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FFA Hedging in the Supramax Segment

How Alterations of the Baltic Supramax Index Have Affected Hedging Efficiency

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Abstract

This thesis studies how altering the composition of the Baltic Supramax Index (BSI) affects the hedging efficiency of forward freight agreements (FFA) traded with the index as underlying. We evaluate the hedging efficiency using hedged portfolios with both minimum variance hedge ratios and naïve hedge ratios, both within and across subperiods between 2006 and 2018. Bootstrapping techniques and bias-corrected and accelerated confidence intervals are utilised to investigate if the hedging efficiency is affected to a statistically significant degree when the composition of the index is revised.

We find that forward freight agreements can significantly reduce the volatility of freight rates. However, we find no evidence suggesting that reduced weight of a constituent route in the underlying index induces decreased hedging efficiency, or vice versa. Nor do we find that overall hedging efficiency decreases when more routes are added. The cointegrated relationship between individual routes and the FFA time series seems to make changes to the index irrelevant with regard to hedging efficiency.

The thesis provides a basis for further research of the hedging efficiency of freight derivatives. Primarily, the topic of this thesis should be revisited when data points from more dimensions of the shipping cycle become available. Moreover, the impact of changes in the underlying asset to real market participants is an interesting continuation.

We believe our findings are especially important to the producers of freight indices, as their relevance in terms of hedging efficiency is paramount in order to secure volume and quality in the derivatives market. For charterers, shipowners, and other market participants, our findings are interesting with regards to risk management, specifically in understanding how alterations of an underlying asset have historically affected hedging efficiency.

The thesis supplements the rather limited literature on changes in hedging efficiency when the structure of the underlying asset is altered. First, because no such research has been conducted on the FFA market in its current form in recent years. Secondly, because we access trial data of the 10TC FFA before it went live, we can study the differences between overlapping time series of FFA prices with different versions of the BSI as underlying – not only those separated by the date of their alteration. This allows us to compare the hedging performance of two FFAs isolated from time-varying effects. Furthermore, it allows us to evaluate the effect of basis risk caused by differing technical specifications and that caused by a geographical diversification effect due to the addition of more constituent routes.

Preface

This master thesis is written as the concluding part of our Master of Science in Economics and Business Administration at the Norwegian School of Economics (NHH), within our major in Financial Economics.

After attending several shipping courses during our residency at NHH, we wanted to contribute to the existing literature and gain a deeper knowledge of an industry that is the backbone of the global economy. We believe we have found both a topic and results that will be of interest to various participants in the dry bulk shipping market.

We would especially like to thank our supervisor, Roar Os Ådland. First, for the classes we have attended before our thesis semester, which were the primary reason for the choice of shipping as the topic for our thesis. Secondly, for the discussions, shared expertise, and feedback that led to our final product.

Furthermore, we would like to thank Egil Husby and Frederik Ness of Western Bulk for providing both valuable data and guidance. In addition, we would also like to thank James Pendered of The Baltic Exchange for valuable input and Clarksons Research for providing us with supplementary data. Finally, we are grateful for receiving grants from The Norwegian Ship Owners' Association's Fund at NHH.

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1. Introduction

Freight rates fluctuate at a rapid pace in the dry bulk shipping industry. This is a consequence of the inelastic supply of rates in the short-term and the many economic and political factors that determine the demand for freight – which are difficult to estimate and forecast (Kavussanos & Visvikis, 2010). Thus, uncertainty about future cash flows from freight revenue poses a major challenge to market participants. A way of handling freight rate volatility can be found in the derivatives market, where an opportunity to transfer undesirable risk to others more tolerant is available.

The first opportunity to hedge freight rate risk through derivatives came with the creation of the Baltic International Freight Futures Exchange (BIFFEX) contract (Kavussanos & Nomikos, 2000a). However, the BIFFEX contracts provided poor hedging performance and were traded in low volumes (more on this in Section 2). Consequently, Forward Freight Agreements (FFAs) emerged as an alternative in the early 1990s (Alizadeh & Nomikos, 2009). FFAs are either traded as a standard contract on a hybrid exchange, or as a customized contract through a broker over the counter. However, the vast majority of trading is concentrated in standardized contracts, due to a more liquid market (Stopford, 2009). The terms of an FFA contract cover the agreed route, time of settlement, contract size measured in number of lots, and settlement price (The Baltic Exchange, 2018a). The contract can be settled against the indices provided by the Baltic Exchange, or other trusted providers of underlying market information. Clearing services are provided by a clearing house, which guarantees that the involved counterparties fulfil the contract terms. When a contract is cleared the parties either pay or receive the average daily difference between the contract price and price of the underlying.

FFA trading volume is concentrated on indices consisting of the weighted average of multiple routes, such as the Baltic Supramax Index (BSI), as underlying (Alizadeh & Nomikos, 2009). The alternative would be route-specific FFAs, as they are likely to provide a more favourable hedging efficiency than when index based. This is because the physical basis risk is likely to be comparatively lower. However, Adland & Jia (2017) argue that the trade-off between index-based and route-specific contracts is a matter of market liquidity versus short-term hedging efficiency, with route-specific contracts offering less market liquidity (more on this in Section 2).

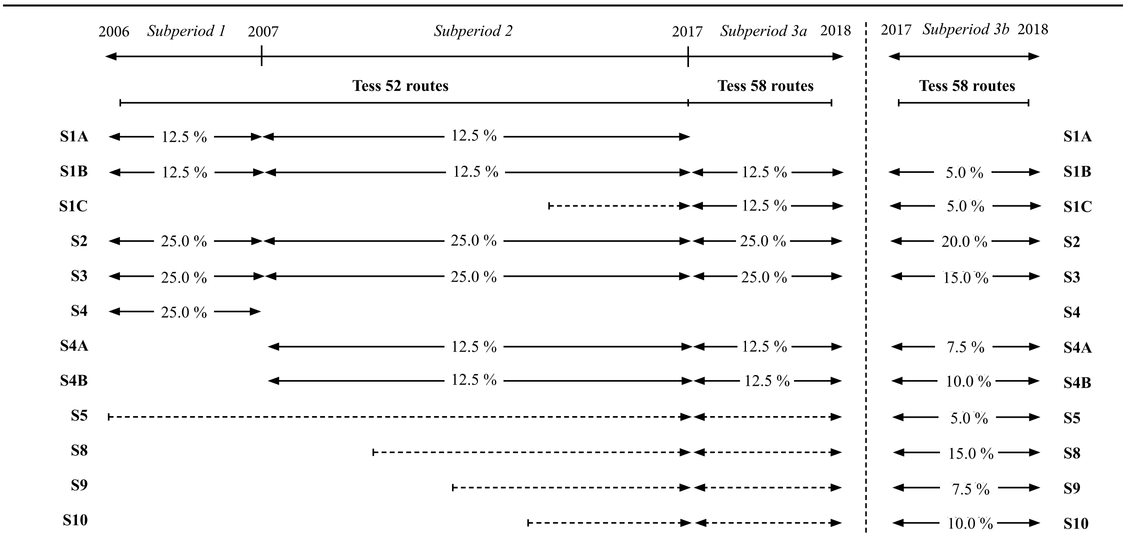
The Baltic indices are based on assessments of multiple daily freight rates made by a panel of competitive shipbrokers appointed by the Baltic Exchange (The Baltic Exchange, 2018b).

The indices are comprised of the most important routes within each segment, each assigned a weight reflecting their respective importance in the world freight market (Kavussanos & Visvikis, 2010). The Baltic Exchange checks the reported data, queries panellists if necessary, and publishes the weighted averages of all inputs as the Baltic indices (Pendered, 2014). Panellist assessments are based on all relevant information available to them at the time of reporting, and it is expected that their assessments are anchored in real fixtures, such as transactional data or ongoing negotiations (The Baltic Exchange Information Services Ltd., 2018). While this method enables the Baltic Exchange to pool the liquidity and the rather non-standardised nature of the international bulk shipping markets, this also results in freight indices that could vary less than actual freight rates captured by market participants. This is because an assessment of freight rates based on the average of multiple quotes provides us with a somewhat diversified portfolio of freight rates, offsetting the often extreme day-to-day, port-to-port, and vessel-to-vessel movements seen in the actual market.

The Baltic Exchange has reported that the indices always will be subject to changes in order to ensure their accuracy in reflecting the underlying freight markets (Hampstead, 2018). Index changes are a product of the Baltic Exchange's effort to collect feedback and input from its members to keep the indices relevant and efficient, and in turn ensure activity in the freight derivative markets. Since its launch in 2006, the BSI has been subject to three substantial structural changes. The alterations are presented in Figure 1.1 (see Table A.6.2 for route specifications).

FIGURE 1.1

Development of the Baltic Supramax Index Constituent Routes



Source of Composition: The Baltic Exchange (2018c)

Indicates route present in the BSI

Indicates route active or in trial

The first alteration was the split of route S4 into S4A and S4B on January 2, 2007. This was a result of the Baltic Exchange reacting to market feedback that S4 was not traded on a round-voyage basis (J. Pendered, personal communication, May 8, 2018)[1]. A split into one route for inbound and one for outbound would provide a more accurate representation of the overall global time charter value of the Supramax segment. The second change happened on April 3, 2017, when the Tess 52 was replaced by the Tess 58 as the Standard Supramax benchmark vessel (see A.6 for technical specifications). This change was based on the increase in average vessel size and fleet numbers fixing in the market. The third change was the increase from six to ten constituent routes, with the 10TC trial commencing on October 24, 2016[2]. According to the Baltic Exchange, basing the BSI on 10TC instead of 6TC provided a better representation of how Supramax vessels were trading. Furthermore, the interest for 6TC FFAs was decreasing, and as a result the Baltic Exchange has decided to cease the reporting of 6TC_58 on December 21, 2018 (Jackson, 2017).

We could reasonably expect that the well-intentioned revisions by the Baltic Exchange of the underlying Baltic Supramax Index would have a positive effect on hedging efficiency. Moreover, that the theoretical average hedging efficiency of FFAs on the Baltic Supramax routes would increase after each alteration. However, for derivatives where the underlying asset is a diverse index composed of a weighted average of several shipping routes, increased diverseness, through the increased number of constituent routes, could lead to a failure to accurately reflect the volatility of individual routes (Adland & Jia, 2017). Thus, the hedging efficiency of the derivative would suffer. Herein lies the foundation of this thesis. We investigate the hedging performance of FFAs on the constituent routes of the BSI from 2006 to 2018. We utilise Baltic Exchange data on 54 quarterly FFA contracts with the BSI as underlying and twelve index constituent trading routes in order to answer the following questions:

1. Has the inclusion of more routes negatively affected the individual hedging efficiency of the routes that have had their weight in the index consequently reduced? Specifically, does reduced weight in the index equal reduced hedging efficiency, and vice versa?
2. Has the increased number of constituent routes also brought with it an undesirable diversifying effect, leading to an overall decreased hedging efficiency?

[1] E-mail correspondence.
[2] Live July 3, 2017

We expect that a route's reduced weight in the index will decrease the hedging efficiency of that individual route, and vice versa. However, in line with Adland and Jia (2017), we expect that an expansion of constituent routes will have an overall negative effect on all routes' hedging efficiency due to increased geographical diversification.

We believe our findings will be especially important to the Baltic Exchange, as well-functioning indices are paramount in order to secure volume and quality in the FFA market. Moreover, for charterers, ship owners, and other market participants, our findings are useful for their risk management, specifically to understand how index changes have historically affected hedging efficiency. Furthermore, this thesis contributes to the existing literature in two ways. Most importantly, it sheds light on how various index changes affect hedging performance. To our knowledge, no research has been conducted to determine the effect of changes in the composition of the Baltic indices on FFA hedging efficiency. Moreover, we access trial data for the current 10TC_58 FFA with data points that overlap parts of both the discontinued 6TC and the soon-to-be discontinued 6TC_58. Unlike Kavussanos and Nomikos (2000a), this allows us to compare the intraperiod differences in performance of different index compositions – not only interperiod. Thus, time-varying effects are neutralised.

The thesis is divided into four sections. Following the introduction, Section 2 contains a review of relevant literature on the hedging of freight rates. Section 3 provides a description of the data and methodical framework used, while the results and analysis are presented in Section 4. In the concluding remarks we discuss limitations and provide suggestions for further research.

2. Literature Review

The literature on the hedging performance of shipping derivatives is limited compared to that of other commodities and financial assets. Historically, Kavussanos and Visvikis (2006) point to the lack of available data from the notoriously secretive shipping industry as the primary reason for this.

Glen and Rogers (1997) investigated the effect of changing the weighting of the constituent routes in the Simpson, Spencer, and Young (SSY) Capesize index, to its ability to reflect sector trends. They found no statistically significant sensitivity to variations in the weights employed in its construction. They argue that the cointegrated nature of the change in freight rates across different routes neutralises any changes in the composition of the underlying index. Likewise, we will assess if there are any significant changes to the ability of the BSI to reflect its constituent routes in regard to hedging efficiency, when altering its construction.

Haralambides (1992) examined the hedging efficiency of BIFFEX contracts. He found that hedging efficiency can be increased when utilising minimum variance hedge ratios (MVHR), rather than naïve one-to-one hedge ratios. However, he notes that the MVHR will not always outperform the naïve, but rather that – on average, and in the long run – it could provide superior hedging efficiency. Alizadeh & Nomikos (2012) also used MVHR to examine the possibility of hedging ship price risk using FFAs, and found that FFAs could reduce variance significantly. Kavussanos & Visvikis (2010) investigated hedging efficiency in the Capesize market, and found that the MVHRs' out-of-sample results indicate that naïve hedge ratio strategies produce the highest variance reduction. Similarly, we will compute route and subperiod specific minimum variance hedge ratios. Furthermore, we will evaluate the performance of both MVHR and naïve hedge ratios, and investigate whether FFAs can be used to reduce spot exposure.

Myers and Thompson (1989) and Kroner and Sultan (1993) argue that the MVHR assumption of constant risk in spot and futures markets is too restrictive, as empirical findings in various markets show that prices have a time-varying distribution. In support of this criticism, Kavussanos and Nomikos (2000b) found that routes constituting the Baltic Freight Index were characterised by time-varying distributions. When new information arrives in the market, a portfolio with a static hedge ratio would thus suffer by not utilising it. Nonetheless, an empirical study by Kavussanos and Nomikos (2000a) found that time-varying VECM-GARCH hedge ratios were outperformed by static minimum variance hedge ratios in 24 out of 33 cases when investigating the hedging efficiency of BIFFEX contracts on BFI constituent routes. Similar findings have been reported in the wheat futures market (Myers, 1991) and the soy bean futures market (Garcia et al. 1995). Kavussanos and Nomikos (2000a) argues that the time variability in the second moments of spot and future returns is too small to justify the use of time-varying hedge ratios, and that – while statistically appropriate – they might be justified for some commodities, but not for others. Given these findings, we do not pursue time-varying hedge ratios.

