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From Operations to Policy: Integrating the CII Index into Analytical Frameworks for Airline Decarbonization

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ABSTRACT

The aviation industry, contributing 2–3 % of global CO_2 emissions annually, faces growing pressure to balance environmental responsibilities with economic performance. With the International Air Transport Association's (IATA) net-zero carbon goal by 2050, airlines must address challenges such as carbon tax policies, fleet optimization, and consumer affordability. This study examines the impact of market-based emission policies—carbon taxes, trading systems, and offset mechanisms—on Full-Service Carriers (FSCs) and Low-Cost Carriers (LCCs). Findings reveal that LCCs, with high efficiency and short-haul operations, adapt better to regulations than FSCs, which face higher costs due to long-haul networks. Strategies like fleet modernization, increased load factors, and sustainable aviation fuels (SAFs) are explored as pathways to mitigating passenger cost burdens while ensuring compliance. Methodologically, the study employs a Log-Mean Divisia Index (LMDI) decomposition model alongside a decoupling analysis to assess the environmental and financial performance of airlines. Highlighting the importance of tailored strategies, this study provides actionable insights and emphasizes collaboration between governments, airlines, and consumers to achieve sustainable growth in aviation. In addition, the study adapts the Carbon Intensity Indicator (CII) from the maritime sector to aviation, providing a novel metric for assessing carbon efficiency. Integrating CII with LMDI and profitability indicators enables a more transparent evaluation of airline sustainability and offers policymakers a robust tool for emission management.

1. Introduction

The global aviation sector plays a critical role in facilitating economic growth, international trade, and human mobility. However, it remains one of the fastest-growing sources of greenhouse gas (GHG) emissions, accounting for approximately 2–3 % of global CO_2 emissions (IATA, 2021). As climate change mitigation efforts intensify, the aviation industry faces increasing pressure to balance environmental responsibilities with operational efficiency and financial viability. The International Air Transport Association (IATA) has committed to achieving net-zero carbon emissions by 2050, yet reaching this target remains a considerable challenge due to complex operational structures and the financial burdens associated with emission reduction strategies.

Although market-based emission policies—including carbon taxes, emission trading systems (ETS), and offset mechanisms—have been introduced to regulate the environmental footprint of the aviation sector, the financial and operational impacts of these policies on airlines with different business models are not yet fully understood (Pang and Chen, 2023). Full-Service Carriers (FSCs) and Low-Cost Carriers (LCCs) differ fundamentally in their route structures, operational models, and cost strategies. These differences result in asymmetric exposure to emission-related costs and varying capacities for operational adjustment (Chang et al., 2017). Furthermore, the potential for emission policies to indirectly increase passenger fares and affect airlines' fleet modernization investments has been underexplored.

This study seeks to fill this gap by examining the impacts of market-based emission policies on both the environmental and financial performance of full-service carrier (FSC) and low-cost carrier (LCC) airlines in the United States. It proposes a strategic framework to optimize operational decision-making under emission constraints while minimizing financial burdens and ensuring network sustainability. The study also provides practical insights for policymakers by identifying the conditions under which emission policies can promote both environmental sustainability and economic efficiency.

Previous studies have examined the effects of carbon taxes and emission trading systems on airline operations and pricing strategies (Brueckner and Zhang, 2010; Dray et al., 2014; Becken and Carmignani, 2020). Others have focused on the role of price elasticity and demand

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shifts in the effectiveness of market-based environmental policies (Zhou and Hansen, 2012; Fu and Kim, 2016). However, recent research emphasizes that the interaction between emission policies and airline business models deserves closer attention, particularly given the distinctive operational characteristics of FSC and LCC networks (Liao et al., 2024; Jiang, D'Alfonso & Post, 2024). Additionally, new evidence highlights how policies such as sustainable aviation fuel (SAF) mandates and carbon pricing affect airline competition dynamics and fleet decisions (Chen et al., 2024; Zheng et al., 2024).

Despite these contributions, comparative analyses focusing on how emission regulations affect FSC and LCC airlines differently remain scarce. Studies such as those by Yue and Byrne (2024) and Isik et al. (2020) using decomposition techniques like Log Mean Divisia Index (LMDI) have primarily centered on aggregated emission trends without separating the effects by airline business model. This gap underscores the need for detailed, disaggregated analyses to evaluate financial and operational sustainability in the context of environmental regulations (Kaffash et al., 2024).

To address these gaps, this study applies a Log-Mean Divisia Index (LMDI) decomposition model alongside a decoupling analysis framework to evaluate changes in emissions, energy efficiency, and financial performance variables in the U.S. commercial airline industry over the period 2000–2020. Operational and financial data were obtained from the Massachusetts Institute of Technology (MIT) Airline Data Project and the cooperative programme for monitoring and evaluation of the long-range transmission of air pollutants in Europe (EMEP)/European Environment Agency (EEA) 2023 Emission Inventory Guidebook, covering a sample of 15 U.S. airlines (3 FSC, 4 LCC, and 3 Hybrid carriers). The analysis includes variables such as carbon intensity, energy intensity, load factor, profit per mile, and passenger yield, enabling a nuanced evaluation of operational and financial outcomes under emission policy scenarios.

Theoretically, this study contributes to the aviation literature by offering a comparative, business model-specific evaluation of emission policy impacts using an integrated decomposition framework. Practically, the findings provide actionable recommendations for policymakers and airline managers, highlighting pathways to balance environmental responsibilities with operational profitability and fare affordability. The results are particularly relevant for shaping future emission policy designs that consider the heterogeneity of airline business models and operational realities.

The International Air Transport Association (IATA) has adopted a net-zero carbon target by 2050, emphasizing that this transition in the sector must be balanced with economic sustainability (IATA, 2021). This is because all these economic indicators and limitations are mainly for 2 reasons.

a) to ensure that the air travel industry continues to make progress towards reducing emissions (Becken and Carmignani, 2020) and,
b) Encourage investments in carbon reduction and removal technologies and alternative energy sources (Dray et al., 2022).

These actions ultimately follow the 2050 net-zero target signed by 196 countries in 2015 (Bodansky, 2016). The total number of commercial flights continues to increase daily, while demand for commercial jets is also rising, and total flight demand is expected to return to its pre-pandemic level by 2025 (S&P Global, 2024).

Governments implement various carbon regulations to manage carbon emissions, including the carbon tax policy (CTP), carbon cap policy (CCP), carbon cap-and-trade policy (CCTP), and carbon offset policy (COP) (Cao et al., 2017). Under the CTP, a tax is imposed for each ton of carbon emitted into the atmosphere, without any cap on total emissions. However, companies must pay for their emissions, which may influence their decisions on whether to meet demand. The CCP has no tax on carbon emissions, but a strict limit is placed on the total allowable emissions, which cannot exceed a defined threshold. The CCTP allows for the buying and selling of carbon credits. Like the CCP, a cap is set on total emissions, but companies can trade their emission allowances in carbon markets. The COP shares similarities with the CCTP; however, it permits only the purchase of carbon credits, without the option to sell (Rahmati et al., 2024). Various carbon reduction policies have also forced many airlines to make changes to their fleets and become more efficient (Albert et al., 2025). Not only changes that are carbon-neutral, but also strategies to avoid emitting too much carbon for more profit by limiting the pricing strategy have been used (Cui, 2019). Some limit the price of the ticket sold, while others aim to reduce emissions by limiting the amount of greenhouse gases that can be emitted by the company or route (Cantos-Sánchez et al. (2023). As a result, the measures and regulations implemented are market-based (Scheelhaase et al., 2018).

While determining all these rules, it would be more useful to decide on the quality limits and environmental responsibility areas of the industry in some areas by evaluating the operational structure adopted by the airline as a Full Service Carrier (FSC) or Low-Cost Carrier (LCC) in terms of all these financial and environmental impacts (Yilmaz and Kose, 2021). This is because the service attitude of airlines plays an important role in the operations of small or large airports (Spitz et al., 2015). Therefore, although there are many studies in the existing literature with separate evaluations, the scarcity of studies evaluating both financial and environmental impacts has been the driving force for this study.

Balancing both environmental and economic responsibilities is becoming an increasingly vital issue for airlines (Wandelt et al., 2024). Assessing the impacts of policies such as carbon tax and price cap plays a critical role in creating strategic roadmaps for the future of the industry (Sobieralski, 2021).

This study could provide a critical opportunity to understand the impacts of such regulations on companies' environmental and economic performance. Moreover, assessing the economic lifetime of different aircraft types in fleets (small, medium, and wide-body) in the face of carbon tax policies is an important dimension that can help airlines optimize their long-term strategies (Rosskopf et al., 2014). In this context, we are looking for answers to the following research questions.

RQ1 How can different emission policies differ in terms of LCC and FSC? Can this affect the network policies of these companies?
RQ2 What are the limits of the policies that need to be adopted to be both financially advantageous and environmentally friendly in terms of emissions?
RQ3 What strategies can be implemented to mitigate the cost burden of emission policies on passengers while maintaining airlines' operational profitability?
RQ4 How do the efforts made to obtain a more environmentally friendly flight network with emission policies affect the service life of the fleet and the accessibility of technological innovations?

This study aims to evaluate how market-based emission policies impact the operational, financial, and environmental performance of FSC and LCC airlines, offering strategic recommendations for sustainable network planning.

2. Motivation and relevant studies

The fast expansion of the aviation industry has increased both intercity travel and cargo transportation. More than 100,000 aircraft operate every day throughout the world, emitting huge volumes of carbon dioxide and other pollutants that cause major environmental and climate problems. The International Air Transport Association (IATA) estimates that aviation emitted 915 million tons of carbon dioxide worldwide in 2019, accounting for 2.4 % of all carbon emissions worldwide (IATA, 2020). Most airplane emissions occur at high altitudes; therefore, they have a greater direct impact on the greenhouse effect. As a result, their contribution to climate change is disproportionately bigger than their share of overall carbon emissions. (Lee et al., 2010). Despite a global strategic consensus to reduce aircraft carbon emissions, achieving net-zero carbon emissions in the aviation sector remains challenging. There are four main techniques to reduce aircraft carbon emissions: technology developments, operational improvements, sustainable aviation fuels, and market-based policies (ATAG, 2021). Furthermore, the annual growth in carbon dioxide emissions from the aviation sector may offset or even overwhelm other sectors' emission reduction efforts, delaying the accomplishment of national carbon neutrality targets. The primary reason for this could be that carbon policies do not always correspond with economic efficiency or produce unanticipated outcomes. Therefore, it will contribute to the literature to conduct separate examinations and present them for companies operating with two different flight policies, namely FSC and LCC. As a result, the aviation industry is facing tremendous pressure to reduce its carbon footprint. The general scope of this article and the content of the literature review will mostly be related to the examination of the differences between FSC and LCC and the separation of cost components of studies on active trade-offs and cooperation between operational improvements and market-based policies used to contribute to aviation emission policies. The study aims to provide opinions and suggestions on exposing companies with different flight policies implemented on an operational basis to carbon policies under the same conditions. In this study, Full-Service Carriers (FSCs) refer to airlines that offer a wide range of pre- and in-flight services, typically operating hub-and-spoke networks and long-haul international routes. Low-Cost Carriers (LCCs), in contrast, focus on cost minimization through point-to-point services, high aircraft utilization, and fewer amenities. In the U.S. market, the sample includes 3 FSCs (such as Delta, United, American), 4 ULCCs (such as Spirit, Frontier, Allegiant, Hawaiian), and 3 Hybrid carriers (e.g., Southwest, Alaska, JetBlue), classified based on operational and service model characteristics. While the dataset focuses on U. S.-based airlines due to comprehensive data availability, the findings and policy implications offer valuable insights applicable to international contexts with similar regulatory and operational dynamics.

