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Covid-19 and the energy trade: Evidence from tanker trade routes

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A B S T R A C T

We employ a cointegration setup to explore route-specific off-equilibrium deviations related to Covid-19 that have affected clean (petroleum products) and dirty (crude oil) tanker freight rates, over and above the expected macroeconomic reactions. We find that the additional deviation caused by Covid-19 is route-specific. In particular, deviation caused by Covid-19 is found to be more significant for clean tankers, with an average impact of 0.15, an expected outcome given that these products are more reliant on economic developments because of their uses. The clean tanker impact is more evident in Japan-related routes, while no specific pattern can be extracted with regards to the additional off-equilibrium Covid-19 deviation for dirty tanker routes. Results suggest that time-charters and hedging against the stock markets can help ship-owners ameliorate demand-driven shocks.

1. Introduction

Since the financial crisis in 2007–2008, the world economy has bounced back to growth, following the ultra-low interest rate environment (Michail, 2019), which has in turn led to an increase in international trade. Most of the trade barriers that have been blocking the development of commerce the last century were lifted leading to countries and industries exchanging their goods more freely. Nevertheless, as of November 2019, a global pandemic has hit the globe. Sars-Cov-2 started in Wuhan, China (Sohrabi et al., 2020), with explanations citing human interaction with bats (Rothan & Byrareddy, 2020) or pangolins (Zhang, Wu, & Zhang, 2020). Over the course of the next three months, the SARS-Cov-2 virus evolved to a global pandemic, the first to have registered so many cases in a short amount of time since the Spanish flu of 1918 (Barro, Ursua, & Weng, 2020).

In order to minimize the risk of their citizens been infected, countries took a variety of measures, mostly related to curfews (Koh, 2020) and social distancing (Thunström, Newbold, Finnoff, Ashworth, & Shogren, 2020) on the basis of a cost-benefit analysis between economic downturn and an increase in the spread of the virus. The measures had an impact both on the world economy (Fernandes, 2020) as well as transportation services (Kim, 2021).

The recent demand-shock of covid has led to a major disruption in world economy, which in return has led to a decrease in the demand for transportation services. Following this unprecedented demand-side shock, which would imply a shift in the demand curve under standard economic theory (Bernanke & Blinder, 1988), the oil price futures turned negative for a short period of time, giving rise to arbitrage opportunities (Regli & Adland, 2019; Michail & Melas, 2020a).

Nevertheless, even this very turbulent period, the trade of oil follows predetermined routes due to the specific areas that exhibit shortages and excesses of oil production. As a result of the widespread geographical requirements between the producers and consumers of oil, its transport takes place via a variety of means, namely by oil tankers, pipelines, railways and trucks (Cheng & Duran, 2004; Cheng et al., 2019). Of the above, the most common means of

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Table 1
Top ten countries in exports and imports of crude oil.

Crude Oil Exporting Countries	Percentage of Total Exports	Crude Oil Importing Countries	Percentage of Total Imports
Saudi Arabia	12,64%	China	17,59%
Russia	11,45%	United States of America	12,80%
Kuwait	8,19%	Undeclared	10,04%
United Arab Emirates	7,83%	India	8,43%
Iraq	6,72%	South Korea	5,84%
Canada	5,90%	Japan	5,60%
United States of America	3,99%	Netherlands	4,09%
Nigeria	3,92%	Germany	3,26%
Iran	3,54%	Italy	2,68%
Oman	3,29%	Spain	2,46%
Total	67,47%	Total	73%

Table 2
Top ten countries in exports and imports of refined oil.

Refined Oil Exporting Countries	Percentage of Total Exports	Refined Oil Importing Countries	Percentage of Total Imports
United States of America	11,85%	Undeclared	7,88%
Russia	9,38%	United States of America	6,94%
Netherlands	6,57%	Singapore	5,88%
Singapore	6,08%	Netherlands	5,77%
India	5,81%	Mexico	3,74%
South Korea	5,40%	Germany	3,10%
United Arab Emirates	5,30%	China	2,94%
China	4,20%	United Kingdom	2,74%
Belgium	3,97%	Belgium	2,73%
Saudi Arabia	2,86%	France	2,55%
Total	61,42%	Total	44,26%

transport is via oil tankers, due to the low cost per barrel (Chu, Chu, Zhou, Chen, & Shen, 2012).

To elaborate on this, Tables 1 and 2 show the major oil exporting and importing countries both for crude and refined oil. Gulf countries, such as Saudi Arabia, Kuwait and United Arab Emirates, along with Russia are on the top of the list and they account for the 40.11% of the total exports of crude oil. On the contrary, major industrial countries such as China, the United States of America, India and South Korea account for the 44.66% of global imports of crude oil.

Following the extraction of crude oil, this is then refined and acts as the base ingredient for various other products such as gasoline, other fuels, plastics and pharmaceuticals (Brinkmann, 2016). The refined products are then consumed either by households (Álvarez, Hurtado, Sánchez, & Thomas, 2011) or the industry (Mignard, 2014). Thus, as per Marchese et al., (Marchese, Kyriakou, Tamvakis, & Di Iorio, 2020), the refined oil trade is of high importance for global economic activity. As a result of the specific locations of the world's refineries, oil products have different sea trading routes, given that most of the countries have refineries of their own. The major clean (refined) products exporters are the United States of America, Russia, Netherlands and Singapore and they account for the 33.88% of the total trade. At the same time, some of these countries are also the world's largest importers (Table 2), with the top three accounting for 18.59% of total imports.

