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ORIGINAL ARTICLE

Environmental sustainability performance of US airlines: implications of financial performance and technical efficiency

Sepideh Kaffash[a], Fahimeh Chomachaei[b] and Emel Aktas[c]

[a]Sawyer Business School, Suffolk University, Boston, USA; [b]College of Management, University of Massachussetts Boston, Boston, MA, USA; [c]Cranfield University, Cranfield, UK

ABSTRACT

Air transportation significantly contributes to global CO_2 emissions. The US Aviation Climate Action Plan introduced in November 2021 aims to decarbonize the aviation sector by 2050. Aligned with this initiative, our study applies Data Envelopment Analysis and fixed-effect panel regression to empirically explore how financial performance and technical efficiency impact Environmental Sustainability Performance (ESP) in the airline industry. We curated panel data of nine US passenger airlines from 2010 to 2019 to examine three key areas: the impact of financial performance on environmental sustainability performance, the influence of efficiency on environmental sustainability performance, and the relationship between flight stage length and environmental sustainability performance. Our findings indicate that improved Financial Performance, higher technical efficiency, and longer stage lengths positively contribute to enhanced environmental sustainability performance. Our study provides valuable insights for managers and policymakers, emphasizing the pivotal role of financial stability in achieving environmental goals within the airline industry. It underscores the intricate connection between economic viability and sustainability, offering guidance for policymakers seeking to balance financial success with environmental goals.

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Airline industry; environmental sustainability performance; financial performance; empirical study; data envelopment analysis; panel regression

1. Introduction

Approximately 2.5% of global CO_2 emissions are attributable to the aviation sector (Ritchie, 2024). Considering other effects of aviation on global warming, Lee et al. (2021) quantify its overall effect as 3.5%. While this percentage may seem relatively small compared to other sectors, aviation emissions have a disproportionately high impact on the climate due to the altitude at which they are released (Timperley, 2017). Nitrogen oxides, together with contrails and cirrus clouds induced by airplanes, amplify the environmental impact of the aviation sector. The impact of effective radiative forcing induced by these non-CO_2 emissions is comparable to or greater than that of CO_2; however, it is not possible to quantify this impact precisely (Ansell, 2023). To make matters worse, the forecast by the International Air Transport Association (IATA) of the number of flights by 2050 is double the number today globally, suggesting that the sector will generate four to six times more CO_2 than it did in 2010 (Cui et al., 2020).

The aviation sector attracts significant attention from policymakers, practitioners, and academia owing to its environmental footprint (Zieba and Johansson, 2022). Consequently, there is an increasing interest in examining the extent and effectiveness of the initiatives taken by airlines to alleviate their adverse effects and contribute to sustainable development (Fukui and Miyoshi, 2017; Liu et al., 2020). Evidence from the US airlines suggests that introducing an aviation fuel tax reduces CO_2 emissions in the short run, but the effect dissipates over time, and emission levels rebound to their earlier values (Fukui and Miyoshi, 2017). Modeling of the inclusion of non-European airlines in the Emissions Trading Scheme of the European Union resulted in these non-European airlines gaining a competitive advantage over European airlines (Scheelhaase et al., 2010).

Studies on the relationship between carbon emissions and financial performance, irrespective of the sector focus, resulted in variable conclusions. For example, a meta-analysis of 32 empirical papers found a positive correlation between carbon performance and financial performance; in other words, lower carbon emissions lead to higher financial performance (Busch and Lewandowski, 2018). It is also critical how the financial performance is measured, ie, whether market-based or accounting-based indicators are used to test the relationship between

CONTACT Emel Aktas emel.aktas@cranfield.ac.uk Cranfield University, Cranfield, UK

carbon performance and financial performance. The positive correlation between carbon and financial performance is higher for market-based measures. Another meta-analysis of 198 papers found a positive correlation between sustainability performance and financial performance (Lu and Taylor, 2016), more with environmental than social sustainability. An examination of the relationship between environmental and financial performance with data from the casinos, hotels, restaurants, and airlines finds a negative correlation (Tan et al., 2017) while the negative correlation is offset by the slack resources, measured as the quick ratio of the companies. However Nguyen et al. (2021)'s study on Chinese heavy-polluting industries indicates no significant relationship between financial performance and environmental performance.

Contrarily, the literature evidence highlights the absence of an impact of sustainability reporting on the financial performance of airlines (Karaman et al., 2018). On the other hand, sustainable practices in the aviation sector lead to better financial performance based on data from 38 airlines collected over ten years from 2009 to 2019 (Abdi et al., 2022). A study of the relationship between sustainability performance and efficiency of airlines indicates that full-service carriers demonstrate a higher commitment to Corporate Social Responsibility (CSR) activities, and CSR engagement is positively correlated with overall production efficiency (Kao et al., 2022). Implementing CSR practices is crucial for global airlines to effectively address the challenges within the dynamic landscape of the airline industry.

Many studies investigated the cause-and-effect relationship of sustainability performance on financial performance; however, the opposite direction, whether financial performance leads to better sustainability performance, has not been studied extensively (Hang et al., 2019). This is critical in the context of the airline industry, where slack resources obtained due to higher financial performance may lead to better sustainability performance. Exploring this reverse relationship is essential for several reasons. Firstly, it provides an understanding of how financial resources and efficient operations can act as catalysts for environmental sustainability (Renzhi and Baek, 2020). In essence, financial stability may provide the necessary capital for investment in green technologies and practices. Secondly, by highlighting the role of financial performance in enhancing environmental sustainability performance, it underscores financial stability as a crucial factor in driving environmental sustainability. Moreover, the unique characteristics of the airline industry warrant specific attention. Unlike the manufacturing sector, which has been the focus of much empirical research on sustainability performance, the airline industry operates in a different context. The airline industry is a service-oriented industry marked by high investment needs and a limited number of major players. National airlines, often supported by governments, add another layer of complexity to the industry's landscape. Given these distinct features, studying the reverse causal relationship between financial performance and sustainability performance becomes crucial for developing tailored strategies that account for the intricacies of the airline industry.

The focus of this study on US airlines is motivated by the notable supply of air transport in the US. The US aviation industry is a major contributor to CO_2 emissions. In 2019, domestic flights leaving the US airports were responsible for 23% of the world's CO_2 emissions related to passenger transportation (Graver & Rutherford, 2019). This is significantly higher than the collective emissions of the 28 members of the European Union, which were second behind the US (Graver & Rutherford, 2019). Recognizing this significant impact, the Federal Aviation Administration (FAA) has implemented sustainability initiatives aimed at creating an aviation system with zero net emissions by 2050. This plan includes developing sustainable aviation fuels, improving aircraft and engine technologies, and enhancing air traffic operations. The FAA collaborates with industry partners to reduce greenhouse gas emissions, noise pollution, and fuel consumption. These efforts support the FAA's broader environmental goals of a cleaner, quieter, and more sustainable aviation future (Federal Aviation Administration, 2024).

According to the "United Nations Conference on Environment and Development" (UNCED) in 1992, one of the primary indicators for measuring environmental sustainability performance is the emissions of greenhouse gases (Warhurst, 2002). Therefore, in this study, we quantify environmental sustainability performance by using an airline's CO_2 emissions. We employ quarterly data from nine US airlines spanning the years 2010 to 2019. The data from 2020 and 2021 are excluded to mitigate the impact of the COVID-19 pandemic.

Our main research question in this paper is "*What is the impact of financial sustainability on environmental sustainability in the airline industry?*" The primary goal of this study is, therefore, to empirically examine the effect of financial performance and technical efficiency on environmental sustainability performance within the US airline industry. Besides the primary objective, this study also investigates the influence of technical efficiency on environmental sustainability performance. Moreover, we assess how an airline's stage length affects its environmental sustainability performance. In this study, we measure the efficiency of US airlines using non-parametric Data Envelopment Analysis (DEA), a widely adopted approach for this purpose. DEA was introduced by Charnes et al. (1978) under constant returns to scale (CRS), and later extended to variable returns to scale (VRS) by Banker et al. (1984).

Our study makes significant contributions to the literature. First, while numerous studies have explored the effect of environmental sustainability practices on financial performance, this perspective often overlooks the potentially transformative impact that financial performance can have on a company's environmental sustainability performance. Our study pioneers in examining this reverse dynamic, shedding light on how robust financial performance might enable and drive environmental sustainability performance.

Secondly, to the extent of our knowledge, no research in the literature examines the effect of technical efficiency on environmental sustainability performance in this industry. Our study addresses these gaps by empirically investigating the impact of financial performance and technical efficiency on US airlines' environmental sustainability performance, measured by CO_2 emissions. While this work is focused on the airline industry, its findings have the potential to be relevant and beneficial to other industries as well.