2.1. Market-based emission policies of the aviation sector

Market-based techniques are crucial to reducing aircraft carbon emissions. Market-based approaches offer the advantage of lowering excess emissions when other measures fail to meet reduction goals. Essentially, this includes purchasing qualified carbon units on the market to offset emissions. For airlines, the cost of market-based initiatives is determined by carbon pricing or the cost of purchasing one certified carbon unit. It seems reasonable that fuel emissions compounded by the carbon price would result in carbon offset expenditure for airlines. This has an immediate influence on operating expenses and shapes their strategic decisions. (Brueckner and Zhang, 2010). Prior studies have mostly concentrated on the financial effects on airline ticket pricing, earnings, and market shares; the consequences from the standpoint of the aviation network have received less attention. The network of air transportation is essential to both regional and international economic growth. The aviation network is growing as the level of global economic integration keeps rising. The crucial issue is for airlines to determine whose network policies will allow them to continue operating. An essential component of aviation's green development will be the network structure of airlines (Zhao et al., 2023). Usually, a large amount of an airline's overall expenses is related to fuel prices. The fuel and cost efficiency of commercial airplane operations can be enhanced by route optimization (Xu et al., 2014). Airlines can help achieve overall sustainability goals by strategically designing their routes to minimize fuel usage, which can result in both financial savings and environmental advantages. The network structure of the airline is established in this planning activity, which also indicates whether the LCC or FSC tendencies it will be closest to. As countries promise to subsidize airlines for their carbon footprints (IATA, 2013) and support carbon removal initiatives, carbon offsetting by monetary measures is on its way to becoming an obligatory policy instrument, along with research and development (R&D) in more environmentally friendly technologies and energy sources, such as sustainable aviation fuel (SAF). According to Pagoni and Psaraki-Kalouptsidi (2016), airlines are expected to pass these charges on to customers via a transparent and consistent process. In certain instances, such as Switzerland, the national government suggested placing a direct carbon price on airline tickets (Wild et al., 2021).

The national and international analyses that inform aviation environmental policies are predicated on the premise that air demand reacts consistently to price-based policy interventions, as demonstrated by the use of a general price elasticity of demand (Becken and Carmignani, 2020; Zheng and Rutherford, 2022). However, it has been demonstrated that the price elasticity of demand varies significantly between airports and regions (Brons et al., 2002; Schiff and Becken, 2011). Although it is anticipated that environmental laws will be applied on a national level, different jurisdictions will not have the same consequences and results. In light of these studies, it has been observed that price-based approaches have largely revolved around the concepts of supply and demand and price elasticity. In this case, it is known that these relationships underlie the price-based policies that need to be examined. Generally speaking, the price for airlines is usually referred to as the ticket price, and pricing is assumed to be the direct ticket price (Zou and Hansen, 2012). However, one of the major factors affecting this assumption is capacity. If we broaden the concept of capacity, the capacity of airports or airplanes limits the number of flights that can be sold or operated (Dixit and Jakhar, 2021). This leads to changes in ticket prices and, therefore, to different ticket prices arising from differences in demand. However, since airplanes do not always fly at full capacity, it is not possible for the capacity to fully reflect the ticket prices. This is usually expressed as a percentage, called the load factor of the aircraft, and ticket prices are shaped by the average occupancy rate and the amount of overbooking allowed by civil aviation rules. Although this complex web of supply-demand relationships has created an academic literature that has been studied for years, ever-changing regulations have also differentiated the scope and content of studies in this field.

The link between aviation supply and demand has been researched for more than 40 years, although price has been approached in many ways throughout that literature. The majority of studies (Ippolito, 1981; Agarwal and Talley, 1985; Jorge-Calder, 1997; Mohammadian et al., 2019) assume that to adapt to changes in passenger demand, airlines will only alter their capacities and not their airfares. Airline prices are considered an exogenous variable in these situations. Some contend that airfare is endogenous and that airlines modify their rates in response to shifts in demand (Suzuki and Audino, 2003; Fu and Kim, 2016; Kuok et al., 2023). According to Cattaneo et al. (2018), there is a complicated link between capacity decision variables and airfare. Enplanement numbers and flight frequency generally have a positive association with airport demand (Hansen, 1995; Hsu and Wen, 2003). Pitfield et al. (2010) realized that higher demand results in a greater increase in flying frequency by comparing aircraft size, while Wei and Hansen (2005) Findings indicate that growing flight frequency generates more demand than aircraft size. Although the rates of increase differ by flight length, LFs rise in response to rising demand (Mohammadian et al., 2019). The intricate relationships between air passenger demand, airfare, flight frequency, aircraft size, and flight delays are further influenced by airport infrastructure and operating capabilities (Zou and Hansen, 2012).

Numerous studies have been carried out in conjunction with these initiatives to examine the function of carbon taxes, which come in a variety of forms, including fuel taxes and distance-based air transportation taxes (Larsson et al., 2019). Tol (2007) used an international visitor flows model to examine the impact of a kerosene tax and showed that, despite the tax's large amount, there was little reduction in carbon emissions. Using the same model, Mayor and Tol (2007) investigated how the UK's Air Passenger Duty (APD) affects the release of carbon and demand from passengers. They discovered that raising the APD had the unanticipated impact of increasing carbon emissions. Additionally, Mayor and Tol (2010) discovered that the UK APD reduced emissions worldwide beyond the Netherlands Flight Tax after using the same model to examine the effects of different carbon pricing schemes on arrivals and emissions in Europe. When Hofer et al. (2010) imposed a ticket tax on the US aviation sector, they found that the tax's amount would directly correlate with a reduction in carbon emissions. Dray et al. (2014) used an integrated model to investigate how a worldwide carbon tax might affect aviation fuel. They found that because of the carbon price's extreme volatility, regulators and airlines would have to deal with significant administrative expenses and market uncertainty. González and Hosoda (2016) investigated the influence of Japan's aviation fuel tax on the release of carbon and discovered that a 30 % drop in jet fuel tax resulted in a nearly 10 % increase in emissions of carbon. Fukui and Miyoshi (2017) examined the impact of an aviation fuel tax on jet fuel consumption and carbon emissions within the U.S. airline industry. Their findings revealed that increasing the tax by 4.3 cents per gallon, from $0.044 to $0.087 per gallon, would result in a 0.14–0.18 % reduction in carbon emissions in the short term (one year after the tax adjustment). However, the long-term effect (three years post-increase) would be significantly smaller, with emissions decreasing by only 0.008–0.01 %. Seetaram et al. (2018) evaluated UK outbound travelers' readiness to pay the APD using distance bands and discovered that travelers were willing to pay a higher APD for business class and long-haul travel. It is precisely at this point that no study has been found that examines the limits of carbon taxation according to the length of routes airlines operate and the type of services they offer. This is one of the problems reflecting the originality of this study. Recent research by Jiang et al. (2024) offers a comprehensive review of aviation decarbonization policies and the technologies supporting emission reduction, providing a policy framework relevant to this study. Likewise, Chen et al. (2024) assess the effects of sustainable aviation fuel mandates on airline competition, particularly the differing impacts on FSCs and LCCs. Additionally, Zheng et al. (2024) highlight the trade-offs between environmental and welfare outcomes of various emission policies, underlining the complexities airlines face in balancing operational and regulatory pressures.

2.2. Operational improvements-based emission policies

In actuality, operational network layouts and carbon pricing are closely related. Shortly, flight networks may be arranged by airlines largely based on passenger flow patterns. Long-term variations in the cost of purchasing carbon across different network configurations, however, will force airlines to modify their aviation networks (Liao et al., 2024). For example, higher carbon pricing translates into higher connecting travel expenses, which forces airlines to choose more direct flights. As a result, in the long run, airlines will need to prioritize this strategic imperative: flight network optimization. For example, Parsa et al. (2019) claim that airlines may cut fuel consumption by up to 8–10 % by improving route networks and flight patterns.

Regarding the environment, several academics think that CORSIA and the EU ETS aircraft carbon trading can successfully encourage carbon reduction in the aviation sector. As accountability for reducing emissions increases over time, CO2 emissions will be further reduced (Leggett et al., 2012; Meleo et al., 2016; Scheelhaase et al., 2018). Moreover, airlines have a strong incentive to lower emissions through technological and operational advancements when carbon costs are high, resulting in effective and ecologically beneficial economic outcomes (Preston et al., 2012). Still, many disagree. Certain academics argue that although the EU ETS aircraft carbon trading and CORSIA can aid in slowing down the increase of carbon emissions, they do not result in a complete decrease in emissions within the sector (Fageda and Teixid'o; 2022, Winchester, 2019; Zhang et al., 2021). The EU's excessive distribution of free permissions to the aviation industry is another point of criticism, as it unintentionally increases greenhouse gas emissions (Nava et al., 2018). Within the transportation sector, aviation is a prime example of a network-oriented industry (Jiang et al., 2021), in which the choice of aviation network architecture is closely related to both company supply and market demand, making it an essential business strategy for airlines.

In recent years, low-cost carriers have taken advantage of travelers' growing need for shorter travel durations by mass-entering high-demand areas via direct flight networks. They have been able to consistently outperform more established, major airlines thanks to this tactical move (Fageda and Glores-Fillol, 2015; Fu et al., 2019; Silva et al., 2014). In general, although the literature on aviation carbon pricing or aviation networks in isolation is very extensive, relatively few researchers have sought to investigate the interaction between these two aspects (Brueckner and Zhang, 2010; Hsu and Eie, 2013; Ko et al., 2017; Liao and Wang, 2021). Previous research demonstrates certain shortcomings. For example, Brueckner and Zhang (2010) used a game-theoretic model to examine how aviation carbon emission levies affect network selection; however, their research was limited to hub-and-spoke and direct-flight networks. In their assessments, Hsu and Eie (2013) and Ko et al. (2017) did not take hub-and-spoke networks into account. The impact of aviation emission taxes on the choice of network, including hub-and-spoke, mixed, and direct flight networks, was investigated by Liao and Wang (2021). In reality, a few of the world's largest airlines use multi-hub networks because of their broad geographic reach and capacity to take advantage of horizontal product diversification (Doganis, 2009; Wang and Wang, 2019; Wang, 2016). When analyzing airline network selection, taking into account 2-hub networks might have a big impact on policy. Thus, by thoroughly analyzing the effects of carbon pricing on aviation network structures through LCC and FSC airline companies, this research expands on the body of current studies. Building upon this, Liao et al. (2024) examine how carbon pricing mechanisms influence airline network selection strategies, offering insights into network adjustments under environmental constraints.

2.3. Understanding the effects and impacts of policies

Although the effectiveness of the aforementioned policies remains inconclusive, the introduction of CORSIA, coupled with the expected growth in air travel demand, places airlines in a challenging position. They must balance meeting this rising demand with adhering to the emissions targets set by regulations. To ensure profitability, airlines need to achieve this balance at the lowest possible cost. Pinpointing the factors that contribute most significantly to an airline's CO2 emissions is crucial for identifying the operational areas where emissions reductions can be maximized. Decomposition analysis serves as a valuable tool to uncover these key factors. Index decomposition analysis, originally introduced by Vartia (1976), includes two indices, Vartia I and II, which measure relative changes in the price or volume of commodities. This approach was later expanded by Ang and Choi (1997), who developed the Log-Mean Divisia Index (LMDI) model to analyze the total carbon emissions intensity index within the Korean industry. They observed that the effectiveness of the LMDI model decreases when applied to highly disaggregated data. To address this issue, Ang and Liu (2001) introduced the LMDI I model, which became a common tool for disaggregating energy consumption and carbon emissions data. Further refinements were made by Ang and Liu (2007), who resolved the zero-value problem by substituting zero values with a small number approaching zero. Another noteworthy contribution comes from Cantos-Sánchez et al. (2023), who analyze the environmental and economic implications of short-haul flight bans, presenting an alternative regulatory measure to market-based carbon pricing instruments. This advancement ensured that the LMDI method could be applied across all sectors, cementing its status as a reliable and versatile tool. Decomposition analysis is particularly valuable for exploring the relationships between variables, such as identifying the driving forces behind changes in carbon emissions. This quantitative approach provides policymakers with critical insights into the effects of energy policies and technological developments. Among decomposition methods, the LMDI remains one of the most widely utilized due to its effectiveness and adaptability. The studies conducted in the airline sector using the LMDI method are summarized in Table 1 below.