For both crude oil and refined products, due to economies of scale arising from the increase in vessel capacity through time, the transportation cost of oil via the sea has been considered insignificant (Stopford, 2013), especially when compared to its total distribution cost (Demirbas, Omar Al-Sasi, & Nizami, 2017). Nevertheless, the financialization of the commodity markets (Basak & Pavlova, 2016) which has led to information spillover between different asset classes (Ferraro, Rogoff, & Rossi, 2015), in conjunction with the recent exogenous shock of the coronavirus period has raised transportation cost, as a percentage of the price of oil, significantly. As can be observed from Fig. 1 while historically, the transportation cost was around 0.5% of the cost of oil, it has increased to 4.5% during the pandemic. Thus, the short-term oil demand curve has not shifted solely due to the change of fuel demand preference, but additionally due to the dramatic increase of transportation costs.

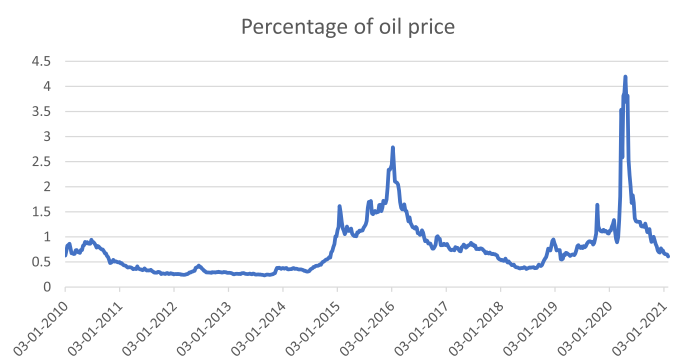

Fig. 1. Cost of Transportation.

From a maritime perspective, freight rates have been documented to be affected by macroeconomic factors for a while (Stopford, 2013). The most prominent ones are the world GDP (Michail, 2020), financial markets (X. Zhang, Podobnik, Kenett, & Eugene Stanley, 2014) and economic growth (Michail, Melas, & Batzilis, 2021). Nevertheless, since macroeconomic factors are affecting freight rates the same goes for political and social events that will undoubtedly have an impact on the macroeconomic environment. Recent studies have shown that, on the whole, the recent Covid-19 pandemic has affected both the shipping (Michail & Melas, 2020b) and the port industry (Notteboom & Haralambides, 2020).

In the current paper, we explore how the Covid-19 pandemic has affected the freight rates of specific trade routes as they are provided by Clarkson's and are included in the Baltic Dirty Tanker Index and Baltic Clean Tanker Index. Sharp rises in freight rates can increase the price of oil and affect both the cash flows of the oil companies (Boyer & Filion, 2007; Osmundsen, Asche, Misund, & Mohn, 2006) as well as the global economy (Fernández, Schmitt-Grohé, & Uribe, 2017; Kamber & Wong, 2020).

The recent research on the matter have provided some important findings. Initially, Devpura and Narayan (2020) provide evidence that coronavirus cases are explaining the volatility that was documented in crude oil prices oil and furthermore that the Covid-related investor anxiety further enhanced this volatility (Bourghelle, Jawadi, & Rozin, 2021). However, given that crude oil is one of the major raw materials for the world economy (Ma, Zhang, Ali, Kirikkaleli, & Khan, 2021), changes in its price can have an adverse effect on GDP and unemployment rates (Welfens, 2020), stock markets (Prabheesh, Padhan, & Garg, 2020), supply chains (Alshater, Atayah, & Khan, 2021; Coluccia, Agnusdei, Miglietta, & de Leo, 2021) and commodity prices (Sun, Su, Mirza, & Umar, 2021). These disruptions led to a significance decrease in global trade as a whole (Vidya & Prabheesh, 2020), but more importantly in the oil and petrochemical trade. Norouzi (2021) provides evidence that while the short-term reduction is consumption is bouncing back, in the long-run oil companies seem to invest less in capital expenditures and research and development given the recent disruption.

Given the above, in the current paper, we explore how the energy trade has been affected by the Covid-19 pandemic, using data on clean and dirty tanker routes. By employing a dataset of 1176 daily observations, we show that clean tankers rates have been affected more by the pandemic when compared to the dirty tankers. Furthermore, we also find that the overall relationship between the macroeconomic variables and clean tankers lies mostly on the size of the vessel, since larger vessels are affected less when compared to smaller ones. On the other hand, the distance of the route appears to be the most important factor in determining the relationship between the macroeconomic variables and the dirty tankers. As such, the results suggest that longer-distance routes' rates have been hit harder by the Covid-19 pandemic.

Our results bare serious implications for the stakeholders of the energy sector. While in crisis events, alike the Covid-19 pandemic, the demand function shifts, we show that the supply equation shifts as well given the changes that appear in the transportation costs. Our results are in accordance with long documented literature that provides evidence that exogenous shocks shift the supply function of oil (Gisser & Goodwin, 1986). These two shifts create a new equilibrium price that not only affects the cash flows of oil companies and the Organization of the Petroleum Exporting Countries but additionally given the strong substitution effects that exist within the energy sector can lead to substitution effects (Koetse, de Groot, & Florax, 2008).

The rest of this paper is organized as follows: Section 2 reviews the literature on the issue; Section 3 outlines the methodology followed and describes the dataset; Section 4 presents the empirical results and Section 5 concludes the paper.

