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Has IMO 2020 changed bulk shipping?

An empirical study on how vessel speeds, trading patterns, charter types and freight rates for individual fixtures have been affected by IMO 2020

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Abstract

This thesis examines how the IMO 2020 low-sulphur regulation has affected drybulk shipping. Firstly, we examine which routes scrubber vessels sail compared to what maritime economic theory would suggest. Secondly, we determine if scrubber vessels increase speeds compared to non-scrubber vessels after IMO 2020. Thirdly, we analyze whether scrubber vessels are less likely to be used for short-term time charter fixtures (trip charter) than voyage charter fixtures. Lastly, we examine if IMO 2020 has caused scrubber vessels to trade at lower $/tonne rates relative to non-scrubber vessels.

We use the difference-in-differences methodology to estimate the effects of the policy change on the Capesize fleet. We include two-way fixed effects to control for both time differences and vessel heterogeneity. 30,806 individual voyages and 120,047 weekly speed observations are calculated from 36,767,462 Automatic Identification System (AIS) positions in 2019-2020. Further, 1,016 individual fixture contracts are extracted from Clarksons Shipping Intelligence Network to analyze the effects on the freight market.

We find that scrubber vessels sail on longer voyages than non-scrubber vessels. However, the difference in voyage distance does not increase between the two groups as a result of IMO 2020. Our analysis further suggests that the difference in speeds increases for scrubber vessels compared to non-scrubber vessels after IMO 2020. In addition, scrubber vessels are less likely to be offered on a trip charter than a voyage charter after IMO 2020. Lastly, our results indicate that scrubber vessels on average trade at similar $/tonne rates as non-scrubber vessels, suggesting that shipowners investing in scrubbers are gaining the potential savings from the lower fuel costs.

Keywords – IMO 2020, drybulk shipping, AIS, Difference-in-Differences, speed, freight rates, fuel prices

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1 Introduction

The shipping industry accounts for approximately 12% of the global sulphur oxide (SOx) emissions (GEF-UNDP-IMO GloMEEP Project and IMarEST, 2018). Exposure to SOx has damaging effects on both human health and the environment (Ackermann et al., 1999). Therefore, on January 1. 2020, the UN International Maritime Organization (IMO) introduced a new regulation named IMO 2020 to reduce the ship-to-air emissions of sulphur oxide, by restricting sulphur contents in marine fuels from 3.5% to 0.5%.

Shipowners can comply with the regulation in two ways. First, by installing a scrubber cleaning system, the exhaust is cleaned post-combustion to meet the emission requirements. The second option is changing fuel type from heavy fuel oil (HFO) to low sulphur fuel oil (VLSFO) with sulphur contents below 0.5%. The two options create a trade-off between investing in a cleaning system and keeping the marginal costs at the current level versus changing to the more expensive bunker type, resulting in increased marginal costs.

In this thesis, we study the impacts of IMO 2020 by its effect on the choice of either installing a scrubber or switching to VLSFO on a variety of micro-market behaviors in the drybulk market. As Capesize vessels are the largest drybulk carriers operating on intercontinental voyages, the Capesize fleet is a substantial polluter of SOx emissions. The contribution of the paper is fourfold. Firstly, we explore if scrubber fitted vessels, hereafter called "scrubber vessels", sail on longer voyages compared to non-scrubber vessels after IMO 2020. Secondly, we analyze if the regulation has affected vessel speeds for the two groups. Thirdly, we examine if scrubber vessels are less likely to be used for time charter fixtures. Lastly, we investigate if scrubber vessels trade at a lower voyage charter spot rate on specific routes after IMO 2020.

As the capital, operating and cargo handling costs increase disproportionate to the cargo capacity, the unit cost of transport generally falls when the vessel size increases (Stopford, 2009). The economies of scale make Capesize vessels preferred on the long-haul routes as their $/tonne costs are lower than for the smaller vessels. In addition, the average fuel cost for a bulk carrier is estimated to account for 60-70% of the total voyage costs (Stopford, 2009; Rehmatulla and Smith, 2015). Due to port time being relatively fixed (Clarksons Research, 2021c), the result of scrubber installation and reduced fuel costs would suggest that scrubber vessels sail on longer voyages. Hence, spending more time at sea and taking advantage of the lower fuel costs. Braemer ACM Shipbroking (2021) identifies that the average voyage duration is approximately 14% longer for scrubber vessels than non-scrubber vessels in 2020. However, our results do not indicate that scrubber vessels sail on the longer routes after IMO 2020.

Ronen (1982) argues that the optimal vessel speed depends on the ratio of freight rate and fuel price. In times of low freight rates and high fuel prices, slow steaming has become a widely adopted practice to reduce fuel costs (Lee et al., 2015). IMO 2020 imposes an increase in fuel costs for non-scrubber vessels, suggesting that the sailing speeds between the two groups could differ. When studying the effects of stricter sulphur requirements in the North Sea, Adland et al. (2017a) find no reduction in vessel speeds within Emission Control Areas (ECAs). However, our results indicate that scrubber vessels increase speeds compared to non-scrubber vessels after IMO 2020.

Shipowners have the flexibility to offer their vessels on either voyage charter contracts or time charter contracts. The shipowner is responsible for all costs on a voyage charter, and freight rates are paid per tonne of cargo transported. Conversely, a trip charter is fixed on a time charter basis, paid per day for the period determined by the voyage and specific cargo, where the charterer pays for voyage costs such as fuel (Stopford, 2009). Interestingly, scrubber vessels conducted 143 voyage charter contracts and only ten trip charter contracts after the implementation of IMO 2020 (Clarksons Research, 2021c). Therefore, the shipowner's choice of charter type does not seem randomly selected and should be analyzed further.

Previous research has thoroughly investigated market failures such as the principal-agent problem in the time charter market, where the shipowner invests in the energy-efficient technology and the savings in fuel expenditure accrue to the charterer (Agnolucci et al., 2014; Adland et al., 2017b; Longarela-Ares et al., 2020). Our results suggest that shipowners are less likely to offer their scrubber vessels on trip charter contracts after IMO 2020. It is essential to clarify that scrubber installation is not an investment in energy efficiency *per se* as all vessels need to reduce emissions. However, it illustrates that the shipowner's incentives for investing in a scrubber change depending on the contract type.

The spot freight market is established by negotiations between shipowners and charterers, where the freight price reflects the balance of ships and cargoes available (Stopford, 2009). Adland et al. (2016) argue that the freight market consists of several micro-markets as only the ships able to reach laycan can bid for a voyage contract. Traditionally, the marginal vessel is a non-scrubber vessel. However, after IMO 2020, the marginal ship could either be a scrubber or non-scrubber vessel. Consequently, if scrubber vessels cluster on similar routes, the freight rate formation can potentially decrease to the marginal cost of a scrubber vessel, which is lower due to their reduced fuel costs. Our results suggest that scrubber vessels do not trade at a different rate than non-scrubber vessels after IMO 2020, indicating the shipowners offering their vessels on voyage charter contracts accrue the potential fuel cost savings.

The remainder of this thesis is structured as follows. Section two presents a literature review covering theory and empirical testing of vessel speed optimization, principal-agent theory and freight rate formation theory. Further, section three presents the data foundation. Then, in section four, we present the empirical strategy. Thereafter, we present and discuss the results in section five before finally rounding off with concluding remarks in section six.

2 Literature Review

The bulk spot freight market is described by Norman (1979) as a textbook example of a perfectly competitive market, where the $/tonne freight rate is determined by the marginal cost of the marginal vessel required to meet the demand for transportation. The market of the cargo transported, international seaborne trade and the world economic activity determine the demand side (Stopford, 2009). The supply-side depends on the fleet size, the available tonnage of the fleet, newbuilding of vessels, bunker prices, scrapping rate and the fleet's operational efficiency at any given time (Strandenes, 1983; Beenstock and Vergottis, 1989).

A perfectly competitive market depends on six conditions (Colander, 2012); (1) both buyers and sellers are price takers, (2) the number of firms is large, (3) there are no barriers to entry, (4) firms' products are identical, (5) there is complete information about the market and (6) selling firms are profit-maximizing entities. The drybulk market meets these conditions on a macro level. A fleet of several thousand vessels operated by hundreds of different owners are competing for the same transportation service. Shipbrokers assist both the buying and selling sides and create a transparent market with efficiently distributed information (Strandenes, 2000). Financing of vessels is generally available, and both ships and their owning companies can move their operation to light regulatory- and low tax regimes (Adland et al., 2016).

The research on freight rate formation is separated by a macro and micro perspective. The first wave of freight market research in drybulk shipping focused on the interaction of supply and demand on a macro-level (Tinbergen, 1959; Norman, 1979; Wergeland, 1981; Charemza and Gronicki, 1981; Strandenes, 1986; Evans, 1994). Later studies use stochastic modeling to forecast freight rate formation. Both time series models (Kavussanos and Alizadeh, 2001; Kavussanos, 1996) and univariate continuous-time models (Bjerksund and Ekern, 1995; Adland, 2006) solely consider historical and current spot freight rate information. These models disregard market information such as the age profile of the fleet and the size of the order book entirely. Lastly, studies combine the previous frameworks by modeling the supply and demand of transportation as stochastic processes within a dynamic equilibrium setting. Adland and Strandenes (2007) develops a freight market equilibrium model that incorporates a time-varying shape of the supply curve from microeconomic analysis of vessel-specific characteristics of the fleet.

The recent focus on micro-level analysis on determinants of freight rates using individual contracts considers the heterogeneity of geographical regions and vessel specifications. Tamvakis and Thanopoulou (2000) investigate if there exists an age-premium in the drybulk freight market and find no significant difference between freight rates paid for newer versus older vessels. Alizadeh and Talley (2011) expand the research on microeconomic determinants of drybulk spot freight rates to include the lead time (time between contracting date and the earliest date for loading) and macroeconomic proxies representing the market conditions, such as the Baltic Capesize Index (BCI) and its rolling one-month standard deviation as a measure of volatility. Adland et al. (2016) propose a model for freight rate formation in individual contracts incorporating charterer and owner heterogeneity and owner-charterer match effects. Although market conditions and routes remain the most influential covariates, they conclude that fixed effects related to the identity of the charterer and owner-charterer match are significant contributors to the Capesize spot freight rate.

Adland et al. (2017c) discuss the potential circularity problem and flaw of including a macro freight index derived from micro data as a control variable for freight rate formation on individual contracts. Their results suggest that using BCI as a control variable on fixture data analysis substantially affects the vessel's estimated coefficients and contract-specific factors. Furthermore, they claim this circularity potentially causes an endogeneity problem in the estimated regressions. As a counter to the circularity problem, they develop a methodology for deriving objective market indices from micro-level fixture data.

