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Does oil price volatility matter for the US transportation industry?

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ABSTRACT

Although the US transport sector is one of the major users of fossil fuel (e.g., crude oil), the impact of energy price volatility on transport stock sector indexes remains under-researched. The present study addresses this research void by investigating the impact of energy implied volatility on transportation stock returns in the US. Using the crude oil volatility index (OVX), as a proxy of energy price volatility, and three Dow Jones indexes tracking the performance of the airlines, marine and trucking stock subsectors, we employ a GARCH-jump model. The main results show that the oil market sends volatility to the US transport subsector stock indexes, suggesting that oil implied volatility plays a role in pricing US transport stocks. The impact of OVX shocks is asymmetric, indicating that increases and decreases in oil implied volatility have a heterogeneous impact on the transport subsector stock markets. Jumps are significant in the three transport subsector stock indexes, and are time-dependent. Notably, the three transportation subsector stock indexes are more sensitive to OVX shocks than the S&P 500 index. These results have important implications for investors, policymakers, academics, and managers of the US transportation industry.

1. Introduction

The US transport sector has been one of the major consumers of fossil fuel (e.g., crude oil) over the years. Ref. [1], for example, argue that an important sector, where a significant and substantial part of input costs depends on oil prices, is the transportation industry. The US Department of Energy reports that, in 2019, the transport sector accounted for 69% of all US petroleum product consumption.[1] Although the usage has decreased in recent years, the dependency is still quite high. Recent estimates reveal that the US transport sector is currently consuming nearly 14.14 million barrels per day (b/d), representing 68.8% of all US petroleum product consumption.[2] Of the various transport modes, light vehicles consume around 60% of the total energy used for transportation of people and goods. The second largest consumer is the trucking subsector, which accounts for 22%, whereas airlines and shipping subsectors use 9% and 3% respectively. Furthermore, the operating cost of the US transportation industries due to consumption of oil-based fuels is also very significant. Data published by the American Transport Research Institute (ATRI) for 2019 suggest that fuel costs account for 24% of the total operating cost in the US trucking subsector. This figure is also high for the airlines subsector, around 25%, representing the largest operating cost.[3] Compared to these two sectors, the US shipping division experiences more operational cost due to fuel consumption, around 55%.[4] Overall, this information evidently indicates that the costs

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of oil-based energy are crucial for the US transportation industries and hence oil price movements are likely to play a pivotal role in pricing the country's transport sector stocks.

While the transportation industry is the largest user of oil-based fuels, whether oil price uncertainty influences the US transport sector equity indexes is surprisingly under-studied. The objective of this research is to address this void in the literature, by examining whether and to what extent oil price volatility affects the equity prices of the US transport subsectors (airlines, marine, and trucking). Our prime objective is to test whether crude oil volatility is transmitted to the returns of various transport subsector stock indexes, namely airlines, marine and trucking. In particular, we address the following research questions: 1) Does there exist a significant negative association between oil implied volatility and the trucking sector, as this industry is a major customer of oil-based fuels? 2) Is the airlines subsector, in comparison to the trucking subsector, less affected by oil price variations, since the later consumes more crude oil? 3) Do oil price shocks really impact the marine subsector as operating costs in this subsector due to consumption of crude oil are distinctly cheaper than the other subsectors under study?

Using a recent daily data set and a robust GARCH-jump methodology, we make an effort to respond to these research questions. The GARCH-jump approach (initially proposed by Ref. [2]) offers various key features. Firstly, compared to the conventional GARCH process, the GARCH-jump allows users to examine the impact of abnormal information arising from random events [3]. Secondly, the GARCH-jump model enables us to understand whether time-dependent jumps occur in the price indexes [4], in our case the three transportation indexes. As the proxy for energy price volatility, we rely on the oil implied volatility index (OVX), which reflects the expected 30-day volatility of the crude oil market, calculated based on the option prices of the United States Oil Fund. The importance of OVX is well recognized in the oil-stock literature [3,5–7].

Understanding the relationship between oil price shocks and equity market performance is vital, given that fluctuations in oil prices commonly impact stock market returns and hence the entire economy (see [8]).[5] Generally, positive oil returns should lead to an increase in production costs, given that crude and its by-products constitute a major production input [16]. The increase in production costs should lead to higher prices, which should, in turn, push the demand and consumption lower. Lower demand should lead to a decrease in output level and therefore lower expected cash-flows. Accordingly, and given that stock prices are influenced by the present value of the future cash flows, one would expect stock prices to decline. Several studies are conducted in this regard. [17]; for example, documents an inverse association between oil and stock price indexes, which is supported by Ref. [18].[6] Furthermore, some studies (e.g. Refs. [21–23])[7] examine the uncertainty transmission mechanism between the international oil market and various equity markets. However, these studies focus on some country-specific financial markets, and very little attention is paid to the transmission of volatility between oil and equity sector returns (e.g. Refs. [16,24–28]). Further assessment of such links is essential, as oil price volatility might affect some industries more harshly than others, depending on the intensity of the sector or industry in consuming fossil fuel energy (notably, crude oil) (see Refs. [7,16,25]). Ref. [27] argue that, as diverse industries could react to oil market shocks differently, investors and sector participants should be aware of these responses. Notably, [29] argue that crude oil consumption represents a large portion of the overall operating costs of the marine industry, and indicate that, because tanker ships are major carriers of the global oil supply, the importance of crude oil for the marine shipping industry is amplified.

Our paper adds to various aspects of the previous literature. Firstly, we are among the earliest studies to investigate the influence of OVX on the stock prices of US transportation firms. Unlike most previous studies, which generally consider aggregate stock market indexes (e.g. Refs. [3, 30]) or sector indexes other than transportation [6,7,16,25,27,28,31, 32], we consider transportation indexes and how they are affected by the OVX. Specifically, we complement previous studies dealing with the impact of crude oil on only shipping firms [29,33], logistic firms [34], and the Baltic Dirty Tanker index [35], by examining the impact of OVX on the US transportation industry and the intensity and presence of jumps in the stock indexes across various time periods. Accordingly, our analysis differs in its focus on three transportation stock indexes (airlines, marine, and trucking), which exhibit various levels of dependence on energy consumption, and by considering the GARCH-jump modelling approach.

Secondly, we add to the literature on risk transmission among oil and US sector market returns. Studying the volatility linkage is important, since the volatility of an asset is associated with the rate of information flow to a particular market, and understanding asset price volatility is crucial for pricing derivatives [36]. Refs. [7,16,25] state that understanding volatility spillovers between energy and stock markets plays a pivotal role in building accurate asset-pricing models and reliable forecasts for market risk.

Thirdly, our analysis investigates the impact of various crisis periods, namely the 2008 global financial crisis, the oil price crash of 2014, and the COVID-19 outbreak,[8] on the risk transmission from energy to various transportation sector stock markets. Since financial markets can behave differently under tranquil and turbulent market conditions (see [7]), this inspection matters to various market participants concerned with the flow of information and jumps during troubled periods for the transportation industry (notably the COVID-19 outbreak), and thus could lead to interesting and refined conclusions.