Furthermore, Kavussanos and Nomikos (2000a) used bootstrapping techniques to investigate the change in hedging efficiency across subperiods where the underlying index changed. They found statistically significant changes caused by a change in the underlying index in only three out of 19 cases. Kavussanos and Nomikos (2000b) found that the BIFFEX contracts failed to reduce the risk of the spot position compared to that of other markets and commodities. They suggest that contracts being employed as a cross-hedge against the volatility of the constituent routes of the underlying index will suffer from the large basis risk and inaccurate tracking of rate fluctuations by the futures contracts. The BIFFEX contracts investigated in their paper used the Baltic Freight Index (BFI) as underlying. The BFI was comprised of substantially different sub-indices. For example, at one point both a 21,000 dwt grain route and a 150,000 dwt iron ore route were index constituents. Furthermore, the indices used a combination of spot and trip charter rates. Conversely, the object of study in this thesis – the FFA contract – uses the relatively less diverse BSI as underlying, where all routes are time charter rates of the same Baltic Supramax Standard Vessel. Thus, there is reason to believe that the basis risk of BIFFEX contracts was of a greater magnitude, than that of the FFA contracts investigated in this thesis. Like Kavussanos and Nomikos (2000a), we will use bootstrapping techniques to investigate if there are any statistically significant differences in hedging efficiency across subperiods.

Adland and Jia (2017) simulated the physical basis risk for FFA hedging in the Capesize segment and found that the basis risk was greater for short hedging horizons. They discuss five main sources of physical basis risk in the freight market. First, deviations in technical specifications between the hedged vessel and the Baltic Standard Vessel also cause deviations in what freight rates they capture[3]. Secondly, fuel costs are a major factor in shipping

[3] While the Supramax segment studied in this thesis consists of a relatively narrow range of ships in terms of deadweight tonnage, other factors such as differing vessel age will influence freight rates. A Supramax is defined as dry bulk vessels between 50,000 and 60,000 dwt (Clarksons, 2018). The range is less narrow for the Capesize vessels studied by Adland and Jia (2017), 100,000 to 400,000+ dwt (Clarksons, 2018). See Table A.6.1 for Standard Supramax Vessel specifications.

operations. Deviations between actual operating speeds and fuel consumption observed in the market and those specified for the standard vessel, are thus a source of physical basis risk. The third factor is due to the discrepancy between the regional rates obtained by the hedged vessel and the global average time charter rates of the BSI (Adland & Jia 2017; Alizadeh & Nomikos, 2010). However, their findings suggest that the regional differences are smaller for smaller vessels, such as the Supramax. The fourth factor is the timing mismatch due to the ship being fixed less frequently than the settlement of the FFA contract. Furthermore, it is caused by the differences between the duration of the actual trip and the defined trip durations of the constituent Baltic routes. The fifth source of basis risk is the possibility of a vessel's unemployment, thus not capturing any earnings. A weighted index will not reflect the absence of any earnings whatsoever. Furthermore, the financial basis risk is high for FFAs because of a weaker cost-of-carry relationship, due to the non-storable nature of freight, than for other commodities (see e.g. Kavussanos & Nomikos, 2000b; Alizadeh & Kavussanos, 2002; Adland & Cullinane, 2005). This results in the spot and future prices not moving perfectly together. Thus, FFAs only reflect a time-varying risk premium and expectation. Overall, we expect that hedging the exposure to freight rate volatility with a portfolio consisting of both spot and FFA will generate a reduction in the variability (as for Kavussanos & Nomikos, 2000a; Kavussanos & Visvikis, 2010; Alizadeh & Nomikos, 2012; etc.). However, it will not perfectly do so because of physical and financial basis risk.

Moreover, Adland & Jia (2017) argue that the trade-off between index-based and voyage-based contracts is a matter of market liquidity versus short-term hedging efficiency. Voyage-based contracts will offer improved hedging efficiency for that individual route, but risk reducing liquidity as the market becomes increasingly dispersed as the number of different contracts increases. Conversely, index-based contracts will concentrate market liquidity. However, they will offer a comparatively lower hedging efficiency, as the index becomes less good at tracking individual route fluctuations when more routes are added. Empirically, the market for voyage-based contracts has largely disappeared, and the majority is concentrated on index-based contracts. Overlapping FFA series allow us to formally investigate if hedging efficiency decreases when more constituent routes are added, both for routes that are already a constituent and those that become constituents. Furthermore, as Kavussanos and Nomikos (2000b) argue that the low hedging efficiency of the BIFFEX contracts led to low trading volumes, we will assess if the Baltic Exchange risks a reduction in hedging efficiency when they increase the number of constituent routes, and if they consequently risk a reduction in trading volumes due to decreased hedging efficiency.

3. Data and Methodology

3.1 Description of Data

This thesis utilises data from multiple sources. The futures prices are from the Baltic Exchange[4] and consist of time series of daily prices (excluding weekends and holidays) of BSI FFA contracts from January 3, 2006 to March 5, 2018. This is opposed to Kavussanos and Nomikos (2000a), who use weekly data to compute hedging ratios and efficiency. Lower frequency in the data is preferred because of the long horizon for operations in the shipping industry. Consequently, the hedging horizon is rarely day-to-day. Adland and Jia (2017) found that the volatility from basis risk increased with a decreased hedging horizon. A potential cointegrating relationship between spot and future prices could possibly lead to a better hedging efficiency with a long hedging horizon. Conversely, because of more noise and deviations in the short term, the calculated hedging ratio and efficiency using daily data are likely to suffer. However, reducing the frequency of the price data would decrease our sample size. Considering Figure 1.1, the short first and last periods would be particularly negatively affected by a reduction in their sample size (see also Section 3.4). An argument could therefore be made that our decision to favour sample size over actual market dynamics is reasonable, though not ideal.

It is assumed that the hedger purchases quarterly contracts, as they are considered the most liquid in the dry bulk FFA market (Alizadeh, 2013). The hedger would purchase the contract with maturity the following quarter and hold this contract until the last trading day of the present quarter, before rolling over to the contract with maturity the next quarter. For example, on the last trading day of 2006, the hedger would purchase a contract expiring in the second quarter of 2007. He will hold this contract until the last trading day of March 2007 (Q1), then sell it and purchase a new contract expiring in the third quarter of 2007 – and so on. The hedger rolls over to the next-nearest contract in order to reduce the effect of thin markets and expiration effects (Kavussanos & Visvikis, 2010). Effectively, this produces one time series lasting from January 3, 2006 to March 5, 2018.

The data is separated into three subperiods in order to measure the degree of change in hedging efficiency. The cut-off points are chosen based on when substantial changes to the

[4] Kindly provided by Western Bulk.

BSI have occurred, as outlined in Section 1. If nothing else is stated in the respective table notations, Subperiod 1 starts on January 3, 2006 when the BSI went live and replaced the BHMI, and lasts until January 2, 2007 when Subperiod 2 starts with the split of route S4 into S4A and S4B[5]. Subperiod 2 lasts until April 3, 2017 when Subperiod 3 starts. Subperiod 3 offers two different index alterations that can be evaluated. First, how specification changes to the Baltic Standard Supramax Vessel affect hedging efficiency[6]. Secondly, we can investigate how an increase in constituent routes from six to ten affects hedging efficiency. We can do this because the Baltic Exchange initiated a trial of 10TC FFAs with the 10TC_58 composed BSI as the underlying on October 24, 2016, overlapping parts of the time series for both 6TC and 6TC_58. The corresponding FFAs are 5TC in Subperiod 1, 6TC in Subperiod 2, and 6TC_58 in Subperiod 3. Furthermore, the separate 10TC FFA time series is referred to as 10TC_58.

The price data for the Baltic Supramax routes and the Baltic Supramax Index are provided by Clarksons Shipping Intelligence Network (2018). As seen in Figure 1.1, new routes have been added and existing routes discontinued or changed. The routes have varying starting points and endpoints. For all data series, logarithmic returns are used instead of real price change or simple returns.

3.2 Descriptive Statistics

Consulting the normality plots (Appendix A.4), we see that all route and FFA time series exhibit significant departures from normality across all subperiods. The conducted Ljung-Box (1978) Q tests (Table A.1.4) imply that the model residuals are autocorrelated for all variables. Augmented Dickey Fuller (1981) and Phillips-Perron (1988) unit root tests on the levels and first-differences (logarithmic change) indicate that the levels are first-difference stationary *I(1)* variables (see A.1.1). As all spot and FFA time series are integrated to the same order, we investigate if there exists a long-run cointegrated relationship between them. Results from the Engle-Granger (1987) two-step method (see A.1.3) indicate that all routes are cointegrated with both FFA time series. Considering that the BSI is relatively geographically diversified

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[5] Routes S8, S9, and S10 do not start with Subperiod 2, but on October 1, 2009; November 22, 2010; March 1, 2012; respectively.

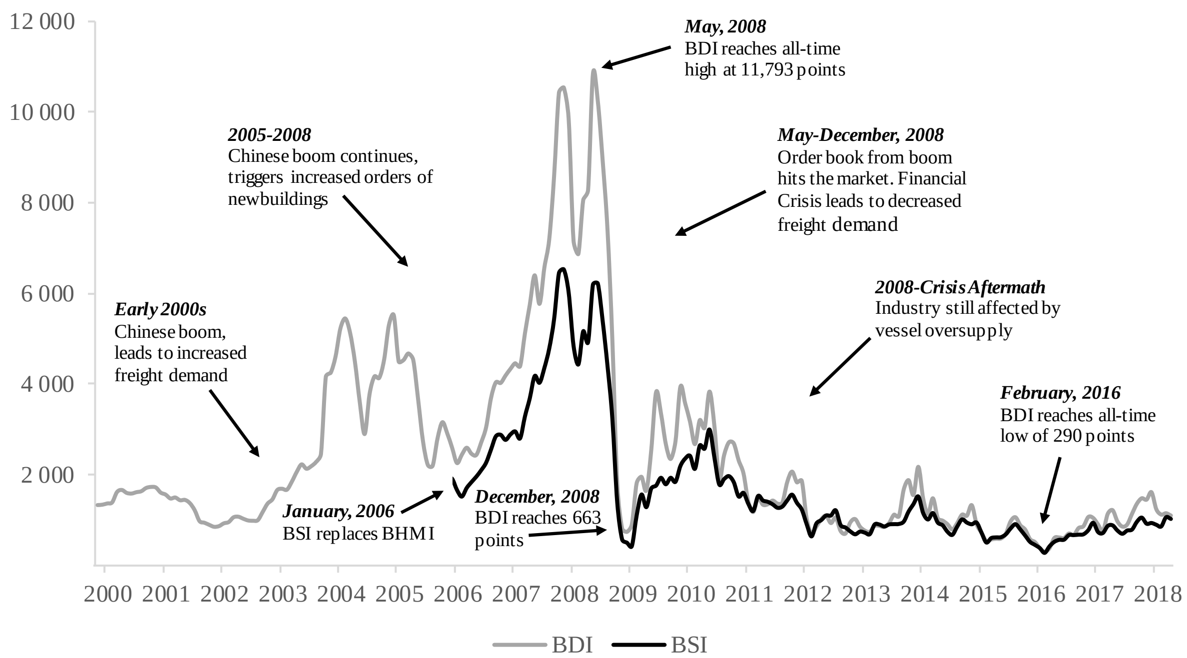
[6] The Baltic Standard Supramax Vessel was changed from Tess 52 to Tess 58 (denoted *i*_58). See Table A.6.1 for technical specifications.

across all subperiods, all constituent routes are reported for the Standard Baltic Supramax vessel, carries relatively similar cargo, and that the constituent routes' freight rates are an average of assessments that day – a long-run cointegrated relationship could be expected for the routes and the FFA.

Figure 3.2.1 presents the Baltic Dry Index and the Baltic Supramax Index from 2006 to 2018. The indices do not tell us the exact level of freight rates on specific routes and their volatility is often less than that of real fixtures or even negatively correlated (Adland, Benth, & Koekebakker, 2017). They do, however, visualise some of the volatility and cyclicality of the dry bulk segment on an aggregate level.

FIGURE 3.2.1

Baltic Dry Index (BDI) and Baltic Supramax Index (BSI) Development (1999 – 2018)



Source of index level data: Clarksons Shipping Intelligence Network (2018)

Table 3.2.1 presents the descriptive statistics for Subperiod 1. The FFA series, *5TC*, has consistently higher/lower parameters than the constituent routes of the underlying Baltic Supramax Index, indicating that the FFA contracts are more volatile than the routes they hedge. We will later see that this will influence the chosen hedge ratio and efficiency (considering eq. (2) and (4), Section 4.3). Subperiod 2 consists of a longer period than Subperiod 1, and Table 3.2.1 indicates that both the mean and median daily change are reduced compared to the previous subperiod. However, this subperiod includes both the BSI all-time high and its all-time low. Consequently, Figure 3.2.1 indicates that the volatility is substantial.