As can be seen from Table 1, many studies have been conducted and published to investigate carbon impacts in the airline sector, but not all of these studies provide comparative information. Since the service strategy adopted by airline companies is thought to be effective in reducing carbon emissions, and there are no similar studies in the existing literature, the necessity of the study has become apparent. Moreover, this is directly related to RQ1 and RQ4. On the other hand, the necessity of RQ2 and RQ3 can be understood from this point, since not only decomposition but also the decoupling model will be used to present how policies should be developed for these two strategies comparatively in the future.

Table 1
Literature review on decomposition analyses in the transport sector.

Author Year	Scope of Study
Andreoni, V., & Galmarini, S. (2012)	Carbon emissions in the water and air transportation sectors in Europe are analyzed using the LMDI method. This study reveals that economic growth is the main reason for the increase in carbon emissions.
Arjomandi, A., & Seufert, J. H. (2014)	The technical and environmental performance of major airlines worldwide has been evaluated. The LMDI model was used in this assessment and factors such as population size, GDP per capita, and turnover per GDP were found to contribute to the increase in carbon emissions.
Luo, X., Dong, L., Dou, Y., Liang, H., Ren, J., & Fang, K. (2016)	analyzed the factors affecting emissions and used the Gini coefficient to assess regional inequalities. The results show that economic structure is the main driver of emissions change and that there are significant regional differences and inequalities.
Wu, C., He, X., & Dou, Y. (2019)	It analyzes the regional variations of CO2 emissions in China's domestic air transport sector and the driving forces behind these emissions.
Isik, M., Sarica, K., & Ari, I. (2020)	The study decomposes the effects of economic growth, population growth, fuel type changes, transport intensity, and transport modes on emissions. The results show that economic growth and population growth dominate in increasing emissions, but the use of more efficient vehicles and fuel type changes contribute to emission reductions.
Yu, J., Shao, C., Xue, C., & Hu, H. (2020)	The findings show that the increase in transportation is the largest factor in increasing CO2 emissions, while energy consumption intensity plays an important role in reducing emissions. The study emphasizes the need for comprehensive emission reduction policies.
Yue, X., & Byrne, J. (2024)	Changes in capacity were found to affect more than 40 % of emission changes for most airlines. The decoupling analysis examines airlines' success in breaking the link between expanding scale and carbon emissions and suggests strategies to achieve the targeted decoupling.
Dannet, F. et al. (2024)	Examines the evolution of civil aviation CO_2 emissions, highlighting efficiency improvements from aircraft fleet renewal and operational changes. Provides historical trends and projections useful for understanding sectoral emission pathways.
Chen, H., & Ai, W. (2024)	Applies a system dynamics model to predict future aviation carbon emissions under various policy scenarios. Highlights the role of technology adoption and operational measures in meeting long-term emission targets.
Dietz, S. (2024)	Discusses the methodology for assessing airline carbon performance in the context of the Transition Pathway Initiative (TPI). Provides a benchmarking framework for comparing airline emissions trajectories against climate targets.
Zheng, Y. (2025)	Conducts a decomposition of carbon emission driving factors using the LMDI approach and discusses regional/policy implications. Emphasizes the roles of energy intensity and structural effects in emission reduction strategies.

3. Materials and methods

In this study, the LMDI (Logarithmic Mean Divisia Index) model will be used to analyze the sustainability performance of airline companies. The analysis aims to examine the relationship between carbon emissions and the economic growth of two main groups of airline companies - Full-Service Carrier (FSC) and Low-Cost Carrier (LCC). The LMDI method is widely used in sectoral analysis to analyze productivity changes and the link between emissions and economic factors. This approach provides an in-depth look at sustainability analysis by decomposing the impact of different variables in the sector.

This model helps to determine the extent to which growth and environmental damage are decoupled and whether sustainable growth can be achieved. In this study, the degree of decoupling between emissions and revenue of FSC and LCC airlines will be compared, taking into account their sectoral differences. This methodological approach aims to gain an in-depth understanding of the impact on environmental sustainability of FSC and LCC groups with different strategic and operational structures. The flowchart of the study is shown in detail in Fig. 1 below.

This study utilizes a panel dataset covering operational, financial, and environmental performance data of 15 U.S.-based commercial airlines between 2000 and 2020. The sample includes 6 Full-Service Carriers (FSCs), 5 Low-Cost Carriers (LCCs), and 4 Hybrid carriers, classified based on their business models and operational networks. The dataset was compiled from publicly available sources, including the MIT Airline Data Project, the U.S. Bureau of Transportation Statistics (BTS), and emission factors from the EMEP/EEA 2023 Emission Inventory Guidebook. A summary of key descriptive statistics for the sample is presented in Table 2 below.

This study adopts a Log-Mean Divisia Index (LMDI) decomposition method, combined with a decoupling analysis framework, to examine the relationship between operational variables and carbon emissions. The analysis is structured in three stages.

1. Calculation of emission costs for each airline based on fuel consumption, emission factors, and operational output (profit per mile, load factor, ASM).
2. Decomposition of emission changes into six factors — carbon intensity, energy intensity, cost ratio, passenger yield, load factor, and available seat miles — using the LMDI model.
3. Comparative analysis of cumulative effects by business model (FSC vs. LCC vs. Hybrid) over the 2000–2020 period, identifying decoupling trends between emissions and financial performance.

All emission calculations were conducted using emission factors from the EMEP/EEA 2023 Guidebook, while operational and financial data were sourced from the MIT Airline Data Project and BTS.

Many models have been used in the airline industry to assess environmental performance and financial sustainability, some of which are route-based, while others focus on financial performance and expenditures (Fageda and Teixid'o; 2022). However, it should not be forgotten that in the current system, emission strategies can affect financial performance directly. However, not only environmental strategies but also the economic performance of airlines should be taken into consideration. Various measurement and evaluation methods are used in the aviation industry to optimize both profitability and environmental performance. One of the most important of these is PPNM (Profit Per Available Seat Mile), a profitability-oriented performance metric (Zhao et al., 2010). PPNM measures an airline's profit per passenger and cargo carried and reflects the overall efficiency of the airline (Vasigh et al., 2018). However, PPNM ignores environmental sustainability as it only evaluates economic efficiency. In its simple form, PPNM is shown in equation (1).

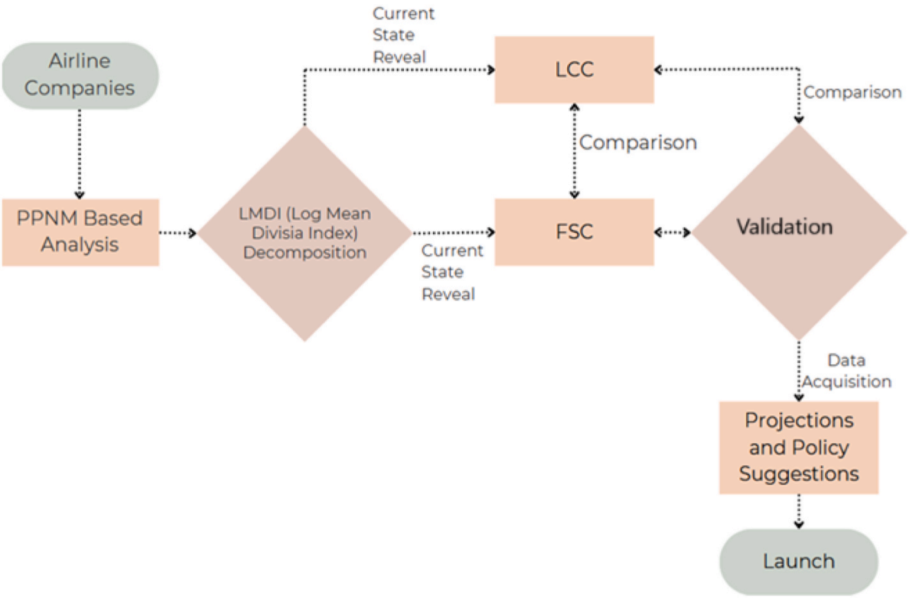

Fig. 1. Flowchart of study.

Table 2
Descriptive statistics of the study.

Variable	Mean	Std. Dev.	Min	Max
Profit per Nautical Mile (USD)	0.048	0.036	−0.112	0.182
Load Factor (%)	80.45	6.23	61.20	91.40
Fuel Consumption (Million Gallons)	1640.8	1145.2	130.5	4785.1
Available Seat Miles (ASM, Billion)	231.4	186.7	18.7	740.9
Carbon Emissions (ktonnes)	12,445	9330.1	987.4	40,217

$$PPNM = \frac{Total\ Revenue - Total\ Cost}{Flight\ Distance} \tag{1}$$

In this context, environmental metrics such as the Carbon Intensity Indicator (CII), which is not used in the airline industry but is used in maritime transportation to better assess environmental impacts, come into play. CII is used to analyze the environmental impact of operations by measuring carbon emissions per passenger-kilometer or ton-kilometer (Yuan et al., 2023). In general terms, the general formula used for CII calculation is shown in Equation (2) below.

$$CII_{Attained} = \frac{M}{W} = \frac{\sum_{j} FC_j \times C_{fj}}{C \times D_t} = \frac{Fuel\ Consumption\ (kg)x\ Emission\ Factor\ (kgCO2/kg)}{Cargo\ Carried\ (tons)x\ Distance(nautical\ miles)} \tag{2}$$

Where j is the fuel type, FC_j is the amount of fuel consumption (grams), C_{fj} is the fuel mass to CO2 mass conversion factor for fuel type j, Dt is the total distance traveled in nautical miles, and C is the capacity of the ship (IMO, 2022). At this point, from a general point of view, since PPNM is calculated, ACMI costs are included in the total costs, but possible carbon costs or taxes are ignored. This assumption is not a very useful basis for profitability ratios and emission class ratings. Therefore, the carbon cost obtained by multiplying the carbon emission index calculated in the CII index by the determined tax amount should be considered in the PPNM. In this case, to calculate PPNM for an airline with a heterogeneous fleet using multiple aircraft, the following formulation should be used. The Equation shows the formulation, where Rj represents the distance of route j, and the other terms follow the definitions used in Eq. (3).

$$PPNM_k = \frac{\left(\sum_{j=1}^{N} pax_{k,j}\ .P_{kj}\right) - \left(\sum_{j=1}^{N} x_{k,j}\ .c_{kj}\right)}{\left(\sum_{j=1}^{N} pax_{k,j}\ .R_{kj}\right)} \tag{3}$$

Among the variables, $pax_{k,j}$ represents the total number of passengers on route j with aircraft k, P_{kj} represents the revenue per passenger mile of aircraft k on route j. Similarly, $x_{k,j}$ represents the total number of flights made by aircraft k on route j, and c_{kj} represents the cost of aircraft k on route j. Through this usage, it is possible to determine the amount of emission cost and profitability on a route-by-route basis.

