Estimating vessel payloads in bulk shipping using AIS data

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Abstract: The cargo payload of a merchant vessel is a crucial variable in calculating revenue for a particular voyage and estimating global trade flows for key commodities. However, due to the opaque nature of the industry, payload information is usually not publicly available. This research utilises, for the first time, vessel draught information reported by the automatic identification system (AIS) to estimate vessel payloads. The applicability and reliability of draught measurements from AIS captured via satellites and terrestrial receivers are addressed in the process of identifying the most efficacious way to estimate vessel payloads. The performance of estimating vessel payloads using AIS draught data is compared to two models that rely on principles from physics and naval architecture, and the results show similarity and consistency. Being able to reliably estimate a vessel's payload is essential in assessing vessel utilisation, fleet productivity, and subsequently the supply and demand conditions in shipping markets.

Keywords: automatic identification system; AIS; cargo payload; draught; capacity utilisation; maritime big data; bulk shipping; line-up reports; trade flow; commodity; satellite; naval architecture.

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1 Introduction

The cargo size or payload of a merchant vessel is a crucial variable in many aspects of shipping. At the micro level it determines, together with the freight rate, the revenue and earnings for a particular voyage. In port management it influences the loading and discharging times of vessels and, thus, berth scheduling and cargo handling equipment usage. For terminal operations (e.g., oil storage tanks) it is important to know whether there is sufficient onshore capacity to cater to volumes on inbound vessels. At the macro level, payloads influence the magnitude of international trade flows for key industrial commodities such as coal, iron ore and crude oil. Yet, despite its importance, global, comprehensive and accurate figures for the payloads of ships on individual voyages are in practice impossible to come by. This is mainly due to the opaque nature of the industry, where the official payload as noted on the ‘bill of lading’ is usually not publicly available or disseminated according to any international standard (a notable exception is the US Customs Agency which makes bill of lading data for US imports available to third-party publishing companies). The idea of using bill of lading data is not new, and has been applied in the estimation of the trade balance on a particular shipping route (Deakin and Seward, 1973). Due to the difficulty in obtaining real payload data, the maritime literature has typically had to make simplifying assumptions such as constant deadweight tonnage (DWT) utilisation in percentage terms (Adland and Strandenes, 2007) or using information contained in fixtures as a proxy (Alizadeh and Talley, 2011a, 2011b). Both are likely to be inaccurate. Firstly, the relationship between cargo size and total carrying capacity (DWT) is not constant with regards to increasing vessel size (e.g., because fuel and fresh water needs do not increase proportionately with size). Secondly, public fixture information is incomplete and the corresponding cargo sizes are estimates only, with the final number known only after the completion of loading.

In this paper, we show how reported vessel draught measurements from the global automatic identification system (AIS) can be used as a basis for the estimation of payload. AIS was originally designed for the purpose of collision avoidance, requiring vessels over 300 GT to broadcast messages containing information on vessel identity and location at high frequency. The large volume of high-frequency AIS data currently available for tracking the world fleet using satellites and terrestrial receivers offers great and largely untapped potential for the monitoring of global trade flows on a real-time basis. As a result, the academic research community recently has shown growing interests in applying AIS data in various research areas. For instance, in the third IMO GHG study, Smith et al. (2014) use AIS data to track global fleet emissions. Adland and Jia (2016) use AIS data to investigate dynamic speed choice in the drybulk segment. Jia et al. (2017a) propose an automatic algorithm to generate seaborne transport pattern maps based on AIS. Adland et al. (2017a) estimate crude oil export volume using vessel tracking AIS data. Adland et al. (2017b) and Jia et al. (2017b) use AIS data to investigate the impact of environmental and port policy.

The contributions of our paper are threefold. First, we pioneer in proposing the use of AIS draught information in estimating cargo payload. In combination with our unique dataset on port calls from ship agents, we are able to verify the AIS messages before incorporating the reported draught information, together with other vessel and voyage specific information, to estimate cargo payload. Secondly, the effectiveness of real-world draught in estimating cargo payload is evaluated in a multi-factor regression framework and the performance of the model is compared to models that are based on the principles of naval architecture. Thirdly, in performing these comparisons we evaluate the reliability of the AIS-reported draught measurements and do so as an extension to the literature on AIS data quality (Banyś et al., 2012; Harati-Mokhtari et al., 2007; Tsou, 2010) by utilising both terrestrial and satellite AIS data.