2. Literature review

The relation between freight rates and oil prices have long been revealed in the literature. The first evidence between the latter relationship has been documented before the Second world war by Isserlis (1938), who has created one of the first indices on the matter. Then, Zannetos (1959) in his doctoral thesis has tried to capture the demand and supply curves for oil by including transportation services needed. Nevertheless, despite the vague findings of their research both the above authors acted as predictors of the vast interest that the research and professional community would show on the matter.

It was not until the mid-nineties that Kavussanos (Kavussanos, 1996) has started to shed more light on the matter by employing advanced econometric methodologies on the relationship between oil prices and the shipping industries fundamentals. In his first research, by using an autoregressive conditional heteroskedasticity model, he has shown that the oil prices are negatively related to tanker prices but positively related to their volatility. Building on the latter findings, Chen and Wang (Chen & Wang, 2004) have shown that negative changes in the freight rates lead to larger volatility of the freight rates when compared to positive changes. Based on this asymmetry Drobetz, Richter, and Wambach (2012) have shown that macroeconomic variables, such as oil prices provide better explanatory power to the forecasting models of tanker freight rates.

Shi, Yang, and Li, (2013), by employing the framework of Kilian (2009), have shown that demand shocks of oil do not affect the tanker freight rates but on the contrary it is the supply shocks that have an effect on them. Despite this findings, Gavriilidis, Kambouroudis, Tsakou, and Tsouknidis (2018) have shown that the inclusion of aggregate oil demand shocks and oil-specific demand shocks improves the explanatory power of the forecasted volatility of 1 year time charter rates for all the vessel sizes.

More recently, Angelopoulos, Sahoo, and Visvikis (2020) have provided evidence more thoroughly on the relationship that holds between the tanker freight markets and the oil prices. Initially, they have examined the prices of crude oil and the equivalent freight rates for route TD3 (Middle East to Far East). They show that any new information is instantly transmitted from crude oil prices to the tanker vessel prices and subsequently to their freight rates. Moreover, the latter information has an eight-month lag period as to be absorbed by product tanker rates. The very large crude carrier freight rates are the ones that lead the market as they spillover information the smaller tanker vessels (Tsouknidis, 2016).

It should be mentioned that there are already fruitful findings in the literature concerning the differences between the different vessels' sizes. Kavussanos (2003) has shown that smaller tanker vessels bare less risk for investors when compared to the larger ones. More recently, Michail and Melas (2020b) have shown that during the Covid-19 pandemic product tankers (which are normally handysize vessels) have been immune to the economic shock, partly due to the oil contango arbitrage techniques used by speculators in the market.

When it comes to shocks that affect both oil demand and demand for transportation services, the recent research has provided evidence on the high correlation between the two. Khan, Su, Tao, and Umar (2021) have shown that global uncertainty affect both oil prices and the tanker freight rates and their correlation. Additionally, both shipping companies (Kamal, Chowdhury, & Hosain, 2021) and shipping investors (Marobhe, 2021) have been affected by the demand shock on a behavioral level by over-reacting to news announcements.

3. Methodology and dataset

In order to correctly assess the impact of the pandemic, we propose the use of an equilibrium model, where freight rates are connected with macroeconomic variables in a long-run equation. In such a setup, shocks such as Covid-19 can be viewed as off-equilibrium deviations, in addition to the impact that can be observed via the change in macroeconomic variables. To capture these, we propose the use of the general Vector Error Correction specification, following Johansen & Juselius (1990), which is defined as:

$$\Delta M_{j,t} = \alpha_j + \sum_{i=1}^{p} \beta_{1,i,j}\Delta M_{j,t-i} + \sum_{k=1}^{K-1}\sum_{i=1}^{p} \gamma_{k,i,j}\Delta \boldsymbol{W}_{t-i} + \varphi_j \boldsymbol{Z}_t + \delta_j(M_{t-1} - \theta_{1,j}\boldsymbol{W}_{t-1} - \theta_{0,j}) + \varepsilon_{j,t} \quad (1)$$

where the total number of variables is K, $M_{j,t}$ is the natural logarithm of variable j, and $\boldsymbol{W}_t$ is a $(K-1 \times N)$ matrix that contains all variables included in the estimation, other than variable j. Δ is the first difference operator, while $\beta_{i,i,j}$ and $\gamma_{k,i,j}$ refer to the own and other variable coefficient values in each of the K equations. Again, j signifies that the coefficient refers to the equation identified with variable j, while k refers to the specific variable within matrix $\boldsymbol{W}_t$. $\boldsymbol{Z}_t$ is a matrix of the exogenous variables potentially included in the estimation, with φ_j being the equation-specific estimates of the coefficients, and $\varepsilon_{j,t}$ refers to the error processes in each equation.

Table 3
Clean and Dirty Tanker Routes.

Clean Tanker Routes	Dirty Tanker Routes
BCTI TC1: 75,000 mt, CPP/UNL Naphtha Condensate, Middle East Gulf to Japan	BDTI TD1: 280,000 mt, Middle East Gulf to US Gulf
BCTI TC2_37: 37,000 mt, CPP/UNL Continent to USAC	BDTI TD2: 270,000 mt, Middle East Gulf to Singapore
BCTI TC6: 30000 mt CPP/UNL Algeria/Euromed	BDTI TD6: 135,000 mt, Black Sea/Mediterranean
BCTI TC9: 22,000 mt CPP/UNL middle distillate, Ventspils – Le Havre	BDTI TD7: 80,000 mt, North Sea to Continent
BCTI TC7: 30,000 mt, Singapore – EC Australia	BDTI TD8: 80,000 mt, Crude and/or DPP Heat 135 F, Kuwait to Singapore
BCTI TC10: 40,000 mt CPP/UNL South Korea – Vancouver/Rosarito range	BDTI TD9: 70,000 mt, Caribbean to US Gulf
BCTI TC11: 40,000 mt CPP South Korea – Singapore	BDTI TD12: 55000 mt, fuel oil, ARA range to US Gulf
BCTI TC8: 65,000 mt CPP/UNL middle distillate, Jubail – Rotterdam	BDTI TD14: 80,000 t SE Asia - EC Australia
BCTI TC12: 35,000 mt Naptha Sikka (WCI) to Japan	BDTI TD15: 260,000 t West Africa - China
BCTI TC14: 38,000 mt, CPP/UNL/Diesel US Gulf to Continent	BDTI TD3C: 270,000 t Middle East Gulf to China

