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Post-COVID-19 recovery and resilience in passenger and cargo traffic: A Bayesian vector autoregressive analysis of India's top 10 busiest airports

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ABSTRACT

This study examines the post-COVID-19 resilience of India's ten busiest airports using passenger and cargo traffic data from 2016 to 2024. A Bayesian vector autoregression (BVAR) model generates counterfactual forecasts, enabling a comparative assessment to classify airports as outperformers, forecast achievers, or underperformers. Beyond performance categorisation, the study investigates the role of airport infrastructure in shaping resilience outcomes through Spearman correlation and ordered logistic regression (OLOGIT) analysis. Results indicate that infrastructure attributes such as cargo terminal availability, runway capacity, and metro connectivity are significantly associated with higher resilience. Airports with stronger and more adaptive infrastructure recovered more effectively from pandemic disruptions. These findings offer actionable insights for infrastructure planning, crisis preparedness, and long-term policy strategies aligned with national initiatives such as the UDAN regional connectivity scheme.

1. Introduction

The airline industry has consistently demonstrated resilience by adapting to disruptions, recovering from crises, and implementing strategic adjustments for long-term sustainability (Tabares, 2021). Despite air travel's reputation as the safest mode of transportation (see Oster and Strong, 2013; Stoop and Kahan, 2020), pandemics such as SARS, H1N1, and most notably COVID-19 have posed serious challenges, with aviation among the most heavily affected sectors (Sun et al., 2022; WHO, 2020; H. Wu et al., 2024). The COVID-19 pandemic, in particular, led to unprecedented losses. Global airport revenues fell by USD 125 billion in 2020–66.3% below pre-crisis projections (ACI, 2021)-as governments imposed international travel restrictions, sharply curtailing both passenger and cargo flows. Major Indian airports such as Delhi, Mumbai, and Bangalore were forced to reduce operational capacity (e.g., Dhillon, 2020; Dongare et al., 2020).

Nonetheless, aviation played a critical role in emergency logistics, including the transport of essential cargo and vaccines (Sun et al., 2023; Wu et al., 2025). As India emerges as one of the fastest-growing aviation markets, with GDP growth of 6.5–7% (OAG, 2024) and rising middle-class demand, its aviation sector is projected to become the world's third largest within the next decade (IATA, 2025). Government initiatives such as the UDAN scheme-aimed at enhancing regional connectivity-underscore this growth trajectory, despite mixed outcomes (e.g., Das et al., 2020; Iyer and Thomas, 2020). The pandemic, however, disrupted this momentum. National lockdowns in March 2020 grounded nearly all scheduled flights, bringing the sector to a standstill. Although domestic operations resumed in May, recovery remained gradual, with passenger numbers rising from 58,000 to over 500,000 by November (Arora and Garg, 2020; Sidhu and Shukla, 2021). The sector's rebound was bolstered by proactive government measures, including mass vaccination and enhanced airport surveillance (Aroskar et al., 2022).

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Despite these efforts, India's aviation sector faced widespread disruptions. Passenger volumes plummeted, aircraft were grounded, and airport operations were significantly constrained (Ahmed et al., 2020; Budd et al., 2021; Sobieralski, 2020). Uncertainty surrounding future operations revealed structural vulnerabilities (Gandhi and Gandhi, 2020), reinforcing the importance of accurately forecasting airport performance to guide crisis response and recovery strategies.

Traditional forecasting models struggled to account for the scale and volatility of the COVID-19 shock (Rodríguez and Olariaga, 2024). As a result, more robust methods such as Bayesian vector autoregression (BVAR) have gained prominence. BVAR enhances forecast accuracy by integrating prior information and handling high-dimensional datasets (e.g., Spencer, 1993; Woźniak, 2016; Zeng and Li, 2021). In this study, BVAR is used to estimate the counterfactual performance of India's top 10 busiest airports-assuming no pandemic disruption-and compare it with actual passenger (PAX) and cargo outcomes. This gap analysis enables the classification of airports as outperformers, forecast achievers, or underperformers.

While many studies have focused on PAX recovery, this research also examines airport cargo traffic as a resilience indicator, as it served as critical infrastructure during the pandemic (Nath and Upadhyay, 2024). Indian airports played a vital role in maintaining global supply chains, despite facing challenges such as limited infrastructure and demand uncertainty. Evaluating both PAX and cargo recovery offers a comprehensive view of airport resilience.

To further assess the factors influencing resilience, the study employs an ordered logit (OLOGIT) model, examining the impact of airport characteristics-such as runway capacity, cargo terminals, and metro connectivity-on classification outcomes. This robustness check enhances the explanatory value of the BVAR findings and provides empirical evidence on infrastructure's role in shaping post-crisis performance.

This study contributes to the airport resilience literature in three ways. First, it applies a Bayesian Vector Autoregressive (BVAR) framework, an approach situated within modern machine–learning–based forecasting techniques, to construct airport–specific counterfactual trajectories for passenger and cargo flows, enabling a more robust assessment of post–COVID–19 resilience relative to forecasted baselines rather than realised trends alone. Second, the analysis jointly evaluates passenger and cargo traffic, recognising their distinct recovery behaviours and addressing the limited empirical attention to cargo–side resilience in airport–level studies. Third, the study employs an OLOGIT model to empirically examine how infrastructure characteristics are associated with the observed heterogeneity in resilience outcomes, thereby identifying structural determinants of airport recovery across a major emerging aviation market.

To clarify the overall analytical logic, this study follows a three-stage methodological pipeline. First, the BVAR framework is used to generate counterfactual passenger and cargo traffic trajectories, representing expected airport performance in the absence of the COVID-19 shock. Second, deviations between observed and counterfactual outcomes are used to classify airports into resilience categories (outperformers, forecast achievers, and underperformers). Third, an OLOGIT framework is employed to examine how airport infrastructure characteristics are associated with these observed resilience outcomes. The incremental contribution of this integrated framework lies in combining forecast-based resilience measurement with structural interpretation, enabling a more systematic and policy-relevant assessment of airport resilience beyond descriptive recovery analysis.

The paper is structured as follows: Section 2 reviews the relevant literature; Section 3 presents the data and methodology; Section 4 discusses the empirical findings; and Section 5 concludes with key policy implications and suggestions for future research.

2. Literature review

In industrial contexts, resilience is vital for complex organisations facing hazardous processes. Dinh et al. (2012) stressed its role in preventing incidents even with robust risk management, especially in technical operations.

Kajitani et al. (2009) quantified resilience by assessing how disruptions to lifeline services-like electricity and water-impact industrial output. In the U.S., Di Tommaso et al. (2023) described resilience as the ability of sectors to recover from shocks, using composite indicators to compare sectoral performance with counterfactuals. In the Indian context, Borchert and Mattoo (2010) noted that services trade was more resilient than goods trade, largely due to its lower reliance on external finance. Mandal (2012) examined supply chain resilience in India's IT sector, highlighting the role of technology in enhancing agility amid disruptions. Similarly, Namvar and Bamdad (2021) viewed resilience as a safety management framework combining technical and social aspects to stabilise systems in industries like oil refining. Wood et al. (2019) further mapped resilience across organisational threat phases, with a focus on large institutions such as defence forces.

In aviation, resilience encompasses the ability of airlines, airports, and regulatory systems to anticipate, adapt to, and recover from disruptions. Zapola et al. (2024) underscored the need for systems to respond swiftly to environmental shifts, a key trait for the air transport network (ATN) during crises like COVID-19. Evaluating resilience often involves metrics such as aircraft movements, passenger volumes, and cargo throughput (e.g., Guo et al., 2021a), with comparative recovery patterns indicating an airport's capacity to withstand and rebound from external shocks.

2.1. *Resilience in aviation: Post-COVID-19 adaptation and global challenges*

The COVID-19 pandemic exposed significant vulnerabilities in the global aviation system, prompting a wave of scholarly inquiries into resilience mechanisms. Serrano and Kazda, 2020b offered a practical perspective on post-pandemic recovery, identifying financial optimisation, technological adaptation, and stakeholder collaboration as key resilience pillars. Their mixed-methods study provided actionable strategies, such as contactless technologies and revenue diversification, though it was limited by its case-specific data and lack of empirical validation.

Warnock-Smith et al. (2021) explored market-level disruptions in China, Europe, and Asia, highlighting the differential recovery rates between domestic and international air travel. By segmenting analysis across airline types and route classes, their study offered valuable policy insights-particularly on China's "Five One" rule. However, it lacked qualitative depth and overlooked environmental impacts, limiting a comprehensive understanding of resilience dynamics. Focusing on airport networks, Guo et al. (2021b) applied complex network theory to assess the resilience of the Chinese (CAN) and European (EAN) systems. Their findings demonstrated that centralised governance accelerated recovery in CAN, whereas fragmented responses hindered EAN's resilience. Despite methodological strengths, the study's limited geographic scope and exclusion of interdependent network dynamics curtailed broader applicability.

Tabares (2021) proposed infectious disease-free zones within terminals through advanced health screening aligned with ICAO's Public Health Corridors (PHCs). While the study contributed a phased, scalable implementation model, it was constrained by untested technological assumptions and insufficient attention to privacy, cost-effectiveness, and real-world deployment, raising questions about feasibility. Meanwhile, Arora et al. (2021) advanced the discourse by proposing a multi-tier pandemic response framework based on existing ICAO safety protocols. Their comprehensive review of pandemic impacts, including empirical evidence from passenger and cargo operations, highlighted the need for globally standardised protocols. Yet, their reliance on international cooperation, amid varied national priorities, and the absence of detailed cost-benefit analyses weakened practical implementation prospects.

