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# Tracking oil price shocks and airline stock reactions using entropy-based approaches

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ABSTRACT

The relationship between oil prices and the airline industry is economically important yet empirically complex, presenting significant challenges, with prior research yielding conflicting evidence on the nature, strength, and direction of their interaction. This study contributes to the literature moving beyond traditional linear assumptions, applying Shannon and Rényi transfer entropy to evaluate the nonlinear and state-dependent information flow between oil, oil volatility, and six international airline indices. The empirical findings reveal a significant but heterogeneous information flow between West Texas Intermediate (WTI) and airline indices, suggesting a relationship of mutual influence, where the directional information flow from WTI to airline indices consistently surpasses the reverse flow. In the case of the Crude Oil Volatility Index (OVX), results show a dominant flow of information from each airline index to the OVX index, indicating that sector-specific shocks can shape market expectations of oil volatility. The Rényi entropy analysis further uncovers tail-driven dynamics: at low orders of Rényi entropy, the entropy values remained predominantly negative between WTI and airline indices, while they remained predominantly positive, particularly from OVX to airline indices. However, at very high orders of entropy, there is a more traditional flow of information from WTI to airline indices. These findings enable policymakers to develop more effective, targeted, and economically sound energy policies for the transportation sector and the wider economy.

## 1. Introduction and literature review

The tourism sector is a vital economic driver, generating substantial revenue and employment globally. The tourism industry faces significant challenges stemming from volatile oil prices, a situation compounded by a confluence of geopolitical, economic, and environmental factors. Ongoing conflicts and political instability, particularly in oil-producing regions, introduce substantial uncertainty into global energy markets. Simultaneously, conflicts and inflation impact travel costs and affordability. Furthermore, transitioning towards sustainable energy sources, while essential for long-term environmental viability, creates an interim period of

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continued reliance on fossil fuels, exacerbating the industry's susceptibility to oil price volatility. The airline industry, a critical component of the tourism sector, remains particularly vulnerable to these price shocks, necessitating strategic adjustments that can ultimately impact travel accessibility.

The tourism industry relies heavily on air transport for the movement of tourists. Any disruption in airline operations due to oil price volatility can directly affect tourism flows and revenues (Blau et al., 2023; Mohanty et al., 2014). Rising oil prices can lead to higher travel costs, which may reduce the demand for air travel and, consequently, tourism income and exports (Al-Mulali et al., 2020; Hesami et al., 2020). Moreover, increases in oil prices, resulting in higher travel costs, have a stronger impact on tourism arrivals than decreases in oil prices, both in the short run and the long run (Hesami et al., 2020), in connection with the global economic and financial crisis, particularly (Hadi, 2023). On the other hand, the relationship between oil prices and airline stocks is complex and multifaceted, influenced by numerous factors and exhibiting distinct dynamics in both short- and long-term periods (Arouri & Nguyen, 2010; Asadi et al., 2023). Given the significant economic contribution of the tourism industry and the complex relationship between oil prices and airline stocks, analyzing the information flow between these variables is crucial. Such analyses facilitate accurate forecasting of financial risks and tourism impacts caused by fuel cost-induced airfare volatility, thereby enabling optimized strategic and operational decision-making.

Researchers in the energy finance literature have investigated this nexus from different perspectives, highlighting the significant influence of fuel prices on airline stock prices. The impact of oil prices on airline stocks varies based on the airline's business model, with low-cost carriers exhibiting different sensitivities compared to traditional airlines (Asadi et al., 2023; Gaudenzi & Bucciol, 2016). Research indicates that changes in crude oil prices directly affect airline operational costs, which, in turn, influence stock market performance. Kathiravan et al. (2019) note that fluctuations in crude oil prices lead to variations in airline costs, ultimately impacting cash flows and stock prices in the Indian aviation sector. Moreover, the effect of oil price changes appears to differ according to firm size. For example, Sadorsky (2008) found that medium-sized firms experience a stronger impact from oil price movements than large or small firms, and Yun and Yoon (2019) reported that smaller airline stocks are more sensitive to fluctuations in oil prices. This apparent contradiction—arising from factors such as cost sensitivity, operational adjustments, volatility spillover, firm size, data frequency, geopolitical events, and direction of oil price changes—adds further nuance to this relationship.

Additionally, the relationship between oil prices and airline stocks is a critical area of study, particularly due to the significant impact that fuel costs have on airline profitability. Fuel expenses accounted for nearly 30% of the operating airline costs in 2024, up from 25% compared to the pre-pandemic level in 2019 (Asadi et al., 2023; Cai, Zhang, & Xu, 2025; IATA, 2019, 2024). An increase in fuel prices not only increases the operating expenses of airline enterprises, causing a decrease in their net earnings, but also affects the stock prices and causes significant volatility in airline stocks. This volatility can lead to heightened uncertainty among investors as oil price dynamics complicate earnings predictability in the airline sector (Wang & Gao, 2020). Given that airline enterprises constitute a critical segment of the travel and leisure industry, such fluctuations in fuel costs directly impact airfares, potentially elevating the overall cost of air travel. Consequently, higher fuel prices may increase air travel costs, diminishing consumer propensity to travel, resulting in a reduction of earnings for travel and leisure firms across the supply chain, of which airline enterprises are integral components (Asadi et al., 2023; Becken, 2011; Becken & Lennox, 2012). Conversely, falling oil prices can boost airline profitability and stock prices. This relationship, in which oil returns have a negative influence on airline stock, is characterized as an economically based correlation and supported by several empirical studies (Aggarwal et al., 2012; Elyasiani et al., 2011; Mollick & Amin, 2021; Yun & Yoon, 2019). The most common and intuitive explanation is that fuel [a significant expense for airlines] accounting for about 30% of total costs on average (Cai, Zhang, & Xu, 2025), Cai, Zhang, & Zhang, 2025irectly impacts airline operating costs, particularly in the short-term (Asadi et al., 2023; Dar, 2022), which in turn affects stock prices (Horobet et al., 2022; Kathiravan et al., 2019; Yun & Yoon, 2019).

In contrast, another strand of the research based on market inertia theory suggests a positive correlation between airline stock returns and oil price fluctuations (Kristjanpoller & Concha, 2016; Narayan & Sharma, 2011; Qin et al., 2021). According to this perspective, rising oil prices may be interpreted as an indicator of economic expansion (Kristjanpoller & Concha, 2016) or a catalyst for economic development (Qin et al., 2021), thereby stimulating demand for air transport. During periods of economic growth, demand for air transport, encompassing both cargo and passenger travel, typically increases, reflecting a positive association between air transport and economic prosperity (Balsalobre-Lorente et al., 2021; Zhang & Graham, 2020). Moreover, the asymmetric response of airline stocks—where increases in oil prices have a more pronounced effect on stock returns than decreases—further underscores the complexity of this relationship and highlights the sensitivity of airline stocks to rising fuel costs, leading to the expectation of a positive relationship under the market inertia-based channel (Mollick & Amin, 2021).

Oil price volatility plays a crucial role in shaping airline stock performance. Fluctuations in oil prices impact operating costs directly and lead to higher volatility in stock prices, particularly in smaller airlines, and vary between countries (Yun & Yoon, 2019). Strategic responses of airlines to oil price fluctuations, such as hedging strategies, are essential for mitigating risks associated with fuel price volatility. For instance, using the Long Short-Term Memory (LSTM) model, Choi and Choi (2023) suggested that airlines can employ financial instruments to hedge against oil price movements. The historical strain caused by significant oil price volatility highlights the importance of effective risk management strategies (Zou, 2024).

The relationship between oil prices and airline stocks becomes more complex as multiple factors influence it, including time horizons, volatility spillovers, and macroeconomic conditions. In addition, the decisions of the Organization of Petroleum Exporting Countries (OPEC) decisions, geopolitical events like the Russia–Ukraine war, fluctuations in the US dollar exchange rate, and weather events have added to the complexity. Specifically, the appreciation of the US dollar tends to increase fuel costs for airlines operating outside the US, thereby reducing profit margins. Conversely, depreciation can ease cost pressures and improve financial performance in non-dollar economies. Moreover, currency volatility affects investor sentiment and capital flows, influencing the dynamics of stock prices in the airline sector. Similarly, the depreciation of local currencies or increases in international oil prices negatively affect airline stock markets in the short-term, reinforcing that airlines are vulnerable to external economic pressures (Akusta, 2024). This vulnerability is further supported by findings from Horobet et al. (2022), who demonstrate that the share prices of airlines are significantly influenced by West Texas Intermediate (WTI) pricing behavior, with a more pronounced effect observed during price declines.

Additionally, the cyclical nature of oil prices often correlates with broader economic conditions, which can exacerbate the impact on airline stocks. Yin (2023) discusses how global economic downturns, typically associated with rising oil prices, attenuate air travel demand, negatively affecting airline revenues and stock performance. Recently, this relationship has been echoed by Gelirli and Kısacık (2024), who found that supply-driven oil price shocks have a more detrimental effect on airline earnings predictability than demand-driven shocks, indicating that the nature of oil price changes matters significantly. Some studies indicate a lack of sustainable long-term co-movement between oil prices and airline stocks, suggesting that other factors may play a more significant role over extended periods (Dar, 2022). Indeed, several studies have reported a significant volatility spillover effect between crude oil prices and airline stock prices, indicating that changes in oil prices can lead to increased volatility in airline stocks (Cai, Zhang, & Zhang, 2025; Yun & Yoon, 2019). Furthermore, the volatility spillover effect is more pronounced than the return spillover effect. Likewise, the impact of oil price movements on stock prices varies with the airline's size. Medium-sized firms tend to be more affected by oil price changes compared to large firms (Sadorsky, 2008).

Beyond the identified fundamental drivers, market sentiment and speculation, driven by financial markets and uncertainty, further amplify volatility in oil prices and airline stocks. The interaction between fundamental economic factors and investor behavior creates additional layers of complexity, making it challenging to predict price movements with certainty. Understanding these dynamics is crucial for investors and policymakers to develop more informed strategies that mitigate risk, optimize portfolio allocation, and enhance resilience within the airline industry.

Several econometric methods have been employed to estimate the linkage between oil prices and airline stock returns. Traditional approaches include the Generalized Forecast Error Variance Decomposition (GFEVD) method (Cai, Zhang, & Zhang, 2025), Autoregressive Distributed Lag (ARDL) model (Okoyeuzu et al., 2023), Panel ARDL model with the Pooled Mean Group (PMG) estimator (Horobet et al., 2022), Autoregressive Moving Average (ARMA) models with Mixed Frequency Exogenous Variables (Asadi et al., 2023), and fixed-effects regression models (Cai, Zhang, & Zhang, 2025). Volatility models such as the Generalized Autoregressive Score (GAS) model (Ivanovski & Hailemariam, 2021), Vector Autoregressive (VAR), and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models, more precisely the VAR-GARCH-BEKK model (Yun & Yoon, 2019), and the Hedging-Stock Pricing model (Felix et al., 2023), have also been widely utilized. These standard econometric models are valuable in applications where linear relationships prevail, but they often rely on pre-specified parametric forms.

