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Modelling for insight: Does oil price uncertainty have directional predictability for travel and leisure firms?

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ABSTRACT

This study investigates how uncertainty surrounding crude oil prices affects the stock returns of travel and leisure (T&L) companies. Through a comprehensive analysis, we address three key questions: (a) Does oil price uncertainty predict T&L stock returns directionally? (b) How does varying oil uncertainty affect T&L returns under different market conditions? (c) Is this association consistent across continents? Using the implied oil volatility index (OVX) as a proxy for oil price uncertainty and cross-quantilogram modelling, our study reveals significant impacts of OVX on T&L stock returns, with varying predictability across continents. We find that stock returns are more vulnerable mainly during bearish market conditions, with predictability strength varying over time horizons. Our findings highlight the importance for T&L firms to mitigate oil risk exposure, potentially leveraging emerging technologies like electric vehicles. This study provides insights into the interplay between oil uncertainty and T&L stock returns, with implications for industry practitioners, investors, and policymakers aiming to foster sustainable tourism development amidst oil market volatility due to geopolitics.

1. Introduction

The critical role of crude oil (oil) in the global economy and business performance has been well-recognized in the past literature (Hamilton, 1996; Kilian, 2008). Travel and leisure (T&L) is one of the industries that could be substantially vulnerable to oil uncertainties. A growing stream of empirical studies models firms' oil price uncertainty exposure by gauging their stock market movement to measure business performance (Dutta, 2017; Xiao et al., 2018; Joo and Park, 2021). These studies advocate that a precise cognisance of this association is relevant to framing energy and macroeconomic policies, designing financial risk-mitigating strategies, and detailing international oil demand and supply regulations. We believe that fluctuations in oil prices can impact the stock returns of the T&L industry for at least three reasons. First, oil is a vital input resource for the T&L industry due to its intrinsic travel element (Becken, 2008). In addition, leisure activities such as boat cruises, jet boating, and wildlife safari fleets are oil-dependent and, thus, exposed to oil price volatility (Becken and Lennox, 2012; Becken and Simmons, 2002). Since oil expenses are a direct cost factor to the T&L industry, large oil fluctuations could destabilize their profitability. The dwindling profitability could translate into weaker stock market fundamentals. Second, oil price uncertainties could often stimulate inflationary conditions (Castillo et al., 2020). Under such circumstances, tourists may hesitate to opt for faraway destinations and avail themselves of leisurely services due to their limited disposable income. The constrained consumption demand by tourists may impede the T&L firms from generating sufficient revenues, making their stocks unattractive to investors. Therefore, the T&L market indexes could underperform. Third, besides oil being a central commodity, it also manifests certain financial attributes. Oil as a financial instrument is liquid and is often used in hedging equity market downside risks effectively (Basher and Sadorsky, 2016). Jalkh et al. (2021) posit that oil is a suitable instrument to hedge T&L stocks effectively. Such growing hedging strategies and financialization of oil are likely to intensify the connectedness between oil and T&L stock markets. Modelling the relationship carefully can provide useful insights to mitigate financial

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[1] The direct effects include the immediate impact of oil price uncertainty on firms' operational costs, such as aviation, cruise operations, and long-distance transportation. Increased uncertainty in oil prices raises cost variability, thereby affecting future cash flows and ultimately influencing stock prices. The indirect effects are more strategic and stem from firms' responses to mitigate oil-related risks. T&L companies may often employ financial hedging tools such as futures, options, or swaps to lock in oil prices and reduce earnings volatility.

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risks and design macroeconomic policies related to tourism and oil regulations.[1]

An emerging stream of studies in tourism literature examines the role of macroeconomic instabilities on the stock returns of T&L firms. For instance, Chen and Bin (2001) examine the impact of the US government's decision to deregulate casino gaming on the online gaming firm's stock return. Demiralay and Kilincarslan (2019) assess the impacts of geopolitical risk on the stock returns of T&L firms. Yeon et al. (2021) claim that the stock returns of socially responsible tourism and hospitality industry firms are largely insulated from the COVID-19 shocks. On a similar note, Chen et al. (2022) observe that the stocks of hotels committed to environmental, social, and governance (ESG) compliance are more resilient during the COVID-19 pandemic. Therefore, the literature on tourism management has largely appreciated stock returns as a reliable proxy for firm performance. Moreover, it is also imperative to recognize that T&L is a capital-intensive industry (Nunkoo et al., 2020). The listed T&L firms raise money from the public through the issue of stocks for capital expenditure and facility development investments. Thus, a precise understanding of how different macroeconomic episodes potentially affect stock prices may help the managers of the T&L firms in shaping fund-raising strategies. Additionally, understanding the dependence structure of T&L stocks with respect to macroeconomic shocks is relevant to existing and prospective investors from an investment perspective. Therefore, it is pertinent to derive insights into how the T&L stock prices respond to various macroeconomic events to proliferate sustainable tourism development.

To that end, we deliberate on the following questions: (a) Can oil price uncertainty directionally predict the stock returns of the T&L industry? (b) How do the different degrees of oil uncertainty predict the returns of the T&L industry in different market states? and (c) Is the association between oil uncertainty and the T&L industry returns similar across the geographic continents? Given the economic and policy-relevant implications, these questions are intriguing for unravelling the nexus between oil uncertainty and the T&L industry. Nevertheless, very few studies in the tourism and economics literature delve into these questions. To the best of our knowledge, this is one of the first studies to highlight the directional predictability of oil price uncertainty and quantile dependence of the T&L industry returns by employing cross-quantilogram modelling of Han et al. (2016). We consider the implied oil volatility index (OVX) as a proxy for the oil price uncertainty following previous literature (see Dutta (2017) and Luo and Qin (2017)). Prior to this paper, the role of oil volatility in the T&L industry returns is recognized by only a few studies. Shahzad and Caporin (2020) examine the predictability of OVX to tourism firms' composite stock volatility using the heterogeneous auto-regression (HAR) model. The results suggest that oil uncertainty can predict the volatility of tourism stocks only in the short run. Using the dynamic conditional correlation models, Jalkh et al. (2021) evaluate the hedging effectiveness of T&L stocks to the various implied volatility indexes in the US. Their study concludes that OVX is consistently negatively correlated with T&L stocks. Hence, OVX is a suitable hedge to T&L stocks. Our paper is fundamentally distinct from these two studies as the questions we pose above differ greatly.

In the vein of tourism, several other studies examine the exposure of tourism/T&L stocks towards oil price changes. Chatziantoniou et al. (2013) adopt a structural vector autoregression (SVAR) approach and report that oil-specific demand shocks significantly influence tourism stock indexes. Employing the asset-pricing framework of Fama and French (1997), Mohanty et al. (2014) study the oil risk susceptibility of the US T&L industry considering the stock indexes of the T&L sub-sectors. They conclude that the sensitivity of index returns towards the oil prices varies across sub-sectors. However, the airline appears to be the most vulnerable sub-sector. Qin et al. (2021) investigate the role of oil prices in the Chinese T&L industry using the time-varying parameter (TVP) VAR model. The authors report mixed evidence, asserting that the T&L industry oscillates between positive and negative returns in response to oil price movements. Hadi (2023) uses causality-in-quantiles and wavelet coherence analysis to examine the nexus between oil prices and tourism stock returns of 12 major tourism destination countries. The results show a weaker causal and positive association between the variables for only 3 countries. Recently, Liang et al. (2024) also examined the oil and the T&L industry return link using the maximum overlap discrete wavelet transformation (MODWT) based Bayesian TVP models. They find that oil price changes induce volatility in the T&L industry returns. Further, the association varies across time and scales. The research trends show that after the seminal theoretical framework on the link between oil and tourism proposed by Becken (2008), Becken and Lennox (2012), a series of studies have gradually explored different dimensions of this relationship over the last decade.

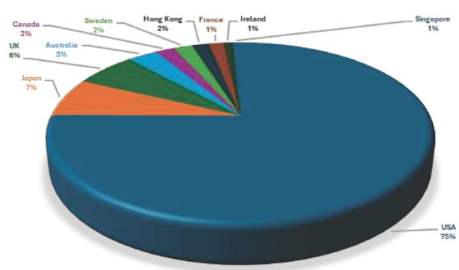
We contribute to the growing literature in at least three ways. First, while most of the past studies use oil price changes as a proxy for oil uncertainty, we consider OVX instead. This has some potential advantages. OVX is a forward-looking (30-days ahead) gauge of oil price uncertainty, which is composed and published by the Chicago Board Options Exchange (CBOE). This index is derived from oil option prices, and several other studies consider OVX to be a reliable marker of oil price uncertainty (Das et al., 2023; Liu et al., 2013). Moreover, as OVX is an implied volatility index, it envelopes investors' future market expectations in addition to historical volatility information (Maghyereh et al., 2016). Furthermore, studies suggest that OVX has more information content than oil price changes or conditional volatility (Das et al., 2022a,c). Second, we resort to the cross-quantilogram modelling proposed by Han et al. (2016). This enables us to examine the directional predictability and quantile dependence between OVX and T&L stocks across various quantiles rather than solely focusing on the median value. The cross-quantilogram technique provides a correlation statistic derived from quantile hit processes, allowing for an assessment of the dependence between the quantile ranges of two time-series variables (Han et al., 2016). Particularly relevant to financial time-series analysis, this technique does not require fulfilment of the moment condition. It is widely acknowledged that finite fourth moments are often non-existent for stock returns despite some time-series models assuming their existence (Zhou et al., 2019).

Lastly, we also contribute by examining whether the influence of oil price uncertainty is similar across the geographic continent. We first consider the global T&L industry index and then analyse the disaggregated continent-specific indexes of North America, Europe, and Asia. The continent-specific analysis is relevant since the impact of oil uncertainty may differ across continents due to: (a) heterogeneity in the degree of oil imports and (b) heterogeneity in the level of destination attractiveness. Thus, a precise understanding of whether oil uncertainty affects the T&L indexes across different continents alike could help in shaping tourism policy decisions. We believe that the contributions of our study are relevant from the policy standpoint since the T&L industry is expected to grow at a compound annual growth rate (CAGR) of 21.8% between the year 2024–2030.[2] Managing oil uncertainty risks is pivotal to translating the T&L industry growth projections into reality.

We find that the OVX has a statistically significant impact and directional predictability towards the T&L firm stock returns. We also observed that stock returns are more vulnerable when the returns are bearish. In the bullish state, the negative effects are weakened. In terms of directional predictability, we find that the strength of predictability varies over the time horizon of lag days. Nevertheless, the pattern of predictability remains qualitatively identical across all geographic continents. We argue that the T&L firms should minimize their oil

[2] Virtue Market Research (VMR) estimates the value of the global leisure travel market at USD 1.46 trillion in 2023. This market is projected to achieve a market volume of 5.81 trillion by 2030 – Source: https://virtuemarketresearch.com/report/leisure-travel-market.

(a) Geographic coverage of STOXX T&L Global index



(b) Weights of STOXX T&L Global index

Fig. 1. Geographic coverage and country-weights of STOXX T&L Global index.
Note: These graphs show the country coverage and weights of the STOXX T&L Global index. The country weights are as follows: USA: 74.90%, Japan: 6.90%, UK: 6.20%, Australia: 3.00%, Sweden: 1.90%, Canada: 1.90%, Hong Kong: 1.70%, France: 1.50%, Ireland: 0.90%, and Singapore: 0.80%.

risk exposure by dissociating themselves from higher oil dependence. Leveraging the emergence of electric vehicles (EVs), these firms can restrict negative spillovers from oil price oscillations.

The remainder of the document is organized as follows. Section 2 offers a concise overview of the theoretical framework. Section 3 outlines the data utilized and the methodological approach. In Section 4, the empirical findings are examined, while Section 5 explores the implications of the study. Finally, Section 6 provides concluding remarks.

2. Theoretical framework

In this section, we discuss the theoretical framework that guides our analysis. To understand the influence of oil price uncertainty on T&L stock's return, we refer to the dividend discount model (DDM), which is a canonical fundamental stock price valuation model. This model assumes that the stock price of a firm depends on future earnings (or dividend income) and the rate at which it is discounted (or the rate of return demanded by the equity holders). Following Hillier et al. (2019) and Chen (2011), we can write the DDM as:

$$P_{i,t} = \sum_{t=1}^{T} \frac{Div_{i,t}}{(1+r)^t} \tag{1}$$

where, $Div_{i,t} = p_{i,t} \times Net\ Income_{i,t}$
$Net\ Income_{i,t} = EBIT_{i,t} - I_{i,t} - T_{i,t}$
$EBIT_{i,t} = R_{i,t} - COS_{i,t} - OE_{i,t}$

In Eq. (1), $P_{i,t}$ represents the stock price of firm i at time t; $Div_{i,t}$ denotes the dividend paid by firm i at time t; r stands for the discount rate or expected rate of return; $p_{i,t}$ signifies the dividend payout ratio of firm i at time t; $R_{i,t}$ indicates the total revenue earned by firm i at time t; $COS_{i,t}$ represents the cost of goods sold by firm i at time t; $OE_{i,t}$ stands for the operating expense of firm i at time t; $I_{i,t}$ denotes the total interest amount paid by firm i at time t; and $T_{i,t}$ represents the tax expense incurred by firm i at time t. As can be observed, the change in stock price depends on the changes in the firm's future earnings and the rate of return demanded by the equity holders. Next, we discuss how oil price uncertainty can influence both the future earnings of T&L firms and the rate of return demanded by stockholders, thus impacting the return of T&L stocks.

There are three potential mechanisms through which oil price uncertainty can affect the T&L stock returns. First, the cost of oil is a direct expense for the T&L firms, so any uncertainty regarding the oil price can increase the uncertainty regarding the firm's future earnings (Becken and Simmons, 2002; Becken and Lennox, 2012). Stockholders can demand a higher rate of return from T&L stock due to this increased uncertainty in the firm's future earnings, which in turn leads to a reduction in stock price. Second, higher oil price uncertainty induces inflationary pressure in the economy, which results in lower demand for travel and leisure activities (Castillo et al., 2020). This can create downward pressure on the T&L firm's earnings and reduce the dividend payout of the T&L firms. As can be seen from Eq. (1), this can lead to a reduction in stock price. Lastly, oil, being a central commodity with financial attributes, is used by investors to hedge any adverse movement in the T&L stocks (Jalkh et al., 2021). Hence, when oil price uncertainty increases, the effectiveness of the oil as a hedge reduces, which can increase the risk exposure of investors who, in turn, can increase the demanded rate of return from T&L stocks. This can lead to a reduction in the stock price. Taken together, an increase in oil price uncertainty can simultaneously decrease future earnings and increase the return demanded by stockholders from T&L stocks, causing lower stock prices.

Additionally, it is also possible that investor sentiment, cognitive biases, and risk perceptions during periods of heightened oil price uncertainty can lead to overreactions or underreactions in stock prices (Barberis et al., 1998). The behavioural perspective may drive market responses to oil volatility, which may not always align with fundamental valuations alone. The previous studies have noted that changes in investors' sentiment due to oil price movements can impact stock returns (Gupta and Banerjee, 2019).

