IATA Long-Term Air Transport Passenger Demand Projections

Executive Summary

The International Air Transport Association (IATA) has developed a new proprietary model to generate Long-Term Demand Projections (LTDP) for passenger air transport to 2050. The projection model utilizes the organization's industry-leading demand data at the most granular level, sourced from its Direct Data Solutions (DDS). The long-term projections are provided at the country, regional, region-pair, and global levels and aim to serve as a critical source of information for aviation stakeholders, policymakers, investors, and the international air transport community in their long-term strategic planning and decision-making.

Aiming to provide transparent and rigorous projections of the industry's Revenue Passenger Kilometers (RPK), we present in this report the compiled dataset, the econometric modeling approach, and the estimation results used for the long-term RPK projections. Experts in this field from ten leading organizations were invited to provide peer reviews of the model. Their feedback has contributed significantly to the quality of both the model and the report. The organizations that contributed to the peer review process are: the World Bank, the International Energy Agency (IEA), Airbus, Boeing, Airlines for America (A4A), the Latin American and Caribbean Air Transport Association (ALTA), University College London (UCL), the University of St. Gallen, the International Council on Clean Transportation (ICCT), and China Civil Aviation University. We thank them for their invaluable contribution to this work.

All models can only produce estimates of a future that remains inherently uncertain. The reliability of the projections generated by the IATA LTDP is high, as demonstrated by a mere 2.2% difference between projected and historical RPKs at the industry level and a 3.5% difference at the regional level. This strong validation performance is underpinned by a uniquely rich empirical foundation and a robust modelling framework. The LTDP is based on a comprehensive origin–destination country-pair dataset covering over 570,000 observations across nearly 41,000 directional country pairs over the period 2011–2024. The dataset integrates observed passenger demand, fares, network supply characteristics, and macro-economic indicators sourced from IATA and other authoritative external datasets.

The rich empirical data enable the model to capture structural demand drivers accurately and to be calibrated using a state-of-the-art Poisson Pseudo Maximum Likelihood estimator with Instrumental Variable (PPML-IV)[1] designed for large-scale transport demand analysis, providing a solid and credible basis for long-term demand projections. A distinctive feature of the LTDP modeling framework is the explicit treatment of supply–demand interactions: air transport supply is modeled separately and enters the demand equation as a control variable, ensuring that long-term RPK projections reflect realistic capacity constraints rather than being driven solely by demand-side factors.

The LTDP incorporates three growth scenarios, i.e., high, mid, and low, that are driven by long-term economic growth, population growth, global aviation fuel price trends, and air transport supply-side capacity development. The scenarios are linked to the global energy transition via the long-term economic projections, thereby putting our long-term RPK projections in the context of the airline industry's transition toward net zero carbon emissions by 2050. The long-term economic projections are obtained from the publicly available global long-run economic scenarios from the Organisation for Economic Co-operation and Development (OECD).[2]

In the high-growth scenario, the industry RPK is projected to reach 21.9 trillion in 2050 from the 9 trillion seen in 2024, with a Compound Annual Growth Rate (CAGR) of 3.3% from 2024 to 2050. Under this scenario, we expect

[1] Silva J, and Tenreyro S., 2006. The Log of Gravity. *The Review of Economics and Statistics*, 88 (4): 641-658.
[2] OECD (2025), "OECD global long-run economic scenarios: 2025 update", *OECD Economic Policy Papers*, No. 36, OECD Publishing, Paris

global economic expansion to be driven by high labor efficiency, robust capital stock growth, and rapid technological progress. Price for aviation fuel is assumed to decline over time, and countries are expected to actively invest in building new airports to address the capacity constraints faced by the airline industry. However, this scenario reflects a “business-as-usual” trajectory where decarbonisation merely maintains its historical pace (at zero mitigation cost), falling short of the Paris Agreement’s net zero targets. The airline industry is assumed to remain almost entirely dependent on fossil fuels through 2050, and the carbon-based sources still comprise three-quarters of the global primary energy mix by mid-century.

While the 'business-as-usual' scenario suggests stronger GDP growth through 2050 by avoiding immediate transition costs, this path commits the economy to global warming beyond 2°C. Consequently, the second half of the century faces escalating climate damage, potentially reaching 9% of global GDP by 2100. This would likely outweigh any economic gains pre-2050, leaving sectors such as air transport to bear the brunt of a significantly weakened global economy in the post-2050 era.

The mid-growth scenario projects the global total RPK to increase to 20.8 trillion in 2050, with a CAGR of 3.1% over 2024-2050. This scenario assumes a smooth energy transition that would achieve the climate goals set by the Paris Agreement. The successful transition would come at the price of carbon abatement costs, which would weigh on global economic growth during the transition phase to 2050. However, the economic consequences of the transition will turn net positive globally around 2085, thanks to the longer-run benefits of avoided climate damage, with the global warming limited to 1.6 °C in 2100. In this scenario, the average aviation fuel price will be higher compared to “business-as-usual” due to the use of sustainable aviation fuels (SAF). The supply of SAF would follow the scaling-up pace as estimated in the IATA Net Zero Roadmaps. The cost of the transition would mean lower investment in aviation infrastructure. Global airport capacity would still increase, albeit at a slower rate.

Our low-growth scenario projects industry total RPK to increase to 19.5 trillion by 2050, with a CAGR of 2.9%. In this scenario, we assume that the world will still achieve the climate goals set by the Paris Agreement, but with a bumpier energy transition journey than in the mid-growth scenario. Slow progress in reducing carbon emissions in the early years of the transition means that carbon abatement costs will remain high for a much longer period, and more aggressive, disruptive change will be required in later years to achieve the same climate goals. This more disorderly transition scenario would result in a higher price of SAF and in slower economic growth than under a smooth transition. Therefore, countries would invest less in new airport infrastructure, and growth in demand for air travel would be more capacity constrained.

The regional projections highlight the impressive growth potential of all regions through 2050. We expect Asia Pacific, Africa, and the Middle East to be the main engines of growth. Asia Pacific is projected to have the strongest growth across all regions, with a CAGR of 3.9% in the high-growth scenario, 3.8% in the mid-growth scenario, and 3.5% in the low-growth scenario. Africa is ranked a close second, with CAGRs between 3.2% and 3.9% across the three scenarios. The Middle East is the third fastest-growing O-D regional market in our projections, with a CAGR of 3.5% in the high-growth scenario, 3.1% in the mid-growth scenario, and 2.5% in the low-growth scenario (as our model provides O-D traffic estimates, it tends to project lower growth for the Middle East than models accounting for transfer traffic or connectivity.) Asia Pacific, Europe, and North America are expected to remain the world’s three largest markets in 2050 in terms of absolute RPK levels.

RPKs between regional pairs are projected to grow fastest for intra-African (4.4%-5.2% CAGRs across the three scenarios), Africa-Asia Pacific (4.1%-4.7% CAGRs), and intra-Asia Pacific (3.6%-4.1% CAGR) routes. This reflects the strong economic growth potential of these markets, driven by their economic links, population size, and momentum in passenger flows. In comparison, the developed markets such as intra-Europe and Europe-North America are projected to have CAGRs at the lower end of the spectrum, at 2.0%-2.5%, with a slight exception for the intra-North America market at 2.6%-2.9%, due to stronger economic growth projections for the region.

It should be noted that countries that actively pursue exceptional aviation growth through policy-led economic diversification, large-scale tourism initiatives, and infrastructure investments may achieve higher RPK expansion than what is projected in this model. These drivers lie beyond purely macro-economic demand fundamentals and, in the absence of adequate data, cannot be fully captured in our current modeling framework.

The IATA LTDP shows continued long-term expansion in global air travel demand through 2050, and a stable growth trajectory. While the projected global RPK growth rates of 2.9%-3.3% per year between 2024 and 2050 are lower compared to the earlier periods, this moderation largely reflects the base effects from current larger traffic volumes rather than a weakening of demand fundamentals. As markets mature, air transport transitions from rapid expansion to more stable growth. Crucially, our long-term RPK projections demonstrate that the growth momentum remains intact in absolute terms. Even at a lower percentage rate, the projected trajectory implies substantial additions to global RPK volumes. In this sense, the post-2024 growth path represents continuity rather than slowdown, and demand continues to expand steadily under all three growth scenarios.

The covid pandemic has permanently altered the trajectory of global air travel demand. Prior to 2019, global RPK closely tracked real PPP[3]-adjusted GDP for nearly three decades, reflecting a stable long-run relationship between economic growth and air travel. The pandemic caused an unprecedented collapse in demand, creating a structural gap that is not expected to close in any of our post-2024 recovery scenario. Even under high-growth assumptions, the projected RPK growth through 2050 remains insufficient to converge with the pre-covid GDP-aligned trend, illustrating the long-lasting scarring effect of the pandemic.

[3]PPP = Purchasing Power Parity, the exchange rates that equalise the purchasing power of different currencies by eliminating differences in price levels between countries.

Introduction

The International Air Transport Association (IATA) has long been known as a data hub for the global airline industry, benefiting from valuable partnerships with its 370 airline members in over 120 countries. The organization provides data and statistics on passenger and cargo air transport demand to the public every month, which have proven to be the most trusted source for aviation stakeholders to track the industry's traffic movements. IATA's more granular global traffic data, at the airport level, is housed its Direct Data Solutions (DDS). The coverage and accuracy of the DDS data on air transport passenger demand, both in terms of enplaned passenger numbers and revenue passenger kilometers (RPK), in addition to airfares and airlines' operation networks, are second to none.

Backed by extensive and high-quality data available to the organization, IATA is well-positioned to develop data-driven econometric models that produce long-term projections for air transport passenger demand. Such models are not only essential for estimating the airline industry's long-term growth but also provide a foundation for modeling the possible pathways for the industry to reach net zero carbon emissions by 2050, a mission that is critical to the industry's sustainable development.

This report presents a comprehensive discussion of the IATA Long-Term Demand Projections (LTDP) model of global passenger air transport. The report consists of two parts. The first part describes the output of the LTDP, i.e., the projected air passenger demand measured by Revenue Passenger Kilometers (RPK) from 2025 to 2050 at regional and global levels, under our high-, mid-, and low-growth scenarios linked to the global energy transition. The second part provides a detailed technical discussion of the data sets compiled for the model, the econometric modeling framework, the estimation methodology and outcomes, and the validation results of the model's predictive performance.

Part 1: Scenarios and long-term projection outcomes

Different types of models are used for answering different types of questions or different facets of the same question. Seemingly simple questions, such as "Will global air transport demand continue to grow from now on to 2050, and by how much?", can be approached by using various types of forecasting models, such as economic and econometric models, machine learning models, and other statistical models. Inevitably, different forecasting methods tend to produce different forecasts, even when using the same set of input data. The same modeling methods will also tend to produce different forecasts if the data sets differ. To evaluate the reliability of the projections and forecasts produced by various models, three aspects are important:

(i) The predictive power of the model: how accurate the model's projected values are compared against the actual data, regardless of the methods used.

(ii) The interpretability of the model: what factors or variables are used in developing the model, and why these variables are selected for the projections.

(iii) The transparency in making projections and forecasts: what assumptions about the future are made in producing the projections, and why the assumptions are made in such a way.

In this report, we aim to discuss our model and long-term projections explicitly from the above three aspects so that the modeling approach and scenarios can be assessed by the wide aviation community when using the IATA LTDP for their long-term planning and decision-making.

1. Key demand drivers of the IATA long-term demand projection model

Air transport passenger demand is driven by countless factors. While it is impossible to include the totality of influences, we can draw on the existing literature which identifies some of the most critical drivers of air passenger demand using historical data. Based on this literature and data availability, the IATA Long-Term Demand Projection (LTDP) model comprises the following key demand drivers:[4]

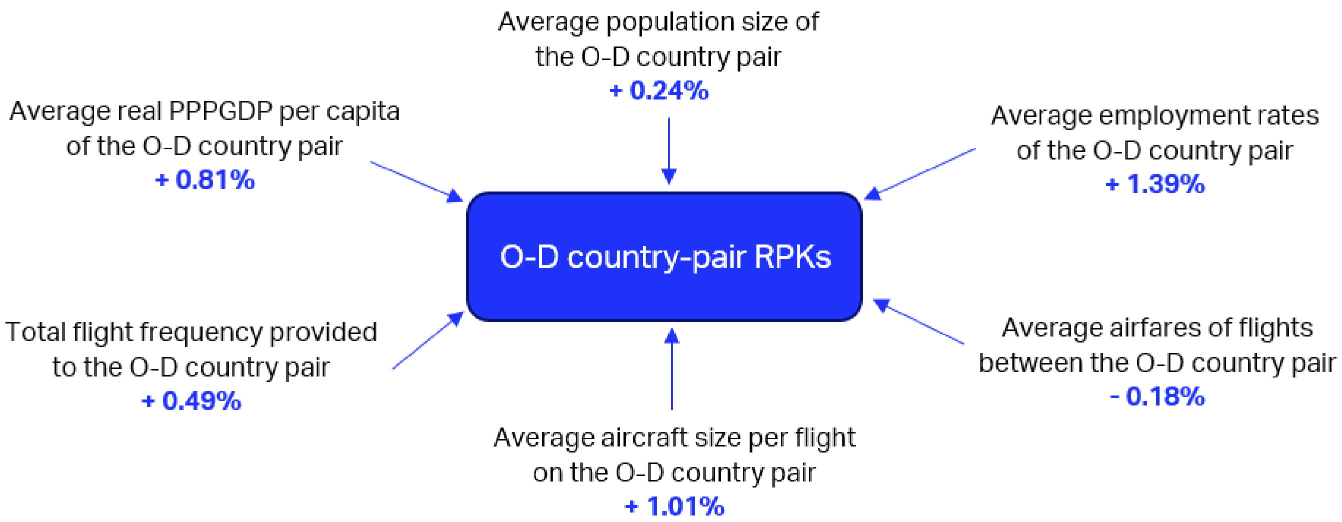
- Countries' total economic activity, measured by real Gross Domestic Product (GDP) based on Purchasing Power Parity (PPP) in 2021 US dollars
- Countries' total population
- Countries' real PPP GDP per capita, as a proxy of the average income level
- Countries' average employment rates
- The average ticket price of air travel between the countries of origin and destination, weighted by O-D passenger demand
- The "bottleneck" flight frequencies between the countries of origin and destination
- The average size of the aircraft operated between the countries of origin and destination

The LTDP model, based on origin-destination (O-D) country pair annual RPKs from 2011 to 2024 in the IATA Direct Data Solutions (DDS) database, is calibrated using a Poisson Pseudo Maximum Likelihood estimator with Instrumental Variables (PPML-IV). This econometric modeling approach produces coefficients that reflect how

[4] The considerations of selecting these demand drivers are discussed thoroughly in Part 2 of this report.

individual demand drivers affect air transport passenger demand from historical data. The estimated coefficients are then used for the long-term RPK projections. Chart 1 shows the estimated historical relationship between the selected demand drivers and RPK estimated by the PPML-IV model.

