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Oil price uncertainty and the relation to tanker shipping

Panos K. Pouliasis[1] | **Christos Bentsos**[2]

[1]Bayes Business School (formerly Cass), City, University of London, London, UK

[2]Independent Researcher

Correspondence
Panos K. Pouliasis, Bayes Business School (formerly Cass), City, University of London, Faculty of Finance, 106 Bunhill Row, London EC1Y 8TZ, UK.
Email: panos.pouliasis@city.ac.uk

Abstract

This article investigates whether time variation in the returns' co-movement of oil and Baltic Dirty Tanker Index can be linked to oil market uncertainty. We measure uncertainty using a battery of different proxies considering both parametric and non-parametric methods and study its role from both statistical and economic perspectives. Using a regression framework combined with regime switching analysis, we show that oil price uncertainty and the future correlation of oil and dirty-tanker returns are negatively associated. This negative association is more pronounced in highly volatile periods. The identified regimes are directly linked to high-low crude oil volatility periods with implications on the level of correlation they exhibit to oil returns. Results are robust across crudes and volatility measures. Additional robustness checks corroborate that results hold for individual dirty-tanker routes and clean-tanker cargoes.

KEYWORDS

regime-shifting analysis, tanker shipping, time-varying correlation, uncertainty, volatility

1 | INTRODUCTION

The inherent high volatility of tanker rates and crude prices reflects the variety of risks that the relevant sectors face. Oil prices and tanker freight are linked in two major ways. First, connecting, inter alios, producers, refiners, power plants and distributors or storage facilities. Second, with respect to the operational cost of vessels, oil supply and demand shocks impact tanker rates by directly adjusting transportation costs, that is, fuel/bunker cost. An unanticipated surge in oil prices inevitably leads to higher costs and, ceteris paribus, lowers shipowners' profit potential (Gavriilidis et al., 2018).[1] After the 2008 financial crisis, freight market volatility spillovers have strengthened (Tsouknidis, 2016). This marked elevated volatility is often credited to non-storability, that is, inventories cannot be used to smooth out positive demand shocks in the freight market. This constitutes a challenge for tanker market players to mitigate freight volatility and reduce cash flow variability. It is a well-known fact that demand for sea transport is uncertain and volatile while supply adjusts sluggishly due to entry costs, time to build, and convex operating costs of ships (see Kalouptsidi, 2014).[2] Demand for tanker services is derived from seaborne global oil trade which in turn is governed by international economic activity and marine trade (Stopford, 2009), together with oil price shocks, wars/conflicts nearby oil production sites, proven/new reserves, environmental conditions, climate and regulations to restraint carbon footprint of vessels, political decisions (e.g., OPEC policies) (Lyridis et al., 2017). All in all, tanker supply and demand shocks have persistent effects on tanker rates as well as the volume of oil exports, fuel prices and profits (Kilian et al., 2023). Therefore, tanker rates have manifested exacerbated volatility and increased sensitivity price fluctuations in the oil market (Hummels, 2007).

In this article, we consider different volatility frameworks to investigate information linkages, predictability and the association between oil market uncertainty and tanker freight rates. Risk awareness with respect to oil market shocks can result in efficient international logistical networks and effective supply chain management. Kleindorfer and Visvikis (2009) state that 'as global logistics networks have grown and developed, they also have presented new challenges in managing risk and volatility across these broad, global networks … the integration of financial and physical markets is a driving force behind the emergence of global logistics.'

There is much literature on the subject of price interrelationships and causality in the tanker and oil markets. Alizadeh and Nomikos (2004) examine linkages between the Brent or Bonny physical markets, futures on WTI and tanker freight and confirm the existence of a cointegrating relationship between oil US prices and freight rates. Yet, the authors do not find evidence to indicate a connection between tanker rates and physical crude oil or futures price differentials. Generally, fluctuations in commodity prices – especially commodities that are inputs to industrial production – are expected to encompass information about economic prospects. Chung and Kim (2011) investigate the effects of oil price fluctuations on dry bulk freight and the interdependencies among dry bulk rates, to conclude that, oil price changes do not affect freight shipping indices in a uniform way.

Other studies explore linkages among oil prices, freight and other oil supply or demand variables. For instance, Poulakidas and Joutz (2009) underscore an association of crude oil prices, oil inventories and tanker freight. When demand for tanker services is high, oil price upward movements or even expectations about upward movements drive tanker rates up as well. Conversely, spot tanker rates fall with high-inventory levels. Moreover, Shi et al. (2013) indicate that tanker freight is more prone to oil supply while tanker market responses to both supply and non-supply shocks, have a positive sign. The direct impact of oil price shocks can be perceived as input-cost consequence, resulting in elevated transportation and energy costs (Chang et al., 2013). In turn, tanker sentiment reflects a strong predictor because of the importance and implications of oil on the economy (Driesprong et al., 2008).

In this article, we implement a distinct approach to explore tanker freight and oil price fluctuations relation. Our primary contribution lies in studying the time variation in the relationship that describes dirty tanker returns and oil price changes with a particular focus on the effect of oil price uncertainty on tanker-oil return correlation. Therefore, our research adds to the literature on freight and oil shocks through the use of our modelling approach to measure quantitatively the magnitude of the distinct effect of oil volatility on the tanker-oil relation and to assess whether this impact differentiates when employing different uncertainty proxies. In the process, we first evaluate freight return predictability power of oil price uncertainty in a vector auto-regressive (VAR) framework. Second, we examine co-movements from the perspective of the conditional return distribution of tanker freight, to identify whether the latter can provide forward-looking information about subsequent oil-freight short-run co-movements. Third, by employing a Markov regime switching (MRS) approach we further our analysis to consider structural breaks and regime shifts in the tanker-oil return relation. We extend prior work (among others, Alizadeh & Nomikos, 2004; Poulakidas & Joutz, 2009; Chung & Kim, 2011) by investigating whether oil price uncertainty can explain the dynamics of the tanker-oil return relation. Note that, although we use the Baltic Dirty Tanker Index (BDTI) as a case study,[3] we also extend our analysis to clean-tanker cargoes (Baltic Clean Tanker Index; BCTI), as well the dry bulk market (Baltic Dry Index; BDI). A battery of robustness experiments is performed controlling for seasonality and using freight-oil correlation as exogenous variable.

Our findings reveal that lagged oil price volatility or 'uncertainty' can significantly explain tanker shipping returns. We measure uncertainty in crude oil markets both parametrically and non-parametrically (free from the potential look-ahead bias), to model and control for the time evolution in the co-movement of tanker freight rates and crude oil returns. Thus, our analysis provides robust results for different schemes of estimating oil uncertainty. Empirically, we show a negative association between oil uncertainty and the future oil-tanker return correlation. This association is more pronounced when the sector experiences periods of high volatility. Low volatility in oil (and freight) market leads to no statistical association, albeit with a tendency to positive values. The identified regimes can be directly linked to periods of low-high oil volatility with implications on the level of correlation they exhibit to oil returns. Regime switching results draw insights from the MRS model that allows for time variation in the transition probabilities (TVTP) but also from a restricted version with constant transition probabilities (CTP). Findings are robust across crudes and volatility measures.

Baltic Indices are composite freight indices widely used by practitioners as general indicators and they constitute 'barometers' of the freight markets (Alizadeh &

Nomikos, 2009; Moutzouris & Nomikos, 2019). As such, it cannot be concluded that all our findings can be generalised to what is termed 'freight.' A potential reason is that the composition and the weights of each route included in the Baltic Indices are chosen by the Baltic Exchange and may vary over time, making the indices not consistent with themselves over time. In addition, BDTI can be considered the shipping cost of oil, based on the average costs of different routes; Baltic Exchange calculates the average rate of each route and BDTI is defined as the sum of average rates of all routes. Hence, another limitation is that BDTI contains routes that are primarily served by vessels of different sizes (e.g., VLCC, Suezmax, Aframax), yet, aggregating different routes and vessel sizes aggregates the dynamics of each shipping subsegment. Therefore, in order to capture the discussed features, we also extend our analysis to individual dirty-tanker routes. Our robustness checks show further evidence to support our main findings in the context of individual dirty-tanker routes.

The rest of the article is structured as follows. Section 2 reviews the data and their statistical properties. Section 3 provides an analysis on the conditional volatility of oil and tanker rates. Section 4 explores predictability in oil and tanker shipping returns. In Section 5 the key results on the relation of oil and BDTI are discussed; robustness checks are also presented. Section 6 implements a regime switching approach to model oil and tanker shipping co-movement. Some additional results for specific tanker routes and other sectors are also presented. Section 7 concludes.

2 | DATA DESCRIPTION AND PRELIMINARY ANALYSIS

We employ data of two marker crudes (WTI and Brent); and, the most popular benchmark indicator for the tanker freight market (Baltic Dry Tanker Index, BDTI). BDTI is composed of daily Worldscale[4] assessments of international dirty tankers (Baltic Exchange, 2020).[5] The sample period spans from 7 June 2000 through 27 May 2020. Daily crude oil spot quotes are collected from Refinitiv database while BDTI is obtained from the Clarkson's Shipping Intelligence Network. We also use data on individual tanker routes, the BDI (Baltic Dry Index) and BCTI (Baltic Clean Tanker Index) to perform additional robustness checks; also from Clarkson's.

Figure 1 shows that WTI and Brent move in proximity to one another. The upward 2000–2008 trend can be attributed to, inter alia, the attacks of 9/11, the US-Iraq military conflict after 2003, the missile tests/launches of North Korea, the 2006 Israel-Lebanon war, Iran's nuclear brinkmanship. After the July 2008 peak, the subsequent sharp decline due to the 2008 financial crisis is then followed by an upward trend until 2012. The price drop after mid-2014 can be attributed to oversupply, shifts in OPEC policies, geopolitical volatility and the increase in US dollar strength. Despite the two crudes share common dynamics, there are short-run divergences as well. For instance, post-2010 the observed excess US supply and production uncertainty in the Middle East regions lead to more pronounced WTI-Brent price decoupling relative to historic patterns. Thus, while any significant disruption in a regional crude oil market is expected to transmit globally and vice versa not all disruptions are alike; for example, an unexpected refinery power outage in the US may not be spilled over the Brent market because it affects regional refining capacity and local demand/supply and not global crude supply (Nomikos & Pouliasis, 2015).

Turning to BDTI, several abrupt short-term changes are evident. During the sudden price drop – an aftermath of the 2008 financial crisis – the index lost more than 79% of its value. After that, there is an upward movement from the second half of 2018 with the index fluctuating widely; the period of crude oil oversupply.

Table 1 reports summary statistics for the mean (log) returns of BDTI, Brent and WTI in Panel A. BTDI has experienced a decrease of approx. 360 basis points per annum (p.a.), yet oil prices still note a positive yield in excess of 0.5% p.a. As expected, BDTI is more volatile than oil, with annualised volatility of 56% versus 44% (41%) for Brent (WTI).[6] The marked elevated freight volatility is often attributed to the non-storable nature of the asset which makes it quite prone to short run jumps (Kyriakou et al., 2017; Nomikos et al., 2013). This has been recognised in the literature as a major challenge, that is, the need to mitigate freight rate variations in costs for shippers or charterers and fluctuations in revenues of tanker operators and owners is of paramount importance (Alizadeh et al., 2015).

