Ups and downs: Modeling Shipping Freight Rates in a Markov Regime Switching Framework

Vegard Enerstvedt[1*] and Haiying Jia[1]

[1]Department of Business and Management Science, Norwegian School of Economics, Helleveien 30, 5045 Bergen, Norway.

[*]Corresponding author: Vegard.Enerstvedt@nhh.no

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Abstract

In this paper, we employ economic theory to examine the supply-demand relationship in the freight market to assess the stochastic dynamics during different marked conditions. We propose the existence of two distinct regimes: elastic and inelastic tonnage supply situations. To empirically investigate these regimes, we apply a Markov regime-switching model to estimate a discrete autoregressive regime-switching model using freight rate data for Handysize, Panamax, and Capsized dry bulk vessels as well as Aframax, Suezmax, and VLCC crude oil tankers, represented by the Baltic indexes for these vessel types and sizes. Our findings indicate that these regimes exhibit differing volatility levels and, in the case of tanker vessels, distinct patterns mean reversion. Furthermore, we analyze the transition probabilities between regimes, revealing that the current shipping rate level is a significant factor in modeling the probability between supply regimes.

1 Introduction

Shipping is the backbone of international trade, with over 11 billion tonnes of goods - accounting for more than 80 percent of trade volume - transported by sea in 2021 alone ("World seaborne trade – UNCTAD Handbook of Statistics 2023", n.d.). Understanding the price dynamics in the shipping market is therefore of great interest to both academics and industry practitioners. Freight rates, in theory, should represent the equilibrium price that shipowners and charterers agree upon at a specific time, acting as the balancing point where supply meets demand to facilitate the efficient and affordable movement of goods from sellers to buyers (Stopford, 2008). Consequently, the mechanism governing the equilibrium price has long been a central issue in academics and industry. The first modern attempts to model freight markets were partial equilibrium models proposed in the seminal works (Tinbergen, 1934) and (Koopmans, 1939). Subsequent research has continued to investigate the issue through partial equilibrium models, in the tanker and dry-bulk markets, including studies by (Zannetos, 1964), (Hawdon, 1978)(Norman, 1978), (Beenstock, 1985)(Norman & Wergeland, 1981), (Strandenes, 1986) and (Tvedt, 1995).

Research on freight rate modeling has gradually shifted from comprehensive equilibrium to the development of univariate models. This strand of research has generally diverged into two main research areas: one focusing on discrete time series models and the other on stochastic differential equations (SDEs) for continuous-time modeling of freight rates. The time series research is notably extensive, with various methodologies proposed, including the Vector Error Correction model (VEC) (A. W. Veenstra & Franses, 1997) (A. H. Alizadeh et al., 2007)(Kavussanos & Nomikos, 2001) (Batchelor et al., 2007)(Goulas & Skiadopoulos, 2012), Autoregressive Integrated Moving Average (ARIMA)(Munim & Schramm, 2017) (Chen et al., 2012) and (Generalized) Autoregressive Conditional Heteroskedasticity ((G)ARCH) (Kavussanos, 1996)(Gavriilidis et al., 2018)(Drobetz et al., 2012)(A. H. Alizadeh & Nomikos, 2011). Many studies, particularly those focused on forecasting, compare multiple model types.

The second area of research in univariate freight rate modeling focuses on continuous time models that utilize SDEs. A key early work in this area is (Bjerksund & Ekern, 1995), where freight rates are modeled using a continuous-time Ornstein-Uhlenbeck process - a mean reverting Gaussian process. This concept was later extended in (Tvedt, 1997). Subsequently, more general univariate models have been developed and introduced, such as those by (Adland & Cullinane, 2006) (Adland et al., 2008)(Poblacion, 2015)(Benth et al., 2015) and (Población, 2017). In addition to univariate models, researchers have developed more complex continuous-time models. For example, (Población & Serna, 2018) proposes a two-factor model, while (Poblacion, 2015) proposes a three-factor model.

(Tvedt, 2003) seeks to bridge the conceptual and methodological gap between equilibrium and univariate models.

Recent advances in machine learning and artificial intelligence have catalyzed research into the effectiveness of these models for freight rates prediction (Zeng & Qu, 2014)(Leonov & Nikolov, 2012) (Santos et al., 2014) (Uyar et al., 2016) (Eslami et al., 2017) (ŞAHİN et al., 2018) (Yang & Mehmed, 2019). While these models often demonstrate highly predictive accuracy, their lack of interpretability restricts their utility for providing insights into underlying market mechanisms.

The mean-reverting property of freight rates has been a topic of extensive debate within the freight rate literature (Ke et al., 2022). Mean reversion is a property of many stochastic processes where, over time, the process will tend to move towards a long-term mean level (Filipović, 2009). Some studies have iden-

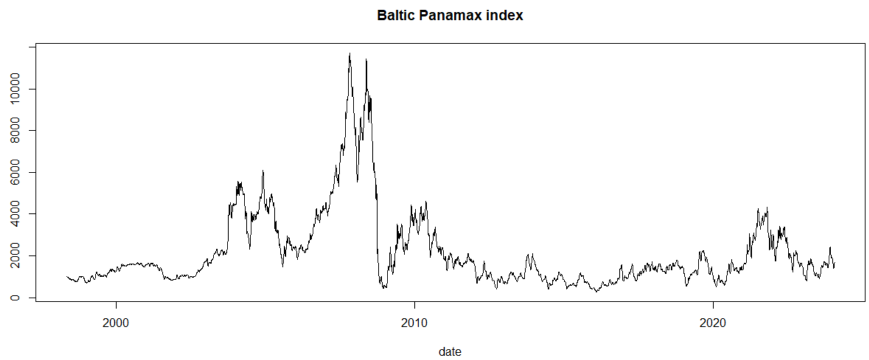

Figure 1: The Baltic Panamax Index between 1998-2023. Note the rise in rates before 2008 and the sharp fall afterward.

tified evidence of a unit root in freight rate data, suggesting a lack of mean reversion (Kavussanos, 1996) (Berg-Andreassen, 1997) (Yin et al., 2017). Conversely, other research aligns with economic theory, providing evidence that freight rates exhibit mean-reverting behavior (Adland & Cullinane, 2006) (Koekebakker et al., 2006). (Adland & Cullinane, 2006) further argue that mean reversion in freight rates is non-linear, which may limit the ability of standard stationarity tests, such as the Augmented Dicky-Fuller (ADF), to detect it. (Kou et al., 2018) finds that the discrepancy between theoretical expectations and empirical findings stems from variation in the sample window, which impact the results of mean-reversion tests.

The application of Markov regime switching in shipping research has been limited. Studies by (W. M. T. Abouarghoub & Mariscal, 2011) and (W. Abouarghoub et al., 2014) explore the volatility patterns in tanker markets using a Markov regime switching framework. Additionally, (W. Abouarghoub et al., 2012) analyzes multiple aspects of the tanker market through a multi-regime Markov regime-switching model. Lastly, (A. H. Alizadeh et al., 2015) evaluates hedging performance within a Markov regime-switching GARCH framework, providing further insight into dynamic risk management in shipping.

In this paper, we argue that mean reversion in freight rates, a long-debated topic, is influenced by market conditions, suggesting that the parameters in an Auto-regressive (AR) process are state-dependent. Specifically, we propose that these parameter estimates are conditional on the prevailing market dynamics and the balance of supply and demand. Furthermore, we extend the existing regime-switching literature in the shipping sector by analyzing the dry-bulk freight markets. Additionally, we compare the dry-bulk and tanker markets in terms of mean-reversion, stationarity, and volatility. Our study analyzes indices across two market segments for various vessel sizes, including Handysize, Panamax, and Capize dry-bulk carriers, as well as Aframax, Suezmax, and VLCC tankers. We employ stochastic filtering techniques to estimate a Markov regime-switching model, following the approach by (Hamilton, 1989).

2 Literary review

2.1 Maritime Economic Theory

(Marshall, 1890) is frequently regarded as the foundational text of marginal economic theory, which underpins many branches of modern economics. The marginal economic theory argues that consumers will continue to consume a good until the marginal utility is equal to the marginal cost. Marshall's contributions, alongside other works on partial equilibrium, are foundational to the study of shipping markets. Leon Walras is credited with pioneering the aggregation of individual preferences to the economy-wide level (Walras, 1874), a framework known as general equilibrium theory. The principal distinction between partial and general equilibrium models is that partial equilibrium models assume no feedback" effects from other markets in the economy not explicitly modeled, whereas general equilibrium markets model all markets in the economy

(Mas-Colell et al., 1995).

