Journal of Air Transport Management 115 (2024) 102536

Contents lists available at ScienceDirect

Journal of Air Transport Management

journal homepage: www.elsevier.com/locate/jairtraman

Airlines and climate policy uncertainty: Are the sector's stocks soaring or stalling?

Mutaju Isaack Marobhe [a,b,*], Jonathan Mukiza Kansheba [c,d]

[a] SSM Research Centre, Swiss School of Management, Bellinzona, Switzerland
[b] Department of Finance & Accounting, Tanzania Institute of Accountancy, Dar Es Salaam, Tanzania
[c] Thomas College of Business and Economics, University of North Carolina at Pembroke, North Carolina, USA
[d] School of Business and Law, Universitetet i Agder, Kristiansand, Vest-Agder, Norway

ARTICLE INFO

Original content: Climate Policy Uncertainty (Reference data)

Keywords:
Climate policy uncertainty
GARCH-MIDAS
Airline sector
Stock volatility
Greenhouse gases

ABSTRACT

The present study examines the impact of uncertainties around climate policy on the stock returns of eight US airlines between 2007 and 2023. To examine how climate policies impact daily airline stock volatility through the long-run component of total volatility, the monthly climate policy uncertainty index is utilized. Using full-sample and out-of-sample estimations, we investigate the problem using the Generalized Autoregressive Conditional Heteroscedasticity-Mixed Data Sampling model. To further assess forecasting accuracy, the Diebold and Mariano as well as Superior Predictive Ability methodologies are applied. According to the full-sample estimation results, just two airlines showed a significant relationship with climate policy uncertainty. Meanwhile, six airlines including three of the "big four" airlines were significantly affected by the former, according to the out-of-sample data. Forecasting results indicate that the climate policy uncertainty-based model outperforms the other models in projecting airline returns. The results have significant theoretical and applied ramifications for comprehending sectoral asset valuations in the context of uncertain climate policy.

1. Introduction

One of the biggest issues facing humanity in the twenty-first century is climate change, which is also a major concern for academics, legislators, and environmental activists (Xu et al., 2023). Climate change exerts a substantial economic impact on the broader economy, encompassing both the aggregate stock market and other sector-specific stocks (Lv and Li, 2023). The airline industry has been recognized as the most environmentally detrimental form of transportation in terms of greenhouse gas (GHG) emissions. Although the industry accounts for only 2% of worldwide carbon dioxide (CO2) emissions, its pace of emissions growth surpasses that of other transportation sectors such as road, railway, and sea (International Energy Agency, 2023; Falk and Hagsten, 2021). Due to these concerns, the airline industry has come under increased scrutiny, with regulators urging a decrease in CO2 emissions and a decarbonization of the industry. The operations of the airline industry may therefore be impacted by growing uncertainties related to climate change policies. Climate policies have the potential to cause economic and financial disruptions with sector-unique effects (Paroussos et al., 2019). They can result in abandoned or stranded assets, a rise in the cost of doing business, and financing restrictions for the airline sectors. These factors have the potential to affect investors' sentiments towards the airline sector in line with the investor sentiment hypothesis (Martins and Cró, 2022). This could change their investing behaviour, forcing them to engage in panic selling, which may increase stock volatility with ramifications for asset pricing (Chen et al., 2023). Thus, the purpose of our article is to address the question of how stock returns in the airline sector are impacted by climate policy uncertainty (CPU).

The existing body of literature has provided evidence of the vulnerability of airline stocks to various forms of uncertainty. Prior research has investigated the impact of various factors, such as oil price shocks, financial crises, health crises (e.g., COVID-19), and acts of terrorism (e.g., the September 11 attacks), on the performance of airline stocks (Kotcharin et al., 2023; Atems and Yimga, 2021; Martins and Cró, 2022; Chen et al., 2022; Kang et al., 2021; Mollick and Amin, 2021; Carter et al., 2022; Drakos, 2004). This study represents one of the initial endeavours to investigate the impact of uncertainty arising from measures addressing global climate change on the performance of airline stocks. A rising body of research has examined how CPU affects stock markets (Treepongkaruna et al., 2023; Lv and Li, 2023; Alqaralleh,

* Corresponding author. SSM Research Centre, Swiss School of Management, Bellinzona, Switzerland.
E-mail address: mutaju.marobhe@tia.ac.tz (M.I. Marobhe).

https://doi.org/10.1016/j.jairtraman.2024.102536
Received 20 November 2023; Received in revised form 22 December 2023; Accepted 2 January 2024

2023; Hoque et al., 2023). Nonetheless, there is still limited research that concentrates on various economic sectors such as energy, transportation, power generation, and medicines (Xu et al., 2023). In light of the airline industry's well-documented role in causing climate change, our research fills this knowledge vacuum by concentrating on the stocks in this sector and their possible vulnerability to CPU.

The subsequent sections shall be structured in the following manner: An exhaustive literature review is presented in Section 2. Subsequently, a detailed account of the data and methodology utilized in this study is provided in Section 3. The data obtained is presented in Section 4 of this paper, whereas the discussions and implications that emerge from these findings are addressed in Section 5. In Section 6, the conclusions that have been drawn from the research outcomes are presented.

2. Review of relevant literature

2.1. Airline sector and climate policy uncertainty

Uncertainty regarding climate policy arises via two distinct channels. The initial channel regards the potential physical ramifications of increasing concentrations of GHG in the atmosphere. The subsequent channel concerns the unpredictability surrounding the financial implications of reducing GHG emissions. The economic vulnerability of various sectors to climate change is heightened via both channels, as the expenses associated with reducing emissions and fulfilling mitigation obligations, such as paying penalties, escalate (IEA, 2007). These factors are reflected in the policy decisions of businesses, particularly regarding investment matters.

The airline sector has been put under scrutiny for its role in contributing to rising GHG emissions. Emissions from the airline sector are considered more detrimental than those from other transportation sectors. Moreover, air transport is considered to be the most environmentally hazardous mode of transportation in terms of climate change (Falk and Hagsten, 2021). Despite constituting two per cent of the worldwide CO2 emissions, the sector's rate of emissions growth remains concerning when compared to other modes of transportation. The escalating worldwide need for aviation travel, which consistently contributes to the sector's GHG emissions, has been identified as the cause of this. The situation has been exacerbated by the global deregulation of aviation markets and the subsequent emergence of low-cost airlines, which has led to an increase in the proportion of holiday air travel (Álvarez-Díaz et al., 2019).

The airline industry faces significant obstacles in its efforts to reduce GHG emissions, which exacerbates the situation (Ryley et al., 2020). To achieve net-zero emissions by 2050, numerous technical measures involving low-emission fuels, airframe and engine improvements, operational optimization, and demand restraint solutions are required to curtail the rise of emissions (IEA, 2023). Airlines will have to make significant capital investments in these, which could have an impact on how they operate. Investor behaviour may be influenced and stock volatility may increase as a result of regulatory requirements, such as those outlined in the Carbon Offsetting and Reduction Scheme for International Aviation (CORSIA) that airlines disclose their CO2 emissions (International Air Transport Association, 2016).

2.2. Volatility of airline stocks during uncertain times

The airline sector is susceptible to a variety of risks and uncertainties that impact the operational and investment decisions of businesses, including workforce decisions. These encompass geopolitical events such as wars and terrorism, energy price fluctuations, financial risks, and government regulations. Literature from the past demonstrates how the uncertainty generated by these risks affects the volatility of airline stocks. For example, Kang et al. (2021) present empirical findings that illustrate the substantial impacts that economic policy uncertainty and crude price volatility have on airline stocks. Carter et al. (2022) noted that airlines with high leverage incurred negative stock returns as a result of the economic hardships imitated by travel restrictions imposed during the COVID-19 pandemic. Popular Asian airline stocks also experienced extremely negative returns after the global financial crisis (2007–2009) caused economic turbulence (Goh et al., 2014). Their results, however, imply that low-cost carriers' stock returns in the area were less vulnerable to the crisis's negative effects. Drakos (2004) examines how global airline stocks respond to geopolitical risks, with a particular emphasis on the aftermath of the September 11th terrorist attacks. The results showed clear evidence of growing idiosyncratic risks associated with stock returns following the attacks. Furthermore, at and around the start of the Russia-Ukraine conflict, Martins and Cró (2023) saw notable negative stock price reactions for airlines worldwide, with European airlines displaying enhanced unfavorable impacts.

Uncertainty has grown as a result of the intensifying discussions about climate change on international forums, particularly in industries with significant CO2 emissions. Climate change has created issues for stock markets, and one of the most important study questions in academic discourse right now is how CPU affects stock market volatility. For example, Xu et al. (2023) demonstrate that rising CPU affects short-term stock market volatility in both economies by comparing the stock markets in China and the United States. Lv and Li (2023), concentrating on US sectoral stock indices, point out that the growing CPU intensifies the volatility of the consumer discretionary, energy, materials, industrials, health care, and utilities sectors. By lowering investments in Chinese stock markets, Alqaralleh (2023) offers more proof of the substantial effects of CPU on stock markets. The body of scholarly work examining the impact of CPU on the volatility of the stock market has been steadily expanding. Consequently, it is imperative to do a comprehensive assessment of this issue, specifically concerning various economic sectors. This is particularly crucial due to the limited availability of empirical information in this domain (Xu et al., 2023). Because of the airline industry's well-documented role in contributing to climate change, as previously noted, we use the innovative CPU index to investigate the volatility effects in the airline industry (Ryley et al., 2020).

3. Data and methods

3.1. Data

This study uses the CPU index to represent the uncertainty associated with climate policy, according to Gavriilidis (2021). The index is updated every month, and its construction is based on a selection of articles from prominent US media outlets that have significant terms associated with climate change, such as "global warming", "greenhouse gases", "climate change" and "EPA". The heightened level of uncertainty surrounding climate policy has been influenced by several factors. These include the withdrawal of the United States from the Paris Accord, the rejection of the new emission rule by President Trump, and the EPA's publication of new global GHG emissions standards (Fig. 1). It has been observed that the CPU outperforms alternative environmental proxies in terms of volatility forecasting performance (Liang et al., 2022).