3 | CRUDE OIL AND TANKER VOLATILITY DYNAMICS

Quantifying oil price uncertainty is a nontrivial task. Several studies discuss the determinants of oil price and oil price uncertainty; to name a few, Kilian (2008, 2009), Baumeister and Kilian (2016), Baumeister and Hamilton (2019), Gao et al. (2022). Kilian (2009) documents that the underlying cause of a shock has diverse effects on the real oil price. The author disentangles the sources behind oil price fluctuations into three main drivers (structural shocks), namely, supply shocks, aggregate demand shocks, oil-specific demand shocks. The latter reflects

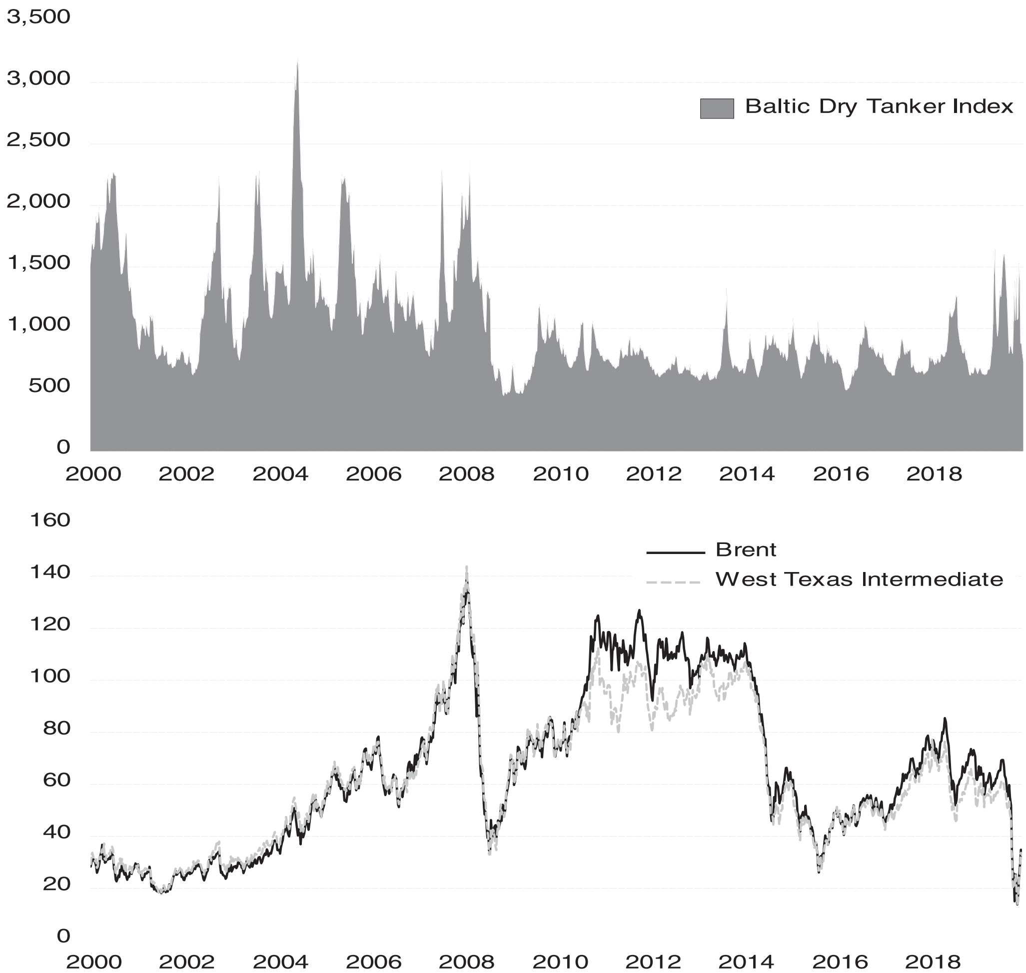


FIGURE 1 Baltic Dry Tanker index (top, index points), Brent and WTI crude oil (bottom, $/bbl) prices 2000–2020.

precautionary oil demand (see also Pindyck, 2004); shifts in uncertainty concerning the shortfall of expected supply compared to expected demand. For instance, if precautionary crude oil demand increases, it is anticipated that the real oil price will move upwards instantaneously in a persistent way. Instead, positive shocks of industrial commodities demand on the whole will cause a rather delayed yet sustained and substantial increase. Oil supply disruptions also cause price relatively smaller increases but transitory in nature. In fact, even in cases of major supply disruptions (e.g., Iranian Revolution in 1978, Gulf War in 1990–1991) the effect on price is mainly due to increased precautionary oil demand triggered by high uncertainty about probable oil supply shortages (Kilian, 2009). Along this line of thought, the structural decomposition of oil shocks into their underlying supply/demand components has been extensively used (e.g., Baumeister & Kilian, 2016; Kilian & Murphy, 2014) as a way to distinguish among supply uncertainty, demand uncertainty and oil price uncertainty.

In this context, we study the element of economic uncertainty related to the oil price volatility, following literature such as Elder and Serletis (2010), Gao et al. (2022), among others. That is, we do not differentiate between demand-driven and supply-driven shocks but rather interpret uncertainty as an average composition of both demand and supply. Supply shocks alone cannot fully explain oil price variations while quantification of demand shocks is nontrivial and faces data limitations (Kilian, 2009). On the other hand, the expectation shifts associated with precautionary demand shocks are unobservable. The oil uncertainty proxy used in this article is related to the overall price uncertainty; while a shock to uncertainty regarding potential oil scarcity in the framework of Kilian and Murphy (2014) would only impact one price component. Note that, since oil price uncertainty is obtained from the oil price itself it may be thought as a measure of the demand for freight; since the latter is merely a derived demand for the 'underlying' transported commodity (Stopford, 2009).[7]

TABLE 1 Descriptive statistics and unit root tests

	BDTI	Brent	WTI
Panel A: Descriptive statistics			
Ann. Mean	−3.593	0.723	0.567
Ann. Vol.	56.12	43.89	41.19
Skew	−0.108	−0.729	−0.525
Kurt	7.988	20.01	15.94
JB test	1082***	12,652***	7314***
Q (1)	85.43***	1.339	5.240**
Q (5)	87.51***	27.18***	19.46***
Q^2 (1)	21.35***	325.0***	60.05***
Q^2 (5)	312.2***	1176***	330.1***
Panel B: Unit root tests			
ADF (levels)	−4.196***	−2.039	−2.095
ADF (returns)	−21.48***	−33.41***	30.08***
PP (levels)	−3.856***	−2.114	−2.285
PP (returns)	−23.38***	−33.40***	−30.09***

Note: This table reports summary statistics and unit root tests for the BDTI, Brent and WTI. The sample period spans from 7 June 2000 to 27 May (1043 weekly observations). In Panel A, statistics refer to the log-return series'. Mean and Volatility figures are annualised and are expressed in percentage terms. Skew(ness) and Kurt(osis) are the third and fourth moments of the distribution; JB test is the Bera and Jarque (1980) normality test. In Panel B, ADF is and PP are the Augmented Dickey and Fuller (1981) and Phillips and Perron (1988) unit root tests. Asterisks *, **, *** indicate significance at 10%, 5% and 1% significance level.

To quantify oil price uncertainty, both parametric and nonparametric measures of volatility are considered. Traditionally, autoregressive conditional heteroscedasticity (ARCH) models (Engle, 1982) have been employed to describe the conditional volatility of asset prices, because of their flexibility.[8] To this end, we apply the generalised ARCH (GARCH) model (Bollerslev, 1986) to estimate the volatilities of WTI, Brent and BDTI. Mathematically, this can be expressed as:

$$\sigma_t^2 = \omega + \alpha(r_t - \mu)^2 + \beta\sigma_{t-1}^2, \tag{1}$$

where $(r_t - \mu)$ are the demeaned return series, σ_t^2 the conditional variance at time t.

Results are presented in Table 2. All series' display ARCH and GARCH effects and high degree of persistence; $\alpha + \beta$ is close to one.[9] Shocks tend to die out slowly and volatilities in both the tanker sector and oil show long memory. Average annualised volatility estimates for BDTI, Brent and WTI are respectively 50.8%, 37.5% and 37%.

In Figure 2 GARCH annualised volatilities of Brent and WTI illustrate similar patterns; both are driven by the same underlying conditions prevailing in the global oil markets. Yet, any differentiation is mainly due to short-run market-specific regional effects, attributed to differences in market structure leading to relative autonomy. For example, European markets are more dependent on middle distillates and more susceptible to extreme weather conditions compared to the US (Nomikos & Pouliasis, 2015).

In Figure 2 a strong co-movement between BDTI and oil volatilities is drawn. This is also supported by the unconditional correlation of these volatilities - close to 80% for the two crudes (Table 2). As oil is indispensable to shipping, both as fuel and cargo, tanker freight rates will be dependent on oil prices and the behaviour of oil traders. For instance, news of an oil production cutback might drive oil prices up since traders normally have an incentive to rush and buy oil and charter vessels to avoid future shortages. This might cause a surge in demand for tankers and a sharp increase in freight, leading to exacerbated volatility. Still, Figure 2 portrays short run differences as well, since market fundamentals are not identical and good/bad news tend to transmit differently across markets.

GARCH models tend to produce high persistency in shocks; misleadingly implying high degree of predictability which is merely the effect of heavy tailed distributions, asymmetries and structural breaks.[10] Acknowledging this, some provisions for robustness are in order. Therefore, we

TABLE 2 GARCH volatility model estimates

GARCH coefficients	BDTI	Brent	WTI
ω	2.700**	0.801**	1.643*
	(1.285)	(0.360)	(0.874)
α	0.137***	0.153**	0.140**
	(0.034)	(0.067)	(0.064)
β	0.824***	0.834***	0.809***
	(0.048)	(0.060)	(0.078)
Average volatility			
$\overline{\sigma}$ p.a.	50.79	37.48	36.98
Diagnostics			
$\rho(R_{BDTI}, R_{oil})$	–	−21.17***	−14.90***
$\rho(\sigma^2_{t,BDTI}, \sigma^2_{t,oil})$	–	81.36***	78.53***
Q (1)	0.556	4.794**	1.749
Q (5)	3.674	8.400	7.070
Q^2 (1)	0.014	1.446	4.187*
Q^2 (5)	7.859	5.530	4.515

Note: The table reports the GARCH parameter estimates for the period 7 June 2000 to 27 May 2020 (1042 return observations). Numbers in () are the corresponding standard errors based on Bollerslev and Wooldridge (1992). The conditional mean equations (not presented here) include a constant for the two crudes and a constant and two autoregressive (AR) terms for BDTI returns (see Table 1 for serial correlation tests on the raw returns). Asterisks *, **, *** indicate significance at 10%, 5% and 1% significance level. $\overline{\sigma}$ p.a is the per annum long run volatility. $\rho(R_{BDTI}, R_{oil})$ and $\rho(\sigma^2_{t,BDTI}, \sigma^2_{t,oil})$ refer to the unconditional correlations between (i) the two returns and (ii) the two variance processes, that is, BDTI and crude oil; where oil = {Brent, WTI}. Asterisks *, **, *** indicate significance at 10%, 5% and 1% significance level.

also estimate volatility nonparametrically by computing realised measures derived from returns of higher frequency. We consider also the same approach for the BDTI-oil correlation dynamics.

Let $\{P_{\tau_0}, P_{\tau_1}, P_{\tau_2}, \ldots, P_{\tau_h}\}$ denote a sequence of prices at days $\{\tau_0, \tau_1, \tau_2, \ldots, \tau_h\}$. Realised volatilities and correlations at week t are proxied by, respectively:

$$RC_{oil,BDTI} = \frac{\sum_{t_h=1}^{M} ln\left(\frac{P_{oil,\tau_h}}{P_{oil,\tau_h-1}}\right) ln\left(\frac{P_{BDTI,\tau_h}}{P_{BDTI,\tau_h-1}}\right)}{RV_{oil} RV_{BDTI}},$$

$$RV = \left[\sum_{\tau_h=1}^{M} ln\left(\frac{P_{\tau_h}}{P_{\tau_h-1}}\right)^2\right]^{0.5}, \tag{2}$$

where the sampling frequency is 1-day and we set $M = 1$, 3, 6, 12 months worth of daily data. Henceforth, these are denoted as RV_{1m}, RV_{3m}, RV_{6m} and RV_{12m}, for $M = 1$, 3, 6 and 12, respectively.

In Figure 3 the two plots at the top portray the volatilities of Brent and WTI. Perturbing M allows these estimators to be either slow ($M = 6$) or fast ($M = 1$) moving with respect to the speed of response to new information. Therefore, high (low) M indicates that market shocks dissipate relatively slow (fast) and thus, the volatility process appears smooth (erratic). The pattern of volatility is very close to GARCH volatility (see Figure 2 vs 3) with similar volatility levels in terms of average volatility across time. On the other hand, standard deviation of the GARCH volatility series for Brent and WTI is lower than RV_{1m} but higher than RV_{6m}. Regarding correlation estimates, both BDTI-Brent and BDTI-WTI present a similar pattern with the latter having a relatively wider range. We can observe several abrupt short-term changes but correlation is primarily negative, yet ranging from 50% to less than −75%.

As a baseline proxy of oil uncertainty, the GARCH model is applied. Nevertheless due to its parametric nature, GARCH potentially introduces a look-ahead bias into our results. However, robustness tests in the ensuing analysis using realised measures of conditional second moments suggest this is not a significant concern.

4 | PREDICTABILITY OF WEEKLY CRUDE OIL AND BDTI RETURNS

If a certain component of returns is expected, its removal, prior to any analysis, may be prudent so that the focus is on the co-movement between the unexpected parts of returns. To this end, we adopt an augmented vector autoregression (VARX) to evaluate return predictability.

