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The energy efficiency effects of periodic ship hull cleaning

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ABSTRACT

This paper investigates the impact of periodic hull cleaning on oil tankers' energy efficiency using real 2012–2016 fleet performance and weather data extracted from noon reports for a fleet of eight identical Aframax-size crude oil tankers. The impact of changes in fuel consumption is estimated around the discontinuity when a vessel is cleaned and rely on both before-after and difference-in-differences estimators. The main results show that (i) periodic hull cleaning leads to a significant reduction in the daily fuel consumption; (ii) dry-docking leads to greater and significantly different reductions in fuel consumption than underwater hull cleaning, approximately −17% *versus* −9%; (iii) hull cleaning energy efficiency effect is greater when the vessel is sailing laden rather than in the ballast condition. These findings represent a key building block for the optimization of maintenance intervals.

1. Introduction

While ocean transport is considered to be the most energy-efficient transport mode in comparison to rail, road and air (IMO, 2009), the cumulative CO_2 emissions from international shipping are nevertheless substantial, estimated at about 2.2% of global emissions (IMO, 2015). This share is likely to increase due to growth in international trade and a slower rate of decarbonization than in land-based transportation (Energy Transitions Commission, 2017). Fuel is also a major cost driver in international shipping, accounting for 50–70% of a ship's total running costs (Rehmatulla and Smith, 2015). In aggregate, based on the estimated 201–272 million tonnes of fuel consumed annually for the 2007–2012 period (IMO, 2015), international shipping's fuel bill exceeds $80 billion per year.

The maritime industry has mostly focused on improving energy efficiency through technological and operational measures, and has a low uptake of alternative fuels and renewable energy sources (Rehmatulla et al., 2017). However, a large number of energy efficiency measures have been identified as being cost effective (IMO, 2009; Eide et al., 2011; Faber et al., 2011; Psaraftis and Kontovas, 2013).

Bouman et al. (2017) review several technologies for improving energy efficiency in shipping, such as using renewable energy sources (solar or wind propulsion), using fuel with lower carbon content (liquid natural gas or biofuel) or using emission reduction technologies (power and propulsion system). Their review of 150 studies concludes that it is possible to reduce GHG emissions by 50–60% per freight unit transported with current technologies within 2050. Rehmatulla et al. (2017) point out that only a few such measures are implemented by a large proportion of shipowners. Out of the 30 technologies for energy efficiency and CO2 reduction reviewed by the authors, the most common initiatives include bulbous bow designs, pre/post swirl devices to improve propeller efficiency, and the tuning, derating and waste-heat recovery of ship engines. A reason mentioned by Poulsen and Johnson (2016) is the lack of reliable data on energy efficiency measures or even sometimes a distrust on fuel consumption noon-reports. This lack of information represents a major barrier to energy efficiency, and this article contributes to lowering such a barrier to the implementation of operational measures.

The importance of operational measures was formalized with the adoption of the Ship Energy Efficiency Management Plan (SEEMP) by the International Maritime Organization (IMO) in 2011, mandating every ship owner to put in place a formal system to manage and optimize ship and fleet performance (Jensen et al., 2018). Key operational measures include general speed reduction,

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weather routing and periodical cleaning of the vessel's hull and propeller. Jensen et al. (2018) also emphasize how training in energy-efficient operation and awareness (using simulator training of crew) can improve energy efficiency. The study concludes that raising the awareness of the crew can save approximately 10% fuel, an effect particularly important for small shipping companies that may lack the resources to implement other energy efficiency solutions (Johnson et al., 2014; Poulsen and Johnson, 2016).

Using hull cleaning as a measure to curb emissions and improve the energy efficiency of the world fleet is also important for at least two reasons. First, hull fouling is a substantial contributor to increased emissions. For example, the third IMO greenhouse gas study (IMO, 2015) applies a fixed 9% yearly increase in fuel consumption across the world fleet to account for the resulting loss in energy efficiency. Second, it is the only main driver over which the ship owner has a large degree of control. Specifically, while the rate of marine growth on the hull (i.e. the 'fouling') is largely exogenous, the frequency and quality of periodic maintenance on the underwater hull (i.e. hull cleaning and propeller polishing) is decided by the ship owner.

In comparison, weather conditions are exogenous and exposure can only be minimized subject to an increase in journey time. General speed reduction as a measure of improving energy efficiency is important, but market-wide implementation has been hampered by the 'split incentives problem' as the savings (fuel costs) and costs (longer voyage) may be allocated to different agents as discussed in Rehmatulla and Smith (2015).

While it is clear that periodic hull cleaning can significantly improve the world fleet's energy efficiency, accurately measuring its impact is challenging due to the numerous other time-varying drivers of a vessel's fuel consumption, like speed, wind direction, wave height, rudder use and water temperature, to name only a few. In the literature, the impact of hull condition on fuel consumption is typically derived from 'resistance modelling' as developed in Todd (1967). This involves estimating a ship's total resistance and then removing or correcting for external factors such as wind, waves and other factors, leaving only the effects of hull and propeller fouling (Aas-Hansen, 2011).

This paper takes advantage of the improved availability of empirical fleet performance data and weather data to measure the energy-efficiency impact from two types of periodic hull maintenance: underwater cleaning and dry-docking. Compared to the theoretical model-based approach in the literature, the proposed measure is purely data-driven and implemented using two different estimators around the discontinuity when a vessel is cleaned (a 'before-after' estimator and a difference-in-differences estimator). The empirical analysis relies on data extracted from noon reports from January 2012 to December 2016 for a fleet of eight identical Aframax-size crude oil tankers.

The remainder of the paper is organized as follows. Section 2 reviews the literature on fuel consumption drivers and the impact of hull fouling and hull cleaning on fuel efficiency. Section 3 presents the vessel performance data set. Section 4 develops the econometric model to measure the effect from hull cleaning. Section 5 discusses the empirical results for our estimators and implements several robustness checks. Finally, Section 6 concludes.

2. Literature review

Due to the importance of ships' hull condition for both the environment and the economics of ship operation, it has attracted interest in a wide range of disciplines from naval architecture to biology and material science (antifouling paint technology).

In general, the empirical modelling of vessel performance is a technologically complex and expensive process that requires full-scale ship trials for a large dataset covering a multitude of ship and environmental conditions and this may take many years to accumulate. The theoretical foundation and analytical methods, as developed in Telfer (1926) and Todd (1967), are often termed 'resistance modelling' and involve estimating a ship's total resistance and then removing or correcting for external factors such as wind or waves, leaving only the effects of hull and propeller fouling (Aas-Hansen, 2011).

Resistance modelling has been criticized because it requires the estimation of several unknown friction-related coefficients. Pedersen and Larsen (2009) argue in favor of using artificial neural networks to predict propulsion power from the variables influencing ship resistance, such as ship speed, relative wind speed and direction, air temperature and sea water temperature. Sailing speed v is always considered as the principal determinant of a ship's resistance (Psaraftis and Kontovas, 2013; MAN Diesel and Turbo, 2004), but its influence changes (Meng et al., 2016) with the propeller and residual resistance that is mainly caused by waves and weather conditions (Lo and McCord, 1995). The influence of waves and wind is considered to be much more significant than that of ocean currents (MAN Diesel and Turbo, 2004; Carlton, 2012).

Generally, wind and waves coming towards the ship's bow and sides (beam wind or waves) will increase resistance and fuel consumption, while following wind or waves are beneficial. However, determining the precise quantitative influence of sailing and weather conditions on fuel efficiency is extremely complicated (Carlton, 2012). If wind and waves are generally the main reason for involuntary loss of speed (Herradón et al., 2016) and if waves usually constitute an important part of the vessel s total resistance (often 15%–30% of the ship's calm-water power), the added resistance in waves is the most difficult to predict. Bertram (2016) reviews approaches on added power in seaways and concludes that there is no practical approach to quantify the required added power in waves. It is worth noting that added resistance due to wind is important for certain types of ships with large windage areas (cruise ships, containerships and car carriers for instance).

A vessel's hull condition impacts energy efficiency due to the deterioration that occurs in hull and propeller performance over time, mainly as the result of biological fouling and mechanical damage (Kovanen, 2012). Even minor biofilms affect the hydrodynamics of a ship's hull by increasing drag and, therefore, the required propulsive power (Dennington, 2010). Fouling conditions can be exacerbated if the vessel has long idle periods or low activity such as frequent stays in port, and the rate of growth increases with sea temperature (Kovanen, 2012). The state of the underwater hull is most commonly assessed by visual inspection. However, fouling may not be uniform in coverage over the hull surface and heavy fouling may not be visibly seen from above-water inspection. Diving contractors are then hired for underwater hull condition inspection.