Table 1
Descriptive statistics of the T&L index returns.

Stats	OVX	Global	North America	Europe	Asia-Pacific
Mean	−0.0007	0.0189	0.0325	−0.0018	0.0036
Median	−0.3855	0.0460	0.0809	0.0435	0.0251
Std. Dev.	5.6862	1.0725	1.4398	1.7054	1.0820
Skewness	1.5762	−0.5762	−0.5160	−0.3367	−0.1032
Kurtosis	29.7507	11.7380	12.8287	10.1038	7.0967
Max	85.7700	9.0761	13.7804	11.6395	8.0861
Min	−62.2251	−10.1459	−14.6008	−15.8468	−7.9950
ADF	−70.017***	−57.216***	−65.682***	−61.604***	−67.093***
PP	−71.111***	−57.072***	−65.741***	−61.529***	−67.211***
Obs.	4213	4213	4213	4213	4213

Note: ADF and PP are the Augmented Dickey–Fuller and Phillips–Perron tests for unit roots.
*** Indicates statistical significance at a 1% level.

3. Data and methodological framework

3.1. Data

To econometrically quantify the impact of oil price uncertainty on the T&L industry, we consider four T&L stock indexes representing global and continent-specific performance following Demiralay and Kilincarslan (2019). They are: (a) STOXX Travel & Leisure Global, representing global performance; and (b) STOXX Travel & Leisure North America, (c) STOXX Travel & Leisure Europe, and (d) STOXX Travel & Leisure Asia-Pacific, representing continent-specific performances. The T&L indexes are extracted at a daily frequency from the Bloomberg database. The country-wise coverage and weights of the STOXX T&L Global Index are presented in Fig. 1.[3] We can observe that most of the T&L firms covered under the index are from the US. Additionally, the index is mainly dominated by developed markets. The T&L index ensembles various sub-industries, such as recreational services, travel and tourism, hotels, gambling, restaurants and bars, and airlines. With the diverse inclusion of traded travel, hospitality, and leisure firms, these T&L indexes provide a broader outlook. Further, it is relevant to mention that the STOXX T&L indexes comprise constituent companies based on free-float market capitalization. Thus, leading global and continent-wise T&L companies are included in the index, such as Lufthansa Airlines, Accor Hotels, McDonald's Corporation, The Lottery Corporation, Aristocrat Leisure Ltd., Odakyu Electric Railway Co. Ltd., Starbucks Corporation, Marriot International, AIRBNB A, Qantas Airways Ltd., and many others. The T&L stock indexes are composite indicators that track the performance of tourism and allied companies. This facilitates us to analyse and understand the behaviour of this industry to the oil fluctuations. Moreover, some studies in the past opine that considering industry-level indexes is helpful as it enables researchers to track industry-based sensitivities to macroeconomic uncertainties closely and compare across regions (Das and Kannadhasan, 2020; Demiralay and Kilincarslan, 2019; Zopiatis et al., 2019).

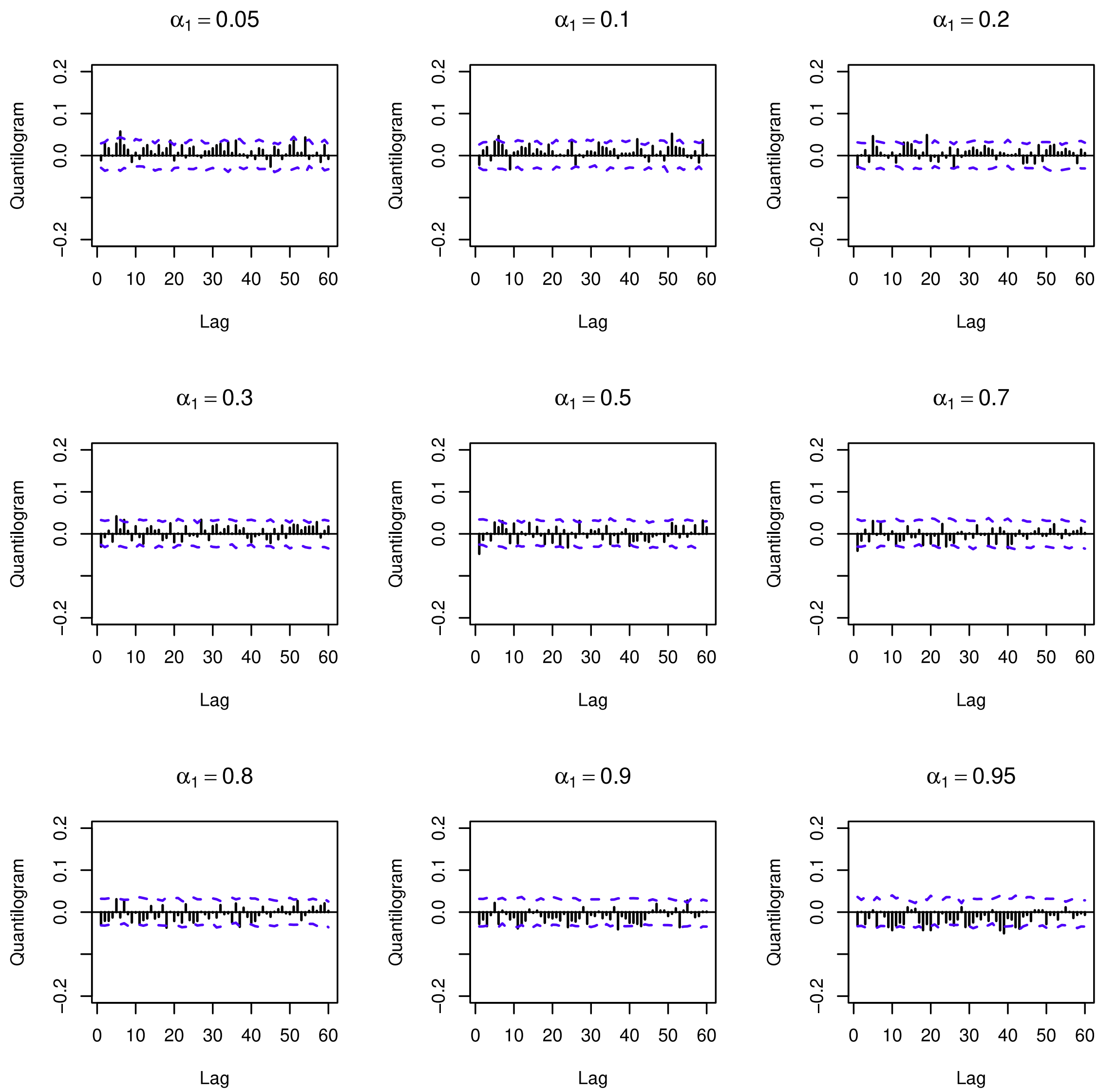
As mentioned before, the oil price uncertainty is represented by OVX published by CBOE following past studies (Liu et al., 2013). OVX has been recognized in prior literature as a superior indicator of oil market volatility. For example, Dutta (2017) compares OVX with various range-based volatility estimators in predicting clean energy stock returns and finds that OVX demonstrates greater predictive accuracy and richer information content. Similarly, Das et al. (2022c) provides empirical evidence that OVX outperforms realized volatilities derived from both spot and futures oil prices in terms of predictive ability. The data for OVX is availed at a daily frequency from the St. Louis FRED database. The study period spans from 11th May 2007 to 28th March 2024, enclosing 4213 daily observations. The earliest availability of the OVX data determines the starting time-point of the study. For the purpose of analysis, all time-series variables are transformed, taking first logged differences. Table 1 describes the summary statistics and the results of the unit root tests for all the variables under consideration. The average value of OVX is weakly negative but most volatile across all the indexes, suggesting a jittery nature of this index. The skewness value of OVX is positive, implying there are more frequent occurrences of positive than negative values. This indicates that OVX tends to rise over time, suggesting more volatile behaviour in oil prices. Among the T&L indexes, all show positive mean returns except for Europe. The North American T&L index depicts the highest mean return value. Further, the unconditional risk described by the standard deviation measure is highest for the European index, followed by the North American. The skewness coefficients show negative values for all the T&L indexes. It denotes that the negative return values occur more recurrently than positive returns. The distribution of the index returns is leptokurtic, signifying the higher likelihood of observing extreme negative returns. The Augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) tests reject the presence of a unit root. Thus, the indexes are stationary and appropriate for proceeding with statistical analysis.

3.2. Methodological framework: The cross-quantilogram

In this section, we provide a brief overview of the cross-quantilogram model proposed by Han et al. (2016), which is valuable for revealing cross-quantile predictability between two-time series. This method offers an improved measure of predictability, especially when dealing with heavy-tailed distributions, as is often the case in our analysis. Given these advantages, we utilize the cross-quantilogram model to specifically examine how the dependence and predictability between OVX and T&L stock returns vary across different risk levels (quantiles).

The cross-quantilogram has emerged as a widely adopted methodology in recent years within the fields of economics and quantitative finance, particularly for analysing directional predictability and dependence across different quantiles. For example, Cho and Han (2021) employed this technique to explore the tail behaviour of safe-haven currencies in response to macro-financial uncertainties. Jiang et al. (2016, 2019) applied the method to examine spillover effects and directional predictability between the Chinese and U.S. agricultural futures markets. Similarly, Todorova (2017) investigated the quantile-based dependence structure among major Australian stocks, while Su et al. (2023) utilized the cross-quantilogram to assess the spillover dynamics between green bonds and green stocks in the Chinese market. Specifically, within the energy markets, Ghosh et al. (2024) reports

[3] The country-wise weights of the other three indexes are spread as (a) STOXX T&L North America: US (97.60%), Canada (2.40%), (b) STOXX T&L Europe: Ireland (32.60%), UK (31.70%), France (17.00%), Sweden (14.60%), Germany (4.10%), and (c) STOXX T&L Asia-Pacific: Japan (52.00%), Australia (23.60%), Hong Kong (16.60%), Singapore (7.80%).



a) The sample cross-quantilogram $\hat{\rho}(k)$ with $\alpha_2 = 0.1$ to detect directional predictability from the OVX to STOXX Travel & Leisure Global index returns. Bar graphs describe the sample cross quantilogram, and blue dashed lines are the 95% bootstrap confidence intervals centered at zero.

Fig. 2. Quantile dependence and directional predictability running from OVX to the STOXX Travel & Leisure Global index returns at $\alpha_2 = 0.1$.

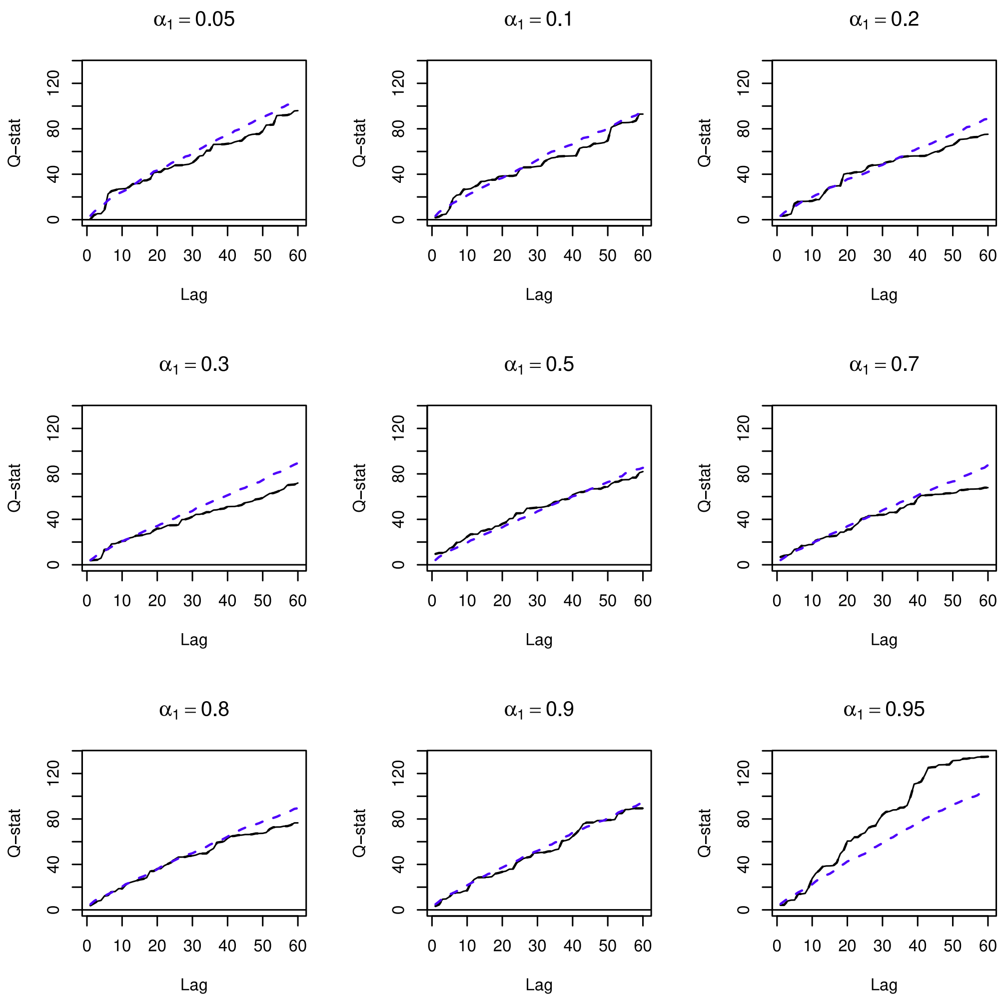
spillover and predictability between US gas and crude oil markets. Niu and Cao (2024) studies the dependence and spillover between the Chinese new energy stocks and carbon markets. Zhou et al. (2019) investigates the directional predictability of OVX for stock returns in the BRICS (Brazil, Russia, India, China and South Africa) countries.

The cross-quantilogram (CQ) approach offers distinct advantages over traditional mean-level methods, particularly when analysing directional predictability across different parts of the distribution of stock returns, such as during extreme market conditions. Additionally, the cross-quantilogram approach does not rely on moment conditions for the underlying time series. This is particularly important given that stock returns often do not possess finite fourth moments. Nevertheless, commonly used models such as multivariate Generalized Autoregressive Conditional Heteroskedasticity (GARCH) typically assume the existence of finite fourth moments, which may yield biased inferences (Zhou et al., 2019).

The previous studies show that the impact of OVX on financial time series, such as stock returns, is asymmetric (Zhou et al., 2019; Xiao et al., 2018). Similar asymmetric impacts of OVX are also observed on the stock implied volatility index (Xiao et al., 2019) and the financial stress index (Das et al., 2023). The asymmetric impact implies that different degrees of oil volatility can impact the stock returns differently. Thus, the impact of OVX on stock returns may differ across the bearish and bullish states. Thus, the cross-quantilogram method is suitable to assess directional predictability of OVX across different parts of the distribution of stock returns, providing a better understanding of the relationship in extreme market conditions.