Thirdly, this research empirically examines the effect of stage length as a key cost variable affecting an airline's operational expenses and CO_2 emissions.

All of these investigations in this study enrich the airline industry's environmental sustainability literature by presenting a comprehensive view of the important factors driving sustainability in this industry.

In terms of methodology, our study contributes in two main ways. Firstly, we apply the novel boosting DEA model introduced by Guillen et al. (2023a, 2023b) to estimate airlines' technical efficiency. Secondly, to mitigate the risk of endogeneity issues arising from unobserved confounding factors, we utilize fixed effects with Driscoll-Kraay standard errors. To our knowledge, this study is the first to apply a novel integrated approach combining a DEA and Machine Learning model within the US aviation sector. In addition, there is no empirical research in this area that specifically addresses the endogeneity issue in the empirical analysis. Neglecting endogeneity could potentially lead to biased estimations, and our methodology ensures the robustness of the findings.

The rest of this paper is structured as follows: Section 2 covers the theoretical background and outlines the hypotheses and Section 3 explains data collection, variable measurement, modeling, and estimation methodology. The study's findings are presented in Section 4, followed by the reports of some robustness tests in Section 5. The next section presents the discussion and policy implications, and Section 7 offers the study's conclusion and the direction for potential future studies.

2. Background and literature review

2.1. Background

The extensive use of DEA in the airline sector highlights its critical significance and utility in assessing and improving operational efficiency (Barros and Peypoch, 2009). In Cavaignac and Petiot (2017)' review, out of 461 articles on the application of DEA in the transportation sector from 1989 to 2016, 14.3% focus on the aviation and airline industry. Mahmoudi et al. (2020) review research studies applying DEA within the transportation industry from years 2000 to 2010 and report that roughly 30% of the reviewed papers focus on subjects relating to air transport systems. In addition, Ali et al. (2021) evaluate forty years of studies on the productivity and efficiency of airlines. Remarkably, from 1989 to 2018, a predominant fraction of the most frequently cited studies preferred DEA as their research method because it is versatile, and compared to other methods, it has less extensive data requirements (Ali et al., 2021).

For US airlines, most early studies that employ DEA to evaluate efficiencies were conducted in the 1990s, a time characterized by the US industry deregulation and the European industry liberalization (Distexhe and Perelman, 1994; Good et al., 1995). Some other pioneering studies that established the groundwork for applying conventional DEA evaluate forty years of studies on the productivity and efficiency of airlines Greer (2006, 2008); Bhadra (2009); Barros et al. (2013). Zhu (2011)'s research is among the pioneers in applying network DEA to the airline industry. This study assesses the US airlines's efficiency by dividing the airline into two subsystems: (1) the production process and (2) the consumption process. More recently, there has been an increasing trend for researchers to use conventional and network DEA combined with Machine Learning (ML) models to address specific questions, both in terms of applications and methodologies.

DEA has also been utilized by scholars to address the sustainability and efficiency of airline fuel within the US. For example, Zou et al. (2014, 2016) examine the efficiency of fuel in the domestic airline industry operating in the US using four models: (1) ratio-based, (2) deterministic frontier, (3) stochastic frontier, and (4) conventional DEA. Their research indicates that efficiency assessments are consistent across these methods, with minimal impact from regional affiliates or route planning, highlighting stable relative efficiency among mainline airlines. Cui and Li (2015) introduce a virtual frontier envelopment DEA cross-efficiency model to evaluate the impact of CO_2 emissions on productivity across 35 airlines, including those in the US They find that traditional productivity growth measurements, which exclude CO_2 emissions, overestimate actual productivity, as pollution reduction efforts decrease productivity growth. Xu et al. (2021) incorporate greenhouse gas emissions and in-flight delays as undesirable outputs in their Network DEA model, for 12 US airlines from 2013 to 2016 and find significant changes in efficiency scores. Saini et al. (2023) develop a two-stage DEA with two phases assessing an airline's operations and showing that integrating operational cost and ecological factor yields a more precise evaluation of the efficiency of airlines operating in the US

From a methodological standpoint, integrating DEA with ML techniques has gained considerable attention for its potential to enhance efficiency predictions across various domains. Traditional DEA models, while effective, require substantial computational resources when recalculating efficiency scores for new DMUs (Aparicio and Esteve, 2023). This limitation necessitates rerunning the DEA model, consuming significant memory and CPU time. To address these computational challenges, Zhu (2022) advocated for integrating DEA with advanced ML techniques in big data scenarios, suggesting that this combination can significantly enhance analytical capabilities. By leveraging ML algorithms such as neural networks (Misiunas et al., 2016; Zhu et al., 2021), support vector machines (Valero-Carreras et al., 2021; Zhu et al., 2021), random forests (Rebai et al., 2020; Thaker et al., 2022), and regression trees (Rebai et al., 2020), the hybrid DEA-ML approach provides more accurate and computationally efficient predictions, making DEA more suitable for big data applications. In this paper, we use the model developed by Guillen et al. (2023c), which adapts the Gradient Tree Boosting algorithm to ensemble Efficiency Analysis Trees (EAT) models, creating the EATBoosting algorithm. In this paper, we employ the EATBoosting radial DEA model to assess the airlines' technical efficiency.

2.2. Theoretical and empirical literature review

By 2050, the demand for air travel is projected to exceed 10 billion passenger journeys, which is expected to result in approximately 1.8 billion tons of CO_2 emissions from the aviation sector (EESI, 2022). In 2019, this figure was 920 million tons (Overton, 2023). As part of the global air transport industry's commitment to achieving net-zero carbon emissions by 2050, it is expected that 65% of the emission reductions will come from the use of Sustainable Aviation Fuels (SAFs). New propulsion technologies, like hydrogen, are expected to contribute an additional 13% reduction. Efficiency enhancements are projected to account for approximately 3% of the reduction. The residual emissions may potentially be managed by utilizing carbon capture, carbon storage, and carbon offsets (EESI, 2022).

The United States has launched the Aviation Climate Action Plan to address the climate crisis by promoting innovation and sustainable practices in the aviation sector. This comprehensive strategy includes introducing fuel-efficient aircraft, improving engine efficiency, enhancing aircraft design, optimizing flight paths, expanding sustainable aviation fuels (SAF) consumption, exploring electrification and hydrogen for short flights, funding climate impact research, and participating in international efforts like Carbon Offsetting and Reduction Scheme for International Aviation (CORSIA) (Federal Aviation Administration, 2021b). Reaching sustainability targets in the aviation industry, particularly due to the high power and energy demands of current transport-class aircraft, is significantly more daunting compared to other forms of transportation (Ansell, 2023). The aviation sector's direct emissions are primarily influenced by fuel type, engine type, and engine load (Nojoumi et al., 2009) as well as travel demand (Oguntona, 2020).

Efforts to reduce aviation emissions are multifaceted, including the adoption of low-emission alternative fuels, advancements in aircraft engine technology, improvements in air traffic operations, and international regulations such as CORSIA. Observing the tangible impacts of applying renewable fuels and low-carbon technologies takes time, due to the gradual integration of these advanced aircraft into the existing global fleet (Ranasinghe et al., 2019). For long-term solutions, there is growing interest in exploring diverse sustainable fuel options (Afonso et al., 2023; Undavalli et al., 2023). Scholars have also explored topics like aircraft design (Ajaj et al., 2021; Towsyfyan et al., 2020), route optimization (Debbage and Debbage, 2019; Jalalian et al., 2019), and air travel demand management (Chao et al., 2019) to enhance environmental sustainability in aviation.

According to Soytas et al. (2019), the correlation linking sustainability performance and financial performance raises uncertainty about its direction. Additionally, they assert that different operationalizations of sustainability measures yield varying results and inferences about this relationship. To the best of the authors' knowledge, there is a lack of sufficient evidence in the literature regarding the reverse relationship, meaning the impact of financial performance on environmental sustainability performance, which is measured using CO_2 emissions in this study. In this paper, we explore this relationship along with two other relationships: the individual impacts of technical efficiency and stage length on environmental sustainability performance.

2.3. Hypothesis development

According to the Resource-Based View (RBV) (Wernerfelt, 1984), organizational resources, such as financial assets, empower a firm to produce its market offerings (products or services) both efficiently and effectively, leading to more sustainable practices (Hunt, 1999; Hang et al., 2019; Zhang et al., 2018). Similar to the RBV, the Natural-Resource-Based View (NRBV), as articulated by Hart, (1995), states that resources including physical and financial assets, are essential for firms aiming to meet both operational and sustainability goals.