Hull fouling results in excess fuel use at a maintained speed or speed loss at a maintained engine power (Kane, 2012). As a secondary effect, hull fouling can also damage the structural integrity of the ship due to corrosion induced by the fouling. Regular hull cleaning and propeller polishing can assist in negating these effects. An additional environmental benefit of hull cleaning is the removal of potential invasive species (biofouling), the transfer of which is a major threat to the world's oceans and to the conservation of biodiversity. As current technologies for underwater hull cleaning focus on the removal of hull fouling and typically does not collect the biological waste, invasive species are only contained if the procedure is undertaken in dry-dock.

There are two different types of cleaning operations on a ship's hull. The quickest and cheapest is underwater hull cleaning, where

divers equipped with powered brushes mechanically removes marine growth along the hull. This can only take place when the vessel is stationary in a port that allows hull cleaning to take place, and where the shipowner has access to reputable service providers. The second type of cleaning operation takes place when the vessel is in dry-dock for a special survey, roughly every fifth year following delivery. The special survey is a mandatory requirement imposed by the vessel's classification society and flag state administration in order to renew the vessel's safety and environmental certificates and remain eligible for insurance (Apostolidis et al., 2012). Certain periodic maintenance operations can only be performed when the vessel is in dry-dock, including the cleaning, sandblasting and coating of the hull with new antifouling paint. The total cost of dry-docking is substantial, ranging from USD 1.2 to 1.6 million for tankers, depending on vessel size (Apostolidis et al., 2012).

There is a general agreement in the literature (including policy reports, industry reports and other 'grey literature') that hull fouling is a significant contributor to a loss in energy efficiency. The Clean Shipping Coalition (CSC, 2011) report submitted to the IMO estimated that over a typical 4–5 years sailing interval, inadequate hull and propeller performance could reduce the efficiency of the entire world fleet by 15–20%. However, the comparison of individual empirical studies is often hampered by different ways of measuring the energy efficiency loss (either as speed loss, increase in fuel consumption, or increase in power/resistance). For instance, Kraap and George Vranakis (2013) argue in favor of the evaluation of hull and propeller performance based on the relative speed loss in percent, calculated by comparing the measured speed with the speed that is expected for the measured shaft power value. This follows the ISO-19030 standard that defines a practical approach for hull and propeller performance monitoring (Solonen, 2016). Similarly, Logan (2011) proposes to use a ship's propeller as a speed or power measuring device to monitor ship hull condition.

Additionally, researchers apply different time intervals to measure the energy efficiency loss and consider different ship types and sizes for which results are not comparable. For instance, Krapp and George Vranakis (2013) study 32 vessels over 48 dry-docking intervals and conclude that the average energy efficiency loss attributable to hull and propeller performance for a typical vessel was between 11% and 18% and that a typical vessel trading over a 60-month interval was found to use 36% more power at the end of the dry-docking interval than in the beginning. Van Ballegooijen and Muntean (2016) reports an increase in the measured total ship resistance over 1.5 years of 9.2% for a large (13,000TEU) container ship.

Gundermann and Dirksen (2016) evaluate the added resistance prior to 237 dry-dockings and find that most vessels have added resistances in the range between 10% and 40%, with implied growth rates between 0.3% and 1.5% per month. The work of Gundermann and Dirksen (2016) is the only one of these studies that explicitly evaluate the impact of hull cleaning. Specifically, their analysis of the level of added resistance before and after dry-docking shows an average reduction in the level of added resistance by two-third of the pre-dock level. They also evaluate the impact from 127 independent hull cleanings, including divers-with-brushes and robotic cleaners, where the hull cleanings are not performed jointly with a propeller polish or a dry-docking. This type of hull cleaning operation shows a reduction in added resistance of around one-fourth of the pre-cleaning result. Moreover, for the 394 combined events (propeller polishing and hull cleaning), the reduction in added resistance is one-third of the pre-cleaning level.

This paper contributes to the existing literature in two important ways. First, it proposes a model-free and purely data driven methodology to evaluate the impact of hull cleaning that does not rely on the 'black art' of resistance modelling (Logan, 2011). Second, it takes advantage of the improved availability of fleet performance data based on daily noon reports to empirically evaluate the energy efficiency impact of both underwater hull cleaning and dry-docking for a sample of Aframax crude oil tankers in global trade.

3. Vessel performance data

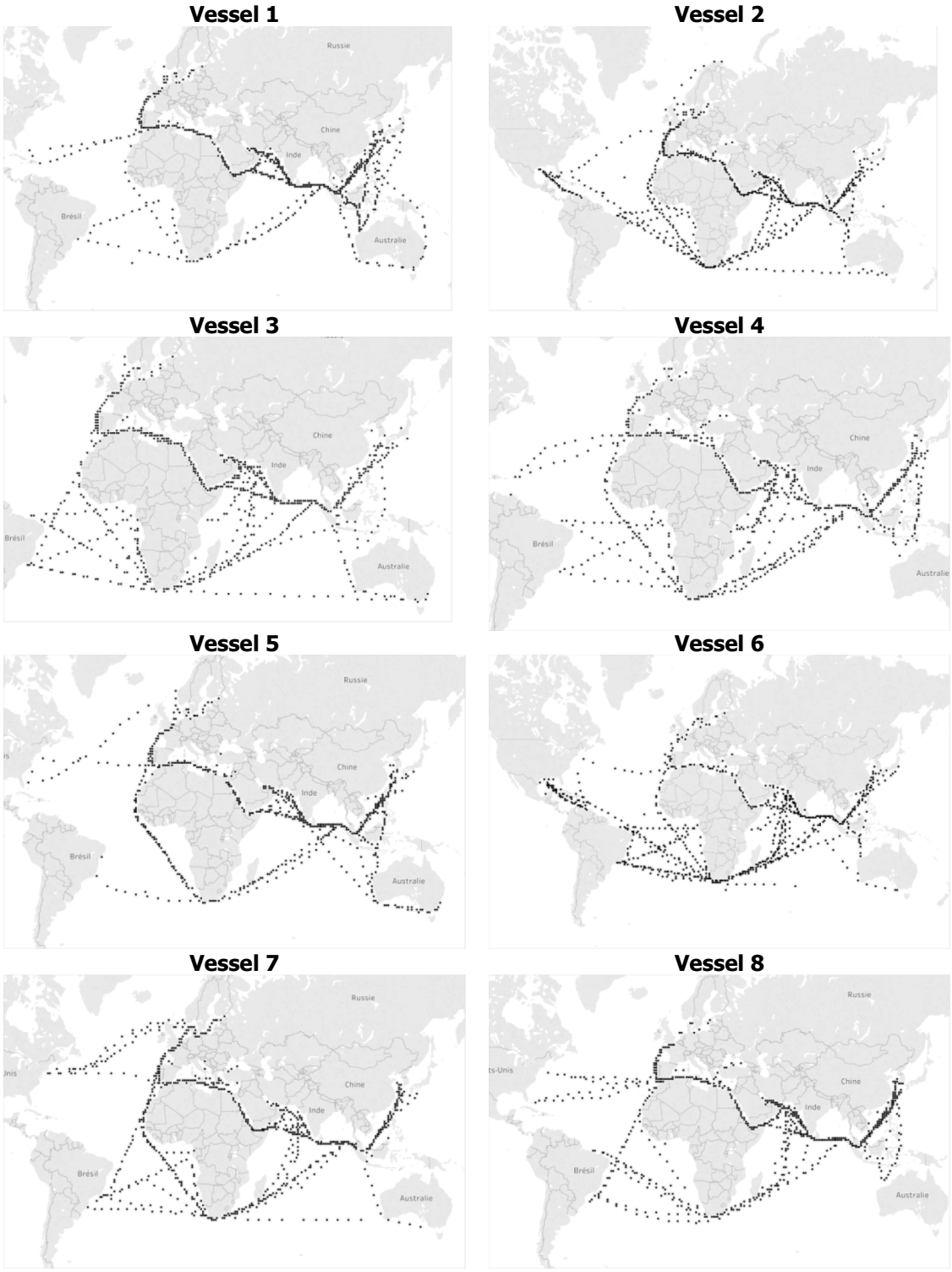
Vessel performance and weather data were extracted from daily noon reports collected between January 2012 and December 2016. The data concerns a fleet of eight sister ships belonging to one (anonymous) shipping company which also provided information on the timing of maintenance operations on the hull. The fleet consists of Aframax crude oil tankers with a carrying capacity of around 120,000 DWT.

A noon report is manually compiled by the crew and details the vessel's position and weather conditions as snapshots at noon, along with the cumulative sailed distance and fuel consumption since the previous report. Aldous et al. (2013) discuss the data quality of noon reports compared to the more costly, but high-frequency continuous monitoring systems. The database includes the following covariates: a vessel identifier, the date (year, month, day), time since last report (in hours), port of departure and port of destination, draft forward and draft aft (in meters), whether the vessel is in ballast, two measures of daily average speed expressed in knots (GPS speed – speed over ground – and LOG speed – speed through water), fuel consumption expressed in tonnes per day, relative wind direction, wind type, sea state, swell direction and swell type.