The long-run relationship between the K variables is within the brackets of Eq. (1) with δ_j determining the speed of adjustment to the long-run equilibrium. As usual, the δ_j term is expected to be negative in order for a return to the equilibrium to be ensured after a shock (see also Enders, 1995).[1] In total, we employ three variables (i.e. K = 3), which will form the equilibrium equation. More specifically, our data selection is constrained by the high data frequency of the analysis, and hence we are only able to employ the price of Brent oil as a proxy of supply costs, the Wilshire 5000 index as a proxy of the state of the world's stock markets, and naturally the freight rates. Given our aim for a disaggregated approach, we have chosen to use specific route data, based on both availability as well as their significance in creating the BDI Clean and Dirty Tanker index. Table 3 presents an overview of the trade routes employed in the estimation.

The shipping trading routes, despite being usually viewed in an aggregate, sectoral view, are documented in high detail by Clarksons Shipping, and are known to market practitioners. The database is updated on an annual basis, and provides the specific routes, vessels, and the commodities transported, given that changes occur either because of political conflicts (Mohammed & Williamson, 2004) or even the climate change (Lindstad, Bright, & Strømman, 2016).[2] Via this database, we employ data for the 20 most important trade routes for dirty and clean tankers (10 for each). Regarding the macroeconomic variables, data for the Wilshire 5000 index and for the price of Brent oil were obtained from the St.Louis Federal Reserve Bank Database (FRED). The data range from 04 January 2016–20 August 2020, for a total of 1176 observations.

To assess the impact of the Covid-19 crisis, we follow Michail and Melas (Michail & Melas, 2020b) and use the evolution of daily coronavirus cases across the world. The data source for that data is ourworldindata.com, a data platform supported by the University of Oxford, providing free access to a variety of series. Also similar to Michail & Melas (2020b), we use the natural logarithm of the series in order to avoid any potential issues when they are included in the estimation. We note here that while freight rates are route-specific, it does not mean that this will be the final destination of the oil cargo. For example, if a vessel goes to Rotterdam, then the cargo may be then shipped to Germany, France, Belgium, the Netherlands, or any other country. In such a case, having high Covid-19 number in the Netherlands may not matter much given that most of the demand will come from other countries. In other words, while the route is specific the end-consumer is not limited geographically. This is especially true for clean tankers, given that such products are even more geographically dispersed. Furthermore, given that the pandemic was not country-specific, and neither was the impact on oil demand (as the developments in oil prices had shown), the use of global coronavirus cases helps to better capture these developments.

As per the specification of Eq. (1), the Covid-19 variable is included as exogenous, given that the impact is not likely to cause a permanent equilibrium deviation, also given that it was virtually zero until early 2020. To confirm this, we have also examined for the presence of a cointegrating relationship between the three variables and Covid-19 cases, with the estimates suggesting that such a relationship does not exist. The results of that exercise are available upon request. Tables 4 and 5 present the descriptive statistics of the freight rates employed in our estimation. As it can be seen from the estimates, a large standard deviation is evident, in accordance with Theodossiou, Tsouknidis, and Savva (2020).

To observe the impact of Covid-19 on the long-run equilibrium relationship between the variables, we need to establish first a cointegrating relationship. In other words, there needs to be an empirical justification for the use of the term in the brackets. However, before we are able to perform the Johansen test for cointegration we first need to establish that both variables are I(1), i.e. they follow a unit root process (for more details see Hendry and Juselius, 2000, 2001). The unit root tests confirm that the series are I(1), however, to avoid over-burdening the paper with tables, we do not report them here; they are available upon request.

Using the Johansen (1991) method, we test for the presence of a cointegrating relationship in a vector autoregressive setup. The rank of the error-correction matrix δ is found to be one in both the maximum eigenvalue and the trace tests, hence confirming the existence of one co-integrating relationship (Tables 6 and 7). Following the Granger representation theorem (Engle & Granger, 1987), if two variables are cointegrated, then at least one variable should Granger-cause the other and, by default, they can be combined in an equilibrium relation. To obtain this equilibrium relation, we use a Vector Error Correction (VEC) model, as it is justified by the data generating processes. Furthermore, the VEC model will allow us to observe any deviations from the equilibrium, on the basis of unexpected, non-permanent shocks. To avoid the use of a large number of routes in the same model, hence resulting in lower degrees of freedom, we run a separate estimation for each route. Two lags were used in each route-VEC, on the basis of the AIC and BIC criteria. In the following section, we present the results from this estimation.