Fourthly, we investigate the asymmetric impacts of oil price uncertainty on stock prices by splitting OVX into positive and negative portions. To serve this purpose, we employ likelihood ratio tests for assessing asymmetric relationships, which adds to previous studies [29, 33–35] which tend to overlook such an asymmetric effect in the oil-transportation nexus.

Finally, we detect the presence of time-varying jumps in transportation stocks employing the GARCH-jump process. Doing so is crucial, given that jumps in stock prices, which could occur due to extreme events such as recessions, terrorist activities or pandemics, represent an important element of risk. Earlier studies (e.g. Refs. [39, 40]), argue that jumps in financial time series represent a major source of non-diversifiable risk, which should be modelled precisely. To this

[5] Ref. [9] contends that a rise in energy price tends to increase the manufacturing costs which, in turn, impact inflation, consumer behavior and therefore economic progress. Since stock market performance is considered as a good indicator of economic activity, it is thus essential to understand the dynamic link between energy and equity prices. Ref. [10] documents that uncertainty in crude oil price sends volatility to financial sectors leading to instant turbulences in the overall economic activities. Other studies focus on the effect of crude oil shocks on the job market [11,12] and economic growth [13], whereas [14] look at the oil-food nexus [14,15] highlight the impact of the COVID-19 outbreak on the spillover effect between oil market shocks and green bond markets.

[6] Other studies (Refs. [19,20] and others), however, report a positive link between energy and equity market returns.

[7] Employing the bivariate VAR-GARCH approach, Ref. [23] finds that the Brent oil market sends volatility to Lebanese equity prices, and that the said association gets stronger throughout the 2008 recession period and becomes weaker during the post-crisis period.

[8] Some studies consider the economic worries in response to the pandemic (e.g. Ref. [37]) and the political economy of health in conflict during the pandemic (e.g. Ref. [38]).

end, applying an appropriate model for capturing time-varying jumps is essential to avoid the specification errors in conventional estimation methods.[9] Moreover, since jumps occur as a consequence of occasional events, the existence of large price swings in a specific sample period could have a significant effect on the volatility prediction [42]. Hence, adopting an appropriate volatility model such as the GARCH-jump process, which can simultaneously capture both jumps and time-varying volatility, plays a pivotal role in understanding the volatility dynamics of transportation stocks. It is also noteworthy that jumps occurring in asset returns might have predictive content for downturns in global financial markets. Previous literature (e.g. Refs. [2,43]), argues that future market downturns could be realized in a series of jumps over a short interval (see, [44]). In this study, we explore whether the intensity of jumps for airlines/marine/trucking sector stocks rises during crisis periods. This adds a new dimension to the transportation sector literature.

The main results show that all transportation sectors are affected by OVX, but the trucking subsector in particular responds most, followed by airlines, and finally the marine subsector is least affected by OVX. The impact seems to depend on the level of oil (energy) consumption of the transportation subsector under study. Of the three transportation subsectors, trucking is the largest consumer of fuel (22%), followed by airlines (9%) and shipping (3%). The impacts vary over time and occur during some crisis periods. A jump component is detected in the volatility of the three transportation subsector indexes, and its intensity varies over time. For comparison purposes, we find that transportation stocks are more sensitive to OVX shocks than the S&P 500 index.

These findings should matter for the volatility predictability of the three transportation subsectors, and possibly for the volatility modelling, while accounting for jumps during stable and turbulent periods. Specifically, the discussion on the impact of oil implied volatility on the airlines, marine, and trucking indexes should help these subsectors better understand their responsiveness to oil implied volatility during various periods and thus improve their capability to deal with crude oil market risk.

The structure of the paper is as follows. Section 2 gives a review of the relevant studies. Section 3 describes the data used in the empirical analysis. Section 4 outlines the VAR-GARCH methodology. The presentation and discussion of the results take place in Section 5. We conclude in Section 6.

2. Literature review

A growing body of literature examines the linkages between crude oil and stock markets. A major strand of this literature investigates how volatility is transmitted from energy to stock markets. For example, a study by Ref. [21] uses the BEKK–GARCH (1,1) specification in order to assess the volatility connections among the global crude oil market, the US and several Middle East Gulf equity markets including Saudi Arabia. The authors find that oil volatility has substantial effects on the stock markets considered. The Saudi Arabian stock market sends volatility to the crude oil market. Ref. [22] explore the uncertainty transmission between international energy prices and equity market returns in Ghana using the VAR–GARCH, VAR–AGARCH and DCC–GARCH models. Their results confirm a bidirectional volatility linkage between the energy and stock markets with the spillover effect being relatively strong when the causality goes from oil to the equity index. Moreover, applying the bivariate VAR-GARCH approach, Ref. [23] finds that volatility significantly runs from Brent oil to the Lebanese stock index, and that the said association gets stronger throughout the 2008 recession period and becomes weaker during the post-crisis period. Ref. [45] investigate the effect of oil price volatility on South Asian equity markets. Using the bivariate VAR-GARCH approach, the authors find return and volatility linkages among these markets. Ref. [46] study the spillover effect between oil and European financial markets in both the time and frequency domains. They show evidence that the spillover is generally weak, but intensifies during economic crises and turmoil in the oil market. During economic and stock market turbulence, the cross-correlation and causal flow from stock to crude oil markets intensify, whereas during turbulent periods in the oil market, the causal flow running from the oil market increases without impacting the correlation[10].

A second strand of literature digs into the oil-stock nexus by considering the sectoral level of stock data. Ref. [24] adopt a multivariate GARCH model and show that the oil market sends volatility to most of the US stock sector indexes. Ref. [52] investigate whether the energy market is correlated with the Turkish electricity sector stock market. Employing the Cheung–Ng causality method, they report a causal connection between global energy prices and equity returns of power sector firms. Ref. [26] uses multivariate and bivariate GARCH models and find significant evidence of risk transmission between oil and alternative energy equity returns. Ref. [16] apply a multivariate GARCH methodology to the link between the second order moments of global energy and sectoral equity prices in Europe and the US. The authors show that, in Europe, uncertainty transmits from energy to the stock markets, but not the other way around. For the US market, however, the association appears to be bidirectional. Ref. [25] report similar results, highlighting the significant volatility linkages between crude oil and sector stock returns and the resulting portfolio implications. Ref. [53] conduct quantile regression analysis to explore the structure and degree of the oil price impact on Indian sectoral stock indexes. The authors show that diversification benefits are possible if these sectoral stocks are included in a portfolio of oil assets. The use of the frequency domain causality test suggests that there is interdependence between oil and sectoral equity markets in India. Ref. [27] consider the nexus between oil price shocks and 10 European stock sector returns in a time-varying setting. They show that the relationship is affected by the source of the oil shock and is generally sector-specific, and that during the 2008 global financial crisis some stock sectors offered diversification benefits to crude oil investors. Ref. [28] study the nexus between oil price volatility and stock sector returns in the Gulf Cooperation Council (GCC) region using an approach combining wavelets with quantiles. They find that all the stock sectors are associated with oil price volatility, except for the bank and insurance stock sectors at low and high quantiles. Furthermore, transport and telecommunication companies are unresponsive to oil price volatility at high quantiles. Ref. [54] examine the influence of crude oil price changes on the returns and volatility of airline companies in China and South Korea. Using a multivariate GARCH model, their results suggest that volatility spillovers are more important than return spillovers, and that smaller airline companies are more responsive to oil returns than larger companies. Ref. [55] focus on the influence of economic policy uncertainty (EPU) and oil prices on the returns of US airline companies using a structural VAR model. The results show that higher oil prices, EPU, and jet fuel volatility are negatively associated with stock returns. Ref. [56] argue that the impact of crude oil prices on fuel, electric and electric vehicle sales is industry-specific, and tends to vary at various quantiles.