The raw data pooling all vessels comprises 11,589 daily observations, with around 1400–1500 noon reports per vessel. The following filtering process was applied to the raw data. First, observations with missing or null speed were excluded (2060 observations deleted) as these observations typically represent port days. Second, to avoid potential outliers, observations with speed above 15 knots (which corresponds approximately to the 99th percentile, 139 observations deleted) and below 8 knots (508 observations) were also deleted. The reason is that low average speeds are likely to refer to specific situations where vessels are maneuvering close to shore or accelerating/decelerating in connection with a port call. This represents from 2% to 7% of the noon reports depending on the vessel. Third, noon reports where the time since last report is outside of the range between 20 and 25 h (865 observations deleted) were excluded. Finally, observations with either missing or extreme weather conditions (like stormy wind and long and heavy waves) were excluded (149 observations deleted). The final sample comprise 7868 noon reports: 1044 reports for vessel 1982 for vessel 2993 for vessel 3926 for vessel 4932 for vessel 5966 for vessel 6, 1008 for vessel 7, and 1047 for vessel 8.

Fig. 1 presents a visualization of the trading patterns of the vessels based on reported positions in the noon reports. Most vessels are operating in the same area, with a notable absence of any transpacific trades. The main routes are between Western Europe and the Persian Gulf (either through the Canal de Suez or South Africa depending on whether the vessel is transporting oil or not) and between the Persian Gulf and Asian countries. On the one hand, there is no specific vessel spending long periods in tropical waters only, when the biofouling problem is expected to be at its highest level. On the other hand, the similarity of routes between vessels evidenced in Fig. 1 suggests that the geographical trade pattern is not the main factor explaining the variety in the number of underwater cleaning per vessel.

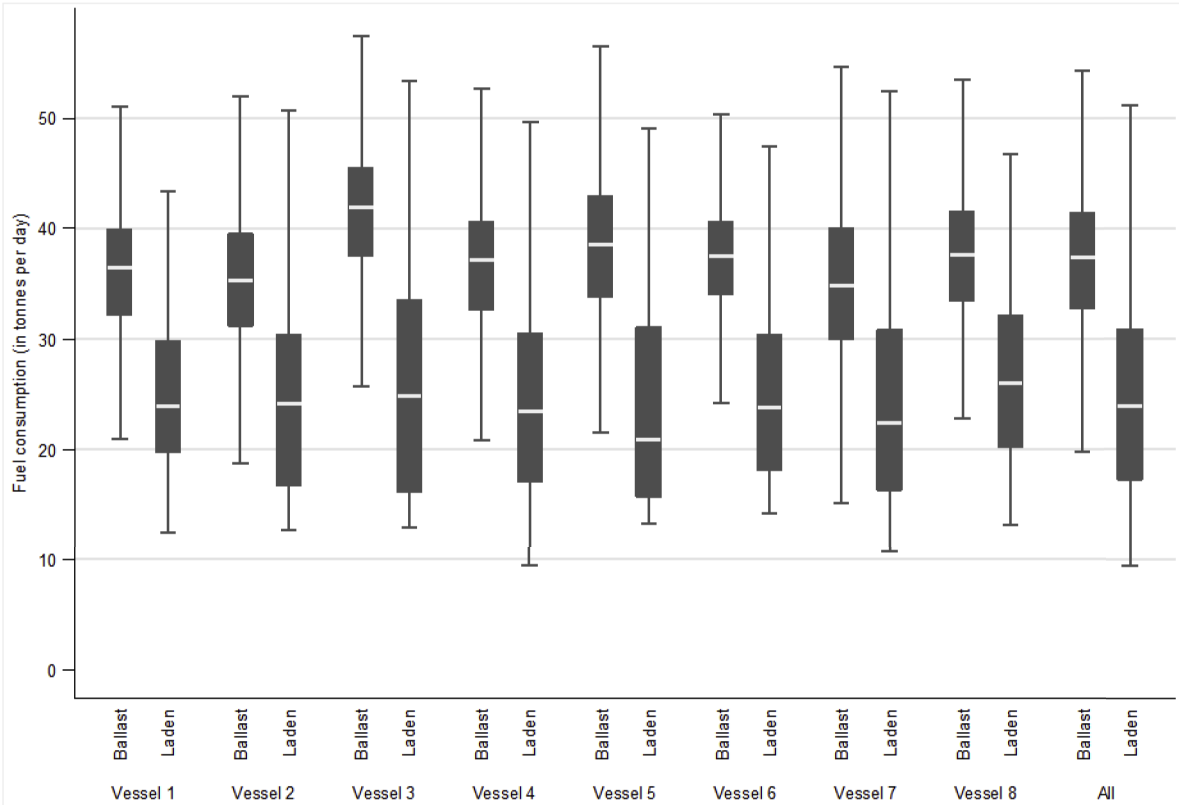
Fig. 2 shows the reported daily fuel consumption per vessel in tonnes per day. When considering the whole fleet, the average daily consumption is equal to 37.3 tonnes when vessels are laden (transporting cargoes) and 25.1 tonnes when vessels are sailing in



Source: data from a maritime company, authors' calculations.

Fig. 1. Trading pattern of vessels.

ballast (empty). This corresponds to a ratio between laden and ballast conditions of 1.49, but this is strongly related to differences in the distribution of sailing speeds in the two loading conditions. When considering only speeds between 12 and 14 knots, the average daily consumptions are 37.79 tonnes laden and 31.74 tonnes in ballast. The ratio in this case is equal to 1.19, which is extremely close to the ratio of 1.2 stated in Psaraftis and Kontovas (2013). In laden condition, the average fuel consumption for



Source: data from a maritime company, authors' calculations.

Fig. 2. Average fuel consumption of vessels.

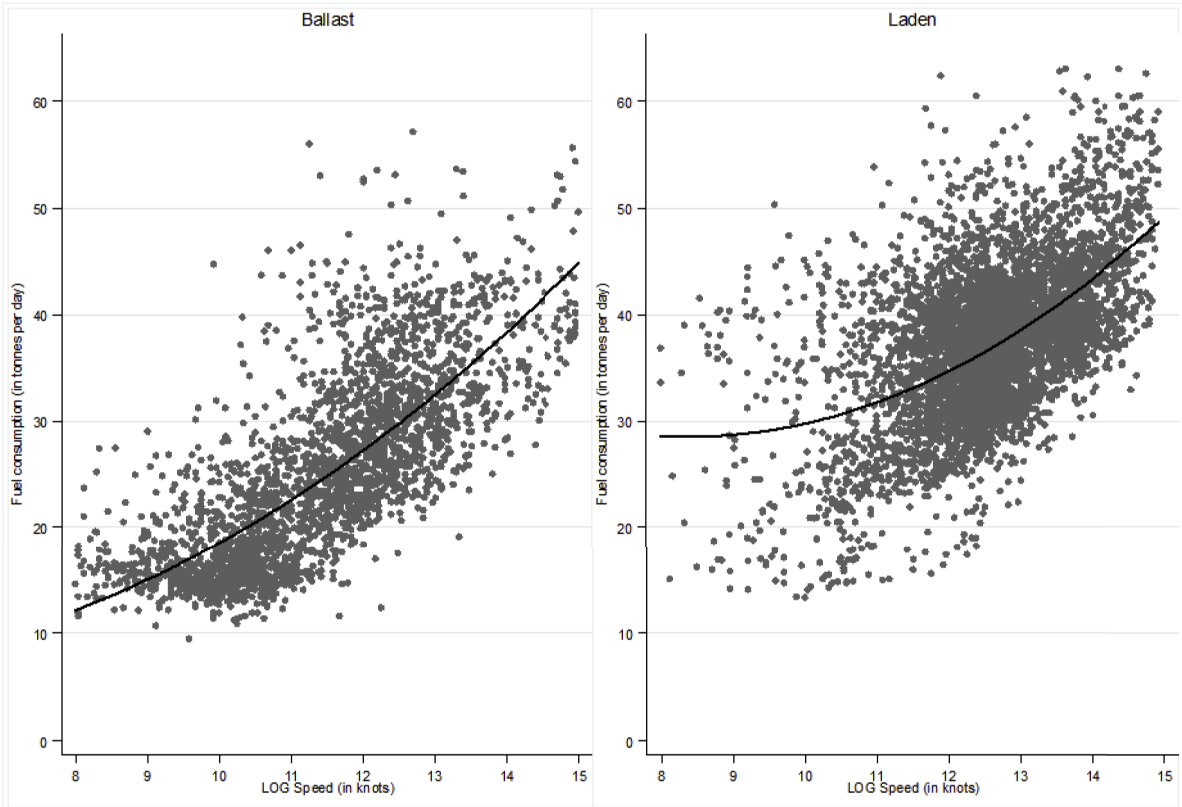
individual ships ranges between 34.8 tonnes (vessel 7) and 41.9 tonnes (vessel 3). In ballast, the average fuel consumption ranges between 23.6 tonnes (vessel 7) and 26.8 tonnes (vessel 8). For sister ships with identical technical designs, such differences in average fuel consumption will relate mainly to differences in the speed profile and external operating environment.