The formula calculates the fuel consumption per unit capacity, specific to each aircraft used on a route-by-route basis, and multiplies it by the capacity utilization rate, then divides it by the total distance traveled, and calculates the amount of carbon emitted per kilogram of cargo transported per kilometer. What makes the formula important here is that the freight and distance traveled are taken into account, and the capacity utilization rate is made important. In this case, even without access to all data items, airline companies can be classified according to their emissions, and inferences can be made on their profitability ratios by obtaining only operational data without departing from the basic principle. Thus, this index created for ships was transformed for airline companies and referred to as the Airline Carbon Intensity Indicator. Hence, this cost factor is combined with the PPNM method, and the following final equation is formed.

$$PPNM_{ACII} = \frac{\left(\sum_{j=1}^{N} pax_{k,j}\ .P_{kj}\right) - \left[\left(\sum_{j=1}^{N} x_{k,j}\ .c_{kj}\right) + \frac{\sum_{j} FC_j \cdot C_{fj}}{C \cdot D_t}\right]}{\left(\sum_{j=1}^{N} pax_{k,j}\ .R_{kj}\right)} \tag{4}$$

On the other hand, since these cost data are not included in the data of airline companies, there may be deviations in the calculations made. Therefore, the calculation of the above cost data will be included in the cost data in the LMDI model. In this case, variables are needed for the use of the LMDI model. At this point, it can be said that variables have been used and determined many times in the literature in terms of related studies, as shown in Table 3.

Table 3
Factors influencing the CO_2 emissions of airlines (Yue and Byrne, 2024).

Category	Factor	Definition	Significance
Carbon Efficiency	Carbon Intensity	Represents the airline's CO_2 emissions per unit of energy consumption.	Highlights environmental performance.
Energy Efficiency	Corporate Energy Intensity	The ratio of energy consumption to direct operational costs for an airline.	Reflects energy efficiency and cost control.
Cost Efficiency	Cost Ratio	The ratio of direct operating costs to passenger revenue.	Indicates profitability margins.
Revenue Efficiency	Passenger Yield Effect	Division of passenger revenue by revenue passenger miles (RPMs).	Measures revenue per unit of passenger demand.
Operational Efficiency	Load Factor Effect	The proportion of revenue passenger miles to available seat miles.	Assesses operational capacity utilization.
Capacity Efficiency	Available Seat Miles	Measures the airline's revenue-generating capabilities.	Evaluates overall network efficiency.

Airlines' CO2 emissions are divided into six elements, which are as follows:

$$CO_2 = \frac{CO_2}{Energy}\cdot\frac{Energy}{Operation\ Cost}\cdot\frac{Operation\ Cost}{PassengerRevenue}\cdot\frac{PassengerRevenue}{RevenuePerMiles}\cdot\frac{RevenuePerMiles}{AvailableSeatMiles}\cdot AvailableSeatMiles \tag{5}$$

The change in carbon emissions in a system (e.g., air transportation) can be broken down into the following factors.

- Activity level: For example, total flight demand.
- Energy intensity: Per unit of energy consumption.
- Carbon Intensity: CO_2 emissions per unit of energy.

This decomposition is based on the following general model:

$$\Delta C = \Delta C_{activity} + \Delta C_{intensity} + \Delta C_{carbon} \tag{6}$$

Carbon emissions (C) can be broken down into the following factors:

$$C = A\cdot \frac{E}{A}\cdot\frac{C}{E} \tag{7}$$

In this formula.

A: Activity level (e.g., total transportation capacity or RPM - Revenue Passenger Miles).

E/A: Energy intensity (i.e. energy consumption per unit activity).

C/E: Carbon intensity (e.g. emissions per unit of energy).

LMDI uses logarithmic average weights to decompose changes. This ensures that the model remains robust even when any component approaches zero. To explain the total change of a variable (C), the equation is decomposed as follows by using formula 5;

$$\Delta C_{activity} = L(C_1, C_0)\cdot\ln\left(\frac{A_1}{A_0}\right) \tag{8}$$

$$\Delta C_{intensity} = L(C_1, C_0)\cdot\ln\left(\frac{E_1/A_1}{E_0/A_0}\right) \tag{9}$$

$$\Delta C_{carbon} = L(C_1, C_0)\cdot\ln\left(\frac{C_1/E_1}{C_0/E_0}\right) \tag{10}$$

Where $L(C_1, C_0)$ is the logarithmic mean function:

$$L(x,y) = \frac{x-y}{\ln(x)-\ln(y)}, x \neq y, if\ x = y, then \quad L(x,y) = x \tag{11}$$

To investigate the roles of all six of these components decomposed by the extended Kaya identity equation, we employ the LMDI model in the decomposition investigation. The LMDI model is one of the most commonly used methods for assessing rapid fluctuations in CO_2 emissions and identifying the contribution of certain factors to CO_2 emissions. We utilize this to calculate and compare the impact of each factor on changes in CO_2 emissions across the sample period. Assuming there are i airlines from the base year 0 to year t, the changes in CO_2 emissions (ΔCO_2) of the i airline from years 0 to t are decomposed as follows:

$$\begin{aligned}\Delta CO_{2_i}^t = CO_{2_i}^t - CO_{2_i}^0 = {} & \Delta CO_2Intensity_i^t + \Delta EnergyIntensity_i^t \\ & + \Delta CostsRatio_i^t + \Delta PassengerYield_i^t \\ & + \Delta LoadFactor_i^t + \Delta AvailableSeatMiles_i^t\end{aligned} \tag{12}$$

$\Delta CO_{2_i}^t$ represents the difference on carbon emissions between years of t and 0 for any airline i, where analyzed by using formula 8,9 and 10 each of them respectively.

In these calculations, all data were taken from the compiled reports provided by the MIT Airline Database Project and used. In addition, the EMEP/EEA air pollutant emission inventory guidebook 2023 (EAA, 2023) was used to calculate the fuel consumption accurately and to base it on an official source. The main reason for focusing on the US is its high data availability, significant share in carbon emissions, and ability to make LCC and FSC comparisons. The period of data includes pre-COVID-19 years.

4. Results

This section presents the empirical findings derived from the application of the Log-Mean Divisia Index (LMDI) decomposition model and decoupling analysis framework to the operational, financial, and environmental data of selected U.S. commercial airlines from 2000 to 2020. The analysis delineates the differential impacts of market-based emission policies on Full-Service Carriers (FSCs) and Low-Cost Carriers (LCCs), highlighting variations in carbon intensity, energy efficiency, cost structures, and profitability metrics. By disaggregating changes in CO_2 emissions into key contributing factors—such as load factor, passenger yield, energy intensity, and available seat miles—this section provides a systematic assessment of how emission-related pressures translate into measurable performance outcomes across distinct airline business models. The results offer a robust basis for evaluating the operational feasibility and policy responsiveness of FSC and LCC strategies under carbon regulation regimes.

Fig. 2 presents the temporal progression of profit per nautical mile for a range of U.S.-based airlines between 2000 and 2020, categorized by business model types such as Full-Service Carriers (FSCs), Low-Cost Carriers (LCCs), Hybrid carriers, and Ultra-Low-Cost Carriers (ULCCs). The data indicate a general upward trend in profitability across most carriers from the early 2000s up to 2019, suggesting improved operational efficiency, cost control, and network optimization efforts during this period. However, the graph also highlights the sector's sensitivity to macroeconomic shocks, with notable downturns during the 2008 global financial crisis and a dramatic decline across all carrier types in 2020, corresponding to the COVID-19 pandemic and the resulting collapse in

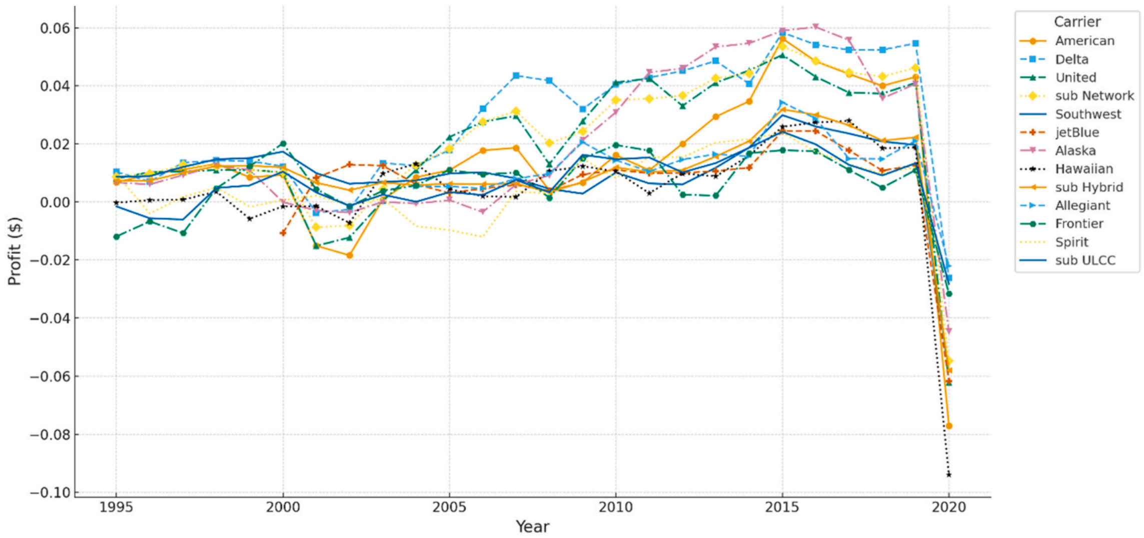

Fig. 2. Yearly variation of airlines' profit per nautical mile.

air travel demand. While FSCs such as Delta, United, and American exhibit broader fluctuations due to their complex network structures and long-haul operations, ULCCs like Spirit and Frontier maintain relatively stable, albeit lower, profit margins, reflecting their lean operational models and short-haul focus. Hybrid carriers, including Southwest and JetBlue, demonstrate moderate volatility and consistent performance, occupying a middle ground in terms of profitability and resilience. The subgroup trends further reinforce these distinctions, with "sub Network" carriers showing higher amplitude in profit variation compared to the more stable "sub ULCC" and "sub Hybrid" averages. Overall, the figure underscores the importance of business model selection in shaping financial outcomes and highlights the varying degrees of vulnerability and adaptability across carrier types in response to both internal efficiency changes and external market disruptions.

Fig. 3 represents sector fuel use for each year from 1995 to 2020. The Vertical Axis (Percent Fuel Used in Total Sector) shows the percentage breakdown of total sector fuel use for each company, among others. American, Delta, and United Airlines are the three major carriers in the graph and represent a large part of the industry (especially between 1995 and 2005). Their share of fuel use appears to have declined over time. Southwest appears to have increased its share of industry fuel use after the 2000s. ULCC and Hybrid Carriers (such as Allegiant, Frontier, Spirit, and JetBlue) started to increase their share in fuel use after the 2000s. However, their share in total fuel use is still small. Hawaiian and Alaska Airlines have a small but stable share. Around the 2008 crisis and 2020 (COVID-19 impact), it seems that the dynamics across the sector may have changed. Especially towards 2020, it can be observed that the proportion of relatively smaller companies tends to increase. This chart shows the percentage breakdown of fuel use in the US airline industry across companies over the years. In particular, it shows that the major carriers (American, Delta, United) have lost market share over time, while Southwest and other low-cost carriers (ULCC) have increased their share. This change can be attributed to the industry's business model transformations and customer preferences.