Denote Y_t and X_t vectors which contain endogenous and exogenous variables, respectively. The econometric model we employ to shed some light on the short-run dynamics can be expressed as:

$$Y_t = A_0 + \sum_{k=1}^{p} A_{Y,k} Y_{t-k} + A_X X_{t-1} + \boldsymbol{\varepsilon}_t; \boldsymbol{\varepsilon}_t = \begin{pmatrix} \varepsilon_{oil,t} \\ \varepsilon_{BDTI,t} \end{pmatrix} \sim iid(0, \Sigma),$$

$$Y_t = \begin{pmatrix} R_{oil,t} \\ R_{BDTI,t} \end{pmatrix}, X_t = \begin{pmatrix} \rho_{oil,BDTI,t-1} \\ \ln(\sigma_{oil,t-1}) \\ f(t) \end{pmatrix}, \tag{3}$$

where oil is either WTI or Brent crude (i.e., we estimate two separate VARX models). A_0 is a 2×1 vector of constants for each pair of simultaneous oil-BDTI equations and $\boldsymbol{\varepsilon}_t$ is a white noise disturbance term with covariance matrix Σ. A_Y is a 2×2 coefficient matrix measuring the response to the endogenous variables. A_X summarises the response to exogenous variables, namely conditional correlation and oil price volatility – which are the main

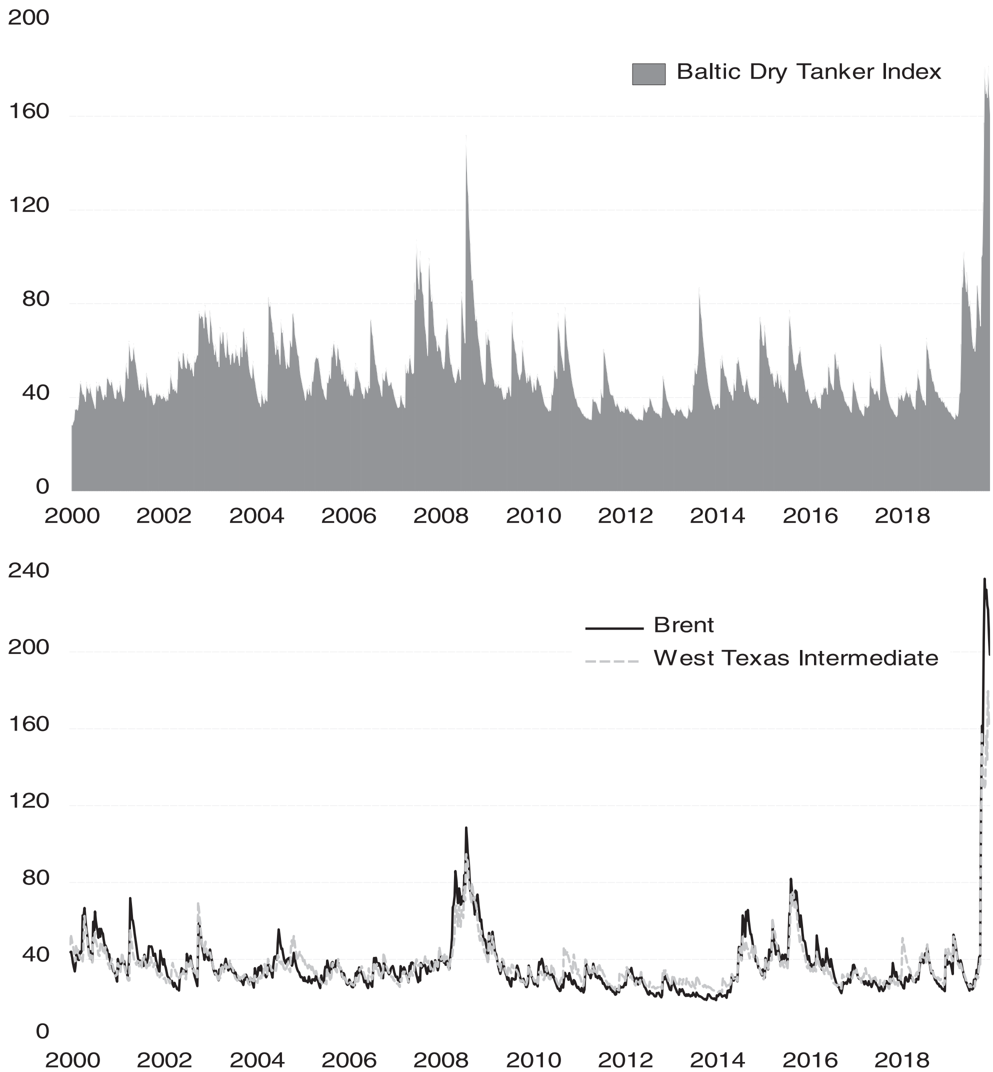


FIGURE 2 Baltic Dry Tanker index (top), Brent and WTI crude oil (bottom) annualised % volatility estimates 2000–2020 as implied by a GARCH (1,1) model (see Table 2 for parameter estimates).

variables also in the analysis in the ensuing sections – and potential seasonal fluctuations by means of sine and cosine functions, that is, $f(t) = \left(sin\left(\frac{2\pi t}{52}\right)\ cos\left(\frac{2\pi t}{52}\right)\right)'$. For comparison, we also consider the restricted case of $X_t = \left(\rho_{oil,BDTI,t-1}\quad \ln(\sigma_{oil,t-1})\right)'$.

Table 3 presents key information on VARX models in Panel A (B) for BDTI-Brent (BDTI-WTI) as endogenous variables, using alternative specifications, that is, with and without seasonal controls and oil volatility proxies, that is, GARCH and realised volatilities with $M = \{1, 3, 6, 12\}$ (definitions in Section 3).

For brevity, the coefficients of the VAR models are not presented here. We outline some of the main findings as follows. First, for both Brent and WTI returns, none of the considered variables are statistically significant. Second, for the BDTI return, the lagged own values of BDTI returns are highly significant, as are the seasonal terms. Third, lagged crude oil returns load with significantly positive signs at 1% level. Forth, the coefficients for lagged correlation $\rho_{oil,BDTI,t-1}$ and lagged volatility $\ln(\sigma_{oil,t-1})$ are positive and negative, respectively, yet, irrespective of the crude. The former coefficient is non-significant at conventional significance levels; the latter is marginally significant at the 10% level.

As Table 3 dictates, Equation (3) explains very little of the weekly crude oil returns; R^2s are below 1.7% while they seem higher when controlling for seasonality; marginal increment of 30 basis points (bps) on average. On the other hand, the VARX model does explain to some extent fluctuations in BDTI returns; R^2s are in excess of 9.2% in all cases. In the case of Brent (WTI), R^2s range between 12% and 12.7% (9.3%–9.7%) while the figure is only marginally different across volatility proxies. Again, adding seasonal controls somewhat improves the range to 13.5%–13.9% (10.4%–10.6%).

For a more thorough examination of variables' interactions we also perform causality tests (Granger, 1969) in Table 3. The results reveal that, in the short-run (1-week period), $R_{oil,t}$ has predictive explanatory power

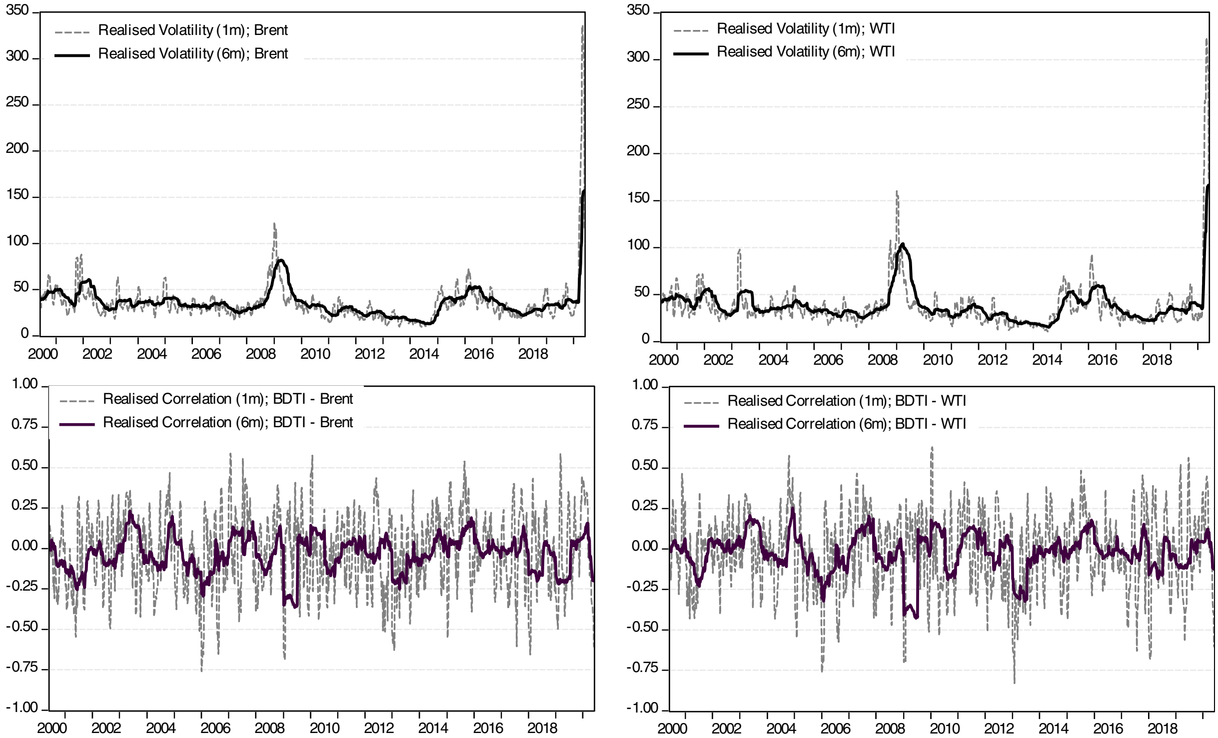


FIGURE 3 Weekly annualised realised volatility and correlation. Volatility (top) and correlation (bottom) measures are shown for $M = 1$ (1 m, dark grey dotted line) and $M = 6$ (6 m, black solid line), that is, estimates derived from 1 to 6 month worth of daily data, respectively. [Colour figure can be viewed at wileyonlinelibrary.com]

on $R_{BDTI,t}$ at 1% significance level, but not vice versa at 5% significance level. The fact that the level of tanker rates, as reflected in the BDTI, does not affect Brent or WTI is in line with other literature, for example, Alizadeh and Nomikos (2004). Nevertheless, Brent is weakly affected by BDTI at the 10% significance level, although the null of no causality can only be marginally rejected. This reflects the fact that tanker operations play a key role in the market of oil, balancing demand and supply which, in turn, can help stabilise oil prices (Khan et al., 2021). Yet, it is worth mentioning that Europe, Middle East and Africa tend to use Brent as the main benchmark, with a production accounting for approx. two-thirds of crude oil global trade. Contrary, WTI is primarily a local benchmark. In addition, of all the routes included in the BDTI it is only TD1 (Middle East Gulf to US Gulf) involving the US so any linkages with this particular crude might be weaker.

To reduce the likelihood that linkages are sample specific we also carry out rolling causality tests/estimation which explicitly consider the prospect that some series may be more connected during some periods but less so during others. For this reason, we repeatedly estimate the VARX model in rolling five-year sub-samples. Collectively, causality from Brent (WTI) to BDTI is confirmed for more than 61.99% (55.10%) over the sub-samples. Causality in the opposite direction, from BDTI to oil is rather weak in all cases (less than 20% of the samples, at maximum).

Finally, Table 3 reports the average rolling R^2 across sub-samples along with their 90% confidence intervals from the rolling VARX estimation. Predictability of BDTI ranges from 4.9% to 26% (3.5%–21%) when Brent (WTI) is used as endogenous variable. On the other hand, predictability of crude oil is limited with a range of 0.24%–7.1% across sub-samples.

All things considered, results corroborate some degree of BDTI return predictability robust to the volatility proxies used, and whether or not seasonality is accounted for; though this varies across periods. Results also confirm oil return unpredictability.

5 | PERSPECTIVE OF CONDITIONAL BDTI DISTRIBUTION

Since we focus on oil market uncertainty, our main interest is specific to how $E(R_{BDTI,t}|R_{oil,t})$ might vary with oil price uncertainty. We are interested in characterising any potential statistical association as a function of oil price volatility to identify whether the latter can provide forward-looking information about subsequent oil-BDTI short-run co-movements. To this end, we formulate our experiment in the following expression:

$$R_{BDTI,t} = a_0 + \left(a_1 + a_2 \ln(\sigma_{oil,t-1}) + a_3 \rho_{oil,BDTI,t-1}\right) R_{oil,t} + \varepsilon_t, \tag{4}$$

where $oil = \{Brent, WTI\}$, $(\sigma_{oil,t-1})$ the lagged conditional volatility of oil, and $\rho_{oil,BDTI,t}$ denotes the conditional correlation between crude oil and BDTI and is used as a control variable. The innovation term is assumed to follow the normal distribution, that is, $\varepsilon_t \sim N\left(0, \sigma_\varepsilon^2\right)$.