A third strand of literature uses OVX to capture the consequence of energy market volatility on asset prices. Ref. [30], for example, highlight the positive impact of oil price shocks on Chinese stock returns and

[9] As Ref. [41] state: ‘Jump risks are not only important for investors who may demand a large premium to carry these risks, but also vital for policy makers who must make decisions in real time during times of jump-inducing chaotic conditions in financial markets’.

[10] Other studies examine environmental movement [47], climate change challenges [48], environmental policy objectives [49] and emission taxes [50], bearing in mind that monetary policies are affected by a changing financial environment [51].

argue that OVX shocks have significant negative effects on the Chinese stock market. Ref. [3] investigate the effect of OVX on the stock markets of MENA countries using various specifications of GARCH models and report significant impacts on the majority of the stock markets under study. Ref. [31] finds that the information in OVX is of paramount importance for understanding and projecting the time-varying variability of clean energy equity prices. Ref. [32] reveal that OVX is an important instrument, capable of hedging clean energy equities. Ref. [57] shows that OVX has a substantial impact on the US energy sector volatility index. Ref. [33] apply univariate GARCH models to study the impact of oil returns on the return volatility of global shipping firms in Germany, South Korea and Taiwan. They report evidence that the leverage effect shock impacts are asymmetric. Ref. [58] focus on the impact of oil price shocks and policy uncertainty on the returns of Chinese travel and leisure stocks using a time-varying parameter VAR model. They find that the impact of oil price shocks is generally positive, whereas that of policy uncertainty swings between positive and negative. Ref. [59] study the ability of the US implied volatility index (VIX) and OVX to hedge the downside risk of travel and leisure stocks in developed economies. The results show that OVX is more negatively correlated with the returns of travel and leisure stocks than VIX, which points to the superior hedging role of OVX. Ref. [34] apply equicorrelation and spillover approaches and show evidence of the linkages between crude oil and logistics firms. Notably, the linkages increase during the global financial crisis of 2008 and oil price war of 2015–2016. Ref. [6] examine the spillovers across the returns of US stock sector indexes while separating high volatility regimes from low volatility regimes, and relate the spillovers to OVX. They find that, irrespective of the volatility regime, the energy sector plays a central role in the spillover analysis, and the return spillover effect strengthens following the COVID-19 outbreak. Notably, they conduct a Granger causality analysis and show OVX Granger causes the return spillover index, especially during the high volatility regime. Ref. [7] examine the impact of OVX and geopolitical risk on the returns and volatility of GCC stock sectors, using a quantile-based approach, differentiating various return and volatility states. The results show that the impact of OVX is generally more significant than that of geopolitical risk on stock sectors. Notably, the impact is positive at the higher quantiles of the return distribution but stronger for volatility. However, some sectors such as the energy, material, industrial, and financial sectors respond negatively during bear markets and positively during bull markets. Further evidence suggests that OVX has a higher impact on the volatility of some stock sectors during the COVID-19 pandemic. Ref. [35] examine the relationship between oil price uncertainty and the Baltic Dirty Tanker index using a regime switching regression. The results show a negative association, which is more notable during periods of high volatility. Ref. [29] focus on the volatility connectedness between crude oil and the marine shipping industry (tanker and dry cargo markets). They show stronger connectedness for the tanker market than the dry cargo market, and report evidence of the important role played by oil volatility in the tanker market. Their analysis shows that hedging is not effective during crisis periods, such as the pandemic and oil price crash of 2014, due to the increased relationship between shipping and oil markets during such events. Besides the above-mentioned studies covering the pandemic, other studies also highlight the impact of COVID-19 on US travel and leisure (see Ref. [60]) and the shipping industry [61].

3. Data

We use the daily observations of crude oil VIX (OVX) published by CBOE. OVX measures the market expectation for future 30-day crude oil price volatility, calculated following the same methodology used to construct the US volatility index (VIX). Specifically, the calculation relies on the real time bid and ask prices of nearby and second nearby options on the United States Oil Fund, having at least 8 days to expiration. We also use the Dow Jones index to track the equity prices of the airlines, marine and trucking sectors. The sample covers the period May 10, 2007 to December 31, 2021, providing 3689 data points for each time series. Note that OVX data are available from May 10, 2007. Our data are collected from the Thomson Reuters DataStream database.

Table 1 reports the summary statistics for the logarithmic returns of each of the three stock indexes considered and for the levels of the OVX index. The results suggest that the mean return is higher for airlines stocks followed by trucking sector stocks, while the marine sector stocks, on average, experience negative returns. The standard deviation is found to be higher for the airlines sector in comparison to the rest. All the return series are negatively skewed, and each of the indexes is leptokurtic, implying that the data do not follow the normality assumption. The results of the Jarque-Bera test further confirm that the null hypothesis of normality of the return distribution is rejected at the 1% significance level. The results of the augmented Dickey–Fuller (ADF) and Phillips-Perron (PP) tests confirm the stationarity of the three return series and the OVX index. We further apply the autoregressive conditional heteroscedasticity (ARCH)-Lagrange multiplier (LM) test of [62], and the results indicate the significant presence of the ARCH effect in squared residuals of the airlines, marine and trucking sector returns, and thus the suitability of applying a GRACH-based test on the return series.

Fig. 1 depicts the stock indexes under study. We note that all these indexes behave similarly and experience several downturns during the sample period. For instance, a significant fall in the price indexes is observed during the 2008 global financial crisis and around the COVID-19 pandemic. We also plot in Fig. 2 the returns of the airlines, marine and trucking indexes, where a large variability in these return series is noticed around the global financial crisis and the pandemic. Next, Fig. 3 displays the OVX index, where we also see a number of spikes. The first is seen during the 2008 recession, when the oil market experiences a huge drop in its price levels. In addition, the oil market uncertainty increases evidently during the 2014 oil price decline. Finally, an extreme situation is observed when the pandemic hits the global crude oil market and the per-barrel price of the Brent crude slips to $22.58 at the end of March 2020.

4. Methodology

The GARCH-jump approach is widely used in empirical finance research (see Refs. [3,4,44,63–67]), given its ability to capture not only smooth persistent changes in volatility, but also discrete jumps in asset returns. Notably, the GARCH-jump approach allows the jump parameters to vary over time. This is an important feature, because the assumption of constant jump intensity is unlikely to reflect reality, resulting in persistence in high volatility or the overestimation of volatility [68]. In this regard, accurate detection of time-varying jumps impacts investors' portfolio allocation strategies [65].