TABLE 3.2.1

Descriptive Statistics for Active Routes and FFA Data Series

Statistic		FFA	Tess 52 Routes Average[a]	S1A	S1B	S2	S3	S4	S5	S4A	S4B	S8	S9	S10
Obs.	j=1	245	245	245	245	245	245	245	245	-	-	-	-	-
	j=2	2522	2522	2522	2522	2522	2522	-	2522	2522	2522	1805	1561	1222
Mean	j=1	0.40 %	0,20 %	0.06 %	0.01 %	0.25 %	0.32 %	0.21 %	0.10 %	-	-	-	-	-
	j=2	0.02 %	-0,02 %	0.01 %	0.00 %	-0.01 %	-0.04 %	-	-0.01 %	-0.03 %	-0.03 %	0.05 %	-0.01 %	0.09 %
S.D.	j=1	1.60 %	0,79 %	0.68 %	0.91 %	0.78 %	0.77 %	0.82 %	0.65 %	-	-	-	-	-
	j=2	2.32 %	2,41 %	1.59 %	1.68 %	2.28 %	2.48 %	-	2.11 %	4.02 %	2.47 %	2.20 %	2.70 %	2.28 %
Min.	j=1	- 4.78 %	-2,68 %	-1.89 %	-3.17 %	-3.37 %	-2.41 %	- 2.41 %	-2.13 %	-	-	-	-	-
	j=2	-16.18 %	-26,84 %	-10.95 %	-10.22 %	-12.43 %	-15.02 %	-	-40.66 %	-117.10 %	-21.55 %	-13.76 %	-26.85 %	-12.86 %
Median	j=1	0.30 %	0,20 %	0.13 %	0.01 %	0.25 %	0.32 %	0.14 %	0.18 %	-	-	-	-	-
	j=2	0.04 %	0,00 %	0.00 %	0.00 %	0.00 %	0.00 %	-	0.00 %	0.00 %	0.00 %	0.00 %	-0.05 %	0.00 %
Max.	j=1	7.45 %	2,77 %	1.45 %	2.36 %	2.74 %	3.47 %	2.97 %	1.90 %	-	-	-	-	-
	j=2	11.67 %	31,65 %	22.13 %	22.59 %	15.24 %	19.46 %	-	41.89 %	115.98 %	23.11 %	29.26 %	30.46 %	18.82 %
Statistic		**FFA**	Tess 58 Routes[c] **Average[a]**	**S1C_58**	**S1B_58**	**S2_58**	**S3_58**		**S5_58**	**S4A_58**	**S4B_58**	**S8_58**	**S9_58**	**S10_58**
Obs.	j=2	2522	2522	410	410	410	410	-	410	410	410	410	410	410
	j=3	229	229	229	229	229	229	-	229	229	229	229	229	229
Mean	j=2	0.02 %	-0,02 %	0.02 %	0.00 %	0.09 %	-0.02 %	-	0.02 %	-0.04 %	0.02 %	0.11 %	-0.02 %	0.16 %
	j=3	0.13 %	0,10 %	0.19 %	0.13 %	0.05 %	0.03 %	-	0.02 %	0.26 %	0.08 %	0.11 %	-0.02 %	0.12 %
S.D.	j=2	2.32 %	2,41 %	1.87 %	1.42 %	2.19 %	2.53 %	-	1.56 %	2.12 %	2.79 %	1.76 %	1.95 %	2.28 %
	j=3	1.60 %	1,41 %	1.50 %	0.99 %	1.37 %	1.53 %	-	1.05 %	1.76 %	1.26 %	2.07 %	1.44 %	23.62 %
Min.	j=2	-16.18 %	-26,84 %	-6.54 %	-4.03 %	-13.49 %	-10.59 %	-	-3.20 %	-9.75 %	-15.38 %	-6.47 %	-4.32 %	-12.03 %
	j=3	-5.98 %	-4,32 %	-3.85 %	-2.25 %	-4.10 %	-4.71 %	-	-3.50 %	-5.26 %	-5.61 %	-6.52 %	-4.89 %	-251.13 %
Median	j=2	0.30 %	0,00 %	-0.01 %	0.00 %	0.00 %	0.00 %	-	0.00 %	0.00 %	0.00 %	-0.05 %	-0.08 %	0.00 %
	j=3	0.10 %	0,02 %	0.13 %	0.00 %	0.00 %	0.00 %	-	0.11 %	0.14 %	-0.08 %	0.00 %	0.08 %	0.00 %
Max.	j=2	11.67 %	31,65 %	10.39 %	14.41 %	13.42 %	14.38 %	-	9.01 %	15.79 %	15.54 %	7.55 %	10.62 %	10.04 %
	j=3	5.55 %	4,97 %	4.39 %	4.67 %	3.97 %	5.23 %	-	3.50 %	7.56 %	4.73 %	9.30 %	3.84 %	250.70 %

a The computations are weighted as indicated in Figure 1.1, *j* = 1,2,3 refers to Subperiod 1, 2, 3, respectively

b Routes S8, S9, and S10 start dates in Subperiod 2 are equal to the date of their trial introductions, see Section 4.1

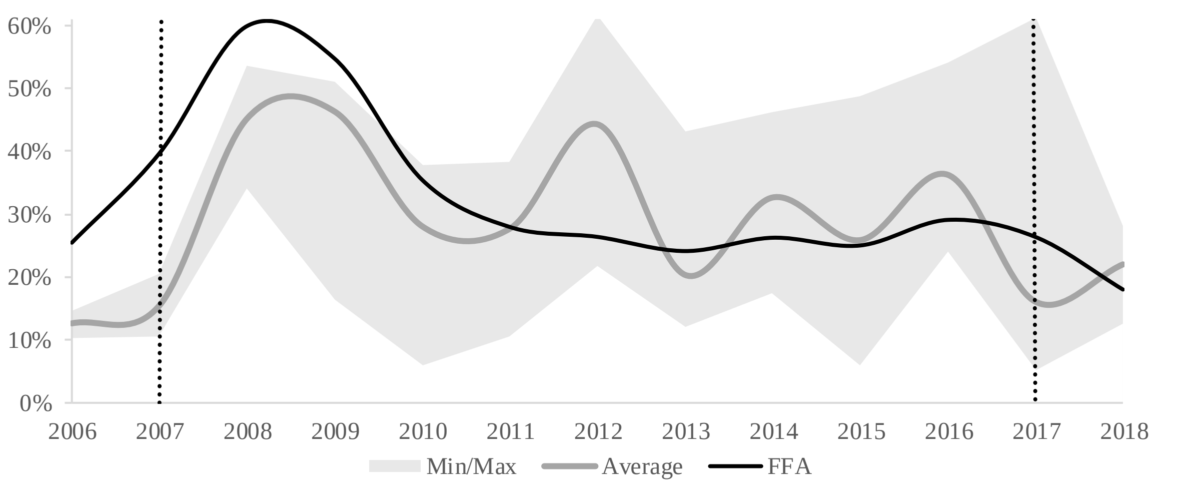
c The Tess 58 routes' start dates in Subperiod 2 are all equal to the date of their trial introduction, July 31, 2015.

This is also illustrated by the increased standard deviations and minimum/maximum values, compared to Subperiod 1[7]. The FFA series reports parameters (to a larger extent than in Subperiod 1) in line with the averages for the routes, which could indicate a better fit in this subperiod.

Subperiod 3 starts on April 3, 2017 when reporting changes from Tess 52 to Tess 58. The FFA series seem to fit better compared to the route averages than in Subperiod 1. Dropping the two outlying entries of S10_58[8], the difference between FFA and average route standard deviation is reduced compared to those of Subperiod 2. Figure 3.2.2 compares the annualised average volatility of both routes and FFA between the three subperiods. The light grey area of the figure shows the highest and lowest annualised volatility of all routes, and lines for the FFA series and the average for the index constituent routes. The rates are clearly volatile regardless of subperiod, however a clear volatility spike is visible between 2007 and 2009, where the dry bulk market experienced an extreme growth in freight rates before a complete collapse, as seen in Figure 3.2.1.

FIGURE 3.2.2

Annualised Volatility of BSI Routes and FFA



Annualised volatility per year = $\sigma_t\sqrt{252}$, where *t* equals years from 2006 to 2018 and 252 trading days per year is assumed.
Dotted lines indicate subperiod start/end.
Average weighted as indicated in Figure 1.1

[7] S4A had both the lowest and highest reported daily change, with a high of 115.98 % and a low of -117.10 %. However, both of these returns were reported consecutively on March 9 and 10, 2017, respectively. Consulting Figure A.4.2, the S4A high and low are easily identified as outliers. Considering that the high is followed by the low the day after, these observations are dropped in further analysis. Ignoring the high and low entries, the standard deviation is reduced to 2.33 %, suggesting that dropping the entries on these two dates is reasonable. Likewise, this is true for route S5 on the same dates.

[8] S10_58 has both the lowest and highest reported daily change with -251.13 % and 250.70 %, respectively. Similar to routes S4A and S5 in Subperiod 2, these entries are also reported on two consecutive days and are dropped in further analysis. Similarly, S10_58 has the highest standard deviation of 23.62 %. This is reduced to 2.37 % when the outliers are ignored.

3.3 Minimum Variance Hedge Ratio

The primary goal and objective of hedging is to control or reduce price movements in a portfolio. For example, for each unit of spot exposure in a long position, the hedger takes a short position in a derivative that corresponds with the spot exposure. Thus, an owner of a Supramax vessel has a natural long position in the freight market, and could limit her spot exposure by taking a corresponding short position in FFAs with the Baltic Supramax Index as the underlying. Assuming the freight rates and the FFA are positively correlated, a natural long position in freight rates paired with a short position in the hedging instrument is called a cross-hedge (Kavussanos & Visvikis, 2006). The shipowner could choose a portfolio of the same number of FFA contracts and spot day exposure. This is called a naïve one-to-one hedging strategy and fails to recognise that the correlation between the freight rates captured by the shipowner and the movement in FFA prices is imperfect, as discussed in Section 2.

By applying portfolio theory, the imperfect correlation between spot and forward freight rates can be taken into account (Ederington, 1979). The minimum variance hedge ratio (MVHR), *h**, is given by the ratio of the covariance between the spot and forward price changes and the variance of the forward price changes. Applying the formula for variance of a portfolio consisting of two risky assets, the variance of a hedged portfolio can be defined as:

$$\mathrm{Var}\left(\Delta P_{i,t}\right) = \mathrm{Var}(\Delta S_{i,t}) - 2h\mathrm{Cov}(\Delta S_{i,t}, \Delta F_t) + h^2\mathrm{Var}(\Delta F_t) \begin{cases} \Delta S_{i,t} = \ln S_{i,t} - \ln S_{i,t-1} \\ \Delta F_t = \ln F_t - \ln F_{t-1} \\ \Delta P_{i,t} = \Delta S_{i,t} - h\Delta F_t \end{cases} \tag{1}$$

where *h* is the hedge ratio. The minimum variance hedge ratio, *h**, is provided when taking the partial derivative of eq. (1) with respect to *h*, setting it equal to zero. Solving for *h* provides the formula for $h_{i,j}^*$, where *j* is subperiod number and *i* is route investigated:

$$h_{i,j}^* = \frac{\mathrm{Cov}\ (\Delta S_{i,j}, \Delta F_j)}{\mathrm{Var}\ (\Delta F_j)} \tag{2}$$

The MVHR from eq. (2) can also be estimated by the slope coefficient, $\overline{h_{i,j}^*}$, in the following regression:

$$\Delta S_{i,j} = \alpha_i + \overline{h_{i,j}^*}\, \Delta F_j + \epsilon_j \quad , \epsilon_j \sim \mathrm{iid}(0, \sigma^2) \tag{3}$$

From Section 3.2, we know there is reason to believe that the OLS assumptions of homoscedasticity and no autocorrelation are violated. To account for this, the Newey-West (1987) method is applied to correct the standard errors in for autocorrelation and heteroskedasticity in the error term for eq. (3).

Furthermore, Kavussanos and Visvikis (2010) discuss several problems with eq. (3) that should be noted. First, the estimated slope coefficient will be biased and inconsistent due to the simultaneity bias. This bias is caused by the price of spot and the forward contract being set simultaneously. Second, the regression uses data points for the entire period to identify the MVHR, before going "back in time" to apply this hedge ratio from day one. Lacking clairvoyance, this approach is not possible in the live market. However, the primary question in this thesis is whether structural changes to the BSI have affected hedging performance. An argument could be made that we therefore want the FFA to perform to the best of its ability in each subperiod, implying that we assume the hedger to be clairvoyant. Third, the equation is likely misspecified, ignoring the existing long-run cointegrating relationship between the spot and FFA prices established in Section 3.2. Furthermore, the short-run dynamics are not utilised because of the exclusion of relevant lagged variables. Lastly, eq. (3) assume constant risk of spot and FFA. The implications of this is discussed under Section 2. Because of these drawbacks of estimating hedge ratios through eq. (3), we also estimate hedging efficiency through naïve hedge ratios. A naïve hedge implies that the hedge ratio, *h*, equals one.

In line with similar literature, such as Kavussanos and Nomikos (2000a) and Kavussanos and Visvikis (2010), we define the hedging efficiency (*HE*) as the degree variance reduction (*VR*) obtained from hedging:

$$\mathrm{HE}_{i,j} = \mathrm{VR}_{i,j} = 1 - \frac{\mathrm{Var}\,(\Delta \mathrm{S}_{i,j} - \mathrm{h}^{*}_{i,j}\Delta \mathrm{F}_{j})}{\mathrm{Var}\,(\Delta \mathrm{S}_{i,j})} \tag{4}$$

Thus, the closer to zero $\Delta S_{i,j} - h^{*}_{i,j}\,\Delta F_j$ becomes; the greater the fit of the FFA for the investigated route, the higher degree of hedging effectiveness. The hedging efficiency can also be estimated through the R^2 of regression eq. (3). Hedging efficiency will from now on be referred to as variance reduction.

In order to account for both the change in the underlying BSI and reflect subperiod-specific volatility, the MVHR is independently calculated for each route, subperiod, and FFA used.

3.4 Bootstrapping and Adjusted Bootstrap Percentile Confidence Intervals

In order to compare the variance reduction between subperiods, implied hedged portfolios are constructed. This is done for each subperiod, finally providing a calculation of the variance reduction for each route for each subperiod through eq. (4). Using the definition of variance reduction from eq. (4), the change in variance reduction between subperiods j and j-1 for route i is defined as:

$$\Delta VR_{i,j-(j-1)} = VR_j - VR_{j-1} \tag{5}$$

In order to establish whether the observed $\Delta VR_{i,j-(j-1)}$ is statistically significant or not, bootstrapping techniques are utilised to create confidence intervals. If the confidence intervals include zero, the change in variance reduction is not statistically significant. Bootstrapping is a statistical simulation method that allows the use of the empirical distribution of the test statistic, rather than the theoretical distribution from statistical theory, to suggest statistical significance (Kavussanos & Nomikos, 2000a). This is especially useful when the standard error of the statistic of interest is difficult to estimate analytically, as is the case for the difference between variance reduction across subperiods.

The change in degree of variance reduction is computed through eq. (5) by drawing independent bootstrap samples with replacement of $\Delta S_{i,j}$, $\Delta S_{i,j-1}$, ΔF_j, and ΔF_{j-1}. This process is repeated 10,000 times, resulting in 10,000 estimations of the test statistic, $\Delta VR_{i,j-(j-1)}$. To preserve subperiod specific variation, each variable is resampled from the original data series within each subperiod separately. Regarding the discussion on data frequency in Section 3.1, using daily data rather than data of a lower frequency, the bootstrap can utilise more observations of $\Delta S_{i,j}$, $\Delta S_{i,j-1}$, ΔF_j, and ΔF_{j-1}.

