2017	209 (18)	35	37	0 (0)	32	32
36	Agra	Northern	Underserved	8 Dec 2017	451 (14)	36	35	64 (6)	31	31
37	Bhatinda	Northern	Unserved	27 April 2017	621 (15)	37	33	0 (0)	32	32
38	Pathankot	Northern	Unserved	5 April 2018	597 (15)	38	31	604 (15)	27	28
39	Bhavnagar	Western	Underserved	1 May 2018	15 (13)	39	39	0 (0)	32	32
40	Jagdalpur*	Northern	Unserved	14 June 2018				2028 (70)	10	12

Table A1: Connectivity score and relative ranking among the RCS airports on account of only RCS flights using fixed wing aircraft

*****Airports not operational in February 2020

Sr No	Variables	1	2	3	4	5	6	7	8	9	10	11
1	passavg	1										
2	netscan	**0.92**	1									
3	mnetscan	**0.88**	**0.95**	1								
4	lnpcsi	0.08	0.08	-0.09	1							
5	Edu	0.08	0.08	0.22	**-0.43**	1						
6	lnpop	0.14	0.23	0.28	-0.26	0.14	1					
7	lnhub.time	0.31	0.21	0.21	0.00	-0.28	**-0.38**	1				
8	aptin400	-0.25	**-0.33**	**-0.35**	0.02	0.03	0.26	-0.22	1			
9	state.road	-0.24	-0.23	-0.27	-0.24	0.27	0.27	-0.22	**0.49**	1		
10	state.rail	-0.14	-0.01	0.02	**-0.33**	0.20	**0.44**	**-0.49**	0.30	**0.56**	1	
11	easebus	0.08	0.20	0.23	0.00	-0.20	**0.39**	0.08	-0.23	**-0.39**	0.07	1
N = 39. Correlations significant at $p < 0.05$ are printed in bold.												

Table A2: Correlation of the various factors

lnpcsi	edu	lnpop	lnhub.time	aptin400	state.road	state.rail	easebus
1.59	1.47	2.09	1.89	1.46	2.64	2.50	2.19

Table A3: Variance Inflation Factor (VIF) of the variables