Ups and downs: modeling spot freight rates with regime switching.

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Abstract

The shipping industry is famous for its ups and downs. The fortunes of shipowners have always been interwoven with the great events of history like war and peace. Huge amounts of wealth have been lost and gained in a matter of weeks. What are the dynamics in the different regimes? This paper aims to study the stochastic properties of the shipping spot rate during "good" times and "bad" times in the context of a mean reverting Ornstein-Uhlenbeck process with Markov regime-switching. Firstly, we use economic theory to justify why there should be two distinct regimes. Then we propose a continuous time model of the spot freight rates. Thirdly, we use a Markov regime-switching model to estimate a discrete version of the model. Our results show that the different regimes have different levels of volatility and for tankers, different strengths of mean reversion. Lastly, we study the transition probabilities between the regimes in an exogenous and an endogenous matter. Here we find that the current level of the shipping rate is a significant factor in modelling the probability of transitioning between regimes.

1 Introduction

If global commerce is the lifeblood of the modern world then international shipping is the arteries and veins the blood flows through. The history of maritime transportation is long and illustrious. Since ancient times vessels sailing on the high seas have transported goods from one harbor to another. Vessels on the high seas have been the source of great prosperity but also helped enable horrible atrocities like the international slave trade (Haws & Hurst, 1985). Today, maritime trade is still one of the most important means of transportation. In 2021 alone 11 billion tons of goods were transported by sea ("World seaborne trade – UNCTAD Handbook of Statistics 2023", n.d.). Understanding the price dynamics in the shipping market has therefore been of interest to academics and practitioners alike for a long time.

Freight rates represent the equilibrium price that is agreed upon by shipowners and charterers at a given point in time. The prevailing freight rates are thus the prices that ensure that the forces of supply and demand balance and that goods can flow from seller to buyer as fast and affordable as possible (Stopford, 2008). Therefore, the market mechanism that determines the equilibrium price has always been a central issue in academics and industry.

The long-standing debate in the literature is on the mean reverting properties of freight rates. Mean reversion is a property of many stochastic processes where over time the process will tend to move towards a long-term mean level. The process might deviate from the mean level at times, even substantially, but the process will eventually find its way back to the mean level. Understanding the stochastic properties of a price process can yield valuable insights into the dynamics of a market. A mean-reverting freight rate could demonstrate a shipping market's ability to meet changing market conditions. Understanding the stochastic properties also allows us to value contracts and vessels more accurately. Studies on different segments and periods have resulted in different empirical results (Adland & Cullinane, 2006). In this paper, we argue that the mean reversion process is state-dependent, that is, the parameters in an Autoregressive (AR) process of the freight rate are time-varying. Specifically, the parameter estimates are conditional on the market dynamics between supply and demand. We therefore argue that the statistical properties observed are different depending on the balance between supply and demand in a market.

Markets for shipping services are often hailed as some of the closest examples of competitive markets. However, this is not the case for liner shipping as this market has an oligopolistic market structure, i.e. a few large firms with a lot of market power (Stopford, 2008). Transportation services in tramp shipping are identical, and the fractured market structures with many firms and low cost of entry prevent the development of market power (Stopford, 2008). All factors contribute to a highly competitive market with low margins. Therefore, we argue the price in the market should be governed by the marginal cost of the most efficient vessel (Mas-Colell et al., 1995). The marginal cost depends in large part on the price of fuel. Most vessels are still fueled by fuels derived from petroleum. Hence, the price of oil should indirectly affect the prevailing shipping rate.

On the other hand, building new tonnage is a time-consuming undertaking. Therefore, the supply of shipping capacity is limited in the short term (Tvedt, 1995). We expect different dynamics to emerge when demand is great and supply is constrained, as opposed to market conditions where demand is less and supply is abundant. When supply is not able to keep up with demand the limited number of vessels available are auctioned off to the highest bidder (Stopford, 2008). This drives the freight rates higher and can ensure a handsome income for the shipowner far exceeding the marginal cost.

These two stories are both true but at different times. During the years before the financial crisis in 2008 the latter story was true. High economic activity

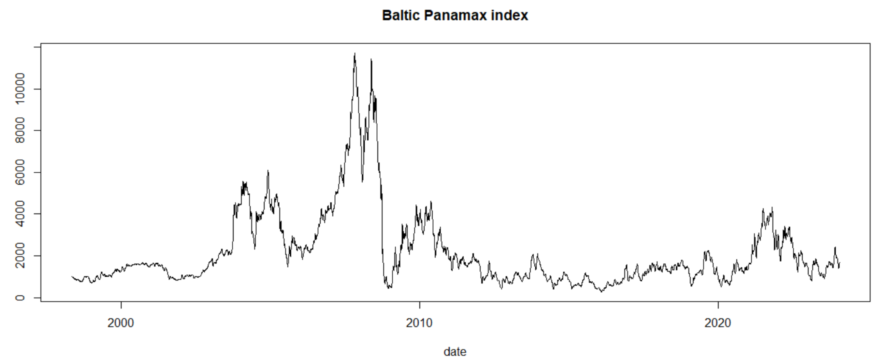

Figure 1: The Baltic Panamax Index between 1998-2023. Note the rise in activity up until 2008 and the sharp fall afterward.

