Norwegian School of Economics Bergen, Fall 2019



Statistical Arbitrage in the Freight **Options Market**

Applying trading strategies to profit from volatility misspecification in the dry bulk shipping industry

Lars Eirik Nord-Varhaug Ånestad & Bjarte Tysdal Abrahamsen Supervisor: Roar Os Ådland

Master thesis, Economics and Business Administration Major: Financial Economics

NORWEGIAN SCHOOL OF ECONOMICS

This thesis was written as a part of the Master of Science in Economics and Business Administration at NHH. Please note that neither the institution nor the examiners are responsible – through the approval of this thesis – for the theories and methods used, or results and conclusions drawn in this work.

Acknowledgements

This thesis is written as a concluding part of our Master of Science in Economics and Business Administration, within our Major in Finance, at NHH, the Norwegian School of Economics.

We would like to thank our supervisor, Roar Os Ådland, for great discussions and constructive feedback throughout the process. His insights in the field of maritime economics have been invaluable for the outcome of this thesis.

We hope that our thesis will prove to be interesting for its readers, relevant for market participants in the dry bulk sector and that it can serve as a basis for further research.

Norwegian School of Economics Bergen, December 2019

ders Einh anester

Lars Eirik Nord-Varhaug Ånestad

Barte Abrahausen

Bjarte Tysdal Abrahamsen

Abstract

The purpose of this thesis is to investigate trading strategies that can exploit misspecification of volatility in the freight options market. We have, using observed market prices, derived smooth forward rate curves from daily observations. These forward curves promote a representation of the historical volatility term structures for the Capesize, Panamax, and Supramax sub-sector of the dry-bulk shipping industry. The volatility term structures present consistent behavior across vessel sizes, with increasing volatility over a six week time horizon before the volatility converges towards an apparent long term equilibrium. The dynamics coincides with the general belief that spot freight rates are mean reverting in the long term and positively auto-correlated in the short term. A comparison of the historical volatility term structure and the volatility estimates implied by the options market reveals differences. Based on deviating volatility estimates, we execute trading strategies in what we believe is a realistic representation of the market dynamics. Our findings can be interpreted as a sign of inefficiency in the freight options market.

Keywords – Forward freight agreements, dry bulk, volatility term structure, volatility trading

Contents

1	Intr	oduction	1
2	Lite	rature Review	3
3	Dat 3.1	a Descriptive Statistics	6 6
	$3.1 \\ 3.2$	Volumes	9
4	The	oretical Framework	10
	4.1	The Forward Freight Rate Function	10
	4.2	Freight rate options	12
5	Met	hodology	14
	5.1	A smooth forward freight rate function	14
	5.2	Data set of smooth forward curves	16
	5.3	Historical volatility structure	17
6	Tra	ding Strategies	21
	6.1	Delta Hedging	21
	6.2	Modified Delta Hedging	26
	6.3	Weaknesses with Delta Hedging	28
	6.4	Straddle	29
	6.5	Time Spreads	33
7	Con	cluding Remarks	36
R	efere	nces	38
\mathbf{A}	ppen	dix	43
	A1	Hedging with implied volatility	44
	A2	Hedging with historical volatility	48
	A3	Hedging with modified delta	52
	A4	Hold Straddle	56
	A5	Adjusting Straddle	60
	A6	Time Spread	64

List of Figures

3.2 Forward Freight Agreements				
			•	7
3.3 Volatility implied from options prices			•	8
5.1 Examples of smooth forward freight rate function $\ldots \ldots \ldots$			•	17
5.2 Estimated smoothed forward curve functions for Capesize			•	18
5.3 Estimated historical volatility structure of the forward freight fun	nctio	n	•	18
5.4 $$ Yearly historical volatility term structures across vessel sizes $$			•	20
6.1 Delta hedging strategy with implied volatility for Capesize \ldots			•	26
6.2 $$ Delta hedging strategy with historical volatility for Capesize $$			•	26
6.3 Hold straddle strategy $\ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots$				31
6.4 Adjusting straddle strategy			•	32
6.5 Holding calendar spread strategy for Capesize $\ldots \ldots \ldots$			•	35

List of Tables

Descriptive statistics for FFAs - data in log-differences	8
Data on FFA and Options volume (Baltic Exchange, 2019)	9
Descriptives for delta hedging strategy with implied volatility	24
Descriptives for delta hedging strategy with historical volatility	25
Descriptives for modified delta hedging strategy	28
Descriptives for holding a straddle	31
Descriptives for buy/sell straddle strategy	32
Descriptives time spread strategy	35
Descriptives for delta hedging strategy with implied volatility	44
Descriptives for delta hedging strategy with historical volatility	48
Descriptives for modified delta hedging strategy	52
Descriptives for holding a straddle	56
Descriptives for buy/sell straddle strategy	60
Descriptives time spread strategy	64
	Data on FFA and Options volume (Baltic Exchange, 2019) Descriptives for delta hedging strategy with implied volatility Descriptives for delta hedging strategy with historical volatility Descriptives for modified delta hedging strategy Descriptives for holding a straddle

1 Introduction

Despite its volatile nature, the shipping business has a relatively short history of exploiting financial derivatives in the design of risk management strategies. Baltic International Freight Futures Exchange (BIFFEX) introduced a freight futures market in 1985, offering shipowners, charterers, and speculators exposure to future freight rate formations. However, the market participants perceived the contracts' broad specifications to be poorly overlapping with their hedging needs, giving the market place low volumes, which eventually led to its closing in 2002 (Kavussanos and Nomikos, 2003). Since 1992, forward freight agreements (FFAs) have been offered OTC, as a Contract-for-Difference between sellers and buyers who agree to settle a freight rate for a pre-specified quantity of cargo or type of vessel for a specific route or basket of routes in the sub-sectors of the shipping industry (Alexandridis et al., 2018). While the entry of FFAs represented a valuable innovation to shipping markets, the added flexibility offered by options enabled market participants to specify non-linear freight rate exposures.

For freight options, the payoff is determined by the average spot freight rate over some predetermined time interval. They belong to the family of Asian options, are frequently offered in thinly traded commodity markets, and possess pricing qualities that makes them naturally harder to manipulate (Nomikos et al., 2013). Koekebakker et al. (2007) note that the averaging effect is appealing to hedgers and that the non-storable nature of freight make average-based options a solution to consumers, who demand a continuous flow of the service. On the pricing of freight options, Nomikos et al. (2013) register that market practice has been to assume log-normal spot freight rates and quote a price applying the formulas described by Turnbull and Wakeman (1991) and Lévy (1997). Moreover, practically implementing option pricing formulas require the specification of input parameters, where the legitimacy of the solution is heavily reliant on the parameters' ability to accurately summarize real world dynamics. While some of the determining pricing factors are observable, the estimate of freight rate volatility is based on predicting future freight rate dynamics. Predicting volatility is subject to much research and is the main reason why market participants assign different values to the same claims.

The market's expectation of future spot freight volatility can, conditional on a particular

pricing model, be implicitly derived from the quoted options prices. The implied volatility term structure describes the expected fluctuation of freight, and while short term freight rates generally are believed to be formed by the market participants' expectations of future market conditions, long term freight rates are believed to be a reflection of a long-term equilibrium between the supply and demand of freight (Stopford, 2009). Furthermore, Koekebakker and Ådland (2004) have shown that the volatility term structure of freight rates, historically, has been consistently bump-shaped. However, even if there is evidence of mispricing in options markets, arbitrage activity is complicated by the absence of a physical relationship linking current freight rates with future ones, owing to the non-tradable and non-storable nature of the former.

Koekebakker et al. (2007) establish a theoretical linkage between FFAs and freight rate options that promotes replication of the options' payoff and an opportunity to expose the derivatives' misspecification of volatility. Natenberg (1994), Taleb (1997), and Wilmott (2013) have provided extensive research on the practical implementation of volatility trading and offer methods to capitalize on the mispricing. Through option trading strategies and dynamic hedging, they show that the market's estimate of volatility can be isolated, traded, and under the right circumstances, arbitraged.

The objective of this thesis is to study how discrepancies between the implied and historical volatility term structure of freight rates can practically be exploited using volatility trading strategies. This thesis expands on the current literature by applying explicit trading strategies to investigate market efficiency in the freight options market, a topic which hopefully is of interest to market participants.

The remainder of this thesis will be structured as follows: Section 2 provides a review of related literature. Section 3 describes the data. Section 4 presents the theoretical framework of our approach. Section 5 estimates the historical volatility structure. Section 6 covers trading strategies, while Section 7 concludes.

2 Literature Review

The academic literature on freight derivatives has, to a large degree, focused on elaborating different aspects of the market's efficiency, initially in the BIFFEX futures market and later in the OTC FFA market. Kavussanos and Nomikos (1999, 2003) utilize cointegration techniques to explore whether futures contracts in the BIFFEX market can be regarded as unbiased estimates of future realized spot freight rates. They find that the unbiasedness hypothesis holds for maturities up to 2 months. Kavussanos et al. (2004) explore the FFA market and concludes similarly that forward contracts are unbiased predictors of spot prices until reaching maturities of 2 months. Alizadeh et al. (2007) find that implied forward time charter rates are unbiased estimates of future forward rates.

The hedging effectiveness of the BIFFEX contracts has been investigated by Kavussanos and Nomikos (2000a,b,c). For the FFA market, Kavussanos et al. (2010) compare the hedging performance of time-varying and constant hedge ratios in the Capesize segment. Out-of-sample tests lead to the conclusion that the highest variance reduction is achieved by matching freight rate exposure with forward contracts of equal size. Alizadeh et al. (2015a), use a regime-switching GARCH model to improve the hedging efficiency for six different tanker routes with mixed results. Adland and Jia (2017) show that there is a benefit of diversification accompanied by an increasing fleet size, but that this effect is small beyond a fleet size of ten vessels. They also show that physical basis risk is increasing with shorter hedging duration. Sun et al. (2018) acknowledge the volatility spillovers between crude oil futures and FFAs, and consequently, highlight the importance of considering the dynamic relationship between cost and revenues markets when determining an optimal hedging strategy.

Further, the interaction between the spot and the forward markets is subject to much research. Disclosure of FFA market data opened up for Kavussanos and Visvikis (2004) to explore the lead-lag relationship between forward and spot freight markets. Their study reveals that, despite the non-storable nature of freight, FFA prices are important factors in the price discovery of spot prices. Li et al. (2014) investigate spillover effects between spot and FFA prices. They find evidence of unilateral spillovers from one-month FFA returns to spot rate returns. And, a bilateral spillover effect between the one and two month FFA markets. Additionally, they find bilateral volatility spillovers between spot and FFA markets. Alexandridis et al. (2017) extend the research of spillover effects by including freight options when they examine the interaction between freight futures, time charter rates, and freight options. Their study concludes that there is significant information transmission in both volatility and returns between the markets. Interestingly, they find that freight options lag behind freight futures and physical freight rates, a result they assign the low liquidity found in the options market.

While FFA contracts present an effective means of hedging freight rate risk for specified periods, their lack of flexibility has created a demand for options on freight rates (Alexandridis et al., 2018). Tvedt (1998) priced the European options that were present on BIFFEX. Relevant to current markets, Koekebakker et al. (2007) derive an analytical pricing formula for Asian type freight options by approximating the FFA rate dynamics. This thesis is heavily dependent on their derivation. While Koekebakker et al. (2007) rely on assumptions of log-normally distributed FFA rates, Nomikos et al. (2013) suggest that the risk-adjusted spot freight rates follow a jump-diffusion model, allowing for jumps prove to be a significant improvement to the pricing of freight options. The jump-diffusion pricing formula of Nomikos et al. (2013) is then extended by Kyriakou et al. (2017), who incorporate the mean-reverting property of freight rates. An extension of the log-normal assumption of the freight rate returns to include mean reversion is shown to provide significantly lower errors in the pricing of the options.

The pricing of options is highly dependent on reliable estimates of the volatility structure of the underlying asset. Koekebakker and Ådland (2004) model the forward curve dynamics using a smoothing function on implied forward prices. They find that the volatility structure is bumped and that there are low and even negative correlations between different parts of the term structure. Alizadeh and Nomikos (2011) apply augmented EGARCH models and concludes that volatility of freight rates is affected by the shape of the current term structure, in particular, that volatility is higher when the market is in backwardation compared to when it is in contango. Kavussanos and Alizadeh-M (2001, 2002) explore the seasonality in shipping and find that for dry bulk, freight rates rise in early spring and drop in June/July while the freight rates increase in November/December and decline from January to April. Similar in both markets is the tendency of higher seasonal variation when the market is in recovery. Lim et al. (2019) investigate the fundamental drivers of volatility in the freight market using panel regression. Their findings indicate that expectations of general economic growth and increasing spot freight rates reduce implied volatility, a result that similarly to Chen and Wang (2004) support the notion of a leverage effect in freight rates. Another interesting finding is that the slope of the implied volatility curve follows that of the forward curve, meaning that generally, when the slope of the forward curve gets steeper - so will the slope of the implied volatility curve.

The non-storable nature of freight services interferes with the concept of the efficient market. Based on historical data, Adland and Strandenes (2006) apply technical trading techniques to identify trends in the freight market cycles. They discredit any hypothesis of a freight market that is semi-strong efficient when they obtain excess returns utilizing their chartering strategy. Trading rules have later been explored by Nomikos and Doctor (2013), who prove that excess returns can be made in the FFA market by trading according to momentum and trend strategies. They expect the trading opportunities to diminish as the FFA market is gaining liquidity.

While there have been successful attempts to demonstrate profitable trading strategies in the FFA market, to our knowledge, there is no published study revealing the profitability of volatility trading in the freight options market. The purpose of this thesis will therefore be to fill this gap in the academic literature. Our thesis starts by deriving an historical volatility structure from observed FFA prices. With the assumption that the historical volatility estimate is an accurate representation of future volatility we investigate if there is mispricing in the options market. To exploit the mispricing we apply option strategies suggested by Natenberg (1994), Wilmott (2013), and Taleb (1997).

3 Data

Using data of FFA prices, we estimate volatility structures for three time charter basket routes. The time charter basket routes are the C5TC; Capesize time charter average of five routes, P4TC; Panamax time charter average of four routes, and S6TC; Supramax time charter average of six routes. The data is collected and granted by Baltic Exchange. The basket routes make up their respective indices revealing the development of the different market segments and create the basis for which forward and option contracts can be settled.

The prices of the Asian style options, quoted by implied volatility, are provided by Baltic Exchange. We use LIBOR as the risk-free interest rate in the period. Time Charter indices and interest rates are obtained from Clarkson Research Services.

3.1 Descriptive Statistics

We plot the time charter indices for Capesize, Panamax, and Supramax in the time interval spanning May 2014 to the end of 2018, seen in figure 3.1. The time series reveal some key characteristics of the different market segments. The time period is chosen to handle the change in practice in the reporting of Capesize vessel routes. In the time interval, it is evident that volatility increases with vessel size. This is a trait that has been shown previously by (Kavussanos, 1996), and explained by smaller vessels being more diverse in the range of routes and ports they can handle. As a consequence, smaller vessels are expected to be less affected by market fluctuations than their larger peers.

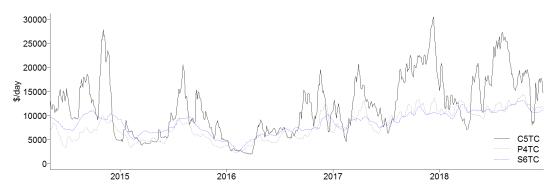


Figure 3.1: Time Charter Indices

Further, when we look at time series for the FFAs, as illustrated in figure 3.2, it is clear that volatility is also decreasing with time to maturity. The short term contracts can be seen to fluctuate around the longer term contracts. Also, in times of low freight rates, the long term freight rates look to be above the short term rates. Similarly, in times of high freight rates, the long term rates seem to be below the short term rates. This supports the general notion that freight rates are mean-reverting in the long term (Koekebakker et al., 2006). An assumption backed by the competitiveness of the shipping industry, where the mechanics of supply and demand inevitably will pull the freight rates toward the long-term costs prevalent in the market (Stopford, 2009).

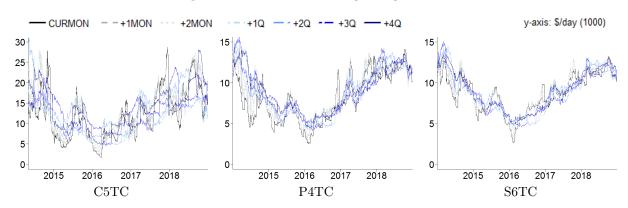


Figure 3.2: Forward Freight Agreements

The Asian style options' implied volatility, shown in figure 3.3, reveals the market consensus of what the volatility is expected to be for the spot freight rate until the contract specified maturity date. The volatility is decreasing with time to maturity across all three vessel sizes in the period. It's a trait that is shared with storable commodities, is termed the Samuelson-effect, and is usually explained by the market participants' expectations being smoothed under a mean-reverting process (Routledge et al., 2000). Jaeck and Lautier (2016) find evidence for the Samuelson-effect in electricity markets, and as a consequence, reject storage as a necessary precondition. It is also noticeable that the market's expectation of volatility has been declining since 2016 for C5TC, P4TC, and S6TC. We suspect that contracts with maturity longer than +4Q ahead are thinly traded, and therefore decide not to include these in our analysis.

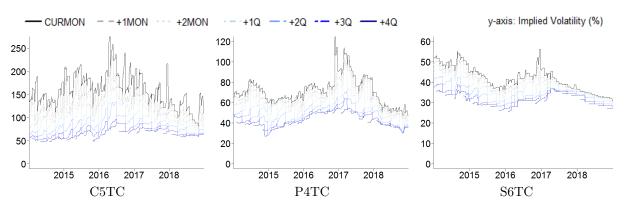


Figure 3.3: Volatility implied from options prices

From table 3.1 we see that average returns are zero percent for all contracts and vessel sizes while standard deviation is decreasing with vessel size and with time to maturity. However, we are careful of interpreting this as proof of volatility decreasing with maturity. If we assume that the underlying freight rate follows a mean reverting stochastic process, the volatility of the average of these will be less volatile than the freight rates themselves. Thus, if we increase the averaging period, the volatility of the average based contracts will necessarily be reduced as well (Koekebakker and Ådland, 2004).