Chart 1: The estimated relationship between the selected demand drivers and RPK growth



Source: IATA Sustainability and Economics

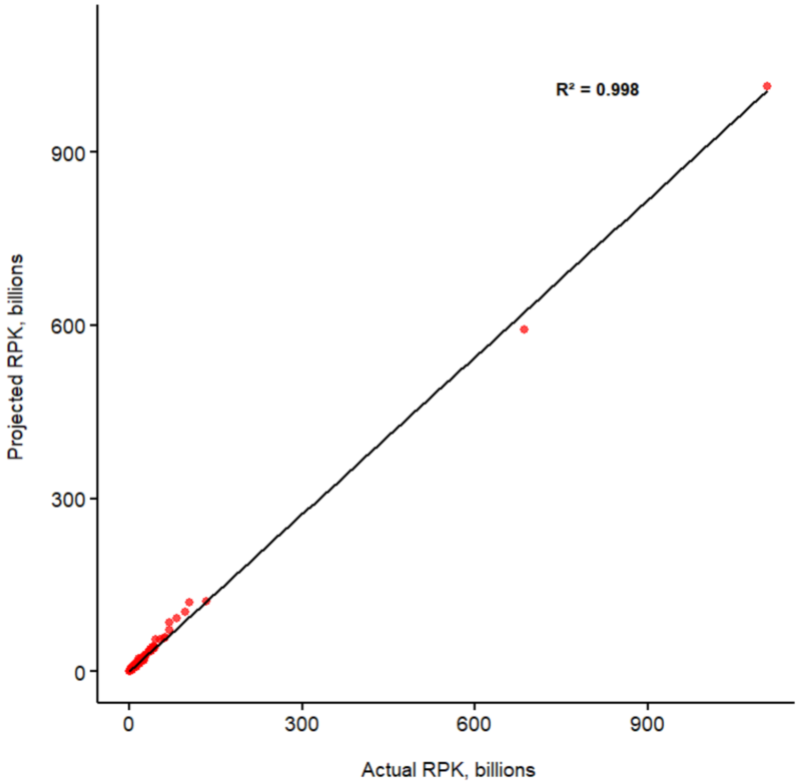
From Chart 1, it is evident that air transport passenger demand can be positively and negatively affected by various factors, and the final RPK levels achieved are a result of the complex dynamics among these factors. Increases in average PPP GDP per capita, population, employment rates, flight supply, and the average size of aircraft all contribute to RPK growth. Conversely, an increase in average airfares will have a negative impact on demand. The relationships shown in Chart 1 can be interpreted as the percentage increase or decrease in demand observed when demand driver X increases by one percent, all else equal. However, in reality, all these elements change simultaneously to different extents, and are interrelated. Assuming that changes in a single demand driver would lead to a particular RPK increase or decrease would be an over-simplification of likely real-world impacts.

For that reason, the RPK projections provided in this work are our “best guesses” regarding the possible future demand of the air transport industry, using the data-driven econometric models. All economic models are a reduced form of reality, and the estimated outcomes and forecasts are indeed estimates, subject to many assumptions that may or may not be valid in general or specifically.

2. Model performance evaluation

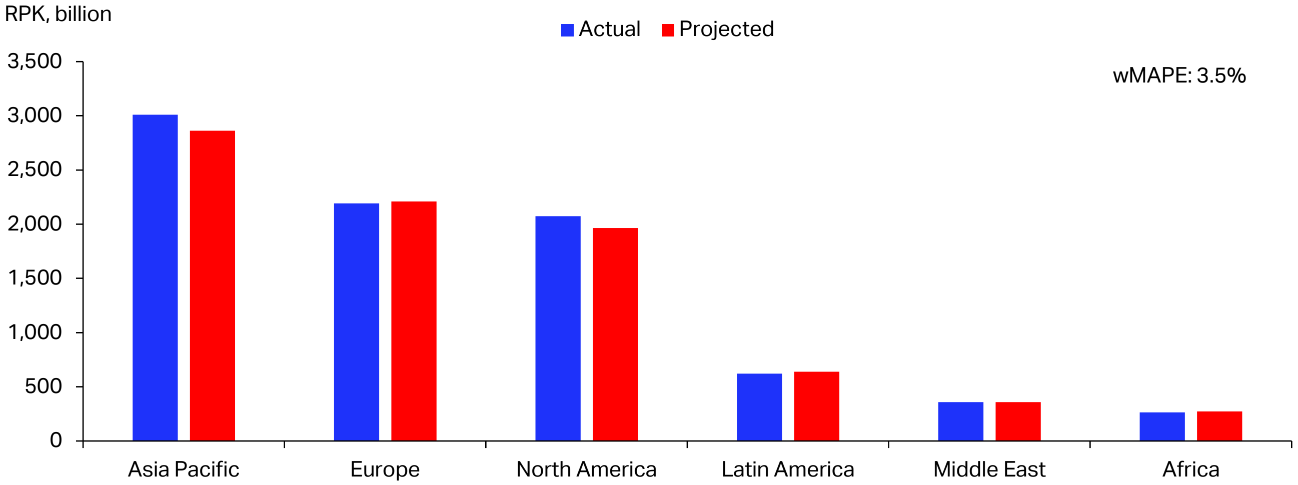
The performance of any projection model should be evaluated by comparing the projected values against the actual data, regardless of the methods used. The closer the predicted values are to the actual data, the greater the confidence one can have in the projections into the future, where no observed data is available. To evaluate the performance of the IATA LTDP, we conduct an out-of-sample (OOS) model validation. The OOS validation tests how stable and accurate the model projections are when applied to periods for which data has not been included in the modeling. Specifically, we use our final O-D panel dataset that excludes 2019 (i.e., 2011-2018/2020-2024) to “train” the model and use the estimated coefficients from the training to project O-D country pair RPKs in 2019. The projections are then compared against the actual RPKs in 2019. We select 2019 as it is the last “normal” year pre-covid. The assessment of how well our model projects 2019 RPKs provides valuable insights regarding its reliability for long-term future demand projections (see Part 2 for further details).

Chart 2: Out-of-sample model validation, actual versus projected RPK in 2019 at the country level, billion



Source: IATA Sustainability and Economics

Chart 3: Out-of-sample model validation, actual versus projected RPK by origin region in 2019, billion

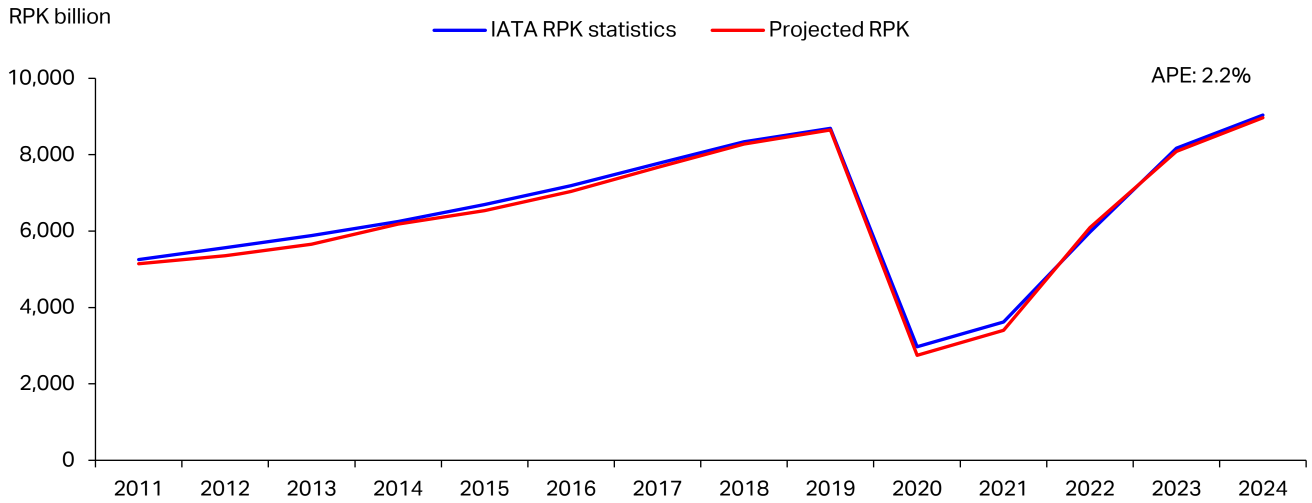


Source: IATA Sustainability and Economics

The scatter plot shown in Chart 2 compares the model-projected 2019 O-D RPKs against the actual observed RPKs at the country-pair level, based on our model estimation using a sample that excludes 2019. In total, there are 27,428 O-D country pairs in 2019, and each red point represents a bilateral O-D country-pair market. The 45-degree line indicates perfect prediction accuracy. As shown, most points lie very close to the diagonal, suggesting that the model replicates the scale and distribution of RPKs across country pairs with very small prediction errors. Overall, our model demonstrates excellent out-of-sample projection performance at the country-pair level. The R^2 of 0.998 indicates that the modeling approach captures nearly all of the cross-sectional variation in observed RPKs for 2019.

The projected RPKs are also very close to the actual values when aggregated to the region level, with a weighted mean absolute percentage error (wMAPE) of 3.5% (Chart 3).[5] This suggests that, without observing the data, the model can make projections for the future with a 3.5% error range around what the actual RPK levels are likely to be.

Chart 4: In-sample model validation for global total RPKs, 2011-2024, billion



Source: IATA Sustainability and Economics

The in-sample model validation (i.e., using all data from 2011 to 2024 as the training set to estimate the model and making projections for the same years), aggregated at the industry level, yields an even smaller average absolute percentage error (APE) of 2.2%[6] (Chart 4). For 2024, the percentage difference between the actual IATA RPK statistics and the projected RPK is merely 0.7%.

3. Future scenarios for the long-term RPK projections

The robust out-of-sample and in-sample model validation performances suggest that our model is able to produce reliable projections for future RPKs. The next step is to prepare projections for the demand drivers discussed previously, from either external sources or IATA's estimations. Of course, there is inherent uncertainty regarding how these drivers will evolve. To reflect this, we present three scenarios (high, mid, and low) for the industry's long-term demand growth. These scenarios reflect possible long-term developments of global economic and population growth, aviation fuel price trends, and air transport supply under various capacity-constraint settings. In particular, the long-term economic projections employed in this work, which are sourced from the OECD,[2] capture the impact of the global energy transition on GDP growth, thereby putting our long-term RPK projections in the context of the airline industry's transition toward net zero carbon emissions by 2050.

GDP growth scenarios

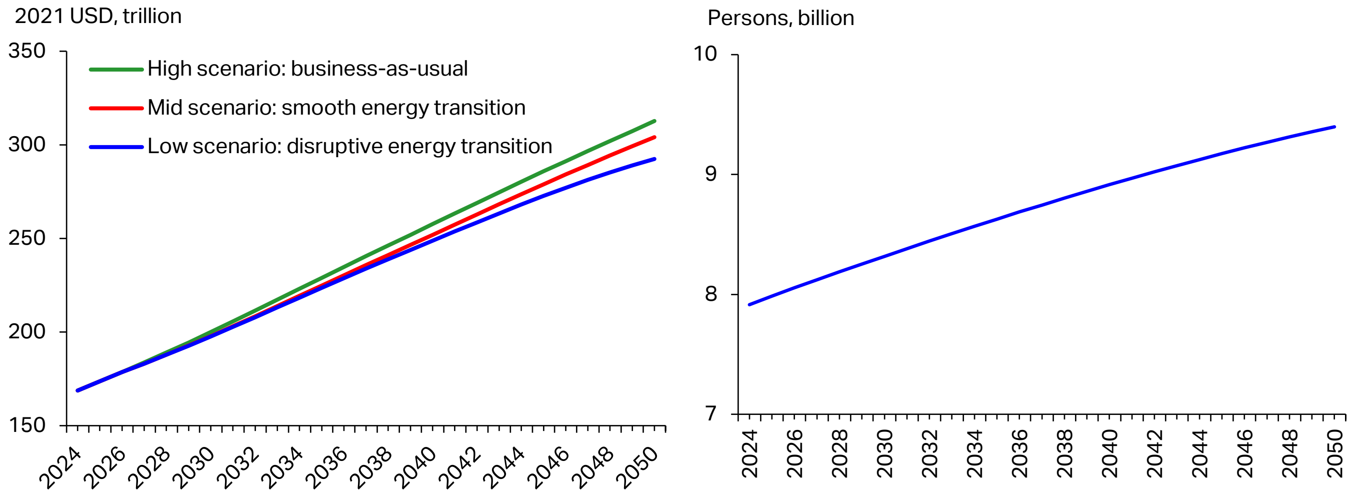
Economic growth is arguably the most important driver of air transport demand. GDP growth generates higher household incomes, and air transport demand tends to rise in tandem. Our primary source of global and

[5] Weighted mean absolute percentage error (wMAPE) is a commonly used metric to measure the accuracy of a model's predictions. In our case, it calculates the overall average error magnitude as a percentage of the total RPK by region, giving greater importance (weight) to regions with larger air travel demand.
[6] We use wMAPE as the evaluation metric for the country-pair validation as it puts more weight on the prediction accuracy on the country pairs with heavy traffic, while for the industry aggregated level, every year has equal weight, so the simple APE is used instead.

country-specific PPP GDP forecasts for the near term (2025-2030) is the latest edition of the World Economic Outlook (WEO)[7] produced by the International Monetary Fund (IMF).[8] For years beyond the IMF's forecast horizon, i.e., 2031-2050, we utilize the long-term economic projections from the OECD's growth scenarios as discussed above.[9] Notably, both sources provide real PPP GDP in 2021 US dollars, ensuring consistency between the near- and long-term PPP GDP projections.

Global real PPP GDP is projected to increase from USD 168.8 trillion in 2024 to USD 312.7 trillion in 2050 under the high-growth scenario, USD 304.1 trillion under the mid-growth scenario, and USD 292.5 trillion under the low-growth scenario, respectively (Chart 5, left). This is equivalent to Compound Annual Growth Rates (CAGRs) of 2.3% (high), 2.2% (mid), and 2.1% (low) over the period 2024-2050.

Chart 5: Global real PPP GDP scenarios, 2021 USD, trillion (left), and world population projection, billion, used in this work (right)



Source: IATA Sustainability and Economics; OECD

The high-GDP growth scenario envisions global economic expansion driven by high labor efficiency, robust capital stock growth, and rapid technological progress (Table 1).[10] However, this scenario reflects a "business-as-usual" trajectory where decarbonisation merely maintains its historical pace (at zero mitigation cost), falling short of the Paris Agreement's net zero targets. Under these conditions, the airline industry will remain almost entirely dependent on fossil fuels through 2050, with carbon-based sources still comprising three-quarters of the global primary energy mix by mid-century. Consequently, this insufficient decarbonisation would result in global warming beyond 2 °C and trigger escalating physical climate damage and significant economic losses, potentially reaching 9% of global GDP by 2100. This would likely outweigh any early-stage gains, leaving sectors like air transport to bear the brunt of a significantly weakened global economy in the post-2050 era.

[7] The IMF WEO is one of the most widely used and trusted sources of global macro-economic forecasts, including GDP and population. The IMF publishes the WEO twice a year, with updates in between.
[8] We use GDP and population projections from two sources (i.e., IMF and OECD) because the IMF WEO only provides near-term forecasts for the next five years. Using IMF data ensures frequently updated, granular insights for the short-term outlook. By using the single GDP forecasts from the IMF for the near term, we assume no significant divergence in economic growth across the net zero transition paths until 2030, as early-stage transition impacts on air travel are expected to be minimal. Under this approach, aviation fuel price evolution is the primary driver of our scenarios through 2030, after which the distinct economic costs and benefits of the long-term transition scenarios from the OECD take effect.
[9] The OECD provides long-term projections for 49 countries and all the world regions. The 49 economies accounted for around 80.5% of the global total PPP GDP in 2024. The remaining countries' projections are estimated from the projections of the region in which a given country is located and its PPP share of the world's total in 2030, provided by the IMF WEO. A normalization procedure is performed to ensure that the sum of all countries' PPP GDP equals the global total PPP GDP provided by the OECD.
[10] For more details on the OECD long-run economic projections, see Appendix A.

