Norwegian School of Economics
Bergen, Spring 2023

Portfolio optimization of chartering contracts

An empirical study of the chartering policies for Western Bulk Chartering ASA in the period from 2016 to 2022

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Master thesis in Financial Economics (FIE) &

Business Analytics (BAN)

NORWEGIAN SCHOOL OF ECONOMICS

Abstract

This thesis looks at how the shipping operator Western Bulk can structure their chartering decisions through a portfolio approach. This entails looking at chartering contracts as single investments, which are part of a universal investment set. Looking at the period 2016-2022 we seek to discover how an optimal portfolio can be constructed and how it compares with the actual operations of Western Bulk.

Traditionally portfolio optimization has been common within securities and corporate finance. However, its applications have been extended to a wide array of industries. Our paper builds on this and implements this approach into bulk shipping. Through the Markowitz model we investigate what constitutes an optimal portfolio in terms of contract- and geographical distribution. The optimal solution finds evidence for deviations to the historic operational data of Western Bulk. These results and preceding calculations have not been subjected to a full set of possible constraints. Thus, our findings do not provide a complete realistic application to Western Bulk's operations.

Acknowledgements

This thesis has been written as the final assignment of the master profiles in Financial Economics and Business Analytics. We would like to express our gratitude to our first supervisor, Professor Roar Os Ådland for helping us along the journey. Your expertise in the shipping business and academic writing have been invaluable for us. Moreover, we would like to thank Egil Husby at Western Bulk for providing us with the data allowing us to complete our thesis. Our appreciation extends to your comments along the way, as well as providing us with valuable insights about the bulk shipping industry. Lastly, we would like to thank Professor Haiying Jia for being our supervisor in the final stages of our thesis.

Bergen, May 2023

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Contents

Introduction

As a shipping company, Western Bulk is considered an “operator” rather than a “shipowner”. This entails that Western Bulk does not own its shipping fleet, but contract in the vessels they desire. These vessels are then put on appropriate charters, often based on decisions concerning risks, profits, traditions and experience (Berg-Andreassen, 2011). As an operator Western Bulk is positioned between vessel- and cargo owners but does not serve as broker. Currently (10.02.2023) Western bulk have employment of 127 vessels on the water, serving over 300+ customers worldwide. An operator offers two services in terms of service for freight and trading, where trading accounts for the majority of operations. The trading business model of Western Bulk consists of exploiting static arbitrage between chartering in ships on a USD/day basis, before chartering out the ships on another period. To perform these operations Western Bulk, rely on three tools: time charter (TC) contracts, cargo contracts and FFAs (Husby, 2023).

Commonly an operator conducts different strategies depending on numerous factors. Strategies can include chartering a ship and then either secure a cargo immediately or holding the TC until the market is more favorable. The operator can also fix a TC in advance in hope for a stronger market in the future. Strategies can also involve speculations on geographies where providing vessels and/or freight to other markets could create a profitable spread. FFAs also serve as a tool as timing and fluctuations on these contracts in different geographies is an attractive trading opportunity for the operator (Husby, 2023).

For an operator it is important to handle the risk involved with its operations. Factors such as chartered fleet size, exposure to different geographies and different cargo and vessels can be important to ensure diversification. As there are known differences in freight rates between geographies, modern portfolio theory is a great tool to find a profit optimal allocation of vessels.

Our problem statement relates to finding optimal chartering policies of Western Bulk. This is done through an empirical study and portfolio optimization of data regarding chartering policies of Western Bulk between 2016 -2022. The knowledge gained from this thesis contributes to broadening the existing maritime academic literature. Further it will provide useful insights into how an operator should allocate its capital to maximize returns. We hope that our calculations can provide a new perspective to Western Bulk and other operators in the dry-bulk market.

The thesis is introduced by a literature review arguing for the relevance of our project. The theory section that follows is divided between shipping theory and portfolio theory. The first part describes the relevant contracts and how an operator may conduct business including hedging. The second part involves description of our chosen theoretical modular foundation, Markowitz portfolio theory. Key concepts such as the efficient frontier and portfolio variance are introduced. The theoretical section is accompanied by the method section which describes how our model operates. Further we describe our data and provide some key descriptive statistics which will provide essential insights. This section will later serve as a benchmark when we introduce our empirical results. Finally, we introduce our empirical results. The thesis ends with critique of our findings and recommendations for Western Bulk.

Literature review

Our thesis seeks to explore an optimal portfolio of contracts for shipping operators. This is inspired by the work of (Adland, Benth, & Koekebakker, 2018) and (Adland, Bjerknes, & Herje, 2017) where they further prove that there is a freight rate premium on the cross-Atlantic route in the dry bulk market. The purpose of this thesis is to extend the current literature in dry bulk shipping by exploring how and if there exists an optimal portfolio of contracts. To our knowledge there has yet been published an article with this specific topic in mind, although there are published some articles with similar topics.

The articles of (Carisa, Tsz, & Siu, 2019) and (George Alexandridis, 2018) seek to find optimal portfolios of vessels/ contracts. The article by Carisa et.al is particularly interesting as this article constructs portfolios of carefully selected vessel types to find an optimal mixture of different types and size of vessels. Although our thesis does not account for different vessel types the mean variance approach is similar to our own methodology. The article also approaches the market as an operator. The works of Cullinane hold great relevance. By considering shipowners financial commitments as investments, he constructs an optimal portfolio theory using Markowitz modern portfolio theory in the dry-bulk market (Cullinane K. , 1995). Different to our approach is that choice of corporation. Our approach is solely used on an operator contrary to Cullinane where the company owns the vessels. Additionally, our work does not factor in several types of vessels. Still this article holds great relevance for our approach and is similar to our own simulations. The works of (Adland & Jia, 2017) finds that there are some diversification benefits when increasing the fleet size due to the diversification on geography and time. Our model is based on a large number of trades and will also show benefits of diversification in terms of optimal profits.

Our attention is further focused on relevant articles from other markets. Our chosen methodology is applied to numerous fields spanning from the securities market to the selection of military equipment (Sokri, 2012). In the following section we will only list a select number of relevant articles displaying some of the variability in applied methods. Articles written on markets/ companies who operate in similar way as Western Bulk will be mentioned.

The articles of (Algarvio, Lopez, Sousa, & Lagarto, 2017) and (Atmaca & Gökgöz, 2012) are of interest. The first articles explore how an electricity retailer can optimize its profits by combining a portfolio of four different contracts (Algarvio, Lopez, Sousa, & Lagarto, 2017). The second article investigates the Turkish electricity market. This article also focuses on the allocation between contracts and how that affects its revenue potential. Both articles use Markowitz' portfolio theory and contain roughly the same approach as this thesis applied on another market.

Theory

In the subsequent analysis it is assumed that the shipping operator seeks to find an optimal portfolio of contracts. The process entails a maximization of return on investments, while managing risk at an appropriate level. Consequently, the operator will be able to employ the ships in the voyage and (or) time charter markets. At the same time contracts of affreightment (CoA) can be applied for hedging. The chosen chartering strategy will thus determine if the operator goes long or short on tonnage[1]. Given these aspects, the limitations that fleet size and composition have on the business options of the operator is removed (Berg-Andreassen, 2011). The shipping operator will then be able to allocate capital between a wide array of charters, where the importance of a well-constructed portfolio of contracts is vital for company performance (Carisa, Tsz, & Siu, 2019).

[1] The term shipowner is used in the literature. However, the methods and implications described are of equal relevance to an operator. Thus, the term operator is used in accordance with the mentioned literature.

Understanding the composition of an optimal portfolio entails assessing various practical constraints in the subsequent optimization calculations[2]. This can include constraints on the concentration of the portfolio in segments, which can be contract types and geographical region. Having this constraint will prevent overexposure in one segment, reducing risk of drawdowns if the segment proves to be wrong. Furthermore, the general structure of the trades can also be included as a constraint, which includes the availability of time charters. Additionally, working capital constraints will be possible. This will ensure that capital is not depleted (locked) if an investment opportunity should arise.

These constraints are all related to practical matters of Western Bulk's operations. Including them will improve the realism and potential impact of the portfolio optimization. This will require extensive information about the operations of Western Bulk. We will not present such metrics and have opted for a less practical approach in the forthcoming calculations. Doing so will still keep the theoretical significance of our results intact. Our approach will therefore have a more theoretical approach as these constraints are not included.

Chartering choices for a shipping operator

In the following subchapter the thesis will briefly discuss the relevant contracts used in Western Bulk's operations. The first half of the operations is to hire a vessel. The two relevant options are Voyage Charter (Trip Charter), Time Charter and Contract of Affreightment. Where the trip charter is a contract for a specific voyage between two specific ports the time Time Charter is leasing of a vessel for a specific period (Stopford, 1997).

Cargo contracts

On the other side of the operations is the freight contracts. These contracts are often settled with a broker as an intermediary. The contracts are ether customized as a form of time charter or trip charter. The specific rate is determined by the underlying contract and the price per ton of the specific cargo. In sum the price which the cargo owner is paying is determined by the current rate of the specific cargo multiplied by the VC/TC contract (Stopford, 1997).

[2] Assessment of constraints on shorting are mentioned later in the thesis.

Hedging a contract

In addition to the contracts described above Freight Forward Agreements serve as a useful tool in Western Bulks operations. A typical starting point for a shipping operator is to lease a vessel through a period. The period is most of the time set as an interval. This means, for instance, that for a period of 3-5 months the operator is obligated to lease the vessel for a minimum of three months but have the option of delaying the return of the vessel by an additional two months (Husby, 2023). The uncertainty and pricing of optionality is indeed a part of the business model for many ship operators. A TC usually holds two sources of optionality: the extension and the redelivery area optionality (Adland & Prochazka, 2021). The extension of the chartering period is important as it enables the charterer to fully capitalize on a potentially strong market. The charterer extends his period if the rates lead to net positive profits and conversely redelivers the vessel at minimum chartering period if the market is weaker. The area optionality is also important as it can enable the charterer to take advantage of the documented fronthaul-backhaul in the dry-bulk market (Adland & Prochazka, 2021).