2 Literature review

A merchant vessel's primary function is to transport cargo from A to B, with carrying capacity as the maximum mass that the ship can safely carry. For high-density cargos on bulk carriers, DWT is typically quoted as the maximum carrying capacity, while for other vessels types, it may refer to, for instance, cubic metres for gas carriers, TEU for container vessels or lane metres for RoRo vessels (Adland et al., 2016). The share of a vessel's total carrying capacity occupied by paying cargo, i.e., payload, is referred to as vessel capacity utilisation or load factor (Alizadeh and Talley, 2011a). Together with sailing speed and ballast ratio, capacity utilisation is a determining factor for overall fleet supply (Wijnolst and Wergeland, 1996), which in turn has an impact on the freight rate fluctuation (Glen and Martin, 1998; Kavussanos, 2003; Kavussanos and Alizadeh, 2002; and Alizadeh and Talley, 2011a). For shipping companies, the payload or capacity utilisation is one of the main factors for their profitability and unit transport cost. Payload, as implied by a vessel's draught is also a key input in calculating vessel fuel consumption (MAN, 2013) and, thus, a key input in the estimation of air pollution from ships (Smith et al., 2014). Despite the importance of the payload in the shipping industry, both from an economic (micro and macro) and environmental viewpoint, little academic research has focused on the issue. As Hjelle (2011) points out, load factors are "critical input factors with scarce empirical evidence, …possibly because such information is regarded as highly sensitive".

Indeed, most previous research assumes that the load factor or payload is a fixed percentage of a vessel's carrying capacity, irrespective of how such capacity is measured (see, for instance, Hjelle, 2011; Sandvik, 2005; Knorr, 2008; Adland and Strandenes, 2007). In a case study focusing on ferry services in Scandinavia, where payload is directly observed from company data, Styhre (2010) investigates the determinant factors in capacity utilisation. Styhre (2010) suggests that service frequency, trade imbalance and demand variations, types of customers and cargo, and the competitive situation are the four main characteristics impacting vessel capacity utilisation. Alizadeh and Talley

(2011a) compile the cargo size from fixture information and find that the ratio of cargo size to DWT negatively affect tanker freight rates during 2006 to March 2009. In a related study, Alizadeh and Talley (2011b) investigate the factors impacting micro-level drybulk freight rates from 2003 to July 2009 and find similar results. Fixture data is a good source for reported cargo sizes, however, it is only available for a fraction of all observed voyages (Veenstra and Dalen, 2008; Adland et al., 2016). Adland et al. (2016) construct a dataset of actual vessel capacity utilisations for a fleet of 4,000 dry bulk carriers over a six-year period and find that freight market conditions, fuel prices, sailing distance and vessel size influence the vessel capacity utilisation of drybulk carriers.

As shown in Adland et al. (2016), the assumption of constant capacity utilisation is generally flawed. AIS-reported vessel draughts provide an alternative indirect measure of utilisation or payload, though large-scale application of such a micro model (in the absence of detailed technical models of vessels) requires a suitable and generic framework for the translation of draught information into payloads. In this paper we contribute to the literature by proposing and comparing the performance of various such models when benchmarked against real cargo sizes obtained from a unique database of ship agent reports.

3 Data and methodology

3.1 The port line-up reports

We collect a set of vessel lineup reports from port agents as a benchmark and basis for the geographical scope of this research. These port call reports indicate vessel's name, estimated times of arrival (ETA), berthing (ETB), and departure (ETD), cargo type, and cargo size. 7,647 such reports were collected from the Monson Agencies and the LBH Group in 2012. Collectively, these reports offer information on the export and import of the major dry-bulk ports across Australia, Brazil, China, India, and South Africa. In particular, they cover loading and discharging events completed by 1,487 dry-bulk vessels with a capacity of 100,000 deadweight tonnes or more (Capesize to Valemax). This dataset is summarised by country in Table 1.

Table 1 Port line-up reports coverage

Country	*Ports*	*Vessels*	*Reports*	*Average cargo size (tonnes)*	*Cargo types*
Australia	12	968	3,604	165,734	Coal, iron ore
Brazil	5	809	1,532	195,343	Iron ore
China	17	924	2,069	174,232	Iron ore
India	3	49	76	131,793	Coal, iron ore
South Africa	2	275	366	173,575	Coal, iron ore

3.2 AIS coverage and validation

All commercial vessels above 300 GT are required to be equipped with AIS transponders and emit messages periodically to identify themselves and provide information on their current position, heading, speed, draught, and other parameters. Satellite and terrestrial receivers capture these messages, and they can be used not only to track vessels, but also, for instance, to identify loading and discharging events (by looking for changes in draught between two points in time), or understand each vessel's operational profile (for example, to estimate fuel consumption, Smith et al., 2014).