The real stock returns of eight U.S. airlines are employed (Table 1). American Airlines (AAL), Delta Air Lines (DAL), United American Airlines (UAL) and Southwest Airlines (LUV) are the "big four" U.S. airlines that we initially identified. These account for a minimum of 74% of the total airline seats available in the United States. Furthermore, we incorporate four more airline companies based in the United States, which are Hawaiian Holdings Inc. (HA), Alaska Air Group Inc. (ALK), and SkyWest Inc. (SKYW) (Kang et al., 2021). To capture the dynamics of volatility in the face of climate policy uncertainty, a blend of airlines of various sizes is essential. The sample period was purposefully selected to range between June 1, 2007 and August 31, 2023, generating a total of 5936 daily observations for stock returns and 195 for CPU index (Fig. 2). The returns of all eight airlines exhibit varying degrees of

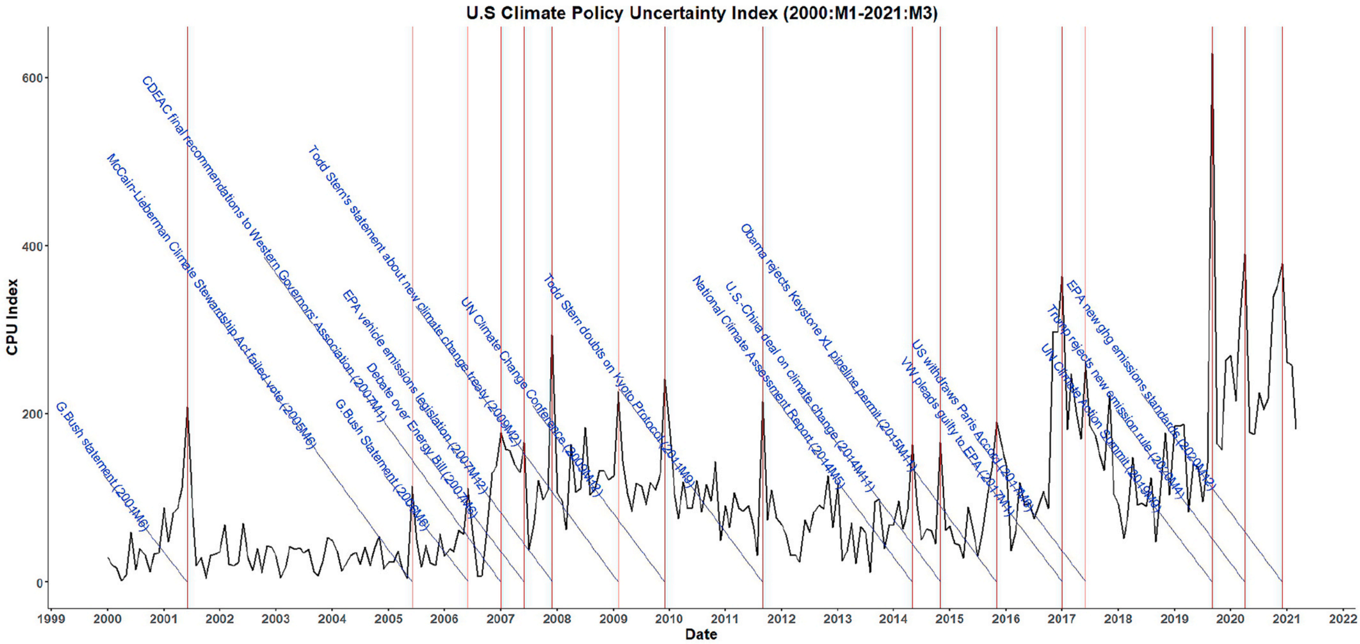

Fig. 1. US climate policy uncertainty index.
Source: https://www.policyuncertainty.com/climate_uncertainty.html.

Table 1
List of sampled US airlines and their market capitalization at August 31, 2023.

No.	Company	Stock market	Market Cap. (Billion USD)
1.	United Airlines Holdings Inc (UAL)	NASDAQ	12.84
2.	American Airlines Group (AAL)	NASDAQ	7.69
3.	Delta Air Lines, Inc (DAL)	NYSE	22.06
4.	Southwest Airlines Co (LUV)	NYSE	15.71
5.	Alaska Air Group, Inc (ALK)	NASDAQ	4.28
6.	Hawaiian Holdings, Inc (HA)	NASDAQ	0.25
7.	Allegiant Travel Company (ALGT)	NASDAQ	1.34
8.	SkyWest Inc (SKYW)	NASDAQ	1.71

volatility over the observed period, with the presence of volatility clustering evident in different time intervals. The starting date created was deemed representative of all eight companies to overcome variations in time spans of return data. The ending date represents the last month for the publication of CPU index data. The data on airline returns were obtained from the investing.com website, whereas the CPU index data was sourced from the policyuncertainty.com/climate_uncertainty.html page.

For several reasons, the USA provides a rich context in which to investigate how CPU affects airline stock volatility. First off, the nation is home to American Airlines Group, Delta Airlines, Inc and United Airlines Holdings, the top three airlines in the world in terms of revenue and people flown. Because of the scale of their operations, US airlines may therefore be more vulnerable to the challenges brought on by rising CPU than airlines in other nations. Second, until China overtook the US in 2019, the US had been the world's largest market for passenger air travel for a considerable amount of time. Therefore, any climate policy aimed at lowering CO2 emissions in the aviation industry is probably going to have a significant impact on the USA's aviation industry. Thirdly, the aviation industry in the USA is the primary source of GHG emissions into the atmosphere, making it the focus of environmental issues pertaining

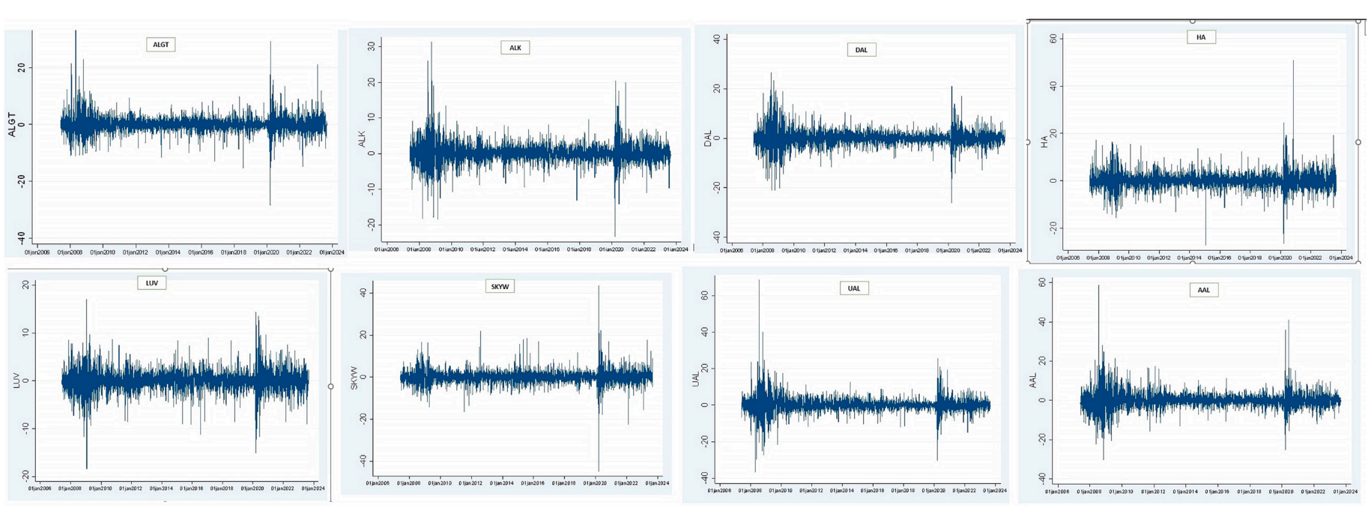

Fig. 2. Trends of US airlines' stock returns from June 2007 to August 2023.

to aviation sector emissions. Ultimately, the CPU index is compiled using news from the main media outlets in the USA that cover climate policy issues. Thus, it is more appropriate to study the phenomenon in the context of the USA than in other countries like China and European Union nations.

3.2. Methods

3.2.1. Generalized autoregressive conditional heteroskedasticity-mixed data sampling (GARCH-MIDAS)

The GARCH model with mixed data sampling (MIDAS) is employed in this study to examine the reciprocal relationship between the CPU index and daily airline stock returns (Engle et al., 2013). The GARCH-MIDAS methodology allows for the prediction of high-frequency financial time series by including low-frequency macroeconomic variables (Chen et al., 2023). In light of the monthly publication of the CPU index (Gavriilidis, 2021), we examined the relationship between daily airline returns and the CPU index. The use of high-frequency data, specifically daily data, is imperative in the identification of significant underlying patterns that may not be immediately discernible in data collected on a weekly, monthly, or annual basis (Marobhe and Kansheba, 2023).

We followed the procedures by Yu et al. (2021) to build the GARCH-MIDAS model.

To begin, we assume that the individual airline stock return on day “i” in month “t” follows the following process:

$$r_{1,t}=\mu+\sqrt{\tau_t\times g_{i,t}}\varepsilon_{i,t}, \forall l=1,N_l\varepsilon_{ut}|\Phi_{l-1,t}\sim N(0,1) \tag{a}$$

N_l = the number of trading days in month “t” and $\Phi_{l-1,t}$ = the information set up to $(i-1)^{th}$ day of period t. Equation (a) expresses the variance into a short-term component expressed by $g_{i,t}$ and a long-term component expressed by τ_t. Engle et al. (2013) distinguish the short- and long-term components of volatility to isolate the influence of other variables on daily stock price variations. The short-term component accounts for the transient nature of daily fluctuations in stock returns. Market sentiments and news pertaining to the company, industry, and macroeconomics (Wang et al., 2010) influence the changes in the supply and demand dynamics of stocks, which are responsible for the daily fluctuations. Low-frequency variables such as realized volatility or macro variables can describe the long-term component, which in this case is CPU.

