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Sustainability-Linked Debt in Shipping

A study on the effects of SLD on shipowners' cost of capital

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Abstract

This study analyzes whether issuing sustainability-linked debt (SLD) reduces shipowners' cost of capital. In light of the existing research on green bonds indicating increased investor appetite for sustainability, along with pressure from the IMO towards zero emission, it is interesting to investigate whether this new addition in the sustainable finance landscape can play a role towards a more sustainable shipping industry. We analyze the cost of capital with a dual-lens approach, investigating the impact on the cost of debt and equity separately. By conducting a difference in differences analysis of the effect of bond and loan issuances on the cost of equity within one year after issuance, we find that shipowners generally achieve a slight but significant reduction in the cost of equity. However, the effect is heterogeneous among individual shipowners in direction, size, response time, and development over time. We do not find a trend of specific shipping segments standing out in a particular direction. On the debt side, we match sustainability-linked bonds with conventional counterfactuals to investigate the presence of a "greenium". We conclude that inferring an effect on the cost of debt is challenging as the current number of SLBs is too limited. Investigating an effect on the cost of debt from the SLLs is also difficult due to a lack of transparency in the loan data. Nevertheless, our results provide a basis for rejecting the null hypothesis, which states that SLD does not affect shipowners' cost of capital. In conclusion, SLD seems to reduce the cost of capital for shipowners through positive reactions from investors about the commitment towards sustainability, consistent with existing research on green financing.

Keywords: Sustainability-linked Debt, SLB, SLL, ship finance, sustainability, shipping

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1. Introduction

In recent years, several financial innovations have entered the market to support companies in reaching their sustainability goals. Green bonds or loans have historically been the most common types of sustainable debt financing. But with the emergence of the sustainability-linked financing framework in 2017, sustainability-linked debt instruments have started to rise as the fastest-growing tools within the sustainable finance landscape (IFC, 2022). Unlike green bonds and loans, where the proceeds are earmarked for specific sustainable projects, sustainability-linked bonds (SLB) and loans (SLL), collectively referred to as SLD, provide general-purpose financing. These instruments are designed to incentivize sustainable efforts by involving either penalties or rewards for meeting, or failing to meet, predefined sustainable performance targets (SPTs) (IFC, 2022). SLBs typically incorporate mechanisms such as a coupon step up or step down, early repayment stipulations, or changes to the redemption price, whereas, for loans, companies are incentivized through discounts or premiums in loan rates based on their performance regarding the SPTs.

Since the International Maritime Organization (IMO) introduced the IMO GHG Strategy in 2018, the path towards zero emission has become a central topic for the shipping industry. This focus has resulted in an increased investor appetite for sustainable investment. One manifestation of this is initiatives such as The Poseidon Principles, committing banks to reduce emission footprints in their shipping loan portfolios. Another is the evidence we see of oversubscribed green bond and SLB issuances, indicating that investors pay a "greenium" for participating in these sustainability-labeled investments (Löffler, Petreski, & Stephan, 2021) (Kölbel & Lambillon, 2022). On the equity side, both institutional and retail investors have directed more capital toward stocks with sustainable profiles, and we see evidence of positive market reactions to sustainable debt issuances (Thang & Zhang, 2020) (Flammer, 2021) (Zhang, Li, & Liu, 2021). Driven by the strong demand for sustainable investments, shipowners have shown increased interest in sustainable finance. A substantial portion of the debt issuances in the industry has carried sustainability labels (Clarksons Shipping Intelligence Network, 2023), highlighting sustainable finance's potential role in the industry's transition to zero emissions. As for SLD, Clarksons (2023) reports four shipowners having issued SLBs and 17 having acquired SLLs since the introduction of the IMO GHG Strategy.

As shipowners navigate the shifting currents of the sustainability transition, the issuance of sustainable debt instruments, such as SLD, presents clear incentives. First, SLD issuances potentially offer access to cheaper debt financing. With a growing investor appetite for sustainable investments, evidenced by the oversubscription of green bonds and SLB issuances, SLD may provide shipowners with an advantageous platform for securing funds at favorable rates (Kölbel & Lambillon, 2022). Second, the issuance of SLD can be used as a tool for constructing a compelling equity narrative. In an increasingly sustainability-conscious market, shipowners are incentivized to showcase their commitment to the green transition and to reaching the IMO's GHG reduction target. The adoption of SLD, with its predefined SPTs, may potentially send a powerful message of commitment and facilitates the build-up of a positive equity story.

While these incentives are attractive, they raise an important question: do these financing instruments truly motivate shipowners toward sustainability transformations? This question relies on the balance between the financial benefits at the time of issuance and the potential financial penalties associated with the varying rate structures embedded in these instruments. If the benefits from factors such as oversubscription of an SLB, initial[1] favorable borrowing rates or positive equity market reactions substantially exceed the potential costs inherent in these instruments, then the effect of the incentive mechanism designed to motivate achievement of the SPTs could be reduced. This potential scenario should provide motivation for future financial innovation on SLD. In particular, ensuring that the instrument's inherent incentive mechanism is material enough to incentivize a drive toward sustainability.

However, one key challenge in assessing the effectiveness of SLD is its relative novelty. At the time of writing, very few SLD facilities have reached their SPT dates (target observation date) or maturity dates, which limits our knowledge of whether firms have successfully met their predefined targets. Therefore, our investigation into SLD focuses on understanding its impact on the cost of capital, thereby providing insights into the legitimacy and effectiveness of the instrument. This benefits investors, financial institutions, legislators, and the shipowners themselves.

[1] Due to the bank's incentive to increase its number of sustainable loans, it could attract more borrowers for such loans, with offering more favorable initial loan rates.

Given the novelty of SLD, current research on the topic is relatively scarce. To the best of our knowledge, no research on SLD investigates specific industries, and as such, no past research has been conducted about SLD in shipping. By contrast, green financing, with its longer history, has attracted more scholarly attention, reflecting its established presence in the sustainable finance landscape. The green bond literature explores various aspects, including the presence of a "greenium" (green bond premium), stock market reactions, and impact on the cost of capital. While the current research on SLDs examines some of the similar topics, the research is limited and should be explored in greater detail (Kölbel & Lambillon, 2022). Our study aims to complement the current research by examining the impact of SLD on both the cost of equity and debt for shipowners. Through this dual-lens approach, we aspire to offer a holistic analysis of SLD's impact on shipowners' cost of capital. This leads us to our research question:

Does the issuance of sustainability-linked debt reduce shipowners' cost of capital, and how does it affect the cost of equity and debt capital?

From our research question, we produce two hypotheses

$H_{Decrease}$: Shipowners' cost of capital decreases as a result of the issuance of SLD.

H_0 : Shipowners' cost of capital is not affected by the issuance of SLD.

Disregarding the effect of capital structure and tax implications, a change in the cost of capital will stem from a change in the cost of equity or debt. In light of the above discussion, issuers' cost of capital may reduce due to the acquisition of SLD because the novel financing instrument may be attractive to investors, and the issuer's dedication to sustainability may send positive signals, leading to high demand and lower financing costs.

The structure of the thesis begins with a literature review, presenting an overview of existing research relevant to the research question and identifying gaps. Next, the methodology presents the research design and analytical tools used, followed by a section on the data, explaining the data applied to the methodology and any pre-processing steps. Lastly, the empirical results are presented, along with a discussion and conclusion.

2. Literature Review

Research on sustainable debt instruments has primarily focused on green bonds as these have been the main types of debt-financing within in the sustainability-category. While there is extensive research on green financing, the research on SLD is currently limited. This is largely due to the novelty of the sustainability-linked financing framework. However, the rapid growth in SLD issuances has resulted in an increase in data availability, thus progressively encouraging for and facilitating research within the topic of SLD. This literature review provides a thematic overview of relevant existing research related to our research question. It does so by first reviewing relevant literature on green financing, and subsequently comparing it with the current available research on SLBs and SLLs. Finally, it comments the state of current relevant research within the shipping industry.

Most of the leading research in the field of green financing, has revolved around green bonds. Thang and Zhang (2020) has conducted one of the largest studies to date on green bonds. It utilizes a comprehensive dataset comprising of green bonds issued by firms in 28 countries, over the course of a decade. The study finds positive stock market reactions with higher returns after the green bond issuance. Moreover, it does not find significant evidence of a green bond premium, or "greenium", implying that the observed positive stock returns are not fully driven by a reduction in the cost of debt. Similarly, Flammer (2021) also finds a positive effect on stock returns after the announcements of green bond issuances. Additionally, the study finds a stronger reaction for first-time issuers and bonds certified by third parties. Flammer's (2021) findings are consistent with the signaling argument, which suggests that by issuing green bonds, companies communicate a credible signal of commitment towards sustainability. Löffler, Petreski and Stephan (2021) find conflicting evidence compared to Thang and Zhang regarding the existence of a greenium. By matching bond pairs of green and conventional bonds, the study finds green bonds yields to be issued at, on average, 15-20 basis points lower, compared to the non-green counterfactuals. The study also finds that green bonds on average have larger issue-sizes and lower ratings. A later study by Zhang, Li and Liu (2021) matches green and conventional bonds and find evidence of a greenium following the issuance of green bonds. Particularly relevant to our study, it finds evidence that green bond issuance not only reduce the issuers cost of debt through a greenium, but it also reduces the overall cost of capital for the green bond issuers.

Regarding SLBs, similar research has been conducted to investigate the existence of a greenium. Kölbel & Lambillon (2022), investigates the yield differential between SLBs and a conventional counterfactual issued by the same company. The results suggest that at issuance, SLBs are on average, issued at a 9 basis point premium compared to the conventional counterfactual. Furthermore, the study finds evidence of the premium decreasing over time. Interestingly, the study also finds that the penalty embedded in the SLB instrument appears to be lower than the issuance premium. This suggests that the issuer can potentially benefit from issuance despite not reaching the predefined SPT. Another article by Berrada et al., (2022) provide evidence suggesting that overpriced SLBs experience negative returns in the secondary market after issuance. Under the same circumstances, stock price reactions are positive, consistent with a wealth transfer from debtholders to equity holders. Finally, Vulturius, Maltais & Forsbacka (2022) emphasizes the scarcity of academic research on this relatively new instrument. Among multiple topics, the study encourages future research to assess if bond characteristics and changes in capital costs support issuers in meeting or even increasing their climate targets and deter unsustainable investments.

As for SLLs, relevant existing research is scarcer. However, similar to SLBs, the research on SLL suggests a positive relation between stock market reaction and SLL issuance (Carrizosa & Ghosh, 2022). A paper by Sehoon, et. al, (2023) also finds that stock markets express vigilance towards potential greenwashing as the positive relation only holds for firms with high-transparency issuances, thus highlighting the importance of transparency for SLLs. Sehoon et. al (2023) also provides insights into the characteristics of firms that typically acquire SLL. Notably, the study suggests that SLLs are issued between reputable banks and firms with superior ESG profiles. The results regarding issuer characteristics are however somewhat inconsistent, as Schmittmann & Han Teng (2021) find no link between lower emission intensity and SLL issuance.

Research on sustainable finance in the shipping industry is relatively scarce. Thus, the contribution of this study intends to provide insights into the potential role of sustainable finance for incentivizing the green transition in shipping. As far as we are aware, the specific topic of this study has not yet been examined within the shipping industry.

3. Research Methodology

This study aims to analyze the effect of SLD issuance on the cost of capital by estimating its effects on the cost of equity and debt separately. This section first presents the methodology used for estimating the effect on the cost of equity. Subsequently, it presents the methodology for the cost of debt estimation, and lastly, it presents the methodologies for the matching procedures used to create our sample data.

3.1 Estimating Effect on r_E with Difference-in-Differences

Our research strategy for investigating the issuance of SLD's effect on the cost of capital is to conduct a quasi-experiment using a difference-in-differences (DiD) model. A premise for the DiD model is the parallel trends assumption, which states that, in the absence of treatment, the outcomes of the treatment group and control group would have followed parallel trends over time. For this assumption to hold, it requires "as if" random treatment assignment. If treatment is not "as if" random, and the parallel assumption is violated, this leads to bias in the estimated treatment effect, as the estimator will not correctly separate the impact of the treatment from confounding factors affecting the outcome variable. To ensure that the parallel trend assumption holds, we construct an appropriate control group that makes up the counterfactual for the issuing shipowners using a matching technique described in 3.2. As we deal with panel data, we include two-way fixed effects to control for time-invariant unobserved characteristics specific to each shipowner and time-varying factors that affect all shipowners identically. Lastly, as the experiment has heterogeneity in treatment timing, we use the Callaway Sant'Anna (2021) method for estimating the DiD-estimator.

3.1.1 Traditional difference-in-differences regression models

We utilize a difference-in-differences model without covariates, which is the simplest form of DiD estimation. The simplest DiD model computes the causal effect on treatment by comparing the outcome variable of entities (or groups of entities) that received treatment to entities that did not receive treatment. It compares the groups both before and after treatment occurs. As such, the simplest DiD-setting can be explained as a series of 2x2 comparisons because we have two groups: a treatment group and a control group, and these groups are observed at two time periods: before and after treatment occurs. The average change in the outcome for the control group is subtracted from the average change in the outcome for the treatment group. This difference represents the estimate for the causal effect of the treatment, or the DiD estimator, under the assumption of parallel trends in the absence of treatment. We call this the average treatment effect on the treated (ATT), given by eq. (1).

$$ATT = E[Y_t - Y_{t-1} | \, D = 1] - E[Y_t - Y_{t-1} | \, D = 0]$$

(1)

$$, where$$
$$D = 1 \; for \; treated \; units \; and \; 0 \; for \; untreated \; units$$

Although the ATT can be computed by calculating the differences in the 2x2s, we typically compute the estimator using regression, as this gives us both the estimator and the standard errors simultaneously (Baker, Larcker, & Wang, 2021). The simplest DiD regression model without covariates is provided by eq. (2).

$$y_{it} = \alpha + \beta_1 TREAT + \beta_2 POST + \beta_3 (TREAT \cdot POST) + \epsilon_{it}$$

(2)

$$, where$$
$$y_{it} = oucome \; variable \qquad \alpha = the \; constant \quad \beta_i = coefficients$$
$$TREAT = dummy \; for \; treatment$$
$$POST = dummy \; indicating \; whether \; treatment \; has \; occured \; yet$$
$$\beta_3 = The \; treatment \; effect \; coefficient, \; and \quad \epsilon_{it} = the \; error \; term$$

3.1.2 Two-way fixed effects

As we deal with panel data, this allows for utilizing a two-way fixed effects model to control for both time-invariant characteristics of the shipowners and shared temporal variation. This will enable us to mitigate potential omitted-variable bias from unobserved characteristics that are constant across entities over time, such as market reputation or company culture, as well as shared influences affecting all entities at a specific point in time, such as common market conditions. We thereby exploit within-entity variation over time to isolate the causal effect of interest, enhancing the reliability of our estimates. Therefore, including any control variables that vary over group but not over time is unnecessary since we already have group-fixed effects (Huntington-Klein, 2021). The DiD regression model, when using two-way fixed effects, is given by eq. (3).

$$y_{it} = \alpha_i + \lambda_t + \delta^{DD} D_{it} + \epsilon_{it} \tag{3}$$

$$, where$$

$$\alpha_i = a\ set\ of\ fixed\ effects\ for\ the\ entity$$

$$\lambda_t = a\ set\ of\ fixed\ effects\ for\ the\ time\ period$$

$$\delta^{DD} = The\ treatment\ effect\ coefficient$$

$$D_{it} = Dummy\ variable\ indicating\ wheter\ a\ unit\ i\ in\ time\ t\ is\ treated\ or\ not$$

$$\epsilon_{it} = The\ error\ term$$

3.1.3 Proof of a biased estimator with traditional TWFEDD regression under staggered treatment timing

The problem

As shipowners acquire SLD at different points in time, our quasi-experiment naturally has a staggered rollout design, where treatment timing is heterogeneous. Two-way fixed effects DiD (TWFEDD) regression models with staggered treatment have recently come under scrutiny, as researchers have proved the TWFEDD-estimator, $\widehat{\delta^{DD}}$, to be biased when using this traditional model with staggered designs (Haultfæuille, 2020), (Borusyak, Jaravel, & Spiess, 2021), (Sun & Abraham, 2021) (Goodman-Bacon, 2021), (Callaway & Sant'Anna, Difference-in-Differences with multiple time periods, 2021), (Baker, Larcker, & Wang, 2021).