4. Findings

Tables 8 and 9 show the results from the equilibrium VEC model, with CE, i.e. the cointegrating equation, suggesting that the model is well-behaved and has the anticipated negative sign in change. Furthermore, the equilibrium relationship is as expected, with the Brent oil price having a negative relationship with the freight index across all clean and dirty tanker routes. This result, in line with Kavussanos

[1] The long run, as per Johansen and Juselius (1990), refers to the equilibrium relationship between the variables, i.e. one that would be reached in the absence of any external shocks. Similarly, short run refers to the fluctuations which take place and allow for deviations from the equilibrium value. As such, the terms "long run" and "short run" do not refer to any predetermined time period – it is simply how econometricians refer to these relationships, derived from theoretical models which define the long run as a period with no shocks.

[2] The interested reader can find an interactive map of the trading routes discussed in this paper on the webpage of Clarksons (https://www.balticexchange.com/en/data-services/routes.html)

Table 4
Clean Tanker Descriptive Statistics.

	BCTI TC1: 75,000 mt, CPP/UNL Naphtha Condensate, Middle East Gulf to Japan	BCTI TC2_37: 37,000 mt, CPP/UNL Continent to USAC	BCTI TC6: 30000 mt CPP/UNL Algeria/Euromed	BCTI TC9: 22,000 mt CPP/UNL middle distillate, Ventspils – Le Havre	BCTI TC7: 30,000 mt, Singapore – EC Australia	BCTI TC10: 40,000 mt CPP/UNL South Korea – Vancouver/Rosarito range	BCTI TC11: 40,000 mt CPP South Korea – Singapore	BCTI TC8: 65,000 mt CPP/UNL middle distillate, Jubail – Rotterdam	BCTI TC12: 35,000 mt Naptha Sikka (WCI) to Japan	BCTI TC14: 38,000 mt, CPP/UNL/Diesel US Gulf to Continent
Mean	111.3	130.0	154.4	148.7	187.3	27.0	9.9	24.4	133.1	98.7
Median	101.6	125.3	143.4	140.0	178.4	25.1	9.1	22.5	126.6	92.9
MaX	507.5	432.8	641.3	437.1	425.0	74.1	24.2	90.6	462.2	265.0
Min	54.7	70.0	78.8	88.6	90.4	16.8	5.5	15.8	54.7	49.6
Std. Dev.	51.2	36.8	53.9	39.5	39.5	6.5	2.7	9.0	40.1	29.1
Skewness	4.8	2.5	3.6	2.1	1.4	2.6	1.7	4.1	3.8	1.6
Kurtosis	32.9	18.5	25.8	13.9	9.9	16.5	7.3	26.2	26.1	7.7
Jarque-Bera	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Obs.	1176	1176	1176	1176	1176	1176	1176	1176	1176	1176

Table 5
Dirty Tanker Descriptive Statistics.

	BDTI TD1: 280,000 mt, Middle East Gulf to US Gulf	BDTI TD2: 270,000 mt, Middle East Gulf to Singapore	BDTI TD6: 135,000 mt, Black Sea/Mediterranean	BDTI TD7: 80,000 mt, North Sea to Continent	BDTI TD8: 80,000 mt, Crude and/or DPP Heat 135F, Kuwait to Singapore	BDTI TD9: 70,000 mt, Caribbean to US Gulf	BDTI TD12: 55000 mt, fuel oil, ARA range to US Gulf	BDTI TD14: 80,000 t SE Asia – EC Australia	BDTI TD15: 260,000 t West Africa - China	BDTI TD3C: 270,000 t Middle East Gulf to China
Mean	112.1	105.9	93.1	124.2	110.8	63.0	64.1	34.1	109.1	64.0
Median	110.4	101.1	85.1	111.4	106.7	54.9	56.1	27.1	101.4	56.7
MaX	191.9	242.8	281.7	401.1	269.2	313.3	322.1	209.7	248.3	288.8
Min	51.7	55.9	45.4	61.9	58.1	32.6	33.3	16.0	69.7	35.8
Std. Dev.	24.3	26.6	31.5	49.8	30.5	29.4	30.0	21.8	27.7	26.1
Skewness	0.6	1.3	1.9	2.1	1.6	2.9	2.9	3.5	2.2	2.8
Kurtosis	4.2	6.0	8.3	9.9	7.3	16.7	17.1	19.4	9.0	15.8
Jarque-Bera	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Obs.	1176	1176	1176	1176	1176	1176	1176	1176	1176	1176

Table 6
Cointegration Tests for Clean Tankers.

	BCTI TC1: 75,000 mt, CPP/UNL Naphtha Condensate, Middle East Gulf to Japan	BCTI TC2_37: 37,000 mt, CPP/UNL Continent to USAC	BCTI TC6: 30000 mt CPP/UNL Algeria/Euromed	BCTI TC9: 22,000 mt CPP/UNL middle distillate, Ventspils – Le Havre	BCTI TC7: 30,000 mt, Singapore – EC Australia	BCTI TC10: 40,000 mt CPP/UNL South Korea – Vancouver/Rosarito range	BCTI TC11: 40,000 mt CPP South Korea – Singapore	BCTI TC8: 65,000 mt CPP/UNL middle distillate, Jubail – Rotterdam	BCTI TC12: 35,000 mt Naptha Sikka (WCI) to Japan	BCTI TC14: 38,000 mt, CPP/UNL/Diesel US Gulf to Continent
Trace Test (Rank=1)	50.86*	47.44*	42.36*	44.53*	57.33*	50.98*	51.21*	48.50*	57.38*	60.33*
Trace Test (Rank=2)	15.95	16.55	17.87	17.87	18.05	13.03	14.57	15.74	19.63	19.74
Max Eigenvalue (Rank=1)	34.91*	30.88*	24.49*	26.66*	39.29*	37.95*	36.64*	32.77*	37.76*	40.58*
Max Eigenvalue (Rank=2)	9.74	9.83	11.44	11.34	14.05	8.38	7.74	8.52	15.26	15.34

Critical values of the Trace and Max Eigenvalue statistics on the basis of Johansen (1999) and MacKinnon et al. (Mackinnon, Haug, & Michelis, 1999) are at 35.19 and 20.26 for the trace test and at 22.30 and 15.89 for the max eigenvalue test. A rejection of the hypothesis suggests the existence of a cointegrating relationship. * denotes significance at the 5% level.