The conditional variance dynamics of the component $g_{i,t}$ i follows a daily GARCH (1,1) process as follows;

$$g_{i,t}=(1-\alpha-\beta)+\alpha\frac{(r_{l-1,t}-\mu)^2}{T_t}+\beta g_{i-1,t} \tag{b}$$

whereas τ_t is defined as smoothed realized volatility (RV) in the spirit of the following MIDAS regression equation;

$$\tau_t=m+\theta_n\sum_{k=1}^{K}\varphi_k(\omega_1)RV_{t-k} \tag{c}$$

$$RV_t=\sum_{i=1}^{Nt}r_{i,t}^2 \tag{d}$$

RV_t = monthly smoothed realized volatility (RV) with the fixed-span and K = the number of periods over which the realized volatility (RV) is smoothed. Then equation (c) is subsequently modified by introducing the macroeconomic variable (CPU) alongside RV. This is purposefully done to evaluate the effects of these variables on the long-run return variance, as follows:

$$\tau_1=m+\theta_{rv}\sum_{k=1}^{k}\varphi_k(\omega_1)RV_{t-k}+\theta_{cpu}\sum_{k=1}^{k}\varphi_k(\omega_1)CPU_{t-k} \tag{e}$$

CPU_{t-k} = the change in monthly CPU index denoted by log difference of CPU. We lastly specify the total conditional variance as follows:

$$\sigma_{it}^2=\tau_1.\,g_{i1,t} \tag{f}$$

The weighting scheme employed in equation (c) and equation (d) is described by beta lag polynomial as follows:

$$\varphi_i(\omega_1)=\frac{(k/_K)^{\omega_1-1}}{\sum_{j=1}^{K}(j/_K)^{\omega_1-1}} \tag{g}$$

n.b. the weights in Equation (e) sum up to 1.

Equations (a), (b), (c), and (d) construct the GARCH-MIDAS model with CPU effects. In contrast, Equations (a), (b), (c), and (e) build the GARCH-MIDAS model with RV effects. The two models illustrate volatility predictions utilizing long-term components, such as monthly data on daily airline companies' returns. The GARCH (1,1) model, which reflects the short component of volatility returns (Bollerslev, 1986), is used to compare these models. The following is the GARCH (1,1) model specification:

$$r_t=\mu+\varepsilon t \tag{h}$$

Variance equation;

$$\sigma_t^2=\alpha_0+\sum_{i=1}^{q}\alpha_i\,\varepsilon_{t-1}^2+\sum_{j=1}^{p}\beta_j\,\alpha_{t-j}^2 \tag{i}$$

σ_t^2 = Conditional variance; μ = Average return and εt = residual returns.

3.2.2. Forecasting performance

We investigated how well the three models listed above predicted the volatility of the stocks of airline firms using a variety of metrics. Following Asgharian et al. (2013), a total of four loss functions were used: mean absolute error (MAE), root mean absolute error (RMAE), mean square error (MSE), and root mean square error (RMSE). They are shown in the following order:

$$MAE=\frac{1}{T}\sum_{i=1}^{T}\left(\left|\sigma_i^2-\delta_i^2\right|\right) \tag{j}$$

$$MSE=\frac{1}{T}\sum_{i=1}^{T}\left(\sigma_i^2-\delta_i^2\right)^2 \tag{k}$$

$$\text{RMSE}=\sqrt{\frac{1}{T}\sum_{i=1}^{T}\left(\sigma_i^2-\delta_i^2\right)^2} \tag{l}$$

$$RMAE=\sqrt{\left(\frac{1}{T}\sum_{i=1}^{T}\left(\left|\sigma_i^2-\delta_i^2\right|\right)\right)} \tag{m}$$

T = the number of total observations; T_i = the first observation in out-of-sample. σ_i^2 *and* δ_i^2 = the actual and predicted conditional variance at time t respectively.

The GARCH model that exhibits the lowest Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE) scores out of many GARCH models is regarded as the most effective in predicting volatility. To evaluate the predictive performance of two separate models, the Diebold and Mariano (DM) test, as introduced by Diebold and Mariano (1995), is also used. The loss differential used in the DM test, denoted as the discrepancy between the squared prediction errors, may be expressed in the following manner:

$$DM=\frac{\bar{d}}{\sqrt{\frac{1}{T}\text{var}(d)}}\sim N(0,1) \tag{n}$$
$$d_t=e_{0,t}^2-e_{1,t}^2$$

whereby;

$e_{0,t}$ = the benchmark model's prediction error; $e_{1,t}$ = the completed model's prediction error; T = the total number of forecasts; $\bar{d}$ = the time series' mean for d_t; and $\mathrm{var}(d)$ = the time series variance for d_t.

Furthermore, we use a combination of the GARCH model, the GARCH-MIDAS-RV model, and the GARCH-MIDAS-RV + CPU model in our analysis. To evaluate the predictive performance of these models, we adopt the Superior Predictive Ability test as proposed by Yu et al. (2021). The Superior Predictive Ability (SPA) test, first proposed by Hansen (2005), provides a means to assess the relative performance of a given forecasting methodology compared to other prediction techniques. This is shown as follows;

$$d_{k,t} = L(\delta_{0,t}) - L(\delta_{k,t}), k = 1, \ldots, m \tag{o}$$

whereby;

$d_{k,t}$ = the performance of model k in relation to the benchmark at time t. d_t, $d_t = (d_{1,t}, \ldots d_{m,t})'$ = the vector of the relative performances. We utilize the standardized test statistic for SPA (Hansen, 2005) as follows:

$$T_n^{SPA} = max\left[\max_{k-1,\ldots,m} \frac{n^{1/2}\bar{d}_k}{\widehat{\omega}_k}, 0\right] \tag{p}$$

Subsequently, a stationary bootstrap implementation of the SPA test is utilized:

$$\left\{d_{b,t}^{*}\right\} = \left\{d_{T_{k,1}}\right\}, b = 1, \ldots B \tag{q}$$

$d_{b,t}^{*}$ = the pseudo time series for the resamples of d_t B = the number of bootstrap resamples; $\{\tau_{b,1} \ldots \ldots \ldots \ldots \tau_{b,n}\}$ is constructed by combining blocks of $\{1, \ldots, n\}$ with random lengths. This is shown as follows:

$$\widehat{\omega}_{k,B^{*2}} = B^{-1}\sum_{b=1}^{B}\left(n^{1/2}\bar{d}_{k,b}^{*} - n^{1/2}\bar{d}_k\right)^2, k = 1, \ldots, m \tag{r}$$

$\bar{d}_{k,B}^{*} = n^{-1}\sum_{b=1}^{B} d_{k,b,t}$, *which* by the law of large numbers, the estimator is consistent for the true variance, ω_k^2.

$$Z_{k,b,t}^{*} = d_{k,b,t}^{*} - g(\bar{d}_k), b = 1, \ldots, B; t = 1, \ldots, n g(\bar{d}_k) = \bar{d}_{k\cdot 1}\left\{x \geq \sqrt{(\bar{\omega}_k^2/n)2\log\log n}\right\} \tag{s}$$

whereby $1\{.\}$ represents the indicator function. Based on the assumptions of the preceding test above, we calculated the $T_{b,n}^{SPA^*}$ and the bootstrap p score as follows:

$$T_{b,n}^{SPA,*} = max\left[0, \max_{k-1,\ldots,m} \frac{n^{1/2}\bar{Z}_{k,b}^{*}}{\widehat{\omega}_k}\right] \tag{t}$$

$$Z_{k,b} = n^{-1}\sum_{t-1}^{n} Z_{k,b,t}^{*}, k = 1, \ldots, m \tag{u}$$

$$\widehat{P}_{SPA} = \sum_{b=1}^{B} \frac{1\left\{T_{b,n}^{SPA^*} > T_{b,n}^{SPA}\right\}}{B} \tag{v}$$

4. Empirical results

4.1. Descriptive statistics

At the outset, the basic descriptive statistics on the returns of the airline companies that were sampled and the CPU index were computed (Table 2). Positive mean returns of 3–8 percent were observed for the eight airline securities. The patterns of the standard deviations for the returns were largely comparable. The observed results may be effectively highlighted by the substantial degree of correlations among the sampled airline returns (Table 3). The CPU index and return data exhibited a positive skewness, except for LUV exclusively. Furthermore, all of the returns and CPU index exhibited positive kurtosis values exceeding 3.0, indicating that their distributions were leptokurtic in nature (Marobhe and Kansheba, 2023).

Subsequently, we tested the statistical properties of airline returns and CPU index data (Table 4). The Augmented Dickey-Fuller (ADF) and Phillips-Perron (P-P) unit root tests were conducted to test for stationarity of the none time series (Yu et al., 2021). The results showed no evidence of unit root in the returns data of all airline companies, except for the CPU index. We then conducted the first differencing of the CPU index and re-performed the two-unit root tests, with the results indicating stationary behaviour. Concerning normality, the Jarque-Bera (J-B) test results revealed the fact that the residuals for the nine variables were not normally distributed (Marobhe and Kansheba, 2023). Moreover, the ARCH test statistics for airline returns and CPU index were greater than 100 with critical values less than 0.05, which is evidence of heteroskedastic traits (Engle, 1982). Lastly, we carried out a Portmanteau white noise test for serial correlation for each of the nine time series data incorporated in the study. The results present evidence of serial correlation "white noise" in all the time series, a phenomenon that is prevalent in this kind of data, i.e., stock returns.

4.2. GARCH-MIDAS estimation results

Our findings encompass the estimation of the GARCH-MIDAS-RV and GARCH-MIDAS-RV + CPU models in addition to the conventional GARCH (1,1) model. Still, one big problem with the GARCH-MIDAS model is that it doesn't take structural breaks into account. This is something that has been called a "stylized fact" when it comes to the price changes of commodities and financial assets (Pan et al., 2017). According to Malik (2022), emerging evidence indicates that neglecting structural disruptions in volatility within the returns of financial assets may lead to an overestimation of volatility. To keep the effects of structural breaks in model estimation to a minimum, we use the Regime Switching GARCH-MIDAS. This means splitting the study period into sub-periods and looking at how stock volatility changes in different time regimes (Yu et al., 2021; Pan et al., 2017).