In order to account for the non-normal distribution of the variables, we adjust the confidence intervals for bias and skewness. In the distribution of the bootstrap estimates of the test statistic, bias-corrected and accelerated (BCa) bootstrap confidence intervals (Efron, 1987), rather than percentile confidence intervals, are used. To compute the BCa confidence intervals, a bias-correction parameter, z_o, is estimated. This is related to the proportion of the test statistics that are less than the observed statistic in the sample data. Next, an acceleration parameter, a, is estimated. This is related to the skewness of the distribution of the bootstrapped test statistics. The acceleration parameter can be estimated through the jackknife method. The bias-correction and acceleration parameters are then used to adjust the endpoints of the confidence intervals. If the bootstrap test statistic distribution is negatively skewed, the confidence interval is adjusted to the left. If positively skewed, the interval is adjusted to the right. If zero fall within the interval, the null hypothesis of a similar degree of variance reduction between the periods cannot be rejected. This process is conducted using the *boot()* package for *R* (Hornik, 2002)[9].

[9] The code used for the bootstrapping procedure can be found in Appendix A.5.

4. Results and Analysis

This section will present and discuss the bootstrapped results in order to establish whether a change in the underlying Baltic Supramax Index has had an impact on the variance reduction in a constructed portfolio, as outlined in Section 3. First, we will look at the results using the 5TC, 6TC, 6TC_58 FFAs for Subperiods 1, 2, and 3, respectively. Second, we will present the results with a 10TC_58 FFA portfolio for Subperiods 2 and 3. Finally, we compare the 10TC_58 to the 6TC and 6TC_58 FFAs. For the first and second section, we will first present the minimum variance hedge ratio and variance reduction for each route isolated within each subperiod (described in Section 3.3), before we look at the bootstrap results comparing the variance reduction across subperiods (described in Section 3.4). Finally, we will first investigate interperiod differences between Subperiod 2 and 3 for the 10TC_58 FFA. We then compare interperiod differences between a portfolio hedged with 6TC in Subperiod 2 and 10TC_58 in Subperiod 3. Lastly, we evaluate the intraperiod differences between the 6TC/6TC_58 and the 10TC_58 FFAs.

4.1 Intraperiod MVHRs and Variance Reduction for the 5TC/6TC/6TC_58 FFA

The computed minimum variance hedge ratio, $h^*_{i,j}$, for Subperiods 1 through 3 are presented in Table A.3.1. The resulting degree of variance reduction and the variance reduction through a naïve hedge are presented in Table 4.1.1.

In Subperiod 1, the MVHR portfolios outperform the naïve-hedged portfolios for all routes, in accordance with Haralambides (1992). Considering that the standard deviation of the FFA is relatively larger than that for the individual routes, combined with eq. (2), this is unsurprising. In the case of a naïve hedge, the hedge ratio, $h^*_{i,j}$, in eq. (4) would equal one and effectively impose the portfolio with the full (relatively higher) variance of the FFA to the (relatively less volatile) freight position. The MVHRs for routes S2, S3, and S5 are statistically insignificant, implying that the FFA contract does not provide a way to reduce the variance. Looking at the correlation matrix for this subperiod, Table A.2.1, route S1B has the highest correlation with the FFA, resulting in the highest hedge ratio, which leads to the highest variance reduction. This line of reasoning is also valid for the other routes, for example S1A having the second highest correlation with the FFA, leading to the second highest hedge ratio of 6.19 %, resulting in the second highest variance reduction of 14.07 % - et cetera.

TABLE 4.1.1

Variance Reduction for all Routes and Periods with 5TC/6TC/6TC_58 FFA and Naïve and Minimum Variance Hedge Ratios

HR	Naïve			Minimum Variance[c]		
FFA	5TC	6TC	6TC_58	5TC	6TC	6TC_58
Route	$\mathbf{VR}_{j=1}$	$\mathbf{VR}_{j=2}$	$\mathbf{VR}_{j=3}$	$\mathbf{VR}_{j=1}$	$\mathbf{VR}_{j=2}$	$\mathbf{VR}_{j=3}$
S1A	- 41.12 % ***	39.07 %$^{+}$ ***		14.07 %$^{+}$	26.26 % ***	
S1B	20.54 %	41.81 %$^{+}$ ***		26.04 %$^{+}$ *	23.14 % ***	
S2	- 24.83 %	60.69 %$^{+}$ ***		1.63 %$^{+}$	31.14 % ***	
S3	- 32.86 % **	63.01 %$^{+}$ ***		0.73 %$^{+}$	29.08 % ***	
S4°	- 6.12 %			12.37 %$^{+}$		
S5	- 61.89 % ***	49.46 %$^{+}$ ***		6.92 %$^{+}$	18.93 % ***	
S4A		61.93 %$^{+}$ ***			28.11 % ***	
S4B		60.49 %$^{+}$ ***			22.57 % ***	
S8[a]		66.43 %$^{+}$ ***			28.54 % ***	
S9[a]		64.49 %$^{+}$ ***			9.89 %	
S10[a]		71.31 %$^{+}$ ***			34.18 % ***	
S1B_58[b]		48.86 %$^{+}$ ***	20.23 %$^{+}$ ***		21.05 %	0.98 %
S1C_58[b]		62.58 %$^{+}$ ***	54.08 %$^{+}$ ***		28.07 % **	18.02 %
S2_58[b]		69.72 %$^{+}$ ***	51.86 %$^{+}$ ***		35.84 % **	21.69 % ***
S3_58[b]		74.38 %$^{+}$ ***	61.92 %$^{+}$ ***		42.76 % ***	23.33 % *
S4A_58[b]		67.68 %$^{+}$ ***	61.23 %$^{+}$ ***		35.40 % ***	19.78 %
S4B_58[b]		71.56 %$^{+}$ ***	38.83 %$^{+}$ ***		38.39 % ***	1.17 %
S5_58[b]		54.19 %$^{+}$ ***	31.66 %$^{+}$ ***		23.06 % **	16.57 %
S8_58[b]		63.46 %$^{+}$ ***	68.04 %$^{+}$ ***		35.46 % **	32.92 % **
S9_58[b]		62.94 %$^{+}$ ***	54.89 %$^{+}$ ***		25.25 % ***	20.68 % *
S10_58[b]		69.10 %$^{+}$ ***	81.81 %$^{+}$ ***		49.95 % **	37.76 % ***
Average	**- 24.38 %**	**61.16 %[d]**	**52.46 %**	**10.29 %**	**29.35 %**	**19.29 %**

$\mathbf{VR}_{i,j}$ columns show the empirical variance reduction for route *i* in subperiod *j*.

***,**,* denote significance at the 1 %, 5 %, and 10 % levels, respectively, for $VR_{i,j}$. Because of the non-normal nature of the data, the Brown & Forsythe (1974) Test for Homogeneity of Variances is used.

° Route S4 was split into S4A and S4B on January 3, 2007 (i.e. only active in *j*=1).

[a] For routes S8, S9, and S10, *j=2* start date is defined as their respective trial start date (see Section 3.1) - not January 3, 2006 as is the case for the remaining non-Tess 58 routes.

[b] For the Tess 58 routes, *j=2* start date is defined at the date of their trial introduction (August 3, 2015).

[c] See Table A.3.1 for the calculated MVHRs.

[d] Average for index constituent routes is 50.81 %.

$^{+}$ Denotes the model with the highest degree of variance reduction.

Considering Table 3.2.1, where all the routes' variances are equal within four decimal places[10]; eq. (4); and the relation between covariance and correlation - this is to be expected as, when calculating the MVHRs, the numerator changes more for all routes relatively to the denominator. Unexpectedly, considering that it is the only route not contributing to the BSI

[10] Considering the square of the standard deviations reported.

(see Figure 1.1), S5 has a higher correlation with the FFA, and thus a higher degree of variance reduction, than both S2 and S3 – both individually contributing with 25 % to the index. One reason for this could be that S5 has a higher average correlation with the other constituent routes compared to S2 and S3. The variance reduction for the MVHR hedge is non-significant for all routes except the 26.04 % reduction for S1B, which is statistically significant at the ten per cent level. The naïve hedge results are statistically significant for routes S1A, S3, and S5 – however, the hedged portfolio would in this case have a higher variance than an unhedged position. Hence, they will not be used in further analysis.

With the split and discontinuation of route S4, Subperiod 2 starts on January 3, 2007. Unlike in the study by Haralambides (1992), the naïve-hedged portfolios outperform the minimum variance hedge ratios for all routes. Possibly because of the often extreme variations in this subperiod – containing both the all-time high and the all-time low of the BSI. Furthermore, Figure 3.2.2 suggests that the volatility of the FFA at times is lower than the average volatility of the individual routes. Thus, it could be expected that the hedge ratio needs to be higher to sufficiently offset route volatility. Hence, the following discussion will focus on the naïve hedge results. The average degree of variance reduction is more than 50 percentage points (pp.) higher than in Subperiod 1. All the routes report statistically significant variance reductions at the one per cent level. From the correlation matrix for Subperiod 2 in Table A.2.4, the line of reasoning explaining the relationship between correlation, hedge ratio, and the degree of variance reduction in Subperiod 1, is less clear when applied to Subperiod 2. For example, route S1A has the highest correlation with the FFA in this subperiod, but the lowest degree of variance reduction. Table 3.2.1 implies that route S1A is less volatile than the FFA, and with a naïve hedge the portfolio gets the full volatility of the FFA. This argument is similar to the one explaining that MVHR outperformed naïve hedge ratios in Subperiod 1. However, the difference is that the routes' correlation with the FFA has increased, enabling the naïve hedge ratio to still outperform the MVHR and provide a statistically significant degree of variance reduction.

The index contributing routes report an average variance reduction of 50.81 %, more than 10 pp. lower than the subperiod average. While this seems counterintuitive, these routes have twice the number of observations compared with the average of the subperiod. Furthermore, the routes capture the highly volatile period around 2008, where Figure 3.2.2 suggests the volatility gap between the FFA and the routes is substantial. Conversely, the remaining routes start when this gap is somewhat closed. The five routes with data points the entire subperiod, is thus likely affected negatively by this gap early in the subperiod.

Lastly, in Subperiod 3 the naïve hedged portfolios keep outperforming the MVHR portfolios. Furthermore, all active routes except S8_58 and S10_58 have had their variance reduction decreased compared to the previous subperiod. The statistical significance and possible explanations will be discussed in the next section.

4.2 Interperiod Change in Variance Reduction for the 5TC/6TC/6TC_58 FFA

Table 4.2.1 summarises the results from the bootstrapping procedure outlined in Section 3.4. From Table 4.1.1, the hedging model that provided the highest degree of variance reduction is chosen. The median of all bootstrapped calculations of the difference in degree of variance reduction across subperiods, $\Delta VR_{i,j-(j-1)}$, is close to the difference between observed variance reduction between subperiods from Table 4.1.1. This suggests that the bootstrapping procedure has been successful in preserving the subperiod specific variation. Here, we evaluate the effect of a structural change in the index (Subperiod 1 vs Subperiod 2) and the effect of potentially decreased basis risk due to the change from the Tess 52 to the Tess 58 standard vessel (Subperiod 2 vs Subperiod 3, see also Table 4.2.1 notation *d*).

Looking at the difference between Subperiods 2 and 1, the variance reduction has increased for all routes, though significantly only for routes S2, S3, S5, S4A, and S4B. Two factors emerge as arguments for why we can attribute the overall increase to the split of route S4 into S4A and S4B. First, correlations matrices A.2.1 and A.2.4 suggest that the average route correlations with the FFA are doubled for the constituent routes and increased 50 % overall. Because of this, routes S4A and S4B now have a statistically significant variance reduction approximately 50 pp. higher than the non-significant reduction for S4 in Subperiod 1. Consulting the corresponding correlations matrices, the correlation between S4 and the FFA is nearly the same as the correlation between S4A/S4B and the FFA in Subperiod 2. However, because of the increased correlation of all constituent routes on the FFA is increased, the variance reduction increases.

The second factor is that the correlation between routes is significant at the one per cent level for all routes in Subperiod 2. Conversely, in Subperiod 1 several route-on-route correlation coefficients are significant only at a lower level. S4 was split and discontinued because the route was not traded on a round-voyage basis. Thus, one could argue that the statistically significant correlations of S4 between it and the other routes should not be interpreted causally, as there was little basis in the market for this link. For example, route S5 has a higher correlation with S4 in Subperiod 1 than with S4A and S4B in Subperiod 2. However, its FFA correlation increased and the variance was reduced by more than 40 pp.

TABLE 4.2.1

Comparison of Degree of Variance Reduction between Subperiods
Using 5TC/6TC/6TC_58 FFA

	Selected Model[c]			Bootstrap Results		
Route	j=1	j=2	j=3	$\Delta VR_{j2\text{-}j1}$	$\Delta VR_{j3\text{-}j2}$[d]	
S1A	MVHR	1:1		24.62 %	6.77 %[e]	
S1B	MVHR	1:1		15.89 %	-32.28 %	*
S2	MVHR	1:1		60.12 % ***	-16.64 %	
S3	MVHR	1:1		62.51 % ***	-10.92 %	
S4°	MVHR					
S5	MVHR	1:1		43.38 % ***	-40.59 %	**
S4A		1:1		50.24 % ***	-15.92 %	
S4B		1:1		49.04 % ***	-34.83 %	*
S8[a]		1:1			2.03 %	
S9[a]		1:1			-6.35 %	
S10[a]		1:1			9.74 %	
S1B_58[b]		1:1	1:1		- 26.51 %	
S1C_58[b]		1:1	1:1		- 8.25 %	
S2_58[b]		1:1	1:1		- 17.65 %	
S3_58[b]		1:1	1:1		- 12.41 %	
S4A_58[b]		1:1	1:1		- 6.06 %	
S4B_58[b]		1:1	1:1		- 32.56 %	*
S5_58[b]		1:1	1:1		- 22.05 %	
S8_58[b]		1:1	1:1		4.62 %	
S9_58[b]		1:1	1:1		- 7.76 %	
S10_58[b]		1:1	1:1		12.15 %	
Average				**43.74 %**	**- 12.77 %**	

$\Delta VR_{i,t\text{-}(t\text{-}1)}$ show the median bootstrap test statistic from 10,000 bootstrap samples comparing the variance reduction between Subperiod *j* and Subperiod *j-1* for route *i*. For $\Delta VR_{j2\text{-}j1}$ the calculation is $VR_{i,6TC} - VR_{i,5TC}$, while the calculation for $\Delta VR_{j3\text{-}j2}$ is $VR_{i,6TC58} - VR_{i,6TC}$.