In this study, we specify the GARCH-jump process as follows[11]:

$$R_t = \pi + \mu R_{t-1} + \delta \Delta OVX_t + \epsilon_t \tag{1}$$

where R_t indicates the logarithmic return of the transportation stock index at time t, $\Delta OVX_t = OVX_t - OVX_{t-1}$ and ϵ_t, the noise term, is defined as:

$$\epsilon_t = \epsilon_{1t} + \epsilon_{2t} \tag{2}$$

where, ϵ_{1t} takes the form:

$$\epsilon_{1t} = \sqrt{h_t} z_t, \quad z_t \sim NID(0,1)$$

$$h_t = \omega + \alpha \epsilon_{1t-1}^2 + \beta h_{t-1} \tag{3}$$

Additionally, ϵ_{2t} refers to a jump innovation defined as:

[11] The AR(1) process is chosen based on the Akaike information criterion (AIC) and Bayesian information criterion (BIC).

Table 1
Summary statistics of daily data series - stock returns and OVX index.

Index	Mean	Standard Deviation	Skewness	Kurtosis	Jarque-Bera Test	ADF	PP	ARCH-LM
Airlines	.0137	1.1348	−.1463	7.5455	2399.85***	−56.25***	−56.27***	105.21***
Marine	−.0077	.9271	−.6872	9.1544	599.70***	−56.04***	−56.05***	233.81***
Trucking	.0121	.7096	−.2931	8.4313	3451.81***	−60.70***	−60.86***	81.79***
OVX	38.2077	18.5417	4.5271	41.0536	235310.61***	−4.02***	−7.14***	–

Notes: The table provides the summary statistics for the logarithmic returns of each of the three stock indexes (airlines, marine, and trucking) and for the OVX index. The sample period is May 10, 2007–December 31, 2021. Augmented Dickey–Fuller (ADF) and Phillips-Perron (PP) are conducted with an intercept. Autoregressive conditional heteroscedasticity Lagrange multiplier (ARCH-LM) is the test of [62]. *** indicates statistical significance at the 1% level.

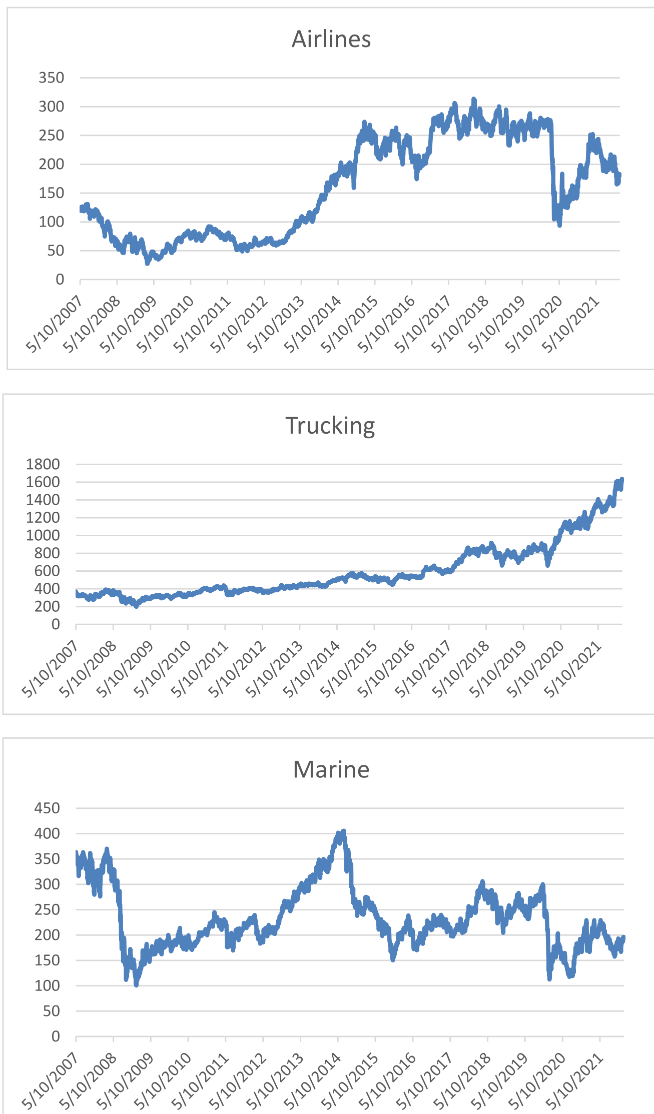

Fig. 1. Stock price indexes for transportation sectors.

$$\epsilon_{2t} = \sum_{l=1}^{n_t} U_{tl} - \theta\lambda_t \tag{4}$$

where U_{tl} specifies the size of the jumps and follows a normal density function with first and second order moments θ and d^2 respectively. $\sum_{l=1}^{n_t} U_{tl}$ refers to the jump factor, while n_t indicates jump frequency. n_t is supposed to follow a Poisson distribution with an autoregressive conditional jump intensity (ARJI) modelled as:

$$\lambda_t = \lambda_0 + \rho\lambda_{t-1} + \gamma\xi_{t-1} \tag{5}$$

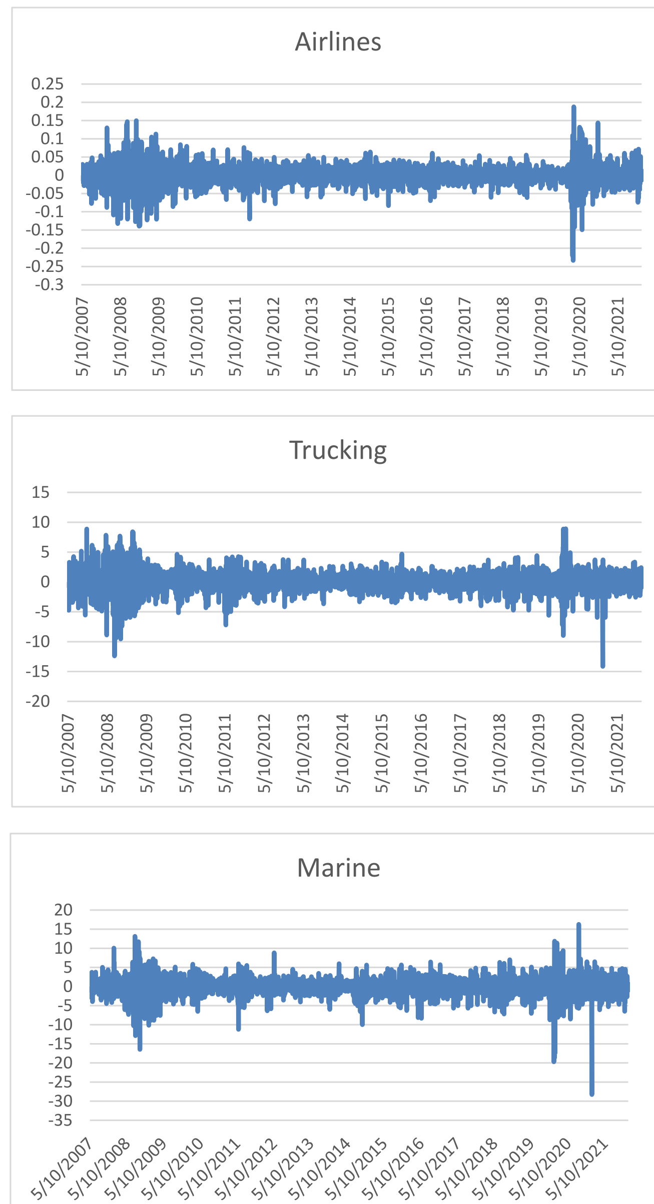

Fig. 2. Stock returns for transportation subsector indexes.

where $\lambda_t > 0$, $\lambda_0 > 0$, $\rho > 0$ and $\gamma > 0$.