The relationship between fuel consumption and LOG speed is presented in Fig. 3. A simple quadratic functional form suggests the existence of a convex profile. In idealized 'flat water' conditions, the theoretical relationship is typically given as $C = B*(v)^n$, where C is the fuel consumption, v is the sailing speed (expressed in knots) and B and n are vessel-specific parameters (Manning, 1956). However, the vessel's actual fuel consumption at sea is expected to depend on many other parameters such as loading condition and weather conditions. As these factors are not taken into account in the bivariate analysis, this explains the heterogeneity in fuel consumption at a given speed observed in Fig. 3.

Table 1 presents some descriptive statistics on the covariates used for the empirical analysis to explain fuel consumption. A first set of variables includes speed (in knots), average draft (in meters), and trim (in meters) defined as the difference between draft forward and draft aft. From a theoretical point of view, a vessel that is deeper in the water will have increased resistance and therefore higher fuel consumption, all else equal (MAN Diesel and Turbo, 2004). The second set of controls refers to weather conditions. The influence of wind direction (head, astern, side), wind force (gentle breeze or less, moderate breeze, fresh breeze, strong breeze, near gale), and swell type (low or less, light, moderate, moderate rough, rough or high) are considered. Results show that there are large differences both in fuel consumption, speed and weather conditions between laden and ballast conditions. For instance, the average level of fuel consumption is 37.3 tonnes in laden and 25.1 tonnes in ballast. Vessels operate at higher speed in laden than in ballast (12.6 *versus* 11.4 knots).

As preliminary evidence, regressions explaining the logarithm of fuel consumption as a function of the logarithm of speed, draft, weather conditions and vessel fixed effects (with robust standard errors) were estimated. According to estimates reported in Table 2, all coefficients are highly significant and results are broadly in line with expectations. Specifically, fuel consumption is strongly increasing with speed. When accounting for the entire range of operating speeds (ballast and laden condition), the elasticity between speed and fuel consumption is equal to 1.72 (column 1). This elasticity is much lower than the coefficient of 3 suggested by Psaraftis and Kontovas (2013), though the latter is generally taken to hold for tankers and bulk carriers sailing at a speed close to their design speed and in idealized calm-water conditions. Accounting for speed, average draft and trim explains 69.9% of variations in fuel consumption.

In column 2 of Table 2, weather conditions are taken into account. This leads to an increase in the R^2 of 7.5 percentage points (from 0.699 to 0.774). As expected, the coefficients associated to wind direction are positive for head wind (+4.1% with $\exp(0.040) - 1 = 0.041$) and negative for wind from astern (−7.3% with $\exp(-0.076) - 1 = -0.073$), respectively. Fuel consumption increases both with wind force and swell. For instance, the



Source: data from a maritime company, authors' calculations.

Fig. 3. Fuel consumption and vessel speed.

Table 1
Descriptive statistics of the sample.

Variables	(1) All	(2) Ballast	(3) Laden	(4) = (3)–(2)
Fuel consumption in tonnes per day (log)	3.450	3.161	3.598	0.437***
LOG speed in knots (log)	2.493	2.427	2.527	0.100***
Average draft in meters (log)	2.408	2.092	2.571	0.479***
Negative trim in meters (draft forward − draft aft)	0.268	0.692	0.050	−0.642***
Wind face	0.518	0.552	0.499	−0.053***
Wind side	0.144	0.158	0.138	−0.020**
Wind back	0.338	0.289	0.363	0.074***
Wind force: Gentle breeze or less (less than 10 knots)	0.283	0.316	0.266	−0.050***
Wind force: Moderate breeze (11–16 knots)	0.281	0.279	0.282	0.003
Wind force: Fresh breeze (17–21 knots)	0.163	0.154	0.167	0.013
Wind force: Strong breeze (22–27 knots)	0.092	0.075	0.100	0.025***
Wind force: Near gale (≥28 knots)	0.023	0.016	0.027	0.011***
Swell type: Low or less (no swell or short/long and low wave	0.283	0.305	0.272	−0.033***
Swell type: Light (short and moderate wave)	0.249	0.256	0.246	−0.010
Swell type: Moderate (average and moderate wave)	0.198	0.186	0.205	0.019*
Swell type: Moderate rough (long and moderate wave)	0.069	0.063	0.073	0.010
Swell type: Rough or high (short/average and heavy wave)	0.041	0.029	0.047	0.018***
Number of observations	7868	2671	5197	

Source: data from a maritime company, authors' calculations.
Note: (4) reports results from mean-comparison tests. Significance levels are 1% (***), 5% (**) and 10% (***).

consumption is higher by 14.2% with moderate rough swell and 24.5% with rough or high swell.

As shown in columns 3 and 4 of Table 2, there are significant differences in the estimates across loading conditions, with a much higher speed-consumption elasticity for vessels in ballast (2.14) than in the laden condition (1.45). Conversely, the draft-consumption elasticity is higher for vessels in the laden condition (0.425) than in ballast (0.168). As expected, vessels in ballast are systematically more sensitive to wind conditions than a laden vessel. For instance, fuel consumption increases by 17.1% with wind near gale when the vessel is in ballast, but only 7.4% when it is laden. This can be explained both by the larger area exposed to wind and the lower displacement of a vessel in ballast. Overall, the R^2 is much higher for vessels in ballast (73.1%) than in the laden condition (57.1%).

A unique feature of the dataset is that the exact timing of

Table 2
Estimates of fuel consumption (in tonnes per day).

Variables	(1) All	(2) All	(3) Ballast	(4) Laden
LOG speed in knots (log)	1.717*** (54.07)	1.841*** (67.86)	2.144*** (64.55)	1.452*** (43.14)
Average draft in meters (log)	0.457*** (18.89)	0.404*** (17.82)	0.168*** (2.66)	0.425*** (19.30)
Trim in meters (draft forward − draft aft)	−0.043*** (−4.04)	−0.066*** (−6.76)	−0.110*** (−7.69)	−0.019* (−1.72)
Wind face (ref: wind side)		0.040*** (6.95)	0.048*** (4.40)	0.039*** (6.82)
Wind back		−0.076*** (−12.75)	−0.105*** (−8.87)	−0.061*** (−10.27)
Wind force: Moderate breeze (ref: gentle breeze or less (less than 10 knots))		0.011** (2.38)	0.038*** (4.05)	0.001 (0.24)
Wind force: Fresh breeze (17–21 knots)		0.034*** (5.59)	0.081*** (6.20)	0.011* (1.70)
Wind force: Strong breeze (22–27 knots)		0.066*** (7.65)	0.133*** (6.93)	0.029*** (3.34)
Wind force: Near gale (≥28 knots)		0.113*** (5.92)	0.158*** (4.27)	0.071*** (3.55)
Swell type: Light (short and moderate wave) (ref: low or less (no swell or short/long and low wave))		−0.007 (−1.53)	0.001 (0.09)	−0.011** (−2.12)
Swell type: Moderate (average and moderate wave)		0.056*** (9.77)	0.063*** (5.31)	0.050*** (8.31)
Swell type: Moderate rough (long and moderate wave)		0.133*** (13.72)	0.150*** (7.48)	0.118*** (12.26)
Swell type: Rough or high (short/average and heavy wave)		0.219*** (15.11)	0.281*** (9.92)	0.190*** (13.14)
Constant	−1.955*** (−30.62)	−2.164*** (−39.81)	−2.419*** (−18.86)	−1.221*** (−11.85)
Vessel fixed effects	YES	YES	YES	YES
Number of observations	7868	7868	2671	5197
R-squared	0.699	0.774	0.731	0.571

Source: data from a maritime company, authors' calculations.
Note: estimates from OLS regressions with robust standard errors. Significance levels are 1% (***), 5% (**) and 10% (***).

maintenance operations for each vessel is known. In Table 3, the dates of delivery, underwater cleaning and dry-docking for each vessel are provided. While all vessels have been subject to dry-docking (essentially in 2015 except for vessel 3 which was dry-docked in December 2014), there are variations in the number of underwater cleaning operations. One vessel (vessel 2) has been subject to one cleaning, two vessels have experienced two underwater cleaning operations (vessels 3 and 5), and the five other vessels have been cleaned three times. Section 4 presents the econometric strategy to investigate the causal effect of hull cleaning on fuel consumption.

4. Econometric framework

The change in fuel consumption around the discontinuity when a vessel is cleaned is estimated using regression estimators of the causal effect of a change in hull condition. The overall effect of cleaning operations (whatever their type) on the whole set of treated vessels is investigated first and a distinction is then made between underwater cleaning and dry-docking operations. Given that dry-docking entails a thorough hull cleaning and renewal of the antifouling paint, thus bringing the hull closer to its 'as new' condition, the *a priori* expectation is that dry-docking will have a greater impact on energy efficiency than underwater hull cleaning.