Table 7
Cointegration Tests for Dirty Tankers.

	BDTI TD1: 280,000mt, Middle East Gulf to US Gulf	BDTI TD2: 270,000mt, Middle East Gulf to Singapore	BDTI TD6: 135,000mt, Black Sea/Mediterranean	BDTI TD7: 80,000mt, North Sea to Continent	BDTI TD8: 80,000mt, Crude and/or DPP Heat 135 F, Kuwait to Singapore	BDTI TD9: 70,000mt, Caribbean to US Gulf	BDTI TD12: 55000mt, fuel oil, ARA range to US Gulf	BDTI TD14: 80,000 t SE Asia - EC Australia	BDTI TD15: 260,000 t West Africa - China	BDTI TD3C: 270,000 t Middle East Gulf to China
Trace Test (Rank=1)	50.66*	53.21*	57.52*	57.33*	52.92*	50.90*	52.45*	55.52*	54.17	53.07*
Trace Test (Rank=2)	19.71	17.26	18.66	19.53	19.25	17.87	18.00	19.89	18.13	18.34
Max Eigenvalue (Rank=1)	29.90*	32.00*	33.10*	41.81*	30.76*	33.09*	34.45*	36.71*	32.04*	31.94*
Max Eigenvalue (Rank=2)	13.54	14.16	15.03	14.68	13.92	14.52	14.97	13.26	13.74	14.81

Critical values of the Trace and Max Eigenvalue statistics on the basis of Johansen (1991) and Mackinnon et al. (1999) are at 35.19 and 20.26 for the trace test and at 22.30 and 15.89 for the max eigenvalue test. A rejection of the hypothesis suggests the existence of a cointegrating relationship. * denotes significance at the 5% level.

Table 8
Clean Tanker Estimates.

	BCTI TC1: 75,000 mt, CPP/UNL Naphtha Condensate, Middle East Gulf to Japan	BCTI TC2_37: 37,000 mt, CPP/ UNL Continent to USAC	BCTI TC6: 30000 mt CPP/ UNL Algeria/ Euromed	BCTI TC9: 22,000 mt CPP/UNL middle distillate, Ventspils – Le Havre	BCTI TC7: 30,000 mt, Singapore – EC Australia	BCTI TC10: 40,000 mt CPP/UNL South Korea – Vancouver/Rosarito range	BCTI TC11: 40,000 mt CPP South Korea – Singapore	BCTI TC8: 65,000 mt CPP/UNL middle distillate, Jubail – Rotterdam	BCTI TC12: 35,000 mt Naptha Sikka (WCI) to Japan	BCTI TC14: 38,000 mt, CPP/ UNL/Diesel US Gulf to Continent
$l(Brent_t)$	-1.93*** (0.24)	-0.954*** (0.248)	-1.074*** (0.328)	-0.92*** (0.273)	-1.884*** (0.327)	-1.635*** (0.215)	-1.601*** (0.248)	-1.934*** (0.275)	-1.496*** (0.251)	-0.653*** (0.281)
$l(SM_t)$	2.89*** (0.443)	1.589*** (0.419)	1.613*** (0.484)	1.447*** (0.458)	2.208*** (0.535)	2.592*** (0.353)	2.589*** (0.410)	3.057*** (0.454)	2.209*** (0.413)	1.292*** (0.463)
Constant	1.24	1.05	1.54	1.71	2.14	2.62	3.74	3.78	0.24	0.965
CE	-0.024*** (0.006)	-0.037*** (0.008)	-0.019*** (0.004)	-0.024*** (0.006)	-0.012*** (0.002)	-0.001*** (0.002)	-0.011*** (0.003)	-0.012*** (0.003)	-0.023*** (0.004)	-0.034*** (0.005)
$Covid_t$	-0.249*** (0.048)	-0.218*** (0.044)	-0.135*** (0.028)	-0.151*** (0.032)	-0.152*** (0.031)	-0.101*** (0.021)	-0.101*** (0.023)	-0.115*** (0.028)	-0.200*** (0.037)	-0.109*** (0.034)
Obs	1176	1176	1176	1173	1173	1173	1173	1173	1173	1173

Dependent variable is the respective BDI index as specified in the first row. *** denotes significance at the 1% level.

Table 9
Dirty Tanker Estimates.