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 more 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 supply of tonnage and the inelasticity of demand for shipping services. The mechanisms of supply exemplified in the supply curve provide crucial insights. The supply curve in shipping markets is shaped like a hockey stick, one part is nearly horizontal and the other nearly vertical. 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 this supply dynamic affects the equilibrium price in the market. We show that there are two distinct regimes and they behave like economic theory would suggest.

To accomplish this we study indices of freight rates in two different markets for different size vessels, Handysize, Panamax, and Capmax dry-bulk carriers and Aframax, Suezmax, and VLCC tankers. We use stochastic filtering to estimate a Markov regime-switching model similar to (Hamilton, 1989). This means that we use the Hamilton filter to separate the data into two groups and estimate an AR(1)-model for each group. Then, we model the transition probabilities and lastly, we use a formula reminiscent to (Tvedt, 1995) to translate the discrete AR(1) estimate to continuous ones.

This paper builds on the work done in (A. H. Alizadeh et al., 2015). Our paper diverges and contributes to the literature in the following ways. Firstly, we propose two models, one in continuous time and one in discrete time. Secondly, we study whole market segments as opposed to single routes. Studying market segments as a whole can give insight into the global market and not just limited geographic routes. Moreover, vessels can move between routes over their lifetime, and a model that takes this into account can therefore be more useful on vessel-related matters. We also contribute by expanding the study to include the dry bulk market as well as the tanker market, as opposed to (A. H. Alizadeh et al., 2015) who instead only consider clean and dirty tanker routes. Lastly, we believe that our model can provide close-form solutions to some financial derivatives.

2 Literary review

Understanding the forces at play in the market for shipping services also has a long history in the academic literature. 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 work in this field sought to model this interaction in a partial or general equilibrium framework. Dutch economist Jan Tinbergen published one of the first seminal papers on the subject of freight rates in 1934, Tonnage and Freight. Tinbergen constructed supply and demand indexes using historic data and then found a linear relationship between the parameters (Tinbergen, 1934). A few years later Tjalling Koopmans published his seminar paper Tanker Freight Rates and Tankship Building. The central part of Koopmans's work is concerned with analyzing the short-term general equilibrium of the tanker market and the shipbuilding market for tankers (Koopmans, 1939). For a review see (Rothbarth, 1939). Zannetos continued on the work of Koopmans for his Ph.D. thesis in the 1950s This was later reworked into the monograph The Theory of Oil Tanker Rates. Zannetos gave crucial insights into the markets for oil and tankers during the period, and many of his insights still ring true today. For example, Zannetos argues that paradoxically even though the petroleum industry during the 1950s was concentrated with the oil majors, the tanker market exhibited a perfectly competitive market (Zannetos, 1964). An excellent summary of Zanneto's work can be found in (A. W. Veenstra & De La Fosse, 2006)

The microeconomic and econometric approach to studying freight markets did not stop with Zennetos. With the increased availability of computers, we started seeing even more detailed models emerge. Norman and Wergeland's Nortank model from 1981 set a new standard for this kind of model. Nortank is a model of the tanker market for tankers greater than 200 000DWT. The model considers both the demand and the supply part of the market. In particular, the supply side of the market is modeled in detail (Norman & Wergeland, 1981). In 1986 Siri Strandenes published the generalized and improved Norship-model (Strandenes, 1986). The microeconomic and econometric research has also been extended to include the second-hand vessel market. The modeling of ship value as a capital asset was pursued in a series of papers by Michael Beenstock and Andreas Vergottis. They mainly model vessels as a capital asset and apply this model to dry bulk and tankers (Beenstock & Vergottis, 1989) (**Vergottis1989b**). This line of inquiry was also followed by Jostein Tvedt as he also included the market for shipbuilding into a stochastic partial equilibrium model (Tvedt, 1995).

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

During recent decades the literature on freight rate modeling has increasingly been moving away from the extensive econometric methods and towards univariate time series models. Many of the papers investigated the freight markets from a financial perspective. A common theme in this newer stream of literature is the stronger emphasis on financial aspects, like derivative contracts. The introduction of the Baltic Freight Index in 1985 and the subsequent proliferation of financial derivatives (Stopford, 2008) might have contributed to the shift in research. For example, the relationship between forward rates and spot rates has been extensively studied (Chang & Chang, 1996) (Kavussanos & Nomikos, 1999)(Kavussanos & Nomikos, 2001) (Kavussanos & Visvikis, 2004) (Yin et al., 2017)

One of the earlier papers in this direction was (Bjerksund & Ekern, 1995). Bjerksund and Ekern model freight rates using a continuous time mean reverting Ornstein-Uhlenbeck process. This was followed up in (Tvedt, 1997). More general univariate models have also been proposed based on Stochastic Differential Equations (SDEs) (Adland & Cullinane, 2006)(Adland et al., 2008)(Poblacion, 2015)(Benth et al., 2015)(Población, 2017). This paper fits well into this tradition.

The bridge between equilibrium models and univariate models has been attempted to be bridged. For example, (Tvedt, 2003).

A wide range of time series methodologies has also been employed for modeling the spot freight rate such as 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 of these papers, especially those concerned with forecasting, investigate multiple models.

Recent innovations in freight rate modeling involve the introduction of various machine learning and artificial intelligence methods for predicting freight rates (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). However, despite often having superior performance many machine learning models are exceedingly hard to interpret.