	CURMON	+1MON	+2MON	+1Q	+2Q	+3Q	+4Q
C5TC							
obs.	1177.00	1177.00	1177.00	1177.00	1177.00	1177.00	1177.00
mean	0.00	0.00	0.00	0.00	0.00	0.00	0.00
std. dev	0.07	0.07	0.06	0.06	0.05	0.04	0.04
median	0.00	0.00	0.00	0.00	0.00	0.00	0.00
\min	-0.55	-0.52	-0.48	-0.68	-0.68	-0.58	-0.55
\max	0.65	0.35	0.26	0.55	0.35	0.43	0.36
skew	1.51	0.13	-1.30	-2.22	-5.46	-1.39	-2.48
kurtosis	24.37	4.96	14.28	50.87	81.85	62.63	72.83
P4TC							
obs.	1262.00	1262.00	1262.00	1262.00	1262.00	1262.00	1262.00
mean	0.00	0.00	0.00	0.00	0.00	0.00	0.00
std. dev	0.04	0.04	0.03	0.03	0.02	0.02	0.02
median	0.00	0.00	0.00	0.00	0.00	0.00	0.00
\min	-0.47	-0.22	-0.22	-0.26	-0.22	-0.21	-0.14
max	0.36	0.37	0.29	0.42	0.23	0.27	0.24
skew	1.27	1.58	0.45	1.51	-0.17	0.29	3.09
kurtosis	39.56	10.99	10.24	39.63	23.24	40.51	43.27
S6TC							
obs.	1262.00	1262.00	1262.00	1262.00	1262.00	1262.00	1262.00
mean	0.00	0.00	0.00	0.00	0.00	0.00	0.00
std. dev	0.03	0.02	0.02	0.02	0.02	0.02	0.01
median	0.00	0.00	0.00	0.00	0.00	0.00	0.00
\min	-0.25	-0.20	-0.30	-0.33	-0.28	-0.18	-0.12
\max	0.34	0.16	0.19	0.20	0.19	0.19	0.12
skew	2.86	-0.16	-1.29	-3.43	-3.04	0.43	0.96
kurtosis	46.40	10.60	29.98	57.97	56.91	46.50	25.28

 Table 3.1: Descriptive statistics for FFAs - data in log-differences

3.2 Volumes

As almost all of the FFA trades are now cleared, counter-party risk is negligible, leaving liquidity risk the major concern for market participants in the freight derivatives market (Alizadeh et al., 2015b). Liquidity risk describes the extent to which investor are able to trade large quantities quickly, at low cost, and with little price impact. Amihud and Mendelson (1986) show that less liquid assets are priced lower and require higher expected returns. The same effect is also found for freight derivatives, where a study by Alizadeh et al. (2015b) show that less liquidity have a positive effect on the forward premium. Their study also note that FFA volumes have stabilized after reaching a peak in 2008, that quarterly contracts are perceived to be most liquid and that market participants are seemingly unaffected by liquidity in their decision to invest in quarterly contracts. Furthermore, data from Baltic Exchange (2019) describes a market where trading activity is primarily concerned on the larger vessel sizes, implying that the liquidity risk is relatively lower for Capesize than it is for Panamax and Supramax. However, Taleb (1997) note that financial markets can suffer from liquidity holes when market participants are unable to comprehend the impact and size of an upcoming event - creating an environment where lower prices bring accelerated supply, and conversely, higher prices bring accelerated demand. Morris and Shin (2004) describe a momentum effect following a liquidity hole, where sales become mutually reinforcing and spiralling down to an outcome similar to that of a bank run. Thus, while the freight derivatives market has gained liquidity in the recent years, the risk of illiquidity will always be present.

	Capesize	Panamax	Supramax	Handysize	Combined
Dry FFA Volume					
No of lots traded	481,725	$571,\!850$	141,078	2276	$1,\!196,\!929$
% by sector	40%	48%	12%	0%	
Dry Options Volume					
No of lots traded	182,575	$82,\!987$	3,414	0	268,976
% by sector	68%	31%	1%	0%	

Table 3.2: Data on FFA and Options volume (Baltic Exchange, 2019)

4 Theoretical Framework

4.1 The Forward Freight Rate Function

The dynamics of the forward freight rate is usually estimated in one of two ways. The first method describes the spot freight rate process and derives the corresponding forward freight rate subject to an estimated or assumed risk premium. Geometric Wiener process (Koekebakker et al., 2007), Ornstein-Uhlenbeck process (Bjerksund and Ekern, 1995), (Adland and Cullinane, 2006), and the more general Lévy-processes (Benth et al., 2014) have all been proposed to the literature. To ensure accuracy in the aforementioned spot freight rate models, it is necessary to decide on an appropriate market price of risk. Adland and Cullinane (2005) argue, using logic and industry knowledge, that the risk-premium should be time-varying. This has also been proved empirically by Kavussanos and Alizadeh (2002). As there is not yet a suitable method for specifying the risk premium in an endogenous forward curve model, the practice has been to assume that the risk premium is zero, exemplified by Tvedt (1997).

Given the risk premium's unobserved nature, this thesis will model the forward freight dynamics in the framework of Heath et al. (1992). The forward freight rate dynamics will be derived empirically by smoothing the observed forward prices - creating a continuous forward price function for each trading day in our sample. By smoothing observed market prices, we avoid considerations concerning the specification of a potential risk-premium. We consider a market where the uncertainty can be described by a Wiener process, W, defined on an underlying probability space $(\Omega, \mathbf{F}, \mathbf{Q})$, with the filtration $\mathbf{F} = \{F_t \in [0, T^*]\}$ satisfying the usual conditions and representing the disclosure of market information. The probability measure Q represents the risk-adjusted pricing measure. We will keep the interest rate constant when we estimate the forward freight rate function.

We let the forward freight market be represented by a continuous forward price function, where $f(t, T_N)$ denotes the forward price at date t for delivery of transportation at time T_N , where $t < T_N < T^*$. Given constant interest rates, it can be shown that forward prices are by construction martingales under Q. We model the dynamics of the forward freight rate in line with what Koekebakker and Ådland (2004) has done before us, where

$$\frac{df(t,T_N)}{f(t,T_N)} = \sum_{i=1}^K \sigma_i(t,T_N) dW_i(t), \quad t \le T_N$$
(4.1)

with the solution

$$f(t,T_N) = f(0,T_N)exp\left(\frac{-1}{2}\sum_{i=1}^K \int_0^t \sigma_i(s,T_N)^2 ds + \sum_{i=1}^K \int_0^t \sigma_i(s,T_N) dW_i(s)\right)$$
(4.2)

and the distribution of the natural log of the forward price is given by

$$\ln f(t, T_N) \sim \mathcal{N}\left(\ln f(0, T_N) \frac{-1}{2} \sum_{i=1}^K \int_0^t \sigma_i(s, T_N)^2 ds, \sum_{i=1}^K \int_0^t \sigma_i(s, T_N)^2 ds\right)$$
(4.3)

 $\mathcal{N}(s, v)$ denotes a normally distributed variable with mean s and variance v.

By the definition of the forward rate, we can describe the spot freight rate as

$$S(t) = f(t,t) = \lim_{T_N \to t} f(t,T_N) \quad \forall t \in [0,T^*]$$
(4.4)

which implies that the forward freight rate converges to the spot rate, in the limit.

In our model, we let $F(t, T_1, T_N)$ be the constant FFA price a shipowner receives at time t for the duration $[T_1, T_N]$. When $R(t, T_N)$ is the value at t of entering into a forward freight contract, the profit/loss of the contract at T_N will be the difference between the agreed FFA price and the average spot freight rate over the period $[T_1, T_N]$. At maturity, the profit/loss can be formulated as

$$R(T_N, T_N) = \frac{1}{T_N - T_1} \int_t^{T_N} e^{-r(u-t)} (f(u, u) - F(t, T_1, T_N)) du$$
(4.5)

As the forward price is set to be the expectation of future spot rates, the initial value of the contract must be zero under Q. Thus, as shown by Koekebakker and Ådland (2004)

$$0 = E_t^Q \left[\frac{1}{T_N - T_1} \int_{T_1}^{T_N} e^{-r(u-t)} (f(u, u) - F(t, T_1, T_N)) du \right]$$
(4.6)

$$0 = E_t^Q \left[\frac{1}{T_N - T_1} \int_{T_1}^{T_N} e^{-r(u-t)} f(u, u) du \right] - \frac{F(t, T_1, T_N)}{T_N - t} \int_{T_1}^{T_N} e^{-r(u-t)} du$$
(4.7)

$$0 = \frac{1}{T_N - T_1} \int_{T_1}^{T_N} e^{-r(u-t)} f(t, u) du - \frac{F(t, T_1, T_N)}{T_N - t} \int_{T_1}^{T_N} e^{-r(u-t)} du$$
(4.8)

which can be rearranged to

$$F(t, T_1, T_N) = \int_{T_1}^{T_N} w(u; r) f(t, u) du$$
(4.9)

where

$$w(u;r) = \frac{e^{-ru}}{\int_{T_1}^{T_N} e^{-ru} du}$$
(4.10)

As noted by Lucia and Schwartz (2002), $1/(T_N - t)$ is a good approximation for $e^{-ru}/\int_t^{T_N} e^{-ru} du$ for reasonable levels of the interest rate.

4.2 Freight rate options

From equation 4.9, we can interpret the FFA contract $F(t, T_1, T_N)$ as today's t price for delivering the average value of transportation in the period $[T_1, T_N]$ at date T_N . As noted by Koekebakker et al. (2007), this implies that we can value an Asian option on the spot freight rate as a European option on the forward contract. By the law of one price, we can argue that the price of the forward contract at T_N equals the price of the underlying in the corresponding period. Thus, the payoff for an Asian call option at T_N with strike K and maturity T_N can be formulated as

$$D \times max \Big[F(T_N, T_1, T_N) - K, 0 \Big]$$
(4.11)

similarly, a put option can be formulated as

$$D \times max \left[K - F(T_N, T_1, T_N), 0 \right]$$
(4.12)

where D denotes the number of days the FFA contract covers.

The value of a contingent claim can be expressed as the expected payoff at maturity under Q discounted by the risk-free rate. The value at time t of the Asian call and put option,

with maturity T_N can be written as

$$C(t, T_N) = e^{-r(T_N - t)} D \times E_t^Q \Big[max[F(t, T_1, T_N) - K, 0] \Big]$$
(4.13)

and

$$P(t,T_N) = e^{-r(T_N-t)}D \times E_t^Q \Big[max[K - F(t,T_1,T_N),0]\Big]$$
(4.14)

Applying the Black-Scholes framework on the above Asian option we can, as shown by Koekebakker et al. (2007) formulate the price at time t for the call option as

$$C(t, T_N) = e^{-r(T_N - t)} D(F(t, T_1, T_N) N(d_1) - K N(d_2))$$
(4.15)

where

$$d_1 = \frac{ln\left(\frac{F(t, T_1, T_N)}{K}\right) + \frac{1}{2}\sigma_F^2}{\sigma_F}, \qquad d_2 = d_1 - \sigma_F \tag{4.16}$$

where σ_F is the volatility of the forward contract, and N(x) is the cumulative normal distribution function. Applying the put-call parity, we can derive the price of the put as

$$P(t,T_N) = e^{-r(T_N-t)} D(KN(-d_2) - F(t,T_1,T_N)N(-d_1))$$
(4.17)

We price the Asian option on spot freight rate as a European option on the FFA. However, our data of FFA prices are quoted by volatility, as implied by the Asian style options on spot freight rate. Therefore, in order to get a meaningful comparison between the two, we establish a linkage between the two volatility measures. As described by Koekebakker et al. (2007) we can define the volatility of FFA contracts as a function of the volatility of the spot rate, and the time specifications of the FFA contract

$$\sigma_F^2 = (T_1 - t)\sigma^2 + \frac{1}{3}(T_N - T_1)$$
(4.18)

where the 1/3-term is a result of continuous settlement.

5 Methodology

5.1 A smooth forward freight rate function

To derive the volatility structure of the forward freight rate function, we compute a continuous forward price function from each day's average based forward freight rates. The smoothing procedure is based on the principle of maximum smoothness suggested by Adams and Van Deventer (1994). They prove, for fixed income, that the yield curve with the smoothest possible forward rate function is a fourth-order polynomial spline fitted between each knot point on the yield curve.

The smoothness algorithm has later been applied to various commodity markets. Benth et al. (2007) build on Adams and van Deventer's work when they show how to adjust the smoothing procedure to handle average based contracts in the electricity market, while Koekebakker and Ådland (2004) demonstrate its applicability in the forward freight market.

Applying the methods described by Koekebakker and Ådland (2004) and Lim and Xiao (2002) we establish the smoothness criterion for the forward rate function as the one that minimizes the functional

$$\min \int_{0}^{T} f''(t,s)^{2} ds$$
 (5.1)

while simultaneously fitting the observed market prices. Where f(t,s), denotes the forward freight rate at time t with maturity at time s.

To find the parameters of the spline function

$$x^{T} = [a_{1}, b_{1}, c_{1}, d_{1}, e_{1}, a_{2}, b_{2}, c_{2}, d_{2}, e_{2}, \dots, a_{n}, b_{n}, c_{n}, d_{n}, e_{n}]$$
(5.2)

we solve the linear equation

$$\begin{bmatrix} 2H & A^T \\ A & 0 \end{bmatrix} \begin{bmatrix} x \\ \lambda \end{bmatrix} = \begin{bmatrix} 0 \\ b \end{bmatrix}$$
(5.3)

where A is the constraint matrix ensuring connectivity and smoothness of derivatives at the knots, j=1,...,n-1

$$(a_{j+1} - a_j)t_j^4 + (b_{j+1} - b_j)t_j^3 + (c_{j+1} - c_j)t_j^2 + (d_{j+1} - d_j)t_j + e_{j+1} - e_j = 0$$
(5.4)

$$4(a_{j+1} - a_j)t_j^3 + 3(b_{j+1} - b_j)t_j^2 + 2(c_{j+1} - c_j)t_j + d_{j+1} - d_j = 0$$
(5.5)

$$12(a_{j+1} - a_j)t_j^2 + 6(b_{j+1} - b_j)t_j + 2(c_{j+1} - c_j) = 0$$
(5.6)

$$\int_{T_i^s}^{T_i^e} a_i t_i^4 + b_i t_i^3 + c_i t_i^2 + d_i t_i + e_i = FFA_i * (T_i^e - T_i^s), \quad i = 1, ..., n$$
(5.7)

and the boundary condition

$$f'(t_n) = 4a_n^3 + 3b_n^2 + 2c_n + d_n = 0$$
(5.8)

making the forward rate curve flat at the long end, a common assumption in financial modeling (Van Deventer et al., 2013).

For H we have

and

$$\Delta_j^l = t_{j+1}^l - t_j^l, \qquad l = 1, ..., 5$$

The solution $[x^\star,\lambda^\star]$ is found through QR factorization.

We compute smooth forward freight curves for each day in our sample period. Every day, 7 contracts are used; CURMON, +1MON, +2MON, +1Q, +2Q, +3Q and +4Q. Hence, our forward curve functions up to 15 months into the future.

5.2 Data set of smooth forward curves

The forward freight model in (4.2) describes the stochastic evolution under an equivalent martingale measure, and not under the real-world measure where observations are made. From Girsanov's Theorem, we learn that even though there might be an unobservable price of risk in the market, causing the forward freight rate to follow a non-zero drift process, the diffusion term remains equal under the two probability measures Q and P (Hull et al., 2009). This enables us to estimate the volatility function from equation 4.2 from real-world data. As noted by Cortazar and Schwartz (1994), this is only strictly correct when observations are sampled continuously. In our following analysis, we approximate this condition through daily sampling of observations. From our continuous forward freight functions, we construct a data set of *forward freight rates* with weekly maturities $T_1, ..., T_m$.

For a set of weekly maturity dates, we construct a data set $X_{(N \times M)}$ with forward freight rate returns

$$\ln f(t_n, T_m) - \ln f(t_{n-1}, T_m) = x_{n,m}$$
(5.9)

where n=1,...,N.

$$X_{(N \times M)} = \begin{bmatrix} X_1 & X_2 & \dots & X_M \end{bmatrix} = \begin{bmatrix} x_{1,1} & x_{1,2} & \dots & x_{1,M} \\ x_{2,1} & x_{2,2} & \dots & x_{2,M} \\ \vdots & \vdots & \ddots & \vdots \\ x_{N,1} & x_{N,2} & \dots & x_{N,M} \end{bmatrix}$$
(5.10)

From the data set of daily returns, we estimate the historical volatility function as

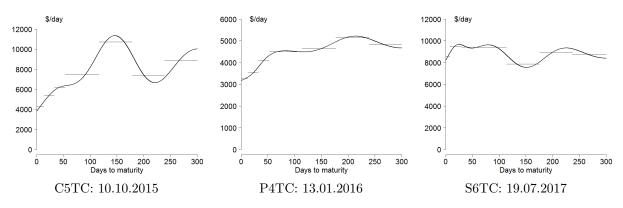
$$\hat{\sigma}(t, T_M) = s\sqrt{252} \tag{5.11}$$

where s is a $1 \times M$ vector of historical standard deviations, representing each of our M weekly maturities. We annualize the volatility estimate by the number of trading days for every given year.

5.3 Historical volatility structure

With the data of FFA prices for Capesize, Panamax, and Supramax described in the data section, we apply the smoothing procedure to produce a smooth forward curve for every day in our sample. Thus, for each vessel size, we get N smoothed forward curves, N corresponding to the length of the sampling period. Examples of graphs of the estimated smooth forward freight function for the different vessel types are illustrated below, where the horizontal lines are the actual FFA prices.

Figure 5.1: Examples of smooth forward freight rate function



Alizadeh and Nomikos (2013) describe the dry bulk market to be characterized by clear seasons, where the first quarter carries a significant increase in freight rates across all vessel sizes while the summer months are subject to declining rates. The reason for these particularities is generally believed to be a consequence of reduced industrial activity and trade in the summer months. Plotting the forward curve functions over time does not immediately reveal the aforementioned trends of seasonality. However, historically, the period 2014 to 2018 can be described as having low rates, which Alizadeh and Nomikos (2013) believe will dampen the seasonality effect, as there is likely capacity to absorb the seasonal increase. For Koekebakker and Ådland's (2004) sample of Panamax dry bulk, they describe the term structure to generally follow a "hump-shape", in which short and long-term rates are below medium-term rates. As seen from figure 5.2, our data is, to some extent, indicative of the same trend; however, this trend is weak.

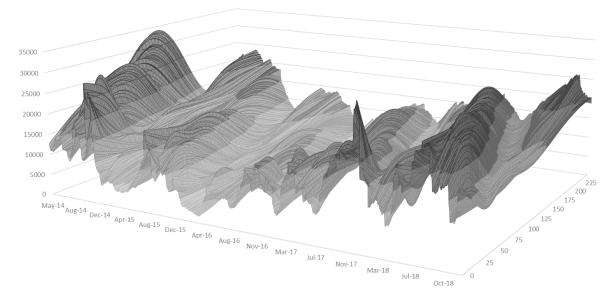


Figure 5.2: Estimated smoothed forward curve functions for Capesize

In figure 5.3, we have plotted the estimated average volatility function for each vessel size. Generally speaking, volatility is decreasing with increasing time to maturity. This is a trait that coincides with the mean reversion displayed through the spot freight dynamics. It is again evident that volatility is strictly decreasing in vessel size, an attribute that has been explained by Kavussanos (1996) of larger ships being more specialized toward specific commodities and their physical limitations in operating certain ports. Larger ships' limited flexibility will naturally be manifested through higher volatility.