	BDTI TD1: 280,000 mt, Middle East Gulf to US Gulf	BDTI TD2: 270,000 mt, Middle East Gulf to Singapore	BDTI TD6: 135,000 mt, Black Sea/ Mediterranean	BDTI TD7: 80,000 mt, North Sea to Continent	BDTI TD8: 80,000 mt, Crude and/or DPP Heat 135F, Kuwait to Singapore	BDTI TD9: 70,000 mt, Caribbean to US Gulf	BDTI TD12: 55000 mt, fuel oil, ARA range to US Gulf	BDTI TD14: 80,000 t SE Asia – EC Australia	BDTI TD15: 260,000 t West Africa – China	BDTI TD3C: 270,000 t Middle East Gulf to China
$l(Brent_t)$	-1.85*** (0.481)	-1.251*** (0.393)	-0.803*** (0.305)	-0.553*** (0.199)	-1.359*** (0.259)	-1.147*** (0.424)	-1.313*** (0.269)	-1.231*** (0.253)	-1.180*** (0.352)	-1.237*** (0.393)
$l(SM_t)$	1.93*** (0.787)	1.741*** (0.644)	1.572*** (0.500)	1.002*** (0.327)	2.218*** (0.424)	2.094*** (0.699)	1.931*** (0.443)	1.871*** (0.414)	1.534*** (0.576)	1.749*** (0.645)
Constant	1.53	0.727	0.159	2.07	0.53	0.696	0.680	0.583	1.44	0.622
CE	-0.014*** (0.004)	-0.021*** (0.005)	-0.017*** (0.004)	-0.036*** (0.005)	-0.008*** (0.003)	-0.020*** (0.004)	-0.009** (0.004)	-0.008** (0.003)	-0.019*** (0.005)	-0.021*** (0.005)
$Covid_t$	-0.049 (0.052)	-0.101*** (0.004)	-0.089*** (0.034)	-0.129*** (0.033)	-0.067*** (0.029)	-0.165*** (0.048)	-0.082** (0.036)	-0.062** (0.026)	-0.084* (0.044)	-0.101** (0.047)
Obs	1173	1173	1173	1173	1173	1173	1173	1173	1173	1173

Dependent variable is the respective BDI index as specified in the first row. *** denotes significance at the 1% level.
*,**,*** denote significance at the 10%, 5%, and 1% level respectively.

(1996) and Siddiqui and Basu (2020), suggesting that there is a negative relationship between the value of the cargo and freight rates.

Interestingly, the results expand these previous findings and suggest that the larger the vessel, the greater this impact will be. For example, for BCTI-TC1 and BCTI-TC8 routes (Table 8) from the Middle East to Japan and Rotterdam respectively, when the largest vessels are used, the impact stands at 1.93, while for vessels at around 40,000mt the impact is lower at around 1.60. The only two exceptions to the rule are BCTI-TC12, where distance is probably the reason for the largest impact on the trip from Sikka (India) to Japan, and BCTI-TC7 where an overall expectation is observed as neither the distance or the vessel size justify the elasticity observed.

It also interesting to note that the higher the elasticity of the freight rates to Brent prices, the higher the elasticity with the stock market (Wilshire 5000 index). In particular, the stock market has a positive relationship with freight rates, again supporting the findings of Michail & Melas (2020b), and Michail (2020), who also demonstrate that the global economic environment has a strong impact on freight rates.

A quick overview suggests that the highest impact is observed in BCTI-TC8, followed by BCTI-TC1, while BCTI-TC7 still remains an outlier. It is interesting to observe, however, that the equilibrium elasticity of freight rates to the stock market is always greater than unity, with the lowest value observed in BCTI-TC14, at 1.292. This again highlights the higher volatility observed in the shipping markets, also a well-known fact in the literature (Theodossiou et al., 2020).

Moving to the main thrust of the paper, it appears that Covid-19 has had a strong off-equilibrium impact on each route of the clean tanker vessels, with the effect heavily depending on route characteristics, and in particular the destination. As it appears, the highest deviations are related to Japanese destinations, with BCTI-TC1 and BCTI-TC12 registering strong responses. In particular, the former suggests that a 1% increase in Covid-19 cases would result in a 0.249% decrease in the freight rate, while the impact would stand at 0.20% in the latter. Similarly, the BCTI-TC2_37 rate, the trade route between the European continent and the USA, has also reported a strong decline. The smallest off-equilibirum deviations were registered in the Canada, Singapore, and Rotterdam routes, as the US Gulf to Continent route. The latter is most likely due to the already existing contracts of transport to and from the refineries at the US coast. It should be noted here that the off-equilibirum deviation should be viewed as over and above the deterioration in macroeconomic conditions. Overall, the average impact from the pandemic stands at 0.15.

Moving to dirty tankers (Table 9), the relationship between Brent prices and freight rates still remains negative, as expected, but to a smaller extent. This can be justified by the fact that petroleum products are more valuable than crude oil, given the processing they have to go through. Furthermore, here the extent of the relationship relates both to distance and size: the highest elasticity is found in the BCTI-TD1 at 1.85, where the vessel can carry 280,000 mt, even though the second and third highest ones are for vessels that are three and five times smaller (BCTI-TD8 and BCTI-TD12 at 1.359 and 1.313 respectively). Nonetheless, the larger vessels have a strong relationship with Brent oil, at around 1.20 for BCTI-TD2, BCTI-TD15, and BCTI-TD3C.

At the same time, the shorter the distance, the smaller the extent of the relationship: for BCTI-TD6 and BCTI-TD7, the impact is much smaller compared to similar-sized or even smaller vessels. The easiest comparison is between BCTI-TD7 and BCTI-TD9 as well as BCTI-TD14, where the latter two vessels have twice the elasticity size even though their size is similar, due to the longer distance they have to cover. This provides an additional dimension to the Brent price-freight rate relationship, and highlights the importance of the average haul, as theoretically posited by Stopford (2013).