Ship operators should adjust speeds to maximize profits (Strandenes, 1983). The traditional speed optimization theory is anchored in the model proposed by Ronen (1982). Based on the cubic law, he illustrates that speed is a function of the square root of the ratio between the freight rate and fuel price. Further, Beenstock and Vergottis (1989) are the first to empirically test Ronen's theory finding a positive correlation between the freight rate and fuel price ratio and speeds in the tanker market. Research by Devanney (2010) later finds that vessels in the voyage and time charter market face the same optimization problem, as charterers can re-offer a vessel on time charter to the spot market.

The availability of micro-level positional vessel data through the Automated Identification System (AIS) has made it easier to empirically test traditional economic theories on speed optimization. Aßmann et al. (2015) find evidence that supports the theory by Ronen (1982), but to a lesser extent and primarily regarding the ballast leg. Contrary, Adland and Jia (2016, 2018) conclude that shipowners do not adjust vessel speeds based on freight market conditions and the level of fuel prices. They suggest that speeds are mainly determined by factors outside their models, such as weather conditions and contractual constraints on both charter parties and port policies. Adland et al. (2017a) find that the stricter sulphur regulations in the North Sea did not affect vessel speeds once macro-factors were considered. However, they acknowledge that external factors such as weather conditions and charter party clauses limit the ability of the shipowner to optimize speeds on the laden lag. Adland et al. (2020) later question the correctness of the cubic relationship assumption put forward by Ronen (1982) if actual speed differs substantially from the vessel design speed.

There exists an extensive amount of research on market failure and principal-agent problems regarding investments in energy efficiency. The principal-agent problem refers to the observation that the economic benefits of energy conservation do not accrue to the person who is trying to conserve (Golove and Eto, 1996). The time charter market in drybulk shipping represents such a market. A shipowner can invest in energy-efficient vessels, but any savings in fuel expenditures accrue to the charterer. Agnolucci et al. (2014) investigate if there exists a rate premium for fuel efficiency in the Panamax time charter market and find that on average, only 40% of financial savings delivered by energy efficiency accrue to the shipowner for the period 2008-2012. Adland et al. (2017b) expand this study to several vessel sizes and a more extended sample period to include an entire market cycle. They find that only 14-27% of fuel cost savings are reflected in a higher rate during normal market conditions. However, in poor market conditions, they find that inefficient energy vessels attract a premium.

3 Description of Data

This section presents the different data sources and the descriptive statistics. We utilize data on Capesize vessels from 2019-2020 to study multiple effects of the IMO 2020 regulation on the drybulk market. Clarksons Research (2021b) categorizes Capesize vessels as bulk ships ranging from 100,000 deadweight tonnes (DWT). In addition, Very Large Ore Carriers (VLOC) are included in the sample and range from 220,000 to 400,000 DWT.

3.1 Data Collection

3.1.1 AIS Data

IMO requires the use of AIS to increase the safety and security of the maritime industry, improve regulations and monitor ship traffic (Lee et al., 2019). Therefore, all vessels from 300 gross tonnage on international voyages must be equipped with an AIS transponder (IMO, 2021). The AIS transponders send out information on vessel identity (IMO number), position, speed and course using Very High Frequency (VHF) radio waves. In addition, AIS data can be exchanged with nearby vessels, satellites and AIS base stations. Each AIS component is explained in detail in appendix A1.

We have been granted AIS data by Vesseltracker GmbH, containing information on drybulk vessels in 2019-2020. This dataset originates from two datasets of different AIS reporting frequencies, with a shorter time difference between each observation in January 2019 to August 2019 compared to August 2019 to December 2020. This is discussed closer in appendix A2.3. We extract information on vessel location, corresponding speed, and draught level for each vessel from the AIS data. We combine the dataset with Clarksons World Fleet Register (WFR) using the IMO number to include vessel-specific characteristics such as age, size and scrubber information.

3.1.2 Signal Ocean Voyage Data

We have been granted access to voyage data on The Signal Ocean Platform by The Signal Group. This dataset contains voyage information on the laden and ballast legs for Capesize vessels in the sample period. The voyage data consists of the IMO number and route information based on AIS data, including port, regions and time for loading and discharging of cargo. We use the Signal Ocean voyage dataset to establish a starting port (area) and an ending port (area) for each voyage with the corresponding starting and ending time. This allows us to establish the start- and endpoints for each trip in the AIS data.

3.1.3 Fixture Data

The fixture data is extracted from Clarksons Shipping Intelligence Network (SIN) and consists of both voyage and trip charter contracts for Capesize vessels in 2019-2020. The main difference between these two contract types is the allocation of voyage expenses, particularly the fuel cost, between the owner and charterer. The IMO number for each vessel is not included in the fixture data. Hence, we first match the contracts with ship-specific data based on vessel name, year of build and DWT. Secondly, we match remaining contracts with vessels by ex-name, year of build and DWT.

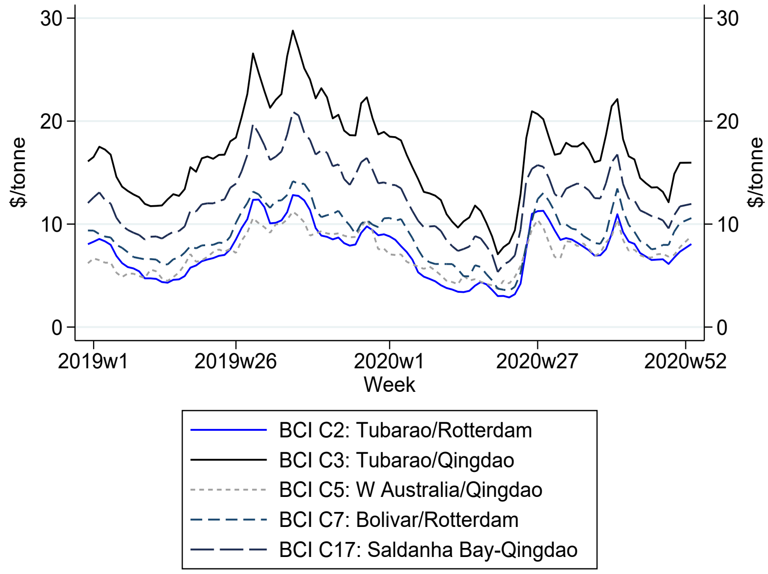
3.1.4 Macro-level data

Clarksons SIN also provides additional data on freight market conditions and fuel prices regarding the Capesize segment.

Freight rate indices

The Baltic indices are freight market indicators giving insight into supply and demand trends for different routes and consist of weekly average earnings ($/tonne) for a typical non-scrubber Capesize vessel. We note that the literature has moved away from the freight market index as an explanatory variable for micro freight rate formation (Adland et al., 2017c). However, when analyzing vessel speeds, we include the appropriate freight rate from BCI C2, BCI C3, BCI C5, BCI C7 or BCI C17. In cases where voyages are on routes without a corresponding Baltic rate, proxies based on distance traveled are applied. For example, BCI C3 is the longest route traveling from Brazil to China (approx. 11,500 nm) and BCI C5 is the shortest route traveling from West Australia to China (approx. 3,500 nm) in our specification. The difference in voyage length affects the differences in the $/tonne freight rates, illustrated in Figure 3.1.

Figure 3.1: BCI freight rates ($/tonne) for 2019-2020



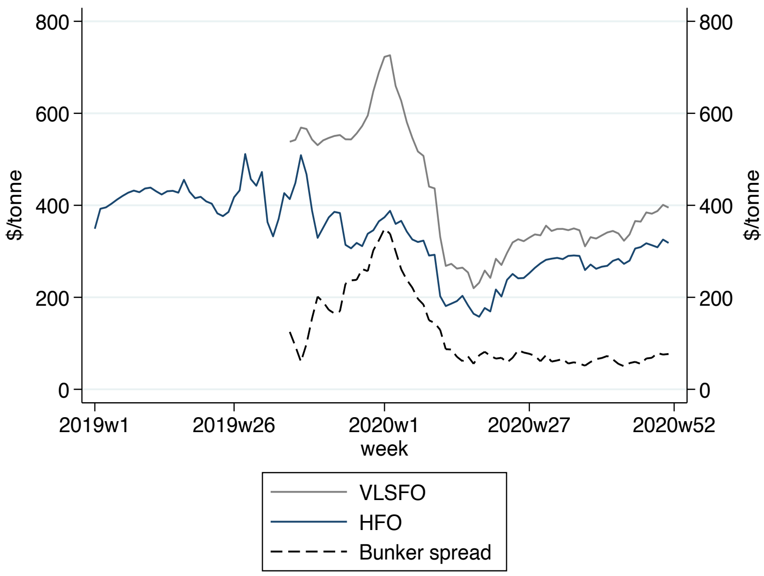
Bunker prices

The development in bunker prices is important for shipowners and charterers as fuel costs account for a large proportion of the voyage costs (Stopford, 2009). Historic weekly bunker prices from the main bunker locations Fujairah, Panama, Singapore, Rotterdam and Gibraltar are extracted from Clarksons (SIN). In addition, we specify a bunker price proxy for each voyage leg by locating the nearest bunker location at the starting date of both the laden and ballast legs.

In this thesis, we use two fuel types, IFO 380 representing HFO and VLS IFO representing VLSFO. The bunker price is measured in $/tonne. VLSFO bunker price data is only available from November 2019 and onwards. We assume that all vessels use HFO before IMO 2020 as this is the cheapest fuel option. As non-scrubber vessels would not be allowed to carry HFO after January 1, 2020, a vessel is categorized as carrying VLSFO if the ending date of the voyage is after the policy change, in order to comply with the regulation.

Braemer ACM Shipbroking (2021) argue that many market participants expected a fuel price spread of 200 $/tonne before Covid-19 and the sharp oil price decline in March 2020. However, after the initial shocks, the fuel price spread stabilized at around 100 $/tonne for the rest of 2020, supported by Figure 3.2.

Figure 3.2: Average weekly bunker prices (Singapore) for 2019-2020



3.2 The Capesize fleet

The capital expenditure for scrubber retrofitting ranges from $2 million to $6 million, depending on the scrubber solution (Danish Ship Finance, 2018). The bunker spread is an essential factor determining the payback period. For example, with a bunker spread of $100, the payback period is nearly four years, while a spread of $200 would result in a payback period less than two years. Therefore, older vessels near the end of their life cycle find it less attractive to invest in a scrubber, as uncertainty in the bunker spread impacts the profitability of the scrubber investment. Interestingly, 80% of vessels built after 2017 have a scrubber installed in our AIS sample. Furthermore, 72% of these vessels installed the scrubber at the design stage, while 28% are retrofitted. However, only 18% of vessels built before 2005 have a scrubber installed.

Age and size characteristics of the Capesize fleet are presented in Table 3.1. The cleaned AIS sample consists of 501 scrubber vessels and 1,104 non-scrubber vessels. VLOC vessels are presented in a separate panel due to the difference in vessel characteristics.