Su et al. (2023) employed an ordered Probit model to analyse resilience factors in Europe, identifying airline concentration and LCC dominance as positive determinants. They also noted the adverse effects of high-speed rail competition and stringent quarantines. While the study provided statistically robust insights, it lacked financial and labour-related variables and was geographically limited to Europe, narrowing its global relevance. Concurrently, Wandelt et al. (2024) developed the Global Airport Resilience Index (GARI), an integrated model incorporating network characteristics, ground transportation links, and hub activity. While GARI bridged the gap between network theory and real-world application, its simulation-based design may limit real-time utility. Similarly, Mota et al. (2022), using the Mexico City Multi-Airport System, demonstrated how strategic infrastructure planning can shape long-term resilience under pandemic stress.

Janić (2022) introduced a multi-dimensional framework evaluating operational, economic, social, and environmental resilience at major North American and UK airports. The study exposed high vulnerability and low resilience at two of the busiest airports, London Heathrow (LHR) and New York's John F. Kennedy (JFK), particularly in economic dimensions. Its breadth was notable, yet the reliance on only two airports and complex analytical models limited scalability and transferability. Finally, Zapola et al. (2024) proposed a simulation-based framework targeting passenger terminal resilience, integrating metrics such as individual passenger and aircraft delays. Their approach marked a methodological advancement but was bounded by a narrow disruption type (airport access blockage) and application to a single Brazilian airport, limiting generalisability.

Together, these studies contribute significantly to the theoretical and practical understanding of aviation resilience-highlighting financial recovery, governance models, technological adaptation, and network structures. Nonetheless, their relevance to developing regions, particularly those characterised by fragmented governance, limited infrastructure, and varied socio-economic settings such as India, remains limited. This underscores a persistent gap in the literature concerning context-specific interpretations and assessments of resilience within the aviation sector.

2.2. Resilience strategies for Indian aviation: a review of challenges and gaps

Ganguly et al. (2020) examined India's pandemic response, highlighting significant socio-economic and public health disruptions, with critical implications for the aviation sector. Their qualitative review of secondary data revealed systemic vulnerabilities-particularly the aviation industry's lack of preparedness-but lacked sector-specific strategies and primary stakeholder insights. While the study underscored aviation's potential role in pandemic mitigation (e.g., medical logistics, repatriation), it fell short of actionable recommendations, limiting its policy relevance. Nonetheless, it set the stage for integrating aviation and public health frameworks in future crisis planning. Similarly, Gupta et al. (2021) showed how air travel accelerated viral spread, with districts housing major airports reporting higher infection rates. This urban-centric transmission pattern reflected the tight interlinkages between urbanisation, transport networks, and health risks, reinforcing the urgency of aviation resilience during public health crises.

Dash et al. (2021) explored aviation's economic fragility using data from 2005 to 2020, identifying economic uncertainty as a more disruptive force than pandemics. Their econometric analysis revealed interdependencies between aviation and the hotel sector, with hotel cost volatility aligning positively with aviation activity, while disease-related fatalities had a dampening effect. While methodologically robust, the study lacked consideration of policy, infrastructure, and stakeholder perspectives-critical elements in crafting holistic resilience strategies. Rai et al. (2021) analysed organisational resilience and sustainability during COVID-19 using SEM on 261 industry responses. They identified three dimensions-crisis anticipation, robustness, and recoverability-as essential to sustaining social and economic outcomes. Despite addressing an empirical gap in emerging economies, the study's exclusion of environmental sustainability and qualitative insights limited its comprehensiveness. The suggestion to incorporate broader frameworks and mixed methods provides a meaningful pathway for advancing future research.

Thounaojam and Dolla's (2020) systematic review of resilience in public–private partnerships (PPPs) offered valuable lessons for airport governance. Analysing 100 peer-reviewed studies, they highlighted strategies such as flexible contracts, risk-sharing, and dynamic governance-particularly relevant for long-term airport PPP projects. However, the study did not delve into sector-specific resilience testing or stakeholder coordination, both of which are crucial for real-time airport crisis response. In contrast, Gopichandran and Subramaniam (2020) adopted a more action-oriented lens, critiquing India's public health response and calling for structural reforms-an urgency also relevant to the aviation sector's institutional readiness.

Despite growing literature on aviation resilience post-COVID-19, notable gaps remain. Most studies generalise airports within broader transport systems, neglecting their unique vulnerabilities and operational contexts. Empirical validation of resilience frameworks, particularly in developing nations, remains limited, as does the application of advanced forecasting techniques (e.g., machine learning) to assess adaptive capacity. Furthermore, while financial and network-based strategies dominate existing analyses, cross-regional comparisons, cargo-handling robustness, and the integration of multi-method approaches remain underexplored.

Overall, the literature provides critical insights into resilience across aviation and related sectors but reveals persistent gaps in scope and application. In the Indian context, the role of infrastructure in post-pandemic airport performance is especially understudied, with limited focus on airport-specific strategies addressing both passenger and cargo dimensions. Despite growing interest in aviation resilience, most studies subsume airports and airlines within broader transport systems, offering little on their specific institutional and operational contexts. Existing frameworks often lack empirical grounding, particularly in developing regions, and overlook cargo dynamics and stakeholder perspectives. These limitations reflect a fragmented understanding of resilience in Indian aviation, underscoring the need for more integrated, sector-specific analysis.

3. Methodology

Advanced statistical models are vital for forecasting during periods of disruption, such as the COVID-19 pandemic, due to their capacity to incorporate domain knowledge and account for structural breaks. Over the past decade, machine learning (ML) techniques have gained prominence as alternatives to classical models, particularly in time series forecasting for business decision-making (Ahmed et al., 2010; Athiyarath et al., 2020). The BVAR model exemplifies this shift, blending Bayesian inference with regularisation to enhance forecast accuracy (Rudakouski, 2023). Unlike traditional econometric models based on frequentist estimation, BVAR introduces prior distributions that improve parameter estimation and mitigate overfitting, a core feature of ML approaches (Athiyarath et al., 2020; Cramer and Thams, 2021; Kang and Hansen, 2018). Though grounded in structured probabilistic modelling (Zeng and Li, 2021), BVAR shares ML characteristics such as data-driven learning and improved prediction through informed priors, bridging classical econometrics and contemporary ML techniques.

Among forecasting tools, BVAR presents a credible alternative to standard Vector autoregression (VAR) models, particularly in assessing passenger (PAX) and cargo trends before and after the COVID-19 shock. While the VAR framework remains foundational in economic forecasting due to its capacity to generate relatively accurate long-term predictions (e.g., Christiano, 2012; Sims, 1980), it is constrained by issues such as multicollinearity and reliance on linear relationships (Spencer, 1993), which limit its effectiveness in volatile or complex environments. BVAR addresses these limitations through Bayesian priors, offering better parameter stability and improved performance on smaller datasets (Song and Witt, 2006; Woźniak, 2016). Its ability to reduce the number of parameters and produce more accurate forecasts makes it particularly suitable for evaluating resilience under disruption (Gupta and Sichei, 2006; Rudakouski, 2023).

This study adopts a univariate autoregressive approach based on BVAR (Gupta and Sichei, 2006) to forecast PAX and cargo trends at individual airports. Although BVAR is commonly used in multivariate settings (Berg, 2016), applying it at the airport level allows for analysis of internal dependencies between passenger and cargo movements and their response to external shocks. Historical monthly time series data from 2016 to 2024 for ten of India's busiest airports are used to assess variations in operational performance and recovery trajectories.

Equations (1) and (2) present the autoregressive models used to forecast passenger traffic and cargo volume, respectively.

$$PAX_t = \alpha_0 + \sum\nolimits_{i=1}^{p} \alpha_i \mathrm{Pax}_{t-i} + u_t \tag{1}$$

$$Cargo_t = \delta_0 + \sum\nolimits_{i=1}^{p} \delta_i Cargo_{t-i} + \varepsilon_t \tag{2}$$

Where PAX_t *and* $Cargo_t$ represent the number of passengers (in persons) and cargo (in metric tonnes, MT) at time t respectively. α_0 and δ_0 are the intercepts (constant term), α_i and δ_i are the coefficients that represent the relationship between the current value and its lagged values, p is the number of lags included in the model, u_t *and* ε_t *are* the error terms, capturing random noise or unexplained variability.

Unlike classical VAR, which relies on ordinary least squares (OLS) or maximum likelihood estimation (MLE), BVAR employs Bayesian inference by integrating prior distributions with the likelihood function to derive posterior parameter estimates. This framework has gained traction in transport studies (e.g., Rodriguez-deniz, 2023), largely due to advances in computational methods such as Markov Chain Monte Carlo[1] (MCMC), notably the Gibbs sampler (e.g., Hu, 2023; Washington et al., 2004). These methods enhance flexibility and robustness, particularly for forecasting complex phenomena like airport resilience.

In BVAR, the coefficients α_i and δ_i are estimated differently from standard VAR models. By incorporating prior information, BVAR mitigates overfitting and enhances model stability, especially with sparse or noisy datasets. This regularisation is critical for contexts with irregular trends, such as disruptions caused by COVID-19, allowing the generation of probabilistic forecasts that account for uncertainty in passenger and cargo trajectories. The Bayesian approach, applied to Equations (1) and (2), allows the inclusion of external knowledge or constraints, which improves estimation accuracy when the data alone may be insufficient (Ramos, 2003).