Table 1: Key input factors that drive the three growth scenarios (2024-2050)

Changing factors	Source	Role in the scenarios	High	Mid	Low
Long-run economic projections					
Productive capital stock growth, CAGR	OECD	Capital input	2.5%	2.4%	2.3%
Trend average employment rate, CAGR	OECD	Labor input	0.2%	0.2%	0.2%
Growth in labor efficiency, CAGR	OECD	Labor input	1.9%	1.8%	1.7%
Global technological progress, CAGR	OECD	Labor input	1.0%	4.0%	1.0%
Climate damage in 2050	OECD	Higher climate damage → lower labor efficiency + lower capital accumulation → lower GDP growth	Medium	Medium	Medium
Carbon abatement costs in 2050	OECD	Higher carbon abatement cost → lower labor efficiency + lower capital accumulation → lower GDP growth	None	Low	High
Economic loss in 2100, % of GDP	OECD	Net effect of transition and climate damage, measured by global GDP	9%	Net benefit	Net benefit
Real PPP GDP (in 2021 USD), CAGR	IMF (2025-2030) OECD (2031-2050)	Economic projection output, a main demand driver	2.3%	2.2%	2.1%
Global population growth, CAGR	IMF (2025-2030) OECD (2031-2050)	Exogenous input, a main demand driver	0.6%	0.6%	0.6%
Aviation fuel price trends					
Share of SAF in air transport's energy demand in 2050	IATA Net Zero Roadmaps	Input in determining the average aviation fuel price	0%	87%	87%
Average minimum selling price of SAF in 2050 (USD per tonne)	IATA Net Zero Roadmaps	Input in determining the average aviation fuel price	n/a	1,947	3,246
Global average fuel price for air transport, CAGR	IATA Net Zero Roadmaps	Average aviation fuel price, weighted by the share of CAF and SAF in total aviation energy demand; a main determinant of air travel demand	-1.3%	2.3%	5.3%
Supply-side capacity growth					
Growth in countries' total number of active airports (CAGR)*	IATA projections	Main determinant of aviation supply; capturing infrastructure constraints	0.8%	0.4%	0.03%
Average aircraft size by O-D country pair	OAG, IATA DDS	Main determinant of aviation supply	Fixed as in 2024	Fixed as in 2024	Fixed as in 2024
Growth in O-D country-pair 'bottleneck' flight frequency	IATA projections	Output of the supply model; main determinant of air travel demand	2.8%	2.7%	2.4%

Note: *Based on OAG historical data, the CAGR of the global total number of active airports between 2011 and 2024 is 1.0%.

Source: IATA Sustainability and Economics

Given the highly uncertain nature of climate change impact modeling, the OECD adopts a stylized *median* climate damage curve that represents a plausible *median* estimate within the wide spectrum of scientific literature. Hence, we use the *median* climate damage curve for all three GDP growth scenarios in this report for direct comparisons. [11] It is important to note that, from the more aggressive climate impact models (i.e., high climate damage curve), without decisive action on climate change mitigation, climate damages could reduce global GDP by 36% in 2100.

The mid-GDP growth scenario assumes a smooth energy transition that would achieve the climate goals set by the Paris Agreement, limiting global warming to 1.6 °C in 2100. The successful and smooth transition would come at the price of a near-to-medium-term (including the transition phase to 2050) transition costs, modelled as a uniform carbon mitigation cost that declines at a rate of 4% per annum. Carbon mitigation cost would reduce labor efficiency and the cumulative capital stock, leading to lower GDP growth (i.e., a cumulative impact of 3% of global GDP in 2050) than in the "business-as-usual" case.[12] However, the economic consequences of the transition will turn net positive globally around 2085, thanks to the longer-run benefits of avoided climate damages. Under this scenario, carbon-based energy sources are projected to represent only about 15% of the primary energy mix in 2050 at the global level, and the sustainable aviation fuel (SAF) supply would follow the expected pace outlined in the IATA Net Zero Finance Roadmap.[13]

In the low-growth scenario, we assume that the world would still achieve the Paris climate goals, but the process would be bumpier due to slow progress made in the early phase of the transition. The carbon mitigation cost is expected to decline more slowly than the mid-growth case at 1% per annum, and the cost of reducing carbon emissions in 2050 will still be about 75% of what it would be from using today's technology. A more disruptive transition would therefore be required in later years. Essentially, the slower decline in the carbon mitigation cost means that it would cost the economy more to achieve the Paris climate goals by 2100, leading to slower global economic growth compared to mid-growth scenario (Chart 5, left). For the airline industry's net zero transition, this scenario assumes that the same quantity of SAF will still be available compared to the smooth transition case, while the price of SAF will be considerably higher.

Growth scenarios of other demand drivers

In addition to long-term economic growth, we also include three other input factors in our scenarios: population growth, aviation fuel price trends, and air transport supply-side capacity growth (Table 1). We obtain the long-term projections of countries' populations from the IMF WEO for the near term (2025-2030) and from the OECD for the mid-to-long term (2031-2050).[8] Countries' average employment rates (both historical and projections) are sourced from the OECD and the United Nations International Labor Organization (ILO). The projected values of these two demand drivers are the same across the three scenarios. Therefore, it is the countries' real PPP GDPs (and real PPP GDP per capita) that are the principal differentiators between the scenario outcomes from the macro-economic side.

The service-related demand drivers, i.e., the cost of air travel measured by passenger-weighted average airfares, the total number of flights, and the average aircraft size used between the origin and the destination countries, are all derived from IATA's in-house data.[14] We expect that the future price of air travel will be

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[11] According to the OECD, Individual-country damage curves are related to the global one via country-specific relative sensitivities to climate damages, in such a way that individual-country curves aggregate up to the global one.
[12] This assumption can be overturned, as acknowledged by the OECD, given that the counterfactual "business-as-usual" economy is not necessarily at full allocative efficiency, and investments in renewable energies and energy efficiency may move the economy to a more efficient allocation with equal or higher output than in a no-transition scenario. However, these economic channels require more complex modeling beyond the scope of the OECD's current long-run economic projections.
[13] IATA Net Zero Finance Roadmap, September 2024.
[14] Details on the data, model, estimation methods, and results will be discussed in Part 2.

influenced significantly by global aviation fuel price trends under various energy transition settings.[15] In the high-growth scenario (i.e., business-as-usual), the global aviation fuel price is exclusively determined by the price of conventional aviation fuel (CAF), abstracting from any energy transition and therefore excluding any SAF in this setting. In the mid-growth scenario (i.e., smooth energy transition), the aviation fuel price would be jointly determined by the prices of CAF and SAF, as well as the corresponding quantities supplied to air transport. The estimated future prices of SAF and CAF, as well as the demand for the fuels, are obtained from the IATA Net Zero Finance Roadmap.[13] The global average aviation fuel price is calculated as the weighted average of SAF and CAF prices, with demand for CAF and different SAFs by production pathways serving as weights. Finally, in the low-growth scenario (i.e., a disruptive energy transition), we assume that the weighted average SAF price would be more expensive than in the mid-growth scenario in line with existing IATA research, while the CAF price trend would remain the same as in the other two scenarios.[16]

To determine the total number of flights scheduled between the origin and the destination country, a flight frequency model is developed to project flight frequencies under the high-, mid-, and low-growth scenarios.[14] Notably, in the flight frequency model, we incorporate the average number of airports for the O-D country pair as an independent variable to reflect the fact that along with GDP and population growth, investment in aviation infrastructure is also a critical driver in realizing the potential of supply-side growth. In our scenarios, the total number of airports grows at varying rates by country, driven by countries' economic and population development (categorized into Advanced Economies, Emerging Market Economies, and Low-income Developing Economies as defined by the IMF), as well as the physical constraints imposed by a country's total land area.[14] For instance, in the mid-growth scenario, countries are expected to invest more in building new airports, thanks to the economic benefits from a smooth energy transition compared to the low-growth scenario.

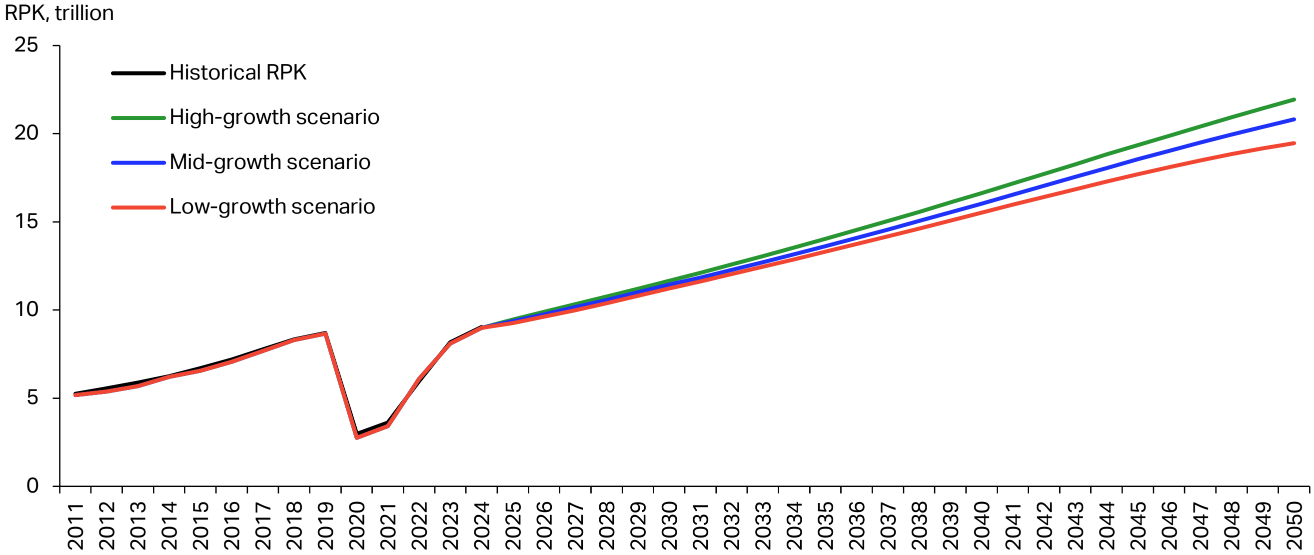
The key input factors for our three growth scenarios described above, which drive the different long-term RPK projections, are summarized in Table 1.

4. IATA long-term RPK projection outcomes

Driven jointly by the long-term economic projections, population growth potential, global aviation fuel price trends, and supply-side capacity growth set in our three scenarios (Table 1), the IATA LTDP produces RPK projections to 2050 at the country, regional, and global levels. In the high-growth scenario, the industry's total RPK is projected to increase from 9.04 trillion to 18.8 trillion in 2044 and 21.9 trillion in 2050 (Chart 6). This is equivalent to a CAGR of 3.6% per year over the period 2024-2044 and 3.3% per year over the period 2024-2050. Our mid-growth projections suggest that the global total RPK could reach 18.1 trillion (3.3% CAGR) in 2044 and 20.8 trillion (3.1% CAGR) in 2050. In the low-growth scenario, global total RPK is projected at 17.3 trillion in 2044 (3.1% CAGR) and 19.5 trillion in 2050 (2.9% CAGR). The projections for the different scenarios remain within a relatively narrow range, primarily because the input PPP GDP long-term growth projections (the most influential determinant of air travel demand) are within a similarly narrow range (Chart 5, left).

[15] Part 2 will discuss in more detail our approach of using the product of the lagged global jet fuel price and O-D distance as the instrumental variable for airfares in our demand model estimated by the PPML-IV method.
[16] In theory, there would be lower volumes of SAF available in the disruptive transition compared to the smooth transition, and the average SAF price would be higher. However, for simplicity, we use the same SAF quantities estimated in the IATA Net Zero Finance Roadmaps for the mid- and low-growth scenarios, while changing the CAGR of the average SAF price by 2% per year in the disruptive transition case. This assumption is broadly aligned with our scenario definition, where both the mid- and low-growth scenarios would eventually achieve the Paris Agreement goals, albeit with different transition costs.

Chart 6: IATA long-term industry RPK projections, trillion. RPKs over 2011-2024 are for model validation, and RPKs over 2025-2050 are projections



Source: IATA Sustainability and Economics

Table 2: Projected global RPK, trillion, for 2044 and 2050; and the compound annual growth rates (CAGR) over the 2024-2044 and 2024-2050 periods, under high-, mid-, and low-growth scenarios

Scenarios	Global RPK trillion				
	2024	2044	2050	CAGR 2024-2044	CAGR 2024-2050
High	9.04	18.81	21.92	3.6%	3.3%
Mid	9.04	18.05	20.81	3.3%	3.1%
Low	9.04	17.28	19.46	3.1%	2.9%

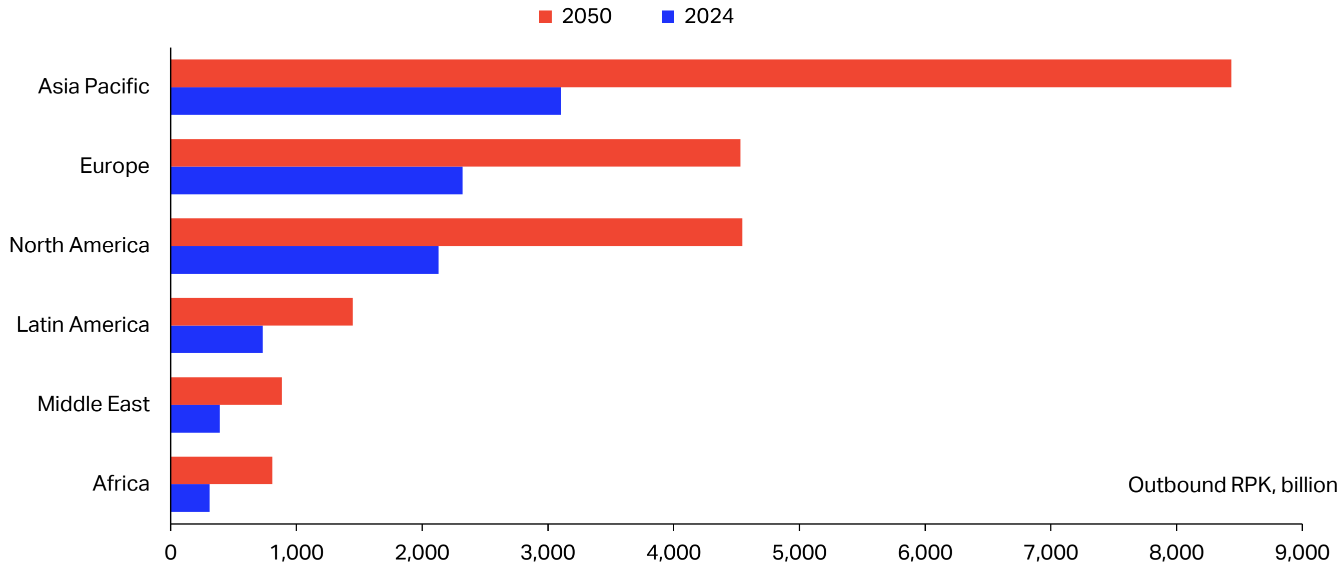
Source: IATA Sustainability and Economics

Turning to the regional level, our projections indicate that all regional markets are expected to experience significant growth in RPK departed from the region from 2024 to 2050 (Chart 7). The Asia Pacific region is likely to maintain its dominant position in terms of its share of the global total RPK in 2050, followed by North America and Europe. Outbound RPKs generated from the Asia Pacific region are projected to increase 2.7-fold, from 3,100 billion in 2024 to 8,400 billion in 2050. The North American region is projected to generate a total outbound RPK of 4,500 billion in 2050, from 2,100 billion in 2024. Air travel from Europe is also expected to increase considerably, from 2,300 billion in 2024 to 4,500 billion in 2050.