Table 3.1: Characteristics for vessels with AIS observations in 2019-2020

(a) Capesize

	Built		DWT	
	Scrubber	Non-Scrubber	Scrubber	Non-Scrubber
N	388	987	388	987
Mean	2012	2012	187,276	185,167
SD	4	4	13,999	13,311
Min	2003	2003	149,733	120,397
Max	2020	2020	216,461	216,656

(b) VLOC

	Built		DWT	
	Scrubber	Non-Scrubber	Scrubber	Non-Scrubber
N	113	117	113	117
Mean	2014	2015	332,306	290,470
SD	3	4	68,556	48,611
Min	2004	2004	226,371	226,381
Max	2019	2020	403,919	402,303

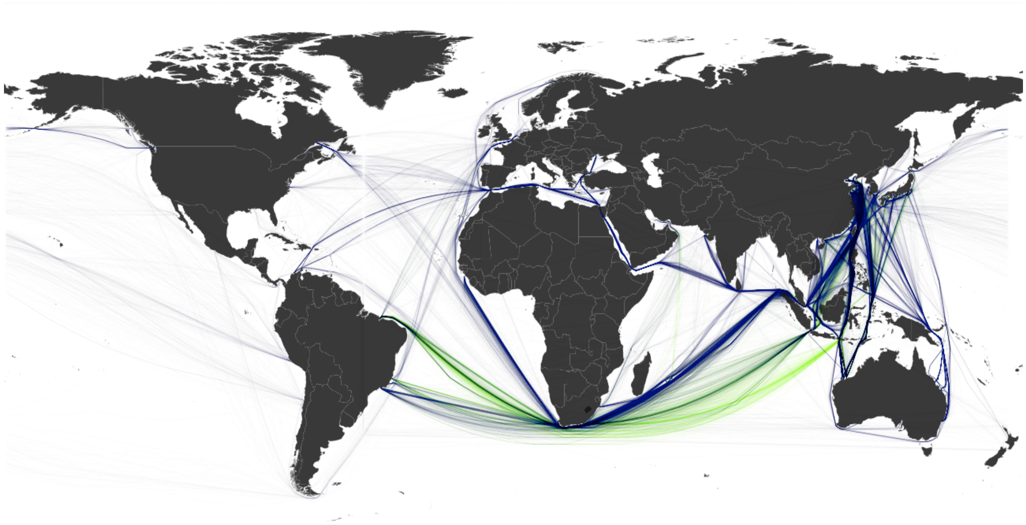
Panel (a) displays similar vessel characteristics for the two groups consisting of 388 scrubber and 987 non-scrubber Capesize vessels. Contrary, the VLOC vessels in Panel (b) are more balanced with 113 scrubber vessels and 117 non-scrubber vessels. The average vessel size between the group of VLOC vessels differs substantially.

3.3 Routes

Figure 3.3 illustrates the movement and trading patterns of the Capesize fleet for 2019-2020. The blue lines represent Capesize vessels, while the green lines represent VLOC vessels. We observe that the main routes are from Australia to the Far East, Atlantic America to the Far East and Africa to the Far East. The main drybulk areas in the Far East are China, Taiwan, Japan, Korea and Singapore. Further, the figure illustrates the fixed travel pattern of VLOC vessels mainly sailing between Brazil and China.

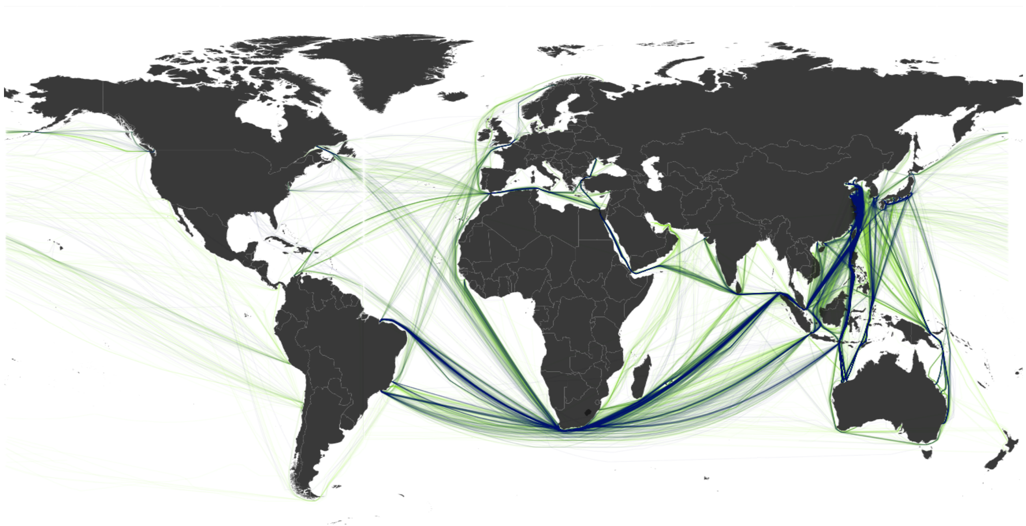
The sailing patterns between the respective areas correspond with the supply and demand patterns of iron ore. According to Statista (2020a,b), Australia, Brazil and South Africa are the top three iron ore exporting countries, while China, Japan and South Korea are the top three iron ore importing countries

Figure 3.3: Capesize voyages in 2019-2020



We have further utilized AIS data for 2020 to illustrate the movement of scrubber vessels and non-scrubber vessels after the implementation of IMO 2020, illustrated in Figure 3.4. The blue lines represent scrubber vessels, while the green lines represent non-scrubber vessels. Interestingly, the trading patterns of scrubber vessels are mainly on the routes from Australia to the Far East, from Atlantic America to the Far East and from Africa to the Far East. Appendix A3 points out that these three routes account for 84% of all scrubber voyages, and the percentage of scrubber vessels on each route is 27%, 50% and 22%, respectively.

Figure 3.4: Capesize voyages by scrubber status in 2020



3.4 Descriptive Statistics

3.4.1 Summary statistics

The voyage distance and speed analysis are based on 36,767,462 AIS positions, derived into 30,806 uniquely identified voyages and 120,047 weekly speed observations. A detailed description of the data pre-processing and speed calculations are found in appendix A2. The fixture data consists of 157 trip charter fixtures and 859 voyage charter fixtures in 2019-2020. Table 3.2 presents the summary statistics for the four main regressions.

Table 3.2: Summary statistics

(a) Summary statistics for distance

	N	Mean	SD	Min	Max
Distance	30,806	5,555	3,202	1,501	17,302
Sailing days	30,806	24	15	5	75
Built	30,806	2012	4	2003	2020
DWT	30,806	198,938	42,880	120,397	403,919

(b) Summary statistics for speed

	N	Mean	SD	Min	Max
Speed	120,047	11.43	1.43	8.00	17.32
Freight rate	120,047	11.02	5.41	2.88	28.79
Fuel price	120,047	366.90	87.95	124.75	775.50
Built	120,047	2012	4	2003	2020
DWT	120,047	202,927	50,765	120,397	403,919

(c) Summery statistics for charter type

	N	Mean	SD	Min	Max
Trip charter	1,016	0.15	0.36	0	1
Built	1,016	2011	4	1998	22
DWT	1,016	179,875	10,077	106,355	261,761

(d) Summary statistics for voyage charter contracts

	N	Mean	SD	Min	Max
$/tonne rate	832	11.42	5.91	3.40	32.08
Distance	832	6,844	3,755	2,857	14,592
Age	832	2011	4	2000	2020
DWT	832	180,511	9,987	106,355	261,761

The minimum and maximum freight rates in Panel (b) capture the market fluctuations over time and differences between routes. Similarly, the values on fuel price capture the price volatility over time and differences in HFO and VLSFO, illustrated in Figure 3.2. We note that the average design speed in our sample is 14.9 knots, which is substantially higher than the average observed speeds. The mean value for the variable Trip charter in Panel (c) represents the average number of trip charter contracts relative to the total number of contracts in 2019-2020. It implies that there are 15% trip charter contracts and 85% voyage charter contracts in the sample. Finally, we note that DWT is lower in panels (c) and (d) compared to panels (a) and (b). A reasonable explanation is that VLOC vessels predominantly operate on fixed routes between Brazil and China, as illustrated in Figure 3.3, and therefore not appearing in the spot market.

3.4.2 Descriptive statistics by scrubber status and year

Panel (a) in Table 3.3 displays descriptive statistics on distance both before and after IMO 2020 for scrubber and non-scrubber vessels. Further, Panel (b) illustrates similar statistics for average weekly speeds.

Table 3.3: Descriptive statistics for distance and speed

(a) Distance by scrubber status for 2019-2020

	Pre-policy (2019)		Post-policy (2020)	
	Scrubber	Non-Scrubber	Scrubber	Non-Scrubber
N	887	14,531	4,776	10,612
	16%	58%	84%	42%
Distance	5,357	5,432	6,289	5,410
	(3,055)	(3,102)	(3,618)	(3,104)
Sailing days	23	24	27	25
	(13)	(14)	(15)	(15)
Built	2013	2011	2014	2011
	(4)	(4)	(4)	(4)
DWT	204,969	197,341	215,159	193,320
	(43,068)	(41,476)	(58,709)	(33,466)

(b) Speed by scrubber status for 2019-2020

	Pre-policy (2019)		Post-policy (2020)	
	Scrubber	Non-Scrubber	Scrubber	Non-Scrubber
N	3,310	54,649	20,127	41,961
	14%	57%	86%	43%
Speed	11.79	11.43	11.74	11.25
	(1.45)	(1.43)	(1.44)	(1.39)
Freight rate	13.39	11.58	11.31	9.98
	(5.88)	(5.71)	(5.13)	(4.87)
Fuel price	388.19	402.77	274.71	362.71
	(59.31)	(45.64)	(50.16)	(110.11)
Built	2014	2011	2014	2011
	(4)	(4)	(4)	(4)
DWT	210,977	222,626	200,970	195,391
	(50,742)	(67,019)	(49,505)	(39,634)

Note: % of scrubber status group, SD in parenthesis

In Panel (a), we note an apparent increase in voyages by scrubber vessels and a decrease in voyages by non-scrubber vessels. The average distance traveled and the number of sailing days increase for scrubber vessels in 2020, implying that scrubber vessels are placed on the long-haul routes. Further, we experience an increase in average DWT for scrubber vessels. A greater DWT for scrubber VLOC vessels compared to non-scrubber VLOC vessels in Table 3.1, can partially contribute to the difference in DWT shown in Panel (a).

These findings correspond with Braemer ACM Shipbroking (2021), arguing that scrubber vessels are of greater size and used on long-haul voyages. As vessels on long-haul routes generally spend more time at sea and less time handling cargo in port, the ship operators take advantage of the fuel cost savings.

The increase in the number of observations from 2019 to 2020 and the age difference between scrubber vessels and non-scrubber vessels can potentially be explained in two ways. Firstly, it can indicate that newer vessels are utilized to a greater extent compared to older vessels. Secondly, as pointed out in Section 3.2, 80% of vessels built after 2017 have a scrubber installed. In addition, 72% are newbuilds entering the market, and 28% are retrofitted vessels, both positively impacting the year of build. Finally, it is worth noting that the statistics for non-scrubber vessels in Panel (a) are relatively similar in 2019 and 2020.

