Historical Distribution, Volatility and Value-at-Risk in the Tanker Shipping Market

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ABSTRACT

The shipping market is characterised as a risky market, which makes it even more important to get a deeper understanding of the risks and its dynamics. We have examined freight rates for the five most popular tanker routes, using price data for January 2004 to January 2012. The historical distributions reveal fat tails and high peaks for all freight rates when compared to a Gaussian distribution and the right tails appear to be heavier than the left tails. Indicating higher historical tail risk for producers compared with shipowners. The volatility analysis reveals stochastic volatility and high volatility levels. The dirty routes appear more volatile than the clean routes, which also are supported by the Value-at-Risk results. The VaR results show considerable fright rate risk for all the routes and also indicate that the distribution of the returns and the volatility should be carefully considered when choosing VaR method.

ACKNOWLEDGEMENTS

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1 INTRODUCTION

Fat tailed distributions are one of the most important topics in financial economics. According to Haug (2007b) it is not surprising if the most ground breaking discoveries in financial economics in the future are concerning fat tails. However, the assumption of normally distributed returns is still a common assumption because of the simplicity that follows (Bodie, Kane and Marcus 2009). In risk management and nearly all aspects of the investment process it is important to know the actual distribution of the assets, and it is a key part of derivatives valuation and consequently hedging. Another common assumption in several financial models is that the volatility is constant. In reality this assumption usually does not hold because the volatility is often time-varying or stochastic (Hull 2012). It is hard to implement rational risk managing techniques if you do not know the risks involved. Understanding the risks and their dynamics is therefore important for the constructions of portfolios and asset allocations, pricing and trading of derivatives and Value-at-Risk estimation. Hence, the measurement and quantification of risks is one of the most essential steps of risk management (Alizadeh and Nomikos 2009). It is therefore critical to get a deeper understanding of the volatility and the distribution of an asset.

The shipping industry is characterised by highly volatile prices, seasonality, strong business cycles and capital intensiveness, and taking part in the shipping industry might be very expensive (Alizadeh and Nomikos 2009).

“A ship is always referred to as "she" because it costs
so much to keep one in paint and powder”
- Chester W. Nimitz

Several different factors, such as fluctuations in freight rates, bunker prices, interest rates and exchange rates might have a severe impact on the profitability and viability of a shipping company or a shipowner. Actors in the tanker market have also claimed that the volatility in the tanker market has decreased the last couple of years. However, we found no research regarding this issue.

1.1 Objectives

In order to illuminate the risks in the tanker freight rates we will:

1. Study the historical distribution for freight rates in the shipping tanker market
2. Examine the freight rate volatility in the shipping tanker market
3. Quantify freight rate risk and illuminate problems attached to assumptions concerning distribution and volatility using Value-at-Risk.

The shipping tanker market contains many different routes. We have chosen to focus on the five most liquid tanker routes traded at Marex Spectron. The tanker market is divided in to clean and dirty routes. Clean tankers carry refined oil products, while dirty tankers transport black oil products mainly crude oil. The routes are described in Table 1.

Route Description				
	Name	**Freight route**	**Vessel**	**Size**
Clean	TC2	Continent - USAC	MR	37,000 mt
	TC5	Arabian Gulf - Japan	LR	55,000 mt
Dirty	TD3	Arabian Gulf - East	VLCC	260,000 mt
	TD5	West Africa - USAC	Suezmax	130,000 mt
	TD7	North Sea - Continent	Aframax	80,000 mt

Table 1: *Specifications of the tanker routes analysed in this thesis.*

1.2 Review of recent literature on the topic

Kavussanos and Dimitrakopoulos (2011) have used data from the period from 1998 to 2006 to investigate the shipping tanker market, focusing on the four most liquid dirty routes (TD3, TD5, TD7 and TD9) and two Baltic indices (BDTI and BCTI). They have characterised the distributions of the indices and routes and examined the volatility and several Value-at-Risk methods. The results indicate the presence of fat tails in the distributions and the assumption of normality is rejected. They also find that simpler risk measurement methods should be selected in preference to more complex methods for freight rates. Furthermore, a study by Angelidis and Skiadopoulos (2008) explored the performance of different types of VaR estimation techniques of various popular freight markets for dry and wet cargoes. They find that the simplest non-parametric methods are best suited for freight rate risk estimation.

This thesis contributes to the literature with illustrations and characteristics of the distributions and examines the volatility of the tanker freight rates for a more recent time period compared to existing research. We will also provide a quantified measure of the risk in the freight rates and illuminate the risks surrounding the distributions and the volatility.

1.3 Line of action

In order to answer the objectives we have chosen to structure our thesis accordingly.

Chapter two provides a general overview of the shipping tanker market. This chapter intends to give a brief introduction to readers not familiar with the market and its basic dynamics. We briefly explain some of the most important contracts in the shipping market, before a more thorough discussion about the derivatives market follows. This thesis will have its focus on the derivatives market. Further on, the chapter describes the supply and demand dynamics of the freight rates, and the key risks in the shipping market.

Chapter three contains a presentation of relevant theory. Firstly we use the risk management to argue why it is important to have a thorough understanding of risks. The chapter continues with a presentation of distribution theory and explain methods used to detect abnormal distributions. The following part contains a presentation of time-varying volatility models; GARCH (1.1) and EWMA, and a description of Rolling Window volatility. Finally we discuss Value-at-Risk and Value-at-Risk estimations with three different methods; Model Building Approach, Historical Simulation and Filtered Historical Simulation.

Chapter four start with a description of our data and continues with a discussion on splicing of futures contracts. We end the chapter by explaining the inputs in the analysis.

Chapter five contains the results and a discussion of them. We start with a brief introduction of the routes and its historical price changes. The chapter continues with an analysis of the historical distributions and the volatility for each route separately. The chapter ends with a presentation and discussion of the Value-at-Risk results.

Chapter six is the conclusion of this thesis.

2 THE TANKER MARKET

The tanker market is also known as liquid bulk or wet-bulk. The main commodities transported by tanker vessels are crude oil and petroleum products, which accounts for one third of all world seaborne trade by volume (Hoffman, Rubiato and Miroux 2011). There are two categories of tankers, clean and dirty. The clean tankers carry clean oil products such as gasoline, diesel fuel and jet fuel while the dirty tankers carry crude oil and black products. Tanker freight rates are closely linked to the world trade demand, and petroleum is used in a vast amount of manufactured products[1]. Alterations in supply and demand for petroleum products and these manufactured goods might cause tanker freight rates to fluctuate wildly and abruptly (Stopford 2009).

The number of operating tankers is also a factor affecting the freight rates. In 2011 there were 611 new tankers of various types to be delivered over the next three years, totalling 105 million dwt[2] and representing 27.5 per cent of the existing fleet (Hoffman et al. 2011). Tanker vessel size varies from a few thousand tons to half a million tons in the case of crude oil. Table 2 explains the vessels in the tanker market.

The tanker shipping market		
Vessel type	**Ship size (dwt)**	**Approximate speed (knots)**
Handysize (MR)	20 000 - 45 000	14 - 16
Panamax (LR)	50 000 - 70 000	14 - 16
Aframax	70 000 - 120 000	13 - 15
Suezmax	130 000 - 160 000	12 - 14
VLCC - ULCC	160 000 - 500 000	12 - 14

Table 2 *Vessel classes within the tanker shipping market.*

2.1 Seasonality and cyclicality

It is a known fact that the shipping market is highly influenced by seasonality in traded commodities. Seasonality is often divided in to short-term and long-term (Stopford 2009). Short-term seasonality in the tanker market is affected by seasonal energy consumption in the main energy markets which often implies that the tanker freight rates preform best during the first and last three months of a year, better

[1] Up to 70000 different products, e.g. medicines, synthetics, fabrics, fertilizers, paint and varnishes, acrylics, plastics and cosmetics

[2] dwt = deadweight ton, and refers to the maximum weight a ship can carry when loaded to its marks, including cargo, fuel, fresh water, stores and crew.

known as “the cold seasons” (Alizadeh and Nomikos 2009). Consequently there are to some extent predictable price fluctuations in the tanker shipping market.

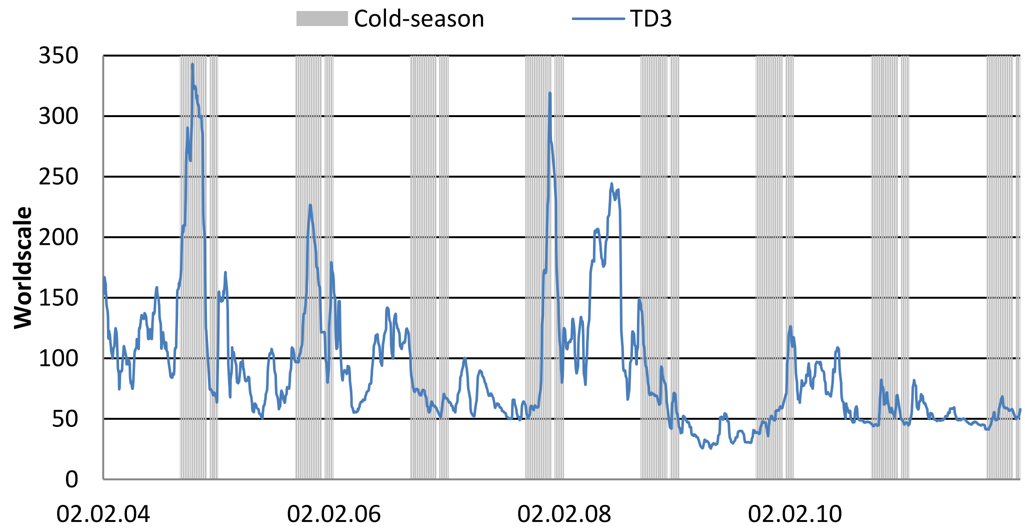


Figure 1 *TD3 spot and the cold seasons from 02.02.2004 to 17.01.2012.*

The short-term seasonality is illustrated in Figure 1, which especially shows the tendency from 2004 to 2008. However, in the years following the financial crisis there are peaks in the cold-seasons, though less significant. The years prior to 2008 were characterised by periods of high demand while the supply capacity was limited. This led to an increased order income for the shipyards. When the financial crises in 2008 occurred, the demand dropped and at the same time a large number of tankers started to be delivered to the market. This led to an overcapacity in the tanker market and caused lower peaks in the cold seasons after 2008[3].

Long-term seasonality trends are best investigated by studying the economic characteristics of the industries which produce and consume the traded commodities (Stopford 2009). Furthermore, long-term seasonality can also be studied by looking at some macroeconomic factors for major economies, which have been proven to be highly seasonal[4] (Alizadeh and Nomikos 2009). Research has found it tends to be four to seven years cycles in the shipping market (Stopford 2009, Alizadeh and Nomikos 2009).

[3] Confirmed by Mr. Andereas Holst Thorsen, Frontline Ltd

[4] A time series, measured more than once a year (at monthly, quarterly or semi-annual intervals, for example) is said to contain a seasonal component when there are systematic patterns in the series at the measured points (seasons) within the year (Alizadeh and Nomikos 2009).

2.2 Freight market

The freight market is a marketplace where sea transport is traded, and is divided in to numerous routes covering all continents. Trade is arranged in many ways by several categories of contracts.

2.2.1 Voyage contracts

Transport is bought and sold at a fixed price per ton of cargo. The buyer leaves the management and the operational control of the transport to the shipowner. There are two main types of agreement in the voyage market (Stopford 2009).

- *The voyage charter*: A contract for transport for a specific cargo from port A to port B for a fixed price per ton.
- *The contract of affreightment (CoA)*: A contract where the shipowner agrees to deliver a series of cargo parcels for a fixed price per ton, often at specific intervals over a specific period of time.

These types of agreements give the shipowner an income hedge by contractually fixed prices. While the income is hedged, the costs are not, since the shipowner still has the operational control. For the buyer, the hedge works the opposite way by fixing the shipping costs. Contracts in the voyage market often include options to extend the contract at predetermined specifications[5].

2.2.2 Time-charter contracts

Vessels with or without crew are leased for a specific period of time. There are two types of time-charter contracts (Stopford 2009):

- *The time charterer*: is a contract that gives the charterer the operational control of the ships they have chartered. The ownership and management of the vessels are still in control of the shipowner.
- *The bare boat*: a contract that gives the full operational control of a vessel to the charterer for a specific period of time, and only the ownership remains in the hands of the shipowner.

These contracts give two different hedging strategies. The time charterer gives the shipowner fixed income and reduced costs by giving full operational control to the charterer. With a bare boat contract this hedge includes the costs attached to the management of the ship and therefore further reduces the risk for the shipowner. Figure 2 summarizes cost allocations for a shipowner for the four different types of agreements in the voyage and the time charter market.

[5] Mr. Andreas Holst Thorsen, Derivatives dealer at Frontline Ltd., has provided this information.

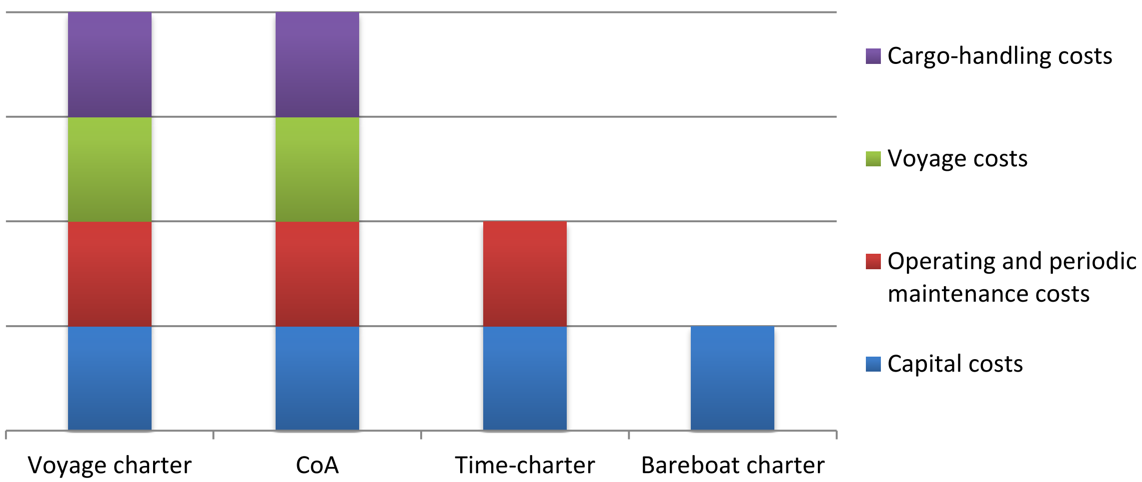


Figure 2: *This figure provides an overview of the shipowners cost allocation for the different contracts. The proportions of different costs are only explanatory, and do not provide an accurate illustration of the actual costs. The figure is adapted from Alizadeh and Nomikos (2009).*

2.3 Freight market derivatives

The derivatives market consists of financial instruments for trading in future levels of freight rates. This sub-market descended from the Roman Empire from where a bill of lading dated AD 236 has been discovered. This bill is considered to be the first future freight contract, and shows that Roman shipowners worried about the payment, just as shipowners do today. This contract is much like the charter-parties discussed in chapter 2.2.2 and proves that there have been written freight contracts long before any establishment of indices or exchanges (Stopford 2009).