The reason for the problem

Goodman-Bacon (2021) proves that the reason for this bias under staggered design is because the 2x2 comparisons that the regression estimates are "forbidden" in the sense that newly treated units get compared with already-treated units. Baker, Larcker, and Wang (2021) rely on the Goodman-Bacon decomposition to illustrate that this first becomes a problem when combining heterogeneity in treatment timing with treatment effects that are unequal and dynamic across the entities. In short, the reason why TWFE regressions are not robust to treatment effect heterogeneity is that, in a TWFE regression, units whose treatment status does not change over time serve as a comparison for units whose treatment status does change over time. With multiple periods and variations of treatment timing, some of these comparisons become: newly-treated units to never-treated units (favorable), newly-treated units to not-yet-treated units (favorable), and newly-treated units to already-treated units (forbidden). This is problematic because, revisiting the underlying principle of DiD model, the fundamental idea is to measure the difference in the change of the outcomes of the treated and the untreated counterfactual, as shown in eq. (4). Consequently, when treatment effects are heterogeneous, and take some time to affect the outcome value, making these forbidden comparisons results in subtracting some of the treatment effect. This will generally attenuate the estimates towards zero and change their sign in the most severe cases. As a result, the treatment effect estimator becomes biased.

$$\delta^{DD} = E\left[\left(Y_{t=1}^{Treated} - Y_{t-1}^{Treated}\right) - \left(Y_{t=1}^{Untreated} - Y_{t-1}^{Untreated}\right)\right] \tag{4}$$

Consequences of the problem

This problem results in difficulties interpreting the results from the estimator. Although shifting signs of the estimator are among one of the most severe consequences, instances where the sign does not shift also complicate the interpretation of the treatment effect.

Bias in the DiD estimator is likely to occur in the design of our research design for the following reasons. We argue that the treatment effect of our research is heterogeneous by the time of adoption, as we expect early issuers of SLD to experience more significant effects on both the cost of debt and equity through the greenium effect and signaling effect, respectively. Additionally, it is likely that the treatment effect is dynamic, as the effect on the cost of equity is likely larger around the issuance.

3.1.4 Callaway & Sant’Anna (2021) – A solution to the problem

Callaway and Sant’Anna (2021) provides a solution to the problem. Simply put, it introduces a framework for computing the ATT with heterogeneous treatment times and treatment effects by essentially guaranteeing no forbidden comparisons. It does so not by regression but by computing the ATTs with only desirable comparisons separately, and subsequently aggregating the ATTs of each treated group into an unbiased overall ATT for all the treated groups. A treated group is defined as a group of shipowners that all received treatment in the same treatment period.

Introducing this step by step, it first computes the group-time effects ($ATT_{g,t}$), which are unique estimates for a group at a specific point in time, given by eq. (6). For example, the treatment effect for group one in time four. Then, it aggregates all the group-time ATTs ($ATT_{g,t}$) for a particular group into a single number, giving us the aggregate ATT for each group across the entire time dimension, $\theta_S(g)$, given by eq. (7). In addition to providing an estimate of the treatment effect for each group. Callaway and Sant'Anna (2021) also lets us compute the dynamic treatment effect, meaning the average treatment effects for each time, $\theta_D(e)$, given by eq. (9). For example, the average treatment effect across all groups for time four.

C&A also allows us to use not-yet-treated shipowners as controls. As a result, the size of the control group is increased, at the same time as the quality of the control group likely increases since we allow firms that eventually are treated to serve as controls until they are subject to treatment. This extension of the parallel trend assumption is defined in eq. (5). The notation going forward can seem relatively complicated but is standardized for practical use in the "did" and "cdid" packages for R and Stata, respectively. These are developed by Callaway and Sant'Anna (2022) themselves.

$$For\ all\ \ \mathrm{g} = 2, \dots, T, s, \qquad t = 2, \dots, \qquad T\ \ with\ \ \mathrm{t} \geq \mathrm{g}\ and\ \mathrm{s} \geq \mathrm{t}:$$

$$E[Y_t(0) - Y_{t-1}(0) | G = g] = E[Y_t(0) - Y_{t-1}(0) | D_s = 0, G \neq g] \tag{5}$$

Table 1: Notation for C&A.

Further information can be consulted in (Callaway & Sant'Anna, Difference-in-Differences with multiple time periods, 2021) and for particularly easier interpretation (Callaway & Sant'Anna, 2022).

s	s represents a time period during which units are not-yet treated, with $(s \geq t)$
$Y_{it}(0)$	Unit i's untreated potential outcome, meaning the outcome that unit i would experience in period t if not being treated.
$Y_{it}(g)$	Unit i's potential outcome in time period t if it had become treated in treatment period g.
G_i	Time period in which unit i becomes treated. The reason for using G is because the groups are defined by the treatment period they first become treated.
D_{it}	Indicator variable for whether a unit i has been treated by time t.
Y_{it}	Unit i's observed outcome in time period t. Never-treated units have $Y_{it} = Y_{it}(0)$ in all periods. For units in other groups, $Y_{it} = 1\{G_i > t\}Y_{it}(0) + 1\{G_i \leq t\}Y_{it}(G_i)$ This notation is relatively complicated, but it explains the following: We observe untreated potential outcomes for units that have not yet been treated, and we observe treated potential outcomes for units once they start to participate in the treatment (and these can depend on when they became treated).
e	Number of time periods having participated in the treatment

$$ATT_{g,t} = E\left[Y_t - Y_{g-1} \middle| G = g\right] - E\left[Y_t - Y_{g-1} \middle| D_t = 0, G \neq g\right] \tag{6}$$

$$\theta_S(g) = \frac{1}{T - g + 1}\sum_{t=2}^{T} 1\{g \leq t\}ATT(g,t) \tag{7}$$

$$\theta_S^O = \sum_{g=2}^{T} \theta_S(g)P(G = g) \tag{8}$$

$$\theta_D(e) = \sum_{g=2}^{T} 1\{g + e \leq \mathrm{T}\}ATT(g, g + e)P(G = g|G + e \leq \mathrm{T}) \tag{9}$$

3.1.5 Other statistical methods in our model

Apart from including not-yet-treated units in the control group, we also cluster the standard error on the entity level to control for heteroskedasticity. Additionally, we allow for no anticipation periods, as we doubt that anticipation of SLD issuance is significant given the research question. Lastly, we employ a doubly robust difference in differences estimator as proposed by (Sant'Anna, 2020), as it is the standard used in Callaway and Sant'Anna (2021).

3.2 Estimating the r_D with a Static Test

To answer if the cost of debt changes post SLB issuance, we will first perform a matching procedure at the company level. We will pair each SLB issuer with a non-SLB issuer that is as similar as possible based on pre-defined characteristics. Subsequently, we will match each SLB with the most similar non-SLB of the non-SLB issuer and form bond pairs. Once we have established the bond pairs, we will proceed by identifying the spread between each bond's coupon rate over their respective reference rate. After the spread of each bond is estimated, we will test whether the difference in the spread between SLBs and their non-SLB counterfactuals is significant. This procedure will enable us to claim whether SLBs are issued at a sustainability premium or not. In our cost of debt analysis, we will perform a Paired T-test as well as a Wilcoxon signed-rank sum test. While the paired t-test assumes that the samples are normally distributed, and the variances are equal between the groups, the Wilcoxon signed rank sum does not assume a specific data distribution (Xia, 2020). By conducting both tests, we aim to reinforce the validity of our results and assess their reliability. After having completed both tests, we will conduct a power analysis. This test will enable us to determine the probability of our test's possibility to detect an effect when the effect is present. Essentially, it is the probability of rejecting a null hypothesis when it is incorrect (Cohen, 1977). Additionally, we will examine the necessary sample size to detect a significant effect at different significance levels and determine the corresponding statistical power of these.

3.2.1 Paired t-test

The paired sample t-test is a statistical procedure to determine whether the mean difference between two sets of observations is zero. In a standard paired t-test, each entity is measured twice, which results in pairs of observations (Keller, 2011). Such a test is typically employed when you are interested in measuring the effect of a treatment, such as a program, before and after the program has been completed. However, our case differs as we do not measure the exact same entity twice. Instead, we are examining two different entities we have deemed as similar: an issuer of SLB and one non-SLB counterfactual, with the aim of forming them into equivalent pairs as if they were obtained from a single entity.

To conduct the test, we start by defining the null and the alternative hypothesis. The null hypothesis assumes that the true mean difference between the spread of SLBs and its non-SLB counterfactuals is zero, while the alternative hypothesis assumes that the true mean difference between the two is not equal to zero (two-sided). The equations can be seen in eq. ((10) below:

$$H_0: \mu_s = 0$$

$$H_1 = \mu_s \neq 0$$

(10)

For the paired t-test results to be reliable, four assumptions must hold. The first assumption requires the dependent variable to be continuous. The second assumption is that the observations should not be dependent on one another. The third assumption is that the dependent variable should follow a roughly normal distribution. Lastly, the fourth assumption requires the dependent variable to have no outliers (Rietveld & van Hout, 2017).

Conducting the t-test is a relatively straightforward process consisting of four steps. The first and second step is to calculate the sample mean and standard deviation. Following this, the test statistic is calculated before the p-value of the test is calculated in the final step (Rietveld & van Hout, 2017). The equations for the four steps can be found below:

$$\bar{s} = \frac{s_1 + s_2 + \cdots s_n}{n}$$

(11)

$$\hat{\sigma} = \sqrt{\frac{(s_1 - \bar{s})^2 + (s_2 - \bar{s})^2 + \cdots + (s_n - \bar{s})^2}{n - 1}}$$

(12)

$$t = \frac{\bar{s} - 0}{\frac{\widehat{\sigma}}{\sqrt{n}}}$$

(13)

$$p = 2 * \Pr(T > |t|)$$

(14)

The p-value of the test will tell you the probability, for a given statistical model, that, when the null hypothesis is true, the statistical summary would be equivalent to or more extreme than the observed results in the test (Nahm, 2017). A smaller p-value suggests a lower probability of obtaining your results, given that the null hypothesis was true. The standard threshold for the p-value is set at a significance level of 5 percent (Biau, Jolles, & Porcher, 2009). This means that if you obtain a p-value at or below this level, the null hypothesis will be rejected. Obtaining a p-value at or below 5 percent provides statistical evidence that the mean difference between the spread of the two bonds is not equal to zero. Conversely, obtaining a p-value above the threshold, the conclusion would be to retain the null hypothesis, suggesting that there is no statistically significant difference in the mean spreads between the SLBs and their non-SLB counterfactuals.

3.2.2 Wilcoxon signed rank test

The Wilcoxon signed-rank (Wilcoxon) test is a nonparametric alternative to the paired t-test (Xia, 2020). The Wilcoxon is used when the goal is to conduct a similar analysis of the comparison of two related samples as in the paired t-test, only that the nonparametric test does not assume that the samples are normally distributed as it is utilizing ranked or ordinal data (Rietveld & van Hout, 2017).

The first step in conducting a Wilcoxon test is to calculate the difference of the repeated measurement, which in our case is the difference in the spread of the bond pairs. In the next step, you will assign a rank to each of the bond pairs based on the absolute level of the difference, e.g., a low difference will receive a lower rank than a higher difference. In the Wilcoxon test, cases where the difference is equal to zero, are ignored. For the next step, a negative sign to the ranks with a negative difference will be added. Following this, you will calculate the absolute value of the rank sums into V+ (sum of the absolute values of the positive ranks) and V- (sum of the absolute values of the negative ranks) (Rey & Neuhäuser, 2014). If there is no difference between the V+ and V-, the SLB and its non-SLB spread should be approximately equal. The null hypothesis will be defined as no difference in the mean spread of SLBs and their non-SLB counterfactuals. Conversely, the alternative hypothesis is that the difference in spread is not equal to zero (two-sided).

$$H_0: \mu_s = 0$$

$$H_1 = \mu_s \neq 0$$

(15)

To calculate the test statistics for the Wilcoxon test, use the formula below.

$$V = \min\,(V+, V-)$$

(16)

In the next steps of the Wilcoxon test, the expected value of V and its standard deviation will be calculated using the formulas below.

$$\mu_V = \frac{n(n+1)}{4}$$

(17)

$$\sigma_V = \sqrt{\frac{n(n+1)(2n+1) - \sum \frac{(t_i^3 - t_i)}{2}}{24}}$$

(18)

As a last step, we calculate the z-value using the formula below.

$$z = \frac{V - \mu_V}{\sigma_V}$$

(19)

3.2.3 Power analysis

Paired t-test

We want to conduct a power analysis on both of our tests to ascertain the power – the probability that we will correctly reject the null hypothesis. For the t-test, our initial step involves using our sample data to calculate the power of our test at significance levels of 5 percent, 1 percent, and 0.1 percent. Next, we will estimate the required sample size to achieve the standard power threshold of 0.8 for the equivalent levels of significance. Additionally, we will conduct the test for a higher threshold of 0.9 at similar levels of significance. This will enable us to determine how much the sample size must be enlarged to increase the power of the test, considering the different levels of significance (Cohen, 1988).

To conduct the power analysis for a paired t-test, we will start by calculating the standardized effects size for our test by using the formula for calculating *Hedges'g,* which is suitable when dealing with small sample sizes (Normann, van Emmerik, & Morina, 2014). The formula for calculating *Hedges'g* can be seen in eq. (21) below.

$$PooledSD = \sqrt{\frac{SD_1^2 + SD_2^2}{2}} \tag{20}$$

$$Hedges'g = \frac{M_1 - M_2}{PooledSD} \tag{21}$$

$$, where$$

$$M_1 = mean\ spread\ SLB, M_2 = mean\ spread\ non - SLB$$

After having calculated the effect size of our test, we employ the statistical software program R to perform multiple power analyses, using various inputs such as sample size, power, and levels of significance.

Wilcoxon signed rank sum

When performing a power analysis on the Wilcoxon test, we utilize both the mean and the standard deviation of both SLB and non-SLB issuers (Mollan, Ferrer, Bay, Baldoni, & Hudgens, 2020). In the following step, we use these inputs and specify the minimum and the maximum sample size we want to test. Additionally, we specify the size of the steps between each sample size we want to test for, ranging from the defined minimum to the maximum sample size. In the following step, we run Monte-Carlo simulations to determine the power of tests. We chose to run 1000 Monte-Carlo simulations as it is the recommended number of simulations (Oberle, 2015). Similar to the t-test, we utilize R to perform this analysis.