The principal method we will employ in this paper involves Markov regime-switching models. The Markov regime-switching model was introduced in the seminal paper (Hamilton, 1989). Hamilton employed the model on macroeconomic data. Later methodological improvements have been made by extending to 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). However, the applications of Markov regime switching in shipping markets have been limited. Abouarghoub et.al. investigates the freight rate risk as measured by Value-at-Risk (Abouarghoub et al., 2014) and Alizadeh et.al. investigate the hedging performance of derivatives contracts (A. H. Alizadeh et al., 2015), both using Markov Switching GARCH models.

for a further review on Markov regime switching see (Phoong et al., 2022).

One of the longest-standing questions in the literature is the question of stationarity. A stochastic process is said to be stationary if the probability distribution does not depend on time (Benth et al., 2008). According to theory, shipping rates should be mean reverting and stationary (Tvedt, 2003). However, the empirical literature does not seem to contain satisfactorily definitive answers to this question in one way or another. (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 was such an important market for these kinds of vessels denominating the rates in local currency better reflects the fundamental mechanisms. Hence, he argues, the non-stationarity comes from the exchange rate and not the fundamental shipping market. Koekebakker et.al attack this question head-on in (Koekebakker et al., 2006) and suggest that non-stationarity is difficult to reject because the stationarity could be non-linear. This is followed up in (Adland & Cullinane, 2006) where they find that the freight rates are mean reverting at the edges of the process, thus ensuring a global mean reversion. A different view towards stationarity was investigated by (Kou & Luo, 2015) who found that there were structural breaks in the freight rates. This prompted (Kou et al., 2018) to investigate if the empirical results regarding stationarity are 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. Usually by finding that the Augmented Dicky-Fuller test yields significant results about the existence of a unit root. A review of this question in the literature can be found in (Kou et al., 2018)

Seasonality is an important factor in most commodity markets. Bulk vessels are used to transport other commodities like petroleum and grain, both of which are affected by seasonality, we expect shipping markets to also exhibit some form of seasonal effects. The nature of the possible seasonality is 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.

Shipping does not exist in a vacuum, and the surrounding world affects freight markets. What these factors are have been extensively studied. (Ke et al., 2022) argues that most of this work has been focused on temporal dynamics and less on cross-sectional dynamics. Temporal dynamics are the dynamics of the market that change over time, and cross-sectional dynamics are the dynamics of the market that change between vessels.

Understanding the cross-sectional dynamics is important for understanding how the individual features of a vessel affect the price of hiring that particular vessel on a particular contract. A theoretical study of the VLCC market was conducted in (Tvedt, 2011). Empirical studies have been conducted in different markets. Adland et.al. constructed a hedonic price index on offshore vessels (Adland et al., 2017). The same group of authors also studied the charterer and owner effect on rates in wet and dry bulk markets (Adland et al., 2016). They found some of the same vessel characteristics also applied to the wet and dry bulk markets, but that route, charterer, and owner fixed effects were important. 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 investigated in (Adland & Alizadeh, 2018). Some studies investigate how different vessel characteristics create a two-tiered quality segmentation (Köhn & Thanopoulou, 2011) (Tamvakis, 1995). The results vary (Köhn & Thanopoulou, 2011) find affirmative evidence for dry bulk during the period 2003 to 2007, but (Tamvakis, 1995) (Tamvakis & Thanopoulou, 2000) finds less convincing evidence. (**agnolucc**) investigates how energy efficiency affects the value of TC contracts. The common denominator between these papers is the reliance on fixture data.

Vessel types differ concerning what factors should influence their rates. In general things like age, size, and speed are important. For offshore vessel designers, design country and technological equipment like 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, 1995)(Tamvakis & Thanopoulou, 2000)

To bridge equilibrium models and univariate models has been attempted, for example in (Tvedt, 2003).

3 Theory

This paper follows in the footsteps of papers like (Bjerksund & Ekern, 1995) and uses stochastic processes in continuous time to model the spot freight rates in shipping markets. This entails the use of a stochastic differential equation (SDE) to describe the dynamics of the spot freight rate. However, our approach is also inspired by (Hamilton, 1989). Moreover, we wish to employ the established theory of shipping economics to lay the foundations for our model. To accomplish this dual goal, we propose using a mean reverting stochastic process governed by a Markov process.

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. SDEs are a flexible class of differential equations that can describe sophisticated behaviors we can observe in random phenomena in the real world. One such behavior is mean reversion.

Mean reversion is a property of some stochastic process where a process tends to move towards a long-term mean value. This is common to observe in the price process in many commodity markets, for example, electricity and natural gas (Benth et al., 2008). This is reasonable from an economic point of view. Consider an electricity market. When the price of electricity rises, the consumers will reduce their demand, or producers will increase their supply. A decrease in demand or increase in supply is going to cause prices to drop. On the other hand, if the price of electricity falls, consumers will increase their demand, or producers will decrease their supply. This rise in demand or fall in supply should cause a rise in prices. The long-term mean can be interpreted to be the long-term average equilibrium between supply and demand. Hence, if prices deviate too far from the long-term mean incentives are created to bring the price back.