Freight Forward Agreements (FFAs) also make a suitable hedging opportunity for an operator. As the name suggests a Freight Forward Agreement (FFA) is a forward contract for vessels and is typically used by operators/charterers as a hedging strategy to ensure predictable freight rates (Kasimati & Veraros, 2018). For the operator these contracts serve as an opportunity to earn additional revenue if the market if favorable or hedge against further volatility. Although the process might seem simple (Adland & Jia, 2017) elaborates on several sources for deviation between a hedge revenue stream and a sport rate. Important factors include technical specifications, actual operating speed, geographical trading patterns and timing mismatches. Although FFAs are an important strategy for an operator they will not serve as a specific portfolio choice in our model. For that reason, FFAs will not be discussed any further.

Different operational strategies

To understand how a shipping operator might conduct business we will showcase some operational trade-offs that the operators must consider. Assuming that the operator charters a ship it has to decide on the contract depending on the speculative forward-looking view of the operator. As the ship is chartered the operator needs to fix a cargo to freight. As different regions specialize in a selective number of products the operator has to carefully consider where the ship is chartered as well as in which region the vessel operates in. Based on the ship operator's knowledge and experience it will try to position the ship in a region where it expects the rates to excide expected level (Husby, 2023).

How the rates fluctuate is determined by several factors including macroeconomic developments, geopolitics, results of harvest, climate etc. (Stopford, 1997). The operators' profits will be a function of the difference in rates and how it's able to maximize the utilization of the ship. A number of fixtures can be made to make profits, including chartering ships in one region and then take on cargo with a loss in order to move the vessel to another region with a potential profitable freight rate (Husby, 2023).

In addition to the operational decision the timing of entering the specific contracts will have great impact on the overall results. By agreeing to transport a cargo in advance the operator can speculate on falling chartering rates. Furthermore, one can charter a vessel in the belief that the market will evolve positively or to move the vessel to a more profitable region to earn profits from unmet demand. Lastly the operator can speculate with hedging in FFAs.

Markowitz and portfolio optimization

Background for portfolio optimization

Western Bulk is faced with a variety of investment opportunities in their chartering decisions. In a perspective of investment planning and risk management, the choice of charter investments can be determined through portfolio optimization. The concept of portfolio optimization is common in corporate finance and its applications extend to shipping, as well as other industries (Lorange, 2009). Often referred to as Modern Portfolio Theory (MPT), the concept was introduced by Harry Markowitz in 1952.[3] He initially published the theory in the Journal of Finance under the title "Portfolio Selection", where he presented his findings on the principles of diversification in portfolio selection. Using the same methodology, we can apply it to the case of Western Bulk.

Comparing portfolio management in traditional stock markets with shipping markets, we find a number of similarities but also differences. The approach in the stock market is twofold

[3] Harry Markowitz, "Portfolio Selection", *Journal of Finance,* March 1952.

through, a stock picking approach or an index-based portfolio management approach (Lorange, 2009). Conversely, the strategic composition of income yielding chartering contracts can be determined through a portfolio approach. This constitutes that shipping operators have a given preference in their risk/return payoff, in deciding which trades to take part in (Berg-Andreassen, 2011).

Moreover, stock market portfolio management allows for differentiation between asset selection, risk selection and market timing. The same goes for shipping portfolios when a shipping operators' financial commitments are considered as investments (Cullinane K. , 1995). The shipping portfolio will then differentiate between leverage decisions (risk), asset mix selection and chartering/trading strategy (timing). Risk selection will therefore come from both asset selection and leverage, which in turn determines the return conditional on expected normal performance (Lorange, 2009).

As mentioned, the Markowitz model of portfolio selection includes calculations of expected returns, risks and risk attitudes. Applying these measurements, one could derive any optimal portfolio to given risk/return requirements for the available set of market investments. Finally, the application of the model treats market conditions and the shipping operator's risk preference as inputs in the selection of an optimal portfolio (Cullinane K. , 1995).

Shipping contracts available for portfolio optimization

The available set of investments in our thesis is comprised of three strategies. Corresponding with each strategy is the use of specific contracts, which are the following: *Spot, Short Period and Forward Cargo.* A spot contract has the shortest duration and includes fixing a cargo forward (usually 30 days), before fixing a TC to cover the cargo. Short period contracts include fixing a vessel for a period of 4-6 months, where the aim is making generating profits from trades. This is a long position and aims to take advantage of rising market sentiment, while also factoring in geographical and basis risk. The contract for forward cargo is similar to the spot contract but is considered as a pure short position. This stems from the cargo having a laycan which is 30 days (or more) ahead in time at the time of fixing (Husby, 2023).

These three contract types are then available for a variety of trades across the world. In our paper we have grouped these trades to three main geographical areas: *Atlantic, Indian Ocean and Pacific.* All three contracts are available for each region, which constitutes 9 possible contracts or investment opportunities. This investment set could have been extended to include another contract type for *index vessels*. As this is a relatively new contract type for Western Bulk it has few data points relative to the other contract types. Hence, it was chosen to omit this contract from the investment set.

In the forthcoming methodology and calculations, our model does not include the possibility of shorting these contracts directly. Doing so does not exclude the possibility of shorting assets the investment set. As stated above the forward contract is a pure short position. Hence, the possibility of shorting is still present. The contracts can therefore be considered to be a form of "market neutral". A "market neutral" approach seeks to profit from such mispricing of assets and creating a portfolio of said assets (Jacobs & Levy, 2005). This is directly related to the business model of Western Bulk, which seeks to capitalize on market inefficiencies and price movements.

Framework of the Markowitz model

The universal investment set

Applying the theory of Markowitz, a universal set of available market investments must be present. Thus, it is necessary to identify these investments, which constitute the universal set of investments. By allocating available funds between these individual "assets", the combination will make out the portfolio for the shipping company (Cullinane K. , 1995). To illustrate the available set of investment set we can look at the figure of the minimum variance frontier below.

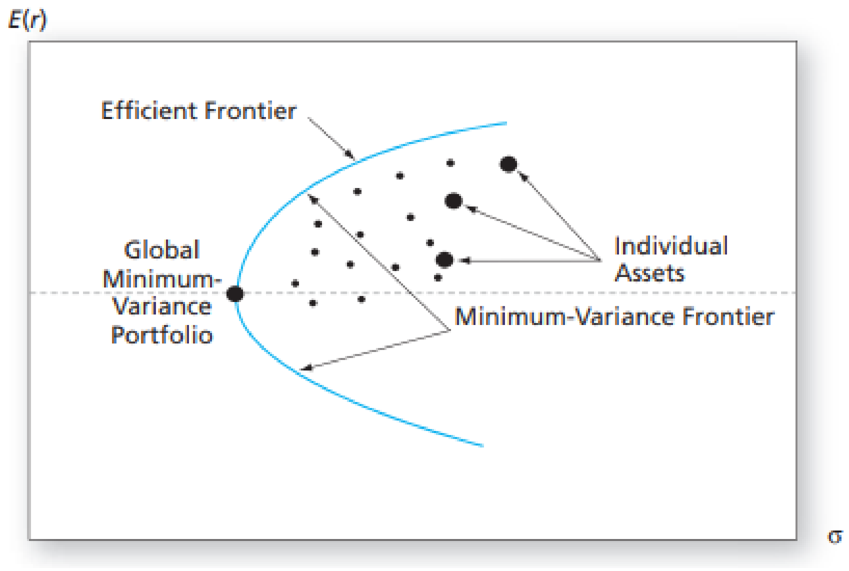

Figure 1 - The minimum variance frontier of risky assets (Bodie, Kane, & Marcus, 2014)

The figure depicts a set of *n* individual assets (investments) available to the investor. The efficient frontier portrays the lowest possible variance achievable for a given expected portfolio return. Given the available individual investments, we need to consider their properties. This includes return of assets, variance and standard deviation (SD). Additionally, these returns are likely to differ in terms of observations. E.g., contracts will have different lengths, making returns occur at different intervals. Thus, it will be necessary to annualize the returns to make them comparable investments. Through diversification among these investments, it will be possible to obtain a portfolio which is more efficient than holding a single asset (Berk & DeMarzo, 2017).

Covariance

From the same set of investments, the covariance between the return of investment i and j is measured. Through covariance we can measure the relationships between two sets of observations, which is necessary in determining the risk of a portfolio (Cullinane K. , 1995). The covariance is calculated using the following equation:

$$Cov\left(x_i, x_j\right) = \frac{1}{m-1}\sum_{k=1}^{m}\left(x_{k_i} - \bar{x}_i\right)\left(x_{k_j} - \bar{x}_j\right) \qquad (1.)$$

Here the equation depicts the covariance between investment i and j.

Covariance matrix

The full set of calculations of variances and covariances can be stored in a matrix. This matrix contains the properties needed to calculate the risk of a portfolio, and takes the following form (Carisa, Tsz, & Siu, 2019):

$$\mathbf{V}_{N*N} = \begin{bmatrix} \sigma_1^2 & \sigma_{1,2} & \cdots & \sigma_{1,N} \\ \sigma_{2,1} & \sigma_2^2 & \cdots & \sigma_{2,N} \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{N,1} & \sigma_{N,2} & \cdots & \sigma_N^2 \end{bmatrix} \tag{2.}$$

Since the set of returns from n possible investments can be used, the matrix is symmetrical of order $n * n$. Thus, the main diagonal consists of the variance (σ^2) of the investments. Along the diagonal we have symmetrical covariances of the returns (Sydsæter, Hammond, & Strøm, 2012).

Expected return of a portfolio

The return for each individual investment can be denoted by $E[r_i]$. Through the process of portfolio optimization, a portfolio will be comprised of various assets with different expected returns. Taking the weight invested in each of the assets in the portfolio will give us the overall return of the portfolio, as shown here:

$$E(r_P) = \sum_{i=1}^{n} w_i * E(r_i) \tag{3.}$$

The weight of total capital allocated in each investment is given by w_i (Bodie, Kane, & Marcus, 2014).

Portfolio variance

The calculation of the portfolio variance follows the same intuition as with the portfolio return. For the variance and covariance of assets in the portfolio, we sum the product together to obtain the variance of the portfolio:

$$Var(r_P) = \sigma_P^2 = \sum_{i=1}^{n}\sum_{j=1}^{n} w_i * w_j * Cov(r_i, r_j) \qquad (4.)$$

$$Var(r_P) = \sigma_P^2 = \sum_{i=1}^{n}\sum_{j=1}^{n} w_i * w_j * \sigma_{ij} \qquad (5.)$$

The portfolio variance is denoted by σ_P^2 (Bodie, Kane, & Marcus, 2014).

