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Integration of Shipbuilding Markets

A Quantitvative Study of the Newbuilding Prices for Bulk Carriers, Tankers and Containerships from 1994 to 2015

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Master thesis in Finance

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Abstract

This thesis investigates whether the newbuilding prices for bulk carriers, tankers and fully cellular containerships (FCC) are joined in a mutual long-run equilibrium, and thus providing evidence of an integrated shipbuilding market for these shipping segments. By using hedonic pricing models, we construct newbuilding price indices that represent the underlying determinants of price. This method enables the creation of objective indices that control for ship- and contract-specific characteristics, in addition to shipyard and ship owner heterogeneity. Further, the Johansen method is applied to study the existence of cointegration. The findings of the analysis suggest that newbuilding prices are joined in collective long-run equilibria through the existence of two cointegrating relationships. This supports a view of flexible shipyard capacity, indicating that the product ultimately offered in the shipbuilding markets for bulk carriers, tankers and FCCs is capacity. Consequently, newbuilding prices may be affected by the opportunity cost of available shipyard capacity, providing an explanation for the existence of an integrated market.

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1. Introduction

The shipbuilding market is often regarded as one of the world's most global and open markets. Analogous to most markets, it represents a point of interaction where ship owners and shipyards exchange payments for products. For ship owners, the product constitutes a specific type of ship that fulfils a desired purpose at sea, for instance a very large crude carrier (VLCC) carrying crude oil from the Middle East Gulf to China. In a shipyard's perspective, the product offered is arguably its capacity. Stott (2017, p. 83) supports this view by stating that a shipyard's actual trade is a promise of future capacity to build a ship at a predetermined time. Furthermore, due to vast differences in complexity and size, newbuilding prices vary considerably among ships and segments. Hence, shipyards face a strategic decision of what ships to build in order to optimally define their product mix. Figure 1-1 visualises this decision by illustrating the extensiveness of the orderbooks among the world's eighth largest shipbuilder groups.

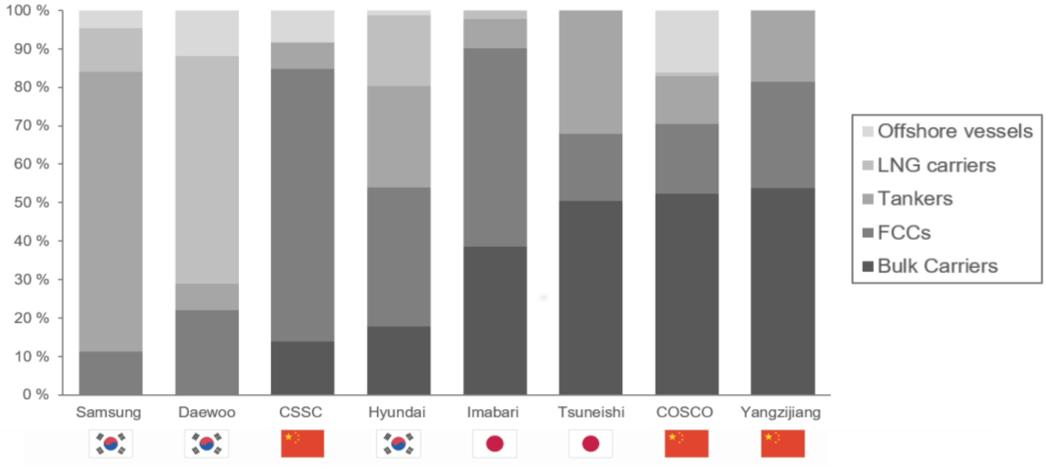

Figure 1-1: The distribution of the orderbooks at the world's eighth largest shipbuilder groups. Note that segments like tug boats , LPG carriers and ferries represent a minority of the orderbooks and are thus excluded from the graph. Source: Authors' calculations, based on data retrieved from Clarksons Shipping Intelligence Network (SIN) (2018b)

Since most shipyards are able to construct a wide range of ships, they will strive to use their capacity when orderbooks are short, by tendering for ships they would not normally consider building (Stopford, 2009, p. 630). Consequently, as ship owners across different segments arguably face the same supply, the shipbuilding market can be viewed as a marketplace for capacity, in addition to a platform where ships are sold. Hence, newbuilding prices may be affected by the underlying value of available capacity, which should result in similar price movements across segments. Following this line of thought, one can argue whether the shipbuilding market constitutes a single market or if it is divided into smaller markets, serving the different shipping segments. This rationale makes up the hypothesis of this master thesis, suggesting that a long-run equilibrium between newbuilding prices of different shipping segments exist, and that the shipbuilding market is integrated.

Due to vast differences in ship size and complexity, we focus our analysis on the large cargo ships, as these ships are most likely to compete for the same capacity. Hence, we disregard ships like tug boats and ferries. Furthermore, as most contracts are agreed under confidentiality clauses, most prices remain undisclosed, limiting our data sample. Nevertheless, bulk carriers, tankers and fully cellular containerships (FCCs) provide a sufficient selection for empirical analysis and will therefore form the basis of the analysis.

To investigate whether a long-run equilibrium exists across these segments, we apply modern econometric techniques to find evidence of cointegration between the newbuilding prices. By using data from Clarkson Research Services' World Fleet Register (WFR) (2018a), and the concept of hedonic pricing models, we construct newbuilding price indices for each segment. This procedure enables us to account for heterogeneity across ships, contractual terms, shipyards and ship owners, resulting in price indices that ultimately reflect the underlying price drivers. These indices will be tested for cointegration by applying the Johansen method. Finally, we analyse short-run effects and the speed of adjustment to deviations from long-run equilibrium by using a vector error correction model.

Research in the field of shipbuilding markets has received less attention in maritime economics than many of the other aspects of the shipping industry (Heaver, 2011; Woo, Bang, Martin, & Li, 2013; Stott, 2017). To our knowledge, there has been no research investigating the cointegrating relationships of prices across segments in the shipbuilding market. Therefore, we hope this thesis proves valuable to maritime economics by shedding light on this aspect of the industry.

The remainder of this thesis is structured as follows. Section 2 includes a review of relevant literature. Next, in section 3, the dataset used and its descriptive statistics is presented. In section 4, we elaborate on the empirical methods used in the analysis. The methods are then applied to the dataset in section 5, and the findings are presented. By applying the same methods to different datasets, the robustness of the findings are tested in the section 6. Finally, a conclusion is drawn in section 7.

2. Literature review

The literature on shipbuilding can broadly be segmented into two streams, covering both competitiveness and price formation in the shipbuilding market. Furthermore, with an objective to investigate the relationship between newbuilding prices in different shipping segments, literature on the interdependence of shipping segments will also be covered in the following section.

2.1 Competitiveness in the Shipbuilding Market

Jiang and Strandenes (2012) analyse the relative competitiveness of China by assessing shipbuilding costs in the period from 2000 to 2009. By evaluating the three major components of shipbuilding – steel, labour and ship equipment – the authors map out China's advantages and constraints in shipbuilding and compare it to its main shipbuilding competitors; South Korea and Japan. They find that China's cost advantage mostly stems from their lower labour unit costs. However, considering ship equipment, they argue that evaluating shipbuilding costs is far more complex than simply comparing labour costs, and that China's absolute advantage has narrowed due to increasing labour and ship equipment costs. In order to illustrate the changes in shipbuilding competitiveness, the authors combine shipbuilding costs and market share in a 2 x 2 matrix. Their results imply that China has advanced from an emerging state to a growing one, whereas South Korea finds itself in a maturing state and Japan in a declining one.

In a later paper, Jiang, Bastiansen and Strandenes (2013) state that a comprehensive perspective is important when evaluating international shipbuilding competitiveness. This perspective involves addressing both internal factors as costs, price and delivery time, as well as external factors as government influence and market conditions. Consequently, the authors introduce profit rate as a more relevant measure. By quantifying the profit rates of China and its main competitors in shipbuilding - South Korea and Japan - in the period from 2000 to 2009, the authors find that profitability was higher and sustained for a longer time in China. Furthermore, results from their econometric model suggest that competitiveness in all three markets is highly dependent on the market conditions and demand. However, even though less influential, China's competitiveness is also driven by shipbuilding costs, whereas positive contract price deviations prove influential for South Korean and Japanese shipbuilding.

Research shows that shipyard heterogeneity affects the competitiveness of shipyards and thus the ability to secure new contracts (Stott, 1995; Sauerhoff, 2013). By conducting a survey among potential new ship owners, Stott (1995) finds that certain attributes of a ship design increase its marketability, and that a shipyard offering such a design has a higher probability of receiving new orders. However, ship owners seem hesitant to pay a premium above the market price for such attributes. Sauerhoff (2013) tests several hypotheses that question the importance of competence in the field of services for shipyards. By using market expertise, practical expertise, cooperation with suppliers and cooperative exchange of information as metrics to determine competency, his findings suggest that higher competency increase competitiveness, which again increases the number of received orders.

2.2 Price Formation in the Shipbuilding Market

According to Stopford (2009, p. 630), newbuilding prices are determined by the demand of new ships and the supply of shipyard capacity, defined as the number of available berths. If the demand of newbuildings increases, relative to the number of berths available at the shipyards at a given time, the price will increase until a new equilibrium is reached. Key factors determining the demand for newbuildings are freight rates, the price of modern second-hand ships, the buyers' financial liquidity, the availability of credit and shipowners' expectations about the future. On the supply side, the key issues are production costs, the number of berths available and the size of the orderbook.

In a paper from 1985, Beenstock (1985) describes a theoretical model in which freight markets and ship markets are jointly determined. Beenstock argues that a ship is a capital asset, and that ship prices should be investigated by applying capital allocation theory, rather than supply and demand driven models. For simplicity, the model assumes that new and second-hand prices are perfectly correlated, albeit this condition is not likely to be fulfilled as newbuilding prices are relatively sticky, compared to second-hand prices. This model was further investigated by Beenstock and Vergottis (1989b; 1989a) and applied to the dry bulk and tanker markets. In these papers the assumption of perfect correlation between new and second-hand prices was replaced by a more dynamic approach in which newbuilding and second-hand prices, freight rates, along with other variables are jointly determined.

Strandenes (1984) studied the relationship between time charter rates and second-hand ship prices. The model divided the second-hand ship prices by two determinants, the present value of short run profits and expected long run profits. The rationale behind this split is that prices of older ships, with expected shorter remaining lifetimes, are highly influenced by short-run freight rates, whereas the younger ships, with expected longer lifetimes, are influenced by the long-run freight rates. She found statistical evidence suggesting that both determinants have significant influence on the second-hand values for tankers. In other words, second-hand ship values can be regarded as a weighted average of short and long-term profits. In a later paper, Strandenes (1986) applies the same logic of using the term structures of freight rates to model a ship's newbuilding price. In this model, long term equilibria freight rates are used to calculate the present value of a ship's future income, and thus its price. Supported by the rationale of how the term structure of freight rates impact ship prices, short-run freight rates are excluded in the calculations of newbuilding prices, as new ships naturally have a longer lifetime.

Tsolakis et al. (2003) conducted an econometric analysis of second-hand ship prices by using an error correction model. It was found that newbuilding and time charter rates have the greatest effect of all variables when determining second-hand prices, both in the short- and the long-run. In Haralambides et al. (2004) an error correction model was applied to the shipbuilding market. Shipbuilding costs were found to have the most significant effect on the determination of newbuilding prices for all ship types, except Handysize carriers. This result supports what is observed in the shipbuilding market, where shipbuilding historically has shifted to countries with a comparative cost advantage. However, freight rates were found to have the strongest impact on newbuilding prices in the long-run for Handysize carriers. The authors argue that Handysize carriers are cheaper to build, making it a shipyard's last resort to maximize revenue. Therefore, newbuilding prices for dry bulk carriers may be driven by the demand and price of alternative vessels like tankers, as orders often takes place when prices and demand for new tankers have fallen.

Adland et al. (2006) further extend the literature by investigating whether the boom in the drybulk freight market in the period of 2003-2005, caused asset values in the second-hand market to deviate from the underlying fundamentals. The empirical results suggest that the second-hand market was closely cointegrated with the fundamental freight and shipbuilding market, with no evidence of a short-term asset bubble.

Some research has been devoted to the observation that newbuilding prices appear non-stabilising. Newbuilding prices appears far less volatile than time charter rates and seem to adjust slowly to changing market conditions (Dikos, 2004). Zannetos (1966) argues that this is because of the existence of market imperfections such as production smoothening incentives. Strandenes (2010) states that the strong presence of labour unions in the shipbuilding industry has led to lower flexibility and that the presence of subsidies distorts newbuilding prices. These arguments were challenged by Dikos (2004), who suggest an alternative explanation of the suboptimal newbuilding prices and propose a perfectly competitive paradigm that successfully accommodates the observed patterns of newbuilding price behaviour. The perception that the low volatility of newbuilding prices is due to market inefficiency is also challenged by Adland and Jia (2015). In this article, an equilibrium relationship is used to illustrate the presence of a term structure of newbuilding prices, which means that newbuilding prices are not comparable across time. It is shown that the price for the newbuilding contract is a kind of futures contract that explains the lower volatility of newbuilding prices.

Adland et al. (2017) investigated the impact of buyer and seller heterogeneity at the micro-level. Using data on individual contracts in the bulk carrier, tanker and FCC segments, the empirical method relies on fixed effect regressions to capture heterogeneous effects of shipyards and ship owners. Although the paper concludes that market conditions, salary costs, steel prices and yard experience are influential covariates, the main finding is that shipyards and ship owners are contributors in the price formation in all segments.

2.3 The Interdependence of Shipping Segments

In order to analyse the interdependence between different shipping segments, Beenstock and Vergottis (1993) investigated spillover and feedback effects between the dry cargo and tanker segments. In this paper, the authors integrate econometric models on bulk and tanker markets, developed in previous work (1989b; 1989a). They argue that there are three main links between the segments: (1) shipbuilding, where tankers may be built at the expense of bulk carriers, and vice versa; (2) combination vessels may be switched between the two freight markets to maximize profits; (3) the scrap market where a change in scrapping in one market affects scrapping in the other market through scrap prices. The simulations suggest that the spillover and feedback effects are quite large. Hence, an analysis of one sector without the simultaneous analysis of the other might be incomplete.

The cointegration and lead-lag relationship between dry bulk and container freight markets have recently been investigated by Hsiao et al. (2014). A cointegration test suggests that there exists a long-run equilibrium relationship between the Baltic Dry Index (BDI) and the China Containerized Freight Index (CCFI). However, they find no significant lead-lag relationship in the analysis of the full sample period.

Haddal and Knudsen (1996) analyse the correlation between historic prices for the newbuilding of different shipping segments and discuss whether it is relevant to talk about one global shipbuilding market. Correlation in price movements prove strong and their hypothesis is supported with an average correlation coefficient of above 0.7 across segments and ship size. However, ships with extreme exterior dimensions that demand correspondingly special shipyards, is an exception and has a lower correlation with the other segments.

Wijnolst and Wergeland (2009, pp. 62-63) further discuss this hypothesis by arguing that an aggregation of the shipbuilding market make sense if products are clearly homogenous or shipyard capacity is fairly homogenous and technology diffusion is rapid. With a world fleet ranging from complex chemical tankers to simple dry bulk carriers, ships do clearly not represent homogenous products. However, considering the findings of Haddal and Knudsen (1996), they argue that shipyard capacity can be regarded as fairly homogenous. Concerning technology diffusion, the authors observe the segment of ferries (fast ships) to find support. In this segment technological development has been rapid and the final product is advanced, making it a viable basis to test whether technology diffusion is rapid. By comparing the number of active yards to the production of fast ships over time, a directly proportional relationship is observed. This indicates that almost any yard can produce fast ships, implying that technology diffusion is rapid in shipbuilding and that shipyard capacity is to some extent flexible.