From exactEarth, we extract both satellite and terrestrial AIS messages for the 1,487 vessels that are covered in the port lineup reports during the sample period. We utilise this AIS dataset to verify that the event reported in a port call report occurred, and to obtain the draught measurement that we can then associate with the cargo size stated in the port call report. Whilst messages containing information on the vessel's position and speed can occur at very high frequency – up to a message every few seconds – messages containing the vessel's draught are less frequent. Draught measurements are also entered manually. The low frequency of these messages with draught measurements introduces some uncertainty about each draught measurement we need to attribute to a particular cargo size, whilst the fact that draught measurements are input manually raises concerns about their reliability. We introduce checks to reduce the uncertainty in the data in this section and try to ascertain reliability.

To isolate messages reported by these vessels around the time of the report and close to the reported port, we construct a set of time and space windows[1] for each report to ensure that a sufficiently populated sample of AIS messages was captured – in particular, to ensure that enough observations of the less frequently reported draught variable was captured before arrival and after departure. To ratify the validity of the port call reports, we then want to make sure that the vessel approached and was sufficiently close to the port from which the report originated around the dates noted in the report by introducing stricter time and space filters.[2] Meanwhile, for all loading ports (i.e., non-Chinese ports), we ensure that the minimum draught before arrival is less than the maximum draught after departure. For example, we check that the maximum draught before arrival was observed at most seven days prior to the minimum distance to port date for Chinese reports. Similarly, we require the maximum draught after departure to be reported within 14 days for Brazilian reports, ten days for Australian reports, and seven days for the rest. A final step in the filter thereafter merges duplicate or updated reports where the minimum distance to port and the minimum distance to port dates are the same. Thus a final verified subset of 4,928 port call reports was achieved. Adjusting the parameters of these filters changes the number of reports deemed verifiable and the distribution of those reports between the five countries. Our chosen filter provides a reasonable return on both the number of valid reports and their distribution across countries.

Table 2 Impact of verification filter

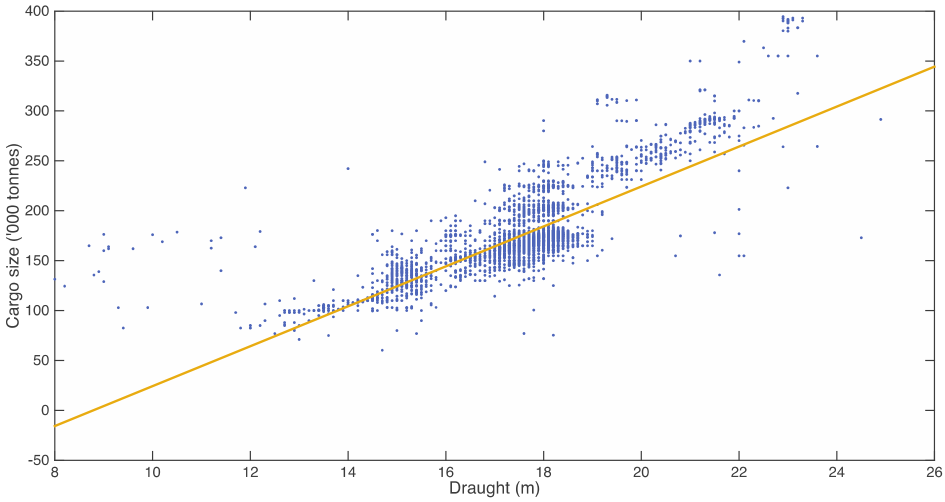
	Australia	*Brazil*	*China*	*India*	*South Africa*	*Totals*	*Loss rate*
Total reports	3,604	1,532	2,069	76	366	7,647	
In AIS windows	3,488	1,522	1,895	73	360	7,338	4.04%
AIS verifiable	2,428	1,445	760	12	283	4,928	32.84%
% verifiable	69.61%	94.94%	40.11%	16.44%	78.61%	67.16%	

It is worthwhile to point out that those remaining unverifiable need not be invalid, but we have omitted them at this time because of the inherent uncertainties that they contain and until they can be validated in some other way. This final sample covers 1,402 of the 1,471 vessels with at least one message in our AIS dataset (95.3%). The loss of reports by country depicted in Table 2 correlates with the parameters and conditions used in the filter and the AIS coverage statistics.