We conducted two distinct varieties of analytics in this instance: full-sample and out-of-sample analysis. The full-sample comprises estimations spanning from June 2007 to August 2023. Nevertheless, structural breaks in airline stock prices may have occurred during this time period due to the global financial crisis of 2008 and the COVID-19 pandemic of 2020. Additionally, we conducted an out-of-sample analysis encompassing the sub-period from July 2015 to August 2023 in order to first circumvent any potential structural breakdowns caused by the global financial crisis. Furthermore, the CPU index reached unprecedented levels during the carefully chosen sub-period due to significant climate policy events, providing an additional rationale for using out-of-sample estimation. The US pulling out of the Paris Agreement, Volkswagen admitting to manipulating CO2 emissions from its cars, and President Donald Trump's controversial statements regarding climate change issues (Fig. 1). To find possible structural breakdowns in the out-of-sample estimates during the pandemic (from 2020 to 2022), picking an extra sub-period would not have been possible because it would have produced too few observations for the monthly CPU index, making the results less reliable.

The full-sample and out-of-sample GARCH-MIDAS estimations for the effects of CPU on airline stock returns are displayed in Tables 5 and 6, respectively. The tables are subdivided into three main subsections, the first showing the GARCH (1,1) estimation results, the second representing the GARCH-MIDAS-RV results, and the third involving the GARCH-MIDAS-RV + CPU. Commencing with full-sample results, the GARCH (1,1) parameters, namely, k, α, β and μ were significant for all eight airlines, which is evidence of the fact that the GARCH (1,1) model

Table 2
Descriptive statistics.

Returns	Obs	Mean	Std. Dev	Min	Max	Skew	Kurtosis
ALGT	5936	6.840	2.7045	−28.33	33.72	0.739	18.049
ALK	5936	8.800	2.6772	−23.24	31.28	0.677	17.783
DAL	5936	5.020	3.0189	−25.99	26.55	0.257	12.636
HA	5936	6.320	3.2263	−26.97	50.83	0.91	20.66
LUV	5936	3.830	2.0833	−18.45	17.06	−0.166	9.294
SKYW	5936	7.090	3.0161	−44.81	43.66	0.224	25.06
UAL	5936	7.560	3.8384	−36.77	68.54	1.193	32.348
AAL	5936	3.390	3.9409	−30.3595	58.7361	1.128	20.412
CPU	195	139.889	67.427	38.092	411.289	1.105	4.014

Note: This table shows descriptive statistics of CPU index and stock return series for the airline companies.

Table 3
Pairwise correlations.

	ALGT	ALK	DAL	HA	LUV	SKYW	UAL
ALGT	1.000						
ALK	0.5837**	1.000					
DAL	0.5596**	0.7310**	1.000				
HA	0.4932**	0.5810**	0.5558**	1.000			
LUV	0.5517**	0.6810**	0.7024**	0.5736**	1.000		
SKYW	0.5366**	0.6343**	0.6070**	0.5381**	0.5794**	1.000	
UAL	0.5352**	0.7176**	0.8260**	0.5216**	0.6484**	0.5981**	1.000
AAL	0.5171**	0.7034**	0.7830**	0.5361**	0.6362**	0.5699**	0.8086**

Note: ***, ** and * denote significance at 0.01, 0.05, and 0.1 level, respectively.

Table 4
Statistical properties of variables.

	ADF	PP	J-B	ARCH	W. Noise
ALGT	−60.41**	−4470**	0.884**	339.02**	486.59**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ALK	−58.805**	−4284**	0.880**	870.88**	564.93**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
DAL	−57.68**	−4110**	0.887**	634.94**	707.70**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
HA	−57.29**	−4238**	0.900**	844.26**	597.88**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
LUV	−59.59**	−4470**	0.936**	1233.53**	488.52**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
SKYW	−58.60**	−4338**	0.880**	1326.61**	630.62**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
UAL	−56.27**	−4043**	0.830**	124.77**	785.50**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
AAL	−56.23**	−4088**	0.873**	312.13**	796.37
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ΔCPU	−5.62**	−49.5**	0.912	12.01**	1492.30
	(0.001)	(0.001)	(0.000)**	(0.000)	(0.000)

Note: The table shows the statistical properties of the ΔCPU index and the eight US airline companies stock return data. The numbers in parentheses are the p-values of the tests. ***, **, and * denote significance at the 0.01, 0.05, and 0.1 levels, respectively.

fits the daily returns data extremely well. The results are, however, different for GARCH-MIDAS models, which do not fit well with the majority of airline returns. Of utmost importance are the values for the parameter θcpu, which measures the effects of climate policy uncertainty on the long-term component of the airline stock returns' total volatility. From Table 5, it can be observed that the coefficients of the θcpu for ALGT and HA, which were −0.004 and −0.003, respectively, were statistically significant at the 0.05 level. The θcpu coefficients for the six remaining airline stocks were not significant at either level of significance. The full-sample results demonstrate that CPU does not play a vital role in influencing airline stock returns. Moreover, neither of the "big four" airline stocks seem to be affected by CPU.

As previously stated, we conducted an out-of-sample analysis for robustness purposes by studying the phenomenon during periods of escalating climate policy uncertainty (Table 6). The out-of-sample results for the period from 2015 to 2023 show that the CPU has an empirically significant effect on the majority of airline stocks. The θcpu coefficients for six airlines, which include three of the "big four," i.e., AAL, UAL, and DAL, out of all the airlines, only ALGT and LUV were not affected by CPU because their θcpu coefficients were statistically insignificant.

4.3. Model fitness

We then utilize the Akaike information criterion (AIC), the Bayesian information criterion (BIC), the Shwartz information criteria (SIC), the Hannah-Quinn information criteria (HQIC), and the optimal log-likelihood function (Log-L) to test the fitness of each of the three models. The goal is to evaluate whether incorporating CPU into the GARCH-MIDAS model can help make it best fitted. The model with the lowest scores for AIC, BIC, SIC, and HQIC among the three models for each airline is considered to be best fitted; on the contrary, the model with the highest Log-L score is better fitted to model the returns (Marobhe and Dickson, 2022). The analysis of model fitness is done for GARCH-MIDAS models based on both full-sample and out-of-sample data. The results for full-sample estimations indicate that the GARCH (1,1) was better fitted to model airline returns for AAL, LUV, and SKYW stocks (Table 7). On the other hand, the returns for two airline stocks, namely, DAL and ALK, were better fitted using the GARCH-MIDAS-RV model. Of much interest to the study is the GARCH-MIDAS-RV + CPU model, and the model fitness results indicate that this particular model fits well with returns for ALGT, HA, and UAL.

We proceeded to do similar model fitness analytics based on out-of-sample estimation results. The results indicate that GARCH (1,1) fits well with the returns for ALGT alone, while GARCH-MIDAS-RV was observed to better fit those of LUV. More importantly, the robustness of GARCH-MIDAS-RV + CPU for measuring the impact of CPU on airline returns was improved by using out-of-sample estimations. The returns for the six remaining airlines, namely, DAL, UAL, AAL, ALK, HA, and SKYW, seemed to be significantly affected by the inclusion of the CPU component in the GARCH-MIDAS model. These results indicate that the out-of-sample GARCH-MIDAS estimations were more efficient in studying the effects of policy uncertainty relating to climate change.

Table 5
Full-sample estimates of the three models for eight airline stock returns.

Model	DAL	LUV	UAL	AAL	ALGT	ALK	HA	SKYW
GARCH (1,1)	**Est.**	**Est.**	**Est.**	**Est.**	**Est.**	**Est.**	**Est.**	**Est.**
k	0.096*	0.099*	0.088*	0.059	0.101*	0.118*	0.067*	0.112*
	(0.000)	(0.000)	(0.001)	(0.074)	(0.000)	(0.000)	(0.014)	(0.000)
α	0.085*	0.244*	0.108*	0.078*	0.205*	0.138*	0.535*	0.376*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
β	0.907*	0.663*	0.886*	0.915*	0.743*	0.835*	0.162*	0.504*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
μ	0.076*	0.428	0.127*	0.109*	0.453*	0.189*	3.484*	1.327*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
GARCH MIDAS-RV								
μ	0.133**	0.110*	0.146*	0.083	0.131*	0.168*	0.176*	0.157*
	(0.005)	(0.000)	(0.018)	(0.125)	(0.001)	(0.000)	(0.021)	(0.007)
α	0.083**	0.240*	0.156*	0.062	0.309	0.152*	0.955*	0.372
	(0.011)	(0.003)	(0.001)	(0.263)	(0.059)	(0.003)	(0.000)	(0.059)
β	1.635*	0.852*	1.712*	1.519*	0.743*	1.450*	0.319*	0.983*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.003)	(0.000)	(0.000)	(0.003)
θ_{rv}	0.089*	0.134	0.053	0.058	0.078*	0.138*	0.179*	0.271
	(0.000)	(0.061)	(0.148)	(0.073)	(0.021)	(0.001)	(0.035)	(0.601)
w	3.764	1.273	6.629	3.066	1.580*	1.720	3.349*	2.656
	(0.119)	(0.093)	(0.058)	(0.425)	(0.033)	(0.472)	(0.001)	(0.173)
m	3.980*	1.800*	5.573*	4.345*	1.665*	2.776*	3.546*	3.629*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.028)	(0.000)	(0.000)
GARCH MIDAS-RV + CPU								
μ	0.075*	0.086*	0.076*	0.051	0.106*	0.098*	0.091*	0.096*
	(0.008)	(0.001)	(0.021)	(0.160)	(0.002)	(0.000)	(0.034)	(0.014)
α	0.047*	0.189*	0.081*	0.038	0.251*	0.088*	0.492*	0.227
	(0.015)	(0.010)	(0.001)	(0.338)	(0.078)	(0.005)	(0.000)	(0.114)
β	0.919*	0.671*	0.892*	0.937*	0.604*	0.843*	0.164*	0.599*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.003)	(0.000)	(0.000)	(0.006)
θ_{rv}	0.050*	0.106*	0.028	0.036*	0.063	0.080*	0.092	0.165*
	(0.000)	(0.004)	(0.058)	(0.001)	(0.160)	(0.001)	(0.149)	(0.003)
θ_{cpu}	−0.002	0.001	−0.004	−0.002	−0.004**	0.001	−0.003**	0.001
	(0.466)	(0.422)	(0.087)	(0.473)	(0.013)	(0.796)	(0.000)	(0.471)
w	2.115	1.002	3.453	1.893	1.284*	1.000	1.726*	1.620
	(0.170)	(0.292)	(0.070)	(0.545)	(0.044)	(0.842)	(0.002)	(0.332)
m	2.236*	1.417*	2.902*	2.682*	1.354*	1.614*	1.828*	2.213*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.050)	(0.000)	(0.000)

Note: Table 5 presents the parameter estimates of our three models based on the full-sample data for the eight airline companies. The parameter space for GARCH (1,1) model is Θ = {k, α, β, μ}. The parameter space for the GARCH-MIDAS-RV model is Θ = {μ, α, β, θrv, w, m}. And the parameter space for the GARCH-MIDAS-RV + CPU model is Θ = {μ, α, β, θrv, θcpu, w, m}. *, **, *** denotes significance at 0.01, 0.05 and 0.10 respectively.