It is important to note that the empirical framework employed in this study is designed to identify associations between forecast-based resilience outcomes and airport characteristics, rather than to establish causal relationships.

[1] The Monte Carlo method estimates the properties of a distribution through random sampling. In this approach, random samples are drawn from the distribution, and their properties, such as the sample mean, are calculated. MCMC extends this by generating samples sequentially, where each sample depends on the previous one, forming a 'chain.' This sequential dependency enables efficient exploration of complex distributions.

3.1. Data overview and key insights

Table 1 presents the top 10 busiest airports[2] in India, along with key infrastructure characteristics. Their post-pandemic performance in passenger and cargo handling is assessed against a baseline derived from pre-pandemic data (2016–2020), which assumes uninterrupted operations without COVID-19 disruptions. The comparative analysis is based on data obtained from the Directorate General of Civil Aviation (DGCA) and Airports Authority of India (AAI). Fig. 1 maps the geographic distribution of these airports, which are located across major metropolitan and economic centres.

As of August 2024, India has 34 international airports. Of these, 18 are managed by the Airports Authority of India (AAI), six operate under public–private partnership (PPP) arrangements, seven are joint ventures, and three are directly managed by state governments (AAI, 2024b). These airports are ranked by passenger traffic and cargo volume. Indira Gandhi International Airport, New Delhi (DEL), remains the busiest, handling the highest passenger volumes, air traffic movements, and cargo operations. In contrast, Dabolim International Airport, Goa (GOI), recorded lower passenger traffic, partly due to the pandemic's adverse impact on tourism.

Growth in India's aviation sector has been driven by rising air cargo volumes and record passenger traffic at major hubs such as DEL, Chhatrapati Shivaji Maharaj International Airport, Mumbai (BOM), and Kempegowda International Airport, Bengaluru (BLR) in 2023. Tables 2 and 3 present a mean comparison of passenger and cargo performance across three phases: pre-pandemic, post-pandemic, and the full period from 2016 to 2024. Logarithmic transformation was applied to address scale variation and skewness, improving model performance. The Gap Value (GV), defined as the difference between post- and pre-pandemic means, quantifies the net change in airport performance, capturing the extent of recovery or decline following COVID-19.

Descriptive statistics for the 2016–2024 period, encompassing both pre- and post-pandemic phases, reveal varying levels of resilience among India's major airports. The GV, defined as the difference between post- and pre-pandemic passenger means, offers a measure of each airport's recovery capacity following the COVID-19 disruption.

Indira Gandhi International Airport, New Delhi (DEL), exhibited the highest resilience with a relatively small gap of −0.18, suggesting a strong recovery trajectory likely supported by its infrastructure capacity and strategic national importance. In contrast, Chhatrapati Shivaji Maharaj International Airport, Mumbai (BOM), showed a larger gap of −0.27, indicating greater disruption, possibly due to the pandemic's severe impact on Maharashtra's economic activity.

Kempegowda International Airport, Bengaluru (BLR), recorded a gap of −0.14, reflecting robust recovery, potentially linked to the city's role as a major IT hub and the airport's modern facilities. Rajiv Gandhi International Airport, Hyderabad (HYD), emerged as the most resilient with a gap of −0.07, pointing to effective operational management and the city's growing business significance.

Chennai International Airport, Chennai (MAA) and Cochin international Airport, Cochin (COK) both registered gaps of −0.26, suggesting comparable levels of disruption, possibly influenced by regional factors affecting southern India. Netaji Subhas Chandra Bose International Airport, Kolkata (CCU), showed moderate resilience with a gap of −0.16, indicating relatively stable recovery in eastern India.

Smaller airports displayed mixed outcomes. Goa's Dabolim Airport (GOI) had a gap of −0.25, reflecting the vulnerability of tourism-dependent regions. Pune International Airport, Pune (PNQ) and Sardar Vallabhbhai Patel International Airport, Ahmedabad (AMD) recorded

[2] The data from AAI (2016—2024) includes total passenger traffic (covering all arrivals, departures, and transit passengers), total aircraft movements, and total cargo handled in metric tonnes, encompassing both freight and mail arriving at or departing from the airport.

Table 1
India's 10 busiest airports by passenger and cargo traffic (2016–2024) along with infrastructure details based on AAI data.

Airport Name	IATA Code	State	No. of Runways	No. of Domestic Terminals	No. of International Terminals	No. of Cargo Terminals	No. of Metro rail Terminals
Chhatrapati Shivaji Maharaj International Airport, Mumbai	BOM	Maharashtra	2	1	1	1	2
Kempegowda International Airport, Bangaluru	BLR	Karnataka	2	1	1	3	0
Rajiv Gandhi International Airport, Hyderabad	HYD	Telangana	2	1	1	1	0
Cochin International Airport, Kochi	COK	Kerala	1	2	1	1	0
Pune International Airport, Pune	PNQ	Maharashtra	1	1	1	1	0
Indira Gandhi International Airport, New Delhi	DEL	Delhi	4	2	1	2	1
Chennai International Airport, Chennai	MAA	Tamil Nadu	2	2	1	1	1
Netaji Subhas Chandra Bose International Airport, Kolkata	CCU	West Bengal	2	1	1	1	1
Sardar Vallabhbhai Patel International Airport, Ahmedabad	AMD	Gujarat	1	1	1	1	0
Dabolim International Airport, Dabolim	GOI	Goa	1	1	1	0	0

Fig. 1. Geographic distribution of the top 10 busiest airports in India.
Source: Knowindia.net (2025).

gaps of −0.18 and −0.15, respectively, indicating comparatively better resilience among mid-tier airports.

Overall, while all airports experienced post-pandemic declines in passenger volumes, the degree of resilience varied considerably. These differences likely stem from a combination of infrastructure capacity, regional economic profiles, and local pandemic response measures. The findings highlight the importance of context-specific strategies to strengthen airport resilience, particularly for tourism-driven and smaller airports more exposed to systemic shocks.

In cargo handling, BLR, demonstrated the highest resilience among major cargo hubs, with a positive gap value of 0.02, indicating a slight improvement in post-pandemic operations. This reflects Bengaluru's strength as a logistics hub and its effective recovery capacity. In contrast, MAA recorded a gap of −0.09, suggesting moderate difficulties in restoring cargo volumes, possibly due to shifts in trade routes or logistical disruptions. DEL showed a minor decline of −0.04, suggesting a stable recovery supported by its extensive freight infrastructure. BOM experienced a slightly larger decline of −0.08, likely reflecting the economic pressures Maharashtra faced during the pandemic. HYD displayed strong performance with a gap of −0.03, while GOI maintained

Table 2
Passenger volume (millions) summary by airport and time period (2016–2024).

Airport Code	Pre-pandemic 2016–2019 Mean	Post-pandemic 2020–2024 Mean	All period 2016–2024 Mean	Gap Value
AMD	5.89	5.74	5.81	−0.15
BLR	6.36	6.22	6.29	−0.14
BOM	6.59	6.32	6.44	−0.27
CCU	6.2	6.04	6.11	−0.16
COK	5.91	5.65	5.77	−0.26
DEL	6.73	6.55	6.63	−0.18
GOI	5.8	5.55	5.66	−0.25
HYD	6.18	6.11	6.14	−0.07
MAA	6.23	5.97	6.09	−0.26
PNQ	5.82	5.64	5.72	−0.18

Table 3
Cargo volume (metric tons) summary by airport and time period (2016–2024).

Airport Code	Pre-pandemic 2016–2019 Mean	Post-pandemic 2020–2024 Mean	All period 2016–2024 Mean	Gap Value
AMD	3.89	3.81	3.85	−0.08
BLR	4.48	4.5	4.49	0.02
BOM	4.87	4.79	4.82	−0.08
CCU	4.15	4.01	4.08	−0.14
COK	3.8	3.65	3.72	−0.15
DEL	4.9	4.86	4.88	−0.04
GOI	2.57	2.58	2.58	0.01
HYD	4.06	4.03	4.04	−0.03
MAA	4.51	4.42	4.46	−0.09
PNQ	3.52	3.34	3.42	−0.18

near pre-pandemic levels with a value of 0.01, despite its reliance on tourism-driven traffic. Several airports faced more pronounced challenges. AMD recorded −0.08, while CCU and COK saw larger declines of −0.14 and −0.15, respectively, indicating slower recovery trajectories. PNQ had the steepest drop at −0.18, highlighting significant pandemic-related disruptions.

Post-pandemic variability in both passenger and cargo volumes increased, underscoring the need for adaptive strategies to manage fluctuating demand and operational constraints. While some airports approached or surpassed pre-pandemic levels, others showed more gradual recovery, reflecting region-specific dynamics and infrastructural capacity.

Although descriptive statistics offer valuable snapshots of overall trends, they do not capture the interdependencies between variables. To address this, the study applies a BVAR framework. BVAR enables analysis of how shocks propagate over time and influence airport performance by incorporating lag structures and cross-variable dynamics. This approach provides a more robust understanding of recovery patterns, distinguishing between short-term fluctuations and longer-term structural shifts in resilience.