In his doctoral dissertation, Stott (2017) suggests that there is strong empirical evidence for the existence of an international commercial shipbuilding market. The author argues that the market is constituted partially by products, but also by shipbuilding capacity. He further suggests that a shipyard’s capacity normally is flexible, enabling it to react to changes in demand for different products over time, within the boundaries of its product mix. Thus, the products that form its product mix can be regarded as substitutes. Hence, the price of a ship is determined by, among other factors, the underlying value of shipyard capacity. Through a correlation analysis of prices for vessels larger than 5,000 gross tons in different segments, he reaches the same conclusion as Wijnolst and Wergeland (2009). Additionaly, Stott (2017) conducts a correlation analysis between prices and demand, as measured by the backlog of all shipyards. He argues that the positive correlation between prices cannot solely be explained by coincidence of demand, as the positive correlation persists in periods where correlation between newbuilding demand in different segments where negative or absent. Furthermore, the correlation analysis indicates that the demand for FCCs and tankers had the strongest effect on prices in the period, whereas the demand for bulk carriers had the weakest effect on prices. At last, he argues that the strong positive correlation between prices for all products and the total backlog in the shipbuilding market suggests that the value of capacity has an effect on prices in all segments.

3. Data

Seeking to construct objective and representative newbuilding price indices for bulk carriers, tankers and FCCs, collecting and refining data has been important. The following sections will discuss this process, evaluate the representativeness of the data and present some key insights from the dataset.

3.1 Data Collection

To extract data on newbuilding contracts, we turn to Clarksons World Fleet Register (2018a). The database contains data on more than 100,000 ships from the period between 1864[1] and 2015. However, due to limited observations in earlier years, as well as fewer observations in the most recent years, we limit our dataset to the period of 1994-2015. We regard all ships as relevant and have accordingly chosen to include demolished and lost ships, in addition to ships from the current fleet. Each observation is defined by a wide range of ship- and contract-specific characteristics, ranging from vessel name, segment and carrying capacity to shipyard name, newbuilding price and contract date. As ships serve a wide range of different services, both ship- and contract-specific details vary significantly in the dataset.

3.2 Data Refining

The unrefined dataset covers a total of 59,921 ships, but as most newbuilding contracts are agreed under confidentiality clauses, most prices remain undisclosed, limiting our data sample. This information is essential to our analysis, and we consequently exclude all observations lacking newbuilding prices, limiting our dataset to a mere 8,453 observations. As most newbuilding prices are quoted in million U.S. dollars, those that are reported otherwise[2] are converted to U.S. dollars using exchange rates extracted from the Bloomberg database (2018), at the time of contract signing. Further, to avoid unwanted trend affects, and to make newbuilding prices comparable across time, newbuilding prices are deflated to 2017-levels using U.S. CPI, as reported by the U.S. Bureau of Labor Statistics (2018).

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[1] Observations from before 1950 do only comprise 1% of the database, and a mere 20 registered ships are built in the 19th-century. The oldest ship registered in the database is the current Egyptian presidential yacht, built in 1864 under the name *El Horreya*.

[2] Other contract prices were quoted in the following currencies: EUR, GBP, CNY, JPY, DKK, SEK, SGD, DEM.

Table 3-1 presents newbuilding prices per compensated gross tonnage (CGT) for each shipping segment. CGT is a measure indicating the workload needed to build a ship and is commonly used to measure shipbuilding output, making it a suitable measure to compare segments. Bulk carriers, tankers[3] and fully cellular containerships (FCCs) are the dominant segments concerning number of vessels, followed by offshore service ships, gas carriers, and cruise and passenger ships. Pure car carriers (PCCs), reefers, Ro-Ro's, miscellaneous[4] and other dry cargo[5] ships represent the smaller segments of the dataset. As a result, caution must be exercised when using these data, due to the lack of data points and the potential impact of outliers. Varying significantly in technical complexity and need of equipment, prices per CGT and standard deviations vary considerably across segments. Bulk carriers, tankers and FCCs show similar values concerning mean prices per CGT and standard deviations, arguably making them more suited for comparison. The remaining segments show wider price intervals, implying that these ships vary to a greater extent in complexity and that the CGT measure does not capture all intersegmental differences.

	Observations	Mean	Std. Dev.	Median	Min	Max
Bulk	2,257	2,417	652	2,380	1,030	6,715
Tanker	1,999	2,562	903	2,365	834	12,851
FCC	1,704	2,671	646	2,713	479	6,187
Offshore Service	621	6,317	3,698	5,715	756	31,908
Gas Carrier	573	3,151	734	2,861	1,608	5,829
Cruise/Passenger	482	5,414	6,771	5,170	280	145,033
Other Dry Cargo	360	2,534	1,010	2,411	876	8,801
Miscellaneous	189	13,554	9,842	15,070	753	106,761
PCC	136	2,577	2,034	2,223	777	18,504
Ro-Ro	100	3,374	904	3,289	2,007	6,357
Reefer	16	3,113	719	3,337	1,665	3,831
All segments	8,437	3,281	3,172	2,628	280	145,033

Table 3-1: USD per CGT for shipping segments (1994-2015). Source: Authors' calculations, based on data retrieved from Clarksons (WFR) (2018a).

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[3] The tanker segment is composed of product, crude, chemical and special tankers.

[4] Miscellaneous ships include a broad spectrum of more specialized ships ranging from drill ships to tug boats.

[5] Other dry cargo ships include multipurpose and smaller general cargo ships.

We focus our analysis on bulk carriers, tankers and FCCs, and therefore discard observations on all the remaining segments. Even though this limitation excludes the majority of the different shipping segments, these three segments account for the majority of the observations, adding up to a total of 5,960 observations. As observed in Table 3-1, the similarities between these segments may indicate that they compete for the same shipyard capacity, which is highly relevant in the further analyses.

In addition to limiting our dataset to the three most prevalent and arguably most standardised shipping segments, some additional measures have been made to construct an applicable and complete dataset. These measures involve removing data lacking information on either ship- or contract-specific characteristics, ensuring that all observations are analysed on the same basis. A total of 434 observations were deleted due to missing information on design speed, 267 tankers lacked information on whether the ship was equipped with heating coils and ten tankers were deleted due to missing information on total number of pumps. An additional two bulk carriers and nine FCCs were excluded due to lacking information on whether sufficient gear for independent loading and discharging of cargo was installed. Finally, five FCCs were discarded as their reported prices were regarded as anomalies in the dataset[6]. Following these measures, our dataset totals at 5,238 newbuilding's, consisting of 2,082 bulkers, 1,550 tankers and 1,606 FCCs, respectively.

3.3 Validation and Representativeness

As the majority of the observations in the unrefined dataset were excluded due to undisclosed newbuilding prices, it can be argued whether our data constitutes a representative selection of the current and historical world fleet. However, we have reason to believe that the refined dataset is representative, as historical newbuilding prices are similar in both magnitude and development as price indices reported by Clarksons Shipping Intelligence Network (SIN) (2018b). This relation is shown in Figure 3-1, where newbuilding prices from the refined dataset and an average of Clarksons newbuilding price indices are graphed across the relevant time period.

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[6] The containership *Noro* has a CPI-adjusted price of 1.3 million USD and a registered CGT of 23,633, resulting in a price per CGT constituting a mere 2% of average FCC prices per CGT. Further, the four Chinese ships *Glory Guangzhou, Glory Zhendong, Glory Shengdong* and *Glory Guandong* were bought at 12.7% of average FCC prices per CGT. These numbers are regarded as anomalies in the dataset and are thus discarded.

The variation in spread between the two graphs can be explained by the difference in number of observations. Clarksons indices are reported monthly, whereas the observed contract prices consist of an average of 80 observations per year. The wider spread within contract prices is a result of differences in each segment. Furthermore, CGT represents a highly generalised measure, explaining some of this variation.

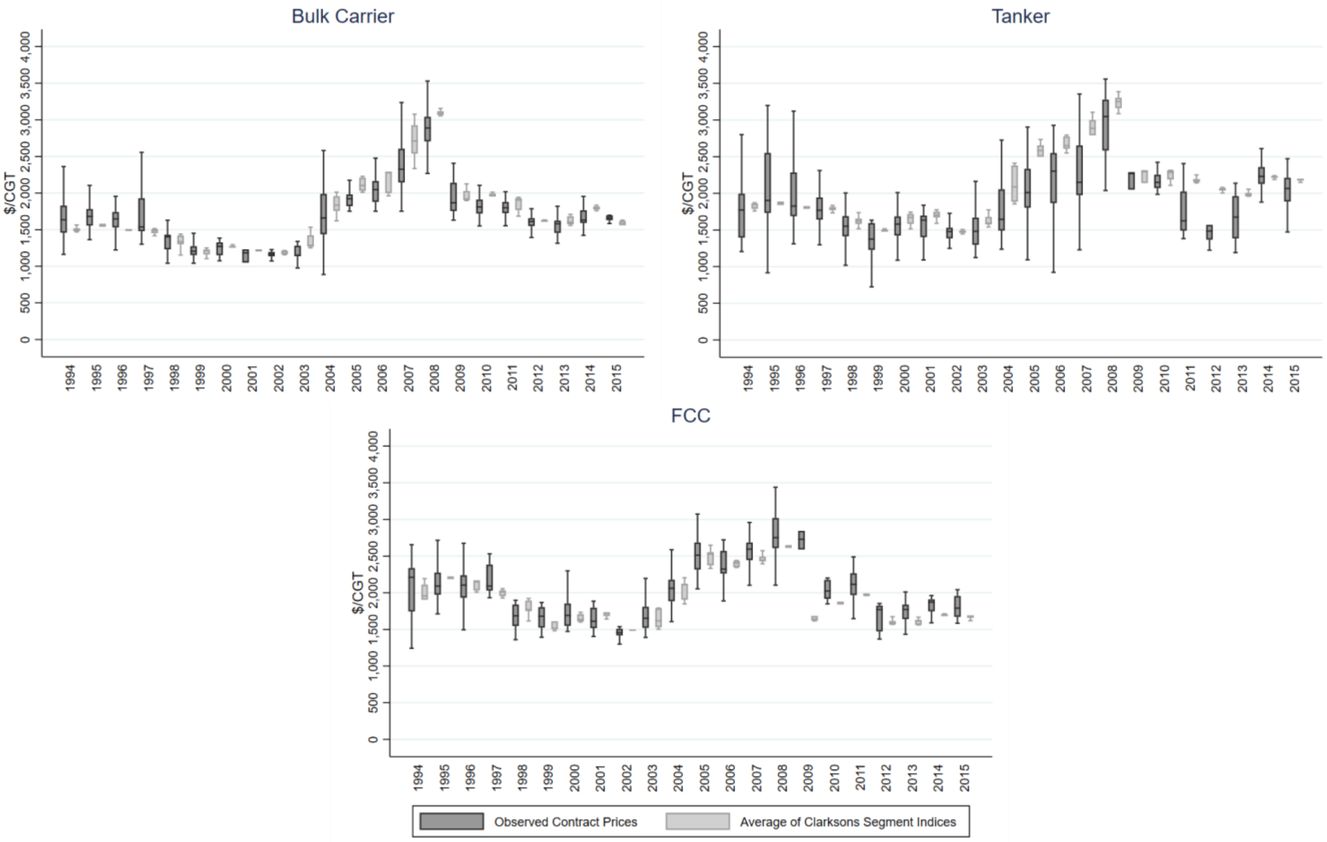

Figure 3-1: Contract prices and averages of Clarksons segment newbuilding indices from 1994-2015. Source: Authors' calculations, based on data from Clarksons (WFR) (2018a) and SIN (2018b).

Table 3-2 presents statistics on prices per CGT, where the segments are categorised by vessel size[7]. The table indicates a positive correlation between carrying capacity and price per CGT for tankers, whereas this relation is less prominent for bulk carriers and FCCs. However, prices per CGT do vary in each segment, thus explaining some of the variation in the spread of contract prices observed in the graph. The smallest size categories of each segment contain few observations, and their statistics can thus be highly affected by outliers and should be interpreted cautiously.

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[7] Bulk carriers and FCCs are categorised based on the most general and applied size scheme, reaching from Small to Capesize bulk carriers and Small Feeders to Ultra Large Container Vessels. Tankers are categorised using the AFRA (Average Freight Rate Assesement) scale, first established by Shell in 1954 (EIA, 2017), providing a representable and intuitive overview of the tanker fleet. Chemical tankers and special tankers, in addition to crude and product tankers with a carrying capacity of below 10,000 dwt., are excluded from this scale and categorised as "Other Tankers". The size of bulk carriers and tankers are measured in terms of dwt., whereas FCCs are measured in terms of twenty-foot equivalent units (TEUs).

Bulk Carrier	Dwt.	Obs.	Mean	Std. dev.	Median	Min	Max
Small	< 10,000	5	3,999	493	4,089	3,173	4,501
Handysize	10,001 < 35,000	302	2,759	693	2,757	1,181	6,715
Handymax	35,001 < 59,000	712	2,432	580	2,477	1,493	4,842
Panamax	59,001 < 80,000	383	2,130	606	2,027	1,123	6,358
Capesize	> 80,001	680	2,468	616	2,434	1,310	4,754
Bulk carriers		2,082	2,439	644	2,434	1,123	6,715

Tanker	Dwt.	Obs.	Mean	Std. dev.	Median	Min	Max
General Purpose (GP)	10,000 < 25,000	20	3,190	1,088	3,017	1,472	5,267
Medium Range (MR)	25,001 < 45,000	147	2,073	473	1,966	1,311	3,412
Long Range 1 (LR1)	45,001 < 80,000	376	2,221	506	2,251	1,262	3,852
Long Range 2 (LR2)	80,001 < 160,000	433	2,656	790	2,534	1,542	8,988
Very Large Crude Carrier (VLCC)	160,001 < 320,000	194	2,948	994	2,747	1,951	9,600
Ultra Large Crude Carrier (ULCC)	> 320,001	15	3,108	581	2,988	2,297	3,987
Other Tankers		365	2,719	943	2,493	834	6,074
Tankers		1,550	2,558	832	2,374	834	9,600

FCC	TEU	Obs.	Mean	Std. dev.	Median	Min	Max
Small Feeder	< 1,000	60	3,047	822	2,999	1,854	4,800
Feeder	1,001 < 2,000	291	2,824	725	2,870	1,039	6,187
Feedermax	2,001 < 3,000	205	2,513	754	2,509	479	4,357
Panamax FCC	3,001 < 5,100	456	2,824	527	2,842	1,629	4,938
Post-Panamax	5,101 < 10,000	369	2,634	576	2,470	1,580	4,038
New Panamax	10,001 < 14,500	176	2,656	555	2,935	1,630	3,425
Ultra Large Container Vessel (ULCV)	> 14,501	49	2,343	371	2,122	1,854	2,792
FCCs		1,606	2,716	637	2,764	479	6,187

Table 3-2: Statistics on USD per CGT, categorised by segment and ship size.
Source: Authors' calculations, based on data from Clarksons (WFR) (2018a).

3.4 Descriptive Statistics

3.4.1 Ship-Specific Characteristics

To describe how ships differ in terms of complexity and equipment, we choose to include descriptive statistics on some of the most prominent features within the three segments. The statistics are summarised in Table 3-3, where it is evident that design speed increase by size for all segments. Furthermore, the feature gear describes whether equipment for loading and discharging of cargo is installed for bulk carriers and FCCs. In both segments, it is clear that the smaller ship categories typically are equipped with gear. A possible explanation for this observation, is that larger ships tend to dock in larger ports where necessary gear already is installed.