The log-likelihood function is given by:

$$L(\Psi) = \sum_{t=1}^{T} \log f(R_t | I_{t-1}; \Psi)$$

where $\Psi = (\pi, \mu, \delta, \omega, \alpha, \beta, \theta, d, \lambda_0, \rho, \gamma)$.

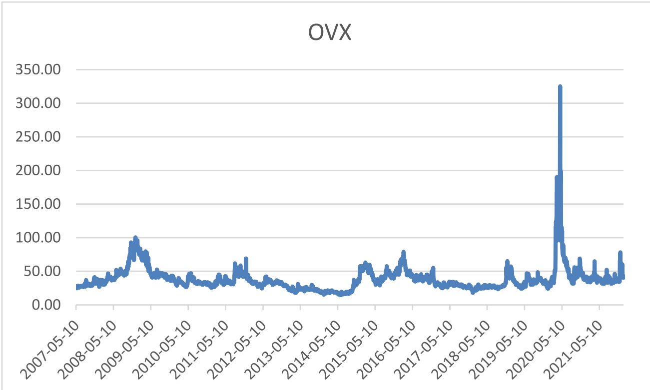

Fig. 3. Crude oil implied volatility index (OVX).

5. Empirical results

5.1. Estimates of GARCH-jump model

The output of the GARCH-jump process for the full sample period is shown in Table 2. The results reveal that the parameters of the GARCH model are highly significant and hence there is evidence of GARCH effects in transport sector asset returns. Additionally, the combined value of α and β reveals the presence of strong persistence in the volatility of the transportation stock indexes. In particular, the persistence of shocks equals 0.9929, 0.9557 and 0.9791 for the airlines, marine and trucking subsectors, respectively. Such high persistence further implies that negative effects from increased market risk decay very slowly. Moreover, the half-life decay, perhaps the most interpretable measure of persistence, indicates half-lives ranging from around 15 (marine) to 97.27 (airlines) days.[12] Hence, our results suggest that the volatility of these stocks exhibits long memory.

Next, the three transportation subsector stock indexes (airlines, marine, and trucking) seem to react significantly to oil price volatility measured by OVX. In particular, the parameter δ, which measures the effect of OVX, is statistically significant at the 1% level and equals −0.0934, −0.0809 and −0.1397 for the airlines, marine, and trucking sectors, respectively. This finding is not surprising, given that the US transport sector has emerged as a leading user of fossil-based fuels and therefore a volatile energy market tends to impact the firms operating in this sector. Notably, the effect of OVX on these subsector indexes seems negative, meaning that an upturn in oil price volatility would cause a significant drop in transport sector stock prices. One could expect that, since the underlying sector uses oil as a main input, oil price volatility has substantial effects on its financial activities, and hence there is an inverse association between transportation subsector stock returns and oil market volatility. Moreover, the impact of OVX appears to be higher for the trucking sector than the airlines sector. The marine sector is the least affected. These results thus support the hypotheses discussed in the introductory section.

Table 2
Estimates of the GARCH-jump model for the full period.

Variable	Airlines	Marine	Trucking
π	.0423** (.02)	.0248*** (.00)	.0303*** (.00)
μ	−.0082 (.65)	−.0534*** (.00)	.0103 (.56)
δ	−.0934*** (.00)	−.0809*** (.00)	−.1397*** (.00)
ω	.0003 (.79)	.0044*** (.00)	.0021 (.12)
α	.0196*** (.00)	−.0010 (.66)	.0061 (.27)
β	.9733*** (.00)	.9557*** (.00)	.9791*** (.00)
θ	−.1182 (.21)	−.0081 (.19)	.0980* (.08)
d^2	1.1768*** (.00)	.4720*** (.00)	0.9747*** (.00)
λ_0	.0298 (.25)	.0157*** (.00)	0.0078** (.02)
ρ	.8428*** (.00)	.9909*** (.00)	.9825*** (.00)
γ	.1902 (.11)	.4354*** (.00)	.2857*** (.00)
$Q^2(10)$	3.18 (.34)	2.49 (.28)	3.91 (.14)
LogL	−3767.07	−2348.26	−3007.01

Notes: The full sample period is period is May 10, 2007–December 31, 2021. δ measures the effect of OVX, while λ_0, ρ, and γ are the jump intensity parameters. $Q^2(10)$ is the Ljung-Box test statistic for serial correlation in the squared standardized residuals with 10 lags. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively. The *p*-values are given in parentheses.

The results shown in Table 2 indicate the presence of time-dependent jumps in equity markets as the corresponding coefficients are statistically significant. Therefore, it can be concluded that the volatility of the US transport sector equity indexes contains a jump component. We also note that the jump intensity has a tendency to change over time. For example, the parameter ρ, which measures the persistence in the conditional jump intensity, is estimated to be 0.9825 for the trucking sector index, suggesting that the intensity of jumps is highly persistent.[13] A similar behaviour is observed for the airlines and marine subsector indexes. The γ coefficient, measuring the sensitivity of λ_t to a lagged shock ξ_{t-1}, reveals that an upsurge in ξ_{t-1} might cause a diminished effect on the future jump intensity. Notably, the intensity coefficients are all positive (i.e., $\lambda_0 > 0, \rho > 0$ and $\gamma > 0$) and hence the results confirm that the approach adopted is a suitable model for detecting time-varying jumps in the equity prices of the three transportation subsectors. The results of our empirical investigation support the findings of earlier studies (see Refs. [4,63,67] among others), which show the existence of time-dependent jumps in global equity markets. In addition, according to the Ljung-Box Q^2 statistics, the standardized residual series cannot reject the null hypothesis, indicating the absence of correlations in the squared residuals. This finding further advocates the application of the GARCH-jump model.

Considering Fig. 4, which depicts the jump intensities for various transportation subsector indexes, it is evident that both airlines and marine subsectors experience a significant number of jumps during the 2008 global financial crisis. Furthermore, we observe a cluster of jumps for these two subsectors amid the COVID-19 pandemic. The expected number of jumps tends to increase substantially in April 2020. Hence, jumps seem to be increasing during turbulent periods, signalling a potential downturn in stock prices. Notably, the intensity of jumps is much higher during the COVID-19 crisis compared to the 2008 global financial crisis. It is also worth noting that the number of jumps is much lower in the trucking subsector than in other transportation subsectors. This finding is also in line with Fig. 1, where we notice that the trucking subsector is the least affected by these crises.