Fig. 4 shows airlines' "Fuel Expense/Total Assets" ratios stacked by year, revealing the contribution of fuel costs to total assets for each

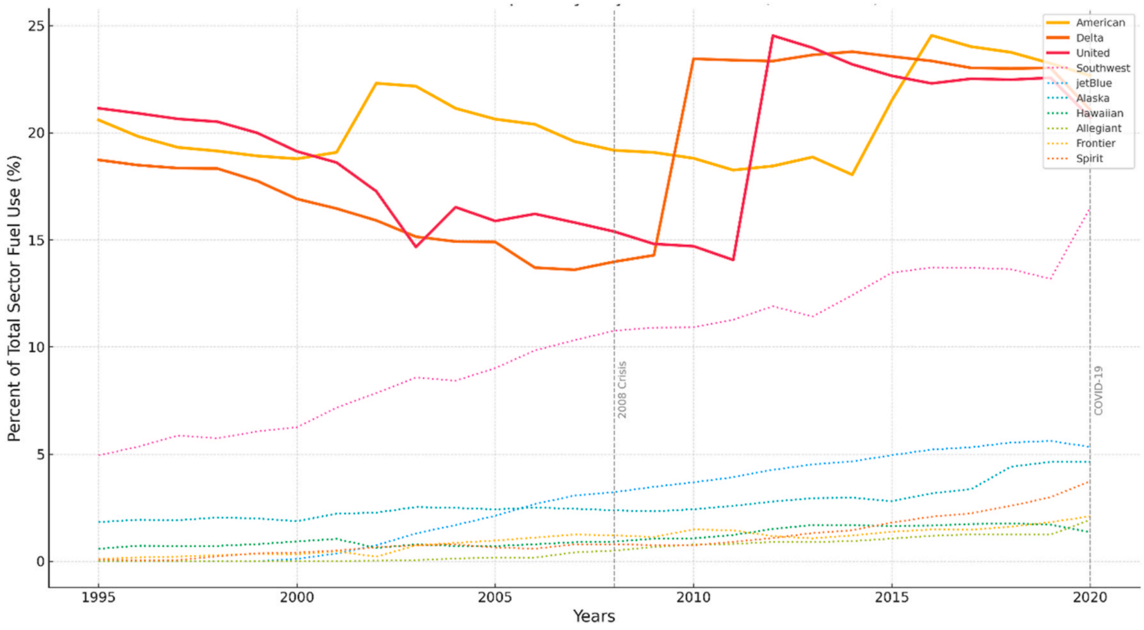

Fig. 3. Change in Fuel Consumption of all Airlines for each Year in Percent.

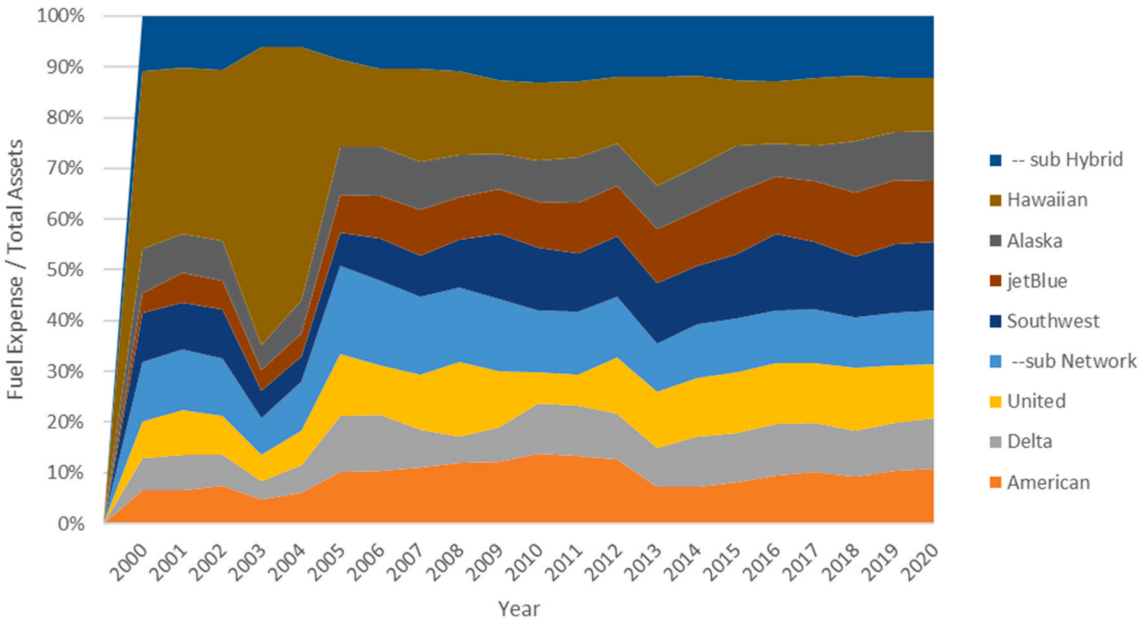

Fig. 4. The ratio of airline fuel costs to total assets by years.

company or sub-group over time. There was a clear peak in the aggregate ratio in 2004–2005, which can be attributed to the increase in oil prices and the disproportionate growth of operational costs compared to asset values. In particular, the large players in the Network category (American, Delta, and United) carried a significant portion of the increase in fuel costs during this period. They accounted for a large share of the graph. In addition, low-cost airlines such as Southwest seem to have contributed at a more stable rate, reflecting the stability of low-cost business models. Post-2015, there has been a general decline in the fuel/asset ratio across all categories. The decline in global oil prices can explain this, the adoption of fuel-efficient aircraft, and improvements in airlines' cost control strategies. The lower representation of players in the hybrid category (Hawaiian and Alaska) points to the differences in their operational structures. Overall, the graph clearly illustrates both the competitive dynamics within the industry and how airlines are responding to macroeconomic shocks and industry trends.

Fig. 5 shows the comparative changes in airlines' carbon intensity over the period 2011/2010–2020/2019 and allows us to assess their environmental sustainability performance. In general, carbon intensity is stable or slightly fluctuating for most airlines, while a significant increase is observed in 2020/2019 due to the impact of the COVID-19 pandemic, which can be attributed to the decrease in aircraft occupancy rates and reduced operational efficiency. There are differences in carbon intensity between different business models (Network, Hybrid, ULCC); for example, ULCC and Hybrid carriers generally have lower carbon intensity, while Network carriers (such as American, Delta, and United) have higher contributions due to the size of their fleet. This highlights the importance of young fleet utilization and fuel efficiency policies and underlines the need for sustainable fuels, fleet modernization, and efficiency-oriented strategies to reduce carbon intensity in the future.

Fig. 6 shows the changes in Corporate Energy Intensity over the years

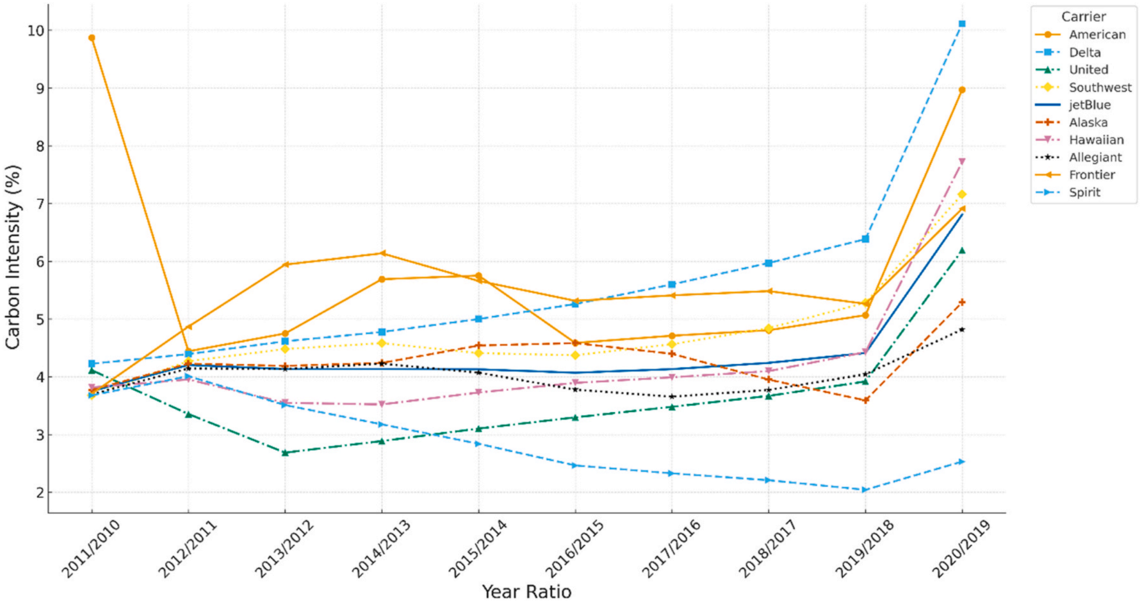

Fig. 5. Carbon intensity changes of major U.S. Airlines (2010–2020).

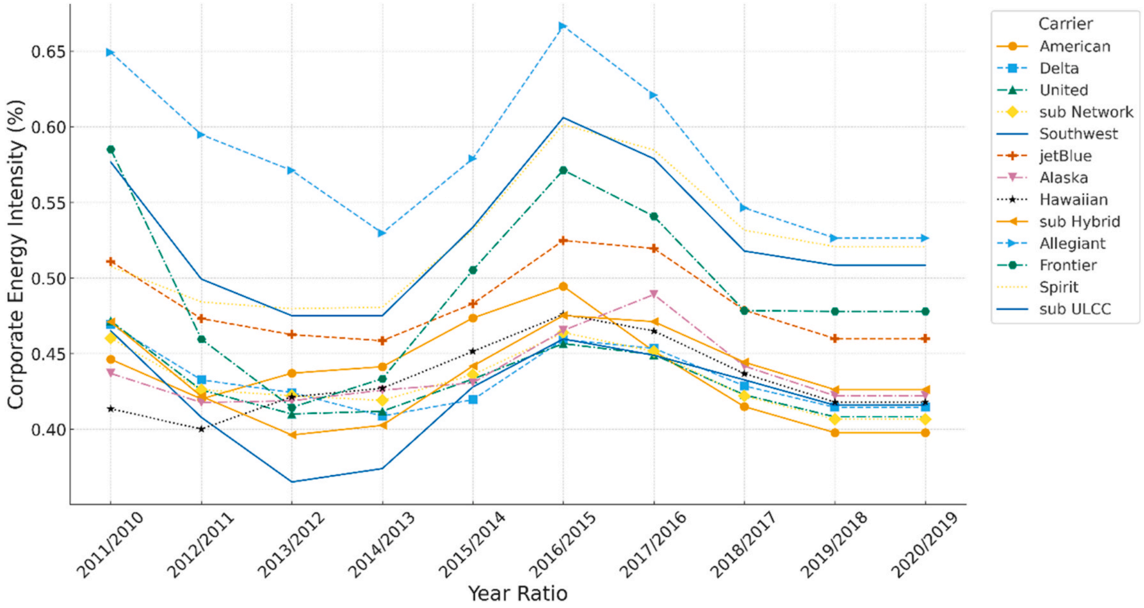

Fig. 6. Corporate energy intensity trends of U.S. Airlines (2010–2020).

for airlines categorized into ULCC (Ultra Low Cost), Hybrid, and Network. ULCC carriers (Spirit, Frontier, Allegiant) have the highest energy intensity, with Allegiant and Frontier in particular increasing over the years, while Spirit's energy intensity is more stable. Hybrids (Hawaiian, Alaska, JetBlue, Southwest) have medium energy intensity, with Hawaiian and Alaska showing a more stable trend, while JetBlue and Southwest have fluctuations. Network carriers (United, Delta, American) generally have the lowest and most stable energy intensity values, with American showing a more volatile trend compared to the other two. The years 2011–2014 (shades of blue, orange, gray, yellow) are relatively stable, while the period 2015–2019 (shades of light blue, green, dark blue, brown) shows a general upward trend in energy intensity. The 2020/2019 period (yellowish brown) has seen significant changes in some companies due to the pandemic. In general, ULCC companies have higher energy intensity, while Network carriers manage energy efficiency better.