As tankers carry liquids, they demand different types of gear and equipment, and we therefore choose to describe the total number of pumps and whether heating coils are installed instead. In terms of total number of pumps, it is clear that the smaller, chemical and special tankers use more pumps than the larger tankers. Larger tankers often carry vast quantities of crude oil in large chambers, whereas the product, chemical and special tankers typically carry different liquids, thus demanding several chambers with separate pumps. Furthermore, tankers that carry less viscous liquids typically have heating coils installed, in order to increase the pumpability of transported liquids. However, such installations are rarely existent in the larger size categories, and non-existent among ULCC's in our samples. For the product, chemical and special tankers, heating systems are more prominent, as these liquids often have different needs and requirements in terms of transportation and pumping.

FCC	Obs.	Avg. design speed (knots)	Gear Installed
Small	5	12.1	20.0%
Handysize	302	13.9	91.7%
Handymax	712	14.2	93.7%
Panamax	383	14.1	24.8%
Capesize	680	14.5	0.3%
Bulk Carriers	2,082	14.2	50.1%

Tanker	Obs.	Avg. design speed (knots)	No. Pumps (avg.)	Heating Coils Installed
General Purpose (GP)	20	13.0	7.9	55.0%
Medium Range (MR)	147	14.5	12.0	64.0%
Long Range 1 (LR1)	376	14.8	10.4	56.7%
Long Range 2 (LR2)	433	15.0	3.5	92.2%
Very Large Crude Carrier (VLCC)	194	15.7	3.5	21.7%
Ultra Large Crude Carrier (ULCC)	15	16.5	3.6	0.0%
Other Tankers	365	14.1	16.3	70.7%
Tankers	1,550	14.7	9.1	65.6%

FCC	Obs.	Avg. design speed (knots)	Gear Installed
Small Feeder	60	16.9	53.3%
Feeder	291	19.1	52.2%
Feedermax	205	21.4	64.4%
Panamax FCC	456	23.1	10.1%
Post-Panamax	369	24.4	0.0%
New Panamax	176	23.9	0.0%
Ultra Large Container Vessel (ULCV)	49	22.7	0.0%
FCCs	1,606	22.3	22.5%

Table 3-3: Statistics on ship-specific characteristics.
Source: Authors' calculations based on data from Clarksons (WFR) (2018a).

3.4.2 Contract-Specific Characterisitcs

As vessels in the dataset originate from 188 different shipbuilders and are owned by 1,101 different owners, we chose to display shipyard experience and delivery time on a national basis, addressing the ten largest shipbuilding nations in our dataset, in terms of newbuilding contracts. Shipyard experience is calculated as the difference between a contract year and a shipyard's first delivery year. Note that as several shipyards have constructed multiple ships in the time period, the mean values represent the average experience of all contracts in a given nation. In addition, the maximum value represents the largest difference observed between a contract signing year and the first year of delivery of any contract in our sample. Table 3-4 present descriptive statistics for these two variables. Excluding the smaller shipbuilding nations, China has the lowest average experience, which is mainly due to its recent emergence in the industry and that the country has significantly more shipyards than their competitor nations. With regard to delivery time, the countries show similar values, but with a somewhat longer delivery time in China. The wide spread in delivery time can be a result of several factors, where difference in ship complexity, market fluctuations, technical and financial difficulties might explain much of the variation.

			Shipyard Experience (Years)				Delivery time (Years)				
Nation	Contracts	No. yards	Mean	Std.dev.	Med.	Max	Mean	Std.dev.	Med.	Min	Max
South Korea	2,074	20	18.6	11.7	21	43	2.4	0.9	2.3	0.6	5.8
China P.R	1,911	74	12.3	12.7	8	48	2.9	1.1	2.8	0.3	8.5
Japan	575	22	27.8	9.6	29	54	2.0	0.8	1.9	0.5	6.7
Taiwan	116	1	25.6	6.4	24	36	2.4	1.0	2.1	1.3	7.3
Germany	105	9	20.2	20.5	14	84	1.9	0.7	1.8	0.6	5.0
Poland	65	5	31.4	4.5	31	40	2.5	1.1	2.4	0.7	6.9
Croatia	61	3	39.2	11.7	43	49	3.0	1.5	2.9	1.4	13.0
Vietnam	47	2	2.5	2.5	2	8	2.9	1.8	2.6	0.9	8.9
Philippines	46	2	3.7	3.6	3	16	2.4	0.7	2.3	1.3	3.9
Romania	33	3	7.8	3.7	8	15	3.0	0.8	2.9	1.7	4.6
Overall	5,238	188	17.5	13.4	19	84	2.6	1.0	2.4	0.3	13.0

Table 3-4: Statistics on shipyard experience and delivery time by nation.
Source: Authors' calculations, based on data from Clarksons (WFR) (2018a).

3.4.3 Market Concentration

In order to describe the concentration of shipyards and ship owners in the dataset, we present the ten largest shipyards and ship owners of each segment in Table 3-5. In terms of shipyard owners, the bulk segment stands out with a significantly lower market concentration than observed in the FCC and tanker segments. One explanation is that bulk carriers often are considered less technically complicated, thus enabling more yards to engage in shipbuilding. It is worth noting that the "Big Three" Korean shipbuilders, Samsung, Hyundai HI and Daewoo, dominate the tanker and FCC segments in our sample, with a 39% and 48% market share respectively. As for the ship owners, the competition is larger, and concentration of ownership is less concentrated. Nevertheless, players like COSCO Group and A.P. Moller still stand out with significant shares of the fleet represented in our dataset. However, as our dataset represents a mere 14% of the world fleet, the representation of both shipyard and ship owners do not necessarily constitute a representable picture of the actual market situation and should thus be evaluated accordingly. To provide a more representable overview of the market, a similar table based on the unrefined dataset is included in the Appendix A.

Bulk Carrier	Contracts	Percent	Cumul.
Shipyard (Owner Group)			
Hyundai HI Group	145	7.0 %	7.0 %
COSCO Shipping HI	87	4.2 %	11.1 %
Hudong Zhonghua	85	4.1 %	15.2 %
STX Offshore & SB	80	3.8 %	19.1 %
China Merchants	71	3.4 %	22.5 %
Oshima Shipbuilding	67	3.2 %	25.7 %
Sinomach	66	3.2 %	28.9 %
Jiangnan SY Group	60	2.9 %	31.8 %
Shanghai Waigaoqiao	55	2.6 %	34.4 %
Japan Marine United	51	2.5 %	36.8 %
Other	1,315	63.2 %	100.0 %
Total	2,082	100.0%	
Total number of shipyard owners		121	

	Contracts	Percent	Cumul.
Ship Owner (Group)			
COSCO Group	147	7.1 %	7.1 %
China Merchants	53	2.6 %	9.6 %
Pan Ocean	36	1.7 %	11.3 %
Fredriksen Group	29	1.4 %	12.7 %
Oldendorff Carriers	27	1.3 %	14.0 %
Pacific Basin Shpg	26	1.3 %	15.3 %
Eagle Bulk Shipping	23	1.1 %	16.4 %
Genco Shpg & Trading	23	1.1 %	17.5 %
Cardiff Marine	22	1.1 %	18.5 %
HOSCO	18	0.9 %	19.4 %
Other	1,678	80.6%	100.0 %
Total	2,082	100.0%	
Total number of ship owners		624	

Tanker	Contracts	Percent	Cumul.
Shipyard (Owner Group)			
Hyundai HI Group	348	22.5 %	22.5 %
Samsung HI	149	9.6 %	32.1 %
Daewoo (DSME)	102	6.6 %	38.7 %
STX Offshore & SB	94	6.1 %	44.7 %
CSSC Offshore Marine	69	4.5 %	49.2 %
DSIC Group	64	4.1 %	53.3 %
SPP Shipbuilding	40	2.6 %	55.9 %
ShinaSB Yard	39	2.5 %	58.4 %
Japan Marine United	35	2.3 %	60.7 %
Brodosplit	27	1.7 %	62.4 %
Other	583	37.6 %	100.0 %
Total	1,550	100.0%	
Total number of shipyard owners		102	

	Contracts	Percent	Cumul.
Ship Owner (Group)			
TORM A/S	37	2.4 %	2.4 %
Bahri	31	2.0 %	4.4 %
Petronas	30	1.9 %	6.3 %
Teekay Corporation	29	1.9 %	8.2 %
Stolt-Nielsen	28	1.8 %	10.0 %
Minerva Marine	22	1.4 %	11.4 %
Scorpio Group	21	1.4 %	12.8 %
Stena	20	1.3 %	14.1 %
Team Tankers	20	1.3 %	15.4 %
Tsakos Group	20	1.3 %	16.7 %
Other	1,292	83.4 %	100.0 %
Total	1,550	100.0%	
Total number of ship owners		416	

FCC	Contracts	Percent	Cumul.
Shipyard (Owner Group)			
Hyundai HI Group	342	21.3 %	21.3 %
Samsung HI	206	12.8 %	34.1 %
Daewoo (DSME)	132	8.2 %	42.3 %
HHIC	105	6.5 %	48.9 %
CSBC Corporation	82	5.1 %	54.0 %
Yangzijiang Holdings	71	4.4 %	58.4 %
DSIC Group	55	3.4 %	61.8 %
Genting Hong Kong	46	2.9 %	64.7 %
Shanghai Shipyard	41	2.6 %	67.2 %
Hudong Zhonghua	33	2.1 %	69.3 %
Other	493	30.7 %	100.0 %
Total	1,606	100.0%	
Total number of shipyard owners		68	

	Contracts	Percent	Cumul.
Ship Owner (Group)			
COSCO Group	183	11.4 %	11.4 %
A.P. Moller	139	8.7 %	20.0 %
CMA CGM	86	5.4 %	25.4 %
MSC	73	4.5 %	30.0 %
Hapag-Lloyd	62	3.9 %	33.8 %
Seaspan Corporation	48	3.0 %	36.8 %
Reederei C-P Offen	31	1.9 %	38.7 %
Costamare Shipping	28	1.7 %	40.5 %
Danaos Shipping	27	1.7 %	42.2 %
Yang Ming Marine	22	1.4 %	43.5 %
Other	907	56.5 %	100.0 %
Total	1,606	100.0 %	
Total number of ship owners		221	

Table 3-5: Ten largest shipyard and ship owners by segment.
Source: Authors' calculations, based on data from Clarksons (WFR) (2018a).

4. Method

4.1 The Hedonic Pricing Model

We seek to apply a framework that constructs objective newbuilding price indices by using micro-level data from newbuilding contracts. A method that is particularly suitable for this purpose is hedonic pricing models. This method is commonly used to value real assets, where the asset represents a bundle of characteristics of which each contribute to the value (Brooks, 2008, p. 112). Thus, in relation to our analysis of newbuilding prices, it allows us to construct price indices and control for micro-level data such as ship- and contract-specific characteristics.

4.1.1 Dependent Variable

The dependent variable applied in the model is the natural logarithm of the price of contract i, denoted by P_i. One argument in favour of a logarithmic transformation of the dependent variable, is that the contracting price is strictly greater than zero. When variables are strictly greater than zero, logarithmic models are likely to follow the central limit theorem more closely than models using level. Additionally, strictly positive variables often have conditional distributions that are heteroskedastic or skewed, an issue in which taking a logarithmic transformation can mitigate (Wooldridge, 2016, p. 172). To construct a time series of newbuilding prices, we first run an ordinary least squares regression as specified in equation (1).

$$P_i = \delta_1 + \sum_{t=2}^{T} \delta_t \times \theta_t + \varepsilon_i \tag{1}$$

Here θ_t represents a quarterly dummy variable equal to 1 in quarter t and 0 otherwise. The residual, ε_i, represents an error term with zero mean and constant variance. To avoid multicollinearity among the dummy variables, the first quarterly dummy is excluded. This quarter constitutes the reference quarter, δ_1, and represents the average newbuilding price of this period. Furthermore, the various coefficients δ_t (with $t = 2, \dots, T$) correspond to the quarterly price deviations with respect to the reference quarter. The drawback of this specification is that it does not account for the impact of ship- and contract-specific characteristics on the formation of newbuilding prices. Hence, we include several time-variant and time-invariant micro-level variables to control for ship- and contract-specific variation, not captured by the quarterly dummy variables. These variables are elaborated in the following paragraphs.

4.1.2 Explanatory Variables

Ship-Specific Variables

The resources required to build one gross ton differ significantly among ship types. Therefore, in order to enable a more accurate evaluation of shipbuilding workload, than possible on a pure deadweight or gross tonnage basis, the Organization for Economic Co-operation and Development (OECD) introduced a measurement known as compensated gross tonnage (CGT). The CGT-value is calculated by multiplying a ship's gross tonnage with a type-specific factor A and rising it to the power of a factor B[8]. These factors are defined by the OECD to represent ship type and ship size respectively (OECD, 2007). We expect CGT to have a positive impact on newbuilding prices, as it seems fair to assume that the number of man-hours and input factors needed to construct a ship, increase with its size.

Ships within the same segment might be equipped with different configurations which affect the price. Such variation is not captured by CGT, as the only variable included in addition to the segment specific factors is gross tonnage. We therefore include several other ship specific characteristics. Design speed is included to account for differences in hull type and engine power and is expected to have a positive impact on the price. For tankers, we have included the total number of pumps as a proxy for pump capacity, and a dummy variable for whether the ship has heating coils installed or not. Both variables are expected to have a positive impact on the price formation within the tanker segment, as they are considered additional equipment. Furthermore, for bulk carriers and FCCs, a dummy variable for gear is included. A geared ship has necessary loading and discharging equipment integrated to the ship, whereas a gearless ship is dependent upon terminal equipment. Hence, such equipment makes the ship more flexible in regard to ports for docking. Consequently, this variable is expected to have a positive impact on price in both segments, as it is considered additional equipment and improve flexibility.

Contract-Specific Variables

The first contract-specific variable is delivery time, defined as the difference between the built date and the contract date. When ordering a new ship, the buyer is faced with a delivery lag, due to both limitations in the availability of shipyard capacity and the comprehensive shipbuilding process. A study conducted by Adland et. al (2006) shows that the average delivery lag for bulk carriers, tankers

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[8] $Compensated\ Gross\ Tonnage = A\ \times Gross\ Tonnage^{B}$

and FCCs built at Chinese, Japanese and South Korean shipyards is between 1.86-3.52 years. Consequently, as a ship only generates revenues when operative, expectations is an important matter when agreeing on contractual terms (Stopford, 2009, p. 631). Since longer delivery time increase time to cash flow, which leads to a lower net present value of future earnings, a negative sign of the coefficient can be expected. However, as argued by Adland et. al (2017), higher newbuilding demand and growing orderbooks result in longer delivery time and higher prices. Hence, a positive coefficient might also be expected, making it unclear which effect is the most influential and what sign the variable ultimately should be expected to have.

The next variable of interest is shipyard experience, defined as the difference between the contracting year and the shipyard's first year of delivery. This variable is included to control for the impact of experience on price formation, as it is reasonable to believe that the most experienced shipyards manage to obtain some price premiums. In addition, we assume that experienced shipyards construct more complex and expensive ships. Hence, we expect shipyard experience to have a positive impact on newbuilding prices.