Thus, frameworks such as the VAR and multivariate GARCH models, with different specifications, have been instrumental in quantifying volatility spillover effects (Yun & Yoon, 2019). Similarly, the GFEVD method, as used by Cai, Zhang, and Zhang (2025), provides a robust, order-invariant measure of connectedness between these markets. These models are powerful tools for capturing well-defined features of financial time series, such as volatility clustering and linear dependencies in returns. However, a critical limitation of these established approaches is that they are fundamentally parametric, that is, they presuppose a specific, and often restrictive, functional form for the relationships between variables and rely on strong assumptions about the underlying data-generating process, such as the normality of error terms. Financial time series, however, are widely known to exhibit "stylized facts" that violate these assumptions, including significant leptokurtosis (fat tails), skewness, and complex nonlinear dependencies (Xie et al., 2025).

Our own preliminary analysis in this study confirms this characteristic. As reported in the Preliminary Results subsection, all return series exhibit substantial excess kurtosis (e.g., kurtosis $>10$), providing direct empirical evidence that the normality assumption is untenable for our dataset. Relying on models with misspecified assumptions can lead to biased estimators and, consequently, unreliable inferences about the true nature of risk transmission.

Both the VAR-GARCH and GFEVD frameworks, despite their sophistication, have inherent constraints when faced with deep nonlinearity. The GFEVD approach, while elegantly solving the variable ordering problem of traditional variance decompositions, is derived from an underlying VAR model that primarily captures linear interdependencies in the conditional mean (Wiesen et al., 2018). If the true relationship between oil and airline stocks contains significant nonlinearities beyond the conditional variance, such as state-dependent or asymmetric spillovers, the VAR framework may be misspecified. Consequently, the GFEVD may provide a precise measure of a flawed linear representation of the system, potentially overlooking more complex transmission channels (Isakin & Ngo, 2020). Likewise, while multivariate GARCH models do account for nonlinearity in the conditional second moment (volatility), they impose a rigid parametric structure on this dynamic and may not effectively capture other forms of information flow unrelated to volatility persistence (Yun & Yoon, 2019).

To overcome these limitations, this study employs the Transfer Entropy (TE) approach (Shannon and Rényi). The TE measure, introduced by Schreiber (Schreiber, 2000), quantifies the direction and strength of information flow between entities (Kwon & Oh, 2012; Kwon & Yang, 2008; Osei & Adam, 2020). TE is a nonparametric, information-theoretic measure that identifies both the source and recipient of information, an essential feature for understanding market dynamics (Kwon & Oh, 2012; Kwon & Yang, 2008). Its primary advantage lies in being model-free; TE quantifies the directed flow of information by measuring the reduction in uncertainty about the future of one variable, given the past of another, without imposing any assumptions about the functional form of the interaction or the marginal distributions of the variables (Papana et al., 2016). As a nonlinear generalization of Granger causality (GC), TE can detect complex causal relationships that linear models are inherently unable to capture (Diks & Fang, 2017). This "model-agnostic" property makes it particularly suitable for financial markets, where relationships are often complex, dynamic, and state-dependent (Xie et al., 2025).

Furthermore, this study leverages Rényi Transfer Entropy (RTE). RTE has been applied in several studies, underscoring its robustness in capturing the intricate dynamics of information flow in financial markets. Notably, RTE can emphasize or suppress specific parts of probability distributions, making it a powerful tool for analyzing market volatility and sector performance (He & Shang, 2017; Tabachová, 2024). Thus, RTE offers superior explanatory power by introducing a weighting parameter, $q$, that allows the analysis to be tailored to different moments of the probability distribution. By varying $q$, we can investigate information flow under different market conditions. For $0 < q < 1$, RTE gives higher weight to the tails of the distribution, making it an ideal tool for examining information transfer during periods of extreme market stress, such as price crashes or sharp volatility spikes. This ability to provide a granular, state-contingent assessment of risk transmission, particularly tail-event-driven information flow, offers a more profound and nuanced understanding of the oil–airline nexus than is achievable with conventional parametric models that provide a single, averaged measure of spillover.

There is evidence that the energy sector, including oil and gas, exhibits substantial information flow dynamics (Duppati et al., 2023; Nasiri et al., 2021), which could be analogous to the airline sector, given its dependency on fuel prices. In this context, this study is unique and makes four main contributions to the existing literature. First, it evaluates the direction and intensity of information flow between oil prices and six international airline indices to identify the source and receiver of information. Second, it employs the Shannon and Rényi TE approaches to quantify the information flow between oil returns, oil volatility, and the returns of six international airline indices. Third, this study provides a more detailed analysis by incorporating the WTI crude oil prices and the Crude Oil Volatility Index (OVX) to better capture and reveal the market dynamics. Lastly, it explicitly addresses limitations identified in prior empirical studies, such as the reliance on linear or parametric econometric models in analyzing the oil-airline nexus, which, although powerful, are inherently constrained in detecting nonlinear, asymmetric, and tail-driven transmission mechanisms. The combined use of Shannon and Rényi TE allows for the full distributional complexity of information flow to be uncovered, including dynamics that intensify during extreme market events. This state-dependent and nonlinear perspective constitutes a meaningful conceptual advancement, particularly given the airline sector's highly exposure to rare, high-volatility shocks originating in energy markets. Furthermore, by incorporating both WTI and OVX, it distinguishes between price-level information flows and volatility-expectation spillovers, which were previously overlooked. Thus, the contribution extends beyond methodological innovation, offering new economic insights into how oil markets and airline stocks interact under varying market conditions, especially in the presence of tail risks.

The remainder of this paper is structured as follows. Section 2 presents the data and methodology, followed by the empirical results in Section 3. The last section, Section 4, presents the concluding.

## 2. Data and methodology

### 2.1. Data

The study uses daily prices of Crude Oil WTI, CBOE Crude Oil Volatility Index, and six prominent global airline indices, namely the FR Global Airlines Total Return Index, the ARCA Global Airline Index, the MSCI World Passenger Airlines Industry Price Index, the Dow Jones Airlines Index, the FR Global Emerging Markets Airlines Index, and the FR G7 Airlines Price Return Index.

The selection of both crude oil–related indices (WTI and OVX) is a deliberate methodological choice driven by the need for analytical coherence. The OVX is specifically designed to measure the market's expectation of 30-day volatility as priced through options on the United States Oil Fund (USO), an exchange-traded fund structured to track WTI futures. This intrinsic link ensures that the volatility measure (OVX) corresponds directly to the price series being analyzed (WTI). Using an alternative benchmark, such as Brent, against the OVX would introduce a fundamental inconsistency, compromising the validity of the TE results. Furthermore, WTI is widely recognized as a leading global benchmark for price discovery in the crude oil market, and its long-term price movements show a strong correlation with those of Brent, making it a robust proxy for the purposes of this study.

The daily data ranges from January 2, 2015, to October 25, 2024, and was fetched from LSEG Refinitiv. The list of airline indices is listed in Table 1. The starting point of January 2015 was selected due to the availability of the airline indices.

### 2.2. Methodology

To estimate the information flow between WTI, OVX, and airline indices, we used both the Shannon (STE) and Rényi (RTE) transfer

**Table 1**
WTI-STE results.

| S.No. | Variable | Symbol |
|---|---|---|
| 1 | FR Global Airlines Total Return Index | FR Global |
| 2 | FR Global Emerging Markets Airlines Index | FR_Emerging |
| 3 | FR G7 Airlines Price Return Index | FR G7 |
| 4 | MSCI World Passenger Airlines Industry Price Index | MSCI World |
| 5 | Dow Jones Airlines Index | Dow_Jones |
| 6 | ARCA Global Airline Index | ARCA_Global |
| 7 | Crude Oil WTI | WTI |
| 8 | CBOE Crude Oil Volatility Index | OVX |

Note: "S.No." represents the time series number.

entropy. Information-theory-based measures, such as TE, have gained popularity. These measures allow for quantifying information flows and have been applied in several scientific areas, such as finance, economics, ecology, neuroscience, and thermodynamics. The STE, introduced by (Schreiber, 2000), is a non-parametric method that allows the measurement of directed and asymmetric information transfer between systems bi-directionally. By capturing nonlinear dependencies, the STE has been widely applied in several fields, including finance and economics, to evaluate market dynamics, risk transmission, and interdependencies between asset prices (Dimpfl & Peter, 2013; Marschinski & Kantz, 2002). The theory behind transfer entropy is given below.

Let $Y$ and $X$ be two discrete random variables that have marginal probability distributions $p(x)$ and $p(y)$ with joint probability distributions $p(x,y)$. Considering that these variables follow stationary Markov processes of order $k$ and $l$ respectively, the probability of observing $X$ at state $i$ at time $t+1$, given (conditional) the $k$ previous states of $X$, is calculated as defined in Eq. (1):

$$p(x_{t+1}|x_t, \dots, x_{t-1+k}) = p(x_{t+1}|x_t, \dots, x_{t-k}), x_i \epsilon X \tag{1}$$

The STE introduced by (Schreiber, 2000) can be estimated as defined in Eq. (2):

$$STE_{Y\to X}(k,l) = \sum_{xy} p\left(x_{t+1}, x_t^{(k)}, y_t^{(l)}\right) log \frac{p\left(x_{t+1}|x_t^{(k)}, y_t^{(l)}\right)}{p\left(x_{t+1}|x_t^{(k)}\right)} \tag{2}$$

where $STE_{Y+X}$ consequently measures the information flow from Y to X, $x_{t+1}$ of $X$ is affected by $k$ previous states of $X$ *(lagged values)* and by $l$ previous states of $Y$ *(lagged value)*. According to Schreiber (2000), the most natural choices for $k$ and $l$ are $k = l$ or $l = 1$, with the latter being preferable for computational reasons. Thus, to ensure a methodologically robust and parsimonious estimation, the Markov orders were set to $k = l = 1$ for all TE estimations. Furthermore, this choice is grounded in three key considerations: (i) the nonparametric estimation of TE is susceptible to the "curse of dimensionality," where the data requirements for reliable probability estimation grow exponentially with the number of lags included (Runge et al., 2012). Using higher-order lags with finite time series can lead to biased and inefficient estimates due to the sparse population of high-dimensional conditional probability distributions. A first-order specification mitigates this risk by adhering to the principle of parsimony, which is critical for the robust application of information-theoretic measures (Aste & Di Matteo, 2017); (ii) This choice is theoretically sound within the context of daily financial data. According to the weak-form Efficient Market Hypothesis, all past price information is already reflected in the current price, making the most recent observation the most relevant predictor of the next period's return (Fama, 1970); (iii) the selected $k$ and $l$ values are consistent with established best practices in the literature applying TE to financial markets. For example, Turner et al. (1989) argue that return series may be modeled as Markov processes of order one. This setting also aligns with the default, validated parameters of the RTransferEntropy package by Behrendt et al. (2019), which was used for our computations, thereby enhancing the study's reproducibility and comparability.

