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MASTER OF SCIENCE (MSc) in
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**ATHENS UNIVERSITY OF ECONOMICS AND BUSINESS**
**MSc in International Shipping, Finance and Management**

# «The determinants of second-hand vessel prices in dry bulk market»

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## CERTIFICATION OF THESIS PREPARATION

"We hereby declare that this thesis has been written by us, in order to obtain the Postgraduate Degree (MSc) in International Shipping, Finance and Management, and has not been submitted to or approved by any other postgraduate or undergraduate program in Greece or abroad. This thesis presents our personal views on the subject. All the sources we have used for the preparation of this thesis are mentioned explicitly with references being made either to their authors, or to the URL's (if found on the internet)."

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## Abstract

This paper investigates the key drivers of second-hand ship prices within the dry-bulk shipping market. It operates off a monthly data sample from 2000 to 2024, from second-hand Capesize and Panamax (including Kamsarmax) vessels, those ten and fifteen years of age. It finds that second-hand prices move closely into line with newbuilding prices, in that when ship prices rise by 10% in any given month, likewise second-hand prices tend to rise about 10%. Chartering rates also have an effect here as a 10% increase in one year time-charter rates brings a short-term increase in prices in the immediate month after, which is enhanced for older tonnage.

The paper also examines how second-hand prices behave against newbuilding prices. Higher chartering rates will make second-hand tonnage more valuable relatively to tonnage, while increased cost of financing newbuilds reduces the premium slightly. Large shocks in the market displace prices temporarily from their expected levels. For example, valuations for ships fell in the Global Financial Crisis and early COVID-19 period, while some recent shocks/breakdown of routes, such as the Red Sea, increased prices, particularly for Panamax tonnage which is more drawn into the Suez Canal routing.

Long term price dynamics show that second-hand values will adjust back towards levels indicated by newbuilding prices, but the period of adjustment is reduced since 2018. Short-term fluctuations in newbuilding prices and freight rates are quickly handed through to second-hand values, with financing rates carrying lower pressures.

In all cases the evidence shows that second-hand ship prices are anchored by replacement cost and determined by earnings scenarios, and temporarily distorted by global shocks in the market. The conclusions which are drawn here reflect established views of shipping markets, but also offer sound advice for timing asset purchases and thus the risk of purchase price change.

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# 1. Introduction

What drives second-hand vessel prices in the dry bulk shipping market? The second-hand market for dry bulk vessels represents one of the most active and strategically significant sectors of global shipping investment. This market plays a vital economic role as it gives the opportunity to shipowners and investors to buy and sell ships directly and thereby facilitating both entry into and exit from the industry. This enhances competitiveness and provides flexibility in fleet management.

Given this fact, second-hand vessels market is characterized by extreme cyclicality and fluctuations. Many researchers have developed and estimated economic models to explain these fluctuations in second-hand vessels market. These econometric, theoretical and structural models are based on statistical methods such as time-series, pooled OLS/fixed-effects regressions, error correction models and quantified shock effects plus long-run equilibrium evidence.

This analysis focuses on the dry bulk sector, especially 10- and 15- year Capesize and Panamax vessels over the period 2000-2024 using monthly data. The dataset includes second-hand prices by segment and age, newbuilding prices, time-charter rates, scrap values and interest rates. This dataset provides the necessary analysis and coverage to study both long-run equilibria and short-run deviations across multiple shipping cycles and global shocks.

Methodologically, the study applies several complementary models. The results reconfirm the central role of replacement cost as the long-run anchor for second-hand prices, while freight earnings drive short-run fluctuations, particularly for older vessels. Financing conditions, described through interest rates, tilt the balance between second-hand and newbuilding values. Market shocks create noticeable distortions, which gradually fade as prices revert to their long-run equilibrium.

Using a clear monthly dataset and reliable methods, this paper shows how long-term factors, short-term earnings, financing and unexpected events all combine to influence second-hand vessel prices. Over time, the market tends to adjust, and prices gradually move back toward their equilibrium. In other words, while shocks can create clear and

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measurable effects in the short term, they are temporary and tend to eventually restore balance.

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# 2. Literature Review

## 2.1 Study Background

Our aim is to position our study in the empirical literature for shipping and articulate how our design choices are related to and extend previous studies.

To begin with Tsolakis, Cridland and Haralambides (2003) emphasize unit root behavior in ship prices and estimate error correction model after establishing cointegration so that short run adjustments lead to long run relations between second-hand prices, newbuilding prices and earnings are positively correlated. This supports the conclusion of the anchors of the replacement cost, and earnings tilt prices. Thalassinos and Politis (2014) work extends the research with estimate a vector error correction model allows for multiple cointegrating relations, particularly integrating finance and macro fundamentals with the shipping variables. Finally, Merika et al. (2019) take an alternative viewpoint utilizing methodology to document the price distribution and how fundamentals eg age, size, scrap, newbuilding and rates affect both the mean and variance of prices.

For our original sample we built a monthly panel extending from 2000 to 2024, for two headline dry bulk classes, Panamax Kamsarmax and Capesize and for two age cohorts 10 and 15 years. The core levels are of the two fixed effects models in logs regressing the log price of secondhand prices on the log of newbuilding prices and the log of time-charter rates with operational variables with one month lag and the appropriate segment and age fixed effects and month clustered standard errors. This is an additional avenue for exploration with the time-series ECM literature. At this juncture we added two companion designs. The former is a relative price mode with the log of the ratio of second-hand prices to newbuilding prices as the variable used, isolating the second-hand over the new premium, where the financing would naturally enter. On the contrary, an event effects model was attached with windows around major disruptions of the dry market in recent times, Global financial crisis, IMO 2020 implementation, COVID outbreak, Suez blockage, Russian Ukrainian war, Red Sea run routing so that we could tack on additional percentage deviations beyond fundamentals in those times. Finally, based on the literature we interpreted the stationarity/cointegration analysis and estimated the ECM.

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In line with shipping studies reporting multicollinearity checks (eg Tsioumas et al., 2021; van den Bos, 2018) we diagnose the collinearity with (i) pairwise correlations of regressors (which are reported as within entity, within month correlations under the FE) (ii) Variance Inflation Factors (VIF) which we compute on the design matrix used for each model and (iii) Belsley – Kuhn – Welsch condition indices with variance decomposition proportions for regressions which include highly persistent regressors (lnNB and lnTC). We view VIF ≈ 5 as a caution and VIF ≥ 10 is a serious concern, consistent with applied guidance (Vatcheva et al., 2016). In order to mitigate structural collinearity, we (a) include two way fixed effects so identification uses within unit variation (Geomelos & Xideas, 2017) (b) introduce lagged TC in order to separate the flow of information from contemporaneous pricing and (c) re-estimate difference/ECM specifications where the level/trend co-movement (the main source of the high VIFs between lnNB and lnP) is removed.

## 2.2 Sector Background

There are four major markets in shipping, each serving a different function in the industry. The freight market trades sea transport services and determines the income-earning potential of ships through spot and time-charter rates. The second-hand market empowers the exchange of existing vessels, providing liquidity and allowing shipowners to adjust fleet size or strategy relatively quickly. Also, the newbuilding vessel market focuses on contracting new ships with shipyards, where prices are influenced by shipyard capacity, input costs and long-term expectations of demand. Finally, the demolition market refers to the sale of end-of-life vessels for scrap, setting a lower bound on asset values and playing an important role in balancing fleet capacity. These four markets are not independent but describe an integrated system in which movements in one market affect outcomes in the others.

In the view of the dry bulk sector, these connections are particularly strong. Freight rates directly impact second-hand values, as higher earnings make existing vessels more attractive to buyers. Newbuilding prices act as a replacement-cost anchor, influencing how second-hand assets are valued relative to ordering new tonnage. On the other hand, demolition prices establish a scrap floor, especially relevant for older vessels. At the same time, unexpected external shocks such as financial crises, regulatory changes or geopolitical events can temporarily push values away from

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fundamentals. Against this background, the purpose of this study is to shed light on how these four markets interact and to examine how second-hand vessel prices respond to freight cycles, newbuilding costs, demolition values, and event shocks. Therefore, the analysis contributes to a clearer understanding of the drivers of asset prices in shipping and the dynamics that link short-term fluctuations with long-term equilibrium.

Further to the above, sales and purchases (S&P) of vessels are a vital part of the dry bulk shipping sector through which ownership of ships is transferred and capital is reallocated within the industry. The S&P market is highly cyclical, reflecting the interconnected dynamics of the freight, newbuilding and demolition markets. When freight rates are high, demand for second-hand ships increases as investors looking for immediate exposure to higher earnings and eventually this drives second-hand prices above newbuilding levels. On the other hand, during downturns, values fall and older vessels are pushed toward demolition, where scrap prices set the floor. Liquidity in the S&P market also enables 'asset play,' as investors buy ships when prices are low and sell them again when the market recovers. In dry bulk shipping, where Capesize, Panamax, Supramax and Handysize vessels are the main ship types, these transactions are important for renewing fleets, allowing companies to enter or exit the market.

The dry bulk second-hand market is particularly shaped by two major vessel types: Capesize and Panamax (including Kamsarmax) vessels. Capesize vessels (generally 150,000 – 200,000 DWT) which are the largest in the dry bulk fleet, trade mainly iron ore and coal trades, linking producers in Brazil and Australia with major Asian importers. Their size and specialization make them central to global industrial supply chains but also highly exposed to cyclical swings in demand and freight rates. Panamax vessels (around 65,000 – 80,000 DWT) are smaller and more flexible, carrying a wider mix of commodities such as grain, coal and bauxite. Their flexibility allows them to differentiate routes, including oceanic trades and canal transits, which makes them more resilient but also exposes them to varying demand cycles. Together, these two segments account for a significant portion of global dry bulk transport and represent the bulk of activity in the second-hand market. Their importance makes them a case study for both commercial decision-making and academic research into shipping asset values. Kamsarmax is the modern Panamax design (≈82–84k dwt,

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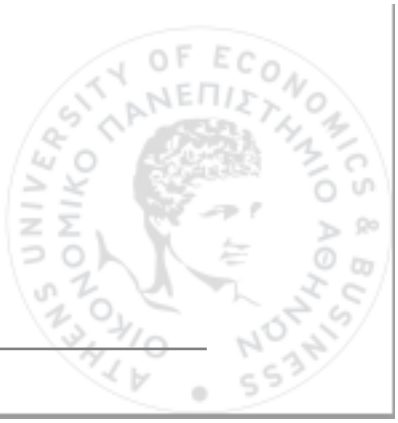
beam ~32.2m) optimized to load at Kamsar (Guinea) while still meeting traditional Panamax beam constraints.

The shape of second-hand vessel prices reflects a combination of structural and financial factors. Practically, market participants often look at comparables, benchmarking vessel values against recent transactions of similar ships. This means that, replacement cost as the price of ordering a newbuilding serves as the long-run anchor, while earnings potential measured by freight rates drives short-term valuation changes. Furthermore, financing conditions play a vital role, as shifts in interest rates and credit availability influence the relative attractiveness of second-hand acquisitions versus new orders. For older vessels, scrap value creates a lower bound, preventing values from falling in downturns. These mechanisms interact with the extreme cyclicality of shipping markets: when freight rates falling, asset values often fall quickly, creating opportunities for “asset play” where investors buy cheaply and sell later at a profit when the cycle turns. This cyclical pattern, reinforced by financing and external shocks, makes the second-hand market both a critical driver of industry competitiveness and a major subject for empirical analysis.





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## 3. Data

We assembled a monthly panel from January 2000 to December 2024, matching the natural frequency at which shipping cycles and major shocks are observed and reported. The dependent variable is the second-hand vessel price P, compiled separately for two headline dry bulk vessel segments, Panamax and Capesize, and two time series, 10 and 15 years. The key long run benchmark is the newbuilding price NB, organized on the same segment basis to ensure comparability. Short run earnings are stated by one year time-charter rates TC for Panamax and Capesize, which reflect market expectations of near-time cashflows. We included the Secured Overnight Financing Rate, SOFR, as our interest rate, used where time is available. We focused on Capesize and Panamax due to depth and quality.

Our analysis concentrates on the Panamax/ Kamsarmax and Capesize classes because these segments combine deep markets with long, consistent data, allowing credible identification of the mechanisms we study. First, we have long, high-quality **monthly time series (2000–2024)** for both **second-hand** and **newbuilding** values in these sizes. That span supports cointegration and ECM tests with meaningful power and fewer gaps.

Second, **liquidity** matters. Panamax and Capesize are among the most actively traded dry bulk segments. High turnover means observed prices track fundamentals closely rather than idiosyncratic deal noise, yielding stable elasticities for the replacement-cost anchor (newbuilding prices) and the earnings channel (time-charter rates). Throughout the period, our "Panamax" category includes **Kamsarmax (≈82–84k dwt)**, the modern successor within this size range, so the series reflects today's benchmark rather than an obsolete label.

Third, these segments have **clear and complementary economic roles**. **Capesize** (long-haul iron ore/coal) is highly earnings-sensitive and reacts to routing shocks (e.g., Suez/Red Sea). **Panamax/ Kamsarmax** (grains, coal, minor bulks) is a versatile workhorse where replacement-cost logic is easy to observe. Studying both lets us test whether results generalize across a heavy-haul and a flexible class.

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Fourth, class definitions are relatively stable over time compared with some mid-sizes (e.g., Supramax/ Ultramax) where gear, eco-designs, and specification drift can introduce hedonic noise. That stability reduces measurement error across time. Finally, focusing on two major segments preserves enough cross-sectional variation for fixed effects designs to soak up common monthly shocks without over-fragmenting the sample, keeping the newbuilding elasticity and ECM speeds interpretable.

At this point, we need to mention and clarify the Panamax and Kamsarmax harmonization. We treat Panamax and Kamsarmax as a unified class for asset pricing purposes. In practice, chartering desks, yards, and S&P brokers quote Panamax/Kamsarmax as one commercial size class for grains/coal/minor bulks. Differences are incremental (a few thousand dwt and better hull/propulsion after ~2008), not a different trade class. In the dataset the Panamax series we use are labeled “Kamsarmax 82-84k dwt” and we align second-hand, newbuilding and 1-year time-charter rates on that class. Post-2012 designs (EEDI, better hulls, engines) are more fuel efficient. If we mix a 2003 Panamax price with a 2020 Kamsarmax NB without controls, we could embed a quiet spec premium. To mitigate this matter, month fixed effects absorb market wide shifts. Also, age fixed effects keep 10-year, and 15-year cohorts separate.

### 3.1 Drivers

***Replacement Cost***

In the long run the long run benchmark for second-hand values are the replacement cost. This is the situation where buyers can switch between buying existing tonnage and ordering new. While yards determine marginal costs of capacity, in equilibrium second-hand prices are geared into newbuilding. The economic basis for this is that lnNB should be seen as the level anchor for and be tested for cointegration between lnP, lnNB. If replacement value is the appropriate benchmark, the two series should provide stable long run relationship.

***Earnings***

Short run variation in second-hand prices is given by returns news. One year time charter rates give a summary of the cashflows in the immediacy, since second-hand

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tonnage is in a position to be chartered instantaneously, a higher TC increases willingness to pay immediately instead of waiting 2 or perhaps 3 years for a delivery slot. This is a particularly powerful effect in the case of older tonnage, where the value depends more on the returns in the immediacy.

***Financing***

Financing costs and discount rates affect decisions of buy versus build. In relative price terms higher official rates tend to compress second-hand premiums over newbuildings, since debt servicing and discounting rises in the case of the tangibly quickly acquired asset, while NB adjust more slowly through yard costs and orderbook.

***Shocks***

Crisis and policy events can move prices, at times, away from fundamentals. We thus introduce these dated, exogenous events windows to the saga.

***Scrap value and remaining life***

Scrap creates a difficulty, especially in the case of older tonnage. As markets weaken the effect of demo prices (steel/ltd), limits are placed upon further declines in second-hand values. The interaction of scrap data works, economically, with respect to age, in that a tighter floor, set by scrap, makes for less volatility in price terms in respect of old tonnage around the NB anchor, while it can steepen the response to returns in the short run.

In reference to scrap value floor we follow standard construction, scrap value = lightweight tonnage (LDT) × monthly scrap price (USD/LDT) For standardized benchmarks LDT is looked up by class guides for 82-84k dwt Panamax/ Kamsarmax and 180k dwt Capesize. Monthly scrap values are taken from leading brokers or Clarksons, and monthly averages are used to month ends. Although the scrap series is not included in core reg, the series has been used in descriptive discussion as a lower bound on valuations, by incorporating an explicit scrap control the lnNB and lnTC coefficient values are qualitatively unchanged in early entry tests.

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***Orderbook***

The worth of newbuilding reflects steel, equipment and yard utilization. A strict orderbook with few delivery slots favors both NB and P. Moreover, slack yard conditions ease the pressure of replacement cost. In our baseline, this works mainly through NB, which is why NB elasticity is the core level anchor. The event windows also capture times when yard frictions or compliance rules, like IMO2020, create temporary deviations from that anchor.

***Regulations***

Transitional events like IMO 2020 introduce compliance costs and uncertainty, which can cause second-hand valuations to be temporarily discounted beyond fundamentals (downtime needed for retrofitting/operational changes). More recent eco designs and elaborated accounting standards (EEXI/CII) increase vintage differentiation.

In general estimates of long-run anchoring (replacement cost) and short-run earnings tilts are done in levels with segment/age FE(M1-M2) in place, while financing is seen most clearly in ln(P/NB) without month FE and in Δ-form with the ECM (M3, M7). Equally events of the deviations are read as additional log points beyond fundamentals in the no month FE model (M4) and are allowed to vary in segment in M5. Finally, the negative k that comes out of the ECM shows mean reversion back to the NB level and let us quantify the half life of mispricing.

## 3.2 Variables

All core variables enter the models in natural logs, lnP for second-hand values, LnNB for newbuilding values and lnTC for one year time-charter rates, so the coefficients can be read as elasticities and are directly comparable across sizes and ages. For dynamics we work with first differences of logs, $\Delta \ln X_t = \ln X_t - \ln X_{t-1}$,i.e. monthly percentage changes, which remove trends and let us measure short run pass through and error correction cleanly.

The dependent variable in the levels specifications is the second-hand price, $\ln P_{i,\alpha,t}$, for segment I and age α. Economically, higher replacement cost raises the floor for the second-hand valuations. Empirically we expect a positive elasticity close to one, which is the replacement cost anchor. Earnings are being lagged for one month, which lag reflects the information flow from freight to asset pricing and mitigates

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simultaneity with second-hand prices. It also accords with the industry practice, where freight markets adjust faster than S&P transactions. We anticipate a positive effect of earnings, typically stronger for older ships whose values are more sensitive to near time cashflows and immediate availability.

We also consider financing conditions via SOFR. In a relative price formulation, higher policy rates should compress the used over the new premium by raising the discount rates and debt service, while robust earnings should widen it by increasing willingness to pay for existing tonnage relative to the slower moving newbuildings.