The above equation focuses on the co-movement between BDTI and oil returns and examines whether measures of oil price uncertainty have a connection to fluctuations in the BDTI-oil relation. Since tanker and oil markets hold inextricable relations with each other, we pay specific interest to times with sustained positive or negative correlation or periods with relative extreme correlations. In other words, the equation suggests that

TABLE 3 Causality tests, predictability and robustness

From–To:	GV	RV_{1m}	RV_{3m}	RV_{6m}	RV_{12m}
Panel A: Brent – BDTI VAR $_{(lags=2)}$					
I. VARX model w Brent volatility and Brent-BDTI correlation as exogenous variables					
$R_{BRENT} \rightarrow R_{BDTI}$	30.27***	28.76***	30.91***	31.23***	30.02***
R^2	12.65	12.23	12.66	12.36	12.01
Roll. p-val.	0.172 (61.99)	0.173 (61.99)	0.168 (61.99)	0.158 (62.11)	0.172 (61.99)
Roll. R^2	15.06 (4.92/23.6)	14.74 (4.91/22.4)	15.09 (5.07/24.3)	14.59 (5.19/22.4)	14.63 (5.08/22.3)
$R_{BDTI} \rightarrow R_{BRENT}$	4.705*	4.800*	4.875*	4.782*	4.931*
R^2	1.12	0.90	1.11	1.47	1.29
Roll. p-val.	0.448 (8.29)	0.452 (8.03)	0.426 (7.02)	0.419 (4.97)	0.395 (8.03)
Roll. R^2	2.43 (0.98/5.20)	2.17 (0.81/4.31)	2.30 (0.89/4.86)	2.85 (0.90/5.40)	2.54 (0.80/5.25)
II. VARX model w Brent volatility, Brent-BDTI correlation and seasonality controls as exogenous variables					
$R_{BRENT} \rightarrow R_{BDTI}$	32.63***	31.50***	32.26***	32.92***	32.82***
R^2	13.85	13.64	13.86	13.62	13.46
Roll. p-val.	0.152 (62.24)	0.153 (61.99)	0.152 (62.50)	0.152 (62.50)	0.157 (62.11)
Roll. R^2	16.82 (7.44/25.6)	16.62 (7.43/25.2)	16.64 (7.23/26.0)	16.25 (7.33/24.8)	16.57 (7.43/24.6)
$R_{BDTI} \rightarrow R_{BRENT}$	4.590	4.613*	4.732*	4.681*	4.706*
R^2	1.39	1.22	1.37	1.63	1.60
Roll. p-val.	0.468 (4.34)	0.479 (3.32)	0.461 (3.06)	0.427 (2.42)	0.416 (2. 81)
Roll. R^2	3.94 (1.62/7.05)	3.63 (1.19/6.90)	3.76 (1.33/6.80)	4.02 (1.34/7.00)	3.96 (1.38/6.43)
Panel B: WTI – BDTI VAR $_{(lags=1)}$					
I. VARX model w WTI volatility and WTI-BDTI correlation as exogenous variables					
$R_{WTI} \rightarrow R_{BDTI}$	10.34***	9.347***	10.06***	10.06***	9.80***
R^2	9.58	9.35	9.65	9.49	9.28
Roll. p-val.	0.207 (55.36)	0.209 (52.55)	0.206 (56.90)	0.190 (55.10)	0.212 (56.00)
Roll. R^2	11.71 (4.20/18.2)	11.63 (4.18/18.4)	11.66 (3.65/19.4)	11.38 (3.86/18.4)	11.58 (3.53/18.2)
$R_{BDTI} \rightarrow R_{WTI}$	0.017	0.003	0.001	0.002	0.002
R^2	1.20	0.54	0.68	0.88	0.82
Roll. p-val.	0.352 (14.41)	0.372 (6.38)	0.357 (11.61)	0.365 (19.51)	0.352 (16.07)
Roll. R^2	1.55 (0.56/3.11)	1.53 (0.26/3.67)	1.35 (0.24/2.85)	1.48 (0.31/2.79)	1.31 (0.27/2.43)
II. VARX model w WTI volatility, WTI-BDTI correlation and seasonality controls as exogenous variables					
$R_{WTI} \rightarrow R_{BDTI}$	11.28***	10.39***	10.06***	10.77***	10.85***
R^2	10.50	10.42	10.57	10.48	10.36

(Continues)

TABLE 3 (Continued)

Panel B: WTI – BDTI VAR $_{(lags=1)}$					
Roll. p-val.	0.155 (57.91)	0.155 (59.69)	0.154 (59.82)	0.158 (59.18)	0.162 (58.54)
Roll. R^2	13.27 (6.42/20.6)	13.11 (6.48/20.6)	12.93 (5.84/21.0)	12.82 (6.13/20.6)	13.07 (5.99/20.4)
$R_{BDTI} \rightarrow R_{WTI}$	0.113	0.041	0.064	0.058	0.043
R^2	1.51	0.93	1.03	1.14	1.19
Roll. p-val.	0.386 (14.67)	0.399 (2.93)	0.393 (10.08)	0.382 (16.96)	0.379 (16.32)
Roll. R^2	2.97 (0.85/5.49)	3.07 (0.68/7.09)	3.07 (0.40/6.39)	2.71 (0.56/6.09)	2.71 (0.51/5.53)

Note: The table shows causality tests and provides information on the explanatory power of the estimated VARX models (see Equation 3). Note that, correlation figures in vector X_t of Equation (3) are paired with the corresponding volatilities only; that is, for $M = \{1, 3, 6, 12\}$, if $\ln(\sigma_{oil}) = RV_m$ then $\rho_{oil,BDTI} = RC_m$; GARCH volatilities are paired with the realised correlations that maximise R^2. The lag length of the models was selected on the basis of the Schwarz (1978) Bayesian information criterion. Panel A (B) reports the results for the case of BTDI and Brent (WTI) as endogenous variables; for definition of the exogenous variables please refer to Section 4. Rows labelled as $R_X \rightarrow R_Y$ test the null hypothesis that variable X does not Granger cause variable Y; asterisks *, **, *** indicate significance at 10%, 5% and 1% significance level, that is, rejection of the null against the alternative of causality. The test follows the $\chi^2(df)$ distribution with degrees of freedom (df) equal to the number of restricted coefficients. Rows labelled R^2 are derived from the full sample VARX model estimation; from 7 June 2000 to 27 May 2020. Roll. p-val display the average p-value using rolling statistics. These are conducted by applying causality tests to rolling weekly 5-year sub-samples. For example, the first statistic is obtained by using observations from the beginning of the sample through to the 260th observation, the next statistic is obtained by using data from the 2nd through to the 261st observation, and so on, until the sample is exhausted. Numbers in () correspond to the % number of times that the null hypothesis of no causality can be rejected at conventional significance levels. Finally, we also obtain the rolling R^2 estimates and report the averages and 90% CI (confidence intervals in []).

relatively high or low oil price uncertainty may be linked to either high or low likelihood of a negative correlation henceforward. As oil price exhibits considerable volatility – due to various factors, for example, supply/demand dynamics, inventory surpluses/shortages as well as global politics/economics – this volatility directly impacts the BDTI-oil relation. When modelling uncertainty, this equation aims at describing the dynamic relationship between tanker rates and the price of oil and evaluating whether the BDTI-oil return co-movements are consistently related to our oil price uncertainty (lagged) proxies.

Table 4, Panel A reports the results of Equation (4) OLS regression for Brent and WTI as crude oil. The main coefficient of interest is a_2; shows how the oil-BDTI returns relation changes with (lagged) volatility. We estimate the full model and assess two types of restrictions: (i) $a_3 = 0$. This is meant to assess whether oil volatility offers additional information about the oil-BDTI relation, beyond the information already inherent in the control variable $\rho_{oil,BDTI,t-1}$. (ii) $a_2 = a_3 = 0$. This restricts the regression slope to a constant (a_1), and thus, it is implied that $E(R_{BDTI,t}|R_{oil,t}) = \left(\sigma_{BDTI,oil}/\sigma^2_{oil}\right) R_{oil,t}$.

Looking at the restricted OLS version ($a_2 = a_3 = 0$), coefficient a_1 is significant for both crudes at conventional significance levels. The R^2 for Brent is modest at 4.30% and only 2.15% for WTI. Turning to $a_3 = 0$, we see that the oil-BDTI return relation varies negatively with the lagged crude oil volatility. Coefficients a_2 are significant at 1% level for both crudes. What is more, substantial increases are noted in the R^2s; for Brent (WTI) the figure experiences a more than twofold (threefold) increase to 8.62% (6.48%).

As for the unrestricted OLS we conclude that the negative relation between lagged crude oil volatility and oil-BDTI co-movement remains consistent; even after accounting for recent historical conditional correlations. The estimated a_3 coefficient is negative and significant at the 5% level, irrespective of the crude oil. Therefore, there is some information that can be extracted from realised correlations, reflected also at the modest increases in R^2s; R^2 for Brent (WTI) increases to 9.1% (8.1%), that is, an improvement of 50 (150) basis points relative to the $a_3 = 0$ case.

To assess R^2 consistency, Figure 4 portrays R^2 extrapolated from rolling regressions of BDTI returns on crude oil returns ($a_2 = a_3 = 0$) versus the unrestricted OLS for Brent (left) and WTI (right) as the variable for crude oil. The incremental R^2 appears to be substantial across all periods. We can also note higher values associated with the 2008 financial crisis and its aftermath. In general, rolling R^2 for two-year (five-year) subsamples when Brent is the crude oil variable are within the 90% internal of 1%–14.9% (0–7.9%) for the unrestricted model and 0.6%–10.2% (0–2.2%) for the restricted one. For WTI the figures are 0.8%–15.8% (0–3.8%) and 0.1%–9.9% (0–1.4%), respectively. All in all, the achieved improvement in R^2 (unrestricted vs. restricted) is on average, above 4.2% (3.1%) for the 2-year (5-year) subsamples across both crudes.

Next, Figure 5 plots the implied slope estimates derived from Equation (4) for Brent (top) and WTI (bottom) crude oil variable. There is clear association

TABLE 4 Crude volatility and the relation between BDTI and oil returns

	Crude oil = Brent			Crude oil = WTI		
	$(a_2 = a_3 = 0)$	$(a_3 = 0)$	(Unrestr.)	$(a_2 = a_3 = 0)$	$(a_3 = 0)$	(Unrestr.)
Panel A: Unrestricted OLS model versus restricted versions						
a_0	−0.0007	−0.0003	−0.0006	−0.0007	−0.0001	−0.0003
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
a_1	−0.2694**	−1.1660***	−1.2354***	−0.2004*	−1.5758***	−1.6963***
	(0.105)	(0.150)	(0.165)	(0.113)	(0.222)	(0.204)
a_2	–	−0.3608***	−0.3758***	–	−0.5090***	−0.5394***
		(0.066)	(0.069)		(0.082)	(0.073)
a_3	–	–	−1.1071**	–	–	−1.7693**
			(0.562)			(0.545)
R^2	4.44	8.62	9.17	2.16	6.48	8.06
Robust. (VARX)						
a_2	–	−0.3958***	−0.4162***	–	−0.5595***	−0.5864***
R^2	5.41	11.04	12.22	2.23	7.67	9.43
Panel B: Unrestricted model versus restricted versions with GARCH error structure						
a_0	−0.0013	−0.0011	−0.0011	−0.0013	−0.0011	−0.0011
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
a_1	−0.1547***	−1.2399***	−1.2556***	−0.0804	−1.4371***	−1.5082***
	(0.053)	(0.271)	(0.269)	(0.053)	(0.479)	(0.463)
a_2	–	−0.3788***	−0.3694***	–	−0.4582***	−0.4686***
		(0.091)	(0.090)		(0.159)	(0.153)
a_3	–	–	−1.1282*	–	–	−1.5155*
			(0.656)			(0.656)
R^2 (%)	3.63	8.55	9.09	1.38	6.41	7.94
Robust. (VARX)						
a_2	–	−0.3865***	−0.3853***		−0.4801***	0.5009***
R^2	4.07	11.02	12.13	1.00	7.53	9.28

Note: Table 4 reports results from estimating the regression of Equation (4). The sample period is June 2000 to May 2020. The regression is estimated by OLS (Panel A) and the autocorrelation and heteroskedastic-consistent Newey and West (1987) standard errors are in (). The regression is also estimated with GARCH error structure (Equation 5; Panel B) and standard errors in () are based on Bollerslev and Wooldridge (1992). For comparison, we also show the coefficient estimates a_2 and R^2 when the residuals from the VARX of Equation (3) are used, rather than the raw data.

between oil volatility and BDTI (see also Figures 2 and 3). Slopes are highly negative for high oil volatility periods and approach zero or turn positive during less volatile periods.[11] The slopes' interquartile ranges for Brent and WTI are [−0.11 0.0] and [−0.09 0.05], respectively. The corresponding 5% percentile thresholds are −0.297 and −0.277. Observations that belong to the 5th percentile correspond to three main periods, that is, August 2008 to April 2009 (financial crisis) and the first quarter of 2016 (crude bottomed out to mid-$20 s by mid-January, then to increase in 7–8 weeks by more than 40%) and March–May 2020 (COVID19); slopes averaging below −0.34 in the former two and below −0.69 in the latter period. Volatilities in crude oil market during the former two periods exceeded 68% p.a. while during COVID pandemic, this figure exceeded the level of 150% p.a.