As proposed by Dimpfl and Peter (2013), the bootstrap method (particularly well-suited to deal with non-stationarity and nonlinearity of time series) was used to evaluate the existence of information flow. For reliable estimation of model significance (standard errors and *p-values*), the bootstrapping process was performed with 300 replications. Several studies in literature used 300 replications (Almeida et al., 2024; Assaf et al., 2022; Banerjee et al., 2022; Behrendt et al., 2019). This bootstrapping setting provides a more reliable inference of the information flow between two variables. To identify the pairwise influence on each other, the Shannon Net TE (NET STE) can be calculated using Eq. (3):

$$NET\ STE_{YX} = STE_{Y\to X} - STE_{X\to Y} \tag{3}$$

Thus, if $STE_{Y\to X}(k,l) > STE_{X\to Y}(k,l)$ the dominant direction of the information flow will be from $Y$ to $X$, meaning a positive value of $NET\ STE_{YX}$. Conversely, if $STE_{Y\to X}(k,l) < STE_{X\to Y}(k,l)$, it means that the dominant direction of the information flow is from $X$ to $Y$, corresponding to a negative value of $NET\ STE_{YX}$. Finally, if $STE_{Y\to X}(k,l) = STE_{X\to Y}(k,l)$ it corresponds to equal dominance of information flow in both directions.

Just like $STE_{Y\to X}(k,l)$, the $RTE_{q;\ Y\to X}(k,l)$ [introduced by Rényi in 1961 (Rényi, 1961)] measures the information flow from $Y$ to $X$, but allows to consider the tail events. The RTE is a directional measure of information transfer used for causality detection in complex systems. Its ability to emphasize or suppress specific distribution regions, particularly tails, makes it valuable in financial market analysis, where extreme event risks are crucial (Tabachová, 2024). Thus, the RTE was estimated as defined in Eq. (4). However, unlike in Shannon's case, $RTE_{q;\ Y\to X}(k,l)$ could also be negative (on account of nonlinear pricing). Moreover, if $RTE_{q;\ Y\to X}(k,l) = 0$, it does not imply the independence of both processes (Jizba et al., 2012). The variant of TE based on Rényi entropy, proposed by Jizba et al. (2012), is defined according to Behrendt et al. (2019) as shown in Eq. (4):

$$RTE_{Y\to X}(k,l) = \frac{1}{1-q} \log\left(\frac{\sum_x \phi_q\left(x_t^{(k)}\right) p^q\ \left(x_{t+1}|x_t^{(k)}\right)}{\sum_{x,y} \phi_q\left(x_t^{(k)}, y_t^{(l)}\right) p^q\left(x_{t+1}|x_t^{(k)}, y_t^{(l)}\right)}\right) \tag{4}$$

Where, $\phi_q$ represents the escort distribution given by $\phi_q(x) = \frac{p^q(x)}{\sum_x p_x^q}$ and $q$ is a positive weighting parameter that controls the measure's sensibility to different regions of the probability distribution (Jizba et al., 2012). The parameter $q$ acts as a focusing mechanism, allowing for the evaluation of tail events. For values of $0 < q < 1$, it gives higher weight to extreme, low-probability events. Thus, an information flow detected at $q=0.01$ signifies the transfer of information specifically during the most extreme (rare) observations or shocks in the return time series (tail events). On the other hand, high values of $q$ (e.g., $q > 0.5$) bias the measure towards more frequent events (the center or mode of the distribution) where the probability density is highest.

The selection of $q \in [0.01, 0.99]$ is common in the financial literature utilizing RTE, as it ensures the entire spectrum of event frequencies is captured while avoiding numerical instability at the mathematical limits of $q = 0$ and $q = 1$. As $q \to 0$, the transfer of information focuses on the rarest events (the deepest tails). We choose $q = 0.01$ as a stable proxy for the $q \to 0$ limit, effectively capturing the most extreme tail dependence. Likewise, as $q \to 1$ the measure approaches the standard STE, which equally weights all events (i.e., the average information flow). So, we choose $q = 0.99$ as a stable proxy for the $q \to 1$ limit, capturing near-average behavior.

All the TEs' estimates were made using the R package RTransferEntropy.[1]

## 3. Empirical findings

### 3.1. Preliminary results

The summary statistics of daily returns for all airline indices, WTI, and OVX are reported in Table 2. Fig. 1 shows the trajectories of raw (left y-axis) and daily returns (right y-axis). The daily returns were calculated according to $R_t = \frac{P_t - P_{t-1}}{P_{t-1}}$, where $P_t$ and $P_{t-1}$ shows daily closing values of a given series on days *t* and *t-1*, respectively. Discrete daily returns were used instead of logarithmic returns primarily to accommodate the negative prices observed in the WTI series during the sample period, for which logarithms are undefined. Moreover, given the daily frequency of the data, and since $\mu \approx 0$ and $\sigma$ has small values, the difference between discrete and continuous returns is negligible and does not materially affect the results (Dorgleitner, 2003). The summary statistics reveal that all airline indices offer almost zero average returns. While this finding can be interpreted as an indication that, on a day-to-day basis, there are no persistent abnormal gains or losses—an outcome that is sometimes associated with short-term market efficiency—it should be noted that such a result is based solely on daily data. Market efficiency encompasses several key factors, including the speed and completeness with which information is incorporated into prices and risk adjustments across different time horizons. The highest average return is displayed for OVX (0.0021), whereas WTI reveals a slightly negative average return of −0.0009. The WTI reveals the highest standard deviation (0.0723), reflecting substantial price fluctuations the oil market—a factor that, according to the literature, impacts airline operating costs and, consequently, their financial performance. Among the airline indices, the MSCI World exhibits the minimum standard deviation (0.0151), while Dow Jones Airlines revealed the highest standard deviation (0.0236), suggesting greater volatility and risk for investors. These differences highlight the varying sensitivities of the airline indices to external shocks, such as oil price fluctuations, which impact return and risk profiles in several ways. All the time series in exhibit fat-tail distributions with positive kurtosis ($>$ 10.66), meaning that extreme positive and negative returns are more likely than predicted by the normal distribution. These fat tails emphasize the potential for rare but significant market events, which have important implications for investors, risk managers, and portfolio strategists. The significant *p-values* of the Augmented Dickey–Fuller and Shapiro–Wilk tests allowed us to reject the null hypothesis of a unit root (i.e., non-stationarity) and normality for all the time series. This combination of stationarity alongside fat-tail behavior suggests that although the series does not contain persistent trends, the extreme values and non-normality may challenge traditional linear models. Consequently, more advanced methods are required when modeling and forecasting returns in the airline and energy sectors.

### 3.2. Entropy results

Considering the analysis of bidirectional information flow between WTI and the airline indices, the WTI→ARCA_Global Index exhibited the most substantial information transfer, with a Net TE of 0.0023, which was 0.0070 (statistically significant at a 5% significance level) from WTI to ARCA-Global index, and 0.0047 in the reverse direction. This was followed by WTI→FR_Emerging (Net TE = 0.0022) and WTI→MSCI_World (Net TE = 0.0020), indicating a pronounced influence of WTI price fluctuations on these indices. Conversely, the FR_G7 Index revealed a divergent pattern, i.e., the information flow from WTI to FR_G7 (0.0070) was significantly lower than the flow from FR_G7 to WTI (0.0087), resulting in a Net TE of −0.0017. This suggests a potentially distinct relationship or reduced sensitivity of the FR_G7 Index to WTI price variations. The results are presented in Table 3.

The information flows between WTI and FR Global and between WTI and Dow Jones are statistically significant, at least at a 5% significance level, in both directions, suggesting a significant relationship of mutual influence, where fluctuations in the price of oil have an impact on the airline stocks and vice versa. Although the information flow in both directions is statistically significant, the information flow from WTI→FR Global Index (0.0082) is higher than in the reverse case (0.0075), resulting in a Net TE of 0.0007. Similarly, for the WTI and Dow Jones indices, the information flow from WTI→Dow Jones is 0.0081, compared to 0.0069 in the opposite direction, corresponding to a Net TE of 0.0012. This result indicates a directional relationship and, in a certain way, the predictive power of the WTI on these airline indices, with WTI returns impacting their behavior. Thus, changes in the WTI returns (and prices consequently) have a greater impact on these airline returns, which may indicate fluctuations in the price of oil directly affect the operating costs of airlines, impacting their profit margins and, consequently, the financial performance of the indices associated with the sector, corroborating, with (Cai, Zhang, & Zhang, 2025; Yun & Yoon, 2019). For the pairs WTI–FR Emerging and WTI–FR_G7, the information flow in both directions is statistically significant, at least at a 10% significance level. However, the information flow from WTI→FR_G7 Index is lower than in the reverse direction (FR_G7→WTI), suggesting a certain predictive power of FR G7 over WTI.

[1] The details are available at https://cran.r-project.org/web/packages/RTransferEntropy/RTransferEntropy.pdf.

**Table 2**
Summary statistics of WTI, OVX and Airline Index Returns.

| | FR_Global | FR_Emerging | FR_G7 | MSCI_World | Dow_Jones | ARCA_Global | WTI | OVX |
|---|---|---|---|---|---|---|---|---|
| Mean | 0.0001 | 0.0002 | 0.0000 | 0.0000 | 0.0002 | 0.0001 | −0.0009 | 0.0021 |
| Median | 0.0004 | 0.0002 | 0.0003 | 0.0002 | 0.0000 | −0.0002 | 0.0015 | −0.0047 |
| Maximum | 0.1272 | 0.4538 | 0.2202 | 0.1403 | 0.2068 | 0.1594 | 0.3766 | 1.3577 |
| Minimum | −0.1473 | −0.1211 | −0.1902 | −0.1472 | −0.2031 | −0.1782 | −3.0597 | −0.4633 |
| Std.Deviation | 0.0158 | 0.0178 | 0.0196 | 0.0151 | 0.0236 | 0.0197 | 0.0723 | 0.0700 |
| Skewness | −0.3487 | 9.3232 | 0.0623 | −0.4822 | 0.1469 | −0.0823 | −31.7241 | 5.1064 |
| Kurtosis | 11.5773 | 230.9424 | 18.6374 | 13.0840 | 10.6671 | 11.5166 | 1292.4590 | 80.2584 |
| ADF | −12.4*** | −13.598*** | −12.353*** | −12.107*** | −12.621*** | −12.188*** | −14.971*** | −14.461*** |
| Shapiro Wilk | 0.8984*** | 0.6298*** | 0.8620*** | 0.8943*** | 0.9056*** | 0.8963*** | 0.2220*** | 0.7479*** |

Note: *p-values*: <0.001 '***', <0.01 '**', <0.05 '*', <0.1 '.'