The Ornstein-Uhlenbeck process (OUP) is a common example of a mean reverting process. This particular stochastic process was proposed as a model for freight rates in (Bjerksund & Ekern, 1995). Moreover, the OUP has seen wide use as a model for short-term interest rates. In the interest rate literature, the UOP is often called the Vasicek model (Filipović, 2009). Following the notation in (Filipović, 2009), the UOP is defined as the solution to the SDE,

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

where a, b, σ are measurable real functions (the arguments have been omitted for simplicity) and $dW(t)$ denotes the Itô integral. There are other formulations as well. For example, an alternative formulation is presented in (Tvedt, 1995) where $b = \kappa$ and $a = \kappa\alpha$.

An explicit solution of (1) can be found,

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

(Filipović, 2009)

The statistical properties of this stochastic process can be explored from this form. Note some properties of Itô integrals(Øksendal, 2007),

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

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

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.

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

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

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, then we expect that the process will converge to a/b, which is the long-term mean.

We want to introduce stochastic regime-switching into this model without ruining the Levy structure embedded in the OUP. To do this we specify that the measurable functions a, b and σ depend on a Markov process X with state space $\mathcal{S} = \{1, 2\}$ and transition matrix P. A Markov process is a "memoryless" stochastic process (Ross, 2019). This means that the only relevant information about the future state of the process is the current state of the process.

One central aspect of any Markov process is the transition matrix. This matrix models the probability of the process moving from one state to another, or remaining in that state (Ross, 2019). The transition probability matrix P is 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.

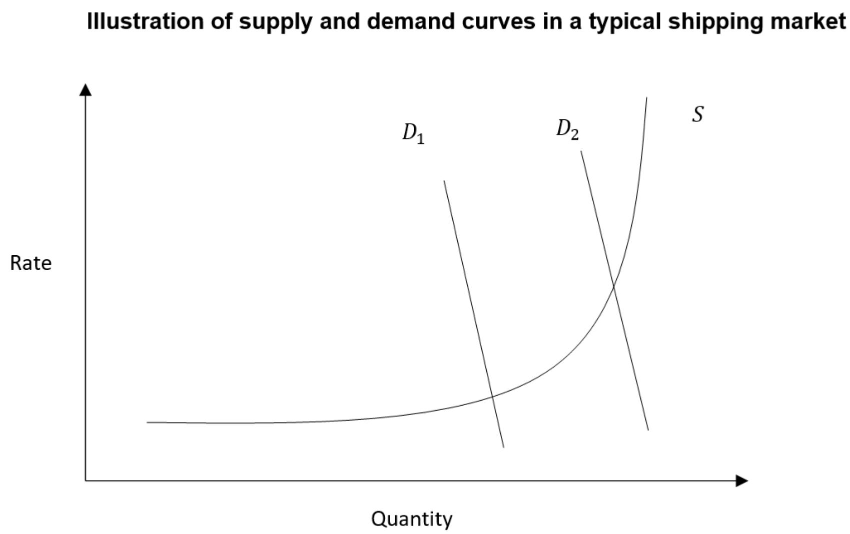

Figure 2: Supply and demand curves in a typical shipping market

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). If the freight rate is less than the marginal cost of operating a vessel, then it is no longer economical to employ the vessel in the market. Therefore, it should exit. In actuality, the friction and cost associated with putting a vessel in lay-up means that the vessel might continue to operate for a time despite the freight rate being less than the marginal cost (Sødal et al., 2008). However, this mechanism provides a lower limit to the supply function of any vessel, and this is reflected in a nearly flat supply curve for low rates. There is also an upper limit on the operations of a vessel, but the upper limit is in the quantity of shipping services provided. If the rates are high enough it might make sense to operate a vessel at uneconomically high speeds. Vessel speed is limited by the technical specifications of the vessel and therefore supply is limited. For the freight rates between the two extremes, the supply function has a grading between horizontal and vertical. For the market as a whole, the lower limit is determined by the marginal vessel in the market. The marginal vessel is the least efficient vessel currently in operation. On the other hand, the upper limit is reached when all vessels are operating at their maximum speed. Hence, the market as a whole has a supply curve shaped like a hockey stick (Stopford, 2008).

The demand for shipping services is usually considered inelastic. Shipping cost generally constitutes a small part of the cost of a good and therefore the customer is less sensitive to the freight rate (Stopford, 2008). Thus, the market for shipping services can in the short term be illustrated in Figure 2.

When the shipping transport supply is abundant relative to demand, i.e., close to D_1, the supply is elastic. When the market is in this state vessels are available for employment and shipowners can provide additional supply rapidly. For example, by increasing sailing speed, taking vessels out of lay-up, or making port operations more efficient. This allows the supply to absorb demand increases quickly. The markets for shipping services are often used as examples of near-perfectly competitive markets. This means that no shipowner can charge higher rates, because other shipowners will undercut them. 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. One of the main drivers of cost for a vessel is the bunker price (Stopford, 2008). Since the bunker is a petroleum product its price is closely linked to the price of oil. Oil price seems to follow a non-stationary stochastic process that follows a random walk. Since the marginal cost indirectly depends on the oil price, we would expect the marginal cost to fluctuate accordingly. This means that on the one hand, the market price should follow a random walk. On the other hand, even in a calm market, there are incentives to add more capacity, although the incentive is weak. These forces compete. Thus, we would expect the shipping rates to be on average lower, volatility lower, and if there is mean reversion it should be nearly negligible.