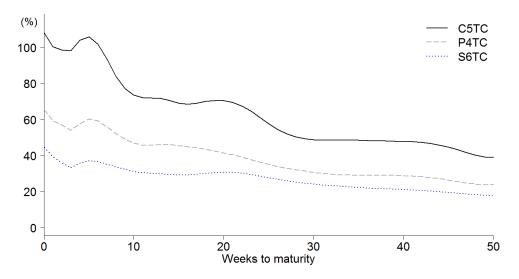


Figure 5.3: Estimated historical volatility structure of the forward freight function

The volatility structures of the different vessels experience increasing deviations from each

other approaching maturity. Annualized volatility can be seen to converge to levels of 40%, 30%, and 20% for the respective vessel sizes as the time to maturity reaches one year. These findings are consistent with the general belief in shipping literature that the volatility of long-term freight rates should mirror the volatility in prices of newbuildings (Strandenes, 1984). Data from Clarkson Research Services on newbuilding prices show annualized volatility estimates around 30%. Deviations from the long-term volatility estimates of freight rates could be explained by strong labor unions and governmental policy of subsidy that ultimately distort the mechanics of supply and demand in the market of newbuildings (Strandenes, 2002). It is also possible that a time period spanning one year is too short for the freight rates to revert to their long-term expected equilibrium.

Another striking quality of the estimated volatility structure is the spike that appears around five weeks to maturity. The hump feature could be a result of investors' elastic expectations, as explained by Zannetos (1959), where the supply of freight services is determined by the shipowners' expectations of freight rates more so than of the current freight rates. Zannetos (1959) argued, in the context of tanker freight rates, that expectations of changing freight rates will establish a dynamic relationship of supply and demand between time periods. Benth and Koekebakker (2016) have later documented short-run positive autocorrelation in the Supramax dry bulk segment and propose a continuous ARMA model to capture the observed dynamics. In the market for dry bulk newbuildings, Alizadeh and Nomikos (2013), explain how expectations of high freight rates make investors place orders of new vessels to capitalize on the positive outlook. Similarly, the shipowners are likely to delay offering their services to gain from the expected increase, and the charterers will want to lock the current market price. Market forces will push the short-term freight rates upwards. However, since there is no cost-of-carry relationship that links today's rate with tomorrow's, future freight rates are simply determined by the market participants' expectations of freight rates. These expectations are transmitted into forward price formations faster than the determination of spot rates, causing the volatility of short-term forward freight rates to be higher than the volatility of spot rates. The fact that our estimate of one month volatility is below that of spot volatility is believed to be a result of the smoothing method, where the spot rate is not accounted for but is merely a result of equation 4.4.

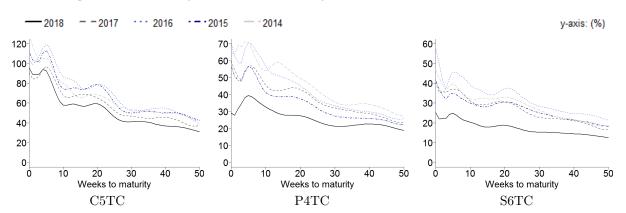


Figure 5.4: Yearly historical volatility term structures across vessel sizes

When we estimate yearly volatility term structures, we observe the same characteristic trends across maturities as can be seen from the full sampling period, ensuring that the historical volatility term structure in figure 5.3 is actually revealing the general behavior of the forward freight rate and is not too heavily influenced by what could be atypical behavior from an abnormal year. Further, we see that the spread between yearly volatilities are relatively larger for Panamax and Supramax than it is for Capesize. Meaning that even though Capesize freight rates are more volatile, the general level of volatility is more stable.

6 Trading Strategies

Following our estimation of the volatility structure of the forward freight rate, we want to explore statistical arbitrage opportunities in the pricing of Asian options. Our focus will be to exploit the consistent volatility dynamics present in the forward curve to spot discrepancies between the volatility implied by the quoted option and our historical volatility estimate. Thus, our focus is to explore trading strategies that isolate the exposure of the underlying volatility, without being affected by the general direction of the market. In what follows, we will present and discuss results obtained through simulating three different trading strategies. The strategies are; delta hedging, straddles, and time spreads.

6.1 Delta Hedging

Ahmad and Wilmott (2005) show that in cases where implied volatility differs from actual volatility, profit can be extracted through delta hedging the option. The arbitrage is possible in a stylized world with constant volatility, and where we know the future realized volatility, the *actual volatility*. The profit is secured through delta hedging, either with implied or actual volatility. The difference between hedging with implied and actual volatility becomes apparent in the process of marking to market. Hedging with actual volatility secures a profit equal to the initial mispricing of the options. However, the path required to reach the correct volatility estimate is random - opening up for large losses before gaining. In a time interval $[t, T_N]$ where implied volatility (σ_{IV}) is higher than actual volatility (σ_a) , and we hedge with actual volatility , the expected profit is

$$O(t, U; \sigma_a) - O(t, U; \sigma_{IV}) \tag{6.1}$$

with U representing the underlying asset of the option value O at time t.

On the other hand, hedging with implied volatility, secures a deterministic daily profit, yet the final profit becomes path-dependent. Ahmad and Wilmott (2005) show that the profit in the time interval $[t, T_N]$ can be formulated as

$$\frac{1}{2}(\sigma_a^2 - \sigma_{IV}^2) \int_t^{T_N} e^{-r(s-t)} U^2 \Gamma_{IV} ds, \qquad \Gamma = \frac{\partial^2 O}{\partial U^2} = \frac{\partial \Delta}{\partial U}$$
(6.2)

ensuring deterministic gains as long as the implied volatility is higher than actual volatility when buying volatility. And opposite, that implied volatility is lower than actual volatility when selling volatility.

We simulate a delta hedging strategy on real market data. At time t, the first trading day of the contract, we compare the option's implied volatility with the historical volatility, as stated by our estimated volatility term structure. If the implied volatility is sufficiently above/below our historical volatility estimate, we want to sell/buy volatility. We apply a filter (ϕ) to determine what constitutes a sufficient deviation from our estimate. The filter (ϕ), differentiates between the vessel sizes, with the argument being that greater absolute variation in the volatility structures opens up for greater mispricing of the options, and ultimately a lower margin of error when deciding on the direction of the volatility deviation. The filters for Capesize, Panamax, and Supramax contain the trigger values [0,6,12,18,24,30], [0,4,8,12,16,20], and [0,2,4,6,8,10], respectively, where the trigger values are percentage deviations from our historical volatility to be 18% higher (or lower) than our historical volatility estimate to take a position. We expose ourselves to the volatility by selling/buying a call and hedging our portfolio through buying/selling $\Delta \times FFA$ establishing a delta neutral position. The delta (Δ) of the call is calculated as

$$\frac{\partial(Call_{Asian})}{\partial FFA} = D \times N(d_1) \tag{6.3}$$

where D represents the number of calendar days covered by the FFA contract.

It is important to highlight that our investment decision at time t is strictly based on available information prior to t. For every trading day prior to roll-over, $[t, \ldots, T_R]$, we adjust our portfolio by buying/selling the underlying FFA to remain delta neutral. On the day, T_R , that the contract rolls-over to a new period, we clear our position. Thus, for monthly contracts, the trading period will span around 1 month, while quarterly contracts will be traded for approximately 1 quarter, establishing the time frame of relevance, $[t, T_R, T_1, T_N]$. We assume that we can borrow/place money at the risk-free rate, LIBOR, and transaction costs are set at 0.01 % for FFAs and 0.25% for options. When short selling, we assume that all positive cash flow will be held as collateral. Our results when hedging using implied volatility are listed in table 6.1. Return, (μ) , is the total return, from t to T_R , on the absolute value of what we initially buy and sell. The volatility, (σ) , is the standard deviation of the previously mentioned total returns. # is the number of positions that are taken during the sample period for the specific contracts, as expected, the number of positions taken are declining with higher filter values. Maximum drawdown, (MDD), is the maximum observed loss from a local maximum to a local minimum during the time interval $[t, T_M]$ of the contract. It is important to emphasize that MDD for the strategy is the reported maximum downturn in one specific trading period in the four year time interval we simulate the trading strategies. The MDD is calculated as

$$MDD = \left| \frac{Local \ Minimum - Local \ Maximum}{Local \ Maximum} \right| \tag{6.4}$$

The reported return and volatility estimates are not directly comparable across monthly and quarterly contracts because of the varying holding period. Annualizing the return and volatility estimates could solve this, however, we believe the downside risk metric, maximum drawdown, is more informative when compared to the actual return and volatility realized over the period. Looking at table 6.1, we see that downside risk, volatility, and return is typically higher for shorter contracts and larger vessels. Furthermore, a trading signal requiring a larger deviation from our historical volatility estimate is generally followed by higher returns and lower volatility across all contracts. This supports freight rates' mean-reverting nature and establishes historical volatility as a better estimate of future realization of volatility than the market's estimate of volatility in the sampled time frame. A critical assumption is that the realizations of freight rate returns are actually representative of the true freight rate distribution. If this assumption holds, our historical volatility estimate can prove to be an accurate representation of future volatility.

From the maximum drawdown estimate, we observe identical values for many different trigger values, hence, the largest downturn must stem from one specific trading period. Moreover, the simulations reveal that the largest fall is occurring in the same time interval for many of the different contracts. Considering that we compare a backward-looking volatility estimate (historical) with a forward-looking estimate (implied), there could be instances when there is information in the market affecting future volatility that our backward-looking estimate does not capture. And, as such, downside risk is highest when the difference between the two estimates are greatest. However, because of the random nature of the freight rate process, it is difficult to conclude whether higher deviations actually increase downside risk.

			+11	MON			+1Q				+3Q				
Index	$\operatorname{Filter}(\%)$	$\mu(\%)$	$\sigma(\%)$	MDD(%)	#	$\mu(\%)$	$\sigma(\%)$	MDD(%)	#	$\mu(\%)$	$\sigma(\%)$	MDD(%)	#		
	0	4.47	3.34	8.14	48	6.92	3.53	3.83	16	5.43	2.32	2.78	16		
	6	4.51	3.41	8.14	46	6.92	3.53	3.83	16	5.43	2.32	2.78	16		
C5TC	12	4.66	3.29	8.14	43	6.92	3.53	3.83	16	5.43	2.32	2.78	16		
0310	18	4.79	3.31	8.14	40	7.35	3.19	3.83	15	6.01	2.10	2.78	13		
	24	5.06	3.24	8.14	35	7.35	3.19	3.83	15	6.01	2.10	2.78	13		
	30	4.96	3.30	8.14	33	8.18	2.87	3.83	10	7.66	1.39	0.78	6		
	0	1.44	2.01	2.80	48	2.25	1.39	1.81	16	2.50	1.12	0.51	16		
	4	1.91	2.01	2.80	32	2.66	1.34	1.81	12	2.60	1.08	0.51	15		
DATEC	8	2.26	2.13	2.80	24	2.68	1.40	1.81	11	2.72	1.02	0.51	14		
P4TC	12	2.13	2.17	2.80	22	2.91	1.46	1.81	9	2.86	0.91	0.37	13		
	16	2.39	2.14	2.80	18	2.91	1.46	1.81	9	3.25	0.82	0.37	9		
	20	2.39	2.21	2.80	17	3.30	1.19	1.81	7	3.56	0.54	0.23	7		
	0	0.08	0.95	2.79	48	0.87	0.61	0.95	16	1.13	0.65	1.36	16		
	2	0.15	0.95	2.79	35	0.88	0.63	0.95	15	1.13	0.65	1.36	16		
CETC	4	0.25	1.03	2.79	21	0.98	0.56	0.95	12	1.13	0.65	1.36	16		
S6TC	6	0.39	1.07	2.79	16	1.23	0.48	0.49	6	1.13	0.65	1.36	16		
	8	0.71	0.72	1.23	10	1.51	0.09	0.41	2	1.13	0.65	1.36	16		
	10	0.89	0.47	0.72	7	1.44	-	0.15	1	1.32	0.52	0.27	13		

Table 6.1: Descriptives for delta hedging strategy with implied volatility

If our historical volatility estimate is correct, the expected profit is, given continuous hedging, path-independent, and equal to equation 6.1. For this to be true, it is also required that the strategy is upheld until T_N , giving the volatility time to reach its expected level. Thus, our trading strategy rests on the assumption that volatility converges towards our historical volatility estimate prior to T_R and that the options are priced according to the information prevalent in the market.

Compared to hedging with implied volatility, hedging using historical volatility yields higher returns with higher volatility. While the volatility estimates, as reported in table 6.2, are close to the estimates received from the hedging strategy using implied volatility, the fluctuations in the P&L processes are higher using our historical volatility estimate. Additionally, hedging using a historical volatility estimate will not account for upcoming events that are expected by the market to have measurable effects on the freight prices and ultimately will support a period with abnormal levels of implied volatility. Consequently, delta hedging with historical volatility will necessarily increase downside risk.

			+1l	MON			+	1Q		+3Q				
Index	$\operatorname{Filter}(\%)$	$\mu(\%)$	$\sigma(\%)$	MDD(%)	#	$\mu(\%)$	$\sigma(\%)$	MDD(%)	#	$\mu(\%)$	$\sigma(\%)$	MDD(%)	#	
	0	4.73	3.67	13.92	48	7.23	3.13	5.84	16	5.62	2.45	3.96	16	
	6	4.79	3.75	13.92	46	7.23	3.13	5.84	16	5.62	2.45	3.96	16	
C5TC	12	4.97	3.64	13.92	43	7.23	3.13	5.84	16	5.62	2.45	3.96	16	
0310	18	5.12	3.68	13.92	40	7.69	2.63	5.84	15	6.19	2.26	3.96	13	
	24	5.38	3.73	13.92	35	7.69	2.63	5.84	15	6.19	2.26	3.96	13	
	30	5.30	3.82	13.92	33	8.12	2.85	5.84	10	7.94	1.64	0.44	6	
	0	1.50	1.96	2.93	48	2.33	1.47	1.55	16	2.58	1.15	0.44	16	
	4	1.99	1.92	2.93	32	2.78	1.39	1.55	12	2.69	1.11	0.44	15	
P4TC	8	2.36	2.01	2.93	24	2.81	1.46	1.55	11	2.80	1.06	0.44	14	
1410	12	2.23	2.05	2.93	22	3.08	1.48	1.55	9	2.94	0.95	0.36	13	
	16	2.44	2.13	2.93	18	3.08	1.48	1.55	9	3.35	0.86	0.36	9	
	20	2.45	2.19	2.93	17	3.51	1.21	1.55	7	3.64	0.68	0.36	7	
	0	0.10	0.96	2.81	48	0.88	0.61	0.98	16	1.16	0.64	1.43	16	
	2	0.17	0.96	2.81	35	0.89	0.63	0.98	15	1.16	0.64	1.43	16	
S6TC	4	0.27	1.05	2.81	21	0.98	0.57	0.98	12	1.16	0.64	1.43	16	
5010	6	0.42	1.10	2.81	16	1.25	0.48	0.51	6	1.16	0.64	1.43	16	
	8	0.75	0.74	1.28	10	1.56	0.14	0.31	2	1.35	0.48	0.30	13	
	10	0.97	0.41	0.60	7	1.46	-	0.16	1	1.35	0.48	0.30	13	

 Table 6.2: Descriptives for delta hedging strategy with historical volatility

From figure 6.1 and 6.2, we see the P&L development of every position throughout the trading period. The purpose of delta hedging is to protect the option's value against price movements in the underlying FFA contract. The concept's weakness is that while the position is protected against the underlying price movement, it is not accounting for the underlying price movement's effect on volatility. This is especially relevant for the positions with shorter maturities, which historically have, and theoretically, should be subject to larger variation in volatility over the trading period. Consequently, hedging against underlying price movements will be relatively less efficient holding positions with shorter maturities. Comparing data of +3Q with data of +1MON and +1Q it is clear that changes in FFA prices seldom are followed by changes in implied volatility for longer maturities. This effect is something that can be observed in figure 6.1 and 6.2, where the P&L processes follow a more steady growth rate.

A comparison of the P&L processes obtained hedging with historical and implied volatility reveals more extreme movements when hedging with historical volatility estimates. This is especially evident for Capesize, where MDD is noticeably increasing using historical volatility. This effect on MDD is not present for the Panamax and Supramax contracts. The more volatile P&L processes are an expected feature given that differences in implied volatility and our historical volatility estimate will give different hedging ratios. Since the value of the option always will be priced using the market's estimate of future volatility, movements in the underlying FFA price, without the implied volatility converging to our historical estimate will unveil a non-zero delta position and a corresponding change in the value of our portfolio. A portfolio adjusted according to implied volatility will, therefore, be delta neutral according to the market, and subsequently, account for changes in the option price caused by changing market expectations of future volatility.

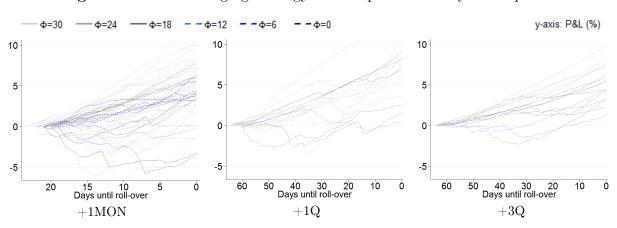
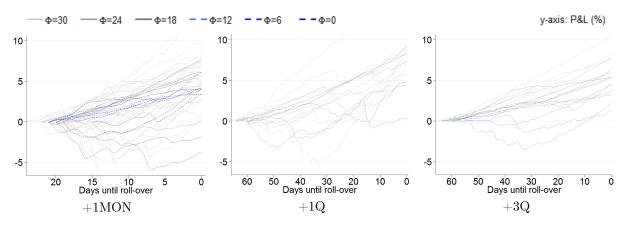


Figure 6.1: Delta hedging strategy with implied volatility for Capesize

Figure 6.2: Delta hedging strategy with historical volatility for Capesize



6.2 Modified Delta Hedging

The analytical delta value is a partial derivative and describes the change in option value for an infinitely small change in the price of the underlying. According to Taleb (1997), the idea of adjusting a position corresponding to infinite small price changes in the underlying is irrelevant due to the mere non-existence of infinite small price changes, and if they were to exist - they would not be worth adjusting to. He therefore proposes a numerical estimation of the delta, where

$$\frac{\Delta O(t,U)}{\Delta U} = \frac{1}{2} \left(\frac{O(t,U+h) - O(t,U)}{h} + \frac{O(t,U-h) - O(t,U)}{-h} \right)$$
(6.5)

which ensures that adjustments are made to reflect set changes in the underlying. Hull and White (2017) derive an alternative delta that accounts for price changes as well as expected changes in implied volatility conditional on changes in the price of the underlying. A delta that minimizes the variance of the changes in the value of the option is estimated as

$$\Delta_{MV} = \frac{\Delta O(t, U)}{\Delta U} + v \frac{\Delta E(\sigma_{IV})}{\Delta U}$$
(6.6)

where

$$v = \frac{1}{2} \left(\frac{O(t, U; \sigma + s) - O(t, U; \sigma)}{s} + \frac{O(t, U; \sigma - s) - O(t, U; \sigma)}{-s} \right)$$
(6.7)

The numerical approach of calculating the derivatives forces us to define economically small h and s for which our portfolio will be locally delta neutral. We believe 1% is a small change to the price of the underlying, and 1% is a small change to the implied volatility. Applying the minimum variance delta also requires us to estimate the expected change in implied volatility for a set change in the price of the underlying. We do not have data on options with strikes that are out/into the money, and as such, decide to estimate the movement of implied volatility due to movement in the underlying price with OLS. We estimate the expected change in implied volatility for equation 6.6 using implied volatility estimates.