After including n ship- and contract-specific variables, the regression model is now specified as in equation (2). The coefficients β_i (for $i = 1, \dots, n$) represent the impact of the unique ship- and contract-specific characteristics on the newbuilding prices. Furthermore, the various coefficients δ_t (with $t = 2, \dots, T$) correspond to the deviations from the reference quarter, net of the impact of ship- and contract-specific characteristics.

$$P_i = \delta_1 + \sum_{t=2}^{T} \delta_t \times \theta_t + \sum_{i=1}^{n} \beta_i \times X_i + \varepsilon_i \tag{2}$$

Shipyard and Ship Owner Heterogeneity

Additional variation in the newbuilding prices may be explained by unobserved characteristics. Adland et al. (2017) argue that unobserved shipyard and ship owner heterogeneity has a significant impact on the formation of newbuilding prices, which can be accounted for by including shipyard and ship owner fixed effects in the model. Heterogeneity across shipyards could be related to specialisation premiums, bargaining power or superior ship designs. For owners, the fixed effects might capture variation resulting from an owner's ability to time markets. To cope with these heterogenous effects, fixed effects are included in the model. As a result, we end up with the model described in equation (3).

$$P_i = \delta_1 + \sum_{t=2}^{T} \delta_t \times \theta_t + \sum_{i=1}^{n} \beta_i \times X_i + \sum_{j=1}^{J} \gamma_j \times \theta_j + \sum_{k=1}^{K} o_k \times \theta_k + \varepsilon_i \tag{3}$$

In this equation, γ_j and o_k represent the fixed effect coefficients specific to yard j and owner k, respectively. Finally, the various coefficients δ_t (with $t = 2, \dots, T$) now correspond to the deviations from the reference quarter, net of the impact of ship- and contract-specific characteristics in addition to heterogeneity effects of shipyards and shipowners. Next, these coefficients are extracted to form newbuilding price indices for each segment. The following table summarizes the aforementioned variables, denoted by X_i, and their expected effect on newbuilding prices.

Variable	Expected impact on newbuilding price
Ship-specific	
Bulk Carrier	
Gear	Positive (+)
Tanker	
Total number of pumps	Positive (+)
Heating coils	Positive (+)
FCC	
Gear	Positive (+)
Contract-specific	
Delivery time	Uncertain (+/–)
Shipyard experience	Positive (+)
CGT	Positive (+)
Design speed	Positive (+)

Table 4-1: Overview of ship- and contract-specific variables and their expected effect on newbuilding prices.

4.2 Cointegration and the Vector Error Correction Model

To investigate whether the shipbuilding markets for bulk carriers, tankers and FCCs are integrated, we want to assess the long- and short-run relationships among the three indices. In a standard regression framework, such as ordinary least squares, variables have to be stationary[9] in order to avoid finding spurious relations (Granger & Newbold, 1974). Hence, as we expect the time series to be non-stationary, we start by elaborating on how to analyse the stationarity properties of the price indices.

4.2.1 The Augmented Dickey-Fuller Test

The augmented Dickey-Fuller (ADF) test is applied to determine the price indices' order of integration. This test is preferred over the standard Dickey-Fuller test because it allows for control of serial correlation, with a model of the form:

$$\Delta y_t = a + \delta t + \beta y_{t-1} + \zeta_1 \Delta y_{t-1} + \cdots + \zeta_k \Delta y_{t-p} + \varepsilon_t \tag{4}$$

where p is the number of lags included. The appropriate number of lags in the model is determined by the use of the Schwarz's Bayesian information criterion (SBIC) and the Hannan and Quinn information criterion (HQIC)[10], as suggested by Brooks (2008, p. 293). The terms a and δt are optional but must be included if y_t constitutes either a linear or quadratic trend. The constant term a is included when testing the levels of the price indices, as we suspect the series to fluctuate around an average which is nonzero. In contrast, the constant term a is not included when testing the first differences for stationarity, as we suspect the change in the indices to fluctuate a sample average of zero. The null hypothesis in the ADF test is that $\beta = 0$, which implies that y_t follows a unit root process and is non-stationary.

4.2.2 The Johansen Method

Cointegration analysis provides a framework for estimating long-run equilibria among multiple non-stationary variables. This is based on the idea that a linear combination of the non-stationary variables

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[9] A time series y_t is stationary if, for all t and $t - s$, $E(y_t) = \mu$, $var(y_t) = \sigma^2$ and $cov(y_{t,}y_{t-s}) = \gamma_s$ (Enders, 2015, p. 52).

[10] $SBIC = -2\left(\frac{LL}{T}\right) + \frac{\ln(T)}{T} t_p$ and $HQIC = -2\left(\frac{LL}{T}\right) + \frac{2ln\{\ln(T)\}}{T} t_p$, where T is the number of observations, t_p is the total number of parameters in the model and LL is the log likelihood.

might be stationary, given that all variables are integrated of the same order (Enders, 2015, p. 343). In relation to market integration, the existence of one or multiple cointegration relationships provide evidence of market integration (Ghosh, 2003). Furthermore, Ghosh (2003) states that an increase in the number of cointegration vectors in a multivariate model implies an increase in the strength of market integration. Hence, the number of cointegration relationships between the three price indices will be of interest in the analysis.

A commonly used procedure to identify cointegration relationships is the Engle-Granger two-step method. However, one limitation of this procedure is that it only identifies one cointegration relationship (Enders, 2015, p. 373). Generally, in the presence of K variables integrated of the same order, there may be at most $K-1$ cointegrating relationships (Enders, 2015, p. 378). Consequently, as we have three price indices, there might be at most two distinct cointegration relationships. The Johansen method is a commonly used procedure to identify multiple cointegration relationships and is therefore suitable for the intended purpose. The Johansen method starts with a vector autoregressive model (VAR) in levels with p lags of the form:

$$y_t = v + \mathrm{A}_1 y_{t-1} + \mathrm{A}_2 y_{t-2} + \cdots + \mathrm{A}_p y_{t-p} + \varepsilon_t \tag{5}$$

where y_t is a $K \times 1$ vector of variables integrated of the same order, v is a $K \times 1$ vector of coefficients, $\mathrm{A}_1 - \mathrm{A}_p$ are $K \times K$ matrices of coefficients and ε_t is a $K \times 1$ vector representing the error term. Further, the VAR model in equation (5) can be transformed into an equivalent differenced form, including lagged differences and a set of cointegrating vectors as explanatory variables, estimated by using maximum likelihood methods (Johansen, 1995, p. 45). This is known as the vector error correction model (VECM), and is specified as follows:

$$\Delta y_t = v + \Pi y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \times \Delta y_{t-i} + \varepsilon_t \tag{6}$$

where $\Pi = \sum_{j=1}^{p} \mathrm{A}_j - \mathrm{I}_k$ and $\Gamma_i = -\sum_{j=t+1}^{p} \mathrm{A}_j$. Additionally, v and ε_t in equation (5) and (6) have the same properties, whereas I_k is a $K \times K$ identity matrix. When selecting lag length, we choose the number of lags that minimize the SBIC and HQIC of a vector autoregressive model containing the three indices. Lütkepohl (2005, p. 326) demonstrates that this method provides consistent estimates of the true lag order. Further, Nielsen (2001) states that the lag order selection statistics, used to specify a VAR, can also be applied to a VECM in the presence of $I(1)$ variables. The only difference is that the lag order of the corresponding VECM is always one less than the VAR, since the VECM is in first difference.

Given that the variables y_t are $I(1)$ it can be shown that the matrix Π has a rank[11] of $0 \leq r < K$, where r is the number of linearly independent cointegrating vectors. When $\mathrm{r} = 0$, it implies that the variables y_t are non-stationary, which means that the VAR(p) in equation (5) is misspecified, as y_t should have been in d^{th} difference. Further, when the rank is $0 < r < K$, a VAR in first difference is misspecified as it omits the lagged term Πy_{t-1}. If Π has rank of $0 < r < K$, it can be expressed as $\Pi = \alpha\beta'$, where both α and β are $r \times K$ matrices of rank r. The matrices α and β contain information about the long-run equilibrium relationship between the variables. More specifically, β contains the coefficients in the cointegration vector describing the long-run equilibrium relationship among the variables y_t. Moreover, the parameters in α represent the weights at which the cointegration vector enters the VECM. This term is commonly referred to as the speed of adjustment, because the value of α embodies how quickly the variable reacts to deviations from long-run equilibrium. Contrary to α, the coefficients in Γ_i represent the short-run dynamics between the variables.

To determine the number of cointegrating vectors, Johansen (1995, pp. 92-93) considers two test statistics. The first test is known as the trace test, where the null hypothesis is that the rank of Π is less than or equal to r cointegrating vectors. The trace-statistic is computed as:

$$LR_{trace} = -T \sum_{i=r+1}^{K} \ln\left(1 - \hat{\lambda}_i\right) \tag{7}$$

where T is the number of observations and $\hat{\lambda}_i$ are the estimated eigenvalues[12]. For any given value of r, large values of the trace statistic form the basis of evidence against the null hypothesis that there are less than or equal to r cointegrating vectors in the VECM.

The second test is the maximum-eigenvalue test, where the null hypothesis is that r cointegrating vectors exist. This is tested against the alternative hypothesis that there are $r + 1$ cointegrating vectors. The maximum-eigenvalue statistic is calculated as:

$$LR_{max} = -T \ln\left(1 - \hat{\lambda}_{r+1}\right) \tag{8}$$

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[11] The rank r of a $n \times n$ matrix is equal to the number for lineary independent rows (columns) in the matrix (Enders, 2015).

[12] If A is an $n \times n$ matrix , the scalar λ is called an eigenvalue of A if $|A - \lambda I| = 0$, where I is an $n \times n$ identity matrix (Enders, 2015).

Critical values for both test statistics are obtained using Monte Carlo simulation. The distribution of the test statistics is dependent on the number of non-stationary and deterministic components in the VECM (Brooks, 2008, p. 352). Hence, it is important to correctly specify the model. The deterministic components included in the VECM depend on the properties of the time series, y_t. To illustrate, we can rewrite the VECM in equation (6) to the form:

$$\Delta y_t = \gamma + \tau t + \alpha\left(\beta' y_{t-1} + v + \rho t\right) + \sum_{i=1}^{p-1} \Gamma_i \times \Delta y_{t-i} + \varepsilon_t \tag{9}$$

where v and ρ are $r \times 1$ vectors and γ and τ are $K \times 1$ vectors. The deterministic term in the cointegrating equations $v + \rho t$ represents the means and linear trends in the equilibrium relationships among y_t. Further, the terms $\gamma + \tau t$ represent a linear and quadratic trend in y_t. Graphical analysis of the variables may provide some input with regard to which specification that should be applied. In addition, Becketti (2013) suggests a theoretical method to define the optimal deterministic term specification. This method applies a likelihood ratio test, where a nested model with restricted coefficients is tested against the unrestricted model.

5. Analysis and Findings

5.1 Hedonic Regressions

In the following sections we use the hedonic pricing model to construct newbuilding indices for the bulk carrier, tanker and FCC shipping segments. For each segment, five separate model specifications will be applied to best describe the variation in prices. The models are estimated using robust standard errors to avoid any unwanted influence of heteroscedasticity (Wooldridge, 2016, p. 244). In addition, to ensure that the models are compliant with the assumptions of OLS, and thus represent the best linear unbiased estimators, necessary tests have been conducted [13]. Based on these results, we consider the regression models as compliant and well-suited for the desired purpose. The following sections will analyse the regressions conducted on each segment separately. It is worth repeating, that the dependent variable is logarithmic, leading the regression coefficients to represent the percentage change in newbuilding price of a one-unit change in the explanatory variables, all else equal[14].

5.1.1 Bulk Carriers

The first specification yields an adjusted R-squared of 37.7%, indicating that the quarterly dummy variables capture substantial variation caused by cycling markets. The second specification includes ship- and contract-specific variables, which all prove significant, with the exception of experience. Delivery time is significant at the 5% significance level with a positive coefficient. As previously discussed, in times of high demand of new ships, shipyard capacity becomes a limited resource and delivery times tend to increase. Consequently, as prices increase with higher demand, the positive effect of delivery time on prices can be explained.

Shipyard experience does only prove significant when CGT is included in the third specification. However, it does meet our expectations considering its positive effect on prices. In accordance with our expectations, design speed shows a significantly positive effect on prices, whereas the ship-specific variable gear contradicts our expectations with its negative effect. As observed in Table 3-3, larger bulk carriers tend to be gearless, whereas more than 90% of all Handysize and Handymax bulk

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[13] In Appendix B, the distribution of the residuals and residuals vs. fitted values have been plotted for all models, in order to check for normality and heteroscedasticity in the residuals respectively. In addition, we examine the Variance Inflation Factors of the independent variables of each model to control for multicollinearity.

[14] For example: in a regression of the form $y = \alpha + \beta \times X + \varepsilon$, where y is the logarithmic transformation of Y, $100 \times \beta$ is the expected percentage change in Y, for a one-unit change in X, all else equal.

carriers are geared in our data sample. As a result, the gear variable might capture variation in price due to differences in ship size, thus explaining its negative sign. This relation of size and gear is confirmed when CGT is included in the third specification, and the coefficient of gear decreases in magnitude from -42% to -4.93%. Even though less influential when size is accounted for, the coefficient unexpectedly remains negative. The adjusted R-squared of the second specification increases to 68.6%, indicating that the included variables are relevant predictors for newbuilding prices.

The effect of CGT is in line with our expectations, as it imposes a positive and significant effect on newbuilding prices when included in the third specification. By including CGT, the adjusted R-squared increases to 91.0%, indicating the impactful explanatory power of CGT on newbuilding prices. However, in this specification, delivery time becomes insignificant, whereas shipyard experience becomes positive and significant. The latter supports our beliefs and might indicate that more experienced shipyards obtain some price premiums. On the other hand, it might also prove that these shipyards tend to build more complex and expensive ships. When accounting for shipyard fixed effects in the fourth specification, shipyard experience becomes less significant, indicating the fixed effects captures some of this variation. The adjusted R-squared increases to 93.8% when accounting for shipyard fixed effects. Finally, when including owner fixed effects, shipyard experience and design speed becomes insignificant and the adjusted R-squared increases to 97.6%.

Even though the model’s explanatory power can be perceived as very high, it can be explained by the inclusion of time dummies and the CGT-variable. As no variables account for market fluctuations or macroeconomic effects, like steel prices and gross domestic product (GDP), in the model, the time dummies capture most of the prominent effects of cycling markets and time. In addition, CGT represents a general measure for both ship size and complexity, which naturally will explain substantial variation in ship prices.

Bulk carriers

Model specification #	1	2	3	4	5
Constant	3.715***	1.907***	2.710***	2.596***	3.180***
	(0.0744)	(0.171)	(0.0943)	(0.187)	(0.102)
Delivery Time		4.46e-05**	-1.26e-05	1.33e-05	-1.71e-05
		(1.90e-05)	(1.06e-05)	(1.11e-05)	(1.27e-05)
Shipyard Experience		0.000113	0.00131***	0.000706**	-5.39e-05
		(0.000585)	(0.000365)	(0.000331)	(0.000393)
Design Speed		0.148***	0.0321***	0.0184***	-0.00346
		(0.0115)	(0.00634)	(0.00545)	(0.00500)
Gear		-0.420***	-0.0493***	-0.0290***	-0.0477***
		(0.0118)	(0.00952)	(0.0101)	(0.0125)
CGT			3.98e-05***	3.85e-05***	3.87e-05***
			(7.12e-07)	(6.84e-07)	(8.54e-07)
Quarterly Dummies	YES	YES	YES	YES	YES
Shipyard fixed effects	NO	NO	NO	YES	YES
Owner fixed effects	NO	NO	NO	NO	YES
Observations	2,082	2,082	2,082	2,082	2,082
Adjusted R-squared	0.377	0.686	0.910	0.938	0.976

Robust standard errors in parentheses
*** Significant at the 1% level, ** Significant at the 5% level, * Significant at the 10% level
Dummy variables are not included in the regression output

Table 5-1: Regression output for bulk carriers.