Table 3
Timing of cleaning operations.

Vessel	Delivery date	Underwater cleaning	Dry-docking
Vessel 1	02.2011	06.03.2014	24.10.2015–07.11.2015
		21.10.2014	
		26.03.2015	
Vessel 2	07.2010	05.02.2014	01.05.2015-16.05-2015
Vessel 3	01.2010	04.05.2012	20.11.2014–03.12.2014
		25.01.2013	
		19.01.2014	
Vessel 4	11.2010	25.10.2012	19.10.2015–02.11.2015
		20.04.2015	
Vessel 5	04.2011	22.05.2012	07.11.2015–19.11.2015
		03.02.2015	
Vessel 6	05.2010	15.02.2013	16.03.2015–04.04.2015
		07.09.2013	
		18.01.2014	
Vessel 7	09.2010	05.13.2012	11.08.2015–27.08.2015
		27.06.2013	
		25.10.2014	
Vessel 8	03.2010	23.10.2012	24.02.2015–27.03.2015
		13.09.2013	
		31.10.2014	

Source: data from a maritime company, authors' calculations.

Let $\ln C_{vt}$ be the logarithm of fuel consumption for a given vessel v at date t, with $v = 1, \ldots, V$ and $t = 1, \ldots, T$. The time unit t is one day. Fuel consumption is expected to be influenced by a set of observable characteristics X_{vt} like speed, average draft, wind direction, wind force or swell type. Let $k(v)$ as subscript denote each cleaning operation, which can be either underwater cleaning $k(v) = UC$ or dry-docking $k(v) = DD$. Note that k depends on v since each cleaning operation (and its timing) is specific to each vessel. Each vessel undertakes a set of $K(v)$ cleaning operations with $k(v) = 1, \ldots, K(v)$. The conditions resulting from the cleaning operation $k(v)$ are observed during the period $t_{k(v)} \le t < t_{k(v)+1}$. Two different estimators are estimated to assess the change in fuel consumption around the set of discontinuities $t_{k(v)}$ with $k(v) = 1, \ldots, K(v)$ and $v = 1, \ldots, V$. Define a time window of w (days) before and after the cleaning operation $k(v)$ for vessel v and consider a before-after estimator that compares the level of fuel consumption before the cleaning operation $(t^{w^-}_{k(v)} \le t < t_{k(v)})$ and after the cleaning operation $(t_{k(v)} < t \le t^{w^+}_{k(v)})$, respectively, with $t^{w^-}_{k(v)} = t_{k(v)} - w$ and $t^{w^+}_{k(v)} = t_{k(v)} + w$. For illustration, Fig. 4 presents the situation of four fictitious vessels in panel A.

For instance, vessel 1 was subject to three cleaning operations (underwater cleaning twice and dry-docking once) while vessel 2 was subject to two cleaning operations (underwater cleaning once, dry docking once). For each vessel and for each operation, data comprised within each grey interval centered over $t_{k(v)}$ are selected. Let $\mathbb{1}^{AFTER_w}_{vt}$ be a dummy variable such that $\mathbb{1}^{AFTER_w}_{vt} = 1$ if $t_{k(v)} < t \le t^{w^+}_{k(v)}$ and $= 0$ if $t^{w^-}_{k(v)} \le t < t_{k(v)}$. Since the dependent variable is continuous, the determinants of fuel consumption can be estimated using Ordinary Least Squares applied to the dataset pooling the V vessels:

$$\ln C_{vt} = \delta_w * \mathbb{1}^{AFTER_w}_{vt} + X_{vt}\beta + \vartheta_v + \varepsilon_{vt} \quad (1)$$

where δ_w is the parameter associated with the before-after hull-cleaning estimator, β is the vector of coefficients associated with the explanatory variables X_{vt} (i.e. reported weather variables), ϑ_v is a

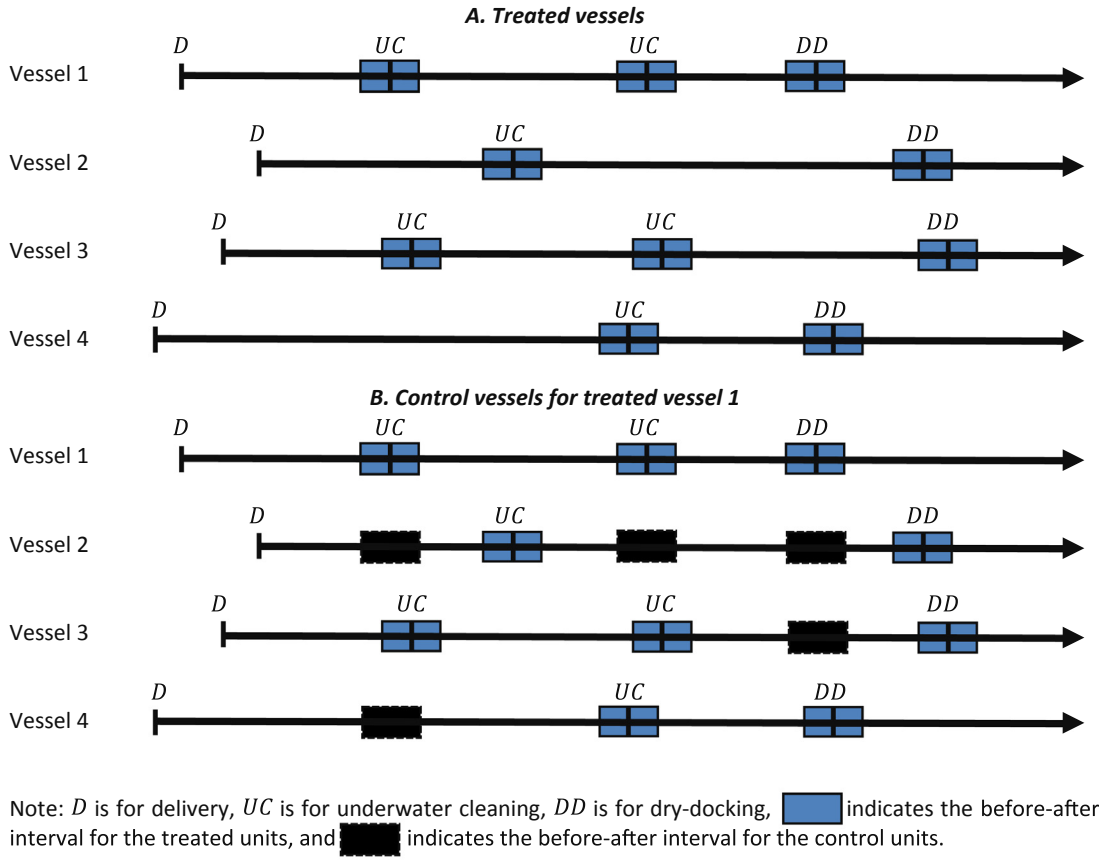


Fig. 4. Selection of data around the discontinuity: treated and control vessels Note: *D* is for delivery, *UC* is for underwater cleaning, *DD* is for dry-docking, indicates the before-after interval for the treated units, and indicates the before-after interval for the control units.

vessel fixed effect, and ε_{vt} is a residual perturbation such that $E(\varepsilon_{vt}) = 0$ and $V(\varepsilon_{vt}) = \sigma^2$. As the panel data is unbalanced (the date of delivery varies between vessels), the vessel fixed effect picks up unobserved characteristics of vessels which remain time-invariant over the period. For instance, the vessel fixed effects are expected to control for differences in operating conditions across the fleet that are not accounted for in our empirical model. In Equation (1), the evaluation of the cleaning operations is provided by the coefficient δ_w. The marginal effect of cleaning operations is given by $\exp(\widehat{\delta}_w) - 1$ with $\widehat{\delta}_w$ the estimated coefficient. The impact of the size of the time window w around the discontinuity is considered later as a robustness test.