Empirical evidence also supports this association. For instance, Makni et al. (2009) empirically demonstrate that an entity's financial performance is positively correlated with its sustainability performance. Their study, conducted on a sample of 179 publicly traded Canadian firms using the corporate social performance metric as a sustainability indicator for the years 2004 and 2005, highlights the influence of financial resources on a firm's ability to engage in sustainable practices. Additionally, Akbar et al. (2021) reveal that financial constraints pose a significant obstacle to a firm's capacity to make investments in environmental protection. Moreover, this association appears to be more prominent in privately owned firms.

In the context of the aviation industry, the environmental challenges posed by CO_2 emissions have led to global regulatory pressures, such as those outlined in the US Aviation Climate Action Plan and FAA's environmental initiatives which require substantial investments in technology, training, and infrastructure upgrades (Federal Aviation Administration, 2024). Airlines with robust financial health are more capable of investing in the necessary resources to adopt innovations such as rolling to the runway, trajectory-based operations, time-based flow management, optimized profile descents, development and implementation of fuel-efficient technologies, alternative fuel sources, and cutting-edge aircraft designs. By implementing these advanced operational strategies, airlines can reduce fuel consumption, decrease CO_2 emissions, and improve operational efficiency. Financially robust airlines can afford to purchase or lease fuel-efficient aircraft, contributing to reducing CO_2 emissions. They are also equipped to implement sophisticated flight planning systems for optimal fuel usage and undertake maintenance programs that reduce aircraft downtime and extend its lifespan. Therefore, the ability of an airline to engage in these environmentally beneficial practices is closely tied to its overall financial strength.

Accordingly, we posit that financial performance plays a pivotal role in an airline's ability to engage in sustainable practices. We develop our first hypothesis to test the relationship between financial performance and sustainability.

> **Hypothesis 1:** Higher financial performance in airlines is associated with lower CO_2 emissions.

Porter and Linde (1995) posits that firms that invest in technological innovations and resource efficiency can simultaneously improve their environmental performance while maintaining or even enhancing their competitiveness. This idea aligns with the broader concept of eco-efficiency, where firms reduce waste, emissions, and other environmental impacts by optimizing their resource usage (Ambec and Lanoie, 2008). The theory suggests that through continuous innovation and efficiency improvements, firms can reduce their ecological footprint but also enhance operational performance, offsetting the expenses of pollution reduction with gains in productivity.

Several empirical studies have demonstrated the positive effects of technological innovations and efficiency improvements on environmental performance. Schilirò (2019) finds that technological innovation has a significant positive impact on total factor energy efficiency. Wang and Wang (2020) highlights that sustainability relies on innovation and efficiency, with environmentally friendly technologies being crucial for long-term resource management and policy development.

In the airline industry, implementing a range of operational optimization strategies reduces fuel consumption and emissions. Optimization strategies include but are not limited to investment in fuel-efficient technology (Zou et al., 2014), research and development (Payán-Sánchez et al., 2019), fleet modernization (Pinheiro Melo et al., 2020), and effective flight operations, including route and schedule optimization (Eskenazi et al., 2023). Continuous research and development improve fuel efficiency and enable planes to carry more payloads for the same amount of fuel. Additionally, efficient management of cargo and passengers ensures that flights operate at full capacity. An airline with broader access to advanced technological innovations leverages these opportunities to enhance fuel efficiency and reduce CO_2 emissions per ton mile. In general, firms' technological innovation activities have positive benefits by enhancing resource efficiency (De Long and Summers, 1991; Fernando et al., 2019).

Investing in technical efficiency is expected to influence environmental performance positively, as efficiency investments typically lead to enhanced or superior environmental outcomes (Lee et al., 2015). Therefore, we explore whether airlines with higher technical efficiency in using their resources and optimizing their capacity have lower CO_2 emissions. Airline technical efficiency is intricate, and a single indicator may not adequately shed light on the subject (Li et al., 2015; Seufert et al., 2017).

Thus, we estimate the airline's technical efficiency using the DEA, assuming free disposability, which postulates that when DMU is a member of a production technology, increasing any of its inputs or reducing any of its outputs keeps the DMU within the technology (Mehdiloo and Podinovski, 2019). DEA's returns to scale assumption suggests that changes in outputs will be proportional to the changes in inputs (Elsner et al., 2014). Finally, DEA's convexity assumption posits that composite units are formed by convex combinations of other units' inputs and outputs (Emrouznejad and Amin, 2009).

Initially introduced by Charnes et al. (1978) under CRS, DEA evaluates the relative efficiencies of DMUs with several input and output variables. Banker et al. (1984) then formulate the original DEA model as VRS. Going forward, we use the term efficiency to reflect the technical efficiency estimated by DEA. DEA has since been extensively refined and applied across various fields including the airline industry (Kyriacou et al., 2019; Liu et al., 2020; Merkert and Hensher, 2011; Nguyen et al., 2022; Yen and Li, 2022; Yu et al., 2022). Following Lee and Worthington (2014) we use flown miles, number of employees, and total assets as inputs. For output, we use available ton miles measured as passenger plus freight and mail.

Building on both theoretical and empirical evidence, we posit that airlines with higher efficiency, are able to achieve lower CO_2 emissions. By leveraging operational optimization strategies and innovative technologies, technically efficient airlines are better equipped to meet sustainability targets. Therefore, we develop our next hypothesis to examine the connection between technical efficiency and sustainability.

> **Hypothesis 2:** Higher technical efficiency in airlines is associated with lower CO_2 emissions.

In the airline industry, cost drivers are categorized into "executional" (influenced by managerial decisions) and "structural" (derived from the airline's economic framework) (Shank and Govindarajan, 1993). Among structural drivers, average stage length—the distance flown per flight—is crucial for sustainability, as it directly impacts fuel consumption and emissions. This highlights the importance of aligning operational strategies with environmental goals.

Araújo et al., (2011) and Ryerson and Hansen (2013) claim that airlines with longer average stage lengths generally tend to achieve lower operating costs per unit of production. Fuel costs are no exception to this trend. The improved fuel efficiency in aircraft that operates over longer stage lengths is driven by several key factors including prolonged cruising at higher altitudes, the utilization of advanced aircraft technologies, and a reduction in flight frequencies. Long-haul flights, which spend a larger part of their journey at cruising altitude, achieve higher fuel efficiency. This improvement in fuel efficiency is largely because the relative fuel consumption for takeoff and landing becomes less significant over long-haul flights (Peeters et al., 2016; Sacchi et al., 2023; Turgut et al., 2019). Aircraft designed for extended flights frequently boast advanced technology, and this is particularly evident in wide-body aircraft built for long-haul ranges. The wide-body aircraft excel in fuel consumption, leading to reduced environmental emissions. This suggests that airlines with longer average stage length with increased passenger capacity are more economical regarding fuel usage and have reduced carbon dioxide emission, compared to their airline with shorter average stage length (Dhara and Lal, 2021; Morrell, 2009). Airlines with longer average stage lengths need lower flight frequency to meet the same demand for passengers or cargo, while also enhancing load factors for both. US airlines, which typically have longer average stage lengths, mostly depart from and land at airports equipped with advanced Terminal Flight Data Manager which reduces taxi times and delays, leading to reduced emissions (Federal Aviation Administration, 2022). This improved operational efficiency leads to a reduction in CO_2 emissions for each passenger or per ton of cargo transported.

Therefore, we investigate that airlines operating with longer average stage length achieve reduced CO_2 emissions per passenger-mile traveled. This reduction in emissions is primarily due to improved fuel efficiency, measured on a per-passenger-mile

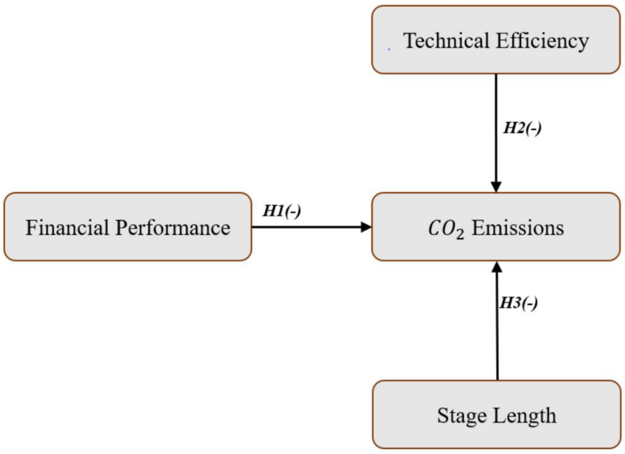

Figure 1. Research model.

basis. As a result, the following hypothesis is proposed:

> **Hypothesis 3:** Longer stage length in airlines is associated with lower CO_2 emissions.