The first exchange was established in the early 1980s. Shipowners, charterers and other parties involved in shipping wanted to apply the financial risk-management techniques, such as hedging using forwards, futures, swaps and options. This resulted in the first daily freight index, the Baltic Freight Index (BFI), published by the Baltic Exchange in January 1985 (Alizadeh and Nomikos 2009). The BFI was produced by a board of shipbrokers around the world, which gave their valuation of dry cargo routes. Traders could then buy or sell standardised contracts, known as futures contracts, for settlement against the BFI. All of the traders were registered with a clearinghouse and their portfolio was “marked to market” at the close of each trading day. The registration of trades with a clearinghouse was done in order to deal with the credit risk. Since 1985 the derivatives market has developed, but the Baltic Exchange is still the leading exchange. Today there are more than 40 daily routes, forward prices, a sale and purchase index, fixture lists and market reports available at the Baltic Exchange[6].

The shipping derivatives market is still an emerging market and is characterised by low volumes in several routes. Tanker derivatives give a trader an opportunity to take a position in the tanker freight market. Participants in the tanker market can use derivatives to reduce their risk exposure to an existing position, or speculate to possibly increase profits. The tanker derivatives market contains several financial instruments, and Forward Freight Agreements (FFA) are the most frequently used derivatives in shipping today (Alizadeh and Nomikos 2009).

2.3.1 World tanker nominal freight scale

World tanker nominal freight scale is usually referred to as “Worldscale”. This is an index provided as a joint venture between two non-profit organizations, the Worldscale Association Limited (London) and the Worldscale Association Inc (New York). Both companies are under control of a Management Committee, consisting of senior brokers from leading tanker broking firms in London and New York[7].

	TC2	TC5	TD3	TD5	TD7
2004	$7.48	$12.87	$13.11	$10.16	$4.00
2005	$7.56	$13.14	$13.39	$10.36	$4.45
2006	$8.52	$14.19	$15.16	$11.79	$4.74
2007	$9.97	$17.47	$17.72	$13.93	$5.09
2008	$10.20	$17.80	$18.05	$14.19	$5.40
2009	$13.78	$24.71	$25.00	$19.63	$6.53
2010	$10.53	$18.42	$18.72	$14.68	$5.59
2011	$12.56	$22.33	$22.61	$17.73	$6.30
2012	$14.95	$26.65	$26.95	$21.05	$7.11

Table 3: *Worldscale flat rate quoted as USD/mt per day*

Worldscale flat rate is representing the cost of chartering a tanker for a specific voyage at a given time. The flat rate is quoted in Worldscale 100, which is the price in dollars per ton for carrying oil at the given rate (Stopford 2009). When the spot price or a contract is given in Worldscale points it represents a percentage of the flat rate value. For instance, if the quoted price for TD7 is 105 Worldscale points it means 105% of the flat rate. If the flat rate is 7.11 USD/mt per day it means that the actual price per metric ton is USD 7.11 * 105% = 7.47 USD/mt per day. In order to obtain the actual contract value, this amount must be multiplied with the lot size and the number of lots. See Equation 1.

[6] For more information see The Baltic Exchanges homepage, http://www.balticexchange.com/default.asp?action=article&ID=395, last visited 4/12-2012.

[7] See http://www.worldscale.co.uk/ for more information, last visited 04/16.2012.

2.3.2 Forward freight agreements (FFA)

Alizadeh and Nomikos (2009, p. 125) (2009) (2009) (2009) (2009) (2009) (2009) define a forward freight agreement (FFA) as an *"agreement between two counterparties to settle a freight rate or hire rate, for a specified quantity of cargo or type of vessel, for one or a basket of the major shipping routes in the dry-bulk or the tanker market at a certain day in the future".* The underlying asset of these contracts is a freight rate assessment for the appurtenant shipping route.

In the late 1990s FFA replaced futures contracts, which allowed the trader to customise the contract. The FFAs key features are that they are known as principal-to-principal contracts, usually arranged by a broker, though they can also be traded on screens provided by a number of freight derivatives brokers (Stopford 2009). The arrangement of FFAs is similar to the way shipping has traditionally arranged time charters but no physical commitments are involved.

FFAs are traded either over-the counter (OTC) or through hybrid exchanges. Figure 3 shows the trading structure for the FFA market.

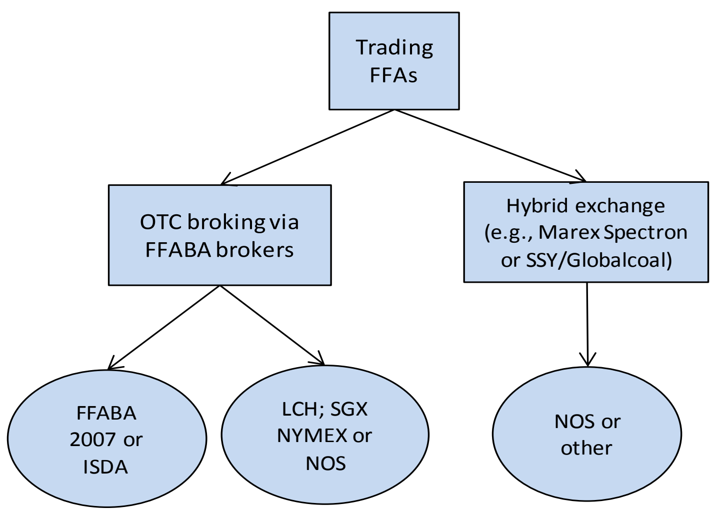


Figure 3 *Trading structure for the FFA market* (Alizadeh and Nomikos 2009).

The leading hybrid exchange is Marex Spectron, previously International Maritime Exchange (IMAREX), which provides a marketplace for standardised FFAs. They are then cleared straight through the Norwegian Futures and Options Clearing House (NOS). Trades executed through Marex Spectron are known as "straight-through clearing", which means that the trades are automatically cleared.

In this thesis we will focus on FFAs traded on Marex Spectron written with the Baltic Exchange (TC2, TD3, TD5 and TD7) and Platts (TC5) as providers of the underlying spot index. The contract prices are quoted in Worldscale points, explained in chapter 2.3.1. Equation 1 describes the calculation of the FFA contract value.

$$Contract\ value = \#Lots\ \times\ Lot\ size\ \times Worldscale\ Flatrate\ \times (Contract\ Price \div 100)$$

Equation 1 *Describes the calculation of the Contract value.*

As an example on the value of a FFA contract, assume that a charterer want to buy one-month contract. The contract price for a TD3 monthly contract was 58.1 Worldscale points on January 17.2012. The Worldscale flat rate is $26.95 in 2012 and the lot size is 1,000mt. Further on, assume that the number of lots in the contract is 10. The price of the FFA contract would then be:

$$Contract\ value\ = 10 \times 1{,}000 \times 26.95 \times (58.10 \div 100)$$

$$Contract\ value = \$\ 156{,}579.50$$

2.3.3 FFA specifications

Marex Spectron offers several FFA products, such as weekly, monthly, quarterly and yearly contracts. We will focus on the monthly contract, which is constructed using the following five parameters; the route, the price, the contract month, the quantity required, and the settlement index.

- *Contract price quotation:* Worldscale points
- *Minimum fluctuation:* 0.25 Worldscale points
- *Contract value:* see Equation 1
- *The delivery period:* is the first index day of the period to the last index day of the period.
- *The final settlement day:* is the last settlement day in the delivery period for all contracts.
- *The settlement price:* is calculated by the arithmetic average of the spot price for the relevant underlying product over the number of index days in the delivery period.
- *Lot size:* varies with the length of the contracts and 1 lot equals 1,000 mt for the weekly and monthly contracts.
- *Minimum lot:* per contract are 0.01 lots in all the contracts.
- *Product structure:* for the monthly contracts are traded for six consecutive months starting with the current month. A new month product is introduced once the current month is no longer available for trading.

2.3.4 Tanker Options

As the FFA market grew bigger and more mature, participants wanted to investigate the possibility of using other financial instruments. Options provide more flexibility than FFAs because the options offer the opportunity to limit the downside. Like the FFAs, the freight rate options are traded OTC or on hybrid exchanges and with the same trading structure. Tanker options products traded on Marex Spectron are Asian options, and have the appurtenant FFA as the underlying asset. The option value is calculated using Black 76 with the Turnbull and Wakeman approximation (Alizadeh and Nomikos 2009).

2.4 Formation of spot freight-rate

As in other industries and markets spot freight rates are dependent on supply and demand factors. The shipping industry, as a global industry is affected by several factors worldwide, and various routes might be influenced differently by the same occurrence. Table 4 summarises the most important factors affecting the supply and demand, and hence the formation of spot freight rates.

Demand	Supply
1. The world economy	1. World fleet
2. Seaborne commodity trades	2. Fleet productivity
3. Average haul	3. Shipbuilding production
4. Random shocks	4. Scrapping and losses
5. Transport costs	5. Freight revenue

Table 4 *Factors that influence the supply and demand in the shipping industry (Stopford 2009)*

The supply of shipping services depends on the world fleet and the productivity of the fleet. The growth rate of the world fleet is simultaneously dependent on deliveries of new ships and the scrapping of old ones, including those ships lost at sea. Low freight rates will increase the amount of ships laid up. Older ships are usually more costly to operate and if the freight rates are low, shipowners net income might be negative. This may in some cases make it less costly to move ships to lay-up, while waiting for better times, rather than carry on with the operation (Stopford 2009). Freight rates are highly dependent on total tonne miles available, and the shape of the supply curve is therefore convex as shown in Figure 4. This means the supply for shipping services is highly elastic for low freight rates and inelastic for high freight rates (Alizadeh and Nomikos 2009). When freight rates are low, a positive shift in demand will give a relatively large increase in the supply due to free capacity. On the other hand, when the freight rates are high there is inelasticity on the supply side, because the capacity is limited.

The demand for shipping services is highly dependent on the world economy. Cycles and random shocks in the economy influence the global or local trade of commodities, and the shipping industry will halt if there no trade. The average distance in miles one tonne is carried, called the average haul, also has an effect on the demand for ships. This is illustrated several times by the closure of the Suez Canal, which increases the average haul from the Arabian Gulf to Europe from 6,000 miles to 11,000 miles. As a result, there has been a freight market boom on each occasion because of a sudden increase in ship demand (Stopford 2009). Shipping economic literature has shown that the demand for shipping services is inelastic, which means that the demand for shipping services will not change drastically with a change in freight rates (Alizadeh and Nomikos 2009, Stopford 2009). Hence, the demand curve can be illustrated as a straight line, with a steep decline.

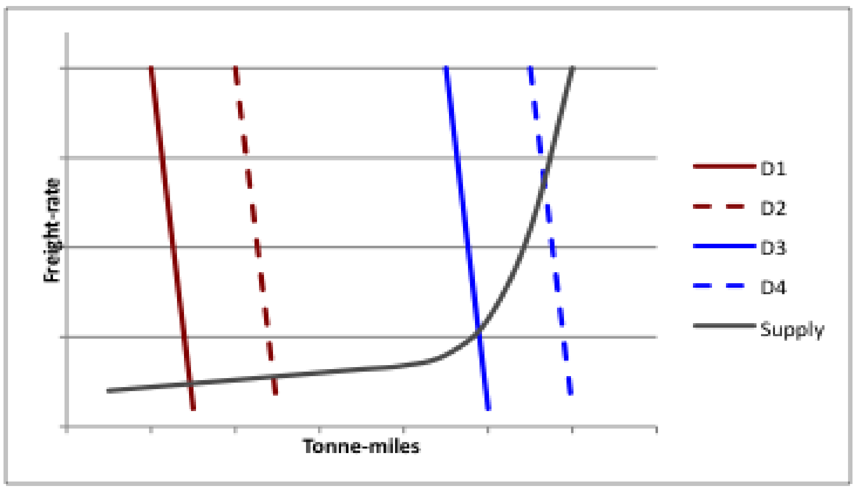


Figure 4 *Market-clearing supply-demand framework in shipping freight-rate determination (Alizadeh and Nomikos 2009)..*

If there is a shift in demand for shipping services from D1 $\Rightarrow$ D2, there will only be a small change in the freight rate. The supply curve in this case indicates a surplus capacity on the supply side. However, if the shipping services are at the limits of its capacity, a shift in demand will give larger fluctuations in freight rates, as shown in Figure 4, from D3 $\Rightarrow$ D4. The new equilibrium (D4=Supply) will in this case give a freight-rate more than twice the amount of the old equilibrium (D3=Supply). This explains large fluctuations in the freight rates.

3 THEORY

3.1 Risk Management

The famous Modigliani-Miller theorem implies that a firm's value is independent of its risk structure and that firms should maximize profits not considering the risk entailed in doing so. Investors can diversify their risk by appropriate portfolio allocations (Miller and Modigliani 1958). However, the assumptions[8] required of the Modigliani-Miller theorem are in reality often violated and this creates a role for risk management (Christoffersen 2003).

Any factor that may negatively impact on the expected net cash flow is identified as a risk factor (Alizadeh and Nomikos 2009). Risk occurs in every aspect of firms operations, from its physical damage to handling financial risk. Harrington and Niehaus (2004) classify business risks in three categories; price risk, credit risk and pure risk. Price risk refers to uncertainty over the magnitude of cash flows, due to possible changes in output and input prices. These factors are mainly external which means that the individual company does not have direct control over the price determination. The main price risks a shipping company are exposed to are freight-rate risk, operating-cost risk, interest-rate risk and asset-price risk (Alizadeh and Nomikos 2009). The credit risk refers to the uncertainty surrounding whether the counter-party to a transaction will fulfil its financial obligations. Credit risk is also commonly known as the "counter-party risk". Pure risk is defined as the risk of reduction in the value of business assets due to physical damage, accidents and losses (Alizadeh and Nomikos 2009).