When the world fleet has a high utilization rate and demand is close to D_2, supply is far less elastic. Thus, the shipowner can charge a premium for shipping services without being afraid of a competitor undercutting them. This imbalance between supply and demand forces freight rates to rise. This rise in rates creates a stronger incentive to add more supply. This incentive would be reflected in higher levels of mean reversion. Hence, we would expect the rates to be higher on average, to have vastly higher volatility and a higher level of mean reversion. It is therefore reasonable to expect that the spot rates have different stochastic properties depending on the level of demand-supply balance. This is the motivation behind modeling the spot rates as a regime-switching mean reverting process.

To capture the change from elastic to inelastic supply, we propose a Markov regime-switching mechanism in the same vein as (Hamilton, 1989). 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.

This means that if $X_t = 2$, then there are still available vessels in the market, or that could be added to the market. In this state, older and less efficient vessels may not be in the market, but rather in lay-up or in other more profitable segments and most vessels operate as economically as possible. Since shipping markets are competitive, the price in such a market should be close to the marginal cost of the marginal vessel in the market. As previously discussed, this means that the price should be indirectly affected by the price of oil and should behave more like a random walk.

Now suppose that demand rises. Then we would expect that all available vessels are employed to meet this rise in demand. As every vessel currently in the market is employed a further rise in demand means that shipowners can raise prices. This constitutes a switch in regime from 2 to 1. This price rise incentivizes more efficient vessel operations, e.g. increasing the speed of vessels, reducing time in port, fewer ballast voyages, and so on. In addition, there is an incentive to take vessels out of lay-up and even order new tonnage. The sum of these operational options can thus lead to an increase in supply and a reduction in the price. Hence, we would expect the freight rates to be mean reverting.

On the other hand, suppose that the world fleet is highly utilized and the demand suddenly starts to fall. This will cause prices to fall as shipowners have to reduce the price of their services to ensure that they can find 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. If demand is sufficiently low for long enough, the premium the shipowners were able to charge disappears. Then the shipping rates are again determined by the marginal cost of the marginal vessel. The market has thus transitioned from state 1 to state 2. The dynamics of the market move back to being indirectly affected by the oil price, and the shipping rate dynamics are again closer to a random walk.

4 Methodology

The structure of our model provides some interesting challenges when estimating the parameters. We do not only in effect have two UOPs but we also have an underlying unobservable Markov process with transition parameters that need to be estimated.

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, exogenous transition probabilities, and autoregressive models with lag 1 (AR(1)). Then, we use a logit model to estimate the transition probabilities of a model with endogenous 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,

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

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 every point in time. This means that the algorithm will give us a probability of the Markov process at time t being 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).

Estimating the parameters of the UOP is done via an algorithm called the expected maximization algorithm. This is an algorithm that works by switching between estimating the expected likelihood function and maximizing the expected likelihood function (Sundberg, 1976). As Sundberg argues, this makes the algorithm useful in a plethora of situations where the number of variables makes the maximum likelihood difficult to compute and in situations where there is missing data (Sundberg, 1976).

The transition probability is central to any Markov model. In this paper, we will present two different models of the transition probability, an exogenous and an endogenous.

The exogenous model presents the transition probability as a number in a 2×2 matrix. This can be calculated at the same time as the parameters of the OUP. The exogenous model can tell some interesting facts about how long the process takes in each regime, and which regime is the most stable.

The endogenous model incorporates the current shipping rates into the transition probability. This means that we model how the rates influence the future evolution of the Markov process. This can be interesting for multiple reasons. For one, this could tell us how the rates, or any other possible factor, influence the dynamics of the regime-switching. From an economic point of view, it makes sense that the freight rates or other factors like economic activity or the price of oil can affect the freight market via regime-switching.

To estimate the endogenous model we fit a logit model to the state of the Markov process. Using standard non-linear models we can thus add the covariates, like current freight rate, to the model with ease. A logit model is a model on the form,

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

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 $t-1$, and lastly, $Y(t-1)$ are possible other covariates. S and Y do not differ, but S is highlighted since it emphasises the endogenous nature of the model.

The method described above will provide us with two $AR(1)$-models, one for each regime, and the transition probabilities. However, this is not the ultimate goal of our model. We therefore need to "translate" the parameters of the $AR(1)$-models to a continuous time framework. To do this, we follow the same basic idea as in (Tvedt, 1995).

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 some slightly different calculations 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,

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

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

This paper aims to model the spot price obtained in the market. The market prices in shipping markets are not immediately obvious. It can be argued that the good we wish to study, the shipping service, is not a homogeneous commodity. The observable transactions in the market are the hiring of vessels. Vessels are heterogeneous and their characteristics affect the price they fetch on the market. Moreover, different shipping companies and ports might differ in the services they provide. Therefore, we need to infer the price of the shipping service. This is done with market indexes.

We choose to study third-party indices and there are multiple reasons why. Firstly, this makes the results transparent and reproducible to a greater extent.

Secondly, financial contracts in shipping are written on indexes. Thus, for a financial investor modeling the index might be more important than modeling the fixtures in the market. Third, even though the service of transporting a good on any vessel is in itself homogeneous, the individual vessels are diverse. This means that the price reported in the fixture reflects both the ”typical” price in the market at the time of agreement and the characteristics of the vessel. A third-party index would give the ”typical” price in the market for a standard vessel.