To further examine the influence of airport infrastructure on performance outcomes, supplementary analyses were conducted using ordinary least squares (OLS) and OLOGIT models. Equations (3) and (4) present the OLS models used to evaluate the factors affecting resilience in passenger traffic and cargo volumes. The results and interpretations of these analyses are detailed in Section 4.3.

$$PAX\_res_i = \lambda_0 + \lambda_1 Runways_i + \lambda_2 Terminals_i + \lambda_3 Cargo\_Terminals_i + \lambda_4 Metrorail\_connectivity_i + \varepsilon_i \quad (3)$$

$$CAR\_res_i = \theta_0 + \theta_1 Runways_i + \theta_2 Terminals_i + \theta_3 Cargo\_Terminals_i + \gamma_4 Metrorail\_connectivity_i + \varepsilon_i \quad (4)$$

Where PAX_res_i and CAR_res_i represents the resilience score for passenger and cargo traffic respectively, at airport *i*. The variables $Runways_i$, $Terminals_i$, $Cargo\_Terminals_i$ and $Metrorail\_connectivity_i$ denote the number of runways, number of terminals, presence of cargo terminals, and number of metro terminals at airport *i* respectively. λ_0 and θ_0 are the intercepts, while ε_i represents the error term capturing unexplained variability.

To address the ordinal structure of the resilience scores, Equations (5) and (6) apply OLOGIT models. These models evaluate how airport infrastructure characteristics influence the probability of an airport being classified within specific resilience categories for both passenger and cargo operations.

$$logit(P(PAX\_res_i \leq j)) = \tau_j - (\kappa_1 Runways_i + \kappa_2 Terminals_i + \kappa_3 Cargo\_Terminals_i + \kappa_4 Metrorail\_connectivity_i) \quad (5)$$

$$logit(P(CAR_{resi} \leq j)) = \zeta_j - (\psi_1 Terminals_i + \psi_2 Cargo\_Terminals_i + \psi_3 Metrorail\_connectivity_i) \quad (6)$$

The log-odds of airport *i* having a resilience score at or below category *j* are modelled as a function of key infrastructure variables. The thresholds τ_j and ζ_j represent estimated cut-off points between adjacent resilience categories. Coefficients (κ and ψ) reflect the influence of each predictor on the likelihood of higher resilience, where more positive values reduce the probability of falling into lower categories. Due to non-convergence in estimation, *Runways* was excluded from the cargo resilience model, with the final specification including *Terminals*, *Cargo_Terminals*, and *Metrorail_Connectivity*.

These models assess the relationship between infrastructure and airport performance indicators, including passenger and cargo volumes. While the OLS model captures linear associations, the OLOGIT model accounts for ordinal variation in resilience scores, offering deeper inferential insight. Although distinct from the BVAR framework, these supplementary models act as robustness checks, providing complementary evidence on the role of infrastructure. This layered approach strengthens the overall evaluation by integrating multiple analytical perspectives beyond what descriptive or single-method analyses can offer.

4. Empirical analysis, discussion, and policy implications

The BVAR model estimation for PAX and cargo handling (in metric tons) at India's 10 busiest airports was conducted under the assumption of a counterfactual scenario without the COVID-19 pandemic. The model employed MCMC for posterior estimation, a sampling-based approach well-suited for Bayesian models and increasingly popular in transportation research (Washington et al., 2004). MCMC methods enable robust forecasts by addressing the inherent uncertainties in time series data (Rudakouski, 2023).

Although the BVAR framework yields full posterior predictive distributions, the airport–specific univariate specification produces relatively narrow credible intervals around the counterfactual trajectories. All BVAR figures therefore display the 95% Bayesian credible intervals, which tend to overlap closely with the posterior mean but still make the underlying forecast uncertainty explicit. Importantly, incorporating the full posterior distribution does not alter the classification of airports into outperformers, forecast achievers, and underperformers.

4.1. Bayesian vector auto regression

The comparison between the observed trends and the BVAR-generated forecasts allowed airports to be categorised into three groups: outperformers (airports exceeding forecasted recovery), forecast achievers (airports achieving moderate recovery), and underperformers (airports lagging behind expected recovery).

4.1.1. Outperformers

Unlike some industries that remained relatively resilient during the pandemic, the aviation sector-particularly airports-was disproportionately affected due to its reliance on the physical movement of passengers and cargo. While many sectors adapted to remote or contact-minimised operations, aviation encountered disruptions tied to stringent health and safety protocols. For example, although policies were introduced to ensure only passengers who passed health checks could board flights (Sun et al., 2022), widespread fear of infection suppressed travel demand (Agrawal, 2021). Additionally, concerns among aviation workers over health risks and job security led to reduced productivity (see Farooq et al., 2024; Rawat, 2021; Serrano and Kazda, 2020a).

These interrelated challenges highlight the sector's systemic vulnerabilities during global health crises, particularly in high-density countries such as India. Figs. 2 and 3 identify the most resilient airports based on their post-pandemic PAX and cargo performance.

Five airports-BLR, HYD, COK, BOM, and PNQ-were identified as resilient in terms of PAX handling. This outcome aligns with expectations, as major metropolitan hubs and high-performing non-metro airports like COK and PNQ showed stronger recovery. COK, for instance, has consistently ranked among India's leading international gateways, supported by Kerala's large expatriate population and the airport's robust infrastructure (ICRA, 2023). Its well-developed facilities have enabled higher aeronautical and non-aeronautical revenues, contributing to operational continuity during disruptions. In FY 2023–24, COK handled over 10.5 million passengers, 63.5% of Kerala's total, highlighting the association between infrastructure and observed resilience patterns (CIAL, 2024). Infrastructure has been a key enabler of adaptability. Airports with intermodal connectivity and integrated surveillance systems have generally managed crises more effectively (e.g., Aroskar et al., 2022; Ganguly et al., 2020; Priyadharsini et al., 2021). BLR, for example, expanded its domestic network from 54 to 74 routes in 2021, exceeding pre-pandemic levels (IAR, 2022). Globally, similar patterns are evident; for instance, in Europe, airports with developed infrastructure and higher flight frequencies have been observed to show greater resilience during disruptions (e.g., Boto-García and Pérez, 2023; Su et al., 2023). Facilities serving both FSCs and LCCs can benefit from operational flexibility underpinned by physical and digital infrastructure.

Government interventions may have supported recovery. Expedited vaccination programs eased mobility barriers, and major airports incorporated proof-of-vaccination protocols efficiently, particularly where infrastructure supported rollout. While these examples align with prior literature, such contextual factors are not directly incorporated into our empirical model. These interpretations should therefore be viewed as indicative, and future research with richer city–level data would be required to examine these mechanisms more formally.

Post-COVID-19, airport strategies globally shifted from prioritising high-volume shipments to high-value goods such as perishables and pharmaceuticals, reflecting an evolution in cargo resilience approaches (Hong et al., 2025; Shrinivasan et al., 2024). In India, six airports, AMD, DEL, GOI, CCU, BLR,[3] and HYD, demonstrated strong cargo resilience. As Dash et al. (2021) observed, the rise in pandemics has paradoxically increased aircraft movements, largely driven by cargo demand. Farooq et al. (2024) also reported a surge in cargo flight operations during such periods, with many airlines repurposing passenger aircraft to carry freight. GOI exemplified this trend, with patterns consistent with effective use of its infrastructure to support key exports, particularly agricultural products (Chatterjee, 2024). The continued correlation between cargo movement and aircraft activity, despite broader economic uncertainties, underscores the stabilising role of cargo in aviation sector resilience. Indian carriers, like their counterparts in China, adapted by converting empty passenger cabins into cargo spaces, demonstrating operational flexibility (See Li et al., 2023).

India's role as the leading global supplier of generic medicines and vaccines further reinforced the significance of cargo operations. By May 2023, over 298 million COVID-19 vaccine doses had been delivered to nearly 100 countries under the Vaccine Maitri initiative (PIB, 2023). The export of pharmaceuticals such as hydroxychloroquine during the pandemic (Gandhi and Gandhi, 2020) further boosted cargo throughput. These developments provide literature- and observation-informed evidence that infrastructure readiness and adaptive logistics strategies are likely associated with the ability of Indian airports to sustain critical cargo flows, suggesting a link to resilience during a global health crisis.

To enhance clarity and reduce repetition, the broader mechanisms underpinning cargo resilience and infrastructure–related performance differences across airports are synthesised here. Across multiple hubs, cargo recovery was supported by common structural factors, including the presence of dedicated cargo terminals, operational flexibility through the repurposing of passenger aircraft, strong pharmaceutical and perishables export demand, and established logistics partnerships. Likewise, infrastructure attributes such as runway capacity, terminal design, and ground–access connectivity exerted similar influences on recovery patterns. While airport–specific observations remain relevant, these shared mechanisms provide a unifying framework for interpreting the subsequent airport–level results.

4.1.2. Forecast achievers

This category includes two metropolitan airports each in the domains of passenger and cargo handling. For passenger traffic, MAA and DEL are featured, while for cargo operations, MAA and PNQ are highlighted (see Figs. 4 and 5). These airports show patterns consistent with strong operational efficiency, as evidenced by the close alignment between their forecasted and actual performance, highlighting their observed significance in India's aviation network. Metropolitan hubs such as Chennai and Delhi manage high volumes of passenger and cargo traffic and maintain extensive domestic and international air connectivity. MAA ranks as India's fifth busiest airport for passenger traffic and aircraft movements, and fourth in cargo handling (AAI, 2024a). While these airports have not yet fully realised their forecasted growth trajectories, a projected acceleration suggests they are on course to achieve expected performance levels in the near term.

Building on earlier examples, intermodal transport integration appears to be associated with improved airport accessibility and connectivity. High-speed rail in Europe and metro rail systems in India are notable examples (see Albalate et al., 2015; Mater et al., 2012). DEL, in particular, is set to become India's first multi-modal interstate transport hub, integrating metro lines, rapid rail transit, intercity buses, and an automated people mover. Such developments are consistent with evidence from the literature and operational observations, suggesting a potential association with enhanced passenger movement and overall airport efficiency, in line with projected performance levels (Sinha, 2023).