4.4. Results robustness checks

A range of loss functions were utilized to evaluate the CPU's precision in predicting the volatility of airline stock returns. Analogous to previous analyses, the accuracy of forecasts for the previously mentioned variable is evaluated using both full-sample and out-of-sample estimates (Table 8). To achieve this objective, we employed four distinct loss functions: RMSE, MAE, MSE, and RMAE, as detailed in the methodology section. The comparison of four loss function outcomes for the GARCH-MIDAS-RV + CPU, arranged from lowest to highest scores, is of specific interest. Commencing with the estimations of the full sample, the outcomes for all four functions are inconsistent. As an illustration, the MSE suggests that GARCH-MIDAS-RV + CPU offers more precise predictions regarding the returns of airline stocks, specifically for AAL, ALGT, and HA. In contrast, the CPU variable is demonstrated to forecast the returns of DAL, LUV, ALGT, HA, and SKYW with greater accuracy, as indicated by MAE. Conversely, RMSE suggests that CPU forecasts returns for AAL, ALGT, and HA with greater precision, whereas RMAE indicates that CPU forecasts returns for DAL, LUV, ALGT, HA, and SKYW with a certain degree of accuracy. The discrepancies that arise from applying loss functions to out-of-sample estimation results are similarly evident. The MSE results indicate that CPU predicts volatility returns for AAL, ALK, and SKYW with greater accuracy, whereas the MAE indicates that CPU provides an accurate return forecast for DAL, UAL, AAL, KA, and SKYW. Conversely, RMSE indicates that CPU exhibits superior return prediction capabilities for AAL, ALK, HA, and SKYW, whereas RMAE proposes that the variable provides more precise return forecasts for DAL, UAL, AAL, and SKYW.

As a result of the incongruities produced by the four loss functions pertaining to the accuracy of forecasting, we undertook the Diebold and Mariano (DM) test in order to exhaustively compare the predictive accuracy for each model. In the context of loss function utilization, the DM test is a more suitable approach for mitigating such inconsistencies (Yu et al., 2021). As benchmark models, the GARCH (1,1) and GARCH-MIDAS-RV models are utilized to produce the pertinent test statistics. The statistical analysis commenced with full-sample estimations. The findings revealed that at the 0.05 level, the values for two airlines, ALGT and HA, demonstrate positive trends (Table 9). Consequently, the lowest forecast error is produced when CPU is incorporated into the GARCH-MIDAS model for both ALGT and HA. On the other hand, Table 10's out-of-sample results offer an alternative viewpoint on the CPU's capacity to predict airline return volatility. Based on the two benchmark models, GARCH (1,1) and GARCH-MIDAS-RV, the DM test results show that the six airlines—AAL, UAL, DAL, HA, SKYW, and HA—have the lowest CPU forecast errors when it comes to projecting returns. These findings further demonstrate the robustness of employing out-of-sample data for CPU-based volatility predictions.

Next, we assess the three models' predictive performance of the eight airline returns using the Superior Predictive Ability (SPA) test based on full-sample estimates. As benchmark models, we employ the GARCH (1,1), GARCH-MIDAS-RV, and GARCH-MIDAS-RV + CPU in that order. When compared to other models using the relative loss function, the benchmark model has a lower level of forecast inaccuracy because the SPA test statistic is negative (Hansen, 2005). The benchmark model is

Table 6
Out of sample estimates of the three models for eight airline stock returns.

Model	DAL	LUV	UAL	AAL	ALGT	ALK	HA	SKYW
GARCH (1,1)	**Est.**	**Est.**	**Est.**	**Est.**	**Est.**	**Est.**	**Est.**	**Est.**
k	0.069*	0.057*	0.014	−0.015	0.065*	0.023	0.061	0.171*
	(0.014)	(0.025)	(0.644)	(0.667)	(0.037)	(0.415)	(0.121)	(0.000)
α	0.434*	0.403*	0.427*	0.410*	0.414*	0.457*	0.484*	0.574*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
β	0.900*	1.190*	1.012*	0.979*	−0.397*	1.100*	0.942*	0.822*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
μ	0.040*	0.010*	0.038*	0.058*	2.736*	0.044*	0.092*	0.290*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
GARCH MIDAS-RV								
μ	0.111*	0.080*	0.091	0.005	0.084	0.048	−0.008	0.094*
	(0.073)	(0.046)	(0.143)	(0.260)	(0.300)	(0.137)	(0.763)	(0.038)
α	0.156	0.380*	0.120*	0.089*	0.331	0.158	0.699*	0.278
	(0.174)	(0.001)	(0.021)	(0.043)	(0.217)	(0.095)	(0.000)	(0.001)
β	1.432*	0.463*	1.351*	1.188*	0.975*	0.950*	0.139*	0.824*
	(0.000)	(0.003)	(0.000)	(0.000)	(0.035)	(0.000)	(0.036)	(0.000)
θ_{rv}	0.113*	0.277*	0.044	0.039*	0.260*	0.087*	0.137	0.200*
	(0.014)	(0.002)	(0.127)	(0.039)	(0.042)	(0.015)	(0.237)	(0.000)
w	1.720	2.945	1.530	1.404	2.321*	1.240*	2.417*	2.553*
	(0.145)	(0.161)	(0.142)	(0.056)	(0.056)	(0.020)	(0.000)	(0.003)
m	0.302	1.222*	0.806	0.757	1.935	0.504	0.455	0.326
	(0.688)	(0.016)	(0.410)	(0.123)	(0.095)	(0.150)	(0.227)	(0.183)
GARCH MIDAS-RV + CPU								
μ	0.064	0.064	0.059	0.004	0.049	0.038	−0.005	0.071
	(0.082)	(0.103)	(0.175)	(0.929)	(0.337)	(0.305)	(0.931)	(0.136)
α	0.091	0.307*	0.078*	0.068	0.192	0.127	0.457*	0.211*
	(0.196)	(0.001)	(0.025)	(0.153)	(0.243)	(0.211)	(0.000)	(0.002)
β	0.833*	0.373*	0.883*	0.900*	0.567*	0.766*	0.091*	0.624*
	(0.000)	(0.006)	(0.000)	(0.000)	(0.039)	(0.000)	(0.044)	(0.000)
θ_{rv}	0.066*	0.224*	0.029	0.030	0.151*	0.070*	0.089	0.152*
	(0.016)	(0.004)	(0.155)	(0.140)	(0.048)	(0.033)	(0.290)	(0.001)
θ_{cpu}	−0.007*	0.003	−0.007*	−0.008*	−0.005	−0.006*	−0.011*	−0.017*
	(0.018)	(0.175)	(0.049)	(0.048)	(0.207)	(0.003)	(0.000)	(0.000)
w	1.000	2.375	1.000	1.064	1.349	1.000*	1.580*	1.934*
	(0.163)	(0.359)	(0.173)	(0.200)	(0.063)	(0.044)	(0.000)	(0.011)
m	0.176	0.986*	0.527	0.574	1.125	0.406	0.297	0.247
	(0.773)	(0.036)	(0.500)	(0.438)	(0.107)	(0.334)	(0.276)	(0.653)

Note: Table 9 presents the parameter estimates of our three models based on the out of sample data for the eight airline companies. The parameter space for GARCH (1,1) model is Θ = {k, α, β, μ}. The parameter space for the GARCH-MIDAS-RV model is Θ = {μ, α, β, θrv, w, m}. And the parameter space for the GARCH-MIDAS-RV + CPU model is Θ = {μ, α, β, θrv, θcpu, w, m}. *, **, *** denotes significance at 0.01, 0.05 and 0.10 respectively.

not worse than any of the alternative models, according to the null hypothesis of the SPA test. Similarly, based on the full-sample estimations, the findings for just two airlines, HA and ALGT, demonstrate that the GARCH-MIDAS-RV + CPU model outperforms other models in volatility predictions. This is because, using the GARCH-MIDAS-RV + CPU as the benchmark model, the SPA test statistics for all four loss functions are negative and not significant. Consistent with the DM test results, the SPA test outcomes for the out-of-sample estimations utilizing the identical criteria revealed that CPU provides the most accurate return forecasts for the six airlines (AAL, UAL, DAL, HA, SKYW, and HA).

5. Discussion and implications

5.1. Discussion

The current research has investigated the potential influence of increasing uncertainties arising from climate policies aimed at reducing GHG emissions on the stock returns of the airline industry. The empirical findings from our out-of-sample analysis demonstrate that CPU exerts a statistically significant influence on the stock returns of six US airlines. The findings of this study align with those of Xu et al. (2023), as they give evidence indicating substantial impacts of CPU on stock returns of sectors with high GHG emissions, including energy, medicines, and utilities. Furthermore, the results of our study support the substantial impact of increasing uncertainty surrounding climate change matters on global stock markets (Treepongkaruna et al., 2023; Lv and Li, 2023; Alqaralleh, 2023; Hoque et al., 2023).

The paper offers more proof of the CPU index's greater predictive power over other climate change proxies for asset return volatility, particularly in economies with large GHG emissions like China and the United States (Liang et al., 2022). The body of research has shown that several risks, including those related to geopolitics (e.g., wars and terrorism), pandemics (e.g., COVID-19), oil price fluctuations, and financial crises, can significantly affect airline returns (Kotcharin et al., 2023; Atems and Yimga, 2021; Martins and Cró, 2022; Chen et al., 2022; Kang et al., 2021; Mollick and Amin, 2021; Carter et al., 2022; Goh et al., 2014; Drakos, 2004). Our research highlights the significant risk that climate change policies may pose challenges to the airline industry, given the increasing pressure from around the world on industries such as aviation to decarbonize and achieve zero emissions by 2050.