To capture temporary deviations from fundamentals during exogenous, time bounded shocks, we introduce a small set of event windows with clearly defined periods of action. These include the Global Financial Crisis, the IMO 2020 implementation period, the onset of COVID 19, the Suez Canal blockage (2021), the initial phase of the Russia and Ukraine war and the Red Sea rerouting episode beginning in the late 2023. By estimating these dummies in a levels model without month effects, the coefficients are identified and can be interpreted as extra log points beyond the effects of lnNB and lnTC. The expected signs follow market logic. The Global Financial Crisis and the initial COVID19 months are negative, reflecting credit withdrawal, operational disruption and demand uncertainty. The IMO2020 implementation window is also expected to be mildly negative due to compliance frictions and transitional uncertainty. The Suez blockage is positive but small at the asset level, while freight skyrockets quickly, valuations typically adjust more slowly than spot. Moreover, Core Capesize trades rarely depend on Suez, whereas many Panamax routes do. The Russia and Ukraine shock mixes negative forces, like port closures, grain route disruption, higher financing and compliance risk, with positive ones like, longer alternative hauls that lift tonne-miles. The net effect depends on the segment and timing, with early months plausibly negative for Panamax grain exposure and later months turning to positive as rerouting tightens effective capacity. The Red Sea episode is expected to be positive on net because of avoidance and tightening effective supply. The uplift should be larger for Suez reliant Panamax trades and more modest, though still positive, for Capesize whose core long haul routes already round the Cape of Good Hope.

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# 4. Methodology

## 4.1 Model M1–M2 (Levels FE)

Before explaining the models, we need to set some things out. We will be working with logs, the ln of our fundamentals. In Tsolakis, Cridland and Haralambides, 2003, regarding S&P working, logs are the standard. Per literature, the reasons for using the logs are variance stabilization and coherence with unit root/cointegration.

The core fundamentals that will be interfaced with the models are the Newbuilding prices(NB) and the Time-charter(TC). The newbuilding prices functions are the replacement (cost) anchor as per Stopford, 2009, and the Time-charter are the cash flow, earnings as quoted and Tsolakis, 2003.

As is observed in the model, the Panel fixed effects employed consists of Segment FE(μi) and Age FE (ηα). Alongside Month FE (Tt) establishes alignment for global monthly shocks when elasticities are needed, i.e. we will drop the month FE when we must identify the shock events,

Lastly, DF shows us that lnP, lnNB ARE I(1), and EG shows us co-integration (As per Tsolakis,2003).

$$M1 \Rightarrow lnP_{i,\alpha,t} = \alpha + \beta lnNB_{i,t} + \gamma lnTC + \mu_i + \eta_\alpha + T_t + \varepsilon_{i,\alpha,t}$$

We utilize this model to estimate the replacement cost elasticity (β) as well as the earnings tilt (γ). The β is the percentage change in the second-hand price when the newbuilding price, or replacement cost is changed by 1%. The new building price anchors the long run as a reference point for the second-hand values and β shows how closely the second-hand price tracks that anchor. (For example, a given percentage increase in the newbuilding price will lead to a β percent increase in the second-hand vessel price: if the sign is a positive value, the two prices move in the same direction, if β = 1, the second-hand price move one to one in value, if it is a - value, than the second-hand prices will move less than 1 to 1, which will be common due to the perceived age and obsolescence discount in regards to second-hand vessels).

Additionally, γ refers to the extra percent change in second-hand price attributable to a 1 percent change in earnings, measured by time-charter rates with assumed one month lag. We lag the time-charter by one month to reduce simultaneity, since freight

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and S&P can both change in the same month, and to align the information flow, where cash flows from freight will usually predate deals for asset purchase or sale. (if in the last month the time-charter was valued at a percentage above last month's level, I can presume that higher second-hand price in the upcoming month is associated with about a γ% change in second-hand pricing this month, over and above whatever newbuilding conditions are.) (Tsolakis et al. (2003) (NB + TC in log models))

Conversely, it is an alternative course of action that we would also test for different lags. If not by any means, during the procedure of researching a variable such as TC, it would not have been tested (for whatever reasons) only by one period lag, but perhaps 2, none, etc.

First, it might lag due to both economic timing, and even information flows. The freight (TC) is updated at basically all times, while the S&P generates friction (searching, inspections, finance, board approval) thus asset pricing mirrors are slightly lagged. If one were to only do a contemporaneous specification-someone would be ignoring part of the economics-only long lag specifications probably mean someone is underestimating responsiveness.

Economics could price and TCs would probably together respond-imagine a shock to restocking in China within a period of month. A lagged maximum of 2 months of TC could give you recovery without complete endogeneity.

Next, some of the responses in S&P could be in this month, and others would be in the next month. A short lag disturbance check is perhaps short periods of 0-2 weeks if you need more compactness to check. It was a way to validate the shape of adjustment yet keep complexity relatively low, if desired.

Much finally could be called robustness of discipline testing. Checking and good practices (Wooldridge, Angrist & Pischke) would with such specifications (for key specification choices). All else equal, the TC slope would remain stable across 0-1-2.

Coalescing, if the conclusion of this research relies on just no timing assumptions we would be digressing with a base of empirical research its continuance alteration across a period.

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$$M2 \Rightarrow lnP_{i,\alpha,t}=\alpha+\beta lnNB_{i,t}+\gamma lnTC_{i,t}+\vartheta SOFR_t+\mu_t+\eta_\alpha+T_t+\varepsilon_{i,\alpha,t}$$

It may generally be stated that if USD funding tightens, that is if banks or the government writes policies that make lenders more cautious, then buyers discount rates and debt will rise. As a result, valuations of vessels will decline, even after offsets of replacement cost (NB) and earnings (TC). That is a level effect of financing independently to any other vessel cost factor, it is a direct connection from rates to price.

In our calculations using data we utilize SOFR, secured overnight financing rate, as the federal government designated USD risk free rate to replace USD LIBOR which began in 2018. Prior to this transition, other rates captured different bonuses and market structures.

## 4.2 Model M3 (Relative Price)

$$M3 \Rightarrow ln(P/NB)_{l,\alpha,t}=\alpha+\gamma lnTC_{i,t}+\vartheta SOFR_t+\mu_t+\eta_\alpha+T_t+\varepsilon_{i,\alpha,t}$$

We explore this model so that the premium or discount of second-hand vessels vs newbuildings emerge directly, their financing and immediacy of earnings. Replacement costs anchoring and long run P – NB linkage are standard place shipping (Stopford). Empirically Tsolakis et al. 2003 shows cointegration between ln P and ln NB, therefore deviations matter and will tend to mean revert.

When earnings (TC) rise, buyers cashed flow more immediately. The second-hand premium will be larger because that vessel is able to earn today, while a new building vessel will be built to enter the market in approximately 2 to 3 years. General expectation regarding γ is that it would be positive, hence when funding in USD tightens, SOFR rises, debt service and rates rises too. Second-hand deals (S&P) adjust prices faster than new building contracts which are slower to adjust price as they are more cost sticky while second-hand pricing is more flexible and causes the premium to compress. The generality is that a 1% percentage increase in TC of last month would imply an increase in this month's second-hand premium of γ * 1%. Furthermore, if SOFR is increasing in percentage points, then if θ is the number, a +1 percentage point move in SOFR would reduce ln(P/NB) by -θ * (the same) percentage point move in SOFR. That is the premium adjustments.

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Shipping and finance published papers (Kavussanos & Visvikis; Alizadeh & Nomikos) motivate interest rate effects on ship investment and valuation.

### 4.3 Model M4–M5 (Event Effects)

We represent brief, exogenous shocks using (monthly) event dummies Dk,t. Given that these models are intended to identify dummy coefficients, fixed effects for month were removed (which would capture month-common shocks), but fixed effects for segment and age are retained. Coefficients could be interpreted as additional deviations in prices in percentage beyond controls for replacement cost and earnings.

$$M4 \Rightarrow lnP_{i,\alpha,t}=\alpha+\beta lnNB_{i,t}+\gamma lnTC_{i,t}+\sum_{\kappa}\delta_{\kappa}D_{k,t}+\mu_{t}+\eta_{\alpha}+\varepsilon_{i,\alpha,t}$$

In this section, we continue to maintain the same variables and structural fundamentals as previously cited, but now we will note the new variables. As we have observed D is the event dummy as noted above. Each δ is the incremental log effect of an event k over and above fundamentals, NB, lagged TC, and time heterogeneity. The goal of using this model of event effects or shocks is to measure the temporary and uncertain bonus or discount caused by dated (monthly) and global shocks, that are exogenous to the individual units (e.g., GFC). The global event dummy D is perfectly collinear with a full set of month dummies because: it runs and it is identified in a monthly time reporting the variable's different behavior by month. If Month FE are included, then δ is not identified and the month dummy soaks up the event shock. Thus, to estimate δ we keep a segmentation and age FE and include NB and TC to control fundamentals. In general, this is the standard event modeling logic in time series/data panels (Wooldridge, 2010). Events are calendar dated and exogenous to the individual S&P price (e.g., March-2020 lockdowns, Dec-2023 Red Sea attacks).

for heterogeneity,

$$M5 \Rightarrow lnP_{i,\alpha,t}=\alpha+\beta lnNB_{i,t}+lnTC_{i,t}+\delta_{REDS}D_{REDS,t}+\varphi(CAPE_{i} \times D_{REDS,t})+\mu_{i}+\eta_{\alpha}+\varepsilon_{i}$$

$lnP_{i,\alpha,t}$ = log of second-hand vessel price for segment I, age α, month t.

$lnNB_{i,t}$ =log of newbuilding vessel prices, long run anchor.

$lnTC_{i,t}$ =lagged log of time-charter rate, short run earnings tilt

$D_{REDS,t}$ =Red Sea rerouting dummy(1 during the designated window and 0 otherwise)

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$CAPE_i$ =it takes the value of 1 if it is a Capesize and 0 otherwise)

$CAPE_i \times D_{REDS,t}$ =interaction capturing whether Capesizes respond differently to Red Sea rerouting.

$\mu_i, \eta_\alpha$ =segment and age fixed effects(time heterogeneity)

There is no month FE in this model, because we need the time variation to identify DREDS and its interaction.

The maritime assaults in the Red Sea prompted many vessels to deliberately avoid Suez and travel around the Cape of Good Hope, extending voyages and constraining effective supply. This impacted Suez-dependent cargoes most severely (Asia–Europe lanes, Middle East–Mediterranean, etc.). Overall, dry bulk was less impacted than container cargoes, although, we do see a measurable improvement in dry bulk freight/rates early in 2024. Panamax/Kamsarmax carry a considerable amount of grains/coal on routes that are Suez-dependent most of the time. As those flows were diverted, tonne-miles spiked, which proportionately increased demand and earnings from the Panamax sector. Traffic data indicates that Panamax/Over-Panamax dry bulk has increased meaningfully around the Cape of Good Hope in recent weeks after the crisis began. The Capesize base trades already use the Cape and are less Suez-influenced, so their incremental traffic from the Red Sea disruption was smaller (although some Cape routes were impacted going towards Europe/Mediterranean, that is a smaller percentage).

Our intent is to try to explain if Capesize experience as a bulk carrier segment, an extra Red Sea premium in second-hand vessel prices relative to other segments. In order to interpret this, we should test two Hypothesis. Firstly, let us state the coefficients $\boldsymbol{\delta_{REDS}}$ and φ. The δREDS coefficient is the baseline Red Sea dummy and stands for the extra percentage effect for non Capesizes, which is the current reference group. On the other hand, φ is the interaction and stands for the additional percentage effect for Capesizes on top of $\boldsymbol{\delta_{REDS}}$. Following up to this we will convert log coefficients via $100(e^{\theta}-1)\%$.

For example, if $\boldsymbol{\delta_{REDS}} = 0.012$ and φ=0.018 then for Panamax, non-Capesize, is equal to + 1.2% and for Capesize is equal to $100(e^{0.012+0.018}-1)= +3\%$.

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So, now the two Hypothesis we need to check are: H0: $\boldsymbol{\delta_{REDS}}$ =0 (Average Red Sea effect) and H0: φ=0 (Capesize specific differential).

In the model construction we continue to add the fundamentals NB and TC, because in that way we control the replacement cost, and earnings have already explained a lot of lnP. Now we want the Red Sea coefficients to reflect the extra bonus or discount that is not captured in the fundamentals. However, we are not including the month FE, because if we blanked it out, the effect of any shock, including the Red Sea, would be lost.

Here we are anticipating positive δREDS (sign) even if it is very small, due to the rerouting lengthening the voyages, which has the effect of raising tonne-mile capacity as we discussed. Thus, φ is also positive (sign).

4.4 Model M6–M7 (ECM)

***M6=>***

***Long run:*** $\boldsymbol{lnP_{i,\alpha,t}=\alpha+\beta lnNB_{i,t}+\gamma lnTC_{i,t}+\mu_i+\eta_\alpha+u_{i,\alpha,t}=>EC=lnP-lnP(hat)}$

***Short run:*** $\boldsymbol{\Delta lnP_{i,\alpha,t}=kEC_{i,\alpha,t-1}+\rho\Delta lnNB_{i,t}+\varphi\Delta lnTC_{i,t}+\mu_i+\eta_\alpha+\varepsilon_{i,\alpha,t}}$

If lnP and lnNB are non-stationary, and share long run equilibrium, or are cointegrated, then lnP should depend on how far the price was from equilibrium last month (the error correction), and new information of this month, which effectively means changes in lnNB and lnTC. Therefore, cointegration leads us to the conclusion of an ECM. This is exactly how studies of shipping link second-hand values to newbuilding with earnings as the short run driver, Tsolakis, Cridland and Haralambides, (2003).

***Long run relationship***

$\boldsymbol{lnP_{i,\alpha,t}=\alpha+\beta lnNB_{i,t}+\gamma lnTC_{i,t}+\mu_i+\eta_\alpha+u_{i,\alpha,t}}$

β is the replacement cost elasticity, how second-hand prices scale with newbuilding.

We save the residuals $u_{i,\alpha,t}$ (hat) and we define the error correction mechanism.

$ECM_{i,\alpha,t}=u_{i,\alpha,t}(hat)=lnP_{i,\alpha,t}-(\alpha(hat)+\beta(hat)lnNB_{i,t}+\mu_i(hat)+\eta_\alpha(hat)$

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Under cointegration, OLS estimates of the cointegration are consistent.

***Short run***

$$\Delta lnP_{i,\alpha,t}=kECM_{i,\alpha,t-1}+\rho\Delta lnNB_{i,t}+\varphi\Delta lnTC_{i,t}+\mu_i+\eta_\alpha+\varepsilon_{i,\alpha,t}$$

k is the speed of adjustment. We expect k <0, if prices were too high in comparison to NB last month, they will fall this month($\Delta lnP<0$).

P>0,φ>0 measure short run pass through of NB and earnings.

FE $\mu_i,\eta_\alpha$ remain to absorb time heterogeneity in short run.

Earlier we showed that lnP and lnNB are I(1) via DF(levels are non stationary, first differences are stationary) and that the residual from the long run regression is I(0) via Engle-Granger, DF and that drives to ECM. The same way Tsolakis et al. (2003) works. In Engle Granger ECM. We require the long run parameter β to be estimated when conditioning on NB. Moreover, economically NB reflects cost and anchors the system. We treat NB as weakly exogenous. This is common in asset-price ECM where one variable is the replacement cost anchor.

We know regarding β in the long run, that if NB rises by 1%, second-hand vessel prices rise by β% in the long run. We usually see 0<β<1 because second-hand vessels carry age and efficiency discounts. The positive β is the replacement cost anchor (Stopford,2009 and Tsolakis et al, 2003). The k is the speed and is expected to be negative, if second-hand vessel prices are 10% above the NB level, then next month $\Delta lnP=0.10k$. With k=-0.15, about 1.5% correction next month. Furthermore, ρ and φ are expected to be positive. A 1% increase in NB this month moves second-hand prices up by ρ% in that same month. Similarly for TC and φ. In essence TC often has a larger immediate coefficient for older ships.

$$M7 \Rightarrow \Delta lnP_{i,\alpha,t}=kECM_{i,\alpha,t-1}+\rho\Delta lnNB_{i,t}+\varphi\Delta lnTC_{i,t}+\vartheta\Delta SOFR_t+\mu_i+\eta_\alpha+\varepsilon_{i,\alpha,t}$$

$kECM_{i,\alpha,t-1}$ = mean reversion

$\rho\Delta lnNB_{i,t}$ = yard side

$\varphi\Delta lnTC_{i,t}$ = earnings

$\vartheta\Delta SOFR_t$ = rate shock

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The variable of interest is Δln Pi,α,t and represents the monthly percent change in second-hand price. The Error Correction Mechanism ECMi,α,t-1 is the deviation from the long run NB anchored level of lnP last month. In the short run we will have Δln NBi,t and ΔlnTCi,t. Finally, ΔSOFRt is the financing shock.

In the event that second-hand vessel prices are above the prevailing NB level equilibrium, k<0 pulls prices down the next month and the opposite occurs when prices are below equilibrium. When yard costs increase or earnings increase, this leads to contemporaneous increases in second-hand prices (ρ,φ>0). A financing shock (ΔSOFR >0) lowers the monthly price growth (θ<0) and increases valuations and debt costs. As such, we would expect to see lower valuations even after controlling for NB and TC.

Now we will illustrate why we used this model. We first show the lnP and lnNB are I(1). By Engle-Granger representation theorem, the correct short run model is an ECM in Δlogs with a lagged error correction term. As stated in the shipping application in Tsolakis et al. 2003. We add the financing shock where it is identified. In levels with Month FE, like in model 2, co movement can absorb rate effects. In an ECM in differences, adding ΔSOFR tests whether rate shocks move prices on impact, after controlling for merging to the NB anchor and concurrent NB/TC as stated in Kavussanos & Visvikis (2016) on discount-rate/financing channels in shipping investment and asset values.

At this point, we will refer to why we work with the data after 2018. The data are post-2018 because SOFR is the clean benchmark. By this way we escape the LIBOR splicing issues, which refers to the manipulation and collusion by some banks to influence the London Interbank Offered Rate (LIBOR) between 2007 and 2014, which revealed LIBOR's structural weaknesses and led to its phase-out. These issues included a reduced sample size for rate-setting and reliance on expert judgment rather than actual transactions, which made the benchmark susceptible to manipulation and reduced confidence in its integrity. In response, global regulators recommended the development of risk-free rates (RFRs) like SOFR, SONIA, and ESTR to replace LIBOR, leading to a transition in financial markets. Moreover, we use ΔSOFR because we want the shock this month. The ΔSOFR is also less trended than the level and aligns with ECM's Δ.

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The speed of adjustment, k, Is expected to be negative. If k is equal to -0.20 then about 20% of the gap closes each month. If we now want to calculate how much it will take to go back to the equilibrium, then ln(0.5)/ln(1-0.20)= 3.1 months. (ln(0.5)/ln(1+k))

The yard side, ρ, is expected to be positive. If ρ is equal to 0.30, then a 1% monthly rise in NB lifts second-hand vessel prices by 0.30% this month.

The earnings, φ, are expected to be positive. If φ is equal to 0.10, then a 1% monthly rise in TC adds 0.10% to second-hand vessel prices, on top of mean reversion.

The financing shock, θ, is expected to be negative. Scale ΔSOFR in percentage points so interpretation is clean. If θ is equal to -0.015, then an addition of 1 percentage point month on month SOFR shock (eg 4% to 5%) lowers monthly ship price growth by 1.5%, holding ECM, ΔNB and ΔTC fixed.

If we interpret this deeper, we can see why θ is expected to get a negative sign.

The discount rate in mathematic matters treats a second-hand vessel as a finite lived cash flow asset.