5.1.2 Tankers

The first specification of the tanker segment has an adjusted R-squared of 22.5%, considerably lower than observed in the same specification in the bulk carrier segment. As ship-specific variables are included in the second specification, the adjusted R-squared almost doubles to 53.4%. Note that the constant term is now significant at the 5% level. The coefficients of delivery time, experience and design speed have the same signs as in the corresponding bulk carrier specification. However, now all three variables are positively significant at the 1% level. Furthermore, the ship-specific variables total number of pumps and heating coils also prove significant, but with a negative effect on prices, contradicting our expectations. The negative effect of total number of pumps on prices can be rooted in the difference between crude, product, chemical and special tankers. Crude tankers are generally known for being larger, carrying vast quantities of crude oil, whereas the other tankers are generally smaller and carry a variety of products. This variety in liquid cargo demand different chambers with separate pumps, resulting in a need of more pumps for the relatively smaller product, chemical and special tankers. Thus, the negative sign can be explained by the substantial spread in size for tankers and that larger ships are costlier. The same rationale can be applied to the effect of heating coils, which observed in Table 3-3, are less prominent among the larger tanker segments. In accordance with our expectations, both variables change signs when accounting for ship size by including CGT in the third explanation. The adjusted R-squared increases further to 84.4% in the third specification.

As observed in the bulk carrier regression, shipyard experience becomes less significant when accounting for shipyard fixed effects in the fourth specification. In addition, the adjusted R-squared increases to 93.8%. Now significant at a 10% level, the significance of shipyard experience evaporates entirely in the final specification, joined by the significance of delivery time. Furthermore, the coefficient of the total number of pumps unexpectedly becomes negative in the fifth specification. When including the owner fixed effects adjusted R-squared increases to 97.2%.

Tankers

Model specification #	1	2	3	4	5
Constant	4.356***	0.613**	1.556***	2.004***	2.531***
	(0.199)	(0.297)	(0.126)	(0.144)	(0.125)
Delivery Time		0.000214***	8.66e-05***	5.19e-05***	1.73e-05
		(4.35e-05)	(2.99e-05)	(1.62e-05)	(1.83e-05)
Shipyard Experience		0.00259***	0.00205***	-0.000804*	-0.000602
		(0.000831)	(0.000496)	(0.000458)	(0.000589)
Design Speed		0.245***	0.0824***	0.0491***	0.0186***
		(0.0175)	(0.00761)	(0.00591)	(0.00658)
Total number of Pumps		-0.0124***	0.00607***	0.000709	-0.00578***
		(0.00219)	(0.00130)	(0.00155)	(0.00149)
Heating Coils		-0.0975***	0.112***	0.0750***	0.0494***
		(0.0223)	(0.0140)	(0.0109)	(0.0135)
CGT			4.53e-05***	3.69e-05***	3.40e-05***
			(1.01e-06)	(8.42e-07)	(1.12e-06)
Quarterly Dummies	YES	YES	YES	YES	YES
Shipyard fixed effects	NO	NO	NO	YES	YES
Owner fixed effects	NO	NO	NO	NO	YES
Observations	1,550	1,550	1,550	1,550	1,550
Adjusted R-squared	0.225	0.534	0.844	0.938	0.972

Robust standard errors in parentheses
*** Significant at the 1% level, ** Significant at the 5% level, * Significant at the 10% level
Dummy variables are not included in the regression output

Table 5-2: Regression output for tankers.

5.1.3 Fully Cellular Containerships

The quarterly dummies in the FCC model captures 29.1% of the variation in newbuilding prices, a slight increase compared to the tanker segment, but lower than observed for the bulk carriers. The constant term of the second specification is not significant and there is thus no basis in the empirical evidence to argue that it differs from zero. The covariates included does however prove significant, with an exception of shipyard experience. As observed in the bulk carrier model, the coefficients of design speed and delivery time are positive, whereas the coefficient of gear is negative, once again contradicting our expectations. However, the same relation of gear and size can be observed in Table 3-3 for FCCs, where no ships in the three largest segments have gear, thus explaining the coefficient's negative sign. The second specification yields an adjusted R-squared of 78.8%.

As CGT is included in the third specification all covariates become insignificant, but design speed and CGT. In addition, the constant term becomes significant and positively different from zero, and the explanatory power increases to 92.0%. When including fixed effects in the two final specifications, adjusted R-squared increases to 95.4% and 97.0%, respectively. Signs or degrees of significance do not change for any of the covariates, except delivery time, which becomes positive and significant when including the fixed effects.

FCCs

Model specification #	1	2	3	4	5
Constant	3.835***	0.102	1.726***	2.136***	2.581***
	(0.190)	(0.188)	(0.164)	(0.141)	(0.136)
Delivery Time		0.000121***	-9.76e-06	4.47e-05**	5.48e-05***
		(3.46e-05)	(2.01e-05)	(1.86e-05)	(1.57e-05)
Shipyard Experience		0.000782	-0.000718	0.000237	0.000422
		(0.000795)	(0.000623)	(0.000634)	(0.000681)
Design Speed		0.178***	0.0778***	0.0511***	0.0368***
		(0.00633)	(0.00512)	(0.00543)	(0.00651)
Gear		-0.118***	-0.0136	-0.00814	-0.0116
		(0.0268)	(0.0183)	(0.0147)	(0.0138)
CGT			2.56e-05***	2.44e-05***	2.37e-05***
			(6.37e-07)	(6.10e-07)	(6.54e-07)
Quarterly Dummies	YES	YES	YES	YES	YES
Shipyard fixed effects	NO	NO	NO	YES	YES
Owner fixed effects	NO	NO	NO	NO	YES
Observations	1,606	1,606	1,606	1,606	1,606
Adjusted R-squared	0.291	0.788	0.920	0.954	0.970

Robust standard errors in parentheses
*** Significant at the 1% level, ** Significant at the 5% level, * Significant at the 10% level
Dummy variables are not included in the regression output

Table 5-3: Regression output for FCCs.

5.2 Construction of Hedonic Newbuilding Price Indices

In order to create price indices that represent the underlying drivers of newbuilding prices, we extract the time dummy coefficients from the fifth specification of all models. This specification yields the highest explanatory power and accounts for ship- and contract-specific characteristics, in addition to shipyard and ship owner heterogeneity, leaving only the underlying and unexplained variation to the time dummies. The first quarter of 1994 constitutes the basis for the indices and is set to 100. Once extracted, the coefficients make up a time series applicable for cointegration analysis. However, in order to conduct a cointegration analysis of the three indices, all time series must be continuous and complete. As some quarters lack observations[15], we apply a modification to make the indices compliant. Thus, when gaps occur in the time series, the missing data points are estimated using linear interpolation between the observations prior to and following the gap. This assumption is obviously a shortcoming of our analysis, but we regard the modification as a viable solution, as the indices represent underlying trends in newbuilding prices and a linear average is likely to follow these trends.

At last we plot the constructed indices over the time period of 1994-2015, as seen below in Figure 5-1. A visual analysis of the graph gives indications of similarities in terms of price movements. However, there are prominent differences as well, especially during and following the financial crisis of 2007-2009, where the dataset is highly influenced by a lack of observations. This relation is illustrated by the included bar chart, displaying the total number of newbuilding contracts in all three segments. The bar chart is based on numbers reported in Clarksons (SIN) (2018b)[16], and includes all contracts, independent of whether newbuilding prices are disclosed in the contract or not. Considering that the indices are based on observations containing newbuilding prices, constituting a mere 14% of our unrefined dataset, it is obvious that few observations is a major shortcoming of our analysis and highly affects parts of the indices.

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[15] The following quarters lack data in each segment:

Bulk Carriers:	Q1-Q2 2001 and Q3 2002
Tankers:	Q1-Q3 2009, Q1 2011, Q3 2011, Q4 2012, Q3 2015.
FCCs:	Q4 2008, Q1 2009, Q1-Q2 2010, Q4 2015

[16] Clarksons (SIN) (2018b) do only report contract volumes from 1996 and onwards, and we have therefore supplemented the first two years using contract volumes from Clarksons (WFR) (2018a).

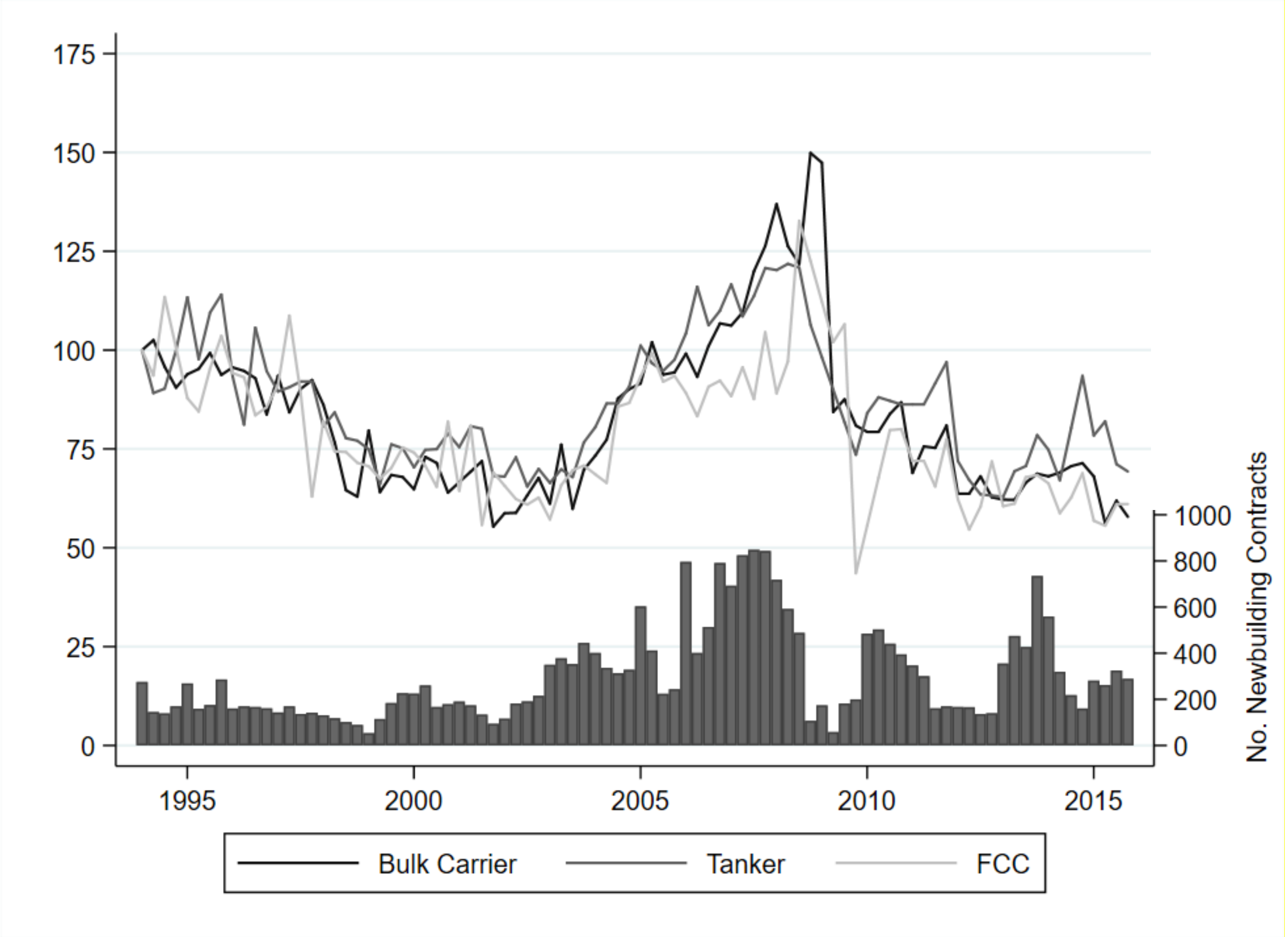

Figure 5-1: Hedonic price indices for bulk carriers, tankers and FCCs, and total number of newbuilding contracts from 1994-2015. Source: Authors' calculations, based on data from Clarksons (WFR) (2018a) and (SIN) (2018b).

5.3 Cointegration Analysis

In the following section we examine whether cointegration exists between the three newbuilding price indices. We specify two vector error correction models, A and B, where model B includes a "crisis"-variable to cope with the turbulence of the Great Recession[17]. First, we investigate the price indices' order of integration, select the optimal lag length and define the optimal deterministic trend specification. Next, we use the Johansen method to define the number of cointegrating equations and elaborate on the long-run equilibrium conditions set by the coefficients. We continue by analysing the speed of adjustment coefficients in model A, and whether these coefficients differ in model B. At last, we will discuss the findings in the light of the shipbuilding market.

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[17] The crisis variable equals 1 in the period from Q1 2008 – Q4 2009, and 0 otherwise.

5.3.1 Stationarity

The ADF-test is specified with a constant as we suspect the indices to follow a random walk without a trend. Further, the Schwarz's Bayesian (SBIC) and the Hannan and Quinn information criteria (HQIC) are used to determine the optimal lag length. Both criteria indicate a lag length of one to be optimal for all three indices. In order to be certain about the robustness of our conclusion with regard to stationarity, we perform the test with various lag lengths. We fail to reject the hypothesis of non-stationarity for all three indices in levels at the 5% significance level. However, we reject the null hypothesis of a unit root for all series in first-differences at the 5% significance level. This implies that the indices contain a unit root and are integrated of order one. The test statistics are presented in Appendix C.

5.3.2 Deterministic Trend Specification and Lag Length Selection

To determine the best fit of the model, we test all possible restrictions against each other by applying a likelihood ratio test. The results from this analysis are presented in Appendix C. The analysis concludes that the restricted trend specification is the best fit, allowing for a trend in the levels of the data and the cointegrating equations. Hence, the following analysis in model A and B is conducted using this particular specification. As previously discussed, we choose the number of lags that minimize the SBIC and HQIC of a vector autoregressive model containing the three indices. As shown in Table 5-4 below, the optimal lag length is one. This implies that there are no significant short-run effects between the indices.

Lags	HQIC	SBIC
0	23.597	23.649
1	**21.697***	**21.905***
2	21.859	22.222
3	22.003	22.522

* Indicates optimal lag length

Table 5-4: Lag length selection for Model A and B.

5.3.3 Rank

The results of the multivariate cointegration tests are presented in Table 5-5. From the trace test, we can reject the null hypothesis of $r = 0$ and $r \leq 1$ at the 5% significance level. However, we fail to reject the hypothesis of $r \leq 2$ at the same level of significance, indicating that the number of cointegration relationships is two. This is in line with the findings from the maximum eigenvalue test, which rejects the null hypothesis of $r = 0$ and $r = 1$, against the alternative hypothesis of $r + 1$

cointegrating relationships at the 5% significance level. We fail to reject the null of $r = 2$ at the same level of significance. Hence, the results are consistent since both the λ-trace and λ-max statistics indicate two cointegrating relationships. These findings are also valid when including the crisis variable in the model. Since the number of variables included is three, the number of common stochastic trends is equal to one. This implies that the three indices are pair-wise cointegrated, which is evidence in favour of an integrated shipbuilding market for bulk carriers, tankers and FCCs.

Trace test			Maximum eigenvalue test		
Null	Trace	5% critical value	Null	Max	5% critical value
Model A					
r = 0	98.51	42.44	r = 0	60.93	25.54
r ≤ 1	37.58	25.32	r = 1	33.97	18.96
r ≤ 2	3.61	12.25	r = 2	3.61	12.52
Model B					
r = 0	104.50	42.44	r = 0	66.59	25.54
r ≤ 1	37.90	25.32	r = 1	36.50	18.96
r ≤ 2	1.40	12.25	r = 2	1.40	12.52

Table 5-5: determination of rank for model A and B.

5.3.4 Cointegrating Equations

To investigate the long-term equilibrium dynamics of the indices, we start by examining the coefficients defined in the cointegrating equations presented in Table 5-6. Following the results above, model A and B are estimated with two cointegration vectors, one lag and a restricted trend specification.

In equation 1A, the Johansen identification scheme defines two constraints, setting the coefficients of the bulk and tanker indices to 1 and 0, respectively. The coefficient $\hat{\beta}_{FCCIndex,1A}$ is significant at a 1% level, indicating a positive long-run relationship between the newbuilding prices of bulk carriers and FCCs. The trend is found to be positive and significant at the 1% significance level, indicating that the equilibrium relationship is increasing in magnitude over the time period.