The results are roughly equivalent to the analytical delta calculated above, as reported in table A3.1 in the appendix. We acknowledge that volatility is not constant over the period, and that implied volatility can be sensitive to changes in FFA prices. Results show that the implied volatility experience large deviations over our holding period. Our estimated regression indicate that our hedge ratio should be reduced compared to the analytical delta, to account for the fact that a positive change in the underlying in general will result in a lower implied volatility estimate. A reduction in implied volatility reduces the value of the option, and our portfolio should thus be adjusted with fewer FFA contracts to remain delta neutral.

			+1M	ON		+10	Ç		+3Q				
Index	$\operatorname{Filter}(\%)$	$\mu(\%)$	$\sigma(\%)$	MDD	#	$\mu(\%)$	$\sigma(\%)$	MDD	#	$\mu(\%)$	$\sigma(\%)$	MDD	#
	0	4.47	3.36	8.13	48	6.93	3.53	3.82	16	5.51	2.27	2.77	16
	6	4.51	3.43	8.13	46	6.93	3.53	3.82	16	5.51	2.27	2.77	16
C5TC	12	4.66	3.31	8.13	43	6.93	3.53	3.82	16	5.51	2.27	2.77	16
0010	18	4.79	3.33	8.13	40	7.34	3.22	3.82	15	6.09	2.03	2.77	13
	24	5.06	3.26	8.13	35	7.34	3.22	3.82	15	6.09	2.03	2.77	13
	30	4.96	3.33	8.13	30	8.17	2.95	3.82	10	7.80	1.40	0.61	6
	0	1.44	2.02	2.81	48	2.23	1.37	1.96	16	2.48	1.04	0.32	16
	4	1.90	2.01	2.81	32	2.63	1.33	1.96	12	2.57	1.00	0.32	15
P4TC	8	2.26	2.13	2.81	24	2.64	1.39	1.96	11	2.69	0.94	0.32	14
Г410	12	2.12	2.17	2.81	22	2.85	1.46	1.96	9	2.80	0.86	0.28	13
	16	2.38	2.14	2.81	18	2.85	1.46	1.96	9	3.16	0.80	0.28	9
	20	2.38	2.21	2.81	17	3.24	1.23	1.96	7	3.47	0.55	0.24	7
	0	0.08	0.95	2.79	48	0.85	0.61	0.95	16	1.10	0.62	1.35	16
	2	0.15	0.95	2.79	35	0.85	0.63	0.95	15	1.10	0.62	1.35	16
S6TC	4	0.24	1.03	2.79	21	0.96	0.57	0.95	12	1.10	0.62	1.35	16
2010	6	0.38	1.08	2.79	16	1.19	0.54	0.55	6	1.10	0.62	1.35	16
	8	0.70	0.72	1.23	10	1.47	0.18	0.39	2	1.10	0.62	1.35	16
	10	0.88	0.47	0.72	7	1.34	-	0.11	1	1.31	0.45	0.32	13

 Table 6.3: Descriptives for modified delta hedging strategy

6.3 Weaknesses with Delta Hedging

The practical implementation of the strategy suffers from real-world dynamics. Delta hedging is risky, and the arbitrage opportunity described by Ahmad and Wilmott (2005) is only attainable had our historical volatility estimate been perfect in its ability to forecast future volatility, which it is not. However, it could be the case that a historical estimate of volatility is a better predictor of future volatility than the market's prediction (as implied by option prices) is. But as long as there exists some uncertainty surrounding the realization of actual volatility, our pricing formula will have a non-zero chance of misspecifying the volatility input parameter. This will have implications for the hedging effectiveness, and more severely, it will imply that increasing the hedging frequency is not a solution to perfectly replicate the payoff of the underlying asset, a result that imposes any position with an additional layer of risk (Karoui et al., 1998).

Assuming a continuous-time world introduces the possibility of continuous hedging, an exact replication of the underlying asset, and the arbitrage-free argument of the Black-Scholes formula, that ensures a zero expected profit from the option strategy (Derman and Taleb, 2005). At the same time as continuous replication seize to exist, there will be an accumulation of replication errors leading to a deviation from the original Black-Scholes

price and a non-zero P&L expectation. While dynamic hedging is path-independent in a continuous-time world, and as such will provide an expected profit equal to equation 6.1 for hedging with actual volatility, the accumulated gains will be highly path-dependent under a discrete hedging regime. The implication of this is that we would prefer to have the large price changes in FFA when gamma is largest, and the small price changes when the FFA is far away from the strike price for strategies that are long gamma (Γ) (Taleb, 1997). Thus, this leads to an inverse relationship between the hedging frequency and the variance of the P&L. While the ambition of zero variance motivates us to approximate continuity, the presence of transaction costs makes frequent hedging unprofitable. As such, market imperfections create a trade-off between variance reduction and hedging frequency (Sepp, 2013).

While we account for transaction costs and only allow for discrete hedging, the risk of illiquidity is not included in our simulation. As previously mentioned, FFA contracts and the options that are written on them can potentially suffer from severe illiquidity, and as such, daily rebalancing of a portfolio is hard and might only be possible at a premium. Furthermore, Wilson (2013) address that the usual minimum trade size for FFA contracts is five days. Such a limitation may have an impact on the ability to remain delta neutral. However, this restriction can be somewhat managed by increasing the number of options and, consequently, increasing the amount of FFAs needed to balance the portfolio to a delta value of zero. While it may not invalidate our results, it is certainly a weakness that should be acknowledged in any practical implementation of the trading strategy.

6.4 Straddle

A straddle consists of a put and a call. Based on its qualities of remaining long/short volatility, having vegas and gammas on the same side of the market, and initially being close to delta-neutral, Taleb (1997) defines the strategy as a first-order volatility trade. A long straddle offers the potential of unlimited profit with a limited downside. However, as noted by Natenberg (1994), buying straddles can be a costly affair. Excess returns are thus obtained by recognizing when options are mispriced and exploit the situation to buy low and sell high.

While the straddle, at time t is close to delta-neutral, changing market conditions will

alter the delta value. The reality of time-varying factors affecting the position of the straddle demands a strategy of countermeasures. Natenberg (1994) suggests one of the following strategies; (1) adjust at regular intervals, (2) adjust when the position becomes a predetermined number of deltas long/short, (3) adjust by feel, (4) don't adjust at all. Adjusting by feel was suggested for individuals that had a feel for the market; we prefer the other three.

Even though we establish a strategy for when to adjust our position to underlying price movements, the straddle will still be exposed to movements in the other input parameters. During our holding period, the option value will also be sensitive to changes in interest rates (rho, ρ) and time-decay (theta, Θ). The risk of changing interest rates will be a negligible part of the overall risk, and the time decay of the value is inevitable for the strategy (Schmitt and Kaehler, 1996). This leads us to not formulate a strategy for how to manage these first-derivatives.

Our investment decision is based on whether the implied volatility is above/below our volatility estimate, equivalent to the pure delta hedging strategy. We first simulate by buying/selling an at-the-money straddle and hold it to T_R , without additional adjustments in the period.

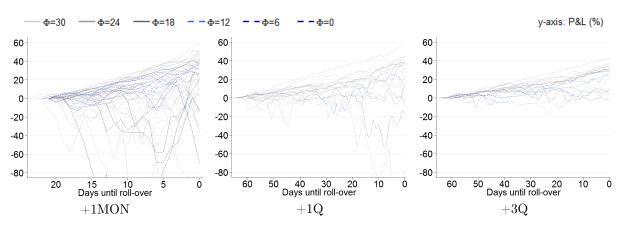
The strategy is approximately delta neutral at t but will drift away along with the market. The return (μ) , volatility (σ) , and maximum drawdown (MDD) are calculated in the same way as for the delta hedging strategy. The holding straddle strategy yields positive returns with high volatility for Capesize and Panamax. For Supramax, we have positions that yield negative returns while upholding high volatility. The trend of higher precision with higher spreads between the filter values is gone for the straddle strategy. Interestingly, comparing Capesize with Panamax, the lower returns obtained for Panamax are not accompanied by lower volatility estimates. These observations make us assign the strategy's modest success for Capesize and Panamax to be a result of randomness. Also, as our historical volatility term structure generally is below that of the implied volatility structure, we are generally short straddles, a position with an unlimited downside, without being hedged.

			+1	MON			+	1Q			+	3Q	
Index	$\operatorname{Filter}(\%)$	$\mu(\%)$	$\sigma(\%)$	MDD(%)	#	$\mu(\%)$	$\sigma(\%)$	MDD(%)	#	$\mu(\%)$	$\sigma(\%)$	MDD(%)	#
	0	14.23	42.24	231.49	48	21.30	33.61	129.56	16	24.87	12.84	18.97	16
	6	16.02	40.83	231.49	47	21.30	33.61	129.56	16	24.87	12.84	18.97	16
C5TC	12	15.19	41.51	231.49	45	21.30	33.61	129.56	16	24.87	12.84	18.97	16
0310	18	15.82	42.57	231.49	41	21.20	34.78	129.56	15	26.17	12.97	18.97	13
	24	15.22	45.00	231.49	36	21.20	34.78	129.56	15	26.17	12.97	18.97	13
	30	16.06	46.09	231.49	34	24.95	39.07	129.56	10	29.93	12.53	16.62	6
	0	2.20	42.87	189.53	48	6.74	25.72	131.04	16	8.38	15.45	49.51	16
	4	-0.70	49.16	189.53	34	7.57	28.30	131.04	13	8.43	16.00	49.51	15
P4TC	8	4.98	54.13	189.53	24	6.45	30.78	131.04	11	8.09	16.54	49.51	14
1410	12	2.59	56.01	189.53	22	3.06	33.30	131.04	9	7.89	17.20	49.51	13
	16	7.40	50.79	189.53	18	3.06	33.30	131.04	9	6.90	20.65	49.51	9
	20	6.20	52.09	189.53	17	-0.094	37.38	131.04	7	6.17	23.21	49.51	7
	0	-6.63	29.44	124.51	48	-2.46	23.92	91.97	16	2.99	16.01	60.88	16
	2	-9.45	28.07	124.51	3	-2.53	24.76	91.97	15	2.99	16.01	60.88	16
S6TC	4	-8.07	24.50	73.71	21	2.84	17.67	86.37	12	2.99	16.01	60.88	16
2010	6	-8.83	26.97	73.71	15	0.57	21.88	86.37	7	2.99	16.01	60.88	16
	8	-7.62	28.19	73.71	12	3.43	4.76	27.45	2	2.99	16.01	60.88	16
	10	-16.18	34.41	73.71	7	0.06	-	27.45	1	6.42	6.09	30.97	13

Table 6.4: Descriptives for holding a straddle

The MDD estimates in table 6.4 illustrate a strategy with considerable risk. From figure 6.4 we see how the P&L unfolds over the trading period, exposing the erratic nature of the strategy and the importance of being able to carry significant losses over prolonged time frames in order to see the portfolio turning profitable. For example, the strategy can be seen to be down by more than 80% for the \pm 1MON and \pm 1Q contracts, which in most scenarios will require margin calls, ultimately putting additional stress on the portfolio holder's liquidity. As the FFA price moves away from the strike price, the delta neutrality is lost, and our portfolio, which initially was a bet on volatility, is turning increasingly sensitive to the direction of the FFA's price change.

Figure 6.3: Hold straddle strategy



Our second approach involves buying or selling straddles and hold it until the delta of the

straddle surpasses a value of ||0.1|| in which the strategy is rolled over. A signal of 0.1 is based on what is practically considered as delta neutral, noted by Schmitt and Kaehler (1996). Our estimate of the delta of the portfolio is based on equation 6.3, in which we acknowledge the symmetrical property of the normal distribution when calculating the delta for puts. Similarly as for the holding strategy, our historical volatility estimate is useful at recognizing cheap and expensive volatility, where the success of the portfolio depends on the actual realized volatility over the period. We see that adjusting the straddle according to delta neutrality dominates the simple holding strategy, yielding higher returns with less risk.

			+11	MON			+	1Q			+	3Q	
Index	$\operatorname{Filter}(\%)$	$\mu(\%)$	$\sigma(\%)$	MDD(%)	#	$\mu(\%)$	$\sigma(\%)$	MDD(%)	#	$\mu(\%)$	$\sigma(\%)$	MDD(%)	#
	0	21.51	24.58	47.24	48	30.14	18.09	19.21	16	29.15	13.84	10.43	16
	6	22.98	22.65	33.40	47	30.14	18.09	19.21	16	29.15	13.84	10.43	16
C5TC	12	22.73	23.12	33.40	45	30.14	18.09	19.21	16	29.15	13.84	10.43	16
0310	18	24.04	23.11	33.40	41	31.84	17.33	19.21	15	32.05	11.77	7.77	13
	24	25.43	22.72	33.40	36	31.84	17.33	19.21	15	32.05	11.77	7.77	13
	30	24.66	23.10	33.40	34	31.11	20.38	19.21	10	37.49	14.12	2.98	6
	0	8.05	11.87	19.92	48	7.47	8.60	15.54	16	11.43	5.80	3.73	16
	4	10.34	11.96	19.92	34	7.34	9.27	15.54	13	11.52	5.99	3.73	15
P4TC	8	11.49	12.15	19.92	24	7.31	9.28	15.54	11	12.21	5.57	3.73	14
F410	12	10.98	12.57	19.92	22	8.02	9.44	15.54	9	12.38	5.76	3.73	13
	16	12.65	12.82	19.92	18	8.02	9.44	15.54	9	12.86	5.75	3.64	9
	20	12.67	13.21	19.92	17	9.11	10.36	15.54	7	13.52	6.46	3.64	7
	0	-0.12	7.07	20.24	48	1.92	7.35	11.77	16	5.66	5.68	10.17	16
	2	0.79	7.18	20.24	34	1.41	7.30	11.77	15	5.66	5.68	10.17	16
S6TC	4	0.76	7.66	20.24	21	3.57	6.28	9.39	12	5.66	5.68	10.17	16
5010	6	1.71	8.01	20.24	15	4.14	7.34	9.39	7	5.66	5.68	10.17	16
	8	4.22	4.43	5.78	12	7.65	4.95	2.62	2	5.66	5.68	10.17	16
	10	4.47	3.58	5.66	7	4.15	-	2.36	1	7.82	3.24	2.11	13

 Table 6.5: Descriptives for buy/sell straddle strategy

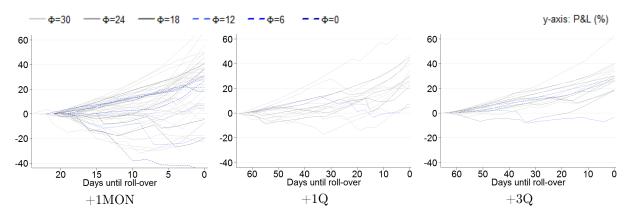


Figure 6.4: Adjusting straddle strategy

6.5 Time Spreads

According to Natenberg (1994), time spreading usually consists of taking opposing positions in the same type of option with the same strike price but with different expiration dates. Taleb (1997) classify the strategy as a complex trade with simple products owing to the dynamics of the greeks, which are characterized by the gamma flipping from positive to negative and the vega reversing as the portfolio matures. Analyzing an at-the-money position, it comes apparent that a long/short time spread will increase/decrease in value as time passes. The position will also gain/lose value if implied volatility rises/declines. The nature of the gains process is due to the fact that time-decay will have a greater impact on the value of the sold short-termed option than the bought long-termed option, and similarly, changes in implied volatility will have a greater effect on the bought long-termed option than the sold short-termed option. While a long time spread would like the implied volatility to increase, it will lose value if the realized volatility of the underlying increases, making the strategy short gamma and long vega. Conversely, a short time spread strategy, is buying short-term options and selling long-term options, making it short vega and long gamma.

In our context, the underlying asset of the option is a forward contract on a non-storable commodity. As noted by Natenberg (1994), time spreads consisting of options based on different underlying assets, can suffer from short-term supply and demand considerations that are uncorrelated across the term-structure. Koekebakker and Ådland (2004) find that the correlation between different parts of the volatility term structure for the forward freight rate is low and sometimes even negative, this finding combined with the fact that deviations from equilibrium cannot be arbitraged away adds an additional layer of risk to the strategy, that would otherwise not be present in cases of a uniform underlying asset. However, our findings from figure 5.3 show clear signs of a converging effect, which in theory could be exploited by utilizing a time spread strategy.

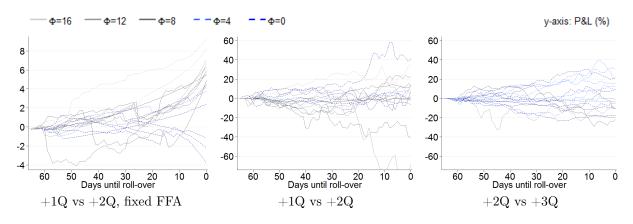
We simulate the time spread strategy with a trading signal based on whether the slope of the implied volatility curve deviates from the slope of our historical volatility term structure. Because volatility in the short end of the curve is seemingly detached from long-term supply and demand considerations of the freight service, we focus on the contracts placed on the long end of the term structure. Thus, given a steeper slope in the implied volatility curve, mean reversion suggests that buying long term volatility and selling short term volatility could be a profitable strategy. We calculate the slopes implied by the term structures and compare them with the slopes given from our historical volatility curve. This is done for the quarterly options on their first trading day. Similar to the other strategies, we differentiate by the degree of deviation by applying a filter. We hypothesize that a larger deviation from the historical slope increases the chance of the implied volatility converging back to the long-term historical volatility estimate. We hold the portfolio until T_R , at which time we close the position and roll over.

We estimate the return based on the absolute value of the portfolio. The strategy's results are characterized by negative returns and high risk. There is no apparent correlation between higher deviation and an increased probability of positive return. This can be explained by the gains process of the strategy. Even if the slope of the implied volatility curve deviates from historical measures, and this causes volatility to converge towards our estimate, the FFA price also need to stay close to the FFA price for the strategy to turn profitable. Furthermore, as changes in the FFA price for one contract not necessarily is followed by the same changes in another contract, it is hard to establish FFA as a homogeneous asset across the term structure. Conversely, information that changes the market participants' expectations of future profitability can have a different effect across the volatility term structure (Koekebakker and Ådland, 2004). Thus, while the time spread theoretically can profit from the mean reversion of volatility, the strategy is poor at isolating the misspecified volatility and is suffering from low correlation across the term structure.