Our findings demonstrate that growing CPU can affect the returns of comparatively smaller airlines like Hawaiian Airlines, Alaska Air, and Skywest, as well as larger ones like American Airlines, Delta Airlines, and United Airlines. These findings differ slightly from earlier research on different kinds of risks affecting airline stocks. Goh et al. (2014), for example, demonstrated that the impact of the global financial crisis on Asian airlines' stock returns differed significantly for both larger and smaller low-cost carriers. The latter demonstrated resilience in the face of economic hardship during the crisis, even as the large airline stocks experienced significant negative effects. Furthermore, the results contradict those of Martins and Cró (2022), whose findings show that COVID-19 has varied effects on airlines that have different characteristics, such as size, ownership concentration, and leverage. We build a case that can imply that, notwithstanding the size and heterogeneity of

Table 7
Model fitness assessment criteria results based on the full-sample.

Models	DAL	LUV	UAL	AAL	ALGT	ALK	HA	SKYW
Full-sample estimations								
GARCH (1,1) AIC	8.193	5.914	11.234	8.321	6.023	9.103	8.321	4.219
BIC	8.306	6.015	10.023	8.103	6.234	9.328	8.602	4.376
SIC	8.237	5.817	11.324	8.563	6.723	9.023	8.532	4.283
HQIC	8.503	5.724	11.482	8.921	6.692	9.692	8.723	4.712
Log-L	764.612	534.926	956.324	753.303	632.321	832.823	775.321	389.823
GARCH MIDAS-RV AIC	7.813	6.382	5.189	9.236	8.328	7.272	9.282	7.950
BIC	7.718	6.493	5.382	9.548	8.162	7.396	9.329	8.229
SIC	7.672	6.724	5.268	9.471	8.523	7.149	9.438	8.874
HQIC	7.291	6.325	5.796	9.683	8.621	7.039	9.193	8.833
Log-L	863.972	674.175	479.482	860.606	748.281	658.034	812.823	834.664
GARCH MIDAS-RV + CPU AIC	11.672	10.232	4.236	13.818	3.091	10.984	5.283	6.562
BIC	11.248	9.964	4.994	12.328	3.382	11.355	5.492	6.674
SIC	10.981	10.537	4.505	13.929	3.723	11.262	5.281	6.451
HQIC	11.07	10.974	4.902	14.123	3.682	11.514	5.732	6.353
Log-L	568.732	926.521	336.166	1176.279	678.890	1023.424	840.281	593.836
Out-of-sample estimations								
GARCH (1,1) AIC	11.223	7.567	14.380	9.236	7.709	6.645	7.496	6.413
BIC	11.374	7.697	12.829	8.994	7.980	6.809	7.750	6.652
SIC	11.278	7.439	14.495	9.505	8.605	6.586	7.686	6.510
HQIC	11.646	7.325	14.697	9.902	8.566	7.074	7.859	7.162
Log-L	1047.858	684.783	1224.095	836.166	809.371	607.900	698.487	592.531
GARCH MIDAS-RV AIC	10.702	6.169	6.642	10.252	10.660	5.308	8.362	12.085
BIC	10.565	6.310	6.890	10.599	10.447	5.399	8.405	12.508
SIC	10.511	6.613	6.743	10.512	10.909	5.218	8.503	13.489
HQIC	9.989	6.095	7.419	10.748	11.035	5.138	8.282	13.427
Log-L	1182.598	463.131	613.737	955.273	957.800	480.317	732.273	1268.689
GARCH MIDAS-RV + CPU AIC	9.119	10.235	6.077	8.582	11.128	3.051	4.127	5.912
BIC	8.782	9.967	5.917	7.657	12.175	3.154	4.291	6.013
SIC	8.580	10.532	6.253	8.651	13.403	3.128	4.126	5.812
HQIC	8.649	10.973	6.515	8.772	13.255	3.198	4.478	5.723
Log-L	444.516	926.563	550.109	730.608	2444.004	284.284	656.470	534.987

Table 7 presents the results for the three models. A total of five model fitness assessment criteria are utilized, namely Log-L, AIC, BIC, SIC, and HQIC. The lower the values of AIC, BIC, SIC, and HQIC, the better the model is fitted, and the higher the Log-L, the better the model is fitted.

Table 8
Loss functions results for volatility forecasting accuracy.

		Full-Sample Estimations				Out-Of-Sample Estimations			
	Model	MSE	MAE	RMSE	RMAE	MSE	MAE	RMSE	RMAE
DAL	GARCH (1,1)	2.724	0.623	1.650	0.789	3.296	0.854	1.815	0.924
	GARCH-MIDAS-RV	1.965	0.532	1.402	0.879	4.763	1.058	2.182	1.028
	GARCH-MIDAS-RV + CPU	2.872[c]	0.772[e]	1.695[c]	0.729[f#]	3.475[c]	0.729[e#]	1.864[c]	0.854[e#]
LUV	GARCH (1,1)	5.550	0.633	2.356	0.796	10.031	0.299	3.167	0.546
	GARCH-MIDAS-RV	6.627	0.881	2.574	0.939	7.020	0.593	2.650	0.770
	GARCH-MIDAS-RV + CPU	7.190[f]	0.311[c#]	2.681[f]	0.558[c#]	10.463[g]	1.145[f]	3.235[g]	1.070[f]
UAL	GARCH (1,1)	8.290	0.218	2.879	0.467	6.715	0.867	2.591	0.931
	GARCH-MIDAS-RV	5.802	0.433	2.409	0.658	8.018	1.207	2.832	1.099
	GARCH-MIDAS-RV + CPU	8.647[g]	0.836[f]	2.941[g]	0.914[g]	8.700[f]	0.426[c#]	2.950[f]	0.653[c#]
AAL	GARCH (1,1)	2.962	0.460	1.721	0.679	3.584	0.631	1.893	0.794
	GARCH-MIDAS-RV	2.137	0.370	1.462	0.608	2.585	0.506	1.608	0.712
	GARCH-MIDAS-RV + CPU	2.123[b#]	0.393[d]	1.457[b#]	0.627[e]	2.569[b#]	0.429[d#]	1.603[b#]	0.655[d#]
ALGT	GARCH (1,1)	6.036	0.688	2.457	0.830	10.909	1.092	3.303	1.045
	GARCH-MIDAS-RV	7.207	0.338	2.685	0.979	7.635	0.645	2.763	0.803
	GARCH-MIDAS-RV + CPU	5.542[d#]	0.958[h]	2.354[d#]	0.582[d#]	11.380[h]	1.245[g]	3.373[h]	1.116[g]
ALK	GARCH (1,1)	9.016	0.797	3.003	0.893	7.304	0.943	2.703	0.971
	GARCH-MIDAS-RV	6.310	0.471	2.512	0.686	8.721	1.313	2.953	1.146
	GARCH-MIDAS-RV + CPU	9.405[h]	0.909[g]	3.067[h]	0.953[h]	6.706[e#]	1.432[h]	2.590[e#]	1.197[h]
HA	GARCH (1,1)	2.445	0.380	1.564	0.616	2.959	0.521	1.720	0.722
	GARCH-MIDAS-RV	1.764	0.305	1.328	0.552	2.134	0.418	1.461	0.646
	GARCH-MIDAS-RV + CPU	1.753[a#]	0.198[a#]	1.324[a#]	0.445[a#]	2.121[a]	0.271[a#]	1.456[a#]	0.521[a#]
SKYW	GARCH (1,1)	4.983	0.875	2.232	0.935	6.029	1.199	2.455	1.095
	GARCH-MIDAS-RV	5.950	0.791	2.439	0.889	7.199	1.084	2.683	1.041
	GARCH-MIDAS-RV + CPU	6.455[e]	0.279[b#]	2.541[e]	0.528[b#]	5.923[d#]	0.383[b#]	2.434[d#]	0.618[b#]

Note: The table shows the full-sample and out-of-sample forecast validation for volatility of the three models * and # indicate that the GARCH-MIDAS-RV + CPU model performs better than the GARCH and GARCH-MIDAS-RV models, respectively. a, b, c, d, e, f, g, h, and i indicate sorting each loss function in order from smallest to largest for the GARCH-MIDAS-RV + CPU model of the eight airlines.

Table 9
SPA test and DM test results for full-sample forecasts of airline returns.

	Models	SPA Test				DM Test	
		MSE	MAE	RMSE	RMAE	GARCH	GARCH-MIDAS-RV
DAL	GARCH (1,1)	4.88 (0.05)	0.75 (0.73)	3.45 (0.02)	1.37 (0.02)		
	GARCH-MIDAS-RV	2.85 (0.19)	0.48 (0.64)	2.36 (0.07)	0.98 (0.53)		
	GARCH-MIDAS-RV + CPU	5.73 (0.19)	1.32 (0.65)	3.66 (0.19)	1.77 (0.11)	3.86 (0.14)	29.86 (0.08)
LUV	GARCH (1,1)	9.92 (0.01)	1.13 (0.03)	4.93 (0.05)	1.66 (0.03)		
	GARCH-MIDAS-RV	9.59 (0.04)	1.27 (0.53)	4.37 (0.02)	5.17 (0.02)		
	GARCH-MIDAS-RV + CPU	12.40 (0.12)	1.94 (0.24)	5.41 (0.31)	2.15 (0.23)	4.43 (0.44)	48.50 (0.19)
UAL	GARCH (1,1)	14.83 (0.06)	1.30 (0.32)	6.01 (0.36)	1.79 (0.81)		
	GARCH-MIDAS-RV	8.41 (0.05)	4.21 (0.25)	4.08 (0.06)	6.47 (0.207)		
	GARCH-MIDAS-RV + CPU	14.93 (0.03)	1.43 (0.65)	5.92 (0.06)	1.85 (0.01)	6.82 (0.70)	−38.51 (0.24)
AAL	GARCH (1,1)	3.96 (0.04)	0.61 (0.58	2.79 (0.01)	1.11 (0.01		
	GARCH-MIDAS-RV	3.37 (0.15)	0.57 (0.52	2.80 (0.06)	1.17 (0.43		
	GARCH-MIDAS-RV + CPU	−4.95 (0.16)	−1.14 (0.56)	−3.16 (0.16)	−1.53 (0.09)	3.33 −0.01	25.80 0.00
ALGT	GARCH (1,1)	8.04 (0.01)	0.91 (0.02)	3.99 (0.04)	1.34 (0.02)		
	GARCH-MIDAS-RV	11.36 (0.03)	1.51 (0.43)	5.17 (0.01)	6.13 (0.01)		
	GARCH-MIDAS-RV + CPU	−10.71 (0.10)	−1.67 (0.21)	−4.67 (0.27)	−1.86 (0.20)	4.83** (0.03)	41.90 (0.26)
ALK	GARCH (1,1)	12.01 (0.05	1.06 (0.25)	4.86 (0.29)	1.45 (0.63)		
	GARCH-MIDAS-RV	−9.96 (0.04	−4.98 (0.2)	−4.83 (0.05)	−7.67 (0.16)		
	GARCH-MIDAS-RV + CPU	12.90 (0.02)	1.23 (0.56)	5.12 (0.05)	1.60 (0.01)	5.89 (0.34)	−33.27 (0.21)
HA	GARCH (1,1)	4.07 (0.04)	0.63 (0.68)	2.87 (0.02)	1.14 (0.02)		
	GARCH-MIDAS-RV	3.15 (0.17)	0.53 (0.58)	2.61 (0.07)	1.09 (0.48)		
	GARCH-MIDAS-RV + CPU	−5.16 (0.17)	−1.19 (0.57)	−3.30 (0.17)	−1.59 (0.09)	3.48** (0.01)	26.92** (0.00)
SKYW	GARCH (1,1)	8.26 (0.01)	0.94 (0.03)	4.10 (0.04)	1.38 (0.03)		
	GARCH-MIDAS-RV	10.61 (0.03)	1.41 (0.48)	4.83 (0.02)	5.72 (0.02)		
	GARCH-MIDAS-RV + CPU	−11.17 (0.10)	−1.75 (0.21)	−4.88 (0.27)	−1.94 (0.20)	3.99 (0.13)	43.72 (0.17)