Risk management involves several key steps regardless of the type of risk being considered. Harrington and Niehaus (2004) identify these steps as:

1. Identification of all significant risks affecting the value of the company
2. Evaluation of the potential frequency and severity of losses due to those risks
3. Development and implementation of appropriate methods for the management of the risks
4. Monitoring the performance and suitability of the risk management methods and strategies on an on-going basis

[8] Absence of taxes, bankruptcy costs, agency costs, asymmetric information, and efficient markets

3.1.1 Why manage risk?

Academics have proposed several arguments (Froot, Scharfstein and Stein 1993, Harrington and Niehaus 2004, Christoffersen 2003). However, they may not be applicable to a shipping company. Alizadeh and Nomikos (2009) have therefore identified four reasons why shipping companies should manage their risk.

Bankruptcy costs

Direct and indirect costs of bankruptcy are factors affecting the firm's value. Bankruptcy costs include the administration cosst of bankruptcy and costs such as loss of customers, loss of key employees, and restrictions imposed in the operation and management of the company. The variability of expected income is reduced when risk management strategies are implemented. Hence, reducing the probability of bankruptcy and might also increase the value of the firm.

Capital structure and cost of capital

Corporate default is often caused by a company's inability to service its debt. When comparing two equal companies with different debt-ratio, the one with the highest debt-ratio is considered as the most risky investment. By incorporating risk management strategies the firm with the highest debt-ratio might be re-evaluated as the least risky investment (Christoffersen 2003).

Benefits for public listed companies

Researchers have examined comparable companies following risk management strategies and companies that do not manage their risk. The studies found that the companies actively following a risk management strategy outperformed the ones who did not (Alizadeh and Nomikos 2009).

Taxes

Employing risk management strategies that reduce the volatility of earnings can reduce tax liabilities. Christoffersen (2003, p. 3) explains this by saying: "*Many tax systems have built-it progressions and limits on the ability to carry forward in time the tax benefit of past losses. Thus, everything else being equal, lowering the volatility of future pre-tax income will lower the net present value of future tax payments and thus increase the value of the firm".*

In addition to these arguments there are a large number of textbooks and articles proposing other reasons why firms should hedge and some argues that firms should not hedge. One of the main arguments why firms should not hedge is the presence of transaction costs. Arguments such as "transaction costs makes hedging too expensive" and "assessing payoff from a given strategy requires costly expertise" are frequently mentioned.

Another argument against hedging is that shareholders can do the hedging themselves. This argument assumes that the shareholders have access to the same information as the management concerning the risk factors faced by a company and in most cases that is not true. Furthermore the argument ignores transaction costs and commissions which would be less per dollar for large transactions compared to small transactions (Hull 2012). One could also argue that employees hold special expertise and market insight superior to that of investors which gives them an advantage regarding hedging. This argument assumes that the market is not completely efficient. There is a lot of research on this topic, which states that emerging markets are often characterised by some inefficiency. This might be the case for the freight derivatives market especially in the first years of the sample period.

Risk management strategies often involve derivatives trading. Derivatives, as a group, have been subjected to some criticism over the years. For example, Mr Warren Buffet has called derivatives "*financial weapons of mass destruction*"[9]. Tirole (2006) points out that risk management can actually cause aggregated risk since hedging often involves assets affected by exogenous macroeconomic shocks. Hidden tail risk represents risk caused by extreme returns. Extreme returns might affect the correlation between two assets. Correlations that are negative in normal times might change to one overnight and a hedged position can become unhedged at the same time (Chan et al. 2005, Rajan 2006). This might inflict substantial losses on originally hedged positions. Derivatives can also cause large losses due to the use of leveraging. By gearing positions investors (speculators) might earn huge amounts from small price changes in the underlying asset and to the contrary, the loss can be equally large.

However, risk management is ranked by financial executives, CEOs, and investors as one of their most important concerns (Tirole 2006). We have also described the shipping market as highly capital intensive and the cost of bankruptcy might become unbearable. It is therefore necessary to understand which risk factor the company is facing and to establish methods to detect the frequency and severity of losses due to those risks. Considering the discussion regarding risk management, employing risk management strategies might be advantageous, however, it is important to consider the cost perspective related to the risk management process.

[9] Berkshire Hathaway Annual Report 2002, available at http://www.berkshirehathaway.com/2002ar/2002ar.pdf, last visited 04/17-2012

3.2 Distribution theory

The normal distribution is well incorporated in academia although it is a well-known fact that the normal distribution theory does not always hold in real world situations. Distributions of the returns often have high peaks and fat-tails, which is important to consider when valuing derivatives and in risk management in general.

The bell-shaped normal distribution appears naturally in many applications. In fact, many variables will exhibit a normal distribution. If the price of an asset is lognormally distributed the returns should be normally distributed, this is for instance an assumption in the Black-Scholes-Merton option pricing formula. According to Bodie et al. (2009) there are three reasons why investment management is far more tractable when rates of returns are assumed to follow a normal distribution:

1. The normal distribution is symmetric and the probability of any positive deviation above the mean is identical to a negative deviation of the same magnitude. Absent symmetry, measuring risk as the standard deviation of returns is inadequate.
2. The normal distribution belongs to a special family of distribution characterised as “stable” because when assets with normally distributed returns are used to construct a portfolio, the portfolio returns are also normally distributed.
3. Scenario analysis is greatly simplified when only two parameters (mean and standard deviation) need to be estimated to obtain the probabilities of future scenarios.

These reasons are without a doubt factors that have contributed to the popularity of the assumption that prices and returns are normally distributed. Furthermore, they simplify the analysis in investment and risk management. However, it is empirically proved that high peak and fat tails exist in the real world. In fact the Italian Villfredo Pareto looked at the fat-tailed distributions of income and developed an early theory for such distributions in the late 1800s (Haug 2007b). Pearson (1905) introduced the idea that actual distributions differed from the normal distributions in terms of peakness. Wesley C. Mitchell, on the other hand, was the first to empirically detect and describe fat-tailed distributions in price data in 1915. Haug (2007b, p. 17) states that *“Mitchell in many ways was to empirical finance what Bachelier was to theoretical quantitative finance. They were both far ahead of their time, and some of their most important discoveries were re-discovered long after they were first published.”* After Mitchell’s discoveries in the early 1900s it seems that Benoit Mandelbrot was the first to mention Mitchell’s findings in his famous paper “The variation of Speculative Prices” from 1963. In this paper Mandelbrot focuses on fat-tailed distributions and also tries to come up with theoretical models that are consistent with fat-tails. Mandelbrot (1963) also states that, to the best of his knowledge, Oliver (1926) and Mills (1927) provided the first unquestionable evidence that empirical distributions of price changes are usually too "peaked" to be normally distributed. In the late 1960s and the beginning of the 1970s several ground breaking models were published that assumed that normal distribution existed in reality, although it had been proven otherwise already in the beginning of the 19th century. The distribution theory has however regained its attention in academia during the last 20-30 years. Researchers have attempted to develop normality tests against heavy tailed and high peaked distributions (Ruppert 1987, Bonett and Seier 2002, Gel, Miao and Gastwirth 2007, Gel and Gastwirth 2008, Jarque and Bera 1980, Bowman and Shenton 1975). This attention has contributed to enlighten the presence of fat-tails and high-peaks.

3.2.1 Coefficient of kurtosis

The coefficient of kurtosis is a statistical measure used to describe the peakness of a distribution and is also known as the fourth moment of a variable around its mean. The term of kurtosis originated from Greek, meaning bulging or convexity. As far as we know, Karl Pearson (1905) was the first to use the concept of kurtosis.

The normal distribution is also called a mesokurtic distribution and has an estimated sample kurtosis of K = 3. A distribution with a higher peak (and also fatter tails) compared to a normal distribution, a so-called leptokurtic distribution, gives a K > 3. This means that relatively small returns but also extreme returns, are more likely to occur opposed to frequent medium-sized returns as would be more often expected if K=3. On the other hand, with a K < 3, the sample distribution is relatively flat compared to the normal distribution. A flat distribution is often referred to as a platykurtic distribution. Modern definitions of kurtosis acknowledge the fact that kurtosis will be influenced by both the peakness and the tail weight of a distribution (Ruppert 1987) and can be formalised in many ways. However this thesis will report the Fischer kurtosis, also known as excess kurtosis (K-3). This is an adjustment of the Pearson kurtosis, so a normal distribution has an estimated sample kurtosis equal to zero. The sample Fisher kurtosis is given by the following formula.

$$K = \left\{ \frac{n(n+1)}{(n-1)(n-2)(n-3)} \sum \left(\frac{x_i - \overline{x}}{\sigma} \right)^4 \right\} - \frac{3(n-1)^2}{(n-2)(n-3)}$$

Equation 2: *n is the number of observations and σ is the standard deviation*

3.2.2 Coefficient of Skewness

The coefficient of skewness (S) indicates whether or not the distribution of a sample or population is skewed around its mean. Like kurtosis, Karl Pearson (1895) is as far as we know the origin of the term skewness. The sample skewness is given by Equation 3.

$$S = \frac{n}{(n-1)(n-2)} \sum \left(\frac{x_i - \overline{x}}{\sigma} \right)^3$$

Equation 3: *n is the number of observations and σ is the standard deviation*

If the coefficient of skewness S = 0, the distribution of the sample is symmetric around its mean. Distributions are often slightly skewed to either the left or the right. If S > 0; the distribution is positively skewed with a majority of positive observations. On the other hand, if S < 0, the distribution is negatively skewed.

3.2.3 Jarque-Bera Normality Test

The most widely used normality test is the Bowman and Shenton (1975) statistic. Subsequently derived by Carlos Jarque and Anil K. Bera (1980) and it is known as the Jarque-Bera Lagrangian Multiplier test or Jarque-Bera test (JB). The test is a goodness-of-fit test of whether a sample has kurtosis and skewness equal to the normal distribution of K=0 and S=0. However, the JB test and other classical normality tests do not necessarily work very well. Although the JB test turns out to be superior in power to its competitors for symmetric distributions with relatively long tails, the test is poor for small samples, asymmetric distributions and distributions with short tails (Thadewald and Böning 2007, Mantalos 2010b). To solve this problem different modifications or approaches to the JB test have been suggested (Urzúa 1996, D'Agostino, Belanger and D'Agostino 1990, Mantalos 2010a). Mantalos (2010a) has also tested the power of these modifications on different sample sizes and concluded that his own method of creating robust "sample" critical values for the JB test is superior to the other evaluated tests for all sizes of samples[10]. Since this method was published recently, we have not been able to find any criticism of the method. However, the research done by Mantalos (2010a) shows that all tests perform well for large samples. This thesis use eight years of daily data and the samples are to be considered as large pursuant to Mantalos. Hence, the JB-statistic will be sufficient to test for normality. The Jarque-Bera statistic is given by:

$$JB = \frac{n}{6} \left(S^2 + \frac{1}{4} K^2 \right)$$

Equation 4: *K is the Fischer kurtosis, S is the skewness and n is the number of observations*

[10] For more see Mantalos, P. 2010a. Robust Critical Values For The Jarque-Bera Test For Normality. Jönköping International Business School.

3.3 Volatility estimation

Volatility is definitely one of the most important measures in finance, and the standard deviation of the returns is often used as a measure for the total risk of an asset (Brooks 2008). Estimating volatilities are for instance relevant to the valuation of derivatives and the calculation of Value-at-Risk. The simplest way to estimate volatility is to calculate the historical constant variance and then the standard deviation of a sample or a population. However, the historical constant standard deviation is not a precise measure of the volatility (Hull 2012).

Mandelbrot (1963) was the first to discover the phenomenon of volatility clustering. He noticed that a large price change tends to be followed by another large price change. This discovery has inspired academics to investigate and model the behaviour of variance in financial time series, and today it is a known fact that volatility is usually are time-varying or stochastic (Alizadeh and Nomikos 2009). Assuming constant volatility, there is a good possibility for incorrect estimates of the true risk. Hence, it is important to get a greater understanding of the volatility.

Over the past decades several volatility estimation models or methods have been developed. For instance, Rolling Window, the Exponential Weighted Moving Average (EWMA) model, more sophisticated GARCH models and stochastic volatility models such as Heston (1993), SaBR (Hagan et al. 2002) and Bookstaber (Bookstaber and Pomerantz 1989). However, there is no best-fit model for capturing the volatility in general. The empirical use of stochastic volatility models has been more limited due to difficulties attached to their estimation of their parameters (Alizadeh and Nomikos 2009). Further on, Alizadeh and Nomikos (2009) have demonstrated that volatility estimated with GARCH and EWMA for different tanker vessels between 1990 and 2007 are close to each other. The same trend with only minor differences is found between a stochastic volatility model (autoregressive stochastic volatility model) and GARCH for TD3 in the same period.

3.3.1 Rolling Window

Klein (1977) tried to capture the dynamics of the volatility of stocks using a Rolling Window, also called moving-window or moving-average-variance. This method is based on the most recent observations in a time series and will detect if the volatility changes over time. For example, assume a sample of 1,000 observations. The volatility can be estimated by calculating the standard deviation of the first 100 observations. One observation is then dropped at the beginning of the sample and one is added at the end. Continuing this way will give a continuous series of 901 observations with volatility for the 100 previous observations.

There are no firm rules concerning the choice of data sampling frequency or the number of lags to include (Andreou and Ghysels 2002). The sampling frequency depends on the available time series and the research purpose. Fama and MacBeths (1973) method, using monthly data and 60-month lag, have gotten many followers. This method requires large time series, and would not be appropriate in this thesis due to the sample size. Another way is to use daily data and take monthly sums, using only returns within one calendar month (French, Schwert and Stambaugh 1987). By estimating volatility with this method we would also obtain monthly volatility estimations, however, they are constant for each calendar month. Considering our sample size, our Rolling Window volatility will be estimated using daily data and 90-day frequency. The Rolling Window is not a very accurate method (Alizadeh and Nomikos 2009). Nevertheless, practitioners compute daily volatilities using this scheme applied to a daily and monthly sampling frequency (Andreou and Ghysels 2002). Furthermore, the Rolling Window provides an illustrative overview of the volatility and its variation over time. We will use the Rolling Window to test for sampling errors in the volatility estimations.