In Fig. 7, ULCC (Ultra Low Cost) carriers (Spirit, Frontier, Allegiant) have the highest cost ratios compared to the other groups, with Allegiant and Frontier in particular seeing their costs increase over time. Hybrid carriers (Hawaiian, Alaska, JetBlue, and Southwest) have moderate cost ratios, with Hawaiian and Alaska relatively stable, while JetBlue and Southwest show a more volatile trend. Network carriers (United, Delta, American) have the lowest cost ratios and exhibit more stable cost management compared to other groups. In 2011–2014, cost ratios were more stable, with a generally upward trend after 2015 and significant changes in cost ratios for some companies in 2020/2019 due to the

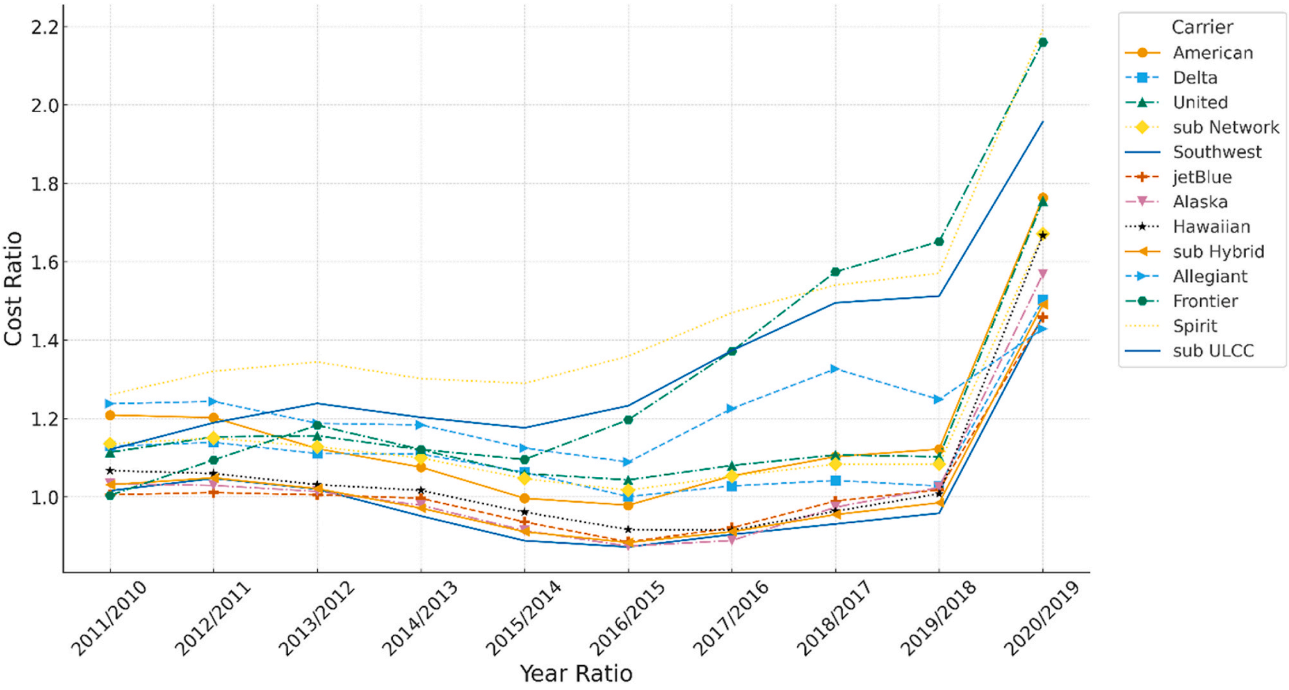

Fig. 7. Cost ratio evolution in U.S. Airlines (2010–2020).

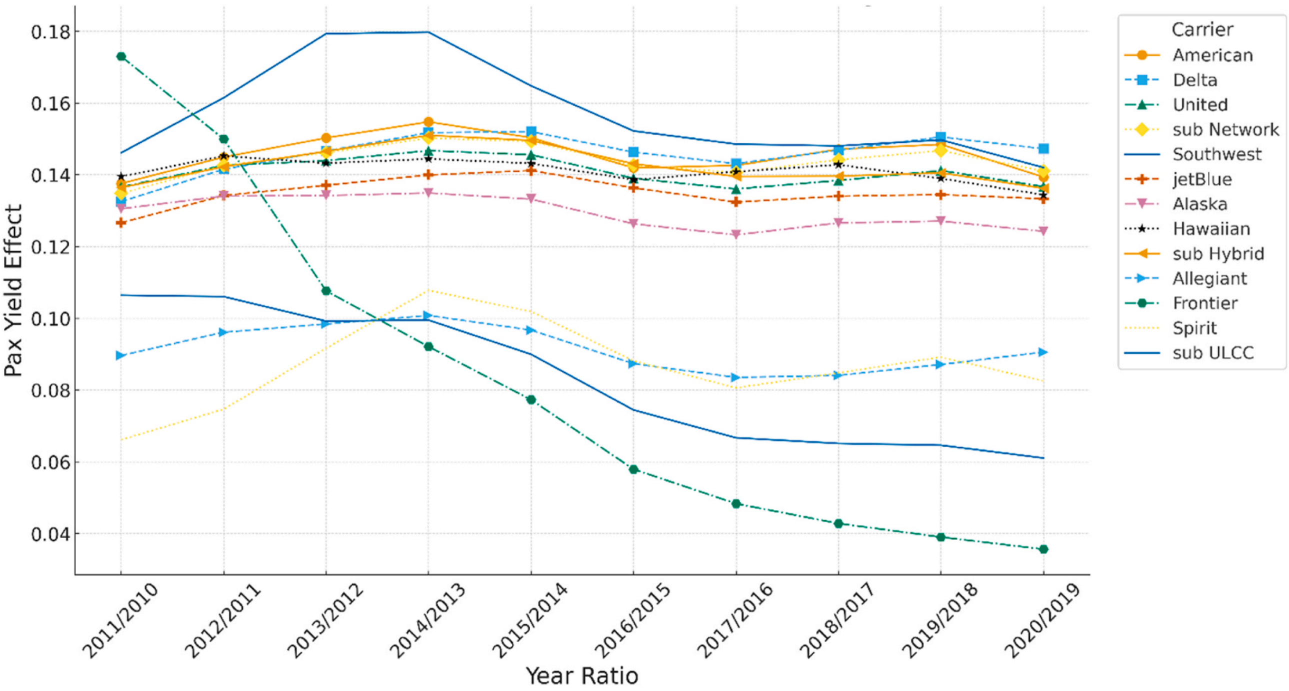

Fig. 8. Passenger yield effect on airline performance (2010–2020).

pandemic impact. In general, ULCC companies have the highest cost ratios, while Network carriers manage their costs more effectively.

Fig. 8 shows the Pax Yield Effect of different airlines by year. ULCC (Ultra Low Cost) carriers (Spirit, Frontier, Allegiant) generally have lower pax yield effect values compared to other groups. This indicates that low-cost airlines generate lower revenue per unit due to aggressive pricing strategies. Hybrid carriers (Hawaiian, Alaska, JetBlue, Southwest) generate higher revenue yields than ULCCs, while Network carriers (United, Delta, American) have the highest pax yield effect values, indicating that they offer a more stable revenue stream. In the period 2011–2014, the pax yield effect was more stable, while after 2015, there was generally more volatility. In the 2020/2019 period, some companies show significant changes, possibly due to demand fluctuations during the pandemic. Taken together with the previous graphs, it can be seen that ULCC carriers have low revenue yields despite their high-cost ratio and energy intensity, while network carriers have a more balanced cost structure and higher revenue per passenger.

Fig. 9 shows the operational efficiency of different airlines by

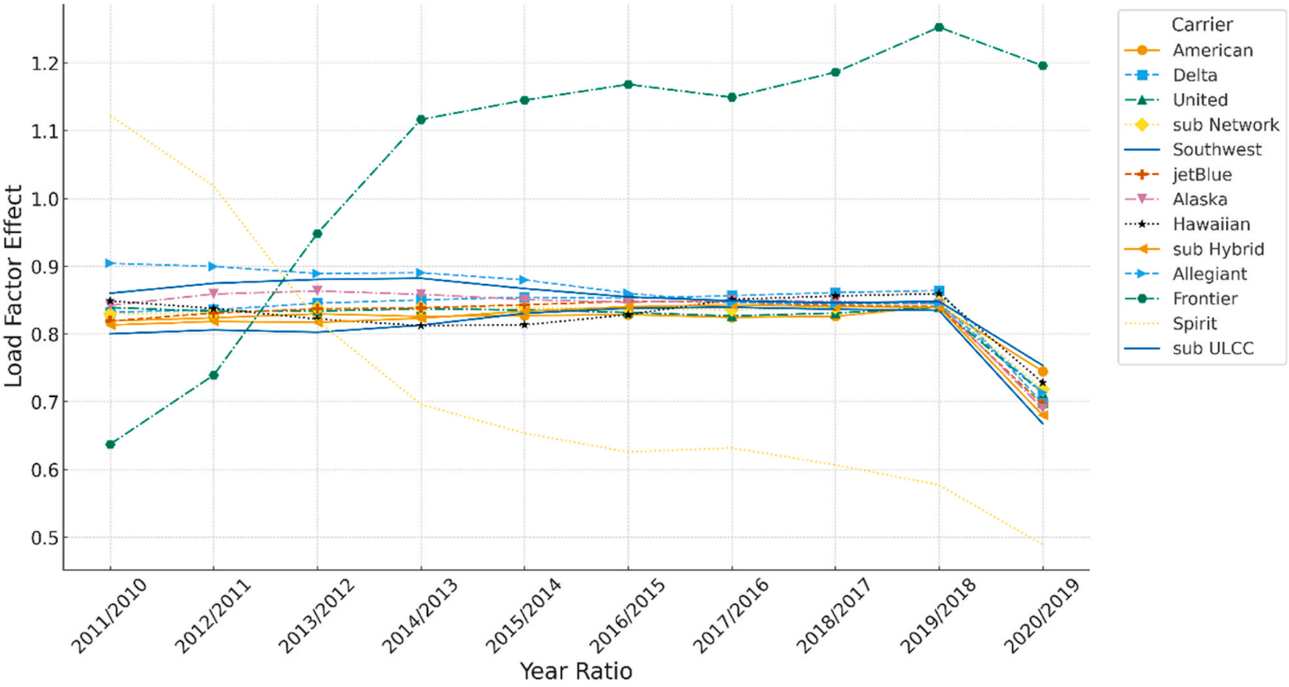

Fig. 9. Load factor effect on U.S. Airlines (2010–2020).