***, **, * denote significance from BCa intervals at the 1 %, 5 %, and 10 % level, respectively.

° Route S4 was split into S4A and S4B on January 3, 2007 (i.e. only active in *j*=1).
[a] For routes S8, S9, and S10, *j=2* start date is defined as their respective trial start date (see Section 3.1). Subperiod 3 data are here from the routes' Tess 58 counterparts, i.e. $VR(S8\_58_{j=3})$ minus $VR(S8_{j=2})$
[b] For the Tess 58 routes, *j=2* start date is defined at the date of their trial introduction (August 3, 2015).
[c] The model that provides the highest degree of variance reduction, see Table 4.1.1. *MVHR* denotes hedge ratio calculated through the formula for minimum variance hedge ratio, while *1:1* denotes a naïve hedge.
[d] Tess 52 routes' start dates for Subperiod 2 are equal to Tess 58 trial introduction and are compared to their Tess 58 counterparts in Subperiod 3, i.e. $VR(S1B\_58_{j=3})$ minus $VR(S1B_{j=2*})$. This makes all the computed changes in variance reduction in this column comparable.
[e] S1A in Subperiod 2 is compared to S1C_58 in Subperiod 3, see also [d].

Nonetheless, an argument could also be made for why the index change was perhaps not the cause of the overall increased degree of variance reduction. The FFA hedge could be performing better in Subperiod 2 than 1 because there is more variation for it to offset in Subperiod 2. Consulting Table 3.2.1 and Figure 3.2.2, Subperiod 1 appears to be less volatile than Subperiod 2 overall. As Subperiod 1 is a mere one-year period, while Subperiod 2 is ten years long and includes the high volatility of the period around 2008, this is unsurprising. For Subperiod 1, the definition of hedging efficiency, eq. (4), will however indicate a lower degree of variance reduction compared to a non-hedged position because of the relatively lower denominator. This could indicate that the performance of the FFA hedge is penalised because there is less volatility for it to offset. Because we do not have overlapping time series for the 5TC and the 6TC FFAs, we cannot isolate the effect from an index change and that of differing subperiod-specific volatility.

Looking at the difference going from Subperiod 2 to Subperiod 3, Tables A.2.4 and A.2.2 suggest that the correlation of both the BSI constituents and the FFA, and all routes on the FFA, have decreased compared to Subperiod 2. Moreover, the correlation is no longer statistically significant. Like the change from Subperiod 1 to 2, there is also the issue of Subperiod 2 appearing more volatile than Subperiod 3[11]. However, results in Figure 3.2.2 suggest that the years leading up to Subperiod 3 are more similar in terms of volatility to Subperiod 3. Fortunately, the Tess 58 trials commenced on July 31, 2015 and Subperiod 3 starts on April 3, 2017, and there are thus some observations that can be utilised for investigating the effect of the index change (see also Table 4.2.1, notations *d* and *e*).

The results in Table 4.2.1 suggest both positive and negative development in variance reduction – though with a clear negative tendency. For the Tess 52 routes, three routes' changes in variance reduction is statistically significant on, at least, the ten per cent level: S1B, S5, and S4B. Consequently, the same three routes' Tess 58 equivalent reports the greatest decrease in variance reduction, significant at the ten per cent level for S4B_58. However, the decrease in variance reduction for the three Tess 58 routes are less than that for the corresponding Tess 52 routes, indicating that the 6TC_58 hedge is more effective for the Tess 58 routes than the Tess 52 routes. This appears to be a reasonable find, as the basis risk caused by differing technical specifications would decrease. However, the differences are statistically insignificant, consequently this cannot be established with sufficient certainty.

Furthermore, routes S8_58 and S10_58 have an insignificant increase in their respective variance reductions, however their correlation with regards to the FFA is reduced. Table 3.2.1 might provide an explanation for this. The standard deviations for these two routes are higher in Subperiod 3 (also when dropping the S10_58 outliers) than the FFA's, while this is not true for the remaining routes[12]. Thus, contrary to the previous discussion, these routes are less penalised by the lack of volatility.

[11] See Table 3.2.1 and Figure 3.2.2.

[12] Except S4A_58. However, S4A_58 has the least non-significant reduction going from Subperiod 2 to 3 among the routes with a VR decrease.

In conclusion, one could argue that we should see an increase in the correlation of routes on the FFA and the variance reduction between Subperiod 2 and 3, as the 6TC_58 was introduced as a better representation of how Supramax vessels were trading in the market. However, the results presented in Table 4.2.1 do not reflect this. Thus, the hypothesis that a change in the Baltic Standard Vessel was beneficial for hedging efficiency due to reduced basis risk is unconfirmed. As previously discussed, Figure 3.2.2 suggests the two periods are relatively similar in terms of volatility. The lack of an improvement in variance reduction could therefore hardly be attributed to differing market conditions. To investigate the effect on introducing the Tess 58 routes further, we now move on to the 10TC_58 FFA.

4.3 MVHRs and Variance Reduction for the 10TC_58 FFA

While we have investigated the effect of the changes to the Baltic Supramax Index in the previous section, these structural changes are relatively minor. There are only two occurrences of changes to the constituent routes of the index, and one where the Baltic Standard Supramax vessel was modified. However, with the launch of the 10TC_58 trial on October 24, 2016, we can investigate how a simultaneous weight change in the index affects variance reduction. It allows us to compare the hedging performance of two FFAs isolated from time-varying effects. The underlying index is now comprised of a weighted average of ten routes, opposed to five and six in the previous subperiods. Thus, we isolate and evaluate the effects of potentially increased basis risk due to an increased geographical diversifying effect. Several routes that were not constituent routes in the 5TC, 6TC, and 6TC_58 FFAs are constituent routes of the 10TC_58. Table A.3.2 presents the calculated minimum variance hedge ratios, $h^*_{i,j}$. It also presents the variance reduction, $VR_{i,j}$, through both a MVHR hedge and a naïve hedge. As this FFA was launched during Subperiod 2, Subperiod 1 is not relevant for the discussion in this section.

With three exceptions, in Subperiod 2 the 10TC_58 naïve hedged portfolios outperform the MVHR portfolios. Naïve hedge ratios for routes S1A, S1B, and S1B_58 provide negative variance reduction, while the MVHR provides them with low and statistically insignificant variance reductions. Table A.2.3 suggests that the S1B routes have a lower correlation with the 10TC_58 FFA than with the 6TC. This seems reasonable, as their weights in the index have been reduced (see Figure 1.1).

Table 4.3.1 summarises the results from the bootstrapping procedure outlined in Section

3.4 using the 10TC_58 FFA in both Subperiod 2 and Subperiod 3. From Table A.3.2 we choose the hedging model that provided the highest degree of variance reduction. The results

TABLE 4.3.1

Comparison of Degree of Variance Reduction between Subperiods Using the 10TC_58 FFA

	Selected Model[a]		Bootstrap Results
Route	j=2[b]	j=3[c]	$\Delta VR_{j3\text{-}j2}$
S1B_58	MVHR	1:1	21.32 %
S1C_58	1:1	1:1	- 1.69 %
S2_58	1:1	1:1	- 10.20 %
S3_58	1:1	1:1	- 10.77 %
S4A_58	1:1	1:1	- 5.67 %
S4B_58	1:1	1:1	- 13.78 %
S5_58	1:1	1:1	1.90 %
S8_58	1:1	1:1	1.98 %
S9_58	1:1	1:1	3.35 %
S10_58	1:1	1:1	13.19 %
Average			**-0.04 %**

$\Delta VR_{i,j\text{-}(j\text{-}1)}$ show the median bootstrap test statistic from 10,000 bootstrap samples comparing the variance reduction between Subperiod *j* and Subperiod *j-1* for route *i*.

***, **, * denote significance at the 1 %, 5 %, and 10 %, respectively (none). The significance is determined by the BCa intervals for the respective significant level.

[a] The model that provides the highest degree of variance reduction, see Table A.3.2. *MVHR* denotes hedge ratio calculated through the formula for minimum variance hedge ratio, while *1:1* denotes a naïve hedge.

[b] Subperiod 2 start date is defined as the date of the 10TC_58 trial introduction, October 24, 2016

[c] Subperiod 3 end date is defined as December 31, 2017, as we do not have access to its data beyond this point

show that there are no statistically significant changes between the degree of variance reduction between Subperiods 2 and 3. Because the analysis is conducted on portfolios hedged with the 10TC_58 in both subperiods, there are no structural changes to the index between the two subperiods. We can therefore argue that the results show that the variance reduction between the two subperiods is inherently indifferent; if we find statistically significant changes in the following analysis, these changes are likely to be caused by the structural changes of the index. It would be harder to argue that any statistical changes in variance reduction are caused by some other factor, such as differing general market conditions. Hence, in order to investigate if changes to the underlying index has affected hedging performance, we therefore proceed to conduct the bootstrapping procedure on portfolios hedged with the 6TC FFA in Subperiod 2, and the 10TC_58 in Subperiod 3. The results are presented in Table 4.3.2.

There are no statistically significant changes between the degree of variance reduction of the two subperiods. S5_58, S8_58, S9_58, and S10_58 have now gone from non-constituent to constituent routes. The variance reduction has increased only for S8 and S10[13], while it has decreased for S5 and S9. These conflicting results complicate the argument that a route's increased influence on the underlying index consequently should increase its variance reduction.

TABLE 4.3.2

Comparison of Degree of Variance Reduction between Subperiods Using the 6TC FFA in Subperiod 2 and the 10TC_58 in Subperiod 3

	Model[c]	**Bootst. Results**		**Model[c]**		**Bootst. Results**
Route[a]	j=2	$\Delta VR_{j3\text{-}j2}$	**Route**	j=2[d]	j=3[e]	$\Delta VR_{j3\text{-}j2}$
S1A	1:1	- 15.82 %	S1C_58	1:1	1:1	- 25.08 %
S1B	1:1	- 18.88 %	S1B_58	1:1	1:1	- 7.18 %
S2	1:1	- 4.92 %	S2_58	1:1	1:1	- 13.95 %
S3	1:1	- 1.64 %	S3_58	1:1	1:1	- 13.01 %
S5	1:1	- 8.29 %	S5_58	1:1	1:1	- 14.43 %
S4A	1:1	- 0.17 %	S4A_58	1:1	1:1	- 5.27 %
S4B	1:1	- 15.16 %	S4B_58	1:1	1:1	- 25.78 %
S8[b]	1:1	2.62 %	S8_58	1:1	1:1	6.85 %
S9[b]	1:1	- 4.75 %	S9_58	1:1	1:1	- 2.70 %
S10[b]	1:1	12.24 %	S10_58	1:1	1:1	14.40 %
Average		**- 5.45 %**				**- 8.62 %**

$\boldsymbol{\Delta VR_{i,j\text{-}(j\text{-}1)}}$ show the median bootstrap test statistic from 10,000 bootstrap samples comparing the variance reduction between Subperiod *j* and Subperiod *j*-1 for route *i*.

***, **, * denote significance at the 1 %, 5 %, and 10 %, respectively (none). The significance is determined by the BCa intervals for the respective significant level.

[a] Subperiod 3 data are here from the routes' Tess 58 counterparts, i.e. $VR(S8\_58_{j=3})$ minus $VR(S8_{j=2})$

[b] For routes S8, S9, and S10, *j=2* start date is defined at the date of their respective trial start date (see Section 3.1) - not January 3, 2006 as is the case for the remaining non-Tess 58 routes.

[c] The model that provides the highest degree of variance reduction, see Tables 4.1.1 and A.3.2. *MVHR* denotes hedge ratio calculated through the formula for minimum variance hedge ratio, while *1:1* denotes a naïve hedge.

[d] For the Tess 58 routes, Subperiod 2 start date is defined at the date of their trial introduction (August 3, 2015).

[e] For all routes, Subperiod 3 end date is December 31, 2017.

To further investigate the relationship between a route's weight in the index and the corresponding variance reduction, we compare intraperiod variance reduction between a portfolio hedge with the 10TC_58 and one with 6TC/6TC_58. The results are presented in Table 4.3.3, where the 10TC_58 FFA hedge on average performs marginally worse than the 6TC in Subperiod 2, and marginally better than 6TC_58 in Subperiod 3. The intraperiod differences between the three FFAs are statistically insignificant for all routes. We would expect routes that have had their weights reduced to have corresponding decrease in variance reduction at the individual route level, and vice versa. Yet for neither subperiod we see such a pattern emerging, and our hypothesis is unconfirmed. Furthermore, there is no evidence of

[13] Both for the Tess 52 and the Tess 58 vessel

TABLE 4.3.3

Intraperiod Comparison of Degree of Variance Reduction Between the 10TC_58 FFA and the 6TC and 6TC_58 FFAs

	Selected Model[a]		Bootst. Results	
Route	j=2[b]	j=3[c]	$\Delta VR_{j2\text{-}j2}$	$\Delta VR_{j3\text{-}j3}$
S1A	MVHR/1:1[d]		- 15.98 %	
S1B	MVHR/1:1[d]		- 8.54 %	
S2	1:1		- 11.02 %	
S3	1:1		11.23 %	
S5	1:1		- 0.19 %	
S4A	1:1		11.22 %	
S4B	1:1		2.87 %	
S8	1:1		5.79 %	
S9	1:1		16.76 %	
S10	1:1		8.30 %	
S1B_58	MVHR/1:1[d]	1:1	- 46.89 %	3.30 %
S1C_58	1:1	1:1	- 4.75 %	1.92 %
S2_58	1:1	1:1	- 2.90 %	4.16 %
S3_58	1:1	1:1	- 1.84 %	-0.20 %
S4A_58	1:1	1:1	0.63 %	0.93 %
S4B_58	1:1	1:1	- 11.15 %	5.94 %
S5_58	1:1	1:1	- 14.75 %	8.50 %
S8_58	1:1	1:1	4.14 %	1.61 %
S9_58	1:1	1:1	- 6.00 %	5.10 %
S10_58	1:1	1:1	0.76 %	2.09 %
Average			**- 3.12 %**	**3.34 %**

$\mathbf{\Delta VR_{i,j}}$ show the median bootstrap test statistic from 10,000 bootstrap samples comparing the variance reduction between the 10TC_58 and 6TC FFAs in Subperiod 2, and the 10TC_58 and 6TC_58 FFAs in Subperiod 3. i.e. $VR(i\_58_{j=2}) - VR(i\_52_{j=2})$.

***, **, * denote significance at the 1 %, 5 %, and 10 %, respectively (none). The significance is determined by the BCa intervals for the respective significant level.