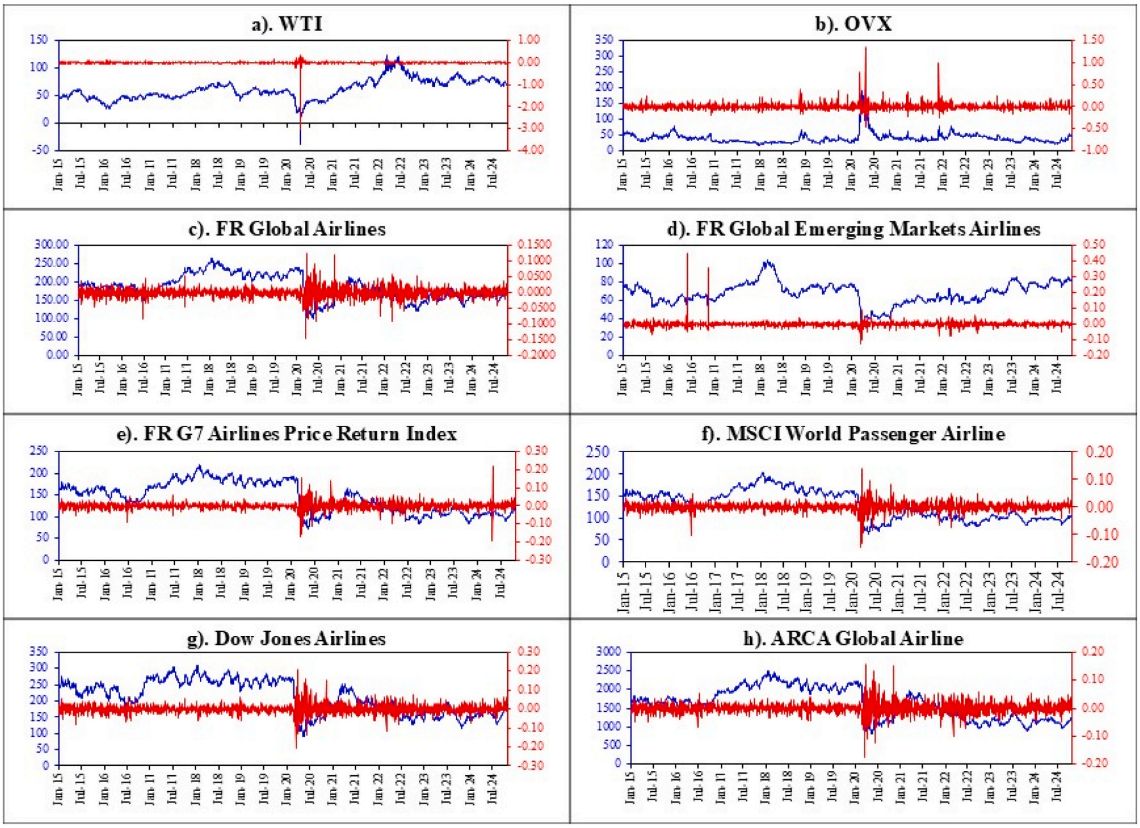


**Fig. 1.** Daily fluctuations in trajectories of raw and daily returns of Oil (WTI), oil volatility (OVX) and airline indices.

In this case, FR G7 returns can impact WTI behavior, meaning the changes in FR G7 returns (and prices consequently) have a greater impact on WTI.

The WTI and ARCA Global pair is the only situation where the information flow is only statistically significant (in this case, at a 5% significance level) in one direction, precisely from WTI→ARCA Global. This indicates a strong directional relationship and, in a certain way, the predictive power of the WTI on ARCA Global.[2] Although the ARCA_Global index is considered a "global" benchmark, it is heavily weighted toward U.S. and North American airlines, whose operating costs are more directly exposed to the WTI benchmark

[2] The Arca Global Airline Index consists of 15 publicly traded global airlines, with a modified weighting system based on liquidity and size. Domestic and international airlines are split 70% and 30%, respectively. Within each group, the top three components are weighted at 15% for U.S. airlines and 4.5% for international carriers, with the remaining weight distributed equally among the other airlines in each group. Major airlines, such as JetBlue, Copa, Delta Air Lines, United Airlines, and Southwest Airlines, have been components of the index. For more details, please visit the official ARCA website https://www.nyse.com/publicdocs/nyse/indices/nyse_arca_global_airline_index.pdf or refer to the financial data provider's website https://www.investing.com/indices/arca-airline-components.

**Table 3**
Shannon transfer entropy (STE) between WTI and airline indices.

| Information flow | TE | ETE | Std.Err. | *p*-value | Net TE |
|---|---|---|---|---|---|
| WTI→FR_Global | 0.0082*** | 0.0043 | 0.0012 | 0.0000 | 0.0007 |
| FR_Global→WTI | 0.0075** | 0.0043 | 0.0012 | 0.0067 | |
| Bootstrapped TE (300 replications): | | | | | |
| Quartiles | 0% | 25% | 50% | 75% | 100% |
| WTI→FR_Global | 0.0013 | 0.0027 | 0.0035 | 0.0043 | 0.0071 |
| FR_Global→WTI | 0.0014 | 0.0030 | 0.0036 | 0.0045 | 0.0083 |
| WTI→ARCA_Global | 0.0070** | 0.0032 | 0.0012 | 0.0067 | 0.0023 |
| ARCA_Global→WTI | 0.0047 | 0.0007 | 0.0012 | 0.2033 | |
| Bootstrapped TE (300 replications): | | | | | |
| Quartiles | 0% | 25% | 50% | 75% | 100% |
| WTI→ARCA_Global | 0.0013 | 0.0028 | 0.0035 | 0.0045 | 0.0077 |
| ARCA_Global→WTI | 0.0014 | 0.0027 | 0.0037 | 0.0044 | 0.0086 |
| WTI→MSCI_World | 0.0106 | 0.0069 | 0.0012 | 0.0000 | 0.0020 |
| MSCI_World→WTI | 0.0086 | 0.0049 | 0.0013 | 0.0033 | |
| Bootstrapped TE (300 replications): | | | | | |
| Quartiles | 0% | 25% | 50% | 75% | 100% |
| WTI→MSCI_World | 0.0013 | 0.0028 | 0.0035 | 0.0045 | 0.0074 |
| MSCI_World→WTI | 0.0012 | 0.0029 | 0.0036 | 0.0043 | 0.0098 |
| WTI→Dow_Jones | 0.0081*** | 0.0041 | 0.0012 | 0.0000 | 0.0012 |
| Dow_Jones →WTI | 0.0069** | 0.0029 | 0.0012 | 0.0067 | |
| Bootstrapped TE (300 replications): | | | | | |
| Quartiles | 0% | 25% | 50% | 75% | 100% |
| WTI→Dow_Jones | 0.0014 | 0.0027 | 0.0035 | 0.0045 | 0.0078 |
| Dow_Jones→WTI | 0.0011 | 0.0028 | 0.0035 | 0.0044 | 0.0071 |
| WTI→FR_Emerging | 0.0086** | 0.0051 | 0.0013 | 0.0033 | 0.0022 |
| FR_Emerging→WTI | 0.0064* | 0.0027 | 0.0012 | 0.0200 | |
| Bootstrapped TE (300 replications): | | | | | |
| Quartiles | 0% | 25% | 50% | 75% | 100% |
| WTI→FR_Emerging | 0.0009 | 0.0026 | 0.0034 | 0.0043 | 0.0104 |
| FR_Emerging→WTI | 0.0010 | 0.0029 | 0.0036 | 0.0044 | 0.0074 |
| WTI→FR_G7 | 0.0070* | 0.0030 | 0.0013 | 0.0100 | −0.0017 |
| FR_G7→WTI | 0.0087** | 0.0048 | 0.0012 | 0.0033 | |
| Bootstrapped TE (300 replications): | | | | | |
| Quartiles | 0% | 25% | 50% | 75% | 100% |
| WTI→FR_G7 | 0.0012 | 0.0028 | 0.0035 | 0.0046 | 0.0082 |
| FR_G7→WTI | 0.0012 | 0.0029 | 0.0037 | 0.0045 | 0.0093 |

Notes: (i) *p-values*: <0.01 '***', <0.05 '**', <0.1 '*'; (ii) Net TE corresponds to the Net STE, defined as the difference between the STE (represented as TE on the table) from WTI → Airline index and Airline index → WTI; (iii) ETE is the effective transfer entropy, as defined by Marschinski and Kantz (2002). It is computed by comparing the original transfer entropy with that obtained from a shuffled version of the source time series. By randomizing the source series, spurious correlations are removed, allowing ETE to isolate the true nonlinear transfer of information between variables; (iv) The bootstrapped part of the table accounts for both the non-stationarity and nonlinearity in data; (v) The quartiles represent the distribution of data points.

(NYSE Euronext Inc., 2014; Zheng et al., 2021). Airlines in these markets rely heavily on jet fuel pricing mechanisms linked to WTI and typically exhibit lower, less stable fuel-hedging ratios compared to their European and Asian counterparts (Berghöfer & Lucey, 2014; Treanor et al., 2014). As a result, shocks in WTI prices translate more immediately into equity valuations for the companies represented in ARCA_Global. Moreover, U.S.-based airlines operate a larger share of long-haul flights, which are fuel-intensive, and maintain fleet structures that amplify short-run sensitivity to fuel price fluctuations (Brueckner & Abreu, 2017; Dobruszkes et al., 2024). These factors help explain the influence of WTI on the ARCA_Global while limiting the extent to which the index transmits information back to the oil market. For MSCI World, although the information flow from WTI to MSCI World is stronger than that from MSCI World to WTI, it fails to reach a level of statistical significance. However, like in the previously analyzed pairs, the information flow from WTI to MSCI World is higher than in the reverse case, indicating a strong directional relationship and, in a certain way, the predictive power of the WTI on MSCI World.

The STE analysis reveals heterogeneous information transfer dynamics between WTI crude oil prices and airline industry indices, suggesting a relationship of mutual and bidirectional influence (Storhas et al., 2020; Xiao & Wang, 2022), where fluctuations in oil prices affect global airline stocks and vice versa. Specifically, except for the FR_G7 Index, the directional information flow from WTI to the airline indices consistently surpasses the reverse flow. This finding aligns with previous studies: Kathiravan et al. (2019) showed that changes in crude oil prices trigger fluctuations in the stock returns of various airlines, including Air India, IndiGo, Jet Airways, and Spice Jet; Killins (2020) reported that equity returns of U.S. airlines are negatively impacted by positive movements in WTI prices, suggesting a strong influence of WTI on airline indices; and Kristjanpoller and Concha (2016), found a strong positive influence of WTI price fluctuations on the daily equity returns of airlines associated with the International Air Transport Association (IATA).

Some studies point to the existence of a direct relationship between the price of oil and the stock market, especially in oil-dependent economies (Alzate-Ortega et al., 2024; Bein, 2019), suggesting that WTI plays a significant role as a transmitter of information to the global market (Escribano et al., 2023; Kathiravan et al., 2019; Yun & Yoon, 2019). This flow reflects the sensitivity of airlines from emerging economies to oil price fluctuations, which impacts both the cost of transportation and the operational viability of airlines in these markets (Kathiravan et al., 2019; Yun & Yoon, 2019).