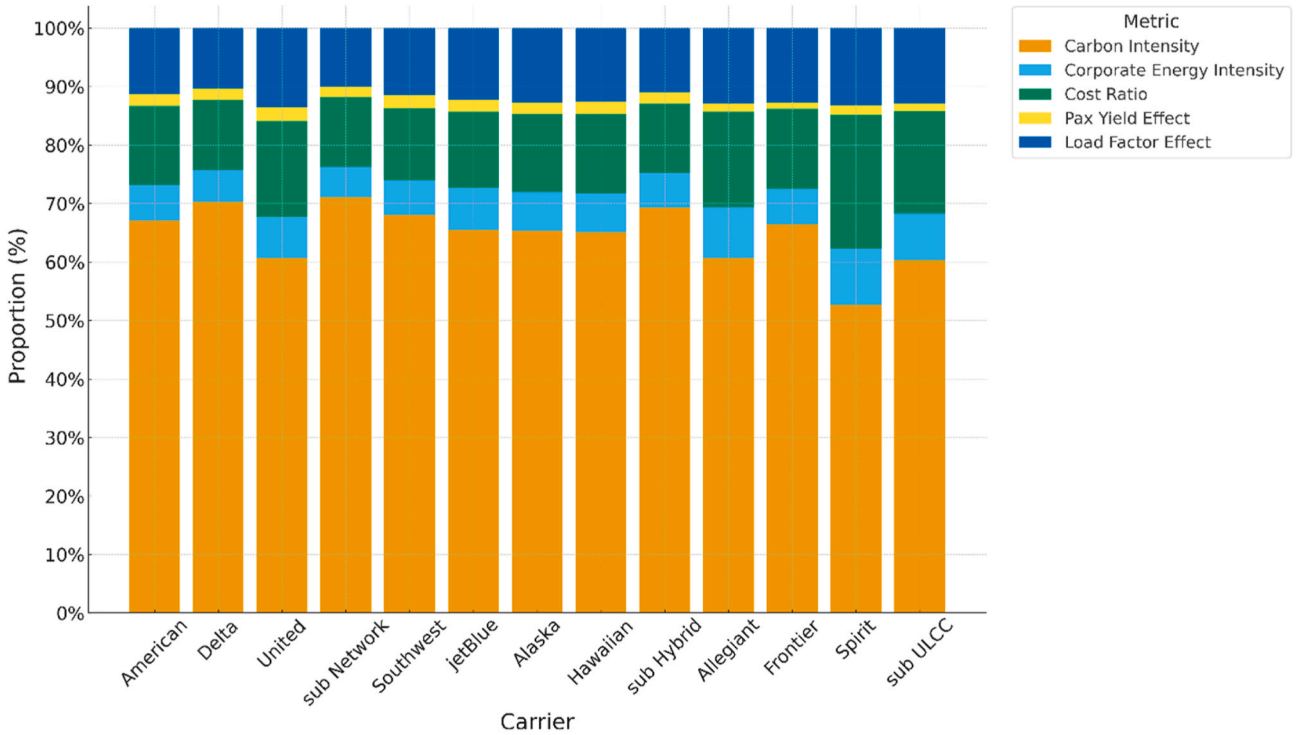

Fig. 10. Cumulative effects of key performance indicators across airlines.

comparing their Load Factor Effect values by year. ULCC (Spirit, Frontier, Allegiant) carriers generally have the highest load factor effect and follow an efficient strategy in capacity utilization, which can lead to increased energy intensity and cost ratios. Hybrid carriers (Hawaiian, Alaska, JetBlue, Southwest) exhibit moderate and more balanced load factor impact, while Network carriers (United, Delta, American) have the lowest values but offset this difference with their wider service networks and premium revenue sources. While the pandemic impact in 2020/2019 has led to significant changes in all groups, in general, ULCCs stand out with aggressive capacity utilization, while Network carriers offer a more sustainable model.

Fig. 10 compares airlines' Load Factor Effect performance over the years, providing important insights into their operational efficiency. Spirit, Frontier, and Allegiant generally show high Load Factor Effect values. In some years, Frontier, in particular, has been significantly different from the other companies, reaching the highest values. This shows that they follow an effective strategy in capacity utilization. The ULCC group seems to be more successful in operating its aircraft generally close to full capacity. However, as we have seen in previous charts, this strategy can increase energy intensity. Hawaiian, Alaska, JetBlue, and Southwest exhibit more balanced and moderate load factor impacts than ULCC. There are no major differences between the companies in this group, with Hawaiian and Alaska trending slightly more stable, and Southwest and JetBlue more volatile. Hybrid carriers may be trying to balance customer satisfaction with capacity utilization. United, Delta, and American show the lowest Load Factor Effect values, but this can be attributed to their wider service networks and customer segmentation strategies. Delta and United are generally more stable, while American is more prone to fluctuations. Network carriers seem to ensure their sustainability through premium services and revenue diversification rather than the passenger load factor.

There is a parallel between the high energy intensity of ULCC companies and the high load factor effect. This suggests that aggressive capacity utilization and frequent flight schedules increase energy consumption. Network carriers' low energy intensity is consistent with a low load factor effect. Wider seat pitches or less intensive flight schedules may make the difference. The high load factor impact of ULCC companies supports their goal of achieving low unit costs. However, high-cost ratios suggest that this effect is not fully reflected in profitability. Network carriers are balanced by better cost control and passenger revenue yield despite the low load factor impact.

There are significant changes in all groups in 2020/2019. The pandemic seems to have severely affected capacity planning and occupancy rates. Especially ULCC and Hybrid carriers may have experienced major fluctuations during this period. The high load factor effect leads to an increase in energy intensity and cost ratio. This may raise questions about the sustainability of the low-price strategy. Network carriers seem to be the most inefficient group in terms of load factor, but they make up for it with premium services and high passenger yields. Hybrid carriers take a balanced position between energy intensity, cost, and load factor. The flexibility of companies in this group can be an advantage, especially in times of crisis. Airline business models and strategies vary in terms of efficiency, cost, and revenue components. ULCCs perform well in the short term but may struggle in the long term due to energy and cost pressures, while network carriers offer a more sustainable model.

In Table 4, Network airlines (American, Delta, United) have the highest total carbon emissions due to their high flight capacity and extensive network. For example, Delta leads in this category with 178,062 ktonnes, but also has the highest carbon intensity (8.4598) and energy intensity (0.3554). United shows the greenest performance among network airlines with a carbon intensity of 4.9085. These airlines have the potential to improve their efficiency by reducing energy intensity and increasing occupancy rates.

Hybrid airlines (Southwest, Jetblue, Alaska, Hawaiian) exhibit lower carbon intensity (5.3482 on average) thanks to mid-sized operations, while some airlines have room for improvement. Southwest stands out with high carbon intensity (4.5301) and energy intensity (0.3619), while Hawaiian has a relatively high carbon intensity (5.0796) despite its small-scale network. In this category, investment in fuel-efficient aircraft and optimization of operational processes are recommended.

Ultra-low-cost airlines (Allegiant, Frontier, Spirit) are leaders in environmental sustainability, providing the lowest carbon intensity. Spirit stands out in the sector with a carbon intensity of only 1.6017 and high occupancy (0.7535). However, Frontier increases its carbon

Table 4

LMDI model results for cumulative CO_2.

	ΔCO_2Int	$\Delta EnInt$	ΔCR	ΔPY	ΔLF	ΔASM	ΔCO_2
American	6,2808	0,3176	1,7628	0,1394	0,7450	176.385,0192	176.394,2647
Delta	8,4598	0,3554	1,5017	0,1472	0,6976	178.051,0538	178.062,2156
United	4,9085	0,3395	1,7549	0,1367	0,7128	168.263,4174	168.271,2698
Sub Network	8,8399	0,3362	1,6708	0,1410	0,7186	522.909,4045	522.921,1110
Southwest	4,5301	0,3619	1,4613	0,1420	0,6676	128.554,7748	128.561,9377
Jetblue	4,4628	0,3824	1,4582	0,1333	0,6957	46.549,6769	46.556,8093
Alaska	3,3918	0,3486	1,5679	0,1242	0,6899	44.043,9253	44.050,0478
Hawaiian	5,0796	0,3307	1,6663	0,1344	0,7281	12.985,8153	12.993,7544
Sub Hybrid	5,3482	0,3621	1,4901	0,1362	0,6800	232.621,1207	232.629,1373
Allegiant	3,0829	0,4969	1,4286	0,0906	0,7137	14.343,5060	14.349,3186
Frontier	4,4710	0,4157	2,1598	0,0357	1,1960	22.056,6977	22.064,9760
Spirit	1,6017	0,4749	2,1914	0,0825	0,4890	34.412,3516	34.417,1911
Sub ULCC	2,7733	0,4612	1,9566	0,0611	0,7535	70.878,4917	70.884,4974

Note: Units are ktonnes.

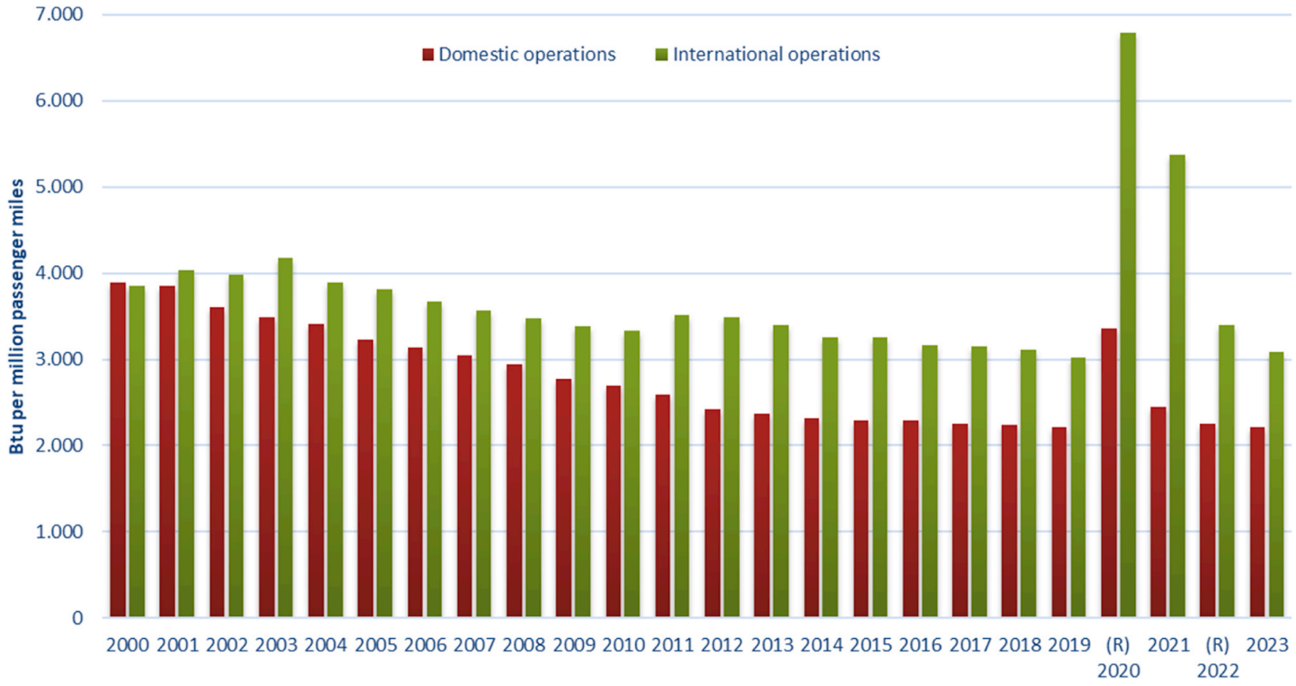

Fig. 11. Energy intensity of certificated air carriers in the U.S (BTS, 2024).

intensity due to its low passenger occupancy (0.0357). This highlights the importance of high occupancy strategies.

Fig. 11 examines the energy intensity (Btu/million passenger miles) of certified air carriers by year, showing the differences between domestic (red bars) and international (green bars) operations. From 2000 to 2019, there was a steady decline in energy intensity for both categories, indicating that energy-efficient technologies and operational improvements have been effective in the airline sector. However, in 2020, due to the COVID-19 pandemic, there was a sharp increase in energy intensity, especially in international operations. This increase can be explained by the low occupancy of aircraft and a higher distribution of fixed energy consumption per passenger carried. Although a pandemic-related increase was also observed in domestic operations, it was more limited compared to international operations.

In 2021 and 2022, energy intensity started to decline again as the effects of the pandemic diminished and approached the pre-pandemic values by 2023. The graph also shows that the energy intensity of international operations is generally higher compared to domestic operations; this difference is due to the higher fuel consumption of long-haul flights and different flight conditions. Overall, this graph reveals that the airline industry has improved energy efficiency in the long term, but extraordinary circumstances such as the pandemic have significant impacts on energy consumption and operational efficiency. This data provides important information for the classification and management of carbon emissions and points to the need for separate assessments for domestic and international operations.

5. Discussion

The airline industry’s efforts to achieve sustainability goals require minimizing environmental impacts while maintaining financial sustainability. Variables such as energy intensity, carbon emissions, occupancy factor, and cost per passenger are important indicators to understand the impact of environmental policies. The graphs and tables used in this study make it possible to analyze in detail the operational performance of different airline categories (LCC and FSC), their compliance with emission policies, and the impact of these policies on the consumer. It also assesses the impact of these policies on fleet renewal processes and the adoption of technological innovations. In this context, the discussion section aims to address how airlines can strike a balance between environmental sustainability and economic efficiency and what strategies should be implemented in this process.