The COVID-19 pandemic exposed critical vulnerabilities in urban public health systems (Mehta and Hingorani, 2021), which, in turn, affected airport operations. Airports that promptly implemented surveillance protocols and adapted passenger and cargo procedures appeared to have gained an early advantage in recovery. Conversely, those slower to respond or facing logistical constraints experienced delays in reaching projected performance levels, despite eventual stabilisation. Major metropolitan cities, often the hardest hit by the pandemic,

[3] BLR's cargo resilience is strengthened by its partnership with Envirotainer, which provides advanced temperature-controlled solutions to ensure an unbroken cold chain for pharmaceutical logistics. Pharmaceuticals account for 13% of the airport's annual international cargo, with key destinations including the US, UK, Australia, Canada, France, Vietnam, the Philippines, Germany, Nigeria, Algeria, Uganda, and Russia (PTI, 2021).

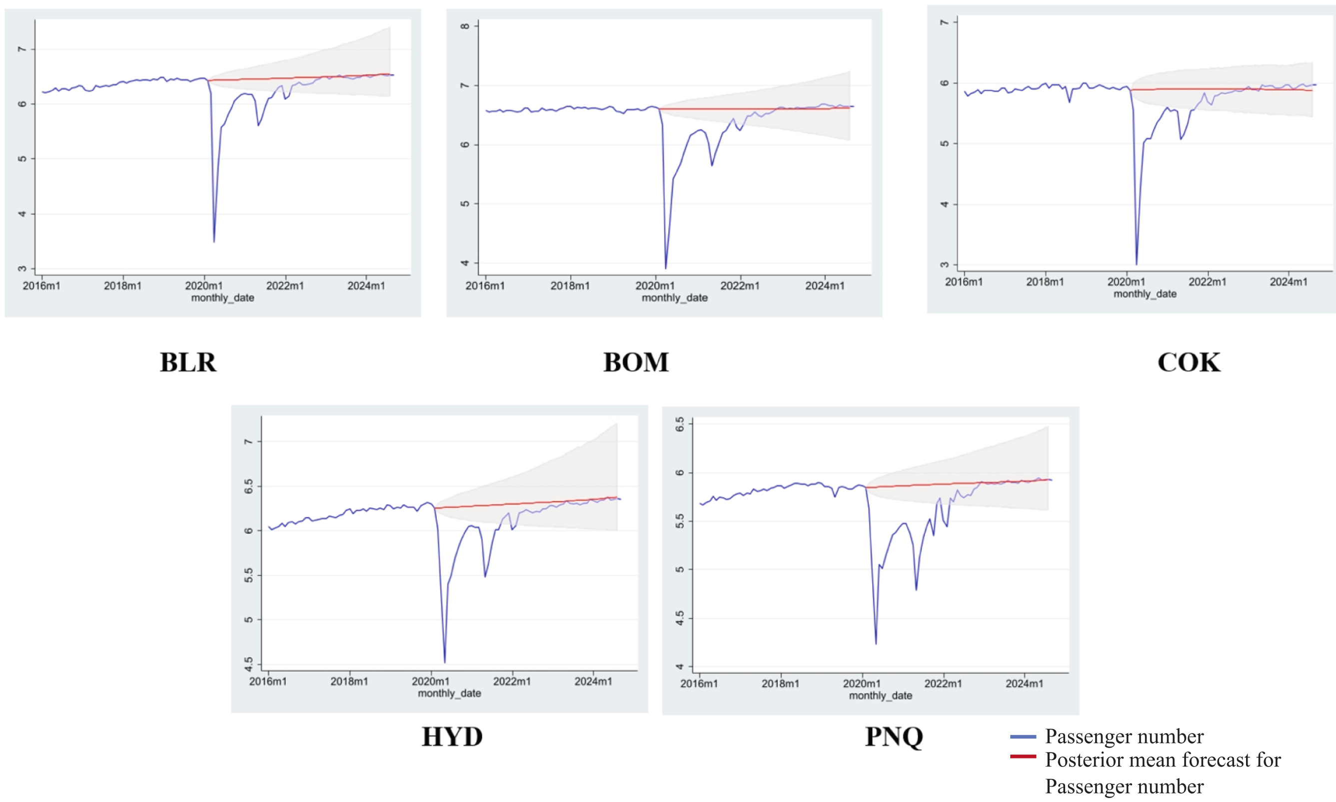

Fig. 2. The resilience growth-based PAX airports.

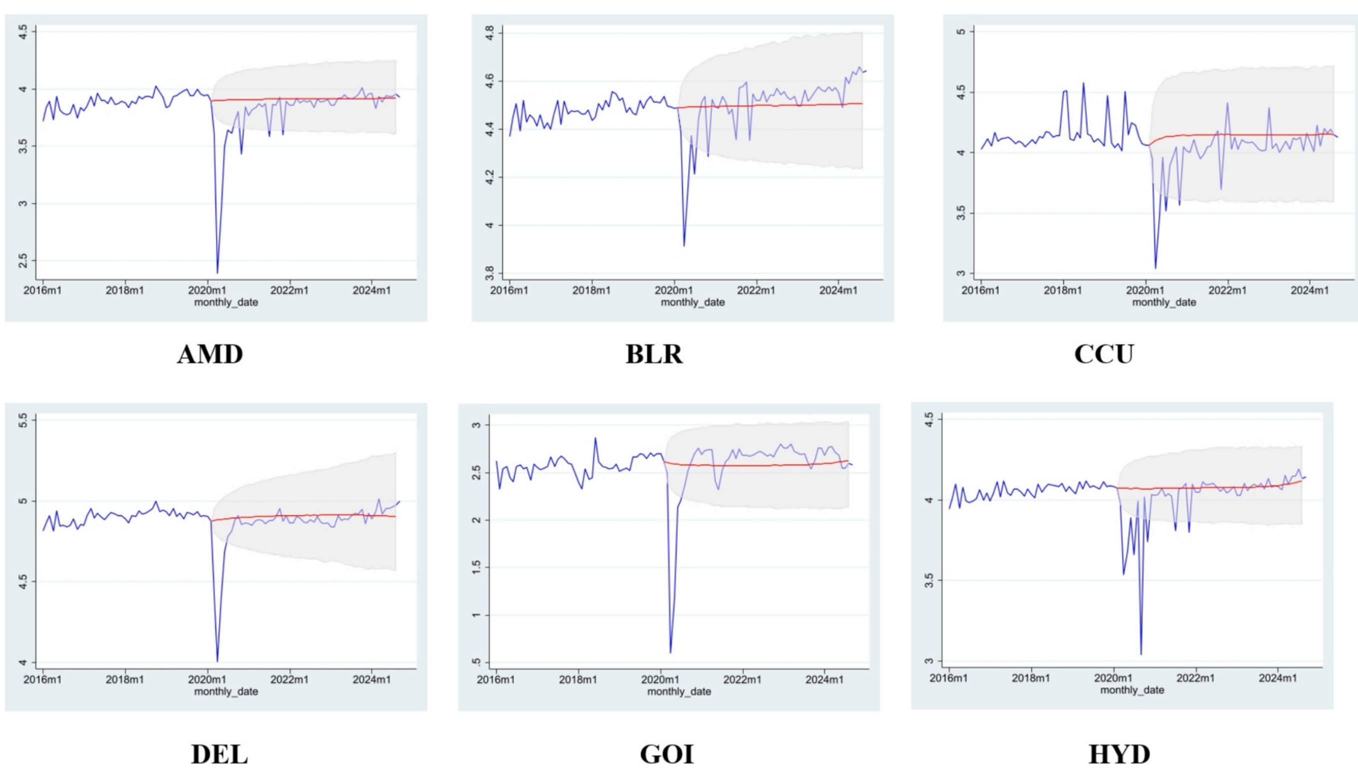

Fig. 3. The resilience growth-based Cargo airports.

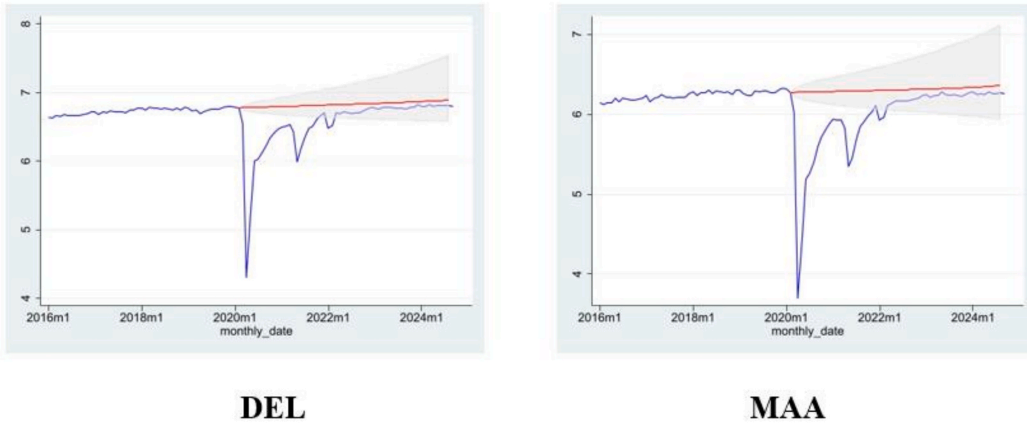

Fig. 4. Passenger airports with moderate recovery.