Some of the loss in reports in China can be attributed to the congestion that makes it difficult for satellites to capture all messages emitted (exactEarth, 2012). The high overall loss rate of 32.84% makes it imperative to compare the properties of the verifiable subset to the unverifiable subset to ensure that our filtering had not introduced undue or uncontrollable non-randomness into the verifiable subset.

The validated sample of 4,928 payloads (cargo sizes) and their corresponding AIS observed draught measurements form the final dataset that is utilised in the following section. Figure 1 illustrates the final sample of cargo sizes and their AIS draught values.

Figure 1 Reported cargo size vs. maximum observed AIS draught (see online version for colours)



Note that the dispersion of observations above trend in the lower left corner of Figure 1 is likely from erroneous observations, principally vessels departing from a loading port that are reporting ballast draughts. Observations substantially below trend are more difficult to dismiss as they could, for instance, relate to partly laden vessels on voyages between two discharge ports in China. In the part loading case, the vessel may simultaneously have cargo and ballast water on-board and so the linear relationship between draught and cargo size breaks down. The impact of ballast water is discussed in the following section. Observations of cargo size are also naturally clustered around the typical stem sizes for Capesize vessels, currently between 150,000 to 170,000 tonnes as per Baltic Exchange route definitions.

4 Estimating payload

According to Archimedes' principle, the displacement of the vessel for a certain draught is equivalent to the sum of the lightweight (an empty ship), the mass of the cargo, ballast water, fuel, fresh water, and any other provisions. Thus, in principle, with complete knowledge of the hull form and any non-cargo masses and assuming still-water conditions, it is possible to accurately map the relationship between cargo size and draught. By transforming the observed draught value into displacement, we can estimate the payload.

There are a few elements affecting the draught measurement and, thus, the mapping process from draught to cargo payload. First of all, ballast water in the ballast water tanks is undoubtedly the usual source for inaccuracy of cargo payload as calculated by draught measurement. As a fundamental insurance for safe operations, ballast water is required to provide for the vessel's seaworthiness as a function of vessel design and construction. Even when a vessel is fully loaded, it can require ballast water operations due to a non-equal distribution of weights on the vessel (e.g., tankers), weather conditions and the consumption of fuel during the voyage. David (2015) suggests that bulk carriers can require 30%–50% of their DWT as ballast water capacity. The existence of ballast water causes upward bias of payload estimation when using draught measurement. Sea conditions (e.g., waves, currents and density) at which the draught is recorded, can affect the measurement. To overcome the effect of temporary current conditions, crews are typically required to read draught marks on different points of the vessels (e.g., forward port and starboard, amidships port and starboard, aft port and starboard and all designated positions). Moreover, the volume of fuel oil in bunker tanks at which time the draught is recorded also affects the mapping from draught to cargo payload. In short, since a vessel's displacement includes the mass of the non-cargo components (e.g., ballast water, bunker, crew and consumables), the accuracy of the payload estimate is contingent on the assumptions we make about the mass of these non-cargo components.

We consider and compare three models designed to estimate a vessel's cargo or payload that utilises draught measurements reported over AIS. The first two are based on the vessel's hydrostatics, whilst the third captures the relationship using a regression.

4.1 Proportional lightweight (PL)

Our most fundamental model assumes that lightweight is a constant proportion of displacement. That is, the proportional lightweight model estimates cargo size as

$$\pi_p = 100TPC \cdot \rho \cdot c \cdot T_d \tag{1}$$

where,

TPC is the vessel's tonnes per centimetre statistic (TPC)

ρ is the density of seawater (1.025)

c is the proportion of displacement we assume to be due to cargo

T_d is the vessel's design or reference draught in metres.

TPC is a measure of the amount of mass, in tonnes, which is required to change a vessel's draught by one centimetre. In theory, the value of TPC is not static and it varies with a vessel's loading condition. We use the TPC values that are provided by Clarksons World Fleet Register measured at design draught. Typically, TPC is expressed in salt water, but can be adjusted to local conditions. For vessels without a TPC value, we replace 100τ with the product of the vessel's length (LOA) and beam as an approximation of the waterplane area in metres squared.

Based on 3D-model simulations of Capesize bulk vessels done at the UCL Department of Engineering, an average for the proportion c was computed to be 0.775.