Analyzing the market forces within the shipping sector has an extensive history in the academic literature. In this context, transportation services are the goods traded in a shipping market, and the shipping rate is the equilibrium price agreed upon by the charterer and the shipowner. Early studies modeled this interaction within a partial equilibrium framework. In his seminal work, Dutch economist Jan Tinbergen constructed supply and demand indices using historical data and found a linear relationship between the indexes (Tinbergen, 1934). Later, Tjalling Koopmans analyzed both the tanker and shipbuilding markets within a partial equilibrium framework (Koopmans, 1939). For a review see (Rothbarth, 1939). Zannetos advanced Koopmans' work in The Theory of Oil Tanker Rates, offering crucial insights into the oil and tanker markets. For instance, despite the petroleum industry's concentration in oil majors, Zannetos observed that the tanker market functioned as a near-perfectly competitive market (Zannetos, 1964). An excellent summary of Zannetos' contributions is available in (A. W. Veenstra & De La Fosse, 2006)

The microeconomic and econometric approach to studying freight markets advanced considerably beyond Zannetos' foundational work. With the increased availability of computers, more detailed models emerge. Norman and Wergeland's Nortank model from 1981 set a new standard for tanker market models. Nortank specifically addresses the market for tankers greater than 200 000DWT and comprehensively models both the demand and the supply part of the market, with a particular emphasis on the supply side (Norman & Wergeland, 1981). In 1986, Siri Strandenes published the generalized and improved Norship-model (Strandenes, 1986). The microeconomic and econometric research has since been extended to include the second-hand vessel market, notably in studies modeling ship value as a capital asset. Michael Beenstock and Andreas Vergottis explored this approach in a series of papers, primarily viewing vessels as capital assets and applying this model to both dry bulk carriers and tankers (Beenstock & Vergottis, 1989) (**Vergottis1989b**). Jostein Tvedt further developed this line of research by incorporating the shipbuilding market within a stochastic partial equilibrium model (Tvedt, 1995).

These models present challenges due to their inherent complexity. Birkeland argues that ”many of the equilibrium models depend on a large number of equations with dubious economic connections and static parameters that are nearly impossible to estimate properly” (Birkeland, 1998). Despite the apparent failure to create models that explain every facet of the shipping market satisfactorily, they provide valuable insight into the mechanisms at play.

2.2 Univariate Freight Rate Models

The freight rate literature has moved away from extensive econometric models and towards univariate models in discrete or continuous time. The newer stream of literature has a stronger emphasis on financial aspects, like derivative contracts. The introduction of the Baltic Freight Index in 1985 and the subsequent proliferation of financial derivatives (“History”, n.d.) might have contributed to the shift in research. A key area of inquiry within this literature is the relationship between forward and spot rates. For instance, (Chang & Chang, 1996) studies how predictable freight rates are based on financial derivatives. (Kavussanos & Nomikos, 1999) show that one and two-month futures are unbiased estimates of the realized spot rate and that all futures provide superior predictions compared to ARIMA models. Additionally, (Kavussanos & Nomikos, 2001) find that futures markets discover and incorporate new information quicker than spot markets. (Kavussanos & Visvikis, 2004) investigates the lead-lag relationships in mean and volatility between futures and spot markets. Lastly, using a VAR framework, (Yin et al., 2017) identifies a long-run bidirectional causal relationship between spot and Future Freight Agreements (FFA) markets.

A wide range of time series methodologies have been employed to model the spot freight rates. (A. W. Veenstra & Franses, 1997) examined freight rates using Vector Autoregression (VAR), finding evidence of a long-term equilibrium. (A. H. Alizadeh et al., 2007) compared price predictions based on the rate forecast based on FFAs with those from various time series models, inducing a random walk, the vector autoregressive model, Autoregressive Moving Average (ARIMA), Vector Error Correction Model (VECM), concluding that the FFA-implied rates offered superior predictive accuracy than time series models. A finding supported by (Kavussanos & Nomikos, 2001). (Batchelor et al., 2007) also investigates VECM, ARIMA, and VAR models and concludes that VECM performs best in-sample but not out-of-sample, limiting its forecasting utility. (Goulas & Skiadopoulos, 2012) use VECM and GARCH models to assess the efficiency of The International Maritime Exchange (IMAX). (Munim & Schramm, 2017) demonstrates that ARIMARCH outperforms ARIMA and ARCH models. (Chen et al., 2012) compare VAR, VEX, ARIMA, and ARIMAX and find that the simple VAR and VAX models have the best forecast performance. (Kavussanos, 1996), (Gavriilidis et al., 2018), (Drobetz et al., 2012) and (A. H. Alizadeh & Nomikos, 2011) all investigates GARCH models. Many of these papers, especially those concerned with forecasting, compare multiple models.

One of the early contributions to the stream of literature using SDEs in continuous time was (Bjerksund & Ekern, 1995). Bjerksund and Ekern model freight rates using a continuous time mean reverting Ornstein-Uhlenbeck process. This approach was subsequently extended in (Tvedt, 1997). Following these seminal papers, more general univariate models have also been proposed based on Stochastic Differential Equations (SDEs). For instance, (Adland & Cullinane, 2006) investigates freight rates using a non-parametric Markov diffusion model. They find that rates mean reverting at the upper limits of the empirical range, which is in line with theory, and an increase in volatility with an increase in freight rate. (Adland et al., 2008) investigates LPG shipping markets and finds that linear SDEs describe the market well and exhibit distinct behavior compared to crude oil tanker markets. (Poblacion, 2015) proposes a three-factor model that incorporates a long-term factor, a short-term factor, and a seasonal component(Benth et al., 2015) use an exponential Lévy process with normal-inverse Gaussian distributed log-return and stochastic volatility models to model spot rates, capturing key features of spot rates such as heavy-tailed returns, stochastic volatility and memory. (Población & Serna, 2018) propose a two-factor model where there is a short-term factor and a long-term factor representing the equilibrium price.

(Tvedt, 2003) seeks to bridge the theoretical and methodological gap between equilibrium and univariate models.

Recent innovations in freight rate modeling have introduced various machine learning and artificial intelligence methods to improve freight rate prediction. (Zeng & Qu, 2014) use empiric model decomposition (EMD) to decompose the freight rate into intrinsic models. (Leonov & Nikolov, 2012) combine wavelet and neural networks to study the volatility structure of dry-bulk routes.. In comparing forecasting models, (Santos et al., 2014) assess the performance of multi-layer perceptron and radial basis function neural networks against an ARIMA model, concluding that neural networks outperform traditional time series models. (Uyar et al., 2016) compares the prediction performance of different machine learning models to ARIMA models on annual freight rates from

1741 to 2008 and concludes that fuzzy neural networks perform best. (Eslami et al., 2017) use an adaptive genetic algorithm to model crude oil tanker rates. They show their adapted genetic algorithm outperforms regression methods and most other neural networks, and (ŞAHİN et al., 2018) forecasts freight rates based on lagged rates using a neural network. (Yang & Mehmed, 2019) incorporates FFAs in neural network models. However, despite often superior performance, many machine learning models are exceedingly hard to interpret and yield little insight into the forces at play despite sometimes superior forecasting performance.

2.3 Stationarity, Seasonality and Other Factors Influencing Freight Rates

One of the longest-standing questions in the literature is the question of stationarity of freight rates. A stochastic process is said to be stationary if the probability distribution is time invariant (Benth et al., 2008). Theoretical models suggest that shipping rates should exhibit mean reversion and stationarity (Tvedt, 2003). However, empirical findings have yet to provide a conclusive answer. (Tvedt, 2003) found that freight rates for ”deep sea” dry-bulk vessels (Handysize, Panamax, and Capsize) were stationary but only when the rates were converted into Yen. Tvedt argues that since Asia is such an important market for these kinds of vessels, denominating the rates in local currency better reflects the fundamental mechanisms. Thus, he argues that non-stationarity comes from the exchange rate, not the fundamental shipping market. Further research by (Koekebakker et al., 2006) suggests that non-stationarity is challenging to detect due to potential non-linear mean reversion. This is followed up in (Adland & Cullinane, 2006) where they find that the freight rates are mean reverting at the upper extremes, thus ensuring a global mean reversion.

A different view of stationarity was investigated by (Kou & Luo, 2015), who found structural breaks in the freight rates. This prompted (Kou et al., 2018) to investigate if the empirical results regarding stationarity were due to different sample lengths or sample windows. They argue that freight rates are stationary over a longer window but that there are fundamental changes in the nature of the market and that rates are stationary within the same window.

On the other hand, (Kavussanos, 1996)(Berg-Andreassen, 1997) (Glen & Rogers, 1997)(A. W. Veenstra & Franses, 1997)(Yin et al., 2017) all argue that shipping rate is non-stationary frequently citing the Augmented Dicky-Fuller test results indicating the presence of a unit root. A comprehensive review of this question in the literature can be found in (Kou et al., 2018)

Seasonality plays an important role in many commodity markets. Since bulk vessels transport other commodities, such as petroleum and grain, both of which are affected by seasonality, shipping markets are expected to exhibit some form of seasonal effects. The specific nature of the seasonality in shipping markets, however, remains debated (A. H. Alizadeh & Kavussanos, 2002) and (Yin & Shi, 2018) find evidence of a deterministic seasonality component for tanker, dry-bulk, and container markets. On the other hand, (Poblacion, 2015) and (Población & Serna, 2018) argue for a stochastic seasonality.