Analyzing the transfer of information between OVX and airline indices, for all the cases, the STE from OVX to the airline indices is not statistically significant, and the dominant direction of information flow from each airline index is to the OVX index. This result means that all the airline indices can impact OVX behavior, meaning the changes in all the airline indices' returns (and prices consequently) have a greater impact on OVX returns. This evidence suggests that OVX is sensitive to uncertainty shocks from other markets, aligning with (Liu et al., 2013), who found a significant influence of other volatility indices on OVX. Although the information flow from airline indices to OVX is statistically significant, at least at a 5% significance level, a varying degree of intensity can be noticed. The FR Global exhibits the highest information flow to OVX, followed by FR G7 and ARCA Global. Dow Jones, FR Emerging, and MSCI World are on the opposite side.

The STE results for OVX and airline indices are presented in Table 4.

These results suggest that the volatility observed in the global airline sector significantly impacts market volatility. These results underscore the airline sector's role as a leading indicator for the stock prices of the airline industry. Furthermore, volatility indices (OVX) demonstrate that the aviation sector can serve as a signal for financial market volatility, highlighting the interdependence between energy and economically sensitive sectors [as identified by Cai, Zhang, and Zhang (2025)]. Laborda and Olmo (2021)

**Table 4**
Shannon transfer entropy (STE) between OVX and airline indices.

| Information flow | TE | ETE | Std.Err. | *p*-value | Net TE |
|---|---|---|---|---|---|
| OVX→FR_Global | 0.0027 | 0.0000 | 0.0012 | 0.7967 | −0.0096 |
| FR_Global→OVX | 0.0123*** | 0.0086 | 0.0011 | 0.0000 | |
| Bootstrapped TE (300 replications): | | | | | |
| Quartiles | 0% | 25% | 50% | 75% | 100% |
| OVX →FR_Global | 0.0009 | 0.0028 | 0.0035 | 0.0043 | 0.0081 |
| FR_Global→ OVX | 0.0015 | 0.0028 | 0.0035 | 0.0043 | 0.0080 |
| OVX→ARCA_Global | 0.0045 | 0.0009 | 0.0013 | 0.1833 | −0.0055 |
| ARCA_Global→OVX | 0.0100*** | 0.0062 | 0.0011 | 0.0000 | |
| Bootstrapped TE (300 replications): | | | | | |
| Quartiles | 0% | 25% | 50% | 75% | 100% |
| OVX→ARCA_Global | 0.0012 | 0.0027 | 0.0035 | 0.0042 | 0.0089 |
| ARCA_Global→OVX | 0.0010 | 0.0028 | 0.0034 | 0.0041 | 0.0070 |
| OVX→MSCI_World | 0.0051 | 0.0013 | 0.0013 | 0.1433 | −0.0037 |
| MSCI_World→OVX | 0.0088*** | 0.0051 | 0.0012 | 0.0033 | |
| Bootstrapped TE (300 replications): | | | | | |
| Quartiles | 0% | 25% | 50% | 75% | 100% |
| OVX→MSCI_World | 0.0013 | 0.0028 | 0.0035 | 0.0044 | 0.0084 |
| MSCI_World→OVX | 0.0013 | 0.0027 | 0.0033 | 0.0041 | 0.0089 |
| OVX→Dow_Jones | 0.0046 | 0.0009 | 0.0012 | 0.2000 | −0.0031 |
| Dow_Jones →OVX | 0.0077** | 0.0040 | 0.0011 | 0.0067 | |
| Bootstrapped TE (300 replications): | | | | | |
| Quartiles | 0% | 25% | 50% | 75% | 100% |
| OVX→Dow_Jones | 0.0013 | 0.0027 | 0.0034 | 0.0042 | 0.0080 |
| Dow_Jones→OVX | 0.0010 | 0.0028 | 0.0035 | 0.0042 | 0.0091 |
| OVX→FR_Emerging | 0.0043 | 0.0006 | 0.0013 | 0.2100 | −0.0039 |
| FR_Emerging→OVX | 0.0082** | 0.0043 | 0.0012 | 0.0033 | |
| Bootstrapped TE (300 replications): | | | | | |
| Quartiles | 0% | 25% | 50% | 75% | 100% |
| OVX→FR_Emerging | 0.0011 | 0.0025 | 0.0034 | 0.0041 | 0.0105 |
| FR_Emerging→OVX | 0.0010 | 0.0027 | 0.0034 | 0.0043 | 0.0086 |
| OVX→FR_G7 | 0.0038 | 0.0001 | 0.0012 | 0.3900 | −0.0066 |
| FR_G7→OVX | 0.0104*** | 0.0067 | 0.0011 | 0.0000 | |
| Bootstrapped TE (300 replications): | | | | | |
| Quartiles | 0% | 25% | 50% | 75% | 100% |
| OVX→FR_G7 | 0.0013 | 0.0027 | 0.0035 | 0.0042 | 0.0077 |
| FR_G7→OVX | 0.0009 | 0.0029 | 0.0035 | 0.0042 | 0.0074 |

Notes: (i) *p-values*: $<0.01$ '***', $<0.05$ '**', $<0.1$ '*'; (ii) Net TE corresponds to the Net STE, defined as the difference between the STE (represented as TE on the table) from OVX→ Airline index and Airline index → OVX; (iii) ETE is the effective transfer entropy, as defined by Marschinski and Kantz (2002). It is computed by comparing the original transfer entropy with that obtained from a shuffled version of the source time series. By randomizing the source series, spurious correlations are removed, allowing ETE to isolate the true nonlinear transfer of information between variables; (iv) The bootstrapped part of the table accounts for both the non-stationarity and nonlinearity in data; (v) The quartiles represent the distribution of data points.

highlighted that sectors such as energy and technology are significant channels for risk transmission, particularly during crises like the COVID-19 pandemic. Thus, since the aviation sector is closely linked with energy, it can signal financial market volatility.

For robustness and to validate the information flow, we applied a more rigorous approach by comparing the empirical results across alternative lag-length specifications (i.e., $k = l = 2$ and $k = l = 3$), following Chen et al. (2025). The STE results between WTI and the airline indices, as well as between OVX and the airline indices at lags 2 and 3, are presented in Appendix 1 and Appendix 2, respectively.

Overall, the finding that the sign of information flow (i.e., the dominant causal direction) between oil prices and airline stock indices changes with different lags (1, 2, and 3 days) using TE suggests that the relationship is dynamic, multi-speed, and complex. The key takeaway is that the relationship between oil and airline stocks is not monolithic but operates through multiple, distinct causal channels that manifest at different time scales. These include physical cost shocks from oil to airlines, driven by feedback mechanisms, sentiment, or macro-signaling from airline performance back to the oil market, and potential realignment with fundamental cost or common macroeconomic drivers.

The RTE was also estimated to account for tail events. For small values of the Rényi entropy parameter ($q < 0.5$), the entropy values between WTI and airline indices are predominantly negative. These negative values could reflect the increased complexity and unpredictability of market behavior (Bouhlal & Sedra, 2022; Junior et al., 2024). The observed negative RTE indicates that knowing the past states of oil prices actually reduces the uncertainty (increases the predictability) of airline stock prices, but in a counterintuitive manner. This inverse predictive power can be attributed not merely to "increased market complexity," but to specific market mechanisms and behaviors during extreme oil price shocks, including hedging mechanisms, operational buffers, and extreme investor sentiment (panic/over-discounting). For instance, when oil prices experience an extreme positive shock (a tail event), major airlines often have pre-existing fuel hedges that temporarily insulate their stock prices from the immediate impact, or they may have substantial cash reserves (acting as an adverse impact buffer). Likewise, during periods of extreme stress driven by oil price movements, the extreme negative RTE may reflect the market over-discounting the expected negative impact. An extreme oil shock may signal a severe and imminent global recession. In such rare events, investors may sell off airline stocks, but simultaneously, the fear of a recession may trigger a demand destruction signal in the oil market, causing oil prices to rapidly fall (Felix et al., 2023; Jizba et al., 2012). Furthermore, the volatility and information flow in financial markets, such as those involving the WTI and airline indices, can be significantly impacted by external events, including the COVID-19 pandemic. During such periods, the entropy measures can reflect heightened uncertainty and risk, leading to negative entropy values. For $q < 0.5$, the negative RTE values suggest that the information transfer is dominated by the tails of the distribution. This finding implies that extreme events in WTI prices (e.g., sudden spikes or drops) are inversely related to the airline indices, possibly due to the adverse impact of such events on the airline industry (Jizba et al., 2012; Li et al., 2016). These negative values suggest an opposite informative relationship between oil prices and airline indices. Such behavior can be interpreted as a compensation relationship, where the uncertainty of the airline sector's performance decreases due to structural volatility in oil prices.

The RTE results between WTI and the airline indices, as well as between OVX and the airline indices, are presented in Tables 5 and 6, respectively.

For $q$ close to 1 (e.g., $q = 0.99$), positive RTE values suggest that, under conditions where frequent and rare events contribute similarly to information transfer, there is a stronger directional information flow from WTI to airline indices, potentially reflecting periods of lower market uncertainty. This flow suggests that when oil prices are more stable, there is a positive informative influence of WTI on the financial performance of airlines, indicating that the stability of oil prices can contribute to reducing operating costs and increasing the predictability of returns in the airline sector. Furthermore, when $q$ is close to 1, the positive RTE values indicate a significant information transfer from WTI to airline indices in the central part of the distribution. This result suggests that the typical WTI price fluctuations influence the airline indices (Jizba et al., 2012; Tabachová, 2024).

The analysis of RTE data between the OVX and airline indices across different values of the Rényi parameter $q$ provides valuable insights into the informative relationship and interdependence between market volatility and airline industry performance. This relationship varies in intensity and direction depending on $q$, reflecting different economic and financial dynamics.

For lower values of the Rényi entropy parameter ($q = 0.01$ to $q = 0.40$), the RTE values between the OVX and the airline indices are predominantly positive, especially from the OVX to the airline indices, suggesting that changes in oil volatility are influencing airline stock prices. The positive RTE values for lower $q$ indicate that the nonlinear effects of oil volatility on airline stocks are significant and predominantly positive. Furthermore, the identified pattern could suggest that in periods of heightened market uncertainty and volatility, the dominant direction of information flow is from OVX to airline indices, reflecting airline indices' sensitivity to fluctuations in financial market volatility. This result can be interpreted as a transmission effect of market volatility to the airline sector, where increased uncertainty in the global market directly impacts the financial stability of airlines, expanding the sector's vulnerability. Such a result aligns with the economic reality that airline industry performance is highly exposed to macroeconomic uncertainty, as increased volatility in the broader financial markets can influence airline stock valuations, risk premiums, and investor sentiment. This transmission effect highlights how greater uncertainty in the global market environment can amplify financial instability in the airline sector, increasing its exposure to external shocks. Considering the transmission of risk and volatility, the relationship between oil volatility and airline indices can be attributed to the direct impact of fuel costs on airline operations. Higher oil volatility can lead to increased uncertainty and risk in fuel prices, which directly affects airline profitability and stock performance (Dimpfl & Peter, 2018; Xiao & Wang, 2022). The positive RTE values indicate that this transmission of risk and volatility is relevant.