In equation 2A, the coefficients of the tanker and bulk indices are set to 1 and 0, respectively. Similar to the findings in equation 1A, $\hat{\beta}_{FCCIndex,2A}$ is significant at the 1% significance level, indicating a positive relationship between tankers and FCCs. However, in contrast to equation 1A, the time trend is significant at the 10% significance level. As observed in Table 5-6, the coefficients change slightly after including the crisis variable in model B, both in significance level and magnitude.

Variable	Bulk Carrier Index	Tanker Index	FCC Index	Trend	Constant
Model A					
Equation 1A	1	0	-1.421***	-0.206***	37.573
	-	-	(0.100)	(0.068)	-
Equation 2A	0	1	-1.070***	-0.139*	2.662
	-	-	(0.114)	(0.078)	-
Model B					
Equation 1B	1	0	-1.364***	-0.186**	32.787
	-	-	(0.130)	(0.076)	-
Equation 2B	0	1	-1.191***	-0.192**	13.971
	-	-	(0.146)	(0.086)	-

Standard errors in parentheses
*** Significant at the 1% level, ** Significant at the 5% level, * Significant at the 10% level

Table 5-6: Cointegrating equations for model A and B.

5.3.5 Speed of Adjustment Coefficients

It is useful to interpret the coefficients of the error correction term in the VECM to better understand the long-run equilibrium dynamics between the three price indices. In the following sections, we will first discuss the coefficients of model A presented in Table 5-7, before elaborating on the impact of including the crisis variable in model B. The coefficients, $\hat{a}_{j,q}$, represent the speed of adjustment for index j to equilibrium deviations in equation q. These coefficients indicate how quickly the price indices adjust to deviations from the long-run equilibrium, defined by the cointegrating equations.

The coefficient $\hat{a}_{BulkCarrier,1A}$ is equal to -0.526, significant at the 1% significance level. The negative sign is as expected, because the bulk carrier index is set to one in the first cointegrating equation. Hence, when the error correction term is positive, the bulk carrier index must be above its equilibrium level and will therefore decrease relatively to the FCC index, until equilibrium is reached. The magnitude of the coefficient indicates that the bulk carrier index reacts relatively quickly to deviations from the equilibrium, adjusting more than half of the deviation in the first quarter. For the FCC index, $\hat{a}_{FCC,1A}$ equals 0.367, significant at a 1% level. The coefficient indicates that the index will increase when the error correction term is positive. Again, this is as expected, because a positive error correction term implies that the index increases relatively to the bulk carrier index, until equilibrium is reached. Similar to $\hat{a}_{BulkCarrier,1A}$, the magnitude of $\hat{a}_{FCC,1A}$ indicates a relatively quick reaction to deviations from the long-run equilibrium.

Interestingly, the coefficient $\hat{a}_{Tanker,1A}$ equals 0.223 and is statistically significant at the 1% significance level, even though the tanker index does not enter equation 1A. This relationship can be explained by examining equation 2A, which includes the tanker and FCC indices. Since the FCC index increases as a response to a positive error correction term in the first equation, it will affect its long-run equilibrium relationship with the tanker index through the second equation. In order to sustain in equilibrium, the tanker index must increase, explaining the positive coefficient.

For equation 2A, the coefficient $\hat{a}_{BulkCarrier,2A}$ equals 0.500, significant at a 1% level. However, as the bulk carrier index is constrained and set to zero in this equation, the interpretation of this coefficient is more intricate and must be explained though the first equation. When the second error correction term is positive, the tanker index must be above its equilibrium level, resulting in an increase in the FCC index until the long-run equilibrium is reached. This mechanism has a spillover effect on equation 1A, and the bulk carrier index must responsively increase in order to sustain the long-run equilibrium. Consequently, $\hat{a}_{BulkCarrier,2A}$ is positive and the magnitude of the coefficient indicates a relatively quick reaction to equilibrium deviations. Furthermore, the coefficients $\hat{a}_{Tanker,2A}$ and $\hat{a}_{FCC,2A}$ equal -0.249 and 0.260, respectively. These opposite signs suggest convergence towards the long-run equilibrium. Both coefficients are significant at the 5% significance level, but lower than $\hat{a}_{BulkCarrier,2A}$ in magnitude.

Model A

Variable	ΔBulk Carrier Index	ΔTanker Index	ΔFCC Index
$1A_{t-1}$	-0.526***	0.223**	0.367***
	(0.097)	(0.087)	(0.106)
$2A_{t-1}$	0.501***	-0.249**	0.260**
	(0.110)	(0.099)	(0.121)
Constant	-0.231	-0.496	-0.0291
	(0.962)	(0.863)	(1.053)
Observations	87	87	87

Standard errors in parentheses
*** Significant at the 1% level, ** Significant at the 5% level, * Significant at the 10% level

Table 5-7: Vector error correction model A.

The impulse response functions in Figure 5-2 show the effect of an imposed shock on one index on the others for model A. More precisely, it illustrates how the indices adjust to deviations from the long-run equilibria through the coefficients discussed above. First, by causing a shock on the bulk carrier index, the response functions illustrate that $\hat{a}_{FCC,1A}$ is slightly greater in magnitude than $\hat{a}_{Tanker,1A}$, as the response by the FCC index is steeper. Similar findings are evident when causing a shock on the tanker index, as $\hat{a}_{BulkCarrier,2A}$ is greater in magnitude than $\hat{a}_{FCC,2A}$, which is illustrated by a steeper response function. Furthermore, the response of the bulk carrier index, when causing a shock on the FCC index, equals the net effect of $\hat{a}_{BulkCarrier,1A}$ and $\hat{a}_{BulkCarrier,2A}$ as the FCC index enters both cointegrating equations. The same logic applies to the response of the tanker index.

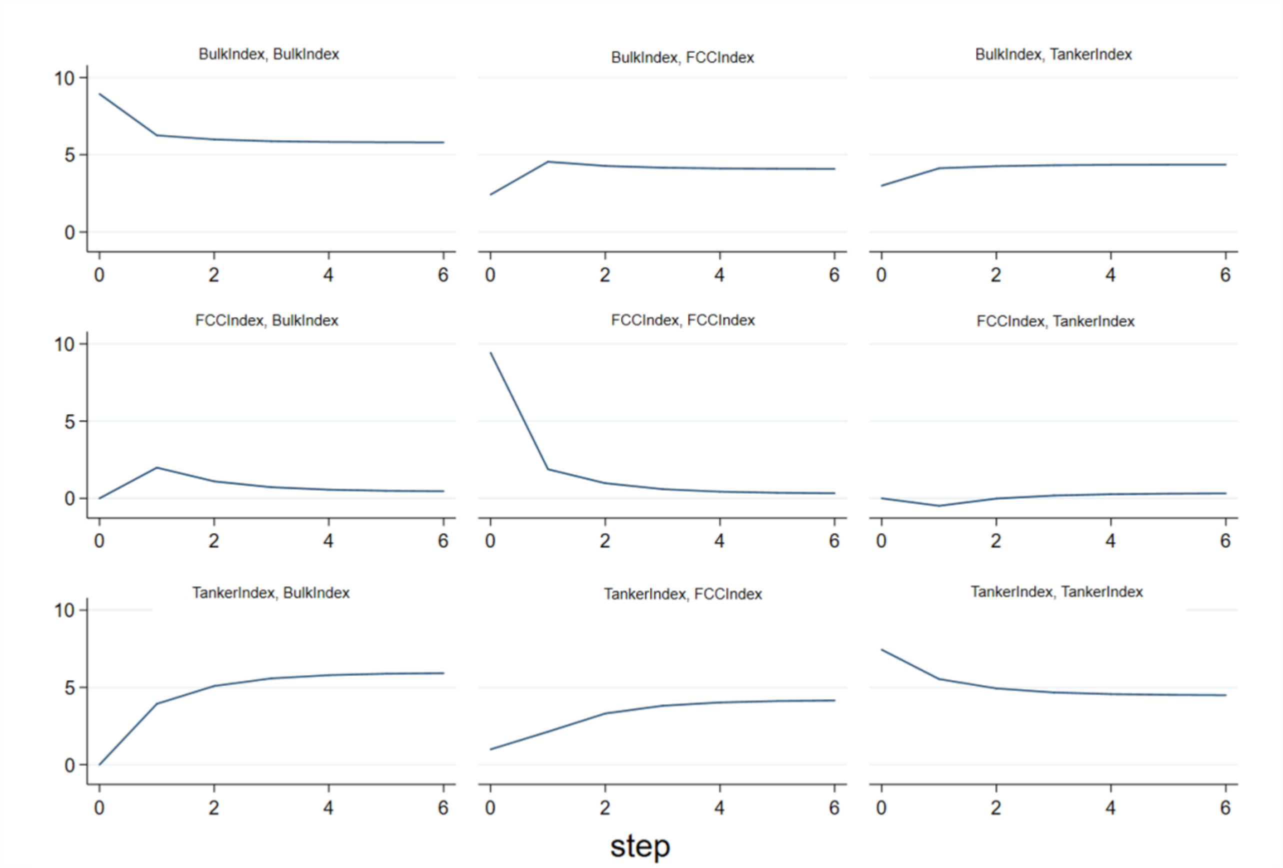

Figure 5-2: Impulse response functions of model A. Graphs by impulse variable and response variable across quarters (steps).

Neither of the constant terms in model A are significantly different from zero, meaning that there is no evidence of a time trend in the levels of the data. However, we want to investigate this further by including the crisis variable in model B, allowing the trend to differ during the period from Q1 2008 until Q4 2009. Since the financial crisis resulted in a sharp decline in the global economy and caused the demand for shipping services to fall, the demand for newbuilding's dropped significantly. As illustrated earlier, this period of our sample is characterised by a sharp decline in both contract volume and newbuilding prices in all segments. As a consequence, we expect the coefficient of the crisis variable to be negative. The results, presented in Table 5-8, provide evidence of a negative time trend for the tanker index, which is statistically significant at a 1% level. However, we fail to reject the null hypothesis that it equals zero for both the bulk carrier and the FCC indices at the 10% significance level. Furthermore, $\hat{a}_{FCC,1B}$ is not significantly different from zero at the 5% level, implying that it does not adjust to deviations from the equilibrium. At last, we observe that $\hat{a}_{Tanker,1B}$ and $\hat{a}_{Tanker,2B}$ increase slightly in absolute value and that the significance level changes from 5% to 1%.

Model B

Variable	ΔBulk Carrier Index	ΔTanker Index	ΔFCC Index
$1B_{t-1}$	-0.567***	0.299***	0.372***
	(0.105)	(0.089)	(0.116)
$2B_{t-1}$	0.488***	-0.361***	0.237*
	(0.116)	(0.099)	(0.128)
Crisis	1.425	-11.86***	-1.949
	(3.827)	(3.268)	(4.221)
Constant	0.128	0.198	0.0367
	(1.002)	(0.856)	(1.105)
Observations	87	87	87

Standard errors in parentheses

*** Significant at the 1% level, ** Significant at the 5% level, * Significant at the 10% level

Table 5-8: Vector error correction model B.

5.4 Findings

In the analysis, we identify two cointegrating relationships between the three newbuilding price indices. These findings provide evidence in favour of an integrated shipbuilding market for bulk carriers, tankers and FCCs, as the newbuilding prices are joined in mutual long-run equilibria. This is in accordance with the perspective that the product offered in the shipbuilding market ultimately is capacity, and that shipyards face a strategic choice in how to optimally define their product mix. As a result, newbuilding prices may be affected by the opportunity cost of available shipyard capacity, which help explain why the long-run equilibria exist.

When analysing the equilibria in a vector error correction model, we find the speed of adjustment coefficients to be significant for all indices in model A, at the 5% significance level. This implies that all three indices adjust to deviations from the long-run equilibria. Further, the impulse response functions illustrate how the indices with larger coefficients adjust faster to deviations, where the bulk carriers adjust almost twice as fast as the other segments. This might be explained by the higher volume of bulk carrier contracts compared to tankers and FCCs. Additionally, bulk carriers are typically regarded as easier to build, suggesting that more shipyards include them in their product mix. Moreover, we fail to find any evidence of short-run effects between the indices in either of the two models. Put differently, the effect of a change in one segment, does not have a significant impact on the other segments in the following quarter. This can be rooted in the nature of the shipbuilding market, which is influenced by its long cycles. As previously mentioned, shipbuilding is a time-consuming process, making shipyards unable to adjust their short-run product mix. Consequently, short-run spillover effects between the segments may be limited.

We also find some differences between model A and B, as the crisis variable is negative and significant for the tanker index. This supports our expectations of a negative time trend in the data from Q1 2008 to Q4 2009. However, even though demand in all three segments plummeted during the Great Recession, the evidence of a negative trend is unexpectedly less prominent for bulk carriers and FCCs. Additionally, $\hat{a}_{FCC,2B}$ is not significantly different from zero at a 5% significance level, indicating that FCC newbuilding prices do not respond to deviations from the equilibrium defined by equation 2B.

6. Robustness of findings

We adjust our analysis in two ways to test the robustness of the findings. First, in model C, we compress the sample period by excluding the period after Q4 2007, as we suspect the low contract volume during the financial crisis to may affect the cointegration analysis. Additionally, as we recognise that the number of observations in our sample is limited due to confidentiality clauses, we use newbuilding price indices reported in Clarksons (SIN) (2018b), to compare the findings. We start by investigating the impact of compressing the sample period.

6.1 Adjustment 1: Compressed Sample Period

Starting with the first adjustment, we again apply the likelihood ratio test to determine the deterministic trend specification. The results are presented in Appendix C, and indicate that this model is best fitted with a trend specification, allowing for a quadratic trend in the price indices. This might be explained by the rapid increase in newbuilding price for all three segments in the years before the Great Recession, as illustrated in Figure 5-1. Furthermore, the optimal lag length and the number of cointegrating equations does not change by compressing the sample period. These test statistics are presented in Appendix C. Hence, we still fail to find evidence of short-term effects between the price indices. Since the number of cointegrating equations is not affected, we still find the three indices to be pair-wise cointegrated, which is evidence in favour of an integrated shipbuilding market for bulk carriers, tankers and FCCs.

We find some differences in the long-run equilibria defined by the cointegrating equations presented in Table 6-1. The first observation is that the relationship between the bulk carrier and FCC indices is slightly lower in absolute value in model C compared to model A. In contrast to this observation, the relationship between the tanker and the FCC indices increases slightly in absolute value.

Variable	Bulk Carrier Index	Tanker Index	FCC Index	Trend	Constant
Equation 1C	1	0	-1,335***	-0,256	32,210
	-	-	(0,112)	-	-
Equation 2C	0	1	-1,200***	-0,290	17,140
	-	-	(0,122)	-	-

Standard errors in parentheses
*** Significant at the 1% level, ** Significant at the 5% level, * Significant at the 10% level

Table 6-1: Cointegrating equations for model C.

In addition, the speed of adjustment coefficients change both in magnitude and significance level, even though the signs remain unchanged. The most interesting finding is arguably that the FCC index does not adjust to deviations from the long-run relationship with the tanker index in model C, as the coefficient $\hat{a}_{FCC,2C}$ is not significantly different from zero, even at the 10% significance level. Hence, the long-run relationship between the two indices is dependent on a response from the tanker index when deviations occur. In relation to this, it is worth noting that the magnitude of $\hat{a}_{Tanker,2C}$ has increased in model C, from -0.249 to -0.600. Moreover, the significance level has increased from 5% to 1%. At last, the trend only proves significant for the bulk carrier index, which might be caused by its more rapid increase relatively to the tanker and FCC indices in the years prior to the Great Recession.