A set of strictly stationary and two-dimensional time series should be noted as $\{y_{it}, t \in \mathbb{Z}\}, i = 1, 2$. Thus, we set the series of stock returns and OVX as y_{1t}, y_{2t}, respectively. Let $F_i(\cdot)$ be the distribution function of the series y_{it} and its density function be $f_i(\cdot)$. Therefore, $q_i(\alpha_i) = \inf\{v : F_i(v) \geq \alpha_i\}$ for $\alpha_i \in (0, 1)$ can be defined as the quantile function of x_{it}. The quantile range for which we are interested in capturing the directional predictability is denoted by $\tilde{\alpha}$. For ease of understanding, the Cartesian product of two close intervals in $(0, 1)$ may be assumed as $\tilde{\alpha}$. Then, $\tilde{\alpha} = \tilde{\alpha_1} \times \tilde{\alpha_2}$, where $\alpha_i = |\alpha_i, \bar{\alpha}_i|$ for $0 < \alpha_i < \bar{\alpha}_i < 1$.

We deem a gauge of serial dependence between two events expressed as $\{y_{1t} \leq q_1(\alpha_1)\}$ and $\{y_{2t} \leq q_2(\alpha_2)\}$ for some arbitrary quantiles. Hence, the quantile-exceedance or quantile-hit process for $i = 1, 2$ is inferred as $\{1[y_{it} \leq q_i(\cdot)]\}$.



b) Box–Ljung test statistic $\hat{Q}_\alpha^{(p)}$ for each lag p and quantile α using $\hat{\rho}_\alpha(k)$ with α_2 =0.1 in STOXX Travel & Leisure Global index returns. The blue dashed lines are the 95% bootstrap confidence intervals centered at zero.

Fig. 2. (*continued*).

Therefore, the cross-correlation of the quantile-exceedances (or quantile-hit process) is defined as the cross-quantilogram, which can be mathematically defined as:

$$\rho_\alpha(\kappa) = \frac{\mathbb{E}[\psi_{\alpha_1}(y_{1t} - q_1(\alpha_1))\psi_{\alpha_2}(y_{2t} - q_2(\alpha_2))]}{\sqrt{\mathbb{E}[\psi^2_{\alpha_1}(y_{1t} - q_1(\alpha_1))]}\sqrt{\mathbb{E}[\psi^2_{\alpha_2}(y_{2t} - q_2(\alpha_2))]}} \tag{2}$$

For $\kappa = 0, \pm 1, \pm 2, \ldots$, where $\psi_\alpha(\mu) \equiv 1[\mu < 0] - \alpha$, thus at various quantile levels, the serial dependence structure between two time series variables can be captured using cross-quantilogram. Further, the processes $\{(y_{1t}, y_{2t})\}_{t\in\mathbb{N}}$ remains well-defined even when considering infinite moments. Similar to the quantilogram, the cross-quantilogram method remains invariant under strictly monotonic transformations applied to a pair of series, such as logarithmic transformations.

To estimate the unconditional quantile functions, we separately solve the following minimization problems:

- $\hat{q}_1(\alpha_1) = \text{argmin}_{v_1\in\mathbb{R}} \sum_{t=1}^T \pi_{\alpha_1}(x_1 - v_1)$
- $\hat{q}_2(\alpha_2) = \text{argmin}_{v_2\in\mathbb{R}} \sum_{t=1}^T \pi_{\alpha_2}(y_2 - v_2)$ Here, $\pi_\alpha(\mu)$ is defined as $\mu(\alpha - 1[\mu < 0])$. These steps help in constructing the sample analogue of the cross-quantilogram for observations $y_1, \ldots, y_T$.

Thus, the sample cross-quantilogram is defined as:

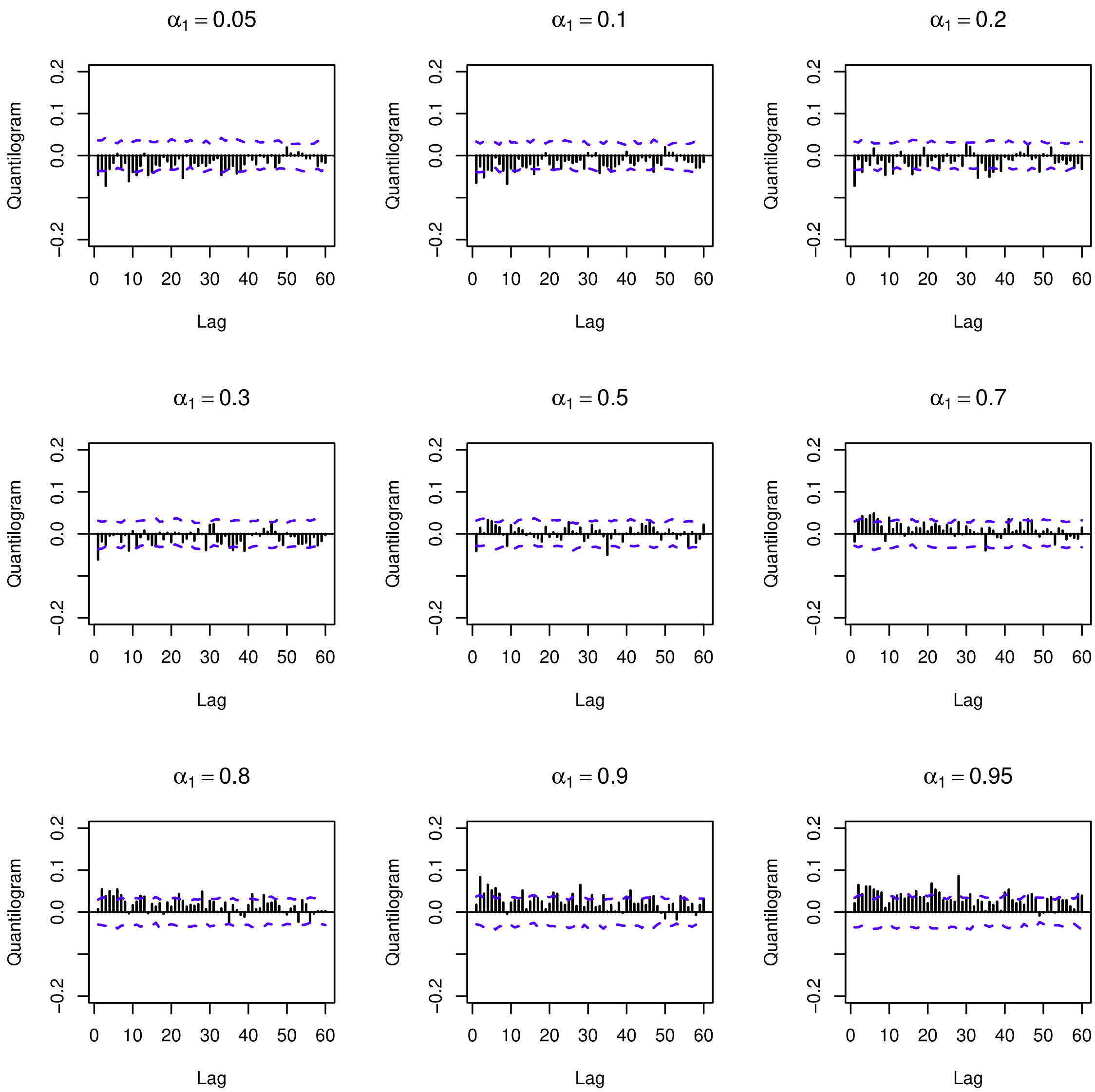
$$\rho_\alpha(\kappa) = \frac{\sum_{t=k+1}^T[\psi_{\alpha_1}(y_{1t} - \hat{q}_1(\alpha_1))\psi\alpha_2(y_{2t-k} - \hat{q}_2(\alpha_2))]}{\sqrt{\sum_{t=k+1}^T[\psi^2_{\alpha_1}(y_{1t} - \hat{q}_1(\alpha_1))]}\sqrt{\sum_{t=k+1}^T[\psi^2_{\alpha_2}(y_{2t-k} - \hat{q}_2(\alpha_2))]}} \tag{3}$$

For $\kappa = 0, \pm 1, \pm 2, \ldots$, $\hat{\rho}_\alpha(\kappa) \in [-1, 1]$ with $\hat{\rho}_\alpha(\kappa) = 0$ in the case of no directional predictability running from OVX to returns of the T&L stock indexes. However, if $\hat{\rho}_\alpha(\kappa) \neq 0$, in that case OVX has directional predictability for the T&L stock returns. If ρ is known, then one may test the following null hypothesis $H_0 : \rho_\alpha(\kappa) = 0$ against the alternative hypothesis of $H_1 : \rho_\alpha(\kappa) \neq 0$ for all $\kappa \in \{1, \ldots, p\}$. For the events up to lag of p, this sets a test of directional predictability $\{y_{2t-k} \leq q_{2,t-k}(\alpha_2)\}$ for $\{y_{1t} \leq q_{1,t}(\alpha_1)\}$, $k = 1, \ldots, p$. To understand the distinction between the stated null and alternative hypothesis, the following version of the Box–Ljung test is used: $\hat{Q}_\alpha^{(P)} = T(T+2)\sum_{k=1}^p \hat{\rho}^2_\alpha/(T-k)$. Therefore, the derived values of the portmanteau test $\hat{Q}_\alpha^{(P)}$ can indicate the directional predictability up to p lags at a quantile pair.

4. Empirical results

4.1. Preliminary results

This section discusses some preliminary results before proceeding to our main results. Table 2 presents the univariate ordinary least

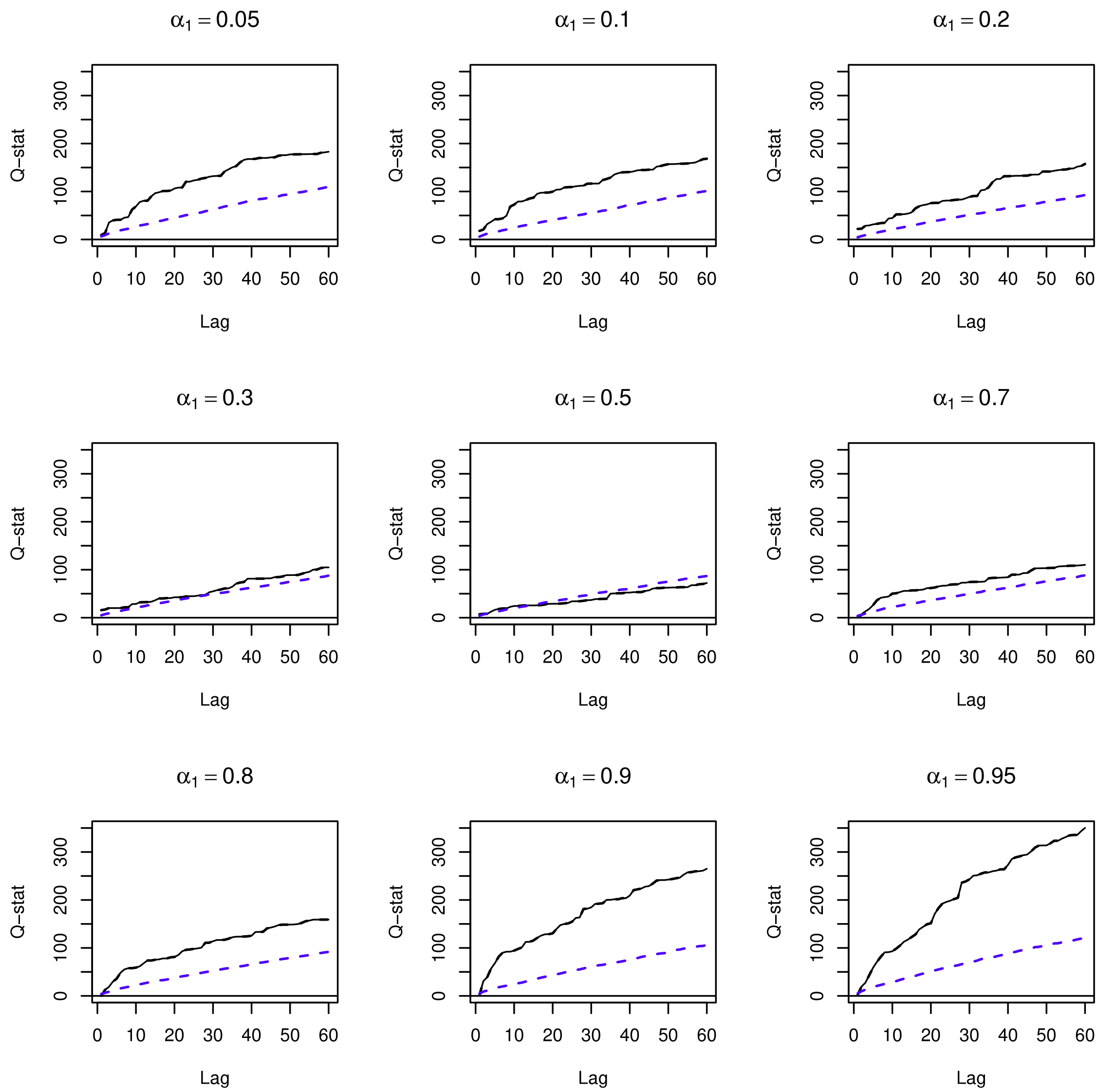


a) The sample cross-quantilogram $\hat{\rho}(k)$ with $\alpha_2 = 0.9$ to detect directional predictability from the OVX to STOXX Travel & Leisure Global index returns. Bar graphs describe the sample cross quantilogram, and blue dashed lines are the 95% bootstrap confidence intervals centered at zero.