The research model, which integrates the hypotheses discussed earlier, is visually represented in Figure 1. This model provides a structured framework that illustrates the relationships and interactions between the key variables under investigation. By organizing the hypotheses within this model, we aim to clarify how each element contributes to the overall theoretical framework and research objectives. It serves as a roadmap for testing the proposed hypotheses, helping to identify direct and indirect effects, and providing a comprehensive view of the anticipated dynamics within the study.

3. Research design

3.1. Data and variables

In this study, we focus on selecting major US passenger airlines based on their operating revenue and data availability from 2010 to 2019. Mainline airlines in the United States are referred to as *major carriers* that operate large, long-haul flights and are not primarily focused on regional operations (Zou et al., 2014). According to the United States Department of Transportation's definition, the airlines are considered the primary mainline US-based passenger airlines as their annual revenue exceeds $1 billion in a fiscal year (DOT, 2021). We chose Alaska Airlines, American Airlines, Delta Airlines, Frontier Airlines, Hawaiian Airlines, JetBlue Airlines, Southwest Airlines, Spirit Airlines, and United Airlines, all of which consistently generate over 1 billion in annual revenue as of 2021 (DOT, 2021). These airlines were selected because they represent the key US passenger carriers with comprehensive data throughout the study period. While generating over USD 1 billion in 2021, Allegiant Air was excluded because it lacked sufficient data during the early years of the study period. Similarly, Atlas Air and Kalitta Air were excluded because they primarily operate cargo services, which is outside the scope of this study on passenger airlines. Additionally, UPS, though also a high-revenue airline, was excluded as it focuses on freight rather than passenger transportation. Therefore, our data set consists of quarterly data from all nine major mainline US passenger airlines from 2010 to 2019, resulting in 360 quarterly observations (four quarters per year for 10 years of nine airlines). The data used in this study comes from the Bureau of Transportation Statistics (BTS, 2022).

3.1.1. Independent variable: Financial Performance

When assessing financial performance, researchers commonly employ two main groups of metrics. The first one involves accounting-based measures such as the Return on Assets or Equity. The second one includes market-based measures such as market returns metrics (Hult et al., 2008; Molina-Azorín et al., 2009; Soytas et al., 2019). Accounting-based metrics offer insights into a company's operational efficiency and effectiveness and are favored in empirical research as they offer a clear and traceable indication of management's impact on the firm's value (Thanos and Papadakis, 2012). However, market-based metrics are forward-looking and influenced by market perceptions (Thaler, 2005). Therefore, in this research, we align with existing studies (Andreou et al., 2014; Fu and Su, 2021; Kuo et al., 2021; Li et al., 2017; Lucas and Noordewier, 2016) and utilize Return on Asset (ROA) as a measure for financial performance. ROA exposes a firm's production efficiency concerning management and asset utilization. Thus, this independent variable reflects firm profitability (Javeed et al., 2020).

3.1.2. Independent variable: Technical Efficiency

In this study, we use the boosting DEA model proposed by Guillen et al. (2023a, 2023b) to estimate the technical efficiency score of airlines for each year, each quarter. This novel boosting DEA model adapts the Gradient Tree Boosting known as EATBoosting to estimate production technologies. Boosting is modified to estimate technologies in alignment with traditional production theory principles while bridging the gap between machine learning techniques and Free Disposal Hull methods for technical efficiency evaluation. To estimate the technical efficiency, input-oriented variable return to scale is being used. For input-output selection, we follow Lee and Worthington (2014) and use miles flown, number of full-time employees, and total assets as inputs and available ton miles (comprises the tonnage of passengers and freight) as output.

3.1.3. Independent variable: Stage Length

Stage length indicates the average flown distance. The stage length of a flight is a key factor that significantly impacts an airline's unit cost and productivity. Hazledine (2010) highlights that the average flown distance is a key factor of costs for the airline industry. As the average stage length extends, significant variable costs, including those for fuel, staff, and maintenance, tend to rise accordingly (Zuidberg, 2014). On the other hand, airlines operating with longer average stage length typically tend to have lower operating costs per production unit (Araújo et al., 2011; Ryerson and Hansen, 2013). Airlines can leverage stage length to effectively manage flight frequencies, select appropriate aircraft, and optimize passenger and cargo loads. Following Wei and Hansen (2003) and Jiang (2014), we estimate the average flight distance for each airline, each year, and each quarter by calculating the average flown miles per departure.

3.1.4. Dependent variable: CO_2 Emissions

As only a limited number of airlines disclose their CO_2 emission volumes and considering that our study spans from 2010 to 2019—a period during which CO_2 emissions were consistently reported—we follow the approach used in existing studies (Girardet and Spinler, 2013; Huang et al., 2020; Pagoni and Psaraki-Kalouptsidi, 2016). We estimate the CO_2 emission volumes for each airline, each year and each quarter, by calculating the product of fuel usage and the emission factor, 3.16, in accordance with the guidelines for national greenhouse gas inventories (IPCC, 2006).

Following the methodology of previous studies, we incorporate multiple control variables at the airline levels to enhance the robustness of our findings.

3.1.5. Control variable: Firm Size

Firm size, a crucial control variable, is computed as total assets, aligning with established research procedures (Fu and Su, 2021; Kuo et al., 2021; Qureshi et al., 2020; Soytas et al., 2019). This variable could significantly influence firms' environmental performance (Fu and Su, 2021; King and Lenox, 2002).

3.1.6. Control variable: Leverage

Leverage, widely used in studies to regulate firms' capital composition (Fu and Su, 2021; Jiang et al., 2018; Ullah et al., 2018), is another control variable that we include. This variable is measured as total liabilities divided by total assets and particularly suitable for the air transport industry (Abdi et al., 2022; Pires and Fernandes, 2012).

3.1.7. Control variable: Growth

The growth is widely used in studies to regulate the potential effect of changes in firms' business (Fu and Su, 2021; King and Lenox, 2002).

3.1.8. Control variable: Fuel-Cost Ratio

We also include the fuel cost ratio, measured as the proportion of total fuel cost to the operating cost, as a control variable ensuring the validity of our findings against potential economic impacts of fuel prices (Scheelhaase et al., 2010). Fuel consumption is critical to the estimation of emissions and allocation of emissions to flights.

We report all variable definitions and their summary of statistics in Table 1.

3.2. Modeling

3.2.1. Efficiency analysis trees

To evaluate the technical efficiency, we use the boostingDEA package in `R` developed by Guillen et al. (2023a). The package includes boosting algorithms by Friedman (2001) for evaluating production frontiers that adapt the Gradient Tree Boosting. The Gradient Tree Boosting is recognized as EATBoosting. This approach combines Efficiency Analysis Trees (EATs) (Esteve et al., 2020), improved Classification and Regression Trees (CART) models for production technology estimation, using a boosting technique. This method ensembles multiple decision trees together to achieve superior performance compared to approaches that rely on building a single decision tree model. This strengthens the overall prediction accuracy (Guillen et al., 2023c). Most recent DEA related models that combine DEA and machine learning apply these models at independent stages. This novel EATBoosting model modifies a well-established machine learning technique by incorporating shape constraints derived from

Table 1. Variable definitions and summary statistics.

Variable	Definition	Mean	std.dev	25%	Median	75%
DEA Efficiency						
Input:						
Miles Flown	Total distance (Miles) flown	$4.23E+6$	$4.00E+6$	$1.22E+6$	$1.97E+6$	$8.01E+6$
Employees	Number of full-time employees	33158	33350	4901	13762	64682
Assets	Total assets	$2.02E+7$	$2.19E+7$	$2.58E+6$	$8.66E+6$	$3.79E+7$
Output:						
Available Ton Mile	Tons of carrying capacity (passengers, freight) multiplied by miles traveled	$9.49E+9$	$9.48E+9$	$2.08E+9$	$4.08E+9$	$1.76E+10$
Econometric modeling						
Independent Variables						
ROA	Net income divided by total assets	0.014	0.019	0.005	0.013	0.02
Technical Efficiency	Boosting Radial DEA	0.400	0.160	0.300	0.334	0.467
Stage Length	Total flown distance divided by total number of departures	$3.87E+5$	$3.38E+5$	$8.80E+4$	$1.78E+5$	$6.70E+5$
Dependent Variable						
CO_2	Fuel consumption multiply by emission factor	$1.04E+9$	$1.03E+9$	$1.78E+8$	$4.28E+8$	$1.93E+9$
Control Variables						
Size	Total assets	$2.02E+7$	$2.19E+7$	$2.58E+6$	$8.66E+6$	$3.79E+7$
Leverage	Total liabilities divided by Total Assets	1.174	0.620	1.150	1.156	1.156
Growth	Revenue at time t - revenue at time $t-1$	1.558	1.430	1.040	1.130	1.30
Fuel-Cost Ratio	Fuel cost divided by total cost	0.278	0.087	0.212	0.270	1.835

production theory for the first time (Guillen et al., 2023c).