Model C

Variable	ΔBulk Carrier Index	ΔTanker Index	ΔFCC Index
$1C_{t-1}$	-0.459***	0.325**	0.558***
	(0.124)	(0.130)	(0.152)
$2C_{t-1}$	0.311**	-0.600***	0.0517
	(0.126)	(0.131)	(0.154)
Trend	0.134**	0.0754	0.0667
	(0.0559)	(0.0584)	(0.0685)
Constant	-3.265*	-1.757	-1.792
	(1.799)	(1.878)	(2.202)
Observations	55	55	55

Standard errors in parentheses

*** Significant at the 1% level, ** Significant at the 5% level, * Significant at the 10% level

Table 6-2: Vector error correction model C.

6.2 Adjustment 2: Clarksons Newbuilding Price Indices

For the second adjustment, we conduct the same analysis but replace the hedonic indices by newbuilding indices reported in Clarksons (SIN) (2018b)[18]. The two indices are plotted against each other for all segments in Figure 6-1. Note that these indices were first reported in 1996, and we therefore define Q1 1996 as the base quarter for both the hedonic and Clarksons indices. A visual comparison of the hedonic and Clarksons newbuilding price indices give indications of similarities in trend and magnitude. However, during and following the Great Recession, the indices differ to a larger extent, which might lead to different results than observed in the previous analysis.

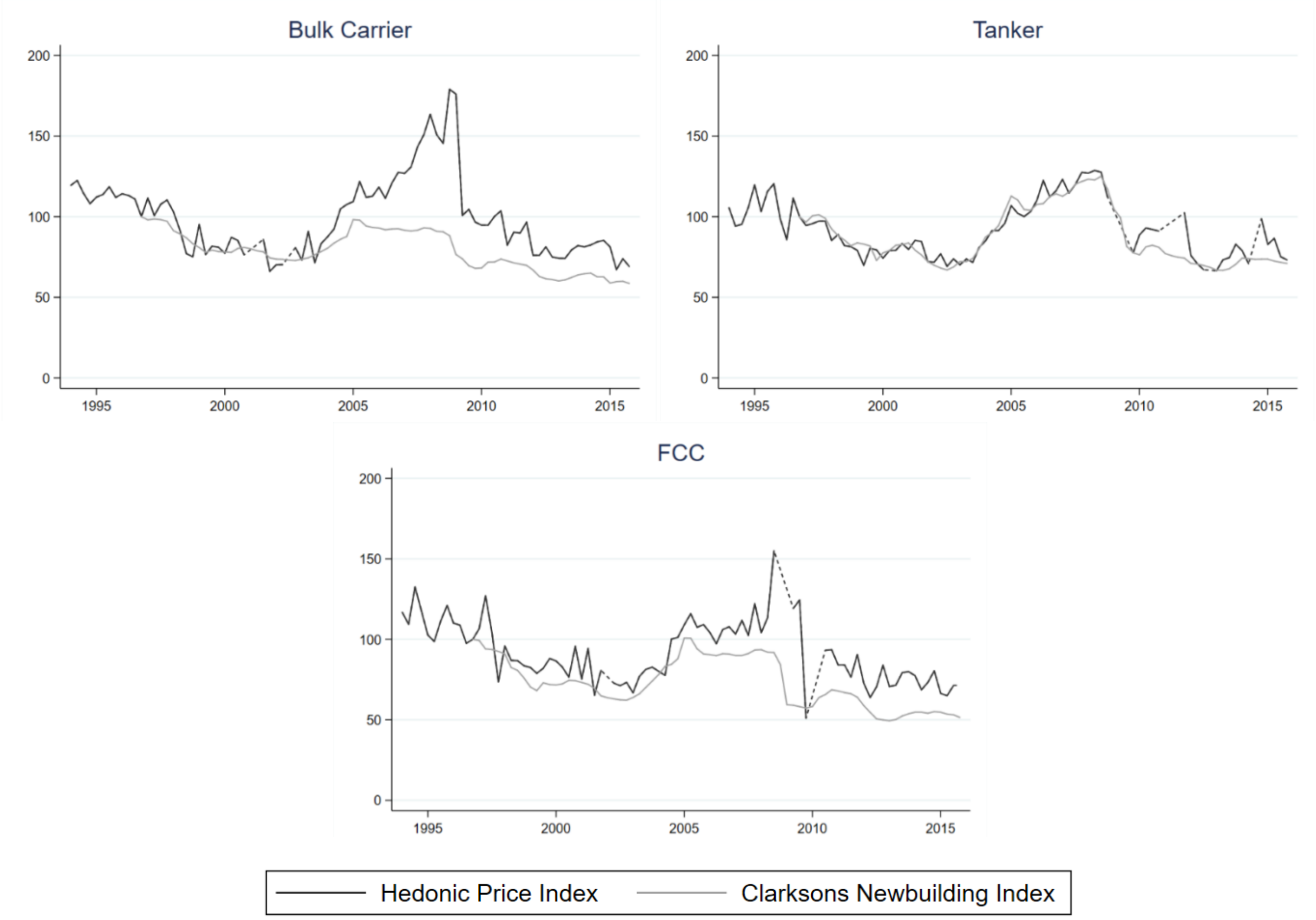

Figure 6-1: The hedonic and Clarksons newbuilding price indices. The dashed sections represent the quarters lacking data. Sources: Authors' calculations, based on data from Clarksons (WFR) (2018a) and (SIN) (2018b).

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[18] The Clarkson Newbuilding Price Index is calculated by averaging the $ per dwt values of the various ship types. In periods lacking observations, estimates are based on brokers' best estimate (Clarksons, 2018b).

Contradicting the results from model A, the likelihood ratio test now suggests a restricted constant to be the optimal deterministic trend specification for model D. The test statistics is presented in Appendix C. One possible explanation of the opposite specification is the observation that the Clarksons indices behave more stable throughout the sample period, especially for the bulk carrier and FCC segments, implying no trend in the indices. Additionally, a restricted constant does not allow for a linear trend in the cointegrating equation, implying that the long-run equilibrium remains constant over time.

Another interesting finding is that the optimal lag length changes from one to two in model D. This is in contrast to the previous findings in model A, and implies an existence of short-run effects between the three indices. Furthermore, the number of cointegrating equations is reduced to one, suggesting a weaker form of market integration. However, it still supports the evidence of market integration and a long-run equilibrium between the three indices. Tables reporting evidence of optimal lag length and the number of cointegrating equations are presented in Appendix C.

The bulk carrier index is normalised to one in equation 1D presented in Table 6-3. Further, all coefficients are statistically significant at a 1% level, implying that all three segments jointly define the long-run equilibrium relationship in the shipbuilding market.

Variable	Bulk Carrier Index	Tanker Index	FCC Index	Constant
Equation 1D	1	0.140***	-0.976***	-19.683***
	-	(0.039)	(0.044)	(1.833)

Standard errors in parentheses
*** Significant at the 1% level, ** Significant at the 5% level, * Significant at the 10% level

Table 6-3: Cointegrating equation of model D

The speed of adjustment coefficients in model D is presented in Table 6-4. An interesting finding is that the bulk carrier index does not adjust to deviations from the long-run equilibrium, as the coefficient $\hat{a}_{BulkCarrier,1D}$ does not significantly differ from zero. In contrast, the adjustment coefficients for the tanker and FCC indices are statistically significant at a 1% level, indicating that these segments jointly sustain the long-run equilibrium.

The coefficient $\hat{a}_{FCC,1D}$ is positive as expected, because the FCC index must increase (decrease) to maintain equilibrium if the bulk carrier index has moved above (below) the equilibrium. The magnitude of the coefficient indicates that half of the deviation from the last quarter is subject to correction in the following quarter. Furthermore, the coefficient $\hat{a}_{Tanker,1D}$ is negative, indicating that the price of tankers will decrease (increase) if the bulk carrier index is above (below) the equilibrium level. This makes sense as a positive error correction term might be explained by the tanker index being above its equilibrium, resulting in a correction towards equilibrium.

At a 5% significance level, the results suggest that the last period's change, in both the tanker and FCC indices, has a positive effect on the change in the bulk carrier index in the next period. This provides evidence for a lead-lag relationship between the three price indices, contradicting the findings from the previous analysis. We also find evidence of such a relationship between the last period's change in the tanker index and the next period's change in the FCC index, suggesting that the tanker index is the leading segment.

As the results of the analysis differ between model A and D, it raises a question of what index that provides the most objective and representable reflection of the market. Clarksons is one of the largest shipbrokers and providers of shipping-related data in the world and can therefore be considered reliable. However, the details of their underlying method of constructing the indices remain unclear, and we can therefore not conclude if Clarksons indices represent a more correct market representation than the hedonic indices.

Model D

Variable	ΔBulk Carrier Index	ΔTanker Index	ΔFCC Index
$1D_{t-1}$	-0.002	-0.466***	0.478***
	(0.106)	(0.179)	(0.173)
$\Delta \text{Bulk Carrier Index}_{t-1}$	-0.358	0.0439	-0.484
	(0.223)	(0.376)	(0.364)
$\Delta \text{Tanker Index}_{t-1}$	0.303***	0.419***	0.507***
	(0.0880)	(0.148)	(0.144)
$\Delta \text{FCC Index}_{t-1}$	0.275**	-0.176	0.505**
	(0.126)	(0.212)	(0.206)
Observations	75	75	75

Standard errors in parentheses
*** Significant at the 1% level, ** Significant at the 5% level, * Significant at the 10% level

Table 6-4: Vector error correction model D.

7. Conclusion

The objective of this thesis has been to investigate whether a long-run equilibrium between the newbuilding prices of bulk carriers, tankers and FCCs exists. By applying the theory of hedonic pricing models, price indices for each segment were constructed. Next, the Johansen method was applied to identify the potential existence of cointegration. Lastly, short- and long-run effects were analysed using a vector error correction model.

The findings provide evidence of two cointegrating relationships between the newbuilding price indices. These findings are in favour of an integrated shipbuilding market for bulk carriers, tankers and FCCs, as the newbuilding prices are joined in a mutual long-run equilibrium. The existence of such an equilibrium supports the view that capacity is ultimately the product offered by shipyards. Hence, as a shipyard's product mix often is regarded as flexible, they can strategically decide what ships to build. Thus, the opportunity cost of a shipyard's available capacity may affect newbuilding prices, providing a possible explanation for the existence of a long-run equilibrium. We find no evidence of short-run effects between the indices, which is likely rooted in the long cycles of the shipbuilding market.

In order to test the robustness of the results, we conduct similar analyses on a compressed data sample, that exclude the period after Q4 2007, and on newbuilding indices reported in Clarksons (SIN) (2018b). The results of the first adjustment are in line with the findings in the analysis, suggesting that the implications of the Great Recession on market integration were limited. However, when using indices reported by Clarksons, only one cointegrating equation is identified, suggesting a weaker form of market integration. In addition, we unexpectedly find evidence of short-run effects, where the tanker segment is found to be leading. The differences are likely rooted in how the indices are constructed and the data they are based on. However, as Clarksons methods of constructing the indices remains unclear, we cannot conclude whether this analysis is more representative, compared to using the hedonic price indices.

We recognise that the limited data sample used in our analysis, potentially affects the results and thus is a weakness of our thesis. However, due to the vast amount of undisclosed contract prices, constructing perfect indices that reflect a fully reliable and correct representation of the market is close to impossible. At last, we regard similar analyses of integration between other segments and across geographies as interesting topics for further research.

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Appendix A: Market Concentration of the Unrefined Dataset

Bulk Carrier	Contracts	Percent	Cumul.
Shipyard (Owner Group)			
Imabari Shipbuilding	1,166	10.0 %	10.0 %
Tsuneishi Holdings	802	6.9 %	16.9 %
Oshima Shipbuilding	652	5.6 %	22.5 %
Namura Zosensho	489	4.2 %	26.8 %
COSCO Shipping HI	463	4.0 %	30.7 %
Hyundai HI Group	441	3.8 %	34.5 %
Mitsui Eng & SB	438	3.8 %	38.3 %
Japan Marine United	394	3.4 %	41.7 %
Shin Kurushima Group	253	2.2 %	43.9 %
China Merchants	234	2.0 %	45.9 %
Other	6,289	54.1 %	100.0 %
Total	11,621	100.0 %	
Total number of shipyard owners		431	

	Contracts	Percent	Cumul.
Ship Owner (Group)			
China COSCO Shipping	382	3.3 %	3.3 %
Nippon Yusen Kaisha	187	1.6 %	4.9 %
China Merchants	126	1.1 %	6.0 %
K-Line	117	1.0 %	7.0 %
Mitsui O.S.K. Lines	115	1.0 %	8.0 %
Pacific Basin Shpg	112	1.0 %	8.9 %
Star Bulk Carriers	111	1.0 %	9.9 %
Fredriksen Group	107	0.9 %	10.8 %
Wisdom Marine Group	105	0.9 %	11.7 %
Mitsubishi Corp	81	0.7 %	12.4 %
Other	10,178	87.6 %	100.0 %
Total	11,621	100.0 %	
Total number of ship owners		2,094	

Tanker	Contracts	Percent	Cumul.
Shipyard (Owner Group)			
Hyundai HI Group	1,326	13.2 %	13.2 %
STX Offshore & SB	363	3.6 %	16.8 %
Samsung HI	340	3.4 %	20.1 %
Daewoo (DSME)	285	2.8 %	23.0 %
Shin Kurushima Group	273	2.7 %	25.7 %
Fukuoka SB	248	2.5 %	28.1 %
CSSC Offshore Marine	238	2.4 %	30.5 %
DSIC Group	219	2.2 %	32.7 %
Japan Marine United	195	1.9 %	34.6 %
SPP Shipbuilding	191	1.9 %	36.5 %
Other	6,404	63.5 %	100.0 %
Total	10,082	100.0 %	
Total number of shipyard owners		680	

	Contracts	Percent	Cumul.
Ship Owner (Group)			
Mitsui O.S.K. Lines	147	1.5 %	1.5 %
China COSCO Shipping	141	1.4 %	2.9 %
SCF Group	124	1.2 %	4.1 %
China Merchants	118	1.2 %	5.3 %
Scorpio Group	115	1.1 %	6.4 %
Ocean Tankers	92	0.9 %	7.3 %
Teekay Corporation	90	0.9 %	8.2 %
Petronas	83	0.8 %	9.0 %
Stolt-Nielsen	81	0.8 %	9.8 %
Bahri	79	0.8 %	10.6 %
Other	9,012	89.4 %	100.0 %
Total	10,082	100.0 %	
Total number of ship owners		2,109	

FCC	Contracts	Percent	Cumul.
Shipyard (Owner Group)			
Hyundai HI Group	853	16.4 %	16.4 %
Samsung HI	349	6.7 %	23.1 %
Daewoo (DSME)	258	5.0 %	28.1 %
HHIC	244	4.7 %	32.8 %
CSBC Corporation	232	4.5 %	37.2 %
Imabari Shipbuilding	201	3.9 %	41.1 %
Yangzijiang Holdings	192	3.7 %	44.8 %
Genting Hong Kong	149	2.9 %	47.7 %
Shipyard Pella	137	2.6 %	50.3 %
CSSC Offshore Marine	135	2.6 %	52.9 %
Other	2,450	47.1 %	100.0 %
Total	5,200	100.0 %	
Total number of shipyard owners		207	

	Contracts	Percent	Cumul.
Ship Owner (Group)			
A.P. Moller	333	6.4 %	6.4 %
China COSCO Shipping	260	5.0 %	11.4 %
MSC	166	3.2 %	14.6 %
CMA CGM	148	2.8 %	17.4 %
PIL	126	2.4 %	19.9 %
Hapag-Lloyd	122	2.3 %	22.2 %
Evergreen Marine	117	2.3 %	24.5 %
Seaspan Corporation	116	2.2 %	26.7 %
Peter Dohle	92	1.8 %	28.5 %
MPC Group	84	1.6 %	30.1 %
Other	3,636	69.9 %	100.0 %
Total	5,200	100.0 %	
Total number of ship owners		565	

Table A-1: Ten largest shipyard- and ship owners by segment.
Source: Authors' calculations, based on data from Clarksons (WFR) (2018a).