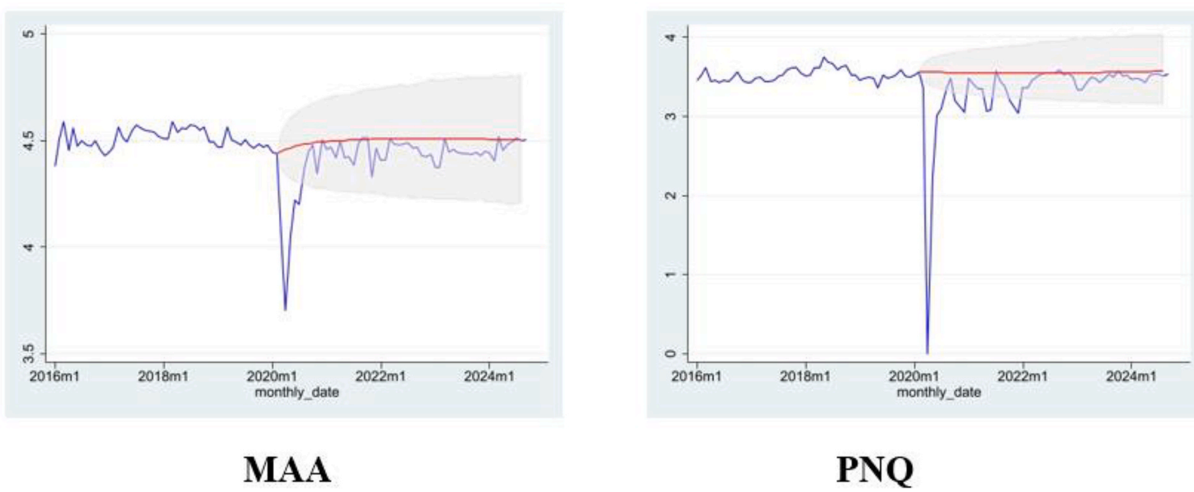

Fig. 5. Cargo airports with moderate recovery.

imposed strict lockdowns, further disrupting aviation activities. In response, national initiatives such as the *Vande Bharat Mission*[4] played a pivotal role in sustaining connectivity. By October 2021, over 217,000 flights under this mission facilitated the movement of more than 18.3 million passengers, maintaining momentum in both passenger and cargo operations (PIB, 2021; Rajan and Batra, 2022). Although Indian air cargo volumes declined sharply in early 2020, recovery followed with the rise of e-commerce and increased exports of essential goods (Nath and Upadhyay, 2024). These cases provide indicative evidence that infrastructure readiness and coordinated policy responses may be associated with observed airport resilience, supporting timely recovery amid evolving operational and public health challenges.

4.1.3. *Underperformers*

The airports that failed to meet expected recovery levels in passenger traffic include AHM, GOI, and CCU, while in cargo operations, BOM and COK lagged behind (see Figs. 6 and 7). This underperformance may be associated with broader vulnerabilities in airport infrastructure and network resilience. As Lordan et al. (2014) highlighted, disruptions in air transport networks (ATNs) can critically affect connectivity, and recovery is often uneven across nodes. GOI's sharp decline illustrates the disproportionate impact on tourism-dependent airports. With limited capacity to adapt to fluctuating demand and a high reliance on leisure travel, its operations show patterns consistent with greater disruption, as observed in prior studies. Dube et al. (2021) emphasised that the pandemic had a particularly acute effect on such airports, leading to significantly lower-than-expected performance levels. Similar recovery challenges were evident at AHM and CCU, where infrastructure constraints and weak demand likely inhibited adaptive responses. In the cargo sector, BOM and COK faced operational setbacks during the pandemic. Jackson et al. (2021) noted that India's temporary suspension of vaccine exports in March 2021, along with region-specific lockdowns (Theerthaana and Arun, 2021), further suppressed throughput. Although air cargo gained strategic importance amid restrictions on passenger flights, Nath and Upadhyay (2024) argued that capacity bottlenecks, regulatory delays, and infrastructure inefficiencies severely appears to limit responsiveness. These findings underscore the critical need for contingency planning and targeted investment to strengthen airport resilience across both passenger and cargo operations. These findings provide indicative evidence of the potential value of contingency planning and targeted investment in supporting airport resilience across both passenger and cargo operations.

Table 4 presents a classification of airport resilience outcomes, grouping airports into outperformers, forecast achievers, and underperformers based on their passenger and cargo performance. The results

[4] As a response to the COVID-19 pandemic, the government of India initiated Operation Vande Bharat, a large-scale repatriation program designed to return stranded Indian nationals to their homeland.

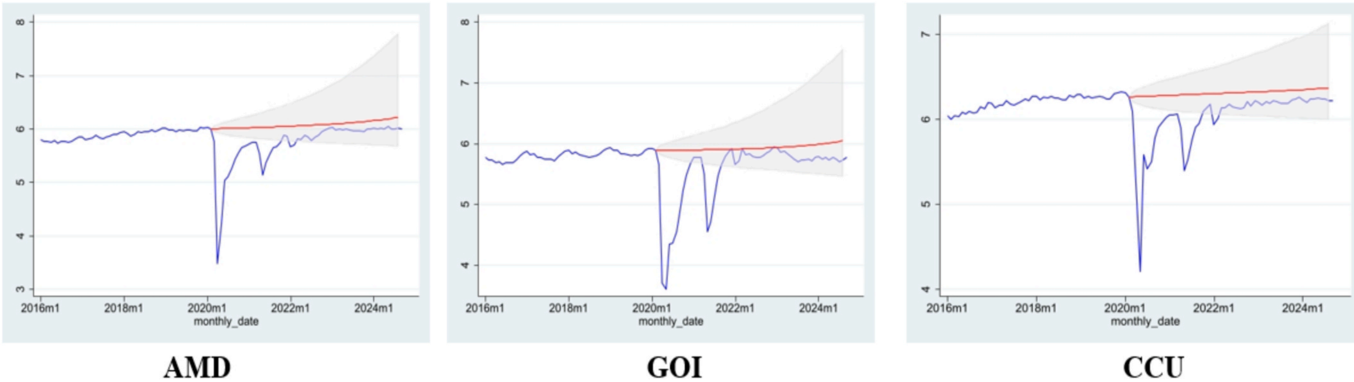

Fig. 6. Airports with lagged recovery in PAX handling.

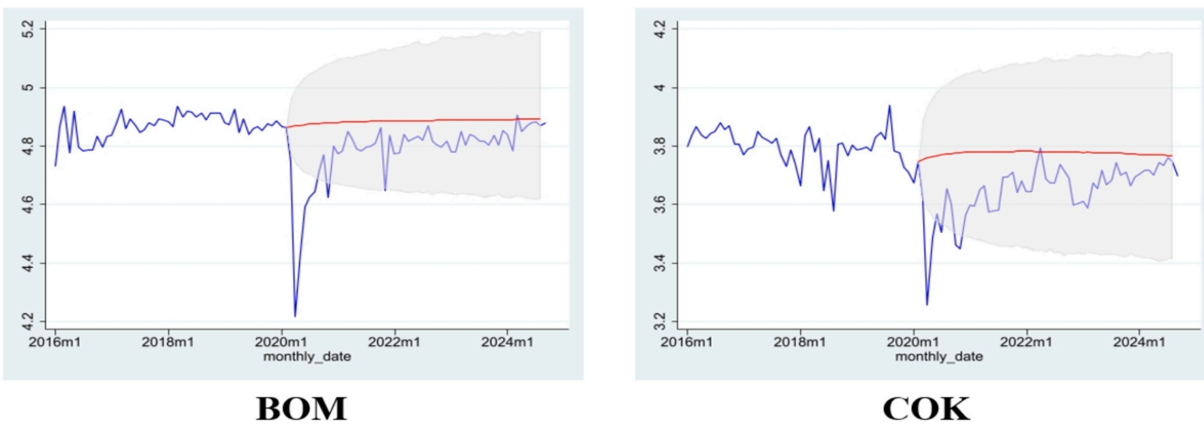

Fig. 7. Airports with lagged recovery in Cargo handling.

Table 4
Summary of airport performance in passenger and cargo resilience.

Category	Airports (Passenger performance)	Airports (Cargo performance)
Outperformers	Kempegowda International Airport, Bengaluru Rajiv Gandhi International Airport, Hyderabad Cochin International Airport, Kochi Chhatrapati Shivaji Maharaj International Airport, Mumbai Pune International Airport, Pune	Sardar Vallabhbhai Patel International Airport, Ahmedabad Kempegowda International Airport, Bengaluru Indira Gandhi International Airport, Delhi Dabolim International Airport, Goa Rajiv Gandhi International Airport, Hyderabad Netaji Subhas Chandra Bose International Airport, Kolkata
Forecast achievers	Chennai International Airport, Chennai Indira Gandhi International Airport, Delhi	Chennai International Airport, Chennai Pune International Airport, Pune
Underperformers	Dabolim International Airport, Goa Netaji Subhas Chandra Bose International Airport, Kolkata Sardar Vallabhbhai Patel International Airport, Ahmedabad	Cochin International Airport, Kochi Chhatrapati Shivaji Maharaj International Airport, Mumbai

Table 5
Spearman correlation matric of airport resilience and infrastructure details.