Note: The table shows the results of the Superior Predictive Ability (SPA) and Diebold and Mariano (DM) tests for how well the different models performed in their full-sample airline return estimates. The SPA technique, which is used to test the null hypothesis of equal prediction performance, indicates that the benchmark model is not less effective than any of the alternatives. The benchmark models for the SPA-test are listed in the second column of the table; the comparable results of SPA tests using the MSE, MAE, RMSE, and RMAE loss functions are shown in the next four columns. The model provided in the row calculates each DM statistic in each cell, and it is compared to the benchmark model provided in the column. The last two columns of the table reflect the DM test results. The numbers in parenthesis are the p-values for the DM and SPA tests. ***, **, and * denote significance at 0.01, 0.05, and 0.10, respectively.

individual airlines, investor sentiments in the aviation sector are influenced by climate policy concerns.

5.2. Theoretical implications

Our results have theoretical implications by demonstrating the significant negative impact of CPU on airline returns, supporting both the asset pricing theory and the investor sentiment hypothesis. Airline stock volatility has been demonstrated to be caused by news coverage of climate policy in major media outlets; this phenomenon can be connected to shifting investor sentiments during uncertain times (Cevik et al., 2022). This line of argument is supported by investor concerns about potential detrimental effects of various climate policies on aviation industry operations. Nevertheless, many different kinds of risks might impact asset prices; in this instance, the focus of our analysis was climate policy concerns. The asset pricing theory states that the price of an asset is equal to the total of its future cash flows, discounted using the risk-free rate, in the absence of risks (Drobetz, 2000). Our results indicate that the value of these discounted cash flows is typically impacted by the occurrence of risks like CPU. To comply with emission laws, CPU may compel airlines to invest in new technologies that could raise operating costs. These changes could have an impact on the stock values of the airlines.

5.3. Practical implications

Gaining an understanding of the reaction of the airline sector towards risks inherent in climate policy uncertainty holds significant significance for managers, investors, and policymakers in the airline sector, as it enables them to effectively address and minimize potential

Table 10
SPA test and DM test results for out-of-sample forecasts of airline returns.

	Models	SPA Test				DM Test	
		MSE	MAE	RMSE	RMAE	GARCH	GARCH-MIDAS-RV
DAL	GARCH (1,1)	6.79	1.04	4.79	1.90		
		(0.06)	(0.11)	(0.03)	(0.03)		
	GARCH-MIDAS-RV	3.96	0.67	3.28	1.37		
		(0.26)	(0.89)	(0.10)	(0.74)		
	GARCH-MIDAS-RV + CPU	−7.96	−1.84	−5.09	−2.46	5.36**	41.51**
		(0.02)	(0.90)	(0.26)	(0.05)	(0.01)	(0.00)
LUV	GARCH (1,1)	11.11	1.26	5.52	1.86		
		(0.01)	(0.03)	(0.05)	(0.03)		
	GARCH-MIDAS-RV	10.75	1.42	4.89	5.79		
		(0.04)	(0.59)	(0.02)	(0.02)		
	GARCH-MIDAS-RV + CPU	−13.88	−2.17	−6.06	−2.41	4.96	54.32
		(0.13)	(0.27)	(0.34)	(0.25)	(0.14)	(0.21)
UAL	GARCH (1,1)	13.64	1.20	5.53	1.65		
		(0.06)	(0.29)	(0.34)	(0.75)		
	GARCH-MIDAS-RV	−7.74	−3.87	−3.75	−5.96		
		(0.04)	(0.23)	(0.06)	(0.19)		
	GARCH-MIDAS-RV + CPU	13.74	1.31	5.45	1.70	6.27	−35.43**
		(0.02)	(0.60)	(0.06)	(0.01)	(0.13)	(0.02)
AAL	GARCH (1,1)	6.45	0.99	4.55	1.81		
		(0.06)	(0.94)	(0.02)	(0.02)		
	GARCH-MIDAS-RV	5.49	0.93	4.56	1.90		
		(0.25)	(0.84)	(0.10)	(0.70)		
	GARCH-MIDAS-RV + CPU	−8.07	−1.86	−5.16	−2.49	5.43**	42.05**
		(0.27)	(0.92)	(0.27)	(0.15)	(0.01)	(0.00)
ALGT	GARCH (1,1)	10.21	1.16	5.07	1.70		
		(0.01)	(0.03)	(0.05)	(0.03)		
	GARCH-MIDAS-RV	14.43	1.91	6.57	7.78		
		(0.04)	(0.55)	(0.02)	(0.02)		
	GARCH-MIDAS-RV + CPU	−13.60	−2.13	−5.94	−2.36	4.86	53.21
		(0.13)	(0.27)	(0.34)	(0.25)	(0.14)	(0.21)
ALK	GARCH (1,1)	10.33	0.91	4.19	1.25		
		(0.04)	(0.21)	(0.25)	(0.55)		
	GARCH-MIDAS-RV	−8.57	−4.28	−4.16	−6.60		
		(0.03)	(0.18)	(0.04)	(0.14)		
	GARCH-MIDAS-RV + CPU	11.09	1.06	4.40	1.38	5.06**	−28.61**
		(0.02)	(0.48)	(0.05)	(0.01)	(0.03)	−0.01
HA	GARCH (1,1)	6.99	1.08	4.94	1.96		
		(0.07)	(1.17)	(0.03)	(0.03)		
	GARCH-MIDAS-RV	5.41	0.92	4.50	1.87		
		(0.30)	(1.00)	(0.11)	(0.83)		
	GARCH-MIDAS-RV + CPU	−8.88	−2.05	−5.68	−2.74	5.98**	46.30**
		(0.29)	(0.98)	(0.29	(0.16)	(0.01)	(0.00)
SKYW	GARCH (1,1)	10.49	1.19	5.21	1.75		
		(0.01)	(0.03)	(0.05)	(0.03)		
	GARCH-MIDAS-RV	13.48	1.79	6.14	7.27		
		(0.04)	(0.61)	(0.02)	(0.02)		
	GARCH-MIDAS-RV + CPU	−14.19	−2.22	−6.19	−2.46	5.07**	55.52
		(0.13)	(0.27)	(0.34)	(0.25)	(0.04)	(0.21)

Note: The table shows the results of the Superior Predictive Ability (SPA) and Diebold and Mariano (DM) tests for how well the different models performed in their full-sample airline return estimates. The SPA technique, which is used to test the null hypothesis of equal prediction performance, indicates that the benchmark model is not less effective than any of the alternatives. The benchmark models for the SPA-test are listed in the second column of the table; the comparable results of SPA tests using the MSE, MAE, RMSE, and RMAE loss functions are shown in the next four columns. The model provided in the row calculates each DM statistic in each cell, and it is compared to the benchmark model provided in the column. The last two columns of the table reflect the DM test results. The numbers in parenthesis are the p-values for the DM and SPA tests. ***, **, and * denote significance at 0.01, 0.05, and 0.10, respectively.

risks and susceptibilities. The results of our study suggest that CPU has significant adverse effects on the stock returns of airlines. Hence, it is imperative for airline sector managers, as well as private and institutional investors, to diligently monitor news trends concerning climate policies, as they have the potential to impact portfolio risk and asset pricing for investors.

The airline sector is one of the few with a global reach. To have a holistic approach to climate change and perhaps reduce uncertainty, governments, aviation authorities, and airlines worldwide must cooperate closely to establish climate change policies and frameworks. Despite encountering obstacles, the International Civil Aviation Organization (ICAO) should continue playing a proactive role in emphasizing to national aviation regulators the significance of having common international GHG emission reduction regulations for international flights.

Despite the considerable capital required for aircraft investment, airlines should progressively enhance their fleets through the acquisition of low-GHG fuel-efficient jets. As part of an effort to reach net zero emissions by 2050, renowned aircraft manufacturers have been collaborating closely with engine manufacturers to develop environmentally friendly jets. Additionally, airlines should prioritize the reduction of GHG emissions as a key focus in their annual reports.