(Ke et al., 2022) argues that much of the existing freight market literature has focused on temporal dynamics, with relatively little attention given to cross-sectional dynamics. Temporal dynamics refer to market changes over time, while cross-sectional dynamics describe variations across different vessels. Understanding cross-sectional dynamics is crucial for assessing how specific vessel attributes influence the price of chartering a particular vessel under specific contractual terms. A theoretical study of the VLCC market was conducted in (Tvedt, 2011), while empirical studies have been conducted in different markets. (Adland et al., 2017) constructed a hedonic price index on offshore fixtures. The same authors also studied the charterer and owner effect on rates in wet and dry bulk markets (Adland et al., 2016). They found that beyond vessel characteristics, route, charterer, and owner fixed effects were significant. The relationship between the laycan period and rates was studied by Alizadeh and Telley (A. H. Alizadeh & Talley, 2011). The difference between Time Charter and Forward Freight Agreements was explored in (Adland & Alizadeh, 2018). Other studies have investigated vessel characteristics and their potential to create a two-tier quality segmentation (Köhn & Thanopoulou, 2011) (Tamvakis & Thanopoulou, 1995). The results vary (Köhn & Thanopoulou, 2011) find affirmative evidence for dry bulk during the period 2003 to 2007, but (Tamvakis & Thanopoulou, 1995) (Tamvakis & Thanopoulou, 2000) finds less convincing evidence. (**agnolucc**) investigates how energy efficiency affects the value of TC contracts. These studies commonly rely on fixture data as a primary source of information.

Vessel types differ substantially in terms of factors that influence their rates. In general, things like age, size, and speed are important. For offshore vessel designers, the design country and technological equipment, such as Dynamic Positioning (DP), were important factors. In addition, type-specific factors like horsepower and Bullard pull were significant factors for Anchor Handling Tug Supply (AHTS), and deck area and carry capacity were important for Platform Supply Vessels (PSV) (Adland et al., 2017). For wet and dry bulk vessel size (DWT), route, owner, and charterer fixed effects, fuel price, commodity price, trade volume, and fuel consumption are commonly studied factors (A. H. Alizadeh & Talley, 2011)(Adland & Alizadeh, 2018)(Tamvakis & Thanopoulou, 1995)(Tamvakis & Thanopoulou, 2000)

2.4 Regime Switching

The principal method we will employ in this paper is the Markov regime-switching model, initially introduced in the seminal paper (Hamilton, 1989). Hamilton employed the model on macroeconomic data. subsequent methodological advancements extended regime-switching models to accommodate ARIMA models (Kim, 1994) and ARCH models (Hamilton & Susmel, 1994). Regime switching has been extensively applied in economics (Filardo, 1994) (Taylor, 2004)(Evans & Lewis, 1995), but also for example in finance (Engel, 1994) (Maheu & McCurdy, 2000)(Chen & Insley, 2012) (A. Alizadeh & Nomikos, 2004) and even medicine (Martínez-Beneito et al., 2008) (Noman et al., 2020). for a further review on Markov regime-switching, see (Phoong et al., 2022).

Despite their wide application across disciplines, Markov regime-switching models have seen limited use in shipping market research.(W. M. T. Abouarghoub & Mariscal, 2011) investigate the volatility structure of tanker freight rates on individual routes denoted in World Scale (WS) using regime-switching GARCH-model for risk management purposes. Here, the World Scale index serves as the reference price, standardizing tanker market prices based on the voyage cost on a standard vessel. The definition of a standard vessel changes over time ("Worldscale", n.d.), and therefore, the changing the standard could bias the results. (W. Abouarghoub et al., 2012) investigates a similar Markov Regime Switching model for tanker markets with multiple regimes. (W. Abouarghoub et al., 2014) proposed a conditional volatility model for tanker markets using a Markov regime-switching model and used the proposed model to investigate the freight rate risk. Lastly, (A. H. Alizadeh et al., 2015) used Markov regime-switching to investigate the hedging performance of freight market derivatives.

2.5 Contribution

This research undertakes a comprehensive analysis of freight rates dynamics across major shipping segments, specifically the dry-bulk and tanker markets, examining multiple vessel classes within each segment. This contribution substantially expands the scope of market coverage, offering valuable insights both across and within these segments. Moreover, we focus on the examination of regime-dependent changes in volatility and potential variations in mean reversion across different market states utilizing Markov regime-switching models. This contribution enables researchers to explore both the first- and second-order properties in freight rate dynamics in greater depth. This dual-level analysis, in a regime-switching framework, provides a comprehensive understanding of the underlying processes that govern freight rate fluctuation. meanwhile, this can enhance the ability to model and predict market behavior across different conditions and regimes. Last but not least, our research provides a comparative analysis of the dry-bulk and tanker markets by identifying similarities and divergences. This study contributes to the literature by providing deeper insights into the fundamental dynamics of these shipping segments.

3 Theory

This paper builds upon studies like (Bjerksund & Ekern, 1995) by incorporating regime-switching and continuous-time stochastic processes to model spot freight rates in shipping markets. This entails applying stochastic differential equations (SDE) to describe the dynamics of the spot freight rate.

A stochastic process is a collection of random variables defined on the same probability space $(\Omega, \mathcal{F}(t), P)$ parameterized by time. Here Ω is the set of possible outcomes, $\mathcal{F}_t$ is the filtration such that the stochastic process is measurable, and P is a probability measure (Øksendal, 2007). This means that the value of a stochastic process is evolving randomly. To describe the random behavior of the process, we use stochastic differential equations (SDE). SDEs represent a flexible class of differential equations that can describe sophisticated behaviors we can observe in random phenomena in the real world.

Mean reversion is a property of stochastic processes where a process tends to return to a long-term mean value. Evidence exists for mean reversing prices in some energy and commodity markets, for example, electricity and natural gas (Benth et al., 2008). This is reasonable from an economic point of view.

In a perfectly competitive market, prices should gravitate toward a long-term equilibrium where supply and demand balance. If prices rise above the marginal cost of production, new producers are incentivized to enter the market, and demand typically decreases in response to higher prices. In shipping markets, for instance, when freight rates exceed shipowners' marginal costs, new vessels may be ordered, and inactive vessels removed from lay-up. The relatively low barriers to entry further facilitate an increase in supply if elevated prices persist, exerting downward pressure toward equilibrium. Conversely, if prices fall below the marginal cost, producers exit the market, and demand may increase due to lower prices. Within the shipping industry, this scenario prompts vessel lay-ups or scrapping when rates dip below operating costs. While market frictions, such as lay-up costs, brokerage fees, and the lead time required to build new vessels, create lags in market adjustments, these forces collectively drive prices back toward the long-term equilibrium over time

The Ornstein-Uhlenbeck process (OUP), the Vasicek model, and the Cox-Ingersoll-Ross model are prominent examples of a mean reverting process. Both (Bjerksund & Ekern, 1995) and (Tvedt, 1995) employ the OUP to model spot freight rates. The OUP is closely related to the Vasicek model and offers several advantages, including mathematical simplicity, extensive theoretical study, and ease of parameter estimation using maximum likelihood or ordinary least square methods. However a potential limitation of the OUP is that its simplicity might be too simple to capture features of freight rate data like volatility clustering. Moreover, the OUP has seen wide use as a model for short-term interest rates (Filipović, 2009). Following the notation in (Filipović, 2009), the UOP is defined as the solution to the SDE,

$$dS(t) = (a(x) + b(x)S(t))dt + \sigma(x)dW(t), \tag{1}$$

where $a(x), b(x), \sigma(x)$ are measurable real functions and $dW(t)$ denotes the Itô integral. There are other formulations as well. For example, an alternative formulation is presented in (Tvedt, 1995) where a and b are coefficients expressed with the constants κ and α.

An explicit solution of (1) can be found,

$$S(t) = S(s)e^{b(x)(t-s)} + \frac{a(x)}{b(x)}(e^{b(x)(t-s)} - 1) + \sigma(x)e^{b(x)t}\int_s^t e^{-b(x)u}dW(u) \tag{2}$$

(Filipović, 2009) Here, the first two terms are deterministic, and the third term is a stochastic integral. The statistical properties of this stochastic process can be explored from this form. Note some properties of Itô integrals(Øksendal, 2007),

$$E\left[\int_s^t f dW(u)|\mathcal{F}_s\right] = 0 \tag{3}$$

$$\int_s^t f dW(u) \sim N\left(0, \int_s^t f(u)^2 du\right) \tag{4}$$

for an integrable function f.