Sharpe ratio

As seen in *Figure 1* we want to hold a portfolio along the minimum variance frontier, preferably in the northwest region. Thus, it becomes evident that the MVP does not offer the best risk return tradeoff. Assessing this tradeoff is done through the Sharpe Ratio, which is given below:

$$Sharpe\ Ratio = S_P = \frac{E(r_P) - r_f}{SD(r_P)} \qquad (6.)$$

By maximizing the Sharpe ratio, we obtain the optimal portfolio to hold together with the risk-free asset (r_f). In the investment set this is represented by the capital allocation line, which is tangent to the efficient frontier (Berk & DeMarzo, 2017).

Method

This section of the thesis seeks to highlight the quantitative methodology applied to solve the problem statement. Through application of concepts described in the theory section, the Markowitz portfolio theory can be used in this setting. Complemented by the use of mathematical software in Excel, we can obtain the desired output of minimum variance portfolio, efficient frontier and optimal portfolio[4].

[4] The choice of risk-free rate in this setting is described in the results section under "*Efficient frontier and optimal portfolio*".

Optimization problem

Through portfolio optimization, the goal is often to find a mix of assets/investments which yields the highest return for a given risk level. Conversely, the goal can be set to yield a minimum of risk for a given level of return. (Carisa, Tsz, & Siu, 2019). With the mentioned investment set of n assets/investments, it is possible to create various portfolios minimizing risk for different levels of return. These portfolios make out the minimum variance frontier, depicted in *Figure 2*, which also includes the minimum variance portfolio (MVP) (Bodie, Kane, & Marcus, 2014). Obtaining the MVP is conditional on the following optimization problem:

$$Minimize: \qquad Var(r_P) = \sigma_P^2 = \sum_{i=1}^{n}\sum_{j=1}^{n} w_i * w_j * \sigma_{ij} \tag{7.}$$

$Subject\ to$:

$$E(r_P) = \sum_{i=1}^{n} w_i * E(r_i) \tag{8.}$$

$$\sum_{i=1}^{n} w_i = 1 \tag{9.}$$

$$w_i \geq 0 \tag{10.}$$

The goal of the minimization problem is to find the portfolio with the smallest variance, given by equation 8. This goal is constrained by equation (13.) to (14.). Equation (12.) states that the sum of weights invested in the assets is equal to the return of the portfolio. The sum of these weights needs to be equal to 1, as equation (13.) states. Finally, the problem does not allow for short selling, where the weight of any asset can't be negative[5].

[5] As mentioned under "*Shipping contracts available for portfolio optimization*", shorting is available through the forward contract which is a pure short position.

Portfolio efficiency

Having summarized the risk return opportunities with the minimum-variance frontier, we can determine the optimal portfolio. This portfolio will be situated in the northwestern region of the minimum-variance frontier (Bodie, Kane, & Marcus, 2014). Together with the capital allocation line (CAL) it is possible to locate the optimal portfolio. The CAL is a straight line taking the following form (Elton, Gruber, Brown, & Goetzman, 2014):

$$CAL = r_f + \sigma_I \left(\frac{E(r_P) - r_f}{\sigma_P}\right) \tag{11.}$$

The slope of the CAL is equal to the Sharpe ratio and its intercept is given by the risk-free rate r_f (Elton, Gruber, Brown, & Goetzman, 2014). Choosing the appropriate risk-free measure will be directly related to the duration of contracts available. The choice differs from traditional equity portfolios and the background for the chosen rate is given in the results section. As the slope of the CAL increases it eventually becomes tangent to the efficient frontier, which can be seen in *Figure 2* below:

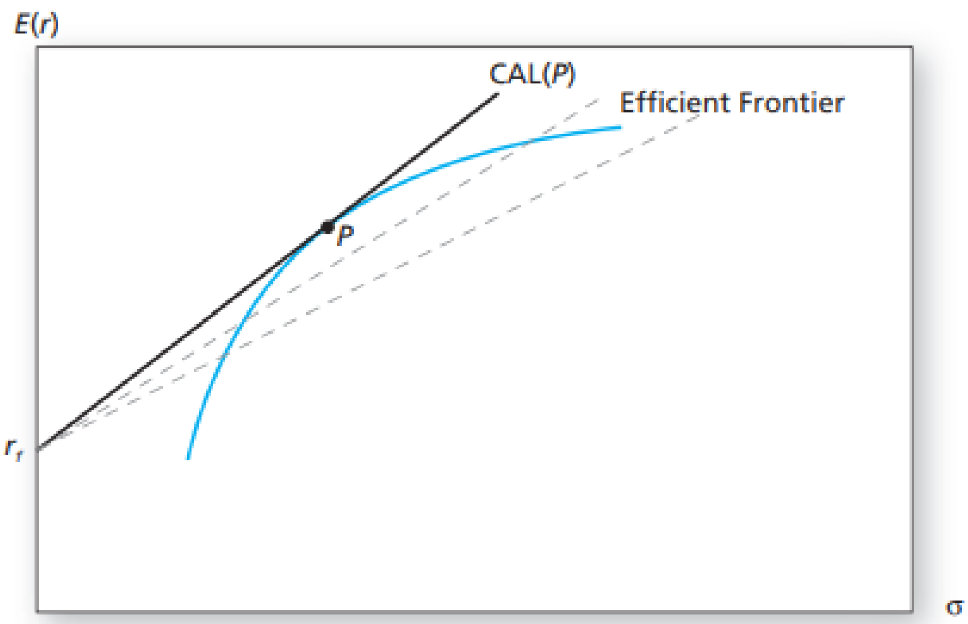

Figure 2 - The efficient portfolio (Bodie, Kane, & Marcus, 2014).

From the figure we can see that the CAL and increases conditional on the Sharpe ratio. As mentioned, the Sharpe ratio is equal to the slope. When the slope of the CAL is tangent to the efficient frontier, the optimal portfolio is obtained in this tangency point. Here the Sharpe

Ratio is maximized, and no other portfolios will offer better risk-return combinations (Bodie, Kane, & Marcus, 2014). The optimal portfolio can therefore be found by constructing the following maximization problem:

$$Maximize: \qquad S_P = \left(\frac{E(r_P) - r_f}{\sigma_P}\right) \tag{12.}$$

$Subject\ to$:

$$E(r_P) = \sum_{i=1}^{n} w_i * E(r_i) \tag{13.}$$

$$\sum_{i=1}^{N} w_i = 1 \tag{14.}$$

$$w_i \geq 0 \qquad for\ all\ i \tag{15.}$$

The problem described above does not allow for short sales, making the weight in each asset/contract positive[6]. The weight imposed on the assets in the optimal risky portfolio is denoted by w_i. As given above, the problem is a quadratic programming problem and can be solved through statistical computer packages (Elton, Gruber, Brown, & Goetzman, 2014).

Having found the optimal risky portfolio through this calculation, the investor (here Western Bulk) will finally assess the allocation of funds between this portfolio and the risk-free asset. Doing so will determine the optimal complete portfolio (Bodie, Kane, & Marcus, 2014). By assessing the risk-return tradeoff through a utility function, it is possible to determine the optimal portfolio with an analysis of historical freight rates, vessel types and charter types (Carisa, Tsz, & Siu, 2019). Any utility function for an investor will likely have individual differences in the risk return tradeoff. This is emphasized in Modern Portfolio Theory as

[6] As mentioned under "*Shipping contracts available for portfolio optimization*", shorting is available through the forward contract which is a pure short position.

indifference curves represent the investor's attitude towards risk (Bodie, Kane, & Marcus, 2014). However, this thesis will not look further into this extension, as we primarily look for the objectively optimal portfolio.

Data collection and validation

Data material

The data set used for this thesis consists of four strategies under three main regions. The four strategies are *spot-spot, short period, index vessel and forward cargo* while the main regions are the *Pacific Ocean, Atlantic Ocean and Indian Ocean*. These contracts stretch from yearly 2015 till mid-February 2023. While the start-date of the contracts cannot be set after the data was collected the termination/ end-date of the contracts stretches as far as October 2025. Structurally the data is divided between the four strategies. Within each strategy key data includes a start and end of contract, portfolio, net trading results (Net TC), total voyage days, time charter equivalent earnings and TC (cargo cost). Net TC, voyage days and TC are essential when we calculate the returns for the individual contracts. In addition to the data provided by Western Bulk we have collected data from the underlying Baltic 10TC SupraMax Index from Clarkson's. This data is paired with the index strategy to fully calculate the costs under this strategy as the costs are reflected as a percentage of the dry bulk index. It is assumed that all contracts under Index strategy is conducted with the similar vessel type.

Data processing and validation

The data from Western Bulk was provided over four strategies, where they commonly differ in duration. This is of relevance as we need to have comparable returns from between each contract type. The spot contracts have the shortest length with an average duration of 33 days in the period 2016-2022. Similarly, over the same period the forward contracts have an average duration of 36 days. Contrary, the short period contracts are longer and usually last for a period of 4-6 months. The longest contracts are held with index vessels and have a duration for 6-12 months.

Additionally, the data arrived in a format where many contracts were not assigned specifically to one of the three mentioned regions specifically. Each contract was therefore assigned to a specific region based on the fronthaul departure port. For example, a vessel from Atlantic to the Pacific where assigned to the Atlantic-region For a spot contract the location of the starting port determined its region, also when the travel is cross-regional. For contracts of longer duration with multiple port entries and departures the contracts are assigned to a region if most ports are in one geographical area.