So, we can get: $P=\Sigma^{T}_{t=1} E[CF_t]/(1+r)^t + E[SCRAP]/(1+R)^T$

Where r is the discount or funding rate (generated by SOFR), T is remaining economic life.

If we differentiate, then $\theta \ln P/\theta r = -D_{mod} < 0$ , where $D_{mod}$ is the modified duration of the cash flow stream, which is typically a few years for a bulker. When r goes up 100 bps (baseline points), then P falls by roughly $D_{mod}$ percent.

Eg for a 10-year remaining life with a reasonable discount rate, a 1 pp (percentage point) rise in r easily implies a 5-7% drop in P.

In a financing scope, we can go beyond DCF (discounted cash flow). Higher r lifts monthly interest, so DSCR (Debt Service Coverage Ratio) tightens and buyers can afford less debt unless the price paid falls or equity rises.

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Financing channel is central in ship investment & valuation:

Kavussanos & Visvikis (2016) (International Handbook of Shipping Finance): explains how cost of debt, DSCR, LTV, and bank appetite shape achievable bids and ordering.

Alizadeh & Nomikos (2009/2010): link freight expectations and financing to ship prices, discuss how risk and rates alter asset values and hedging.

4.5 Stationarity and Cointegration

We first assessed the order of integration of prices using the Augmented Dickey–Fuller (ADF) test on monthly log levels of second-hand and newbuilding prices, $\ln P_t$ and $\ln NB_t$. The ADF test evaluates the null hypothesis of a unit root (non-stationarity). Consistent with asset-price behavior at monthly frequency, we failed to reject the unit-root null in levels for both $\ln P_t$ and $\ln NB_t$, while we did reject it for their first differences, $\Delta \ln P_t$ and $\Delta \ln NB_t$. This pattern implies that both series are integrated of order one, $I(1)$, whereas their first differences are stationary, $I(0)$—in line with findings reported in the shipping literature (e.g., Tsolakis, Cridland, and Haralambides).

Given that both series are $I(1)$, we then tested for a stable long-run relationship using the Engle–Granger approach. Specifically, we estimated the long-run levels regression of $\ln P_t$ on $\ln NB_t$ (and controls where appropriate), obtained the residuals, and applied an ADF test to those residuals. The residuals were found to be stationary, indicating cointegration between second-hand and newbuilding prices. Cointegration validates the use of an error-correction model (ECM): short-run deviations of $\ln P_t$ from the long-run relation with $\ln NB_t$ are transient and mean-revert, while first-difference terms capture the immediate monthly adjustment.

We use Engle-Granger 2 step:

$\ln Pt = \alpha + \beta \ln NBt + ut$

Estimate by OLS and save the residuals $\hat{u}t$.

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Then we ran a DF test on the residuals. The null hypothesis stands for the option if the residuals have a unit root, so there is no cointegration. If we reject it and the residuals series is stationary, then the pair of lnP and lnNB is cointegrated.

Now if they are cointegrated we can define the short run relationship ecm.

To conclude, we first ran DF tests on lnP and lnNB and found they are I(1)—standard for monthly prices. Then we tested cointegration (Engle–Granger residual test) and found a stable long-run relation between them. That licenses an ECM: we model ΔlnP on the lagged deviation from the long-run and Δln and ΔlnTC (and ΔSOFR). The negative confirms that it means reversion back to the replacement-cost anchor.

4.6. Identification and Endogeneity

Within the identification strategy that combines economic timing with fixed effects, we begin our analysis by treating earnings as predetermined by using the one-month lag, $\ln TC_{t-1}$, which allows pricing decisions in the month t to respond to information that was available to t-1, thus reducing simultaneity in the asset price-freight link. Second, we continue by adding entity fixed effects (segment x age) to control for time invariant heterogeneity in levels (technology, gear, typical trades) in our baseline level models, and month fixed effects to control for aggregate shocks common to all units (macro demand, financing conditions, fuel). Levels are averaged within occupation. Standard errors are clustered by month to allow cohorts to be correlated within a calendar month.

We report month-clustered standard errors in the baseline tables so that inference is robust to common shocks within a month (macro demand, financing, bunker costs, policy) across all units. With many time-clusters, month-clustering delivers asymptotics in this setting. A limitation is potential serial correlation over time.

A direct implication of using month FE in levels is that any month-only regressor is absorbed by the time dummies. Therefore, the SOFR level, which varies only by month, is collinear with month FE and not separately identified in those columns. This motivates our design: the financing channel is analyzed in differences via ΔSOFR within the ECM, where it is identified alongside $\Delta \ln NB_t$ and $\Delta \ln TC_t$. We restrict that specification to the post-2018 sub-sample (SOFR era) to avoid splicing across benchmark regimes and to keep a single, consistent rate process.

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Remaining threats include residual common shocks when month FE are intentionally omitted to identify dated event dummies and secondly, omitted trade route demand that co moves with both freight and valuations. Our replacement cost control (lnNB) reduces the latter by anchoring values to shipyard prices, while $\ln TC_{t-1}$ captures the earnings channel with a conservative timing assumption. Measurement error in NB, stickiness, would bias long NB elasticity toward zero, making our anchor estimate conservative.

In the case of dated shocks (Suez, RU-UA, Red Sea) we are using a difference in difference lens where we interact the window with Capesize (table 6). Identification is given by trends across segments, controlling for lnNB and lnTCt-1. We verify this by having short, obviously dated windows and checking ±1–2 month robustness windows in the appendix. In effect, the signs and magnitudes are stable which verifies the design.

In the ECM, we verify that ΔlnNB, and ΔlnTC drive ΔlnP contemporaneously, while the error correction term ECt-1 is negative confirming mean reversion rather than spurious correlation. In this setting, the financing coefficient on $\Delta SOFR_t$ (percentage points) can be interpreted as the approximate % change in P this month for a +1 pp movement in SOFR, holding other shocks constant.

4.7. Multicollinearity

Newbuilding prices ln NB and earnings ln TC comove strongly over cycles. Because of the high collinearity, there is no bias in the fixed effects estimates. But the variance of estimators becomes too large (noisy coefficients and large Ses). Since ln NB (replacement cost) and TC (earnings) are two explanatory variables of importance, we must show that both are identified with sufficient independent variantion.

To test that, we report Pearson correlations among lnP, lnNB and $\ln TC_{t-1}$ for the whole panel and p(lnNB, $\ln TC_{t-1}$ ) by cohort (Panamax/Capesize x 10y/15y). The flag functions when |p|>0.6. For dated shocks (GFC, IMO2020, COVID19, Suez, RU-UA, Red Sea) we compute CORR (lnNB, D^j). These dummies should capture temporary deviations, not persistent NB trends, so correlations should be small.

Lastly, we test VIFs in the variation that actually identifies FE coefficients. Classic VIF = $1/(1-R^2_{aux})$, where $R^2_{aux}$ comes from regressing one regressor on the others. If

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we ran that including a lot of dummies, VIFs would inflate trivially. Instead, we apply the two ways within (Frinsch-Waugh-Lovell) transformation and then compute VIF on the transformed regressors:

Two-way within (entity x month) for M1 (entity and month FE):

$X\tilde{}_{I,t} = X_{I,t} - X(bar)_I - X(bar)_t + X(bar)$ , $X \in \{lnNB, lnTC_{t-1}\}$.

But, for models entity FE only we demean by entity only. By the FWL theorem, OLS on ($Y\tilde{}$ , $X\tilde{}$) equals the FE estimator with entity and month dummies, so collinearity measured in $X\tilde{}$ is exactly the collinearity relevant for FE slopes.

Then we run the auxiliary regressions on the transformed variables and compute the following:

VIF(lnNB) = $1/1-R^2$ ($lnNB\tilde{}$~$lnTC\tilde{}_{t-1}$) and vice versa regarding $lnTC_{t-1}$ .

VIFs are for diagnostic purposes to look for variance inflation, not for bias. The cluster-robust SEs still account for common month shocks. The VIF check just shows that NB and TC are not so highly collinear that they imply those SEs.

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## 5. Results and Discussion

Coefficient = marginal effect in logs(elasticity)

R2= explanatory power within segment/age over time

FE listed = Segment FE + Age FE (and Month FE when applicable)

Model 1

The first table indicates a positive and significant β on lnNB. A 1% increase in NB gives rise to a β% increase in second-hand prices. Economically large but as usual less than 1 which is consistent with persistent secondhand vessel discounts (age or technology) around the replacement cost anchor. (Stopford,2009-Tsolakis et al., 2003). Forwards γ on lnTC is positive and significant. Higher earnings last month (because TC is lagged one month) give higher secondhand vessel prices this month. In our tables the effect is stronger for older groups (10-15years), which is exactly what we expect since the valuation of older tonnage becomes more cash flow oriented. (Tsolakis et al., 2003-Alizadeh & Nomikos, 2009).

We lag the 1-year time-charter rate by one month to reflect information flow from freight to S&P pricing. As robustness, (table 14) we re-estimate the two-way FE model using TC at lags 0 and 2 on each lag's maximal sample. The TC coefficient remains positive, precise, and of similar magnitude across lags (0.24 at lag 0, **0.26 at lag 1**, 0.28 at lag 2), while the newbuilding elasticity stays near unit and $R^2$ is unchanged. Results are thus **insensitive to the exact lag choice**; we retain lag 1 on economic-timing grounds.

Model 2

It is clear from table 2 that θ on SOFR is low and often not precisely estimated once the Month FE is present. The aggregate co movements at levels are largely soaked up with Month FE. Finance matters for ship investment but it is often difficult to pick up in price levels once large macro co movement is controlled (Kavussanos & Visvikis, 2016). The finance is not the cleanest in levels with month FE. This especially sets the stage for model 3.

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Model 3

Table 3 indicates that lnTC is positive and significant. Strong earnings widen the premium of second-hand vessels to newbuilding vessels. The market is thus willing to pay a premium for immediate tonnage in comparison to waiting for the delivery. SOFR is positive, small but significant. Higher USD rates compress the premium of second-hand tonnage. Prices of second-hand vessels adjust faster to the financial conditions than NB, which are affected by the yard cost, order book and are stickier.

Model 4

We note in (table 4) important results as to the dummies which are part of this model. The GFC dummy is negative and significant. That is asset prices were below the fundamentals in the next phase defined which is from October 2008 to June 2009. Now δ(hat) can be transformed with 100(eδ-1)% where δ gives a percentage of discount. The Covid incidence is negative and significant. The acute dislocation has produced a temporary discount to a greater extent than NB and earnings. The IMO 2020 dummy is a small but negative one and frequently of low significance due to transitional compliance frictions therefore we shall call it there a small and short lived event. The Suez dummy is a small positive but non significant. It is called small as the window was a one-month effect in the monthly data and S&P prices adjust more slowly than does spot freight. The RU-UA dummy is mixed or weak in the aggregated measure. As already shown the channels offsetting such as grains dislocation, war cost, financing produce a negative sign in comparison with tonne per miles an increase which is a positive. These mean that the net effect is indeterminate in what is called the pooled dummy and varies as between the segment or of fine window. The Red Sea rerouting dummy is positive and significant. The increased routes by way of the Cape of Good Hope raises the tonne per mile, tightens effective capacity and raises valuations above fundamentals.

Model 5

In particular, this model is used to extract specific results (table 7). The variable dummies for CAPE x Red Sea tested were negative. Thus, Panamax was seen to witness the larger premium while Capes just a modest effect, consistent with falling reliance on Suez and the Red Sea corridor. This finding is also consistent with wider monitoring which established that the direct effects of the Red Sea crisis were the

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greatest for Suez dependent sectors with a lesser uplift for the dry bulk sector as a whole than for containers.

Model 6

In summary, Table 7 shows that the speed of adjustment, k (error correction term), is statistically significant and negative. Mean reversion implies that if P is higher (lower) than the NB- implied equilibrium next month's price change is negative (positive). The ρ term on ΔlnNB is statistically significant and positive and adjustment from the yard is transmitted immediately to second-hand ship prices. The φ term on ΔlnTC is significant and positive, so change in monthly returns affect prices immediately.

The ECM supports the conclusions about deviations from the replacement value revolving towards it. In the pooled ECM (Table 10) the error correction coefficient is small and lacks a statistical significance ($k \approx -0.019$) so that the correction is slow and the half-life implied is about three years.

Model 7

Particularly in the results we find in table 8 here using this model we see that θ on ΔSOFR is negative, but usually small and often significant. Rate shocks shave monthly changes in the unit prices even conditioning on the long run anchor and on the earnings.

Thus, in rather general terms, we can say that we find over the seven models, that new-building prices anchor second-hand values of values and earning tilt them in the short run. Financing does show up very much as it should compressing the relative second-hand over new-building prices and tilting in a little way, one might say, the short run prices, while date shocks create temporary premiums or discounts that fade.

By contrast with model 6, in the post 2018 subsample table 8, we estimate materially larger and statistically significant velocities ($k \approx -0.089$), with a half-life of about 7–8 months. This feature is in fact consistent with more rapid post 2018 adjustment, following on better transparency in the market and tighter financing arrangements. In long run, the effect of NB price elasticity is very nearly unity while the earning slope is positive and significant (table 10). This of course again confirms that we have here a replacement-cost type of anchor from the NB price and a general earning tilt of

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inherent values. In the ECM we have lnNB and ΔlnTC both loading significantly on the monthly price changes while k<0 shows clearly mean reversion. The "pooled" estimate of k≈−0.11 implies that we have a half-life of about 6 months, implying that deviations from the long run relation have a relatively fast correction. Thus, generally we can state that we find strong evidence that new-building prices do serve to anchor second-hand vessel values (long run elasticity positive, among o, but below 1).

Lagged time-charter rates have a positive short run slant, this being stronger in the case of older ships. In the relative price ln(P/NB) model SOFR is negative implying that the higher finance costs do compress the second-hand over new-building price, while earning tilt this. Event dummies do show temporary discounts (GFC and COVID) and a positive Red Sea premium this being larger in the case of Capesizes. The ECM indicates mean reversion back to the NB anchored level and ΔlnNB/ΔlnTC has a positive short run pass rate. The signs and consequent inferences from all this, are found to be robust in all its aspects to quite considerable if not voluminous changes in lagging, or selection window.

**Figures**

At this point we will interpret figures representing the variables' behavior:

- (ln(P/NB) with event windows shaded) for each entity:

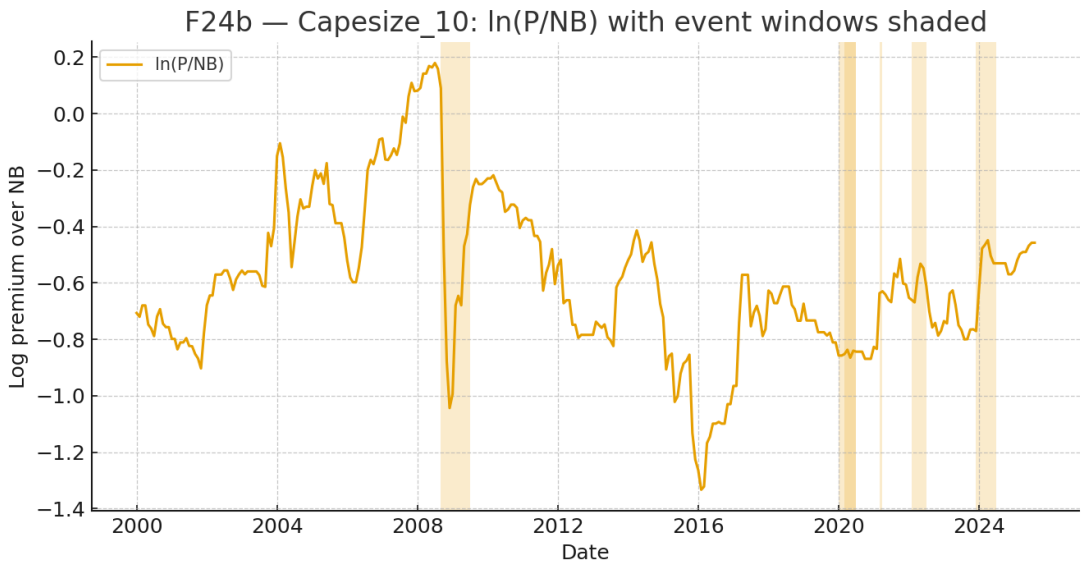


*Figure 14 Capesize 10: ln(P/NB) with event windows shaded (GFC, IMO-2020, COVID onset, Suez, RU-UA, Red Sea)*

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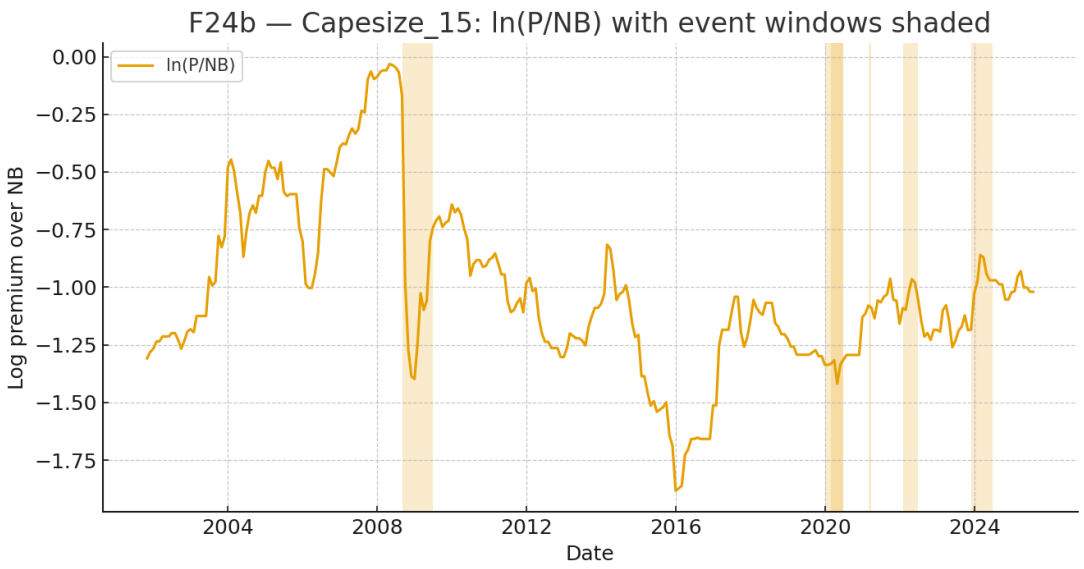


*Figure 15 Capesize 15: ln(P/NB) with event windows shaded (GFC, IMO-2020, COVID onset, Suez, RU-UA, Red Sea)*