4.2 Variable lightweight (VL)

The variable lightweight model overcomes the limitations and potential inaccuracies of the proportional lightweight assumption. Given that total displacement of a vessel is the sum of its deadweight (DWT) and lightweight (LWT), it follows that we can calculate lightweight as

$$LWT = C_{Bd} LBT_d \rho - DWT \tag{2}$$

where

C_{Bd} is the vessel's block coefficient at its design state

L is the Length Overall in metres

B is the beam in metres

T_d is the vessel's design or reference draught in metres.

C_{Bd} is the ratio of a ship's volumetric displacement to the volume of a cuboid of sides equal to the ship's length, beam and draught. When we observe the vessel during operation at a draught of T, the payload or cargo onboard could be estimated as

$$\pi_v - C_B LB\rho T - LWT. \tag{3}$$

C_B now is the block coefficient during operation at draught T which can be approximated according to [MAN, (2011), p.9].

$$C_B = 1 - \left(1 - C_{Bd}\right)\left(\frac{T_d}{T}\right)^{1/3}. \tag{4}$$

Equations (2), (3) and (4) imply that payload can be calculated as

$$\pi_v = C_B LB\rho T - C_{Bd} LB\rho T_d + DWT. \tag{5}$$

We choose to use the coefficient estimates from Kristensen (2012) who estimates the statistical relationship between lightweight and a vessel's dimensions using data from IHS fairplay. For dry-bulk vessels equal to or above 85,000 and below 200,000 tonnes, he estimated equation (2) as $0.97LBT_d(0.817 - 4.86 \times 10^{-8} \times DWT)$; for vessels equal to or above 200,000 tonnes as $0.97LBT_d \times 1.05 \times (0.076 - 2.61 \times 10^{-8} \times DWT)$.

4.3 The multiple regression model

Assuming vertical sides in the relevant draught region of the vessel, the relationship between cargo size and draught should be close to linear for any given dry-bulk vessel. Figure 1 suggests such a broadly linear relationship – keeping in mind that the figure relates to a very wide range of vessel sizes (from around 90,000 to approximately

400,000 tonnes). We include variables that are easily obtained in standard fleet registers and also can indicate the hull shape of a vessel. All else being equal, a more slender vessel will require a deeper draught for the same cargo carrying capacity. Therefore, in the absence of knowledge on actual shape coefficients, we need to control for differences in hull shape using proxies like the product of length and beam (*LB*).

Table 3 Regression results with cargo size in thousand tonnes as the dependent variable

	Model							
	1	*2*	*3*	*4*	*5*	*6*	*7*	*8*
DWT (‘000)	0.916	0.933	0.854	0.680	0.454	0.460	0.491	0.934
	(89.8)	(59.6)	(65.1)	(17.3)	(12.0)	(12.3)	(12.8)	(160.7)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Design draught (m)		–0.586	–5.071	–3.823				
		(–1.7)	(–10.6)	(–7.4)				
		[0.090]	[0.000]	[0.000]				
Observed draught (m)			7.383	7.463	6.927	6.835	6.154	
			(12.3)	(12.3)	(13.2)	(12.3)	(10.6)	
			[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	
LOA × Beam (m^2)				0.003	0.006	0.006	0.005	
				(5.2)	(10.9)	(11.2)	(9.8)	
				[0.000]	[0.000]	[0.000]	[0.000]	
VLC								0.0006
								(14.8)
								[0.000]
Country dummies								
Brazil						–0.424	–1.597	
						(–0.8)	(–3.4)	
						[0.419]	[0.001]	
China						0.427	–1.012	
						(0.7)	(–2.0)	
						[0.477]	[0.052]	
India						–9.112	–4.192	
						(–4.2)	(–1.7)	
						[0.000]	[0.085]	
South Africa						5.186	5.478	
						(5.7)	(7.0)	
						[0.000]	[0.000]	

Notes: t-statistics are in parentheses (…), whilst the p-value of each null hypothesis is in square brackets […].

Table 3 Regression results with cargo size in thousand tonnes as the dependent variable (continued)

	Model							
	1	*2*	*3*	*4*	*5*	*6*	*7*	*8*
Cargo dummy								
Iron ore							6.548	
							(7.7)	
							[0.000]	
Constant	3.71	11.14	–22.98	–53.19	–108.10	–107.84	–99.36	3.44
	(2.0)	(2.6)	(–5.1)	(–6.8)	(–12.9)	(–12.6)	(–11.3)	(1.0)
	[0.043]	[0.011]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.001]
R^2	0.909	0.909	0.947	0.948	0.945	0.946	0.948	0.949
Mean VIF	1.00	3.77	3.57	18.36	12.84	6.22	5.78	1.01

Notes: t-statistics are in parentheses (…), whilst the p-value of each null hypothesis is in square brackets […].