Variables	PAX_res	CARGO_res
PAX_res	1	
CARGO_res	−0.537***	1
Runways	0.087**	0.228***
Terminals	0.041	−0.345***
Cargo_Terminals	0.364***	0.169***
Metrorail_connectivity	−0.128***	−0.267***

Remarks: *** and ** indicate statistical significance with p-values of ≤ 0.01 and ≤ 0.05, respectively.

highlight the observed association between infrastructure and recovery trajectories. Airports with limited capacity, operational inefficiencies, or outdated facilities tended to lag behind in recovery, suggesting a potential benefit from targeted infrastructure upgrades in supporting resilience against future disruptions.

4.2. Infrastructure–resilience relationship: Spearman correlation approach

To examine the association between airport infrastructure and resilience, a Spearman rank correlation analysis was conducted. As a nonparametric measure, Spearman's correlation is suitable for assessing the strength and direction of monotonic relationships without assuming linearity or normal distribution (Hauke and Kossowski, 2011). This is particularly appropriate given that key variables-such as infrastructure characteristics and resilience indicators-are unlikely to follow a normal distribution (Bishara and Hittner, 2012).

The results, summarised in Table 5, reveal statistically meaningful correlations between infrastructure attributes and both passenger and cargo resilience. Passenger resilience (*PAX_res*) is defined as the airport's capacity to restore passenger traffic following disruption, measured by deviations from forecasted or pre-pandemic volumes. Cargo resilience (*CARGO_res*) similarly captures the extent to which cargo operations return to expected levels post-disruption. Infrastructure variables considered include the number of runways (*Runways*), terminal facilities (*Terminals*, incorporating both domestic and international terminals), cargo terminals (*Cargo_Terminals*), and rail connectivity (*Metrorail_connectivity*). These elements collectively inform the airport's overall resilience, as reflected in the strength of observed correlations.

The Spearman correlation matrix reveals several notable associations between airport infrastructure variables and resilience indicators for both passenger (*PAX_res*) and cargo (*CARGO_res*) operations. A negative correlation between *PAX_res* and CARGO_res suggests a potential trade-off in resilience between these two operational domains across the sampled airports. Among the infrastructure variables, *Runways* demonstrates a consistent positive relationship with both *PAX_res* and *CARGO_res*, showing that increased runway capacity is positively associated with observed patterns of resilience, particularly in supporting cargo operations. In contrast, *Terminals* shows no meaningful association with *PAX_res* and is negatively correlated with *CARGO_res*. This may indicate that terminal expansion, while beneficial for passenger services, does not necessarily enhance cargo resilience. The presence of dedicated cargo terminals (*Cargo_Terminals*) is positively associated with both forms of resilience, providing indicative evidence that specialised infrastructure may be associated with more stable operational continuity during disruptions. Interestingly, *Metrorail_connectivity* exhibits a negative relationship with both *PAX_res* and *CARGO_res*. This finding may reflect underlying operational complexities or capacity constraints that emerge when airports are highly integrated into metropolitan transport networks. Overall, these results highlight differentiated associations between infrastructure components and observed airport resilience patterns, suggesting potential value in strategic investments, particularly in cargo-specific infrastructure, to support robustness across both passenger and freight functions.

Overall, these results highlight differentiated associations between infrastructure components and observed airport resilience patterns, suggesting potential value in strategic investments, particularly in cargo-specific infrastructure, to support robustness across both passenger and freight functions.

4.3. *Comparing OLS and OLOGIT approaches to airport infrastructure resilience*

The observed differences in sign and statistical significance between the Spearman correlation and OLOGIT results reflect the distinct analytical purposes of the two methods rather than model inconsistency. Spearman correlation captures unconditional, pairwise monotonic associations between infrastructure characteristics and resilience indicators, without accounting for interactions or confounding effects. In contrast, the OLOGIT model estimates conditional relationships, explicitly modelling the probability of airports transitioning across ordered resilience categories while controlling for multiple infrastructure attributes simultaneously. As a result, certain infrastructure variables may exhibit differing signs once operational complexity, congestion effects, and threshold dynamics are taken into account.

As outlined in Equations (3) and (4) for the OLS model, and in Equations (5) and (6) for the OLOGIT model, the dependent variables *PAX_res* and *CARGO_res* are structured as ordinal indicators of resilience (i.e., Outperformers, Forecast Achievers, and Underperformers). This ordinal nature necessitates the use of the OLOGIT model. OLS relies on the assumption that the dependent variable is continuous and normally distributed. However, this assumption does not hold when analysing ordinal categories, rendering OLS less appropriate for this context. In contrast, the OLOGIT model is specifically designed to handle ordered categorical outcomes. It estimates the log-odds of an observation falling into a higher resilience category, while incorporating threshold effects across categories. This enables more robust and interpretable results, especially in studies involving categorical hierarchies.

Table 6
Comparison of OLS and OLOGIT estimates for airport resilience outcomes.

	OLS		OLOGIT	
	PAX_res	**CARGO_res**	**PAX_res**	**CARGO_res**
Runways	−0.427***	0.977***	−1.701***	–-
	(0.043)	(0.024)	(0.142)	
Terminals	0.323***	−1.024***	0.317**	−1.551***
	(0.057)	(0.032)	(0.153)	(0.154)
Cargo_Terminals	0.700***	−0.305***	3.398***	1.408***
	(0.04)	(0.022)	(0.279)	(0.154)
Metrorail_connectivity	0.249***	−0.982***	0.653***	−1.140***
	(0.044)	(0.025)	(0.120)	(0.107)
Constant (_cons)	0.260**	2.854***	–-	–-
	(0.124)	(0.069)		

Remarks: Statistical significance is denoted by ***, **, and * representing p-values of ≤ 0.01, ≤ 0.05, and ≤ 0.1, respectively.

Table 6 presents a side-by-side comparison of the OLS and OLOGIT estimates using pooled cross-sectional data, clearly illustrating the superior fit and methodological suitability of the OLOGIT model for analysing ordinal outcomes such as *PAX_res* and *CARGO_res*. Note that we could not apply a panel analysis using OLS/OLOGIT due to the insufficient variation issue (i.e., independent variables such as number of runways does not change much over time), so that they all got omitted from the estimations.

The OLOGIT model reveals several nuanced relationships between infrastructure variables and airport resilience. Notably, *Runways* shows a statistically significant negative association with *PAX_res*. This counterintuitive result may suggest that airports with more runways experience operational complexity that can slow the recovery of passenger services following a disruption. For *CARGO_res*, *Runways* was excluded from the final model due to non-convergence, possibly indicating that runway availability does not meaningfully differentiate cargo resilience or may be collinear with other infrastructure indicators. Further research, incorporating larger datasets, is warranted to clarify this relationship. The presence of dedicated *Cargo_Terminals* is positively associated with both *PAX_res* and *CARGO_res*. This finding provides indicative evidence that integrated cargo infrastructure may support more stable operations, including in predominantly passenger-oriented settings. *Metrorail_connectivity* exhibits a divergent pattern: it is positively associated with *PAX_res* but negatively related to *CARGO_res*. This may reflect the association of metro access with improved passenger flow and accessibility, while also being linked to potential constraints on cargo movement due to spatial or regulatory challenges in dense urban environments. The variable *Terminals* also presents contrasting associations, contributing positively to *PAX_res*, possibly due to expanded passenger processing capacity, yet showing a negative association with *CARGO_res*, which could indicate a design and investment emphasis on passenger services that may limit efficient cargo handling.

Taken together, the OLOGIT[5] results, results, supported by the BVAR analysis, highlight that observed airport resilience patterns are

[5] Given that our sample is small, the empirical results presented in this study, while still highlight potential drivers of Indian airport resilience, should be interpreted as indicative rather than definitive causal proof. We look forward to future studies with more data to strengthen our findings.

associated with both internal infrastructure and integration with urban transport networks. The associations involving metro connectivity suggest that city-side accessibility may play a role in supporting operational robustness. Furthermore, airports with diversified revenue streams, including cargo operations, appear better able to withstand shocks primarily affecting passenger traffic, providing indicative evidence that operational diversification may be linked to resilience against sector-specific disruptions.

The main contribution of this study is empirical, supported by a novel methodological integration that advances airport–resilience analysis. First, OLOGIT results provide new insights into the mechanisms underlying airport resilience, showing that airports with stronger and more developed infrastructure tend to be associated with higher levels of resilience across both passenger and cargo operations. Second, although the study makes contributions across methodological, empirical, and policy domains, its primary contribution lies in the integrated approach it develops. The analysis begins by applying BVAR to generate airport–specific counterfactual forecasts for passenger and cargo flows, followed by a model–data gap assessment to classify resilience levels, and subsequently uses OLOGIT to examine the determinants of these resilience outcomes. This combined BVAR, gap analysis and OLOGIT framework, provides a cohesive and transferable method for identifying resilience patterns and their structural drivers, offering applicability beyond the Indian context.

To offer a coherent synthesis of the empirical findings, Table 7 presents an integrated summary of the main results together with their corresponding policy implications.

4.4. Robustness check: Sensitivity to alternative resilience definition

To assess the sensitivity of the resilience classifications to small deviations in the counterfactual forecasts, we estimated an additional LOGIT model using a binary resilience variable, where airports classified as outperformers were coded as 1 and all others as 0. The results, presented in Appendix A (Table A1), show coefficient signs, magnitudes, and significance levels that closely mirror the OLOGIT estimates reported in the main analysis. This similarity indicates that the determinants of airport resilience are robust to alternative operationalisations of the resilience variable and are not sensitive to minor changes in the classification thresholds.

5. Policy implications, conclusion and limitations

The COVID-19 pandemic significantly disrupted the global aviation sector, with widespread impacts documented by ICAO. India's air transport network similarly experienced substantial setbacks, including airport closures, operational halts, and lockdown-induced demand shocks. This study's analysis of passenger and cargo resilience at India's busiest airports underscores the importance of adaptive infrastructure and strategic planning in facilitating recovery.