Panel (b) displays a difference in average weekly speeds between the groups. We observe similar weekly speed observations for scrubber vessels, while non-scrubber vessels experience a decrease in average weekly speeds. The decrease in speeds for non-scrubber vessels is consistent with the presumption that increased fuel costs reduce vessel speeds. The freight rate represented by the Baltic indices indicates a similar decrease for both groups, in line with the change in market conditions from 2019 to 2020. As we would expect, scrubber vessels have a lower average fuel price compared to non-scrubber vessels in 2020.

When examining observed speeds for the laden and ballast leg in Table 3.4, we witness differences in speeds between the two legs. This corresponds with the study by Adland and Jia (2018), where greater average speeds are explained by a lower draught ratio, meaning less resistance and lower fuel consumption. In addition, they argue that charter party clauses constrain the potential for speed optimization on the laden leg.

Table 3.4: Speed comparison for laden and ballast leg for 2019-2020

	Pre-policy (2019)		Post-policy (2020)	
	Scrubber	Non-Scrubber	Scrubber	Non-Scrubber
N (Laden)	1,857	32,192	10,466	22,851
Speed (Laden)	11.25	10.86	11.31	10.78
	(1.22)	(1.20)	(1.28)	(1.25)
N (Ballast)	1,899	24,319	9,215	17,248
Speed (Ballast)	12.37	12.16	12.22	11.88
	(1.41)	(1.37)	(1.46)	(1.33)

Table 3.5: Descriptive statistics for charter type and \$/tonne rates

(a) Charter type by scrubber status for 2019-2020

	Pre-policy (2019)		Post-policy (2020)	
	Scrubber	Non-Scrubber	Scrubber	Non-Scrubber
N	51	490	153	322
	25%	60%	75%	40%
Trip charter	0.27	0.22	0.07	0.08
	(0.45)	(0.41)	(0.25)	(0.27)
Built	2012	2010	2012	2010
	(4)	(4)	(4)	(4)
DWT	182,914	179,133	180,994	179,990
	(12,210)	(9,558)	(10,181)	(10,329)

(b) Voyage charter contract by scrubber status for 2019-2020

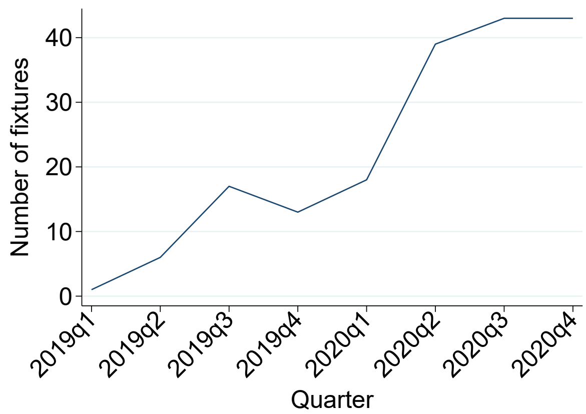
	Pre-policy (2019)		Post-policy (2020)	
	Scrubber	Non-Scrubber	Scrubber	Non-Scrubber
N	37	369	140	286
	21%	56%	79%	44%
\$/tonne rate	12.82	11.76	11.22	10.90
	(6.26)	(6.32)	(5.08)	(5.68)
Distance	6,164	6,370	7,599	7,175
	(3,453)	(3,603)	(3,885)	(3,839)
Built	2012	2010	2012	2010
	(4)	(4)	(4)	(4)
DWT	183,759	179,624	181,329	180,833
	(13,370)	(9,832)	(10,476)	(9,332)

Note: % of scrubber status group, SD in parenthesis

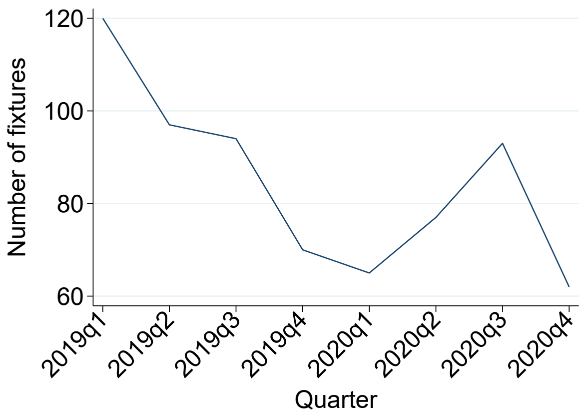
Table 3.5 presents descriptive statistics before and after IMO 2020 for scrubber and non-scrubber vessels in Panel (a) for charter type and in Panel (b) for voyage charter freight rates.

In Panel (a), we observe an increase in scrubber fixtures and a decrease in non-scrubber fixtures from 2019 to 2020. In addition, there is a decrease in both voyage charter and trip charter contracts for non-scrubber vessels in 2020, supported by Figure 3.5. One explanation is that vessels switch to the scrubber group during the sample period. Interestingly, there is a decrease in trip charter contracts and an increase in voyage charter contracts for the scrubber vessels. This supports the fact that shipowners investing in a scrubber want to capitalize on the potential fuel cost savings and prefer to offer their vessels on voyage charter contracts. We note that scrubber vessels are of newer build compared to non-scrubber vessels. Further, the vessel size is similar in the two time periods for both groups.

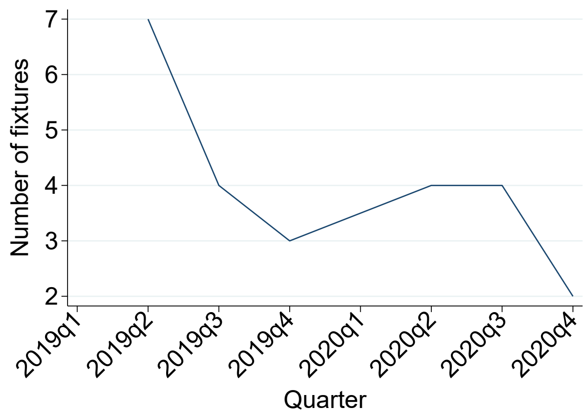
Figure 3.5: Number of fixtures by charter type and scrubber status



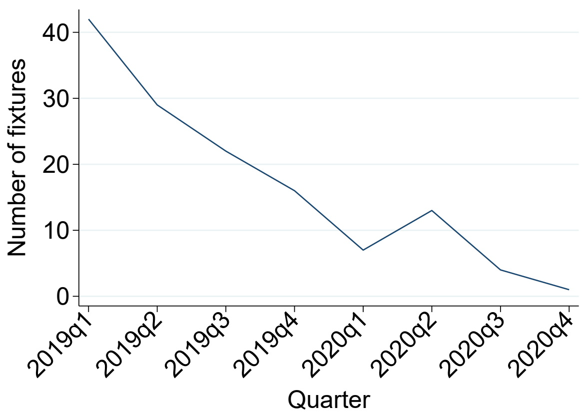
(a) Scrubber vessels on voyage charter



(b) Non-scrubber vessels on voyage charter



(c) Scrubber vessels on trip charter



(d) Non-scrubber vessels on trip charter

Panel (b) consists of descriptive statistics for voyage charter fixtures. The average \$/tonne rate is greater for scrubber vessels, as longer voyage distances can partially explain the differences in rates. In addition, size and age difference affects the rates. The results are reasonable as the distance differences and vessel characteristics are not controlled for in the mean rate. The total number of voyage charter contracts is relatively steady in the sample period, supporting the notion that a decrease in trip charter contracts causes the decrease in the total number of fixtures in Panel (a).

Table 3.6 presents a closer breakdown of the descriptive statistics for selected voyage charter fixtures. The table displays the number of contracts by scrubber status for only 2020 with the corresponding mean freight rates. We have grouped the routes based on geographical regions to increase the sample size of each micro-market with similar \$/tonne rates.

Table 3.6: Voyage charter rates per route in 2020

	N		**Mean (\$/Tonne)**	
	Scrubber	Non-Scrubber	Scrubber	Non-Scrubber
Australia - Far East	63	142	6.87	6.40
Atlantic America - Far East	65	110	15.46	16.44
Africa - Far East	8	26	12.60	12.63

4 Empirical Strategy

4.1 Model specification

We have created a dynamic and flexible model to investigate the effects of IMO 2020 on voyage distance, average weekly speed, charter type and voyage charter freight rates. Applying the Difference-in-Differences (DiD) method with two-way fixed effects (TWFE), as presented in appendix A5, allows us to analyze the causal effects of IMO 2020 with the model:

$$Y_{it} = \beta * Scrubber_{it} * Post_t + \alpha * Scrubber_{it} + \mu * X_{it} + \delta_i + \gamma_t + \epsilon_{it} \tag{4.1}$$

Where i indexes the individual vessels, and t specifies the time by date for regressions on distance, charter type and voyage charter. Further, t specifies the time by week for speed. Y_{it} is the dependent variable. Conditional on the effects we are analyzing, the dependent variable is (1) distance, (2) weekly average speed, (3) binary variable for charter type or (4) the voyage charter freight rate. The coefficient β represents the IMO 2020 implementation effect (DiD estimate) and is labeled SP in the regression outputs.

$Post_t$ is a dummy variable indicating whether an observation is after the policy implementation on January 1. 2020. Further, $Scrubber_{it}$ is a dummy variable defining if an observation is in the treatment or control group. A scrubber vessel is categorized in the treatment group and given a value equal to 1 if the starting date of a voyage is after January 1, 2020. Contrary, a non-scrubber vessel will be in the control group with a value equal to 0. This causes the dynamic aspect to the model, as scrubber vessels have different treatment periods reflecting the scrubber's installation timing.

X_{it} are various covariates that may affect the dependent variable in the model. Based on the findings of Ronen (1982) and Adland and Jia (2016, 2018) regarding speed analysis, we include continuous variables for freight rate and bunker price, and a dummy variable for loading condition. The different freight rates from Baltic Exchange are illustrated in 3.1. The fuel price variable varies by time and geographical location.

The fixed effects are included to absorb much of the residual variation (Kearney and Levine, 2014). By controlling for the heterogeneity in our sample, we can isolate the effects of scrubber installation. Including vessel fixed effects δ_i controls for differences in time-invariant characteristics such as vessel size and age. The time fixed effects γ_t, picks up the time-variant effects such as market conditions. In addition, we apply route fixed effects to the models on speed and \$/tonne spot rate to control for geographical differences.

Regarding inference, Bertrand et al. (2004) argue that one must cluster on the unit of policy implementation if possible. After testing for heteroscedasticity using Breusch-Pagan (Breusch and Pagan, 1979), all our models use clustered standard errors on vessel level as observations within each group may not be independently and identically distributed.