Using this, we can find the conditional expectation and conditional variance of the process on the increment between s and t.

$$E[S(t)|\mathcal{F}_f] = E[S(t)|\mathcal{F}_f] = S(s)e^{b(x)(t-s)} + \frac{a(x)}{b(x)}(e^{b(x)(t-s)} - 1) \tag{5}$$

$$V[V(t)|\mathcal{F}_f] = \frac{\sigma(x)^2}{2b(x)}\left(e^{2b(x)(t-s)} - 1\right) \tag{6}$$

As previously stated, the UOP is mean reverting. To see this, consider what happens when we let the length of the increment converge to infinity.

$$\lim_{t\to\infty} E[S(t)|\mathcal{F}_f] = E[S(t)|\mathcal{F}_f] = \frac{a}{b} \tag{7}$$

if $b < 0$. This means that if b is negative, we expect the process to converge to a/b, which is the long-term mean. If b is greater than or equal to zero, then the process can approach infinity asymptotically.

To incorporate stochastic regime-switching into the model, we define the measurable functions $a(x), b(x)$ and $\sigma(x)$ depend on a Markov process X with state space $\mathcal{S} = \{1, 2\}$ and transition matrix P (Ross, 2019).

A fundamental component of any Markov process is the transition matrix, which represents the probability of the process either transitioning between states or remaining in that state (Ross, 2019). The transition probability matrix P is defined as follows,

$$P = \begin{pmatrix} 1 - P_{12} & P_{12} \\ P_{21} & 1 - P_{21}, \end{pmatrix} \tag{8}$$

where P_{ij} is the probability that the process transitions from state i to state j.

To make the inclusion explicit we let the functions a, b and σ be functions,

$$a(x) = a_1 1_{x=1} + a_2 1_{x=2} \tag{9}$$

$$b(x) = b_1 1_{x=1} + b_2 1_{x=2} \tag{10}$$

$$\sigma(x) = \sigma_1 1_{x=1} + \sigma_2 1_{x=2}, \tag{11}$$

where $1_{x=j}$ is the indicator function denoting that $x = j$. This means that the parameters are constant within each regime.

To motivate our approach, consider the supply and demand functions in a typical shipping market. The supply curve is shaped like a hockey stick (Stopford, 2008). When the freight rate is low, the supply curve is nearly horizontal, signifying elastic supply. Conversely, when freight rates are elevated, the supply curve is nearly vertical, signaling that supply is inelastic.

If the freight rate falls below the marginal operating cost of a vessel, then it is no longer economical to keep the vessel active in the market. However, due to friction and cost associated with putting a vessel in lay-up, a vessel may continue to operate for a time despite the freight rate being less than the marginal cost (Sødal et al., 2008). This mechanism effectively creates a lower bound on the supply function, reflected in a nearly flat supply curve at low rates. There is also an upper constraint on the volume of transportation services a vessel can provide. For example, if the rates are high enough, it becomes profitable to increase vessel speed as the marginal cost of doing so is outweighed by the potential earnings. However, vessel speed is limited by the vessel's technical specifications, capping the cargo volume it can transport within a given timeframe. For the freight rates between the two extremes, the supply function transitions between horizontal and vertical. At the market level, the lower limit is determined by the vessel in the market with the highest marginal cost. On the other hand, the upper limit is reached when all vessels

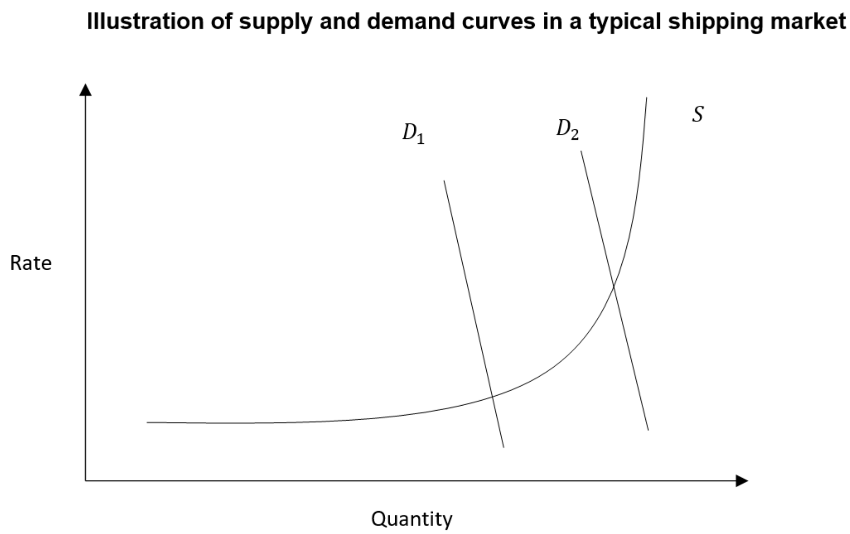

Figure 2: Supply and demand curves in a typical shipping market

are operating at maximum capacity. Hence, the market as a whole has a supply curve shaped like a hockey stick (Stopford, 2008).

On the other hand, the demand for shipping services is typically inelastic. Shipping costs generally represent a minor component of the total cost of a good, making demand sensitive to the freight rate (Merkel et al., 2022). Thus, in the short term, the market for shipping services can be illustrated like in Figure 2.

The supply is elastic when the shipping transport supply is abundant relative to demand, close to D_1. In this state, vessels are available for employment, and shipowners can provide additional supply rapidly. For example, increasing sailing speed, taking vessels out of lay-up, or making port operations more efficient. This elasticity enables the supply side to swiftly accommodate demand increases. The markets for shipping services are often used as examples of near-perfectly competitive markets (Norman, 1978). Hence, prices should be close to the marginal cost of the marginal vessel. The marginal vessel is the least efficient vessel that can break even at the current market rate. When the world fleet has a high utilization rate, and demand is close to D_2, supply is inelastic. This rise in rates creates a stronger incentive to add more supply. This incentive would be reflected in higher levels of mean reversion. Thus, in high-demand conditions, freight rates are expected to exhibit higher averages, substantially increased volatility, and more pronounced mean-reverting behavior. It is reasonable to expect that the spot rates have different stochastic characteristics depending on demand-supply balance. This is the motivation behind modeling the spot rates as a regime-switching mean reverting process.

Building on the theory, we propose a Markov regime-switching framework, following (Hamilton, 1989) to capture the shift between elastic and inelastic supply. Let X be a Markov process with states space $\mathcal{S} = \{1, 2\}$. Here, 1 denotes the state where the supply is inelastic, and 2 denotes the state where the supply is elastic.

In the elastic state ($X_t = 2$), vessels are available in the market that can be deployed to meet additional demand. In this state, older and less efficient vessels may not be in the market but in lay-up or other more profitable segments, and most vessels operate as economically as possible. Given the comparative nature of shipping markets, the price in this state should approximate the marginal cost of the least efficient vessel in the market. We, therefore, expect this market regime to exhibit competitive characteristics, including relatively low freight rates, reduced volatility, and minimal mean reversion.

Suppose demand increases. In response, all available vessels would likely be employed to meet this rising demand, eventually leading to a situation where any further increase in demand enables shipowners to raise prices, signaling a regime shift from 2 (elastic) to 1 (inelastic). This price increase incentivizes more efficient vessel operations, such as increasing vessel speed, reducing time in port, fewer ballast voyages, and so on. In addition, shipowners may take vessels out of lay-up and even order new tonnage, collectively leading to an eventual increase in supply and a corresponding reduction in rates. Hence, we would expect the freight rates to be mean reverting. When the market is in the state, the 1 supply will be inelastic. Hence, an increase in demand would lead to a great change in price, and thus, higher volatility.

Conversely, if fleet utilization is high and demand declines, prices will likely decrease as shipowners reduce rates to secure employment for their vessels. This fall in shipping rates will cause some vessels to reduce speed and take other operational actions to reduce costs. If the reduction in demand for shipping services persists, more vessels are forced to take ballast voyages, and in the medium term, some vessels are removed from the market. Prolonged low demand would eliminate any price premiums shipowners previously commanded, and rates would once again be set near the marginal cost of the marginal vessel. This shift reflects a transition from state 1 (inelastic) to state 2 (elastic).

4 Methodology

The structure of our model provides some interesting challenges when estimating the parameters due to the presence of two Ornstein-Uhlenbeck processes (OUPs) alongside an unobservable underlying Markov process with transition parameters requiring estimation. The transition probability is central to any Markov models. In this paper, we will present two different transition probability models, a static and a dynamic one.

The overall strategy for estimating the parameters is as follows. First, we use stochastic filtering and the Expectation maximization algorithm (EM) to estimate the underlying Markov process, static transition probabilities, and autoregressive models with lag 1 (AR(1)). Estimating an AR model with one lag makes finding the mean reversion simple and allows us to find the parameters of the continuous model. Then, we use a logit model to estimate the transition probabilities of a model with dynamic transition probabilities. Lastly, we convert the coefficients of the AR(1) models to the parameters for the OUP.

This means that we will first estimate an $AR(1)$-model of the type,

$$
\begin{aligned}
S(t) &= \alpha(X(t)) + \beta(X(t))S(t-1) + \epsilon(t) \qquad (12) \\
&= \alpha_2 1_{X(t)=2} + \alpha_1 1_{X(t)=1} + (\beta_2 1_{X(t)=2} + \beta_1 1_{X(t)=1})S(t-1) + \epsilon(t), \qquad (13)
\end{aligned}
$$

where $1_{X(t)=j}$ is the indicator function for the event that the Markov chain, X, is in state j at time t, ϵ is I.I.D. and $\epsilon \sim N(0, \hat{\sigma})$.