Appendix B: Validation of the Hedonic Regressions

Residual Plots

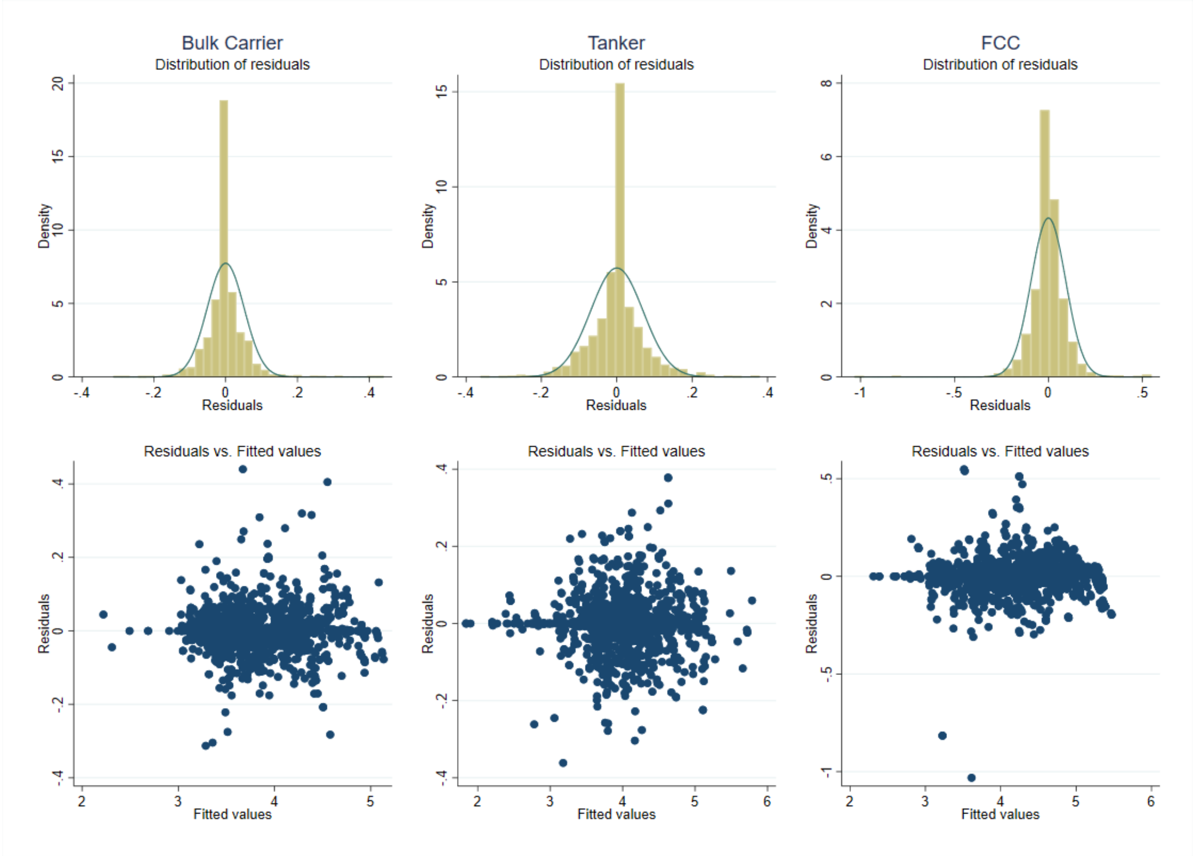

Table B-1: Distribution of residuals and residuals vs. fitted values for the fifth specification of all three segments.

Variance Inflation Factors

Bulk Carrier

Variable	VIF	1/VIF
CGT	2.04	0.49
Gear	1.75	0.57
Design speed	1.18	0.85
Delivery time	1.08	0.93
Shipyard experience	1.07	0.93
Mean VIF	1.43	

Tanker

Variable	VIF	1/VIF
CGT	1.84	0.54
Design speed	1.44	0.70
Total no. of pumps	1.26	0.79
Heating coils	1.13	0.89
Delivery time	1.06	0.95
Shipyard experience	1.02	0.98
Mean VIF	1.29	

FCC

Variable	VIF	1/VIF
CGT	1.81	0.55
Design speed	1.75	0.57
Gear	1.41	0.71
Delivery time	1.17	0.85
Shipyard experience	1.08	0.93
Mean VIF	1.44	

Table B-2: Variance Inflation Factors of variables. Excludes dummy variables and fixed effects.

Appendix C: Cointegration Analysis

Stationarity

Model A/B

Variable	Lags	Test Statistic	MacKinnon p-value	1% Critical Value	5% Critical Value	10% Critical Value
Bulk						
	1	-1.985	0.293	-3.53	-2.901	-2.586
	2	-1.543	0.512	-3.531	-2.902	-2.586
	3	-1.564	0.502	-3.532	-2.903	-2.586
D.Bulk						
	1	-8.496	-	-2.606	-1.950	-1.610
	2	-5.953	-	-2.606	-1.950	-1.610
	3	-4.602	-	-2.607	-1.950	-1.610
Tanker						
	1	-2.037	0.271	-3.530	-2.901	-2.586
	2	-1.612	0.477	-3.531	-2.902	-2.586
	3	-1.962	0.304	-3.532	-2.903	-2.586
D.Tanker						
	1	-8.589	-	-2.606	-1.950	-1.610
	2	-5.310	-	-2.606	-1.950	-1.610
	3	-4.249	-	-2.607	-1.950	-1.610
FCC						
	1	-2.786	0.060	-3.530	-2.901	-2.586
	2	-2.690	0.076	-3.531	-2.902	-2.586
	3	-2.282	0.178	-3.532	-2.903	-2.586
D.FCC						
	1	-8.610	-	-2.606	-1.950	-1.610
	2	-7.199	-	-2.606	-1.950	-1.610
	3	-5.542	-	-2.607	-1.950	-1.610

Table C-1: ADF-test results model A and B. Specified with and without a constant term for the time series in levels and first difference, respectively.

Model C

Variable	Lags	Test Statistic	MacKinnon p-value	1% Critical Value	5% Critical Value	10% Critical Value
Bulk						
	1	-0.133	0.946	-3.574	-2.927	-2.598
	2	0.062	0.963	-3.576	-2.928	-2.599
	3	0.078	0.965	-3.577	-2.928	-2.599
D.Bulk						
	1	-5.707	-	-2.619	-1.950	-1.610
	2	-3.707	-	-2.619	-1.950	-1.610
	3	-3.220	-	-2.620	-1.950	-1.610
Tanker						
	1	-0.826	0.811	-3.574	-2.927	-2.598
	2	-0.082	0.951	-3.576	-2.928	-2.599
	3	-0.344	0.919	-3.577	-2.928	-2.599
D.Tanker						
	1	-8.500	-	-2.619	-1.950	-1.610
	2	-4.716	-	-2.619	-1.950	-1.610
	3	-3.155	-	-2.620	-1.950	-1.610
FCC						
	1	-1.850	0.356	-3.574	-2.927	-2.598
	2	-2.035	0.272	-3.576	-2.928	-2.599
	3	-1.618	0.474	-3.577	-2.928	-2.599
D.FCC						
	1	-7.007	-	-2.619	-1.950	-1.610
	2	-6.259	-	-2.619	-1.950	-1.610
	3	-5.149	-	-2.620	-1.950	-1.610

Table C-2: ADF-test results model C. Specified with and without a constant term for the time series in levels and first difference, respectively.

Model D

Variable	Lags	Test Statistic	MacKinnon p-value	1% Critical Value	5% Critical Value	10% Critical Value
Bulk						
	1	-1.305	0.627	-3.545	-2.910	-2.590
	2	-1.652	0.456	-3.546	-2.911	-2.590
	3	-1.818	0.371	-3.548	-2.912	-2.591
D.Bulk						
	1	-4.049	-	-2.610	-1.950	-1.610
	2	-3.331	-	-2.610	-1.950	-1.610
	3	-3.234	-	-2.610	-1.950	-1.610
Tanker						
	1	-1.977	0.443	-3.545	-2.910	-2.590
	2	-1.985	0.293	-3.546	-2.911	-2.590
	3	-1.821	0.370	-3.548	-2.912	-2.591
D.Tanker						
	1	-4.068	-	-2.610	-1.950	-1.610
	2	-3.953	-	-2.611	-1.950	-1.610
	3	-3.236	-	-2.611	-1.950	-1.610
FCC						
	1	-1.960	0.305	-3.545	-2.910	-2.590
	2	-1.704	0.429	-3.546	-2.911	-2.590
	3	-2.049	0.265	-3.548	-2.912	-2.591
D.FCC						
	1	-4.919	-	-2.610	-1.950	-1.610
	2	-3.676	-	-2.611	-1.950	-1.610
	3	-3.488	-	-2.611	-1.950	-1.610

Table C-3: ADF-test results model D. Specified with and without a constant term for the time series in levels and first difference, respectively.

Deterministic Trend Specification

Assumption	LR chi2	Prob > chi2
Model A		
Restricted trend nested in trend	0.020	0.885
Constant nested in restricted trend	8.750	0.016
Restricted constant nested in restricted trend	9.060	0.028
No trend or constant nested in restricted trend	22.470	0.000
Model B		
Restricted trend nested in trend	0.030	0.856
Constant nested in restricted trend	4.870	0.088
Restricted constant nested in constant	15.610	0.004
No trend or constant nested in constant	29.030	0.000
Model C		
Restricted trend nested in trend	6.090	0.014
Constant nested in trend	13.080	0.005
Restricted constant nested in trend	13.380	0.010
No trend or constant nested in trend	13.080	0.005
Model D		
Restricted trend nested in trend	0.010	0.997
Constant nested in restricted trend	0.290	0.591
Restricted constant nested in constant	4.630	0.010
No trend or constant nested in restricted constant	17.910	0.000

Table C-4: Likelihood ratio test results.

Lag Length Selection

	Bulk carrier index		Tanker index		FCC index	
Lags	HQIC	SBIC	HQIC	SBIC	HQIC	SBIC
1	7,534*	7,568*	7,012*	7,047*	7,792*	7,827*
2	7,557	7,609	7,038	7,090	7,802	7,855
3	7,568	7,637	7,042	7,112	7,833	7,903

Table C-5: Lag selection statistics for the hedonic indices.

	Bulk carrier index		Tanker index		FCC index	
Lags	HQIC	SBIC	HQIC	SBIC	HQIC	SBIC
1	4,811	4,849	5,826	5,864	5,792	5,830
2	4,689*	4,746*	5,582*	5,639*	5,655*	5,712*
3	4,705	4,781	5,607	5,683	5,696	5,772

Table C-6: Lag selection statistics for Clarksons indices.

	Model C		Model D	
Lags	HQIC	SBIC	HQIC	SBIC
0	22.360	22.429	20.045	20.102
1	20.644*	20.922*	14.027	14.253
2	20.914	21.400	13.775*	14.171*
3	21.276	21.970	13.958	14.524

Table C-7: Lag selection statistics for model C and D.

Rank

Trace test			Maximum eigenvalue test		
Null	Trace	5% critical value	Null	Max	5% critical value
r = 0	77.654	42.440	r = 0	40.454	25.540
r ≤ 1	37.199	36.320	r = 1	30.997	18.960
r ≤ 2	6.202	12.250	r = 2	6.202	12.520

Table C-8: Rank tests model C

Trace test			Maximum eigenvalue test		
Null	Trace	5% critical value	Null	Max	5% critical value
r = 0	52.788	34.910	r = 0	41.030	22.000
r ≤ 1	11.759	19.960	r = 1	7.741	15.670
r ≤ 2	4.018	9.420	r = 2	4.018	9.240

Table C-9: Rank tests model D

Plots of the Cointegrating Equations

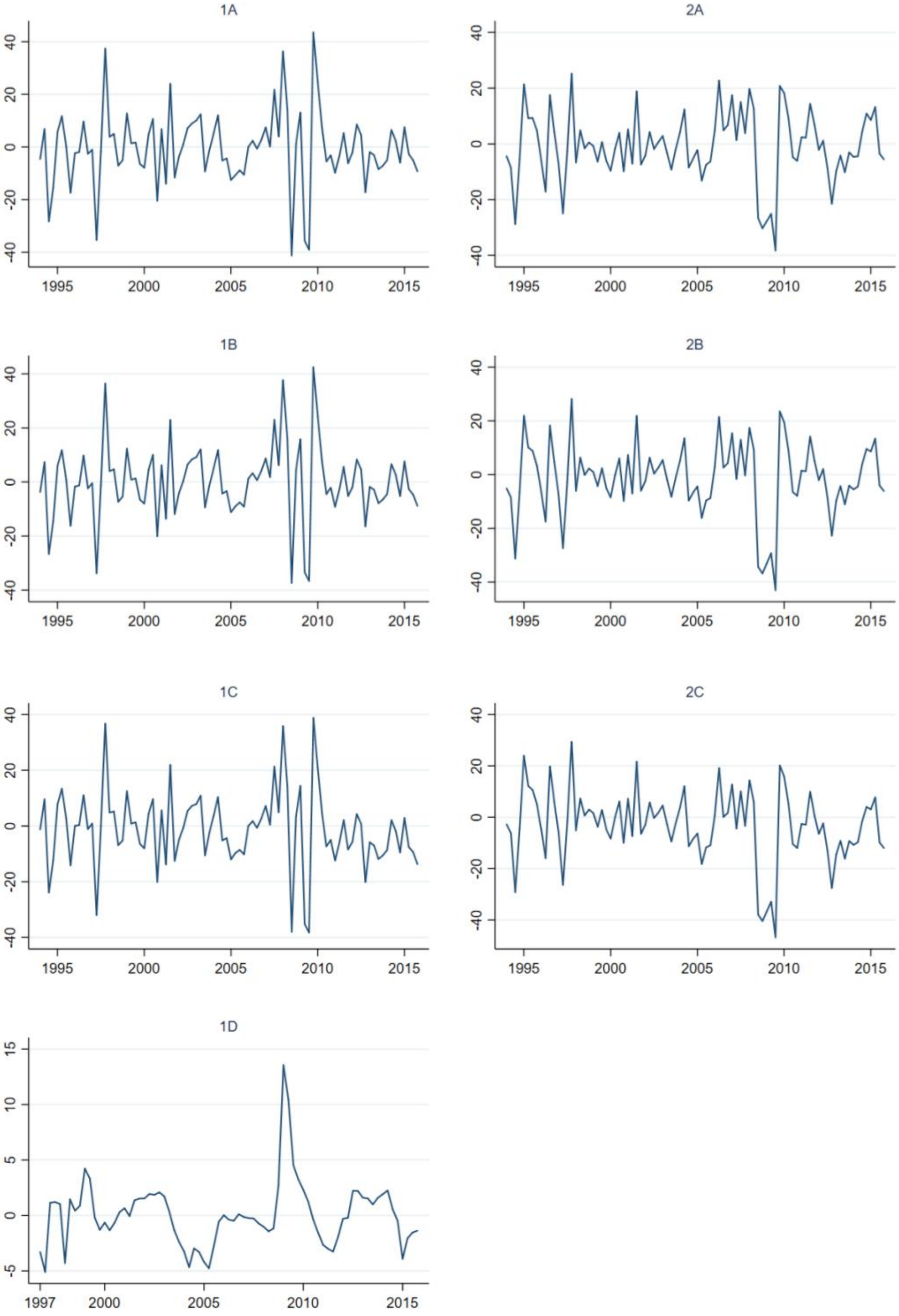

Figure C-1: Graphed cointegrating equations for model A, B, C and D.