			ΔFF	A = 0			+1Q	vs + 2Q			+2Q	vs + 3Q	
Index	$\operatorname{Filter}(\%)$	$\mu(\%)$	$\sigma(\%)$	MDD(%)	#	$\mu(\%)$	$\sigma(\%)$	MDD(%)	#	$\overline{\mu(\%)}$	$\sigma(\%)$	MDD(%)	#
	0	4.19	3.70	5.06	16	2.79	26.31	101.94	16	1.20	16.19	41.84	16
	4	6.12	1.65	4.19	11	-1.59	28.90	101.94	11	1.94	17.15	41.84	11
C5TC	8	6.36	1.65	4.19	10	-2.22	30.39	101.94	10	-15.83	6.17	41.84	9
	12	7.80	1.22	2.27	4	-6.39	44.04	101.94	4	-10.58	-	34.89	1
	16	8.79	0.74	0.83	2	16.80	25.98	20.91	2	-	-	-	0
	0	0.01	2.36	4.87	16	1.52	18.84	60.95	16	2.01	7.62	25.01	16
	1	0.27	2.50	2.68	10	3.58	16.05	36.45	10	2.44	8.08	18.11	13
P4TC	2	1.41	2.43	1.34	4	9.12	14.37	36.45	4	1.96	8.30	18.11	11
	3	1.41	2.43	1.34	4	9.12	14.37	36.45	4	2.27	7.06	18.11	9
	4	-0.68	0.47	1.34	2	8.68	5.03	5.30	2	1.48	7.38	18.11	9
	0	-0.96	0.51	1.78	16	4.16	16.86	32.61	16	3.28	13.48	21.96	16
	1.5	-0.96	0.51	1.78	16	4.16	16.86	32.61	16	-0.87	8.41	21.96	12
S6TC	3	-0.91	0.55	1.78	11	5.90	20.02	32.61	11	-1.15	7.95	15.32	6
5010	4.5	-0.73	0.40	1.11	6	6.56	10.83	20.26	6	-	-	-	0
	6	-0.52	0.29	1.00	4	5.15	13.02	16.24	4	-	-	-	0

 Table 6.6:
 Descriptives time spread strategy

Figure 6.5: Holding calendar spread strategy for Capesize



In an attempt to illustrate the complications that follow the unconventional pricing formation of future freight rates, we simulate the time spread with fixed FFA prices for the different contracts. The results for spreads with +1Q and +2Q can be seen in the first column in table 6.6. The corresponding P&L process can be compared to the unbounded P&L processes of the time spread in figure 6.5. By holding the FFA prices fixed, we see that larger deviations from the historical volatility term structure are accompanied by higher return and lower volatility, indicating that, given high correlation across the term structure, time spreads can profit from mean reversion. Essentially, we demonstrate which conditions need to be in place for the strategy to be successful, and consequently, the considerable risks associated with the strategy.

7 Concluding Remarks

In this thesis, we have proposed trading strategies that can exploit misspecification of volatility in the options market. We have, using observed market prices, derived smooth forward rate curves for each day in our sample. These forward curves enable us to represent the historical volatility term structures for the Capesize, Panamax, and Supramax sub-sector of the dry-bulk shipping industry. The volatility term structures present consistent behavior across vessel sizes, with increasing volatility over a six week time horizon before the volatility converges towards a long term equilibrium around 40%, reflecting the volatility seen in the market for newbuildings. Volatility levels are decreasing with vessel size for all maturities, and we see diverging volatility structures as maturity decreases.

By comparing the historical volatility term structure with the volatility estimates implied by the options market, we identify irregular volatility pricing in the market. We then execute trading strategies in what we believe is a realistic representation of the market dynamics. Our simulations assume perfect liquidity, a weakness that should be incorporated in any consideration of our results. Further, it should be noted that the options are priced assuming log-normal spot freight rates. And if, in reality, the market is simply accounting for fat tails and skewness in the distribution of freight rate returns, and adapt by adjusting the volatility estimate in the Black-Scholes formula, any identification of mispricing could be a result of incorrect assumptions (Haug and Taleb, 2008).

Our first trading strategy exploits deviations from the empirical volatility term structure through delta hedging. The strategy yields positive returns with low volatility. Results indicate that mispricing is increasing with vessel size - an expected result given higher absolute levels of volatility and more distinct features in the volatility structure. Hedging applying the historical volatility estimate seems to be associated with higher returns and higher volatility. Our second strategy tries to profit from volatility misspecification through straddles. Buying straddles when implied volatility is low and selling when high, closing the position according to a rule of delta neutrality yields high returns with lower volatility estimates than a passive straddle strategy. Moreover, time spreading, buying and selling volatility with different time to expiration suffer from low correlation across the term structure, making the strategy vulnerable to changes in supply and demand that cannot be smoothed through a cost-of-carry relationship between forward prices.

Our findings can be interpreted as a sign of inefficiency in the freight options market, which should invite speculators and market participants to investigate the current pricing mechanisms present in the market. Implementation of the mentioned trading strategies should be practically feasible, given market presence and access to capital. We hope our thesis encourages more research within the pricing of volatility in the freight options market.

References

- Adams, K. J. and Van Deventer, D. R. (1994). Fitting yield curves and forward rate curves with maximum smoothness. *Journal of Fixed Income*, 4(1):52–62.
- Adland, R. and Cullinane, K. (2005). A time-varying risk premium in the term structure of bulk shipping freight rates. *Journal of Transport Economics and Policy (JTEP)*, 39(2):191–208.
- Adland, R. and Cullinane, K. (2006). The non-linear dynamics of spot freight rates in tanker markets. Transportation Research Part E: Logistics and Transportation Review, 42(3):211–224.
- Adland, R. and Jia, H. (2017). Simulating physical basis risks in the capesize freight market. *Maritime Economics & Logistics*, 19(2):196–210.
- Adland, R. and Strandenes, S. (2006). Market efficiency in the bulk freight market revisited. *Maritime Policy & Management*, 33(2):107–117.
- Ahmad, R. and Wilmott, P. (2005). Which free lunch would you like today, sir?: Delta hedging, volatility arbitrage and optimal portfolios. *Wilmott*, pages 64–79.
- Alexandridis, G., Kavussanos, M. G., Kim, C. Y., Tsouknidis, D. A., and Visvikis, I. D. (2018). A survey of shipping finance research: Setting the future research agenda. *Transportation Research Part E: Logistics and Transportation Review*, 115:164–212.
- Alexandridis, G., Sahoo, S., and Visvikis, I. (2017). Economic information transmissions and liquidity between shipping markets: New evidence from freight derivatives. *Transportation Research Part E: Logistics and Transportation Review*, 98:82–104.
- Alizadeh, A. H., Ådland, R. O., and Koekebakker, S. (2007). Predictive power and unbiasedness of implied forward charter rates. *Journal of Forecasting*, 26(6):385–403.
- Alizadeh, A. H., Huang, C.-Y., and van Dellen, S. (2015a). A regime switching approach for hedging tanker shipping freight rates. *Energy Economics*, 49:44–59.
- Alizadeh, A. H., Kappou, K., Tsouknidis, D., and Visvikis, I. (2015b). Liquidity effects and ffa returns in the international shipping derivatives market. *Transportation Research Part E: Logistics and Transportation Review*, 76:58–75.
- Alizadeh, A. H. and Nomikos, N. K. (2011). Dynamics of the term structure and volatility of shipping freight rates. *Journal of Transport Economics and Policy (JTEP)*, 45(1):105– 128.
- Alizadeh, A. H. and Nomikos, N. K. (2013). An overview of the dry bulk shipping industry. In *The Handbook of Maritime Economics and Business*, pages 349–384. Informa Law from Routledge.
- Amihud, Y. and Mendelson, H. (1986). Liquidity and stock returns. Financial Analysts Journal, 42(3):43–48.
- Baltic Exchange (2019). Freight derivative trade volumes up in 2018. https://www.balticexchange.com/news/press-announcements/article/freight-derivative-trade-volumes-up-in-2018/3858/.

- Benth, F. E. and Koekebakker, S. (2016). Stochastic modeling of supramax spot and forward freight rates. *Maritime Economics & Logistics*, 18(4):391–413.
- Benth, F. E., Koekebakker, S., and Taib, C. M. I. C. (2014). Stochastic dynamical modelling of spot freight rates. *IMA Journal of Management Mathematics*, 26(3):273– 297.
- Benth, F. E., Koekkebakker, S., and Ollmar, F. (2007). Extracting and applying smooth forward curves from average-based commodity contracts with seasonal variation. *The Journal of Derivatives*, 15(1):52–66.
- Bjerksund, P. and Ekern, S. (1995). Contingent claims evaluation of mean-reverting cash flows in shipping. *Real options in capital investment: Models, strategies, and applications*, pages 207–219.
- Chen, Y.-S. and Wang, S.-T. (2004). The empirical evidence of the leverage effect on volatility in international bulk shipping market. *Maritime Policy & Management*, 31(2):109–124.
- Cortazar, G. and Schwartz, E. S. (1994). The valuation of commodity contingent claims. Journal of Derivatives, 1(4):27–39.
- Derman, E. and Taleb, N. N. (2005). The illusions of dynamic replication. *Quantitative finance*, 5(4):323–326.
- Haug, E. G. and Taleb, N. N. (2008). Why we have never used the black-scholes-merton option pricing formula. Social Science Research Network Working Paper Series, 1(4).
- Heath, D., Jarrow, R., and Morton, A. (1992). Bond pricing and the term structure of interest rates: A new methodology for contingent claims valuation. *Econometrica: Journal of the Econometric Society*, pages 77–105.
- Hull, J. et al. (2009). Options, futures and other derivatives/john c. hull.
- Hull, J. and White, A. (2017). Optimal delta hedging for options. Journal of Banking & Finance, 82:180–190.
- Jaeck, E. and Lautier, D. (2016). Volatility in electricity derivative markets: The samuelson effect revisited. *Energy Economics*, 59:300–313.
- Karoui, N. E., Jeanblanc-Picquè, M., and Shreve, S. E. (1998). Robustness of the black and scholes formula. *Mathematical finance*, 8(2):93–126.
- Kavussanos, M. G. (1996). Comparisons of volatility in the dry-cargo ship sector: Spot versus time charters, and smaller versus larger vessels. *Journal of Transport economics* and Policy, pages 67–82.
- Kavussanos, M. G. and Alizadeh, A. H. M. (2002). The expectations hypothesis of the term structure and risk premiums in dry bulk shipping freight markets. *Journal of Transport Economics and Policy (JTEP)*, 36(2):267–304.
- Kavussanos, M. G. and Alizadeh-M, A. H. (2001). Seasonality patterns in dry bulk shipping spot and time charter freight rates. *Transportation Research Part E: Logistics* and Transportation Review, 37(6):443–467.

- Kavussanos, M. G. and Alizadeh-M, A. H. (2002). Seasonality patterns in tanker spot freight rate markets. *Economic Modelling*, 19(5):747–782.
- Kavussanos, M. G. and Nomikos, N. K. (1999). The forward pricing function of the shipping freight futures market. *Journal of Futures Markets: Futures, Options, and Other Derivative Products*, 19(3):353–376.
- Kavussanos, M. G. and Nomikos, N. K. (2000a). Constant vs. time-varying hedge ratios and hedging efficiency in the biffex market. *Transportation Research Part E: Logistics* and Transportation Review, 36(4):229–248.
- Kavussanos, M. G. and Nomikos, N. K. (2000b). Futures hedging when the structure of the underlying asset changes: The case of the biffex contract. *Journal of Futures Markets: Futures, Options, and Other Derivative Products*, 20(8):775–801.
- Kavussanos, M. G. and Nomikos, N. K. (2000c). Hedging in the freight futures market. *The Journal of Derivatives*, 8(1):41–58.
- Kavussanos, M. G. and Nomikos, N. K. (2003). Price discovery, causality and forecasting in the freight futures market. *Review of Derivatives Research*, 6(3):203–230.
- Kavussanos, M. G. and Visvikis, I. D. (2004). Market interactions in returns and volatilities between spot and forward shipping freight markets. *Journal of Banking & Finance*, 28(8):2015–2049.
- Kavussanos, M. G., Visvikis, I. D., et al. (2010). The hedging performance of the capesize forward freight market. Eds.) Cullinane, K., The International Handbook of Maritime Economics and Business, Edward Elgar Publishing.
- Kavussanos, M. G., Visvikis, I. D., and Menachof, D. (2004). The unbiasedness hypothesis in the freight forward market: Evidence from cointegration tests. *Review of Derivatives Research*, 7(3):241–266.
- Koekebakker, S., Adland, R., and Sødal, S. (2006). Are spot freight rates stationary? Journal of Transport Economics and Policy (JTEP), 40(3):449–472.
- Koekebakker, S., Adland, R., and Sødal, S. (2007). Pricing freight rate options. Transportation Research Part E: Logistics and Transportation Review, 43(5):535–548.
- Koekebakker, S. and Ådland, R. O. (2004). Modelling forward freight rate dynamics—empirical evidence from time charter rates. *Maritime Policy & Management*, 31(4):319–335.
- Kyriakou, I., Pouliasis, P. K., Papapostolou, N. C., and Andriosopoulos, K. (2017). Freight derivatives pricing for decoupled mean-reverting diffusion and jumps. *Transportation Research Part E: Logistics and Transportation Review*, 108:80–96.
- Lévy, E. (1997). Exotic options: The state of the art. Les Clewlow, Chris Strickland. International Thomson Business Press, London.
- Li, K. X., Qi, G., Shi, W., Yang, Z., Bang, H.-S., Woo, S.-H., and Yip, T. L. (2014). Spillover effects and dynamic correlations between spot and forward tanker freight markets. *Maritime Policy & Management*, 41(7):683–696.

- Lim, K. G., Nomikos, N. K., and Yap, N. (2019). Understanding the fundamentals of freight markets volatility. *Transportation Research Part E: Logistics and Transportation Review*, 130:1–15.
- Lim, K. G. and Xiao, Q. (2002). Computing maximum smoothness forward rate curves. Statistics and computing, 12(3):275–279.
- Lucia, J. J. and Schwartz, E. S. (2002). Electricity prices and power derivatives: Evidence from the nordic power exchange. *Review of derivatives research*, 5(1):5–50.
- Morris, S. and Shin, H. S. (2004). Liquidity black holes. *Review of Finance*, 8(1):1–18.
- Natenberg, S. (1994). Option volatility and pricing. Richard Irwin.
- Nomikos, N. K. and Doctor, K. (2013). Economic significance of market timing rules in the forward freight agreement markets. *Transportation Research Part E: Logistics and Transportation Review*, 52:77–93.
- Nomikos, N. K., Kyriakou, I., Papapostolou, N. C., and Pouliasis, P. K. (2013). Freight options: Price modelling and empirical analysis. *Transportation Research Part E: Logistics and Transportation Review*, 51:82–94.
- Routledge, B. R., Seppi, D. J., and Spatt, C. S. (2000). Equilibrium forward curves for commodities. *The Journal of Finance*, 55(3):1297–1338.
- Schmitt, C. and Kaehler, J. (1996). Delta-neutral volatility trading with intra-day prices: an application to options on the dax. Technical report, ZEW Discussion Papers.
- Sepp, A. (2013). When you hedge discretely: Optimization of sharpe ratio for deltahedging strategy under discrete hedging and transaction costs. *Journal of Investment Strategies*, 3(1):19–59.
- Stopford, M. (2009). Maritime economics 3e. Routledge.
- Strandenes, S. P. (1984). Price determination in the time charter and second hand markets. Center for Applied Research, Norwegian School of Economics and Business Administration, Working Paper MU, 6:15.
- Strandenes, S.-P. (2002). Economics of the markets for ships. The handbook of maritime economics and business, pages 186–202.
- Sun, X., Liu, H., Zheng, S., and Chen, S. (2018). Combination hedging strategies for crude oil and dry bulk freight rates on the impacts of dynamic cross-market interaction. *Maritime Policy & Management*, 45(2):174–196.
- Taleb, N. N. (1997). Dynamic hedging: managing vanilla and exotic options, volume 64. John Wiley & Sons.
- Turnbull, S. M. and Wakeman, L. M. (1991). A quick algorithm for pricing european average options. Journal of financial and quantitative analysis, 26(3):377–389.
- Tvedt, J. (1997). Valuation of vlccs under income uncertainty. Maritime Policy and Management, 24(2):159–174.
- Tvedt, J. (1998). Valuation of a european futures option in the biffex market. *The Journal* of Futures Markets (1986-1998), 18(2):167.

- Van Deventer, D. R., Imai, K., and Mesler, M. (2013). Advanced Financial Risk Management.: Tools and Techniques for Integrated Credit Risk and Interest Rate Risk Management. John Wiley & Sons.
- Wilmott, P. (2013). Paul Wilmott on quantitative finance. John Wiley & Sons.
- Wilson, R. (2013). The principles of the dry bulk ffa market. $https://ink.library.smu.edu.sg/lkcsb_research/3571.$
- Zannetos, Z. S. (1959). *The theory of oil tankship rates.* PhD thesis, Massachusetts Institute of Technology.