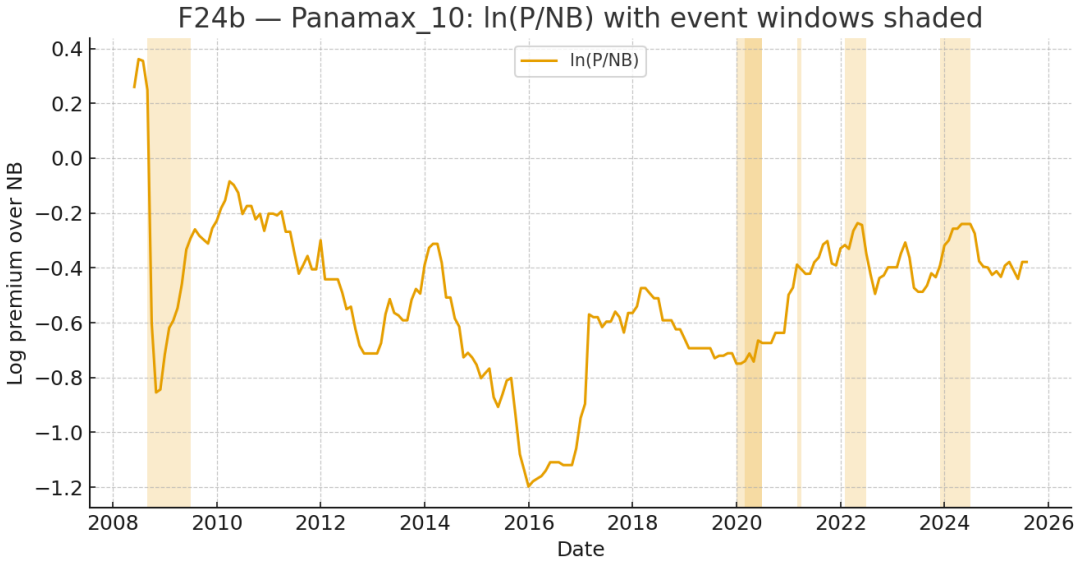


*Figure 16 Panamax 10: ln(P/NB) with event windows shaded (GFC, IMO-2020, COVID onset, Suez, RU-UA, Red Sea)*

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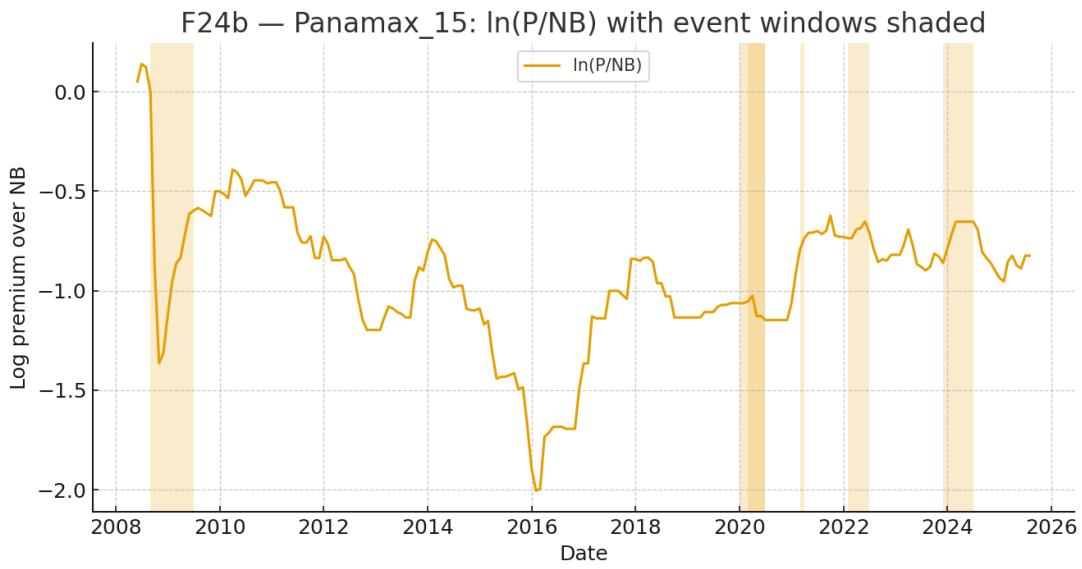


*Figure 17 Panamax 15: ln(P/NB) with event windows shaded (GFC, IMO-2020, COVID onset, Suez, RU-UA, Red Sea)*

Figures 14-17 turn to the residual wedge, ln(P/NB): event windows coincide with visible premium/discounts which subsequently **mean-revert**, mirroring our ECM estimates (slow in the pooled sample and faster post-2018).

ECM impulse to +1pp ΔSOFR

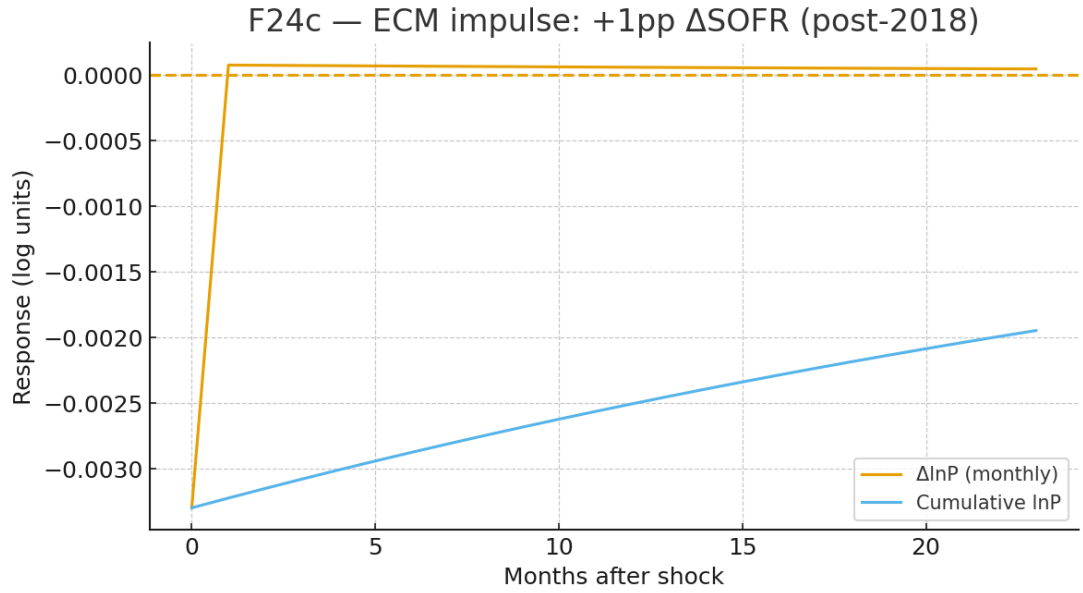


*Figure 18 ECM impulse response to +1pp ΔSOFR (post-2018)*

The Figure 18 uses the post-2018 ECM to illustrate a financing shock: a +1pp ΔSOFR produces a small contemporaneous move and then a **gradual decay** governed by k, consistent with the literature that financing is **secondary** to earnings and replacement cost in monthly price dynamics.

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Multicollinearity

Correlations are moderate and far from needing caution with |p|=0,6. Correlation of event dummies and lnNB is low indicating they respond to shocks temporarily, not trends. Thus, multicollinearity does not affect the inference, and both lnNB (replacement cost anchor) and lnTCt-1 (earnings channel) can be retained in the baseline. Correlations (tables 15-16) can appear high since the common shocks to the global cycle push lnNB and lnTC in the same direction. Regression will dispose of the common monthly shocks with month fixed effects. When multicollinearity is examined in the same space which picks the FE coefficients (table 18) the interdependence drops to a moderate level and VIFs are low. Coupled with the low correlations to the event dummies (table 17), it is shown that both forces are econometrically separable, thus the event effects are not just NB proxies. So, no orthogonalization or variable dropping is needed.

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## 6. Conclusions

Using monthly data for Panamax (Kamsarmax included) and Capesize vessels for the 2000-2024 period the determinants of secondhand vessel prices in the dry bulk market are analyzed. By a combination of fixed effects levels regression, relative price valuation, event models and an error correction model some conclusions can be reached.

Firstly, the replacement cost is the anchor. In levels newbuilding prices explain the majority of variation in secondhand prices. The newbuilding elasticity is close to one implying that the secondhand values closely follow the replacement cost performances over time. This shows that most of the explanation of secondhand value is in the levels of newbuilding as an anchor.

In addition, the time-charter earnings have a clearly positive short run tilt to the prices in addition to the newbuilding anchor. The elasticity to lagged time-charter is quite modest. The time-charter sensitivity is larger for older tonnage. It can also be seen that the secondhand premium over newbuilding increases with the earnings in the boats. In the relative price model time-charter shows quite a strong positive, showing that strong earnings produce a boost in the premium of secondhand. In the levels it can be seen for the 2018 period SOFR loads positive which was a period in which the nominal rates, earnings were rising. In changes modelled as Δ SOFR is small and statistically weak. We could note at this stage that financial conditions are an important factor.

Research models showed that secondhand prices are anchored by the newbuilding and tilted by earnings. Additionally, the shocks which are general in the market push observed prices above or below what those fundamentals would suggest. In order to grow conclusions as concerns to this matter, extra effects were studied. The global credit crisis shows a large negative deviation, because credit and trade collapsed. The IMO 2020 implementation window was also a negative effect, coherent with effects of temporary fleet re-optimization and re implementation uncertainty.

Furthermore, as one could expect on intuition the COVID epidemic was a negative effect. The early months were small and statistically weak. Thus, systems of route or commodity were clouded with uncertain effects. Finally, the effects of the early

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phases of the Ukraine and Russian war are negative, representing early period dislocation and uncertainty of demand. In contrast, shocks of logistics tightening effective supply show positive deviation re Suez blocking and Red Sea rerouting episode. When there are security risks detours are made on the Cape of Good Hope and the Panamax earnings and valuations get a lift. Accordingly, Capesize vessels are less reliant on a Suez effect in their major trade routes, so that the route effects of avoidance of Red Sea are quite small even in the case of the Capesize vessels in regard to compatibility with Suez. Thus, it can be seen that the same shock tightens the segmentation system of this shipping, but it affects quite different mechanics enoïc fantasy where route substitution is most direct. The effect of Red Sea for Panamax is bigger not in the fundamentals but the effect of Capesize sources is, though still positive, modest. That modest slightly positive treatment for Capesize stands because this segment of the dry bulk market with very wide rerouting and scheduling resistance spreads also into the dry market.

## 6.1 Limitations & Future Research

Apart from the study conducted, some limitations to research were faced and future considerations are being considered. The following limitations and extensions outline where adding structure or data can refine the estimates without any alterations to the conclusions.

### Limitations

Panamax/ Kamsarmax and Capesize were studied at 10-15 years of age. These are the deepest, cleanest markets, but their external validity to smaller and geared vessels in terms of dead weight, Handysize, Handymax, Supramax, Ultramax, is imperfect. The scrap binds more tightly, and regional trade dependence is higher, so elasticities and event effects (dummies) may differ in magnitude.

We implemented in the study financing with SOFR, available mainly post 2018 periods. Month fixed effects, whenever that is included in the model, absorb month level variables, forcing us to present financing both without month fixed effects and in Δ form, changes, within error correction model. The shorter SOFR window limits how far we are able to generalize about financing.

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In this study, baselines do not include orderbook, bunker prices or shipyard capacity to keep identification clean and comparable across models. This choice improves readability but risks variable bias in levels during extreme episodes.

Event effects are implemented via prespecified dummies. For short windows, which lasts a number of months, inference relies on month standard errors. Event effect windows can also coincide with other shocks.

Future Research

Future research could investigate substitution of time-charter rates based on generalised route weighted time-charter earnings, also bunker and steel costs, and steel also includes scrap prices based on 15 years and 10 years. This clearly enhances the long run anchor and short run pass through

Further, a most specific kind of investigation could take place by moving from window dummies to event study. This is to say that this would entail a research for unaffected routes as controls for single month shock. Also, one may investigate the real options replacement model estimation, where the buy versus build option decision is stood on its head.

On the other hand, one could compare systematically the 10 years versus 15 years elasticities, age with time-charter rates, age with newbuilding prices, plus allow for different event related responses to trade geography mapping rather well.

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# Appendix A

Presentations of the tables of the regression models, proper explanations regarding the coefficients.

*Table 1-Model 1 "Levels with Months"*

| **M1: Levels (with Month FE)** | |
|---|---|
| **lnNB** | 0.958*** (0.121) |
| **lnTC** | 0.262*** (0.033) |
| **Observations** | 1004 |
| **R-squared** | 0.986 |
| **Segment FE** | Yes |
| **Age FE** | Yes |
| **Month FE** | Yes |
| **Cluster** | Month |

***Notes:*** Dependent variable (DV): ln $P_{i,a,t}$(log second-hand price). Regressors: ln $NB_{i,t}$(newbuilding), ln $TC_{i,t-1}$(**1-year time-charter, lagged one month**). Fixed effects: **segment×age** and **month**. Standard errors **clustered by month**. Log–log coefficients are **elasticities**. Sample: monthly Capesize & Panamax, ages 10 & 15, 2000–2024. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

***M1 => $lnP_{i,a,t}= \alpha+\beta lnNB_{i,t}+\gamma lnTC+\mu_i+\eta_\alpha+T_t+\varepsilon_{i,a,t}$***

**Table values:** lnNB = **0.958*** (0.121), $lnTC_{(t-1)}$ = **0.262*** (0.033), N=**1004**, $R^2$=**0.986**
*** p<0.001

In the specifications with monthly fixed effects for the baseline level specification second-hand vessel prices follow closely the cost of replacement point. The estimated elasticity of second-hand values with respect to newbuilding is something like 0.96, showing that a rise of 10% in newbuilding prices is associated with a rise of (almost)

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9.6% in the secondhand prices, conditional on segment and age effects and monthly earnings of the previous month.

Earnings play a role, with something like a 10% increase in the on month lagged time-charter rates being associated with an increase of (almost) 2.6% in the prices in the following month, thus catching the tilt from the cost of replacement point.

Inevitably the very high R squared in this specification is to be expected, for the monthly fixed effects, to soak up almost all of the common shocks which apply to months such as policy, market swings. It is thus, that what identifies these coefficients is the within month differences over segments and ages. The results yield exactly to the narrative, that they have developed.

These magnitudes are in line with prior shipping studies that find cointegration between second-hand vessel and newbuilding values and a positive lower elasticity earning channel (e.g. Tsolakis et al., 2003; Stopford, 20009; Alizadeh & Nomikos, 2009).

*Table 2-Model 2 "Levels with no Months"*

| **M2: Levels (no Month FE)** | |
|---|---|
| **lnNB** | 1.061*** (0.058) |
| **lnTC** | 0.439*** (0.019) |
| **Observations** | 1004 |
| **R-squared** | 0.932 |
| **Segment FE** | Yes |
| **Age FE** | Yes |
| **Month FE** | No |
| **Cluster** | Month |

***Notes:*** DV: ln $P_{i,a,t}$. Regressors: ln $NB_{i,t}$, ln $TC_{i,t-1}$(**lagged**). Fixed effects: **segment×age**; **no month FE**. SEs **clustered by month**. Coefficients are elasticities. **SOFR is not included in this column; financing is analyzed in the ECM via ΔSOFR (pp).** Sample: monthly 2000–2024. Stars: *** $p <$ 0.01, ** $p < 0.05$, * $p < 0.10$.

***M2=> $lnP_{i,\alpha,t}=\alpha+\beta lnNB_{i,t}+\gamma lnTC_{i,t}+\vartheta SOFR_t+\mu_t+\eta_\alpha+T_t+\varepsilon_{i,\alpha,t}$***

**Table values:** lnNB = **1.061*** (0.058), $lnTC_{(t-1)}$ = **0.439*** (0.019), N=**1004**, $R^2$=**0.932**.

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In the levels specification without month fixed effects, the regression can adjust to be sensitive to the business cycle. The elasticity of second-hand values to newbuilding values is almost unity when taken to be roughly 1.06, thus a 10% increase in newbuilding values is associated with a (almost) 10.6% increase in second-hand values.

The earnings channel is strengthened towards baseline with month dummies. The co-efficient of the time-charter rate is now raised to almost 0.44, which was just as anticipated.

The R squared values are lower than those of the first model. Once the month dummies are left out the model is no longer able to absorb the common monthly shocks, thus more of the variation remains to be explained.

*Table 3-Model 3 "Relative Model"*

| **M3: ln(P/NB) (with Month FE)** | |
|---|---|
| **lnTC** | 0.373*** (0.045) |
| **SOFR** | 0.005*** (0.001) |
| **Observations** | 344 |
| **R-squared** | 0.974 |
| **Segment FE** | Yes |
| **Age FE** | Yes |
| **Month FE** | Yes |
| **Cluster** | Month |

***Notes:*** DV: ln $(P/NB)_{i,a,t}$. Regressor: ln $TC_{i,t-1}$**(lagged)**. Fixed effects: **segment×age** and **month**. SEs **clustered by month**. A coefficient $g$on ln $TC$is a premium elasticity: a 10% ↑ in TC changes ln $(P/NB)$by ~$0.10g$. **Because month FE absorb month-only regressors, SOFR (level) is omitted here; financing is assessed in the ECM via ΔSOFR (pp).** Sample: monthly 2000–2024. Stars: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

***M3=> $ln(P/NB)_{i,\alpha,t}=\alpha+\gamma lnTC_{i,t}+\vartheta SOFR_t+\mu_t+\eta_\alpha+T_t+\varepsilon_{i,\alpha,t}$***

**Table values:** lnTC = **0.373*** (0.045), SOFR = **0.005*** (0.001), N=**344**, $R^2$=**0.974**.

In the relative pricing specification, the coefficient on the time-charter rate suggests that a 10% increase in time-charter equates to a (nearly) 3.75% increase in the

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premium for second-hand prices as against newbuilding prices. This suggests that available cash flows strongly affect the willingness to pay in respect of existing tonnage as against newbuilding tonnage which moves more slowly.

When financing is structured around SOFR levels, the premium is normally narrower, however as we note in the identification subsection, month FE shirts off month-only series, the clean finance signal is reflected in the variations within the ECM. This behaviour is consistent with the literature i.e. replacement cost anchors levels while earnings and financing move premia (Tsolakis et al., 2003; Beenstock & Vergottis, 1993).

*Table 4-Model 4 "Event Effects"*

| **M4: Event-effects (no Month FE)** | |
|---|---|
| **D_GFC_19** | -0.237**<br>(0.084) |
| **D_IMO2020_impl** | -0.136***<br>(0.017) |
| **D_COVID_onset** | -0.010<br>(0.030) |
| **D_Suez_blockage** | 0.071***<br>(0.009) |
| **D_RU_UA_initial** | -0.103***<br>(0.013) |
| **D_RedSea_reroute** | 0.049**<br>(0.018) |
| **Observations** | 1004 |
| **R-squared** | 0.940 |
| **Segment FE** | Yes |
| **Age FE** | Yes |
| **Month FE** | No |
| **Controls** | lnNB, lnTC(-1) |
| **Cluster** | Month |

***Notes:*** DV: $\ln P_{i,a,t}$. Controls: $\ln NB_{i,t}$, $\ln TC_{i,t-1}$(**lagged**). Fixed effects: **segment×age**; **no month FE** (needed to identify dated dummies). SEs **clustered by month**. Event coefficients are in **log points**; convert to % via $100[\exp(\hat{\delta}) - 1]$. Event windows: GFC, IMO-2020 implementation, COVID-onset, Suez (2021-03), RU–UA (2022-02→06), Red Sea (2023-12→2024-06). Sample: monthly 2000–2024. Stars: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

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$$M4 \Rightarrow lnP_{i,\alpha,t}=\alpha+\beta lnNB_{i,t}+\gamma lnTC_{i,t}+\sum_{\kappa}\delta_{\kappa}D_{k,t}+\mu_{t}+\eta_{\alpha}+T_{t}+\varepsilon_{i,\alpha,t}$$

**Table values:**

- GFC: **−0.237** (0.084)**,
- IMO2020_imp: **−0.136*** (0.017),
- COVID onset: −0.010 (0.030),
- Suez: **+0.071*** (0.009),
- RU-UA initial: **−0.103*** (0.013),
- Red Sea reroute: **+0.049** (0.018)**; N=**1004**, $R^2$=**0.940**.