3.3 Matching and Construction of Control Group

Upon conducting this analysis, we face an empirical challenge as the issuance of SLDs is inherently endogenous in relation to a company's cost of equity and cost of debt. The endogeneity challenge can potentially create a spurious correlation between the issuance of SLDs and the company's cost of equity and debt due to unobservable factors. To address this endogeneity challenge ideally requires the introduction of an instrumental variable for the issuance of SLD. However, finding a suitable instrument proves to be complicated as companies' decision to issue SLDs is not a random occurrence, and it is difficult to find an empirical setting where the issuance of SLDs can be considered quasi-random. To be able to estimate the causal effect of the issuance of SLDs, we will first use a matching method with the aim of pairing SLD issuers with control firms that were as similar as possible prior to the issuance of SLDs to mitigate the selection bias (Flammer, 2021). Thereafter, we will employ the Callaway and Sant'Anna (2021) approach described in section 3.1.4 on the matched sample.

3.3.1 Matching criteria

The following part will present our stepwise matching approach used for matching treated firms with their respective control groups. We use five steps to perform our matching, and each step will be explored individually. Figure 1 displays every step of our analysis.

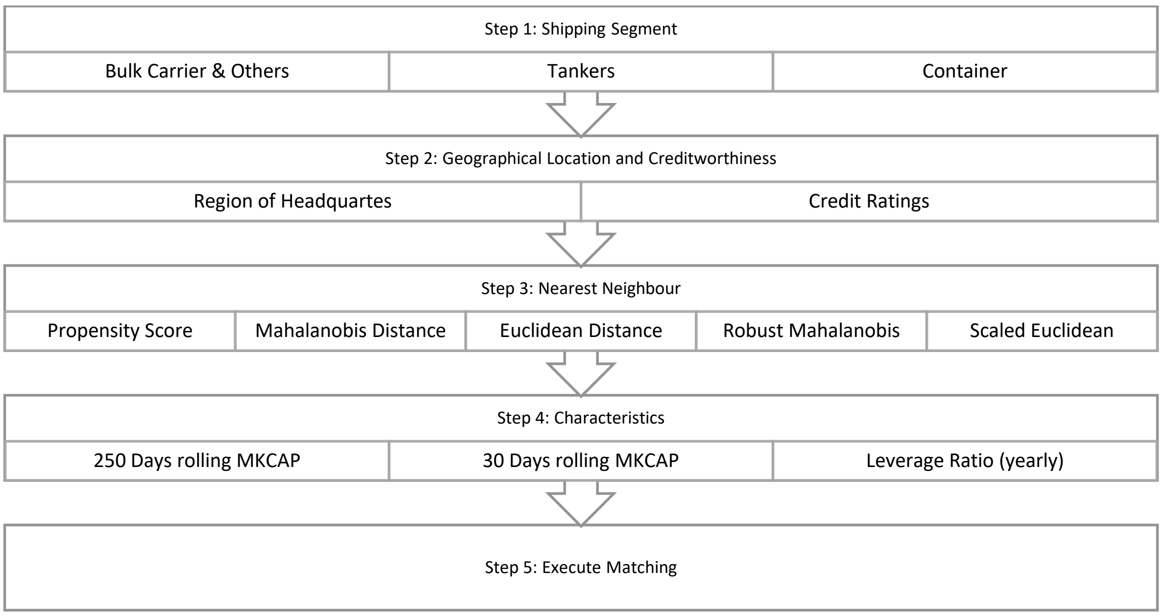


Figure 1: Flow chart for the steps followed for the matching.

As a first step in our matching procedure, we will divide the pool of public shipping companies into three subgroups to account for segment-specific patterns due to their unique supply and demand characteristics: “Bulk Carrier & Others”, “Tanker”, and “Container”. These categories were selected due to their broad coverage of most vessel types. Specifically, the “Bulk Carrier & Others” category covers Dry-Bulk, Ferries, Ro-Ro, and Multi-Purpose Vessels. The “Tanker” category includes Tankers and Gas-carriers, while the “Container” category primarily pertains to vessels engaged in the transportation of containers. The choice of the subgroup for each company corresponds to the primary shipping segment to which the respective company is most significantly exposed. In the process of classifying companies into different segments, we carefully examine each company. The selection of the shipping segment is determined by numerous factors, such as the company’s fleet composition, corroborative information procured from the company’s website, and which segment yields the highest contribution to the company’s total revenue.

As a second step in our matching procedure, we require that the control firms are headquartered in the same region and share the same credit rating as the treated firm. The regional classification is derived from the location of each firm’s headquarters. This selection criterion is predicated on the assumption that companies operating in the same segment and headquartered in the same region will likely encounter a similar economic and regulatory environment. We have chosen to incorporate credit rating as a matching characteristic as it analyses the company’s default risk, thus offering useful insights into the firm’s financial risk profile. As the credit rating is a letter-based scaling rating with multiple variations of the same letter (e.g., AAA, AA+, and AA, see Appendix 1), we get limited control firms for each distinct rating. Consequently, we divide the ratings into investment grade and non-investment grade, where the investment grade corresponds to a default probability of less than 0.20% or an implied letter-rating BBB- or higher (Refinitiv, 2023). Given that the credit ratings are updated daily, we use an estimated average credit rating from the year prior to the issuance.

3.3.2 Nearest neighbor

In the third step of our matching procedure, we will match treated firms with their appropriate control groups using nearest neighbor matching (NN) (Rubin D. B., 1973). NN matching is well-known and widely used in previous studies and comes with the advantage of not requiring heavy computation because the time complexity associated with locating nearest neighbors is relatively low (Lin, Ding, & Han, 2021). When utilizing NN matching in treatment-control studies, NN matching assigns each unit in the treatment group to M units in the control group that are closest in terms of distance. If the M units in the control group are equally close to the treated unit, one of the units in the control group is chosen at random (Austin, 2013).

In our matching procedure, we set M to be equal to 2. This results in each treated unit being matched with the two units in the control group with the closest distance to it. The reason why we choose to include two units from the control group is to enhance the sample size, which in turn increases our ability to detect the treatment effect. Nevertheless, including more than one control unit in the matching might result in a less accurate matching. This occurs as the model only identifies the control units that are as similar as possible to the treated unit based on the chosen covariates. If the additional control units are considerably different from the treated unit, this might lead to biased estimates (Rubin & Stuart, 2008). Our method involves individual matching to pair each treated unit with two units from the control group that is as similar as possible, using five measures of distance: Euclidean distance, Scaled Euclidean distance, Mahalanobis distance, Robust Mahalanobis distance, and Propensity Score. We aim to test the five different distance metrics to utilize the one providing us with the most efficient matching in terms of distance. To achieve this, we will compute the overall average of the difference between each treated unit and its two corresponding control units. Following that will identify the distance measure yielding the smallest aggregated mean difference. Given sufficient data availability, we will construct our sample data for further analysis using the distance measure yielding the lowest aggregated mean difference between each treated unit and its two control units.

Euclidean distance

The Euclidean distance is one of the most commonly used distance measures (IBM). It is somewhat similar to Mahalanobis Distance, however, it does not consider correlation (Huber, et. al (2017)). The Euclidean distance metric measures a straight line between the point in question and the other point being measured (Curriero, 2006). The formula for computing the Euclidean distance can be found in eq. (22) below.

$$d(x, y) = \sqrt{\sum_{i=1}^{n} (y_i - x_i)^2} \tag{22}$$

Scaled Euclidean

As previously mentioned, the standard Euclidean distance is widely used and relatively straightforward. However, an issue with the standard Euclidean distance metric is that it is sensitive to the scaling of covariates. This results in a bias in the calculated distance between the observations, as the covariates with a larger scale will have a larger impact or higher priority when the distance is being calculated. To address this issue, the scaled Euclidean distance metric is the Euclidean distance on the scaled covariates. The scaling ensures that all the covariates are on the same scale, regardless of their original scale unit. This will allow distance computation to be effectively immune to variations in scale (Barret, 2005).

Mahalanobis

Mahalanobis distance is a multivariate distance metric that measures the distance between a point and a distribution (Prabhakaran, 2019). When measuring distance, the Mahalanobis distance accounts for the correlation within the data by calculating the inverse of the variance-covariance matrix of the data we are interested in (Maesschalck, Jouan-Rimbaud, & Massart, 2000). This distance metric can be employed when the aim is to assess whether a treated unit aligns well with various control units. Using Mahalanobis distance for matching can reduce the covariate imbalance, thereby enhancing the efficiency of the estimated treatment effects (Imai & Ratkovic, 2014). The formula for computing Mahalanobis Distance can be found in eq. (23) below.

$$MD_i = (x_i - \bar{x})C^{-1}(x_i - \bar{x})^T \tag{23}$$

$$, where$$

$$C^{-1} = the\ inverse\ covariance\ matrix\ of\ the\ independet\ variable$$

Robust Mahalanobis

Multivariate outliers can impact estimation parameters. A common method for detecting outliers in the data is using the standard Mahalanobis distance metric. However, the standard Mahalanobis distance has its limitations. The limitations stem from using the multivariate sample mean and covariance matrix of the particular dataset, which are sensitive to outliers (Leys, Klein, & Ley, 2018). This results in a detection problem as outliers do not necessarily need to have large Mahalanobis distance values, and opposite, large Mahalanobis distance values do not necessarily need to be outliers (Cabana, Lillo, & Laniado, 2019).

To deal with this issue, different robust versions of the Mahalanobis distance have been introduced. We will use the robust version introduced by Rosenbaum (2010) for our matching. This robust version of the Mahalanobis distance first replaces covariates by their ranks with average ranks. The adjustment of ranks reduces concerns about outliers, and the ties reduce the variance of ranks. However, the covariance matrix of the rank is rescaled, providing every covariate with its united variance (Leys, Klein, & Ley, 2018) (Rosenbaum P. R., 2010) (Rosenbaum & Rubin, 1985)

Propensity Score

The propensity score is defined as the probability of being treated conditional on individuals' covariate values, illustrated in eq. (24) below (Cheng & Wang, 2012).

$$e(x) = pr(A^* = 1|X^* = x) \tag{24}$$

We are estimating the propensity scores for each unit in the control group through multivariate logistic regression. In logistic regression, the dependent or response variable is the treatment indicator and is regressed on the pretreatment covariates for each unit (Zhang Z. , 2017). When the propensity score for all units is calculated, we can match a treated unit with the two controls with the most similar propensity scores. The formula for the propensity score can be found in eq. 25 and follows a logit model (Amoah, et al., 2020).

$$pr(A^* = 1|X^* = x) = \frac{\exp(\theta_0 + x^T\theta)}{1 + \exp\,(\theta_0 + x^T\theta)} \tag{25}$$

3.3.3 Matching characteristics

In the fourth and final step of our matching process, the different matching characteristics utilized in the matching will be presented. The first matching characteristic we will introduce is size. We consider the size of companies as an important factor as it significantly impacts many aspects of the company's operations and performance. As a size measure, we will employ the 250-day and the 30-day rolling average of market capitalization in our analysis. There are two reasons for including this measure: first, we capture the longer-term pre-trend dynamics, and second, we want to seize the more short-term trend upon SLD issuance. To reduce skewness in our data caused by some very large firms and many smaller firms, we use the natural logarithm of market capitalization in our matching.

The second characteristic we will be using in our analysis is leverage. Leverage is included as a firm-specific characteristic as it indicates the company's financial risk, company behavior, and capital structure. It is a plausible assumption that companies exhibiting different levels of financial risk will behave differently. The leverage variable is estimated on a yearly basis as the Long-Term Debt to Total Capital ratio. By including this ratio, we aim to encapsulate the historic leverage ratio and the ratio for the same year for firms issuing SLDs towards the end of the year.

3.3.4 Matching for the cost of debt

A prerequisite for enabling us to conduct an analysis at the bond level between SLB and non-SLB counterfactuals is that these counterparts have outstanding bonds. Therefore, we had to modify the second step in our matching procedure by including a bond issuance requirement for the control group. Consequently, we now require that the control firms share the same geographical headquarter location and comparable standardized letter credit rating as the treated firms, in addition to having issued at least one bond (not Sustainability-Linked Bonds or Green Bonds). The inclusion of this prerequisite for the control firms might result in a different set of matches compared to the ones utilized in the cost of equity part of our analysis, as the original matched controls may not have any outstanding bonds. Additionally, adding the bond issuance requirement might result in a reduction of sample size, which in turn potentially impacts the quality of the matching. For this adjusted part of the matching, we aim to utilize the same methodology previously described, given that the date permits us to. However, if we are facing issues such as a limited matching sample size and suboptimal matching, we are forced to make adjustments to the matching by relaxing some of the matching criteria. Initially, this involves removing the region requirement, and if required, we may also discard or modify the credit rating requirement.

When having successfully matched the SLB issuing companies with one non-SLB counterfactual, we create bond pairs to compare the spread differentials. In this part, we will not limit the treated firms to only being first-time issuers but rather all SLB issuers (allowing for using more than one SLB from the same company to increase the number of bond pairs). To further strengthen our matching, we use a similar bond-level matching procedure as Kölbel & Lambillon (2022). We will examine the bonds issued by the control firms, choosing the bond that is as similar as possible based on *issuance size*, *maturity*, and *issuance date*. In addition, considering the significant impact of the issuer's profile on bond issuance, we will examine each company's creditworthiness in the bond pair (Merrill Lynch & Co. Inc). This is crucial as companies with different credit ratings may impact the spread added to the bond, thus altering the perceived riskiness of the bond.

4. Cost of Capital Measurements

This section explains the cost of capital measurements used in the analysis. First for the cost of equity and subsequently for the cost of debt measurements.

4.1 Cost of Equity

We use the Capital Asset Pricing Model (CAPM) to estimate the shipowners' cost of equity. To ensure robust and comparable estimates, we use Refinitiv's estimates for the cost of equity directly. Refinitiv provides daily estimates for the cost of equity, which we compute into our output variable of the monthly average cost of equity for each shipowner. The CAPM is given by eq. (26) and its components are calculated in the following way. The expected market return is calculated from simple daily market returns (eq. (27)) of the primary local index for each company's primary equity listing. The beta is the covariance of the security's price movement in relation to the market's price movement. The measure for equity's systematic risk is, in order of preference, calculated as the 5-year monthly, 3-year weekly 2-year weekly, 180-day daily, or 90-day daily beta, depending on the data availability. The risk-free rate is calculated as the U.S. Treasury 10-year yield plus the difference between the 10-year country-specific inflation forecast and the corresponding 10-year U.S. inflation forecast.

$$E[r_i] = r_f + \beta_i(E[r_M] - r_f) \tag{26}$$

$$, where$$

$$Systematic\ risk\ of\ stock\ i = \beta_i = \frac{Cov(r_i, r_M)}{\sigma_M^2} \qquad E[r_i] = Expected\ return\ on\ stock\ i$$

$$E[r_M] = Expected\ return\ of\ the\ market \qquad r_f = Risk - free\ rate$$

$$Simple\ returns = \frac{P_t - P_{t-1}}{P_{t-1}} \tag{27}$$

4.2 Cost of Debt

In our analysis of the cost of debt, our focus will be entirely concentrated on SLB and associated counterfactuals. As a measure of the company's cost of debt, we will use the spread between the coupon rate and the reference rate agreed at the time of issuance. This methodological approach will facilitate our investigation into whether SLBs are issued at a premium compared to their non-sustainable counterparts.

As the bonds are either issued with a variable (floating) coupon rate or a fixed coupon rate, it is important to make suitable adjustments to render the coupon rates spread comparable. Our goal is to standardize the measurement parameters by making such an adjustment. This facilitates an accurate comparison across bonds, regardless of whether they have a fixed or a floating coupon rate attached or if the bonds are issued in different currencies. We will start by shortly introducing the two distinct coupon types. Subsequently, we will explain the process of adjusting the coupon rates to make them comparable.