To compare the returns between each contract, we have annualized the returns. Thus, our data have been aggregated from the mentioned durations to a yearly perspective. We then assumed that the returns from each contract have linear yearly returns. This assumption was chosen over compounding returns, as that would incur significantly biased and unlikely large yearly returns. As the contracts for spot, short period and forward are not part of a market they can be created any day of the year. Thus, the linear return for a year is calculated in the following manner.

$$Linear\ yearly\ return = Contract\ return\ \left(\frac{365}{length\ of\ individual\ contract}\right) \quad (15.)$$

In order to calculate the returns for the index vessels, the contracts had to be "matched" against the underlying Baltic 10TC Supramax Index. It is assumed that this strategy is entirely based in the Supramax segment. Data is downloaded from Clarksons Research and filtered for the same period as the data from WB (Clarksons Research, 2023). Where the index contracts are dealt with over a time period the BDI is given for every trade day. To overcome the evident difference in time we have matched all BDI's within the index contract time and then made an average. To derive the cost the BDI average is multiplied by the percentage BDI index value and then multiplied with its respective length of contract, similar to the calculation of the other contracts. This computational approach solves the time period issue, while also providing a reasonable approximation of the cost that were carried by WB of the respective contracts. Since the BDI index is part of a regulated market venue, the possibility to place positions is limited to time of opening and closing. Hence the number of trading days are limited, making the linear return take the following form (Odean, 1999).

$$Linear\ yearly\ return = Contract\ retrun * \left(\frac{252}{length\ of\ individual\ contract}\right) \quad (16.)$$

Descriptive statistics

The section of descriptive statistics is meant to provide some basic insights into the data. It will also be held as a benchmark comparison to the optimal portfolio displayed in the next section.

Number of contracts per region	Atlantic	Indian	Pacific	Sum
Spot-Spot	237	105	181	523
Short Period	359	159	230	748
Index Vessel	60	15	16	91
Forward Cargo	192	51	143	386

Table 1 – overview of contract for different regions aggregated across all years.

Firstly, we glance at the overview of the contracts, its composition between different contracts and the contracts geographic origin. For the interest of our analysis, we can clearly see that there is high number of observations of all contracts excluding the index vessels. As there are few observations spanning over a total of 8 years (2015-2023) the index vessel contract type is removed in our empirical analysis. Few observations increase the impact of a single observation and may skew the overall average and standard deviation affecting our model. This issue will be further discussed in the empirical analysis. Further analysis reveals that the data span from April 2015 till February 2023. Observations are quit evenly split between all full years.

Closest to our empirical results is how the different geographies affect the overall profitability of Western Bulk. The graph below depicts how the different areas affect the overall profitability.

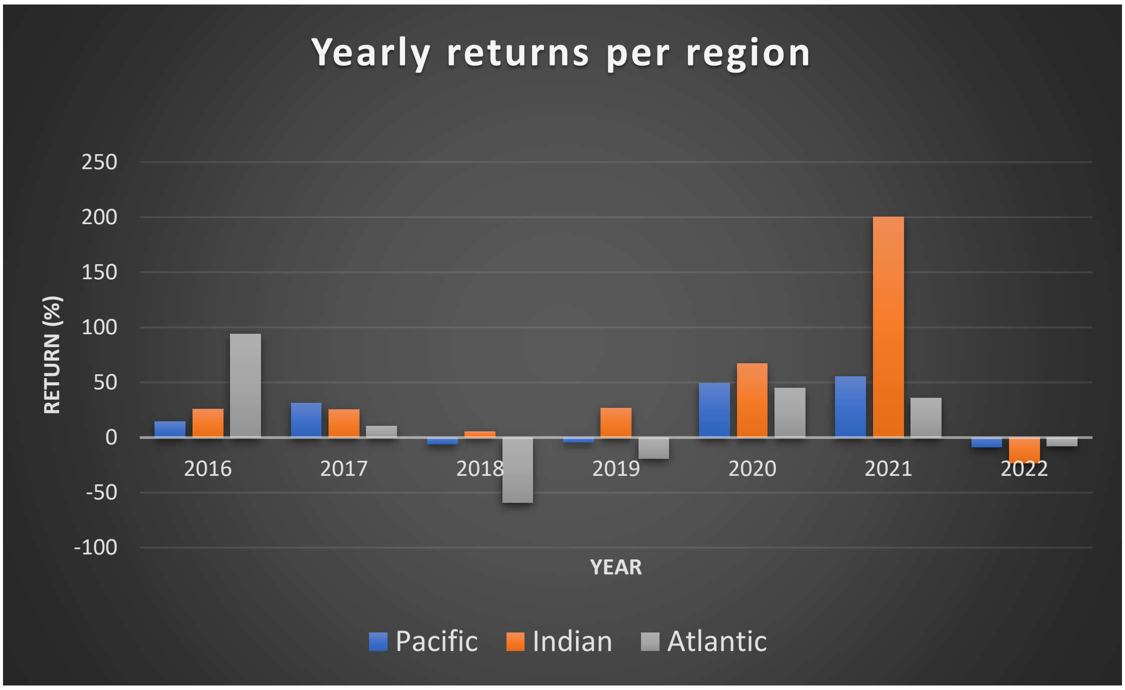

Figure 3 – Yearly returns for each geographical region (2016-2022).

As the graph shows, the three main geographical areas are contributing differently to the overall profits. While some trades and strategies might be profitable in one year, we can clearly see that markets change, and different allocation could be optimal for different years and market circumstances. The main takeaway is that all three geographies prove profitable for most years, but all areas lose money in at least one year. When reading the graph, it is important to recognize that this graph does not account for the composition of different contracts or the inherent risk following those contracts. This is merely a brief overview of how the returns are made between the main geographies.

Reference data - empirical analysis

Below, *table 2* is depicting capital allocation/ investments across the 5 periods. Which regions that are receives the largest investments vary from each period. This insight is important to bear in mind when we later review our empirical analysis. *Table 2* will serve as a benchmark comparison for our model. As the number of datapoints varied substantially we have compiled the 7 years of data points in to 5 periods, as depicted in *table 3*.

Period	Atlantic	Indian	Pacific
1	48,88 %	20,80 %	30,33 %
2	33,35 %	25,73 %	40,92 %
3	48,63 %	21,69 %	29,68 %
4	30,61 %	25,89 %	43,50 %
5	40,37 %	23,53 %	36,11 %

Table 2 - Allocated capital in main geographical regions per period.

Choosing to structure the data in the abovementioned periods stems from the number of observations in our data set. For each individual year in the period 2016 to 2022 the number of observations had substantial variations. This poses an issue in terms of the robustness of portfolio calculations and available contracts in the portfolios[7]. Thus, we aggregated the data over a longer timespan to omit this issue. By doing this we have obtained the following periods to be used in our calculations.

Period 1: 2016 and 2017

Period 2: 2018 and 2019

Period 3: 2020 and first half of 2021

Period 4: second half of 2021 and 2022

Period 5: 2016 to 2022

The periods 1-4 are relatively equal in terms of observations and the timespan are at most 2 years. Period 5 constitutes the whole period, meaning all the years from 2016 to 2022.

Furthermore, Table 3 is added as an additional benchmark for the empirical analysis. As portfolios themselves might provide some insights, our goal is to achieve meaningful insights in how Western Bulk might optimize its capital allocation[8].

[7] The choice of periods is discussed further in the section "*Robustness of data and results*".
[8] Capital allocation stems from the section "*Background for portfolio optimization*" where contracts are considered investments. Consequently, the overall investments can be considered capital allocation.

Spot	Period	Atlantic	Indian	Pacific
	1	53,96 %	2,50 %	43,54 %
	2	58,61 %	10,41 %	30,97 %
	3	52,83 %	24,57 %	22,60 %
	4	38,33 %	34,66 %	27,01 %
	5	45,93 %	25,89 %	28,18 %
Short	1	48,19 %	22,31 %	29,50 %
	2	40,07 %	24,38 %	35,55 %
	3	26,52 %	28,60 %	44,88 %
	4	25,20 %	29,26 %	45,54 %
	5	37,19 %	25,46 %	37,35 %
Index	1	99,21 %	0,00 %	0,79 %
	2	93,37 %	6,59 %	0,04 %
	3	77,69 %	22,17 %	0,14 %
	4	52,89 %	46,55 %	0,56 %
	5	85,57 %	14,27 %	0,16 %
FC	1	62,00 %	1,66 %	36,34 %
	2	50,28 %	6,88 %	42,83 %
	3	47,69 %	13,99 %	38,31 %
	4	47,77 %	16,11 %	36,11 %
	5	48,79 %	13,88 %	37,33 %
Overall allocation		39,69 %	24,09 %	36,22 %

Table 3 - Summary of capital allocation by region and contract.

The table depicts the relative capital allocation in each strategy in its respective region and period. An interesting observation is that Western Bulk allocates a large proportion of its capital to the Atlantic region across all years and strategies. This observation could indicate the well-known Atlantic premium in dry bulk shipping. It could also be a reflection of other factors such as the trading performance of the “Atlantic trading desk”, or that WBs headquarters is in the Atlantic basin.

Empirical results

In this section we put forward our empirical results, as well as discussing the implications and limitations of them. First, we look at the portfolio optimization between contract types in the five mentioned periods between 2016 and 2022. Here we look at both minimum variance portfolios (MVPs) and optimal portfolios. Secondly, we interpret these results and provide a discussion of the implications of these results for Western Bulk. Finally, we will discuss the robustness of the results and provide a discussion of limitations of the same results.

Portfolio Optimization

Following the operational returns from Western Bulk in the period 2016-2022, we have obtained various results regarding portfolio optimization of contracts. From the data used in this thesis, a possible number of 12 contracts were available. As mentioned previously this included four contract types over 3 available geographical regions. After applying the framework of Markowitz, we obtained both MVPs and optimal portfolios for the five time periods. These results are summarized in *Table 10* and *Table 11* below.

Pivotal to the portfolio optimization of Markowitz is the covariance among available assets in the investment set. Due to differences in the number of observations between the contracts to Western Bulk, this causes some contracts to be left out of the calculation. The reason behind this is described in further detail in the subchapter "*Robustness of data and results*". As a result, the available investment set contains 6-7 contracts instead of the possible maximum of 12. Addressing this issue is *Period 5,* which includes all 9 possible contracts. As mentioned, this period considers the whole period 2016-2022. The designated set for each period is given in the table below.