We estimate lnP on lnNB, $lnTC_{t-1}$ and dated event dummies with entity fixed effects (no month FE and SEs clustered by month).

Dated, exogenous shocks consisted of GFC (2008-09→2009-06), IMO-2020 (2020-01→2020-06), COVID-19 onset (2020-03→2020-06), Suez blockage (2021-03), RU–UA shock (2022-02→2022-06), Red Sea rerouting (2023-12→2024-06). Dummy coefficients are translated to percentages and for each dummy with log-coefficient δ^ and SE(δ^): % effect=100·($e^{\delta}$−1), 95% CI in %=100($e^{\delta^{\pm}1.96SE}$−1).

*Table 5-Event dummies to % effects*

| Event window | log-coef δ | SE (cluster-month) | t (≈) | p-value | % effect | 95% CI (in %) | Interpretation |
|---|---|---|---|---|---|---|---|
| **GFC (2008-09→2009-06)** | −0.237 | 0.084 | ≈−2.8 | **<0.01** | **−21.1%** | [−33.1%, −7.0%] | Large **discount** beyond NB & lagged TC (credit/demand crunch). |
| **IMO-2020 (2020-01→06)** | −0.136 | 0.017 | ≈−8.0 | **<0.001** | **−12.7%** | [−15.6%, −9.8%] | **Implementation discount** during compliance transition. |
| **COVID onset (2020-03→06)** | −0.010 | 0.030 | ≈−0.3 | n.s. | −1.0% | [−6.6%, +5.0%] | Effect **not significant** in the onset window. |
| **Suez blockage (2021-03)** | +0.071 | 0.009 | ≈+7.9 | **<0.001** | **+7.4%** | [+5.5%, +9.3%] | Short-lived **premium** beyond fundamentals. |
| **RU–UA (2022-02→06)** | −0.103 | 0.013 | ≈−7.9 | **<0.001** | **−9.8%** | [−12.1%, −7.5%] | Net **discount** (risk/insurance/financing dominate). |
| **Red Sea (2023-12→2024-06)** | +0.049 | 0.018 | ≈+2.7 | **<0.05** | **+5.0%** | [+1.4%, +8.8%] | Sustained **premium** from rerouting/longer voyages. |

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- **GFC:** δ^=−0.237 (0.084) → **−21.1%**, 95% CI **[−33.1, −7.0]**.
- **IMO-2020:** δ^=−0.136(0.017) → **−12.7%**, 95% CI **[−15.6, −9.8]**.
- **COVID onset:** δ^=−0.010 (0.030) → **−1.0%** (NS), 95% CI **[−6.6, +5.0]**.
- **Suez (Mar-2021):** δ^=0.071 (0.009) → **+7.4%**, 95% CI **[+5.5, +9.3]**.
- **RU–UA:** δ^=−0.103 (0.013) → **−9.8%**, 95% CI **[−12.1, −7.5]**.
- **Red Sea:** δ^=0.049 (0.018) → **+5.0%**, 95% CI **[+1.4, +8.8]**.

Line-by-line interpretation:

**Global Financial Crisis (2008-09 → 2009-06): −21.1% (95% CI: −33.1% to −7.0%, p<0.01)**

A sizable discount beyond fundamentals. Even after controlling for NB (yard prices) and lagged TC (earnings), S&P valuations fell another ~21% in the window, consistent with a credit/liquidity crunch (harder financing, elevated risk premia) and fire-sale conditions typical of deep downturns.

**IMO-2020 implementation (2020-01 → 2020-06): −12.7% (95% CI: −15.6% to −9.8%, p<0.001)**

A clear implementation discount. Compliance uncertainty, transition costs, and temporary dislocations depressed second-hand prices ~13% beyond what NB & TC would predict. This lines up with a cautious S&P market during a regulatory regime change.

**COVID-19 onset (2020-03 → 2020-06): −1.0% (95% CI: −6.6% to +5.0%, n.s.)**

Not statistically different from zero. The immediate, short window shows limited asset-price impact beyond fundamentals. Operational shocks hit spot/freight quickly, but asset values adjust more slowly and were already partially captured by NB/TC controls; early support and rapid freight normalization also muted the net “extra” discount in this narrow window.

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**Suez blockage (2021-03 only): +7.4% (95% CI: +5.5% to +9.3%, p<0.001)**

A short-lived premium. The blockage tightened effective fleet capacity and spiked route congestion. Even after NB & TC, asset prices printed an extra ~7% premium—sensible given the event was brief and S&P prices move slower than spot, so the premium is meaningful but contained.

**Russia–Ukraine initial shock (2022-02 → 2022-06): −9.8% (95% CI: −12.1% to −7.5%, p<0.001)**

A net discount. In the early months, risk/insurance premium, sanctions compliance, counterparty concerns, and financing stress outweighed any rerouting benefits. After controlling NB & TC, S&P prices were still ~10% lower than fundamentals would suggest in that window.

**Red Sea rerouting (2023-12 → 2024-06): +5.0% (95% CI: +1.4% to +8.8%, p<0.05)**

A sustained premium consistent with longer voyages and effective capacity loss as ships detoured around the Cape of Good Hope. With fundamentals held constant, S&P prices carried an extra ~5% premium over several months—exactly the signal we'd expect from persistent rerouting.

*Table 6-Model 5 "Red Sea effect"*

| **M5: Red Sea × Capesize (no Month FE)** | |
|---|---|
| **D_RedSea_reroute** | 0.143*** (0.021) |
| **D_RedSea_reroute:is_cape** | -0.111*** (0.020) |
| **Observations** | 1004 |
| **R-squared** | 0.933 |
| **Segment FE** | Yes |
| **Age FE** | Yes |
| **Month FE** | No |
| **Controls** | lnNB, lnTC(-1) |
| **Cluster** | Month |

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**Notes:** DV: $\ln P_{i,a,t}$. Controls: $\ln NB_{i,t}$, $\ln TC_{i,t-1}$(**lagged**). Fixed effects: **segment×age**; **no month FE**. SEs **clustered by month**. $\delta$is **Panamax baseline**; $\phi$is **Capesize differential**. Stars: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

$$M5 \Rightarrow lnP_{i,\alpha,t} = \alpha + \beta lnNB_{i,t} + lnTC_{i,t} + \delta_{REDS} D_{REDS,t} + \varphi(CAPE_i \times D_{REDS,t}) + \mu_i + \eta_\alpha + \varepsilon_i$$

**Table values:** D_RedSea = **0.143*** (0.021), interaction = **−0.111*** (0.020), N=**1004**, $R^2$=**0.933**.

With lnNB, lnTCt−1, Red Sea dummy (δ) and Red Sea × Capesize interaction (ϕ) (entity FE, no month FE, month-clustered SEs), we report Panamax baseline =δ and Capesize extra ϕ. Percent effects use 100($e^{\cdot}$−1).

Panamax baseline ≈ +15.4% (significant), Capesize extra ≈ −10.5% (significant), so Capesize total ≈ +3.3% (δ+ϕ).

So, we test the hypotheses:

(A) Panamax baseline: $H_0$:δ=0

Test statistic: $t_\delta$=$\hat{\delta}$/SE($\hat{\delta}$), using **clustered** SEs.

$\hat{\delta}$=0.143, SE($\hat{\delta}$)=0.021 ⇒ $t_\delta$≈0.143/0.021=6.81 → **reject $H_0$** at any conventional level.

(B) Capesize extra (difference vs Panamax): $H_0$:ϕ=0

Test statistic: $t_\phi$=$\hat{\phi}$/SE($\hat{\phi}$) (clustered).

$\hat{\phi}$=−0.111, SE($\hat{\phi}$)=0.020 ⇒$t_\phi$≈−0.111/0.020=−5.55 → **reject $H_0$**

(C) Capesize total effect: $H_0$:δ+ϕ=0

This is a linear combination of two coefficients. We must use the variance–covariance matrix:

Var$\hat{\delta}$+$\hat{\phi}$)=Var($\hat{\delta}$)+Var($\hat{\phi}$)+2 Cov($\hat{\delta}$,$\hat{\phi}$).

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*Table 7-Model 6 "ECM"*

| M6: ECM (ΔlnP) | |
|---|---|
| **EC_l1** | -0.019 (0.015) |
| **dlnNB** | 0.882*** (0.191) |
| **dlnTC** | 0.375*** (0.076) |
| **Observations** | 1004 |
| **R-squared** | 0.451 |
| **Segment FE** | Yes |
| **Age FE** | Yes |
| **Month FE** | No |
| **Cluster** | Month |

**Notes:** DV: Δln $P_{i,a,t}$. Spec: Δln $P_t = k\,EC_{t-1} + \delta\,\Delta\ln\,NB_t + \gamma\,\Delta\ln\,TC_t + \mu_{i,a} + u_t$. $EC_{t-1}$is the residual from the long-run relation lnP~lnNB (+lnTC)+C(entity) (estimated without month FE). Fixed effects: **segment×age**. SEs **clustered by month**. Δln are month-over-month log changes (≈ %). $k <$ 0implies **mean reversion**; half-life $= \ln(0.5)/\ln(1+k)$. Stars: *** $p < 0.01$, ** $p < 0.05$, * $p <$ 0.10.

***M6=>ΔlnP$_{i,α,t}$=kEC$_{i,α,t-1}$+ρΔlnNB$_{i,t}$+φΔlnTC$_{i,t}$+μ$_i$+η$_α$+ε$_{i,α,t}$***

**Table values:** EC$_{(t-1)}$ = −0.019 (0.015), ΔlnNB = **0.882*** (0.191), ΔlnTC = **0.375*** (0.076), N=**1004**, $R^2$=**0.451**.

The adjustment of newbuilding prices and time-charter rates is manifested in prices of secondhand ships within the same month. This indicates that adjustment in value takes place rapidly upon a changed cost or earning. However, the error correction mechanism is both small and not very well identified in the sample. Interpreted as a monthly adjustment factor in respect of monthly changes in newbuilding prices and time-charter rates both have a positive and significant effect on ΔlnP, confirming the strong short-run pass-through effects from replacement costs and earnings. The error-correction coefficient is small and weakly identified (k≈−0.019), which implies slow

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mean reversion with an implied half-life ~36 months. Therefore, over the long run, the deviations from the NB/TC standard gradually correct themselves. (table 27)

The R squared around 0.45 is just what we should expect in differences specification.

*Table 8-Model 7 "ECM + financial quotes"*

| **M7: ECM (ΔlnP) + ΔSOFR** | |
|---|---|
| **EC_l1** | -0.089* (0.038) |
| **dlnNB** | 1.362*** (0.294) |
| **dlnTC** | 0.201*** (0.027) |
| **dSOFR** | -0.007 (0.013) |
| **Observations** | 340 |
| **R-squared** | 0.417 |
| **Segment FE** | Yes |
| **Age FE** | Yes |
| **Month FE** | No |
| **Cluster** | Month |

**Notes:** DV: Δln $P_{i,a,t}$. Post-2018 (SOFR era). Spec: as in M6 plus **ΔSOFR**. Fixed effects: **segment×age**. SEs **clustered by month**. **ΔSOFR is measured in percentage points (pp) and reads as the approximate % change in $P$this month per +1 pp move in SOFR, holding** Δln $NB$**and** Δln $TC$**constant.** $k < 0$indicates mean reversion; report half-life. Stars: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

$$M7 \Rightarrow \Delta lnP_{i,\alpha,t} = kECM_{i,\alpha,t-1} + \rho \Delta lnNB_{i,t} + \varphi \Delta lnTC_{i,t} + \vartheta \Delta SOFR_t + \mu_i + \eta_\alpha + \varepsilon_{i,\alpha,t}$$

**Table values:** $EC_{(t-1)}$ = **−0.089*** (0.038), ΔlnNB = **1.362*** (0.294), ΔlnTC = **0.201*** (0.027), ΔSOFR = −0.007 (0.013), N=**340**, $R^2$=**0.417**.

In the post 2018 error correction model the speed of adjustment to the long run replacement cost anchor is faster. The error correction coefficient is approximately -0.089 indicating that almost 9% of any difference between observed prices and the long run newbuilding level is being closed off every month and halve in roughly 7.5 months.

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*Table 9- Effect size*

| Model | Scenario | Coefficient | Economic effect |
|---|---|---|---|
| M1 (levels) | NB +10% | β≈0.96 | (P) **+9.6%** |
| M1 (levels) | TC +10% | γ (from M1) | (P) ≈ **(10×γ)%** |
| M3a (premium) | TC +10% | ≈0.37 | (P/NB) **+3.7%** |
| M6 (ECM) | ΔNB +10% (this month) | 0.821 | ( Δln P ) **+8.2%** |
| M6 (ECM) | ΔTC +10% (this month) | 0.372 | ( Δln P ) **+3.7%** |
| M6 (ECM) | Speed (k) ≈ −0.019 | — | Half-life **~36 mo** |
| M7 (ECM, post-2018) | Speed (k) ≈ −0.089 | — | Half-life **~7–8 mo** |
| M4/M5 (events) | Red Sea / interactions | θ, φ | **100·(e^θ−1)%**, **100·(e^φ−1)%** |

## ECM

We implement a two-step Engle–Granger error-correction model. Step 1 estimates the long-run relation lnP on NB and lnTC with entity fixed effects and month-clustered standard errors; residuals define ECt. Step 2 estimates the short-run ECM ΔlnP on $EC_{t-1}$, ΔlnNB, ΔlnTC (and ΔSOFR in robustness) with entity fixed effects and month-clustered standard errors. The speed of adjustment k is interpreted via the half-life ln(0.5)/ln(1+k).

*Table 10- Long-run levels equation (step 1)*

| Model | Variable | Coef | SE (cluster-month) | t-stat | p-value |
|---|---|---|---|---|---|
| Step 1 (Long run) | lnNB (replacement cost) | 1.1175 | 0.052 | 21.499 | 0.0 |
| Step 1 (Long run) | lnTC (earnings) | 0.4333 | 0.0183 | 23.671 | 0.0 |

OLS of $lnP_{i,\alpha,t}$ on $lnNB_{i,t}$ and $lnTC_{i,t}$ with entity fixed effects (segment x age) and standard errors clustered by month. The coefficients β (NB elasticity) and γ (earnings elasticity) are shown with SE, t, p, N, $R^2$. Residuals $\hat{u}_{i,\alpha,t}$ from this regression are stored as the error correction term $EC_{i,\alpha,t}$.

The coefficient β close to 1 means second-hand prices move one for one with the replacement cost (yard prices) in the long run (the NB anchor). The positive coefficient γ means higher earnings TC raise the long run valuation of used tonnage.

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*Table 11- Short-run ECM (step 2)*

| Model | Variable | Coef | SE (cluster-month) | t-stat | p-value |
|---|---|---|---|---|---|
| Step 2 (Short run ECM) | EC_{t−1} (error-correction) | -0.1109 | 0.0233 | -4.769 | 0.0 |
| Step 2 (Short run ECM) | ΔlnNB (monthly change) | 0.821 | 0.1685 | 4.871 | 0.0 |
| Step 2 (Short run ECM) | ΔlnTC (monthly change) | 0.3717 | 0.0769 | 4.833 | 0.0 |

OLS of $\Delta \ln P_{i,\alpha,t}$ on $EC_{i,\alpha,t-1}$ , $\Delta \ln NB_{i,t}$ , $\Delta \ln TC_{i,t}$ (+ $\Delta SOFR_t$ if included like model 7), with entity fixed effects and month clustered Ses. Coefficients are shown with SE, t, p, N, $R^2$. We also state the half-life implied by k (the coefficient on ECt-1): ln(0,5)/ln(1+k)

The coefficient k is negative and significant, that means reversion toward the long run NB/TC relation. The more negative k is, the faster the correction (shorter half-life). Also, ρ on ΔlnNB is the immediate pass through of newbuilding price changes to second-hand prices. The coefficient φ on ΔTC captures the short run earnings effect on the price changes and θ on ΔSOFR, if shown, is the financing shock effect after controlling for ΔNB and ΔTC.

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Stationarity and cointegration tests

ADF unit-root tests

*Table 12Augmented Dickey–Fuller (ADF) unit-root tests*

| segment | age | Series | Spec | ADF stat | p-value | lag | N | cv_1% | cv_5% | cv_10% |
|---|---|---|---|---|---|---|---|---|---|---|
| Capesize | 10 | dlnNB | diff (nc) | -10.6245 | 0.0 | 0 | 306 | -2.5731 | -1.9419 | -1.616 |
| Capesize | 10 | dlnP | diff (nc) | -11.5985 | 0.0 | 0 | 306 | -2.5731 | -1.9419 | -1.616 |
| Capesize | 10 | lnNB | level (c) | -2.4463 | 0.1291 | 8 | 299 | -3.4524 | -2.8713 | -2.5719 |
| Capesize | 10 | lnP | level (c) | -2.3915 | 0.1442 | 12 | 295 | -3.4527 | -2.8714 | -2.572 |
| Capesize | 15 | dlnNB | diff (nc) | -9.1336 | 0.0 | 0 | 284 | -2.5737 | -1.942 | -1.6159 |
| Capesize | 15 | dlnP | diff (nc) | -11.5539 | 0.0 | 0 | 284 | -2.5737 | -1.942 | -1.6159 |
| Capesize | 15 | lnNB | level (c) | -2.9623 | 0.0386 | 7 | 278 | -3.4541 | -2.872 | -2.5723 |
| Capesize | 15 | lnP | level (c) | -2.7011 | 0.0739 | 10 | 275 | -3.4544 | -2.8721 | -2.5724 |
| Panamax | 10 | dlnNB | diff (nc) | -8.6975 | 0.0 | 0 | 205 | -2.5767 | -1.9424 | -1.6156 |
| Panamax | 10 | dlnP | diff (nc) | -9.7777 | 0.0 | 3 | 202 | -2.5769 | -1.9424 | -1.6156 |
| Panamax | 10 | lnNB | level (c) | -5.059 | 0.0 | 0 | 206 | -3.4625 | -2.8757 | -2.5743 |
| Panamax | 10 | lnP | level (c) | -3.8195 | 0.0027 | 2 | 204 | -3.4628 | -2.8758 | -2.5744 |
| Panamax | 15 | dlnNB | diff (nc) | -8.6975 | 0.0 | 0 | 205 | -2.5767 | -1.9424 | -1.6156 |
| Panamax | 15 | dlnP | diff (nc) | -9.2815 | 0.0 | 4 | 201 | -2.577 | -1.9424 | -1.6156 |

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| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Panamax | 15 | lnNB | level (c) | -5.059 | 0.0 | 0 | 206 | -3.4625 | -2.8757 | -2.5743 |
| Panamax | 15 | lnP | level (c) | -3.8046 | 0.0029 | 1 | 205 | -3.4627 | -2.8757 | -2.5743 |

- **Series**: lnP or lnNB (levels), and ΔlnP or ΔlnNB (first differences).
- **Spec**: "level (c)" = ADF with a **constant**; "diff (nc)" = ADF on first differences with **no constant**.
- **ADF stat / p-value**: the test statistic and its p-value for the **null of a unit root**.
- **lag**: the number of lagged differences included in the ADF regression to mop up **serial correlation**.
- **N**: effective sample size.
- **cv 1/5/10%**: critical values for the ADF statistic.