Fig. 3. Quantile dependence and directional predictability running from OVX to the STOXX Travel & Leisure Global index returns at $\alpha_2 = 0.9$.

squares (OLS) regression results to assess the impact of OVX on the T&L industry returns. We find that the impact of OVX is negative and statistically significant at a 1% level. The regression coefficients show that the European T&L index is most impacted, followed by the North American returns. The Asia-Pacific index is least affected by OVX. We apply the quantile regression (QR) model (Koenker and Jr, 1978) for further insights. Using the QR model, we can analyse and interpret the impacts of OVX across different market states of the T&L industry represented by the various quantiles (q). Table 3 reports the results,[4] and q05–q25 indicates a bearish market state, implying the phases of weaker market conditions. Meanwhile, q75–q95 denotes a bullish market state, i.e., phases of the prospective market environment. The q50 represents the normal state of the market. Our foremost observation is that all the coefficients are negative and statistically significant at a 1% level. This suggests that the impact of OVX is consistently negative and significant, irrespective of the market states. Also, like the univariate OLS regression results, we find that the Asia-Pacific index returns are the least impacted. Nevertheless, one crucial observation is that the coefficient values for all the index returns weaken monotonically from lower to higher quantiles. It implies that the impact of OVX is less negative in the higher quantiles. We can attribute two seemingly related reasons for such a behaviour. The first reason could be that volatile oil prices could largely subvert the profitability of the T&L industry, especially when it is not performing well (bearish state). Thus, the negative shocks are strongly translated into adverse firm outcomes in bearish states. The second plausible reason could be that during prospective phases of the T&L industry, there is expected to be more demand for consumption. For instance, higher volumes of tourist movements and demand for leisurely activities could drive the demand and price for oil, causing volatility. Since the consumption propensity is

[4] We use the following QR model specification: $Q_{R_t}(\tau|x) = c(\tau) + \beta(\tau) OVX_t$. Where $Q_{R_t}(\tau|x)$ denotes the τ^{th} conditional quantile of R_t; R_t is the returns for the T&L indexes. The coefficient $\beta(\tau)$ is the estimated parameter of interest and only $\beta(\tau)$ is reported in Table 3 for brevity.



b) Box–Ljung test statistic $\hat{Q}_{\alpha}^{(p)}$ for each lag p and quantile α using $\hat{\rho}_{\alpha}(k)$ with α_2 =0.9 in STOXX Travel & Leisure Global index returns. The blue dashed lines are the 95% bootstrap confidence intervals centered at zero.

Fig. 3. (*continued*).

high, it can substantially counterbalance the negative impacts of OVX on the T&L industry.

4.2. Main results

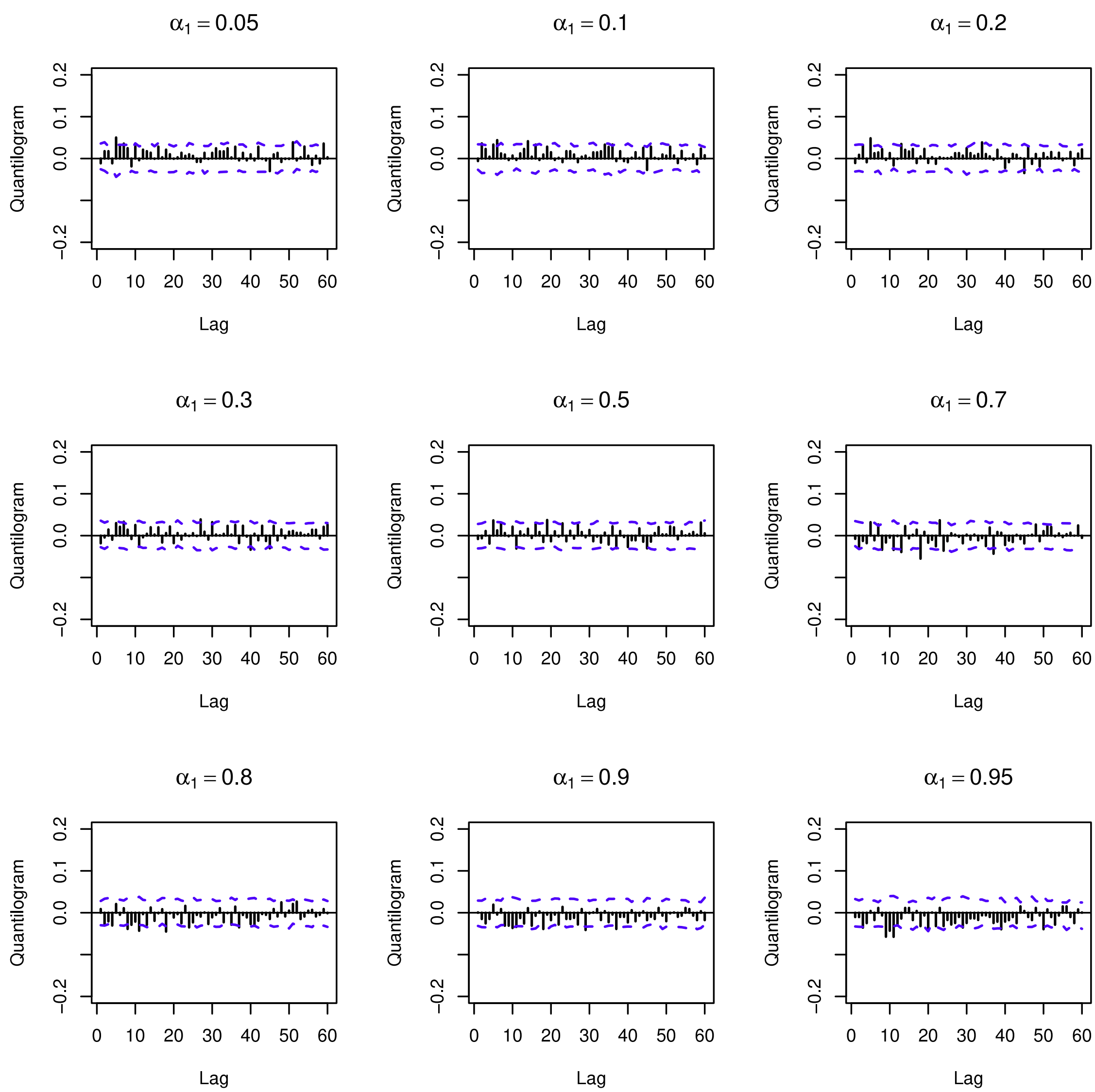
Figs. 2–9 diagrammatically represent the cross-quantilogram $\rho_\tau(k)$ and Box–Ljung test statistics $\hat{Q}_{\tau}^{(p)}$ results for the T&L returns at various quantiles. We can decipher the directional predictability and quantile dependence running from OVX to T&L stock returns using these results. Primarily, we aim to understand the dependence and predictability of index returns when OVX is low and high, i.e., across relatively tranquil and jittery phases. Therefore, for the quantiles of OVX $q_2(\alpha_2)$, we have set α_2 = 0.1 and 0.9. For the T&L stock returns $q_1(\alpha_1)$, we set the following quantiles α_1 = 0.05, 0.1, 0.2, 0.3, 0.5, 0.7, 0.8, 0.9, and 0.95.

The quantile dependence and directional predictability from OVX to stock returns are illustrated in Figs. 2 and 3 of the T&L Global index returns, using Eqs. (1) and (3) for α_2 = 0.1 and 0.9, respectively. Fig. 2(a) shows the cross-quantilogram $\rho_\tau(k)$ representing quantile dependence of the T&L Global index returns when OVX is relatively low, i.e., α_2 = 0.1. The bars in the graph denote the pattern of the returns for a lag up to 60 days. The blue dashed lines are the bootstrapped confidence intervals at 95%. Thus, the bars with an exceedance over the confidence interval are statistically significant responses of the returns. We can observe smaller positive bars; however, they are mostly insignificant for α_1 = 0.05, 0.1, 0.2, and 0.3. However, α_1 = 0.5 onwards, we find some sporadic and significant negative bars implying negative

Table 2
Univariate regressions: impacts of OVX changes on T&L industry stock returns.

	Global	North America	Europe	Asia-Pacific
OVX	−0.0618***	−0.0785***	−0.0714***	−0.0220***
	(−22.504)	(−21.157)	(−15.900)	(−7.559)
Constant	0.0189	0.0324	−0.0018	0.0036
	(1.211)	(1.536)	(−0.071)	(0.215)
Observations	4213	4213	4213	4213
R-squared	0.107	0.096	0.057	0.013

Note: t-statistics are indicated in parentheses.
*** Indicates statistical significance at a 1% level.



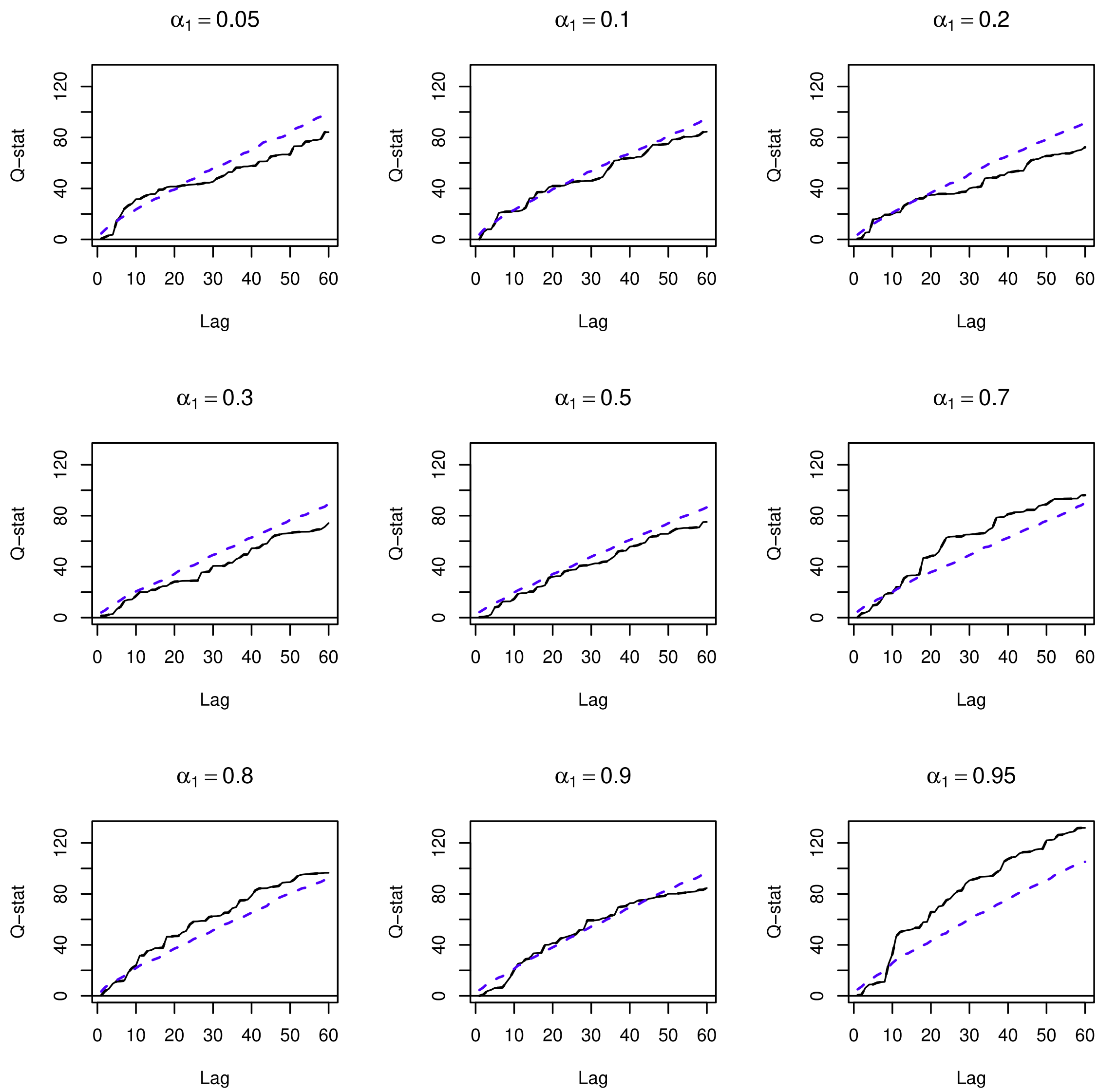
a) The sample cross-quantilogram $\hat{\rho}(k)$ with $\alpha_2 = 0.1$ to detect directional predictability from the OVX to STOXX Travel & Leisure North America index returns. Bar graphs describe the sample cross quantilogram, and blue dashed lines are the 95% bootstrap confidence intervals centered at zero.

Fig. 4. Quantile dependence and directional predictability running from OVX to the STOXX Travel & Leisure North America index returns at $\alpha_2 = 0.1$.

Table 3
Quantile regressions: market-state specific impacts of OVX changes on T&L industry stock returns.

	q05	q10	q25	q50	q75	q90	q95
Global	−0.0811***	−0.0805***	−0.0657***	−0.0509***	−0.0501***	−0.0486***	−0.0499***
	(−10.975)	(−10.924)	(−13.486)	(−13.495)	(−11.435)	(−7.230)	(−5.849)
North America	−0.1078***	−0.1042***	−0.0794***	−0.0676***	−0.0624***	−0.0725***	−0.0614***
	(−9.392)	(−12.635)	(−15.055)	(−15.843)	(−9.107)	(−8.772)	(−5.847)
Europe	−0.1042***	−0.0998***	−0.0784***	−0.0508***	−0.0506***	−0.0512***	−0.0413***
	(−7.030)	(−7.590)	(−14.037)	(−8.775)	(−7.843)	(−4.516)	(−2.786)
Asia-Pacific	−0.0234***	−0.0238***	−0.0178***	−0.0143***	−0.0174***	−0.0204***	−0.0265***
	(−3.030)	(−4.422)	(−4.157)	(−3.608)	(−4.734)	(−3.478)	(−3.464)
Observations	4213	4213	4213	4213	4213	4213	4213

Note: t-statistics are indicated in parentheses.
*** Indicates statistical significance at a 1% level.



b) Box–Ljung test statistic $\hat{Q}^{(p)}_{\alpha}$ for each lag p and quantile α using $\hat{\rho}_{\alpha}(k)$ with α_2 =0.1 in STOXX Travel & Leisure North America index returns. The blue dashed lines are the 95% bootstrap confidence intervals centered at zero.