The regression models for voyage distance and speed consist of linear and log-transformed models, while the voyage charter freight rate models are solely log-transformed. The market conditions have a large impact on spot rates, with a lower bound close to zero in poor markets and greatly increased rates in thriving markets caused by inelastic supply curves in the short term. This leads to a positively skewed distribution, and it is reasonable to use the natural logarithm on the dependent variable for the \$/tonne rate (Alizadeh and Talley, 2011; Adland et al., 2016). The reason for including log-transformed regression models on voyage distance and speed is to ease the interpretation of coefficients. The interpretation of the dummy coefficients in the log-transformed models is the following:

$$\text{If } D \text{ switches from 0 to 1, the \% impact of } D \text{ on } Y \text{ is } 100[exp(c) - 1] \tag{4.2}$$

The identifying assumption underlying this research design is not a random assignment of scrubber vessels and non-scrubber vessel, but rather that these groups would have trended similarly in the absence of IMO 2020 (appendix A5). To verify the identifying assumption, we test for parallel trend in Section 5.5

5 Discussion of Results

The subsequent analysis consists of six sections to present and discuss how IMO 2020 has affected various micro-market behaviors in the drybulk market. The first four sections discuss the effects of scrubber installation on voyage distance, vessel speeds, charter type and voyage charter freight rates. The final two sections review the parallel trend assumption and discuss uncertainties potentially influencing the results.

5.1 Are scrubber vessels sailing on longer routes than non-scrubber vessels after IMO2020?

Firstly, we investigate if installing a scrubber influences the sailing distance after IMO 2020. The descriptive statistics indicate that scrubber vessels operate on longer duration voyages, corresponding with the findings of Braemer ACM Shipbroking (2021). This suggests that vessels with lower marginal costs due to reduced fuel costs, increase the savings by spending more time at sea. The effects of scrubber installation on distance are tested using the regressions in Table 5.1. Models (5) and (6) are log-transformed to ease the interpretation of the coefficients.

Table 5.1: Scrubber effects on voyage distance

	(1) Distance	(2) Distance	(3) Distance	(4) Distance	(5) lnDistance	(6) lnDistance
SP			483.2**	180.1	0.0714**	0.0238
			(176.4)	(138.1)	(0.0271)	(0.0213)
Scrubber	608.7***	422.4***	300.2	275.8*	0.0439	0.0401
	(107.4)	(92.16)	(182.9)	(136.0)	(0.0280)	(0.0210)
Post			-197.3***		-0.0352***	
			(52.79)		(0.00852)	
VLOC	1,393.4***		1,379.4***		0.195***	
	(249.8)		(249.3)		(0.0375)	
N	30,806	30,806	30,806	30,806	30,806	30,806
$Method$	OLS	OLS	DiD	DiD	DiD	DiD
$VesselFE$	No	Yes	No	Yes	No	Yes
$TimeFE$	No	Yes	No	Yes	No	Yes

Standard errors in parentheses. Standard errors clustered on vessel level.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The scrubber dummy in model (1) is significant at a 1% level. The coefficient indicates that scrubber vessels on average sail 609 nautical miles longer than non-scrubber vessels per voyage in the sample period. The model does not account for differences in the year of build or vessel size. As illustrated in Figure 3.3, the VLOC vessels have a fixed trading pattern primarily operating between Brazil and China. Therefore, we include a dummy variable controlling for the effects of VLOC vessels. The variable is significant at a 1% level, indicating that VLOC vessels on average sail 1,393 nautical miles longer than the remaining Capesize fleet.

In model (2), TWFE are included to control for market conditions and vessel heterogeneity. Scrubber vessels are on average larger and of newer build. From panel (a) in Table 3.3, the difference in vessel characteristics increases from 2019 to 2020, as age and size of non-scrubber vessels remain constant. In general, newer vessels are more energy efficient due to improvements in designs (Lindstad and Eskeland, 2015). In addition, larger vessels can take advantage of economies of scale. Both factors impact the route placement and we expect a decrease in the scrubber coefficient once we control for the vessel characteristics. The time fixed effects control for market conditions such as changes in freight rates and fuel prices over time. The model gives a significant coefficient at a 1% level, indicating that scrubber vessels on average sail 422 nautical miles longer than non-scrubber vessels per voyage.

The DiD framework in model (3) allows us to analyze if scrubber vessels sail longer than non-scrubber vessels after the policy implementation. The SP coefficient represents the DiD estimate and is significant at a 5% level. The coefficient suggests that the difference in voyage length between scrubber and non-scrubber vessels increases by 483 nautical miles after IMO 2020. The VLOC coefficient indicates that VLOC vessels on average sail 1,379 nautical miles longer than the rest of the Capesize fleet. Similar to model (3), the log-transformed model in (5) returns significance in the SP coefficient at a 5% level, suggesting that scrubber vessels sail 7.4% longer than non-scrubber vessels after the implementation of IMO 2020. In addition, the VLOC dummy is significant at a 1% level and indicates that VLOC vessels, on average, sail 21.5% longer than the remaining Capesize fleet.

For the same reasons as in model (2), we control for differences in vessel characteristics and market conditions by applying TWFE in model (4). The SP coefficient loses its significance once we control for differences in vessel characteristics and market conditions. This implies that the difference in voyage length between scrubber and non-scrubber vessels does not increase due to IMO 2020. Similar to model (4), we do not experience a significant SP coefficient in the log-transformed model (6).

Overall, our analysis suggests that scrubber vessels sail on longer voyages. However, we do not find evidence that IMO 2020 has resulted in an increased difference in voyage length between scrubber and non-scrubber vessels when accounting for vessel heterogeneity and market fluctuations. The contradiction of results in model (5) and (6) indicate that vessel characteristics such as age and size potentially explain the difference in distance, rather than the scrubber installation or the policy change itself.

5.2 Are scrubber vessels increasing sailing speeds compared to non-scrubber vessels after IMO 2020?

The second topic of investigation is whether scrubber vessels increase speeds compared to non-scrubber vessels after IMO 2020. Table 5.2 presents the regression models. The purpose of models (1), (2) and (3) is to determine if the scrubber dummy affects vessel speeds. Models (4), (5) and (6) examine whether the difference in vessel speeds increases for scrubber vessels compared to non-scrubber vessels after IMO 2020. The dependent variable is weekly average speed, presented in knots. Models (7), (8) and (9) are log-transformed models of (4), (5) and (6).

All variables in model (1) are significant. The scrubber coefficient indicates that scrubber vessels sail 0.32 knots faster than non-scrubber vessels. The laden variable is significant at a 1% level and indicates that vessels sail 1.2 knots slower on laden legs compared to ballast legs. This is in line with the findings of Adland and Jia (2018). The freight rate and bunker price coefficients are significant at a 1% and 5% level, respectively. The coefficient signs correspond with classical speed optimization theory. Simultaneously, the effects of change in freight rates and fuel prices on speed are minor, supporting previous empirical testing of the classical speed theory (Aßmann et al., 2015; Adland and Jia, 2016, 2018).

Table 5.2: Scrubber effects on vessel speed

	(1) Speed	(2) Speed	(3) Speed	(4) Speed	(5) Speed	(6) Speed	(7) lnSpeed	(8) lnSpeed
SP				0.102*	0.135**	0.141***	0.009*	0.012***
				(0.051)	(0.042)	(0.042)	(0.004)	(0.004)
Scrubber	0.316***	0.287***	0.257***	0.282***	0.173***	0.139**	0.024***	0.012**
	(0.032)	(0.029)	(0.028)	(0.052)	(0.044)	(0.044)	(0.004)	(0.004)
Post				-0.162***			-0.014***	
				(0.017)			(0.002)	
Laden	-1.164***	-1.152***	-0.558	-1.164***	-1.153***	-0.549	-0.101***	-0.043
	(0.014)	(0.014)	(0.729)	(0.014)	(0.014)	(0.729)	(0.001)	(0.064)
Freight rate	0.011***			0.009***				
	(0.002)			(0.002)				
Fuel price	-0.000**			-0.000***				
	(0.000)			(0.000)				
ln(Freight rate)							0.011***	
							(0.002)	
ln(Fuel price)							-0.011***	
							(0.003)	
N	120,047	120,047	120,047	120,047	120,047	120,047	120,047	120,047
$Method$	OLS	OLS	OLS	DiD	DiD	DiD	DiD	DiD
$VesselFE$	No	Yes	Yes	No	Yes	Yes	No	Yes
$TimeFE$	No	Yes	Yes	No	Yes	Yes	No	Yes
$RouteFE$	No	No	Yes	No	No	Yes	No	Yes

Standard errors in parentheses. Standard errors clustered on vessel level.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

When time and vessel fixed effects are included in model (2), the scrubber coefficient indicates that scrubber vessels sail 0.29 knots faster than non-scrubber vessels. As vessel characteristics such as age and size are controlled for in vessel fixed effects, the scrubber coefficient decreases but remains significant at a 1% level. We exclude the freight rate and bunker price variables from the model, since the market conditions are controlled for in time fixed effects.

In model (3) we include route fixed effects to control for route differences such as voyage duration and loading condition. Consequently, we observe an insignificant laden dummy. However, the scrubber variable is significant at a 1% level, suggesting that scrubber vessels on average sail 0.26 knots faster than non-scrubber vessels. Furthermore, as we distinguish between a laden- and a ballast leg in our dataset, the route fixed effects capture differences in the two legs, hence explaining the insignificance of the laden dummy.

The DiD framework is applied in model (4) to investigate if IMO 2020 has affected vessel speeds. We experience significance in the SP coefficient at a 10% level. This indicates that the difference in vessel speeds increases by 0.10 knots between scrubber- and non-scrubber vessels after IMO 2020. Time and vessel fixed effects are included in model (5). The SP coefficient is significant at a 5% level, suggesting that scrubber vessels increase speeds by 0.14 knots relative to non-scrubber vessels because of the policy implementation. The freight rate and bunker price variables are excluded for the same reason as in model (2).

Model (6) includes route fixed effects, resulting in a significance at a 1% level for the DiD estimator. The SP coefficient indicates that IMO 2020 has increased the difference in speeds between scrubber and non-scrubber vessels by 0.14 knots. The effects of including route fixed effects on the laden dummy are similar to model (3). The model shows that scrubber vessels increase speeds compared to non-scrubber vessels after the IMO 2020 regulation.

As the effects of scrubber, freight rates and fuel prices on speed are small, model (7) is log-transformed to ease the interpretation of the coefficients. The freight rate and fuel price variables are significant at a 1% level, with a similar sign as in model (4). This suggests that a 1% change in freight rate leads to a 0.01% increase in speed. Further, a 1% change in fuel price leads to a 0.01% decrease in speed. The SP coefficient is significant at a 10% level, indicating that the difference in vessel speeds between scrubber and non-scrubber vessels increases by 0.9% after IMO 2020. Both model (8) and model (9) return similar results as (5) and (6), where the SP coefficients indicate that the difference in vessel speeds between scrubber and non-scrubber vessels increases by 1.2% after the policy change.