		Atlantic-Spot	Indian-Spot	Pacific Spot	Atlantic-Period	Indian-Period	Pacific-Period	Atlantic-Forward	Indian-Forward	Pacific-Forward
2016-2017	Return (%)	258,45 %	-	347,50 %	48,32 %	25,49 %	24,56 %	16,51 %	-	-
	SD	9,98	-	6,34	1,82	0,75	0,90	5,30	-	-
2018-2019	Return (%)	370,51 %	-	262,12 %	-42,09 %	13,80 %	-5,42 %	276,67 %	-	-
	SD	7,58	-	6,19	1,97	0,92	1,77	10,27	-	-
2020-2021	Return (%)	237,17 %	234,20 %	196,25 %	-	99,94 %	64,88 %	58,91 %	-	-123,30 %
	SD	13,92	15,97	6,24	-	1,99	1,27	5,58	-	4,36
2021-2022	Return (%)	241,03 %	371,83 %	187,11 %	-	2,79 %	-	427,54 %	-	327,93 %
	SD	4,81	11,09	8,31	-	1,23	-	7,91	-	5,91
2016-2022	Return (%)	269,86 %	349,62 %	239,74 %	12,68 %	191,69 %	20,69 %	207,99 %	265,47 %	235,26 %
	SD	9,39	12,58	6,70	1,84	1,92	1,29	7,67	7,48	6,99

Table 4 – Returns (%) and standard deviation (SD) for contracts in the investment set in all periods.

Given this reduced investment set, the subsequent portfolios offer less diversification possibilities. However, this is still preferable as the data set contains more observations on the remaining contracts.[9] With the chosen investment set we calculated the covariance between

[9] The data set and following calculations/results are discussed later in the results chapter, under "*Robustness of data and results*".

each contract, before creating a covariance matrix for each period. These matrices are all summarized in *tables 5 to 9*.

	Atlantic-Spot	Pacific-Spot	Atlantic-Period	Indian-Period	Pacific-Period	Atlantic-Forward
Atlantic-Spot	2,29215					
Pacific-Spot	-0,13790	1,52554				
Atlantic-Period	-0,03633	-0,21865	0,21856			
Indian-Period	0,03433	0,03440	-0,00839	0,01722		
Pacific-Period	-0,02211	0,04523	0,00472	0,00626	0,02399	
Atlantic-Forward	-0,06597	-0,03572	-0,02780	0,03228	-0,00417	1,02976

Table 5 - Covariance matrix for period 1: 2016 and 2017.

	Atlantic-Spot	Pacific-Spot	Atlantic-Period	Indian-Period	Pacific-Period	Atlantic-Forward
Atlantic-Spot	2,12334					
Pacific Spot	-0,16395	1,36438				
Atlantic-Period	-0,07642	-0,04666	0,12140			
Indian-Period	-0,03459	-0,00782	0,00214	0,01955		
Pacific-Period	0,00084	0,00403	0,00598	-0,00014	0,00394	
Atlantic-Forward	-0,29718	0,18933	0,19678	-0,02511	0,04297	2,15897

Table 6 - Covariance matrix for period 2: 2018 and 2019.

	Atlantic-Spot	Indian-Spot	Pacific-Spot	Indian-Period	Pacific-Period	Atlantic-Forward	Pacific-Forward
Atlantic-Spot	10,18841						
Indian-Spot	-2,33216	9,51801					
Pacific Spot	-1,06746	0,73202	1,35951				
Indian-Period	0,04072	-0,20068	0,08495	0,16405			
Pacific-Period	-0,27913	0,15868	0,00635	-0,00978	0,06376		
Atlantic-Forward	0,22658	-0,66235	-0,05352	0,00116	-0,01964	0,98538	
Pacific-Forward	-0,47072	-0,43274	0,25293	0,01194	0,03342	0,02600	0,76028

Table 7 - Covariance matrix for period 3: 2020 and first half of 2020.

	Atlantic-Spot	Indian-Spot	Pacific-Spot	Pacific-Period	Atlantic-Forward	Pacific-Forward
Atlantic-Spot	0,69341					
Indian-Spot	-0,05291	2,27063				
Pacific Spot	-0,10202	0,04546	2,36426			
Pacific-Period	0,04908	0,09823	-0,03998	0,05163		
Atlantic-Forward	-0,16626	-0,56694	0,14225	-0,00901	1,12701	
Pacific-Forward	-0,05801	-0,38784	-0,02541	-0,04006	0,29350	0,93249

Table 8 - Covariance matrix for period 4: second half of 2021 and 2022.

	Atlantic-Spot	Indian-Spot	Pacific-Spot	Atlantic-Period	Indian-Period	Pacific-Period	Atlantic-Forward	Indian-Forward	Pacific-Forward
Atlantic-Spot	2,96980								
Indian-Spot	0,46318	5,32592							
Pacific-Spot	0,18592	-0,31273	0,59159						
Atlantic-Period	0,05069	0,09488	-0,04957	0,10307					
Indian-Period	-0,06246	-0,00599	-0,00079	-0,00019	0,01512				
Pacific-Period	-0,02317	0,00198	0,00384	-0,00307	0,00317	0,00963			
Atlantic-Forward	0,01480	0,19984	-0,09719	-0,05324	-0,01203	-0,00451	0,64363		
Indian-Forward	0,24963	-0,29234	0,22946	-0,03427	-0,02016	0,00157	0,00999	0,70750	
Pacific-Forward	0,02592	-0,54746	0,04341	-0,13497	-0,00478	0,03665	0,04787	0,14734	1,62059

Table 9 - Covariance matrix for period 5: 2016 to 2022

Minimum Variance Portfolio

Using the abovementioned covariance tables, we are able to construct the Minimum Variance Portfolios. Applying this with the mentioned methodology in a statistical computational software as Excel, the MVPs are summarized in the table below.

Period	Atlantic-Spot	Indian-Spot	Pacific-Spot	Atlantic-Period	Indian-Period	Pacific-Period	Atlantic-Forward	Indian-Forward	Pacific-Forward	SD	E[r] (%)	SR
1	0,03 %	-	0,00 %	7,07 %	60,57 %	32,33 %	0,00 %	-	-	0,11	26,88 %	2,38
2	0,60 %	-	0,30 %	0,02 %	26,52 %	72,56 %	0,00 %	-	-	0,06	2,74 %	0,07
3	2,37 %	0,60 %	2,03 %	-	23,21 %	65,06 %	4,58 %	-	2,16 %	0,18	76,43 %	4,17
4	1,37 %	0,00 %	3,18 %	-	-	85,80 %	2,12 %	-	7,53 %	0,20	45,41 %	2,15
5	0,96 %	0,00 %	0,99 %	8,77 %	33,52 %	51,75 %	2,67 %	1,35 %	0,00 %	0,07	90,16 %	11,96

Table 10 - Minimum Variance Portfolios (MVPs) for all periods (2016-2022).

The table depicts all five assigned periods in the timespan of 2016 to 2022. Note that "-" refers to the contract not being part of the investment set in the corresponding period. Looking at the table it is evident that period contracts dominate the %-share in the portfolio for each period. In a risk management perspective, this can indicate that period contracts are preferable in terms of minimizing risk.

Efficient frontier and optimal portfolio

Moving on from the Minimum Variance Portfolio, we use its implications in determining the efficient frontier and the subsequent optimal portfolio. Using the MVP as a starting point we have calculated the efficient frontier for each of the five periods. These are all depicted in *Figures 4 to 8* below. Also included in the figures are the capital allocation line (CAL) and the optimal (tangent) portfolio.

Assessing the optimal portfolio requires utilization of the risk-free interest rate. In our case we are faced with an investment set with assets/contracts of different lengths. This differs from traditional equity portfolios comprised of e.g., stocks, where this is not an issue. The risk-free security should therefore optimally, be equal in duration with these contracts (Emilson, 2020). During the period of 2016-2022 the *spot-, period- and forward* contracts had an average duration of 33, 132 and 36 days respectively. Given these numbers a contract has an average duration of 67 days, or 2,2 months. If adjusted for the percentage invested in each contract (majority in period contracts) the average duration is 78 days, or 2,6 months. Hence, a risk-free security with a duration of 3 months will be appropriate to match the duration of the available contracts.

For the duration of 3 months, the US 3-month Treasury bill (T-bill) is commonly used as the risk-free asset in financial practice (Sarno & Thornton, 2003). This asset is therefore chosen as the determinant of the risk-free rate in our case of portfolio optimization (MarketWatch, 2023). With the approach of matching this risk-free rate with the average contract duration, we assume that the yield curve is upward sloping. This entails that the interest rate of the bill increases as the time to maturity increases. Investors are more exposed to fluctuations in the interest rate with longer durations and will therefore require compensation accordingly (Kloster, 2000).

Applying the risk-free rate in the calculation of a portfolio with maximum Sharpe Ratio yields the optimal portfolio (*Figures 4-8*). The %-wise composition of contracts in each optimal portfolio has been summarized in the table below. In the same table the standard deviation (SD), expected return and Sharpe Ratio for each portfolio is also given.

Period	Atlantic-Spot	Indian-Spot	Pacific Spot	Atlantic-Period	Indian-Period	Pacific-Period	Atlantic-Forward	Indian-Forward	Pacific-Forward	SD	E[r] (%)	SR
1	6,35 %	-	12,16 %	25,23 %	37,84 %	17,27 %	1,15 %	-	-	0,20	77,54 %	3,93
2	12,30 %	-	10,81 %	0,00 %	68,61 %	0,00 %	8,28 %	-	-	0,23	106,28 %	4,44
3	3,34 %	1,24 %	6,28 %	-	26,47 %	58,64 %	4,03 %	-	0,00 %	0,19	90,02 %	4,63
4	28,72 %	19,68 %	3,48 %	-	-	0,00 %	28,56 %	-	19,55 %	0,42	335,17 %	7,93
5	1,68 %	0,48 %	1,58 %	4,69 %	83,42 %	0,00 %	3,61 %	3,45 %	1,09 %	0,10	189,74 %	18,61

Table 11 - Optimal (tangent) portfolios for all periods (1 to 5).

Compared to the MVP portfolios one can observe that a large share of the portfolio still consists of *period contracts*. However, this share has been somewhat smaller, as a larger share of spot- and forward contracts are now included in the portfolios. This coincides with what was shown in the investment set, where the spot contracts generally offer superior returns compared to the other contract types. Keep in mind that the spot contracts are riskier and have significant volatility, thus limiting the share of it which can be placed in the optimal portfolios.