Overall, our empirical analysis shows that movements in OVX, in general, have a crucial role to play in pricing US transport sector stocks. These results, therefore, suggest that investors and policymakers should closely observe oil market behaviour in order to make proper investment decisions and predict stock market volatility more efficiently. In addition, firms functioning in this sector should adopt effective measures to reduce the adverse impact of oil price volatility. The occurrence of time-dependent jumps should receive considerable attention, as ignoring such jumps could mislead the risk assessment procedure. Overall, investors financing transport companies should consider the issues related to crude oil volatility as well as jump phenomena to gain a deeper understanding of future market trends.

[12] Half-lives are calculated as $\log(0.5)/\log(\alpha+\beta)$.

[13] See Ref. [2] for further details.

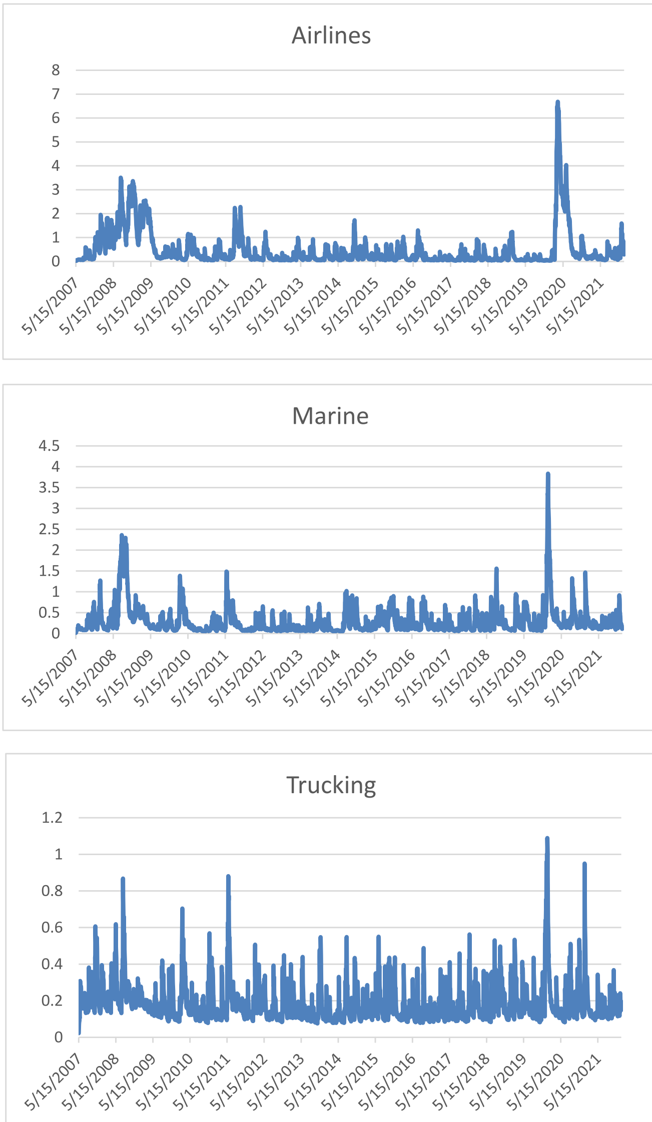

Fig. 4. Intensity of jumps in different transportation sector stock indexes.

5.2. Subsample analyses

We split the full sample into a crisis period (January 2, 2008–June 30, 2009) and post-crisis period (July 1, 2009–December 31, 2021). This analysis should be useful to measure the effect of the 2008 economic downturn on the association under investigation. We define the 2008 recession period according to the National Bureau of Economic Research guidance. Table 3 displays the results of our sub-period examination. Firstly, the impact of oil volatility shocks on equity prices is highly significant, except for the marine sector. Secondly, throughout the crisis period, the parameters of the jump model appear to be more significant than for the full sample (see the results for the airlines sector).

We also explore the relationship during the 2014 oil price decline (July 2014–December 2015) and COVID-19 pandemic (January 2020–December 2021) periods. The 2014 downturn in energy markets, which could be the consequence of a strong US dollar, surplus of crude oil, diminishing demand and the Iran nuclear deal, causes high uncertainty in global crude oil markets. The outbreak of COVID-19, on the other hand, has a substantial impact on several important industries, including the automotive, aviation, high-tech, retail and travel and tourism sectors (e.g., Refs. [60,61]).

We present these results in Tables 4 and 5, respectively. Table 4, for

Table 3
Subsample analysis: 2008 global financial crisis.

Variable	Airlines	Marine	Trucking
π	−.2670 (.21)	.3269** (.04)	.0738*** (.00)
μ	−.0210 (.64)	−.0096 (.85)	−.0784 (.13)
δ	−.1979*** (.00)	.0208 (.67)	−.1137** (.04)
ω	.6031*** (.00)	.0934* (.06)	.0138 (.56)
α	.0759*** (.00)	.0891*** (.00)	.0506*** (.00)
β	.8697*** (.00)	.8996*** (.00)	.9373*** (.00)
θ	.0303 (.98)	−3.8048*** (.00)	−1.0482 (.37)
d^2	6.1612*** (.00)	.0000 (.99)	3.8550*** (.00)
λ_0	.0650*** (.00)	.0697 (.46)	0.0415*** (.00)
ρ	.5294*** (.00)	.5015 (.45)	.4448*** (.00)
γ	.1558 (.49)	.0625 (.62)	.0702 (.65)
$Q^2(10)$	2.31 (.46)	7.87* (.09)	3.43 (.38)
LogL	−1007.34	−970.04	−914.66

Notes: The sample covers the period January 2, 2008–June 30, 2009. δ measures the effect of OVX, while λ_0, ρ, and γ are the jump intensity parameters. $Q^2(10)$ is the Ljung-Box test statistic for serial correlation in the squared standardized residuals with 10 lags. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively. The *p*-values are given in parentheses.

Table 4
Subsample analysis: 2014 oil market downturn.

Variable	Airlines	Marine	Trucking
π	.1088*** (.00)	−.0820 (.46)	.5586*** (.00)
μ	−.0291 (.56)	.0839 (.14)	−.2084*** (.00)
δ	−.1082*** (.00)	−.0089 (.85)	−.0610*** (.00)
ω	.6190*** (.00)	1.9119*** (.00)	.0182** (.04)
α	.0824*** (.00)	.1295 (.10)	.0768*** (.00)
β	.7118*** (.00)	.1361 (.14)	.8619*** (.00)
θ	−.5289 (.56)	−.2546 (.30)	−1.1643*** (.00)
d^2	2.9635*** (.00)	1.9779*** (.00)	0.4263 (.21)
λ_0	.0385** (.04)	.0289 (.39)	.2022*** (.00)
ρ	.3427 (.30)	.9403*** (.00)	.4618*** (.00)
γ	.0573 (.87)	.2822 (.12)	.8184*** (.00)
$Q^2(10)$	6.11 (.12)	2.71 (.33)	5.47* (.09)
LogL	−780.55	−777.63	−746.29

Notes: The period of the 2014 oil market downturn is July 1, 2014–December 31, 2015. δ measures the effect of OVX, while λ_0, ρ, and γ are the jump intensity parameters. $Q^2(10)$ is the Ljung-Box test statistic for serial correlation in the squared standardized residuals with 10 lags. ***, ** and * denote significance at the 1%, 5% and 10% levels respectively. The *p*-values are given in parentheses.