Floating coupon rate

A floating rate bond is characterized by an interest rate that varies over time. It comprises two elements: a reference rate, which is the variable component, and a fixed spread (U.S. Department of the Treasury, 2023). The reference rate is a short-term benchmark rate, such as LIBOR, NIBOR, or the Fed funds rate (Marquit & Curry, 2023). While the reference rate adjusts in response to changes in the market environment, the fixed spread acts as a risk indicator, accounting for additional risks such as credit risk and liquidity risk tied to the bond.

Fixed coupon rate

A fixed-rate bond contrasts with a floating-rate bond, characterized by a coupon rate that is fixed throughout the bond tenure. Consequently, the investor receives regular coupon payments regardless of market conditions. The fixed coupon rate is influenced by a multitude, primarily the prevailing interest rate at the time of issuance, in addition to the credit risk associated with the issuer (U.S. Securities and Exchange Commission, 2013).

Interest rate swaps

From floating coupon rate bonds, we can easily extract the credit risk added to the bond by looking at the spread over the reference rate. However, the process is not as straightforward with fixed coupon rate bonds. We will utilize interest rate swaps to identify the spread on a fixed coupon bond, representing the credit risk embedded in the fixed coupon instrument (PIMCO, 2016). After calculating the fixed interest rate for an interest rate swap at the time of issuance of the bond, with terms similar to the bond (duration, associated floating reference interest rate, coupon payments dates, and day count) we will find an approximation for the risk-free interest rate at the time of issuance of the bond, and subtract this rate from the fixed coupon rate (Refinitiv EIKON, 2023). This procedure will facilitate the identification of the additional spread and yield attributable to the credit risk of the bond, thereby enabling a comparison of the spread between floating-rate bonds and fixed-rate bonds. Additionally, we can compare bonds issued in different currencies. Furthermore, it allows us to compare bonds issued at different time periods, as the utilized data only incorporates the spread and not the interest rate level.

5. Data

This chapter will give an in-depth description of the data-gathering process. We will initially explain our approach to identifying shipowners before we will continue by introducing the SLD issuers and describe various data characteristics related to these. Following this, we will present the sample dataset of the SLD issuers and their respective matching peers. At the end of this chapter, we will explain the data used for the cost of equity and debt analysis. A flowchart has been developed to better understand our data-gathering process, shown in Figure 2 below.

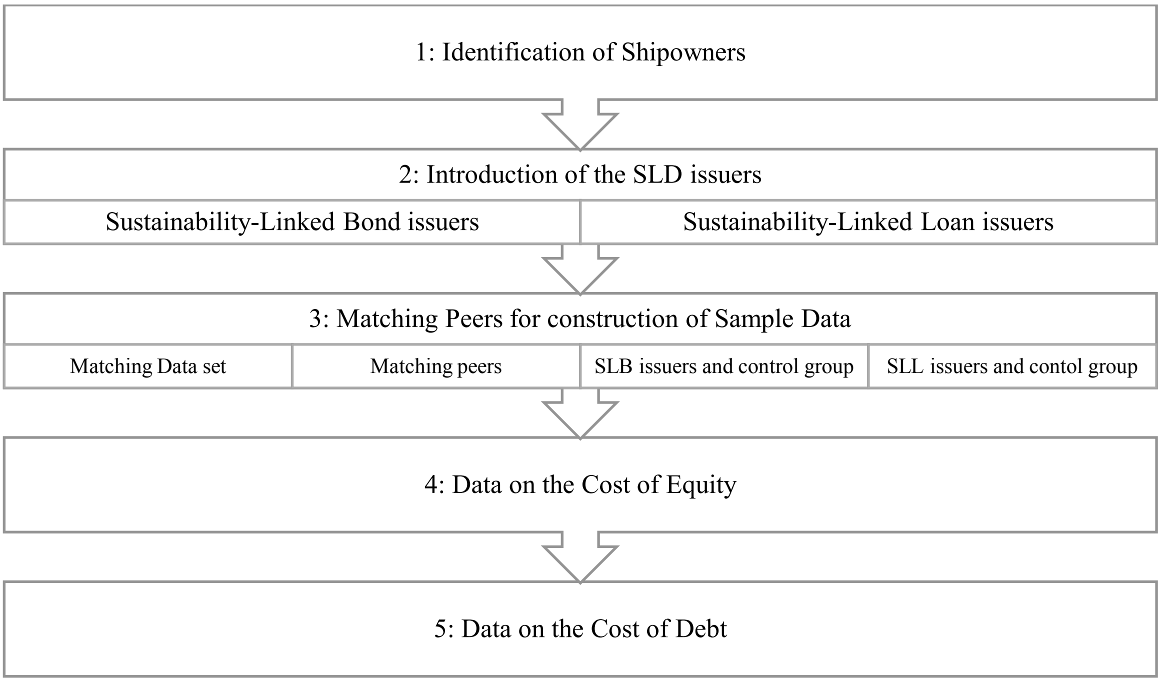


Figure 2: Stepwise explanation of our data-gathering process.

5.1 Data on Public Shipowners

To identify the public shipowners, we have used several sources. As our primary source of financial data (Refinitiv EIKON) does not have a "TRBC Industry Name" applicable to all public shipowners, we started our data-gathering process using the Clarksons Shipping Intelligence Network. According to the report "Clarksons Market Monthly" (2023), as of March 31, 2023, the global landscape consists of 254 public shipping companies. The report lists the top 30 publicly listed shipping fleets based on fleet size measured in million gross tonnages. As a starting point, we created a watchlist in EIKON to include all the companies listed by Clarksons. This approach ensures that we have successfully identified the largest companies in the industry. As a next step, we also include the SLD issuers, as retrieved from Clarksons SIN (2023), who have not been previously included in the list due to their smaller fleet size.

In the next stage, we map the different "TRBC Industry Name" in EIKON that covers other public ship owners. For example, as most of the shipowners can be found in the "TRBC Industry Name" called "Marine Freight & Logistics", it becomes apparent that several companies operating within the "Tankers" (according to the report "Clarksons Market Monthly" (2023)) segment are not included in the mentioned industry name. When mapping all the industry names of interest, we get a list comprising more than 400 companies. As a next step, we need to explore each company individually to determine if they are categorized as shipowners. This process uses data from Clarksons SIN to verify fleet ownership, information from official company websites, and other relevant sources providing reliable and comprehensive information about each company. The final step of our initial data gathering is to allocate a shipping segment to each shipowner. The process for assigning a shipping segment is explained in greater detail in our matching methodology.

5.2 Data on SLD Issuers

As of March 31, 2023, 17 of the 254[2] public shipping companies have issued SLDs. Among these 17 SLD issuers, four have issued SLBs, while the remaining thirteen have issued SLLs. Our sample encompasses fifteen out of the seventeen companies in question. Cool Company Ltd is excluded due to insufficient publicly accessible data, given its recent listing in 2022. Additionally, Avance Gas Holding Ltd is omitted as they issued their SLL in late May 2022, leaving inadequate post-treatment data for inclusion in our analysis.

The following section will describe the SLB issuing firms and the sustainability-linked features incorporated in the bond instrument. Subsequently, a description of the SLL issuers and sustainability-linked features embedded in the loans will be provided.

[2] Clarksons Shipping Intelligence Network

5.2.1 Sustainability-linked bond issuers

As shown in Table 2 (Panel A) below, the four SLB issuing companies: Odfjell SE, Seaspan Corporation, SFL Corporation Ltd, and Wallenius Wilhelmsen ASA, all announced and issued their SLB at different various moments in time. The dates of these events span from January 2021 to April 2022. While Odfjell SE's bond issuance accounted for a relatively large part of their market capitalization, the bonds issued by the three remaining firms accounted for a smaller proportion of their market capitalization at the time of issuance. Table 3 shows that all the issuers are based in Europe or America. The European-based companies Odfjell SE and Wallenius Wilhelmsen ASA operate in the "Tankers" and "Bulk Carrier & Others" segments, while both Seaspan Corporation and SFL Corporation Ltd operate primarily in the "Container" segment. Consequently, the issuers cover all three segments. In terms of fleet composition Seaspan Corporation and Wallenius Wilhelmsen are world leaders in the Container and Ro-Ro shipping segment, while Odfjell SE is one of the world leaders in the global market of transportation of chemicals. On the other hand, SFL Corporation has a more diverse fleet and ranks as one of the world's largest ship-owning companies.

Seaspan Corporation was delisted in February 2020 and became a wholly owned subsidiary of the new holding company Atlas Corp. Consequently, we lack publicly available data on Seaspan Corporation following its delisting. Therefore, we will use Atlas Corp as an approximation for data after the delisting to represent Seaspan Corporation. Atlas Corp's operations are divided into two segments: "Containership leasing" and "Mobile Power Generation". From 2020 to 2022, the "Containership leasing" segment accounted for around 90 percent of Atlas Corp's total revenue (see Appendix 2). Hence, using Atlas Corp as a proxy will likely yield a reasonably accurate representation of Seaspan Corporation.

Sustainability-Linked Bond features and use of proceeds

The prospectus for the SLBs states that Odfjell SE's use of proceeds from the issuance of the SLB focuses on improving the "Average Efficiency Ratio" (AER). The SPT is to reduce this ratio to 8.18 or lower by June 2024. The AER is a metric for carbon intensity rather than an absolute emission measure. To reach their SPT, they plan to initiate several improvements projects for their existing fleet, such as energy-saving devices to improve propulsive efficiency, govern control devices to optimize the vessel movements, and de-rating of engines and turbocharger upgrades. If Odfjell SE fails to deliver supporting verification and review, the redemption price of the bond will be increased by 150 basis points (Odfjell SE, 2020).

Seaspan Corporation's use of proceeds focuses on binding commitments on vessel acquisitions, newbuildings, and vessel retrofits which can be powered by Alternative Fuel Sources. The SPT is to spend a minimum of USD 200 million on these initiatives. Failure to achieve the SPT will result in an increase of 50 basis points on the principal payment upon maturity (Sustainalytics, 2021). For SFL Corporation, the use of proceeds also includes a binding financial commitment towards upgrading their current fleet and acquiring new vessels, with the aim of implementing low-emission solutions which will improve the environmental performance of their fleet. Their SPT is to spend at least USD 150 million on fleet optimization. Failure to achieve the SPT by the target date will result in an increase of 50 basis points on their principal payment upon maturity (SFL Corporation, 2021). Lastly, Wallenius Wilhelmsen's use of proceeds will go towards reducing their carbon intensity by the target observation date. To reduce carbon intensity, they plan to combine initiatives such as fleet digitalization, developing machine learning models, improving voyage planning, and using low-carbon fuels such as biofuels. The SPT is to reduce the carbon intensity to a minimum of 10.1% by the target observation date, and failing to do so will result in an increase in the redemption price by 150 basis points (Wallenius Wilhelmsen ASA, 2022).

5.2.2 Sustainability-linked loan issuers

Table 2 (Panel B) describes all thirteen SLL issuances. The loan origination dates vary for all the SLL issuing firms, apart from BW LPG Ltd and Safe Bulkers Inc, which have the same origination date on the loans. The loan origination dates range from July 2020 to May 2022. Upon examining the loan size to market capitalization, we observe that, in most cases, this ratio is relatively low. However, exceptions exist, such as Klaveness Combination Carriers ASA, Euronav NV, Torm PLC, Diana Shipping Inc, and Navios Maritime Holdings Inc, where the ratio is at or exceeds 19 percent. Table 3, Panel B, provides a company-level description. This description shows that the SLL issuers cover all three regions and represent the three shipping segments "Bulk carrier & Others," "Tankers," and "Container." Among the SLL issuers, we find some of the largest companies in the shipping industry. Nippon Yusen KK operates one of the largest fleets in the world, Euronav NV is the world's largest independent tanker company engaged in the transportation and storage of crude oil, and U-Ming Marine Transportation Corp currently owns and operates a large fleet comprising of oil tankers and dry-bulk carriers.

5.2.3 SLL characteristics

As we have an extensive list of eleven SLL issuing firms, we will not explore every single individually but instead focus on information related to the characteristics of the SLLs on a more aggregated level. The SLLs secured by the SLL issuing firms are linked to the company's SPT targets. SLLs incorporate incentives in the lending terms, such as an interest rate that will be adjusted in accordance with the borrower's sustainability performance. This way, by upgrading its sustainability management or performance, a borrower can get access to funds at more favorable conditions from financial instructions offering ESG loans. Additionally, through SLLs, the borrower must disclose relevant information to the lenders and ensure a transparent process, resulting in potential new relationships with financial institutions favoring ESG loans, which again leads to a potentially more substantial base of funding (Green Finance Portal, 2023).

Table 2: Sustainability-Linked Bond and Loan Description for SLB and SLL issuing firms.

The issuance size in both panels is reported in millions.

Panel A - Sustainability-Linked Bond Description

Companies	*Announcement Date*	*Issuance Date*	*Issuance Size (USD, on issuance date)*	*Coupon Rate*	*Relative bond size vs. Market Capitalization*	*Maturity Date*
Odfjell SE	06.01.2021	21.01.2021	100	NIBOR3M + 5.75%	37%	21.01.2025
Seaspan Corporation (Atlas Corp)	21.01.2021	05.02.2021	200	6.50%	7%	05.02.2024
SFL Corporation Ltd	26.04.2021	29.04.2021	150	7.25%	15%	12.05.2026
Wallenius Wilhelmsen ASA	04.04.2022	06.04.2022	142	NIBOR3M + 4.25%	5%	21.04.2027

Panel B - Sustainability-Linked Loan Description

Companies	*Loan Origination Date*	*Loan Size (USD, on origination date)*	*Interest Rate*	*Relative bond size vs. Market Capitalization*	*Maturity Date*
Klaveness Combination Carriers ASA	06.07.2020	60	LIBOR + 2.75%	33%	01.03.2026
Ardmore Shipping Corp	29.07.2020	15	Not Disclosed	10%	Not Disclosed
Euronav NV	11.09.2020	713	Not Disclosed	34%	11.03.2026
Torm PLC	11.11.2020	150	Not Disclosed	29%	11.11.2027
Nippon Yusen KK	05.02.2021	50	Not Disclosed	1%	05.02.2025
Diana Shipping Inc	18.05.2021	91	Not Disclosed	19%	Not Disclosed
BW LPG Ltd	01.10.2021	40	Not Disclosed	5%	Not Disclosed
Safe Bulkers Inc	01.10.2022	60	Not Disclosed	11%	01.10.2026
Seanergy Maritime Holdings	26.10.2021	17	LIBOR + 3.05%	7%	Not Disclosed
Navios Maritime Holdings Inc	01.12.2021	73	LIBOR + 2.7-2.8%	74%	01.10.2026
U-Ming Marine Transportation Corp	22.02.2022	70	Not Disclosed	4%	Not Disclosed

Table 3: Sustainability-Linked Bond and Loan Company Description.

The min, max, and average market capitalization 12 months pre-issuance is reported in millions.