The Hamilton filter is a stochastic filtering scheme proposed in (Hamilton, 1989) and used to infer the state of the underlying Markov process at each point in time. Specifically, the algorithm gives us the probability that the Markov process at time t is in state j. The Hamilton filter is similar to the Kalman filter and works by iteration, where the joint conditional probability is ”improved” for each iteration (Hamilton, 1989).

Parameter estimation of the AR(1) models is done via the expected maximization algorithm. This algorithm works by switching between estimating the expected likelihood function and maximizing the expected likelihood function (Sundberg, 1976). As Sundberg argues, this makes the algorithm valuable in contexts with a large number of variables that complicate direct maximum likelihood estimation or where data is incomplete, allowing efficient handling of complex estimation problems.

The static model presents the transition probability as a constant within a 2×2 matrix, which can be calculated concurrently with the parameters of the OUP. The static model provides insights into the duration of the process within each regime and which regime is the most stable.

In contrast, the dynamic model incorporates covariates into the transition probability model, such as current shipping rates and crude oil prices. This means that we model how other factors influence the future evolution of the Markov process. This can be interesting for multiple reasons. For one, it could tell us how the rates or other factors influence the dynamics of the regime-switching.

To estimate the parameters of the dynamic model, we apply a logit model to the state of the Markov process. Through this approach, covariates such as the current freight rate can be incorporated into the model using standard nonlinear methods, facilitating a more nuanced analysis of the transition probabilities. The logit model takes the form:

$$P_{i,j}(t) = \frac{1}{1 + e^{-(\beta_{ij,0} + \beta_{ij,1} S(t-1)) + \beta_{ij,2} B(t-1))}}. \tag{14}$$

Here $P_{i,j}(t)$ is the probability that the Markov process moves from regime i to regime j a time t, $\beta_{ij,k}$ are the k coefficients estimated, $S(t-1)$ is the freight rate at time $t-1$. Lastly, $B(t-1)$ is the oil price.

The approach outlined above provides two $AR(1)$-models, one for each regime, and the transition probabilities. However, we can "translate" the parameters of the $AR(1)$-models to a continuous time framework. We follow the same basic idea as in (Tvedt, 1995) to achieve this.

Consider the interval of length 1, i.e., t to $t+1$. An $AR(1)$ is a discrete process with an interval separated by 1. On the other hand, an OUP is a continuous process. However, on the interval of length 1, they should coincide. Therefore, consider (2) when $s = t-1$. Then,

$$S(t) = S(t-1)e^{b(t-(t-1))} + \frac{a}{b}(e^{b(t-(t-1)} - 1) + \sigma e^{bt}\int_{t-1}^{t} e^{-bu}dW(u) \tag{15}$$

$$= S(t-1)e^{b} + \frac{a}{b}(e^{b} - 1) + \sigma e^{bt}\int_{t-1}^{t} e^{-bu}dW(u) \tag{16}$$

Comparing the terms of the equation above with the term of (12) then,

$$\alpha = \frac{a}{b}(e^{b} - 1) \tag{17}$$

$$S(t-1)\beta = S(t-1)e^{b} \tag{18}$$

Solving these equation for a and b gives,

$$a = \frac{\alpha b}{(e^{b} - 1)} \tag{19}$$

$$b = \log(\beta) \tag{20}$$

Lastly, we need to do a slightly different calculation for the σ parameter. Note that we denote the empirical standard deviation of the $AR(1)$ process $\hat{\sigma}$. Note that the conditional variance of the interval from $t-1$ to t is given by,

$$V[V(t)|\mathcal{F}_f] = \frac{\sigma^2}{2b}\left(e^{2b} - 1\right) = \hat{\sigma}^2 \tag{21}$$

Solving for σ^2 yields,

$$\sigma^2 = \frac{\hat{\sigma}^2 2b}{\left(e^{2b} - 1\right)} \tag{22}$$

This strategy is the same as the one employed by (Tvedt, 1995). However, since we use a different specification for (1) we get slightly different results.

5 Data

Shipping fixtures exhibit considerable heterogeneity. The fixtures have different terms, and vessels in the market have characteristics that may influence the price. Consequently, the fixture price, the observable price on the transactions in the market, can not be directly compared between vessels. A proxy is needed to infer the ”typical market price” of shipping services. This is done with market indexes.

The Baltic Handysize Index (BHI) is a weighted average of 7 routes. The standard vessel is 38 200 DWT vessels, a non-scrubber filter under 15 years old, with five cargo holes. The routes are spread all over the world, from South America to the Far East. The Baltic Panamax Index (BPI) is a weighted average of time charter contracts on five routes worldwide. The vessel characteristics used in constructing the index are an 82 500 DWT vessel, younger than 12 years, non-scrubber filter, carrying 97 000cbm grain, and fueled by fuel oil 380c st. The Baltic Capsize Index (BCI) is the index comprised of the largest dry bulk vessels. The index is a weighted average of 5 TC routes. The standard vessel is 180 000DWT and less than 10 years old. The vessel is 290 m long and has a beam of 45 m (Ltd, 2023).

The Baltic Aframax TCE index consists of the weighted average of the time charter equivalent rates on six crude oil tanker routes. Aframax vessels are between 80 000 DWT and 100 000 DWT. The Baltic. The Baltic Suezmax TCE index consists of the average time charter equivalent (TCE) rate of two dirty tanker routes. In the context of this index, a Suezmax vessel is a 160 000 dwt tanker with a non-scrubber filter. The routes in the index are from West Africa to Europe and the Black Sea to the Mediterranean. Lastly, the Baltic VLCC TCE index is the weighted average of TCE rates for three routes, Middle East Gulf - China, West Africa - China, and US Gulf to China.

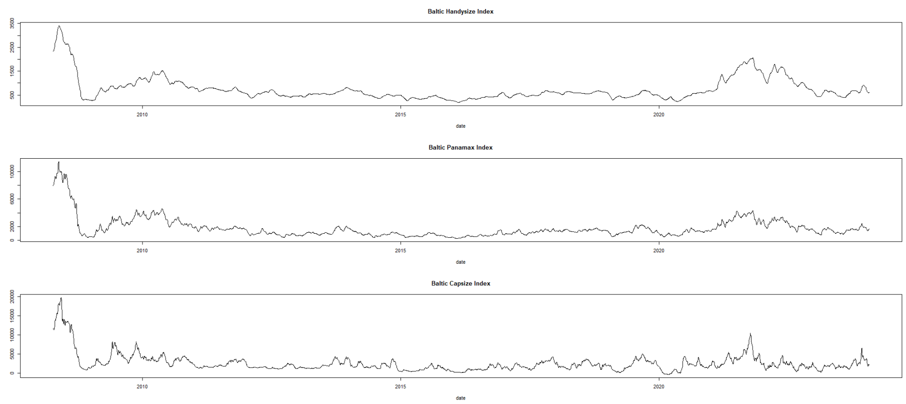

Figure 3: Baltic indices for various sized dry-bulk carriers.

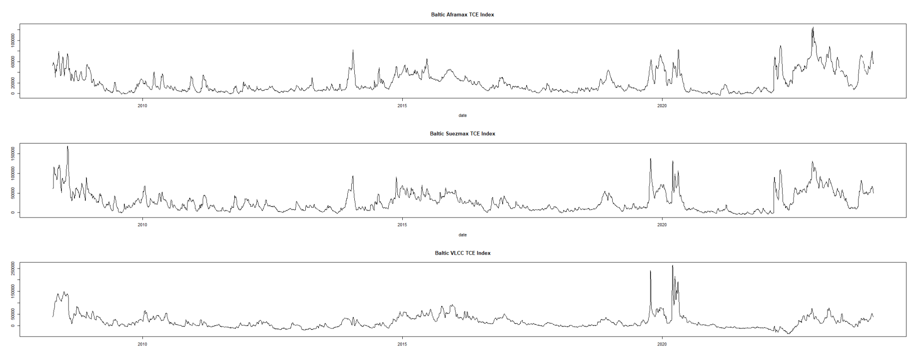

Figure 4: Baltic TCE incises for various sized tanker.

Clarksons Shipping Intelligence Network kindly provides the data. Indices have different starting dates, so the data starts on April 11, 2008, and ends on January 28, 2024. We chose daily data as the time resolution for this paper, which means that we have 3964 points of data for our analysis.

Eikon Datastream provides Brent crude oil prices and are on the same daily resolution and time frame as the freight rate data.

6 Results

6.1 Stationarity test

We conducted an Augmented Dicky-Fuller (ADF) test on all indices to assess the existence of a unit root. The results are presented in Table 1. The null hypothesis that a unit root is present was rejected for all six indexes, suggesting that all six indexes are stationary. (Adland & Cullinane, 2006) suggests that the process is mean reverting at the extreme ends of the market. The period of exceptionally high rates right before the global financial crisis is included in our data set and could be such a situation.