Furthermore, the ARCA Global, FR Global, and FR Emerging indices exhibit higher values of RTE from these indices to OVX than in the reverse direction for the lowest values of $q$ (e.g., $q = 0.01$ and $q = 0.10$). This difference is even higher in the case of the FR Emerging index, suggesting that emerging market airlines may not be the most sensitive to market volatility. While emerging econ-

**Table 5**
Rényi transfer entropy (RTE) between WTI and airline indices.

| $q$ | WTI→FR$_{G}$lobal | FR$_{G}$lobal→WTI | WTI→ARCA$_{G}$lobal | ARCA$_{G}$lobal→WTO | WTI→MSCI$_{W}$orld | MSCI$_{W}$orld→WTI | WTI→FR$_{G}$lobal | FR$_{G}$lobal→WTI | WTI→FR$_{E}$merging | FR$_{E}$merging→WTI | WTI→FR$_{G}$7 | FR$_{G}$7→WTI |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0.01 | 0.0511 | −0.0015 | −0.0020 | −0.0015 | −0.0021 | −0.0018 | −0.0020 | −0.0017 | −0.0024 | −0.0010 | 0.0515 | −0.0017 |
| 0.10 | 0.0223 | −0.0150 | −0.0202 | −0.0154 | −0.0204 | −0.0180 | −0.0199 | −0.0174 | −0.0222 | −0.0100 | 0.0255 | −0.0171 |
| 0.20 | −0.0059 | −0.0290 | −0.0385 | −0.0297 | −0.0383 | −0.0341 | −0.0380 | −0.0343 | −0.0398 | −0.0185 | −0.0014 | −0.0330 |
| 0.30 | −0.0276 | −0.0397 | −0.0521 | −0.0406 | −0.0510 | −0.0459 | −0.0515 | −0.0478 | −0.0514 | −0.0242 | −0.0234 | −0.0451 |
| 0.40 | −0.0407 | −0.0449 | −0.0588 | −0.0459 | −0.0564 | −0.0512 | −0.0580 | −0.0550 | −0.0557 | −0.0261 | −0.0377 | −0.0510 |
| 0.50 | −0.0442 | −0.0436 | −0.0573 | −0.0447 | −0.0536 | −0.0491 | −0.0563 | −0.0545 | −0.0525 | −0.0240 | −0.0427 | −0.0495 |
| 0.60 | −0.0393 | −0.0363 | −0.0484 | −0.0377 | −0.0437 | −0.0405 | −0.0472 | −0.0466 | −0.0430 | −0.0186 | −0.0391 | −0.0414 |
| 0.70 | −0.0285 | −0.0252 | −0.0347 | −0.0269 | −0.0294 | −0.0277 | −0.0334 | −0.0337 | −0.0297 | −0.0115 | −0.0293 | −0.0288 |
| 0.80 | −0.0154 | −0.0128 | −0.0193 | −0.0150 | −0.0140 | −0.0139 | −0.0179 | −0.0188 | −0.0153 | −0.0042 | −0.0165 | −0.0148 |
| 0.90 | −0.0026 | −0.0012 | −0.0048 | −0.0041 | −0.0002 | −0.0013 | −0.0036 | −0.0047 | −0.0021 | 0.0019 | −0.0038 | −0.0018 |
| 0.99 | 0.0072* | 0.0073* | 0.0060* | 0.0039 | 0.0097*** | 0.0078** | 0.0071* | 0.0059 | 0.0077* | 0.0060 | 0.0060 | 0.0078* |

Notes: (i) *p-values*: <0.01 '***', <0.05 '**', <0.1 '*'; (ii) $q$ denotes the weighting parameter.

**Table 6**
Rényi transfer entropy (RTE) between OVX and airline indices.

| $q$ | OVX→$FR_G$lobal | $FR_G$lobal→OVX | OVX→$ARCA_G$lobal | $ARCA_G$lobal→OVX | OVX→$MSCI_W$orld | $MSCI_W$orld→OVX | OVX→$FR_G$lobal | $FR_G$lobal→OVX | OVX→$FR_E$merging | $FR_E$merging→OVX | OVX→$FR_G$7 | $FR_G$7→OVX |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0.01 | 0.1080 | 0.0520 | 0.1067 | 0.1075 | 0.1088 | 0.1077 | 0.1067 | 0.1070 | 0.1644 | 0.2249 | 0.1073 | 0.0519 |
| 0.10 | 0.0819 | 0.0318 | 0.0707 | 0.0782 | 0.0886 | 0.0789 | 0.0704 | 0.0728 | 0.1194 | 0.1708 | 0.0754 | 0.0312 |
| 0.20 | 0.0559 | 0.0138 | 0.0371 | 0.0503 | 0.0673 | 0.0508 | 0.0364 | 0.0405 | 0.0785 | 0.1185 | 0.0449 | 0.0126 |
| 0.30 | 0.0341 | 0.0008 | 0.0114 | 0.0283 | 0.0480 | 0.0278 | 0.0103 | 0.0154 | 0.0472 | 0.0757 | 0.0205 | −0.0008 |
| 0.40 | 0.0173 | −0.0067 | −0.0058 | 0.0127 | 0.0319 | 0.0112 | −0.0071 | −0.0016 | 0.0249 | 0.0435 | 0.0032 | −0.0087 |
| 0.50 | 0.0062 | −0.0090 | −0.0145 | 0.0035 | 0.0198 | 0.0011 | −0.0158 | −0.0104 | 0.0108 | 0.0216 | −0.0068 | −0.0114 |
| 0.60 | 0.0002 | −0.0071 | −0.0162 | 0.0000 | 0.0119 | −0.0028 | −0.0172 | −0.0122 | 0.0034 | 0.0091 | −0.0103 | −0.0097 |
| 0.70 | −0.0017 | −0.0027 | −0.0129 | 0.0005 | 0.0076 | −0.0022 | −0.0136 | −0.0092 | 0.0008 | 0.0038 | −0.0091 | −0.0052 |
| 0.80 | −0.0011 | 0.0028 | −0.0071 | 0.0033 | 0.0057 | 0.0009 | −0.0075 | −0.0036 | 0.0010 | 0.0033 | −0.0052 | 0.0004 |
| 0.90 | 0.0007 | 0.0080 | −0.0009 | 0.0067 | 0.0051 | 0.0050 | −0.0010 | 0.0024 | 0.0025 | 0.0053 | −0.0005 | 0.0059 |
| 0.99 | 0.0025 | 0.0119*** | 0.0040 | 0.0097*** | 0.0051 | 0.0084* | 0.0041 | 0.0072* | 0.0041 | 0.0079* | 0.0034 | 0.0100*** |

Notes: (i) *p-values*: $<$0.01 '***', $<$0.05 '**', $<$0.1 '*'; (ii) $q$ denotes the weighting parameter.

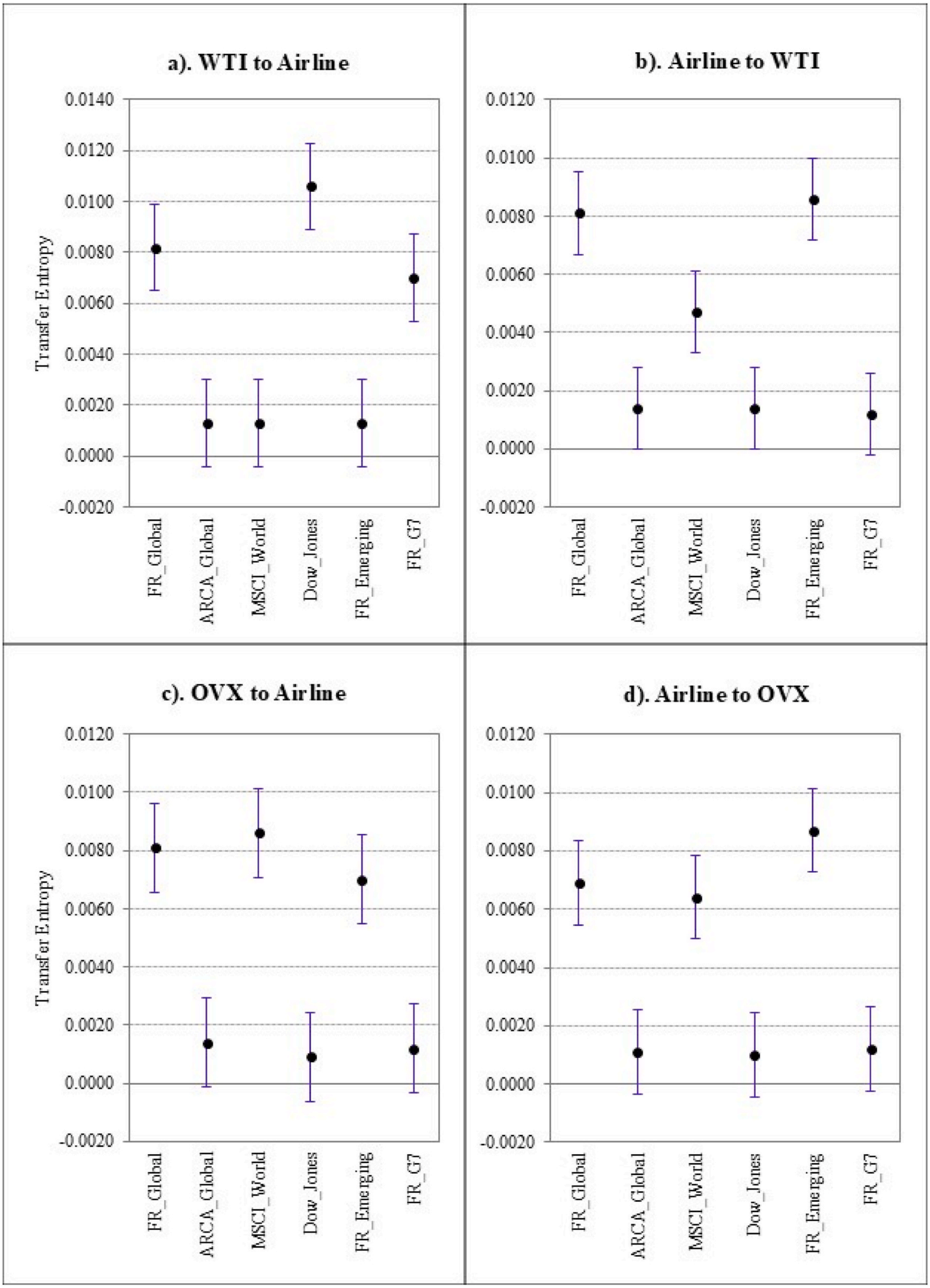


**Fig. 2.** Estimates of Shannon's transfer entropy between WTI, OVX, and airline indices.

omies are traditionally considered less resilient to financial shocks—where volatility directly impacts the cost of capital and access to financing—this result indicates that a distinct set of factors beyond general financial market fluctuations may influence airline stocks in these markets. Explanations may include the influence of government subsidies, regulatory policies, or domestic market conditions that shield the industry from outside volatility. However, a more in-depth analysis is necessary to fully understand the mechanisms underlying this diversified reaction.