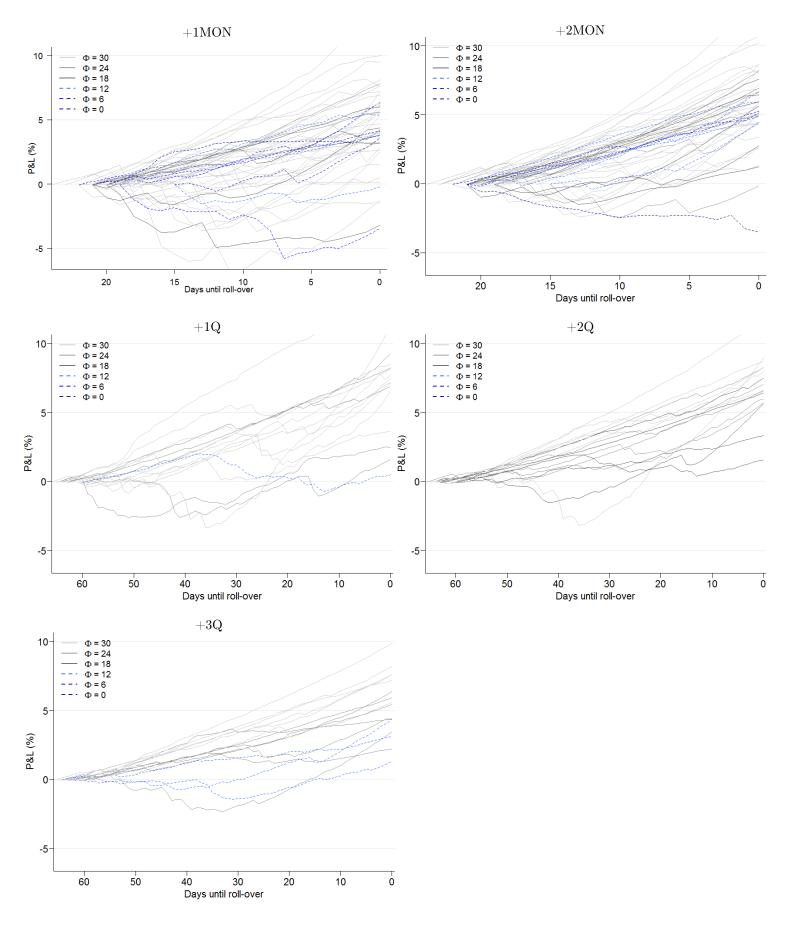
Appendix

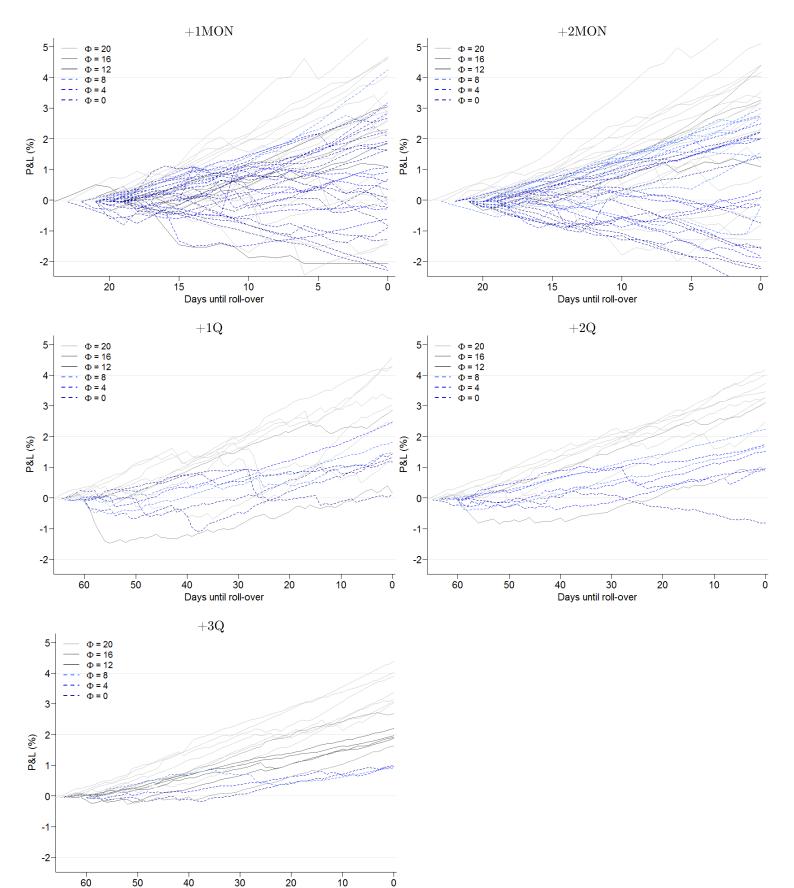
			+1M	ON			+2M	ON			+10	Ç			+20	Ç			+30	Ç	
Index	$\operatorname{Filter}(\%)$	$\mu(\%)$	$\sigma(\%)$	MDD	#																
	0	4.47	3.34	8.14	48	5.65	2.81	3.96	48	6.92	3.53	3.83	16	6.89	2.37	3.74	16	5.43	2.32	2.78	16
	6	4.51	3.41	8.14	46	5.85	2.49	3.96	47	6.92	3.53	3.83	16	6.89	2.37	3.74	16	5.43	2.32	2.78	16
C5TC	12	4.66	3.29	8.14	43	5.88	2.54	3.96	45	6.92	3.53	3.83	16	6.89	2.37	3.74	16	5.43	2.32	2.78	16
0010	18	4.79	3.31	8.14	40	5.92	2.65	3.96	41	7.35	3.19	3.83	15	6.89	2.37	3.74	16	6.01	2.10	2.78	13
	24	5.06	3.24	8.14	35	6.09	2.68	3.96	35	7.35	3.19	3.83	15	7.80	1.79	3.74	11	6.01	2.10	2.78	13
	30	4.96	3.30	8.14	33	6.34	2.63	2.73	29	8.18	2.87	3.83	10	8.73	1.79	3.74	6	7.66	1.39	0.78	6
	0	1.44	2.01	2.80	48	1.45	2.19	2.87	48	2.25	1.39	1.81	16	2.29	1.39	1.03	16	2.50	1.12	0.51	16
	4	1.91	2.01	2.80	32	1.98	1.96	2.40	38	2.66	1.34	1.81	12	2.50	1.16	0.95	15	2.60	1.08	0.51	15
P4TC	8	2.26	2.13	2.80	24	2.41	1.82	2.40	30	2.68	1.40	1.81	11	2.93	1.02	0.95	11	2.72	1.02	0.51	14
1410	12	2.13	2.17	2.80	22	2.55	2.02	2.40	22	2.91	1.46	1.81	9	3.15	1.00	0.95	9	2.86	0.91	0.37	13
	16	2.39	2.14	2.80	18	2.63	2.04	2.40	21	2.91	1.46	1.81	9	3.15	1.00	0.95	9	3.25	0.82	0.37	9
	20	2.39	2.21	2.80	17	2.50	2.10	2.40	19	3.30	1.19	1.81	7	3.48	0.57	0.56	7	3.56	0.54	0.23	7
	0	0.08	0.95	2.79	48	0.49	0.75	1.34	48	0.87	0.61	0.95	16	0.96	0.58	0.91	16	1.13	0.65	1.36	16
	2	0.15	0.95	2.79	35	0.61	0.71	1.34	35	0.88	0.63	0.95	15	0.96	0.58	0.91	16	1.13	0.65	1.36	16
S6TC	4	0.25	1.03	2.79	21	0.64	0.73	1.34	24	0.98	0.56	0.95	12	0.96	0.58	0.91	16	1.13	0.65	1.36	16
5010	6	0.39	1.07	2.79	16	0.57	0.84	1.34	17	1.23	0.48	0.49	6	0.96	0.58	0.91	16	1.13	0.65	1.36	16
	8	0.71	0.72	1.23	10	0.77	0.84	1.34	11	1.51	0.09	0.41	2	1.13	0.53	0.91	12	1.13	0.65	1.36	16
	10	0.89	0.47	0.72	7	0.89	0.93	1.34	6	1.44	-	0.15	1	1.20	0.54	0.33	8	1.32	0.52	0.27	13

$\mathbf{A1}$	Hedging	with	implied	volatility
	0 0		1	

 Table A1.1: Descriptives for delta hedging strategy with implied volatility

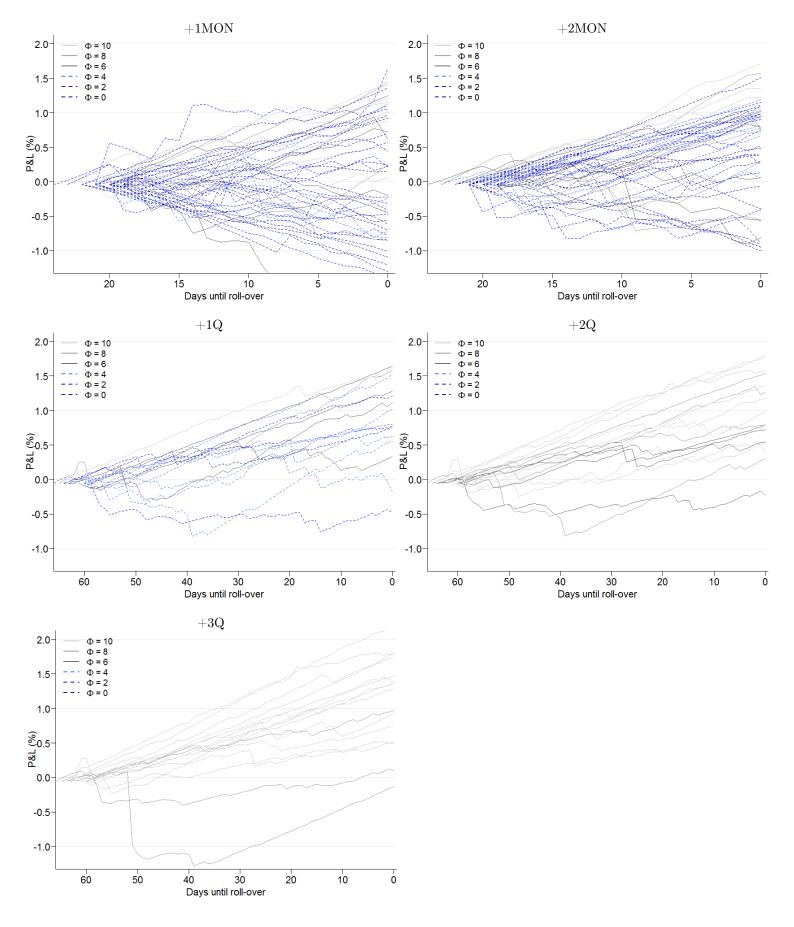
A1.1 Capesize





A1.2 Panamax

Days until roll-over

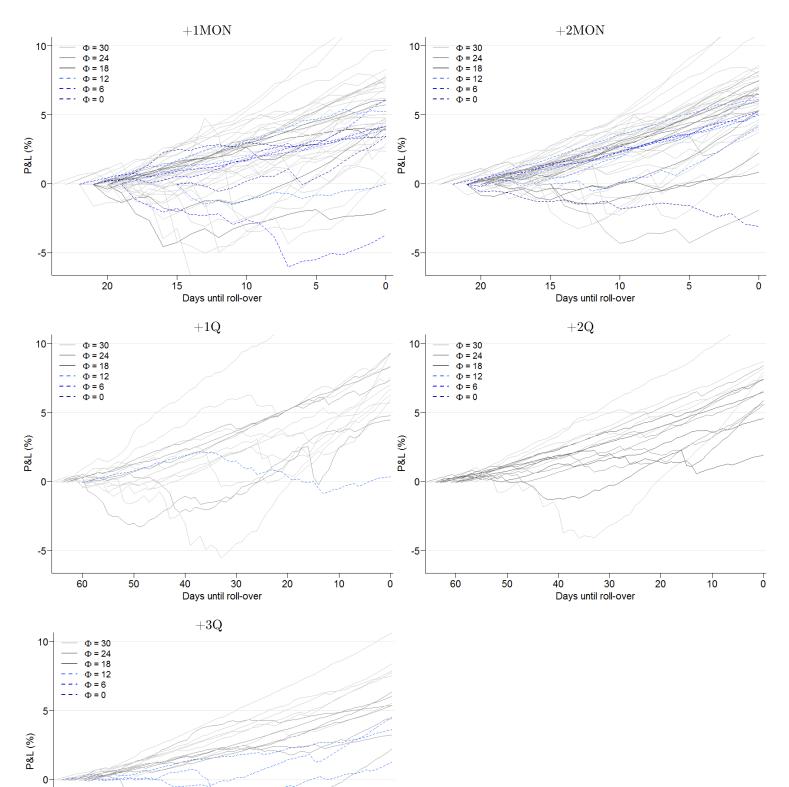


A1.3 Supramax

			+1M	ON			+2M	ON			+10	Ç			+20	Q			+30	Ç	
Index	$\mathbf{Filter}(\%)$	$\mu(\%)$	$\sigma(\%)$	MDD	#	$\mu(\%)$	$\sigma(\%)$	MDD	#	$\mu(\%)$	$\sigma(\%)$	MDD	#	$\mu(\%)$	$\sigma(\%)$	MDD	#	$\mu(\%)$	$\sigma(\%)$	MDD	#
	0	4.73	3.67	13.92	48	5.86	2.95	5.89	48	7.23	3.13	5.84	16	7.01	2.28	4.61	16	5.62	2.45	3.96	16
	6	4.79	3.75	13.92	46	6.05	2.67	5.89	47	7.23	3.13	5.84	16	7.01	2.28	4.61	16	5.62	2.45	3.96	16
C5TC	12	4.97	3.64	13.92	43	6.09	2.72	5.89	45	7.23	3.13	5.84	16	7.01	2.28	4.61	16	5.62	2.45	3.96	16
0010	18	5.12	3.68	13.92	40	6.15	2.83	5.89	41	7.69	2.63	5.84	15	7.01	2.28	4.61	16	6.19	2.26	3.96	13
	24	5.38	3.73	13.92	35	6.39	2.83	5.89	35	7.69	2.63	5.84	15	7.81	1.92	4.61	11	6.19	2.26	3.96	13
	30	5.30	3.82	13.92	33	6.75	2.60	4.88	29	8.12	2.85	5.84	10	8.74	1.96	4.61	6	7.94	1.64	0.44	6
	0	1.50	1.96	2.93	48	1.48	2.18	3.32	48	2.33	1.47	1.55	16	2.32	1.45	1.07	16	2.58	1.15	0.44	16
	4	1.99	1.92	2.93	32	2.02	1.93	3.32	38	2.78	1.39	1.55	12	2.53	1.21	0.81	15	2.69	1.11	0.44	15
P4TC	8	2.36	2.01	2.93	24	2.45	1.77	3.32	30	2.81	1.46	1.55	11	2.96	1.10	0.81	11	2.80	1.06	0.44	14
1410	12	2.23	2.05	2.93	22	2.61	1.96	3.32	22	3.08	1.48	1.55	9	3.19	1.08	0.81	9	2.94	0.95	0.36	13
	16	2.44	2.13	2.93	18	2.69	1.97	3.32	21	3.08	1.48	1.55	9	3.19	1.08	0.81	9	3.35	0.86	0.36	9
	20	2.45	2.19	2.93	17	2.57	2.04	3.32	19	3.51	1.21	1.55	7	3.53	0.74	0.75	7	3.64	0.68	0.36	7
	0	0.10	0.96	2.81	48	0.50	0.75	1.41	48	0.88	0.61	0.98	16	0.98	0.57	0.97	16	1.16	0.64	1.43	16
	2	0.17	0.96	2.81	35	0.63	0.70	1.41	35	0.89	0.63	0.98	15	0.98	0.57	0.97	16	1.16	0.64	1.43	16
S6TC	4	0.27	1.05	2.81	21	0.66	0.73	1.41	24	0.98	0.57	0.98	12	0.98	0.57	0.97	16	1.16	0.64	1.43	16
5010	6	0.42	1.10	2.81	16	0.61	0.83	1.41	17	1.25	0.48	0.51	6	0.98	0.57	0.97	16	1.16	0.64	1.43	16
	8	0.75	0.74	1.28	10	0.81	0.84	1.41	11	1.56	0.14	0.31	2	1.14	0.53	0.97	12	1.16	0.64	1.43	16
	10	0.97	0.41	0.60	7	0.89	0.98	1.41	6	1.46	-	0.16	1	1.22	0.53	0.28	8	1.35	0.48	0.30	13

A2	Hedging	with	historical	volatility
----	---------	------	------------	------------