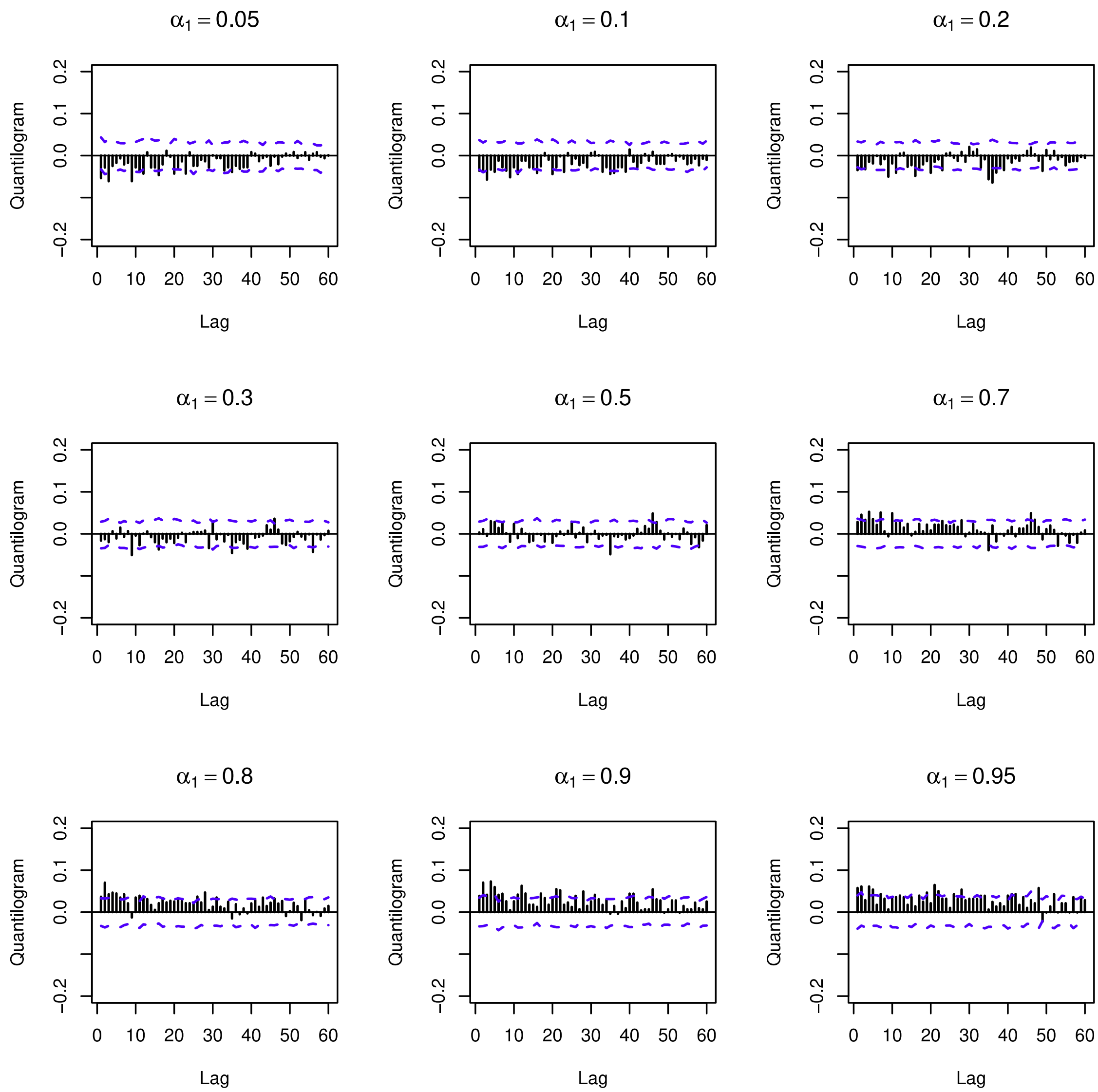
Fig. 4. (*continued*).

responses of the T&L Global index returns. At α_1 = 0.9 and 0.95, the negative responses are frequent up to 40 days. The Box–Ljung test statistics $\hat{Q}^{p}_{\tau}$ results in Fig. 2(b) are summarized in Table 4, Row (1). The predictability is significant if the bold black lines are above dashed blue lines, indicating the bootstrapped confidence intervals. We can infer that except for $\alpha_1 = 0.95$, the stock returns are only partially predictable over different lags.

Next, for the higher volatility of oil prices, we set α_2 = 0.9, and the cross-quantilogram $\rho_{\tau}(k)$ results are reported in Fig. 3(a). We find some interesting results here. In the bearish T&L market states, we can observe certain significant and negative responses. It re-emphasizes that when business fundamentals are weak in this industry, higher oil volatility adversely impacts their revenues and stock returns at α_1 = 0.05, 0.1, 0.2, and 0.3. Nonetheless, during bullish business states, we notice that the impact running from OVX to the stock returns is frequently positive and statistically significant for α_1 = 0.8, 0.9, and 0.95 over various lagged days. As we briefly discussed before, this phenomenon can be explained by the fact that higher oil volatility can hurt T&L businesses more when their performances are weak. Additionally, higher oil volatility derived from oil demand shocks (higher demand for oil due to a flourishing state of the economy) can simultaneously increase the oil volatility and revenues of the T&L industry due to higher consumption demand by the travellers. The positive responses at this state can offset the negative impacts of OVX, which was also indicated by the QR model analysis in the preliminary results. Fig. 3(b) depicts the Box–Ljung test statistics $\hat{Q}^{(p)}_{\tau}$ results, which are also summarized in Table 4, Row (2). We find the existence of significant directional predictability for α_1 = 0.05, 0.1, 0.2, 0.7, 0.8, 0.9, and 0.95. However, it is only partially predictable for α_1 = 0.3, and there is no significant predictability at α_1 = 0.5. Thus, we see that the directional predictability of OVX towards the T&L stock returns is stronger when α_2 = 0.9.

Focusing on the T&L North America, Europe, and Asia-Pacific index returns, we find qualitatively similar results.[5] Figs. 4–9 present the cross-quantilogram graphs for all the constituent continental indexes. We find that the responses to OVX for all three indexes follow a similar

[5] For brevity, we highlight only the main observations. The interpretation is similar to the discussion for the T&L Global index returns.



a) The sample cross-quantilogram $\hat{\rho}(k)$ with $\alpha_2 = 0.9$ to detect directional predictability from the OVX to STOXX Travel & Leisure North America index returns. Bar graphs describe the sample cross quantilogram, and blue dashed lines are the 95% bootstrap confidence intervals centered at zero.

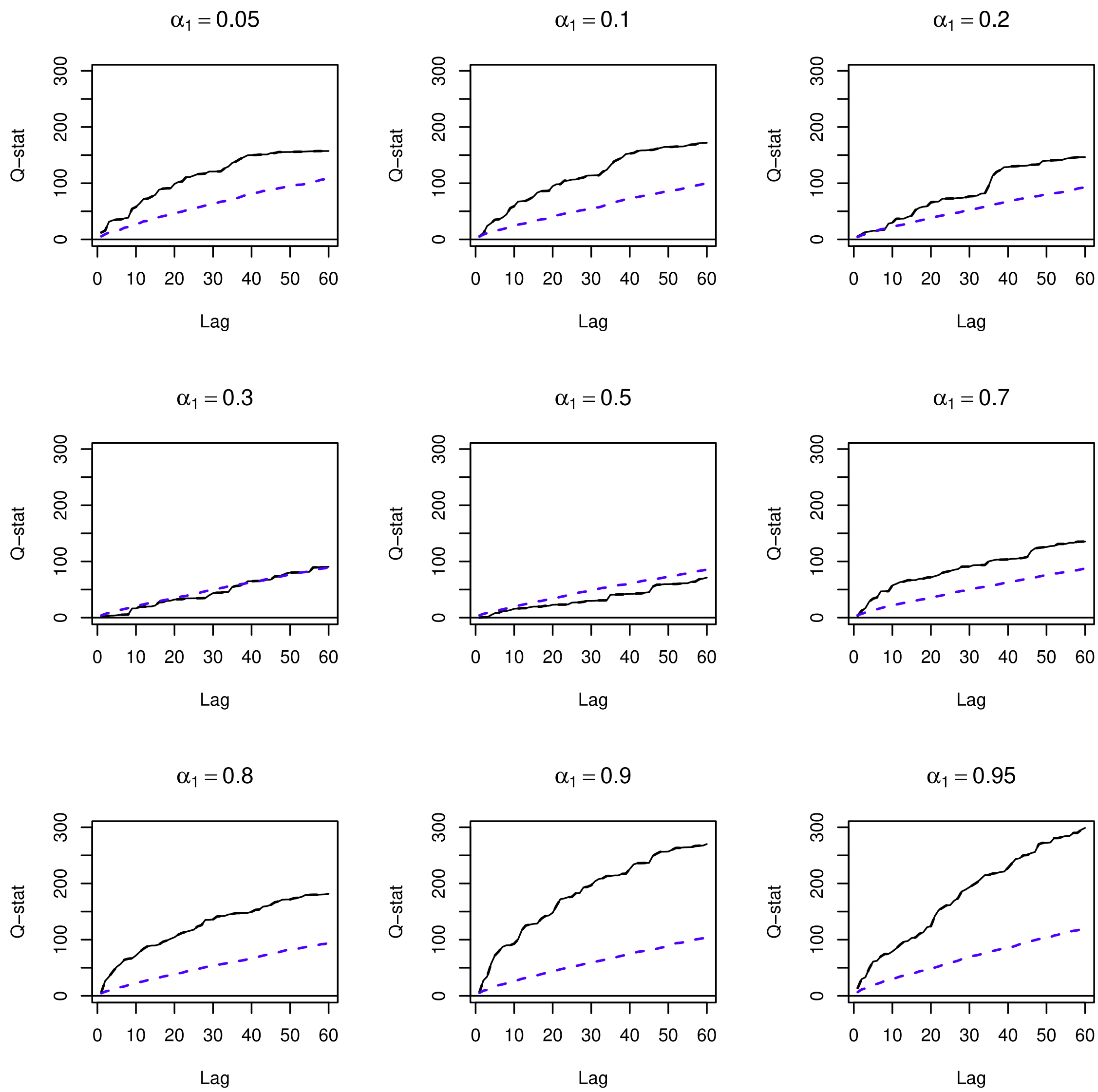
Fig. 5. Quantile dependence and directional predictability running from OVX to the STOXX Travel & Leisure North America index returns at $\alpha_2 = 0.9$.

Table 4
Summary on directional predictability from OVX to T&L industry stock returns.

		OVX	T&L industry stock returns								
		α_2	0.05	0.1	0.2	0.3	0.5	0.7	0.8	0.9	0.95
Global	(1)	0.1	+	+	+	+	+	+	+	+	✓
	(2)	0.9	✓	✓	✓	+	×	✓	✓	✓	✓
North America	(3)	0.1	+	+	×	×	×	✓	✓	+	✓
	(4)	0.9	✓	✓	✓	+	×	✓	✓	✓	✓
Europe	(5)	0.1	×	+	+	+	×	+	+	✓	+
	(6)	0.9	✓	✓	✓	✓	+	✓	✓	✓	✓
Asia-Pacific	(7)	0.1	×	×	×	×	+	+	✓	✓	✓
	(8)	0.9	✓	✓	✓	✓	✓	✓	✓	✓	✓

Note: ✓denotes significant predictability, + denotes partially significant predictability, and ×denotes no significant predictability.

pattern. When the oil volatility is relatively low, i.e., $\alpha_2 = 0.1$, the index returns have a mildly positive response for $\alpha_1 = 0.05$, 0.1, 0.2, and 0.3., meaning the lower volatility is helpful to the T&L firms to revive to some extent. However, some negative responses are frequent for up to 40–50 days at $\alpha_1 = 0.7$, 0.8, 0.9, and 0.95. This can happen due to the investor's overaction effect, as a slight increase in OVX may threaten the stock market participants. The Box–Ljung test results compiled in Table 4 show that OVX predicts T&L stock returns better at $\alpha_2 = 0.9$. Moreover, the T&L Europe index returns are relatively more predictable with respect to OVX, which is also consistent with our QR



b) Box–Ljung test statistic $\hat{Q}_{\alpha}^{(p)}$ for each lag p and quantile α using $\hat{\rho}_{\alpha}(k)$ with α_2 =0.9 in STOXX Travel & Leisure North America index returns. The blue dashed lines are the 95% bootstrap confidence intervals centered at zero.

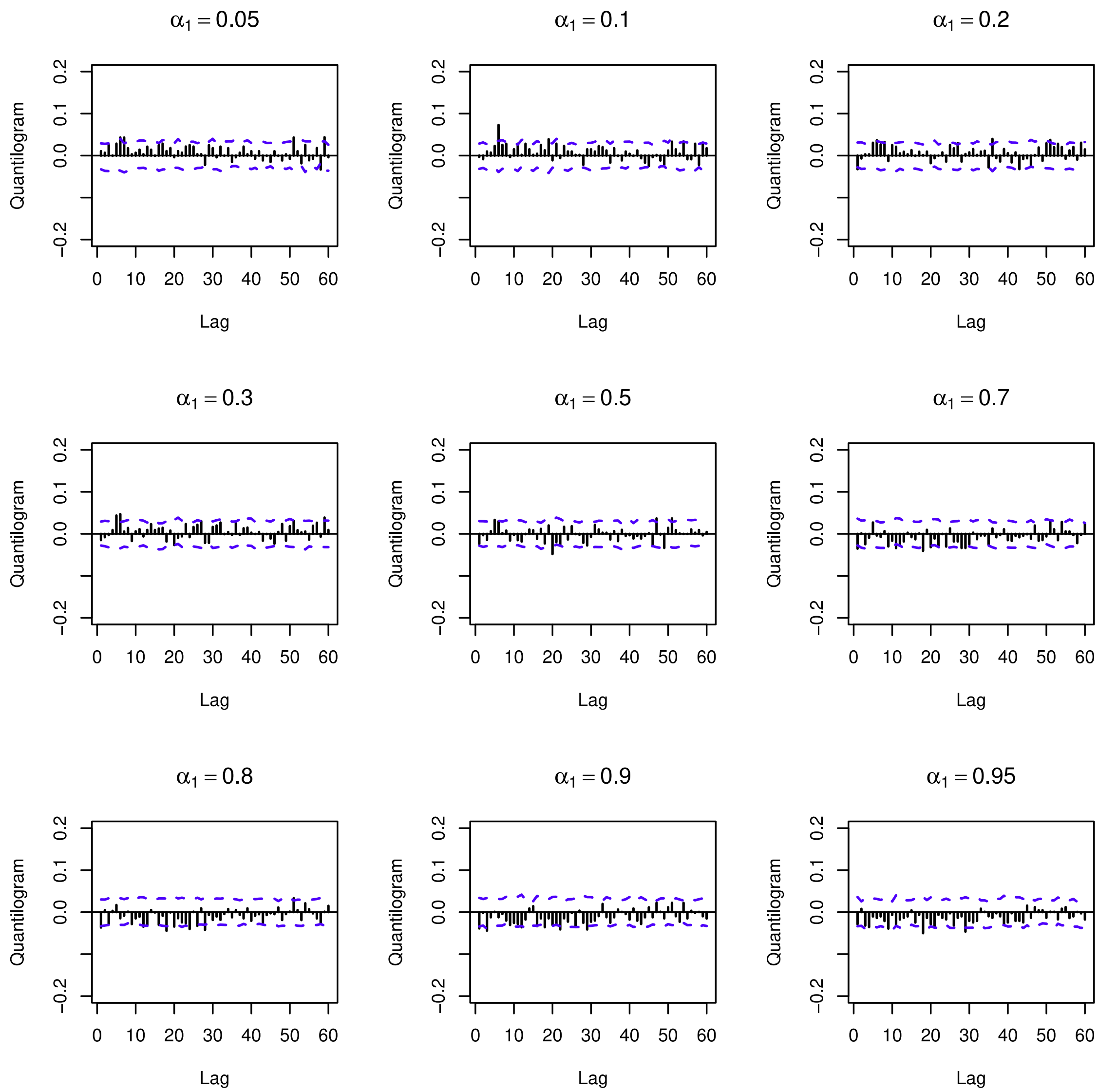
Fig. 5. (*continued*).

results. Overall, we conclude that OVX uniformly predicts the T&L stock returns. However, the intensity of the predictability may vary over time horizon.