While the landscape of regional total outbound RPK shares remains relatively stable in our projections, it is essential to note the high CAGRs projected for the smaller regional markets (Chart 8). Africa and the Middle East regions are projected to join Asia Pacific as the primary drivers of growth over the period 2024-2050. The Asia Pacific region, home to many emerging economies with large populations, leads in annual compound RPK growth, with CAGRs of 3.9% in the high-growth scenario, 3.8% in the mid-growth scenario, and 3.5% in the low-growth scenario. Africa comes second, with CAGRs of 3.9% in the high-growth scenario, 3.6% in the mid-growth scenario, and 3.2% in the low-growth scenario, driven by the region’s strong economic and population growth potential. The Middle East region is projected to be the third fastest-growing regional market, with CAGRs of 3.5% in the high-growth scenario, 3.1% in the mid-growth scenario, and 2.5% in the low-growth scenario. Africa and the Middle East markets have relatively larger differences between the scenario outcomes because the two regions' economic growth is expected to be more affected by the energy transition paths.

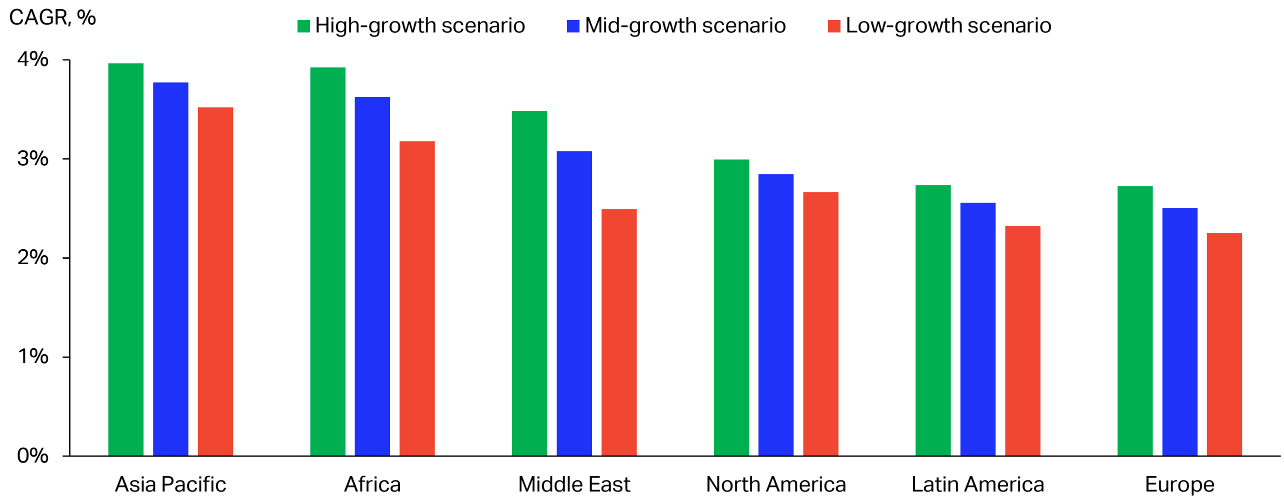
Notably, the Middle East market exhibits a structurally distinct demand profile, in which strong overall traffic growth is to a large extent driven by transfer demand that facilitates long-haul connections between Europe, Asia, Africa, and Oceania. Consequently, our long-term forecasts based on O-D RPK tend to show comparatively lower growth for the Middle East than models focusing on total passenger volumes and connectivity. The Middle East's current role as a global transfer hub implies that the expected O-D RPK growth is structurally more moderate relative to regions with larger domestic or intra-regional markets such as the Asia Pacific. This could change over time through large-scale tourism initiatives and related infrastructure investments in the region.

Chart 7: Projected outbound RPKs by region 2024 versus 2050, billion, under the mid-growth scenario



Source: IATA Sustainability and Economics

Chart 8: Projected RPK growth over 2024-2050 by region and by scenario, %



Source: IATA Sustainability and Economics

Consistent with the projections by region, the O-D region-pair markets that have Asia Pacific, Africa, or the Middle East as one of the endpoint regions are expected to grow strongly. The intra-Africa market shows the highest CAGRs of up to 5.2% across the three scenarios, followed by the Africa-Asia Pacific market at 4.7% and the Asia Pacific-Middle East, intra-Asia Pacific, and Africa-North America markets, all at 4.1% under the high-growth scenario (Table 3). On the other hand, developed markets such as intra-Europe and Europe-North America are projected to have CAGRs at the lower end of the spectrum, at 2.0%-2.5%, with a slight exception for the intra-North America market at 2.6%-2.9%, due to stronger economic growth projections for that region.

Table 3: Projected RPK growth by region and region pair across the three scenarios, 2024-2050

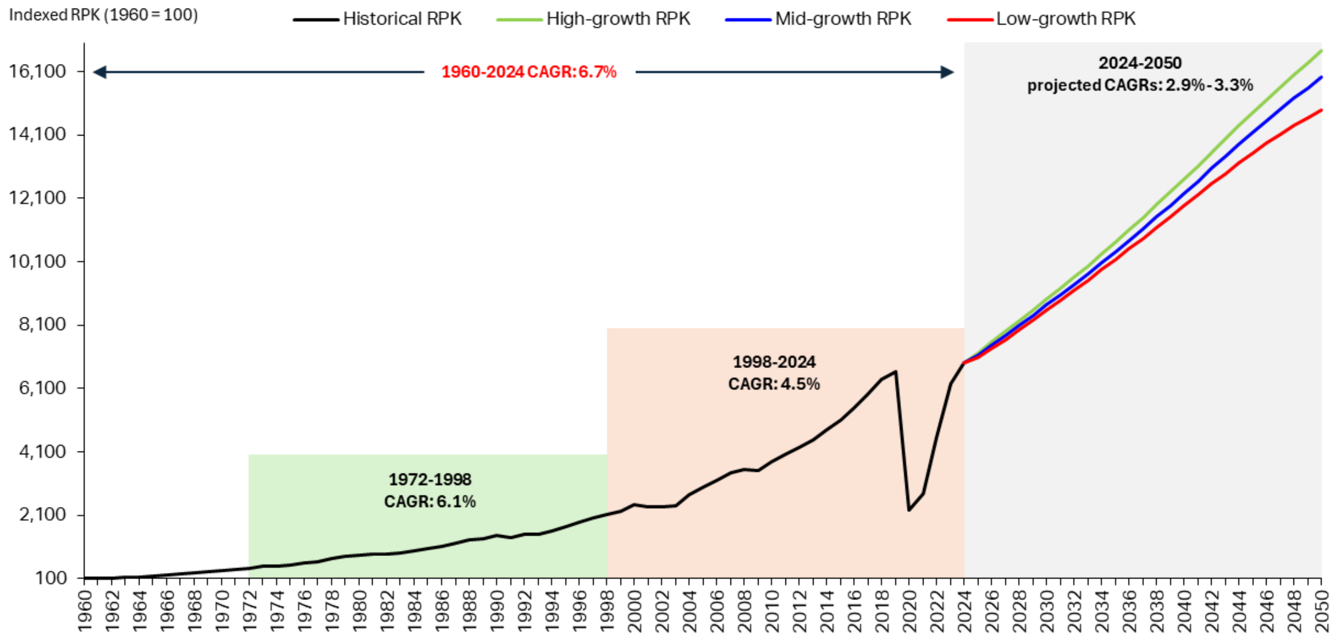
Markets	CAGR (high)	CAGR (mid)	CAGR (low)
Region: total RPK departed from the region			
Asia Pacific	3.9%	3.8%	3.5%
Africa	3.9%	3.6%	3.2%
Middle East	3.5%	3.1%	2.5%
North America	3.0%	2.8%	2.7%
Latin America	2.7%	2.6%	2.3%
Europe	2.7%	2.5%	2.3%
Region pair: bi-directional total			
Intra-Africa	5.2%	4.9%	4.4%
Africa-Asia Pacific	4.7%	4.5%	4.1%
Asia Pacific-Middle East	4.1%	3.9%	3.1%
Intra-Asia Pacific	4.1%	3.9%	3.6%
Africa-North America	4.1%	3.8%	3.5%
Asia Pacific-North America	3.9%	3.7%	3.5%
Africa-Middle East	3.7%	3.2%	2.5%
Asia Pacific-Latin America	3.5%	3.3%	3.1%
Africa-Latin America	3.5%	3.2%	2.8%
Asia Pacific-Europe	3.3%	3.1%	2.9%
Middle East-North America	3.3%	2.9%	2.5%
Africa-Europe	3.2%	2.9%	2.6%
Latin America-Middle East	3.1%	2.8%	2.2%
Europe-Middle East	3.0%	2.7%	2.1%
Intra-North America	2.9%	2.7%	2.6%
Intra-Latin America	2.9%	2.7%	2.5%
Latin America-North America	2.7%	2.5%	2.3%
Intra-Middle East	2.6%	2.1%	1.3%
Europe-North America	2.5%	2.4%	2.2%
Intra-Europe	2.5%	2.3%	2.0%
Europe-Latin America	2.4%	2.3%	2.0%

Source: IATA Sustainability and Economics

Global air travel demand has followed a remarkably consistent upward trajectory (except for the covid period) over the past 64 years, and this momentum is projected to continue through 2050 (Chart 9). Since 1960, global RPK has expanded more than 60-fold, with a CAGR of 6.7%. While the CAGR of global RPKs for the next 27 years (i.e., 2024-2050) is projected to moderate to around 2.9%-3.3%, the overall trend remains firmly positive.

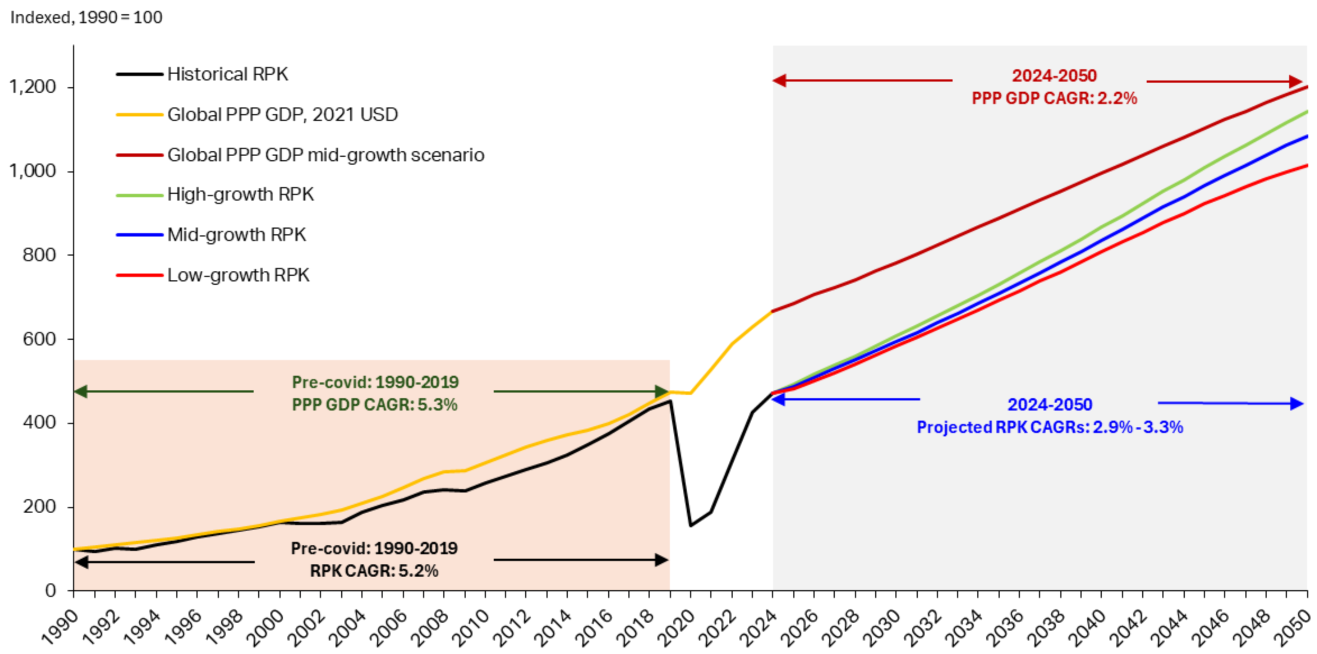
Importantly, the observed deceleration in CAGR should be interpreted primarily as a scale and base-effect phenomenon, rather than as a weakening of underlying demand fundamentals. We illustrate this by comparing our projected growth for the next 27 years with the CAGRs of the previous two 27-year periods (i.e., 1972-1998 and 1998-2024). In the early phase of aviation development, when traffic volumes were relatively small, incremental increases translated mechanically into very high growth rates—reflected in the 6.1% CAGR during 1972–1998. As the industry expanded and the absolute level of RPKs increased substantially, sustaining such high percentage growth became less feasible, even as absolute traffic gains continued to rise.

Chart 9: Projected industry RPK growth in a historical view



Source: IATA Sustainability and Economics

Chart 10: Long-term relationship between global economic growth and air travel demand growth



Source: IATA Sustainability and Economics

The subsequent moderation to 4.5% CAGR between 1998 and 2024, and the projected 2.9%-3.3% CAGRs for 2024–2050, therefore reflects the natural evolution of global air travel along a long-run S-shaped demand curve.[17] As markets mature, air transport transitions from a rapid expansion phase to a more stable growth phase. Crucially, the chart demonstrates that growth momentum remains intact in absolute terms. Even at a lower percentage rate, the projected trajectory implies substantial additions to global RPK volumes, given today's much larger base. In this sense, the post-2024 growth path represents continuity rather than slowdown as demand continues to expand steadily under all three growth scenarios.