One of the most important providers of indices in the shipping industry is the Baltic Exchange. We choose not to stray from this tradition. One advantage of using Baltic indexes is that they are forward-looking. This means that they include some of the beliefs of the market participants. Baltic indexes are constructed by inquiring with shipbrokers about the rates they would demand/offer on a particular voyage with a particular type of vessel (Ltd, 2023). This has advantages. Illiquidity is also an issue for the broker, but prices can be inferred based on experience with similar routes or vessels. One of the potential issues with construction and using an index like this is moral hazard in reporting. If the broker has an interest in pushing the price in some direction then they might be tempted to influence the index away from its true value. A similar methodology was used to calculate LIBOR interest rates. (A. Veenstra & van Dalen, 2008) calls into question the construction of many of the commonly used market indexes altogether.

In addition to choosing an index provider, we also need to choose which indexes in particular we wish to study. Either we can choose to focus on individual routes, or we can study a size segment as a whole. Different types of vessels operate in different markets. Dry bulk carriers and tankers are not competing for the same cargo. However, different size segments also matter a great deal. Some size vessels are preferred in the transport of certain commodities. For example, Suezmax bulk vessels are preferred in the transportation of coal and iron ore but Handysized vessels are preferred in the trade of other commodities like scrap iron (Stopford, 2008). In addition, not all ports are equipped to handle every size of vessel. Hence, port infrastructure dictates which vessels can service which routes. Size differences between vessels are not only theoretical, (Kavussanos, 1996) finds that the freight rate volatility differs between vessels of different sizes. Therefore we elect to study the Baltic indexes for tankers and dry bulk carriers. We choose Handysize, Panamax, and Capsize dry bulk indexes. Tankers are usually fixed in worldscale (WS). WS is a standard scale of prices for transporting oil based on the cost of operating a standard vessel on the route (Stopford, 2008). The problem with worldscale from our perspective is that the standard vessel changes over time (“Worldscale”, n.d.). Therefore we study time charter equivalent (TCE) indexes for tankers. Hence, for tankers, we choose VLCC TCE, Suezmax TCE, and Aframax TCE indexes.

The Baltic Handysize Index (BHI) is a weighted average of 7 routes. The standard vessel is 38 200 DWT vessels, non-scrubber filter, less than 15 years old with 5 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

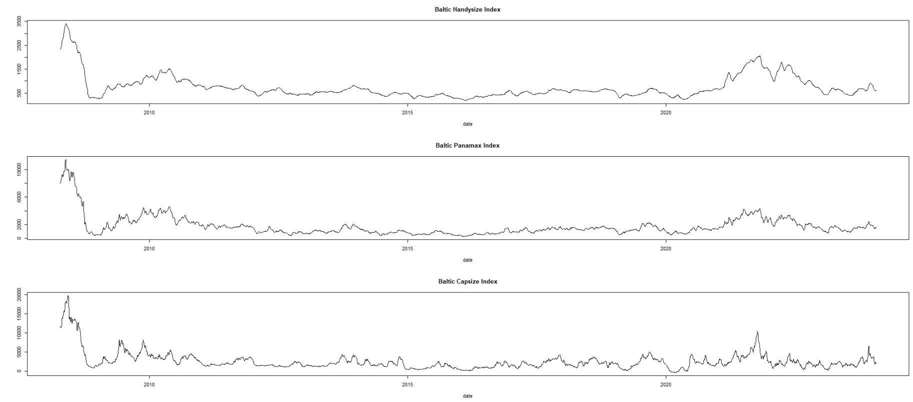

Figure 3: Baltic indices for various sized dry-bulk carriers.

of time charter contracts on 5 routes worldwide. The vessel characteristics used in the construction of 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 6 different 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 different 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 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.

The data is kindly provided by Clarksons Shipping Intelligence Network. Indices have different starting dates, therefore the data starts from the 11th of April 2008 until the 28th of January 2024. We choose daily data as the time resolution for this paper. This means that we have 3964 points of data for our analysis.

6 Results

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

Consider first the results in Table 1. These are the estimates for the regime-

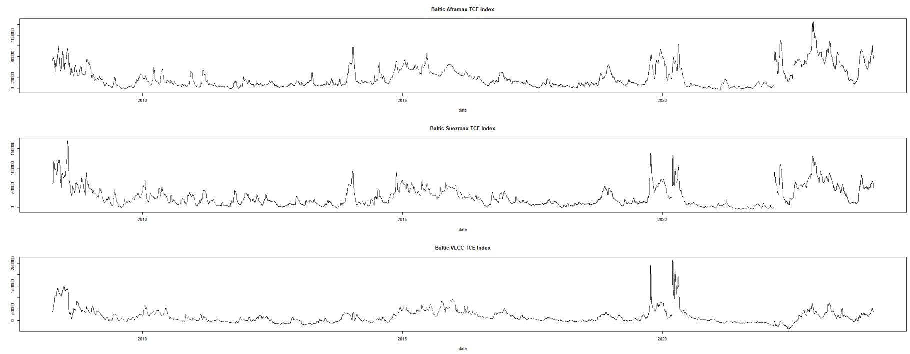

Figure 4: Baltic TCE incises for various sized tanker.

switching $AR(1)$-model. The subscript for each parameter indicates which regime they correspond to. Here regime 1 is the regime where supply is inelastic (the hockey stick handle of the supply curve), and 2 is the regime where supply is elastic (the hockey stick blade of the supply curve).