Table 1: Result of the Augmented Dicky-Fuller test where the null hypothesis is the presence of a unit root.

	ADF Statistic	P-Value
Baltic Handysize Index	-5.042	< 0.01
Baltic Panamax Index	-5.457	< 0.01
Baltic Capsize Index	-6.269	< 0.01
Baltic VLCC Index	-6.139	< 0.01
Baltic Suezmax Index	-5.697	< 0.01
Baltic Aframax Index	-5.128	< 0.01

6.2 Freight Rate Dynamics

We begin the analysis by presenting the estimates for the regime-switching AR(1)-model parameters. These results can be interpreted as a discrete-time model. Subsequently, we present the model parameters in continuous time. Finally, we present and interpret the parameters of the transition matrix.

Consider first the results in Table2, which are the regime-switching $AR(1)$-model estimates. The subscript for each parameter indicates which regime they correspond to. Here, Regime 1 is the regime where supply is inelastic (analogous

	Handysize	Panamax	Capsize	VLCC	Suezmax	Aframax
a_1	-0.12	18.59	29.72	2485.30	2153.20	1226.00
	(1.868)	(7.928)	(14.782)	(427.334)	(510.469)	(280.717)
b_1	0.9982	0.9946***	0.9937**	0.9639***	0.9674***	0.9735***
	(0.00031)	(0.00222)	(0.00308)	(0.00688)	(0.00898)	(0.00646)
$\hat{\sigma}_1$	19.375	97.900	228.882	10511.511	6070.923	4141.455
a_2	-0.40	7.50	2.61	-103.27	-26.57	-32.46
	(0.657)	(2.829)	(3.682)	(18.189)	(36.671)	(21.658)
b_2	1.0011	0.9905***	0.9929***	0.9915***	0.9891***	0.9958***
	(0.00110)	(0.00272)	(0.00219)	(0.00093)	(0.00211)	(0.00130)
$\hat{\sigma}_2$	3.670	20.414	48.154	1093.140	940.424	683.532

Table 2: Estimated parameters for model (12). The upper panel is the estimates for the parameters of the AR(1) model for regime 1, the regime with inelastic supply. The bottom panel corresponds to the parameter estimates for the model in regime 2, i.e. the regime where supply is elastic. The hypotheses test used for b_1 and b_2 is $H0 : b \geq 1$. The numbers inside the parenthesis are the standard error of the coefficients. * means statistically significant at a 10%-level, ** at a 5%-level and *** at a 1%-level.

to the hockey stick handle of the supply curve), and Regime 2 is the regime where supply is elastic (analogous to the hockey stick blade of the supply curve).

The results indicate a vast difference in the volatility between the two states. Calculating the ratio of volatility (σ_1/σ_2) between the two states, we see that Regime 1 has a volatility that is between 4 and 9 times as great as Regime 2. This outcome aligns with the theoretical expectations. If the supply is inelastic, then vessels are fixed via an auction mechanism where the highest bidder secures the fixture of the vessel. Thus, sudden increases in demand can not be met by increasing supply, and the market clears solely due to price adjustments. On the other hand, when the supply is elastic, sudden increases in demand can be met by increasing supply, thereby reducing volatility.

Note the difference between the dry bulk market and the tanker market. The

	Handysize	Panamax	Capsize	VLCC	Suezmax	Aframax
a_1	-0.124	18.643	29.819	2531.263	2189.134	1242.520
b_1	-0.002	-0.005	-0.006	-0.037	-0.033	-0.027
σ_1	19.392	98.167	229.606	10705.302	6171.944	4197.144
a_2	-0.404	7.534	2.618	-103.709	-26.714	-32.532
b_2	0.001	-0.010	-0.007	-0.009	-0.011	-0.004
σ_2	3.668	20.512	48.325	1097.796	945.605	684.979

Table 3: Estimated parameters for model (1). The upper panel is the estimates for the parameters for regime 1, the regime with inelastic supply. The bottom panel corresponds to the parameter estimates for the model in regime 2, i.e. the regime where supply is elastic.

volatility ratio for dry bulk vessels varies between 4.75 and 5.27. On the other hand, the volatility ratio in tanker markets varies between 6 and 9.6. Not only is the volatility ratio generally higher for tankers, but the range of variation is also greater. Moreover, the volatility ratio falls for dry bulk vessels as the size increases, as smaller Handysize dry bulk carriers exhibit a higher volatility ratio than the much larger capsize. On the other hand, for tankers, the volatility ratio increases with the size of the vessel, with larger VLCCs showing a higher volatility ratio than smaller Aframax vessels.

By comparing volatility across vessel size, we see that volatility generally increases with size in line with the findings in (Kavussanos, 1996). Kuvussanos argues that smaller vessels have greater operational flexibility and face fewer size constraints. Consequently, they can serve a wider range of trades than larger vessels and are thus less susceptible to market variations (Kavussanos, 1996).

Consider now mean reversion. A process is mean reverting if $\beta < 0$ (Filipović, 2009). Referring back to the discrete estimates in Table 2. Since, $b = \log(\beta)$, for $\beta < 0$ we require $b < 1$. The stars in Table 2 indicate the hypotheses test that $H0 : b_i = 1$ for $i = 1, 2$. The results demonstrate significant mean reversion in all tanker segments in addition to Panamax and Aframax dry-bulk. Spot rates for Handysize dry-bulk vessels do not significantly mean reverting in either regime. A possible explanation, consistent with (Kavussanos, 1996) on volatility differences by vessel size, is that smaller vessels are more versatile and serve a broader range of markets, rendering them less sensitive to specific market conditions.

To assess the level of mean reversion we see that if $b < 0$, then (5) converge more rapidly to a/b as $t \to \infty$. Hence, a more negative b indicates stronger mean reversion. Referring to the results in Table 3, we find that for the tanker segments, $b_1 < b_2$, consistent with expected behavior: rates are more mean-reverting in the inelastic supply regime. This means that they behave as we expect. When the supply is inelastic, the rates are more mean reverting. On the other hand, this pattern does not appear to hold for all dry-bulk segments.

Moreover, the difference in mean reversion strength across regimes is smaller for the dry-bulk segments than for the tankers. This may be attributed to the broader diversity of markets served by dry-bulk carriers. When localized demand increases with limited vessel availability, cargoes can often be accommodated by vessels of varying sizes, limiting the rapid escalation of freight rates and reducing the impact of supply constraints. On the other hand, the tankers we study serve a narrow range of commodities, predominantly petroleum products. Spot rates can quickly increase once the capacity supply is constrained or demand has increased. Since fewer vessels are available to rebalance the market, leading to more pronounced price fluctuations.

A robustness check (see Appendix A) fails to provide evidence of mean reversion in freight rates for dry-bulk vessels. The robustness check is conducted on a sub-sample between 2012 and 2020. The failure to find mean reversion could support the observation in (Adland & Cullinane, 2006) where Adland and Cullinane observed that freight rates exhibit mean reversion primarily at very high levels. This suggests that mean reversion only occurs in extreme market situations, which may not be present within this subsample. On the other hand, the robustness check supports the findings that tankers have significant mean reversion.

The difference in which regime has the most mean reversion might underscore a fundamental difference between the dry-bulk and tanker vessel types. The reason for this is not clear, but one possible explanation is that dry-bulk vessel markets, due to their broad and more diversified nature, restore market balance more readily. Consequently, the specific regime may impact the mean reversion characteristics of dry-bulk freight rates less.

6.3 Transition matrices

A key component of any Markov model is the transition probabilities, which specifies the probabilities of the process X moving from one state to another or remaining in its current state. In our model, these states represent market regimes or conditions, reflecting whether markets are ”good” or ”bad” depending on supply elasticity. Therefore, one would expect the probability of the market moving from one regime to another depending on the current freight rate and oil price.

We have modeled the transition probabilities using a logit model where the current freight rate and Brent are covariates. This means that the transition probability matrix is on the form,

$$P(t) = \begin{pmatrix} 1 - P_{12} & P_{12} \\ \\ P_{21} & 1 - P_{21} \end{pmatrix} \tag{23}$$

Where,

$$P_{ij}(t) = \frac{1}{1 + \exp(-(\beta_{ij,0}) + \beta_{ij,1} S(t-1))}. \tag{24}$$

Here, $S(t-1)$ is the freigt rate at time $t-1$. Employing the method described yields the parameters in Table **??**.