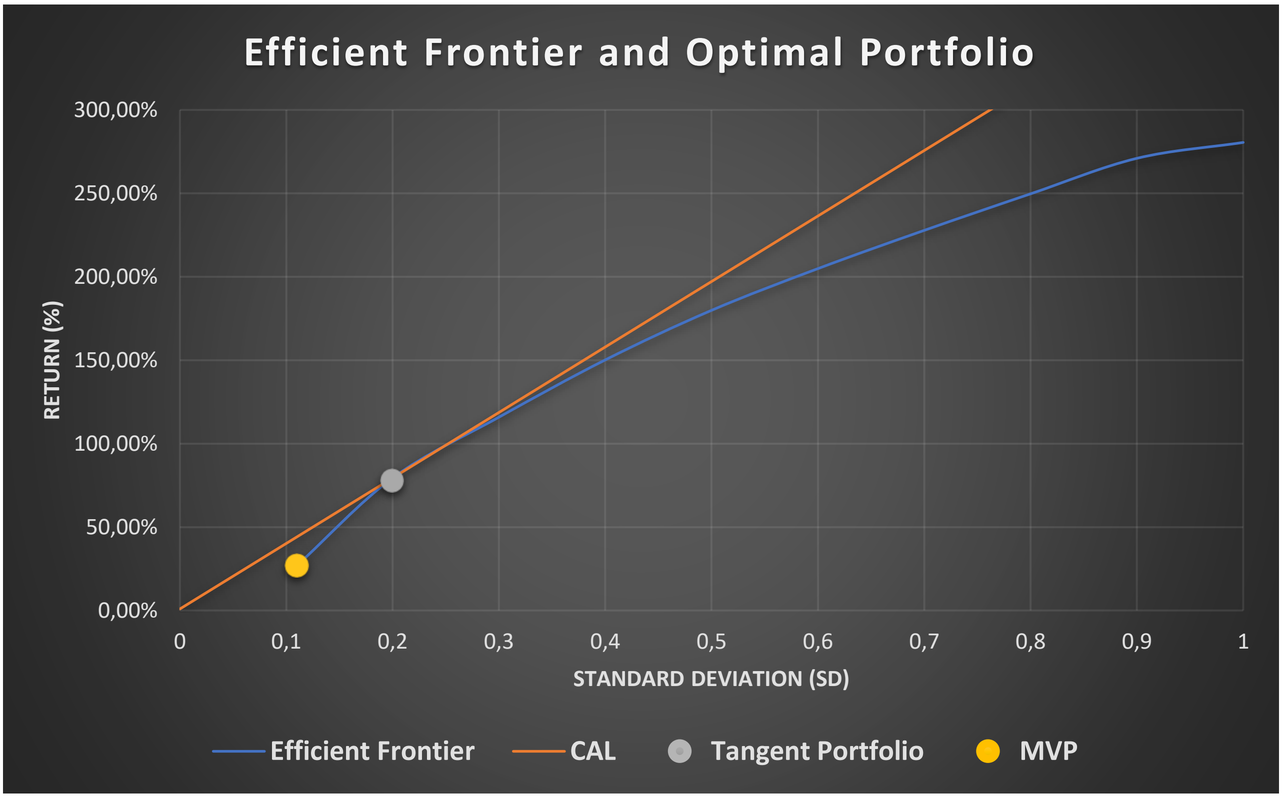

Figure 4 - Efficient frontier and optimal portfolio in Period 1: 2016 and 2017.

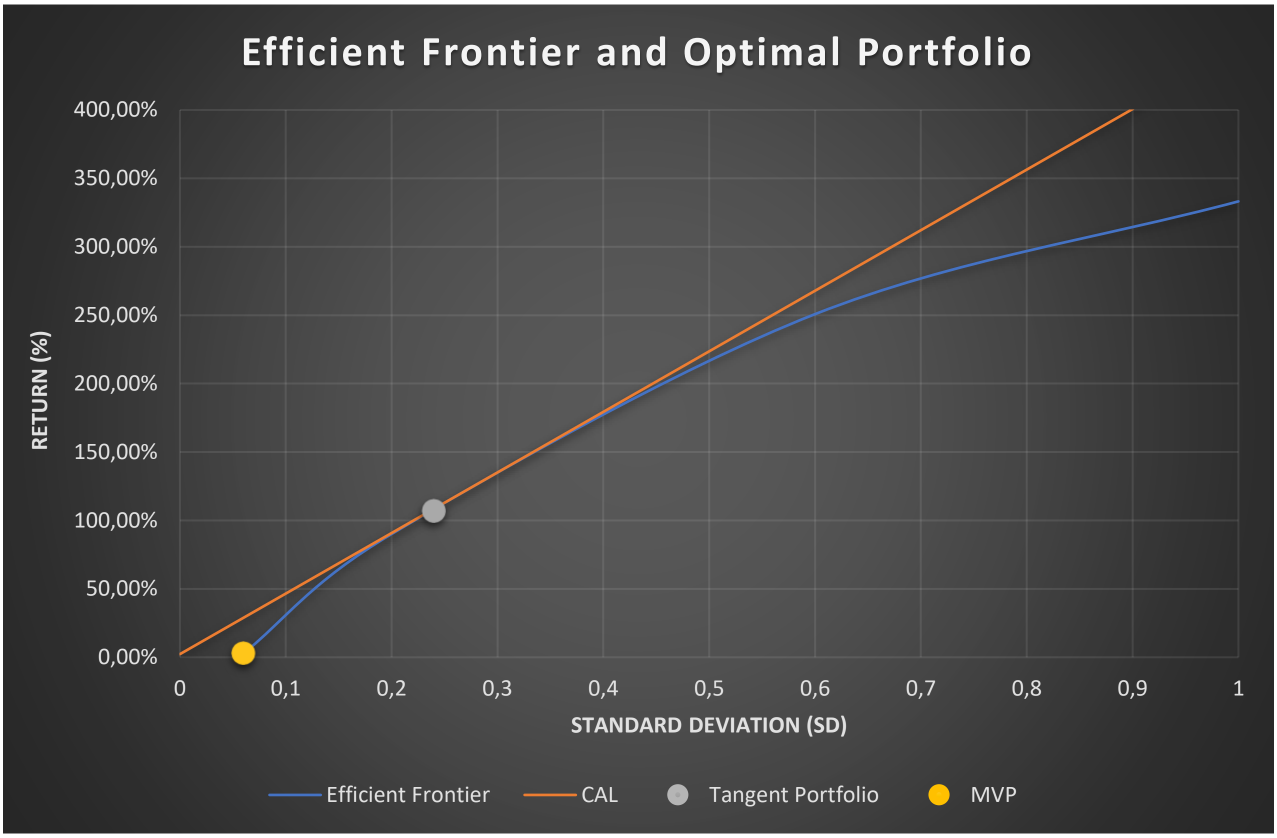

Figure 5 - Efficient frontier and optimal portfolio in Period 2: 2018 and 2019.

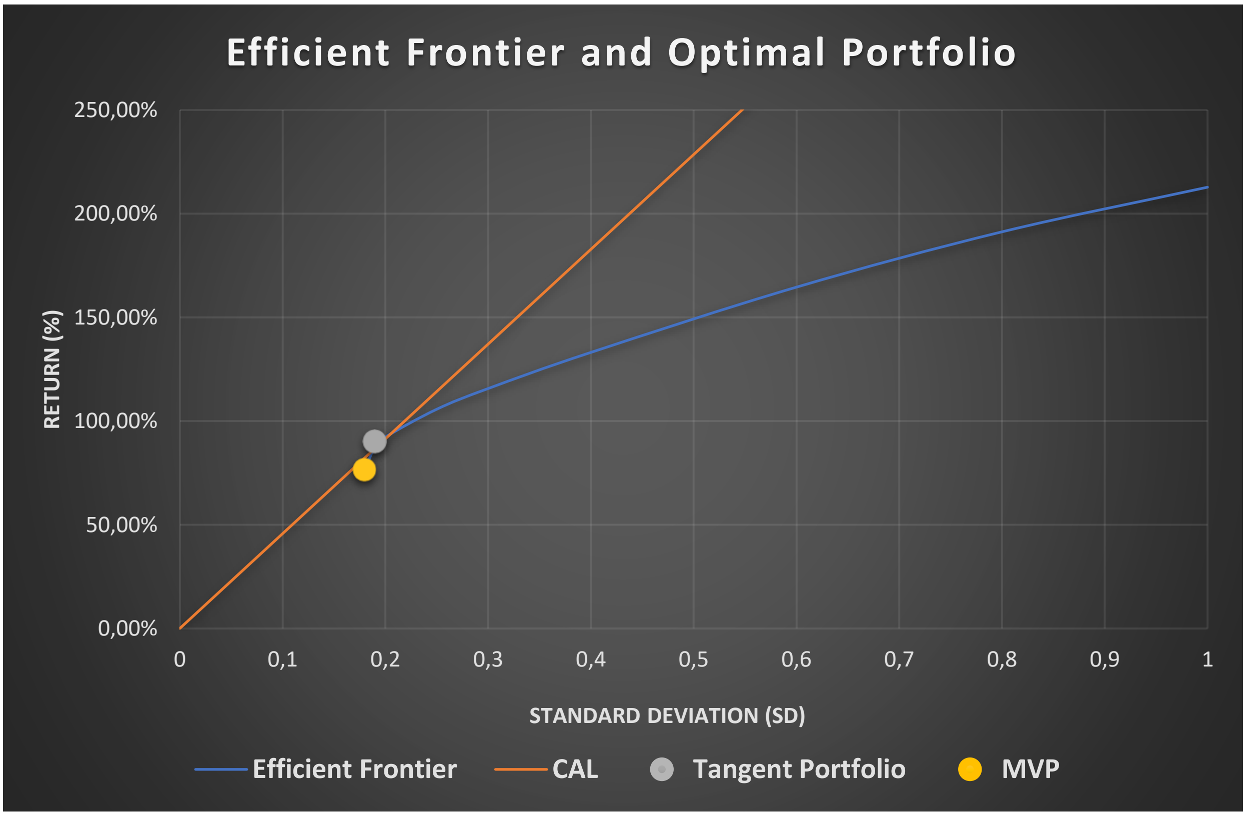

Figure 6 - Efficient frontier and optimal portfolio in Period 3: 2020 and first half of 2021.