3.3.2 Generalised Autoregressive Conditional Heteroscedasticity (GARCH)

Engle (1982) introduced the autoregressive conditional heteroscedasticity model (ARCH) for modelling the time-varying volatility of time series variables. Since 1982 several different modifications of the ARCH model have been made, maybe the most famous one by Bollerslev in 1986, called the generalised autoregressive conditional heteroscedasticity (GARCH) model (Alizadeh and Nomikos 2009). The GARCH(1,1) can be written as Equation 5.

$$\sigma_n^2 = \gamma V_L + \alpha u_{n-1}^2 + \beta \sigma_{n-1}^2$$

Equation 5

The estimated volatility of a variable for day n, σ^2_n, is calculated by a long-run variance rate, V_L, the estimated volatility of a variable for day n – 1, σ_{n-1}, and the most recent percentage return or change in the variable, u_{n-1}. β is the weight given to σ^2_{n-1}, and is also known as the "decay rate". It defines the relative importance of the previous variance rate when determining the current variance rate. In the same way, α, is the weight assigned to u^2_{n-1} and γ to the long-run variance, V_L (Hull 2012). The weights also have to sum up to unity, so

$$\gamma + \alpha + \beta = 1$$

Equation 6

For instance, a higher β gives more weight to previous variance rates relative to recent percentage change in the variable and the long-run variance. The GARCH model acknowledges that, the variance tends to have a drift that pulls it back to long-run variance level, V_L (Hull 2012). However, when γ = 0, the GARCH model is reduced to the Exponentially Weighted Moving Average model. Due to the mean reversion element in the GARCH model, it is usually more attractive than the EWMA model. Even so, when the best-fit value of γ is negative, the GARCH model is not stable, and the EWMA model is more suitable (Hull 2012). The parameters in the GARCH model may be estimated using the maximum likelihood method.

3.3.3 Exponentially Weighted Moving Average (EWMA)

EWMA is estimated by the following equation

$$\sigma_n^2 = \lambda\sigma_{n-1}^2 + (1-\lambda)u_{n-1}^2$$

Equation 7: *Hull (2012) page 500.*

Where σ^2 is the variance rate, u is the daily percentage change in the variable and λ is a constant between zero and one. It has been proved that λ=0.90-0.98 is sufficient to capture the dynamics of time-varying volatility, and we will use λ=0.94 which is best suited for daily data and also used by RiskMetrics (Hull 2012, Alizadeh and Nomikos 2009).

3.3.4 Sampling error

Sampling error is the amount of inaccuracy in estimating a value from only a part of the population, and not the entire population. Sampling error can be minimised by increasing the sample size, since a larger sample will be more representative of the population compared to a smaller sample (Brooks 2008). Confidence intervals can be used as a measure of these types of errors. The confidence interval provides an interval estimate from the sample mean at a certain confidence level. We will use Equation 8 to construct confidence intervals around the estimated standard deviations. The equation uses the chi-square distribution, which is often used to construct confidence intervals. Furthermore the equation is based on the assumption that the returns of an asset are normally distributed (Haug 2007a).

$$P\left[\hat{\sigma}\sqrt{\frac{(n-1)}{{\chi^2}_{(n-1;1-\left(\frac{\alpha}{2}\right))}}} \leq \sigma \leq \hat{\sigma}\sqrt{\frac{(n-1)}{{\chi^2}_{(n-1;\left(\frac{\alpha}{2}\right))}}}\right] = 1-\alpha$$

Equation 8

Where ${\chi^2}_{\left(n-1;\left(\frac{\alpha}{2}\right)\right)}$ represents the value of the chi-square distribution, with n-1 degrees of freedom and significance level of α. The confidence intervals represent the range of what the actual constant historical deviation is. However, if the Rolling Window volatility exceeds the limits of the confidence intervals, there is a probability of 1-α that this is not caused by sampling errors.

3.4 Value-at-Risk

JP Morgan provided the foundations of Value-at-Risk (VaR), by creating the first set of standardised assumptions for calculating the potential loss of a firm (Alizadeh and Nomikos 2009). The concept of VaR was introduced in the late 1980s, triggered by the stock market crash of 1987. Academically trained quantitative analysts had taken large risks because this crisis was unlikely to happen given the standard statistical models at the time. The market realised the need for a new risk measurement (Jorion 2006). VaR is an attempt to solve this problem, by presenting a single number for the total risk of a financial asset or a portfolio.

VaR tries to state that within the next N days we are X% certain that there will not be a loss of more than the VaR estimate (Hull 2012). When large companies are calculating VaR they often have to consider hundreds or even thousands of different market variables, which complicates the estimation process. However, VaR is easy to understand, and for that reason it is an attractive measure that is widely used (Alizadeh and Nomikos 2009, Hull 2012, Linsmeier and Pearson 1996). There are additional arguments for the popularity of VaR (Dowd 2005):

- An increase in VaR means the firm's risk has increased. This gives the management the opportunity to set an overall risk target as a management tool for the firm.
- VaR might be used as guidance for investment, hedging or trading decisions.
- VaR is a useful tool in the boardroom. It is a number anybody should be able to understand, and is therefore a suitable tool for reporting and unveiling possible problems.
- VaR is often used to determine the requirements for capital.
- VaR can be adjusted to measure several types of risks.
- VaR information might be used as a basis for bonus payments for traders or managers.

3.4.1 Criticism of VaR

Despite the advantages, VaR should not be used naively. A debate between Nassim Taleb and Philippe Jorion (1997) has formed the basis for the different views on VaR. Nassim Taleb argued that VaR:

- Ignores 2,500 years of market experience with a co-variance matrix (the model building approach) that was still in its early days (Taleb 1997).

- Is charlatanism because VaR tries to estimate something that is not scientifically possible to estimate, that is the risk of extreme and rare events (Taleb 1997).
- Gives false confidence because it is often based on uncertain estimates of volatility and correlations (Jorion and Taleb 1997).

Philippe Jorion (1997) on the other hand has a different view of VaR. He states that there is a big advantage in the statement of VaR, because the market risk is reported in units that anybody can understand. When VaR is used correctly it might be an important tool in risk management and it might prevent employees taking unwanted risks. However, there is a wide consensus that VaR is dangerous when misunderstood. A common misinterpretation is that VaR is representing the worst-case scenario, which in fact is not true (Kolman et al. 1998). Therefore VaR has to be taken for what it is and nothing else because a misunderstanding of VaR might become very expensive.

The financial crisis in 2008 exposed the weakness of the Model Building Approach for estimation of VaR, which assumes than the returns follow the Gaussian distribution. This approach has been the normative method for banking risks. However, the financial crisis revealed the VaR method's inability to capture the tail risk, which has led to a review of the regulations in the banking sector. The Basel Committee on Banking Supervision (2012) has therefore suggested moving from VaR to an Expected Shortfall method as the norm for banking risk measurement.

Nevertheless, today there is not one VaR model but rather a group of models sharing the same framework. They are often divided into parametric VaR and non-parametric VaR methods (Dowd 2005, Alizadeh and Nomikos 2009).

3.4.2 Model-building approach (MBA)

The Model-Building Approach is one commonly used parametric method to estimate VaR. To illustrate the calculation of VaR using this method we first consider a single-asset case, for instance a tanker company with a $100,000 long position in freight route TD3. Suppose we want to calculate ten-day VaR with a confidence level of 99%. Assume that the volatility of a freight rate is 57.3% per year or 3% per day (3% = 57.3%/√365). Further on, the model assumes that the expected change over time is zero and normally distributed. From the normal distribution we find that with a confidence level of 99% there is a 1% probability of changes larger than 2.33 times the standard deviation. This gives the basis for the VaR estimate.

$$\text{VaR(TD3)} = \$100{,}000 * 3\% * 2.33 * \sqrt{10} = \$22{,}104$$

Consider that the same tanker company is also operating in TD5 with a long position of \$200,000 with a daily volatility of 3.5%.

$$VaR(TD5) = \$200,000 * 3.5\% * 2.33 * \sqrt{10} = \$51,577$$

However, the sum of VaR(TD3) and VaR(TD5) is not equal to the actual total VaR unless the correlation between the variables is equal to 1. Consider this portfolio of TD3 and TD5 and assume that the correlation (ρ) between them is 0.65. We should then be able to calculate the portfolios standard deviation of the change with the following equation:

$$\sigma_{TD3+TD5} = \sqrt{(\sigma^2_{TD3} + \sigma^2_{TD5} + 2\rho\sigma_{TD3}\sigma_{TD5})}$$

σ_{TD3} = the standard deviation of the change in TD3 = \$100,000 * 3% = \$3,000
σ_{TD5} = the standard deviation of the change in TD5 = \$200,000 * 3.5% = \$7,000

$$\sigma_{TD3+TD5} = \sqrt{(\$3,000^2 + \$7,000^2 + 2 * 0.65 * \$3,000 * \$7,000)} = \$9,236$$

VaR for the portfolio consisting of TD3 and TD5 is then:

$$VaR = \$9.236 * 2.33 * \sqrt{10} = \$68.050$$

The benefit of diversification in this example is the difference between the VaR of the portfolio and the sum of the VaR(TD3) and VaR(TD5).

$$\$73,681 - \$68,050 = \$5,631$$

This is a simple example but in reality large companies have to consider a multitude of variables that complicate the VaR calculation. For instance, the correlations between variables have to be calculated and interest rates have to be handled correctly (Hull 2012). Anyways, the advantages of this approach are that the method can easily be adjusted to time-varying volatility models such as GARCH and EWMA and results can be produced quickly. The main disadvantage of the Model Building Approach is its assumption of multivariate normally distributed variables (Hull 2012), which will lead to an underestimated VaR if the distributions of the variables are fat tailed. The simple variant of the Model Building Approach also assumes that the long-term return in a variable is zero.

Backtest

In the case of the Model-Building Approach backtesting is used test how many times the historical data exceeds the estimated VaR limit. For 99% VaR and a sample of 2,000 returns, it is expected that the historical data will exceed the VaR limit 20 times (2,000 * 1% = 20). If the backtest shows that the historical returns have exceeded the VaR limit for instance 40 times, it means that the Model Building Approach has underestimated the actual VaR. Figure 5 illustrates the backtest of 99% Model Building Approach VaR for TC2 spot using both EWMA volatility and the constant historical volatility of the sample period.

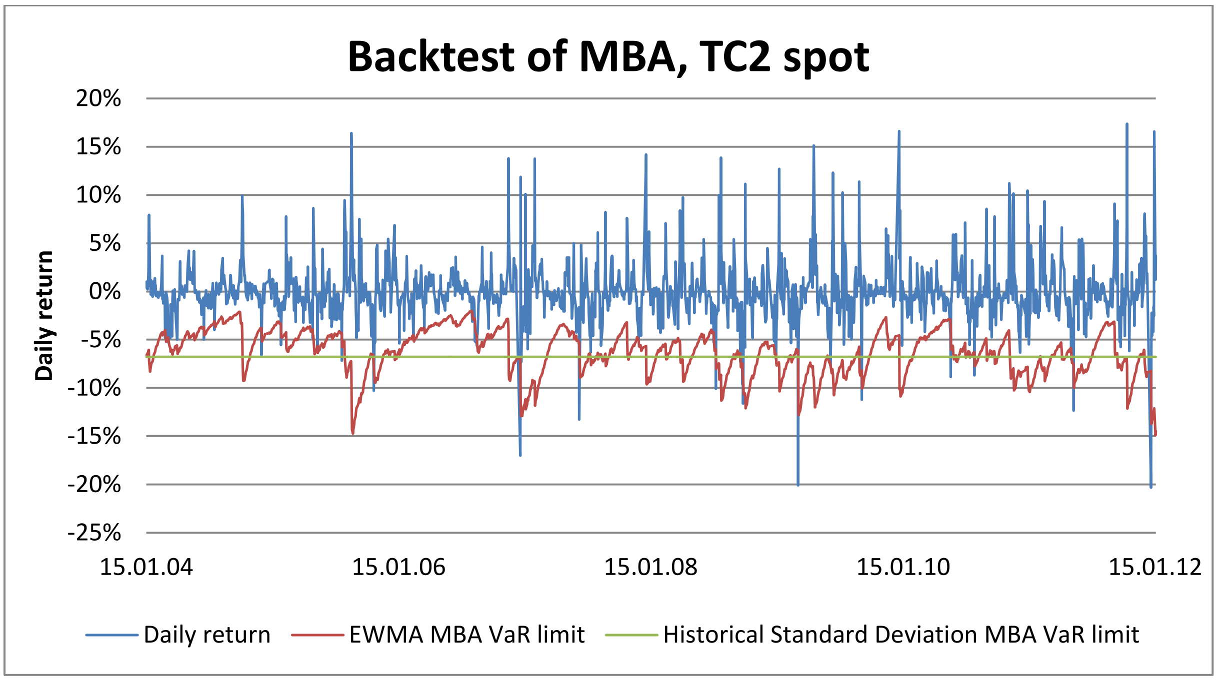


Figure 5 *Illustration of a backtest of 99% MBA VaR for TC2 spot*

3.4.3 Historical simulation (HS)

An alternative to the Model-Building Approach is the historical simulation, which is a non-parametric method. This method assumes that history will repeat itself in the long run and that historical data can be used to predict the future (Hull 2012). Assume that we want to calculate VaR for a freight rate using a one-day time horizon, a 99% confidence level and 2001 days of data. This gives 2000 possible scenarios for the future. This means that the 20th (2000 * 1%) most extreme loss in the past forms the basis for the calculation of VaR. Hence, we are 99% sure that we will not take a greater loss than the VaR estimate, if the 2001 days of data is representative of the future. For instance, assume a $100,000 long position in

TD3 with the 20th largest loss at 10%. We want to calculate 10 days VaR with a 99% confidence level. The HS method will then give the following result:

$$\text{VaR(TD3)} = \$100{,}000 * 10\% * \sqrt{10} = \$31{,}622$$

The Historical Simulation method can be extended using a Monte Carlo application simulating a future distribution based on the historical data. The advantage of the Historical Simulation method is that the historical data and not the normal distribution, determines the expected distribution of the variables. It also anticipates that the volatility is stochastic. However, it is based on the simple assumption that history will repeat itself.