Strengthening resilience requires an integrated approach that prioritises infrastructure modernisation, operational agility, and institutional coordination. Policymakers should develop dynamic contingency frameworks capable of responding to diverse disruptions-pandemics, natural disasters, and security incidents-through flexible resource allocation, scenario-based simulations, and enhanced communication protocols. Embedding lessons from recent crises into operational practices is essential for improving sectoral preparedness. Technological adoption is also critical. AI-driven analytics, real-time forecasting models, biometric check-in systems, and touchless technologies can enhance both efficiency and responsiveness (Amankwah-Amoah, 2021; Nath and Upadhyay, 2024; Sun et al., 2022). Yet, bureaucratic inertia hampers implementation. Streamlined regulatory processes and improved inter-agency coordination are necessary to accelerate digital transformation across the sector. Equally important is workforce development. Training programs tailored to crisis management – especially in tourism-focused and cargo-centric airports – are vital. The study's findings on declining cargo resilience reinforce the urgency of investing in modern logistics infrastructure, such as automated storage systems and multimodal freight connectivity. Targeted subsidies and public–private partnerships can incentivise investment in cargo-handling capabilities, thereby enhancing supply chain robustness during future disruptions.

Building on these general recommendations, the heterogeneous recovery patterns identified in the BVAR and OLOGIT analyses indicate that resilience strategies should be tailored to each airport's functional role. National hub airports such as DEL, BOM, BLR, and HYD require policies prioritising multimodal surface connectivity, cargo-handling modernisation, advanced surveillance technologies, and congestion-mitigating infrastructure, as disruptions at these large hubs propagate widely through the national aviation network. In contrast, regional and tourism-oriented airports such as GOI, PNQ, and COK benefit more from flexible scheduling, contingency planning for seasonal demand fluctuations, route diversification incentives, and targeted financial support during downturns, given their narrower revenue bases and higher exposure to leisure-driven demand. This distinction translates our Table 7 findings into actionable, differentiated policy guidance that strengthens the robustness of India's wider airport network.

Additionally, while ICAO's frameworks such as Council Aviation Recovery Task Force (CART) and Public Health Corridors (PHCs) offer a structured global response, their effectiveness is constrained by inconsistent national-level implementation (see ICAO, 2020, 2021; Tabares, 2021). In populous countries like India, stronger alignment between

Table 7
Summary of key empirical findings and their associated policy implications.

Main empirical finding	Evidence from analysis	Policy implication
Airports exhibit heterogeneous post-COVID recovery patterns	BVAR counterfactual forecasts classify airports into outperformers, forecast achievers, and underperformers for both PAX and cargo	Resilience policies should be differentiated rather than uniform, with targeted interventions based on airport-specific recovery profiles
Cargo operations display greater resilience than passenger traffic at several airports	Positive or smaller post-pandemic gaps in cargo volumes (e.g., BLR, DEL, GOI) compared to passenger traffic	Policymakers should prioritise cargo infrastructure and logistics capabilities as stabilising mechanisms during future disruptions
Dedicated cargo terminals are positively associated with resilience	Consistent positive association in Spearman correlations and OLOGIT estimates	Investment in specialised cargo facilities can enhance operational continuity and crisis resilience
Runway capacity and terminal infrastructure show mixed effects on resilience	Divergent signs across PAX and cargo models, particularly in OLOGIT results	Infrastructure expansion should consider operational complexity and congestion effects, not only capacity increases
Metro rail connectivity supports passenger resilience but not cargo recovery	Positive association with PAX resilience and negative association with cargo resilience in OLOGIT results	Urban transport integration should be complemented with dedicated freight access and logistics planning
Airports dependent on specific traffic segments or market structures show weaker recovery during systemic shocks	GOI (tourism-oriented) and CCU/AMD (distinct regional and market structures) underperform in the BVAR classification	Regional and tourism-focused airports require contingency planning and adaptive support mechanisms during crises

global standards and domestic aviation policies is essential. Comparative insights from similar aviation markets-such as China, Brazil, Indonesia, and the United States-could inform more locally relevant strategies for resilience and reform.

This study employs a BVAR model to assess resilience in terms of forecasted versus actual performance across India's ten busiest airports from 2016 to 2024. By comparing pre-pandemic expectations with post-pandemic outcomes, the analysis reveals varying degrees of recovery. Most airports demonstrated moderate to high resilience, with some achieving forecast levels rapidly. Based on performance, airports were categorised as outperformers, forecast achievers, and underperformers, offering a data-driven understanding of infrastructural adaptability. The findings highlight the central role of resilient airport infrastructure in enabling airlines to sustain operations and profitability during disruptions. Airports with robust facilities are better equipped to support both passenger and cargo flows, underpinning overall system stability. However, India's regional aviation ambitions are constrained by inadequate infrastructure at smaller and tier-2 airports. Addressing these gaps is critical for sustaining national connectivity and realising the objectives of initiatives like UDAN.

Although this study focuses on India's ten busiest airports, the integrated framework that combines BVAR-based counterfactual forecasting with OLOGIT modelling offers a scalable approach that can be applied to other emerging aviation markets with comparable data availability and infrastructure diversity. This methodological structure provides a transferable template for assessing airport-level resilience in broader developing-country contexts, enabling cross–market comparisons and supporting evidence–based policy design beyond the Indian case.

6. Empirical contributions

This study provides an evidence-based assessment of post-COVID-19 airport resilience using BVAR-derived counterfactual trajectories for passenger and cargo operations across India's ten busiest airports. Beyond documenting heterogeneous recovery patterns, the analysis distinguishes resilience outcomes across passenger and cargo segments and links observed deviations from forecasted baselines to specific airport-level infrastructure attributes. In particular, the presence of dedicated cargo terminals and variations in runway and terminal capacity are shown to be systematically associated with resilience classifications. These findings offer empirical clarity on how airport-specific infrastructural characteristics relate to differential recovery outcomes in the post-pandemic period.

7. Normative policy implications

Drawing on these empirical patterns, rather than extending the statistical analysis itself, the study synthesises key policy considerations for enhancing airport resilience. The results suggest that prioritising infrastructure investments, particularly in cargo-handling capacity and multimodal ground connectivity, may strengthen an airport's ability to absorb and adapt to systemic shocks. In parallel, institutional preparedness could be reinforced through clearer crisis-response protocols, targeted workforce training, and improved coordination among airport operators, public-health authorities, and civil aviation regulators. Policies supporting digitalisation, automated processing, and logistics optimisation may further enhance operational adaptability during future disruptions. These insights are intended to inform policymaking and should be interpreted as normative recommendations grounded in the empirical findings, rather than as causal conclusions.

Despite its contributions, this study has limitations. First, its focus on major airports may overlook the specific vulnerabilities and adaptive strategies of smaller regional facilities. The resilience mechanisms effective in larger hubs may not translate to under-resourced airports, limiting the generalisability of the findings. Relatedly, the relatively small number of airports and limited cross-sectional variation may affect the stability and precision of the OLOGIT coefficient estimates used to examine structural associations. As a result, these estimates should be interpreted as indicative rather than definitive, particularly when comparing marginal differences across resilience categories. Expanding the analysis to include a larger set of airports, longer time horizons, or cross-country panel data would allow future studies to strengthen statistical inference and improve generalisability. Second, the exclusive reliance on quantitative analysis-while appropriate for forecasting-misses qualitative nuances related to stakeholder perspectives and on-ground implementation challenges. Additionally, the study does not control for the economic resilience of host cities (e.g., tourism or GDP recovery), which may also influence airport resilience alongside infrastructure. Lastly, future studies could also extend our findings by applying different estimation methods such as deep learning (for resilience analysis) and panel data models (for regression analysis) when more data and variables are available.

Future research should adopt a mixed-methods approach, incorporating qualitative data such as stakeholder interviews to complement model-based findings. Comparative studies with emerging market airports could illuminate best practices in crisis management under similar regulatory and operational conditions. Examining the scalability of resilience strategies across diverse airport types would further enhance understanding of how infrastructure, policy, and practice interact in shaping aviation resilience.

CRediT authorship contribution statement

Ajai Jayathilakan: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Conceptualization. **Thanh Ngo:** Writing – review & editing, Visualization, Validation, Software, Methodology, Conceptualization. **Wai Hong Kan Tsui:** Writing – review & editing, Supervision. **Nives Botica Redmayne:** Writing – review & editing, Supervision. **Faruk Balli:** Writing – review & editing, Supervision. **Xiaowen Fu:** Writing – review & editing, Supervision.

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Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Dr. Xiaowen Fu, one of the authors' PhD supervisors, is the Editor-in-Chief of Case Studies on Transport Policy. Other than this relationship, the authors declare no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. LOGIT robustness check for alternative resilience definition

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Table A1
LOGIT estimates using alternative resilience indicators (*PAX_res* and *CAR_res*).

	LOGIT	
	PAX_res	CARGO_res
Runways	−1.989***	--
	(0.156)	
Terminals	0.797***	−2.284***
	(0.173)	(0.191)
Cargo_Terminals	3.144***	1.729***
	(0.292)	(0.178)
Metrorail_connectivity	0.550***	−1.127***
	(0.126)	(0.116)
Constant (_cons)	1.651***	4.514***
	(0.388)	(0.396)

Remarks: *** and ** indicate statistical significance with p-values of ≤ 0.01 and ≤ 0.05, respectively.

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