This section provides a concise overview of the key concepts associated with the EATBoosting model as proposed by Guillen et al., (2023a). In the context of DEA, the productivity and economic performance of a set of n DMUs are evaluated. Each DMU consumes a vector of m positive inputs $x\in\mathbb{R}_+^m$ to produce a vector of s positive outputs $y\in\mathbb{R}_+^s$. The production technology contains all technically feasible combinations of x,y) (Avilés-Sacoto et al., (2020) and is formally defined as $\psi=\{(x,y)\in\mathbb{R}_+^{m+s}:\mathbf{xcanproducey}\}$. Technical efficiency is measured by the distance from a point in ψ to the production frontier, with the production frontier $\partial(\psi)$ marking the "upper" limit of the technology.

In the literature, both orientation models are being used as measures for technical efficiency. The output-oriented model evaluates the efficiency of a given point (x_k,y_k) by keeping inputs constant while proportionally increasing all outputs and the input-oriented model focuses on minimizing inputs while keeping outputs constant. The efficiency score under output-oriented and input-oriented are relatively defined as:

Output-oriented DEA

$$\phi(x_k,y_k)=\max\{\phi:(x_k,\phi y_k)\in\psi\}. \tag{1}$$

Input-oriented DEA

$$\phi(x_k,y_k)=\min\{\phi:(\phi x_k,y_k)\in\psi\}. \tag{2}$$

Within the framework of DEA, the production technology is determined based on the principles of free disposability, convexity, envelopment, and minimal extrapolation. Banker et al. (1984) provides an estimate of the output-oriented variable returns to scale technology ψ as:

$$\begin{aligned}\phi^{\mathrm{DEA}}(x_k,y_k)&=\max\phi\\ \text{s.t.}\ &\sum_{i=1}^{n}\lambda_i x_i^{(j)}\le x_k^{(j)},\quad j=1,\dots,m\\ &\sum_{i=1}^{n}\lambda_i y_i^{(r)}\ge\phi y_k^{(r)},\quad r=1,\dots,s\\ &\sum_{i=1}^{n}\lambda_i=1\\ &\lambda_i\ge0,\quad i=1,\dots,n\end{aligned} \tag{3}$$

The core concepts of gradient boosting include the following: given a loss function $L(y,f(x))$ and a weak learner $h(x)$, the goal of the formula is developing an additive model that minimizes the loss function.

$$\gamma_q=\arg\min_{\gamma}\sum_{i=1}^{n}L(y_i,f_{q-1}(x_i)+\gamma h_q(x_i)) \tag{4}$$

Adapting the standard Gradient Tree Boosting technique to the production theory, we specify the initial estimation for the boosting algorithm as $f_0(x)=(\max_{i=1,\dots,n}\{y_i^{(1)}\},\dots,\max_{i=1,\dots,n}\{y_i^{(s)}\})$. In the next step, we specify the loss function in the EATBoosting formula as follows:

$$L(y_i,f(x_i))=\frac{1}{2}\sum_{r=1}^{s}\left(y_i^{(r)}-\hat{f}^{(r)}(x_i)\right)^2,\quad\forall i=1,\dots,n. \tag{5}$$

Therefore, the elements of its gradient $r_{iq}^{(r)}$ will be

$$r_{iq}^{(r)}=-\left[\frac{\partial L(y_i,f(x_i))}{\partial\hat{f}^{(r)}(x_i)}\right]_{\hat{f}^{(r)}(x_i)=f_{q-1}^{(r)}(x_i)}=y_i^{(r)}-f_{q-1}^{(r)}(x_i),\quad r=1,\dots,s. \tag{6}$$

For every iteration, a new EAT model $h_q(x)$ (see Esteve et al. 2020) is trained on the components of the negative gradient from the previous iteration's LF. In every single EAT tree, there is a step q at which each leaf node j (where $j = 1, \ldots, J_q$) is specified by a set of limitations in the input space, such as $\{x_j < \delta_j\}$ or $\{x_j \geq \delta_j\}$. Here, j is the input variable used to make the split, and $\delta_j \in \Delta_j$ represents the range of potential thresholds for input j. Consequently, upon completing all the splits and obtaining the ultimate tree composition for step q, the support of its leaf node j is given by:

$$R_{jq} = \{x \in \mathbb{R}^m_+ : a^{(j)}_{jq} \leq x^{(j)} < b^{(j)}_{jq}, \quad j = 1, \ldots, m\}. \tag{7}$$

Therefore, after applying the algorithm linked to EATBoosting the EATBoost output-oriented radial DEA model is as follows:[1]

$$\begin{aligned}
&\phi^{\text{EATBoost}}(x_k, y_k) = \max \phi \\
&\text{s.t.} \sum_{j_1=1}^{J_1} \cdots \sum_{j_Q=1}^{J_Q} \lambda_{j_1 \ldots j_Q} \hat{a}^{(j)}_{j_1 \ldots j_Q} \leq x^{(j)}_k, \quad j = 1, \ldots, m \\
&\sum_{j_1=1}^{J_1} \cdots \sum_{j_Q=1}^{J_Q} \lambda_{j_1 \ldots j_Q} \hat{f}^{(r)}(\hat{a}_{j_1 \ldots j_Q}) \geq \phi y^{(r)}_k, \quad r = 1, \ldots, s \\
&\sum_{j_1=1}^{J_1} \cdots \sum_{j_Q=1}^{J_Q} \lambda_{j_1 \ldots j_Q} = 1 \\
&\lambda_{j_1 \ldots j_Q} \geq 0, \quad j_q = 1, \ldots, J_q, \quad q = 1, \ldots, Q
\end{aligned} \tag{8}$$

Firms are required to comply with environmental regulations. An input-oriented DEA model assists airlines in meeting these requirements by identifying areas where resource usage (miles flown in our case) can be curtailed without compromising output, thus supporting sustainable practices. Therefore, we use the EATBoost input-oriented radial DEA model defined as follows:

$$\begin{aligned}
&\hat{\theta}^{\text{EATBoost}}_{\text{in}}(x_k, y_k) = \min \theta \\
&\text{s.t.} \sum_{j_1=1}^{J_1} \cdots \sum_{j_Q=1}^{J_Q} \lambda_{j_1 \ldots j_Q} \hat{a}^{(p)}_{j_1 \ldots j_Q} \leq \theta x^{(p)}_k, \quad p = 1, \ldots, m, \\
&\sum_{j_1=1}^{J_1} \cdots \sum_{j_Q=1}^{J_Q} \lambda_{j_1 \ldots j_Q} \hat{f}^{(l)}(\hat{a}_{j_1 \ldots j_Q}) \geq y^{(l)}_k, \quad l = 1, \ldots, s, \\
&\sum_{j_1=1}^{J_1} \cdots \sum_{j_Q=1}^{J_Q} \lambda_{j_1 \ldots j_Q} = 1, \\
&\lambda_{j_1 \ldots j_Q} \in \{0, 1\}, \\
&j_q = 1, \ldots, J_q, \quad q = 1, \ldots, Q
\end{aligned} \tag{9}$$

3.2.2. Empirical Modeling

We utilize STATA to conduct data analysis on our balanced panel dataset containing observations from various airlines across different time periods. Given that the individual units under study, which are the airlines, do not constitute a sample extracted from a larger population; ie, they are all major carriers, we adopt the fixed-effect method to manage unobservable variations (namely, the potential influence of unmeasured dissimilarities among comparable airlines impacting their CO_2 emissions) (Clark and Linzer, 2015).

This methodology discerns the causal relationship between financial performance, technical efficiency, and stage length as independent variables and CO_2 emissions as the dependent variable within the US airline industry when each entity has multiple observations. The fixed effect model, compared to a cross-section model, offers the advantage of mitigating the omitted variable problem by controlling for unobserved characteristics that differ among entities but remain consistent over time through within-group variations over time (Borenstein et al., 2010; Lee et al., 2015). Therefore, applying this method to eliminate the impact of the time-invariant characteristics helps us to evaluate the net effect of the predictors on the dependent variables (Bai, 2009). The empirical models are developed based on fixed-effects linear regression.