The covid pandemic is the greatest structural shock to the airline industry in the history of air travel (Chart 10). Between 1990 and 2019, global RPK tracked global real PPP GDP (in 2021 USD) closely, with both series expanding at nearly identical compound annual growth rates of around 5.2–5.3%.[18] This tight co-movement over nearly three decades underscores the strong and stable relationship between economic growth and air travel demand in the pre-pandemic period. However, the covid shock resulted in an unprecedented collapse in RPK, creating a large and persistent gap relative to the underlying GDP trajectory. While passenger demand recovered in absolute terms after 2024, projected RPK growth of approximately 2.9–3.3% per annum remains insufficient to close the cumulative level gap created during the pandemic. Even under the high-growth RPK scenario, global air travel demand does not converge back to the pre-covid GDP-aligned trend by 2050. The pandemic caused a structural break in the historical relationship between global air travel demand and macro-economic growth, leaving a long-lasting and potentially permanent scar on the industry.[19]

[17] The S-shaped curve reflects how a market matures over time, where demand growth accelerates from initially low levels, subsequently slows down, and eventually reaches a plateau when the market approaches maturity (ICAO, 2006).
[18] In this study, historical GDP is measured as real GDP in 2021 USD, PPP adjusted. Therefore, the GDP growth rates are not directly comparable to publications which discuss GDP growth in current USD.
[19] Note that this projection uses coefficients based on the dataset with only two-years observations post covid. The coefficient capturing the GDP and RPK relationship may change when we re-run the model with future data.

Part 2: A technical report on data sets, model specification, estimation methodology, and performance validations

1. Data

1.1 Input data sources

The IATA long-term demand projection (LTDP) model is calibrated using a unique global panel dataset that integrates multiple internal and external sources. The final dataset combines directional origin–destination (O–D) annual passenger demand, prices, capacity, and macro-economic indicators for all country pairs worldwide from 2011 to 2024. The O-D revenue passenger-kilometres (RPKs) and itinerary-level average airfares (passenger-weighted) are obtained from the IATA Direct Data Solutions (DDS) database. Segment-level airline schedules, including total annual flight frequencies and available seats, are sourced from the OAG Global Airline Schedules database.

Historical macro-economic and demographic data on country-specific real purchasing-power-parity-adjusted GDP (PPP GDP), PPP GDP per capita, and population are sourced from the IMF World Economic Outlook (WEO). Data on population age structure by country is obtained from the UN Population Division. Country-level unemployment rates come from the International Labor Organisation (ILO) under the UN. All these macro-economic and demographic data are matched with the traffic data to construct the O-D panel dataset used for the model. This multi-layered integration ensures the O-D panel dataset captures both industry-specific trends and broader socio-economic drivers.

1.2 Construction of the O-D panel dataset

The cleaned O–D panel dataset is constructed using a bottom-up integration of multiple data sources. The process begins with itinerary-level demand data from the DDS database, where annual total RPK and average airfares are computed for each O–D itinerary. The itinerary airfare is defined as the weighted average of ticket prices across service classes, using class-specific passenger volumes as weights. Next, we combine these demand indicators with supply-side operational data from the OAG schedule database. Raw annual flight frequencies and average seats per flight are first extracted at the segment (airport-pair) level. These are then mapped to each itinerary recorded in the DDS dataset. Because an O–D itinerary may consist of up to six flight segments, each itinerary inherits the flight frequency and capacity characteristics from the set of segments that compose its routing.

A key challenge in building O–D level aviation datasets is that a single flight segment typically serves multiple itineraries, and as a result, the true frequency of flights available to a specific O–D itinerary is not directly observable. To address this, we tested several alternative proxy measures.

We first developed a “bottleneck frequency” measure, defined as the minimum segment frequency among all flight segments in an itinerary. This reflects a key supply-side constraint: irrespective of capacity on shorter domestic feeder segments, the overall passenger flow on an itinerary is limited by the segment with the lowest frequency—often the long-haul “trunk” segment connecting the two endpoint countries. We then explored an alternative “effective bottleneck frequency”, which allocates a segment’s total frequency across the itineraries it serves, proportional to each itinerary’s share of total passengers on that segment. The minimum of these proportional allocations is used as the itinerary’s “effective” frequency. While conceptually appealing, this approach embeds itinerary-specific passenger shares directly into the frequency measure, creating mechanical endogeneity[20] between the constructed supply variable and the observed demand (RPKs).

Through extensive diagnostic comparisons, we found that the observed "bottleneck frequency" (i.e., the minimum actual segment frequency, without proportional allocation) provides a more stable and globally consistent representation of itinerary-level supply availability. It captures the structural constraints inherent in multi-segment routing, without embedding itinerary-specific traffic flows into the frequency measure. For these reasons, this variable is retained as our final proxy for itinerary-level flight frequency in subsequent model calibration.

In parallel, aircraft size also varies by segment within an itinerary. To represent itinerary-level seat capacity, we use the largest aircraft type—measured by average seats per flight—operating along the itinerary. This reflects the fact that the largest aircraft typically serve the long-haul trunk segment and therefore drive the primary capacity constraint between the endpoint countries.

Following the construction of the itinerary-level dataset, we aggregate the data to the O–D country-pair level, which forms the unit of analysis for the model estimation. Itinerary-level RPKs and bottleneck frequencies are summed over all itineraries connecting the same pair of countries. Airfares and average seats per flight are converted into weighted averages, with weights proportional to itinerary-level passenger numbers. We also derive the total number of active airports in each country from the itinerary dataset.

Next, we constructed a dummy variable ($\mathrm{Covid}_{od,t}$) that captures the covid pandemic impact on air travel demand between the origin country o and the destination country d in year t. The dummy equals 1 if the year is 2020 or 2021, and 0 otherwise, except in the following cases:

- China: China's zero-covid policy was strengthened in 2022 due to the outbreak of the Omicron variant, restricting domestic and international air travel further in 2022; hence, the dummy also equals 1 for all routes from, to, and within China in 2022.
- Similarly, a few countries or regions also maintained their covid-19-related international travel restrictions in 2022, including Japan, Australia, Canada, and Hong Kong. The dummy also equals 1 for international air travel from and to these countries in 2022.
- In contrast, the US and India resumed their domestic air travel as early as 2021 and saw a relatively faster recovery in air transport traffic than other countries; hence, the dummy equals 0 for domestic air travel within the two countries in 2021.

Finally, country-level macro-economic and demographic data, as well as country totals for active airports, are merged with the O–D country-pair dataset. In this final step, the three external data sources (i.e., the IMF WEO, the UN Population Division, and the UN ILO) do not report or have missing values for some countries. In total, 43 small or island countries have at least one missing value of the above macro-economic and demographic indicators. The complete list of these small or island countries is in Appendix B. To maintain the completeness of the recorded global total RPK, we do not remove these countries from our dataset. Instead, we separate observations with these countries as endpoint countries from our main model dataset. This separate dataset, which includes small countries with missing socio-economic data, is used to calibrate empirical models tailored to traffic in these countries (see Part 2 Section 6).

The resulting panel serves as the complete input dataset for subsequent estimation of the empirical econometric models.

[20] Endogeneity is present when an explanatory variable in a model is correlated with the error term (unexplained factors), making it difficult to determine true cause-and-effect. This can occur because the cause and effect influence each other, or by omitted variables.

1.3 Final dataset

Our cleaned panel dataset contains 573,636 observations from 40,974 O-D country pairs (directional). It is a balanced panel covering 14 years from 2011 to 2024, even though some country pairs have zero-flow observations in some years on the demand side (zero RPK for country pairs without any recorded passenger traffic) and on the supply side (i.e., no records on scheduled flights operated). These zero-flows are retained in the analytical dataset without filtering, as they contain valuable information about market entry, exit, and structural changes over time—particularly for small or peripheral markets and during shock periods such as the covid pandemic.

The descriptive statistics of the final dataset (including the main model dataset and the dataset of small island countries with missing values) for model calibration are summarized in Table 4. Notably, to ensure that the global total RPK is as close as possible to the level from the DDS raw data, we choose not to remove any outliers from the dataset. As a result, the maximum value, particularly for the $\mathrm{Fare}_{od,t}$ variable, tends to be extreme. However, the number of outliers is very small compared to the entire sample size. Hence, we do not expect the model estimation to be significantly affected by these outliers. Following the same principle, the minimum value of the traffic-related variables is mostly zero because we retain all zero flows from the dataset when constructing the balanced panel.

Overall, the descriptive statistics shown in Table 4 highlight the strong heterogeneity in both demand and supply variables across global air transport markets at the country-pair level. They also underscore the importance of using appropriate estimation techniques that can robustly handle highly skewed positive data with many small or near-zero observations while preserving the variation necessary for global RPK forecasting. The model estimation method is discussed in detail in the next section.

Table 3: Summary statistics of the final annual O-D country pair model dataset.

Variable	Mean	Std. Dev	Min	Median	Max
$\mathrm{RPK}_{od,t}$ (million)	157.1	5507.7	0	0.3	1,137,775.3
$\mathrm{Fare}_{od,t}$ (real USD in 2021)	539.8	459.8	0	522.2	40,688.9
$\mathrm{PPPGDPpc}_{od,t}$* (real USD in 2021)	19,485	15,595.0	677	14,859	150,790
$\mathrm{Pop}_{od,t}$* (million persons)	18.7	37.0	0.01	8.8	1,450.9
$\mathrm{EmpRate}_{od,t}$* (%)	63.7	8.4	21.5	64.2	95.8
$\mathrm{Freq}_{od,t}$ (thousand flights/year)	79.8	4822.1	0	1.2	1,350,579.4
$\mathrm{ArcftSize}_{od,t}$ (seats/flight)	197	129.3	0	225	584
$\mathrm{Airports}_{od,t}$*	9.9	17.9	1	4.9	731
$\mathrm{Covid}_{od,t}$ (dummy variable)	0.2	0.4	0	-	1

Note: * These are the geometric means of values of the two endpoint countries.

Source: IATA Sustainability and Economics, IATA DDS database, OAG database, IMF WEO, UN ILO, UN Population Division.

2. Empirical demand model specification

To forecast international air passenger demand, we employ a bilateral gravity framework. Gravity models are widely used for trade, migration, and aviation flows because they capture how economic size, connectivity, and bilateral frictions jointly determine traffic levels. The model is estimated on a country-pair panel and designed to quantify how air travel demand responds to changes in fares, income, population, labor market conditions, and supply-side operational bottlenecks.

Because the dependent variable, i.e., RPK between the origin country *o* and the destination country *d* in year *t*, is strictly non-negative, highly skewed, and exhibits substantial heteroskedasticity[21] (Table 4), we estimate the model using Poisson Pseudo Maximum Likelihood (PPML). PPML is preferred over log-linear ordinary least squares (OLS) because this method does not impose linearity in the dependent variable;[22] instead, it assumes that the conditional mean of $\mathrm{RPK}_{od,t}$ follows an exponential mean function. This allows the model to include zero RPK flows, avoid distortions from log-transformations, and remain consistent under general forms of heteroskedasticity. Additionally, PPML is also empirically superior for forecasting flows because it models level effects directly. In our test, PPML exhibits stronger model performance than OLS estimation with fixed effects.

The theoretical foundation of our demand model follows a multiplicative gravity structure, and the structural gravity model specification is shown in Equation 1. Passenger air traffic between the origin country o and the destination country d at time t is determined by bilateral socio-economic conditions, average ticket prices, service-related factors of the flights, and global shocks:

Equation 1

$$\mathrm{RPK}_{od,t} = \exp(\mathbf{X}_{od,t}\beta' + \mu_{od} + \tau_t) + \varepsilon_{od,t}$$

Where:

- $\mathbf{X}_{od,t}$ is a vector of the bilateral, time-varying determinants of RPKs between the origin country o and the destination country d at time t.
- β' is a vector of coefficients that captures the responsiveness of RPK to each specific driver.
- μ_{od} is the O-D country-pair fixed effect, capturing all time-invariant bilateral frictions, such as distance, cultural ties, historical connectivity, and geography.
- τ_t captures year fixed effects, absorbing global shocks such as business cycles, regulatory shifts etc.
- $\varepsilon_{od,t}$ is the multiplicative error term,[23] consistent with the PPML conditional mean structure.

The empirical model specification corresponds directly to the structural form:

Equation 2

$$\begin{aligned}\mathrm{RPK}_{od,t} = \exp(&\beta_1 \ln(\mathrm{PPPGDPpc}_{od,t}) + \beta_2 \ln(\mathrm{Pop}_{od,t}) + \beta_3 \ln(\mathrm{EmpRate}_{od,t}) + \beta_4 \ln(\mathrm{Fare}_{od,t}) + \beta_5 \ln(\mathrm{Freq}_{od,t}) \\ &+ \beta_6 \ln(\mathrm{ArcftSize}_{od,t}) + \beta_7 \mathrm{Covid}_{od,t} + \beta_8 \mathrm{FS\_FareResidual}_{od,t} + \mu_{od} + \tau_t) + \varepsilon_{od,t}\end{aligned}$$

[21] Heteroscedasticity, or non-constant variance, occurs when the spread of residuals (errors) in a regression model differs across levels of an independent variable, often appearing as a "fan" shape in scatter plots. While it does not bias Ordinary Least Squares (OLS) coefficients, it renders them inefficient and invalidates standard tests (t-tests, F-tests) because standard errors are biased.
[22] In contrast to OLS, where multicollinearity and linear associations between the dependent variable and the regressors influence estimation and interpretation, PPML is a nonlinear estimator whose consistency does not depend on linear correlations. Therefore, a correlation matrix between the dependent variable and the regressors is not reported here.
[23] A multiplicative error term refers to a model where the random noise or "error" is multiplied by the predicted value, rather than added to it in the OLS estimation. This allows the variance (uncertainty) to increase as the predicted value increases, hence directly addressing the heteroskedasticity problem.

Our gravity-based demand model incorporates both macro-economic and operational determinants. We include the geometric mean[24] of the endpoint countries' real PPP-adjusted GDP per capita ($\mathrm{PPPGDPpc}_{od,t}$), population ($\mathrm{Pop}_{od,t}$), and average employment rate[25] ($\mathrm{EmpRate}_{od,t}$) to capture economic "mass". Bilateral frictions and service quality are represented by weighted average airfares ($\mathrm{Fare}_{od,t}$), minimum segment flight frequency of all itineraries that connect the endpoint countries ($\mathrm{Freq}_{od,t}$), and average aircraft size operated between the two countries ($\mathrm{ArcftSize}_{od,t}$), measured by the average seats per flight. Finally, a covid shock dummy ($\mathrm{Covid}_{od,t}$) accounts for the unprecedented disruption to global traffic.

A distinctive feature of this model is the treatment of flight frequency ($\mathrm{Freq}_{od,t}$). As described earlier, the variable represents the minimum segment frequency across all itineraries connecting the endpoint countries. The primary reason for this is to highlight the "bottleneck" of the supply side: even if most segments of an itinerary have high capacity, the total flow of passengers is constrained by the segment with the lowest frequency. Because these segments serve a multitude of diverse O-D itineraries simultaneously, the frequency of a single segment is determined by global network flow rather than the demand of any specific itinerary. Therefore, the frequency variable (aggregated from segment level to the country pair level) used in this model is not endogenous to air travel demand.

The airfare variable, on the other hand, is treated as endogenous, and we employ an instrumental-variable (IV) control-function approach to obtain consistent estimates. Airfare is endogenous to air travel demand due to reverse causality and simultaneity bias. To address the endogeneity of airfares in the gravity demand estimation, we instrument $\ln(\mathrm{Fare}_{od,t})$ with a route-specific cost shifter defined as the product of the lagged global jet fuel price and the bilateral O-D distance. This variable provides a reduced-form proxy for the average fuel-related operating cost of serving a given O-D country pair in year t. Fuel expenses constitute one of the largest and most volatile components of airline operating costs, and their marginal impact scales approximately in proportion to the flown distance. A higher global fuel price therefore raises the cost of supplying longer routes more than shorter routes, generating exogenous cross-sectional and intertemporal variation in operating costs at the O-D level.