As the Rényi entropy parameter increases to intermediate values ($q = 0.5$ to $q = 0.7$), entropy values tend to become negative, particularly in the flow of information from airline indices to OVX, except in the cases of ARCA Global and FR Emerging. This shift suggests a change in the informational relationship, where airline indices exert a more significant influence on market volatility rather than simply reacting to it. This behavior can be interpreted as a feedback effect, in which airline stocks—initially impacted by volatility shocks—help to reflect and even smooth the uncertainty of the general market in a second moment, subsequently transmitting information that contributes to shaping expectations about market risk. This dampening pattern is consistent with the idea that sectors that have already undergone adjustments in response to volatility shocks begin to stabilize and provide more predictable signals to the financial market, reducing aggregate uncertainty.

At the highest Rényi entropy parameter values ($q = 0.99$), the RTE values are once again positive and statistically significant from each airline index to the OVX, indicating a consistent and directional flow of information from airline indices and market volatility. These values suggest that the volatility and airline indices influence each other positively and predictably in the context of lower uncertainty and greater market stability. However, the dominant (and statistically significant) direction is that of the airline indices for the OVX, implying that the financial performance of airlines plays a key role in shaping market volatility expectations under stable conditions. Considering the patterns revealed by the RTE between OVX and the airline indices, there is evidence of a complex dynamic of information transmission and interdependence between market volatility and airline sector performance. At low Rényi entropy parameter values ($q$), market volatility has a strong influence on the airline sector, especially in emerging markets. On the other hand, while at intermediate values of the Rényi entropy parameter, the airline sector helps to buffer OVX volatility. Finally, at higher values of the Rényi entropy parameter, the positive synchrony between the indices reflects a context of stability and economic recovery, where both the financial market and the airline sector benefit from an environment of low uncertainty. These patterns provide valuable insights for portfolio diversification strategies and risk analysis, highlighting how the relationship between volatility and economically sensitive sectors can vary according to the level of uncertainty and the global economic context.

Fig. 3 presents the RTE for a spectrum of $q$ values, providing a multifaceted, state-dependent view of the oil–airline information dynamic. This allows for a more in-depth analysis than the single average value provided by STE. As the parameter $q \rightarrow 1$, the RTE curve

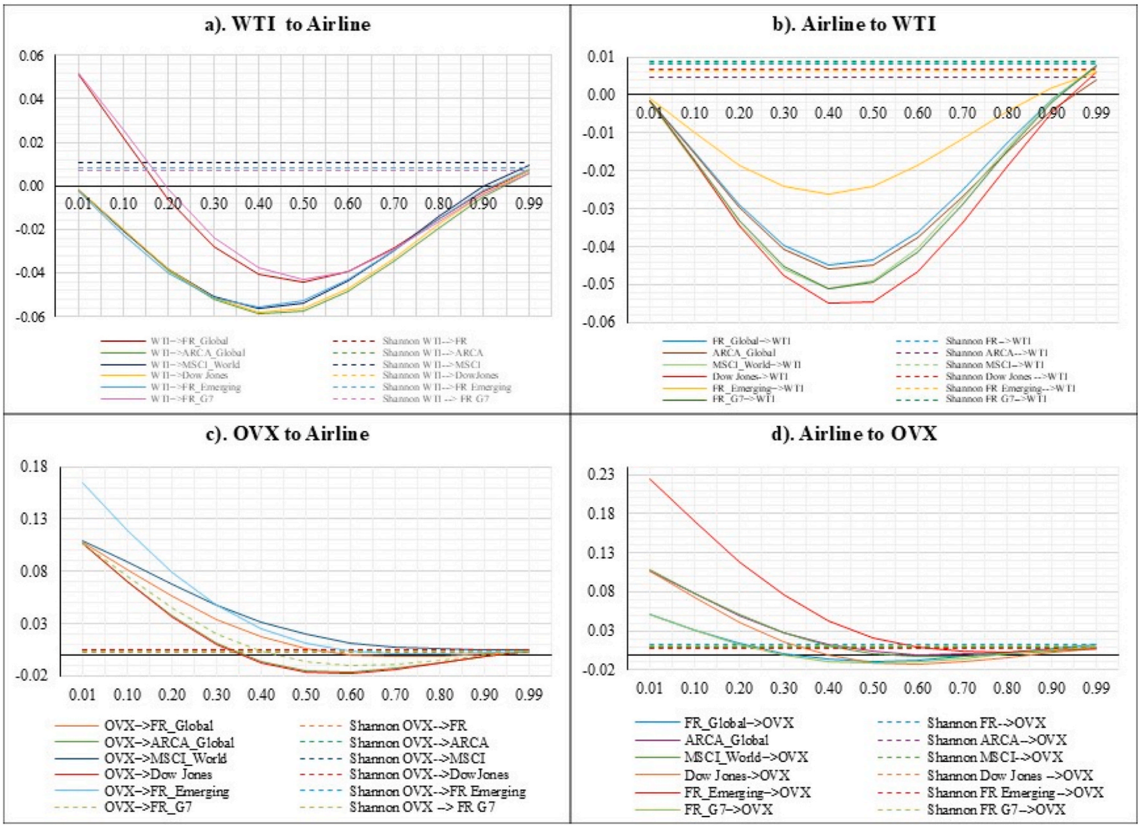


**Fig. 3.** Rényi transfer entropy (RTE) for different $q$ values.

in Fig. 3 smoothly converges to the constant STE value presented in Fig. 2. This convergence confirms the theoretical consistency between the two measures, with the average Shannon case representing a specific point on the broader Rényi spectrum. The most significant finding of the analysis is revealed in the regime where $0 < q < 1$. As $q$ decreases (e.g., to 0.5), the RTE from oil to airlines decreases sharply, reaching a magnitude several times (in absolute value) than that of the STE. This result demonstrates unequivocally that the information flow between the sectors is not uniform across states but is overwhelmingly concentrated in the tails of the return distributions. In particular, the history of a large oil price shock proves to be far more informative for predicting a significant move in airline stocks than the history of normal oil price fluctuations. This finding directly validates the assertion by Jizba et al. (2012) that RTE is indispensable for financial analysis, as it isolates the information flow contained in the "spikes or sudden jumps" that constitute the primary source of market risk. Furthermore, the information flow in this tail-driven regime is highly asymmetric. By adopting the RTE framework, this study moves beyond a simple average effect toward a state-dependent understanding of causality. It reveals that the economic linkage between oil prices and airline stocks is fundamentally nonlinear, with the majority of impactful information transfer occurring precisely within the tail events that matter most to investors and risk managers. This tail-driven causality is a critical feature of the system, one that remains invisible to traditional linear models and is only fully captured by transitioning from the Shannon to the Rényi information-theoretic perspective.

## 4. Concluding remarks and policy suggestions

The relationship between crude oil prices and airline stock performance is dynamic and complex, driven by the crucial role of fuel costs in airline profitability. In 2024, fuel costs represented approximately 30% of total operating costs, up from 25% in 2019 (Cai, Zhang, & Xu, 2025; IATA, 2019, 2024). While conventional economic models suggest a positive correlation between oil prices and airline stock returns, the market inertia hypothesis posits an inverse relationship. Empirical evidence remains inconclusive, underscoring the need for a deeper understanding of information flow dynamics between these variables.

This study addresses this gap by examining the information transfer among WTI crude oil prices, the OVX index, and six international airline stock indices. Employing STE and RTE approaches, the findings reveal a heterogeneous information flow between oil price movements (represented by WTI) and airline stock indices, with the dominant direction and intensity of the information flow varying across different market conditions. The WTI exerts a stronger influence on airline stocks [aligning, for example, with (Dutta et al., 2024)], who concluded that oil market volatility significantly affects transport sector stock indexes], whereas airline indices primarily affect oil volatility expectations (represented by OVX). Furthermore, at lower Rényi entropy parameter values ($q < 0.5$), negative entropy values predominate between WTI and airline indices, while positive values are primarily evident from OVX to airline indices. However, at higher Rényi entropy parameter values ($q = 0.99$), there is a stronger directional information flow from WTI to airline indices.

Our findings provide new insights into the information flow between oil markets and airline stock performance, emphasizing the role of volatility and market dynamics in shaping this relationship. Oil price volatility dominates airline sector performance in high-uncertainty environments, particularly in emerging markets. Conversely, airline stocks play a greater role in shaping volatility expectations under more stable conditions. These results indicate that the airline sector both reacts and transmits information to financial markets, contributing to a dynamic interdependence between the two. Given this interdependence, the results have several targeted policy and practical implications. First, the persistent and statistically significant information flow from WTI to the airline indices indicates that airlines and investors cannot rely solely on equity diversification to hedge oil exposure. For indices where the WTI→airline transmission is the dominant direction of information flow, effective risk mitigation requires the use of oil-linked derivatives (e.g., WTI futures or options) rather than sector diversification alone. Second, the dominant and consistent information flow from airline indices to OVX suggests that sector-specific shocks in the airline industry shape market expectations of future oil volatility. This has a clear regulatory implication: policymakers should require airlines to disclose volatility-sensitive exposures, such as hedging coverage ratios, hedging gaps, and sensitivity to spot-futures basis risk, to reduce informational opacity and help stabilize OVX expectations. Enhanced transparency could also improve the quality of volatility forecasting models used by regulators and market participants. Finally, the RTE results reveal that information flow intensifies during tail events, highlighting the need for stress-testing frameworks (both at the regulatory level and within airlines) that explicitly incorporate extreme oil price scenarios, rather than relying solely on models based on average-conditions. Such stress testing is especially relevant in regions or environments where geopolitical shocks and abrupt supply disruptions are frequent. These implications can guide investors, regulators, and airline executives seeking to strengthen resilience to oil-market volatility and tail-risk dynamics.

Understanding this relationship's shifting nature can enhance portfolio allocation strategies and risk hedging against oil price shocks for investors and portfolio managers, particularly in the tourism and airline industries. For airline and tourism executives, implementing effective fuel hedging and cost management strategies can mitigate the financial impact of oil price volatility. Finally, for policymakers, the regulatory frameworks should account for the feedback loop between oil markets and airline stocks, particularly in stabilizing industry-wide financial risks during periods of economic distress. Furthermore, the findings may help tourism and airline managers to design more stable pricing and budgeting, reducing the risk of sudden cost increases.

The entropy measures provide concrete, actionable insights that go beyond traditional correlation analysis in the context of portfolio management. The dominant information flow from WTI to the airline indices (as shown in the STE results) quantitatively reveals that airline stocks are poor diversifiers of oil price risk, as their performance is informationally subordinate to the oil market. This supports a strategy of direct hedging (e.g., using oil derivatives) rather than relying on simple equity-based diversification to mitigate this specific exposure. Conversely, the significant information flow from airline indices to the OVX suggests that the airline sector can act as a leading indicator of future oil market volatility. Portfolio managers can use this signal as an early warning signal to adjust volatility hedges proactively. Furthermore, the RTE results offer a valuable tool for tail-risk management. By focusing on extreme events (via the $q$-parameter), our findings provide a quantitative input for advanced risk models designed to build portfolios that are more resilient to systemic shocks, a concept increasingly explored in recent literature on entropy-based portfolio optimization.