We can see that there is a vast difference in the volatility between each state. If we take 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 is as expected. If the supply is inelastic, then vessels are fixed via an auction where the highest bidder can hire the vessel. Thus sudden increases in demand can not be met by increasing supply and the only way to clear the market is by increasing the price. On the other hand, when the supply is elastic, sudden increases in demand can be met by increasing supply.

An interesting point here is the difference between the dry bulk and the tankers. The ratio of volatility for dry bulk vessels varies between 4.75 and 5.27. On the other hand, the tankers vary between 6 and 9.6. Not only is the ratio generally higher for tankers, but the span is also greater. Moreover, the difference in the ratio is falling for dry bulk vessels as the size increases, i.e., Handysize dry bulk carriers have a higher volatility ratio than the much larger capsize. On the other hand, for tankers the volatility ratio increases in size as the vessels become larger, i.e., the volatility ratio is greater for the huge VLCC vessels than for the smaller Aframax vessels.

If we look at volatility for vessels of different sizes an interesting pattern emerges. We see that the volatility increases as the vessels grow larger. This supports the findings in (Kavussanos, 1996). Kuvussanos argues that smaller vessels are more diverse, and have fewer size constraints in port. This means that they can serve many more trades than larger vessels and are thus not subject to great variations in the markets (Kavussanos, 1996).

Now consider mean reversion. A process is mean reverting if $\beta < 0$ (Filipović, 2009). Return now to the discrete estimates in Table 1. Since, $b = \log(\beta)$, for $\beta < 0$ we need $b < 1$. The stars in Table 1 correspond to the hypotheses test that $H0 : b_i = 1$ for $i = 1, 2$. The hypotheses test shows that all tanker segments

	BDI Handysize	BDI Panamax	BDI Capsize	BDTI VLCC	BDTI Suezmax	BDTI 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
r^2	0.9991	0.9975	0.9941	0.9405	0.9555	0.9636
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
r^2	0.9998	0.9988	0.9983	0.9978	0.9975	0.9977

Table 1: 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.

are significant mean reverting, in addition to Panamax and Aframax dry-bulk. Spot rates for Handysize dry-bulk vessels are not significantly mean reverting in either regime. This is an interesting result. A possible explanation for this is the same that is presented in (Kavussanos, 1996) for the size difference in volatility. Possibly, the smaller vessels are more diverse and serve a broader market. Hence, they are less affected by market conditions.

To assess the level of mean reversion we see that if $b < 0$, then (5) converge faster to a/b as $t \to \infty$. Hence, a more negative b is more mean reverting. If we return to the results in Table 2 we see that for the tanker segments $b_1 < b_2$. This means that they behave as we expect. When the supply is inelastic, the rates are more mean reverting. On the other hand, the dry-bulk segments do not seem to exhibit this behavior.

Moreover, the difference in mean reversion - i.e. the difference between how strong the mean reversion is in each segment - is smaller for the dry-bulk segments than for the tankers. One can argue that dry-bulk carriers service a more diverse market. Therefore, when there are few vessels in a particular

	BDI Handysize	BDI Panamax	BDI Capsize	BDTI VLCC	BDTI Suezmax	BDTI 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 2: 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.

market and the demand increases, then the goods can be transported on vessels of other sizes. The freight rate can therefore not rise as rapidly. Hence, the market is less affected by constrained supply in markets. On the other hand, the tankers we study serve a more limited set of commodities, mainly petroleum products. Once the supply of capacity is constrained or demand has increased spot rates can increase quickly. Since fewer vessels are transporting other commodities that can quickly bring balance back into the market the swings might be stronger.

A robustness check (see Appendix A) interestingly fails to provide evidence to the effect that freight rates for dry-bulk vessels are mean reverting. The robustness check is done on a sub-sample between 2012 and 2020. The failure of finding mean reversion could support the observation in (Adland & Cullinane, 2006) where Adland and Cullinane found that the freight rates were only mean reverting at the edges. This means that rates could be mean reverting, but only in extreme situations, examples of which might not be found in the sub-sample. 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 highlight an important difference between the two segments. The reason for this is not clear but we might argue that it is for the same reason as above. That is, dry-bulk vessel markets can bring balance to the market more easily because of the diverse and broad market. Hence, the regime does not matter as much for the mean reversion of the freight rate.

The coefficient of determination, r^2, can be thought of as how well the model explains the volatility we observe in the data (Devore & Berk, 2012). Table 1 lists the r^2 for the $AR(1)$ model for each regime and each segment. In general, we see that r^2 is greater for the models fitted to regime 2, the regime with elastic supply. This means that this model is better at explaining the volatility in regime 2 than in regime 1. This could mean that when the market is in regime 1 the volatility is not as well described by our static volatility. Another feature of the data is that the r^2 is greater for dry-bulk than for tanker segments. This is interesting and could be due to tanker markets being more susceptible to shocks from world events. Nevertheless, r^2 is excitingly high.

6.1 Transition matrices

An important part of any Markov model is the transition probabilities. The transition probabilities tell us the probability of the process X moving from one state to another. The states in our model are interpreted as market regimes or market sentiments. Whether the market is "good" or "bad". Therefore, one would expect the probability of the market moving from one regime to the other depending on the current freight rate.

We have modeled the transition probabilities using a logit model where the current freight rate is a covariate. 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 3.