The data reveals significant distinctions in energy and carbon intensity between Low-Cost Carriers (LCCs) and Full-Service Carriers (FSCs). Table 4 shows that LCCs like Spirit and Frontier have lower cumulative CO_2 emissions (34.417 ktonnes and 22.065 ktonnes, respectively) compared to FSCs like Delta and United (178.062 ktonnes and 168.271 ktonnes). LCCs achieve this through shorter routes, higher efficiency, and lower load factor impacts ($\Delta LF = 0.4890$ for Spirit compared to 0.6976 for Delta). Emission policies emphasizing sustainable aviation fuels (SAFs) or carbon offsets may favor LCCs, as they already operate efficiently and can implement these measures without significant network disruptions. In contrast, FSCs, with their expansive networks and higher carbon footprints, may need to restructure operations, focusing on optimizing long-haul routes or investing in fuel-efficient aircraft. These policies could shift FSCs' network strategies toward consolidating routes and increasing fleet modernization, while LCCs might expand, leveraging their efficiency advantage to align with stricter environmental standards.

Fig. 4 indicates that fuel costs represent a significant portion of airlines' total expenses, with fuel-to-asset ratios increasing in periods of high fuel prices or low operational efficiency. The ΔASM values in Table 4 highlight that airlines with extensive flight capacities, like Delta and United, face greater challenges in balancing financial and environmental goals. Policies encouraging SAF adoption and fuel-efficient fleets can reduce emissions but must account for the financial strain of these transitions, especially for FSCs with high operational complexity. For policies to be viable, gradual implementation, tax incentives, and government subsidies for sustainable fuel adoption are critical. Policies mandating minimum load factors (e.g., >70 %) can ensure flights remain financially viable while reducing per-passenger emissions. Thus, limits arise from balancing the high initial costs of environmental upgrades with maintaining competitive ticket pricing and profitability.

Minimizing consumer impact involves enhancing operational efficiency and leveraging technological advancements. Fig. 11 shows a steady reduction in energy intensity over time, illustrating the potential of fuel-efficient practices to offset additional costs. However, Table 4 highlights variability in ΔPY (passenger yield), with FSCs like United (0.1367) and Delta (0.1472) experiencing moderate increases, while LCCs like Spirit (0.0825) show lower passenger cost increases due to their efficient operations. To shield consumers from price increases, airlines can.

1. Optimize route networks to reduce unnecessary emissions.
2. Adopt SAFs with government subsidies to absorb additional costs.
3. Focus on high-load-factor flights to distribute costs more efficiently.

Encouraging consumer participation in offset programs (e.g., voluntary carbon offsets) can also align environmental goals with minimal fare increases. The reflection of policies on consumers is reduced when airlines balance operational efficiency with external support mechanisms.

Table 4 illustrates that ΔENINT (energy intensity) and ΔCO_2 reductions correlate with fleet efficiency improvements. For example, Alaska Airlines, with a ΔENINT of 0.3486 and ΔCO_2 of 44.050 kton, demonstrates moderate emissions improvements, reflecting its investment in efficient fleet technologies. However, efforts to modernize fleets often shorten the service life of older aircraft, as newer, more fuel-efficient models like Boeing 787 or Airbus A320neo are introduced. Fig. 6 shows fluctuations in fuel consumption over time, indicating that older fleets are less adaptable to environmental policies. While technological innovations, such as hybrid-electric engines or SAF-compatible aircraft, improve environmental outcomes, accessibility to these technologies remains uneven across carriers. Large FSCs with higher revenues can adopt new technologies faster than smaller LCCs like Allegiant or Spirit. Government incentives, shared research initiatives, and flexible financing options are essential to ensure equitable access to innovations, supporting the transition to sustainable aviation without disproportionately impacting smaller carriers.

Achieving environmental sustainability in the airline industry is a multidimensional endeavor that requires maintaining financial balance while reducing energy intensity and carbon emissions. This study reveals how the different operational structures of LCCs and FSCs shape their compliance with emission policies and provides a detailed analysis of key indicators such as energy intensity, occupancy factor, and fleet modernization. The findings show that it is possible to minimize the consumer repercussions of environmentally friendly policies and that making technological innovations equally accessible plays a critical role in sectoral transformation. Successful implementation of emissions policies requires a holistic approach of government support, investment in technology, and flexible operational strategies. As a result, airlines must adopt a shared vision of increasing sustainability and efficiency across the sector, while balancing environmental and economic objectives.

6. Conclusion

The airline sector is an industry that accounts for a significant portion of global carbon emissions and attracts attention with its energy-intensive operations. This study aims to examine the relationship between energy intensity and carbon emissions in airline transportation and to evaluate sector-wide trends and company-based performance differences. The graph showing the change in energy intensity over the years and the table detailing the operational data of airline companies allow us to understand how various factors, from periodic effects such as pandemics to technological advances, affect the industry. The study aims to evaluate the impact of variables such as occupancy factor, transportation ratio, and available seat miles on energy efficiency and how these findings can contribute to the process of developing sustainability strategies.

6.1. Relationship between energy intensity and carbon emissions

When the graphs are analyzed mutually, Fig. 11 reveals that energy intensity (Btu/million passenger miles) has shown a downward trend over the years. In particular, a significant increase in energy efficiency was observed in both domestic and international operations between 2000 and 2019, thanks to technological innovations and operational improvements. However, the decline in occupancy rates and lower passenger demand due to the COVID-19 pandemic in 2020 led to a dramatic increase in energy intensity. Relating this trend to the chart, it is possible to say that the rate of increase in carbon emissions (ΔCO2 and ΔCO2INT) of the companies is parallel to the change in energy intensity.

For example, while the Sub Network group contributes to high international energy intensity in the graph, it is noteworthy that this group is the leader in carbon emission increase (522,921 ktons) in Table 4. In contrast, smaller carriers such as Allegiant and Hawaiian Airlines have lower values in terms of both energy intensity (ΔENINT) and carbon emission increases.

6.2. Impact of the occupancy factor (ΔLF)

In Fig. 11, the change in energy intensity in the years before and after the pandemic can be explained by fluctuations in the occupancy factor.

Low occupancy rates during the pandemic period increased energy intensity, leading to more fuel being spent on carrying fewer passengers. Table 4 shows that the changes in the occupancy factor (ΔLF) vary across companies. For example, Frontier Airlines (1.1960) achieved the largest increase in the occupancy factor, while Spirit Airlines (0.4890) underperformed in this area. This may have allowed Frontier Airlines to manage its energy intensity more efficiently.

6.3. *Load factor and operational performance*

The energy intensity trends can also be correlated with changes in the transportation ratio when looking at the table. Spirit Airlines and Frontier Airlines showed the highest increases in the transportation ratio (ΔCR) with 2.1914 and 2.1598, respectively. However, Spirit Airlines' low occupancy factor increase (0.4890) and high energy intensity (0.4749) indicate that this transport increase may have negative impacts in terms of efficiency.

6.4. *Available seat miles (ΔASM) and company scale*

Based on Fig. 11, it is clear that international operations are more energy-intensive than domestic operations. The table sheds light on company scales and available seat miles (ΔASM) to explain the reasons for this. The large-scale operations of the Sub Network group (522,909 ktons ASM) and Delta Airlines (178,051 ktons ASM) contributed to their high carbon emission increases. In contrast, smaller companies, such as Allegiant and Hawaiian Airlines, exhibited lower ASM values and less energy intensity and carbon emission increases.

6.5. *Bidirectional analysis of pandemic impact*

The COVID-19 pandemic has had dramatic impacts on energy intensity and carbon emissions in the airline industry. Changes during this period were driven by both supply and demand side factors, with bidirectional impacts on load factors, operational efficiency, and carbon emissions. The sharp drop in passenger demand during the pandemic significantly reduced the load factor (ΔLF) of flights. Fig. 11 shows that energy intensity (Btu/million passenger miles)4 increased dramatically, especially for international flights in 2020. The main reason for this is that when the occupancy rates of flights decrease, the fuel consumption per passenger carried increases. For example, when an airplane carries fewer passengers while consuming the same amount of fuel, the energy intensity naturally increases.

The data in Table 4 shows that the impact of this varies for different airlines. Companies such as Hawaiian Airlines experienced a relatively smaller drop in occupancy factor (ΔLF = 0.7281) during the pandemic, while companies such as Spirit Airlines (ΔLF = 0.4890) suffered more from this impact. This difference in occupancy can be explained by the companies' flight networks, their dependence on short-haul flights, and their operational flexibility during the crisis period.

International flights were heavily restricted during the pandemic, which led to an increase in the energy intensity of international operations. The graph shows that international flights have higher energy intensity compared to domestic flights. One reason for this is that long-haul flights require higher occupancy rates due to fixed fuel costs. Tabular data also supports this effect; for example, the Sub Network group (522,921 ktons ASM) experienced the highest increase in carbon emissions and energy intensity during the pandemic due to its large-scale international operations. Operational flexibility became a critical factor for companies during this period. Companies such as Hawaiian and Allegiant, which operate mainly regional flights, were able to adapt their operations more easily and keep their energy intensity relatively stable. In contrast, companies that depend on international flights, such as United Airlines and Delta Airlines, have experienced higher increases in energy intensity and carbon emissions due to closed routes and low occupancy rates.

Available seat miles (ASM) have been an important factor during the pandemic. Failure to achieve the minimum operational occupancy required to keep aircraft in the air has put airlines under financial pressure and, in many cases, reduced energy efficiency. The ASM data in the table shows that large carriers (e.g., Delta and United) did not drastically reduce their capacity during the pandemic, but experienced higher energy intensity and carbon emissions due to lower occupancy rates. In contrast, smaller carriers implemented a more flexible strategy by rapidly reducing capacity. For example, Allegiant and Spirit Airlines suffered relatively little impact by focusing on short-haul and less energy-intensive flights.

The impact of the pandemic on carbon emissions is directly related to energy intensity. The graph and table show that carbon emissions (ΔCO2 and ΔCO2INT) increased per passenger during the pandemic. The main reason for this increase is that occupancy rates decreased, and airplanes consumed the same amount of fuel while carrying fewer passengers. However, the different strategies implemented by companies during this period diversified the impact on carbon emissions.

- Large-scale companies (e.g., Delta and the Sub Network group) emitted more carbon emissions due to higher energy intensity on international routes.
- Smaller, regionally focused companies (e.g., Allegiant and Hawaiian Airlines) were able to limit these impacts through flexible capacity management.

The pandemic has shown that airlines need to review their crisis management strategies to reduce impacts on energy intensity and carbon emissions. The lessons learned during this period are as follows.

- Optimizing Occupancy Rates: In future downturns, companies should keep energy intensity under control by quickly adapting flight capacity to demand.
- Use Sustainable Fuels: Fuel-type conversions can be an effective tool to reduce carbon emissions regardless of occupancy fluctuations.
- Focus on Regional Flights in Times of Crisis: Having a more flexible flight network by reducing over-reliance on international operations is critical for both financial and environmental sustainability.

The pandemic has revealed the vulnerabilities in the airline sector in terms of energy intensity and carbon emissions management. When the graph and table are evaluated together, the effects of declining occupancy rates and lack of operational flexibility on energy efficiency are observed. However, this period also highlights the need for airlines to strengthen their sustainability strategies and develop operational models that are more resilient to crises.

Declaration of competing interest

The authors whose names are listed immediately below certify that they have NO affiliations with or involvement in any organization or entity with any financial interest (such as honoraria; educational grants; participation in speakers' bureaus; membership, employment, consultancies, stock ownership, or other equity interest; and expert testimony or patent-licensing arrangements), or non-financial interest (such as personal or professional relationships, affiliations, knowledge or beliefs) in the subject matter or materials discussed in this manuscript.

Data availability

Data will be made available on request.

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