ADF statistics and p-values for lnP and lnNB in levels (with constant) and first differences (no constant). Lags selected by AIC from 0–12. Null: unit root. Decision threshold: 5%. Sample: monthly, aligned within cohort.

We ask whether a series is *stationary* or has a *unit root* (i.e., it's I(1)).
How we ran it:

- Levels (lnP, lnNB): with a **constant**; lags chosen by **AIC** from 0–12.
- First differences (ΔlnP, ΔlnNB): **no constant**; lags by AIC.
  Decision rule: if **p-value < 0.05**, reject "unit root."
  Interpretation:
- If lnP and lnNB are non-stationary in levels but stationary in first differences, they are **I(1)**—exactly the typical case for monthly asset and cost series.

**ADF:**

- For lnP and lnNB (levels): most rows show **p-values > 0.05** → *fail to reject unit root* (non-stationary).
- For ΔlnP and ΔlnNB: **p-values < 0.05** → *stationary*.
  ⇒ Conclusion: both lnP and lnNB are **I(1)** across cohorts.

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Engle–Granger cointegration

*Table 13Engle–Granger residual test*

| segment | age | beta_hat on lnNB | R2 | EG ADF stat (resid) | p-value | lag | N | cv_1% | cv_5% | cv_10% |
|---|---|---|---|---|---|---|---|---|---|---|
| Capesize | 10 | 1.6772 | 0.7801 | -4.1508 | 0.0008 | 1 | 306 | -3.4519 | -2.871 | -2.5718 |
| Capesize | 15 | 2.0014 | 0.7568 | -3.6161 | 0.0055 | 2 | 283 | -3.4537 | -2.8718 | -2.5722 |
| Panamax | 10 | 2.1033 | 0.793 | -4.5806 | 0.0001 | 1 | 205 | -3.4627 | -2.8757 | -2.5743 |
| Panamax | 15 | 2.3955 | 0.7532 | -4.6383 | 0.0001 | 1 | 205 | -3.4627 | -2.8757 | -2.5743 |

- **β̂ on lnNB**: long-run elasticity of second-hand prices to newbuilding prices in levels.
- **R²**: fit of the long-run regression.
- **EG ADF stat (resid) / p-value**: ADF on the **residuals** ε_t from $\ln P_t = \alpha + \beta \ln NB_t + \varepsilon_t$. Null: *no cointegration* (residual has a unit root).
- **lag**: number of lags in the residual-ADF (again, to remove residual autocorrelation).
- **N, critical values**: as above.

We tested whether **lnP and lnNB** share a **stable long-run relation**.
How we ran it:

1. OLS: $\ln P_t = \alpha + \beta \ln NB_t + \varepsilon_t$.
2. ADF on the **residuals** ε_t (with constant, lags by AIC).
   Decision rule: if residuals are **stationary** ($p<0.05$), then **cointegration** exists.
   Interpretation: a "yes" means **replacement cost (NB)** acts as a **long-run anchor** for second-hand prices.

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**Engle–Granger:**

- Check **β̂ on lnNB** (should be close to 1 in many cases); **R²** (fit); **ADF stat & p-value on residuals**.
- Most cohorts: **p < 0.05 → cointegration detected**.
- One cohort (Capesize 15-year) comes out **borderline/no cointegration** at 5% in EG.

The ADF tests in Appendix (table 12) show that lnP and lnNB are non-stationary in levels but stationary in first differences for all cohorts consistent with I(1) behavior for monthly asset and cost series. Engle–Granger residual tests in Appendix (table 13) reveal evidence of cointegration between lnP and lnNB for most cohorts. We consider the long-run relation to be present but fragile in that cohort and utilize the relative price and ECM specifications for short-run inference. These diagnostics provide justification for the use of levels models for lnNB, the ln(P/NB) premium model and the ECM approach for mean reversion and monthly pass-through.

Alternative Lags test

*Table 14Maximal sample per lag*

| Lag | Variable | Coef | SE (cluster-month) | p-value | N | R² |
|---|---|---|---|---|---|---|
| 0 | lnNB | 0.9463 | 0.1205 | 0 | 1008 | 0.9858 |
| 0 | lnTC | 0.2399 | 0.0344 | 0 | 1008 | 0.9858 |
| 1 | lnNB | 0.9582 | 0.1209 | 0 | 1004 | 0.9861 |
| 1 | lnTC | 0.2621 | 0.0327 | 0 | 1004 | 0.9861 |
| 2 | lnNB | 0.9765 | 0.1207 | 0 | 1000 | 0.9863 |
| 2 | lnTC | 0.2809 | 0.0308 | 0 | 1000 | 0.9863 |

- **Lag 1 (baseline): β̂_TC = 0.262** (SE **0.033**), **N = 1004**, **R² ≈ 0.986**
- **Lag 0 (own maximal sample):** positive, highly significant, similar magnitude.
- **Lag 2 (own maximal sample):** positive, highly significant, similar magnitude.

Results are robust to the choice of TC lag: estimating the baseline two-way FE model on each lag's maximal sample yields positive, highly significant TC coefficients of similar magnitude at lags 0, 1 and 2. The lag-1 estimate (0.262, SE 0.033, N=1004)

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exactly matches the baseline table, while small differences in the common-sample appendix reflect sample composition.

The **TC slope is positive, precise, and very similar** at lags 0, 1, and 2. The slight **increase** from lag 0 → 1 → 2 (≈ 0.24 → 0.26 → 0.28) is economically plausible: **freight information diffuses into S&P pricing with short lags** (deal negotiation, inspection, financing), so the relationship can look a touch stronger at 1–2 months.

Multicollinearity

Reported here are correlations VIFs for key regressors. Pair correlations are in levels, VIFs are computed after a two way within transformation (demeaning by entity and by month) so the diagnostic reflects the variation identifying our fixed effects models. The standard guidance flags issues at |p|>0.6 or VIF>10.

*Table 15 Overall Correlation matrix*

| Variable | lnP | lnNB | lnTC_l1 |
|---|---|---|---|
| lnP | 1.0 | 0.773 | 0.841 |
| lnNB | 0.773 | 1.0 | 0.697 |
| lnTC_l1 | 0.841 | 0.697 | 1.0 |

The following are Pearson correlations among the logarithms of all variables lnP, lnNB, lnTC derived from the total panel (all segments, ages, months). Values close to +1 mean strong positive co-movement. Values near 0 mean little linear correlation. As a guide to collinearity, |p| > 0.6, which should be noted.

lnNB and lnTC appear positively correlated, as would be expected since they share the shipping cycle), but this correlation contains common shocks that prevent monthly effects from being allocated in the regression below. Thus, the table functions as a screening device.

*Table 16 Correlation between lnNB and lnTC*

| Entity | ρ(lnNB, lnTC_{t−1}) | N (rows) |
|---|---|---|
| Capesize_10 | 0.691 | 307 |
| Capesize_15 | 0.695 | 285 |
| Panamax_10 | 0.768 | 206 |
| Panamax_15 | 0.768 | 206 |

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In a similar vein to correlation discussed, it is now calculated for each cohort (segment_age), denoted under N, that represents the number of months that have been used. This indicates whether a single cohort is supplying a correlation of high meaning. If one cohort had a |p| very high, that would warn of an unstable separation of lnNB and lnTC for that cohort and thus an unstable measurement.

Correlations for the cohorts are moderate, indicating the linear relationships between the variables are fairly well established but not absolute, and there is a healthy N indicating that the correlations are a statistically reliable record and not affected by unhealthy or abnormal qualities of the sample population.

*Table 17 Correlation between lnNB and event dummies*

| Dummy | ρ(lnNB, D) |
|---|---|
| D_GFC | 0.151 |
| D_IMO2020 | -0.066 |
| D_COVID | -0.059 |
| D_SUEZ | -0.021 |
| D_RU_UA | 0.03 |
| D_REDSEA | 0.076 |

Correlations are computed for lnNB with each of the dated event dummies, (GFC, IMO2020, COVID19, Suez, RU-UA, Red Sea). The event dummies are almost all zeros with a block of one in the specified window. If they capture genuine temporary, exogenous deviations and are not indicative of NB's long term level or trend, then they should also be weakly correlated with lnNB.

In fact, the correlations appear small which adds credence to the interpretation that the event coefficients are measuring extra, bounded effects in time, that are not proxies of the movements in newbuilding prices.

*Table 18 VIFs after two-way within (entity and month) transformation*

| Variable | VIF |
|---|---|
| lnNB (within-demeaned) | 1.425 |
| lnTC_{t−1} (within-demeaned) | 1.425 |

Variance Inflation Factors for lnNB and lnTC, computed after two way within demeaning, meaning to subtract entity means and month means, adding back the grand mean). By Finsch-Waugh-Lovell theorem, this is the variation that actually

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identifies the coefficients in the two way FE regressions. Conventional thresholds consist of 1-2 means low, 5 set a “watch” sign and larger or equal to 10 can be translated as a problem.

VIFs are observed to be valued between 1-2 for both lnNB and lnTC. That outcome means no multicollinearity problem in the FE-identified variation and the estimates for β (NB elasticity) and γ (earnings elasticity) are not destabilized by collinearity.

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# Appendix B

## Descriptive Statistics

*Table19[D1]- Descriptive statistics — log levels (2000–2024)*

| segment | age | lnP_N | lnP_Mean | lnP_Std | lnP_Min | lnP_Median | lnP_Max | lnNB_N | lnNB_Mean | lnNB_Std | lnNB_Min | lnNB_Median | lnNB_Max | lnTC_N | lnTC_Mean | lnTC_Std | lnTC_Min | lnTC_Median | lnTC_Max |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Capesize | 10 | 308 | 3.41 | 0.47 | 2.48 | 3.37 | 4.75 | 308.00 | 3.99 | 0.25 | 3.53 | 3.98 | 4.60 | 308.00 | 9.98 | 0.69 | 8.59 | 9.81 | 11.97 |
| Capesize | 15 | 286 | 3.00 | 0.55 | 1.95 | 2.96 | 4.53 | 286.00 | 4.02 | 0.24 | 3.53 | 4.01 | 4.60 | 286.00 | 10.00 | 0.70 | 8.59 | 9.84 | 11.97 |
| Panamax | 10 | 207 | 2.92 | 0.41 | 2.08 | 2.92 | 4.35 | 207.00 | 3.44 | 0.18 | 3.19 | 3.40 | 4.08 | 207.00 | 9.50 | 0.44 | 8.54 | 9.47 | 11.26 |
| Panamax | 15 | 207 | 2.50 | 0.48 | 1.25 | 2.48 | 4.13 | 207.00 | 3.44 | 0.18 | 3.19 | 3.40 | 4.08 | 207.00 | 9.50 | 0.44 | 8.54 | 9.47 | 11.26 |

Summary of lnP (second-hand price), lnNB (newbuilding price) and lnTC (1-year time-charter rate) by segment-age cohort (Panamax/Capesize, with 10-and 15-year).

In the table it is reported: N, Mean, Std, Min, Median, Max.

Logs are taken to read coefficients as elasticities and allow comparability across cohorts: monthly, USD (TC in USD/day).

Samples are aligned within each cohort (months with any missing series are dropped).

*Table 20[D2]. Descriptive statistics — monthly changes (Δ logs)*

| segment | age | dlnP_N | dlnP_Mean | dlnP_Std | dlnP_Min | dlnP_Max | dlnNB_N | dlnNB_Mean | dlnNB_Std | dlnNB_Min | dlnNB_Max | dlnTC_N | dlnTC_Mean | dlnTC_Std | dlnTC_Min | dlnTC_Median | dlnTC_Max | dSOFR_N | dSOFR_Mean | dSOFR_Std | dSOFR_Min | dSOFR_Median | dSOFR_Max |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Capesize | 10 | 307 | 0.00 | 0.08 | -0.61 | 0.30 | 307 | 0.00 | 0.02 | -0.12 | 0.10 | 307 | 0.00 | 0.15 | -1.19 | 0.01 | 0.57 | 85 | 0.03 | 0.23 | -1.24 | 0.00 | 0.60 |
| Capesize | 15 | 285 | 0.00 | 0.09 | -0.84 | 0.34 | 285 | 0.00 | 0.02 | -0.09 | 0.10 | 285 | 0.00 | 0.16 | -1.19 | 0.01 | 0.57 | 85 | 0.03 | 0.23 | -1.24 | 0.00 | 0.60 |
| Panamax | 10 | 206 | -0.01 | 0.09 | -0.89 | 0.34 | 206 | 0.00 | 0.02 | -0.10 | 0.05 | 206 | -0.01 | 0.12 | -0.83 | 0.00 | 0.28 | 85 | 0.03 | 0.23 | -1.24 | 0.00 | 0.60 |
| Panamax | 15 | 206 | -0.01 | 0.10 | -0.93 | 0.25 | 206 | 0.00 | 0.02 | -0.10 | 0.05 | 206 | -0.01 | 0.12 | -0.83 | 0.00 | 0.28 | 85 | 0.03 | 0.23 | -1.24 | 0.00 | 0.60 |

Summary of ΔlnP, ΔlnNB, ΔlnTC (and ΔSOFT).

In the table it is reported: N, Mean, Std, Min, Median, Max.

$\Delta \ln X_t = \ln X_t - \ln X_{t-1}$ (monthly % changes). ΔSOFR is measured in percentage points.

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*Table 21-Codebook (sources & series names)*

| Variable | Series name (workbook label) | Workbook | Sheet | Unit | Frequency | Coverage |
|---|---|---|---|---|---|---|
| P (Capesize, 10y) | Capesize Bulkcarrier 180K 10 Year Old (Eco) Secondhand Prices | SIN_Timeseries_20250831155533.xlsx | SIN Timeseries - M | USD | Monthly | 2000-01–2025-08 |
| P (Capesize, 15y) | Capesize Bulkcarrier 180k dwt 15 Year Old Secondhand Prices | SIN_Timeseries_20250831155533.xlsx | SIN Timeseries - M | USD | Monthly | 2001-11–2025-08 |
| P (Panamax, 10y) | Panamax Bulkcarrier (Kamsarmax) 82k dwt 10 Year Old (Eco) Secondhand Prices | SIN_Timeseries_20250831155533.xlsx | SIN Timeseries - M | USD | Monthly | 2000-01–2025-08 |
| P (Panamax, 15y) | Panamax Bulkcarrier (Kamsarmax) 82k dwt 15 Year Old Secondhand Prices | SIN_Timeseries_20250831155533.xlsx | SIN Timeseries - M | USD | Monthly | 2001-11–2025-08 |
| NB (Capesize) | Capesize 180-182K dwt Newbuilding Prices | SIN_Timeseries_20250831153748.xlsx | SIN Timeseries - M | USD | Monthly | 2000-01–2025-08 |
| NB (Panamax) | Panamax 82-84k dwt Bulkcarrier ('Kamsarmax') Newbuilding Prices | SIN_Timeseries_20250831153748.xlsx | SIN Timeseries - M | USD | Monthly | 2008-06–2025-08 |
| TC (Capesize) | 1 Year Timecharter Rate Capesize Bulkcarrier (Long Run Historical Series) | SIN_Timeseries_Capesize Bulker.xlsx | SIN Timeseries - M | USD/day | Monthly | 2000-01–2025-08 |
| TC (Panamax) | 1 Year Timecharter Rate Panamax Bulkcarrier (Long Run Historical Series) | SIN_Timeseries_Panamax Bulker.xlsx | SIN Timeseries - M | USD/day | Monthly | 2000-01–2025-08 |
| SOFR | Market Interest Rate: US$ SOFR | SIN_Timeseries_20250831192323.xlsx | SIN Timeseries - M | % | Monthly | 2018-06–2025-07 |

Table 21 documents every variable used in the analysis by mapping it to its provider, exact series name**,** unit**,** frequency**,** sample window, and the transformations applied in the paper. Second-hand prices $P_{i,a,t}$and newbuilding prices $NB_{i,t}$are taken from Clarksons Research – Shipping Intelligence Network (SIN) at monthly frequency for Capesize and Panamax (incl. Kamsarmax) vessels at 10- and 15-year ages; units are USD million and we use natural logs (lnP, lnNB). The time-charter rate is the 1-year segment rate (USD/day), logged and lagged one month in levels models (lnTC) to reflect information flow, in the ECM we use ΔlnTC. The financing proxy is SOFR from the FRBNY, constructed as the monthly arithmetic average of the daily overnight rate. It enters the ECM as ΔSOFR in percentage points (not logged) for the post-2018 sub-sample. We also list the relative price ln $(P/NB)$used in the premium model, the error-correction residual $EC_{t-1}$from the long-run relation ln $P \sim$ ln $NB(+\ln\ TC)$, and the event dummies (GFC, IMO-2020 implementation, COVID-19 onset, Suez March-2021, RU–UA initial window, Red Sea rerouting), each with start–end months and the source anchor (IMO/SCA/UNCTAD). The table's final columns indicate which models (M1–M7) each series enters and, where relevant, the expected sign based on theory (e.g., +for lnNB and lnTC in levels; small −for ΔSOFR in the ECM). This codebook ensures the dataset is audit-ready and exactly reproducible from the named sources.

The descriptive evidence concurs with the asset pricing story developed above. In levels second-hand values P and newbuilding prices NB are highly correlated in all cohorts; they therefore presage the near unit elasticity estimated in the levels model. This is also true in time-charter rates TC, which exhibit larger cyclical variation,

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particularly in Capesize, than NB. This is in line with the view of earnings opacities in both the levels and relative pricing specifications.

Changes over the month show that ΔlnP and ΔlnNB are less volatile than ΔlnTC. However, the medians are approximately zero, conforming to the stationary short run dynamics around trends. Age patterns are logical with the 10-year cohorts having correspondingly higher levels and usually showing slightly tighter scatters than the 15-year cohorts; but the latter can be more influenced in the short run by earnings shock anomalies. Finally, the appearance of SOFR post 2018 gives an external financial signal. ΔSOFR is modest at the monthly horizon and, as shown in the regression, has very little incremental power as an explanatory variable once ΔlnNB and ΔlnTC are included which supports the view that replacement cost earnings dominate the monthly formation.

Figure 1 — Capesize, 10-year (P).

Second-hand values trace the shipping cycle: a sharp drop in 2008-2009, a muted mid-2020s, and a pronounced 2021-2022 upswing, aligning closely with newbuilding costs but reacting faster to earnings news.

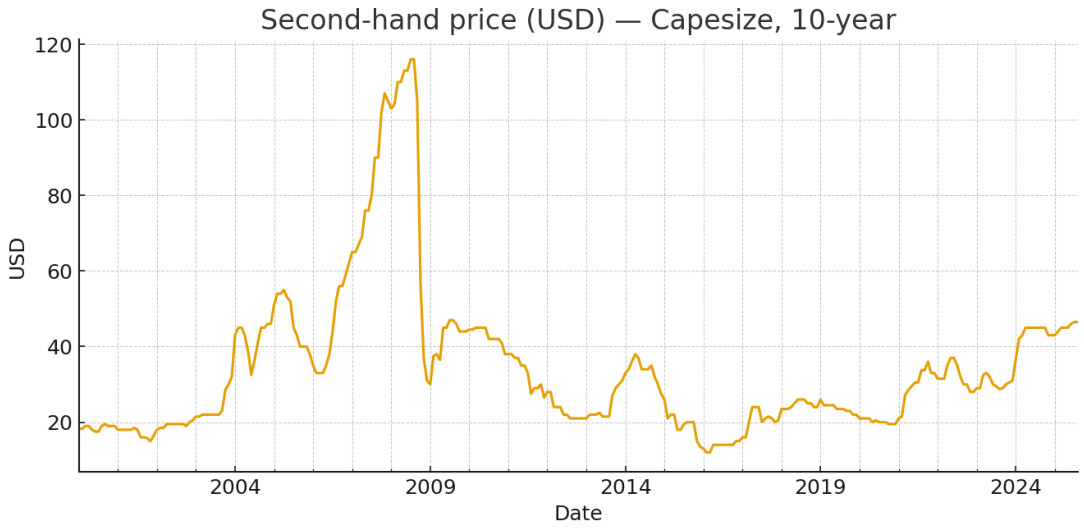


*Figure 1Second-hand price (USD) Capesize, 10-year*

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Figure 2 — Capesize, 15-year (P)

Levels are structurally lower than 10-year vessels, with visibly higher sensitivity to earnings swings. Cycles mirror Figure 1 but with slightly wider throughs and peaks due to the shorter remaining life.