It is straightforward to extend (1) in order to account for the possibility of a differentiated effect between underwater cleaning and dry-docking by using two dummy variables $\mathbb{I}_{vt}^{AFTER_w^{UC}}$ and $\mathbb{I}_{vt}^{AFTER_w^{DD}}$ such that $\mathbb{I}_{vt}^{AFTER_w^{UC}} = 1$ in the period of length w just after an underwater cleaning and $\mathbb{I}_{vt}^{AFTER_w^{DD}}$ has a similar interpretation after dry-docking. The regression model is now:

$$\ln C_{vt} = \delta_w^{UC} * \mathbb{I}_{vt}^{AFTER_w^{UC}} + \delta_w^{DD} * \mathbb{I}_{vt}^{AFTER_w^{DD}} + X_{vt}\theta + \vartheta_v + \varepsilon_{vt} \tag{2}$$

where δ_w^{UC} and δ_w^{DD} provide estimates of the effect of underwater cleaning and dry-docking at the discontinuity, respectively. The Wald test is used to assess the null hypothesis $H_0 : \delta_w^{UC} = \delta_w^{DD}$ corresponding to a similar impact of underwater cleaning and dry-docking on fuel consumption. As the hull condition may deteriorate over time even in the short-time interval $[t_{k(v)}^{w^-}; t_{k(v)}^{w^+}]$, regressions (1) and (2) were further extended by adding a linear time trend with different linear slopes on the left and on the right of the discontinuity. Alternative quadratic and cubic specifications for the time trend were also considered (not shown here), with no influence on the results. The causal impact of hull cleaning corresponds to the variation in fuel consumption at the discontinuity and is here measured as a deviation from the time trends.

The second empirical strategy is based on a difference-in-differences estimator. In the before-after framework described before, the set of treated vessels is selected in the sense that within each interval $[t_{k(v)}^{w^-}; t_{k(v)}^{w^+}]$ each vessel has undergone a cleaning operation. Treated vessels are compared with control vessels. By definition, the counterfactual of treated vessels corresponds to the case of vessels selected during the same period of time and being similar to treated vessels, except that they have not been subject to any cleaning operation during the period.

To construct the control group, the treated group which includes all observations over each interval $[t_{k(v)}^{w^-}; t_{k(v)}^{w^+}]$ for each vessel is defined first. Then, for each vessel v and for each interval $[t_{k(v)}^{w^-}; t_{k(v)}^{w^+}]$, the control group is defined as all vessels that have not been cleaned during this specific interval. By construction, a vessel can be both in the treated and in the control groups, but never during the same time interval. If vessel i is treated during the interval $[t_{k(i)}^{w^-}; t_{k(i)}^{w^+}]$, then control vessels may be any vessels such that $v \neq i$. But if i is not cleaned during the interval $[t_{k(j)}^{w^-}; t_{k(j)}^{w^+}]$ associated to a vessel j, then i will be in the control group associated to vessel j

during that specific period. Note that the control vessels perfectly match the definition of a counterfactual. First, they are observed over the same period as treated vessels but have not been subject to any cleaning operation. Second, the sample is made of sister ships, identical in size and power. Operating conditions like weather or draft may vary, but this is taken into account in the various regressions. Finally, for each control vessel and for each interval, a fictitious shock is imposed, occurring at date $t_{k(v)}$. This is the exact date at which the treated vessel v has been cleaned within the time span $[t^{w^-}_{k(v)}; t^{w^+}_{k(v)}]$.

Panel B of Fig. 4 schematically presents the construction of the control group for one treated unit. Consider the case of vessel 1. When its first underwater cleaning is done, only vessels 2 and 3 were not cleaned during the before-after interval associated to vessel 1. This means that for this first hull cleaning, there will be two control units (vessels 2 and 3) associated to vessel 1. For the second underwater cleaning of vessel 1, there is only one control vessel which is vessel 2. Finally, for the dry-docking operation of vessel 1, vessels 2 and 3 define the group of controls, while vessel 4 cannot be selected as control because it was subject to hull cleaning during that period. Overall, there are 5 control intervals associated to the 3 treated intervals for vessel 1. In a similar vein, there will be 5 control intervals for the 2 treated intervals for vessel 2, 5 control intervals for the 3 treated intervals for vessel 3, and 3 control intervals for the 2 treated intervals for vessel 4. Vessels 1, 3 and 4 are control units for the first underwater cleaning of vessel 2, and vessels 1 and 4 are control units for the dry-docking operation of vessel 2.

The difference-in-differences estimator at the discontinuity is then estimated following Gobillon and Wolff (2017). The treatment effect is defined as the difference-in-differences in fuel consumption between treated and control vessels. Let $\mathbb{T}_{vt}$ be a dummy variable such that $\mathbb{T}_{vt} = 1$ for the treated vessels and $\mathbb{T}_{vt} = 0$ for the control vessels. The corresponding model is:

$$\ln C_{vt} = \gamma_w \mathbb{T}_{vt} + \delta_w * \mathbb{I}^{AFTER_w}_{vt} + \theta_w \mathbb{I}^{AFTER_w}_{vt} \mathbb{T}_{vt} + X_{vt}\beta + \vartheta_v + \varepsilon_{vt} \quad (3)$$

In (3), the parameter of interest θ_w indicates the causal effect of the cleaning operations when comparing the situation of treated vessels (which have been cleaned during the selected intervals) to that of control vessels (which have not been cleaned over the same intervals). Even though the regression includes a set of vessel fixed effects ϑ_v, the coefficient γ_w associated to the treatment dummy $\mathbb{T}_{vt}$ is identified because a given vessel may be both (but never simultaneously) a treated unit when it is cleaned and a control unit when it is not cleaned.

As in the before-after estimation strategy, it is possible to assess the respective impact of underwater cleaning and dry-docking. The difference-in-differences specification (3) will then be adjusted by introducing cleaning-specific dummies $\mathbb{I}^{AFTER^{UC}_w}_{vt}$ and $\mathbb{I}^{AFTER^{DD}_w}_{vt}$ as well as cleaning-specific interaction terms $\mathbb{I}^{AFTER^{UC}_w}_{vt} \mathbb{T}_{vt}$ and $\mathbb{I}^{AFTER^{DD}_w}_{vt} \mathbb{T}_{vt}$. If the null hypothesis of equal coefficients associated to $\mathbb{I}^{AFTER^{UC}_w}_{vt} \mathbb{T}_{vt}$ and $\mathbb{I}^{AFTER^{DD}_w}_{vt} \mathbb{T}_{vt}$ is rejected, then this means that the causal effects of underwater cleaning and dry-docking on fuel consumption are significantly different.

5. Results

The effect of hull cleaning on fuel consumption is first assessed based on an assumed time window of 45 observations before and after each cleaning operation $(w = 45)$. The results from the before-after estimator given by (1) are presented in Table 4. The difference between panel A1 and panel A2 is the introduction of a linear time trend in A2, allowing the coefficient to differ between the left and right sides of the discontinuity. When considering only speed, average draft, trim and vessel fixed effects as controls (column 1), each cleaning operation leads to an average and significant decrease of 11.7% in fuel consumption ($\exp(-0.124) - 1 = -0.117$).

The inclusion of weather conditions improves the R^2 of the model by 7.6 percentage points, from 75.1% to 82.7% (column 2). However, this has very little influence on the marginal effect of the various cleaning operations which is equal to −11.0%. Also, there is no clear difference between the ballast and laden conditions

Table 4
Estimates of cleaning operations on fuel consumption at the discontinuity (time windows = 45 observations before and after).

Variables	(1) All	(2) All	(3) Ballast	(4) Laden
Panel A1. Any cleaning – no time trend				
Cleaning	−0.124*** (−17.65)	−0.116*** (−19.76)	−0.102*** (−8.41)	−0.119*** (−18.69)
Weather	NO	YES	YES	YES
Number of observations	2520	2520	842	1678
R-squared	0.751	0.827	0.772	0.685
Panel A2. Any cleaning – linear time trend				
Cleaning	−0.107*** (−9.61)	−0.106*** (−11.45)	−0.079*** (−4.58)	−0.128*** (−11.89)
Weather	NO	YES	YES	YES
Number of observations	2520	2520	842	1678
R-squared	0.751	0.827	0.776	0.686
Panel B1. Underwater cleaning versus dry-docking – no time trend				
Underwater cleaning	−0.106*** (−14.39)	−0.093*** (−15.34)	−0.069*** (−5.59)	−0.107*** (−15.86)
Dry-docking	−0.176*** (−15.62)	−0.183*** (−19.78)	−0.176*** (−10.04)	−0.162*** (−16.29)
Weather	NO	YES	YES	YES
Test: underwater cleaning = dry-docking	F = 37.8; p = .000	F = 97.1; p = .000	F = 42.3; p = .000	F = 29.6; p = .000
Number of observations	2520	2520	842	1678
R-squared	0.755	0.833	0.783	0.689
Panel B2. Underwater cleaning versus dry-docking – linear time trend				
Underwater cleaning	−0.089*** (−7.89)	−0.084*** (−8.94)	−0.045** (−2.57)	−0.117*** (−10.76)
Dry-docking	−0.158*** (−11.28)	−0.174*** (−15.03)	−0.148*** (−7.08)	−0.171*** (−12.68)
Weather	NO	YES	YES	YES
Test: underwater cleaning = dry-docking	F = 37.6; p = .000	F = 97.1; p = .000	F = 37.4; p = .000	F = 28.1; p = .000
Number of observations	2520	2520	842	1678
R-squared	0.755	0.834	0.786	0.690

Source: data from a maritime company, authors' calculations.