To gauge potential inconsistencies in parameters and findings so far, we relax the assumption of constant variance and estimate the parameters of Equation (4) simultaneously using the following augmented GARCH (1,1) equation:

$$\sigma^2_{\varepsilon,t} = \omega + a u^2_{t-1} + \beta \sigma^2_{BDTI,t-1} + \gamma \sigma^2_{oil,t-1}. \tag{5}$$

Table 4, Panel B presents the results. The reported a_2's, R^2s from the GARCH model are consistent in sign

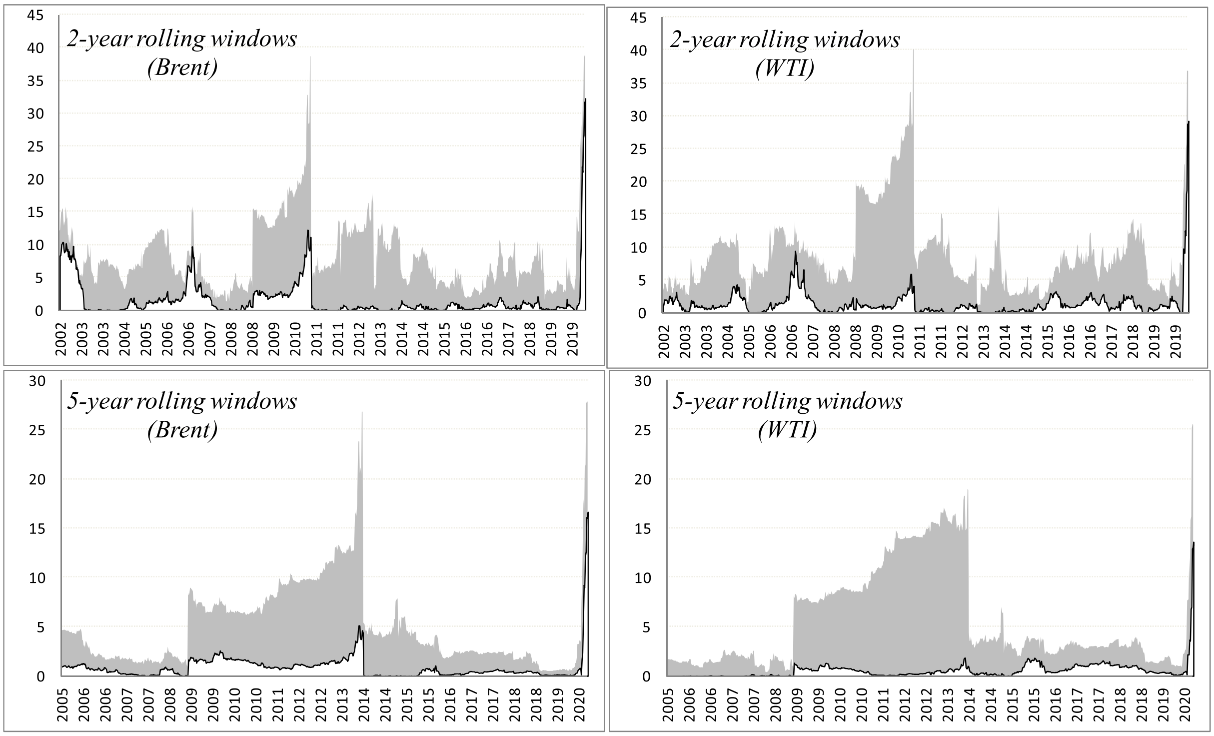


FIGURE 4 Rolling R^2 estimates in percentage terms. This figure presents the R^2 estimates derived from rolling regressions of weekly BDTI returns on weekly crude oil returns (black line). The graph also presents the incremental R^2 achieved when including in the regression lagged crude oil volatility (while controlling for lagged BDTI-oil correlations as well, grey area). The plots to the top consider 5-year subsamples for Brent (left) and WTI (right) as the variable for crude oil using weekly observations. The plots to the bottom consider 2-year rolling subsamples.

and similar in magnitude to the OLS estimation. The negative relation between oil volatility and the oil-BDTI co-movement in both models is further confirmed; as for the estimated a_3 coefficients, these are still negative, yet significant only at 10% level.

Table 4 (Panels A and B) shows that estimating the model using the residuals of the of Equation (3) VARX model (instead of the raw data) improves the R^2s in the Brent (WTI) OLS case by 1.1%–3.1% (0.1%–1.4%). This confirms that oil-BDTI relation varies negatively and consistently with the crude oil lagged volatility. Results are consistent whether or not the variance of ε_t is constant or time-varying.

Futher, we provide further robustness tests and re-estimate Equations (4) and (5) by alternating the proxies of oil market uncertainty using nonparameteric methods; RV_{1m}, RV_{3m}, RV_{6m} and RV_{1m} estimates (see Section 3, Equation 2). A practical aspect of these proxies is that they are free from the look-ahead bias potentially imposed by the GARCH volatilities. Table 5, Panel A (B) reports the results for Brent (WTI). Once again, the evidence that the oil-BDTI return relation varies negatively and very consistently with the oil market lagged volatility validates the results in Table 4.[12] This holds irrespective of the proxy used (Brent or WTI volatility), the method used to extract the proxy (GARCH or realised volatilities), or the method employed to examine this relationship (OLS, GARCH, raw returns or VARX residuals).

6 | REGIME-SHIFTING ANALYSIS

We now test whether a model accounting for regime-switching is able to describe time variation in the oil - BDTI return relation. In particular, introducing Markovian regime shifts to Equation (4) (i.e., when $a_2 = a_3 = 0$)

$$R_{BDTI,t} = a_0^{S_t} + a_1^{S_t} R_{oil,t} + \varepsilon_t^{S_t} \sim N\left(0, \sigma^{2,S_t}\right), \tag{6}$$

where $\varepsilon_t^{S_t}$ is the white noise process with regime dependent standard deviation σ^s. In this context, switching is allowed in all parameters of Equation (6). The state variable s_t follows a two-regime, first order Markov process with transition probability matrix $\boldsymbol{P}$ whose elements are given by $\Pr(s_t = j \mid s_{t-1} = k) = p_{kj}$ that indicates the probability of switching from state k at time $t-1$ into state j at

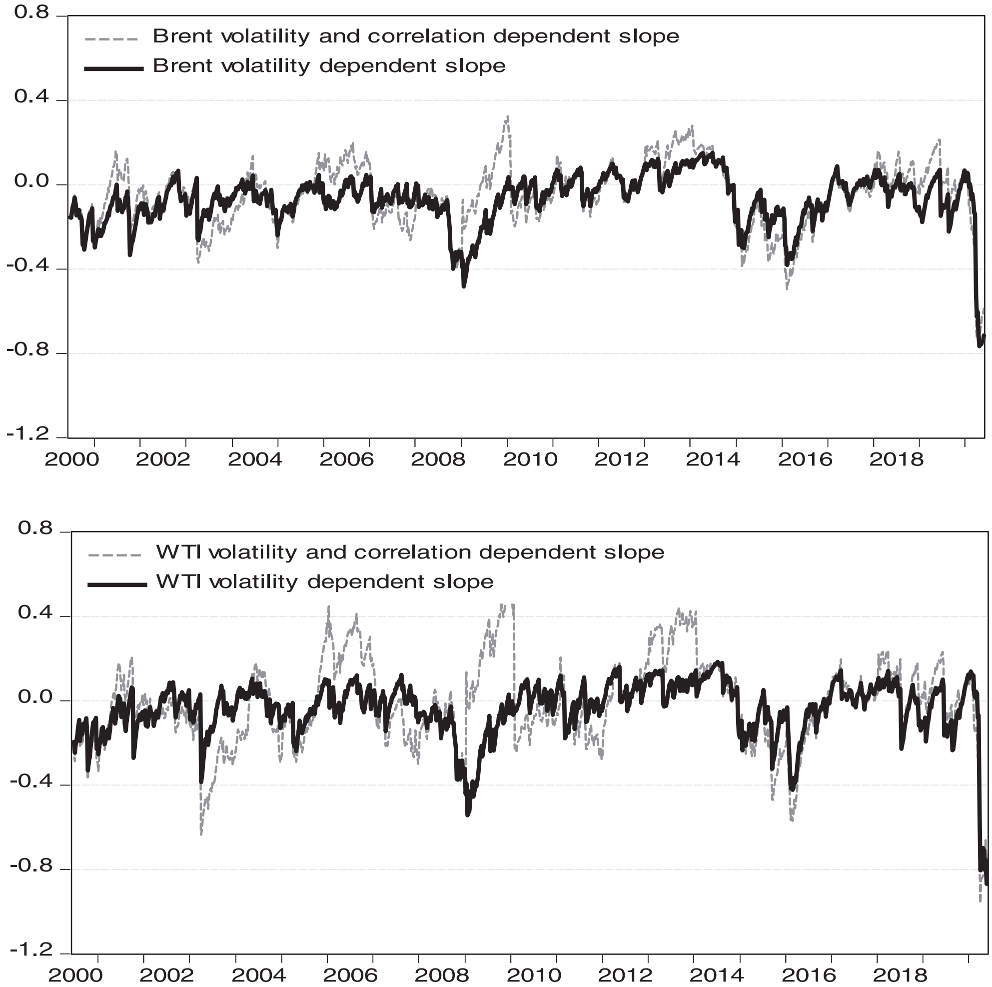


FIGURE 5 Time-varying slopes. This figure presents the implied slope estimates derived from the regressions in Equation (4): $R_{BDTI,t} = a_0 + (a_1 + a_2 \ln(\sigma_{oil,t-1}) + a_3 \rho_{oil,BDTI,t-1}) R_{oil,t} + u_t$. Dark grey dotted lines are calculated as $a_1 + a_2 \ln(\sigma_{oil,t-1}) + a_3 \rho_{oil,BDTI,t-1}$; black solid lines restrict $a_3 = 0$. The plots to the top (bottom) consider Brent (WTI) as the crude oil variable.

t, that is, p_{11} or p_{22} give the probability that the state will not change in the following period, $(1 - p_{11})$ is the probability that state 1 will be followed by state 2 and $(1 - p_{22})$ is the probability that state 2 will be followed by state 1. Parameter vector $\boldsymbol{\theta} = \left(a_0^{s_t=1}, a_1^{s_t=1}, \sigma^{s_t=1}, a_0^{s_t=2}, a_1^{s_t=2}, \sigma^{s_t=2}, \boldsymbol{P}\right)$ can be estimated using maximum likelihood techniques; see Hamilton (1989) for more details.

The transition probabilities in matrix $\boldsymbol{P}$ can be either constant between successive periods or conditioned on some candidate variables. We employ the following logistic function to parameterise $\boldsymbol{P}$ and investigate if transition probabilities vary with lagged oil volatility:

$$P(\mathrm{s_t} = k \mid \mathrm{s_{t-1}} = k; \Omega_{t-1}) = \frac{e^{\delta_k + \zeta_k \ln(\sigma_{oil,t-1})}}{1 + e^{\delta_k + \zeta_k \ln(\sigma_{oil,t-1})}}, \tag{7}$$

where the δ_k and ζ_k are coefficients, and subscript k equals either zero or 1 for regimes one and two, respectively; time-varying transition probability MRS model (TVTP). A restricted specification where $\zeta_k = 0$ across regimes is also estimated; constant transition probability (CTP) MRS model.

Results in Table 6 present the MRS models for BDTI returns. Columns 1–3 and 4–6 correspond to the MRS models for Brent and WTI, respectively. We consider the three alternative MRS specifications outlined in Equations (6)–(7). The baseline CTP (MRS) and two TVP models (MRS-G and RV_{1m}). For the former oil market uncertainty is proxied by GARCH (MRS-G) whereas the latter by realised volatility (MRS-RV_{1m}).

Results are similar across crudes. We see strong evidence of asymmetries across different BDTI states and there are asymmetries in the slopes across regimes. In the high-variance state ($s_t = 1$), the slopes measured by α_1 are consistently negative and significant across models and crudes. In the low-variance state ($s_t = 2$), the same coefficients are of less magnitude in absolute terms, positive and insignificant. This diverse behaviour indicates that oil-BDTI relation experiences shifts and does not respond uniformly to shocks between states.