Overall, the findings suggest that scrubber vessels do increase vessel speeds due to IMO 2020. Even though our results indicate that scrubbers significantly affect vessel speeds, we experience minor effects. The findings contradict the study of Adland et al. (2017a) on speeds in Emission Control Areas (ECAs) with stricter limits on sulphur content in marine fuels. Recent literature on speed optimization denies the magnitude of freight market conditions and fuel price on speed (Aßmann et al., 2015; Adland and Jia, 2016, 2018), especially when observed speeds differ from the design speed (Adland et al., 2020). The calculated speeds are lower than design speeds in our sample and we observe similar limited effects of freight rates and fuel price.

5.3 Are scrubber vessels less likely to be used on trip charter contracts after IMO 2020

The third area of interest is to investigate if shipowners are less likely to offer scrubber vessels on trip charter contracts after IMO 2020. Shipowners have the flexibility to offer their vessels on either voyage charter or trip charter. As investments in energy efficiency rarely result in higher freight rates (Agnolucci et al., 2014; Adland et al., 2017b), the shipowner will primarily benefit from their scrubber investment in the form of potential fuel cost savings, by offering their vessels on voyage charter contracts. Therefore, it is interesting to test if there exists a market failure related to this principal-agent problem, where the charterer in a trip charter contract benefits from the shipowner's investment. We use a linear probability model (LPM) with a dummy for trip charter contracts as the dependent binary variable in Table 5.3. The dummy for scrubber installation is the explanatory variable in models (1) and (2), while the DiD estimator is the explanatory variable in models (3) and (4).

Table 5.3: Scrubber effects on charter type

	(1) Trip charter	(2) Trip charter	(3) Trip charter	(4) Trip charter
SP			-0.068	-0.375*
			(0.079)	(0.187)
Scrubber	-0.045	-0.089	0.056	0.187
	(0.028)	(0.110)	(0.074)	(0.181)
Post			-0.141***	
			(0.025)	
N	1,016	1,016	1,016	1,016
$Method$	OLS	OLS	DiD	DiD
$VesselFe$	No	Yes	No	Yes
$TimeFe$	No	Yes	No	Yes

Standard errors in parentheses. Standard errors clustered on vessel level.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

In model (1), the scrubber variable is insignificant, indicating that the scrubber installation does not influence the shipowner's choice of offering their vessel on trip charter versus voyage charter. The insignificance may be explained by the fact that we study the effects on the entire sample, while the benefits of fuel cost savings only occurred after January 1, 2020. We experience the same outcome when including TWFE in model (2). Including vessel fixed effects has a small impact on charter type, as the vessel characteristics on average are similar between scrubber and non-scrubber vessels. In model (3), the insignificant SP coefficient suggests an existence of market failure in the freight market. The model indicates the shipowners investing in scrubbers do not offer their vessels on less trip charter contracts. This suggests that the charterer accrues the potential fuel cost savings from the scrubber investment.

Contrary, the DiD estimator in model (4) is significant at a 10% level when time- and vessel fixed effects are included. The negative coefficient indicates that a scrubber vessel is 37.5% less likely to be offered on a trip charter than a voyage charter after IMO 2020. The change in significance indicates that important factors regarding market conditions are picked up in time fixed effects, as vessel characteristics are similar for scrubber and non-scrubber vessels. The SP coefficient suggests that shipowners are more likely to offer scrubber vessels on voyage charter contracts, where they pay for fuel costs and benefit from potential fuel cost savings. This indicates a strategic adjustment to the policy change, suggesting the market failure on charter type is not an issue as a result of IMO 2020.

5.4 Are scrubber vessels trading at a lower \$/Tonne rate relative to non-scrubber vessels after IMO 2020?

Finally, we investigate if scrubber vessels trade at lower voyage charter rates compared to non-scrubber vessels. This allows us to investigate if there is a split of potential fuel cost savings between the shipowner and the charterer in the spot market.

The freight rate in a perfectly competitive market is determined by the marginal cost of the marginal vessel, where the bidding on transportation is confined within a specific geographical area (Norman, 1979; Adland et al., 2016). Suppose scrubber vessels cluster on specific routes, the freight rates can decrease below the traditional marginal cost of a non-scrubber vessel. Significant lower rates in our models can be an indication of such a scenario. We analyze the routes of Australia to the Far East, Atlantic America to the Far East and from Africa to the Far East, as these routes represent micro-markets, where scrubber vessels have a substantial impact on the supply side, illustrated in appendix A3. Table 5.4 presents the OLS and DiD models. The dependent variable is the natural logarithm of the \$/tonne spot rate.

Table 5.4: Scrubber effects on voyage charter freight rates

	(1) lnRate	(2) lnRate	(3) lnRate	(4) lnRate	(5) lnRate	(6) lnRate
SP				-0.056	0.449**	0.014
				(0.098)	(0.142)	(0.060)
Scrubber	0.041	0.219	0.016	0.112	-0.166	0.004
	(0.043)	(0.175)	(0.056)	(0.086)	(0.192)	(0.072)
Post				-0.078		
				(0.042)		
N	832	832	832	832	832	832
$VesselFE$	No	Yes	Yes	No	Yes	Yes
$TimeFE$	No	Yes	Yes	No	Yes	Yes
$RouteFE$	No	No	Yes	No	No	Yes

Standard errors in parentheses. Standard errors clustered on vessel level.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

In model (1), the scrubber dummy is insignificant, suggesting that scrubber vessels trade at a similar \$/tonne rate as non-scrubber vessels. Model (2) incorporates fixed effects for both the time differences and vessel individuality. There is no change to the significance of the scrubber dummy, potentially explained by the similarities in vessel characteristics illustrated in Panel (b) of Table 3.5. However, as the \$/tonne rate and distance traveled are greater for scrubber vessels than non-scrubber vessels, we include route fixed effects to control for these differences. We experience the same outcome in model (3) as in models (1) and (2).

Models (4)-(6) incorporate the DiD framework. The SP coefficient in model (4) shows no significance, suggesting that the difference in \$/tonne rates is unchanged between scrubber and non-scrubber vessels after IMO 2020. However, including time and vessel fixed effects to model (5) tells a different story. The DiD estimator is significant at a 5% level, and the coefficient indicates that the difference in \$/tonne rate between scrubber and non-scrubber vessels increases by 56.7% after IMO 2020. This can either indicate that scrubber vessels trade at a premium or that scrubber vessels, to a greater extent, trade on long-haul routes with higher \$/tonne rates. The latter is supported by the descriptive statistics, where scrubber vessels are sailing longer per voyage compared to non-scrubber vessels.

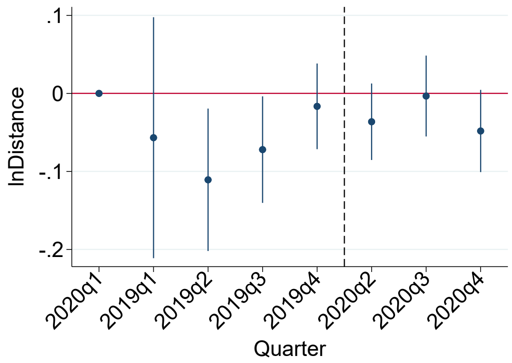
Therefore, we include route fixed effects in model (6) to account for variation in rates for different routes. This leads to an insignificant DiD estimator at any level and indicates that scrubber vessels do not trade at a lower \$/tonne rate compared to non-scrubber vessels after IMO 2020. Overall, our analysis suggests that shipowners of scrubber vessels accrue the potential savings from lower fuel costs. The investment in scrubber contributes to a reduction in marginal costs, while the marginal income remains at the same level for both groups.

5.5 Testing parallel trend assumption

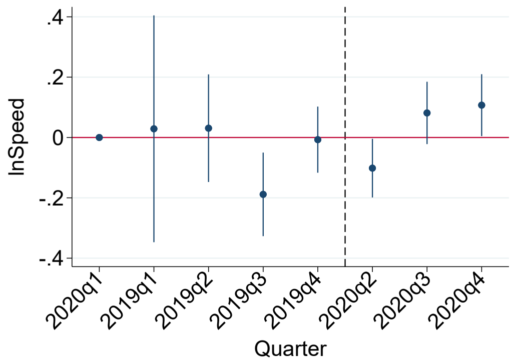
To test for parallel trends, we run a set of regressions using our final DiD model on each topic of investigation. The purpose is to analyze if there exists a parallel trend before the regulation and if the treatment has a clear effect *ex-post*. We control for vessel fixed effects and time fixed effects in all models. In addition, we control for route fixed effects in the models on speed and voyage charter rate.

Figure 5.1 illustrates the coefficient plot of the DiD estimates relative to the first quarter after the IMO 2020 implementation (2020q1). We compare the difference between scrubber and non-scrubber observations against the base quarter. Hence, the reason for placing this point to the far left in each panel. The dot equals the DiD estimate for the respective quarter, while the whiskers indicate the 95% confidence intervals. The dots before 2020q1 should follow the red line, indicating that the treatment and control group have parallel trends. Contrary, if the regulation has an effect on the treatment group, we expect the dots after the dashed vertical line to move away from zero, either in a positive or negative direction. We analyze the parallel trend assumption by visual inspection.

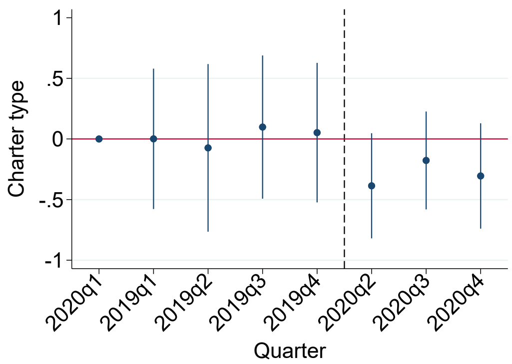
Figure 5.1: Test for parallel trend assumption



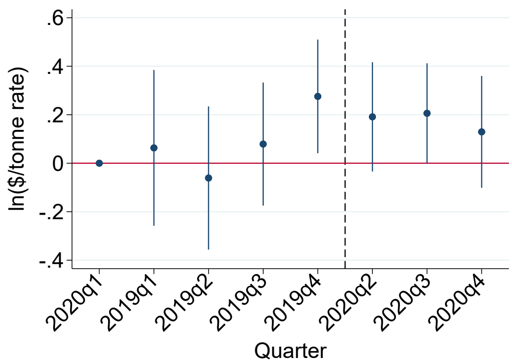
(a) Distance



(b) Speed



(c) Contract type



(d) Voyage freight rate

Panel (a) illustrates some irregularities in the trend, as two of the quarters are significantly different. Visual examination of the pre-trend indicates an upward slope. The dots after 2020q1 indicate similar DiD estimates for the two groups. The treatment effect seems to occur prior to IMO 2020, as we see an increase from 2019q2 before stabilizing. However, the post-period does not return a significant difference on distance.