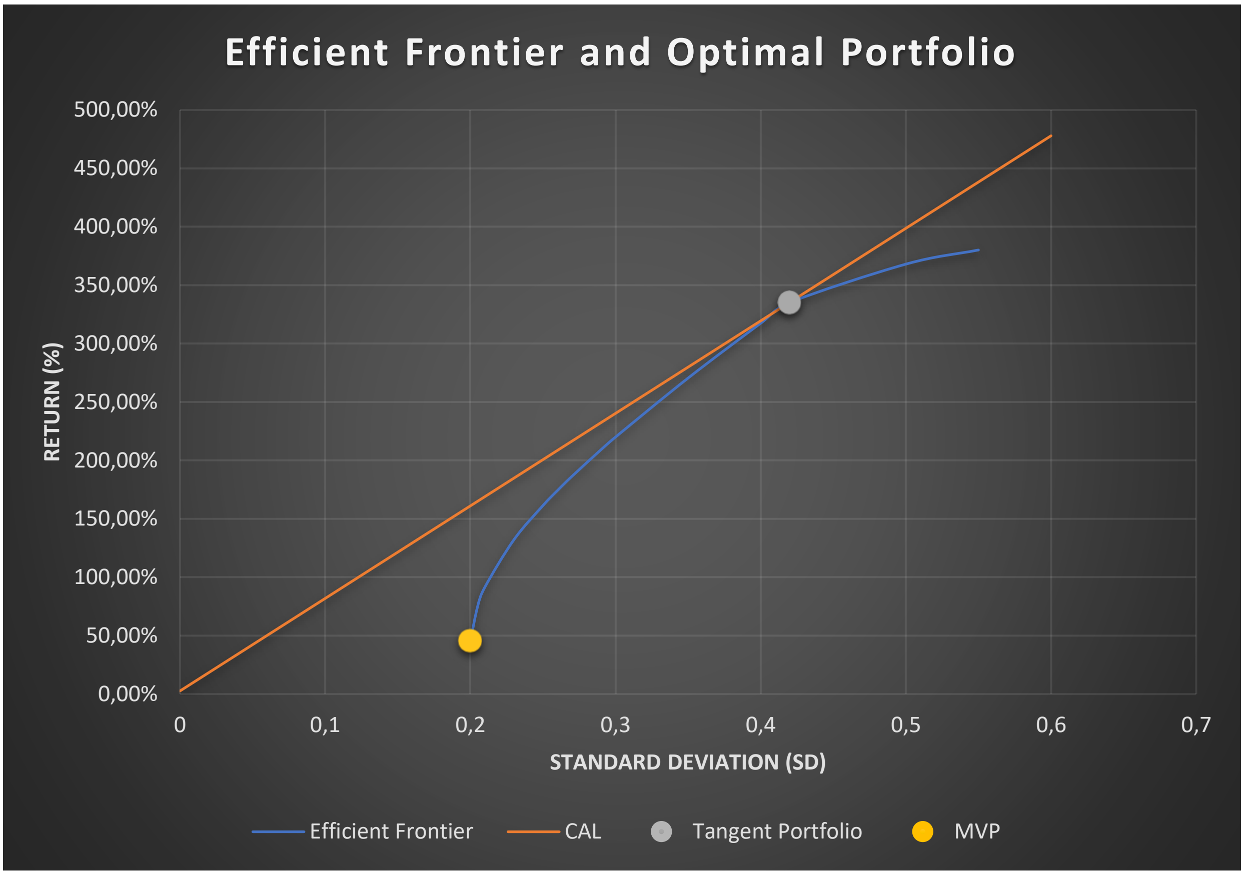

Figure 7 - Efficient frontier and optimal portfolio in Period 4: second half of 2021 and 2022.

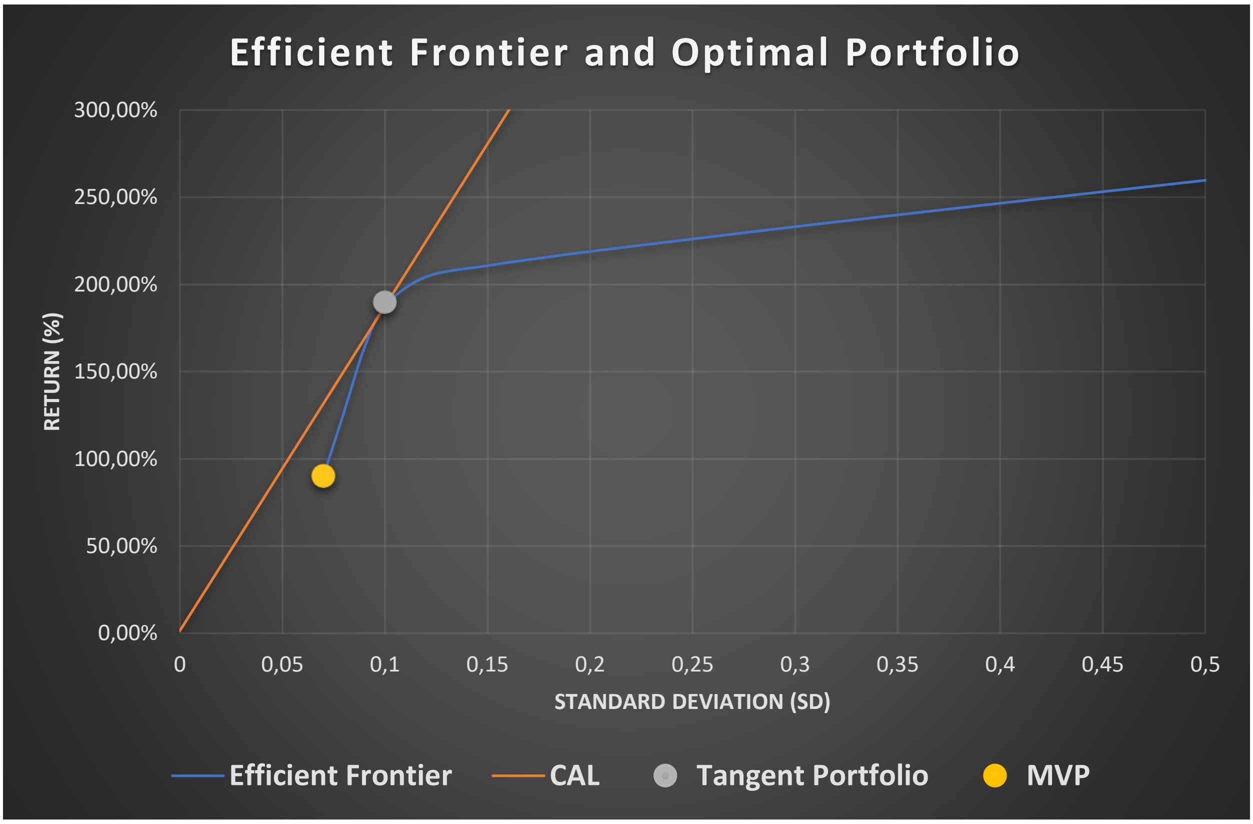

Figure 8 - Efficient frontier and optimal portfolio in Period 5: 2016 – 2022.

Implications of results

From the optimal portfolios we can map out what is the ideal distribution of contracts for Western Bulk. From all five periods we have looked at we can see a general pattern between the contract types. The majority will be held in *period contracts*, with two significantly smaller positions in spot and forward contracts. Keep in mind that this pattern is subject to deviations in each period, but generally keeps its form among these three contract types. Previously mentioned constraints on segment concentration are possible and could be implemented in the optimal portfolios. Given the large share of period contracts in all periods, it could be reasonable to apply such a constraint in practice.

Additionally, the results from these portfolios relate to what would have been optimal portfolios ex-post. This would imply that Western Bulk have perfect knowledge of what would be the outcome of each 2-year period. Having the foresight and understanding of such allocation changes between these periods can be considered difficult and unlikely in a real-world setting. Thus, we have included results over a longer period (2016 – 2022), referred to as *Period 5.* This will provide a more realistic assessment of what could be considered common conditions for Western Bulk. Moreover, looking at a longer period will make it more likely to coincide with shipping cycles and patterns.

Derived from the same optimal portfolios we obtain info on the geographical placement of these contracts. This insight would benefit the desks of Western Bulk, as their operations are structured in separate units. Each of their desks covers a respective ocean basin, and with our results they are provided with a benchmark of where to place their contracts. Using the optimal portfolios in each period, the distribution among the operational areas is the following.

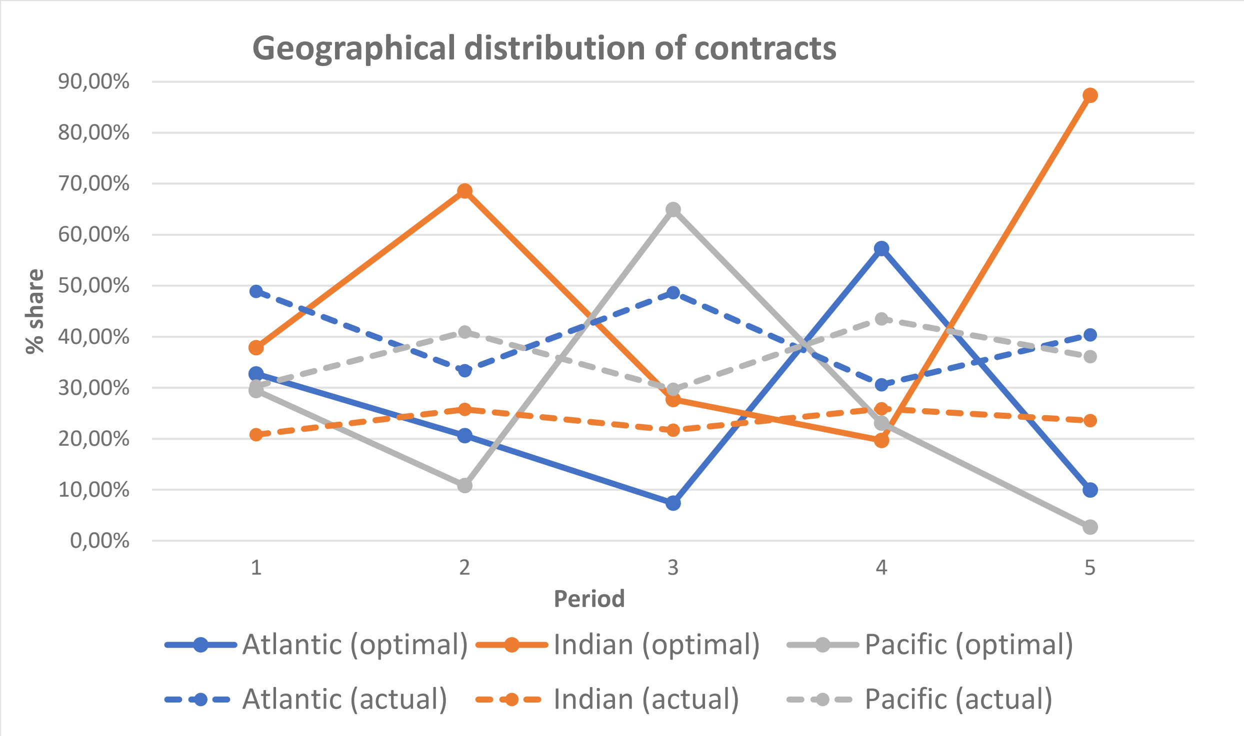

Figure 9 - Actual and optimal geographical distribution of contracts per period.