Table 5
Subsample analysis: COVID-19 pandemic.

Variable	Airlines	Marine	Trucking
π	.0869 (.68)	.1351*** (.00)	.3846*** (.00)
μ	−.0003 (.99)	−.0385 (.51)	−.1176* (.07)
δ	−.0389 (.97)	−.0053 (.45)	.0035 (.56)
ω	.0003 (.79)	.0871** (.02)	.0088 (.46)
α	.1595*** (.00)	.0122*** (.00)	.0342* (.08)
β	.7923*** (.00)	.9642*** (.00)	.9331*** (.00)
θ	.6570 (.63)	1.7875 (.42)	−.3405 (.14)
d^2	1.1768*** (.00)	5.5306*** (.00)	1.5262*** (.00)
λ_0	.0603 (.79)	.1017 (.16)	0.2273 (.20)
ρ	.9629*** (.00)	.1321 (.82)	.5920*** (.00)
γ	1.1951 (.82)	.2894 (.42)	.7960 (.11)
$Q^2(10)$	3.24 (.27)	2.89 (.17)	1.88 (.71)
LogL	−696.36	−632.27	−466.31

Notes: The COVID-19 period is January 1, 2020–December 31, 2021. δ measures the effect of OVX, while λ_0, ρ, and γ are the jump intensity parameters. $Q^2(10)$ is the Ljung-Box test statistic for serial correlation in the squared standardized residuals with 10 lags. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively. The *p*-values are given in parentheses.

example, demonstrates that the impact of oil volatility shocks on the transportation equity prices is highly significant, except for the marine subsector. This result is consistent with that reported in Table 3. Hence, oil price volatility does not have any sort of influence on the marine sector asset class during the downturn periods. The results shown in Table 5 reveal that none of the transport sector stock indexes is sensitive to oil volatility shocks during the COVID-19 pandemic. It seems that the transport sector asset class is insulated from such shocks due to the need for medical isolation and travel bars.

5.3. Testing for the asymmetric effect of oil price volatility

In this section, we examine whether oil price volatility has asymmetric effects on transport sector stock returns. This shows whether positive oil volatility shocks have a larger impact on stock prices than negative shocks. Since increases and decreases in energy price uncertainty levels can cause cyclic variations in investments, testing for asymmetric association plays a pivotal role in risk management and policy formulation. To test the asymmetric connections, the mean equation below is considered:

$$R_t = \pi + \mu R_{t-1} + \varphi_1 \Delta OVX_t^+ + \varphi_2 \Delta OVX_t^- + \epsilon_t \tag{6}$$

where, $\Delta OVX_t^+ = \max(\Delta OVX_t, 0)$ indicates positive energy price volatility and $\Delta OVX_t^- = \min(\Delta OVX_t, 0)$ denotes negative energy price volatility. We then test $H_0 : \varphi_1 = \varphi_2$ to assess the asymmetric link.

Table 6 displays the findings of our asymmetry tests. These results reveal that both positive and negative shocks are significant, with the former having higher impacts than the latter. To make a comparison between the parameters φ_1 and φ_2, we conduct the likelihood ratio (LR) test in which the maximum likelihood functions for the restricted and unrestricted models are given by $L(\widetilde{\Omega})$ and $L(\widehat{\Omega})$, respectively. The LR statistic $(= 2\frac{L(\widetilde{\Omega})}{L(\widehat{\Omega})})$ is distributed as a chi-square variate provided that $H_0 : \varphi_1 = \varphi_2$ is valid. The results of the LR tests show that the symmetry assumption holds only for the airlines sector. Therefore, the effect of energy price variance on the asset returns is asymmetric. Hence, increases and decreases in the crude oil volatility index tend to have heterogeneous impacts on stock returns.[14]

These results carry important information for financial market participants.[15] For investors, understanding such asymmetric linkages between oil and stock prices could be fruitful for taking proper investment decisions. In particular, traders should detect such effects correctly before predicting stock market trends. For academics, a proper knowledge of the nonlinear relationship between energy and equity price indexes could inspire them to develop and use appropriate models that take the asymmetric links into consideration. In addition, policymakers might use our results to design effective strategies, which might help transport firms lessen the adverse impact of oil price uncertainty.

Table 6
Results of asymmetric tests.

Variable	Airlines	Marine	Trucking
π	.0470** (.03)	.0515*** (.00)	.0434*** (.00)
μ	−.0083 (.64)	.0084 (.63)	−.0530*** (.00)
φ_1	−.0998*** (.00)	−.1631*** (.00)	−.1028*** (.00)
φ_2	−.0872*** (.00)	−.1105*** (.00)	−.0597*** (.00)
ω	.0002 (.87)	.0022* (.09)	.0004 (.54)
α	.0194*** (.00)	.0066 (.18)	.00001 (.99)
β	.9733*** (.00)	.9782*** (.00)	.9955*** (.00)
θ	−.1110 (.26)	−.03753 (.14)	−.0019 (.86)
d^2	1.2002*** (.00)	.9891*** (.00)	0.5117*** (.00)
λ_0	0.0280 (.24)	.0076*** (.00)	0.0135*** (.00)
ρ	.8459*** (.00)	.9823*** (.00)	.9906*** (.00)
γ	.1857 (.14)	.2848*** (.00)	.4109*** (.00)
$Q^2(10)$	3.48 (.29)	3.11 (.52)	4.01 (.18)
LogL (constrained)	−3766.99	−3004.46	−2333.29
LogL (unconstrained)	−3767.07	−2348.26	−3007.01
VIF	2.42	3.71	3.86

Notes: The parameters φ_1 and φ_2 measure the asymmetric effect of OVX, while λ_0, ρ, and γ are the jump intensity parameters. $Q^2(10)$ is the Ljung-Box test statistic for serial correlation in the squared standardized residuals with 10 lags. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively. The p-values are given in parentheses. VIF refers to the variance inflation factor statistic.

5.4. Robustness checks

In this subsection, we conduct two robustness checks.

Firstly, the GARCH-jump model, defined in Section 4, assumes that ϵ_{1t} follows a symmetric GARCH(1,1) process. Here, we check the robustness of our results while assuming that ϵ_{1t} follows an exponential GARCH (EGARCH) process, given as:

$$\ln(h_t) = \omega + \frac{\alpha|\epsilon_{t-1}| + \psi\epsilon_{t-1}}{\sqrt{h_{t-1}}} + \beta\ln(h_{t-1}) \tag{7}$$

where, the parameter ψ measures the asymmetry or leverage effect. When $\psi < 0$, positive shocks (good news) generate less volatility than negative shocks (bad news). When $\psi > 0$, positive shocks are more destabilizing than negative shocks.

The results of the EGARCH-ARJI model are presented in Table 7. They particularly show that OVX has significant effects on the stock prices of transportation firms, which is in line with what is reported in Table 2. In addition, jumps still exist in the transportation stock prices and they are time-variant. We also find that the asymmetric parameter (ψ) is statistically significant at the 1% level. Notably, ψ is found to be negative and significant, which suggests that bad news generates more volatility than positive news of the same magnitude.