[a] The model that provides the highest degree of variance reduction, see Tables 4.1.1 and A.3.2. *MVHR* denotes hedge ratio calculated through the formula for minimum variance hedge ratio, while *1:1* denotes a naïve hedge.
[b] For all routes, Subperiod 2 start date is October 24, 2016.
[c] For all routes, Subperiod 3 end date is December 31, 2017.
[d] MVHR is used for 10TC_58 and naïve for 6TC, as per Tables 4.1.1 and A.3.2.

an overall reduction of hedging efficiency for the original constituents when more routes are added. Moreover, the correlation in the overlapping periods of the 10TC_58 FFA and the 6TC and 6TC_58 FFAs is near perfect (see Table A.2.3), even though their underlying indices consist of ten and six routes, respectively. Arguably because of the cointegrated relationship between the routes and the FFA, altering the composition of the underlying index does not seem to have an effect on variance reduction – neither on the individual route level nor overall. In total, the lack of a distinct pattern between weight change and (statistically significant) differences in the degree of variance reduction, makes it problematic to conclude that the differences are caused by changes in the underlying index. These results are in line with the findings of Glen and Rogers (1997), and Kavussanos and Nomikos (2000a). Thus, *ceteris paribus*, these index alterations should not induce reduced trading volumes for the FFA due to decreased hedging efficiency, as was the case of the BIFFEX contract (Kavussanos & Nomikos, 2000b). At the same time, the alterations done by the Baltic Exchange has not led to increased variance reduction, as was likely their intention.

5. Concluding Remarks

In this thesis, we investigated the hedging ability, defined as degree of variance reduction, of FFAs in the Supramax segment with regard to its Baltic constituent routes. Furthermore, we evaluated how changes in the composition of the underlying Baltic Supramax Index affected hedging performance.

We find that FFAs can significantly reduce the volatility of freight rates in most routes and subperiods. Furthermore, that naïve hedge ratios outperform minimum variance hedge ratios in 57 out of 66 cases. However, we have not found sufficient evidence to argue that a reduced weight in the underlying index causes a decreased degree of variance reduction, or vice versa. The first change in the index appears to have significantly increased the variance reduction for most routes. Routes S4A and S4B succeeded S4 because they were believed to be better representations of the actual market. Our results indicate that the co-integrated relationship between these replacements routes and the remaining constituent routes resulted in increased hedging efficiency and correlation of all routes on the FFA. We have not found sufficient evidence of the FFAs with the Tess 58 standard vessel outperforming the Tess 52. Furthermore, there is no basis for arguing that the 6TC or 6TC_58 FFAs outperform the 10TC_58 FFA. Hedged portfolios on routes that are now included in the underlying index do not perform better than they did when they were not a constituent. Nor does the inclusion of more routes negatively affect the hedging efficiency of the original constituent routes. Thus, the hypothesised undesirable diversifying effect of adding more routes is not observed. Moreover, we found that the correlation in the overlapping periods of the 10TC_58 FFA and the 6TC and 6TC_58 FFAs is near perfect, strengthening the argument that the existing cointegrated relationship between all routes voids any index altering irrelevant. These findings are in line with similar literature, namely Glen and Rogers (1997), Kavussanos and Nomikos (2000a). Thus, we cannot argue that altering the composition of the Baltic Supramax Index leads to any statistically significant increases (or decreases) in hedging efficiency. Nor can we argue that these changes should be a source of reduced trade volumes of FFAs for the Baltic Exchange, as was likely the case for the BIFFEX contracts investigated by Kavussanos & Nomikos (2000b).

There are some limitations to our study. Most importantly, daily data was deemed necessary in order to obtain a sufficiently large sample for Subperiod 1 and 3. Daily hedging efficiency is of little importance for operations with longer hedging horizons. Nonetheless, the effect of any index altering would still be visible in our calculations, but the hedging efficiency in itself bears little actual relevance. Furthermore, the freight rates were those reported by the Baltic Exchange. As these are the average of several brokers' estimates, there is reason to believe that they suffer from a diversifying effect where we lose some of the volatility that actual market participants capture.

We believe that our findings open several interesting pathways for further research within the realm of hedging in the shipping industry. The effects of increasing constituent routes to ten could be more easily identified when the current period has data points from more dimensions of the shipping cycle. Moreover, increasing the number of observations would allow the use of weekly or monthly hedging horizons, which is more in line with similar literature and market realities. Furthermore, with more observations for the 10TC_58 FFA, applying our method to real market fixtures would provide better estimates of the FFA hedging efficiency for actual market participants. Lastly, the effects on the results utilising time-varying, rather than static, hedge ratios could be an interesting sequel.

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Appendix

A.1 Descriptive Statistics

TABLE A.1.1

P-values from Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) Tests
H_0: Variable contains a unit root

	Level		First-Difference (logs)	
Route	ADF	PP	ADF	PP
S1A	0.05	0.55	0.01	0.01
S1B	0.05	0.56	0.01	0.01
S2	0.03	0.32	0.01	0.01
S3	0.06	0.44	0.01	0.01
S4	0.26	0.25	0.17	0.033
S5	0.11	0.49	0.01	0.01
S4A	0.07	0.23	0.01	0.01
S4B	0.32	0.77	0.01	0.01
S8	0.08	0.13	0.01	0.01
S9	0.05	0.41	0.01	0.01
S10	0.01	0.36	0.01	0.01
S1B_58	0.13	0.44	0.01	0.01
S1C_58	0.19	0.32	0.01	0.01
S2_58	0.08	0.42	0.01	0.01
S3_58	0.04	0.34	0.01	0.01
S4A_58	0.32	0.50	0.01	0.01
S4B_58	0.09	0.66	0.01	0.01
S5_58	0.04	0.27	0.01	0.01
S8_58	0.08	0.51	0.01	0.01
S9_58	0.05	0.30	0.01	0.01
S10_58	0.07	0.49	0.01	0.01
FFA 5/6/6_58TC	0.29	0.51	0.01	0.01
FFA 10_58TC	0.66	0.66	0.01	0.01

For all ADF non-rejection of the null on the levels, a plot of the data points are consulted and suggests that all time series in question are non-stationary on the levels. Furthermore, considering the presence of autocorrelation and heteroscedasticity in all variables, the Phillips-Perron tests make a non-parametric correction to the t-test and is thus more suitable.

TABLE A.1.2

Descriptive Statistics for 10TC_58 FFA in Subperiods 1 and 2

Statistic	**Subperiod 2[a]**	**Subperiod 3[b]**
Observations	106	184
Mean	0.54 %	0.09 %
St.dev.	0.0161	0.0157
Minimum	-3.75 %	-5.73 %
Median	0.39 %	0.09 %
Max	4.62 %	5.11 %

[a] Start date defined as trial start date: October 25, 2016.

[b] End date December 31, 2017.

TABLE A.1.3

P-values from Engle-Granger Test for Cointegration Between Routes and FFAs
H0: Series are not cointegrated

FFA	5TC	6TC	6TC_58	10TC_58	
Subperiod	1	2	3	2	3
S1A	0.01	0.01		0.01	
S1B	0.01	0.01		0.01	
S2	0.01	0.01		0.01	
S3	0.01	0.01		0.01	
S4	0.01				
S5	0.01	0.01		0.01	
S4A		0.01		0.01	
S4B		0.01		0.01	
S8		0.01		0.01	
S9		0.01		0.01	
S10		0.01		0.01	
S1B_58		0.01	0.01	0.01	0.01
S1C_58		0.01	0.01	0.01	0.01
S2_58		0.01	0.01	0.01	0.01
S3_58		0.01	0.01	0.01	0.01
S4A_58		0.01	0.01	0.01	0.01
S4B_58		0.01	0.01	0.01	0.01
S5_58		0.01	0.01	0.01	0.01
S8_58		0.01	0.01	0.01	0.01
S9_58		0.01	0.01	0.01	0.01
S10_58		0.01	0.01	0.01	0.01

TABLE A.1.4

Ljung-Box Q Test for Autocorrelation
H_0: *Series are independently distributed*

Route	**Lags**[a]	**p-value**	**Route**	**Lags**[a]	**p-value**
S1A	34	0.01	S1C_58	26	0.01
S1B	34	0.01	S1B_58	26	0.01
S2	34	0.01	S2_58	26	0.01
S3	34	0.01	S3_58	26	0.01
S4	23	0.01			
S5	34	0.01	S5_58	26	0.01
S4A	34	0.01	S4A_58	26	0.01
S4B	34	0.01	S4B_58	26	0.01
S8	32	0.01	S8_58	26	0.01
S9	31	0.01	S9_58	26	0.01
S10	30	0.01	S10_58	26	0.01
FFA 5/6/6_58TC	34	0.01	FFA 10_58TC	23	0.01

[a] Lags are from the pacf() function in R

A.2 Correlation Matrices

TABLE A.2.1

Correlation Matrix for the Log. Differences between the BSI Routes and the 5TC FFA in Subperiod 1

	S1A	S1B	S2	S3	S4	S5	FFA[a]
S1A	–						
S1B	87 %[I]	–					
S2	41 %[I]	32 %[I]	–				
S3	21 %[v]	10 %	83 %[I]	–			
S4	85 %[I]	76 %[I]	33 %[I]	20 %[v]	–		
S5	82 %[I]	76 %[I]	39 %[I]	21 %[v]	82 %[I]	–	
FFA[a]	14 %	26 %[I]	2 %	1 %	12 %	7 %	–

[a] The specifics for the construction of the FFA data series are explained in Section 4.1.
[I, v, x] Denote significance level at the 1 %, 5 %, and 10 % level, respectively
Average correlation between BSI routes and FFA = 8.75 % (weighted as indicated in Figure 1.1)
Average correlation between all routes and FFA = 10.33 % (equally weighted)

TABLE A.2.2

Correlation Matrix for the Log. Differences between the BSI Routes and the 6TC_58 FFA in Subperiod 3

	S1B_58	S1C_58	S2_58	S3_58	S4A_58	S4B_58	S5_58	S8_58	S9_58	S10_58	FFA[a]
S1B_58	–										
S1C_58	27 %[I]	–									
S2_58	46 %[I]	44 %[I]	–								
S3_58	40 %[I]	43 %[I]	86 %[I]	–							
S4A_58	20 %[v]	87 %[I]	32 %[I]	32 %[I]	–						
S4B_58	56 %[I]	39 %[I]	33 %[I]	36 %[I]	37 %[I]	–					
S5_58	40 %[I]	34 %[I]	46 %[I]	54 %[I]	26 %[I]	46 %[I]	–				
S8_58	30 %[I]	33 %[I]	78 %[I]	72 %[I]	20 %[v]	14 %	32 %[I]	–			
S9_58	40 %[I]	36 %[I]	45 %[I]	51 %[I]	27 %[I]	45 %[I]	93 %[I]	33 %[I]	–		
S10_58	26 %[I]	31 %[I]	76 %[I]	68 %[I]	19 %[x]	13 %	28 %[I]	97 %[I]	29 %[I]	–	
FFA[a]	1 %	11 %	14 %	14 %	10 %	1 %	13 %	16 %	13 %	17 %[x]	–

[a] The specifics for the construction of the FFA data series are explained in Section 3.1.
[I, v, x] Denote significance level at the 1 %, 5 %, and 10 % level, respectively
Average correlation between BSI routes and FFA = 9.88 % (weighted as indicated in 1.1)
Average correlation between all routes and FFA = 11.00 % (equally weighted)

TABLE A.2.3

Correlation between Routes and 10TC_58 FFA in Subperiods 2 and 3

Subperiod	S1A	S1B	S2	S3	S4A	S4B	S5	S8	S9	S10
2[a]	2 %	4 %	21 %	15 %	4 %	8 %	1 %	17 %	15 %	19 %
Subperiod	**S1B_58**	**S1C_58**	**S2_58**	**S3_58**	**S4A_58**	**S4B_58**	**S5_58**	**S8_58**	**S9_58**	**S10_58**
2[a]	1 %	1 %	19 %	14 %	5 %	8 %	8 %	18 %	7 %	16 %
3[b]	3 %	14 %	21 %	22 %	13 %	5 %	19 %	20 %	18 %	5 %

[a] Subperiod 2 start date is defined as the date of 10TC_58 trial start, October 24, 2016.
[b] Subperiod 3 end date is defined as December 31, 2017 as we do not have access to FFA prices beyond this point.
Average correlation between BSI routes and FFA, Subperiod 2 = 12.43 % (weighted as indicated in Figure 1.1)
Average correlation between all routes and FFA, Subperiod 2 = 10.17 % (equally weighted)
Average correlation between BSI routes and FFA, Subperiod 3 = 15.55 % (weighted as indicated in Figure 1.1)
Average correlation between all routes and FFA, Subperiod 3 = 13.99 % (equally weighted)
Correlation between 6TC and 10TC_58 , Subperiod 2 = 95.65 %
Correlation between 6TC_58 and 10TC_58, Subperiod 3 = 96.78 %
See Tables A.2.4 and A.2.2 for route-on-route correlations for Subperiods 2 and 3.

TABLE A.2.4

Correlation Matrix for the Log. Differences between the BSI Routes
and 6TC FFA in Subperiod 2