Using the lagged fuel price ensures that the instrument is predetermined with respect to contemporaneous OD-specific demand shocks. The inclusion of country-pair fixed effects absorbs all time-invariant bilateral determinants of both fares and demand (e.g., geographic, cultural, and regulatory factors), while year fixed effects capture global economic conditions and common shocks to air transport. Conditional on these fixed effects, the constructed cost shifter varies only through exogenous fluctuations in global fuel markets interacted with the mechanical route-level cost gradient implied by distance.

This instrument is expected to satisfy the relevance condition because fuel prices have a substantial and well-documented impact on airline marginal costs and, consequently, on fares. It also supports the exclusion restriction: global fuel prices are determined outside individual O-D markets and should influence demand only through their effect on the cost — and hence price — of supplying the route. The distance term is time-invariant and absorbed by the country-pair fixed effects, so the identifying variation comes from exogenous changes in lagged fuel costs. Taken together, this IV strategy provides plausibly exogenous price variation appropriate for coefficient estimates in a PPML-IV gravity framework. The presence of the residual from the first-stage fare equation ($\mathrm{FS\_FareResidual}_{od,t}$) in Equation 2 ensures that the model correctly accounts for the endogeneity of fares.

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[24] Geometric mean is calculated as the square root of the product of object A and B. The geometric mean is the commonly used way in gravity models to measure the average attraction level of a given feature, e.g., population size, between the O-D endpoints.
[25] We also included a variable that captures a country's population age structure. i.e., the working-age population share, in the test model. The variable showed a strong correlation with the employment rate variable and was therefore dropped from the final model specification.

3. Demand model estimation and analysis

The estimation results from the empirical demand model using the PPML-IV approach are presented in Table 4. To address the potential endogeneity of airfares, the estimation follows a Two-Stage Residual Inclusion (2SRI) or Control Function approach. The first stage estimates a linear model (Equation 3), which isolates the exogenous variation in fares by regressing $\ln(\text{Fare}_{od,t})$ on the instrumental variable $Z_{od,t}$, a vector of exogenous controls $\mathbf{X}_{od,t}$, and country-pair (ϑ_{od}) and year (γ_t) fixed effects to extract the residuals ($\text{FS\_FareResidual}_{od,t}$). In the second stage, the demand model (Equation 2) is estimated via PPML-IV. With $\text{FS\_FareResidual}_{od,t}$ included in the second stage, the endogeneity is fixed, leaving the coefficient of the Fare variable as the unbiased, exogenous effect.

Equation 3

$$\ln(\text{Fare}_{od,t}) = \pi_1 Z_{od,t} + \pi' \mathbf{X}_{od,t} + \vartheta_{od} + \gamma_t + u_{od,t}$$

Where:

- $Z_{od,t}$ is the instrument variable $\ln(\text{Fare\_IV}_{od,t})$, constructed as the product of the lagged global jet fuel price and the weighted O-D flown distance between the endpoint countries. The weight used is the passenger demand of a given flight itinerary linking the two countries, with its specific total distance flown.
- π_1 is the coefficient of interest, representing the partial correlation between the cost-based instrument and the endogenous airfare, after accounting for all other covariates. The IV is considered strong if π_1 is statistically significant with a high first-stage *F*-statistic.[26]
- The residuals $\hat{u}_{od,t}$ are extracted from the first stage and are included in the demand model as $\text{FS\_FareResidual}_{od,t}$ to control for the endogeneity of the fare variable.

The first stage yields a very strong result, with an *F*-statistic of 420, far exceeding conventional thresholds of 10 for weak-instrument concerns. This high value confirms that the instrument is strong and provides a high degree of relevance, effectively mitigating concerns regarding weak-instrument bias. The coefficient for the instrument is 0.072 and is statistically significant at the 0.1% level. This positive value aligns with economic theory, indicating that exogenous increases in fuel-related operating costs are passed through to passengers via higher fares. The first-stage model achieves an R^2 of 0.881, demonstrating that the instrument and included fixed effects account for a substantial portion of the variation in global air transport fares.

The second stage PPML-IV estimation provides the main results of the empirical demand model. The first-stage residual $\text{FS\_FareResidual}_{od,t}$ is statistically significant at the 5% level with a coefficient of -0.040. This significance confirms the presence of endogeneity in the fare variable and justifies the use of the IV approach over a standard PPML model. This is consistent with concerns that demand shocks may influence fares, leading to upward bias in naïve price elasticity estimates.

[26] Following Stock and Yogo (2005) guidelines, an *F*-statistic exceeding 10 is the traditional rule of thumb for a strong instrument, though higher thresholds are often preferred in modern empirical literature to ensure robust inference.

Table 4: PPML-IV estimation results for the gravity demand model.

	First stage: $\ln(\text{Fare}_{od,t})$		**Second stage: $\text{RPK}_{od,t}$**	
Variables	**Coefficient**	**Standard error**	**Coefficient**	**Standard error**
$\ln(\text{Fare\_IV}_{od,t})$	0.072***	0.003		
$\ln(\text{PPPGDPpc}_{od,t})$	0.086***	0.009	0.812***	0.191
$\ln(\text{Pop}_{od,t})$	0.114***	0.020	0.243	0.280
$\ln(\text{EmpRate}_{od,t})$	-0.574***	0.025	1.388***	0.284
$\ln(\text{Fare}_{od,t})$			-0.184***	0.045
$\ln(\text{Freq}_{od,t})$	-0.003***	0.001	0.496***	0.036
$\ln(\text{ArcftSize}_{od,t})$	-0.005	0.005	1.013***	0.112
$\text{Covid}_{od,t}\ (Yes = 1)$	0.138***	0.006	-0.409***	0.034
$\text{FS\_FareResidual}_{od,t}$			-0.040*	0.021
Fixed Effects	Country pair / Year		Country pair / Year	
No. of observations	366,460		366,460	
No. of country pairs (directional)	30,606		30,606	
R-squared / Pseudo-R^2	0.881		0.994	
First-stage F-statistic	420.1		n/a	

Notes:

1) The model (second stage) is estimated using Poisson Pseudo-Maximum Likelihood (PPML) with an instrumental variable (PPML-IV). The endogenous regressor $\ln(\text{Fare}_{od,t})$ is instrumented using the product of lagged global jet fuel prices and the weighted average O-D distance between origin and destination country; the weight used is the passenger demand of a given itinerary connecting the endpoint countries, with itinerary total flown distance *d*.
2) All regressors except the covid indicator are expressed in natural logarithms; the dependent variable of the second stage is O-D RPK in levels.
3) Country-pair and year fixed effects are included in both the first and second stages but omitted from the table for brevity. Pseudo R^2 is reported for the PPML second stage only.
4) Standard errors are clustered at the country-pair level to account for heteroscedasticity and within-pair serial correlation.
5) The first-stage *F*-statistic refers to the relevance of the instrument in the first-stage regression.
6) Significance levels: *** p < 0.001; ** p < 0.01; * p < 0.05.

Source: IATA Sustainability and Economics

All estimated coefficients have the expected signs and demonstrate that RPK demand is significantly responsive to economic fundamentals and service attributes. PPP GDP per capita (0.812***) and population (0.243)[27] both enter with positive signs, validating their roles as key drivers of air travel propensity. The employment rate (1.388***) exhibits a strong positive effect, indicating that an active labor market is a primary driver of air travel. The coefficient of airfare is negative and highly significant (-0.184***), indicating a relatively inelastic demand for air travel at the global scale. This magnitude is consistent with established results in the air-transport demand literature and with expectations for aggregated country-pair traffic. Frequency exhibits a strong positive elasticity (0.496***), reflecting that improved quality-of-service in terms of schedule convenience increases demand. Aircraft size is also positively associated with traffic volumes. As expected, the covid-19 indicator enters with a large, negative, and highly significant coefficient (–0.409***), capturing the structural downward shift in demand during the global health crisis.

The PPML-IV model achieves a very high Pseudo-R^2 of 0.994, driven largely by the rich set of country-pair and year fixed effects that capture bilateral structural determinants and global shocks. With more than 366,000 observations and 30,606 directional country pairs,[28] the model exploits substantial panel variation to yield stable estimation coefficients. Overall, the PPML-IV results demonstrate that the model is well-specified, the instrument is strong, and the estimated demand elasticities are economically reasonable and statistically robust. These estimates form the foundation for the IATA long-term air transport demand projections.

4. Empirical supply model specification

To generate forward-looking O-D country-pair “bottleneck” segment flight frequencies required for the main RPK demand projections, we estimate a separate supply-side gravity model using PPML.[29] The dependent variable is the observed minimum annual segment frequencies for all itineraries operating on each directional O-D country pair. Notably, by using the minimum annual segment frequency for all itineraries, we are effectively modeling the capacity constraint of the entire route rather than just total volume. The structural form of the supply model is:

Equation 4

$$\mathrm{Freq}_{od,t} = \exp(\mathbf{W}_{od,t}\delta' + \omega_{od} + \sigma_t) + \varphi_{od,t}$$

Where:

- $\mathbf{W}_{od,t}$ is a vector of the bilateral, time-varying determinants of annual minimum segment frequencies of all the itineraries between the origin country o and the destination country d at time t.
- δ' is a vector of coefficients of interest that captures the responsiveness of the “bottleneck” segment frequency to each specific time-varying driver.
- ω_{od} is the O-D country-pair fixed effect on the “bottleneck” frequency, capturing all time-invariant bilateral frictions, such as distance, cultural ties, historical connectivity, and geography.
- σ_t captures the year fixed effect on the “bottleneck” frequency, absorbing global shocks such as business and fuel price cycles, etc.

[27] While the coefficient on population is not statistically significant, this does not imply that population size does not matter for air travel demand, but rather, that its effects operate in conjunction with GDP and employment, and through flight frequency. See relevant discussion in Part 2 Section 5.
[28] The 366,000 observations are included the main model dataset, and the remaining observations are in the dataset for small countries with missing macro-economic data, which we estimate separately. Details see Appendix E.
[29] As with RPK, annual flight frequency is also strictly non-negative, highly skewed, and exhibits substantial heteroskedasticity; thus, it is appropriate to estimate the model using PPML.

- $\varphi_{od,t}$ is the multiplicative error term, consistent with the PPML conditional mean structure.

The empirical model specification corresponds directly to the structural form and is defined as:

Equation 5

$$\mathrm{Freq}_{od,t} = \exp(\delta_1 \ln(\mathrm{PPPGDPpc}_{od,t}) + \delta_2 \ln(\mathrm{Pop}_{od,t}) + \delta_3 \ln(\mathrm{Airports}_{od,t}) + \delta_4 \ln(\mathrm{Freq}_{od,t-1}) + \delta_5 \ln(\mathrm{ArcftSize}_{od,t-1}) + \delta_6 \mathrm{Covid}_{od,t} + \omega_{od} + \sigma_t) + \varphi_{od,t}$$

The dependent variable in Equation 5 is the minimum segment flight frequency of all the itineraries connecting country o and d in year t, while all explanatory variables (except the covid dummy) enter the model in logarithms. Country-pair fixed effects control for all time-invariant bilateral characteristics such as geographic distance, cultural ties, or historical relationships; year fixed effects capture global shocks and shared temporal trends.

The focus of our supply-side gravity model is to provide critical insights into how infrastructure and historical operational patterns shape global flight frequencies. PPP GDP per capita and population are included as the proxy to capture the demand effects on supply exogenously. In comparison, a distinctive feature of this supply equation is the inclusion of the $\mathrm{Airports}_{od,t}$ variable and the two lagged operational variables.

$\mathrm{Airports}_{od,t}$ is the geometric mean of the number of airports in active operation in the origin country o and the destination country d at time t. Our supply model highlights that physical infrastructure capacity acts as a necessary precursor to flight frequency growth, an effect on supply that GDP or population alone cannot capture.[30] Including the airport variable ensures realistic frequency forecasts and prevents the model from overestimating growth in regions that are land-constrained (see Appendix C).

The inclusion of lagged operational variables, specifically prior-year “bottleneck” frequencies ($Freq_{od,t-1}$) and aircraft size ($ArftSize_{od,t-1}$), reveals a high degree of path dependency in airline supply chains, i.e., airlines do not change flight schedules or fleet assignments overnight; they are influenced by last year’s operational reality. These lagged variables introduce realistic temporal dynamics into the supply model to produce credible frequency projections for use in downstream demand projections.

5. Supply model estimation and analysis

The PPML estimates of the supply model are shown in Table 6. The empirical results confirm that aviation supply is driven by an interplay of macro-economic scale, infrastructure availability, and operational path-dependency.

The results show strong persistence in flight supply. The coefficient on lagged frequency is positive and statistically significant (0.482***), indicating that existing network structures strongly influence future scheduling decisions. This persistence reflects both operational path-dependency and the long-term strategic value of maintaining network presence in specific markets. Airline operational constraints and cost considerations also play a role. A larger average aircraft size in the previous period is associated with significantly lower frequencies (–0.577**), consistent with the standard aircraft size–frequency trade-off observed in the aviation economics literature: when airlines upgauge aircraft, they often reduce the number of flights while maintaining total seat capacity.

[30] Ideally, a more accurate capacity measurement of airports globally would be preferred; however, such a database does not exist for public use, as confirmed in discussions with experts in the field.

Table 5: Estimation results of the gravity supply model by PPML.

	Dependent variable: $\mathbf{Freq}_{od,t}$	
Variables	**Coefficient**	**Standard error**
$\ln(\mathrm{PPPGDPpc}_{od,t})$	0.559***	0.090
$\ln(\mathrm{Pop}_{od,t})$	0.818**	0.256
$\ln(\mathrm{Airports}_{od,t})$	0.226**	0.084
$\ln(\mathrm{Freq}_{od,t-1})$	0.482***	0.014
$\ln(\mathrm{ArcftSize}_{od,t-1})$	-0.577**	0.180
$\mathrm{Covid}_{od,t}$ $(Yes = 1)$	-0.214***	0.039
Fixed Effects	Country pair / Year	
No. of observations	318,896	
No. of country pairs (directional)	28,694	
Pseudo-R^2	0.996	

Notes:

1) The model is estimated using Poisson Pseudo-Maximum Likelihood (PPML).
2) All regressors except the covid indicator are expressed in natural logarithms; the dependent variable (flight frequency) is in levels.
3) Country-pair and year fixed effects are included in the model but omitted from the table for brevity.
4) Standard errors are clustered at the country-pair level to account for heteroscedasticity and within-pair serial correlation.
5) Significance levels: *** p < 0.001; ** p < 0.01; * p < 0.05.

Source: IATA Sustainability and Economics

Market size and economic fundamentals also contribute meaningfully to flight supply. Higher PPP GDP per capita (0.559***) and larger populations (0.818**) at the bilateral level are associated with more scheduled flights, suggesting that carriers allocate capacity toward markets with stronger demand potential. Similarly, the number of operational airports in each market (0.226**) increases available infrastructure, enabling carriers to add frequencies. The model demonstrates that while wealth (GDP per capita) and population act as the primary engines of demand, the actualization of that demand into flight frequency is mediated by the number of active airports of a given country. This finding supports the "bottleneck" hypothesis: that supply is not merely a reflection of demand but is fundamentally capped by the nodal capacity of the origin and destination. Additionally, the fixed-effects structure effectively captures time-invariant frictions—such as geographic distance and historical ties—that traditionally affect air connectivity.