3.4.4 Filtered Historical Simulation (FHS)

An alternative to these methods is a semi-parametric method, referred to as Filtered Historical Simulation. The Filtered Historical Simulation method is a combination of Historical Simulation and the Model-Building Approach. Instead of using the normal distribution, the Filtered Historical Simulation method uses the historical distribution to calculate VaR and normally a GARCH model is used to estimate volatility (Barone-Adesi, Giannopoulos and Vosper 1999). However, we will use the EWMA model to estimate daily volatility (see section 4.3). Assume that future returns are given by the following equation (Christoffersen 2003):

$$\mathrm{u}_{t+1} = \sigma_{t+1} z_{\mathrm{t+1}}$$

Equation 9

Where u is the return and the EWMA model is used to estimate σ_{t+1}:

$$\sigma_{t+1}^2 = \lambda\sigma_t^2 + (1-\lambda)u_t^2$$

Equation 10

Given historical returns, $\{\mathrm{u}_{t+1-\tau}\}^{n}_{\tau=1}$, we can estimate the EWMA model and calculate historical standardised returns from the observed returns and the estimated standard deviations as follows:

$$\hat{z}_{t+1-\tau} = \frac{u_{t+1-\tau}}{\sigma_{t+1-\tau}}$$

Equation 11: *for τ = 2, ...n*

The estimated volatility and the standardised returns from Equation 10 and Equation 11 will then give a sample of standardised residuals using Equation 9. By employing a Monte Carlo application it is now possible to simulate a future scenarios based on the historical distribution adjusted to the current level of volatility. The advantage of the FHS method is that it is based on the historical distribution and estimated future volatility level. However, it is not certain that history will repeat itself and the EWMA model has its weaknesses that attach uncertainty to the VaR results.

4 DATA

4.1 Description of the price data

Marex Spectron has provided the price data and the calculations are based on an eight year time period, from 04.01.2004 to 17.12.2012. Baltic Maritime Exchange provides the spot data of TC2, TD3, TD5 and TD7, while Platts provide the spot data for TC5. Marex Spectron provides the FFA data. On the advice of Mr Erlend Engelstad in Marex Spectron, we have chosen to exclude the price data prior to 2004, since low volumes characterised the FFA data. The spot and FFA price data is reported in Worldscale points, however we have chosen to multiply with the Worldscale flat rate as explained in chapter 2.3.3. In this way we exclude the jumps caused by a change in the flat rate and the results are more representative of the actual risk faced by the participants in the market. From 2013 the daily data will be reported in USD/mt per day instead of Worldscale points.

4.2 Splicing of futures contracts

We have chosen to consider monthly FFA contracts traded on Marex Spectron. Each of the monthly contracts contains FFA prices for the last six months prior to the predetermined maturity date. Furthermore, the contracts tend become more liquid when the contract approaches maturity[11]. Our analysis requires large data samples. Consequently it is necessary for us to use several contracts to obtain a continuous time-series containing monthly FFA contracts. The time series should also reflect the actual cash flow for market actors rolling contracts.

When creating continuous time series of monthly FFA contracts the first logical step would be to use the next contract when one expires. This method is called the spot-month continuous, and is the easiest to implement. However the change from one contract to the next can cause jumps at the splice points. Figure 6 shows this effect graphically.

[11] Confirmed by Mr. Erlend Engelstad, Marex Spectron

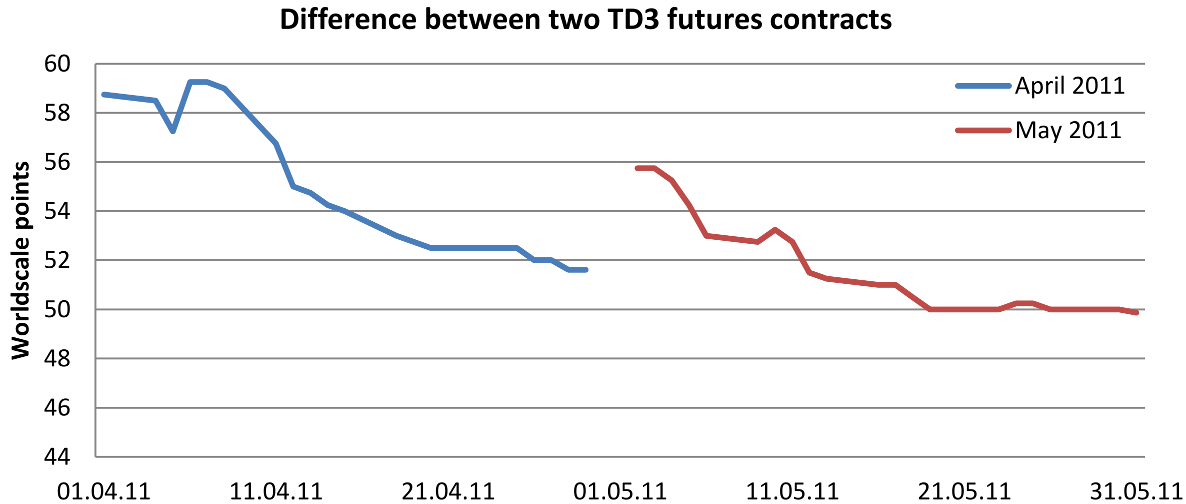


Figure 6 *Difference between the maturity of the TD3 April contract and the start of the TD3 May contract (expiration month).*

This problem can be dealt with in several ways. One method obtained from Skjetne (2005), is to back-adjust time series. This means that when one contract has reached maturity, the closing price of that contract is compared with the closing price of the consecutive contract. The matured contract price is then subtracted from the price of the consecutive contract and the differences are applied to all previous prices. By starting at the most recent contract, the method is applied to the entire data set. Figure 7 shows how this method affects the futures price.

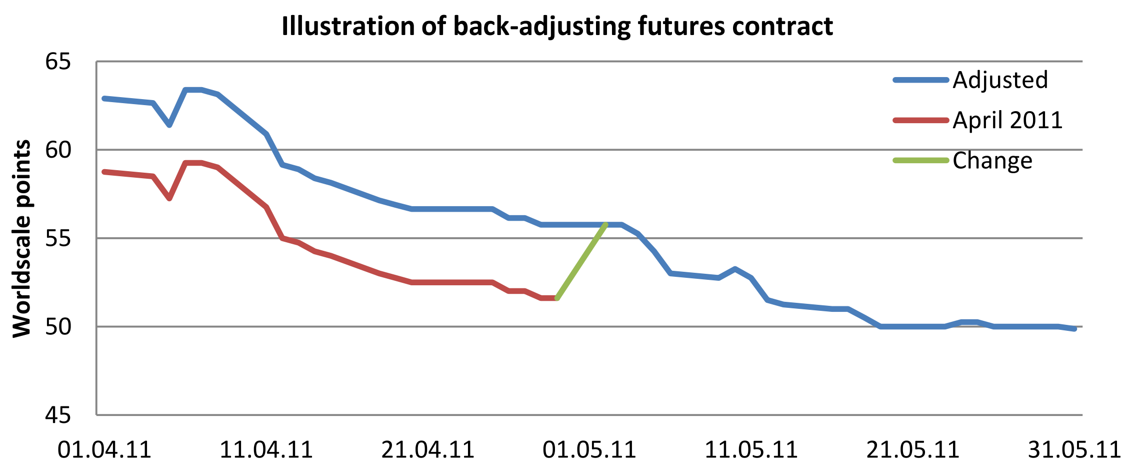


Figure 7 *this figure includes the same contracts as figure 6 and the blue line represents the back-adjusted TD3 April contract. The red line represents the unadjusted TD3 April contract.*

Using this method on our data set with considerable jumps at the splicing points, the jumps would be accumulated to all previous observations and could result in a high permanent basis. Another problem is that this method may result in negative numbers on the adjusted time series. Calculating the returns will not necessarily reflect the actual price change and is therefore not applicable for our analysis

In order to obtain continuous time series of FFA contracts we will splice the contracts at maturity, which also corresponds to what market actors actually do[12]. In this way we will obtain the cash flow as/ in the same way as market actors are exposed to. Splicing at maturity will however lead to overestimated volatility due to jumps at the splicing days. To cope with this problem when analysing volatility and distributions, we have not considered the returns from the splice date in the time series[13].

4.3 Distributions and volatility

For the analysis we have used the monthly spliced FFA without the splicing returns, which we assume will best reflect the risk associated with the historical distribution and volatility estimations. The results are based on the entire sample period. We have however also computed distributions for the last four years, illustrated in Appendix 8.1 to 8.5.

For the estimation of volatility we will use 90-days Rolling Window and EWMA. We will use the EWMA model since the GARCH(1.1) model returned unstable parameters for several routes. According to Hull (2012) when the best fit value of γ turns out to be negative the GARCH(1.1) is not stable, therefore the EWMA model is more appropriate to use. Further on, we have calculated a 99% confidence interval around the historical constant standard deviation of the sample on the 90-days Rolling Window to test for variations in the volatility.

4.4 Value-at-Risk

We will use three different methods to estimate VaR at 18.01.2012 for both a long and short position of $1,000,000. The methods are the Historical Simulation (HS), the Filtered Historical Simulation (FHS) and the Model Building Approach (MBA). However, HS and MBA based on a constant standard deviation will result in constant VaR estimate. We will perform a backtest of MBA on the last 2,000 returns in the sample period. However, for the spliced FFA without the splicing returns we only have 1,908 historical returns.

We will estimate one-day VaR for confidence levels of 90%, 95% and 99%. This means that there is 10%, 5% and 1% probability for a loss on 18.01.12 that is greater than the VaR result. The HS and the FHS

[12] Confirmed by mr. Erlend Engelstad, Marex Spectron
[13] Our supervisor, prof. Espen Gaarder Haug, suggested this method.

methods are in this thesis based on the returns from the period 14.01.2004 to 17.01.2012. It could be discussed if eight years is sufficient to reflect the actual distribution of the freight rates. Ideally, we should have used data from a longer period. Nonetheless, we assume that eight years will capture the seasonality and some of the cyclicality in the tanker market. For FHS we will draw random returns from this period using Excel and simulate distributions of 10,000 returns to form the basis for possible fluctuations on 18.01.2012. The simulation could also be applied to HS, however it will not improve the one-day VaR estimate.

5 RESULTS

5.1 TC2

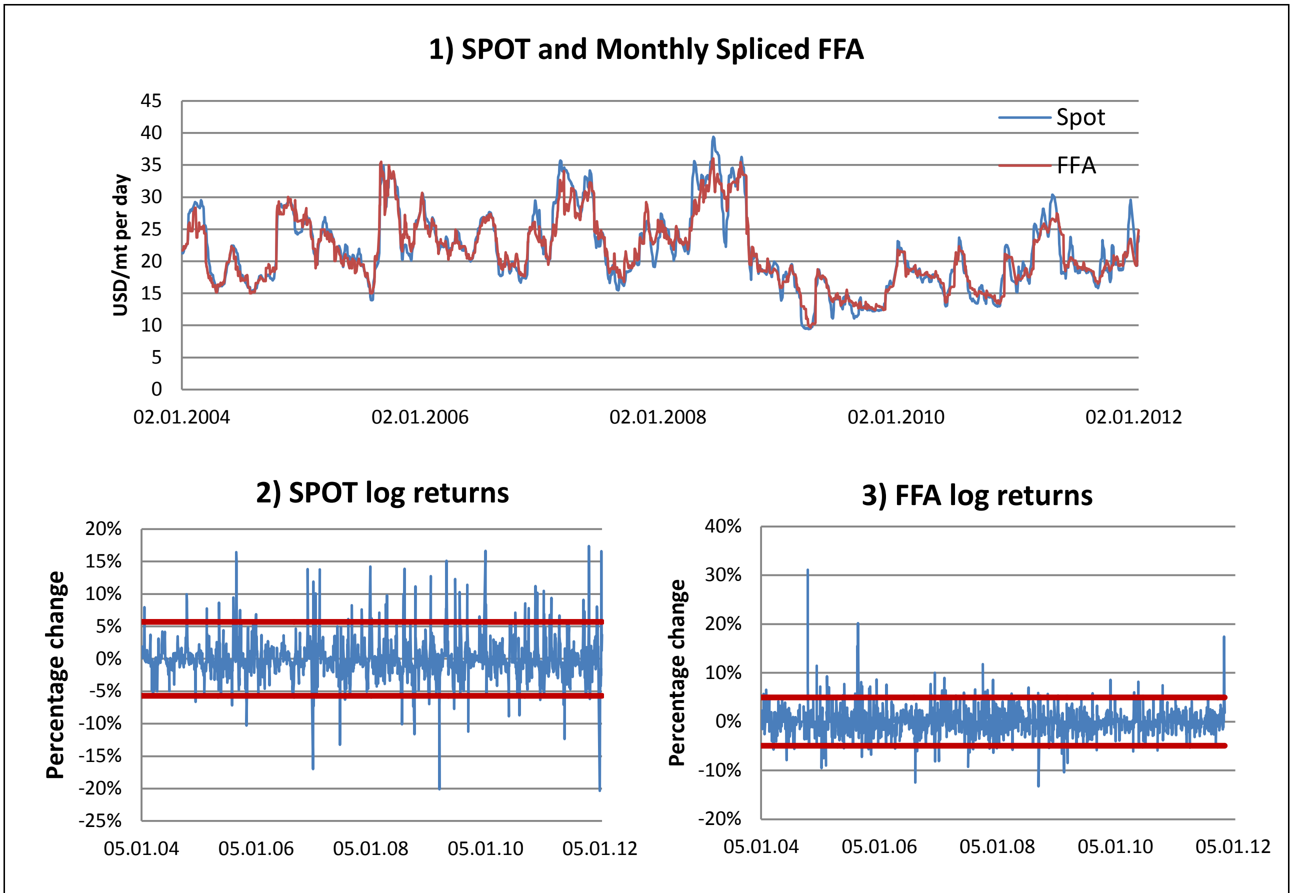


Figure 8: *1).TC2 spot and spliced FFA prices from 2004 to January 2012. 2) Spot log-returns for the same period. 3) FFA log returns for TC2 FFA for the same period. Red lines illustrate a 95% confidence interval around the mean return of the sample.*

TC2 is one of the most important clean tanker routes. The indicative route for TC2 the is transportation from Rotterdam to New York of 37 000 metric tons (mt) of unleaded gasoline (Alizadeh and Nomikos 2009). Economic events and market conditions in Europe and USA are consequently of highly importance for the TC2 freight rate. For the period from 2004 to late 2008 the world economy was characterised by strong economic expansion. The 2008 financial crisis led to a drop in the TC2 freight rate in September 2008 from approximately 35 USD/mt per day to 10 USD/mt per day. At the same time as the demand for oil products started to drop, new tankers ordered in the period before the financial crisis were delivered into the market. Consequently the TC2 freight rate hit the bottom in April 2009. The last few years have been characterised by surplus capacity of tankers, and the TC2 freight rates have stabilized at a lower level than before the crisis in 2008.