Coefficients ζ_2 are significant 5% level when GARCH is the proxy for oil market uncertainty; for RV_{1m} evidence is restricted to Brent at 10% level tough. Yet, ζ_1's are insignificant. This suggests a high-variance state ($s_t = 1$) with

TABLE 5 Robustness and alternative volatility/correlation specification

	RV_{1m}	RV_{3m}	RV_{6m}	RV_{12m}
Panel A: Crude oil = Brent				
a_0	−0.0004 (0.003)	−0.0005 (0.003)	−0.0005 (0.003)	−0.0001 (0.003)
a_1	−1.0893*** (0.107)	−1.5433*** (0.169)	−1.8914*** (0.215)	−2.3511*** (0.283)
a_2	−0.3324*** (0.038)	−0.4842*** (0.059)	−0.5913*** (0.075)	−0.7249*** (0.097)
a_3	−0.0465 (0.263)	−0.6514* (0.371)	−1.6551** (0.453)	−1.8250*** (0.557)
R^2	8.75	9.39	9.31	9.04
Robustness				
$a_2 \mid a_3 = 0$	−0.328***	−0.434***	−0.514***	−0.593***
$\left\{R^2_{a_3=0}\right\}$	{8.75}	{8.81}	{8.33}	{7.70}
GARCH errors:				
a_2	−0.307***	−0.433***	−0.491***	−0.582***
$\{a_2 \mid a_3 = 0\}$	{−0.305***}	{−0.417***}	{−0.463***}	{−0.490***}
R^2	8.69	9.27	9.13	8.84
$\left\{R^2_{a_3=0}\right\}$	{8.69}	{8.76}	{8.27}	{7.58}
VARX resid.:				
a_2	−0.375***	−0.523***	−0.630***	−0.769***
$\{a_2 \mid a_3 = 0\}$	{−0.351***}	{−0.443***}	{−0.531***}	{−0.615***}
R^2	11.18	12.20	11.94	11.37
$\left\{R^2_{a_3=0}\right\}$	{11.01}	{10.6}	{10.1}	{9.54}
Panel B: Crude oil = WTI				
a_0	−0.0006 (0.003)	−0.0007 (0.003)	−0.0008 (0.003)	−0.0003 (0.003)
a_1	−1.1466*** (0.119)	−1.3833*** (0.173)	−1.6654*** (0.223)	−2.0421*** (0.275)
a_2	−0.3822*** (0.040)	−0.4567*** (0.061)	−0.5438*** (0.077)	−0.6575***(0.094)
a_3	−0.3990* (0.231)	−1.1531*** (0.388)	−1.5264*** (0.431)	−2.1293***(0.519)
R^2	7.42	8.01	7.70	7.55
Robustness				
$a_2 \mid a_3 = 0$	−0.358***	−0.405***	−0.477***	−0.552***
$\left\{R^2_{a_3=0}\right\}$	{7.03}	{6.31}	{5.93}	{5.35}
GARCH errors:				
a_2	−0.270***	−0.346***	−0.380***	−0.471***
$\{a_2 \mid a_3 = 0\}$	{−0.271***}	{−0.342***}	{−0.380***}	{−0.398***}
R^2	6.91	7.64	7.10	7.16
$\left\{R^2_{a_3=0}\right\}$	{6.74}	{6.21}	{5.75}	{5.05}
VARX resid.:				
a_2	−0.413***	−0.485***	−0.578***	−0.702***
$\{a_2 \mid a_3 = 0\}$	{−0.384***}	{−0.429***}	{−0.512***}	{−0.598***}
R^2	9.13	9.54	9.02	8.74
$\left\{R^2_{a_3=0}\right\}$	{8.48}	{7.35}	{7.02}	{6.32}

Note: This table presents the results of estimating Equation (4) using alternative specifications for the Brent (WTI) crude oil variance process in Panel A (B); see Equations (1) and (2). We consider four alternatives based on realised measures of variance derived from relatively higher frequency (daily) data. RV_j stands for realised volatility using j months worth of daily data, where $j = \{1\text{ m}, 3\text{ m}, 6\text{ m}, 12\text{ m}\}$. Apart from the coefficient estimates and standard errors in (), the table reports also the coefficient of interest, a_2, when a_3 is restricted to zero, that is, $a_2 \mid a_3 = 0$, along with the relevant R^2 ($R^2_{a_3=0}$). For robustness we also report the abovementioned information when: (i) instead of OLS the error structure follows a GARCH process and (ii) instead of the raw data, the residuals from the VARX model are used. See also notes in Table 4.

TABLE 6 Regime switching estimation results

	Crude oil = Brent			**Crude oil = WTI**		
	MRS	**MRS-G**	**MRS-RV$_{1m}$**	**MRS**	**MRS-G**	**MRS-RV$_{1m}$**
Panel A: Baseline estimation results						
Constants						
$a_0^{st=1}$	0.0015	0.0025	0.0020	0.0016	0.0023	0.0014
	(0.006)	(0.005)	(0.005)	(0.007)	(0.006)	(0.006)
$a_0^{st=2}$	−0.0024	−0.0030	−0.0028	−0.0023	−0.0027	−0.0021
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Slopes						
$a_1^{st=1}$	−0.4294***	−0.4400***	−0.4338***	−0.3978***	−0.3932***	−0.4021***
	(0.075)	(0.060)	(0.059)	(0.095)	(0.061)	(0.063)
$a_1^{st=2}$	0.0141	0.0233	0.0342	0.0559	0.0556	0.0617
	(0.051)	(0.042)	(0.042)	(0.047)	(0.043)	(0.043)
Volatilities						
$\sigma^{st=1}$	0.1072***	0.1061***	0.1056***	0.1124***	0.1108***	0.1125***
	(0.003)	(0.002)	(0.001)	(0.003)	(0.002)	(0.002)
$\sigma^{st=2}$	0.0425***	0.0410***	0.0409***	0.0439***	0.0426***	0.0435***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Transition probabilities						
δ_1	1.9922***	0.0011	2.0314	1.8429***	0.8434	2.1781
	(0.340)	(2.036)	(2.011)	(0.375)	(2.920)	(1.866)
ζ_1		−0.5989	0.0673		−0.3111	0.1613
		(0.677)	(0.641)		(0.968)	(0.609)
δ_2	−2.4712***	3.3700	0.9858	−2.4955***	3.8415	−0.2970
	(0.292)	(2.222)	(1.828)	(0.288)	(2.914)	(1.738)
ζ_2		1.846**	1.0243*		2.0520**	0.6671
		(0.733)	(0.579)		(0.969)	(0.559)
p_{11}	0.880 (8.33)	0.858 (7.27)	0.861 (7.18)	0.863 (7.31)	0.856 (6.96)	0.843 (6.39)
p_{22}	0.922 (12.8)	0.889 (11.9)	0.894 (11.0)	0.924 (13.1)	0.902 (12.8)	0.909 (11.8)
Panel B: Summary of results for VARX residuals						
$a_1^{st=1}$	−0.4933***	−0.4910***	−0.5071***	−0.5778***	−0.6312***	−0.6408***
$a_1^{st=2}$	0.0550	0.0813**	0.0740*	0.1038**	0.1156***	0.1160***
$\sigma^{st=1}$	0.0995***	0.0974***	0.0993***	0.1212***	0.1274***	0.1284***
$\sigma^{st=2}$	0.0416***	0.0398***	0.0408***	0.0469***	0.0477***	0.0478***
ζ_1		0.1586	0.2626		1.7463	1.1581
ζ_2		1.4420*	1.0984*		0.3503	0.4332
p_{11}	0.844 (6.4)	0.818 (5.5)	0.779 (4.6)	0.717 (3.5)	0.498 (2.2)	0.472 (2.1)
p_{22}	0.912 (11.4)	0.877 (9.6)	0.867 (8.9)	0.921 (12.6)	0.894 (9.5)	0.892 (9.6)
Panel C: Summary of results for alternative volatility specifications						
	MRS-RV$_{3m}$	***MRS-RV$_{6m}$***	***MRS-RV$_{12m}$***	***MRS-RV$_{3m}$***	***MRS-RV$_{6m}$***	***MRS-RV$_{12m}$***
$a_1^{st=1}$	−0.4347***	−0.4344***	−0.4335***	−0.3980***	−0.3990***	−0.3941***
$a_1^{st=2}$	0.0349	0.0384	0.0500	0.0631	0.0634	0.0680
$\sigma^{st=1}$	0.1055***	0.1050***	0.1032***	0.1115***	0.1116***	0.1100***

(Continues)

TABLE 6 (Continued)

Panel C: Summary of results for alternative volatility specifications						
	MRS-RV$_{3m}$	*MRS-RV$_{6m}$*	*MRS-RV$_{12m}$*	*MRS-RV$_{3m}$*	*MRS-RV$_{6m}$*	*MRS-RV$_{12m}$*
$\sigma^{st=2}$	0.0408***	0.0405***	0.0390***	0.0429***	0.0428***	0.0419***
ζ_1	−0.0075	−0.1925	−0.6461	0.0440	−0.0095	−0.2289
ζ_2	1.0986*	1.2987*	2.0100***	0.9720	1.0860*	1.4108*
p_{11}	0.861 (7.2)	0.862 (7.3)	0.859 (7.3)	0.847 (6.6)	0.844 (6.4)	0.845 (6.5)
p_{22}	0.895 (11.0)	0.891 (10.9)	0.872 (10.6)	0.906 (11.9)	0.904 (11.7)	0.895 (11.2)

Note: Panel A of this table shows the calibrated estimates of a two-state Markov Regime switching model with constant transition probabilities (MRS) and with time-varying transition probabilities; conditioned on the lagged crude oil (log) volatility as estimated either by a GARCH model (MRS-G) or by realised volatility (MRS-RV$_{1m}$); see also Table 5 and Equations (6) and (7). Transition probability parameterisation is based on the logistic function of Equation (7). Rows p_{11} and p_{22} summarise transition results and show the expected durations ([], measured in weeks). In Panels B and C, we show some additional results for robustness using the residuals from a VARX model to estimate the MRS models (Panel B) or alternatives for the realised measure of variance (Panel C); see also notes in Table 5.

CTP, and a low-variance state ($s_t = 2$) where probabilities p_{22} (and 1-p_{22}) depend on the lagged value of crude oil volatility. In other words, switching from low-to-high variance (zero slope to strongly negative) depends on the level of oil market uncertainty; however, switching from high-to-low variance (negative slope to zero) does not vary significantly with crude volatility. For exposition purposes, we also report (Table 6) the *remaining* probabilities; these exceed 84%, implying that regimes are persistent while p_{22} – with minimum value of 88.9% – indicate that low variance states are more frequent and persistent.

In the Brent market MRS model the transition probabilities imply that the expected duration[13] of regime 1 is 8.3 (=1/[1–0.880]) weeks compared to 12.8 (=1/[1–0.922]) weeks in regime 2. The corresponding values for WTI are 7.3 weeks in regime 1 and 13.1 in regime 2. As a result, high-variance states are less stable and exhibit relatively short durations. For the TVP models, we report the average values across time. Overall, irrespective of the crude oil or model, the high-variance regime (negative slope) is not expected to be longer than approx. 8 weeks while the low-variance state (zero slope) is not expected to be shorter than 11 weeks (while transition from one regime to the other ranges between 7.5% and 16%).