Notably, the large, positive, and highly significant coefficient of the population variable in the supply model proves that airlines look at population centres as the primary justification for adding capacity. Population is the structural prerequisite for frequency. This finding may explain why the population coefficient in the demand model estimation is insignificant (see Table 4). In fact, by running a stepwise PPML estimation for the demand model (Appendix D), we find that the statistical significance for the population variable disappears upon the introduction of “bottleneck” flight frequency. This transition does not imply that population is irrelevant to aviation demand; rather, it suggests that the "population effect" is already fully embodied within the service level. Therefore, the insignificance of population in the full demand model should be interpreted not as a lack of causal power, but as a transmission of that power through the frequency variable.

The model achieves a high pseudo-R^2 of 0.996, indicating an excellent fit for a PPML specification with two-way fixed effects. The estimated parameters are economically intuitive and are used to generate projected flight frequencies for the long-term RPK projections in this work.

6. Empirical demand and supply models for small countries with missing socio-economic data

As mentioned in Part 2 Section 2, a subset of very small states, island territories, or micro-economies (43 in total, accounting for about 2% of the global total RPK in 2024) in the final O-D dataset are not covered by GDP or population statistics from the IMF WEO. However, it is important to keep these countries in our projections to get more precise region and industry level estimates. These missing values present a challenge for the gravity-based PPML demand and frequency models, which rely on economic variables (PPP GDP per capita and population) of both endpoint countries as fundamental drivers of air travel demand. However, inspection of the dataset and preliminary diagnostics revealed a critical structural feature of these small markets. Their aviation activity is dominated by flows to and from a small number of large partner countries. Because the domestic markets of these small countries are tiny or nonexistent, changes in their RPK are primarily determined by the changes in their partner countries' economic scale rather than their own.

Given that growth in the partner country effectively "drives" the bilateral air traffic of these small states, we model the O-D RPKs for these cases using the PPP GDP per capita and population of the large partner country. When estimating the modified models, using only the large partner countries' socio-economic variables, both the RPK and the frequency gravity models produce plausible magnitudes and signs. This indicates that the modeling strategy captures the main underlying drivers of RPK and service frequency even in the absence of formal socio-economic data for the small country itself. Appendix E reports the model estimation results for these small countries with missing socio-economic data.

7. Model performance validation

Out-of-sample validation results are reported in Part 1 to demonstrate forecasting reliability for decision-makers. In this section, we provide further details on model validation, robustness checks, and statistical diagnostics to enhance methodological transparency.

A key modeling choice in long-term RPK forecasting using PPML estimates is how to anchor the Year Fixed Effect (Year FE) when projecting beyond the estimation period. Since the Year FE captures global shocks, technology adoption, regulatory changes, and other system-wide factors not included in the structural variables, its selection can materially affect forecast accuracy.

In the absence of significant structural breaks or idiosyncratic shocks, fixed effects from the most recent observation year typically serve as the most reliable proxies for future projections. Given that 2024 represents the latest available data point in our dataset, it is essential to determine whether the estimates remain confounded by the residual effects of the covid pandemic. To evaluate this, we conducted a targeted out-of-sample validation exercise designed to test how well different Year FEs extrapolate to a known "normal" period.

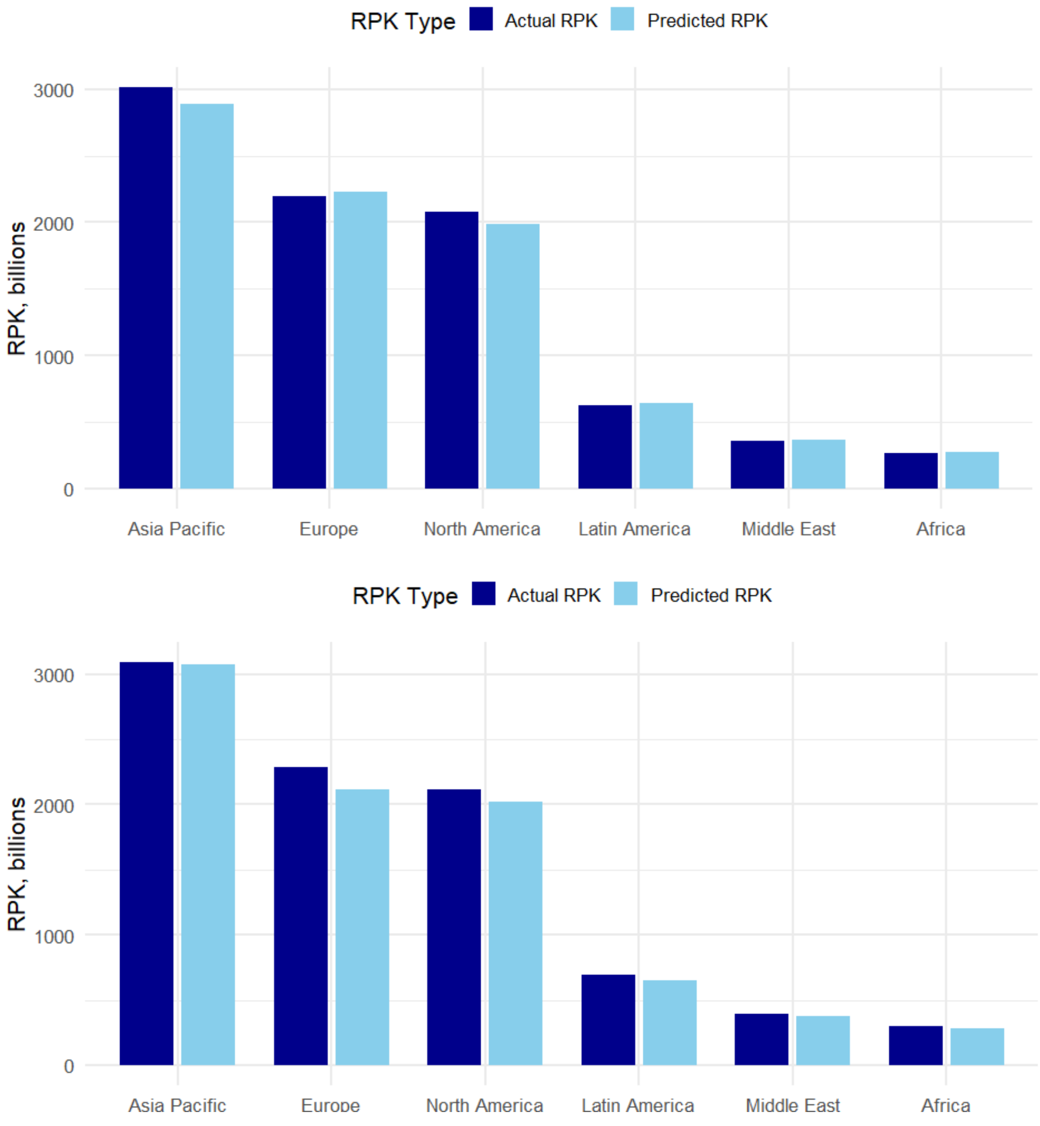
Two separate training/test splits were constructed:

1) Train: 2011–2018 and 2020–2024 → Test: 2019
   This setup excludes 2019 from estimation and assesses how well a model anchored on 2024 Year FE predicts the last pre-covid normal year.

2) Train: 2011–2023 → Test: 2024
   This setup evaluates a model anchored on 2023 Year FE predicting 2024 outcomes.

For each split, the model was estimated using PPML with country-pair and year fixed effects (Equation 2), and RPK was predicted for the withheld test year. Forecast performance was assessed using weighted Mean Absolute Percentage Error (wMAPE) and Root Mean Squared Error (RMSE).

Chart 11: Out-of-sample validation results by region using 2024 Year FE for forecasting (top) and 2023 Year FE for forecasting (bottom).



Source: IATA Sustainability and Economics

The comparison on the validation results shows that using the 2024 Year FE delivers lower wMAPE (3.5%) and RMSE (103.4) when predicting 2019 RPK, compared with using the 2023 Year FE to predict 2024 (wMAPE 6.5% and RMSE 145.8). Additionally, Chart 11 shows that the differences between the actual and predicted RPK at the regional level are smaller with the 2024 Year FE, especially in Europe.

Validation tests indicate that using 2024 Year FE to predict 2019 RPKs yields a highly acceptable wMAPE, suggesting a return to pre-pandemic equilibrium. Notably, this stability was not yet evident in the preceding year; despite its temporal proximity, using 2023 Year FE to predict 2024 results in a substantially higher wMAPE. These findings suggest that 2024 serves as a robust baseline for future year projections, whereas earlier post-pandemic years remain unrepresentative. Accordingly, all scenario-based projections in the IATA LTDP use the 2024 Year FE as the starting fixed-effect level, ensuring consistency and empirical grounding.

8. RPK projections under the global energy transition scenarios

For forecasting purposes, the demand and supply gravity models operate as a sequence:

1. Step 1: Project frequency using the PPML gravity supply model under each scenario (economic growth, infrastructure expansion, recovery trajectories, etc.).

2. Step 2: Feed predicted frequencies into the PPML-IV demand model to forecast route-level RPK while maintaining internal consistency between supply and demand.

3. Step 3: Aggregate and generate scenario-based global and regional RPK forecasts, allowing end-users to understand how supply decisions contribute to demand recovery and long-term traffic evolution.

This integrated design—modeling supply and demand separately but linking them through projected frequencies—ensures that the final RPK forecasts are both econometrically robust and operationally meaningful.

Appendix A: The technical framework for OECD's long-run economic projections[2]

This part is sourced directly from the OECD (2025), "OECD global long-run economic scenarios: 2025 update", OECD Economic Policy Papers, No. 36, OECD Publishing, Paris, Box 1 and their full report contains more details.

The OECD Long-Term Model (LTM) consists of a set of dynamic projection rules and identities for variables of interest, implemented at the country level using annual data. For all countries, the backbone of the model is potential output, assumed to be a function of available inputs (labor and capital) and the efficiency with which those inputs are combined (labor efficiency). The production function is a constant-returns-to-scale Cobb-Douglas function with Harrod-neutral labor-augmenting technical progress. Indexing country and time with subscripts i and t (annual frequency) and using mnemonics as they appear in OECD Economic Outlook (EO) databases, potential output ($GDPVTR_{i,t}$) is:

$$GDPVTR_{i,t} = (EFFLABS_{i,t} \cdot ETPT_{i,t})^{\alpha} \cdot KTPV\_AV_{i,t}{}^{1-\alpha}$$

where $ETPT_{i,t}$ denotes trend employment; $KTPV\_AV_{i,t}$ represents a whole-economy measure of the capital stock, $EFFLABS_{i,t}$ is trend labor efficiency and α is the labor income share, assumed to be 0.67 in all countries. For the countries covered directly in the EO, potential output projections are an extension of the short-term potential output estimates prepared for the EO. A similar but simplified approach is used to estimate and project potential output for other countries using historical data from the World Bank's World Development Indicators (WDI) database. The last historical period in these different sources is the starting point for long-run projections and is referred to as the jump-off point (between historical and projection periods). Potential output is projected out to 2100 by modelling the trend input components separately.

Trend labor efficiency

Trend labor efficiency is projected using a revised framework that mixes elements of absolute and conditional convergence. Convergence is absolute in so far as trend labor efficiency in every economy is ultimately going to a common frontier level. And it is conditional in so far as the speed at which this occurs is a function of country-specific framework conditions. The revised framework is based on a model estimated over the 1996-to-2023 period using data for the 139 individual countries included in the LTM. The estimated coefficients are then incorporated in the closely related projection equation:

$$\Delta e_{i,t} = \varphi + \delta_{i,t}(e_{i,t-1} - e^{*}_{i,t-1}) - \Delta DAMAGE_{i,t} + \Delta ABATCOST_{i,t} + \mu_{i,t}$$

$$\delta_{i,t} = \gamma_0 + \gamma_1 RULELAW_{i,t} + \gamma_2 KOFECGI_{i,t} + \gamma_3 MACROSTABILITY_{i,t}$$

$$\mu_{i,t} = \rho \cdot \mu_{i,t-1}$$

where $e_{i,t}$ is log trend labor efficiency expressed in USD at fixed 2021 prices and Purchasing Power Parity (PPP) exchange rates ($e_{i,t}$= log ($EFFLABS_{i,t}$)). Its projected growth rate ($\Delta e_{i,t}$) is the sum of five components:

- Rate of global technical progress (φ). This component is common to all countries and set to 1% in the scenarios examined in this paper. This assumption is based on the geometric mean trend labor efficiency growth rate of advanced G20 economies over the past 30 years or so.

- Convergence to frontier ($\delta_{i,t}(e_{i,t-1} - e^{*}_{i,t-1})$). This component captures the effect of catching up toward the frontier labor efficiency level ($e^{*}_{i,t}$), assumed to be that of the United States, or a country's own level if already higher than that of the United States. In the latter case the convergence term is zero by construction (this applies to only a handful of economies, notably oil-rich ones). The growth impetus depends on how far a country is relative to the frontier ($e_{i,t-1} - e^{*}_{i,t-1}$) and on a country-specific speed of convergence ($\delta_{i,t}$), which is modelled as a function of a country's framework conditions. Those include the quality of governance (based on the World Bank's Rule of Law indicator, $RULELAW_{i,t}$), the degree of economic globalisation (based on the KOF Swiss Institute's economic globalisation index, $KOFECGI_{i,t}$) and an index of macroeconomic stability (based on the level and variance of a moving average of headline inflation, $MACROSTABILITY_{i,t}$). The need for tractability, broad country coverage and avoidance of data gaps has led to the selection of only three framework conditions but, in practice, these proxy a wider set of correlated structural growth determinants. A country with mean scores on all three structural indicators would close approximately 1.3% of any remaining gap with frontier labor efficiency annually. Better scores on the structural indicators raise this speed and vice-versa (based on estimated coefficients $\hat{\gamma}_1$, $\hat{\gamma}_2$ and $\hat{\gamma}_3$). Implied convergence speeds at the jump-off point vary between zero (no convergence) to 2.6% annually. Framework conditions are assumed to remain at initial values in the scenarios examined in this paper, as has been the convention in previous exercises, so convergence speeds do as well.

- Climate damage ($\Delta DAMAGE_{i,t}$). The output costs associated with global warming are assumed to manifest primarily via lower trend labor efficiency (with knock-on effects on capital accumulation).

- Carbon abatement costs ($\Delta ABATCOST_{i,t}$). In the BAU scenarios, abatement costs are set to zero by design. In energy transition scenarios, abatement of carbon emissions is assumed to impact trend labor efficiency according to country-specific elasticities of output to carbon mitigation. These elasticities are estimated from a range of scenarios produced with the ENV-Linkages model (Château, Dellink and Lanzi, 2014[2]). These elasticities reflect the state of technology today, so a parameter can be adjusted that controls the rate at which carbon abatement costs are assumed to decline over time. See Annex B of Guillemette and Château (2023[1]) for additional details.