4.3. Further analysis using the wavelet coherence technique

We further analyse the time–frequency-based co-movement between OVX and the T&L stock returns using the wavelet coherence analysis.[6] The results of the wavelet analysis are presented in Fig. 10 in the form of the heatmaps. In the wavelet coherence plots, the horizontal axis represents the timeline, while the vertical axis denotes frequency, where lower frequencies correspond to longer time scales (higher periodicities). The plots capture how the co-movement between two time series evolves over both time and frequency domains. The colour intensity in the wavelet coherence plots reflects the degree of local correlation between the two time series. Warm colours such as red and orange indicate regions of high coherence, suggesting a strong local interdependence between the variables at specific time–frequency combinations. In contrast, cool colours like blue represent areas of low coherence, implying weak or negligible correlation. It is important to note that regions lying outside the black contour lines or within the whitish, grey-shaded cone of influence are considered statistically insignificant or potentially influenced by edge effects and should therefore be interpreted with caution. The phase difference information in the wavelet coherence plots is depicted through the orientation of arrows, which indicate the lead–lag relationship and direction of co-movement between the two time series. Arrows pointing to the right (→) signify that the series are in-phase, moving in the same direction, while arrows pointing to the left (←) indicate an anti-phase relationship, meaning the series move in opposite directions. Additionally, arrows pointing right and downward (↘) or left and upward (↖) suggest that the first variable leads the second. Conversely, arrows pointing right and upward (↗) or left and downward (↙) imply

[6] We thank the reviewer for suggesting the additional analysis. We do not discuss the underlying mathematics of wavelet analysis in details for brevity. Rather we mainly focus on its application and interpretation of the wavelet heatmaps. The interested readers may refer (Rua and Nunes, 2009) for the mathematical formulation of wavelet analysis.



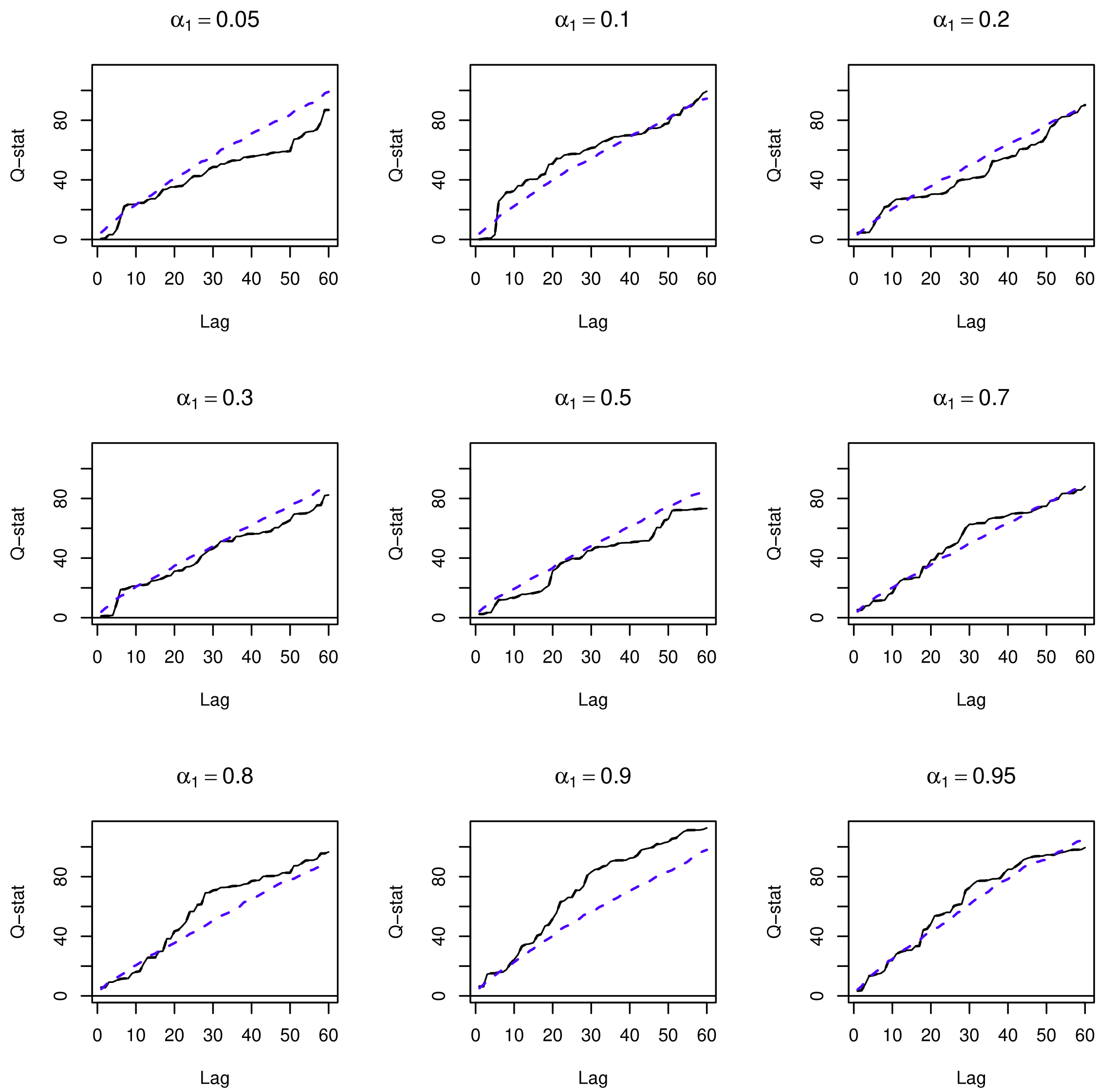
a) The sample cross-quantilogram $\hat{\rho}(k)$ with $\alpha_2 = 0.1$ to detect directional predictability from the OVX to STOXX Travel & Leisure Europe index returns. Bar graphs describe the sample cross quantilogram, and blue dashed lines are the 95% bootstrap confidence intervals centered at zero.

Fig. 6. Quantile dependence and directional predictability running from OVX to the STOXX Travel & Leisure Europe index returns at $\alpha_2 = 0.1$.

that the second variable leads the first. This directional information provides valuable insight into the temporal dynamics and causal interactions between the variables. The wavelet coherence analysis between OVX and T&L stock returns across four regions: Global, America, Europe, and Asia-Pacific, reveals important time–frequency dynamics and directional dependencies. Across all regional indices, periods of significant coherence correspond to major global disruptions, notably the COVID-19 pandemic in 2020 and the Russia–Ukraine conflict in 2022, both of which were marked by elevated oil market uncertainty and substantial stress in tourism markets. In the Global, American, and European T&L indices, coherence is particularly strong in the low-frequency bands (32 256 days), indicating that oil price volatility exerts a persistent and long-term influence on T&L firm performance in these regions. The direction of the arrows in these coherence plots predominantly points leftward (←) or left and upward (↖), suggesting a negative correlation where OVX leads stock returns. This pattern implies that oil market uncertainty tends to precede and predict declines in tourism-related stock performance, especially in energy-intensive regions. In contrast, the Asia-Pacific T&L index exhibits weaker and more sporadic coherence, with limited periods of statistical significance and inconsistent directional patterns. This suggests that Asia-Pacific tourism firms are relatively less exposed to oil price volatility, possibly due to regulatory interventions in fuel pricing. These findings highlight the regional heterogeneity in oil risk exposure within the global tourism sector.

5. Discussion and implications

Over the past two decades, research on the potential effects of oil price fluctuations on tourism has become increasingly important. Several key studies have highlighted the significant connections between oil prices and tourism activities (Becken, 2008; Becken and Lennox, 2012; Becken and Simmons, 2002). However, there has been limited focus on understanding how these fluctuations impact the Travel and Leisure (T&L) industry, despite its integral role in tourism. Therefore, we aim to investigate the relationship between oil price volatility and its potential effects on the stock returns of T&L companies. Given that the T&L sector relies heavily on capital investments, which are



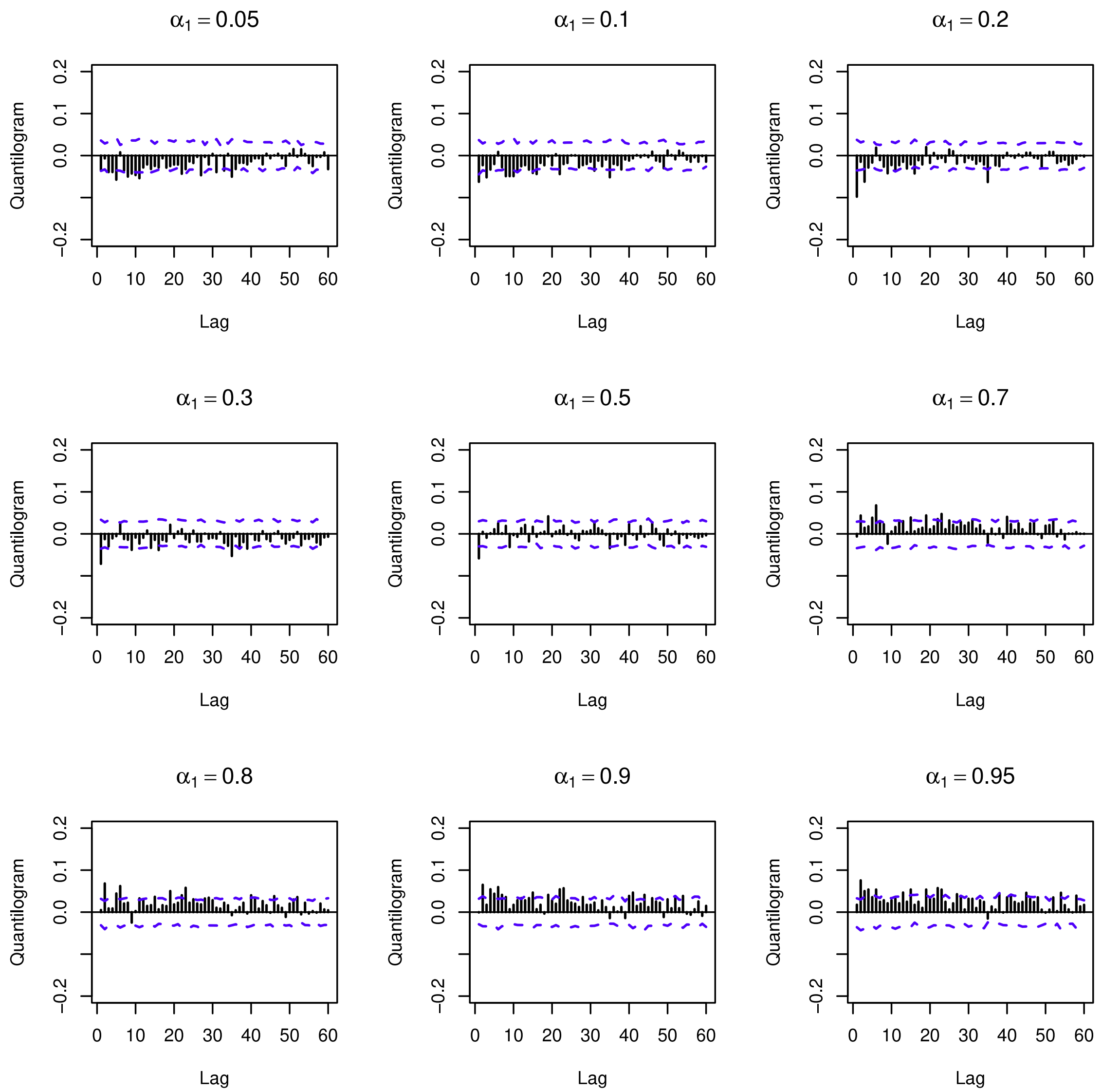
b) Box–Ljung test statistic $\hat{Q}_{\alpha}^{(p)}$ for each lag p and quantile α using $\hat{\rho}_{\alpha}(k)$ with α_2 =0.1 in STOXX Travel & Leisure Europe index returns. The blue dashed lines are the 95% bootstrap confidence intervals centered at zero.

Fig. 6. (*continued*).

often funded through stock issuance, it is essential to explore how uncertainties in oil prices may influence the movement of T&L stocks. Understanding this relationship could provide valuable insights for making informed decisions in the industry.

Our empirical results from the preliminary analysis suggest that oil price uncertainty represented by OVX impacts the T&L index returns negatively and significantly. It implies that the apprehensions about future oil price expectations and its impending spillover to other macroeconomic variables hinder tourism activities and their revenues. The results also suggest that stock returns are more vulnerable when the returns are bearish, which is consistent with Demiralay and Kilincarslan (2019).[7] As the stock returns of T&L companies turn bullish, the negative effects are subsumed. The initial analysis also suggests that the European (Asia-Pacific) T&L index is most (least) affected by uncertainty in oil prices. Similar findings were also reported by Demiralay and Kilincarslan (2019) in the context of GPR. These results re-emphasize the fact that the constituent countries of the index, such as New Zealand, Singapore, Australia, Hong Kong, and Japan, are less susceptible to global uncertainties. For instance, Zopiatis et al. (2019) found that the stock returns of the hospitality and tourism firms in Asia and the Pacific region are least susceptible to geopolitical events. Our study extends these findings to the context of oil price uncertainty. Some other studies also claim that the stock returns of these countries are more sensitive to local risks than uncertainties of global nature (Das and Kumar, 2018; Donadelli, 2015). The baseline results also show that among all continents, the T&L firms in Europe are mostly vulnerable to oil volatility. This seems obvious, given the higher oil import dependence of the European countries (Degiannakis et al., 2013). The greater sensitivity of European markets to oil price volatility may be attributed to their higher reliance on long-haul travel, well-established aviation networks, and fossil fuel-intensive infrastructure. In contrast, our QR results indicate that T&L firms in the Asia-Pacific region experience comparatively lower impacts on stock returns. This could be linked to distinct travel demand patterns and the evolving nature of the tourism sector in the region. In recent years, Asia-Pacific tourism has witnessed significant growth, supported by proactive government

[7] Demiralay and Kilincarslan (2019) examined the impacts of GPR on the stock returns of the T&L stock returns and reported similar results.



a) The sample cross-quantilogram $\hat{\rho}(k)$ with $\alpha_2 = 0.9$ to detect directional predictability from the OVX to STOXX Travel & Leisure Europe index returns. Bar graphs describe the sample cross quantilogram, and blue dashed lines are the 95% bootstrap confidence intervals centered at zero.