Multiple regression panel analysis was developed to test our hypotheses:

$$\begin{aligned}
\text{CO2}_{it} = \beta_1 \text{CO2}_{it-1} + \beta_2 \text{ROA}_{it-1} + \eta Z_{it-1} + c_i \\
+ \mu_t + u_{it}, \qquad \text{(Model 1)}
\end{aligned}$$

$$\begin{aligned}
\text{CO2}_{it} = \beta_1 \text{CO2}_{it-1} + \beta_2 \text{Technical Efficiency}_{it-1} \\
+ \eta Z_{it-1} + c_i + \mu_t + u_{it}, \qquad \text{(Model 2)}
\end{aligned}$$

$$\begin{aligned}
\text{CO2}_{it} = \beta_1 \text{CO2}_{it-1} + \beta_2 \text{Stage Length}_{it-1} \\
+ \eta Z_{it-1} + c_i + \mu_t + u_{it}, \\
\text{(Model 3)}
\end{aligned}$$

Models 1 to 3 correspond to Hypotheses 1 through 3, respectively. The subscript i indexes the airline, and t denotes the time period. Z_{it-1} denotes the control variables of airline i at period $t-1$, and c_i accounts for airline fixed effects.

Incorporating c_i into our model allows us to control for individual airline-specific characteristics that remain constant over time. μ_t represents time-fixed effects. Integrating μ_t into the model enables us to consider consistent time-dependent elements that are constant across all airlines, affecting CO_2 emissions, such as fuel prices. Finally, u_{it} represents the error term for airline i at period t. This comprehensive model structure facilitates the examination of the outlined hypotheses while accounting for various factors that may influence the outcomes.

To make our analysis more reflective of real-world dynamics, we incorporate lagged variables. Recognizing that the influence of financial or technological performance on CO_2 emissions unfolds over time, we acknowledge that immediate changes, eg, one to three months may not instantaneously manifest in changes in CO_2 emissions. To address this, we utilize lagged variables, enabling us to explore the contemporaneous impact on CO_2 emissions (Fukui and Miyoshi, 2017; Johnstone et al., 2010). Furthermore, an airline's CO_2 emissions in one quarter are likely to exhibit a high correlation with emissions in the preceding quarter. Therefore, we control it by considering the lag of the dependent variable as a control variable (Haque and Ntim, 2018).

3.3. Estimation methodology

Including the lagged dependent variable may result in biased estimates and raise endogeneity concerns (Kaushik and Gokpinar, 2023). However, if the number of time periods (T) exceeds the number of entities (N), the bias arising from utilizing fixed effects with lag variables is negligible, and the overall fixed effect estimator remains suitable under these circumstances (Agerton et al., 2017; Roodman, 2009; Wooldridge, 2015). In our specific dataset, where T equals 40 and N equals 9, the introduction of the lagged dependent variable into the fixed effect model does not result in endogeneity concerns. Therefore, there is no need to apply the Generalized Method of Moments (GMM) in our model (Wooldridge, 2015).

While employing the fixed-effect method as our baseline estimation approach, the error term could potentially exhibit heteroskedasticity, autocorrelation, and cross-sectional dependency across different airlines. Neglecting the existence of cross-sectional dependency and heteroskedasticity could introduce considerable bias, rendering the statistical outcomes inherently unreliable (Hassan and Rousselière, 2022; Hoechle, 2007; Joshi et al., 2021).

To address these potential issues, we undertake specific tests. Breusch-Pagan LM test is executed to assess whether the data contains any instances of cross-sectional dependence (Breusch and Pagan, 1980). The Breusch-Pagan LM test is suitable for scenarios involving a long period (T) and a small number of entities (N) (Hassan and Rousselière, 2022). The modified Wald test is employed to examine the potential presence of heteroskedasticity within our set of data. Furthermore, we utilize the Wooldridge test to scrutinize the potential existence of autocorrelation.

Our findings reveal significant outcomes in each model. The cross-sectional dependence statistics are noteworthy at the 1% significance level, suggesting the existence of cross-sectional dependence in our set of data. Similarly, the Modified Wald test reveals significant results at the 1% significance level, signaling the presence of heteroskedasticity in our data set. However, for serial correlation tests, we accept the null hypothesis of the Wooldridge test for autocorrelation. This indicates that, in our case, there isn't substantial evidence to suggest the existence of autocorrelation in the set of data.

To ensure reliable statistical conclusions, relying on "robust" standard errors becomes crucial. Driscoll and Kraay (1998) propose a non-parametric covariance matrix estimator that generates standard errors resilient to heteroskedasticity and autocorrelation, while also remaining robust against unobserved general and temporal patterns of cross-sectional dependence (Hoechle, 2007). Cross-sectional dependence can also lead to endogeneity concerns, particularly when observations across entities are correlated due to common factors. The Driscoll and Kraay estimator considers the existence of cross-sectional dependence and provides standard errors that account for this correlation. Therefore, the fixed effect with Driscoll-Kraay standard error estimator helps mitigate the risk of endogeneity issues caused by unobserved confounding factors.

4. Empirical results and discussion

4.1. Data envelopment analysis results

Table 2 provides a snapshot of the efficiency trends among ten US airlines over a period from 2010 to 2019, showing diverse patterns of change. It shows the average efficiency scores have declined for Frontier Airlines Inc., Hawaiian Airlines Inc., Southwest Airlines Co., and Spirit Airlines from 2010 to 2019 while it increased for the rest.

Full-service carriers such as Delta Air Lines, United Air Lines, and American Airlines exhibit consistently high-efficiency scores with minimal variability, indicating stable technical efficiency. In contrast, low-cost airlines such as Frontier Airlines and Spirit Air Lines show significant variability in their efficiency scores, suggesting fluctuating efficiency. Alaska Airlines and Spirit Air Lines have relatively low efficiencies among network and low-cost carriers. Several researchers have evaluated the technical efficiency of US network carriers compared to those of low-cost ones. The efficiency distribution of each airline is given in Figure 2.

Figure 2 shows that American Airlines, Delta Air Lines, and United Air Lines have higher efficiencies than the rest of the airlines investigated. These findings are not consistent in the literature. Greer (2006) use conventional DEA to show that US low-cost carriers are more technically efficient than network ones. In contrast, Choi (2017) find that US network airlines operate more efficiently than low-cost ones. Conversely, Vasigh and Fleming (2005), Huang et al. (2021), and Kaffash and Khezrimotlagh

Table 2. Efficiency trends of Airlines using EATBoost input-oriented Radial DEA.

	Year									
Airline	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Alaska Airlines Inc.	0.32	0.35	0.37	0.35	0.36	0.40	0.51	0.49	0.67	0.68
American Airlines Inc.	0.80	0.80	0.92	1.00	0.98	0.88	0.81	0.79	0.79	0.79
Delta Air Lines Inc.	0.84	0.89	0.90	0.90	0.88	0.85	0.84	0.87	0.92	0.93
Frontier Airlines Inc.	0.80	0.81	0.84	0.91	0.88	0.86	0.63	0.56	0.50	0.43
Hawaiian Airlines Inc.	0.88	0.76	0.65	0.55	0.55	0.53	0.52	0.53	0.49	0.47
JetBlue Airways	0.43	0.46	0.56	0.56	0.58	0.60	0.67	0.61	0.71	0.72
Southwest Airlines Co.	1.00	0.95	0.79	0.76	0.76	0.72	0.66	0.63	0.60	0.58
Spirit Airlines	0.96	0.85	0.70	0.60	0.53	0.46	0.40	0.51	0.28	0.31
United Air Lines Inc.	0.79	0.80	0.85	0.81	0.74	0.89	0.87	0.91	0.93	0.93

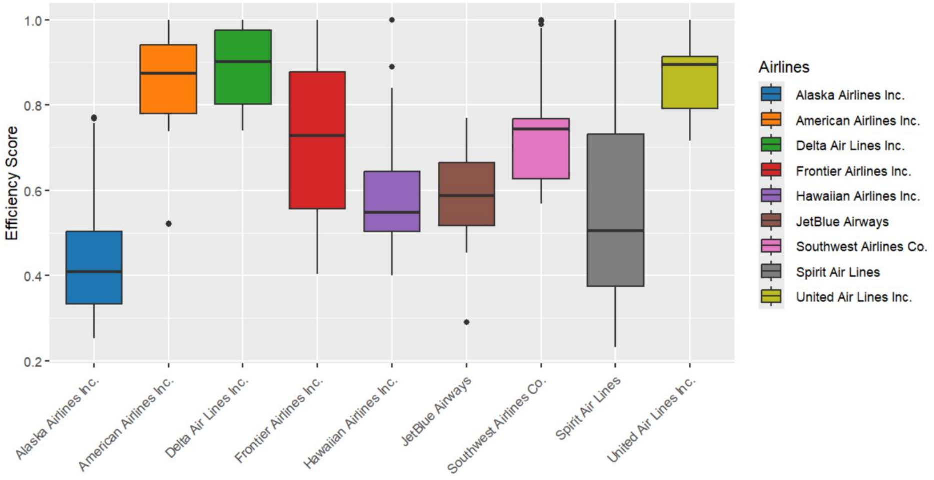

Figure 2. Distribution of US airlines efficiency scores (2010–2019).