- Momentum ($\mu_{i,t}$). This residual component captures that part of trend labor efficiency growth at the jump-off point that is unexplained by other components of the model. The initial value decays over time with a half-life of about 6 years (based on estimated coefficient $\hat{\rho}$). This decay rate ensures a smooth transition from estimated trend labor efficiency growth rates at the jump-off point and longer-run projections. Given the parsimoniousness of the specification, the momentum component captures many country-specific growth determinants beyond those affecting the speed of convergence. The gradual decline of this component implicitly assumes that these determinants are persistent, but not permanent.

In the very long run, save for the impact of mitigation or climate damages, trend labor efficiency growth in all countries converges to the assumed exogenous rate of global technological progress (1% per annum), although for most countries this would occur beyond the 2100 projection horizon.

Trend employment

The evolution of trend employment is primarily the result of three sets of dynamics: the evolving size of the working-age population (defined here as ages 15 to 74); its age composition; and trends in the employment rates of different age/sex groups. The size and composition of the working age population follow the demographic projections of the United Nations World Population Prospects (2024 revision, medium variant) and are exogenous in the LTM. Trends in the employment rates of different age/sex groups are projected by applying a cohort approach to historical employment rates (Cavalleri and Guillemette, 2017[3]). These generational trends reflect societal changes, such as rising female employment rates, but also structural changes such as higher educational attainment. Already-legislated future changes in legal retirement ages are incorporated in projections of the employment rates of people aged 55 and over. Climate damages are assumed not to affect population size or potential employment, although heat-related mortality and international migration could be important drivers of climate-related output costs in some countries.

Capital stock

In the short to medium run, the main source of variation in the capital stock is the net investment rate at the jump-off point. If it is higher than the rate that would be consistent with keeping the initial capital-to-output ratio stable given projections of trend employment and trend labor efficiency growth, then the capital-to-output ratio rises and contributes positively to potential output growth, and vice-versa. In the longer run, investment rates adjust dynamically to target a capital-to-output ratio of 3.4, an historical average among advanced countries. This adjustment happens very gradually, and the target is not attained by all countries by the end of the projection period. The fixed long-run target for the capital-tooutput ratio implies that both climate damages and carbon abatement impact the level of the capital stock proportionally. In equilibrium, given the 0.33 capital income share in the production function, one third of climate damages and one third of any carbon abatement costs come through via a lower ratio of capital per worker.

Potential output per capita growth decomposition

A convenient expository decomposition (used in figures) is to divide changes in potential output per capita, a crude metric for living standards, into productivity, capital intensity and labor utilisation components:

$$\Delta gdpvtr\_cap = \alpha \cdot \Delta efflabs + \{1 - \alpha\} \cdot \Delta(ktpv\_av - etpt) + \Delta(etpt - pops\_1574) + \Delta(pops\_1574 - pops)$$

where $gdpvtr\_cap$ is log potential output per capita, $pops\_1574$ is log trend working-age population, $pops$ is log trend total population and other lower-case variables are logarithms of their upper-case counterparts introduced above. The first term on the right-hand side of this equation measures the contribution of trend labor efficiency growth to potential GDP per capita growth; the second term measures the contribution of capital intensity (capital per worker); the third picks up the contribution of the trend employment rate; and the last term indicates the contribution of the working-age population share, a summary indicator of the population age structure.

Appendix B: List of countries with missing values on socio-economic data from the IMF and UN databases

ID	Country	RPK share of global total in 2024
1	Cuba	0.23%
2	Réunion	0.17%
3	Guadeloupe	0.12%
4	Guam	0.11%
5	Martinique	0.10%
6	Curaçao	0.10%
7	French Polynesia	< 0.1%
8	Virgin Islands (U.S.)	< 0.1%
9	Sint Maarten (Dutch part)	< 0.1%
10	New Caledonia	< 0.1%
11	Northern Mariana Islands	< 0.1%
12	French Guiana	< 0.1%
13	Turks and Caicos Islands	< 0.1%
14	Cayman Islands	< 0.1%
15	Bermuda	< 0.1%
16	Bonaire, Sint Eustatius and Saba	< 0.1%
17	Cook Islands	< 0.1%
18	Mayotte	< 0.1%
19	Gibraltar	< 0.1%
20	Greenland	< 0.1%
21	Western Sahara	< 0.1%
22	Faroe Islands	< 0.1%
23	Virgin Islands (British)	< 0.1%
24	Svalbard and Jan Mayen	< 0.1%
25	American Samoa	< 0.1%
26	Saint Barthélémy	< 0.1%
27	Saint Martin (French part)	< 0.1%
28	Norfolk Island	< 0.1%
29	Eritrea	< 0.1%
30	Korea (Democratic People's Republic of)	< 0.1%
31	Wallis and Futuna	< 0.1%
32	Christmas Island	< 0.1%
33	Anguilla	< 0.1%
34	Niue	< 0.1%
35	Saint Pierre and Miquelon	< 0.1%
36	Cocos (Keeling) Islands	< 0.1%
37	Somalia	< 0.1%
38	Falkland Islands (Malvinas)	< 0.1%
39	Saint Helena	< 0.1%
40	British Indian Ocean Territory	< 0.1%

41	Monaco	< 0.1%
42	Montserrat	< 0.1%
43	Palestine	< 0.1%

Appendix C: Model estimation for countries' total number of active airports

We assume that a country's total number of active airports depends on its population, GDP per capita, and the physical limit of its land area. We obtained countries' active airports between 2011 and 2024 from the OAG database and divided them by each country's land area, sourced from the World Bank. This "airport density" variable, measured by the number of airports per 100k km² by country i in year t, is the target variable for our simple Fixed Effects (FE) panel model specified in the following equation:

$$\text{Airport\_density}_{i,t} = \beta_1 \ln(\text{PPPGDPpc}_{i,t}) + \beta_2 \ln(\text{Pop}_{i,t}) + \emptyset_i + \gamma_t) + \varphi_{i,t}$$

$\emptyset_i$ represents the fixed effects of country i, capturing all time-invariant frictions of a given country, such as culture and geographic location. γ_t captures year fixed effects, absorbing global shocks to this country's long-term air transport infrastructure plans.

We hypothesize that aviation infrastructure development follows a non-linear path, where developing nations exhibit higher rates of airport construction compared to developed nations, driven by their significant economic and demographic growth potential. To capture these distinct development phases, we segment our analysis into three categories defined by the IMF: Advanced Economies, Emerging Market Economies, and Low-income Developing Economies. The empirical results, which reveal a clear transition from rapid infrastructure expansion in lower-income groups to consolidation in advanced economies with mature airport infrastructure, are presented below.

(1) Advanced Economies

```
OLS estimation, Dep. Var.: log(airport_density)
Observations: 546
Fixed-effects: Country: 39,  Year: 14
Standard-errors: IID
              Estimate Std. Error  t value Pr(>|t|)
log(Pop)      0.521711   0.287934  1.81191 0.070610 .
log(GDP_pc) -0.194700   0.117715 -1.65399 0.098768 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
RMSE: 0.211031     Adj. R2: 0.974974
                Within R2: 0.010785
```

For Advanced Economies, the results suggest a decoupling of airport growth from economic and demographic expansion. The coefficient for PPP GDP per capita is negative (-0.19) and statistically significant at the 10% level. This implies that as these nations become wealthier, airport density actually tends to decrease slightly. This could be due to infrastructure maturation, the high maintenance costs of underutilized regional airports, or a shift toward high-speed rail. While population growth has a positive coefficient (0.52), it is only marginally significant. This result suggests that advanced economies have reached a "saturation point." Further growth is more likely to translate into the optimization of existing airports rather than the construction of new ones.

(2) Emerging Market Economies

```
OLS estimation, Dep. Var.: log(airport_density)
Observations: 1,316
Fixed-effects: Country: 94,  Year: 14
Standard-errors: IID
             Estimate Std. Error  t value  Pr(>|t|)
log(Pop)     0.032405   0.150187 0.215764 0.8292086
log(GDP_pc)  0.172802   0.062233 2.776703 0.0055763 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
RMSE: 0.253037     Adj. R2: 0.98695
                 Within R2: 0.006648
```

In contrast, Emerging Markets show a strong, positive correlation between economic wealth and infrastructure expansion. The coefficient for PPP GDP per capita is positive (0.17**) and highly significant. This indicates a robust "catch-up" effect where economic growth directly fuels the demand for new aviation infrastructure. The population coefficient is near zero and statistically insignificant, suggesting that in these markets, wealth (affordability) is a much stronger driver for new airport construction than raw population count. The result from the Emerging Economies suggests that these countries are in an active expansionary phase where rising incomes promote greater domestic and international connectivity.

(3) Low-income Developing Economies

```
OLS estimation, Dep. Var.: log(airport_density)
Observations: 784
Fixed-effects: Country: 56,  Year: 14
Standard-errors: IID
             Estimate Std. Error  t value  Pr(>|t|)
log(Pop)     1.032312   0.332858  3.10136 0.0020023 **
log(GDP_pc)  0.338337   0.103283  3.27582 0.0011045 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
RMSE: 0.307386     Adj. R2: 0.962278
                 Within R2: 0.04015
```

For low-income countries, airport density is highly unevenly distributed and tightly coupled with basic economic development. The coefficient for population is 1.03** and is highly statistically significant. It suggests that for every 1% increase in population, airport density increases by more than 1%, pointing to population growth being a airport infrastructure in low-income developing countries. Similarly, PPP GDP per capita also has a positive and highly significant coefficient of 0.34**. Overall, as low-income countries move out of poverty, there is an immediate and aggressive expansion of aviation nodes to facilitate mobility, trade and integration into the global economy.

Using the estimated coefficients, we project future airport density by country under our three growth scenarios. Finally, the total number of airports is derived by multiplying the projected airport density with the country's land area.

Appendix D: Stepwise estimation results using PPML

	M1	M2	M3	M4	M5	M6	M7
log_OD_Pop	0.416	0.983***	1.096***	1.337***	1.212***	0.229	0.245
	(0.453)	(0.265)	(0.248)	(0.281)	(0.265)	(0.299)	(0.284)
log_OD_GDP_pc		0.989***	0.781***	0.978***	1.044***	0.803***	0.810***
		(0.150)	(0.098)	(0.175)	(0.190)	(0.201)	(0.190)
log_fare			-0.566***	-0.581***	-0.513***	-0.183***	-0.183***
			(0.054)	(0.055)	(0.053)	(0.049)	(0.047)
log_OD_employment_rate				1.870***	1.412***	1.188***	1.405***
				(0.399)	(0.396)	(0.299)	(0.290)
Covid					-0.625***	-0.433***	-0.411***
					(0.061)	(0.037)	(0.035)
log_bottleneck_freq						0.479***	0.495***
						(0.038)	(0.037)
log_arft_size							1.016***
							(0.115)
R-squared	0.989	0.990	0.991	0.991	0.992	0.994	0.994
N	366461	366461	366461	366461	366461	366461	366461
SE Cluster	by: country_pair	by: country_pair	by: country_pair	by: country_pair	by: country_pair	by: country_pair	by: country_pair

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table: Step-wise Regression Results: PPML

Appendix E: Model estimation results and RPK projections for the small countries with missing data on socio-economic drivers

(1) Large partner countries as the destination country

PPML-IV first stage:

```
OLS estimation, Dep. Var.: log_fare
Observations: 28,401
Fixed-effects: country_pair: 3,283,  Year: 13
Standard-errors: Clustered (country_pair)
                      Estimate Std. Error   t value   Pr(>|t|)
log_lag_fare_IV        0.062333   0.009771  6.379330 2.0280e-10 ***
log_O_Pop             -0.018876   0.058657 -0.321806 7.4762e-01
log_O_GDP_pc          -0.026715   0.024316 -1.098646 2.7200e-01
log_O_employment_rate -0.084559   0.067316 -1.256154 2.0915e-01
covid                 -0.025704   0.027005 -0.951824 3.4126e-01
log_arft_size         -0.061939   0.015793 -3.921905 8.9649e-05 ***
log_bottleneck_freq   -0.003089   0.002669 -1.157252 2.4725e-01
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
RMSE: 0.210732     Adj. R2: 0.841315
                 Within R2: 0.004409
```

PPML-IV main:

```
Poisson estimation, Dep. Var.: od_rpk
Observations: 30,085
Fixed-effects: country_pair: 3,279,  Year: 14
Standard-errors: Clustered (country_pair)
                         Estimate Std. Error   z value   Pr(>|z|)
log_D_Pop                 1.708823   0.866118  1.972968 4.8499e-02 *
log_D_GDP_pc              0.705948   0.262832  2.685929 7.2328e-03 **
log_D_employment_rate     0.101389   1.476701  0.068659 9.4526e-01
log_fare                 -0.262675   0.117552 -2.234532 2.5448e-02 *
covid                    -0.721488   0.282057 -2.557952 1.0529e-02 *
log_arft_size             0.497580   0.296601  1.677607 9.3424e-02 .
log_bottleneck_freq       0.382513   0.068057  5.620449 1.9046e-08 ***
fs_small_O_fare_residuals -0.024874   0.044736 -0.556019 5.7820e-01
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Log-Likelihood: -3.745e+10   Adj. Pseudo R2: 0.984387
           BIC:  7.489e+10     Squared Cor.: 0.972137
```

(2) Large partner countries as the origin country

PPML-IV first stage:

```
OLS estimation, Dep. Var.: log_fare
Observations: 28,401
Fixed-effects: country_pair: 3,283,  Year: 13
Standard-errors: Clustered (country_pair)
                       Estimate Std. Error   t value   Pr(>|t|)
log_lag_fare_IV        0.062333   0.009771  6.379330 2.0280e-10 ***
log_O_Pop             -0.018876   0.058657 -0.321806 7.4762e-01
log_O_GDP_pc          -0.026715   0.024316 -1.098646 2.7200e-01
log_O_employment_rate -0.084559   0.067316 -1.256154 2.0915e-01
covid                 -0.025704   0.027005 -0.951824 3.4126e-01
log_arft_size         -0.061939   0.015793 -3.921905 8.9649e-05 ***
log_bottleneck_freq   -0.003089   0.002669 -1.157252 2.4725e-01
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
RMSE: 0.210732     Adj. R2: 0.841315
                 Within R2: 0.004409
```

PPML-IV main:

```
Poisson estimation, Dep. Var.: od_rpk
Observations: 30,506
Fixed-effects: country_pair: 3,326,  Year: 14
Standard-errors: Clustered (country_pair)
                          Estimate Std. Error   z value  Pr(>|z|)
log_O_Pop                 1.293419   0.881951  1.466544  0.142500
log_O_GDP_pc              0.629326   0.284630  2.211031  0.027034 *
log_O_employment_rate     1.015170   1.450441  0.699904  0.483987
log_fare                 -0.208494   0.130142 -1.602055  0.109143
covid                    -0.700739   0.275104 -2.547180  0.010860 *
log_arft_size             0.517919   0.327262  1.582580  0.113517
log_bottleneck_freq       0.411181   0.047864  8.590580 < 2.2e-16 ***
fs_small_D_fare_residuals 0.030053   0.045473  0.660889  0.508684
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Log-Likelihood: -3.832e+10   Adj. Pseudo R2: 0.984089
           BIC:  7.664e+10     Squared Cor.: 0.97094
```

(3) RPK projections for the small countries with missing macro-economic data