Secondly, we consider the S&P 500 index for comparison purposes, which is useful for assessing whether transportation stocks are more sensitive to OVX than the US aggregate stock market index. The last column of Table 7 shows that S&P 500 returns experience time-varying jumps. The most interesting findings concern the parameter δ, measuring the impact of OVX, which is weakly significant (at the 10% level) for the S&P 500 index, and its size is much lower than that of the transportation indexes. These results confirm that transportation stocks are more sensitive to OVX shocks than the US aggregate stock market index, measured by the S&P 500.

6. Conclusion

Previous studies argue that variations in crude oil prices have crucial influences on the US equity market and hence the overall economy. This

[14] In Table 6, we report the variance inflation factor (VIF) statistic, which confirms that collinearity is not a serious issue in this case.

[15] There are several reasons to examine the asymmetric effects of oil volatility shocks on transport sector stock returns. The cash flows of leading consumers of fossil-based fuels such as transportation firms often respond differently to positive and negative oil volatility shocks, thereby leading to the asymmetric associations between oil price uncertainty and stock returns [69]. In addition, understanding the heterogeneous sensitivity of investors to positive and negative oil volatility shocks is crucial for portfolio allocation decisions [70]. Given that proper knowledge of such asymmetric linkages would allow investors and policy makers to determine whether positive oil volatility shocks influence equity prices more than negative shocks, they could choose appropriate hedging strategies during periods of high uncertainty. For example, our analysis shows that the airline sector is insulated from the asymmetric effects of oil volatility shocks, while the marine and trucking sectors are sensitive to such shocks. Hence, for the latter sectors, investors need to identify proper hedging tools in order to manage the risk due to the asymmetric effects of oil volatility shocks.

Table 7
Robustness test.

Variable	Airlines	Marine	Trucking	S&P 500
π	−.0896*** (.00)	.1217*** (.00)	.1214*** (.00)	.0014*** (.00)
μ	−.0087 (.61)	.0101 (.57)	−.0382** (.04)	−.1067*** (.00)
δ	−.1907*** (.00)	−.1194** (.03)	−.1409*** (.00)	−.00001* (.09)
ω	.0136 (.11)	.0117** (.02)	.0024 (.47)	.0001** (.04)
α	.0066* (.07)	.0126*** (.00)	.0288*** (.00)	.1023*** (.00)
β	.9823*** (.00)	.9707*** (.00)	.9576*** (.00)	.8305*** (.00)
ψ	−.0034*** (.00)	−.0006** (.04)	−.0021*** (.00)	−.0046*** (.00)
θ	−.1482 (.13)	−.5398*** (.00)	−.3549*** (.00)	−.0061*** (.00)
d^2	2.2699*** (.00)	2.5252*** (.00)	1.4320*** (.00)	.0083*** (.00)
λ_0	.0049** (.04)	.0144*** (.00)	.0330** (.03)	.0580** (.04)
ρ	.9915*** (.00)	.9604*** (.00)	.8927*** (.00)	.7320*** (.00)
γ	.2526*** (.00)	.3833*** (.00)	.4607*** (.00)	.5514*** (.00)
$Q^2(10)$	2.18 (.41)	3.48 (.21)	4.88 (.13)	1.26 (.81)
LogL	−3109.24	−2190.06	−2899.52	−1909.37

Notes: This table reports the results of the robustness test discussed in Section 5.4. The full sample period is May 10, 2007 to December 31, 2021. δ captures the effect of OVX, while $\lambda_0, \rho,$ and γ are the jump intensity parameters. $Q^2(10)$ is the Ljung-Box test statistic for serial correlation in the squared standardized residuals with 10 lags. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively. The *p*-values are given in parentheses.

should be true for the US transport sector, because firms operating in this sector are heavy users of fossil-based fuels. Nonetheless, the effect of energy market volatility on transport sector stock markets is understudied, especially when it comes to jumps. To address this research void, we examine the impacts of oil implied volatility on the performance of three US transport subsector indexes (airlines, marine, and trucking) using a GARCH-jump model capable of capturing the volatility connections in the oil-transportation nexus. Our daily data cover the period May 10, 2007–December 31, 2021, including various turbulent periods such as the 2008 global financial crisis, the oil price crash of 2014, and the COVID-19 pandemic, which should help explain the dynamic link between oil price volatility and US transport sector stocks.

Our results are summarized as follows: Firstly, all the transport subsector stock indexes are the recipients of volatility shocks from the crude oil market. This result indicates that variations in oil prices are important for pricing the airlines, marine and trucking subsector indexes. Notably, the response of each transportation subsector to oil implied volatility seems to depend on their level of oil (energy) consumption. In fact, the trucking subsector in particular responds most to oil implied volatility, followed by airlines and marine. This reflects the numbers which show that, of the three transportation subsectors, trucking is the largest consumer of fuel (22%), followed by airlines (9%) and shipping (3%). Secondly, the impact of oil price volatility on the transport stocks appears to be asymmetric, indicating that rises and falls in oil implied volatility have a heterogeneous effect on transport stock prices. Thirdly, the subsample analyses demonstrate that our main findings tend to hold during crisis and turbulent periods, except for the lack of significant impact of oil implied volatility on the marine subsector during crisis periods, which might imply that factors other than oil price volatility play a role in marine stock returns under extreme events. Fourthly, the analysis indicates the existence of time-dependent jumps in the returns of the three transportation subsector returns. Finally, we conduct analysis involving the S&P 500 index and show that transportation stocks are more sensitive to oil volatility than the US aggregate stock market index, which further supports our main thesis.

The findings of our empirical analysis deserve particular attention from policymakers and investors participating in the US transportation sector. For example, firms trading in the airlines or trucking sectors should develop appropriate strategies to minimize the impacts of oil price volatility on their stock returns. One such policy could be increasing the use of alternative energies. The application of eco-friendly biofuels could limit the dependency on fossil fuels. In addition, the US should improve their oil reserve systems, which would limit the dependence on foreign oil [57]. Financial market participants should closely examine the oil implied volatility when making investment and risk management decisions on transport stocks, especially trucking and airlines during crisis periods. They may also use our results on jumps and the impact of oil implied volatility to forecast stock market volatility and make more refined investment decisions. The information on oil implied volatility should receive particular attention when predicting trends in US transport sector stocks. Moreover, the results should be useful for those stakeholders who use financial derivatives to hedge energy market risk. Overall, our findings could play a role in planning future transportation policy and analysing portfolio diversification and hedging effectiveness across oil and the US sectoral equity markets.

CRediT authorship contribution statement

Anupam Dutta: Conceptualization, Validation, Analysis, Writing – original draft. **Elie Bouri:** Writing, Editing, Final Revision, Project administration. **Timo Rothovius:** Writing, Editing, Final Revision, Supervision. **Nehme Azoury:** Writing, Editing, Final Revision. **Gazi Salah Uddin:** Writing, Analysis, Final Revision, Supervision.

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.

Data availability

Data will be made available on request.

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