Panel A - Sustainability Linked-Bond Issuing Companies Description

Companies	*Fleet Composition*	*Region of Headquarters*	*Average Market Capitalization 12M Pre-Issuance*	*Min*	*Max*	*Credit Rating*
Odfjell SE	Chemical Tankers	Europe	214	140	296	BBB+
Seaspan Corporation (Atlas Corp)	Container	America	2 186	1547	2941	BB-
SFL Corporation Ltd	Container, Tankers, Dry Bulk, Car Carriers	America	989	716	1289	BBB
Wallenius Wilhelmsen ASA	Car Carriers, Breakbulk	Europe	1 982	1277	3367	BBB-

Panel B - Sustainability Linked-Loan Issuing Companies Description

Companies	*Fleet Composition*	*Region of Headquarters*	*Average Market Capitalization 12M Pre-Issuance*	*Min*	*Max*	*Credit Rating*
Klaveness Combination Carriers ASA	Bulker, Combination Carriers	Europe	214	116	262	A-
Ardmore Shipping Corp	Product & Chemical Tankers	America	211	132	314	A
Euronav NV	Oil Tankers	Europe	2 224	1 741	2 860	BBB
Torm PLC	Product Tankers	Europe	606	478	835	BBB+
Nippon Yusen KK	Dry Bulk, Car Carriers, Container, Tankers	Asia	3 633	2 114	6 677	A
Diana Shipping Inc	Dry Bulk	Europe	303	119	572	BB+
BW LPG Ltd	Gas Carriers	Asia	899	624	1 230	A
Safe Bulkers Inc	Dry Bulk	Europe	294	87	629	BB-
Seanergy Maritime Holdings	Dry Bulk	Europe	160	32	346	B+
Navios Maritime Holdings Inc	Dry Bulk	Europe	98	35	219	B
U-Ming Marine Transportation Corp	Dry Bulk, Oil Tankers	Asia	1 720	967	2 698	BBB+

5.3 Matching Data for Constructing the Sample

The results of our matching process, creating our sample data, can be found in Table 4 below. The three different segments – “Bulk Carrier & Others”, “Tankers”, and “Container” – are displayed in Panels A-C, where each SLD issuer is paired with two non-SLD issuers. To form our sample data, we employ the Euclidean distance, as it is the distance metric that, on average, resulted in the lowest distance between each treated firm and its two control counterparts. When performing our matching process, we encountered challenges related to data availability or insufficient matching results. In the continuance of this section, we will explore some of the adjustments we implemented to address these issues.

In Panel A, describing “Bulk Carrier & Others”, we experienced some challenges upon matching Navios Maritime Holdings Inc (credit rating B) and Seanergy Maritime Holdings (credit rating B+) with two control firms with a credit rating equal to non-investment grade (below BBB-). Therefore, we had to adjust the matching criteria for these two matchings by including firms encompassing a slightly higher credit rating. This enabled us to identify more similar control firms based on the other matching parameters.

In Panel B, which pertains to “Tankers”, we faced some challenges identifying appropriate matching controls for Euronav NV. Initially, Frontline Plc was chosen as one of the matching peers, but due to insufficient data for our cost of equity analysis, we had to exclude Frontline Plc as one of the two control firms. Additionally, we had to make some alterations while searching for appropriate matching peers for BW LPG Ltd, as there were few potential control firms with an investment grade credit rating within Asia. Therefore, we removed the regional requirement in this matching. This adjustment ensured a more efficient match on the other matching parameters.

Lastly, regarding the “Container” segment, presented in Panel C, we had to remove the region criterion upon performing the matching process. This adjustment was necessary as we encountered “N/As” when matching due to a few potential control companies with similar characteristics within the region of “America”. Moreover, for Seaspan Corporation, which holds a non-investment grade rating of BB-, we had to adjust the matching criteria to encompass companies with a higher credit rating to increase the matching efficiency.

Table 4: Matching Peers Company Description.

Panel A – Bulk Carriers & Others					
SLD Issuing Companies	*Matching Control Companies*	*Fleet Composition*	*Region of Headquarters*	*Average Market Capitalization 12M Pre-Issuance (MUSD)*	*Credit Rating*
Klaveness Combination Carriers ASA	Wilson ASA	Multi-Purpose Vessels, General Cargo	Europe	97	BBB+
	Dampskibsselskabet Norden A/S	Dry Bulk, Product Tankers	Europe	584	A-
Nippon Yusen KK	Pan Ocean Co Ltd	Bulker, Tankers, Container, Gas Carriers	Asia	2 064	A
	Transcoal Pacific Tbk PT	Dry Bulk, Tugs	Asia	2 168	A
Diana Shipping Inc	Belships ASA	Dry Bulk	Europe	172	BB+
	Attica Holdings SA	Passenger Ferries	Europe	224	BB
Safe Bulkers Inc	Belships ASA	Dry Bulk	Europe	251	BB+
	Attica Holdings SA	Passenger Ferries	Europe	242	BB
Seanergy Maritime Holdings	Wilson ASA	Multi-Purpose Vessels, General Cargo	Europe	167	BBB+
	Attica Holdings SA	Passenger Ferries	Europe	250	BB
Navios Maritime Holdings Inc	Pangea Logistics Solutions Ltd	Dry Bulk	America	178	BBB-
	Eagle Bulk Shipping Inc	Dry Bulk	America	491	BB+
U-Ming Marine Transportation Corp	COSCO Shipping Spec. Carries Co	Multi-Purpose Vessels, Bulker, Tankers, Container, Car Carriers	Asia	1 703	BBB+
	Pacific Basin Shipping Ltd	Dry Bulk	Asia	1 837	BBB+
Wallenius Wilhelmsen ASA	Star Bulk Carriers Corp	Dry Bulk	Europe	2 248	BBB
	DFDS AS	Ro-Ro, Passenger Ferries, Multi-Purpose Vessels	Europe	3 120	BBB

Panel B - Tankers					
SLD Issuing Companies	*Matching Control Companies*	*Fleet Composition*	*Region of Headquarters*	*Average Market Capitalization 12M Pre-Issuance (MUSD)*	*Credit Rating*
Ardmore Shipping Corp	FLEX LNG Ltd	Gas Carriers	America	409	A
	DHT Holdings Inc	Oil Tankers	America	939	A
Euronav NV	Stolt-Nielsen Ltd	Chemical Tankers	Europe	672	BBB
	GasLog Partners LP	Chemical Tankers	Europe	454	BBB
Torm PLC	Stolt-Nielsen Ltd	Chemical Tankers	Europe	645	BBB
	GasLog Partners LP	Gas Carriers	Europe	346	BBB
Odfjell SE	Okeanis Eco Tankers Corp	Oil Tankers	Europe	228	BBB-
	Hunter Group ASA	Oil Tankers	Europe	227	BBB
BW LPG Ltd	DHT Holdings Inc	Oil Tankers	America	977	A
	Scorpio Tankers Inc	Product Tankers	Europe	927	A-

Panel C - Container					
SLD Issuing Companies	*Matching Control Companies*	*Fleet Composition*	*Region of Headquarters (1)*	*Average Market Capitalization 12M Pre-Issuance (MUSD)*	*Credit Rating*
Seaspan Corporation (Atlas Corp)	Wan Hai Lines Ltd	Container	America	1 776	BBB+
	COSCO Shipping Development Co Ltd	Container	Asia	1 836	BBB-
SFL Corporation Ltd	Costamare Inc	Container, Dry Bulk	Europe	948	BBB-
	Danaos Corporation	Container	Europe	397	BBB-

(1) We had to exclude the region requirement from the container matching due to insufficient data observations.

5.4 Data on the cost of equity

5.4.1 Raw data description

The raw time-series data on the 39 shipowners' daily cost of equity was retrieved from Refinitiv Screener on May 19, 2023. Our analysis time frame is from July 1, 2019, to April 30, 2023. This is because it allows for one year of observations before and after the first and last issuance in July 2020 and April 2022, respectively. We will consider the announcement date as the treatment date for the SLBs, while for the SLLs, the loan origination date will serve this purpose.

To present meaningful descriptive statistics on the raw data, several elements require intervention. Firstly, the raw data includes the securities for both Seaspan Corporation and Atlas Corp. These firms are merged during the period of analysis. Seaspan Corporation's observations were used until it was delisted, and subsequently, Atlas Corp's values were used. Secondly, Refinitiv only allows getting access to historical time-series data counting from today and backward. As the data was collected from May 19, we have excluded the observations for May 2023. This approach ensures a consistent timeframe, starting from the beginning of July 2019 and ending at the end of April 2023. Thirdly, the datasets in EIKON are structured to supply one observation per calendar day and not per trading day. To ensure uniformity across all firms, we use the New York Stock Exchange (NYSE) trading schedule as the standard and remove 18 120 (non-trading days) observations that do not coincide with NYSE's trading days. Table 5 provides a summary statistic of the raw data within this time frame. The corresponding histogram and boxplot in Figure 3 provide information about the distribution and outliers.

Table 5: Descriptive statistics for the sample of 39 shipowners.

Identifier		Company Name		Day		Date		Cost of Equity	
Length:	37596	Length:	37596	Length:	37596	Min.:	02.07.2019	Min.:	0.0105
Class:	character	Class:	character	Class:	character	1st Qu.:	20.06.2020	1st Qu.:	0.0576
Mode:	character	Mode:	character	Mode:	character	Median:	30.05.2021	Median:	0.0833
Unique:	39	Unique:	39	Unique:	7	Mean:	29.05.2021	Mean:	0.0919
						3rd Qu.:	25.05.2022	3rd Qu.:	0.1179
						Max:	23.04.2023	Max:	0.4495
						Sd:	-	Sd:	0.0515
						Na's:	0	NA's:	1141

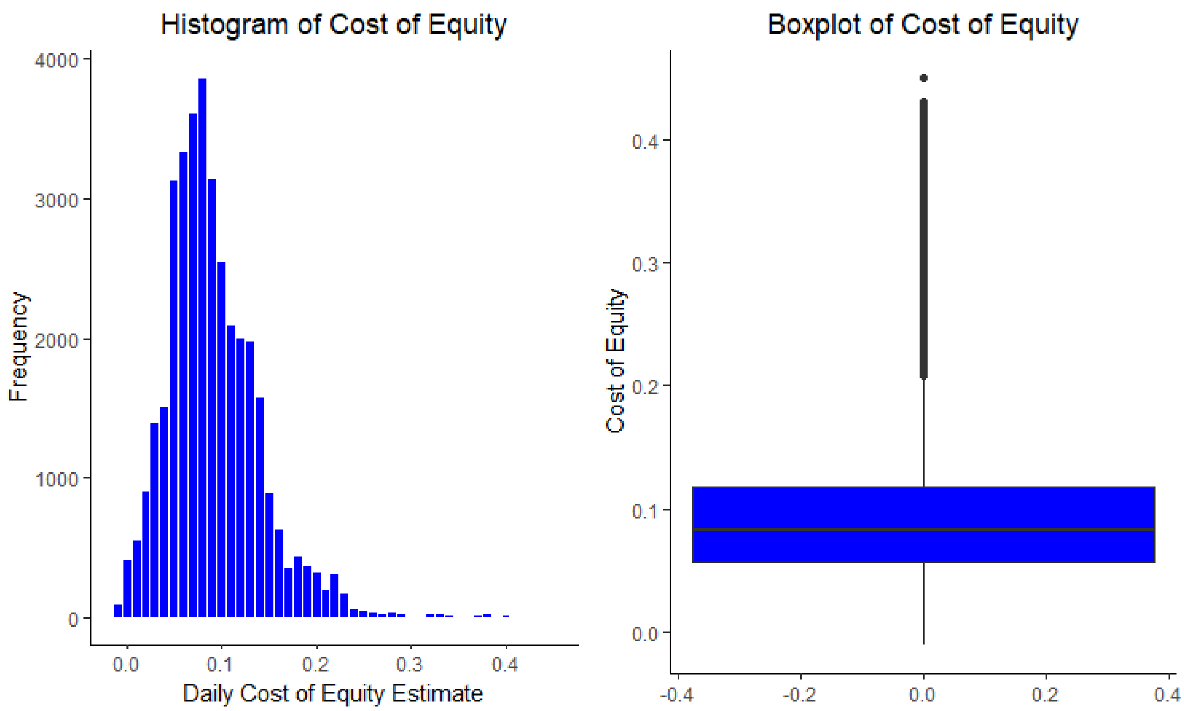


Figure 3: Descriptive statistics for the daily cost of equity.

Histogram of Daily Cost of Equity Estimates: Unwinsorized and not including NAs. Column width is set to showcase 1% increments.

Box plot: We see outliers with the cost of equity estimates of more than 20%. For reference, the cost of equity for Wallenius Wilhelmsen at the time of writing is almost 19%, which is a result of recent equity volatility. The plot excludes all NAs.

5.4.2 Data assessment and intervention

Size and quality of data

The panel consists of 39 securities, each with 964 rows of possible observations. Out of the 1141 NAs, all firms in the sample have 26 missing values for all firms from August 16 to September 21, 2021, accounting for 1014 of the NAs in Table 5. As this is the case for all firms in our sample and considering our inevitable use of the average monthly cost of equity as the outcome variable of interest, we decided to calculate the average cost of equity for all firms in August and September 2021 using 15 and 10 days of observations, respectively. Additionally, we have missing values for Okeanis Eco Tankers until its IPO on January 29, 2021, and for Atlas Corp after its delisting at the end of March 2023. We use the two matched comparable firms for each of the firms to proxy Okeanis Eco Tankers' and Atlas Corp's missing values. Since the missing values for these two shipowners make up entire months, we compute the monthly cost of equity estimates before employing the missing values for these two firms with the comparables' estimates.

Center, distribution, spread, and outliers

The raw data has a mean cost of equity of 9.19% and a standard error of 5.15%. The data is relatively unsymmetric and right-skewed as the mean and median of 8.33% deviate from the mean by almost a percentage point. Additionally, the data exhibits a wide range, with the lowest cost of equity estimated at 1.05% and several outliers with a cost of equity of around 40%. As these figures do not represent the typical cost of equity for shipping companies, we winsorize at 95%, replacing extreme values with values from the 2.5% tails of the distribution. The histogram in Figure 4 represents the distribution of the daily cost of equity after winsorizing the 5% most extreme values. Corresponding descriptive statistics are displayed in Table 6. The data now ranges from 1.28% to 21.75%, which seems more reasonable for the shipping industry. Although the deviation between the mean and median is reduced by 0.1 percentage point, the distribution is still quite right-skewed. We managed to reduce the standard deviation by 0.4 percentage points, although the size of the standard deviation is still around half of the mean.

Table 6: Descriptive statistics for the 39 shipowners after winsorizing at the 95% level.