Looking at the distribution obtained from optimal portfolios (solid lines), the figure depicts significant variations among the distribution in each region. In all periods except *period 1* one region predominantly outweighs the others, with a share of over 50%. This pattern is reinforced if we look at the full period/all years (*Period 5*), where the share in Indian contracts is equal to 87%. If we compare this with the historical figures for Western Bulk, we will be able to obtain more insight into how their contracts can be distributed among regions.

In the same figure we have included the historical figures for invested capital among regions (dashed lines). The historical distribution among the regions deviates to what is implied by the optimal portfolios. Most noticeable is that the optimal portfolio gives a larger variation in regions than historical distributions. For example, the share of capital allocated in Indian is significantly smaller than what has shown to be optimal in certain periods. This is also the case for the full period when comparing the actual and optimal share.

Based on what the optimal portfolio suggests, it would be preferable to increase the share in the Indian region. However, it would be problematic from a risk management perspective to use these results without adjustments. Applying the insights from the optimal portfolio would entail having 87% of contracts in the Indian region. This constitutes a portfolio with too great a concentration in one geographical segment. Having this overexposure increases the risk of possible drawdowns, if wrong about the region. As mentioned in the theory section about potential constraints on portfolio composition, it would be possible to include constraints on geographical segment exposure.

Implementing these constraints would be determined by Western Bulk and their preferences/practices. Not knowing these metrics, we have not included these constraints in our preceding calculations and results. Consequently, the share in the Indian region will be below the abovementioned optimal share, conditional on what the chosen constraints are. This depicts a limitation regarding our results, as the potential realism and impact is somewhat unadjusted. Thus, our results lean towards a higher degree of theoretical relevance, compared to practical uses. By including these and other constraints, it would improve the practical application and realism of our results.

Given the cyclicality of the bulk freight market, a portfolio approach may indicate certain portfolio patterns (*Figure 9)* which coincide with various parts of the cycles. We know that a complete short shipping cycle consists of four stages: *trough, recovery, peak and collapse* (Scarsi, 2007). Note that the duration this paper has examined is 7 full years (2016-2022), which coincides with the industry rule of thumb for duration of a cycle (Chistè & van Vuuren, 2013). Thus, meaning that by understanding how optimal portfolios of contracts have been historically, it can be used in setting a basis for distribution of future contracts. However, it is not given that these periods coincide perfectly with each other. It would therefore be preferable to look at this over a longer period and investigate if these cycles indicate a pattern in terms of portfolio allocation.

Robustness of data and results

Contrary to stock prices (and returns), the returns to Western Bulk are not equal in terms of daily quotes. The observations of movements in price between two or more stocks are commonly quoted in equal observations, making comparison an easier task than with the case of Western Bulk. Since the returns Western Bulk achieves are from contracts with various durations, the observations among the contracts also vary. This poses a problem in determining the covariance between contracts, as covariance calculation requires data sets of equal length. To cope with this, we have opted for random sampling in obtaining an equal number of observations between contracts.

The discrepancy between contracts is obvious in all intra year periods from 2016 to 2022. Thus, we have joined various periods together to obtain more observations in each period. Doing this allows for a greater number of assets/contracts in the investment set. As mentioned, the following periods have been used in the preceding calculations and portfolio optimization.

Period 1: 2016 and 2017

Period 2: 2018 and 2019

Period 3: 2020 and first half of 2021

Period 4: second half of 2021 and 2022

Period 5: from 2016 to 2022

To reduce the discrepancy in the number of observations between contracts in each period, a minimum number of 30 observations for each contract have been used. Hence, the available investment set in each period only consists of contracts with 30 or more return observations. This allows for a larger random sample to be drawn and making the covariance calculations more robust. A drawback with this approach is that certain contracts are not included in the investment set. Thus, a trade-off is made between the number of contracts and the difference in the number of observations between contracts.

Performing the random sampling approach requires insight into the number of observations to each contract in the five designated periods. As they differ, it puts clear constraints on how the sample size is determined. Since sample size can't be larger than population size, the contract with the smallest population points out how large the sample size can be. In each of the five periods the smallest population (observations) of a contract is respectively *45, 37, 31 ,37 and 51*. Consequently, the sample size can't be greater than these sizes in their respective periods. Using these population sizes, it is possible to calculate the optimal sample size through the following equation:

$$n = \frac{N}{1 + N(e)^2} \tag{21.}$$

The sample size is given by n, where N is the size of the population and e is the level of precision (Yamane, 1967). With a 95% confidence level and corresponding P-value = 0,05 the sample sizes calculated are respectively *40, 34, 29, 34 and 45* for periods *1 to 5*. In our simulation a sample of the abovementioned sizes is drawn from each contract (in each period). Doing so generates a table of equal observation/rows for the contracts in the period in question. From this table the covariance between contracts is calculated and stored in a covariance matrix.

Simulation of random sampling

Having determined the sample sizes for the random sampling in each period, we have extended this process to be repeated through simulation. The goal is to make the covariance calculation between contracts statistically robust. Hence it is convenient to remove any bias that might occur from the random sampling. Repeating the random sampling procedure contributes in that manner. For this reason, we have created a simulation of the random sampling process which is used in each of the five time periods. This simulation was created with the statistical programming and computing language R.

In our simulation a sample of the abovementioned sizes is drawn from each contract type (in each period). Doing so generates a table of equal observation/rows for the contracts, in the period in question. From this table the covariance between contracts is calculated and stored in a covariance matrix. This process of drawing a random sample is then repeated and again stored in the covariance matrix, where the average of all constitutes the final covariance matrix. For all the sampling iterations each one is made with replacement. The main reason for choosing replacement is to ensure that the sample values are independent (Triola, 2011).

The replacement of samples is further needed in the simulation of drawing random samples. As mentioned in the previous paragraph, we repeat the sampling to obtain an average for the covariance matrix. In accordance with standard practices in statistical simulations, the sampling process is repeated 10 000 times (Heijungs, 2020). Thus, replacement is necessary to repeat the iterations 10 000 times. Repeating this process ensures that the final covariance matrix is robust (at the 5% level) to be used in the portfolio optimization calculations.

Discussion of limitations with the results

Our thesis has certain limitations which are likely to have implications for the realism and credibility of our results. Firstly, as we have previously discussed there are elements that affect an operator that aren’t captured in our analysis. Factors such as ballast and fuel risk are part of the consideration an operator has to consider. These risks are not included in our analysis where the only risk included is the standard deviation calculated on the variance of earnings. Therefore, our results are only to be considered assuming that all else is equal.

Another objection to our analysis is how Western Bulk conduct business compared to our theoretical model. Our analysis has a numeric relation to risk and the fictitious business could be run by these risk measures if wanted. Such an approach is not directly comparable to how Western Bulk structure its risk measures. Western Bulk handles risk through its experience and capital allocation to different regions (Husby, 2023). As an operator they do not care about the relative volatility in different types of contracts based on historical data. Rather they rely on their skill and knowledge to place ships in different regions. Also, by having a large number of ships active throughout the dry bulk spectrum they have great intel on the market minimizing unforeseen events disregarding market fluctuations.

The most adjacent theoretical concept in use is the concept of diversification. It is obvious that an operator who allocates its resources to multiple geographies will more favorable positioned compared to an operator located in few geographies. Although our calculations show that most observations have a positive co-variance, they still have not the same responds to volatility. Meaning that there are diversification effects to collect from operating on more than a few locations. The operator's mobility is another way of diversifying its portfolio.

As mentioned, the size of the data set could optimally have been larger. With more observations we would likely have had more assets in the possible investment set. Consequently, this would likely have impacted on our results in terms of diversification among more contract types, especially index contracts. Thus, we could gain more insight into how an optimal portfolio could be constructed. Additionally, more observations would provide a more robust risk/return perspective to the case we are looking at.

Finally, it has been mentioned that the optimization methodology doesn't include all possible constraints. These constraints fathom aspects as limitations to contractual- and geographical concentration, working capital and structure of trades. It will therefore be beneficial to include the mentioned constraints in further research, as well as the other above-mentioned limitations. Put together this will contribute to increasing the realism of the portfolio results and the implications they can have in practice for Western Bulk.

Concluding remarks and recommendation

Having looked at the returns from Western Bulk's chartering contracts in the period from 2016 to 2022, we have obtained valuable insights through a portfolio approach. In a geographical perspective Western Bulk have held a smaller position in the Indian region, than what we have found to be optimal. Complementary to this is how the chartering contracts should be distributed, where we have found it optimal to hold a majority in period contracts and smaller positions in spot and forward contracts. These recommendations are more relevant for capital allocation in a longer time perspective, as depicted with the whole period of 2016-2022 (period 5). Furthermore, we recommend extending our findings by including the mentioned constraints in any further portfolio optimization. Doing so will improve the practical use of the corresponding results.

Even though the portfolio approach provides valuable insight into the operations of Western Bulk, the approach can be a bit too static. If you follow this approach rigorously you will likely miss opportunities in the market which are deviations from the portfolio weights. The operations of Western Bulk are centered around exploiting these market imperfections. Thus, we recommend that they continue with this strategy, but include portfolio insights as a benchmark and useful reference point for capital allocation over a time horizon of equal length as 2016-2022.

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