(2023) argue that full-service carriers exhibit lower productivity and efficiency than low-cost airlines.

To enhance the interpretability of the coefficients, we apply a logarithmic transformation to all variables. This transformation allows the coefficients to be understood as elasticities. Additionally, this approach effectively mitigates data skewness (West, 2022).

4.2. Empirical modeling

Table 3[2] presents the outcomes related to Models (1)–(3) utilizing the fixed effects with Driscoll-Kraay standard errors.

Column 1 in Table 3 presents the results for Model (1), illustrating the relationship between financial performance and CO_2 emissions (Hypothesis 1). The estimated coefficient of ROA is −0.43 at a 1% significance level, indicating that the financial performance of an airline has a significant negative impact on CO_2 emissions. This implies that airlines with better financial performance are expected to produce lower CO_2 emissions. This result aligns with previous research in the literature (Akbar et al., 2021; Makni et al., 2009), which suggests that an organization's financial performance positively influences its sustainability performance. The estimated coefficient for $CO2_{-1}$ is negatively significant at the 1% level, indicating a strong correlation between an airline's CO_2 emissions in one quarter and those in the preceding quarter. Additionally, the coefficients for other control variables align with expectations. For example, "Size" is the natural logarithm of total assets for each airline in any time period. It has a positive and significant coefficient, which means that airlines with more total assets have higher CO_2 emissions. This is reasonable because larger airlines generally have more aircraft and operate more flights, leading to increased fuel consumption and, consequently, higher CO_2 emissions due to economies of scale.

Column 2 presents the results of Model (2), explaining the relationship between efficiency and CO_2 emissions (Hypothesis 2). The estimated coefficient for efficiency is −0.10, and it is statistically significant at the 5% level. This result suggests that higher technical efficiency is associated with lower CO_2 emissions. Therefore, the findings strongly support Hypothesis 2, aligning with the hypothesis proposed by Porter and Linde (1995) and the findings of Schilirò (2019) and Wang and Wang (2020).

Column 3 represents the results of Model (3), explaining the relationship between stage length and CO_2 emissions (Hypothesis 3). The fixed-effect Driscoll–Kraay regression reveals that the coefficient value for stage length is −0.13, and it is statistically significant at the 5% level. The negative coefficient suggests that as the stage length increases, the CO_2

Table 3. The estimation results for Hypotheses 1, 2, and 3.

Variable	Model 1	Model 2	Model 3
ROA	-0.43^{***}	–	–
	(0.14)	–	–
Technical Efficiency	–	-0.10^{***}	–
	–	(0.03)	–
Stage Length	–	–	-0.13^{**}
	–	–	(0.06)
$CO2_{-1}$	0.74^{***}	0.70^{***}	0.79^{***}
	(0.05)	(0.05)	(0.07)
Size	0.90^{***}	0.12^{***}	0.12^{***}
	(0.03)	(0.03)	(0.03)
Leverage	0.02	0.02	0.01
	(0.02)	(0.03)	(0.03)
Growth	-0.03	-0.04^{*}	-0.05^{**}
	(0.02)	(0.02)	(0.02)
Fuel-Cost Ratio	-0.24^{***}	-0.21^{***}	-0.26^{***}
	(0.08)	(0.06)	(0.08)
Constant	3.47^{***}	4.35^{***}	3.49^{***}
	(0.73)	(0.72)	(0.87)
Airline fixed effect	Yes	Yes	Yes
Within R^2	0.9	0.91	0.85
F-test	1376^{***}	1478^{***}	569^{***}

*, **, and *** denote significance at 10%, 5%, and 1% levels, respectively. Standard errors in brackets.

emissions decrease. In other words, airlines with a longer stage length are expected to produce fewer CO_2 emissions. In summary, these results strongly support Hypothesis 3 and align with the claims made by Ryerson and Hansen (2013) and Araújo et al. (2011).

Furthermore, the directional consistency of the coefficient signs for control variables in Models (1), (2), and (3) reinforces our expectations and validates the robustness of our model and its conclusions.

5. Robustness checks

We examine the robustness of the main results by increasing the lag and using alternative independent variables. Our findings are robust to these checks.

5.1. Increasing the lag

We examined the robustness of our main findings by analyzing the impact of independent variables—ROA, Technical Efficiency, and Stage Length—at time t on CO_2 emissions at time $t+2$. Results, presented in Columns 1 and 2 of Table 4, indicate financial performance, technical efficiency, and stage length improvements at time t continue to impact CO_2 reductions at time $t+2$. However, this impact varies in terms of both the coefficient magnitude and statistical significance compared to time t. These results indicate that the effect of financial performance, efficiency, and stage length on CO_2 emissions persists over time. These findings underscore the consistency of the results and confirm Hypotheses 1–3.

Table 4. The estimation results for Hypotheses 1, 2, and 3 by increasing lag.

Variable	Model 1	Model 2	Model 3
ROA	-0.61^{**}	–	–
	(0.27)	–	–
Technical Efficiency	–	-0.14^{***}	–
	–	(0.05)	–
Stage Length	–	–	-0.13^{***}
	–	–	(0.03)
CO_{2-1}	0.55^{***}	0.68^{***}	0.75^{***}
	(0.1)	(0.06)	(0.07)
Size	0.15^{***}	0.13^{***}	0.13^{***}
	(0.04)	(0.03)	(0.002)
Leverage	0.002	0.01	0.02
	(0.04)	(0.02)	(0.03)
Growth	-0.05^{***}	-0.06^{***}	-0.07^{***}
	(0.02)	(0.02)	(0.02)
Fuel-Cost Ratio	-0.50^{***}	-0.29^{***}	-0.27^{***}
	(0.09)	(0.07)	(0.09)
Constant	6.82^{***}	4.55^{***}	3.70^{***}
	(1.34)	(0.87)	(0.91)
Airline fixed effect	Yes	Yes	Yes
Within R^2	0.85	0.91	0.86
F-test	613^{***}	1779^{***}	719^{***}

*, **, and *** denote significance at 10%, 5%, and 1% levels, respectively. Standard errors in brackets.

5.2. Alternative independent variables

We examined the robustness of our main results by employing alternative variables for ROA as an indicator of financial performance, as stated in Hypothesis 1, and an alternative efficiency score for EATBoost input-oriented radial DEA as an indicator of technical efficiency, as stated in Hypothesis 2.

We used Unit-Profit as an alternative measure of an airline's ROA in Model (1) to proxy financial performance (Blasi et al., 2018). Unit-Profit at time t is calculated by dividing the airline's profit at time t by its available seat miles (ASM) at time t. This metric indicates profitability per unit of available capacity. It shows the profit an airline is generating relative to its seating capacity over the distance flown. By normalizing profit relative to available seat miles, Unit-Profit accounts for the scale of operations, allowing for more accurate comparisons among airlines of various sizes. This variable is well-established in the literature as a reliable indicator of airline financial performance, capturing both revenue efficiency and cost management (Jiang, 2004; Maung et al., 2022). The outcomes of the model, including this substitute variable, are shown in Column 1 of Table 5.

The fixed-effect Driscoll–Kraay regression reveals that the coefficient value of "Unit-Profit" is -0.05, and it is statistically significant at the 5% level. Therefore, there is support for Hypothesis 1 by incorporating this alternative independent variable.

We also used EATBoost input-oriented Russell DEA model as an alternative measure for EATBoost input-oriented radial DEA in Model (2) to proxy technical efficiency. The Russell measure is a type of non-radial measure used for evaluating the efficiency of DMUs in DEA. Unlike radial measures,

Table 5. The estimation results for alternative independent variables in Hypotheses 1 and 2.