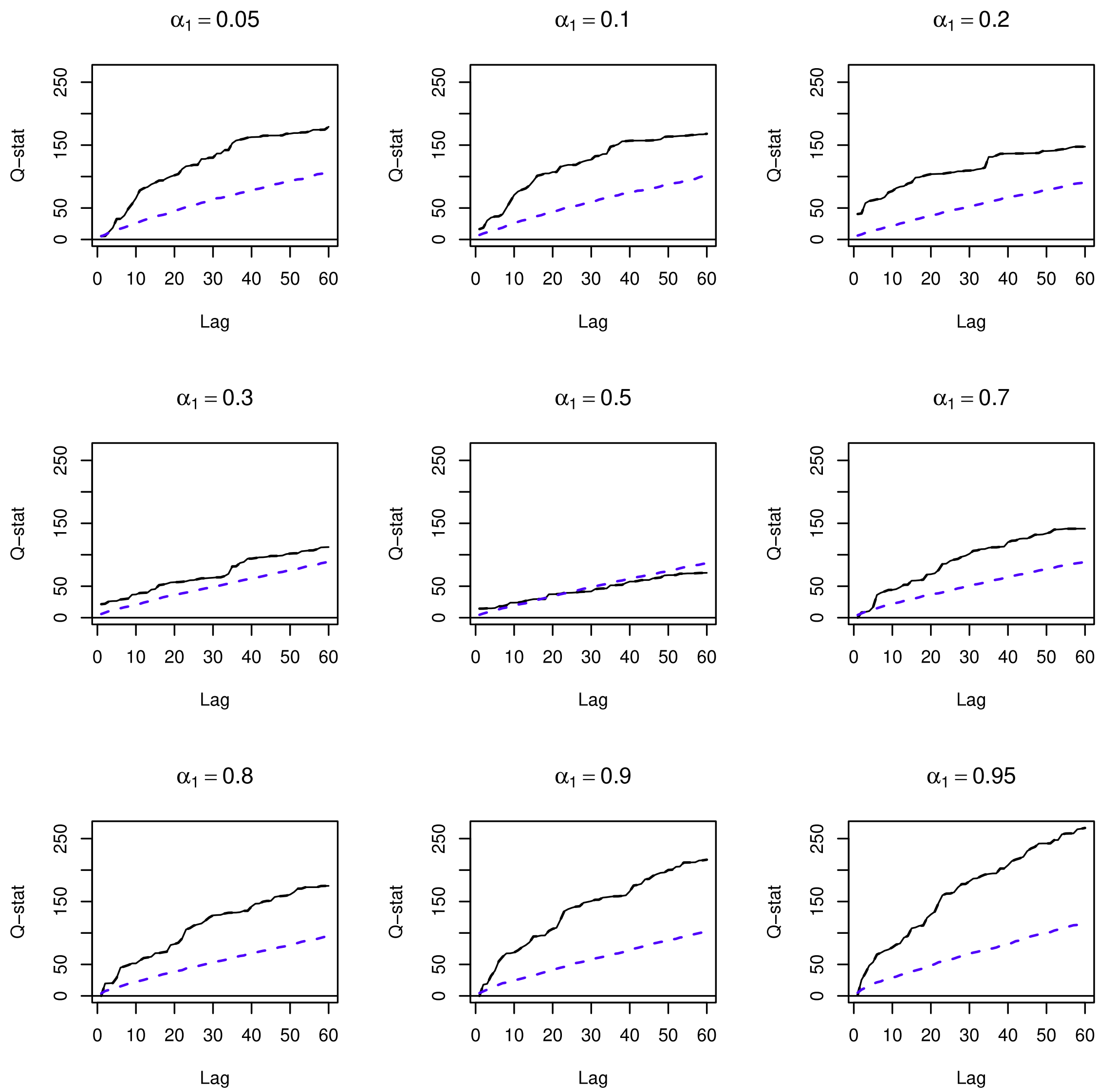
Fig. 7. Quantile dependence and directional predictability running from OVX to the STOXX Travel & Leisure Europe index returns at $\alpha_2 = 0.9$.

policies that recognize its importance as a driver of employment and revenue generation.[8]

From the investor's point of view, we find the existence of directional predictability running from OVX to the T&L industry stock returns. The strength of predictability varies over the time horizon of lag days. We further find that the stock returns are more predictable by OVX when the volatility is high. Importantly, we also notice that the stock returns are more susceptible to higher oil volatilities in the bearish state. This result is complementary to our baseline findings. Nonetheless, in the bullish state, the negative impact disappears and becomes positive. One possible argument could be the fact that oil prices can be volatile during the phases of strong consumption demand. The oil price can increase because of higher demand, and stock returns also increase due to the growing economic fundamentals. Previous studies have documented the simultaneous increase in oil and stock prices (Das et al., 2022b, 2020; Ready, 2018). Besides, the intensifying relationship between oil and the stock returns of the T&L stock index returns could result from the financial hedging activities of the market participants (Batten et al., 2021; Jalkh et al., 2021).

The association between oil and tourism has been well-noted in the recent past (Becken, 2008; Becken and Lennox, 2012; Becken and Simmons, 2002). This paper also shows that oil volatilities can predict the stock returns of the T&L firms. Given the recent adverse geopolitical (Zhang et al., 2023) and health crisis (Sun et al., 2023) events and their potential impact on oil prices, it could be a critical concern for tourism development. Such exposure of the T&L firms can pose a serious challenge for these firms to generate sufficient revenues and

[8] The future of Pacific tourism (March 2023). The full report is available here: https://documents1.worldbank.org/curated/en/099042523100019273/pdf/P177593090432b0c00b335006fc87e47169.pdf.



b) Box–Ljung test statistic $\hat{Q}_{\alpha}^{(p)}$ for each lag p and quantile α using $\hat{\rho}_{\alpha}(k)$ with α_2 =0.9 in STOXX Travel & Leisure Europe index returns. The blue dashed lines are the 95% bootstrap confidence intervals centered at zero.

Fig. 7. (*continued*).

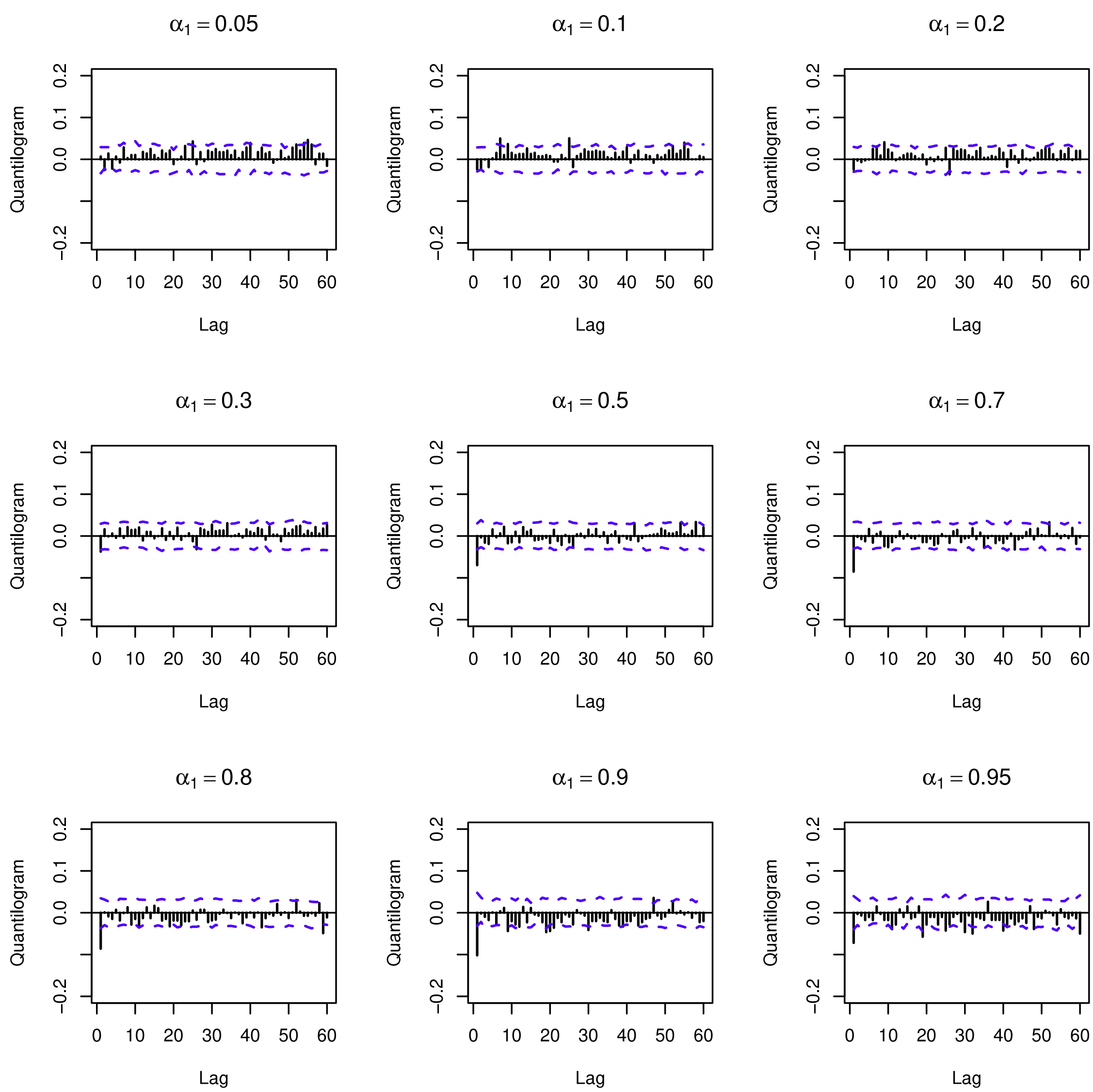
survive in the long run. We believe that these firms can minimize their oil risk exposure by decoupling themselves from higher oil dependence. A recent report by the World Travel and Tourism Council (WTTC)[9] states that there are several T&L firms that have adopted alternatives and helped them reduce dependence on crude oil. For instance, Bucuti & Tara Beach Resort in Aruba has installed solar panels to generate energy. United Airlines has increasingly invested in sustainable aviation fuel (SAF) for their operations. With the advent of EVs, firms such as Taiga have developed battery-operated jet skis. Similarly, firms like Volvo Buses have now launched battery-operated buses, which can reduce crude oil dependence. The EVs could help immensely reduce the adverse effects of oil price volatility. If electricity is produced from renewable sources, it can insulate the negative spillovers from oil markets and reduce carbon dioxide (CO2) emissions. This can ensure stability in the tourism sector and promote the growth of T&L firms.

[9] World Travel and Tourism Council, "A net zero roadmap for travel and tourism: proposing a new target framework for the travel and tourism sector", November 2021, United Nations.

6. Conclusion and future research

Our research reveals a significant relationship between oil price volatility and the financial performance (stock returns) of firms in the travel and leisure industry. Through an extensive analysis, we demonstrate that fluctuations in oil prices can have profound implications for T&L firms, affecting their profitability, investor attractiveness, and stock market performance. The empirical evidence we present underscores the imperative for T&L firms to meticulously manage their exposure to oil market fluctuations, advocating for strategic diversification away from reliance on oil and exploration of innovative approaches, such as the integration of emerging technologies like electric vehicles.

Our research significantly contributes to the existing literature in multiple dimensions. Firstly, we introduce a novel perspective by utilizing the implied oil volatility index (OVX) as a robust proxy for oil price uncertainty. This approach yields fresh insights into the directional predictability of oil price uncertainty on T&L stock returns, shedding light on previously unexplored dynamics. Secondly, employing cross-quantilogram modelling techniques, we examine the quantile dependence between OVX and T&L stocks across various market conditions. This analysis allows for a better understanding of how oil price



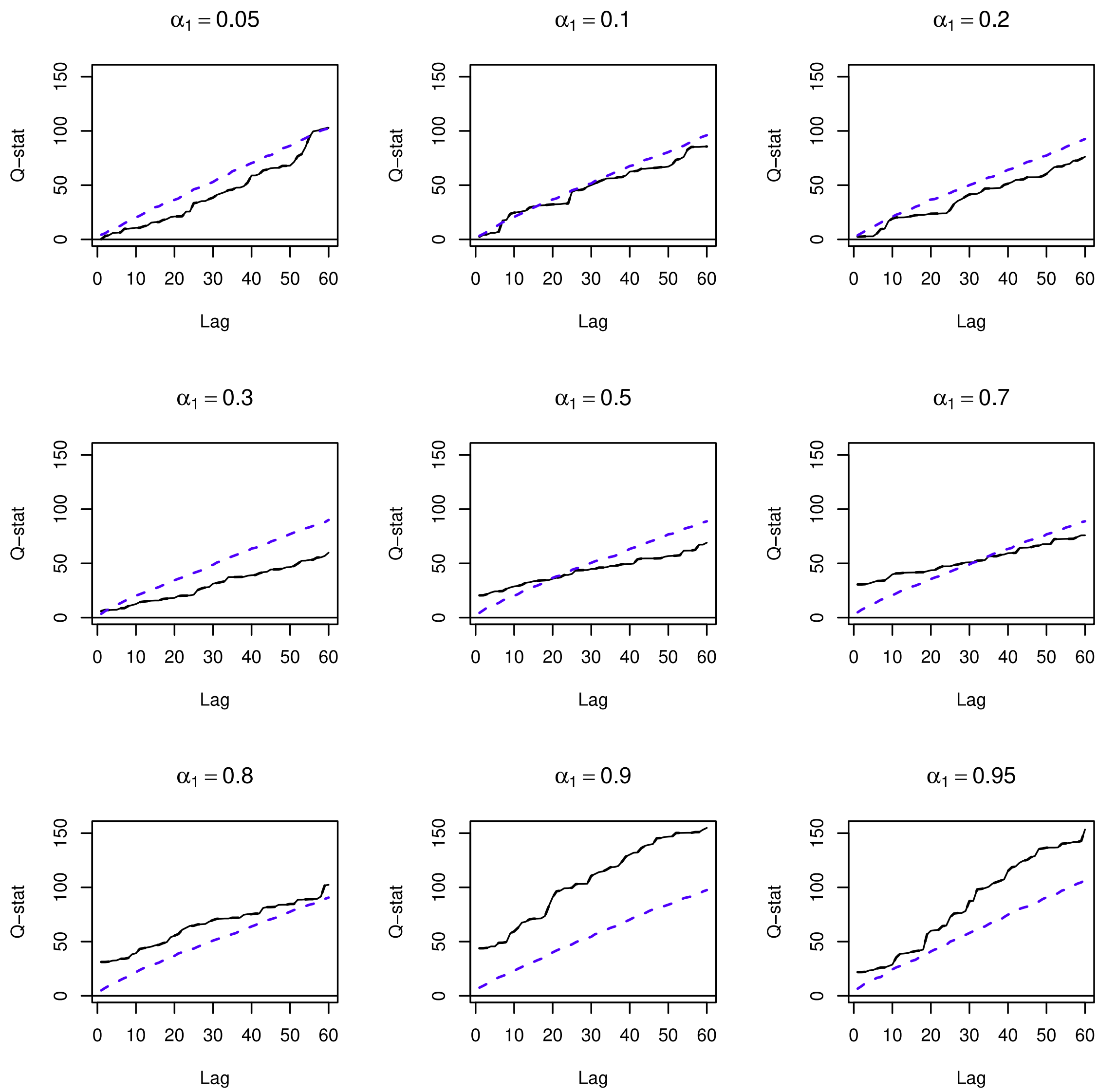
a) The sample cross-quantilogram $\hat{\rho}(k)$ with $\alpha_2 = 0.1$ to detect directional predictability from the OVX to STOXX Travel & Leisure Asia-Pacific index returns. Bar graphs describe the sample cross quantilogram, and blue dashed lines are the 95% bootstrap confidence intervals centered at zero.