With reference to Table 3, our benchmark is the naïve ‘constant utilisation’ specification (1) – where the cargo size is a constant proportion of a ship’s deadweight (DWT_i). In order for AIS-reported draught observations to contribute meaningfully, it should produce further improvements in the model’s explanatory power. To improve on the naïve model we consider various specifications, with each specification progressively adding other variables: design draught ($T_{d,\,i}$) added to specification (2); observed draught ($T_{r,\,i}$) added to specification (3); and gross waterplane area (LB_i) added to specification (4). Due to the fact that design draught ($T_{d,\,i}$) and observed draught ($T_{r,\,i}$) are highly correlated, the design draught is dropped from specification (5) onwards. We also include country dummy variables in specification (6) and a cargo type dummy in specification (7). Our most comprehensive multiple linear regression model is, thus:

$$\pi_{r,i} = \alpha_0 + \alpha_1 \cdot DWT_i + \alpha_2 \cdot T_{i,r} + \alpha_3 \cdot LB_i + \Delta_c \cdot \Lambda_{r,c} + \Omega_n \cdot \Theta_{r,n} + \varepsilon_i \tag{6}$$

where,

$\pi_{r,i}$ is the cargo payload to be estimated for vessel *i*, voyage *r*

DWT_i is the deadweight (tonnes) for vessel i

$T_{i,r}$ is the AIS-reported draught value for vessel *i*, voyage *r*

LB_i is the product of vessel i’s length overall and beam (LOA * Beam)

$\Lambda_{r,c}$ is a dummy variable matrix to indicate the country of the port call, c = 1, 2…, 5

$\Theta_{r,n}$ is a cargo type dummy matrix, n = 1, 2.

The alternative specification (8) includes a variable (*VLC*) that is constructed based on the variable lightweight model [equation (5)]. As can be seen in the presentation of the results in Table 3, specification (8) marginally improves the goodness of fit of the model. This final model specification basically allows for different block coefficient for different vessel sizes, i.e., a structural break in the coefficients, and is formally written as:

$$\pi_{8,i} = \alpha_0 + \alpha_1 \cdot DWT_i + \alpha_2 \cdot VLC_i + \varepsilon_i \tag{7}$$

where

VLC_i is the estimation from variable lightweight model for vessel *i*.

The whole sample is randomly split into two equal sized subsamples, one of which is for in-sample estimation and one is for out-of-sample performance testing. Table 3 shows the in-sample estimated coefficients for various model specifications. Cargo size, the dependent variable, is estimated in thousands. Given the extent of heteroscedasticity (non-constant variance in the standard error) observed in Figure 1, we use robust standard errors throughout. Standard model diagnostic checks suggest that our regressions satisfy the conditions for statistical inference. The variable matrix plot is provided in Figure A1 and it shows there is no obvious leverage effect from any of the variables. Every regression model specification is also checked against multi-collinearity using the reported variance inflation factor (VIF) test (Theil, 1971): a mean VIF above ten is usually an indication that multi-collinearity needs to be dealt with (O'Brien, 2007).

The more complex model specifications typically do a better job of explaining observed cargo sizes than our benchmark 'constant utilisation' model in terms of higher R^2 values and highly significant coefficients for the observed draught variable. Nevertheless, even the simple models perform reasonably well in terms of how much of the variation in the data they can explain, as indicated by their R^2 values at the bottom of Table 3, and also in terms of multi-collinearity, as indicated by overall low VIF values. Though there is a certain degree of collinearity between the *LB* variable (LOA * Beam) and DWT, the former variable provides necessary information on the hull shape when using observed draught information, as confirmed by the incremental increase in R^2. The binary variables, like cargo type or country, increase mean VIF scores with very little comparative gain in explanatory power and we begin to reach a trade-off in VIF and R^2. Although not reported here, when we introduce dummy variables to distinguish between ports within a country, these variables are not statistically significant.

Further, there ought to be some concern about the robustness of the coefficients from the dummy variables, since the inclusion of the cargo type dummy changes the sign and significance of some of the country dummies – when moving from models (6) to (7), for example. There is the possibility that some of the cargo types have been mislabelled, but the country dummies have been validated with AIS. Hence, the coefficients in model (6), for instance, are not robust enough to deduce patterns consistent with the country at which a vessel calls and either picks up or discharges cargo. That is, we cannot conclusively argue that a call occurring in one country relative to Australia will always involve larger or smaller cargoes, given that the country dummies are not robust to the inclusion of cargo type. What may work better is a set of binary variables that indicates the complete origin-destination pair associated with the port call. If this were available, it may be possible to test whether, for example, iron ore shipments from Brazil to China are smaller than those from Australia to Brazil by the difference in tonnes of fuel required for the two journeys of significantly different distances.