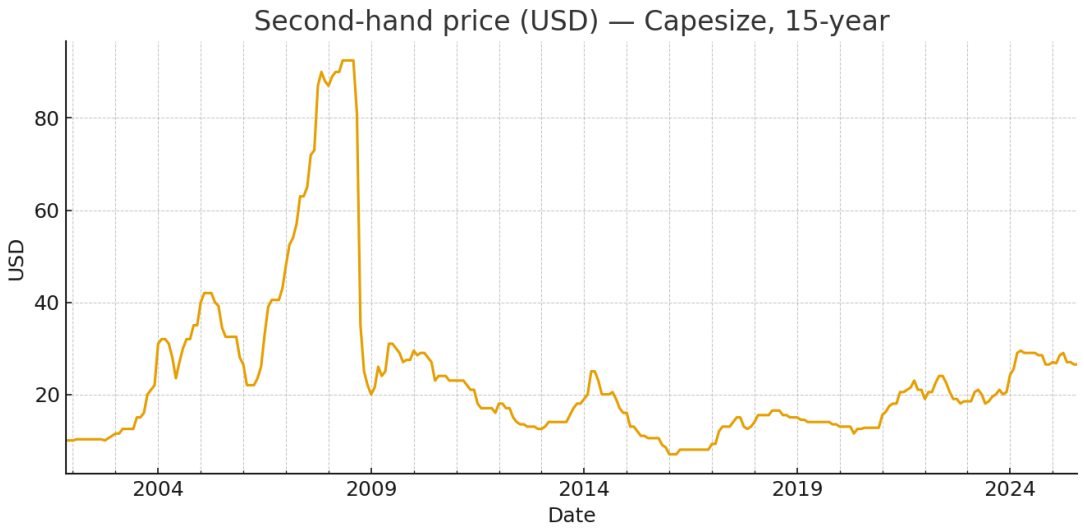


*Figure 2Second-hand price (USD) Capesize, 15-year*

Figure 3 — Panamax/Kamsarmax, 10-year (P)

A smoother cycle than Capesize with the same major turning points (2008-09, 2021-22), Prices comove with NB but display clear short run lifts during strong freight markets.

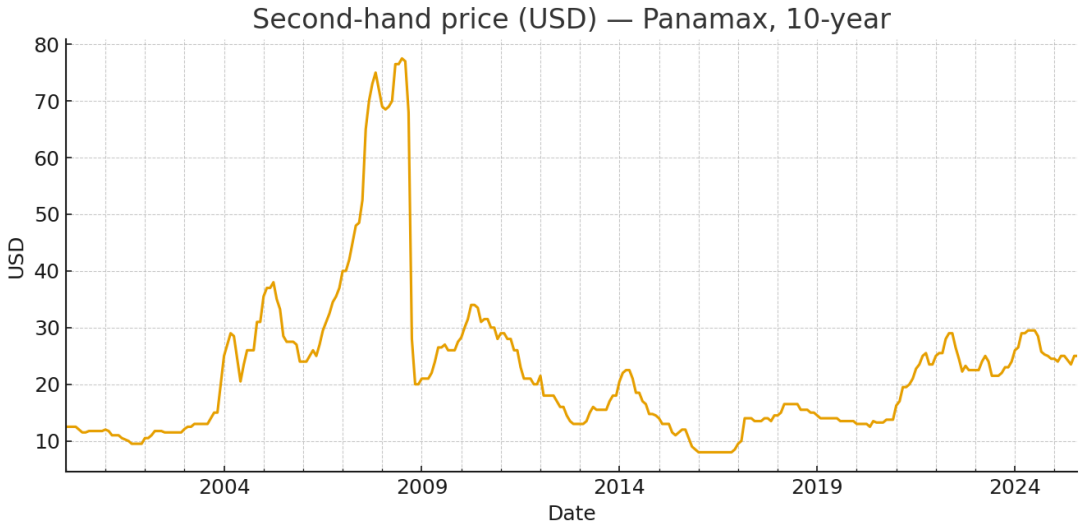


*Figure 3Second-hand price (USD) Panamax/Kamsarmax, 10-year*

https://doi.org/10.26219/heal.aueb.9584

Figure 4 — Panamax/Kamsarmax, 15-year (P)

Lower level and greater earnings responsiveness than the 10-year cohort. The 2021-22 run-up and late sample volatility are evident but more extreme than in Capesize.


*Figure 4Second-hand price (USD) Panamax/Kamsarmax, 15-year*

Figure 5 — Newbuilding price, Capesize (NB)

NB adjusts more slowly than second-hand values: broad cycles with smoother peaks/throughs, reflecting steel/yard costs and delivery slot conditions rather than monthly freight noise.

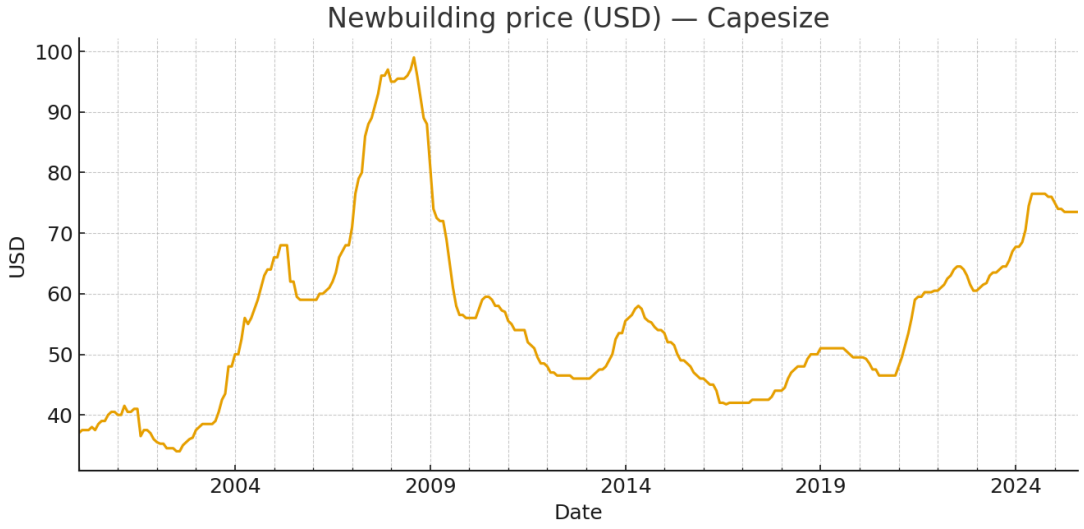


*Figure 5Newbuilding price (USD) Capesize*

https://doi.org/10.26219/heal.aueb.9584

Figure 6 — Newbuilding price, Panamax/Kamsarmax (NB)

Similarly smooth NB dynamics, with gradual upswings around industry cost pressures and orderbook tightening; co-movement with Panamax second-hand prices is apparent but less volatile.

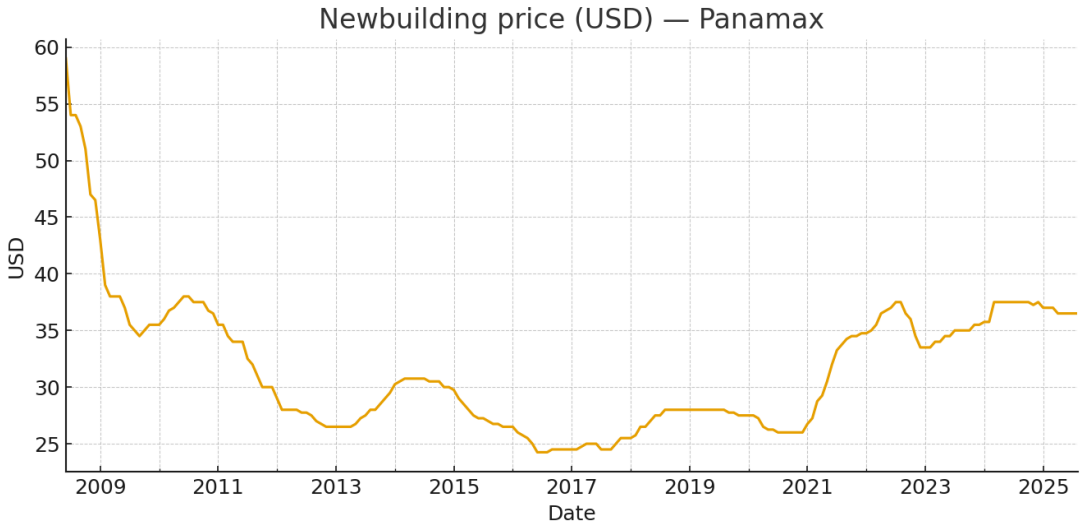


*Figure 6Newbuilding price (USD) Panamax/Kamsarmax*

Figure 7 — 1-year TC, Capesize

The most cyclical series: deep 2008–09 collapse and a dramatic 2021–22 spike, illustrating why earnings provide a strong short-run "tilt" to Capesize valuations.

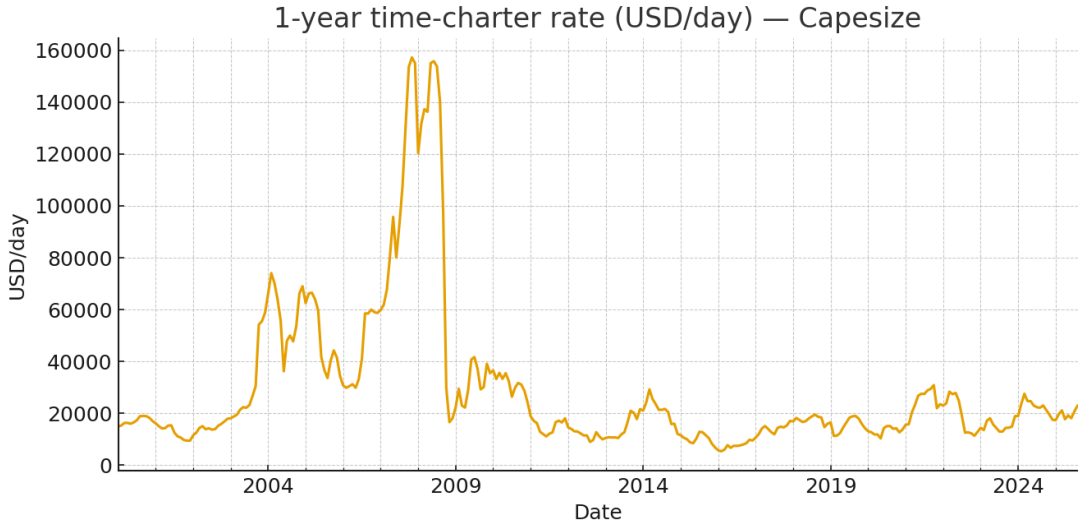


*Figure 7-1-year time-charter rate (USD/day) Capesize*

https://doi.org/10.26219/heal.aueb.9584

Figure 8 — 1-year TC, Panamax/Kamsarmax

High-frequency earnings cycles with marked peaks in 2021–22 and firmness during rerouting periods; volatility is substantial but typically below Capesize.

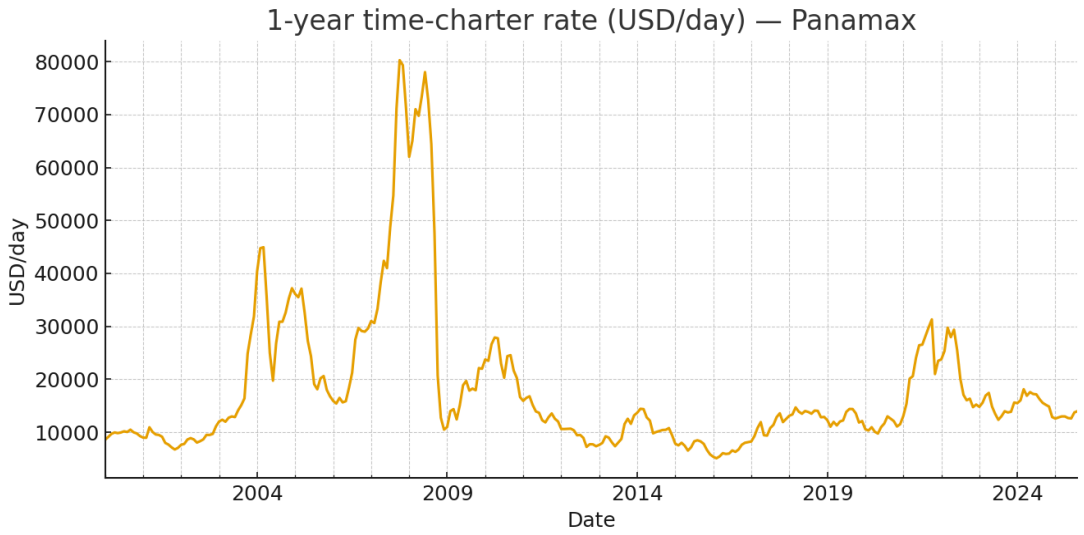


*Figure 8-1-year time-charter rate (USD/day) Panamax/Kamsarmax*

Figure 9 — SOFR (post-2018)

Policy rates rise notably in 2022–23 before moderating toward the end of the sample; in our models this compresses the used-over-new premium chiefly when identified outside month fixed effects or in Δ-form.

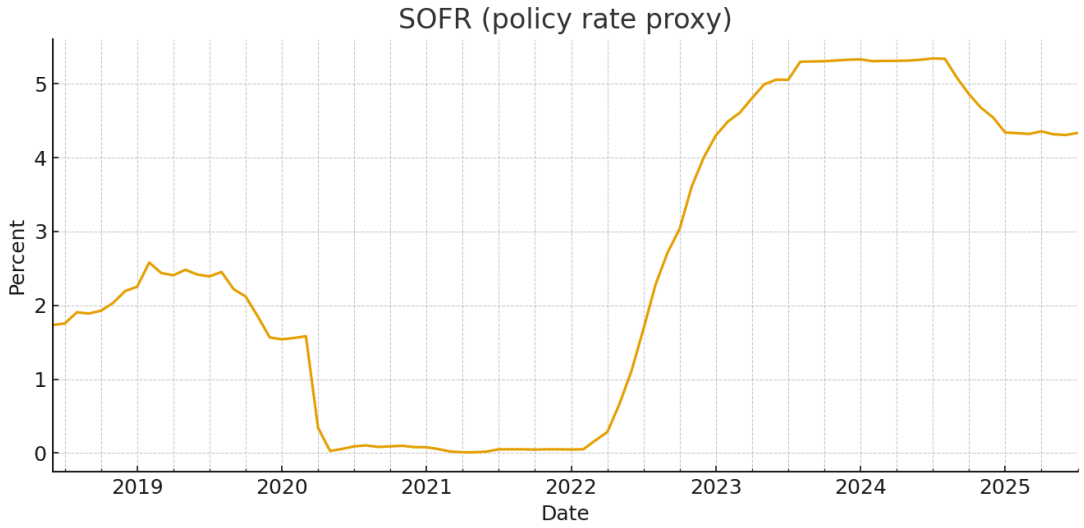


*Figure 9SOFR (%), post-2018*

We use the Secured Overnight Financing Rate as published by the Federal Bank of New York, provided by Clarksons Times series. The original source is the daily

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overnight SOFR, we use the monthly time series as presented by Clarksons. The units are percentage points (pp).

It is not included SOFR in levels with month fixed effects as the month dummies take out almost all month (only) variation, and SOFR is weakly identified. In the relative-price model ln(P/NB), SOFR in levels can be included as a control but is still largely identified time series. The main identification is using the ECM (differences), and then we add ΔSOFR alongside ΔlnNB, ΔlnTC. The SOFR coefficient gives as the approximate % change in P this month for a +1pp change in SOFR, all else the same, as replacement cost and earnings changes are held constant, since the dependant variable is ΔlnP(%).