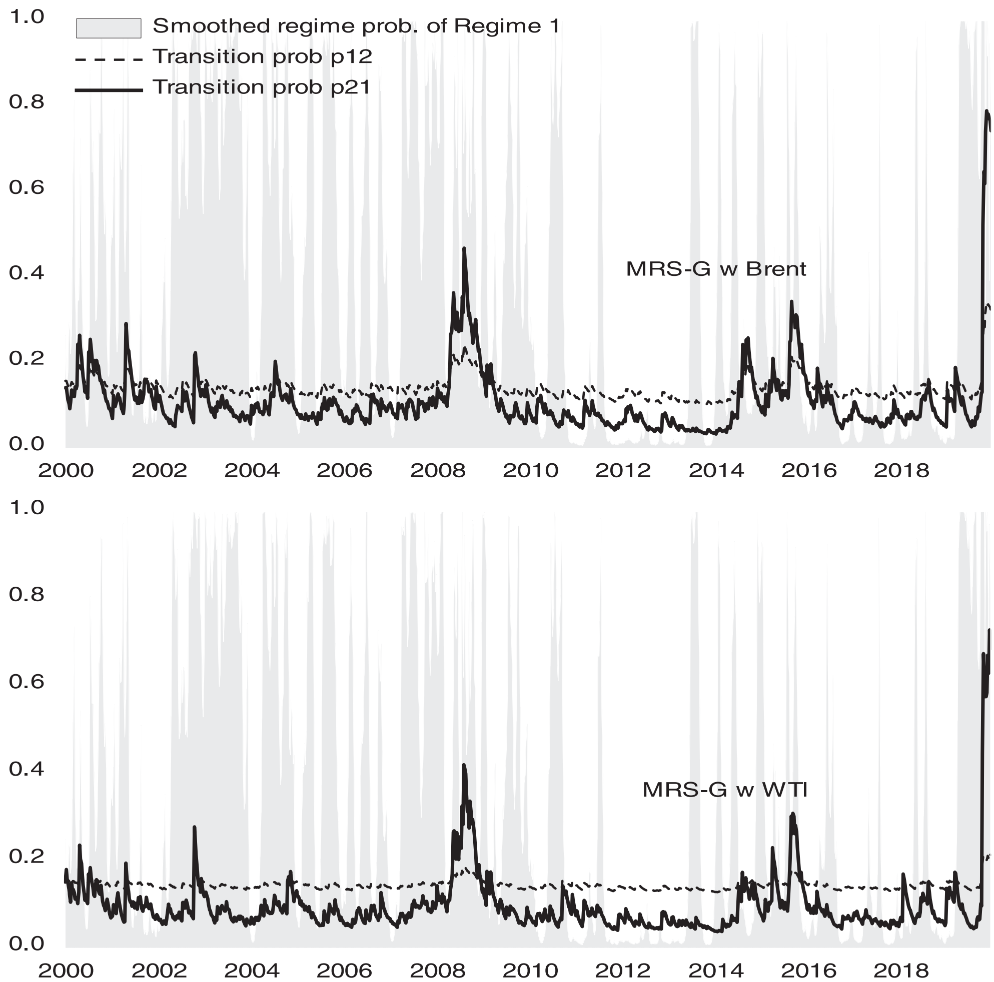
We next proceed with some robustness checks. First, in Table 6, Panel B models are re-estimated with the VARX model residuals instead of the raw data. Although results display a similar pattern, slope coefficients have somewhat increased in magnitude in both states. Second, while most of the slopes in the low variance state remain positive, they now turn significant at 5% level. Another observation is the slightly reduced expected durations (reduced p_{11} and p_{22}); regimes are less persistent (especially for WTI) compared to Panel A. Finally, in Panel C models are re-estimated for different oil market uncertainty proxies, that is, RV_{3m}, RV_{6m} and RV_{12m} instead of GARCH and RV_{1m}. Results are qualitatively similar.

Figure 6 illustrates the regime-switching behaviour over time. To determine the timing of the states, inferences are made based on the Markov probabilities. The '*smooth*' regime probabilities for BDTI market, derived from the estimated MRS-G models with Brent (top) and WTI (bottom) and TVP are presented. This smoothed probability indicates the likelihood of being in state 1 (high variance – negative slope state). State 2 is the one prevailing overall whereas high-variance state is relatively shorter-lasting yet persistent and frequent too. The time-evolution of transition probabilities is also shown in the graph.

Table 7 reports return descriptive statistics in each state and for all models presented in Table 6, that is, MRS (CTP), MRS-G (TVP) and MRS-RV_{1m} (TVP). In Panels A (B) the results for Brent (WTI) are reported. To classify regimes we use the implied smoothed regime probabilities, that is, a return is categorised as an observation belonging to a certain state if the smoothed regime probability being in state 1 (or 2) is greater than a threshold of x%. We use two thresholds, that is, x = 50% and x = 75%. The former involves all the available observations in the calculation of the sample statistics. The latter involves fewer; as regime probabilities within the interval (0.25, 0.5) are removed and not classified in a particular regime.

Several observations merit attention. The identified states of BDTI are associated with crude oil high-low variance states as well. Specifically, an average BDTI annualised volatility of 83%–87% (96%–102%) finds the crude oil market experiencing a volatility of 53%–57% (58%–62%); when classification to regimes is based on the 50% (75%) threshold probability. On the other hand, a relatively low

FIGURE 6 Regime shifts. This figure presents the smoothed regime probabilities of being in the high volatility (high slope) states for BDTI (grey areas). These are derived from the MRS-G model of Equations (6) and (7); for parameter estimates see Table 6. Transition probabilities are conditioned on the lagged (log) crude oil volatility and are also depicted in the graph, that is, $p_{12,t}$ (dotted line) and $p_{21,t}$ (solid line). The plots to the top (bottom) consider Brent (WTI) as the crude oil variable.



average BDTI annualised volatility of 25%–29% finds the crude oil market volatility at approx. 33%. Overall, this corroborates the linkage of the two variables. This is not surprising since oil is indispensable for the tanker sector, both as fuel and cargo (see also Figure 2). In general, synchronisation across markets appears strong. Besides, note also that high (low) variance BDTI regimes 1 (2) are associated with high positive (negative) returns.

Moreover, oil-BDTI correlations across crudes and/or regime classification method are significant and negative in state 1, in all cases presented in Table 7. On the other hand, all oil-BDTI correlations are positive but, overall, insignificant in state 1 if the threshold probability is set to 50% and, significant at (at least) 5% level if the threshold is set to 75%. There is no substantial differentiation between the two crudes and results are consistent irrespective of the crude benchmark used.

All things considered, the key message is that high volatilities in oil (and BDTI) market lead to significantly negative oil-BDTI correlation. Then again, low volatilities in oil (and BDTI) market lead to no statistical association, albeit with a tendency to positive values. Finally, low volatilities in oil combined with 'very' low volatilities in BDTI (regime probability higher than 75%) yield significantly positive correlations.

6.1 | Regime shifting analysis - further results

In this section, we expand our empirical analysis to additional datasets: (a) individual routes that compose BDTI, (b) one alternative tanker index, that is, the BCTI and (c) one freight index from the drybulk sector, namely the BDI. BCTI reflects voyages for clean tanker cargoes (kerosene, gasoline, naphtha and the like) whereas BDI reflects the cost of shipping raw materials (iron ore, steel, cement, grain, coal, etc.).

In unreported work, we have estimated all MRS models presented Section 6 for the expanded dataset. For brevity, we present the general unrestricted MRS model with RV_{1m} crude volatility as a proxy of oil market uncertainty; results are insensitive to the choice of volatility measure (see Table 7). Table 8 reports essential state dependent descriptive statistics. The underlying model in all cases is the MRS- RV_{1m} (TVP) while

TABLE 7 Sample moments across regimes as implied by MRS models

Model/state	Weekly Obs.	R_{BDTI} Mean	R_{BDTI} Std	R_{oil} Mean	R_{oil} Std	Correl. (R_{BDTI}, R_{oil})
Panel A: Crude oil = Brent						
Regime prob. >50%						
$MRS_{(St=1)}$	386	16.27	83.81	0.05	57.40	−29.51***
$MRS_{(St=2)}$	656	−15.28	29.49	1.12	33.53	1.01
$MRS\text{-}G_{(St=1)}$	408	11.88	82.66	−0.11	56.65	−29.66***
$MRS\text{-}G_{(St=2)}$	633	−13.96	27.95	0.75	33.20	4.02
$MRS\text{-}RV_{(St=1)}$	406	14.09	82.90	0.00	56.62	−30.12***
$MRS\text{-}RV_{(St=2)}$	636	−14.88	27.81	1.18	33.35	5.54
Regime prob. >75%						
$MRS_{(St=1)}$	277	14.73	95.21	−15.91	62.76	−31.58***
$MRS_{(St=2)}$	532	−11.42	26.57	3.18	33.25	8.99**
$MRS\text{-}G_{(St=1)}$	273	29.23	96.81	−10.05	61.65	−33.09***
$MRS\text{-}G_{(St=2)}$	488	−22.35	24.96	3.30	33.71	13.26***
$MRS\text{-}RV_{(St=1)}$	276	25.81	96.35	−10.50	62.68	−32.62***
$MRS\text{-}RV_{(St=2)}$	489	−23.28	24.95	2.50	32.95	11.63**
Panel B: Crude oil = WTI						
Regime prob. >50%						
$MRS_{(St=1)}$	341	12.87	88.01	−5.78	53.61	−23.75***
$MRS_{(St=2)}$	701	−11.60	30.29	3.65	33.57	3.94
$MRS\text{-}G_{(St=1)}$	365	13.40	86.16	3.20	52.98	−23.72***
$MRS\text{-}G_{(St=2)}$	676	−13.14	29.10	−1.71	33.06	5.66
$MRS\text{-}RV_{(St=1)}$	342	7.12	88.26	0.32	53.83	−24.60***
$MRS\text{-}RV_{(St=2)}$	700	−8.83	29.81	0.68	33.36	6.40*
Regime prob. >75%						
$MRS_{(St=1)}$	232	29.87	101.8	−16.56	58.72	−28.76***
$MRS_{(St=2)}$	569	−9.85	27.60	4.13	32.63	8.80**
$MRS\text{-}G_{(St=1)}$	240	27.38	100.9	−8.19	56.58	−28.63***
$MRS\text{-}G_{(St=2)}$	544	−16.94	26.49	−1.58	33.17	10.39**
$MRS\text{-}RV_{(St=1)}$	219	29.67	104.8	−19.13	59.36	−29.35***
$MRS\text{-}RV_{(St=2)}$	558	−9.24	26.82	2.90	32.57	11.56***

Note: The results of this table follow the estimation results of Table 6; Equations (6) and (7). This table reports sample moments for each regime, where an observation is classified as belonging to a particular regime if the regime probability of being in regime 1 (or 2) is greater than 50% or 75%. The former involves all the available observations in the calculation of the sample statistics. The latter involves fewer; as regime probabilities within the interval (0.25, 0.5) are not classified in neither of the identified regimes. Note that *MRS-RV* corresponds to the $MRS\text{-}RV_{1m}$. Results for $MRS\text{-}RV_{3m}$, $MRS\text{-}RV_{6m}$ and $MRS\text{-}RV_{12m}$ are similar and are not presented here for brevity (available from the authors upon request).

observations are classified to regimes if the regime probability of being in regime 1 (or 2) is greater than 50%. In Table 8, Panel A the dirty-tanker routes are TD1, TD2, TD6, TD7, TD8, TD9, TD12, TD14, TD15, TD17 and TD18.[14]

The identified states of the individual routes are also associated with crude oil high-low variance states, as was the case with BDTI. To a certain extent, there is diversity in the regime risk–return route-specific profile but this is not surprising as some routes exhibit higher volatility. In regime 1, that is, the high-variance state, route annualised volatilities range from 75.5% to 187.8% (average of 135%), which corresponds to crude oil volatilities of 47%–85% (average of 58%). Regarding the low-variance state, route annualised volatilities range from 10.5% to 51%, (average of 28%) which are linked to crude oil volatilities

TABLE 8 Sample moments across regimes for other freight variables

	R_{Fr}				R_{Fr}			
	Mean	**Std**	σ_{Brrent}	**Correl**	**Mean**	**Std**	σ_{WTI}	**Correl**
Panel A: BDTI routes								
$TD1_{(St=1)}$	149.1	159.9	59.03	−28.5***	161.6	163.8	61.15	−28.8***
$TD1_{(St=2)}$	−80.89	38.07	33.98	−6.4*	−79.81	39.50	33.27	−3.5
$TD2_{(St=1)}$	112.1	175.1	55.26	−22.1***	119.2	177.7	56.34	−21.8***
$TD2_{(St=2)}$	−92.02	43.39	32.33	4.6	−91.84	44.12	31.78	4.0
$TD6_{(St=1)}$	51.29	145.2	53.20	−16.2***	45.92	146.2	53.61	−15.7***
$TD6_{(St=2)}$	−64.82	31.47	30.06	2.2	−56.64	33.37	29.92	−3.9
$TD7_{(St=1)}$	2.93	153.7	47.74	−16.5***	12.30	154.9	47.57	−17.2***
$TD7_{(St=2)}$	−8.66	30.22	39.56	14.2***	−17.59	32.55	39.97	15.0***
$TD8_{(St=1)}$	36.11	85.04	56.23	−13.5***	36.41	85.17	56.06	−13.8***
$TD8_{(St=2)}$	−26.87	17.45	33.54	5.7	−26.95	17.33	33.76	7.0*
$TD9_{(St=1)}$	10.80	158.9	49.59	−10.9***	7.94	158.3	47.94	−10.8***
$TD9_{(St=2)}$	−31.86	26.67	32.33	2.0	−27.70	26.10	36.12	−5.8
$TD12_{(St=1)}$	2.48	76.47	59.14	−5.0	4.81	75.53	58.75	−4.8
$TD12_{(St=2)}$	−10.70	16.85	31.00	11.1**	−12.81	16.57	30.66	10.5**
$TD14_{(St=1)}$	61.75	97.66	59.78	−12.4**	61.51	96.49	61.77	−12.4**
$TD14_{(St=2)}$	−39.88	19.06	35.55	−8.2*	−41.29	18.62	33.11	−5.2
$TD15_{(St=1)}$	4.09	181.6	81.30	−46.8***	31.39	187.8	84.91	−45.3***
$TD15_{(St=2)}$	−0.78	49.55	33.42	6.8*	−6.01	50.65	33.16	2.9
$TD17_{(St=1)}$	−2.02	151.9	49.71	−9.3**	−2.14	152.9	50.02	−9.3**
$TD17_{(St=2)}$	−12.27	10.68	31.74	−2.9	−11.37	10.50	31.20	−2.7
$TD18_{(St=1)}$	118.1	88.97	59.57	7.0	105.9	88.79	71.02	4.8
$TD18_{(St=2)}$	−41.81	25.47	41.26	4.3	−38.10	25.85	34.77	6.6
Panel B: Other indices								
$BCTI_{(St=1)}$	208.99	115.3	66.58	−39.8***	174.5	109.7	71.93	−36.9***
$BCTI_{(St=2)}$	−32.04	27.42	39.74	0.3	−31.49	26.70	37.39	4.0
$BDI_{(St=2)}$	−27.13	75.36	49.47	5.9	−22.78	74.96	49.24	5.7
$BDI_{(St=1)}$	27.59	22.84	33.51	−3.3	21.82	22.70	33.59	−2.1