In Panel (b), we observe pre-trend DiD estimates close to zero, indicating that the parallel trend assumption holds. The exception is 2019q3, returning a significant difference between scrubber and non-scrubber vessels. Further, the treatment effect is positive in the second half of 2020, suggesting that scrubber vessels increase speeds compared to non-scrubber vessels after IMO 2020. However, the treatment effect does not contribute to a significant difference in the quarterly DiD estimates.

Panel (c) suggests that the parallel trend assumption is fulfilled, as there are no deviations from the red line in the pre-trend. After the implementation of IMO 2020, all the coefficients turn negative, suggesting a negative treatment effect. However, the whiskers suggest no significant difference in the percentage of trip charter contracts relative to voyage charter contracts after IMO 2020.

We experience pre-trend DiD estimates close to zero in Panel (d), indicating that the parallel trend assumption holds. The treatment effect seems to positively impact the natural logarithm of voyage charter freight rates, with the effect starting in 2019q4. The whiskers do not indicate a significant difference in $/tonne rates for each quarter after the regulation.

Overall, the parallel trend assumption in panels (a) and (b) seems to be fulfilled by visual inspection, despite some exceptions in the pre-trend estimates. The pre-trend is clear in panels (c) and (d), indicating that the parallel trend assumption holds.

5.6 Elements of uncertainty

Distance calculation based on shortest-path algorithm

There may be some uncertainty in the distance and speed calculations due to the choice of distance algorithm. By using a shortest-path algorithm between the AIS observations, we do not account for non-sailable waters and land areas that may hinder the direct path between two observations. This can potentially underestimate the distance calculations and overestimate the calculated speeds. As the frequency of AIS observations decreases, the duration between two AIS positions increases, causing uncertainty to the actual sailing path. Hence, the estimation errors may increase. This is further discussed in appendix A2.

Short sample period

We only have 12 months of data post-regulation, as IMO 2020 entered into force on 1. January 2020. Consequently, the sample size of fixture data is relatively small. This affects the micro-market analysis and may create uncertainty regarding the results on the charter type and the voyage charter freight rate. In addition, we only account for 2019 as our pre-treatment year. By increasing the sample period before 2020, the market cycles in the drybulk market could be accounted for to a greater extent. Further, increasing the sample size prior to IMO 2020 could improve the testing of the parallel trend assumption.

Covid-19 effects on drybulk shipping

The shipping industry has experienced irregularities through 2020 due to the covid-19 pandemic. According to Clarksons Research (2021a), the total drybulk market experienced trade growth of 0.5% for 2020. However, there are large differences in the trade growth of specific drybulk commodities. For example, the coal trade decreased by 9.4%, while the iron ore- trade increased by 4.8%. As there are several effects occurring in 2020, there exists potential uncertainty regarding the causal effect relationships.

6 Concluding Remarks

In this thesis, we have investigated the effects of IMO 2020 on the drybulk market using the DiD framework. The vessel sample consists of Capesize vessels separated by scrubber vessels and non-scrubber vessels. We have studied how the implementation of the low sulphur emission policy has affected voyage distance and vessel speeds backed by AIS data, as well as charter types and $/tonne rates in voyage charter contracts. Our analysis suggests that IMO 2020 has affected drybulk shipping in different ways when examining various micro-market behaviors.

Our empirical results can be summarized as follows. Firstly, our analysis indicates that scrubber vessels sail on longer routes compared to non-scrubber vessels. However, we do not find evidence that the difference in voyage distance increases as a result of IMO 2020. This suggests that other factors such as age and vessel size potentially affect the route placement to a greater extent.

Secondly, our models show that the difference in speeds between scrubber and non-scrubber vessels increases after IMO 2020. These findings are in line with maritime economic theory suggesting that lower fuel costs for HFO compared to VLSFO results in greater speeds, all else equal.

Thirdly, our model finds little evidence of market failure in the form of a principal-agent problem concerning preferred charter type. The results indicate that shipowners investing in scrubber installation are more likely to offer their vessel on voyage charter contracts after IMO 2020. Hence, shipowners with scrubber vessels are more likely to benefit from the potential fuel cost savings.

Finally, our analysis suggests that there is no difference in voyage charter freight rates for scrubber vessels and non-scrubber vessels. This implies that shipowners of scrubber vessels retain the same marginal income as non-scrubber vessels, while the marginal cost is reduced relative to non-scrubber vessels. Hence, the shipowners of scrubber vessels accrue the potential savings from the difference in fuel price between HFO and VLSFO. Complemented by the fact that a scrubber vessel is less likely to be offered on a trip charter, shipowners would benefit from the potential fuel cost savings.

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Appendices

A1 AIS components

Table A1.1: AIS message components

Message component	Definition	Example
imo	Unique ship identification	9593452
timestamp position	Date and time for the position	2019-02-01T22:18:15Z
lon	Longitude of the position	-128.2225
lat	Latitude of the position	5.219407
speed	Observed speed in knots	10.9
draught	Draught in meters	17.9

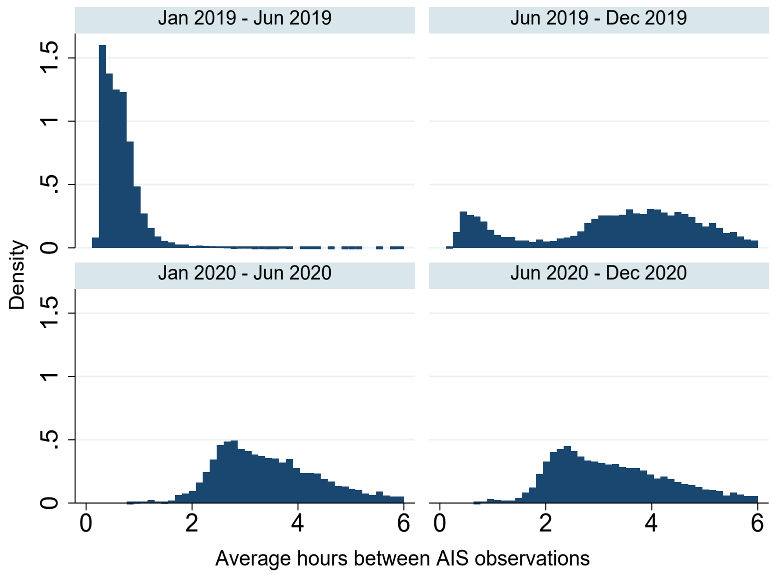
Table A1.1 illustrates relevant components in the initial AIS dataset. All vessels are identified by a unique 7-digit IMO number. Contrary to vessel name, the IMO number is constant throughout a vessel's lifetime.

A2 Data Pre-processing

The data pre-processing is twofold and is separated by data processing of AIS data and fixture data. The pre-processing for distance and speed consists of (1) combining the AIS data with vessel characteristics from Clarksons WFR, (2) combining the dataset from (1) with Signal Ocean voyage data to specify starting- and ending date of each voyage and (3) cleaning the final data sample. The pre-processing for fixture data consists of (1) combining vessel characteristics from Clarksons WFR with the fixture data and (2) cleaning the final data sample.

A2.1 Discussion on AIS reporting frequency

Figure A2.1: Frequency of AIS observations in 2019-2020



When splitting each year into six-month periods to highlight the frequency change in August 2019, the difference in reporting frequency becomes apparent in average time and distance between each AIS observation. Therefore, we have set a cut-off for voyages with an average time between observations of greater than six hours and an average distance between observations greater than 80 nautical miles. We also remove voyages with a total distance of less than 1,500 nautical miles or greater than 18,000 nautical miles and voyages with days sailing less than five days or greater than 75 days.

Table A2.1: Average time and distance between AIS observations

	2019	**2020**
Number of voyages	15,418	15,388
Avg hours between observations	1.95	3.33
Avg nautical miles between observations	22.78	38.13

We have calculated the average time between AIS observations and the average distance between the two points to validate our data further. We compare observations from 2019 with 2020 and experiences greater mean values in both time and distance in 2020. This seems reasonable due to the different frequencies of observation in our dataset.

A2.2 Data pre-processing of sample on distance and speed

The raw AIS dataset consists of 207,084,018 observations. We drop all observations with registered speeds below three knots, indicating that the ship is at port or has an anchorage status to reduce the initial dataset. In addition, we remove observations with speeds over 18 knots. Further, we only keep observations for Capesize vessels determined by the Clarksons WFR dataset by merging IMO numbers from AIS and Clarksons WFR.

The speeds are calculated based on the distance and time traveled from point to point represented by the geographical position. Hence, we use a Haversine formula to compute the geographical distances between two latitude-longitude positions ($Position_{n+1} - Position_n$). The Haversine formula determines the great-circle distance in kilometers between two points on an earth-sized sphere (Nichat, 2013). The distance is converted from kilometers to nautical miles by dividing with 1.852 for speed estimation in knots. Hence, the distances between the points are calculated with a shortest-path algorithm. The speed between the points can be found by dividing the distance traveled by the time difference of two consecutive AIS observations.

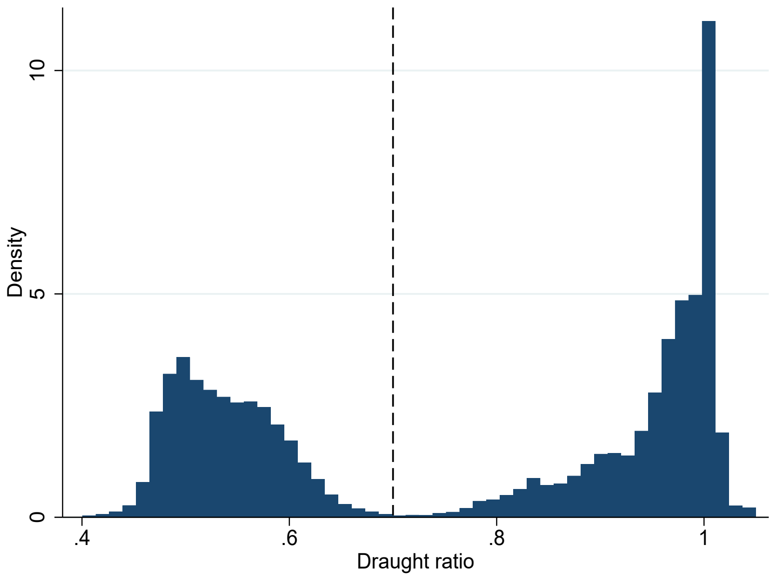
$$Speed = \frac{Position_{n+1} - Position_n}{(Time_{n+1} - Time_n)} * \frac{1}{1.852} \tag{.1}$$

We exclude average speeds lower than 8 knots and greater than 18 knots from our sample. Speeds lower than 8 knots suggests that a vessel is in port or drifting at very low speeds. Further, speeds greater than 18 knots are considered unrepresentative as this would require perfect sailing conditions, in addition to full steam ahead (Adland and Jia, 2016). Lastly, the calculated speeds in knots are converted into time-weighted average speeds for each vessel on a weekly basis.

$$Time\ weighted\ avg\ weekly\ speed = \sum_{n=1}^{N}\left(\frac{Time_{n+1} - Time_n}{\sum_{n=1}^{N}(Time_{n+1} - Time_n)} * Speed\right) \tag{.2}$$

The AIS reported draught and the ship-specific design draught from Clarksons WFR are combined to calculate the draught ratio for each voyage. This allows us to control the accuracy of the laden and ballast leg determination of the Signal Ocean platform. The histogram below illustrates the distribution of the draught ratios for weekly speed observations.