There are multiple insights to gain from investigating the transition matrices. Firstly, the Markov Chain, X, does not have any absorbing states. We can see this by the fact that no elements in any of the matrices are 1. For this to occur the coefficients would have to approach infinity. In an absorbing state, the Markov Chain cannot move away from the absorbing state once it has entered. An absorbing Markov Chain would not make sense in this application. 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, there would never be enough capacity. 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 persistent low freight rates push out inefficient vessels and inefficient shipping companies to avoid loss-making. To achieve this, shipowners would scrap vessels, primarily older and less efficient vessels.

Secondly, we see that the current freight rate is significant for transition probability for all segments and all sizes. We see 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.

	BDI Handysize	BDI Panamax	BDI Capsize	BDTI VLCC	BDTI Suezmax	BDTI Aframax
$\beta_{12,0}$	4.63717***	5.06236***	3.47691***	3.26030***	3.46513***	3.65214***
	(0.22911)	(0.27126)	(0.15583)	(0.09942)	(0.12396)	(0.13308)
$\beta_{12,1}$	−0.00142***	−0.00099***	−0.00028***	−0.00002***	−0.00003***	−0.00003***
	(0.000246)	(0.00015)	(0.00006)	(0.00001)	(0.00001)	(0.00001)
$\beta_{21,0}$	1.88347***	1.56066***	1.42622***	0.50690***	0.41789**	0.76209***
	(0.26689)	(0.30852)	(0.22240)	(0.13057)	(0.17107)	(0.18297)
$\beta_{21,1}$	0.00102***	0.00065***	0.00043***	0.00001***	0.00003***	0.00003***
	(0.00029)	(0.00015)	(0.00008)	(0.000002)	(0.00001)	(0.00001)

Table 3: 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.

Not surprisingly the probability of going from Regime 1 to Regime 2 is decreasing in the freight rate. This means that when the freight rate increases, then the probability of moving from the regime with an inelastic supply to the regime with an elastic supply falls. On the other hand, the probability of changing from Regime 2 to Regime 1 is increasing in the freight rate. This means 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.

6.1.1 Exogenous transition matrices

We can also find the static transition matrix. These are constant transition matrices. It is simple to interpret the matrix. 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.

	1	2
1	0.94	0.06
2	0.03	0.97

Table 4: Exogenous transition matrix for Handysize dry-bulk carrier

Some patterns emerge from the Exogenous transition probabilities. For one, we see that the probability of staying in state 2 is higher than staying in state 1. This could indicate that the market is more stable in state 2. Moreover,

	1	2
1	0.94	0.06
2	0.03	0.97

Table 5: Exogenous transition matrix for Panamax dry-bulk carrier

	1	2
1	0.92	0.08
2	0.06	0.94

Table 6: Exogenous transition matrix for Capsize dry-bulk carrier

the probability of remaining in state 1 is higher for dry-bulk than for tankers. This means that the Markov Chain can generally be expected to remain in the regime with inelastic supply for longer for dry-bulk markets.

7 Conclusion

This paper has aimed to model 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 modeled the indices with a regime-switching Ornstein-Uhlenbeck model inspired by (Hamilton, 1989). This approach allowed us to use stochastic filtering to model the indices in two different regimes. Standard economic theory on shipping markets describes the supply function in a market as a hockey stick (Stopford, 2008). One of the regimes in our model corresponds to the market when the supply is elastic and the other regime corresponds to a situation where the supply is inelastic, i.e. the handle and the blade part of the hockey stick.

As theory predicted, the stochastic properties of the freight rate are different between the two market regimes for both indices. Firstly, the mean reversion is stronger in the regimes where supply is inelastic, but we only found significant support for this in tanker markets. Secondly, volatility is higher in the regimes where supply is inelastic. In addition, the volatility increases with the size of the vessels. Moreover, 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 as great in tanker segments.

We also studied the transition probability, both as a static transition probability and as a dynamic probability. Analyzing the static probability, we found that the process seems to remain in Regime 2 for longer than it remains in Regime 1. However, there is a difference between dry bulk and tankers. The dry-bulk seems to have a more even distribution between states, i.e. the probability of remaining in a state is more even between the two states. On the other hand, tankers have a more uneven transition where the probability of staying in state 1 is lower than for staying in state 2. We also modeled the transition

	1	2
1	0.74	0.26
2	0.06	0.94

Table 7: Exogenous transition matrix for VLCC tanker

	1	2
1	0.81	0.19
2	0.07	0.93

Table 8: Exogenous transition matrix for Suezmax tanker

of moving between states dynamically. Here we found that the current freight rate is significant to explain the transition probability.

There are some interesting possible extensions to this research. We only considered parameters that change with state, but not in time. It could be interesting to look at both time-varying and state-varying parameters. Moreover, we saw that the segments behaved differently. This could be interesting to investigate further, by systematically investigating different routes, segments, and sizes of vessels. A different extension that might have been interesting would have been the inclusion of seasonality. Moreover, the index we use is limited in scope. Our data only extends to 1998. If we had data further back we might be able to model better. 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.

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 endogenous 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,

	1	2
1	0.86	0.14
2	0.05	0.95

Table 9: Exogenous transition matrix for Aframax tanker

	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 10: 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.

and this could influence the hypotheses test.

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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 11: 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 12: 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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