Note: This table reports sample moments for each regime, where an observation is classified as belonging to a particular regime if the regime probability of being in regime 1 (or 2) is greater than 50%. The underlying model is that of Equations (6) and (7) was estimated for a battery of alternative time series for robustness. In this table, we report results on individual routes that comprise BDTI (Panel A), as well as Baltic Clean Tanker Index and Baltic Dry Index (Panel B) for comparison. As the results are insensitive to the choice of volatility measure employed (see Table 7), to save space, all results presented are based on a RV_{1m}. Note that, as of March 2020 BDTI routes are (Baltic Exchange, 2020): TD1 (280,000mt, Middle East Gulf to US Gulf); TD2 (270,000mt, Middle East Gulf to Singapore); TD3C (270,000mt, Middle East Gulf to China); TD6 (135,000mt, Black Sea/Mediterranean); TD7 (80,000mt, North Sea to Continent); TD8 (80,000mt, Crude and/or DPP Heat 135F, Kuwait to Singapore); TD9 (70,000mt, Caribbean to US Gulf); TD12 (55,000mt, fuel oil, Amsterdam-Rotterdam-Antwerp range to US Gulf); TD14 (80,000mt, no heat crude, South East Asia to East Coast Australia); TD15 (260,000mt, no heat crude, West Africa to China); TD17 (100,000mt crude. Baltic to UK-Continent); TD18 (30,000mt fuel oil Baltic to UK-Continent); TD19 (80,000mt, cross Mediterranean); TD20 (130,000mt West Africa to Rotterdam). Here, we consider the routes that have at least 10 years worth of data.

of 30%–41% (average of 34%). Therefore, route-specific dynamics identify distinct regimes, directly linked to oil uncertainty.

Oil-BDTI correlations across crudes are significant and negative in state 1, in all cases, apart from TD12 and TD18 where they are non-statistically different than zero; these figures range from −9.3% (TD17) to 45%–47% (TD15), depending on the oil uncertainty proxy employed. In the low variance state (regime 2) the tendency is for correlations to be insignificant. Few exceptions: positive correlations for TD7 and TD12 (at 1% and 5% significance level) or negative for TD1 and TD14 (albeit at 10% level and Brent-specific). Overall, findings corroborate that high volatilities in oil (and BDTI) lead to significantly negative oil-BDTI correlation while low volatilities in oil (and BDTI) is more likely to result in no statistical association, although small positive or negative correlation is possible and route-specific.

This is also consistent when considering the clean-tanker index results in Table 8, Panel B. That is, the states of BCTI are also associated with crude oil high-low variance states. Specifically, an average BCTI volatility of 110%–115% p.a. (26%–27%) finds the crude oil market experiencing a volatility of 66%–72% (37%–40%). In line with the BDTI results, when volatilities are high oil-BCTI correlations are significantly negative (−36% to −40%). Low volatilities lead to no significant association.

Furthermore, the BDI results differentiate from the analysis so far. However, this is the only non-tanker case presented. Although the states of BDI are associated with differences in crude oil volatility as well, there seems to be no oil-BDI correlation across these regimes. An average BDI annualised volatility of close to 75% (23%) finds the crude oil market experiencing a volatility of approx. 50% (33.5%). When volatilities are high oil-BDI correlations are close to 5% while low volatilities lead a correlation of close to −3%, yet these are non-statistically different from zero in both cases.

Finally, we have repeated our analysis and estimated the regressions of Equations (4) and (5). Overall, a collective view of this unreported work and the results of this section indicate that the studying individual routes, BCTI and BDI neither offers any additional evidence nor it contradicts any of the conclusions that drawn so far. In fact, with the exception of BDI which constitutes a different sector, results are similar to BDTI.

7 | CONCLUSION

This article examines the potential impacts of oil market uncertainty on the variations in the oil-BDTI return relation. Our research indicates that in the short-run (one-week period), oil returns have predictive power on the returns of BDTI but not vice versa, consistent with previous literature, for example, Alizadeh and Nomikos (2004). From a forward-looking perspective, a regression framework reveals strong evidence of a negative relation between oil uncertainty and the future correlation of oil and dirty-tanker shipping returns. The negative relation is more pronounced when crude oil price volatility is high. Results hold when adding lagged realised correlation values as a control variable, as the latter offers only limited increase to explanatory power. Rolling regressions suggest that the explanatory power of oil market uncertainty is sample specific as the negative correlation of oil and dirty-tanker shipping returns holds in relatively volatile periods and is more pronounced in extremely turbulent periods (e.g., 2008 financial crisis or lockdowns due to COVID19). Our conjectures and findings about the nature of the oil volatility and oil-tanker correlations are confirmed also via a MRS framework. The identified regimes of tanker shipping can be directly linked to periods of high–low crude oil volatility with implications on the level of correlation they exhibit to oil returns. Results are robust across crudes (Brent and WTI) and different volatility proxies (parametric and nonparametric) as well as route-specific returns and clean-tanker cargoes as well.

Overall, time variation in the relation between tanker freight rates and oil price volatility over the short term seems to be substantial. Characterising this time variation has important implications for understanding the economics of freight rate formation and has practical applications in asset allocation and risk management of transportation assets and portfolios. These results provide market participants with useful warning signs of market shocks and crises as oil price uncertainty greatly influences tanker transportation freight costs. Predictability and linkages may prove useful to international investors and traders, but also provide essential insights to policymakers and regulators, in terms of commercial strategies, asset positioning, network supply chain modelling, asset investment allocation, budgeting and risk management.

This article measures the effect of oil price uncertainty on the relation of tanker returns and oil; given the importance of oil as a strategic commodity in all aspects of economic activity. The implications of this study are important for various stakeholders in the industry adding to their understanding of this relation, as oil prices affect the shipping market, both as a cargo and as a fuel. Our work can be extended in several directions. First, we have assumed that 'freight' is represented by either BDTI or individual tanker routes. In further research, different definitions of freight could be investigated. For example, Theodossiou et al. (2020) use vessel earnings to orthogonalise freight rates to possible changes on bunker fuel cost and / or operating costs that may affect the nominal freight rate the ship earns (see also Drobetz et al., 2021; Nomikos & Tsouknidis, 2022). Another important aspect to consider is the definition of uncertainty. Creating uncertainty indices of disaggregated supply and demand shocks of the oil or tanker market, albeit an important question, is left for future research.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from Refinitiv database (daily crude oil prices) and Clarkson's Shipping Intelligence Network (shipping data) (https://sin.clarksons.net/). Restrictions apply to the availability of these data, which were used under license for this study. Data are available from Refinitiv and Clarkson's Shipping Intelligence Network.

ORCID

Panos K. Pouliasis https://orcid.org/0000-0002-7389-3722

ENDNOTES

[1] An increase in crude oil price increases costs as bunker fuel is considered a voyage cost and, in the case of a spot charter agreement, this cost is paid by the shipowner. Moreover, if oil prices rise as a result of increased real economic activity, higher freight can compensate increased fuel costs, nevertheless this is not the case if high prices are due to supply disruptions (see Gavriilidis et al., 2018).

[2] Kalouptsidi (2014) employs a dynamic model of entry and exit that features constant required returns and procyclical time-to-build delays and uses second-hand ship prices to study shipping investment cycles. Findings indicate that construction lags and expected revenues have a considerable impact on the level of investment in new ship construction. Moreover, moving from time-varying to constant to no time to build reduces prices, while both the level and volatility of investment increase.

[3] The motivation for the use of the BDTI is threefold. First, Baltic indices have been widely used to proxy global economic growth as they provide information about global demand and supply for seaborne trade (e.g., see Bakshi et al., 2011). Second, BDTI reflects not only the condition of the tanker market but also the macroeconomic elements of tanker rates (Alizadeh & Talley, 2011). Finally, the indices are used by practitioners to settle freight derivatives contracts.

[4] Worldscale (WS) is the primary framework for setting tanker freight rates. Published rates and differentials of tanker voyages reflect the nominal $/ton freight for a standard tanker (sise of 75,000 dwt) with some assumptions on specifications (e.g., 14.5 knots laden at 55 ton/day bunker consumption) based upon a round voyage. This freight rate is known as WS100 or '*flat rate*.' Negotiated rates between shipowners and charterers are then expressed as a percentage of the nominal printed freight.

[5] BDTI is computed from the reported dirty-tanker routes by the Baltic Exchange. The index indicates the cost of tanker shipping based on the average costs of some routes; calculated by the Baltic Exchange and a panel of key shipbrokers.

[6] Moreover, Bera and Jarque (1980) tests reveal normality departures for all series. The Ljung and Box (1978) statistic shows signs of serial correlation: evident for the freight but less so for crude oil. Engle, 1982 test indicates strong heteroscedasticity patterns. Finally, based on the Augmented Dickey and Fuller (1981) (ADF), and Phillips and Perron (1988) (PP) unit root tests (Panel B) both crude oil prices are difference stationary. Conversely, BDTI is integrated of order zero; the mean-reverting behaviour of BDTI is also visible in Figure 1.

[7] One can identify various demand and supply factors for tanker freight rates. To name a few, international trade in oil and oil products, world fleet, shipbuilding production, scrapping, average haul, political events and the legislation framework, vessels' lay-up tonnage, vessel speed (see, among others, Stopford, 2009; Adland & Strandenes, 2007). For example, Nomikos and Tsouknidis (2022) construct indices capturing the economic activity in the shipping sector and provided a framework to identify mutually uncorrelated supply and demand shocks.

[8] For more technical details and applications to oil price volatility modelling and forecasting the reader is referred to Sadorsky (2006), Nomikos and Pouliasis (2011) and Pouliasis and Papapostolou (2018).

[9] Engle, 1982 ARCH test indicates that a GARCH (1,1) is capable to remove the heteroscedasticity effects of the returns (Q^2 in Table 1). Further, there are no signs of autocorrelation in the crude oil standardised residual series, at 1% level. Note that, to remove serial correlation for the BDTI, returns are filtered through an autoregressive process of order 2 before estimating the variance equation.

[10] For instance, Wilson et al. (1996) provides evidence structural breaks in the unconditional oil price volatility of futures contracts. Fong and See (2003) also reports that futures price volatility exhibits regime shifts, in line with the theory of storage (see also Nomikos & Pouliasis, 2011, 2015).

[11] Whether the estimate of the slope is $a_1 + a_2 \ln(\sigma_{oil,t-1}) + a_3 \rho_{oil,BDTI,t-1}$ or $a_1 + a_2 \ln(\sigma_{oil,t-1})$ the overall trend is similar while differences are short-run and period-specific; this confirms that oil market uncertainty captures most of the variation in the slopes (confirmed also in Table 4 – adding correlation marginally improves R^2 in Equation 4).

[12] We also estimate an alternative specification that uses a measure of oil-BDTI weekly co-movement as the dependent variable and lagged crude oil volatility as an explanatory variable; $R^{std\ resid}_{BDTI,t} R^{std\ resid}_{oil,t} = a + a_2 \ln(\sigma_{oil,t-1}) + \varepsilon_t$. The dependent variable is the product of the standardised residuals of the weekly BDTI and oil returns, estimated from the GARCH models in Section 2. In this context, $R^{std\ resid}_{BDTI,t} R^{std\ resid}_{oil,t}$ measures whether the standardised residuals move together, that is, a weekly correlation measure. Results indicate that a_2 coefficients are negative for both crude cases; -0.425 (-0.423) for Brent (WTI) and significant at 1% (%5) level.

[13] We can calculate the average expected duration being in state k (Hamilton, 1989) as: $\sum_{k=1}^{\infty} k p_{11}^{k-1}(1-p_{11}) = (1-p_{11})^{-1}$.

[14] Note that, some routes of BDTI components are excluded as we consider routes that have at least 10 years of usable data. For example data on TD3C (270,000 t Middle East Gulf – China), TD19 (80,000mt, Ceyhan – Lavera) and TD20 (130,000mt, West Africa – Continent) are available, respectively, from December 2015, September 2011, May 2014 onwards and thus excluded from our dataset.

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