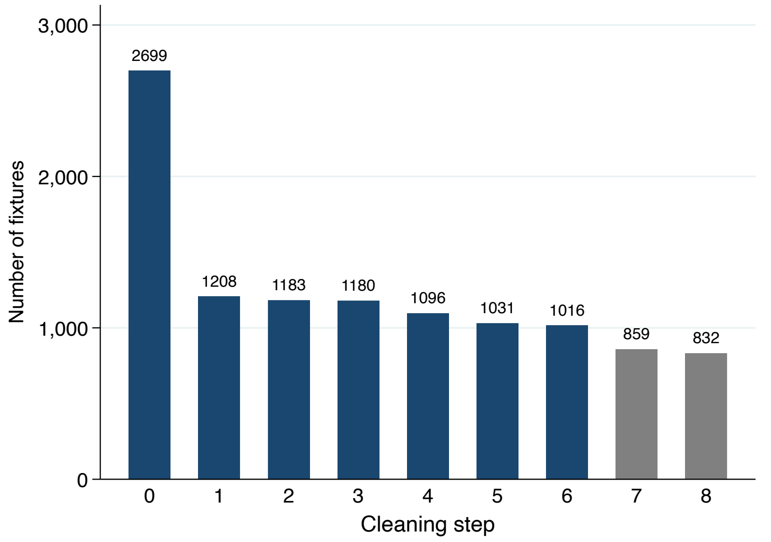
Figure A2.2: Draught ratio and loading condition



There is a clear separation in draught ratios at value 0.7. This fits well with the paper by Adland and Jia (2016), stating that laden- and ballast legs equal a draught ratio from 0.8 to 1 and from 0.25 to 0.64, respectively. In addition, we remove observations of draught ratios less than 0.4 and greater than 1.05. We include observed draught ratios between 1 and 1.05 to account for tropical draught, which is $\frac{1}{48}$ above the summer load line of the vessel and can lead to a draught ratio greater than 1 (Eyres and Bruce, 2012). Further, we remove observations with a laden dummy equal to 1 and a draught ratio less than 0.7. Similarly, this applies to observations with a laden dummy equal to 0 and a draught ratio greater than 0.7.

A2.3 Data pre-processing of sample on fixtures

Figure A2.3: Cleaning of fixture data



Note: Step 6 equals the sample for charter type, while Step 8 equals the sample for voyage charter freight rates

Table A2.2: Explanation of cleaning steps for fixture data

Cleaning step	Reason
0	Raw observations in sample period
1	Dropping missing names and name equal to "TBN" (To be announced)
2	Matching on Name, Built, DWT or Ex-name Built, DWT
3	Dropping missing rates
4	Dropping missing load and discharge values
5	Dropping missing laycan period
6	Dropping duplicate and conflicting rates
7	Dropping trip charter contracts
8	Dropping routes with few scrubber vessels

A3 Most traveled routes

Table A3.1: Main Capesize routes by scrubber status for 2019-2020

	Scrubber (2019)	Non-Scrubber (2019)	Scrubber (2020)	Non-Scrubber (2020)
Australia-Far East	288	4613	1183	3172
Atlantic America-Far East	93	1103	603	611
Africa-Far East	14	576	120	418
Atlantic America-Mediterranean/UK	16	315	65	123
West Coast South America -Far East	6	147	36	105
Far East - India/Pakistan	7	179	20	85
Black Sea/Sea Of Marmara - Far East	3	109	46	98
Africa-India/Pakistan	4	98	27	83
West Coast North America-Far East	13	92	22	58
Atlantic America-Black Sea	6	103	18	52

Table A3.2: Scrubber percentage on specific routes and percentage of scrubber voyages in 2020

	Scrubber on route (2020)	Total Scrubber voyages (2020)
Australia- Far East	27.16%	52.00%
Atlantic America - Far East	49.67%	26.51%
Africa - Far East	22.30%	5.27%
Atlantic America - Mediterranean / UK	34.57%	2.86%
West Coast South America - Far East	25.53%	1.58%
Far East - India / Pakistan	19.05%	0.88%
Black Sea / Sea Of Marmara - Far East	31.94%	2.02%
Africa - India / Pakistan	24.55%	1.19%
West Coast North America - Far East	27.50%	0.97%
Atlantic America - Black Sea	25.71%	0.79%

A4 Validation of distance calculations

Table A4.1: Route distance comparison

Route	1	2	3	2 - 1	3 - 1
Dampier - Qingdao	3443	3594	3582	139	152
Ponta Da Madeira - Dalian	11,973	12,088	12,688	115	715
Saldanha Bay - Tianjin	8024	8272	8564	112	141

Table A4.2: Route distance comparison description

Id	**Description**
1	Our calculation
2	Seadistance.org
3	Signal Ocean

We have compared the average calculated distance from our AIS sample with the ones listed on sea-distance.org and Signal Ocean to validate our distance calculations. We only experience minor differences, indicating that our approximations are reasonable.

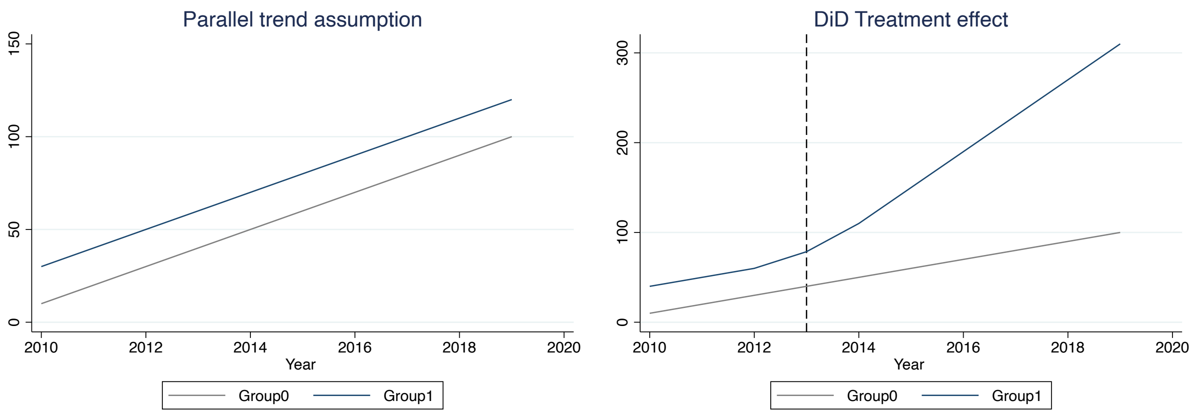
A5 A review of the Difference-in-Differences method

The difference-in-difference (DiD) method is regarded as one of the most popular tools of applied research design to evaluate the causal effect of public interventions (Kropko and Kubinec, 2020). The DiD method consists of two time periods and two groups. In the first period, none of the groups are treated. In the second period, one group is given a treatment, while the other works as a control group. For example, a treatment could be a vaccine or a law regulation only affecting the treatment group. The treatment effect can be estimated by comparing the average change in outcomes experienced by the treated group to the average change in outcomes experienced by the comparison group (Fredriksson and Oliveira, 2019). Hence, the DiD estimate can be presented in the following manner, where $\bar{y}$ is the mean outcome variable:

$$DiD = (\bar{y}_{s=Treatment,t=After} - \bar{y}_{s=Treatment,t=Before}) - (\bar{y}_{s=Control,t=After} - \bar{y}_{s=Control,t=Before}) \tag{.3}$$

The parallel trend assumption is essential. In the absence of a treatment, the two groups should follow a parallel trend over time (Callaway and Sant'Anna, 2020). This implies that the time series of outcomes in each group should differ by a fixed amount in each period and should exhibit a common set of period-specific changes. This would imply that the two groups should follow parallel trend lines as panel (a) in Figure A5.1 (Wing et al., 2018).

Figure A5.1: DiD model



(a) Paralell trend assumption **(b)** DiD treatment effect

We illustrate the general DiD estimate using the OLS framework, where the β coefficient represents the DiD estimate. Y_{it} is the dependent outcome variable for unit i at the time, t. Further, D_{it} can be defined as the value of treatment for unit i, at time t. In addition, δ_i and γ_t are the unit and time fixed effect estimates. Lastly, we have the idiosyncratic error term, ϵ_{it} (Bertrand et al., 2004)

$$Y_{it} = \delta_i + \gamma_t + \beta * D_{it} + \epsilon_{it} \tag{.4}$$

The DiD equation takes account of both time and individual fixed effects. When unit and time fixed effects are included, we account for both unit-specific time-invariant and time-specific unit-invariant unobserved confounders in a flexible way (Imai and Kim, 2020). From the static TWFE model, we can interpret as the overall effect of participating in the treatment across groups and time periods.

Callaway and Sant'Anna (2020) expand on the model above and present a more dynamic model specification of the DiD model as presented below:

$$Y_{it} = \alpha_t + \alpha_g + \sum_{e=-K}^{-2} *\delta_e^{anticip} * D_{it}^e + \sum_{e=0}^{L} *\beta_e * D_{it}^e + v_{it} \tag{.5}$$

The more dynamic model has a more complex mathematical notation, where a_t and a_g in this case are the fixed effects, respectively for time, t and group, g. Callaway and Sant'Anna (2020) describes $D_{it}^e = 1(1 - G_i = e)$ as an indicator for a unit, i being e periods away from the initial treatment time, G_i. Lastly, K and L are positive constants, while v_{it} is the error term. The general interpretation of β_e for $e \geq 0$ in the dynamic model is the measurement of the effect of participating in the treatment at different lengths of exposure to the treatment.

Based on the dynamic model of Callaway and Sant'Anna (2020), the following model is identical but with the same notation as in the static model. This makes the model easier to interpret. Compared to the static model, it also includes the possibility of multiple treatment periods by including several DiD estimates across time:

$$Y_{it} = \delta_i + \gamma_t + \sum_{t=1, t \neq t_0}^{T} *\beta_t * D_{it} + \epsilon_{it} \tag{.6}$$

All β_t coefficients measure the effect relative to period t_0, which indicates the policy implementation. The inclusion of multiple time periods is beneficial in two ways. First, if there are multiple time periods before the policy implementation, it allows for partial testing of the underlying assumptions using pre-trends. Second, if there are multiple time periods after the policy implementation, it is possible to examine the timing of the effect.