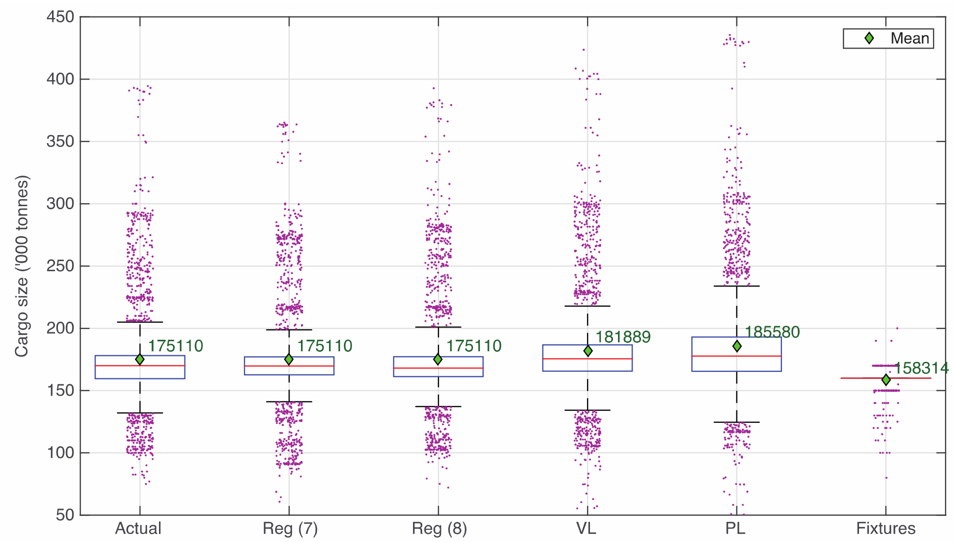
Some of this lack of robustness may also be due to the fact that the number of port calls we can assign as involving iron ore is significantly greater than the number of port calls for coal. Thus, there may not be enough observations to reveal the true effect of cargo type on cargo size – that is, we could not, for example, argue that an iron ore carrier with similar dimensions and design draughts ought to carry *less* cargo on average relative to coal carriers because they typically have strengthened holds.

All of this suggests that the ideal solution if relying on a regression may be to use model (8) that emulates the variable lightweight model from equation (5). Not only does this model explain the largest amount of the variation in the data relative to its peers [models (1)–(7)], but it does so at an ideal and very, very low VIF score (i.e., without any sign of multi-collinearity). The predictive capabilities of model (7) and model (8) are compared to those of the proportional and variable lightweight models introduced earlier (3.1, 3.2) in the next section.

5 Efficacy

This section compares the effectiveness of estimating payload using the models discussed in Section 3. We compare the actual cargo sizes reported in the port call reports to regression (7), regression (8), the PL model, and the VL model. We also consider the cargo sizes reported in spot fixtures reported for Capesize vessels in 2012. These comparisons are based on 2,464 out-of-sample estimates. One way to visualise these results is by looking at their distributions as shown in Figure 3.

Figure 2 Comparative distributions of reference and modelled cargo sizes (see online version for colours)