Identifier		Company Name		Day		Date		Cost of Equity	
Length:	37596	Length:	37596	Length:	37596	Min.:	02.07.2019	Min.:	0.0127
Class:	character	Class:	character	Class:	character	1st Qu.:	20.06.2020	1st Qu.:	0.0576
Mode:	character	Mode:	character	Mode:	character	Median:	30.05.2021	Median:	0.0833
Unique:	39	Unique:	39	Unique:	7	Mean:	29.05.2021	Mean:	0.0908
						3rd Qu.:	25.05.2022	3rd Qu.:	0.1179
						Max:	23.04.2023	Max:	0.2170
						Sd:	-	Sd:	0.0463
						Na's:	0	NA's:	1141

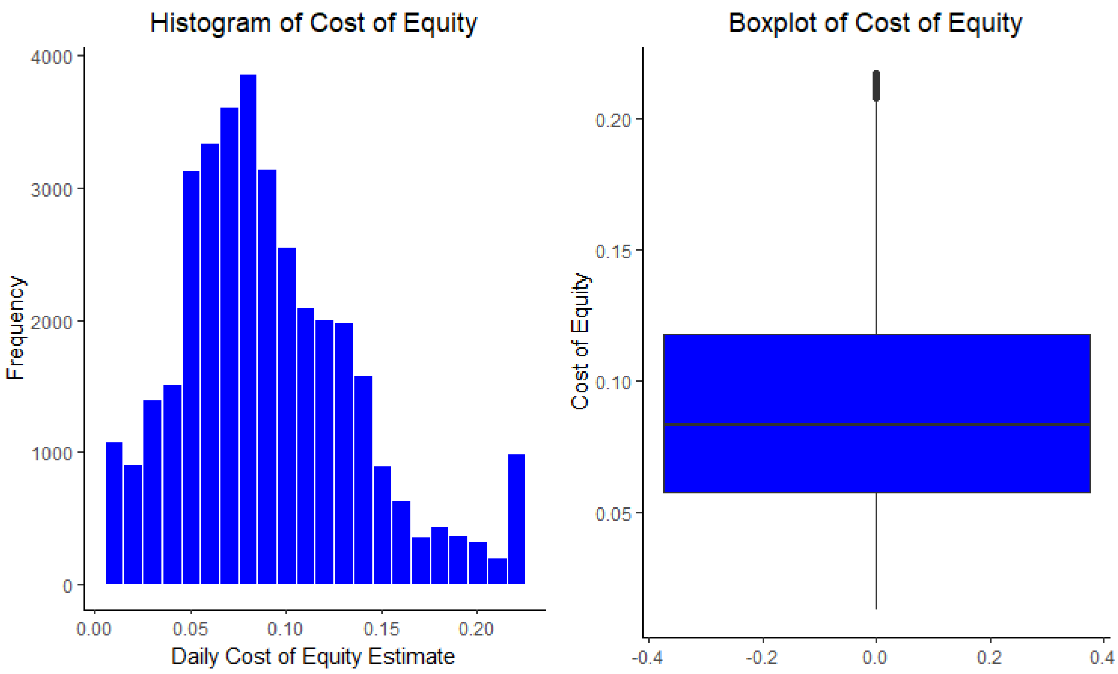


Figure 4: Descriptive statistics (5% most extreme values winsorized).

We see that the extreme values from the raw data are pulled in towards the center, taking the highest and lowest values of the 95 percentile. This is the reason for the high frequency in the tails. The box plot shows that outliers do not seem to pose a problem anymore, as the high tail is substantially reduced. All NAs are removed from the plots.

Table 7: Summary statistics for the complete sample dataset of monthly average cost of equity.

The monthly average cost of equity is computed from the winsorized daily cost of equity estimates. After computing the monthly average cost of equity and filling in the NAs, we get the following summary statistics. Unsurprisingly, the values and plots are almost identical to those of the daily estimates.

Identifier		**Company Name**		**Year - Month**		**Monthly Average Cost of Equity**	
Length:	1794	Length:	1794	Length:	1794	Min.:	0.0127
Class:	character	Class:	character	Class:	character	1st Qu.:	0.0579
Mode:	character	Mode:	character	Mode:	character	Median:	0.0841
Unique:	39	Unique:	39	Unique:	46	Mean:	0.0917
						3rd Qu.:	0.1192
						Max:	0.2170
						Sd:	0.0461
						NA's:	0

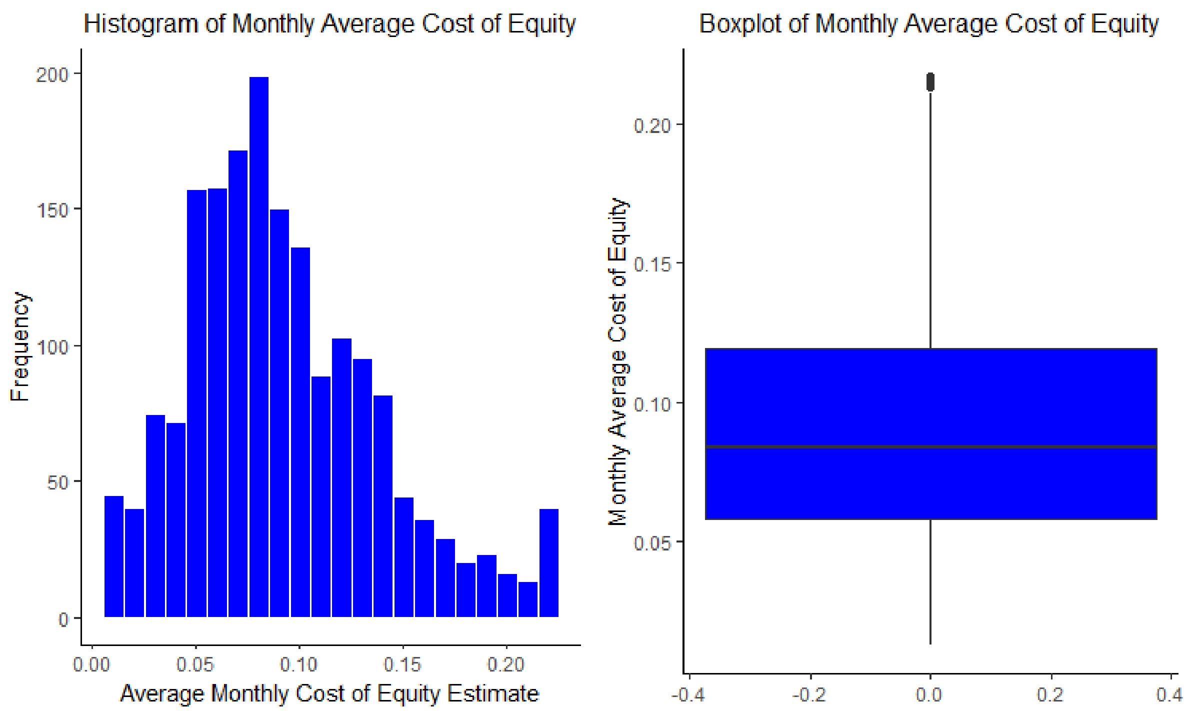


Figure 5: Descriptive statistics of the average monthly cost of equity.

The estimates are computed from daily estimates where the 5% most extreme values are winsorized. We see the distribution is quite similar to Figure 4, which is to be expected, as we simply compute the monthly estimates from the daily estimates.

5.4.3 Necessary data adaptations for the C&A (2021) method

After cleaning the cost of equity data, we merge it with the treatment data and add a time column indicating the *treatment period*. The treatment period variable is centered around the first treatment, which occurs in treatment period 1, and as such, we have a time variable consisting of 46 treatment periods ranging from -11 to 34. We also add the *group* variable indicating the treatment period in which the treated shipowners first get treated. It is worth recalling that a group is a cohort of shipowners treated in the same period. As some of the fifteen treated shipowners are treated in the same treatment period, we get 11 unique groups (12, if including treatment group 0). Untreated firms are assigned treatment group 0, as the reference time for the first treated is set to treatment period 1. An overview of all the treatment groups is displayed in Table 8

Table 8: Overview of all the treatment groups.

Identifier	Company Name	Debt Instrument	Treatment Date	Treatment Group
WAWI.OL	Wallenius Wilhelmsen ASA	Bond	2022-04-04	22
2606.TW	U-Ming Marine Transport Corp	Loan	2022-02-22	20
NM.N	Navios Maritime Holdings Inc	Loan	2021-12-01	18
SHIP.O	Seanergy Maritime Holdings Corp	Loan	2021-10-26	16
BWLPG.OL	BW LPG Ltd	Loan	2021-10-01	16
SB.N	Safe Bulkers Inc	Loan	2021-10-01	16
DSX.N	Diana Shipping Inc	Loan	2021-05-18	11
SFL.N	SFL Corporation Ltd	Bond	2021-04-26	10
9101.T	Nippon Yusen KK	Loan	2021-02-05	8
SSW.N	Seaspan Corp	Bond	2021-01-21	7
ODF.OL	Odfjell SE	Bond	2021-01-06	7
TRMDa.CO	Torm PLC	Loan	2020-11-11	5
EUAV.BR	Euronav NV	Loan	2020-09-11	3
ASC.N	Ardmore Shipping Corp	Loan	2020-07-29	1
KCCK.OL	Klaveness Combination Carriers ASA	Loan	2020-07-06	1

5.5 Data on the cost of debt

This section will explore the data utilized in our cost of debt analysis. At first, we will explore the different bond pairs and their characteristics. Following that, we will investigate each bond pair individually and study the issuer profile associated with each bond within the pair.

The data used for the cost of debt analysis will include all SLBs issued within the shipping industry, unlike our approach in the cost of equity analysis, where we limited our focus to first-time issuance. Moreover, we will not include SLLs in this part of our analysis due to the absence of accessible data on interest rates. As of March 31, six SLBs have been issued by four shipowners within the shipping industry. The four companies are Odfjell SE, Seaspan Corporation, SFL Corporation, and Wallenius Wilhelmsen ASA. Of the four issuers, SFL Corporation and Seaspan Corporation have issued two SLBs each. All the bonds issued are senior unsecured. Seaspan has also issued four sustainability-linked private placements and three sustainability-linked secured notes. However, these will not be explored in our analysis as they were issued via a private placement or holds a different level of seniority.

Table 9 presents the results of our matching process. The six bond pairs were found through a two-stage matching process. At first, we implemented a similar matching method to the one described in section 5.3, adding a bond issuance requirement. This requirement explains why the companies chosen as comparable peers in this part of our analysis differ from the companies used in the cost of equity section. After identifying the most similar companies, we conducted a matching process at the bond level. This allowed us to determine which of the bonds from the non-SLB issuer mostly aligned with the SLB based on issuance date, issuance size, and maturity. We observe that three of the bonds have a floating coupon rate, while the remaining nine have a fixed rate. Furthermore, all the non-SLBs are senior unsecured, indicating that each bond pair shares the same level of seniority.

Table 9: SLB issuing companies and their non-SLB counterfactuals.

Bond pair:	*Companies*	*Issuance Date*	*Issuance Size on issue date (M Local)*	*Issuance Size on issue date (MUSD)*	*Coupon Rate*	*Maturity Date*
1	Odfjell SE	21/01/2021	850	100.5	NIBOR3M+5.75%	21/01/2025
	Stolt-Nielsen Ltd	29/01/2020	1 250	117.3	NIBOR3M+4.5%	29/06/2023
2	Seaspan Corporation (1)	05/02/2021	200	200	6.50%	05/02/2024
	AP Moeller - Maersk A/S	22/06/2016	2 200	206.4	3.31%	22/06/2026
3	Seaspan Corporation (2)	01/04/2021	300	300	6.50%	29/04/2026
	COSCO Shipping Holdings Co Ltd	18/05/2020	1 000	143.7	2.50%	20/05/2023
4	SFL Corporation (1)	29/04/2021	150	150	7.25%	12/05/2026
	Costamare Inc	25/05/2021	100	108.5	2.70%	20/05/2023
5	Wallenius Wilhelmsen	06/04/2022	1 250	142.4	NIBOR3M+4.25%	21/04/2027
	Pacific Basin Shipping Ltd	10/12/2019	175	175	3.00%	10/12/2025
6	SFL Corporation (2)	18/01/2023	150	150	8.88%	01/02/2027
	Danaos Corporation	11/02/2021	300	300	8.50%	11/03/2028

Table 10 offers statistical summaries for the sample of bond pairs, including SLBs and non-SLB counterfactual bonds. Our matching procedure results in a sample of bond pairs with a difference in the maturity of 1.4 years and a relatively small difference in issuance size of just 1.3 million. The average difference in the issuance date is approximately 658 days or roughly 1.8 years. Furthermore, the mean difference in the spread within our bond pairs is approximately 220 basis points. Later in this section, we will provide a more detailed description of the yield spread of each company.

Table 10: Comparison of means between SLBs vs. non-SLB counterfactuals.

Variables	SLBs		Counterfactuals		Diff.
	Mean	SD	Mean	SD	
Maturity (years)	4.3	0.8	5.8	2.6	-1.4
Issue size (USD million)	173.8	69	175.1	71	-1.3
Issue Date	12/09/2021	295	24/11/2019	647	658
Spread (percent)	5.5	0.7	3.3	2.5	2.2

To understand the risk profile of the bond issuers and their respective bonds, we have used the StarMine Combined Credit Risk model in EIKON (Refinitiv, 2023). This model creates robust default predictions and an assessment of the credit risk of each company. Table 11 presents each company along with its credit rating at the time of issuance. In addition, it also describes the yield spread on each bond, found by examining the spread on the floating coupon rate or subtracting the fixed interest rate from an interest swap at the time of issuance.

Table 11: SLB issuers and non-SLB counterfactuals credit rating and spread.

Bond pair:	*Companies:*	*Issuance Date*	*Company Credit Rating*	*Swap Rate*	*Spread*
1	Odfjell SE	21/01/2021	BB-	Floating	5.75%
	Stolt-Nielsen Ltd	29/01/2020	BB+	Floating	4.50%
2	Seaspan Corporation (1)	05/02/2021	BB-	0.33 %	6.17%
	AP Moeller - Maersk A/S	22/06/2016	BB+	1.25 %	2.06%
3	Seaspan Corporation (2)	01/04/2021	BB-	1.04 %	5.46%
	COSCO Shipping Holdings Co Ltd	18/05/2020	BB-	1.69 %	0.81%
4	SFL Corporation (1)	29/04/2021	BB-	1.04 %	6.21%
	Costamare Inc	25/05/2021	BB+	-0.25 %	2.95%
5	Wallenius Wilhelmsen	06/04/2022	BB	Floating	4.25%
	Pacific Basin Shipping Ltd	10/12/2019	BBB	1.74 %	1.26%
6	SFL Corporation (2)	18/01/2023	BBB+	3.71 %	5.17%
	Danaos Corporation	11/02/2021	BB-	1.01 %	7.49%

By carefully examining each bond issuer within the bond pair, we observe that in most cases, the bond issuer with a higher rating has a lower spread on their bond. However, there is a notable difference in the spread of the bonds in bond pair 3, even though the company credit rating at the time were similar at the time of issuance. In Seaspan's case, we could not retrieve the StarMine credit rating from EIKON because the company was delisted in early 2020. Therefore, we had to rely on a corporate and issue-level rating from S&P Global Ratings from July 6, 2021 (Atlas Corp.).

6. Empirical Results and Analysis

This section presents and analyzes the results from applying the methodology to the data. Firstly, it presents the treatment effects for the cost of equity within 12 months after treatment. Secondly, it depicts how the treatment effects evolve with the duration of the shipowner's exposure to the treatment. Lastly, it presents the results from the analysis on the cost of debt.

6.1 The Issuance of SLD's Impact on Cost of Equity

6.1.1 Group treatment effects

The terminology used remains consistent with Callaway Sant'Anna (2021). Since both the methodology and statistical tools used in this research rely on this standardized terminology, this eases the replicability of our work. We, therefore, provide some previously mentioned terminology. As previously highlighted, a "group" is a set of shipowners that were all treated at the same point in time. Group names are set equal to the treatment period in which the group was first treated. The treatment period is a time variable that takes the value 1 if the first group becomes treated. This means that the group names are not necessarily continuous, as shown in Table 12.

The average treatment effect for each group, $\theta_S(g)$, along with an aggregate treatment effect across all groups, θ_S^O, are presented in Table 12. The results are also visualized in Figure 6. We see that the treatment effect, $\theta_S(g)$, is not uniform but varies across the different groups. Groups 3, 8, 10, 18, 20, and 22 stand out as they are all statistically significant with a 95% confidence level. The majority of these groups have negative coefficients, implying a reduction in the cost of equity. However, Groups 8 and 22, which include Nippon Yusen KK and Wallenius Wilhelmsen ASA, respectively, show opposite effects as they have positive coefficients.