	S1A	S1B	S2	S3	S5	S4A	S4B	S8	S9	S10	S1B_58	S1C_58	S2_58	S3_58	S4A_58	S4B_58	S5_58	S8_58	S9_58	S10_58	FFA
S1A	–																				
S1B	75 %^{I}	–																			
S2	49 %^{I}	45 %^{I}	–																		
S3	43 %^{I}	37 %^{I}	81 %^{I}	–																	
S5	58 %^{I}	50 %^{I}	43 %^{I}	38 %^{I}	–																
S4A	37 %^{I}	32 %^{I}	27 %^{I}	25 %^{I}	75 %^{I}	–															
S4B	66 %^{I}	60 %^{I}	44 %^{I}	46 %^{I}	48 %^{I}	34 %^{I}	–														
S8[a]	34 %^{I}	24 %^{I}	81 %^{I}	75 %^{I}	27 %^{I}	15 %	31 %^{I}	–													
S9[b]	43 %^{I}	32 %^{I}	27 %^{I}	26 %^{I}	54 %^{I}	18 %^{x}	39 %^{I}	25 %^{I}	–												
S10[c]	34 %^{I}	26 %^{I}	84 %^{I}	79 %^{I}	23 %^{v}	13 %	36 %^{I}	94 %^{I}	27 %^{I}	–											
S1B_58[d]	50 %^{I}	97 %^{I}	33 %^{I}	37 %^{I}	19 %^{x}	8 %	47 %^{I}	37 %^{I}	25 %^{I}	36 %^{I}	–										
S1C_58[d]	42 %^{I}	37 %^{I}	42 %^{I}	37 %^{I}	22 %^{v}	22 %^{v}	47 %^{I}	37 %^{I}	32 %^{I}	36 %^{I}	35 %^{I}	–									
S2_58[d]	33 %^{I}	30 %^{I}	87 %^{I}	75 %^{I}	18 %^{x}	9 %	38 %^{I}	75 %^{I}	29 %^{I}	75 %^{I}	30 %^{I}	40 %^{I}	–								
S3_58[d]	42 %^{I}	34 %^{I}	84 %^{I}	90 %^{I}	22 %^{v}	11 %	49 %^{I}	82 %^{I}	31 %^{I}	81 %^{I}	34 %^{I}	39 %^{I}	77 %^{I}	–							
S4A_58[d]	47 %^{I}	33 %^{I}	38 %^{I}	38 %^{I}	23 %^{v}	24 %^{I}	48 %^{I}	34 %^{I}	35 %^{I}	35 %^{I}	31 %^{I}	83 %^{I}	35 %^{I}	37 %^{I}	–						
S4B_58[d]	73 %^{I}	54 %^{I}	43 %^{I}	52 %^{I}	25 %^{I}	13 %	95 %^{I}	46 %^{I}	38 %^{I}	47 %^{I}	50 %^{I}	49 %^{I}	41 %^{I}	52 %^{I}	50 %^{I}	–					
S5_58[d]	57 %^{I}	37 %^{I}	41 %^{I}	48 %^{I}	46 %^{I}	12 %	47 %^{I}	44 %^{I}	67 %^{I}	43 %^{I}	36 %^{I}	44 %^{I}	37 %^{I}	44 %^{I}	48 %^{I}	52 %^{I}	–				
S8_58[d]	39 %^{I}	37 %^{I}	83 %^{I}	84 %^{I}	20 %^{v}	8 %	42 %^{I}	97 %^{I}	31 %^{I}	94 %^{I}	37 %^{I}	34 %^{I}	75 %^{I}	82 %^{I}	33 %^{I}	45 %^{I}	43 %^{I}	–			
S9_58[d]	56 %^{I}	35 %^{I}	40 %^{I}	46 %^{I}	44 %^{I}	12 %	46 %^{I}	41 %^{I}	68 %^{I}	40 %^{I}	34 %^{I}	45 %^{I}	36 %^{I}	42 %^{I}	50 %^{I}	49 %^{I}	94 %^{I}	41 %^{I}	–		
S10_58[d]	40 %^{I}	37 %^{I}	84 %^{I}	84 %^{I}	21 %^{v}	9 %	44 %^{I}	95 %^{I}	31 %^{I}	97 %^{I}	37 %^{I}	37 %^{I}	76 %^{I}	83 %^{I}	35 %^{I}	48 %^{I}	44 %^{I}	96 %^{I}	41 %^{I}	–	
FFA[e]	21 %^{v}	19 %^{v}	19 %^{v}	16 %	12 %	11 %	13 %	15 %	4 %	15 %	14 %	15 %	18 %^{x}	20 %^{v}	18 %^{x}	16 %	14 %	21 %^{v}	13 %	19 %^{x}	–

[a] Route S8 Subperiod 2 starting point is defined as the date when its trial started, thus the correlation coefficients for this row is that of the price movements between October 1, 2009 and April 2, 2017.

[b] Route S9 Subperiod 2 starting point is defined as the date when its trial started, thus the correlation coefficients for this row is that of the price movements between November 22, 2010 and April 2, 2017.

[c] Route S10 Subperiod 2 starting point is defined as the date when its trial started, thus the correlation coefficients for this row is that of the price movements between March 1, 2012 and April 2, 2017.

[d] The Tess 58 routes' starting point in Subperiod 2 is defined as the date when their trial started; correlation coefficients are for the period July 31, 2015 to April 2, 2017.

[e] The FFA data series correlation coefficients are computed between the respective routes' start and end date, see [a, b, c, d].

$^{I, v, x}$ Denote significance level at the 1 %, 5 %, and 10 % level, respectively

Average correlation between BSI routes and FFA = 16.75 %^{x} (weighted as indicated in Figure 1.1)
Average correlation between all routes and FFA = 15.65 %

A.3 Minimum Variance Hedge Ratios

TABLE A.3.1

Minimum Variance Hedge Ratios for all Routes with 5TC/6TC/6TC_58 FFA

FFA **Route**	5TC **$h^*_{j=1}$**	6TC **$h^*_{j=2}$**	6TC_58 **$h^*_{j=3}$**
S1A	6.19 %[V]	12.72 %[I]	
S1B	11.62 %[I]	11.80 %[I]	
S2	0.81 %	15.51 %[I]	
S3	0.36 %	14.66 %[I]	
S4°	5.72 %[X]		
S5	3.20 %	10.05 %[I]	
S4A		15.64 %[I]	
S4B		11.86 %[I]	
S8[a]		15.38 %[I]	
S9[a]		5.76 %	
S10[a]		17.83 %[I]	
S1B_58[b]		10.27 %[I]	0.48 %
S1C_58[b]		14.18 %[I]	9.00 %
S2_58[b]		18.50 %[I]	10.58 %[V]
S3_58[b]		22.64 %[I]	11.49 %[V]
S4A_58[b]		18.24 %[I]	10.00 %
S4B_58[b]		20.49 %[I]	0.58 %
S5_58[b]		11.38 %[I]	7.84 %[X]
S8_58[b]		17.76 %[I]	17.01 %[V]
S9_58[b]		12.79 %[I]	10.22 %[X]
S10_58[b]		20.12 %[I]	19.87 %
Average	**4.65 %**	**14.88** %	**9.71** %

$h^*_{i,j}$ columns show the calculated MVHR for route *i* in subperiod *j*.

[I, V, X] denote significance at the 1 %, 5 %, 10 % levels, respectively, for $h^*_{i,j}$. The significance level is from the p-value of the coefficient $\overline{h^*_{i,j}}$ in eq. (3)

° Route S4 was split into S4A and S4B on January 3, 2007 (i.e. only active in *j*=1).

[a] For routes S8, S9, and S10, *j=2* start date is defined at the date of their respective trial start date (see Section 4.2) - not January 3, 2006 as is the case for the remaining non-Tess 58 routes.

[b] For the Tess 58 routes, *j=2* start date is defined at the date of their trial introduction (August 3, 2015).

TABLE A.3.2

Minimum Variance Hedge Ratios for all Routes with
10TC_58 FFA

HR			Naïve		Minimum Variance	
Route	**h*$_{j=2}$^{a}**	**h*$_{j=3}$^{b}**	**VR$_{j=2}$^{a}**	**VR$_{j=3}$^{b}**	**VR$_{j=2}$^{a}**	**VR$_{j=3}$^{b}**
S1A	2.00 %		- 39.87 % **		6.06 %$^{+}$	
S1B	1.70 %		- 38.54 % **		4.62 %$^{+}$	
S2	24.79 %^{V}		67.34 %$^{+}$ ***		41.99 % *	
S3	22.33 %		65.26 %$^{+}$ ***		40.77 % **	
S5	1.75 %		87.42 %$^{+}$ ***		3.49 %	
S4A	15.20 %		84.46 %$^{+}$ ***		63.01 % ***	
S4B	13.15 %		67.40 %$^{+}$ ***		23.96 %	
S8	21.10 %^{X}		64.98 %$^{+}$ ***		36.78 %	
S9	29.74 %		85.48 %$^{+}$ ***		38.05 % *	
S10	26.22 %^{X}		67.77 %$^{+}$ ***		42.40 % **	
S1B_58	0.62 %	2.19 %	- 46.80 % ***	23.53 %$^{+}$	1.97 %$^{+}$	7.50 %
S1C_58	0.91 %	12.21 %^{X}	57.83 %$^{+}$ ***	56.00 %$^{+}$ ***	4.39 %	24.17 %
S2_58	22.75 %^{X}	16.47 %^{I}	66.82 %$^{+}$ ***	56.02 %$^{+}$ ***	38.31 % *	31.04 % **
S3_58	24.02 %	18.09 %^{I}	72.54 %$^{+}$ ***	61.72 %$^{+}$ ***	40.51 % **	36.90 % ***
S4A_58	8.11 %	12.76 %^{X}	68.31 %$^{+}$ ***	62.16 %$^{+}$ ***	16.26 %	24.35 %
S4B_58	11.96 %	4.46 %	60.41 %$^{+}$ ***	44.77 %$^{+}$ ***	20.08 %	10.64 %
S5_58	7.53 %	15.06 %^{I}	39.44 %$^{+}$ ***	40.16 %$^{+}$ ***	12.35 %	29.67 % *
S8_58	22.85 %^{X}	18.17 %^{I}	67.60 %$^{+}$ ***	69.65 %$^{+}$ ***	37.04 % *	32.38 % *
S9_58	9.52 %	19.72 %^{V}	56.94 %$^{+}$ ***	59.99 %$^{+}$ ***	15.86 %	35.03 % **
S10_58	23.79 %^{X}	24.49 %^{I}	69.86 %$^{+}$ ***	83.90 %$^{+}$ ***	38.16 % *	21.59 % ***
Average	**14.50 %**	**14.36 %**	**51.23 %**	**55.79 %**	**26.30 %**	**25.33 %**

h*$_{i,j}$ columns show the calculated MVHR for route *i* in subperiod *j*.

VR$_{i,j}$ columns show the empirical variance reduction for route *i* in subperiod *j*.

***,**,* denote significance at the 1 %, 5 %, and 10 % levels, respectively, for $VR_{i,j}$. Because of the non-normal nature of the data, the Brown & Forsythe (1974) Test for Homogeneity of Variances is used.

$^{I, V, X}$ denote significance at the 1 %, 5 %, 10 % levels, respectively, for $h*_{i,j}$. The significance level is from the p-value of the coefficient $\overline{h^{*}_{i,j}}$ in eq. (3)

[a] Subperiod 2 start date is defined as October 24, 2016 (when trial was launched)

[b] Subperiod 3 end date is defined as December 31, 2017 (end of data set)

$^{+}$ Denotes the model with the highest degree of variance reduction.