This study provides a foundation for future research on volatility transmission, risk management, and strategic decision-making in energy-dependent industries by uncovering the complex interplay between energy markets and airline stocks.

Although this research offers valuable information regarding the relationships between oil prices and airline stocks, its findings open several possibilities for future research. Firstly, the analytical framework could be enriched by introducing a broader set of macroeconomic and geopolitical variables (e.g., interest rates, inflation, and specific geopolitical risks), which may help clarity the contextual drivers behind the observed information flow dynamics. Additionally, a comparative analysis of information flows originating from different global oil benchmarks, such as Brent crude, could offer more nuanced perspectives on the regional sensitivities of the airline industry. Second, a deeper analysis could be achieved by disaggregating oil price shocks into their underlying components, such as supply-side shocks, aggregate demand shocks, and oil-specific demand shocks, as the literature suggests these categories have heterogeneous effects on financial markets (Alzate-Ortega et al., 2024). Third, a particularly important and methodologically distinct direction for future research would be to investigate the transmission of volatility between these markets directly. While our entropy-based analysis reveals the direction of information flow, a dedicated study on volatility spillovers would quantify the propagation of risk and uncertainty, widely recognized as a critical channel of financial interdependence (Ben Rejeb & Arfaoui, 2016). This would require a different methodological approach, likely employing multivariate GARCH models or the well-established spillover index methodology based on vector autoregressions. By measuring the magnitude and direction of volatility spillovers, future research could determine whether the oil market and the airline sector act as net transmitters or receivers of risk, and how these dynamics evolve during periods of market stress, such as the COVID-19 pandemic. This would provide a complementary perspective to the present study, moving the focus from information flow to risk transmission, and contribute to a more comprehensive understanding of the financial interconnectedness of energy-dependent sectors (Bastianin & Manera, 2018). Fourth, employing high-frequency data in conjunction with machine learning-based prediction techniques could also enhance the understanding of short-term market responses and strengthen risk management practices for investors and airline managers. Fifth, research on the effects of alternative energy sources and sustainability measures on airlines' cost structures can provide new insights into changing relationships between fuel markets and the airline sector. Although, transportation sector has growth potential, the aviation industry will have a hard time replacing this with fuel from other sources, even if air traffic remains at current levels (Nygren et al., 2009).

Lastly, an analysis of structural breaks within the sample, such as the period covering the COVID-19 pandemic, could be conducted. This would enable a comparison of information flow dynamics between stable and crisis periods, providing valuable insights into the robustness and temporal stability of the relationships identified in this study.

By addressing these dimensions, future research can build upon the current findings to develop a more comprehensive framework for understanding the transmission of volatility and financial interconnectedness among energy-dependent sectors.

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**Declaration of competing interest**

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

**Appendix 1. Shannon transfer entropy (STE) between WTI and airline indices with lag-length specifications ($k = l = 2$ and $k = l = 3$)**

| Information flow | Lag_X | Lag_Y | TE | ETE | Std.Err. | $p$-value | Net TE |
|---|---|---|---|---|---|---|---|
| WTI→FR_Global | 2 | 2 | 0.0413*** | 0.0224 | 0.0036 | 0.0000 | −0.0030 |
| FR_Global→WTI | 2 | 2 | 0.0443*** | 0.0248 | 0.0033 | 0.0000 | |
| WTI→FR_Global | 3 | 3 | 0.0844*** | 0.0418 | 0.0064 | 0.0000 | −0.0044 |
| FR_Global→WTI | 3 | 3 | 0.0888*** | 0.0438 | 0.0066 | 0.0000 | |
| WTI→ARCA_Global | 2 | 2 | 0.0430*** | 0.0240 | 0.0036 | 0.0000 | −0.0018 |
| ARCA_Global→WTI | 2 | 2 | 0.0449*** | 0.0253 | 0.0033 | 0.0000 | |
| WTI→ARCA_Global | 3 | 3 | 0.0848*** | 0.0410 | 0.0060 | 0.0000 | 0.0020 |
| ARCA_Global→WTI | 3 | 3 | 0.0828*** | 0.0368 | 0.0063 | 0.0000 | |
| WTI→MSCI_World | 2 | 2 | 0.0448*** | 0.0257 | 0.0039 | 0.0000 | −0.0037 |
| MSCI_World→WTI | 2 | 2 | 0.0486*** | 0.0295 | 0.0032 | 0.0000 | |
| WTI→MSCI_World | 3 | 3 | 0.0898*** | 0.0462 | 0.0061 | 0.0000 | −0.0037 |

(continued on next page)

(*continued*)

| Information flow | Lag_X | Lag_Y | TE | ETE | Std.Err. | *p*-value | Net TE |
|---|---|---|---|---|---|---|---|
| MSCI_World→WTI | 3 | 3 | 0.0934*** | 0.0487 | 0.0065 | 0.0000 | |
| WTI→Dow_Jones | 2 | 2 | 0.0393*** | 0.0202 | 0.0037 | 0.0000 | 0.0025 |
| Dow_Jones→WTI | 2 | 2 | 0.0367*** | 0.0175 | 0.0034 | 0.0000 | |
| WTI→Dow_Jones | 3 | 3 | 0.0956*** | 0.0502 | 0.0067 | 0.0000 | 0.0010 |
| Dow_Jones→WTI | 3 | 3 | 0.0946*** | 0.0495 | 0.0063 | 0.0000 | |
| WTI→FR_Emerging | 2 | 2 | 0.0387*** | 0.0208 | 0.0035 | 0.0000 | 0.0005 |
| FR_Emerging→WTI | 2 | 2 | 0.0382*** | 0.0192 | 0.0037 | 0.0000 | |
| WTI→FR_Emerging | 3 | 3 | 0.0806*** | 0.0391 | 0.0070 | 0.0000 | −0.0011 |
| FR_Emerging→WTI | 3 | 3 | 0.0817*** | 0.0371 | 0.0064 | 0.0000 | |
| WTI→FR_G7 | 2 | 2 | 0.0408*** | 0.0215 | 0.0037 | 0.0000 | −0.0051 |
| FR_G7→WTI | 2 | 2 | 0.0459*** | 0.0267 | 0.0033 | 0.0000 | |
| WTI→FR_G7 | 3 | 3 | 0.0872*** | 0.0431 | 0.0071 | 0.0000 | −0.0075 |
| FR_G7→WTI | 3 | 3 | 0.0947*** | 0.0497 | 0.0065 | 0.0000 | |

Notes: (i) *p-values*: <0.01 '***', <0.05 '**', <0.1 '*'; (ii) Net TE corresponds to the Net STE, defined as the difference between the STE (represented as TE in the table) from WTI→ Airline index and Airline index → WTI; (iii) ETE is the effective transfer entropy, as defined by Marschinski and Kantz (2002). It is computed by comparing the original transfer entropy with that obtained from a shuffled version of the source time series. By randomizing the source series, spurious correlations are removed, allowing ETE to isolate the true nonlinear transfer of information between variables.

## Appendix 2. Shannon transfer entropy (STE) between OVX and airline indices with lag-length specifications ($k = l = 2$ and $k = l = 3$)

| Information flow | Lag_X | Lag_Y | TE | ETE | Std.Err. | *p*-value | Net TE |
|---|---|---|---|---|---|---|---|
| OVX→FR_Global | 2 | 2 | 0.0232 | 0.0047 | 0.0034 | 0.0667 | −0.0206 |
| FR_Global→OVX | 2 | 2 | 0.0438*** | 0.0265 | 0.0032 | 0.0000 | |
| OVX→FR_Global | 3 | 3 | 0.0585*** | 0.0163 | 0.0059 | 0.0000 | −0.0105 |
| FR_Global→OVX | 3 | 3 | 0.0690*** | 0.0307 | 0.0060 | 0.0000 | |
| OVX→ARCA_Global | 2 | 2 | 0.0260** | 0.0077 | 0.0035 | 0.0200 | −0.0158 |
| ARCA_Global→OVX | 2 | 2 | 0.0418*** | 0.0243 | 0.0030 | 0.0000 | |
| OVX→ARCA_Global | 3 | 3 | 0.0687*** | 0.0254 | 0.0062 | 0.0000 | −0.0001 |
| ARCA_Global→OVX | 3 | 3 | 0.0687*** | 0.0297 | 0.0057 | 0.0000 | |
| OVX→MSCI_World | 2 | 2 | 0.0309*** | 0.0121 | 0.0037 | 0.0000 | −0.0111 |
| MSCI_World→OVX | 2 | 2 | 0.0420*** | 0.0249 | 0.0033 | 0.0000 | |
| OVX→MSCI_World | 3 | 3 | 0.0622*** | 0.0191 | 0.0066 | 0.0000 | −0.0045 |
| MSCI_World→OVX | 3 | 3 | 0.0667*** | 0.0287 | 0.0055 | 0.0000 | |
| OVX→Dow_Jones | 2 | 2 | 0.0262** | 0.0076 | 0.0034 | 0.0133 | −0.0118 |
| Dow_Jones→OVX | 2 | 2 | 0.0381*** | 0.0204 | 0.0030 | 0.0000 | |
| OVX→Dow_Jones | 3 | 3 | 0.0737*** | 0.0290 | 0.0065 | 0.0000 | −0.0022 |
| Dow_Jones→OVX | 3 | 3 | 0.0759*** | 0.0373 | 0.0058 | 0.0000 | |
| OVX→FR_Emerging | 2 | 2 | 0.0221 | 0.0044 | 0.0034 | 0.1200 | −0.0104 |
| FR_Emerging→OVX | 2 | 2 | 0.0325*** | 0.0148 | 0.0030 | 0.0000 | |
| OVX→FR_Emerging | 3 | 3 | 0.0523** | 0.0120 | 0.0065 | 0.0267 | −0.0038 |
| FR_Emerging→OVX | 3 | 3 | 0.0561*** | 0.0175 | 0.0057 | 0.0000 | |
| OVX→FR_G7 | 2 | 2 | 0.0276** | 0.0086 | 0.0035 | 0.0133 | −0.0157 |
| FR_G7→OVX | 2 | 2 | 0.0433*** | 0.0257 | 0.0031 | 0.0000 | |
| OVX→FR_G7 | 3 | 3 | 0.0655*** | 0.0220 | 0.0059 | 0.0000 | −0.0045 |
| FR_G7→OVX | 3 | 3 | 0.0699*** | 0.0313 | 0.0059 | 0.0000 | |

Notes: (i) *p-values*: <0.01 '***', <0.05 '**', <0.1 '*'; (ii) Net TE corresponds to the Net STE, defined as the difference between the STE (represented as TE in the table) from OVX→ Airline index and Airline index → OVX; (iii) ETE is the effective transfer entropy, as defined by Marschinski and Kantz (2002). It is computed by comparing the original transfer entropy with that obtained from a shuffled version of the source time series. By randomizing the source series, spurious correlations are removed, allowing ETE to isolate the true nonlinear transfer of information between variables.

## Data availability

Data will be made available on request.

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