	Handysize	Panamax	Capsize	VLCC	Suezmax	Aframax
$\beta_{12,0}$	4.093^{***}	5.395^{***}	2.891^{***}	3.469^{***}	3.816^{***}	4.216^{***}
	(0.405)	(0.501)	(0.298)	(0.250)	(0.278)	(0.322)
$\beta_{12,1}$	-0.002^{***}	-0.001^{***}	-0.001^{***}	-0.001^{***}	-0.001^{***}	-0.001^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\beta_{12,2}$	0.009^{**}	-0.004	0.009^{***}	-0.003	-0.005^{**}	-0.007^{***}
	(0.006)	(0.005)	(0.004)	(0.003)	(0.003)	(0.004)
$\beta_{21,0}$	1.860^{**}	2.310^{***}	0.989	0.418	0.494	-0.151
	(0.454)	(0.542)	(0.391)	(0.340)	(0.312)	(0.367)
$\beta_{21,1}$	0.001^{***}	0.001^{***}	0.001^{***}	0.001^{***}	0.001^{***}	0.001^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\beta_{21,2}$	0.001	-0.010^{**}	0.006^{*}	0.001	-0.001	0.011^{***}
	(0.006)	(0.006)	(0.005)	(0.004)	(0.003)	(0.004)

Table 4: Estimates for the transition probabilities. The upper two coefficients relate the transition from regime 1 to regime 2, and the bottom two to the transitions from regime 2 to regime 1. The numbers inside the parenthesis are the standard error of the coefficients. * means statistically significant at a 10%-level, ** at a 5%-level and *** at a 1%-level.

There are multiple insights to gain from investigating the transition matrices. Firstly, the Markov Chain, X, has no absorbing states, as indicated by the absence of elements equal to 1 in any matrix. For this to occur the coefficients in the dynamic model would have to approach infinity. In an absorbing state, the Markov Chain cannot transition away from the absorbing state once it has entered. An absorbing Markov Chain would not make sense in this application.

$$\begin{pmatrix} \frac{1}{1+\exp(-(4.093-0.001S(t-1)+0.009B(t-1))} & 1-\frac{1}{1+\exp(-(4.093-0.002S(t-1)+0.009B(t-1))} \\ 1-\frac{1}{1+\exp(-(1.860-0.001S(t-1)+0.001B(t-1))} & \frac{1}{1+\exp(-(1.860-0.001S(t-1)+0.001B(t-1))} \end{pmatrix}$$

$$\begin{pmatrix} \frac{1}{1+\exp(-(2.891-0.001S(t-1)-0.009B(t-1))} & 1-\frac{1}{1+\exp(-(5.395-0.001S(t-1)-0.004B(t-1))} \\ 1-\frac{1}{1+\exp(-(2.310-0.001S(t-1)-0.010B(t-1))} & \frac{1}{1+\exp(-(2.310-0.001S(t-1)-0.010B(t-1))} \end{pmatrix}$$

$$\begin{pmatrix} \frac{1}{1+\exp(-(5.395-0.001S(t-1)-0.004B(t-1))} & 1-\frac{1}{1+\exp(-(5.395-0.001S(t-1)-0.004B(t-1))} \\ 1-\frac{1}{1+\exp(-(0.989-0.001S(t-1)-0.006B(t-1))} & \frac{1}{1+\exp(-(0.989-0.001S(t-1)-0.006B(t-1))} \end{pmatrix}$$

$$\begin{pmatrix} \frac{1}{1+\exp(-(3.469-0.001S(t-1)-0.003B(t-1))} & 1-\frac{1}{1+\exp(-(3.469-0.001S(t-1)-0.003B(t-1))} \\ 1-\frac{1}{1+\exp(-(0.418-0.001S(t-1)+0.001B(t-1))} & \frac{1}{1+\exp(-(0.418-0.001S(t-1)+0.001B(t-1))} \end{pmatrix}$$

$$\begin{pmatrix} \frac{1}{1+\exp(-(3.816-0.001S(t-1)-0.005B(t-1))} & 1-\frac{1}{1+\exp(-(3.816-0.001S(t-1)-0.005B(t-1))} \\ 1-\frac{1}{1+\exp(-(0.494-0.001S(t-1)-0.001B(t-1))} & \frac{1}{1+\exp(-(0.494-0.001S(t-1)-0.001B(t-1))} \end{pmatrix}$$

$$\begin{pmatrix} \frac{1}{1+\exp(-(4.216-0.001S(t-1)-0.007B(t-1))} & 1-\frac{1}{1+\exp(-(4.216-0.001S(t-1)-0.007B(t-1))} \\ 1-\frac{1}{1+\exp(-(-0.151+0.001S(t-1)+0.011B(t-1))} & \frac{1}{1+\exp(-(-0.151+0.001S(t-1)+0.011B(t-1))} \end{pmatrix}$$

Table 5: Dynamic transition probabilities are shown for each vessel segment. Top row from left to right: Handysize dry-bulk, Panamax dry-bulk, and Capesize dry-bulk. In the bottom row, from left to right: VLCC, Suezmax, and Aframax tankers. $S(t-1)$ is the freight rate at time $t-1$ and $B(t-1)$ is the brent crude oil price at time $t-1$.

In the shipping context, this would mean that the supply in the market is either permanently inelastic or permanently elastic. In a permanently inelastic market, supply would be chronically insufficient, leading to persistently high freight rates. In the long term, shipowners would have incentives to order new vessels since the shipping rates would be high. On the other hand, in a permanently elastic market, it suggests that there would always be abundant capacity. This is also not tenable in the long run as prolonged low rates would drive inefficient vessels and shipping companies out of the market. To achieve this, shipowners would scrap vessels, primarily older and less efficient ones.

Secondly, we see that the current freight rate is significant for transition probability for all segments and all sizes but that the magnitude of the coefficients is small. This should not be interpreted to mean that the spot rate does not have an important impact on the probability of regime change. The freight rate indices are of an order of magnitude of 1000 to 10000.

Not surprisingly, the probability of going from Regime 1 to Regime 2 decreases in the freight rate, indicating that a higher freight rate reduces the probability of moving from the inelastic supply regime to the elastic supply regime. On the other hand, the probability of changing from Regime 2 to Regime 1 is increasing in the freight rate. This suggests that when the process is in the regime where the supply is elastic, the probability of moving into the regime where the supply is increases when the freight rate increases.

Thirdly, the effect of oil prices on transition probabilities is less straightforward. The coefficient for Brent crude oil on the transition probability from Regime 1 to Regime 2 is significant for most dry-bulk segments and all tanker sizes. However, it exhibits an opposite sign across vessel types. On the other hand, oil prices influence both costs and revenues for tanker vessels, as rising fuel costs increase operational expenses while demand-driven revenue effects may offset this increase. For dry-bulk vessels, however, Brent prices primarily impact operational costs. The effect of oil prices on the transition probability from Regime 2 to Regime 1 is less definitive across vessel types.

6.3.1 Static Transition Matrices

The static transition matrix can also be computed. These are constant transition matrices. Interpreting the matrix is straightforward: a transition matrix gives us the probability of moving from one regime or remaining in the same regime. The probability of moving from state i to state j is given by the element on row i and on column j.

$$\begin{pmatrix} 0.94 & 0.06 \\ 0.03 & 0.97 \end{pmatrix} \quad \begin{pmatrix} 0.94 & 0.06 \\ 0.03 & 0.97 \end{pmatrix} \quad \begin{pmatrix} 0.92 & 0.08 \\ 0.06 & 0.94 \end{pmatrix}$$

$$\begin{pmatrix} 0.74 & 0.26 \\ 0.06 & 0.94 \end{pmatrix} \quad \begin{pmatrix} 0.81 & 0.19 \\ 0.07 & 0.93 \end{pmatrix} \quad \begin{pmatrix} 0.86 & 0.14 \\ 0.05 & 0.95 \end{pmatrix}$$

Table 6: Static transition probabilities. Top row from left to right: Handysize dry-bulk, Panamax dry-bulk, Capsize dry-bulk. The bottom row from left to right is VLCC, Suezmax tanker, and Aftamax tanker.

Some patterns emerge from the static transition probabilities. Notably, the probability of staying in state 2 is higher than in state 1, suggesting that the market is more stable in state 2. Moreover, the probability of remaining in state 1 is higher for dry bulk than tankers. This implies that, in general, the Markov Chain is more likely to persist in the inelastic supply regime for extended periods in dry-bulk markets.

7 Conclusion

Tramp shipping markets are often cited as real-world examples approximating perfectly competitive markets. A vessel operating in a tramp service sails from port to port without a regular schedule, which contrasts with liner shipping, which follows regular schedules and often forms part of structured transportation networks. Transportation services offered in tramp shipping are nearly identical between vessels, with primary differences arising from technical constraints such as size or contract differences like the length of the voyage. Bulk shipping is characterized by numerous small firms and a low barrier to entry (Kalouptsidi, 2014). Nearly identical goods, fractured market structures with many firms, and a low entry cost collectively inhibit the development of market power and contribute to a highly competitive market with low margins (Mas-Colell et al., 1995). Therefore, it can be argued that the price in the market is primarily determined by the marginal cost of the least efficient vessel in the market. The marginal cost depends in large part on the price of fuel. Since most vessels continue to rely on petroleum-derived fuels, oil prices are expected to indirectly influence on prevailing shipping rates.