(columns 3 and 4). The marginal effect of cleaning on fuel consumption is lower for laden vessels (−9.7%) than in ballast (−11.2%), which can be explained by the larger submerged area in the laden condition. Accounting for a linear time trend does not change the magnitude of our estimates, with each cleaning operation leading to a decrease in fuel consumption of around 10% (panel A2).

Panels B1 and B2 illustrate the important distinction between underwater hull cleaning and dry-docking as per Equation (2). As shown in column 1 of panel B1, underwater cleaning leads to a reduction in fuel consumption of 10.1% while dry-docking leads to a reduction of 16.1% (which is approximately 60% higher). A Wald test confirms that the estimates are significantly different. This is consistent with our *a priori* expectation, as the hull is completely cleaned and re-coated when in dry-dock, while under-water cleaning is a challenging process that can sometimes remove part of the coating and lead to unsuccessful cleaning (Kovanen, 2012).

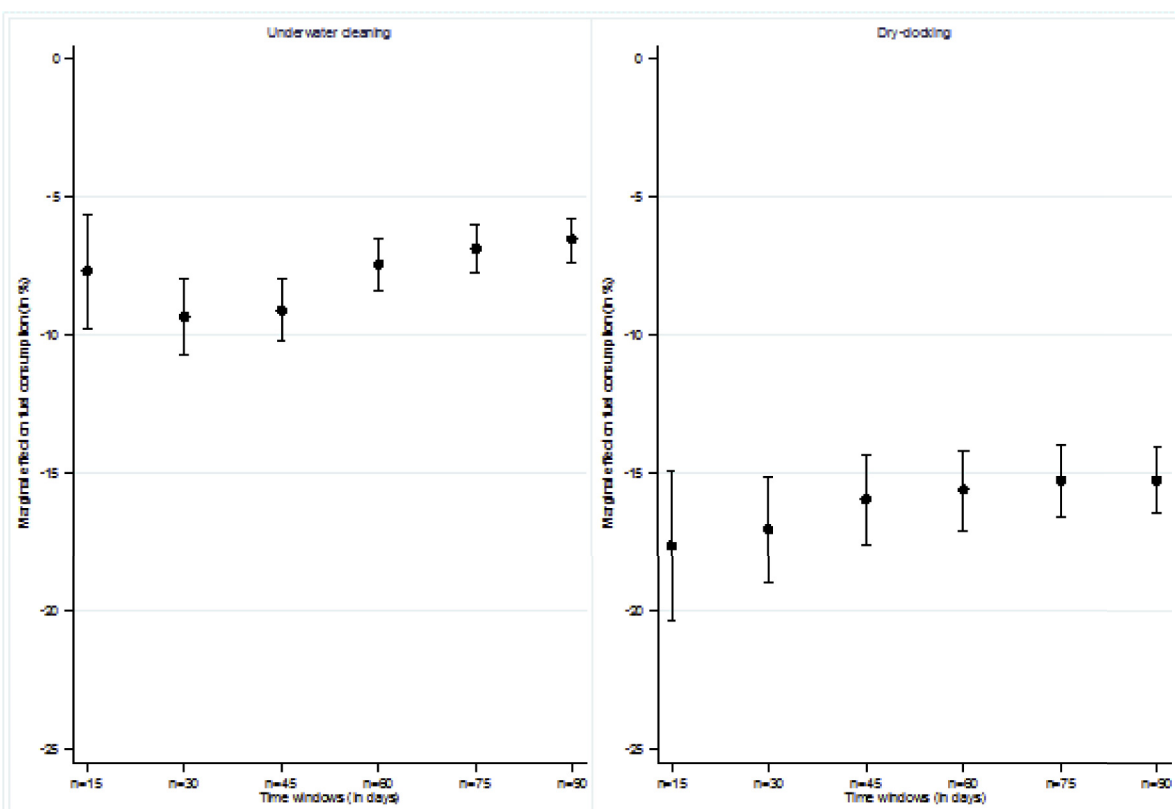
Adding weather conditions as covariates does not affect our findings. Dry-docking is more effective than underwater cleaning in terms of fuel reduction, 16.7% against 8.9% (column 2). Interestingly, the reduction in fuel consumption due to underwater cleaning is larger (in absolute value) when a vessel is laden (−10.1%) than when in ballast (−6.7%), while the effect of dry-docking remains very similar in both cases (−16.1% in ballast, −15.0% when laden). The results are not affected when a linear time trend is considered in our regressions, as shown in panel B2.

To summarize, the before-after estimator shows that hull cleaning has a causal negative effect on fuel consumption. An important question is to what extent results are sensitive to the time window w. As time goes by, a deterioration in the hull condition can be expected so that the level of fuel consumption should progressively increase. Fig. 5 presents the marginal effect of the two types of cleaning operations based on equation (2) and different values for w (15, 30, 45, 60, 75, 90).

For underwater cleaning, the impact in terms of fuel consumption ranges between −6.5% and −9.6% depending on the value of w. The largest marginal effects are found for $w = 30$ and $w = 45$. With longer time windows, the decrease in fuel consumption becomes smaller in magnitude to around 7% for $w = 75$ and $w = 90$. The profile obtained for dry-docking is slightly different, with a continuously decreasing marginal effect (in absolute value) as the time window expands. Overall, the marginal effect from dry-docking ranges between −17.6% and −15.3%.

Next, the difference-in-differences estimator corresponding to equation (3) is used to assess the causal effect of cleaning operations at the discontinuity. Similar conclusions as for the before-after estimator can be drawn. As shown in column 1 of Table 5, the interaction terms crossing being a treated vessel by the cleaning operations is negative and statistically significant. The decrease in fuel consumption is around 12% lower for treated vessels compared to control vessels. In addition, the insignificance of the cleaning dummy and the positive coefficient for treated vessels suggests that it was appropriate to clean those vessels as they were consuming more, on average, compared to the control vessels.

Accounting for weather conditions tends to slightly reduce (in



Source: data from a maritime company, authors' calculations.

Fig. 5. Estimates of cleaning operations on fuel consumption at the discontinuity: sensitivity to time windows. Note: the marginal effect of fuel consumption and the associated 95% confidence interval is obtained from an OLS regression with robust standards errors. For each of the time windows, the regression includes the following control variables: LOG speed, average draft, trim, wind direction (face, back), wind force (moderate breeze, fresh breeze, strong breeze, near gale), swell type (light, moderate, moderate rough, rough or high), and vessel fixed effects.

Table 5
Difference-in-differences estimates of cleaning operations on fuel consumption at the discontinuity (time windows = 45 observations before and after).

Variables	(1) All	(2) All	(3) Ballast	(4) Laden
Panel A. Any cleaning − no time trend				
Cleaning	0.000 (0.01)	−0.012** (-2.55)	−0.047*** (-5.17)	0.010* (1.83)
Treated	0.042*** (6.91)	0.019*** (3.37)	−0.015 (-1.33)	0.035*** (5.62)
Cleaning x Treated	−0.127*** (-14.70)	−0.106*** (-14.00)	−0.056*** (-3.69)	−0.132*** (-15.66)
Weather	NO	YES	YES	YES
Number of observations	6563	6563	2244	4319
R-squared	0.735	0.798	0.764	0.611
Panel B. Underwater cleaning versus dry-docking − no time trend				
Underwater cleaning	0.000 (0.03)	−0.012** (-2.36)	−0.054*** (-5.76)	0.013** (2.28)
Dry-docking	−0.001 (-0.07)	−0.016* (-1.77)	0.004 (0.16)	−0.007 (-0.91)
Treated	0.042*** (6.90)	0.018*** (3.27)	−0.015 (-1.33)	0.035*** (5.62)
Underwater cleaning x Treated	−0.106*** (-11.56)	−0.083*** (-10.47)	−0.017 (-1.10)	−0.121*** (-13.38)
Dry-docking x Treated	−0.181*** (-12.35)	−0.163*** (-12.63)	−0.166*** (-5.62)	−0.160*** (-13.06)
Weather	NO	YES	YES	YES
Number of observations	6563	6563	2244	4319
R-squared	0.737	0.801	0.768	0.614

Source: data from a maritime company, authors' calculations.

absolute value) the estimate associated to the interaction term, but the marginal effect remains high at −10.0% (column 2). Furthermore, the reduction in fuel consumption is more pronounced when the vessel is laden (column 4) than in ballast (column 3). For panel B, where a distinction is made between the two types of hull cleaning, the reduction in fuel consumption following under-water hull cleaning is significantly lower than that following dry-docking. When controlling for weather conditions (column 2), the marginal effect associated to the interaction term is equal to −8.0% for underwater cleaning and −15.0% for dry-docking. The largest effect of underwater cleaning is observed for laden vessels, while the reduction in fuel consumption is very similar for both loading conditions following a dry-docking.