 Table A2.1: Descriptives for delta hedging strategy with historical volatility



Ó

10

20

Capesize A2.1

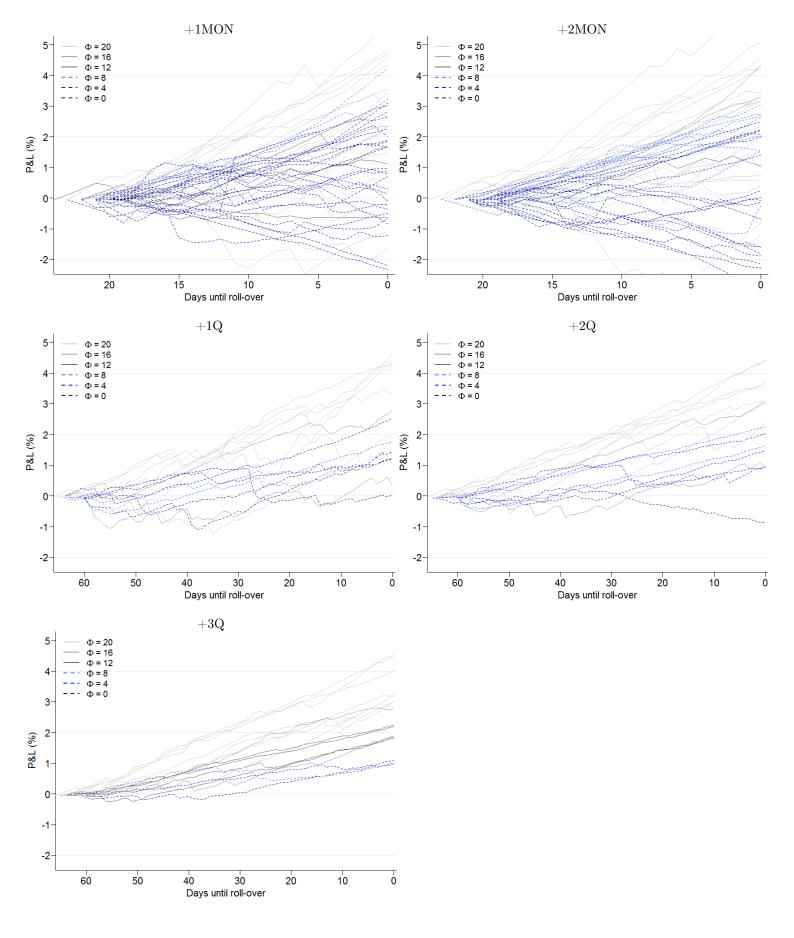
-5

60

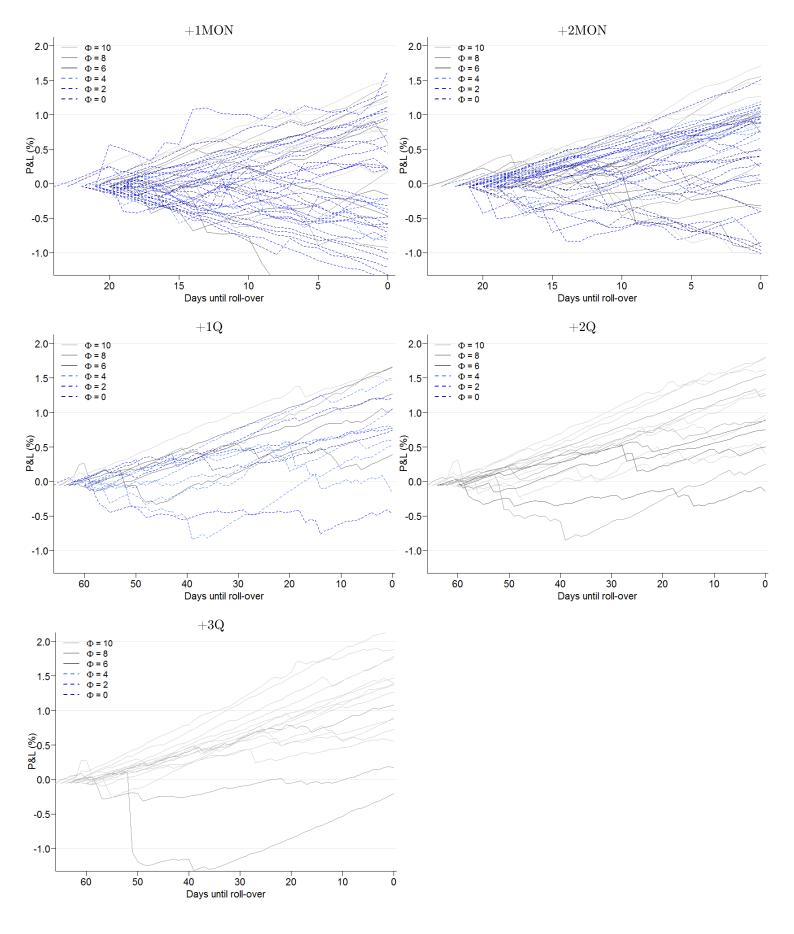
50

40

30 Days until roll-over



A2.2 Panamax



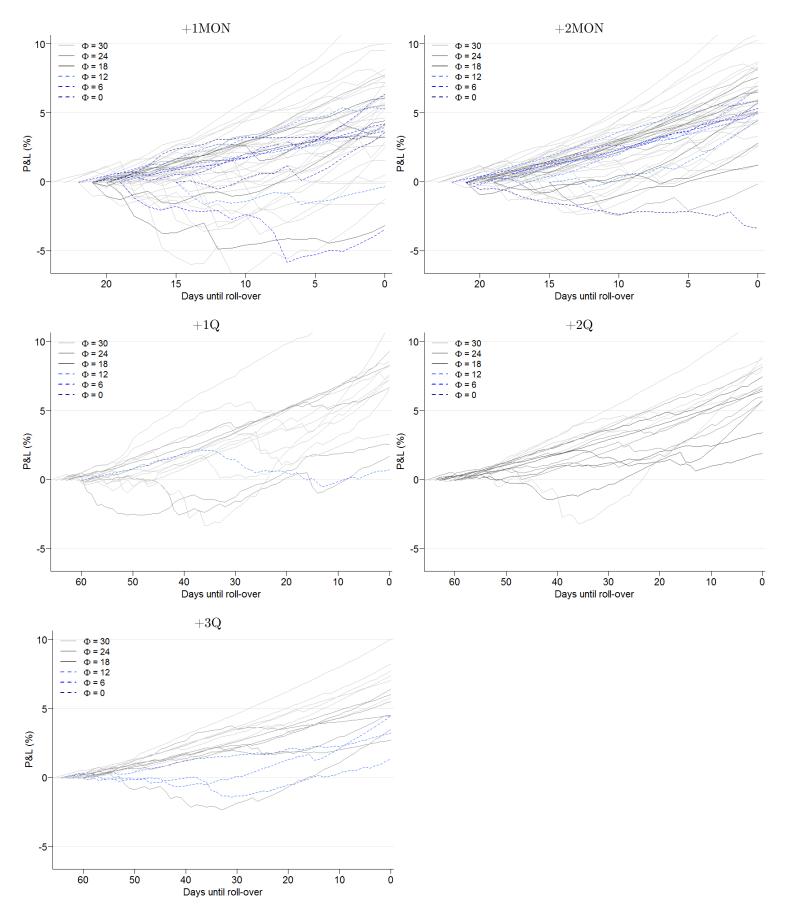
A2.3 Supramax

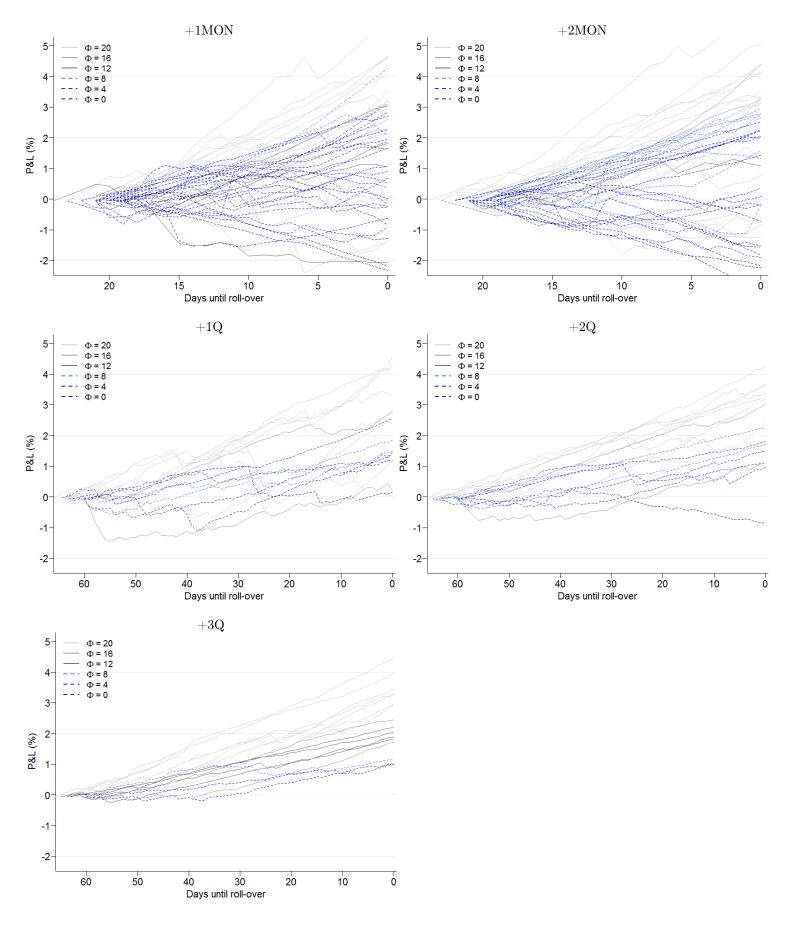
A3	Hedging	with	modified	delta
----	---------	------	----------	-------

			+1M	ON			+2M	ON			+10	Ç			+20	Q			+30	Q	
Index	$\operatorname{Filter}(\%)$	$\mu(\%)$	$\sigma(\%)$	MDD	#																
	0	4.47	3.36	8.13	48	5.67	2.82	3.95	48	6.93	3.53	3.82	16	6.92	2.33	3.76	16	5.51	2.27	2.77	16
	6	4.51	3.43	8.13	46	5.86	2.51	3.95	47	6.93	3.53	3.82	16	6.92	2.33	3.76	16	5.51	2.27	2.77	16
C5TC	12	4.66	3.31	8.13	43	5.89	2.56	3.95	45	6.93	3.53	3.82	16	6.92	2.33	3.76	16	5.51	2.27	2.77	16
0310	18	4.79	3.33	8.13	40	5.93	2.66	3.95	41	7.34	3.22	3.82	15	6.92	2.33	3.76	16	6.09	2.03	2.77	13
	24	5.06	3.26	8.13	35	6.10	2.70	3.95	35	7.34	3.22	3.82	15	7.81	1.81	3.76	11	6.09	2.03	2.77	13
	30	4.96	3.33	8.13	30	6.34	2.65	2.76	29	8.17	2.95	3.82	10	8.78	1.82	3.76	6	7.80	1.40	0.61	6
	0	1.44	2.02	2.81	48	1.45	2.19	2.87	48	2.23	1.37	1.96	16	2.26	1.34	1.06	16	2.48	1.04	0.32	16
	4	1.90	2.01	2.81	32	1.98	1.96	2.38	38	2.63	1.33	1.96	12	2.47	1.09	0.88	15	2.57	1.00	0.32	15
P4TC	8	2.26	2.13	2.81	24	2.40	1.82	2.38	30	2.64	1.39	1.96	11	2.88	0.97	0.88	11	2.69	0.94	0.32	14
1410	12	2.12	2.17	2.81	22	2.55	2.03	2.38	22	2.85	1.46	1.96	9	3.08	0.96	0.88	9	2.80	0.86	0.28	13
	16	2.38	2.14	2.81	18	2.62	2.05	2.38	21	2.85	1.46	1.96	9	3.08	0.96	0.88	9	3.16	0.80	0.28	9
	20	2.38	2.21	2.81	17	2.49	2.11	2.38	19	3.24	1.23	1.96	7	3.39	0.57	0.47	7	3.47	0.55	0.24	7
	0	0.08	0.95	2.79	48	0.48	0.75	1.33	48	0.85	0.61	0.95	16	0.93	0.56	0.92	16	1.10	0.62	1.35	16
	2	0.15	0.95	2.79	35	0.61	0.71	1.33	35	0.85	0.63	0.95	15	0.93	0.56	0.92	16	1.10	0.62	1.35	16
S6TC	4	0.24	1.03	2.79	21	0.63	0.74	1.33	24	0.96	0.57	0.95	12	0.93	0.56	0.92	16	1.10	0.62	1.35	16
5010	6	0.38	1.08	2.79	16	0.56	0.84	1.33	17	1.19	0.54	0.55	6	0.93	0.56	0.92	16	1.10	0.62	1.35	16
	8	0.70	0.72	1.23	10	0.75	0.86	1.33	11	1.47	0.18	0.39	2	1.07	0.52	0.92	12	1.10	0.62	1.35	16
	10	0.88	0.47	0.72	7	0.88	0.92	1.33	6	1.34	-	0.11	1	1.17	0.48	0.31	8	1.31	0.45	0.32	13

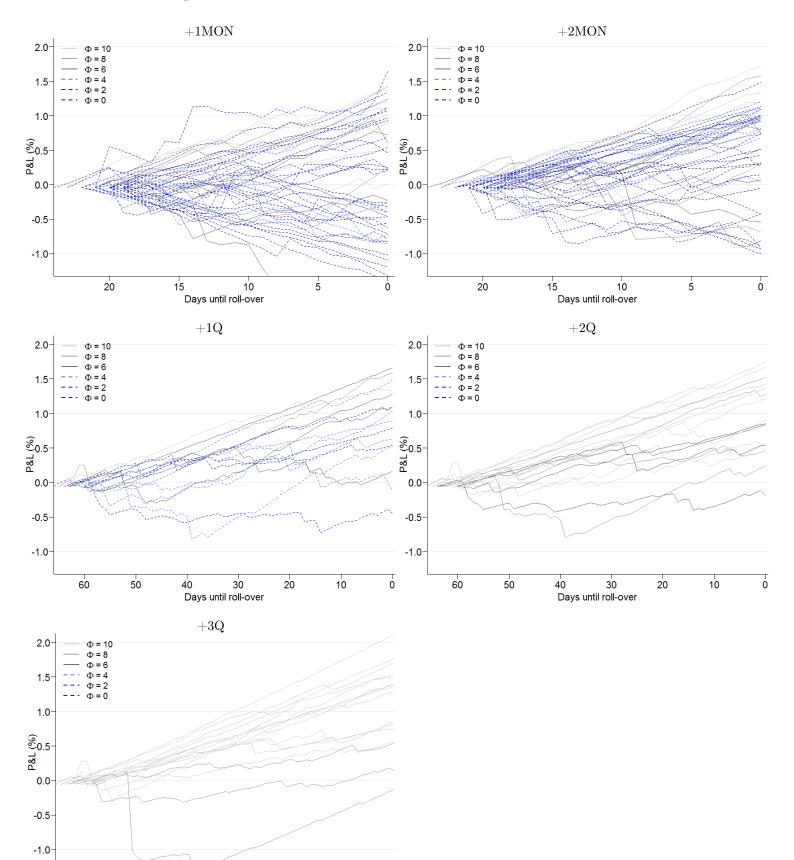
 Table A3.1: Descriptives for modified delta hedging strategy







A3.2 Panamax



A3.3 Supramax

60

50

40

30 Days until roll-over 20

10

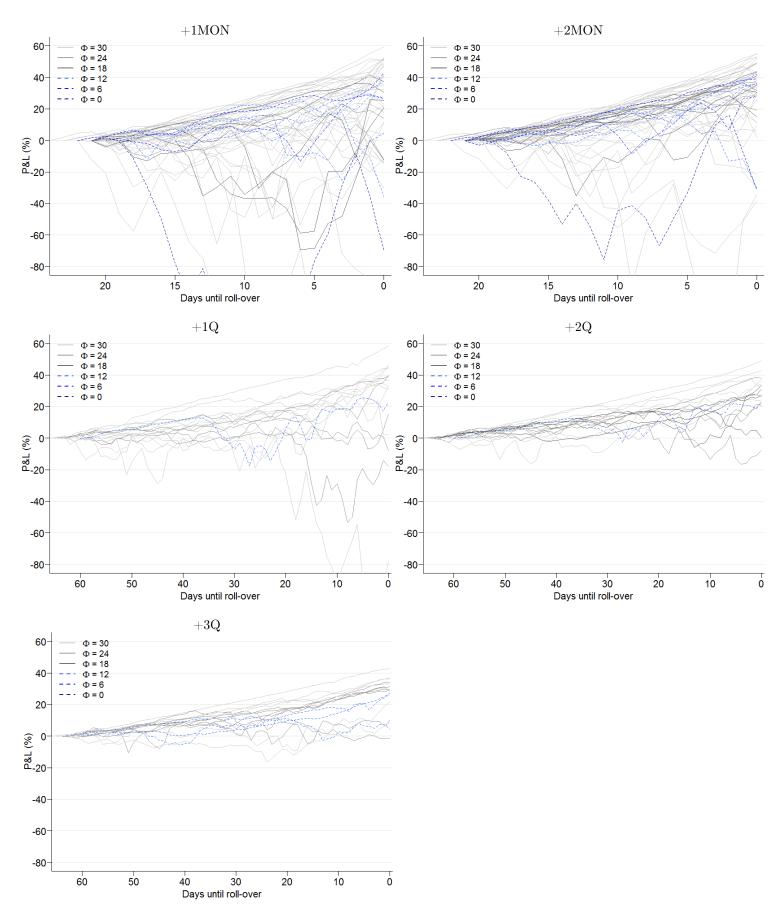
ò

A4 Hold Straddle

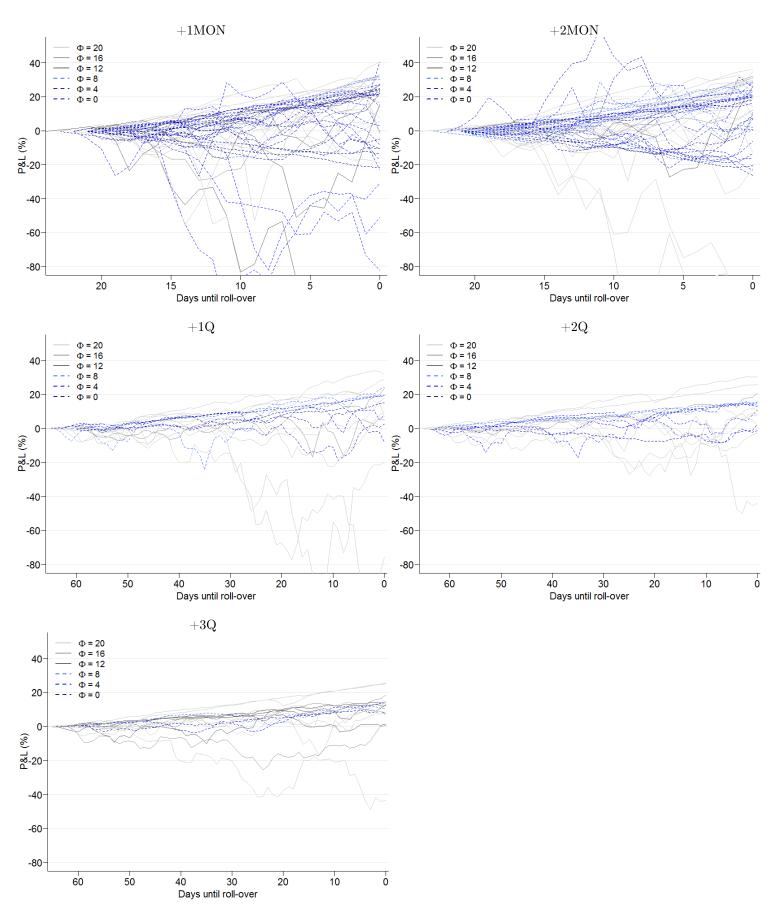
			+1M	ON			+2M	ON			+10	Ç			+20	Ç			+30	Q	
Index	$\mathbf{Filter}(\%)$	$\mu(\%)$	$\sigma(\%)$	MDD	#	$\mu(\%)$	$\sigma(\%)$	MDD	#	$\mu(\%)$	$\sigma(\%)$	MDD	#	$\mu(\%)$	$\sigma(\%)$	MDD	#	$\mu(\%)$	$\sigma(\%)$	MDD	#
	0	14.23	42.24	231.49	48	26.21	25.26	139.56	48	21.30	33.61	129.56	16	27.07	14.35	28.19	16	24.87	12.84	18.97	16
	6	16.02	40.83	231.49	47	27.43	24.06	139.56	47	21.30	33.61	129.56	16	27.07	14.35	28.19	16	24.87	12.84	18.97	16
C5TC	12	15.19	41.51	231.49	45	27.16	24.54	139.56	45	21.30	33.61	129.56	16	27.07	14.35	28.19	16	24.87	12.84	18.97	16
0310	18	15.82	42.57	231.49	41	27.78	23.88	139.56	41	21.20	34.78	129.56	15	27.35	14.80	28.19	15	26.17	12.97	18.97	13
	24	15.22	45.00	231.49	36	26.92	25.50	139.56	35	21.20	34.78	129.56	15	28.97	15.07	28.19	11	26.17	12.97	18.97	13
	30	16.06	46.09	231.49	34	25.36	27.46	139.56	29	24.95	39.07	129.56	10	36.44	8.81	18.19	11	29.93	12.53	16.62	6
	0	2.20	42.87	189.53	48	7.25	34.71	166.15	48	6.74	25.72	131.04	16	8.00	16.64	50.95	16	8.38	15.45	49.51	16
	4	-0.70	49.16	189.53	34	8.37	38.13	166.15	38	7.57	28.30	131.04	13	8.39	17.15	50.95	15	8.43	16.00	49.51	15
P4TC	8	4.98	54.13	189.53	24	8.74	41.81	166.15	30	6.45	30.78	131.04	11	6.47	19.85	50.95	11	8.09	16.54	49.51	14
1410	12	2.59	56.01	189.53	22	6.12	48.50	166.15	22	3.06	33.30	131.04	9	6.47	21.85	50.95	9	7.89	17.20	49.51	13
	16	7.40	50.79	189.53	18	5.17	49.48	166.15	21	3.06	33.30	131.04	9	6.47	21.85	50.95	9	6.90	20.65	49.51	9
	20	6.20	52.09	189.53	17	3.01	51.62	166.15	19	-0.094	37.38	131.04	7	4.70	22.66	50.95	8	6.17	23.21	49.51	7
	0	-6.63	29.44	124.51	48	-3.97	28.23	132.76	48	-2.46	23.92	91.97	16	1.70	16.85	70.24	16	2.99	16.01	60.88	16
	2	-9.45	28.07	124.51	3	-2.94	30.01	132.76	35	-2.53	24.76	91.97	15	1.70	16.85	70.24	16	2.99	16.01	60.88	16
S6TC	4	-8.07	24.50	73.71	21	-7.79	35.74	132.76	23	2.84	17.67	86.37	12	1.70	16.85	70.24	16	2.99	16.01	60.88	16
5010	6	-8.83	26.97	73.71	15	-10.35	40.91	132.76	17	0.57	21.88	86.37	7	1.70	16.85	70.24	16	2.99	16.01	60.88	16
	8	-7.62	28.19	73.71	12	-8.68	42.73	132.76	11	3.43	4.76	27.45	2	1.12	17.91	70.24	14	2.99	16.01	60.88	16
	10	-16.18	34.41	73.71	7	4.63	14.39	29.08	7	0.06	-	27.45	1	4.80	6.11	26.14	8	6.42	6.09	30.97	13