On the other hand, building new ships is a time-consuming undertaking. Therefore, when there are no vessels in lay-up, the shipowner's ability to increase the supply of shipping capacity is limited to operational adjustments like increasing sailing speed. Thus, a point exists at which all vessels are actively engaged in the market and operate at maximum speed. At this point, the supply of shipping services becomes constrained in the short term (Tvedt, 1995). Different market dynamics are expected to emerge when demand is great, and supply is constrained, as opposed to market conditions where demand is lower, and supply is abundant. When supply cannot keep up with demand, the limited number of vessels available are auctioned off ("Chartering Negotiations", n.d.). This drives the freight rates higher and can allow shipowners to achieve returns far higher than marginal cost.

These two market conditions are each accurate representations of different periods. The latter story was true in the years before the financial crisis in 2008. High economic activity drove international trade and, thus, shipping rates to new heights. Constraining the ability of the market to provide enough capacity. On the other hand, after the financial crisis, the former story rings true. The Great Recession that followed the financial crisis led to a slowdown in international trade, and thus, the bulk market shifted into a depressed state. We argue that the shifting nature of the shipping markets is due to the nature of the tonnage supply and the inelasticity of demand for shipping services. The ”hockey stick” shape of the shipping supply curve provides critical insights. One curve segment is nearly horizontal, indicating elastic supply, while the other is nearly vertical, signifying inelastic supply. As for demand, shipping services constitute a minor part of the cost of a good. Therefore, the demand side of the market, the shippers, are insensitive to changes in freight rates. We aim to model how these supply dynamics influence the market's equilibrium price. We demonstrate that the market operates within two distinct regimes, each exhibiting behavior consistent with economic theory.

This paper has modeled the spot rates in dry-bulk and tanker markets represented by the Baltic indices for dry-bulk Handysize, Panamax, and Capsize vessels and for VLCC, Suezmax, and Aframax tankers. We employed a regime-switching Ornstein-Uhlenbeck model inspired by (Hamilton, 1989). This approach allowed stochastic filtering to capture the indices across two different regimes. Standard economic theory on shipping markets describes the supply function in a market as a hockey stick (Stopford, 2008). In our model, one regime reflects conditions of elastic supply, while the other corresponds to inelastic supply, representing the handle and blade segments of the hockey stick, respectively.

As theory predicted, the stochastic properties of the freight rate differ between the two market regimes for both indices. Firstly, mean reversion is stronger in the regimes where supply is inelastic, but we only found significant evidence for this in tanker markets. Secondly, volatility is higher in the regimes where supply is inelastic, and increases with the size of the vessels. Specifically, the volatility in the inelastic regime is between 4 and 6 times greater than in the elastic regime for dry-bulk segments and between 6 and 10 times greater in tanker segments.

We also analyzed the transition probabilities, both a static and a dynamic model. In the static model, the process seems to remain in Regime 2 for longer than in Regime 1. However, distinct patterns emerge between dry-bulk and tanker segments. The probabilities of remaining in either regime are more balanced in dry-bulk markets. On the other hand, tankers have less balanced transition probabilities where the probability of staying in state 1 is lower than for staying in state 2. Additionally, in the dynamic transition model, we found that the current freight rate significantly influences the probability of transitioning between states and that Brent crude oil price affected the transition probability from Regime 1 to Regime 2, but the evidence was less convincing the other way around.

There are some interesting possible extensions to this research. We considered parameters that vary by regime but remain constant over time. Examining parameters varying by state and over time could yield further insights. Moreover, we saw statistical differences between segments. This could be interesting to investigate further by systematically investigating different routes, segments, and vessel sizes. A different extension that might have been interesting would have been the inclusion of seasonality. Moreover, the index we use is limited in time, if the data set extended further back we might be able to enhance model accuracy. The robustness check in the appendix showed that the parameters estimated in the model might not be as significant when looking at a subset in time. Although the robustness check failed to provide the same significant results, the results were not contradictory.

This paper has certain limitations. While using third-party indexes offers benefits such as transparency and reproducibility, it also presents potential drawbacks. For example, (A. Veenstra & van Dalen, 2008) argues that fixture data can be unreliable or incomplete, and therefore, any index based on them can be unreliable. A second limitation is the model's simplicity which may limit its capacity to provide detailed insights into the structure of volatility.

Appendix A: Robustness check

To strengthen the results we did a robustness check using sub-sampling over the period from the 13th of April 2013 to the 16th of April 2020. The results are as follows:

It is interesting to see that mean reversion among the dry-bulk vessels is different. In particular, Panamax vessels do not seem to have a significant mean reversion parameter b_1 for regime one. This weakens the result that spot freight rates are mean reverting for dry-bulk carriers. On the other hand, all the tankers are significant for all sizes. This could indicate that the model is more appropriate in tanker markets than in dry-bulk markets. We see that our observations about the difference in volatility between regimes and between sizes are the same here. The robustness check also shows fewer significant results for the parameters in the dynamic transition probabilities. However, non of the results were contradictory, i.e., there were no significant results with opposing signs in the results or the robustness check.

Note that the robustness check is done on substantially fewer points of data, and this could influence the hypotheses test.

	BDI Handysize	BDI Panamax	BDI Capsize	BDTI VLCC	BDTI Suezmax	BDTI Aframax
a_1	-5.07	15.27	16.93	4413.96	2468.05	1102.90
	(2.210)	(6.955)	(11.949)	(1197.951)	(612.218)	(462.550)
b_1	1.0089	0.9994	0.9922**	0.9435***	0.9542***	0.9717***
	(0.00442)	(0.00540)	(0.00531)	(0.01654)	(0.01285)	(0.01290)
$\hat{\sigma}_1$	6.478	26.780	112.148	15365.817	5759.260	3117.960
r^2	0.9975	0.9953	0.9864	0.8999	0.9401	0.9639
a_2	5.60	11.78	-1.89	-68.94	-60.94	-5.40
	(1.205)	(2.752)	(3.346)	(29.180)	(44.579)	(37.522)
b_2	0.9896	0.9718***	0.9984	0.9941***	0.9935***	0.9956***
	(0.00238)	(0.00283)	(0.00295)	(0.00138)	(0.00254)	(0.00054)
$\hat{\sigma}_2$	2.196	12.019	19.400	1146.637	797.098	629.577
r^2	0.9996	0.999	0.9992	0.997	0.9969	0.9966

Table 7: Robustness check for model (12). The upper panel is the estimates for the parameters of the AR(1) model for regime 1, the regime with inelastic supply. The bottom panel corresponds to the parameter estimates for the model in regime 2, i.e. the regime where supply is elastic. The hypotheses test used for b_1 and b_2 is $H0 : b \geq 1$. The numbers inside the parenthesis are the standard error of the coefficients. * means statistically significant at a 10% level, ** at a 5%-level and *** at a 1%-level.

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	BDI Handysize	BDI Panamax	BDI Capsize	BDTI VLCC	BDTI Suezmax	BDTI Aframax
a_1	-5.052	15.275	16.992	4543.584	2526.382	1118.779
b_1	0.009	-0.001	-0.008	-0.058	-0.047	-0.029
σ_1	6.450	26.788	112.588	15814.838	5894.845	3162.741
a_2	5.631	11.950	-1.895	-69.145	-61.142	-5.416
b_2	-0.010	-0.029	-0.002	-0.006	-0.007	-0.004
σ_2	2.207	12.191	19.415	1150.003	799.717	630.951

Table 8: Robustness check of the model presented in (1). The upper panel is the estimates for the parameters for regime 1, the regime with inelastic supply. The bottom panel corresponds to the parameter estimates for the model in regime 2, i.e. the regime where supply is elastic.

	BDI Handysize	BDI Panamax	BDI Capsize	BDTI VLCC	BDTI Suezmax	BDTI Aframax
$\beta_{12,0}$	3.129584^{***}	3.191805^{***}	3.285738^{***}	3.971347^{***}	3.698720^{***}	3.897576^{***}
	(0.672870)	(0.335203)	(0.355150)	(0.194339)	(0.194586)	(0.225125)
$\beta_{12,1}$	-0.000030	-0.000567^{*}	-0.000360	-0.000033^{***}	-0.000043^{***}	-0.000047^{***}
	(0.001331)	(0.000313)	(0.000262)	(0.000005)	(0.000006)	(0.000009)
$\beta_{21,0}$	2.938634^{***}	2.611338^{***}	1.891761^{***}	0.192375	0.206817	0.457951
	(0.583821)	(0.413374)	(0.366077)	(0.253068)	(0.257272)	(0.289262)
$\beta_{21,1}$	0.000109	-0.000034	0.001184^{***}	0.000017^{***}	0.000033^{***}	0.000052^{***}
	(0.001170)	(0.000323)	(0.000254)	(0.000005)	(0.000007)	(0.000011)

Table 9: Robustness check on the transition probabilities. The hypotheses test used is $H0 : \beta_{ij,k} = 0$. The numbers inside the parenthesis are the standard error of the coefficients. * means statistically significant at a 10% level, ** at a 5%-level and *** at a 1%-level.

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