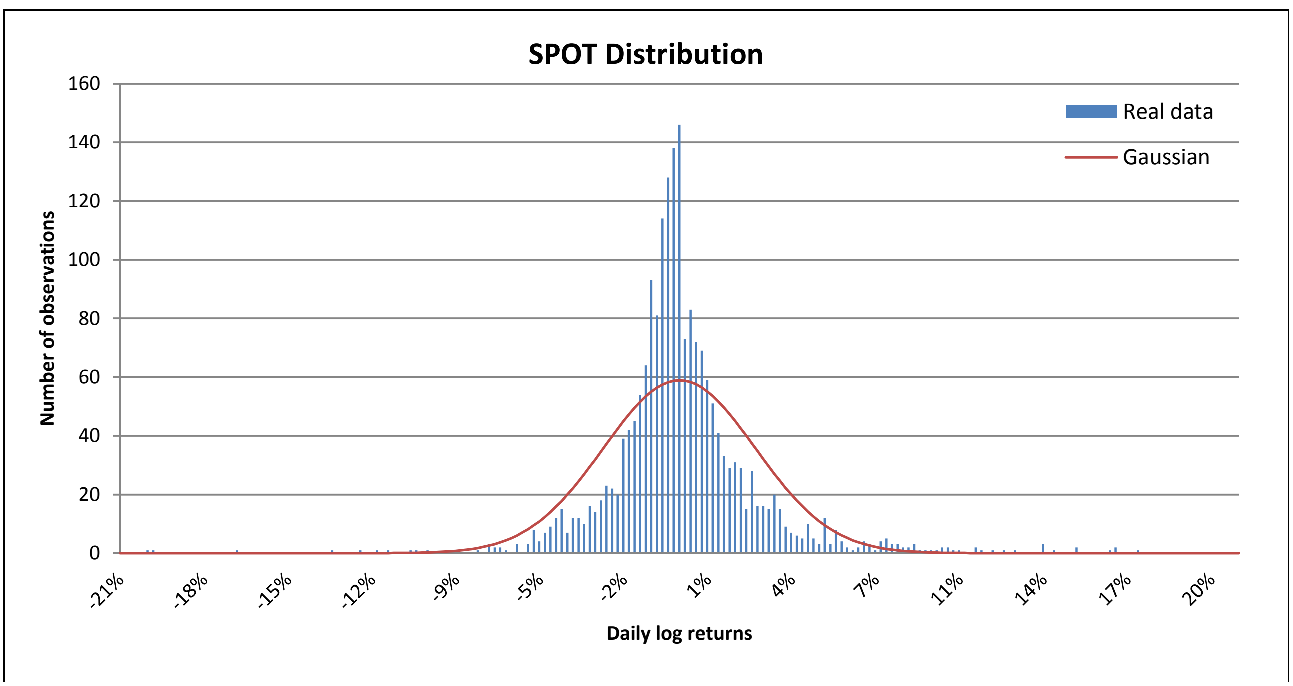
The freight rate for TC2 has varied from almost 40 USD/mt per day to approximately 10 USD/mt per day over the past eight years. Daily log returns have several times exceeded the 95% confidence interval around the mean return, as shown in log-return plots in Figure 8. Peaks in the cold seasons may indicate seasonality in the freight rate. However, this seems to be a bit more evident in the early years of the period.

5.1.1 Distributions

	SPOT	FFA		SPOT	FFA
Number of obs.	2008	1912	Mean	0.01 %	0.01 %
Skewness	0.69	1.69	Median	-0.25 %	0.00 %
Kurtosis	8.35	18.74	Max return	17.38 %	31.14 %
Jarque-Bera	5995	28890	Min return	-20.33 %	-13.24 %

***Table 5**: Descriptive statistics for TC2 spot and TC2 FFA*

By drawing the historical distribution as in Figure 9, we can see that the historical distribution of returns does not follow a Gaussian distribution. This is supported by the JB-statistics in Table 5. Figure 9 indicates the presence of fat tails for the TC2 spot. The left tail is however not as fat as the right tail. As we can see from the figures there have been some relatively large daily returns. We can however, due to our daily data, not say with certainty that these extreme price movements are actual price jumps.



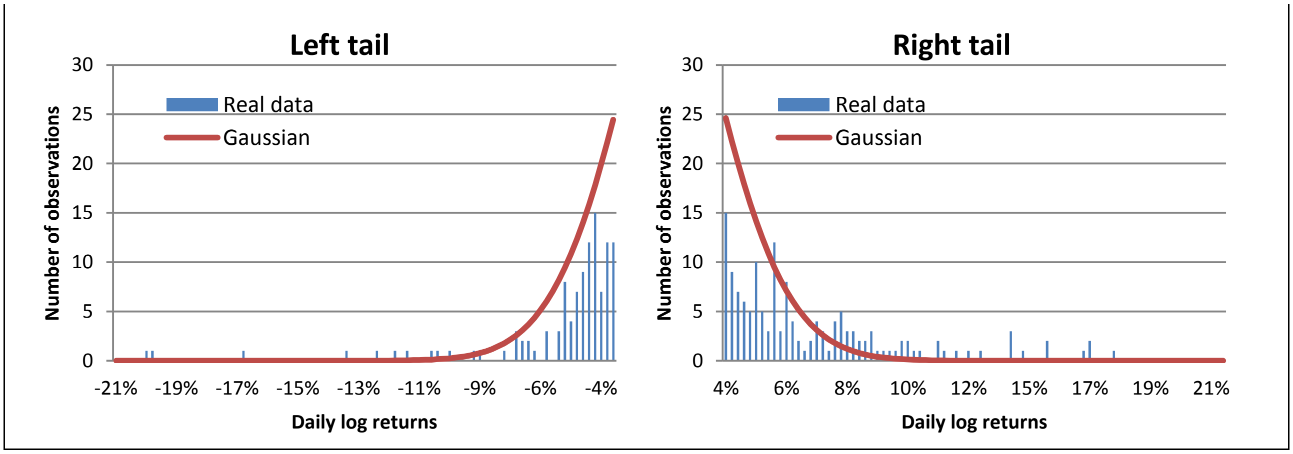
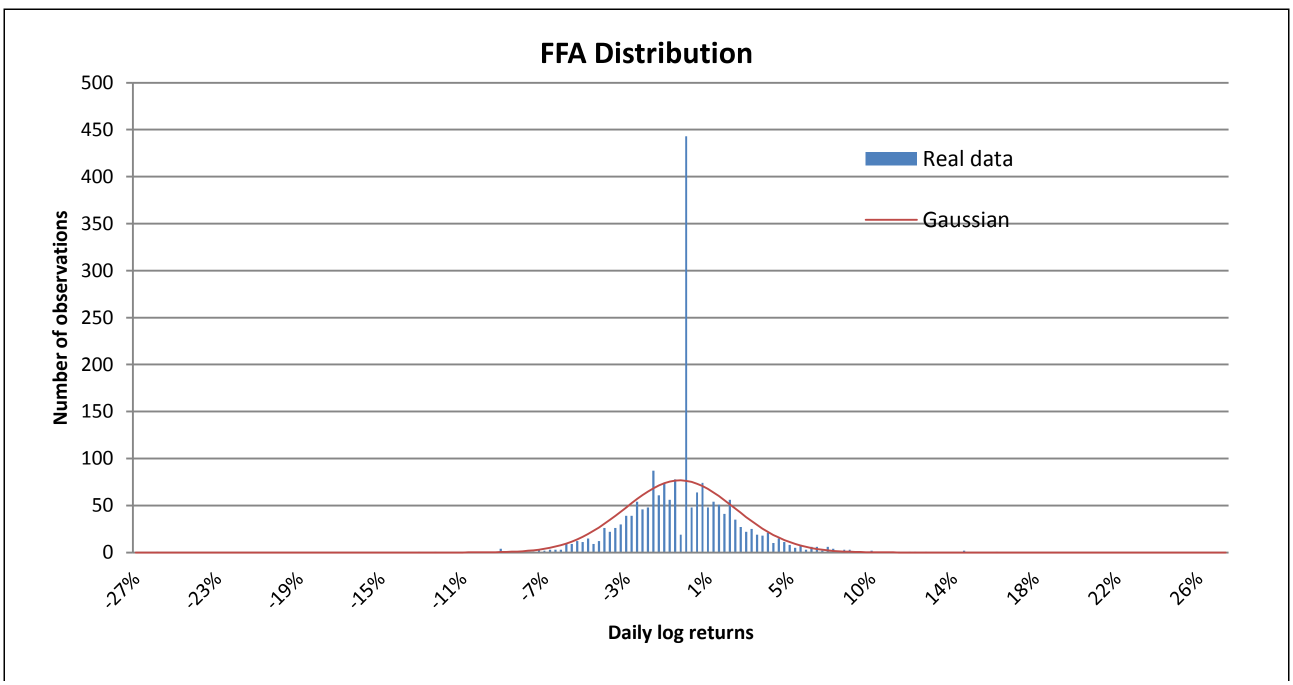


Figure 9: *Distribution (blue bars) for TC2 SPOT, compared to Gaussian distribution (red line). The figures at the bottom are zoomed in on the left and right tail of the distribution.*

The historical TC2 FFA distribution varies from the spot distribution in terms of more daily returns equal to zero. The first years of the period were characterised by lower liquidity than recent years[14], which may explain some of the zero returns. However, they may also be caused by relatively large bid-offer spreads, which might absorb small price changes. Nevertheless, this is the actual market condition the actors are exposed to.



[14] Confirmed by Mr. Erlend Engelstad in Marex Spectron

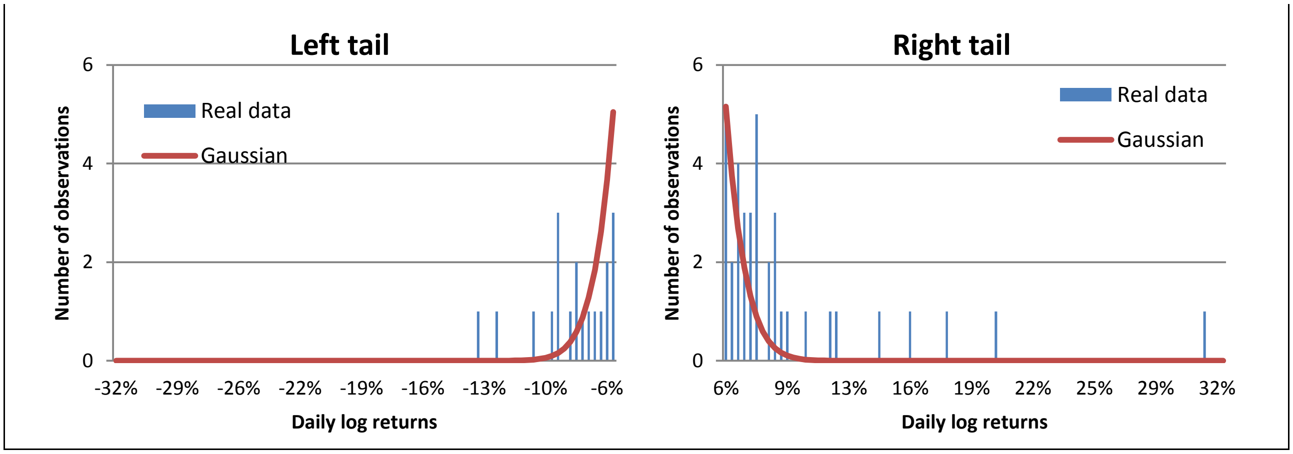


Figure 10: *Distribution (blue bars) for TC2 FFA, compared to Gaussian distribution (red line). The figures at the bottom are zoomed in on the left and right tail of the distribution.*

The distribution shows fat tails compared to the Gaussian distribution and the JB-statistic states with a confidence level at 99% that the historical distribution for the FFA is not equal to the Gaussian distribution. There are naturally some uncertainties attached to the splicing of the FFA. When removing the returns from the splicing dates we are also removing the actual daily return and not only the price jump caused by the splicing of two contracts.

5.1.2 Volatility

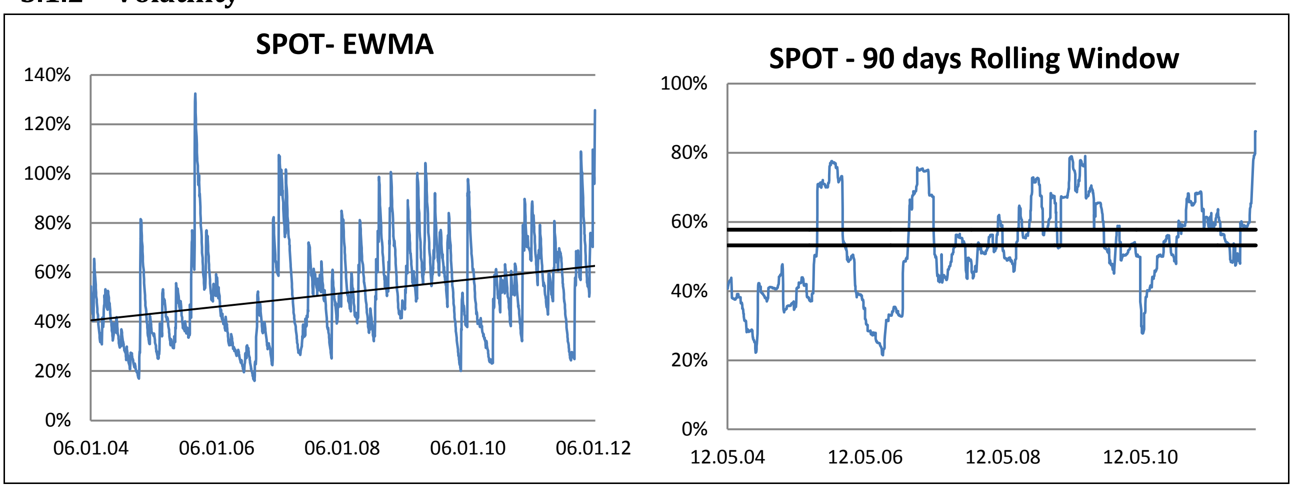


Figure 11: *Yearly volatility calculated with EWMA and 90-days Rolling Window for TC2 spot from 2004 to January 2012. The black line in the EWMA figure illustrates the trend in the sample volatility, and the black lines in the Rolling Window illustrate a 99% confidence interval of the historical volatility.*

The EWMA volatility for TC2 spot indicates that the volatility is stochastic. Over the sampling period the spot volatility has averaged at 51.59%. Rolling Window volatility displays the same trends as EWMA, although it is not as peaked. By calculating volatility in this way, the peaks tend to be less distinct compared to the EWMA method. Mainly since extreme returns are weighted equally to the previous 89 returns, and the EWMA method weights the last returns the most. The 99% confidence interval shown in Rolling Window in Figure 11 illustrates that the volatility clearly exceeds the interval limits, hence the variation in the volatility is not caused by sampling errors. This implies that the volatility is stochastic.