Particularly notably, we see that groups 1, 7, and 16, which, in contrast to all other groups, consist of multiple shipowners, are not statistically significant. A possible reason for this may be that these groups' average treatment effects, $\theta_S(g)$, are computed from a small number of shipowners, resulting in larger variation and a less ambiguous average treatment effect. This is reflected in the relatively larger standard deviation compared to the other groups.

Despite the varying results on the individual group level, the overall treatment effect across all groups, θ_S^O, is statistically significant and different from zero. With an estimated ATT (the average treatment effect on the treated) of 0.79% and a standard deviation of 0.34%, the interval (-1.45% to -0.13%) results in the θ_D^O coefficient being barely statistically significant.

The results seem to indicate that, within a window of 12 months after issuance, we can reject the null hypothesis stating that SLD issuance has no effect on shipowners' cost of equity. The significant coefficient provides grounds for stating that SLD issuance is associated with a slight reduction in shipowners' cost of equity within a 12-month period after issuance.

Table 12: Treatment effect for each treated group

This table shows the treatment effects for each treated group with corresponding standard errors and a 95% confidence band. We call these "group effects". These group effects are the average of all the group-time treatment effects and are computed with eq. (7). We give a pleasant reminder that a "group" is a set of shipowners that were all treated at the same time (treatment time = year, month). This is the reason why the group is not continuous. The "ATT" in the top section of the table provides the weighted average of the individual group effects, computed with eq. (8).

Overall Summary of ATTs based on group/cohort aggregation:

ATT (θ_S^O)	Std. Error	[95% Conf. Int]		
-0.0079	0.0034	-0.0145	-0.0013	*

Group Effects:

Group	Estimate $\theta_S(g)$	Std. Error	[95% Pointwise Conf. Band]		
1	-0.0251	0.0126	-0.056	0.0057	
3	-0.0264	0.003	-0.0338	-0.0189	*
5	-0.0071	0.0043	-0.0176	0.0034	
7	0.005	0.0084	-0.0157	0.0257	
8	0.0108	0.004	0.0009	0.0206	*
10	-0.0141	0.0042	-0.0243	-0.0039	*
11	0.0002	0.0043	-0.0104	0.0107	
16	-0.008	0.0092	-0.0305	0.0144	
18	-0.0385	0.0052	-0.0512	-0.0259	*
20	-0.0166	0.0059	-0.0311	-0.002	*
22	0.0375	0.0062	0.0223	0.0527	*

Signif. codes '*' confidence band does not cover 0

Control Group: Not Yet Treated, Anticipation Periods: 0
Estimation Method: Doubly Robust

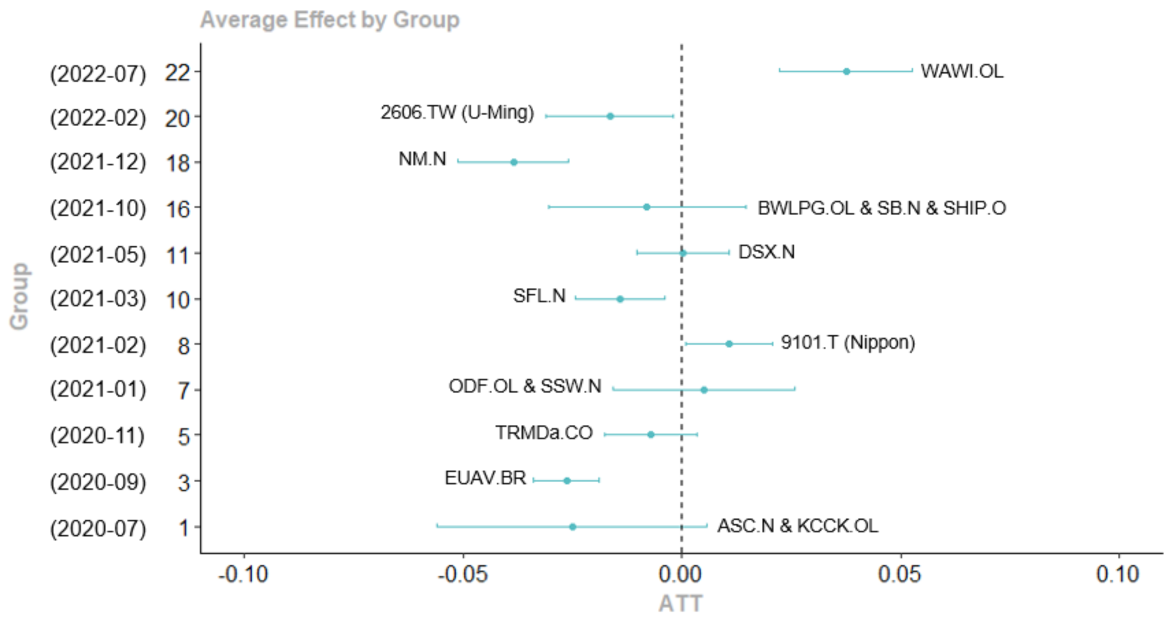


Figure 6: Average Treatment Effect by Group.

This figure plots the group effect estimates from Table 12 with corresponding 95% confidence bands. The X-axis shows the estimated group effect, and the Y-axis shows the treatment group with the corresponding treatment period (Year-Month). The estimates are marked with company identifiers for all shipowners who comprise each treatment group.

6.1.2 Dynamic treatment effects

As the group treatment effects in section 6.1.1 provide varied results for the 12-month post-treatment period, it is interesting to explore how the treatment effect evolves with the duration of exposure to treatment. This contributes to our understanding of the group effects discussed in section 6.1.1.

The dynamic treatment effect for the group of units exposed to treatment for exactly e time periods is given by $\theta_D(e)$, computed using eq. (9). Table 13 and Figure 7 present estimates of the dynamic treatment coefficients, $\theta_D(e)$, for each period within the 12 months following treatment. Within this 12-month post-treatment period, all individual dynamic effects tend to become more negative, except for a slight increase during the last two event times (10 and 11), where there are indications of the dynamic treatment effect slightly decreasing. None of these estimators are statistically significant.

The discrepancy between a significant average group effect and insignificant dynamic effects could indicate that the treatment effect is heterogeneous across time and across groups. Figure 8, which plots the average treatment effect over time for each group, seems to support this claim. It shows that some individual groups respond immediately to treatment, while other groups respond later. As $\theta_D(e)$ gives the average effect at each time point, these effects may cancel each other out, resulting in the dynamic treatment estimators appearing non-significant. This suggests that addressing the treatment effect over time may be difficult for shipowners issuing SLD, as treatment effects are heterogeneous and dynamic.

At first, the discrepancy between the significant average group effect across all groups and the insignificant dynamic treatment effects may seem contradictory. However, it is important to consider that the group effects are an estimate of the static effect, whereas the event-time effects are dynamic, which yields results based on different perspectives of the treatment effect. The following paragraph explains the reason for this.

With a group perspective, the aggregate group estimate, θ_D^O, is an estimate of the treatment effect over a period of time. Therefore, the θ_D^O estimator gives an estimate of the constant effect over the 12-month time period. It suggests that, on average, across all treated groups, there is a significant effect of treatment. From a time perspective, however, the dynamic effect tells us how the treatment effect evolves over time. This estimate computes the average effect across all groups at one point in time (i.e., event-time = 0 or 4).

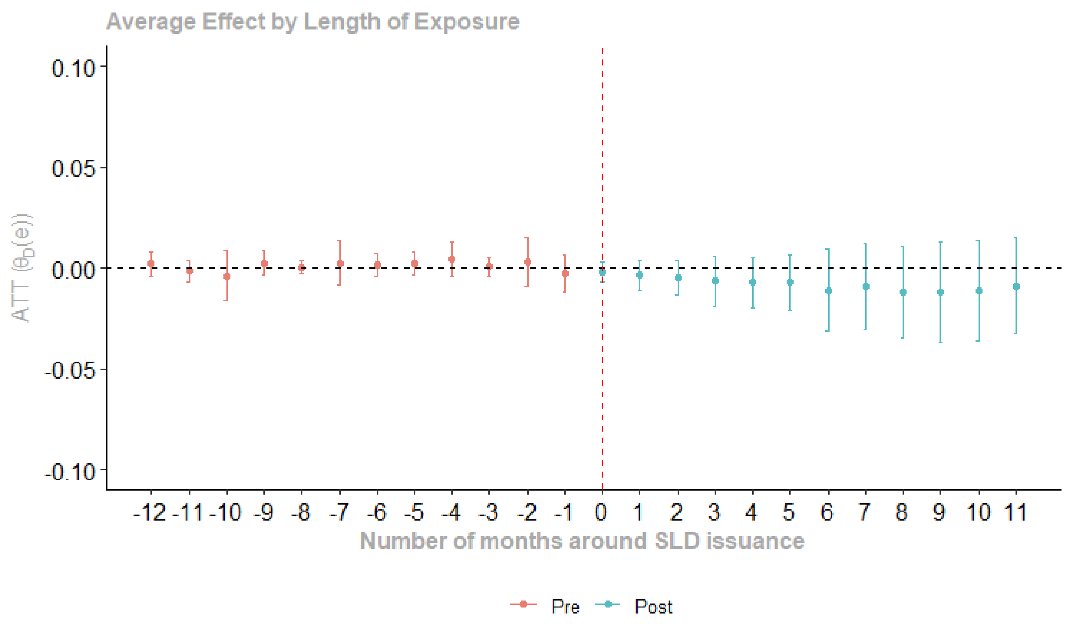


Figure 7: Dynamic treatment effects.

Table 13: Average treatment effects for all post-treatment event times.

This table shows the average treatment effects for all post-treatment event times. The event time is centered at zero for all groups, implying that the first event time (0) is when all shipowners became treated. We emphasize that "event time" and "treatment period" are not the same thing. In line with C&A (2021)*, the "treatment period" is the absolute time dimension, whereas "event time" is the relative time centered around treatment for each unique group. As such, the event time can be interpreted in a conditional way for event studies.*

Overall summary of ATT based on event-study/dynamic aggregation:

ATT	Std. Error	[95% Conf. Int]	
-0.0079	0.0057	-0.0191	0.0033

Dynamic Effects:

Event time	Estimate $\boldsymbol{\theta_D(e)}$	Std. Error	[95% Pointwise Conf. Band]	
0	-0.0017	0.002	-0.0065	0.0003
1	-0.0036	0.003	-0.0104	0.0033
2	-0.0047	0.0034	-0.0126	0.0032
3	-0.0066	0.0053	-0.0188	0.0057
4	-0.0072	0.0048	-0.0182	0.0038
5	-0.0072	0.0057	-0.0205	0.0061
6	-0.0109	0.0084	-0.0304	0.0086
7	-0.0091	0.0083	-0.0283	0.0101
8	-0.0119	0.0098	-0.0347	0.0108
9	-0.0121	0.01	-0.0352	0.0111
10	-0.0111	0.0103	-0.035	0.0128
11	-0.0088	0.01	-0.032	0.0145

Signif. codes '*' confidence band does not cover 0

Control Group: Not Yet Treated, Anticipation Periods: 0
Estimation Method: Doubly Robust

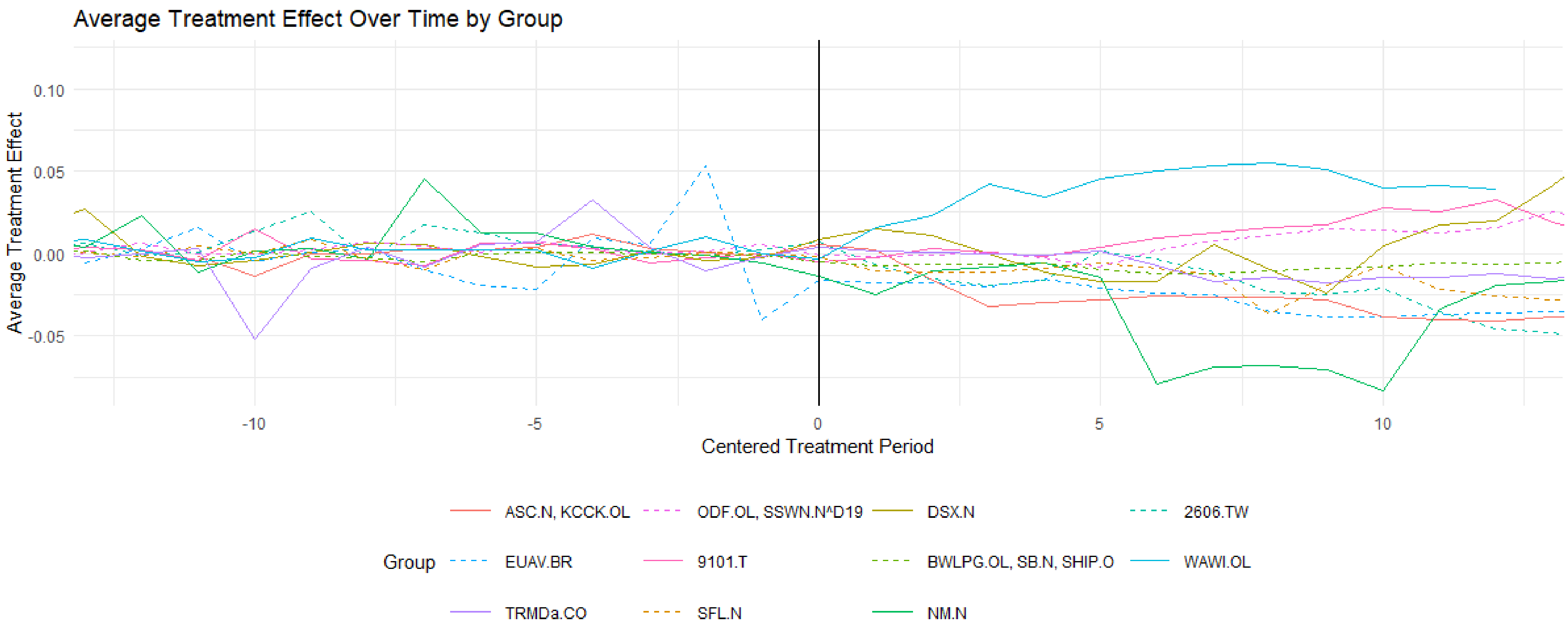


Figure 8: Dynamic treatment effect of each group over time.

6.1.3 Assessing the parallel trends assumption

Assessing the parallel trends assumption is crucial for validating whether the premise we set for the DiD estimation method holds. Only then can we infer a causal relationship between SLD issuance and the cost of equity. Figure 7 allows us to investigate whether the pre-treatment trend is zero, implying that in absence of treatment, the treated firms and the controls would have all followed the same trend.

We see that, on average, there does not appear to be any pre-treatment trend, with treatment effect estimates being statistically insignificant at a 95% confidence level and centered around zero. This suggests that the parallel trends assumption is likely to hold given our model, which increases our confidence in inferring the causal effect of the treatment.

6.2 The Issuance of SLD's Impact on Cost of Debt

In the second part of our empirical analysis, we aim to estimate whether there is a significant spread differential between SLBs and their non-SLB counterfactuals by conducting both a paired t-test and a signed Wilcoxon-ranked sum. Furthermore, we will also present the results from our power analysis of both tests. Table 14 and Table 15 present an overview of our findings from the tests.

Table 14: Paired T-Test.

					95% Confidence Interval of the Difference	
	n	t	p-value	Mean Difference	Lower	Upper
Spread	6	2.23	0.076	0.023	-0.004	0.050

Table 15: Wilcoxon signed rank sum.