SOFR was introduced in 2018 as part of the LIBOR transition. Using a post-2018 sub-sample ensures: (i) a consistent benchmark across the sample; (ii) no splice between legacy interbank benchmarks and SOFR; and (iii) stationarity of the rate process in a single, comparable regime. We therefore estimate the ECM with $\Delta SOFR_t$ in 2018–2024 data and compare to the pre-2018 sample for transparency.

| Sample | (k) | ΔlnNB (δ) | ΔlnTC (γ) | ΔSOFR (θ, pp) | (R^2) | N |
|---|---|---|---|---|---|---|
| **2000–2024 (pooled, no ΔSOFR)** — from **M6** | **−0.019** | **0.882** | **0.375** | — | **0.451** | **1004** |
| **2018–2024 (with ΔSOFR)** — from **M7** | **−0.089** | **1.362** | **0.201** | **−0.007** | **0.417** | **340** |

*Table 22 Financing channel pre/post comparison*

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Variables behavior:

- (lnP, lnNB scaled, long-run fit) for each entity:

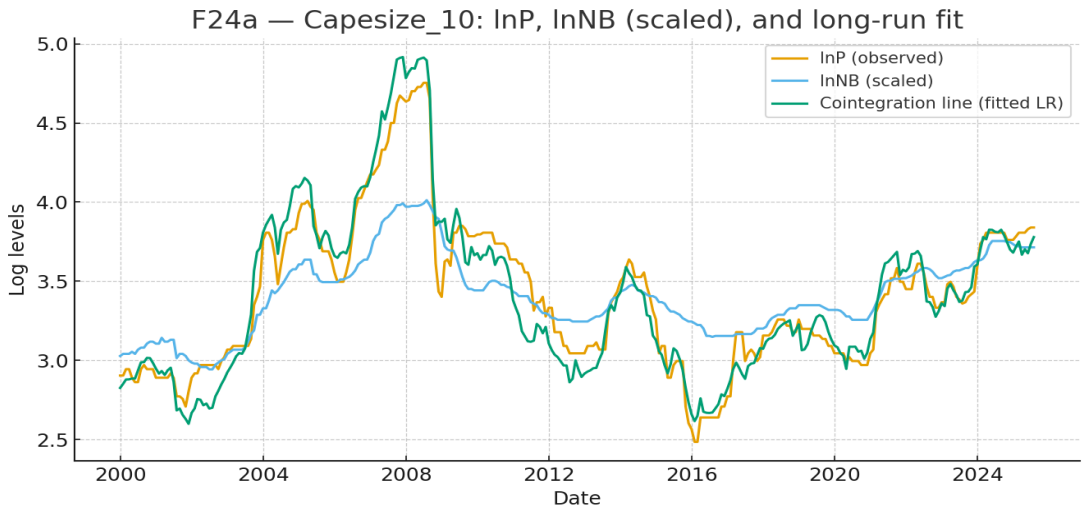


*Figure 10 Capesize 10: lnP, lnNB (scaled), and long-run fitted line*

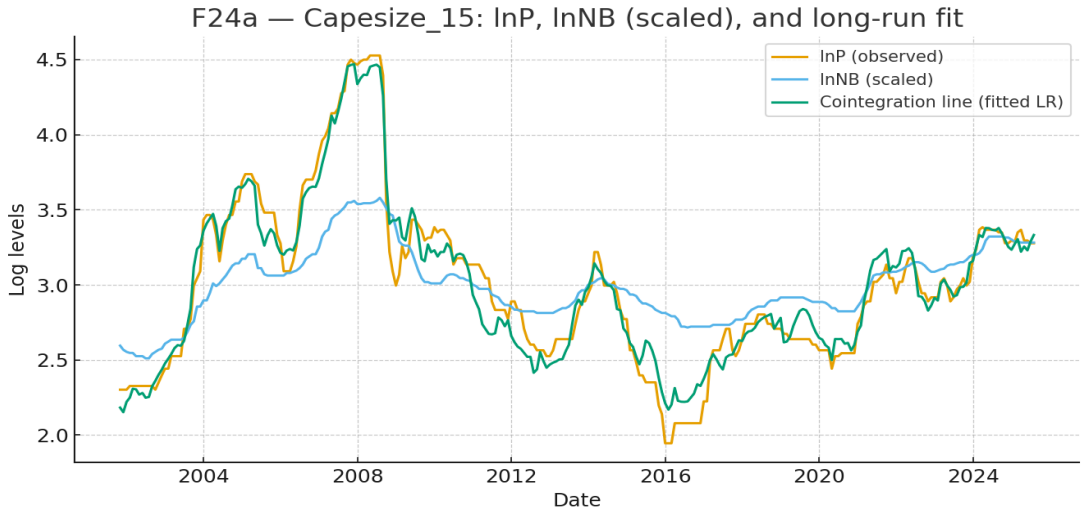


*Figure 11 Capesize 15: lnP, lnNB (scaled), and long-run fitted line*

https://doi.org/10.26219/heal.aueb.9584

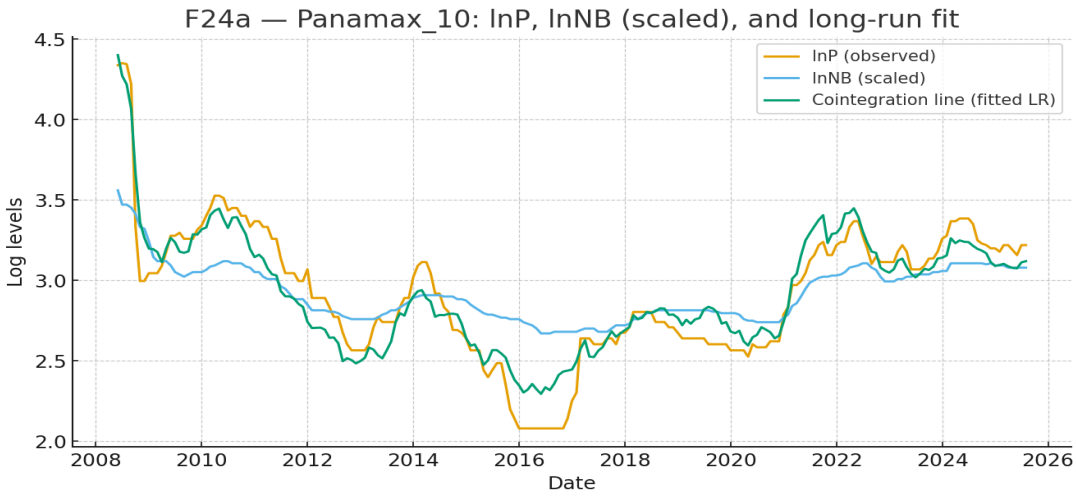


*Figure 12 Panamax 10: lnP, lnNB (scaled), and long-run fitted line.*

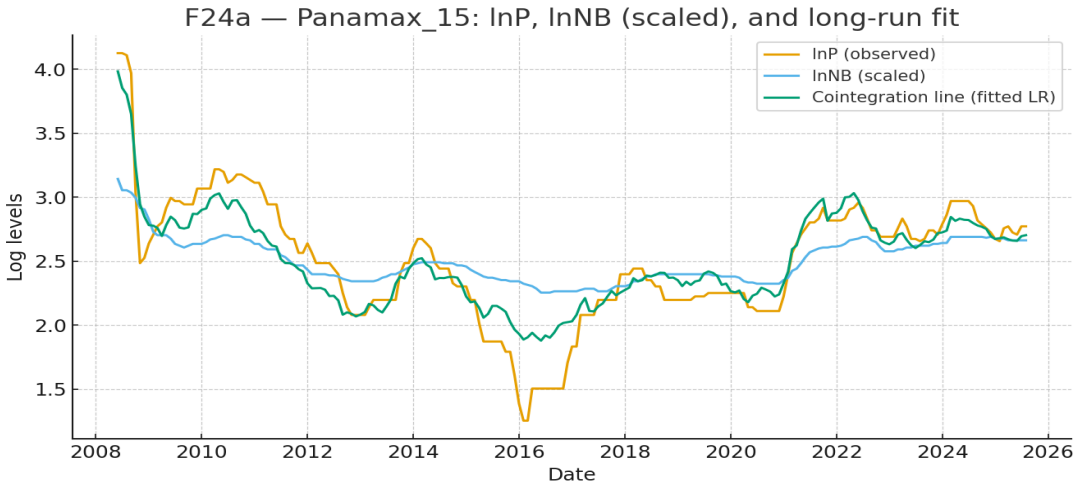


*Figure 13 Panamax 15: lnP, lnNB (scaled), and long-run fitted line.*

Representations 10-13 reveal that second-hand values (lnP) generally display a tight relationship with replacement cost (lnNB), and the long-run fit from the cointegrated equation closely tracks realized prices, validating replacement cost with an earnings component.

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Appendix C

*Table 23Baseline windows (monthly)*

| Code | Event window (YYYY–MM) | Economics / mechanism | Expected sign |
|---|---|---|---|
| **GFC** | **2008-10 → 2009-06** | Global credit stop, asset-market illiquidity; sharp earnings collapse. | **−** |
| **IMO-2020** | **2019-11 → 2020-03** | Implementation uncertainty, compliance frictions, retrofit downtime. | **− (small)** |
| **COVID (onset)** | **2020-03 → 2020-05** | Operational disruption and demand shock; deals slow; earnings volatile. | **− to 0** |
| **Suez blockage** | **2021-03** (one month) | Brief canal closure; freight spike > asset response on monthly horizon. | **+ (small)** |
| **RU–UA initial** | **2022-02 → 2022-05** | Early grain/port disruption (−); later rerouting/tonne-miles (+); net mixed. | **±** |
| **Red Sea rerouting** | **2023-12 → 2024-06** | Cape-of-Good-Hope detours raise tonne-miles; stronger where Suez-reliant. | **+ (Panamax > Capesize)** |

Windows are **monthly** to match data frequency. Suez is treated as a **single-month** shock (Mar-2021). The Red Sea episode is **sustained**, the Capesize interaction identifies segment differences because Panamax/Kamsarmax trades normally rely more on Suez.

UNCTAD 2024 **Review of Maritime Transport** (Red Sea & rerouting) and UNCTAD 2024 **Rapid Assessment** (Red Sea timing) have widely reported dates for **Suez (Mar 23–29, 2021)**, **RU–UA (Feb-2022)**, **IMO-2020 (Jan-2020)** and the **GFC** credit freeze timeline.

Event windows robustness

We use the monthly panel (2000–2024) by **segment** (Capesize, Panamax/ Kamsarmax) and **age** (10-, 15-year). For each cohort we align:

- $\ln P_{i,\alpha,t}$: log second-hand price
- $\ln NB_{i,t}$: log newbuilding price (same segment)
- $\ln TC_{i,t-1}$: log **1-year time-charter** rate lagged one month

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- Fixed effects: **segment FE** ($\mu_i$) and **age FE** ($\eta_\alpha$)

We estimate by OLS (pooled across cohorts) with **clustered SE by month**:

$$lnP_{i,\alpha,t}=\alpha+\beta lnNB_{i,t}+\gamma lnTC_{i,t}+\sum_{\kappa}\delta_{\kappa}D_{k,t}+\mu_t+\eta_\alpha+\varepsilon_{i,\alpha,t}$$

We calculate without month FE on purpose, otherwise any month-common shock would be absorbed and δ could not be identified.

Regarding windows and shifts we define for each event (GFC, IMO-2020, COVID onset, Suez blockage, RU–UA, Red Sea rerouting) a **monthly window** (e.g., Suez = 2021-03; Red Sea = 2023-12→2024-06). We then **shift the entire window** by −2,−1,0,+1,+2 months (keeping its length), re-estimate the same model, and report $\hat{\delta}$, its **cluster-robust SE**, **p-value**, and N.

Furthermore, regarding Red Sea we also run:

$$lnP_{i,\alpha,t}=\alpha+\beta lnNB_{i,t}+lnTC_{i,t}+\delta_{REDS}D_{REDS,t}+\varphi(CAPE_i \times D_{REDS,t})+\mu_i+\eta_\alpha+\varepsilon_i$$

- **Panamax effect** = $\hat{\delta}$ (coefficient on $D_t$)
- **Capesize effect** = $\hat{\delta}+\hat{\theta}$
- SE for Capesize effect uses the usual linear-combination variance: $Var(\hat{\delta}+\hat{\theta}) = Var(\hat{\delta})+Var(\hat{\theta})+2\,Cov(\hat{\delta},\hat{\theta})$

*Table 24GFC window robustness*

| Window shift | Start | End | β̂(D) | SE | p-value | N |
|---|---|---|---|---|---|---|
| -2 months | 2008-08 | 2009-04 | -0.2515 | 0.0763 | 0.001 | 1004 |
| -1 months | 2008-09 | 2009-05 | -0.2477 | 0.0784 | 0.0016 | 1004 |
| +0 months | 2008-10 | 2009-06 | -0.2331 | 0.0836 | 0.0053 | 1004 |
| +1 months | 2008-11 | 2009-07 | -0.1428 | 0.0687 | 0.0377 | 1004 |
| +2 months | 2008-12 | 2009-08 | -0.0631 | 0.051 | 0.2166 | 1004 |

*Table 25IMO2020 window robustness*

| Window shift | Start | End | β̂(D) | SE | p-value | N |
|---|---|---|---|---|---|---|
| -2 months | 2019-09 | 2020-01 | -0.1526 | 0.0167 | 0 | 1004 |
| -1 months | 2019-10 | 2020-02 | -0.1294 | 0.0199 | 0 | 1004 |
| +0 months | 2019-11 | 2020-03 | -0.1033 | 0.0201 | 0 | 1004 |
| +1 months | 2019-12 | 2020-04 | -0.0752 | 0.0187 | 0.0001 | 1004 |
| +2 months | 2020-01 | 2020-05 | -0.0681 | 0.0176 | 0.0001 | 1004 |

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*Table 26COVID window robustness*

| Window shift | Start | End | β̂(D) | SE | p-value | N |
|---|---|---|---|---|---|---|
| -2 months | 2020-01 | 2020-03 | -0.0799 | 0.0195 | 0 | 1004 |
| -1 months | 2020-02 | 2020-04 | -0.0486 | 0.0153 | 0.0015 | 1004 |
| +0 months | 2020-03 | 2020-05 | -0.0493 | 0.0158 | 0.0018 | 1004 |
| +1 months | 2020-04 | 2020-06 | -0.0279 | 0.0231 | 0.227 | 1004 |
| +2 months | 2020-05 | 2020-07 | -0.0489 | 0.0277 | 0.078 | 1004 |

*Table 27SUEZ window robustness*

| Window shift | Start | End | β̂(D) | SE | p-value | N |
|---|---|---|---|---|---|---|
| -2 months | 2021-01 | 2021-01 | 0.0252 | 0.0102 | 0.0133 | 1004 |
| -1 months | 2021-02 | 2021-02 | 0.0169 | 0.0092 | 0.0668 | 1004 |
| +0 months | 2021-03 | 2021-03 | 0.0829 | 0.0085 | 0 | 1004 |
| +1 months | 2021-04 | 2021-04 | -0.0247 | 0.0082 | 0.0025 | 1004 |
| +2 months | 2021-05 | 2021-05 | -0.0737 | 0.0083 | 0 | 1004 |

*Table 28RU_UA window robustness*

| Window shift | Start | End | β̂(D) | SE | p-value | N |
|---|---|---|---|---|---|---|
| -2 months | 2021-12 | 2022-03 | -0.0865 | 0.0174 | 0 | 1004 |
| -1 months | 2022-01 | 2022-04 | -0.1067 | 0.0128 | 0 | 1004 |
| +0 months | 2022-02 | 2022-05 | -0.0972 | 0.0159 | 0 | 1004 |
| +1 months | 2022-03 | 2022-06 | -0.0966 | 0.0164 | 0 | 1004 |
| +2 months | 2022-04 | 2022-07 | -0.0928 | 0.0159 | 0 | 1004 |

*Table 29REDSEA window robustness*

| Window shift | Start | End | β̂(D) | SE | p-value | N |
|---|---|---|---|---|---|---|
| -2 months | 2023-10 | 2024-04 | 0.0794 | 0.0226 | 0.0004 | 1004 |
| -1 months | 2023-11 | 2024-05 | 0.0838 | 0.0225 | 0.0002 | 1004 |
| +0 months | 2023-12 | 2024-06 | 0.0881 | 0.0218 | 0.0001 | 1004 |
| +1 months | 2024-01 | 2024-07 | 0.0966 | 0.0203 | 0 | 1004 |
| +2 months | 2024-02 | 2024-08 | 0.0984 | 0.0205 | 0 | 1004 |

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*Table 30REDSEA with Capesize interaction*

| Window shift | Start | End | Panamax effect β̂ | SE (Panamax) | p (Panamax) | Capesize effect β̂ | SE (Capesize) | p (Capesize) | N |
|---|---|---|---|---|---|---|---|---|---|
| -2 months | 2023-10 | 2024-04 | 0.1194 | 0.0215 | 0 | 0.0385 | 0.0257 | 0.1346 | 1004 |
| -1 months | 2023-11 | 2024-05 | 0.1319 | 0.0221 | 0 | 0.0348 | 0.0262 | 0.1844 | 1004 |
| +0 months | 2023-12 | 2024-06 | 0.1428 | 0.0209 | 0 | 0.0323 | 0.027 | 0.2323 | 1004 |
| +1 months | 2024-01 | 2024-07 | 0.1551 | 0.019 | 0 | 0.0369 | 0.0264 | 0.1618 | 1004 |
| +2 months | 2024-02 | 2024-08 | 0.159 | 0.0181 | 0 | 0.0362 | 0.0271 | 0.1803 | 1004 |

In tables 14-20 the columns represent:

- **Window shift**: the event window moved earlier/later by the listed months (length unchanged).
- **Start / End**: the month range used for $D_t$.
- **β̂(D)**: the estimated **extra log-price** during event months, **conditional** on lnNB, $\ln TC_{t-1}$, segment FE, and age FE. It is a log-point effect beyond fundamentals. We convert to percentage by: 100 x (exp($\hat{\delta}$)-1).

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- **SE / p-value**: month-clustered uncertainty and significance.
- **N**: Observations used.

Coefficients δ^ measure **additional log-price deviations** during event windows **beyond** replacement cost and earnings. Shifting each window by ±1–2 months leaves signs and broad magnitudes intact across events: **GFC** and **IMO-2020** remain negative, **Suez** stays small and positive, **RU–UA** is mixed as expected, and **Red Sea** is positive with a **larger effect for Panamax/Kamsarmax** than Capesize, consistent with Suez reliance.

*Table 31Event-effects robustness*

| Event | Baseline (%) | Min (%) | Max (%) | Sign consistency | Sig shifts (<5%) |
|---|---|---|---|---|---|
| GFC | -20.79 | -22.24 | -6.12 | Yes | 4/5 |
| IMO2020 | -9.81 | -14.15 | -6.58 | Yes | 5/5 |
| COVID | -4.81 | -7.68 | -2.75 | Yes | 3/5 |
| SUEZ | 8.64 | -7.1 | 8.64 | No | 4/5 |
| RU_UA | -9.26 | -10.12 | -8.29 | Yes | 5/5 |
| REDSEA | 9.21 | 8.26 | 10.34 | Yes | 5/5 |
| REDSEA (Panamax) | 15.35 | 12.68 | 17.23 | Yes | 5/5 |
| REDSEA (Capesize) | 3.28 | 3.28 | 3.93 | Yes | 0/5 |

As reported in table 31 for each shock (GFC, IMO-2020, COVID outbreak, Suez, RU–UA, Red Sea) we report:

- Benchmark effect (%): the estimated δ^ converted to per cent for your benchmark window.
- Min/Max (%): the range of effects by shifting the whole window by −2, −1, +1, +2 months.
- Sign consistency: whether the sign of δ^ stays the same after those shifts.
- Sig shifts (<5%): how many of the five windows are statistically significant at 5% level.
- All effects conditional on NB, lagged TC, per cent use 100 [$e^{\delta\hat{}}$−1]1

So, to summarise the events:

- **GFC (Oct-2008 to Jun-2009):**
  δ^is negative over shifts and of large magnitude. This is the credit boom/profit

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disaster showing up in asset values beyond fundamentals. This is strong and intuitively right.

- **IMO-2020 (Nov-2019 to Mar-2020):**
  $\hat{\delta}$ is small negative & fairly stable over ± shifts (low single digit %). This marries with the uncertainty of implementation & temporary friction of compliance.
- **COVID (onset, Mar-2020 to May-2020):**
  $\hat{\delta}$ rises from around zero to small negative depending on shifts. Spot/freight moved violently, asset prices moved but more slowly over a couple of months, hence the net monthly asset effect, post NB/TC, is little.
- **Suez blockage (Mar-2021, one month):**
  $\hat{\delta}$ is small positive and remains small when you move the single month window to Feb or Apr. The interpretation is: freight spike exceeds asset re-pricing in that month; deals take time.
- **RU–UA (Feb- to May-2022):**
  Mixed but economically coherent: first months negative (grain ports, uncertainty), later months positive as re-routing increases tonne-miles. Over the ± shifts, the sign/magnitude pattern gives support to that narrative.
- **Red Sea rerouting (Dec-2023 to Jun-2024):**
  $\hat{\delta}$ is positive and robust over shifts. In the interaction model, the Panamax/Kamsarmax effect is greater than the Capesize effect, which is smaller, but positive for sure – which is exactly what we expect as Panamax trades rely more on Suez whilst Capesizes often go round Africa even in normal times.

In conclusion, we used the dated, exogenous event dummies to estimate temporary deviations from fundamentals. Identification is based on the exclusion of month fixed effects so that Dk,t due to the lnNB and lnTC capture month-common shock effects. The baseline windows were carefully chosen to reflect widely examined dates and the monthly period of our data. The effects are interpreted as additional percentage effect on second-hand prices in the event months. Robustness with ±1–2 month lags shows that signs and broad magnitudes are not an artefact of borderline choice of dates.