TC2 FFA shows lower volatility levels compared to the TC2 spot volatility. The variations in the FFA volatility are less dramatic than the spot, at least in the period after 2005. Due to the average settlement price, it is surprising that the FFA is less volatile compared to the underlying spot. As for the TC2 spot the TC2 FFA has stochastic volatility, due to volatility exceeding the 99% confidence interval. Further on, it appears that the TC2 FFA has been less volatile in the last three years, which corresponds with statements given by market actors. However, there is a peak in the volatility in January 2012 that may indicate the opposite trend for TC2.

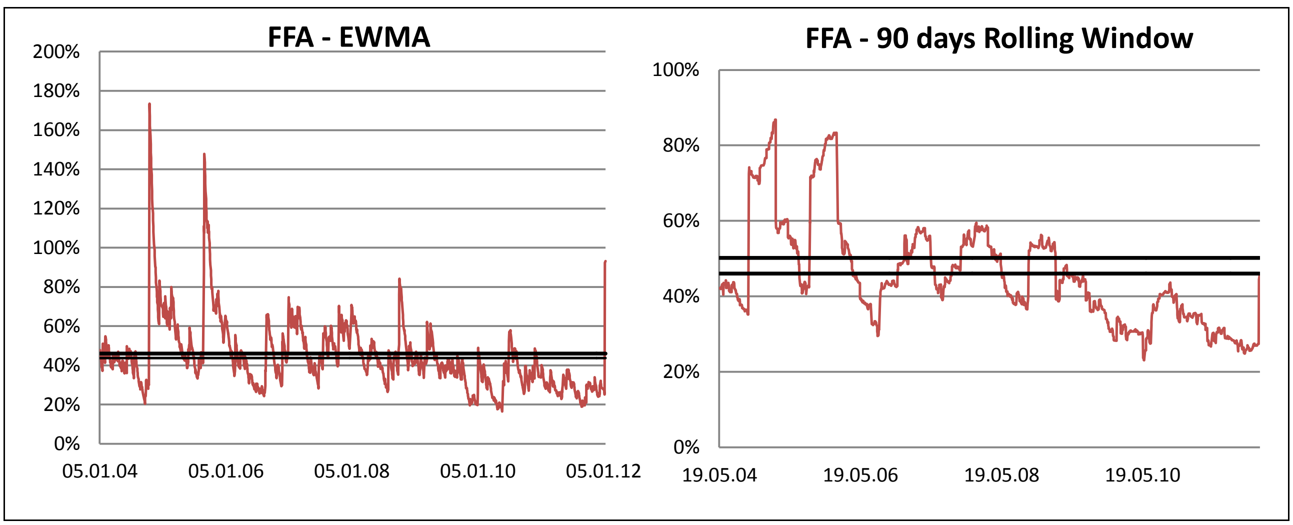


Figure 12: *Yearly volatility calculated with EWMA and 90-days Rolling Window for TC2 FFA from 2004 to January 2012. The black line in the EWMA figure illustrates the trend in the sample volatility, and the black lines in the Rolling Window illustrate a 99% confidence interval of the historical volatility.*

In order to give an example of the difference between FFA with and without the splice returns, we compare Figure 12 and Figure 13. As we can see from Figure 13 the presence of the splicing returns has caused the Rolling Window volatility to be more peaked. This indicates considerable splice returns in the period. For the other tanker routes we will not illustrate the difference between FFA with and without splice returns. However, we will illuminate the problems attached to splicing for FFA contracts in the VaR results.

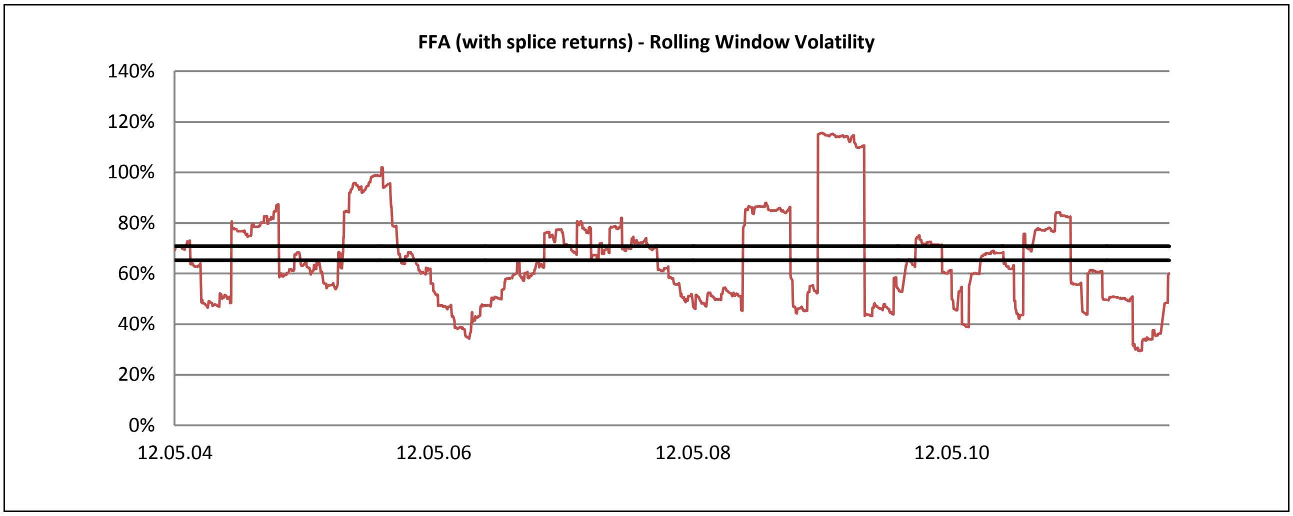


Figure 13: *Yearly volatility calculated with 90-days Rolling Window for TC2 FFA with splice returns*

Table 6 shows the volatility of the volatility for both the spot and FFA. The results in this table confirm that the volatility is not constant. It also seems that the volatility to the volatility varies from period to period.

Volatility of the volatility				
	SPOT daily	**SPOT annually**	**FFA daily**	**FFA annually**
2004 - 2012	0.72 %	13.70 %	0.72 %	13.81 %
2004 - 2005	0.79 %	15.02 %	0.85 %	16.29 %
2006 - 2007	0.78 %	14.86 %	0.47 %	9.02 %
2008 - 2009	0.47 %	8.98 %	0.41 %	7.81 %
2010 - 2011	0.43 %	8.28 %	0.24 %	4.67 %
2011 - 2012	0.38 %	7.25 %	0.19 %	3.60 %

Table 6: *Volatility of the 90-days Rolling Window volatility for various* periods for TC2 spot and TC2 FFA

5.2 TC5

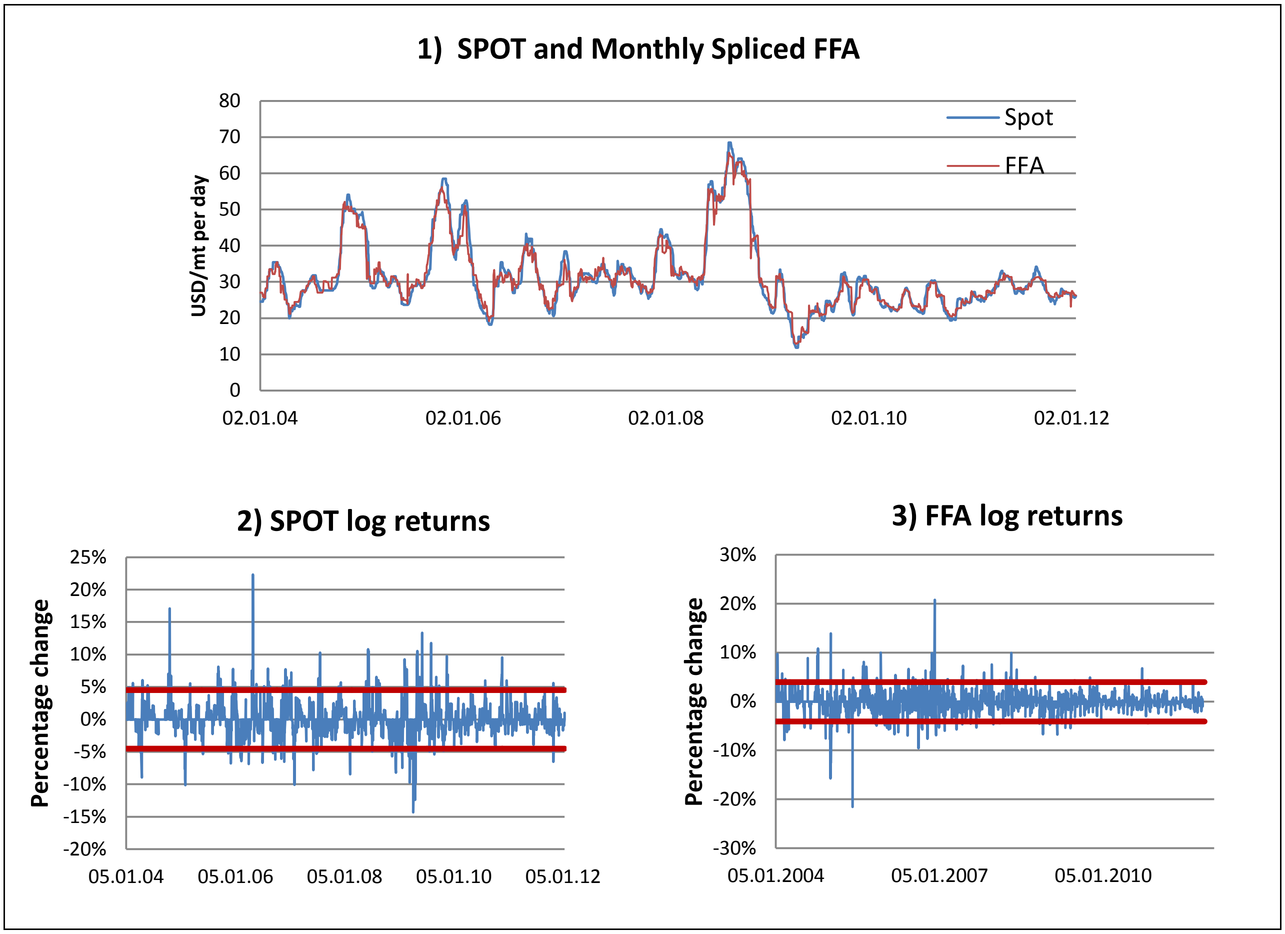


Figure 14: *1) TC5 spot and spliced FFA prices from 2004 to January 2012. 2) Spot log-returns for the same period, 3) log returns for TC2 FFA for the same period. Red lines illustrate a 95% confidence interval around the mean return of the sample.*

TC5 is the route for transportation of 55 000 mt of naphtha condensate from the Middle East Gulf to Japan, or more specifically from Ras Tenura in the eastern province of Saudi Arabia to Yokohama (Alizadeh and Nomikos 2009). Naphtha is an intermediate product from distillation of crude oil. One should expect that the tsunami disaster on March 11. 2011 in Japan, which shut down all the naphtha petrochemical steam crackers situated on the eastern coast of Japan, would affect the TC5 freight rate. However, the spot data shows no significant changes in the period after the tsunami. This might be explained by the conflict in Libya at the same time. The petroleum export from Libya was halted, which increased the export from other regions such as Saudi Arabia to the regions close to Japan. It appears the two events neutralised the effect of each other in the trade of TC5[15]. However, it might also be caused by the surplus capacity in the tanker market, hence smaller changes in the freight rates when there is a shift in the demand as explained in section 2.4.

[15] Confirmed by Mr. Andreas Holst Thorsen in Frontline

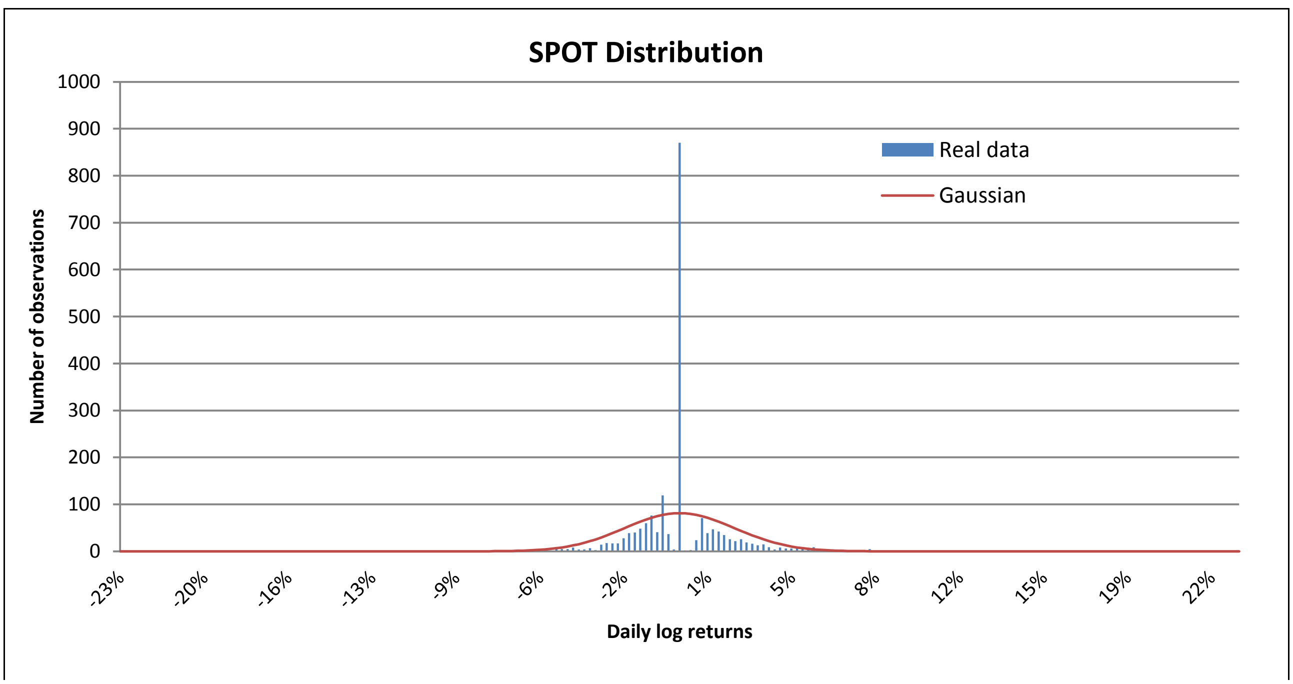
TC5 varied between approximately 70 USD/mt per day to 13 USD/mt per day in the period. When the financial crisis occurred it dropped from over 60 USD/mt per day to approximately 13 USD/mt per day over a period of eight months. In the last couple of years the TC5 freight rate has levelled out between 20 USD/mt per day and 30 USD/mt per day. The relatively low levels of the TC5 freight rate in recent years might be explained by the surplus capacity in the tanker market. As we can see from Figure 14, the FFA follows the spot price steadily, and the daily returns have several times exceeded the confidence interval of the returns. However it seems like there has been less extreme fluctuations in the last years of the period.