6. Conclusion

Our paper investigates the impact of CPU on the volatility of major US airlines. The GARCH-MIDAS model is used to investigate the effects as well as the extent to which the CPU index component can forecast the daily return of each sampled airline via the long-run component of total volatility. We use three major models: GARCH (1,1), GARCH-MIDAS-RV, and GARCH-MIDAS-RV + CPU. The first two models are used as benchmark models to assess whether adding CPU to the models improves forecasting accuracy of airline returns. The third model divides airline return volatility into long-term and short-term components, assuming that CPU influences asset volatility via its long-term component. The full-sample estimation findings suggest that CPU has a substantial impact on only two airlines' returns. Out-of-sample estimation results, on the other hand, demonstrated significant effects of CPU on six airlines, including three of the "big four," namely American Airlines, United Airlines, and Delta Airlines. In terms of forecasting airline returns, the CPU-based model outperforms the other models.

Our research is not devoid of limitations. As mentioned earlier, the implementation of Regime Switching GARCH-MIDAS assisted in reducing the occurrence of structural breaks in airline stock returns. The above method does not completely solve the problem, however, unlike other estimation models like bivariate GARCH models, wavelet coherence analysis, and others that try to accurately predict price changes in assets with structural breaks (Marobhe and Kansheba, 2023; Malik, 2022). Notably, however, the aforementioned techniques are incapable of estimating mixed-frequency data in the same manner as GARCH-MIDAS. So, we encourage econometricians to contemplate extending asymmetric GARCH models, like Power-GARCH and Exponential-GARCH (Marobhe and Dickson, 2022; Yu et al., 2021), to work with mixed frequency data. Furthermore, the limitation of our research to the US potentially hinders the generalization of our results to other regions like Europe and Asia. As detailed in the data section, we utilized the available CPU index, which exclusively compiles climate policy news specific to the US from the country's prominent media outlets. Therefore, applying the index to examine its impacts on airlines in other settings would be impractical. Therefore, we strongly encourage developers to aggregate CPU indices at both the country and global levels, similar to indices such as the global economic policy uncertainty (GEPU) index. Future researchers will be able to evaluate the impact of climate policies on airlines worldwide and make comparisons.

Funding

This research received no financial support for the research, authorship, and/or publication of this article.

Declaration of competing interest

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

CRediT authorship contribution statement

Mutaju Isaack Marobhe: Writing – review & editing, Writing – original draft, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Jonathan Mukiza Kansheba:** Writing – original draft, Software, Formal analysis, Data curation, Conceptualization.

Data availability

Data will be made available on request.
Climate Policy Uncertainty (Reference data) (Policy uncertainty)

References

Alqaralleh, H.S., 2023. The extreme spillover from climate policy uncertainty to the Chinese sector stock market: wavelet time-varying approach. Lett. Spatial Resour. Sci. 16 (31) https://doi.org/10.1007/s12076-023-00352-w.
Álvarez-Díaz, M., González-Gómez, M., Otero-Giráldez, M.S., 2019. Low-cost airlines and international tourism demand. The case of Porto's airport in the northwest of the Iberian Peninsula. J. Air Transport. Manag. 79, 101689.
Asgharian, H., Hou, J., Javed, F., 2013. The importance of the macroeconomic variables in forecasting stock return variance: a GARCH-MIDAS approach. J. Forecast. 32 (7), 600–612. https://doi.org/10.1002/for.2256.
Atems, B., Yimga, J., 2021. Quantifying the impact of the COVID-19 pandemic on US airline stock prices. J. Air Transport. Manag. 97 https://doi.org/10.1016/j.jairtraman.2021.102141.
Bollerslev, T., 1986. Generalized autoregressive conditional heteroskedasticity. J. Econom. 31 (3), 307–327. https://doi.org/10.1016/0304-4076(86)90063-1.
Carter, D., Mazumder, S., Simkins, B., Sisneros, E., 2022. The stock price reaction of the COVID-19 pandemic on the airline, hotel, and tourism industries. Finance Res. Lett. 44 https://doi.org/10.1016/j.frl.2021.102047.
Cevik, E., Altinkeski, B., Cevik, E., Dibooglu, S., 2022. Investor sentiments and stock markets during the COVID-19 pandemic. Financ. Innov. 8 (69) https://doi.org/10.1186/s40854-022-00375-0.
Chen, C., Su, C., Chen, M., 2022. Understanding how ESG-focused airlines reduce the impact of the COVID-19 pandemic on stock returns. J. Air Transport. Manag. 102 https://doi.org/10.1016/j.jairtraman.2022.102229.
Chen, Z., Zhang, L., Weng, C., 2023. Does climate policy uncertainty affect Chinese stock market volatility? Int. Rev. Econ. Finance 84, 369–381.
Diebold, F.X., Mariano, R.S., 1995. Comparing predictive accuracy. J. Bus. Econ. Stat. 13 (3), 134–144.
Drakos, K., 2004. Terrorism-induced structural shifts in financial risk: airline stocks in the aftermath of the September 11th terror attacks. Eur. J. Polit. Econ. 20 (2), 435–446.
Drobetz, W., 2000. Theory of asset pricing. In: Global Stock Markets. Deutscher Universitätsverlag, Wiesbaden. https://doi.org/10.1007/978-3-663-08529-4_2.
Engle, R.F., 1982. Autoregressive conditional heteroskedasticity with estimates of the variance of United Kingdom inflation. Econometrica 50, 987–1007. https://doi.org/10.2307/1912773.
Engle, R., Ghysels, E., Bumjean, A., 2013. Stock market volatility and macroeconomic fundamentals. Rev. Econ. Stat. 3 (95), 776–797.
Falk, M.T., Hagsten, E., 2021. Determinants of CO_2 emissions generated by air travel vary across reasons for the trip. Environ. Sci. Pollut. Control Ser. 28, 22969–22980.
Gavriilidis, K., 2021. Measuring climate policy uncertainty. Available at SSRN: https://ssrn.com/abstract=3847388.
Goh, C., Raslia, A., Khan, S., 2014. Stock investors' confidence on low-cost and traditional airlines in Asia during financial crisis of 2007-2009. Procedia - Soc. Behav. Sci. 129, 31–38.
Hansen, P.R., 2005. A test for superior predictive ability. J. Bus. Econ. Stat. 23 (4), 365–380.
Hoque, M., Soo-Wah, L., Bilgili, F., Ali, M., 2023. Connectedness and spillover effects of US climate policy uncertainty on energy stock, alternative energy stock, and carbon future. Environ. Sci. Pollut. Res. https://doi.org/10.1007/s11356-022-23464-0.
IATA, 2016. Offsetting CO2 emissions with CORSIA. https://www.iata.org/en/programs/environment/corsia/, 19th October 2023.
IEA, 2007. Climate policy uncertainty and investment risk. https://iea.blob.core.windows.net/assets/c2ecc882-14ec-487f-8f88-da5694b1529a/Climate_Policy_Uncertainty.pdf, 19th October 2023.
IEA, 2023. Why is aviation important? https://www.iea.org/energy-system/transport/aviation, 19th October 2023.
Kang, W., Perez de Gracia, F., Ratti, R., 2021. Economic uncertainty, oil prices, hedging and U.S. stock returns of the airline industry. N. Am. J. Econ. Finance 57. https://doi.org/10.1016/j.najef.2021.101388.
Kotcharin, S., Maneenop, S., Jaroenjitrkam, A., 2023. The impact of government policy responses on airline stock return during the COVID-19 crisis. Res. Transport. Econ. 99 https://doi.org/10.1016/j.retrec.2023.101298.
Liang, C., Umar, M., Ma, F., Huynh, T., 2022. Climate policy uncertainty and world renewable energy index volatility forecasting. Technol. Forecast. Soc. Change 182. https://doi.org/10.1016/j.techfore.2022.121810.
Lv, W., Li, B., 2023. Climate policy uncertainty and stock market volatility: evidence from different sectors. Finance Res. Lett. 51 https://doi.org/10.1016/j.frl.2022.103506.
Malik, F., 2022. Volatility spillover among sector equity returns under structural breaks. Rev. Quant. Finance Account. 58, 1063–1080.
Marobhe, M., Dickson, P., 2022. Bearish conditions and volatility persistence during COVID-19: can microchip stocks weather the storm? Rev. Behav. Finance 1–23. https://doi.org/10.1108/RBF-11-2021-0235.
Marobhe, M., Kansheba, J., 2023. High frequency volatility spillover between oil and non-energy commodities during crisis and tranquil periods. SN Business Econ. 3, 91. https://doi.org/10.1007/s43546-023-00463-y.
Martins, A., Cró, S., 2022. Airline stock markets reaction to the COVID-19 outbreak and vaccines: an event study. J. Air Transport. Manag. 105 https://doi.org/10.1016/j.jairtraman.2022.102281.
Martins, A., Cró, S., 2023. Mayday! Mayday! The airlines stock returns are failing. Analysis of the impact of Russia–Ukraine war. J. Econ. Stud. 10.1108/JES-08-2023-0390.
Mollick, A., Amin, M., 2021. Occupancy, oil prices, and stock returns: evidence from the U.S. airline industry. J. Air Transport. Manag. 91 https://doi.org/10.1016/j.jairtraman.2020.102015.
Pan, Z., Wang, Y., Wu, C., Yin, L., 2017. Oil price volatility and macroeconomic fundamentals: a regime switching GARCH-MIDAS model. J. Empir. Finance 43, 130–142.
Paroussos, L., Mandel, A., Fragkiadakis, K., Fragkos, P., Hinkel, J., Vrontisi, Z., 2019. Climate clubs and the macro-economic benefits of international cooperation on climate policy. Nat. Clim. Change 9, 542–546.

Ryley, T., Baumeister, S., Coulter, L., 2020. Climate change influences on aviation: a literature review. Transport Pol. 92, 55–64.
Treepongkaruna, S., Chan, K., Malik, I., 2023. Climate policy uncertainty and the cross-section of stock returns. Finance Res. Lett. 55 https://doi.org/10.1016/j.frl.2023.103837.
Wang, J., Wang, Q., Shao, J., 2010. Fluctuations of stock price model by statistical physics systems. Math. Comput. Model. 51 (5–6), 431–440.
Xu, X., Huang, S., Lucey, B., An, H., 2023. The impacts of climate policy uncertainty on stock markets: comparison between China and the US. Int. Rev. Financ. Anal. 88 https://doi.org/10.1016/j.irfa.2023.102671.
Yu, X., Huang, Y., Xiao, K., 2021. Global economic policy uncertainty and stock volatility: evidence from emerging economies. J. Appl. Econ. 24 (1), 416–440.