A.4 Normality Plots

FIGURE A.4.1

Scatter Plots for Normality for BSI Routes and FFA in Subperiod 1

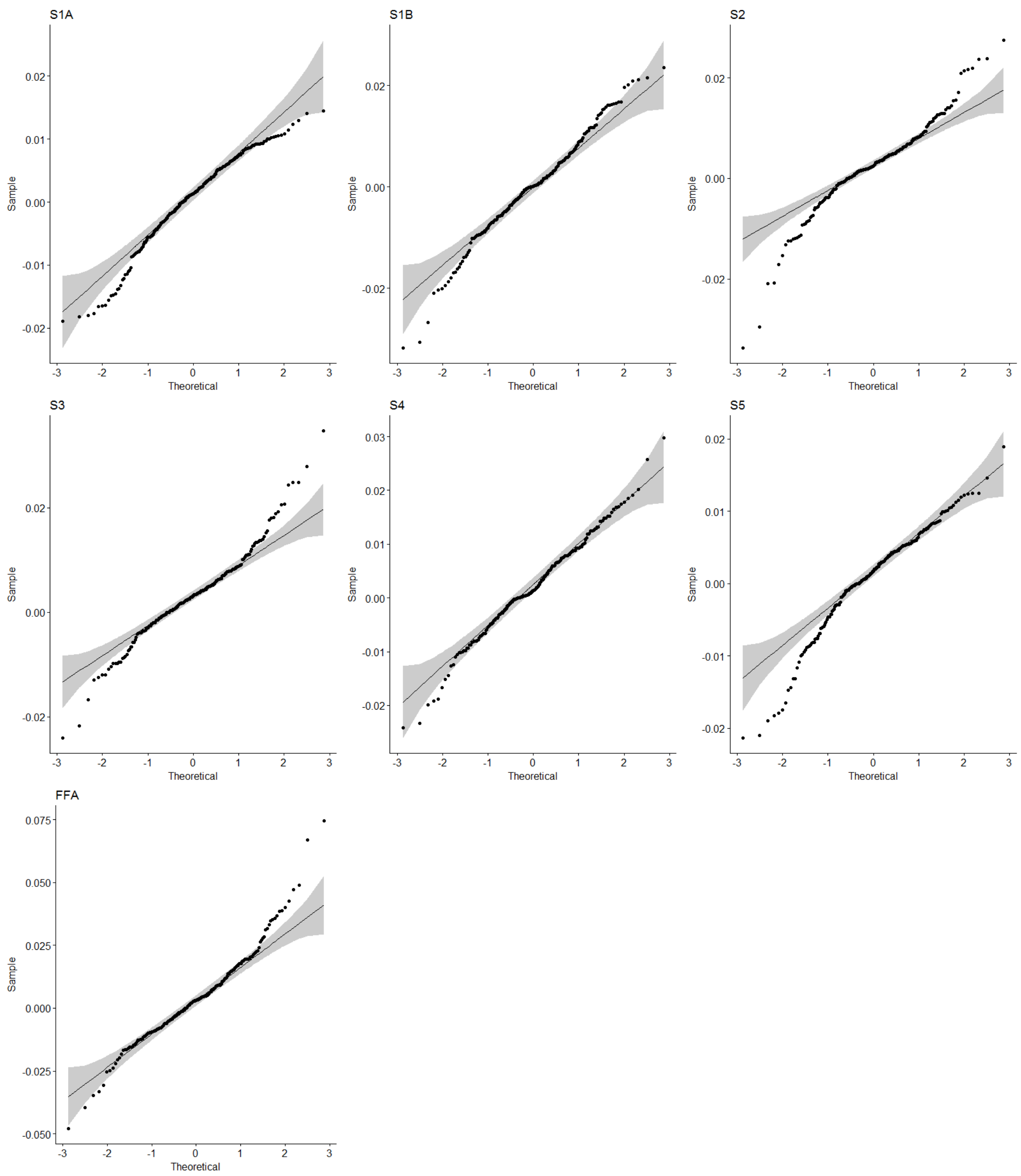


FIGURE A.4.2

Scatter Plots for Normality for BSI Routes and FFA in Subperiod 2

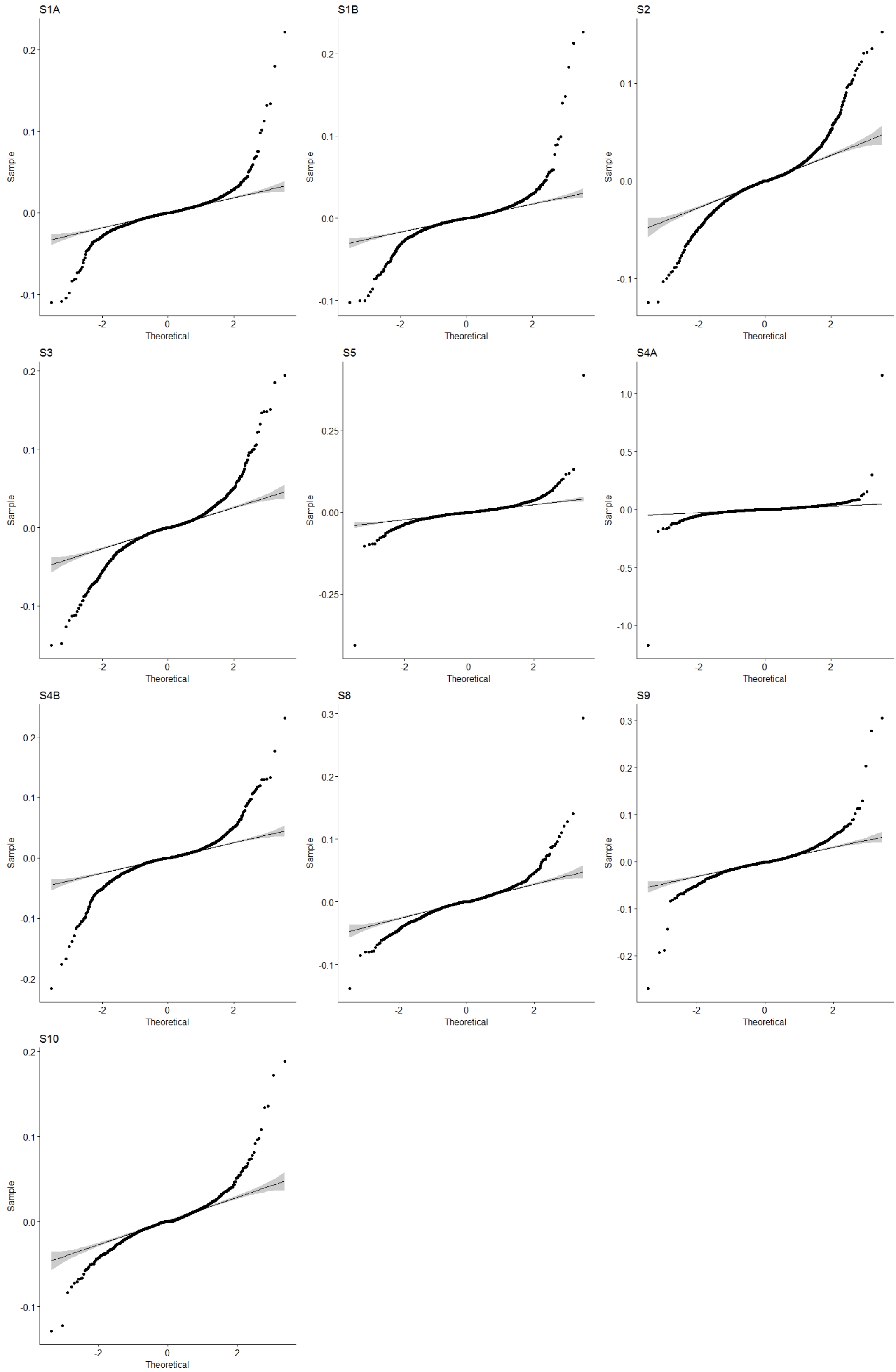


FIGURE A.4.3

Scatter Plots for Normality for BSI Routes and FFA in Subperiod 2

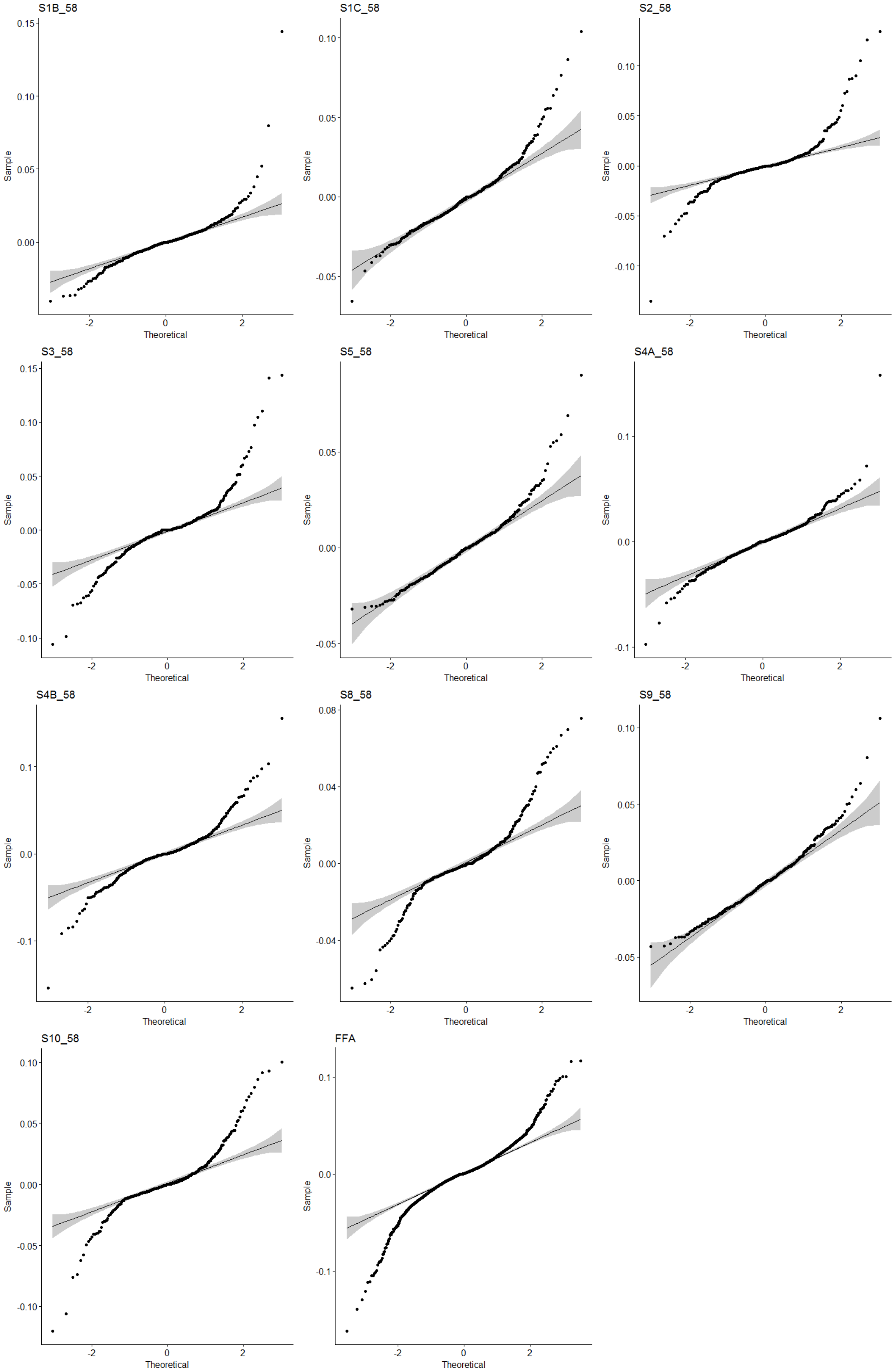
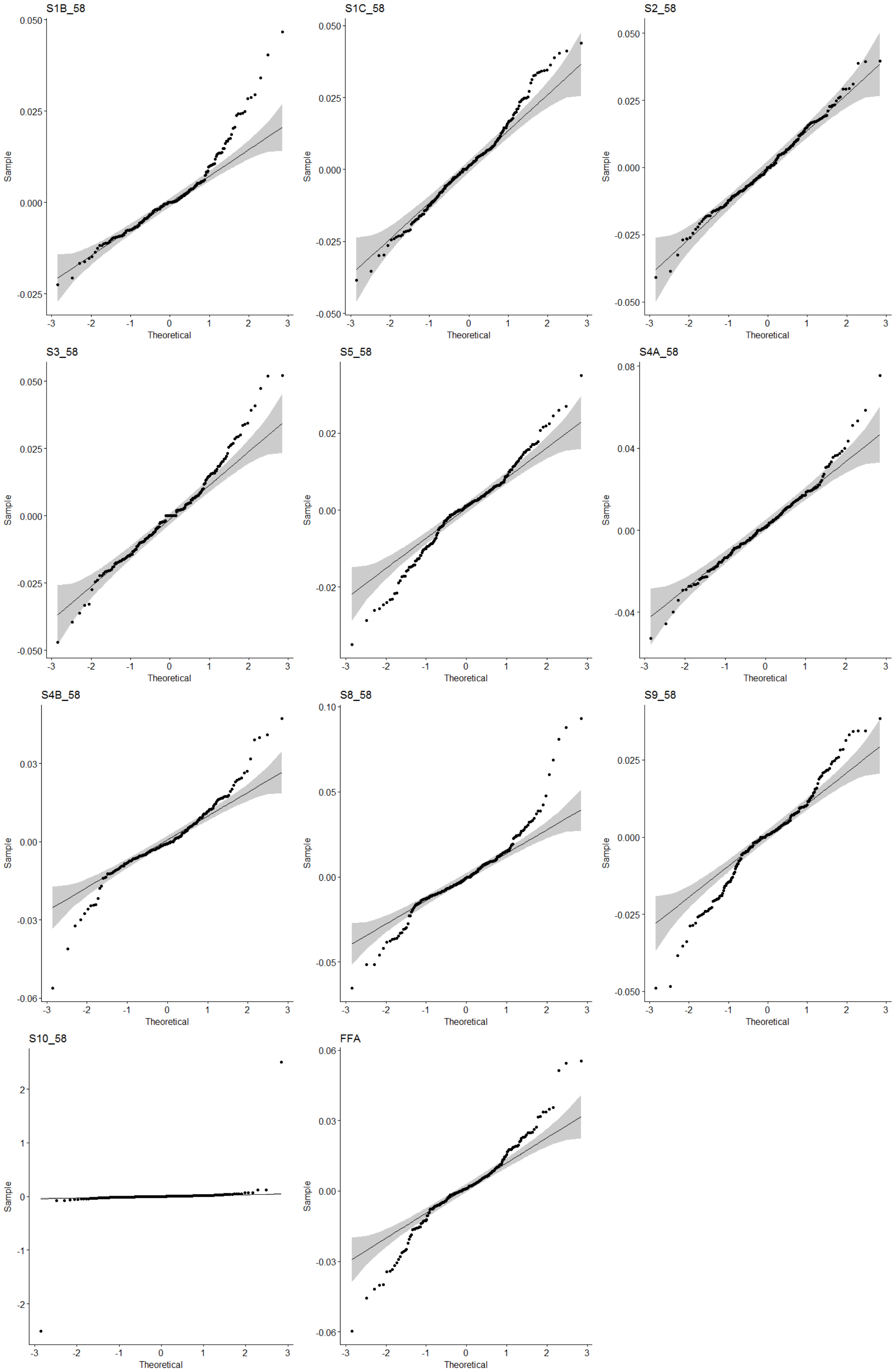


FIGURE A.4.4

Scatter Plots for Normality for BSI Routes and FFA in Subperiod 3



A.5 *R* Code

```
### Bootstrap and BCa Intervals ###

# Install boot() package #
library(boot)

# Set seed
set.seed(1)

# Define variables #
UH1 <- # time series of unhedged portfolio of route i, subperiod j-1 (logs)
UH2 <- # time series of unhedged portfolio of route i, subperiod j   (logs)
 H1 <- # time series of hedged  portfolio  of route i, subperiod j-1 (logs)
 H2 <- # time series of hedged  portfolio  of route i, subperiod j   (logs)

# Define variable lengths for matrix #
UH1len <- length(UH1)
H1len  <- length(H1)
UH2len <- length(UH2)
H2len  <- length(H2)
totlen <- UH1len + H1len + UH2len + H2len

# Define matrix #
DATA = matrix(NA, (totlen+1), 1)
  DATA[(1)                     :(UH2len)] = UH2
  DATA[(1+UH2len)              :(UH2len+H2len)] = H2
  DATA[(1+UH2len+H2len)        :(UH2len+H2len+UH1len)] = UH1
  DATA[(1+UH2len+H2len+UH1len) :(UH2len+H2len+UH1len+H1len)] = H1

# Define boot function with replacements to return the test statistic for #
# change in variance reduction route i between subperiods j and j-1, as   #
# defined in eq. (4) and eq. (5)                                          #

F1 <- function(DATA, index){
  x1 = var(sample(H2,  H2len,  replace = TRUE))
  x2 = var(sample(UH2, UH2len, replace = TRUE))
  x3 = var(sample(H1,  H1len,  replace = TRUE))
  x4 = var(sample(UH1, UH1len, replace = TRUE))

  return( (1 - x1/x2) - (1 - x3/x4) )
  }

# Run 10,000 bootstrap simulations of matrix DATA with function F1. #
# Returning 10,000 simulations of the test statistic                #

BOOTOUT <- boot(DATA, F1, R = 10000)

# Construct histogram of the 10,000 simulated test statistics #
hist(BOOTOUT$t, breaks = 40)

# Compute BCa intervals, as indicated in Section 3.4 #
LEVEL <- x # Chosen confidence level. x(0.90, 0.95, and 0.99) is used.
CI    <- boot.ci(BOOTOUT, conf = LEVEL, type = "bca")

CI_Lower <- CI$bca[1,4] # returns lower limit
CI_Upper <- CI$bca[1,5] # returns upper limit

### END ###
```

A.6 Other

TABLE A.6.1

Baltic Supramax Vessel Specifications

SPEC	Tess 52	Tess 58
Dwt.	52,454	58,328
Grain (cbm)	67,756	72,360
Bale (cbm)	65,600	70,557
SSW draft (m)	12.02	12.80
Max age (y)	15	15
LOA (m)	189.99	189.99
Beam (m)	32.26	32.26
Cranes (no)	4	4
Cranes (mt)	30	30
Grabs (cbm)	12	12
Holds (no)	5	5
Hatches (no)	5	5
Speed ladden (kn)	14	14
Speed ballast (kn)	14.5	14

Source: The Baltic Exchange (2018b)

TABLE A.6.2

Route Specifications

Route	Delivery	Redelivery	Duration[e]
S1A	Antwerp-Skaw	Singapore-Japan	60-65
S1B/S1B_58	Passing Canakkale	China-S.Korea	40-50
S1C_58	SW Pacific	N.China-S.Japan	50-55
S2/S2_58[a]	N. China	N.China	40-50
S3/S3_58	N. China	W.Afr	55-65
S4[b]	Gibraltar-Skaw	Gibraltar-Skaw	45-50
S4A/S4A_58	US Gulf	Skaw-Passero	25-30
S4B/S4B_58	Skaw-Passero	US Gulf	25-30
S5[c]/S5_58	W. Africa	N.China	60-65
S8/S8_58	S. China	E. Coast.India	20-25
S9/S9_58	W. Africa	Skaw-Passero	45-50
S10/S10_58	S. China	S.China	20-25

[a] Australian or trans-Pacific round voyage
[b] Trans-Atlantic round voyage
[c] Trip via East Coast South America
[d] Trip via Indonesia
[e] Trip duration in days