With regards to the stock market, the results are again not similar to the ones of Table 8 for clean vessels. In particular, Table 9 suggests that the more US-related a route is, the higher the stock market impact will be. A large stock market impact can be found in BCTI-TD1, BCTI-TD9, and BCTI-TD12, even though the largest impact, for BCTI-TD8, is non-US related. That said, the stock market impact is overall slightly lower for dirty tankers than clean tankers, given that such trades are also used for other purposes and not merely for fuels or other refined needs. This effectively means that the impact from the macroeconomic environment will be higher for clean tankers, while dirty tankers will still be affected but to a lower extent. In effect, this suggests that both the macro-driven and the oil price-driven volatility of dirty tankers will be lower, and thus justifying the lower standard deviations observed in the descriptive statistics.

Moving on to the Covid-19 impact, Table 9 suggests that this is much smaller in the case of dirty tankers. In particular, the largest impact stands at 0.165 for BCTI-TD9, while the respective figure stood at 0.249 for clean tankers. In addition, while the smallest impact stood at 0.100 for clean tankers, in this case four out of ten dirty tanker routes exhibit an equilibrium deviation of less than 0.10 and the average impact stands at 0.08. This is indicative again of the smaller sensitivity of crude oil cargo to economic conditions, as well as the longer-term contracts between crude oil carriers and the charterers, which are embedded in the fact that crude oil is also used for other production purposes and not just for fuel products. Underlying this is the lack of a significant off-equilibrium deviation for the case of BCTI-TD1, as long-term contracts dominate this route (Alizadeh & Nomikos, 2009).

Overall, this section has led us to three important conclusions: first, dirty tankers are less prone to changes in macro conditions than clean tankers, as per the stock market impact. Nonetheless, both dirty and clean tankers remain very volatile as their elasticity to market conditions is greater than unity. Second, as a result of the lower value of the cargo they carry, their sensitivity to changes in the cargo price (i.e. Brent oil prices) is lower, albeit not by much. The Brent price impact is mostly justified by the size of the vessel in the case of clean tankers, while it depends more on the route distance when it comes to dirty tankers. Third and most important, the additional off-equilibrium deviation caused by Covid-19 is found to be more significant for clean tankers, given that these products are more reliant on economic developments as a result of their uses. It should be again underlined that the off-equilibirum deviation should be viewed as over and above the deterioration in macroeconomic conditions. This also implies that as Covid-19 cases decline, freight rates will continue to increase, unless met with unforeseen macroeconomic developments.

Thus, our results are in line with Michail & Melas (2020b), who demonstrate that Covid-19 was a large one-off demand shock which had a strong impact on freight rates. Our only difference is that we find that clean tankers are more affected than dirty tankers, something that lies in the data range used, as Michail & Melas (2020b) employ data only until April 2020, and the known 8-month lag of clean tankers was not visible at the time (Angelopoulos et al., 2020). Furthermore, we note that the impact is route-specific, as some routes, notably the Japan- and US-related ones, were more hurt than others. Impressively, there has been no additional off-equilibrium deviation for routes that are dominated by longer-term contracts, such as the dirty tanker route from Middle East to the US, while the impact was much higher for other routes.

5. Conclusions

We employ a cointegration setup to explore route-specific off-equilibrium deviations related to Covid-19 that have affected freight rates, over and above the expected macroeconomic reactions. We find that, as expected, the additional deviation caused by Covid-19 is route-specific. In particular, deviation caused by Covid-19 is found to be more significant for clean tankers, given that these products are more reliant on economic developments as a result of their uses.

The clean tanker impact is more evident in Japan-related routes, as those have registered the largest deviation. The smallest off-equilibirum deviations were registered in the Canada, Singapore, and Rotterdam routes, as the US Gulf to Continent route. The latter is most likely due to the already existing contracts of transport to and from the refineries at the US coast. For dirty tankers, the impact exists but it is much smaller, indicative again of the smaller sensitivity of crude oil cargo to economic conditions, as well as the longer-term contracts between crude oil carriers and the charterers. These are embedded in the fact that crude oil is also used for other production purposes and not just for fuel products. The average impact for clean tankers stands at 0.15. No specific pattern can be extracted with regards to the additional off-equilibrium Covid-19 deviation for dirty tanker routes, with the average impact being almost half of the clean tanker one, at 0.08.

In addition to these conclusions, the results also suggest that dirty tankers are less prone to changes in macro conditions than clean tankers, as per the stock market impact. Nonetheless, both dirty and clean tankers remain very volatile as their elasticity to market conditions is greater than unity. Furthermore, as a result of the lower value of the cargo they carry, their sensitivity to changes in the cargo price (i.e. Brent oil prices) is lower, albeit not by much. The Brent price impact is mostly justified by the size of the vessel in the case of clean tankers, while it depends more on the route distance when it comes to dirty tankers.

Our findings imply that large demand shocks tend to have a stronger impact on freight rates, one that is over and above the change in the economic environment. While demand shocks cannot be accurately forecasted ex ante, it is interesting that the impact is larger, the larger the distance of the route, especially for clean tankers. As such, a potential complication would be to employ longer-term charters for such routes, while trading on the spot market would not have such a strong impact for shorter routes. At the same time, the high sensitivity of freight rates to the stock market suggests that the use of hedges such as options or futures against a particular stock market index could be beneficial when it comes to addressing demand shocks.

The above results are useful for both the forecaster, who will wish to more fully comprehend the impact from Covid-19, as well as ship-owners, oil exporters and oil refineries. The findings of the current paper can be further employed for future research for optimization studies that could potentially focus on specifying the optimal routes that should be used in the case of a similar economic shock in the future.

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