Fig. 8. Quantile dependence and directional predictability running from OVX to the STOXX Travel & Leisure Asia-Pacific index returns at $\alpha_2 = 0.1$.

uncertainty manifests within different segments of the T&L industry's stock returns, offering valuable insights for risk management strategies.

Furthermore, our investigation extends beyond traditional boundaries by examining the continent-specific effects of oil uncertainty on T&L stocks. By scrutinizing how oil price fluctuations impact T&L firms across different geographic regions, we uncover patterns and variations in market responses. This continental lens adds a valuable layer of insight, highlighting the global interconnectedness of T&L markets and the diverse strategies that firms may need to adopt in response to oil price uncertainty. Overall, our study not only enriches the scholarly discourse on the intersection of oil markets and T&L stocks but also provides actionable intelligence for industry practitioners and policymakers navigating this complex landscape.

While our study provides incremental insights into the relationship between oil uncertainty and T&L stock returns, several avenues for future research remain open. First, further exploration could be conducted into the underlying mechanisms through which oil price uncertainty affects different segments of the T&L industry, such as airlines, hotels, and recreational services. Understanding these differential effects could inform more targeted risk management strategies for T&L firms. Second, to gain a more comprehensive understanding, future studies could explore how other economic factors or industry-specific characteristics might influence the relationship between oil price uncertainty and T&L stock returns. Exploring these interactions could provide a more comprehensive understanding of the drivers of T&L stock market performance. Additionally, given the dynamic nature of oil markets and the evolving landscape of the T&L industry, longitudinal studies could track the changing relationship between oil uncertainty and T&L stock returns over time. This could help identify emerging trends and adapt risk management strategies accordingly. Third, a similar cross-quantilogram-based methodological framework can be used to assess the influence of OVX on other oil-sensitive sector



b) Box–Ljung test statistic $\hat{Q}_{\alpha}^{(p)}$ for each lag p and quantile α using $\hat{\rho}_{\alpha}(k)$ with α_2 =0.1 in STOXX Travel & Leisure Asia-Pacific index returns. The blue dashed lines are the 95% bootstrap confidence intervals centered at zero.

Fig. 8. (*continued*).

stock returns. Further, given the contemporary geopolitical disruptions, researchers may also test the directional predictability of geopolitical risk on T&L stock returns. Overall, continued research in this area is essential for informing industry practitioners, investors, and policymakers on effective strategies for managing oil uncertainty risks and promoting sustainable development in the T&L sector.

We believe that our findings can be useful to policymakers, which also has implications for global sustainable tourism practices. The sensitivity of T&L stock returns to oil volatility underscores the need for reduced fossil fuel dependency, particularly among transportation-intensive firms such as airlines and cruise operators. This requires greater investment in low-carbon technologies, energy-efficient infrastructure, and alternative fuels. Additionally, firms with higher oil exposure may benefit from robust Environmental, Social, and Governance (ESG) strategies and sustainable energy transition plans, which can enhance resilience and investor confidence. Further, our results may encourage the promotion of green financing instruments to enable tourism firms to align risk management with broader climate and sustainability goals.

CRediT authorship contribution statement

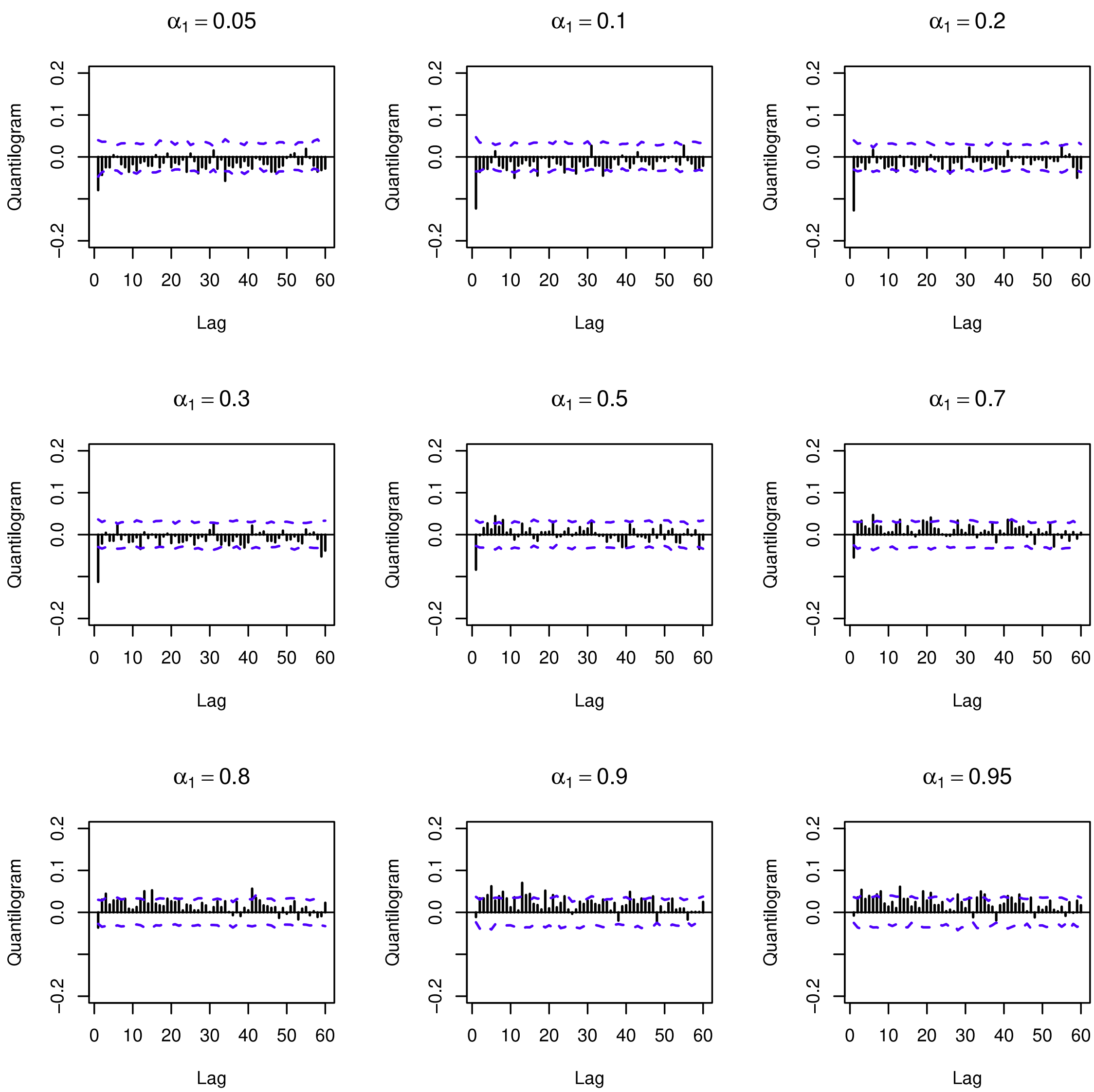
Debojyoti Das: Writing – review & editing, Writing – original draft, Validation, Resources, Methodology, Formal analysis, Data curation, Conceptualization. **Sumit Saurav:** Writing – review & editing, Writing – original draft, Visualization, Resources, Project administration, Methodology, Formal analysis, Conceptualization. **Anupam Dutta:** Writing – review & editing, Writing – original draft, Supervision, Resources, Project administration, Investigation, Conceptualization.

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.

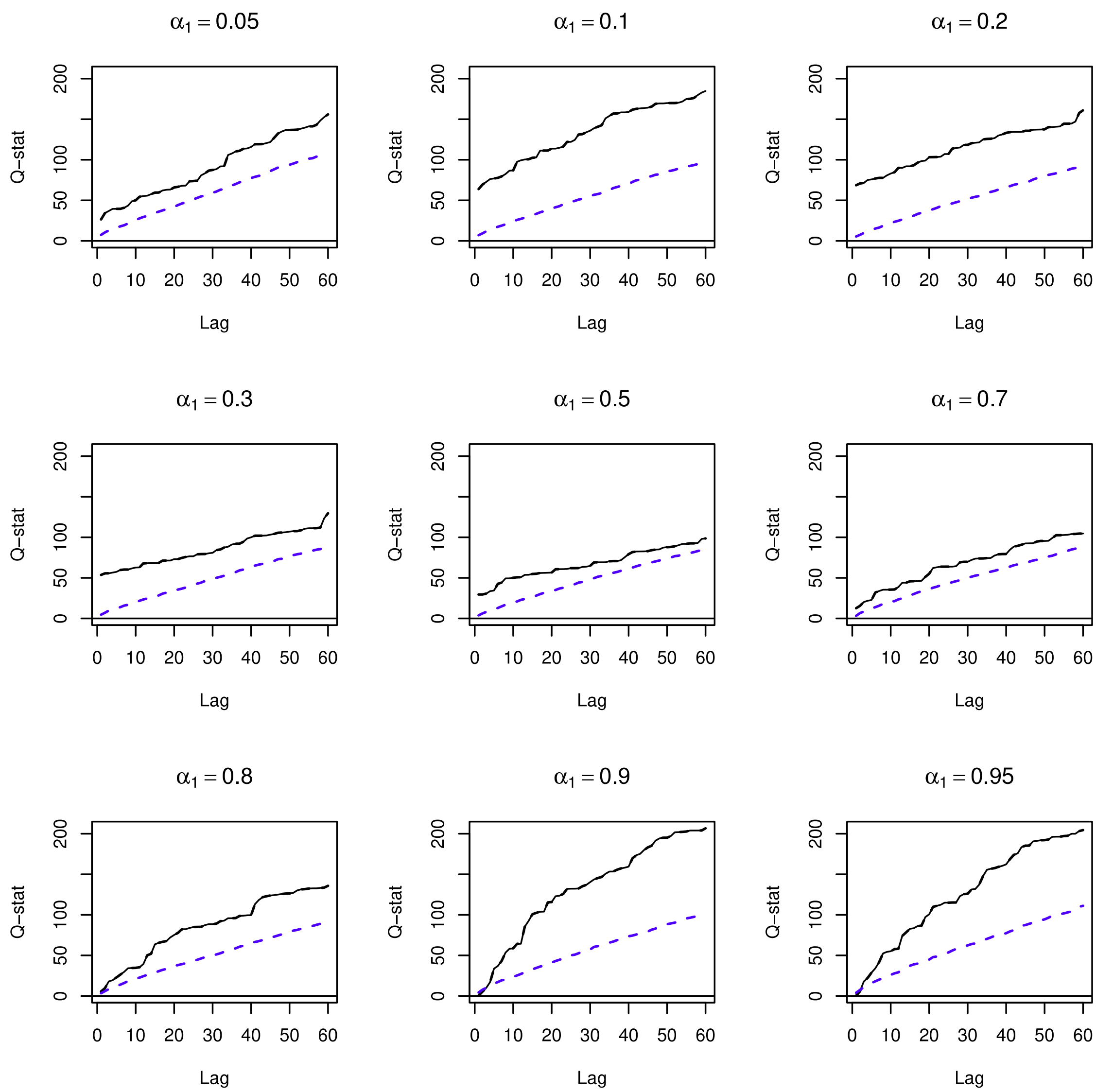
Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.eneco.2025.108887.



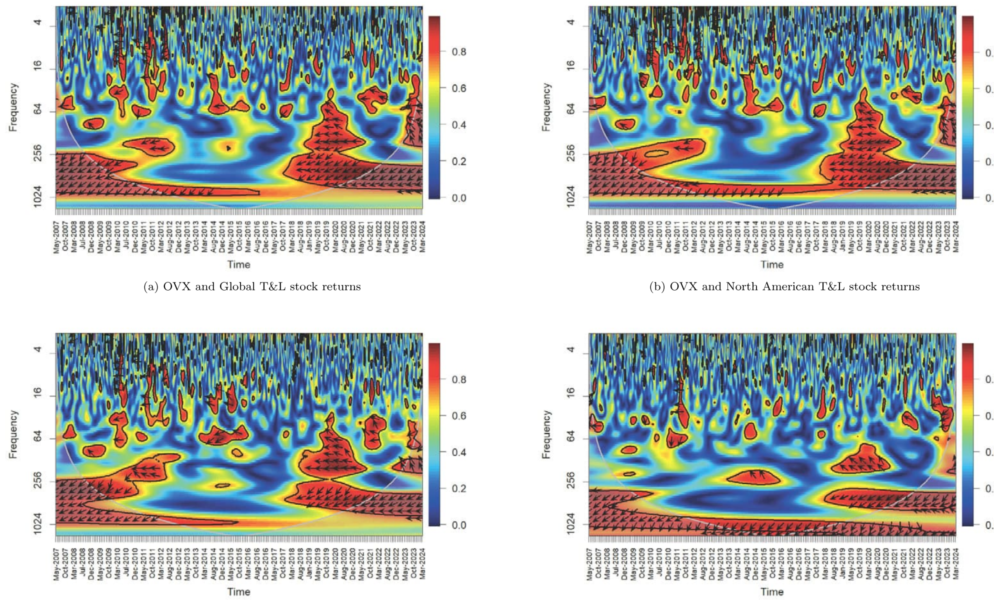
a) The sample cross-quantilogram $\hat{\rho}(k)$ with $\alpha_2 = 0.9$ to detect directional predictability from the OVX to STOXX Travel & Leisure Asia-Pacific index returns. Bar graphs describe the sample cross quantilogram, and blue dashed lines are the 95% bootstrap confidence intervals centered at zero.

Fig. 9. Quantile dependence and directional predictability running from OVX to the STOXX Travel & Leisure Asia-Pacific index returns at $\alpha_2 = 0.9$.



b) Box–Ljung test statistic $\hat{Q}_{\alpha}^{(p)}$ for each lag p and quantile α using $\hat{\rho}_{\alpha}(k)$ with α_2 =0.9 in STOXX Travel & Leisure Asia-Pacific index returns. The blue dashed lines are the 95% bootstrap confidence intervals centered at zero.

Fig. 9. (*continued*).



(a) OVX and Global T&L stock returns

(b) OVX and North American T&L stock returns

(c) OVX and Europian T&L stock returns

(d) OVX and Asia-Pacific T&L stock returns

Fig. 10. Wavelet coherence between OVX and Travel & Leisure STOXX indices.
Note: The heatmaps above depict the wavelet coherence between OVX and T&L stock returns across regions. The horizontal axis represents time, and the vertical axis shows frequency. Warmer colours indicate regions of high coherence, while colder colours represent weak or no correlation. Arrows depict phase relationships. Regions outside the black contour lines or within the white cone of influence are statistically insignificant. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

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