	V	p-value	Alternative Hypothesis
Spread	19	0.094	true location shift not equal to 0

From the t-test above, we observe a t-value of 2.23 and a p-value of 0.076, and from the Wilcoxon test, we observe a p-value equal to 0.094. A relatively low p-value could suggest that we might have some evidence against the null hypothesis. Upon examining the mean difference of 230 basis points, this, in practice, may indicate that there SLB issuers show a willingness to bear a higher cost to issue SLBs. However, several factors should be considered and addressed before arriving at any conclusion from these results.

Firstly, the p-value is not below the conventional significance threshold of 5%. This itself means that we do not have strong enough statistical evidence to claim that the spread differential between SLBs and their counterfactuals is not zero. Furthermore, the sample size consists of only six bond pairs, coupled with the fact that not all issuers within each bond pair share the exact same credit rating. This results in reduced statistical power in the tests conducted. Additionally, the limited sample size may have increased sampling errors, as the bond pairs do not necessarily reflect the broader population. The small sample size also increases the likelihood of encountering outliers, and while Wilcoxon signed rank sum is more robust to outliers, it is not immune to their influence. Lastly, it is important to consider the context. While previous research suggests either no difference in the spread between SLBs and green bonds versus their conventional counterfactuals or points to a “greenium” upon issuance, our findings will challenge these if we assert evidence of SLB issuers paying a higher spread upon issuance. Thus, based on these findings, we do not find evidence of a spread differential between SLBs and conventional bonds leading to an increased cost of debt for SLB issuers.

Table 16 and Table 17 present the power analysis of the t-test and the Wilcoxon signed rank sum. By conducting this analysis, we aim to determine the power of our tests and test how the power will evolve as we increase the number of bond pairs in our sample.

Table 16: Power Analysis T-Test.

Sample Size		α 0.001	α 0.01	α 0.05
Current	n	6	6	6
	Power	0.06	0.33	0.7
Required to detect an effect of 0.8	n	16	11	7
	Power	0.8	0.8	0.8
Required to detect an effect of 0.9	n	19	13	9
	Power	0.9	0.9	0.9

Table 17: Power Analysis Wilcoxon signed rank sum.

Sample Size		α 0.05
Our	n	6
	Power	0.56
8	Power	0.79
10	Power	0.93
12	Power	0.96
14	Power	0.99

From the power analysis of the t-test and the Wilcoxon signed rank sum we see that our sample size yields a power, or put differently, the probability of rejecting the null hypothesis when it is false, of around 0.7 and 0.56. Additionally, we see that adding one bond pair to the t-test and adding two bond pairs to the Wilcoxon signed rank sum will deliver a power of 0.8, given that the effect size stays the same. However, even though increasing the sample size does boost the power of each test, it is important to consider our study's practical context in mind. This suggests that increasing our sample size by just one or two bond pairs is probably insufficient to convincingly argue that the SLBs are issued at a higher spread. As we discussed above, we should be cautious when asserting evidence of a difference in the spread between SLBs and their counterfactuals given the limited sample size, different credit ratings among the issuers within some of the bond pairs, and that our results might potentially contradict results of previous studies.

7. Discussion

This section discusses the main findings and their implications for the current research on SLD. It also states the limitations and provides a direction for future research that enables a deeper understanding of the drivers behind the effect this study has estimated.

7.1.1 Main findings

This study aims to determine whether the issuance of SLD reduces shipowners' cost of capital by investigating its effect on the cost of equity and debt. Within a twelve-month period following issuance, we find evidence suggesting that, in general, there is a significant reduction in the cost of equity. Interestingly, the treatment effect seems to vary among the shipowners, but no segment seems to stand out. While some shipowners see a reduction in their cost of equity, others seem to experience no change or even an increase in their cost of equity after issuance. Additionally, treatment effects seem to be heterogeneous in size, response time, and development. This complicates the assessment of how the treatment effect evolves over time on a general level but suggests that equity investors respond differently to different shipowners' commitment toward sustainability.

Further, when comparing the earlier and later issuances of SLDs, there does not appear to be a trend in equity investors' reactions to new SLD issuances over time. Our findings do not provide significant evidence to infer an effect on the cost of debt, as the data on the debt side is less transparent for SLLs, and the current amount of SLBs is quite limited.

In summary, our findings suggest a slight yet significant reduction in the cost of equity but do not allow us to infer a change in the cost of debt following the issuance of SLD. This provides a basis for rejecting the null hypothesis, which states that the issuance of SLD does not affect shipowners' cost of capital.

7.1.2 Implications and Comparisons to existing research

Our findings reveal a reduction in the cost of capital following the issuance of SLD, aligning with the results of Zhang et al. (2021), who found similar effects for green bonds. However, our results diverge when it comes to the cost of debt; as Zhang et al. (2021) demonstrated a significant effect of a greenium, achieved using a substantially larger sample. We also find positive responses among equity investors, which aligns well with the findings of both Thang & Zhang (2020), and Flammer (2021), who reported positive stock market returns after green bond issuances. Though we emphasize that there is a difference between returns and cost of equity, the evidence that equity investors may view the stock as more attractive is interesting, nonetheless. Both Flammer (2021) and Zhang et al. (2021) suggest that issuing green bonds sends a credible signal to the stock market regarding the company's commitment to sustainability. Consequently, our findings of a positive reaction to SLD issuance, together with the assumption that investors are attracted to sustainability, imply that similar effects may be attributed to SLD. Therefore, the issuance of SLD may serve as an effective tool for communicating the commitment to sustainability to the equity market.

We also emphasize an important aspect when it comes to interpreting the effect on the cost of equity. Specifically, it's important to assess what proportion of the change in the cost of equity is due to the signaling effect and what portion results from alterations in the cost of debt. This relies on the principle of shareholders' residual claim, which implies that changes in shipowners' obligations to debt investors will influence equity investors' risk towards their residual claim to the shipowner's cash flow. Thang & Zhang (2020) finds a significant reduction in the cost of equity along with an insignificant result in the cost of debt. According to the principle of residual claims, this implies that the change in the cost of equity must be attributed to factors other than the change in the cost of debt. Although our study cannot draw a definitive conclusion about the effect of SLB issuance on the cost of debt capital, it remains intriguing to explore the potential reasons for the observed impact on the cost of equity, particularly in light of various potential scenarios for the effect on the cost of debt.

We finally wish to highlight a few implications from the interplay between the cost of debt and equity capital. If the effect on debt is insignificant and the effect on the cost of equity is significant, it would imply that changes in the cost of equity result from factors other than alterations in debt holders' more senior claims. Such an effect could be the signaling effect. On the other hand, if there is a significantly negative effect on the cost of debt and a significantly positive effect on the cost of equity, attributing the changes in equity to signaling would be more challenging, as some of the variations in equity could be accounted for by the reduced claim by debt investors.

7.1.3 Limitations

This study has some limitations. First, regarding research design, this study investigates the potential reduction in the cost of capital for shipowners from issuing SLD. The study divides the total effect into separate effects on the cost of equity and debt. While this analysis provides insights into the effect of SLD on the cost of capital, it is beyond the scope of this study to investigate the causal drivers behind this effect. To supplement our study, further research into factors such as stock liquidity and changes in ownership structure could provide a deeper understanding of these drivers. Secondly, our research does not focus on the potential penalties associated with the SPTs but rather aims to identify whether there are benefits to issuing this novel type of sustainable debt financing. This is primarily due to the research design and the fact that we investigate an industry where there is little available information about SPT achievement.

Other important limitations revolve around the data availability for estimating the effect on the cost of debt, primarily due to the novelty of SLD. Given the limited amount of issuance of SLD, the sample size for estimating the cost of debt is relatively small. Furthermore, loan-related details, such as interest rates and maturity dates, are less transparent than bonds, constraining the data available for our analysis. Loans are usually a bilateral agreement between the issuer/borrower; one or more lenders are rarely traded in the market. Therefore, we are restricted to solely focusing on bonds in our cost of debt analysis. Furthermore, constructing a sample of suitable bond pairs is challenging due to the limited information we have concerning credit ratings, both on company and bond levels. As the issuer profile is important upon issuance, we would ideally like to construct bond pairs consisting of issuers with the exact same company credit ratings while also comparing bonds with a similar bond credit rating to ensure that the risk associated with each bond is as similar as possible. Utilizing such a matching method would have enhanced the overall statistical power of our tests, thereby establishing a more robust basis for asserting whether there is a difference in the spread between SLBs and non-SLB counterfactuals upon issuance.

Given these limitations, the study relies heavily on examining the effect on the cost of equity to analyze the impact of SLD. We still argue that the proposed methodology for estimating the effect on the cost of debt is among the more preferable methods for assessing the direct effect on the cost of debt. Thus, in light of these limitations, we believe there are few alternatives to our current approach besides allowing the natural growth of this instrument to yield more data for more comprehensive future research.

7.1.4 Recommendations

Despite these limitations, we emphasize that the research design is nevertheless suitable for providing insights into the effects of SLD issuance on the cost of capital. The challenges regarding the still small and somewhat untransparent data foundation for the cost of debt will gradually reduce as the instrument increases in popularity. In the interim, we suggest future research focus on analyzing the drivers behind the effect on the cost of equity, as this will offer a more comprehensive insight into the signaling effect of SLD.

8. Conclusion

This study sought to answer the question: does SLD issuance reduce shipowners' cost of capital, and how does it affect the cost of equity and debt capital? Our findings of a significant reduction in the cost of equity on a general level and heterogeneity in individual treatment effects contribute interesting insights into equity investors' reactions to sustainable commitments within the shipping industry. It also illuminates the potential role of sustainable finance and new financial innovations in the shipping industry's transition towards zero emission. This has implications for financial institutions, regulators, and investors regarding these instruments.

This research sought to investigate if issuing SLD decreases the cost of capital for shipowners and its effects on equity and debt capital costs. Our results show a significant overall reduction in the cost of equity and variation in individual treatment effects for the shipowners. These findings provide interesting insights into equity investors' responses to sustainability commitments in the shipping industry and illuminate the potentially important role of sustainable finance and financial innovations in the industry's move towards zero emissions. These insights have implications for financial institutions, regulators, investors, and shipowners.

The study's design of a dual-lens approach to assessing the cost of capital through both the cost of equity and debt capital provides the opportunity for assessing the interplay between SLD issuances' effects on the cost of equity and debt. However, we experience that estimating the effect on the cost of debt is challenging due to the currently limited amount of issuances, especially regarding SLBs, reflecting the novelty of SLD. As a result, the current ability to effectively evaluate the interplay between the cost of debt and equity capital is diminished. Still, the methodology applied in this study lays a foundation for deeper understanding and insights into this interplay as SLD issuances grow in numbers.

In conclusion, this study adds to the understanding of the financial implications of sustainability commitments in the shipping industry. These findings contribute to a better understanding of the topic and can guide shipowners, financial institutions, regulators, and investors in their sustainability initiatives.

9. Appendix

Appendix 1: StarMine Credit Risk Model (EIKON).

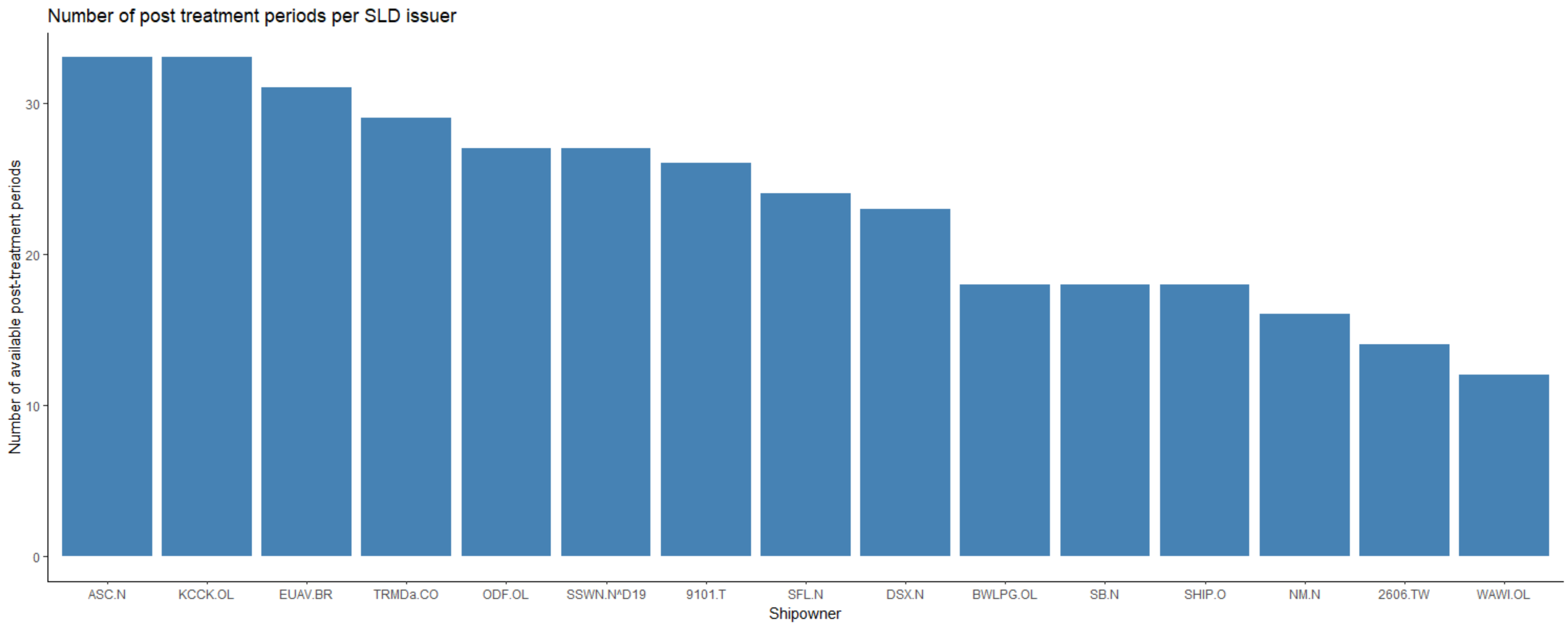
Model Implied Rating & Probability of Default		
Probability of Default (Lower Limit)	Probability of Default (Upper Limit)	Implied Letter Rating
0.000%	0.014%	AAA
0.014%	0.020%	AA+
0.020%	0.028%	AA
0.028%	0.038%	AA_
0.038%	0.052%	A+
0.052%	0.069%	A
0.069%	0.089%	A-
0.089%	0.113%	BBB+
0.113%	0.145%	BBB
0.145%	0.190%	BBB-
0.190%	0.255%	BB+
0.255%	0.354%	BB
0.354%	0.507%	BB-
0.507%	0.757%	B+
0.757%	1.153%	B
1.153%	1.668%	B-
1.668%	2.357%	CCC+
2.357%	3.473%	CCC
3.473%	5.959%	CCC-
5.959%	100%	CC

Description: The model computes a probability of default based on the three component input models. The model outputs a letter grade, termed the Implied Rating, which is based on ranges of probabilities of default. The cutoff for "Investment Grade" is equal to credit score BBB- or higher (probability of default < 0.2).

Appendix 2: Atlas Corp segment reporting.

Atlas Corp Segment reporting:						
Year	*2020*		*2021*		*2022*	
Segment	Seaspan Corporation	Total	Seaspan Corporation	Total	Seaspan Corporation	Total
Revenue (million USD)	1,222.80	1,421.10	1,460.40	1,646.60	1,543.00	1,697.40
Revenue (% of total)	86%	100%	89%	100%	91%	100%

Appendix 3: Number of available post-treatment periods for each SLD issuer.



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