Variable	Model 1	Model 2
Unit-Profit	-0.05^{***}	–
	(0.02)	–
Technical Efficiency	–	-0.21^{**}
	–	(0.07)
CO_{2-1}	0.74^{***}	0.68^{***}
	(0.05)	(0.05)
Size	0.10^{***}	0.11^{***}
	(0.02)	(0.03)
Leverage	0.13	0.02
	(0.03)	(0.03)
Growth	0.03	-0.05^{*}
	(0.02)	(0.02)
Fuel-Cost Ratio	-0.29^{***}	-0.25^{***}
	(0.03)	(0.08)
Constant	3.35^{***}	4.70^{***}
	(0.75)	(0.69)
Airline fixed effect	Yes	Yes
Within R^2	0.91	0.91
F-test	1515^{***}	1202^{***}

*, **, and *** denote significance at 10%, 5%, and 1% levels, respectively. Standard errors in brackets.

the Russell measure does not necessarily classify the same subset of units as efficient. This discrepancy occurs because, in DEA, the Russell measure can identify non-zero slacks even for DMUs on the frontier, which radial measures might overlook (Pastor et al., 1999).

The results of the corresponding model incorporating this alternative variable are shown in Column 2 of Table 5. The fixed-effect Driscoll-Kraay regression reveals that the coefficient value of "Technical-Efficiency" is −0.21, and it is statistically significant at the 5% level. This finding provides additional support for Hypothesis 2, further validating our results with the inclusion of this alternative independent variable. These robustness checks reinforce the reliability and consistency of our main findings.

6. Conclusions, limitations and future research directions

6.1. Summary of findings

This study investigated the effect of financial performance, technical efficiency, and stage length on the CO_2 emissions of nine airlines operating in the US using quarterly data over 10 years from 2010 to 2019. Our data comprised quarterly records from 2010 to 2019, just before the global health crisis significantly influenced the sector and its emissions from 2020 onward. The three hypotheses we set out to test in this paper are supported by empirical evidence. The data of nine major US carriers from 2010 to 2019 provide evidence that substantiates the negative association between financial performance and CO_2 emissions.

6.2. Contributions

Following Turkson et al. (2020)'s suggestion that future studies should explore methodological contributions to improve current models used in multi-criteria sustainability problems, we present and discuss our theoretical contributions to knowledge about the carbon emissions in the airline sector with respect to the four variables that either directly or indirectly affect the CO_2 emissions of airlines. First, we find further evidence for the negative association between the financial performance of an airline and its carbon emissions. When an airline is performing financially well, it has more resources to dedicate to mitigating its negative environmental impact. While Busch and Lewandowski (2018) argue for the positive impact of being green on financial performance, our results suggest that higher financial performance leads to lower carbon emissions, hence better environmental outcomes for the airline. In fact, the circumstances for better financial and environmental performance lie in the size of the company as well as the regulations that govern the market (Ambec and Lanoie, 2008). Higher financial performance is associated with lower carbon emissions, which suggests that the airlines studied used their strong financial performance to improve their operational efficiency and fuel consumption.

Second, higher efficiency leads to lower carbon emissions. Technology advancement leads to more efficient operations by reducing resource consumption (Schilirò, 2019) and improves the firm's environmental, social, and economic sustainability performance (Wang and Wang, 2020). According to the US 2021 Aviation Climate Action Plan, efficiencies can be achieved at every stage of flight within the airline industry, contributing to a reduction in fuel consumption and aviation emissions (Federal Aviation Administration, 2021b). Optimal flight paths, along with effective cargo and passenger management, increase available ton miles while using fewer resources, resulting in a decrease in CO_2 emissions per available ton mile.

Third, longer stage length also leads to lower carbon emissions, but it is a function of the demand in the market, rather than a variable that can be changed as desired. However, a managerial implication of this result is for the airline to strategically consider which origin-destination pairs to serve, and whether to open new flight routes. In any case, the strategic investment decisions made by airline managers could target improving the airline's environmental sustainability performance with higher confidence as the results from our models underscore the negative association of stage length and CO_2 emissions.

6.3. Implications

The FAA's US Aviation Climate Action Plan, published in November 2021, details a comprehensive approach to reaching zero net emissions in the aviation industry by 2050. This action plan emphasizes the advancement of effective technologies related to aircraft, improved operations, sustainable aviation fuels, electrification, hydrogen solutions, and advancements in airport operations alongside international initiatives like CORSIA (Federal Aviation Administration, 2023). This research reinforces the environmental goals outlined in the FAA's plan and is consistent with the United Nations' Sustainable Development Goals (SDGs), particularly by highlighting financial stability and technical efficiency in achieving sustainability in the aviation sector.

The FAA's environmental initiatives require significant investments in technology, training, and infrastructure upgrades. Airlines in a strong financial position are better equipped to invest in the necessary resources to adopt these innovations. The first policy implication of our study is understanding the reverse relationship between financial performance and environmental sustainability performance. It sheds light on how financial resources can serve as a catalyst for environmental sustainability. Financial stability within airlines may enable them to allocate capital towards investments in green technologies and practices. For instance, profitable airlines are better positioned to afford the initial costs associated with transitioning to more sustainable fuel sources or implementing energy-efficient measures in their operations. Therefore, examining how financial performance influences sustainability performance can provide insights into how airlines can leverage their financial strength to drive environmental initiatives.

The negative effect of financial performance on carbon emissions brings a broader implication for the aviation industry: achieving environmental goals, particularly in reducing emissions, is closely tied to the financial capabilities of the airlines. It highlights the importance of economic stability and profitability in enabling airlines to contribute effectively to the global effort of reducing the aviation sector's carbon footprint. This investigation holds importance for policymakers navigating the delicate balance between enhancing financial outcomes and holding to sustainability mandates. By comprehending how financial performance intricately intertwines with CO_2 emissions, policymakers can devise informed strategies that promote profitability while concurrently supporting environmental responsibility (Renzhi and Baek, 2020).

Secondly, airlines and aviation stakeholders focus on better operational efficiency (CIRIUM, 2021). The analysis using DEA demonstrates that airlines with higher technical efficiency effectively utilize their resources to achieve a higher capacity utilization rate. Policymakers should design incentives to encourage airlines to optimize their resource usage. Airlines that achieve higher capacity utilization often benefit from better operational practices, such as advanced flight scheduling, innovative fuel-saving technologies, and strategic fleet management. Promoting these practices helps airlines enhance their technical efficiency, which is associated with lower CO_2emissions and leads to environmental benefits. This focus is twofold: airlines should reduce costs, thereby boosting profitability and also facilitating the integration of innovative technologies that make operations more sustainable. To address the environmental effect of the airline industry, governments, and related administrations should set CO_2 emission reduction targets, reflecting the sector's advancements in efficiency and technological innovation (Federal Aviation Administration, 2021a). Decision-makers should acknowledge that achieving these targets is influenced by the airlines' financial performance. Policymakers must recognize that not all carriers have the financial resilience to invest in eco-friendly technologies. Thus, government subsidies or financial support for airlines with less robust financial standings is necessary.

6.4. Limitations and avenues for future research

This study exhibits a few limitations that present opportunities for future studies. Firstly, while the focus of this research centers on the US airline industry, there is potential for its application in the European airline industry to validate the results across diverse economic regions. Secondly, this study solely explores the effect of financial performance, technical efficiency, and stage length on an airline's CO_2 emissions. However, other sustainability performance metrics including but not limited to energy consumption, water usage, health and safety, employee welfare, and ethical governance, could be considered. Thirdly, in this research, we emphasize the direct CO_2 emissions. However, the indirect greenhouse gas emissions resulting from purchased electricity, heat, or steam generated off-site and used by the airlines are not considered. This limitation arises from the unavailability of relevant data.

Future research could aim to enhance the model by not only introducing a moderating variable but also exploring mediating influences on the relationship between financial performance, technical efficiency, stage length, on environmental sustainability performance. Also, the network DEA approach could be employed in future studies to estimate the technical efficiency. We could not consider the effect of fuel type on CO_2 emissions due to a lack of data. Introducing radical technologies is expected to reduce fuel usage dramatically (Lee et al., 2009). With the increase of sustainable aviation fuels, we expect fuel types to be reported regularly, which will pave the way for new research defining the significance of new fuels in CO_2 emissions reduction from this sector. Although this research primarily focuses on the airline industry, some of its results could also apply to various other industries, suggesting a broader scope of impact.

Notes

1. For a comprehensive derivation of the radial, Russell and directional distance function models based on EATBoosting, refer to the work (Guillen et al., 2023c).
2. As a robustness check, we use fixed effect (robust) and fixed effect (cluster). The results are relatively similar to the fixed effect with Driscoll-Kraay standard errors. This means that the sign of coefficients is the same, and their significance is the same as well, but the value of the coefficient or the level of significance may be different. These results are available upon request from the corresponding author.

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ORCID

Fahimeh Chomachaei http://orcid.org/0000-0001-6772-7384
Emel Aktas http://orcid.org/0000-0003-3509-6703

Data availability statement

Data is available from the corresponding author.

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Kaffash, Sepideh

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