As the comparison is done for vessels just before and after cleaning, the results have a clear causal interpretation. Nonetheless, a simple falsification exercise can be set up as follows to confirm that the decrease in fuel consumption is the result of hull cleaning. First, the reduction in fuel consumption after any cleaning operations is calculated using the before-after estimator given by equation (1). Second, a fictitious cleaning operation is set at a random date and the same before-after estimator is applied using a time window $w = 45$. The procedure is repeated 1000 times and the simulated results are compared to the decrease in fuel consumption obtained from the real cleaning operations.

The simulation results are presented in Fig. 6 for three different cases: all observations, ballast and laden. The density curve corresponds to the density of the point estimates of 1000 fictitious cleaning operations per vessel. The vertical line corresponds to the point estimate of the cleaning operations which is reported in panel A1 of Table 4. When considering both ballast and laden observations, the point estimate is equal to −11.0%, with a confidence interval ranging from −13.2% to −8.8%. Clearly, this real effect is very different from that obtained from fictitious cleaning operations. By comparison, the average point estimate of the fictitious operations is equal to 0.002, with a standard deviation of 0.086. Very similar results are found for the ballast and laden conditions. As shown in Fig. 6, the real effect of the cleaning operation is always located in the left part of the distribution of the fictitious effects. To summarize, this falsification exercise confirms that the reduction in fuel consumption is indeed caused by the cleaning of the hull.

6. Concluding comments

This paper proposes a new methodology to evaluate the energy efficiency impact from periodic ship hull cleaning operations, by comparing fuel consumption around the discontinuity when the vessel is cleaned. The procedure to estimate the reduction in the daily fuel consumption attributable to hull cleaning operations is implemented using both a before-after estimator and a difference-in-differences estimator. The regressions account for a large set of explanatory variables, including speed and draft as well as weather conditions. The method has the advantage of being easily replicable and purely data driven, compared to costly physical model tests or large Computational Fluid Dynamics simulations.

All empirical results are in line with *a priori* expectations. First, periodic hull cleaning leads to a significant reduction in the daily fuel consumption of a vessel. Second, dry-docking leads to greater (and significantly different) reductions in fuel consumption than basic underwater hull cleaning, approximately −17% *versus* −9%. Third, the impact of the hull cleaning operation on energy efficiency is generally greater when the vessel is subsequently sailing laden rather than in the ballast condition. The robustness of these results is confirmed by the fact that empirical estimates are very similar for both estimators. Furthermore, a falsification simulation exercise confirm that the reduction in fuel consumption is indeed caused by the cleaning operations.

The results are important for practitioners and policy makers alike, as they confirm the importance of hull cleaning as a key operational measure to improve energy efficiency and reduce fuel costs and emissions in international shipping. Specifically, estimates are well aligned with the assumptions in recent policy reports such as the third IMO GHG study (IMO, 2015), where the bottom-up analysis of the world fleet is based on an average 9% energy efficiency loss over time due to hull fouling. For ship owners and operators, the findings that hull cleaning leads to an immediate fuel saving of around 9%, equivalent to around 3 tonnes of fuel per day valued at nearly $1000/day, can assist in the evaluation of optimal hull maintenance procedures.

In this context, the focus of this paper was to provide an ex-post evaluation of the energy efficiency impact of periodic hull cleaning operations, and not to investigate whether the observed maintenance operations were optimal or what an optimal hull cleaning policy would look like. This research question leads to some interesting challenges for future research.

First, the timing of cleaning operations is potentially endogenous. Underwater hull cleaning can only be performed when the vessel is in a port that allows hull cleaning and stationary for a sufficient length of time. This means that in reality there are only a few discrete points in time, depending on the trading pattern of the vessel, where such maintenance operations may take place.

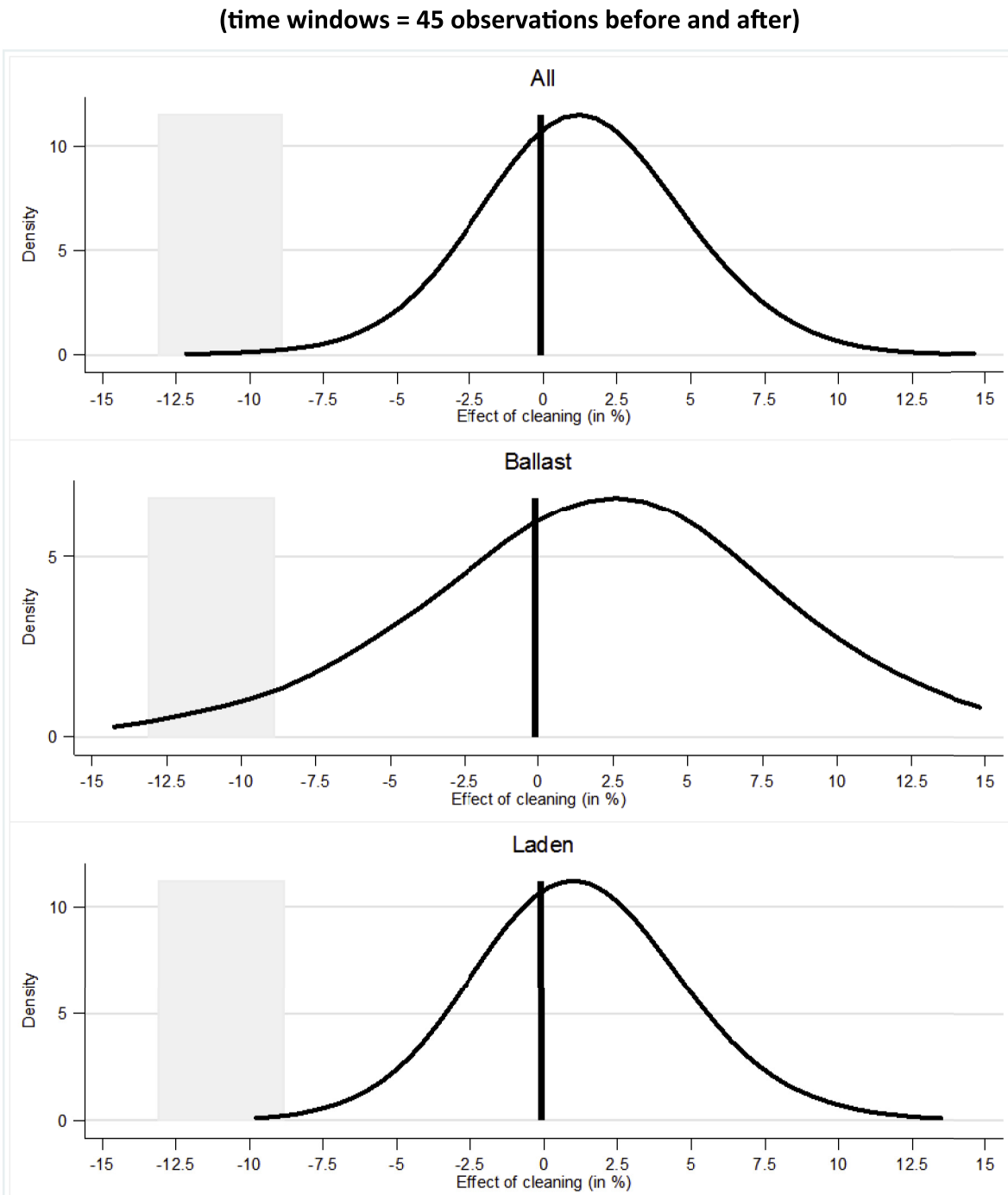


Fig. 6. Estimates of fictitious cleaning operations on fuel consumption at the discontinuity. Note: the vertical line corresponds to the point estimate of the cleaning operations as found in panel A1 of Table 4. The density curve corresponds to the density of the point estimates of 1000 fictitious cleaning operations. The true and the fictitious point estimates are estimated at the discontinuity with a time windows of 45 observations before and after the cleaning operation.

Second, there is a path dependency connecting the trading of the vessel and the rate of hull fouling as well as the impact of cleaning. For example, a vessel sailing primarily in high-temperature areas, at slow speeds and with long periods of idleness will have a higher rate of fouling per time unit, and therefore also a greater energy efficiency impact once cleaning occurs. These interesting problems of hull cleaning procedure optimization should be investigated in future work.

Note: estimates from OLS regressions with robust standard errors. Significance levels are 1% (***), 5% (**) and 10% (***). Each regression includes the following control variables: LOG speed, average draft, trim, wind direction (face, back), wind force (moderate breeze, fresh breeze, strong breeze, near gale), swell type (light, moderate, moderate rough, rough or high), and vessel fixed effects.

Note: estimates from OLS regressions with robust standard

errors. Significance levels are 1% (***), 5% (**) and 10% (***). Each regression includes the following control variables: LOG speed, average draft, trim, wind direction (face, back), wind force (moderate breeze, fresh breeze, strong breeze, near gale), swell type (light, moderate, moderate rough, rough or high), and vessel fixed effects.

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