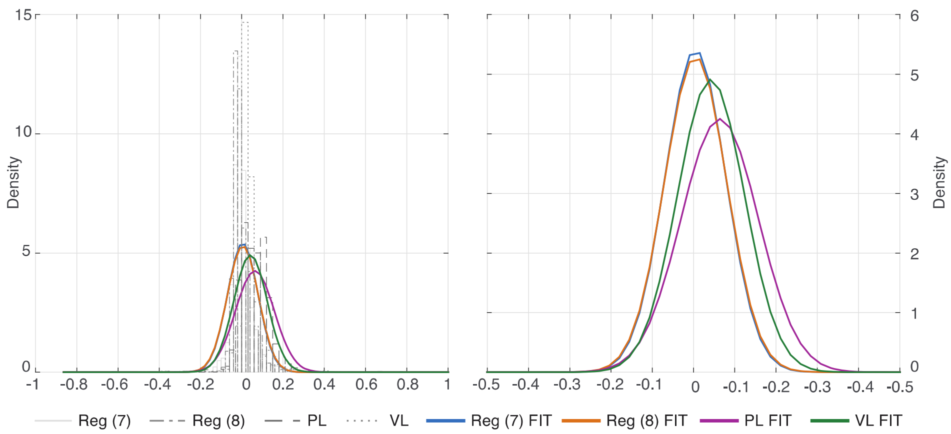
Within each box plot, the box represents the interquartile range of the sample, the line represents the median, and the dots are payloads 1.5 times the interquartile range above the upper quartile or below the lower quartile. If we assume that the port call cargo sizes are accurate, then our two regressions and the variable lightweight model seem to produce the closest matches. Compared to the estimates produced by regression (7), estimates from regression (8) based on the variable lightweight formula appears better at extreme values – in particular, payloads above 350,000 tonnes. The box plots suggest that the variable and proportional lightweight models generally have an upward bias – that is, they on average overestimate cargo size. Compared to the regression models, the lightweight models seem more capable at estimating cargo sizes above 350,000 tonnes.

Table 4 Comparison of relative prediction errors

	Properties of relative errors			
	Mean	*Min*	*Max*	*Std.*
Regression (7)	0.0046	–0.296	1.276	0.074
Regression (8)	0.0050	–0.335	1.279	0.075
Proportional lightweight	0.0634	–0.831	1.522	0.094
Variable lightweight	0.0420	–0.516	1.403	0.081

Table 4 summarises the efficacy of our four models by computing the relative error, $\left(\hat{\pi}_o - \hat{\pi}_A\right)\pi A - 1$, where $\hat{\pi}_o$ is the model's out-of-sample prediction and π_A is the actual cargo size given in the port call report. This is calculated for each of the four models we wish to compare.

Figure 3 Density functions of relative prediction errors (see online version for colours)



The probability density functions of these relative errors are shown in Figure 3, along with a Normal distribution fitted to those errors. The most efficacious model would have the tallest and narrowest density function centred at 0; here we find it to be a close call between regression (7) and (8). Given the better statistical properties of regression (8) over regression (7) in terms of a near perfect VIF score and a marginally better R^2, regression (8) would appear to be our best solution to the problem of estimating payloads using draught measurements reported via AIS.

6 Discussions and concluding remarks

This research is the first attempt in the literature to utilise draught data from AIS to estimate payload at the micro level. Due to the nature of the maritime industry, the cargo size onboard is not publicly available on a large-scale. Our research enables researchers to directly map AIS-reported draught data to cargo payload in combination with vessel and voyage specific information. This information is particularly important for research institutions and government agencies who are interested in regional and global trade flows for key commodities. Currently, published trade data is typically reported in terms of monetary values (e.g., Eurostat) and with a substantial reporting delay. Having a good grasp on the tonnage volume for the underlying trade enables us to calculate the like-for-like volume growth while separating the price element away. Moreover, where environmental measures, such as the global carbon footprint per transport mode, are required, it is the cargo volume transported (in tonnes) that is needed rather than trade in monetary terms. For instance, when we evaluate CO_2 emissions in transportation, efficiency is measured as grams of CO_2 per tonne-km. Therefore, the ability to estimate cargo volumes transported by different vessel types and routes at the micro level is key for any studies of the environmental impact of maritime transportation.

The ability to translate AIS-reported draught data into cargo payloads also sheds further light on the application of maritime big data in for commercial purposes. Arguably, the maritime industry is lagging behind somewhat compared to many other industries in the application of data-driven analysis and technology. With a proper estimation of cargo sizes based on AIS draught data, one can have real-time market information on cargo flows, vessel capacity utilisation and the supply/demand situation. While other data sources, such as port agent reports or Bill of Lading data may be more accurate in terms of cargo size reporting, they can hardly compete with AIS data in terms of availability, scope and timeliness. The AIS system can potentially allow us to cover all ports for various types of vessels including smaller ports where other third-party data is not easily accessible.

Future research should run similar analysis for more vessel types and a wider selection of routes in order to generalise the applicability of our results. It is also possible to include alternative sources of cargo size, such as US customs data, to compare the accuracy of AIS-reported draught data.

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Notes

1 The first time window is set to be –/+ 14 days of ETA/ETD, and space window is 24 decimal degree square of the port.

2 The stricter time window is set to be –/+ 7 days of ETA/ETD, and space window is 1 decimal degree square of the port.

Appendix

Figure A1 Correlation matrix (see online version for colours)