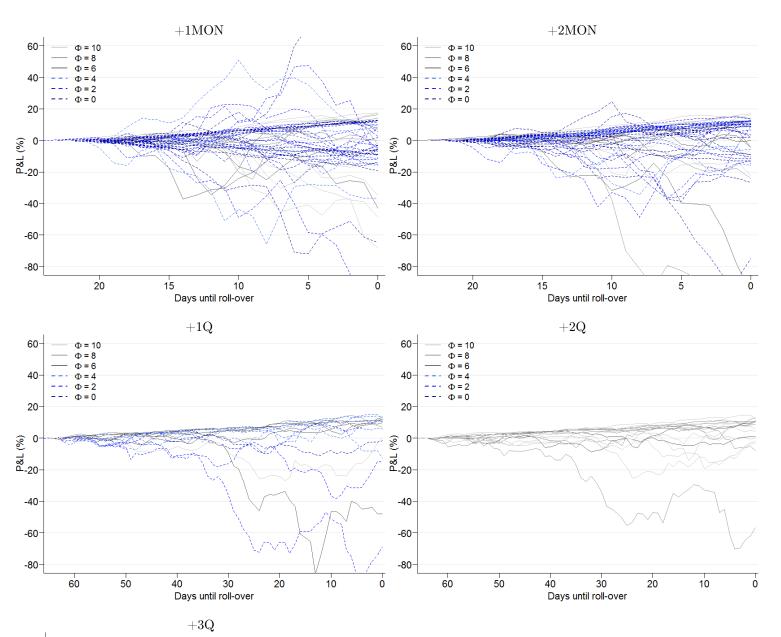
 Table A4.1: Descriptives for holding a straddle

A4.1 Capesize

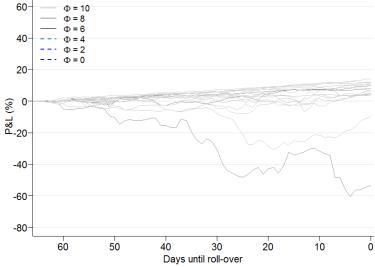


A4.2 Panamax





A4.3 Supramax

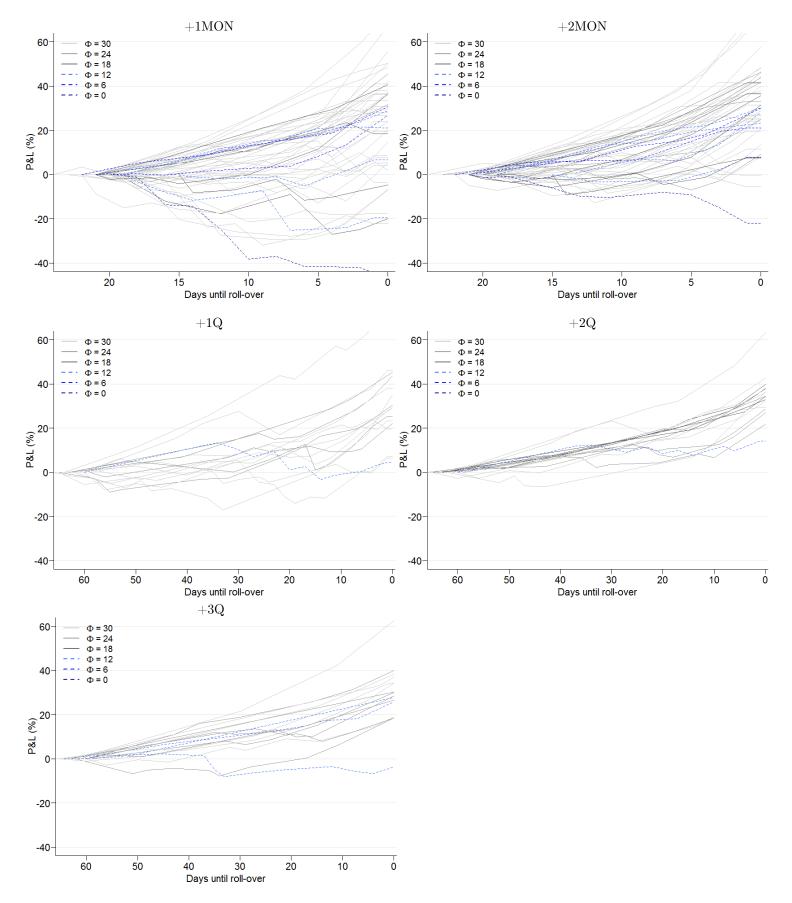


A5 Adjusting Straddle

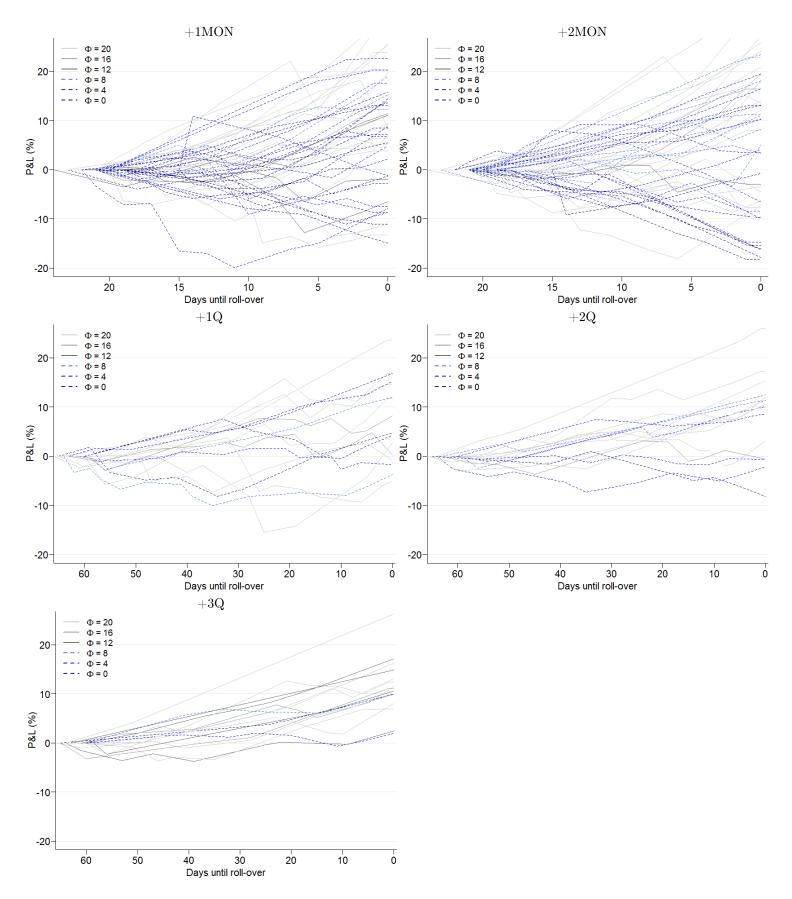
			+1M	ON			+2M	ON			+10	Ç			+20	Q			+30	\mathbf{Q}	
Index	Filter(%)	$\mu(\%)$	$\sigma(\%)$	MDD	#	$\mu(\%)$	$\sigma(\%)$	MDD	#												
	0	21.51	24.58	47.24	48	30.27	19.39	21.98	48	30.14	18.09	19.21	16	34.27	10.47	6.58	16	29.15	13.84	10.43	16
	6	22.98	22.65	33.40	47	31.38	17.99	14.45	47	30.14	18.09	19.21	16	34.27	10.47	6.58	16	29.15	13.84	10.43	16
C5TC	12	22.73	23.12	33.40	45	31.64	18.32	14.45	45	30.14	18.09	19.21	16	34.27	10.47	6.58	16	29.15	13.84	10.43	16
0310	18	24.04	23.11	33.40	41	32.56	18.76	14.45	41	31.84	17.33	19.21	15	35.61	9.31	6.58	15	32.05	11.77	7.77	13
	24	25.43	22.72	33.40	36	33.57	19.32	14.45	35	31.84	17.33	19.21	15	35.39	10.86	6.58	11	32.05	11.77	7.77	13
	30	24.66	23.10	33.40	34	33.65	20.42	14.45	29	31.11	20.38	19.21	10	39.99	12.17	6.58	6	37.49	14.12	2.98	6
	0	8.05	11.87	19.92	48	6.22	14.48	18.33	48	7.47	8.60	15.54	16	8.52	8.44	9.13	16	11.43	5.80	3.73	16
	4	10.34	11.96	19.92	34	10.04	12.51	18.12	38	7.34	9.27	15.54	13	9.63	7.42	7.35	15	11.52	5.99	3.73	15
P4TC	8	11.49	12.15	19.92	24	11.77	12.25	18.12	30	7.31	9.28	15.54	11	11.71	6.91	6.90	11	12.21	5.57	3.73	14
1410	12	10.98	12.57	19.92	22	11.95	12.25	18.12	22	8.02	9.44	15.54	9	11.66	7.72	6.90	9	12.38	5.76	3.73	13
	16	12.65	12.82	19.92	18	12.66	13.80	18.12	21	8.02	9.44	15.54	9	11.66	7.72	6.90	9	12.86	5.75	3.64	9
	20	12.67	13.21	19.92	17	12.10	14.42	18.12	19	9.11	10.36	15.54	7	13.19	6.64	6.90	8	13.52	6.46	3.64	7
	0	-0.12	7.07	20.24	48	2.57	6.50	14.21	48	1.92	7.35	11.77	16	1.89	6.77	11.74	16	5.66	5.68	10.17	16
	2	0.79	7.18	20.24	34	3.14	6.88	14.21	35	1.41	7.30	11.77	15	1.89	6.77	11.74	16	5.66	5.68	10.17	16
S6TC	4	0.76	7.66	20.24	21	2.76	6.49	14.00	23	3.57	6.28	9.39	12	1.89	6.77	11.74	16	5.66	5.68	10.17	16
5010	6	1.71	8.01	20.24	15	2.87	5.68	9.19	17	4.14	7.34	9.39	7	1.89	6.77	11.74	16	5.66	5.68	10.17	16
	8	4.22	4.43	5.78	12	4.40	5.65	9.19	11	7.65	4.95	2.62	2	2.40	6.69	11.74	14	5.66	5.68	10.17	16
	10	4.47	3.58	5.66	7	4.09	4.49	9.19	7	4.15	-	2.36	1	2.77	6.23	9.58	8	7.82	3.24	2.11	13

Table A5.1:Descriptives for buy/sell straddle strategy

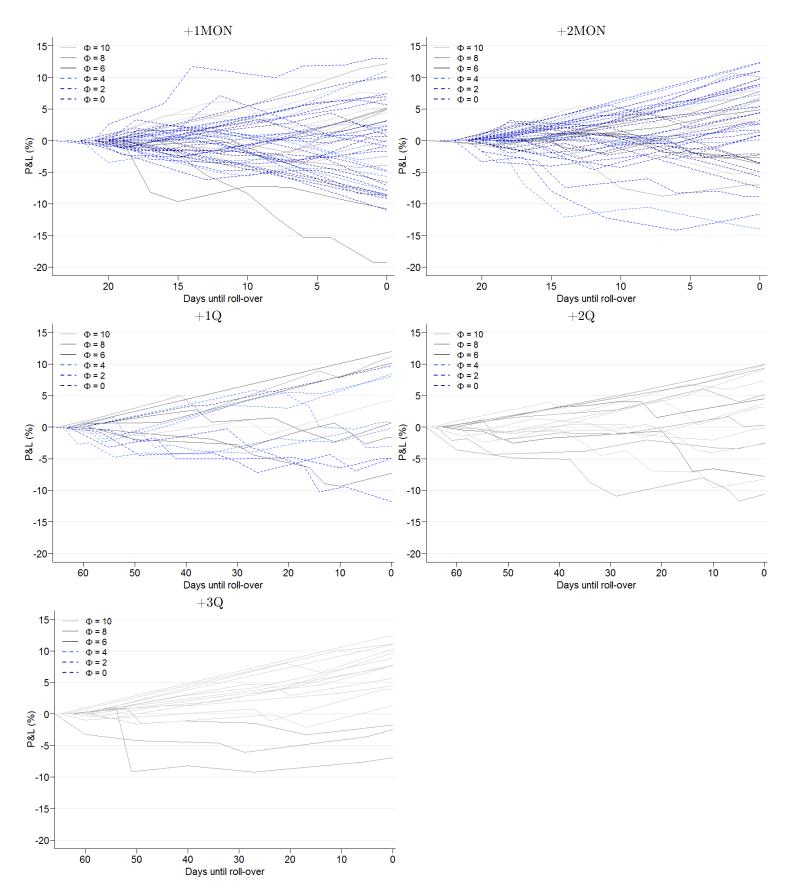




A5.2 Panamax



A5.3 Supramax

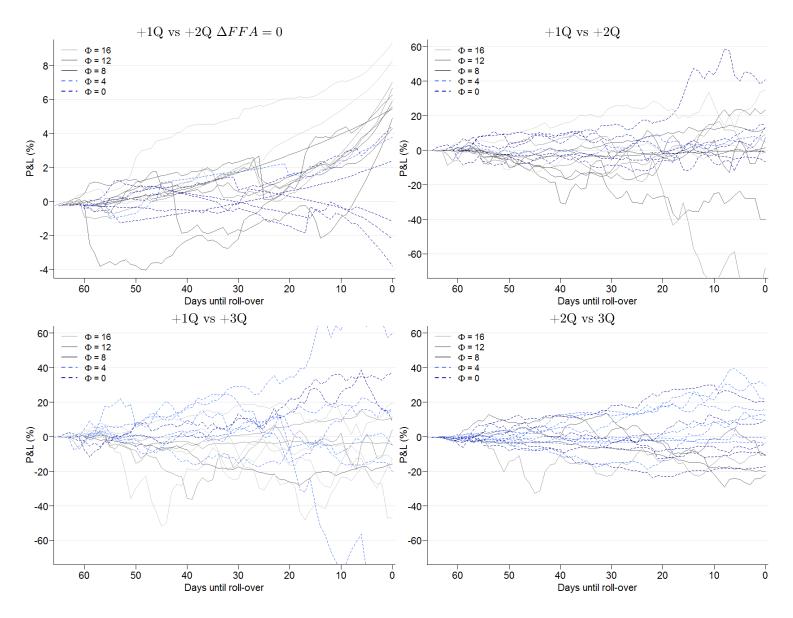


A6 Time Spread

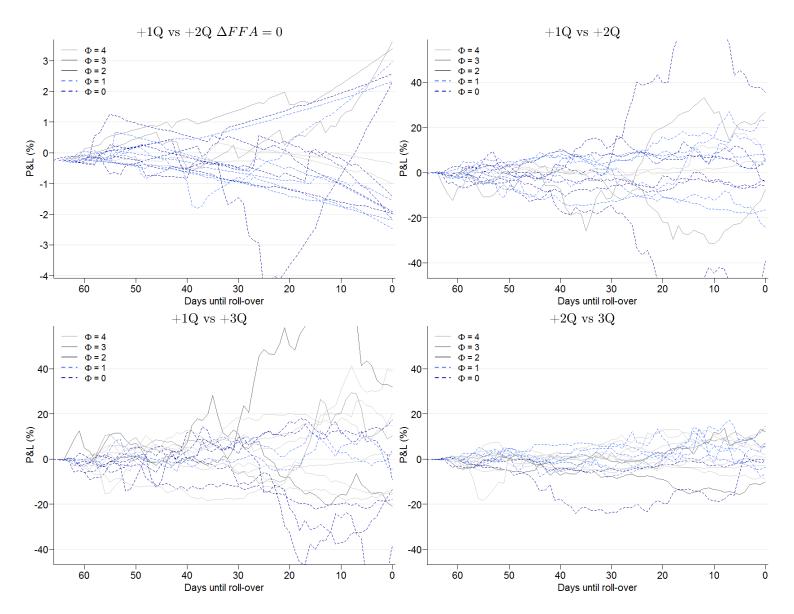
			ΔFFA	= 0		-	+1Q vs	$+2\mathbf{Q}$		-	+2Q vs	$+3\mathbf{Q}$		-	+1Q vs	+3Q	
Index	$\operatorname{Filter}(\%)$	$\mu(\%)$	$\sigma(\%)$	MDD	#	$\mu(\%)$	$\sigma(\%)$	MDD	#	$\mu(\%)$	$\sigma(\%)$	MDD	#	$\mu(\%)$	$\sigma(\%)$	MDD	#
	0	4.19	3.70	5.06	16	2.79	26.31	101.94	16	1.20	16.19	41.84	16	-1.33	31.38	121.42	16
	4	6.12	1.65	4.19	11	-1.59	28.90	101.94	11	1.94	17.15	41.84	11	-4.75	31.71	121.42	12
C5TC	8	6.36	1.65	4.19	10	-2.22	30.39	101.94	10	-15.83	6.17	41.84	9	-7.32	20.35	53.71	8
	12	7.80	1.22	2.27	4	-6.39	44.04	101.94	4	-10.58	-	34.89	1	-6.10	21.67	53.71	7
	16	8.79	0.74	0.83	2	16.80	25.98	20.91	2	-	-	-	0	-13.40	27.01	53.71	4
	0	0.01	2.36	4.87	16	1.52	18.84	60.95	16	2.01	7.62	25.01	16	0.20	20.90	70.38	16
	1	0.27	2.50	2.68	10	3.58	16.05	36.45	10	2.44	8.08	18.11	13	5.94	19.49	70.38	11
P4TC	2	1.41	2.43	1.34	4	9.12	14.37	36.45	4	1.96	8.30	18.11	11	7.42	21.42	70.38	9
	3	1.41	2.43	1.34	4	9.12	14.37	36.45	4	2.27	7.06	18.11	9	7.82	19.40	21.60	7
	4	-0.68	0.47	1.34	2	8.68	5.03	5.30	2	1.48	7.38	18.11	9	7.42	21.22	18.56	6
	0	-0.96	0.51	1.78	16	4.16	16.86	32.61	16	3.28	13.48	21.96	16	7.76	24.22	35.62	16
	1.5	-0.96	0.51	1.78	16	4.16	16.86	32.61	16	-0.87	8.41	21.96	12	7.76	24.22	35.62	16
S6TC	3	-0.91	0.55	1.78	11	5.90	20.02	32.61	11	-1.15	7.95	15.32	6	7.76	24.22	35.62	16
2010	4.5	-0.73	0.40	1.11	6	6.56	10.83	20.26	6	-	-	-	0	5.28	22.87	35.62	15
	6	-0.52	0.29	1.00	4	5.15	13.02	16.24	4	-	-	-	0	5.49	24.43	35.62	11

	Table A6.1:	Descriptives	time spread	strategy
--	-------------	--------------	-------------	----------

A6.1 Capesize



A6.2 Panamax



A6.3 Supramax