5.2.1 Distributions

	SPOT	FFA		SPOT	FFA
Number of obs.	2011	1912	Mean	0.00 %	-0.05 %
Skewness	0.96	0,01	Median	0.00 %	0.00 %
Kurtosis	10.99	18,08	Max return	22.31 %	20.79 %
Jarque-Bera	10 432	26 032	Min return	-14.31 %	-21.55 %

Table 7: *Descriptive statistics for TC5 spot and TC5 FFA*

TC5 spot contains a large number of zero returns in the period, especially in the first three years of the period. As for TC2, large bid-offer spreads may have absorbed small price changes. Since the TC5 spot distribution differs from the other spot freight rates it might indicate that Platts operates with larger bid-offer spreads than Baltic Exchange. The tail figures indicate the presence of fat tails for TC5 spot. Like TC2 the right tail is a bit fatter than the left tail.



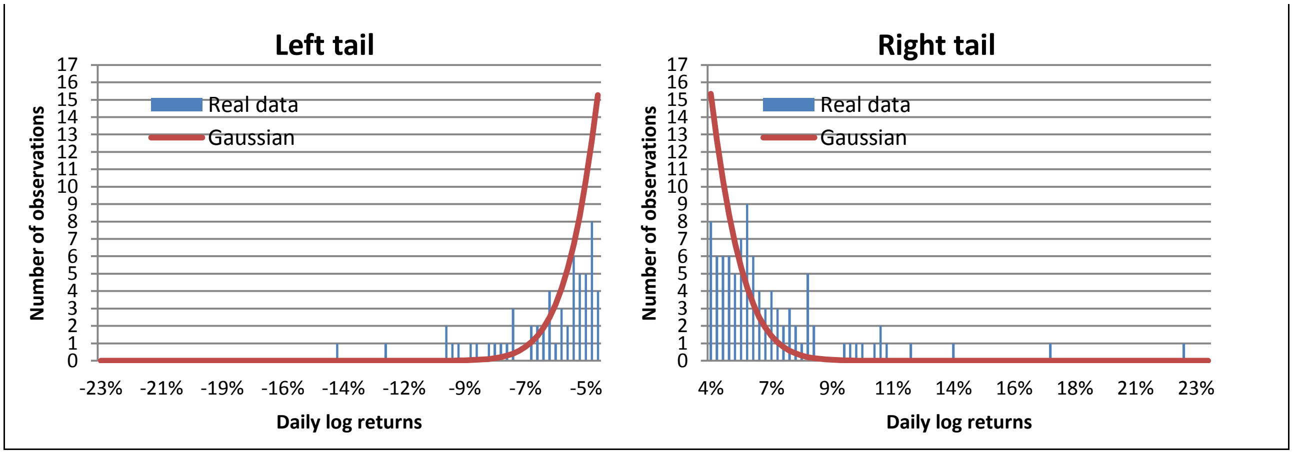
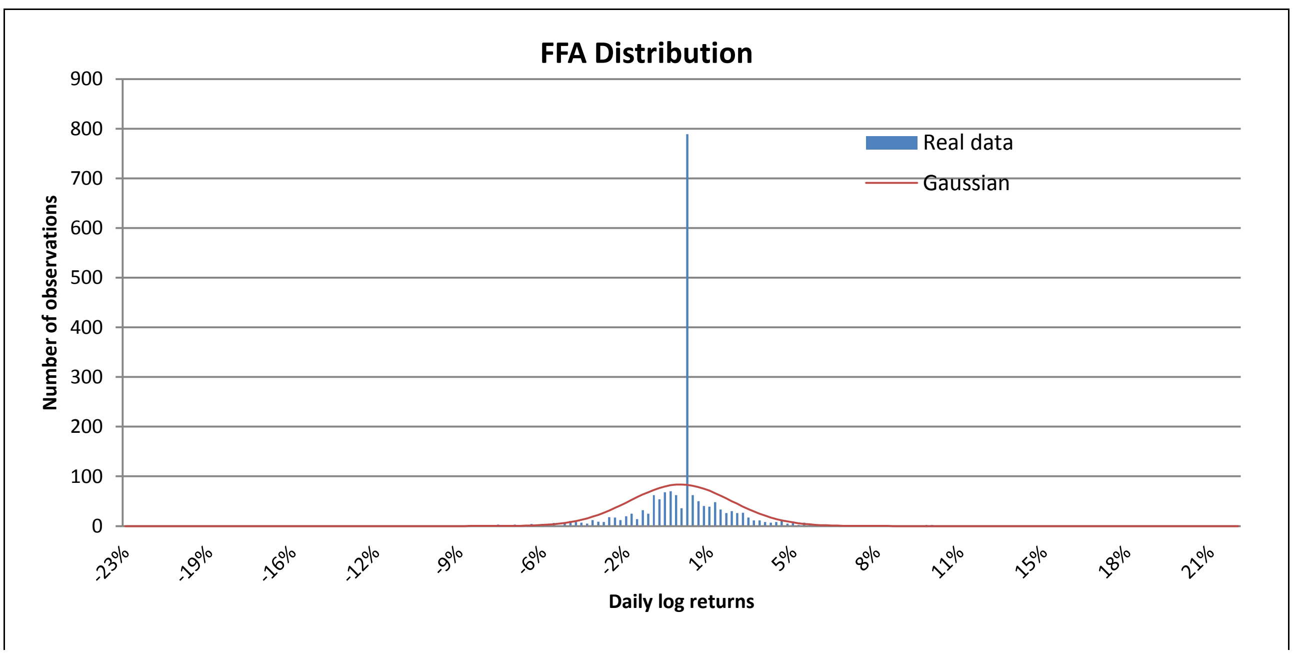


Figure 15: *Distribution (blue bars) for TC5 spot, compared to Gaussian distribution (red line). The figures at the bottom are zoomed in on the left and right tail of the distribution*

TC5 spot is clearly not normally distributed and has both a high peak and fat tails, which are also confirmed by the high JB-statistic in Table 7. The high peak of the distribution is also confirmed by the kurtosis. Further on, the right tail appears to be heavier than the left tail. As for the TC2, we cannot say with certainty that the tail-figures actually show jumps due to our data set with daily market prices.



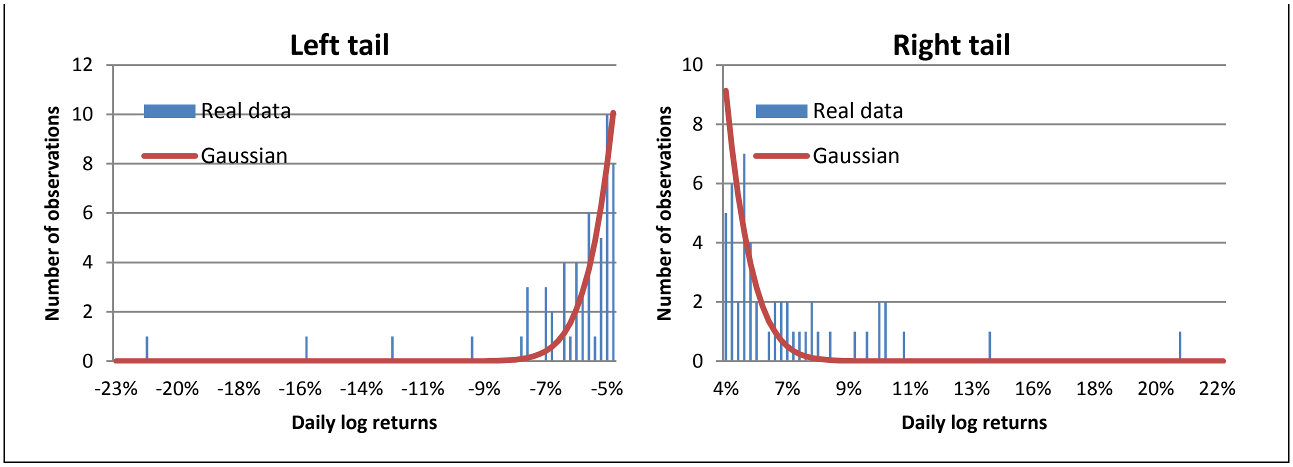


Figure 16: *Distribution (blue bars) for TC5 FFA, compared to Gaussian distribution (red line). The figures at the bottom are zoomed in on the left and right tail of the distribution.*

The TC5 FFA distribution is quite similar to the TC5 spot distribution. TC5 FFA distribution is however slightly less skewed than the TC5 spot, and the mean of the returns is negative for the TC5 FFA. The kurtosis states that the TC5 FFA distribution is peaked, as the figure clearly illustrates. The tail-figures display the presence of fat tails, and there is no doubt that the FFA distribution is not equal to the Gaussian distribution. This is also supported by the JB-statistic.

5.2.2 Volatility

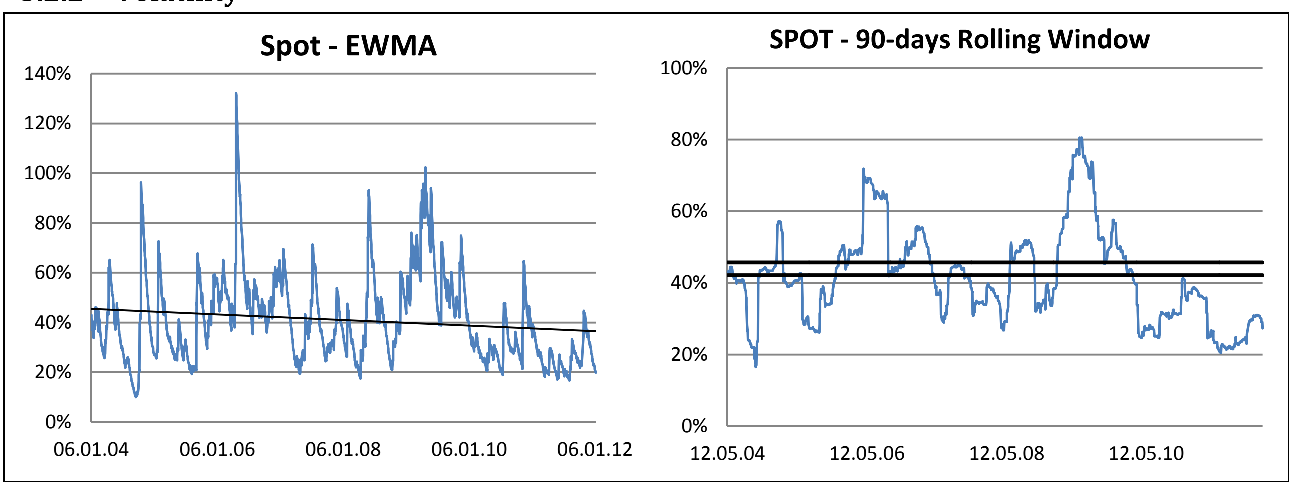


Figure 17: *Yearly volatility calculated with EWMA and 90-days Rolling Window for TC5 spot from 2004 to January 2012. The black line in the EWMA figure illustrates the trend in the sample volatility, and the black lines in the Rolling Window illustrate a 99% confidence interval of the historical volatility*

TC5 spot EWMA volatility shows substantial variations in the volatility. Several volatility peaks in the period indicates that the volatility is stochastic. TC5 Rolling Window volatility also illustrates great variation in the volatility, however, not as peaked as the EWMA volatility. Furthermore, the 90-days Rolling Window figure shows that the volatility varies widely above and below the 99% confidence interval of the historical standard deviation of the sample, which implies that the stochastic volatility cannot be attributed to sampling error.

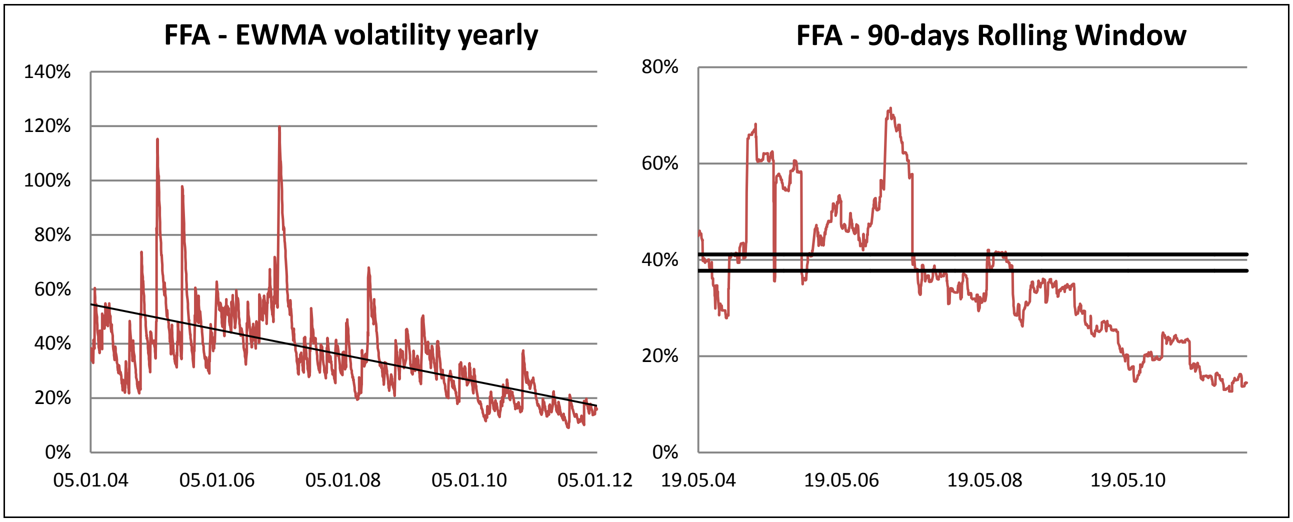


Figure 18: *Yearly volatility calculated with EWMA and 90-days Rolling Window for TC5 FFA from 2004 to January 2012. The black line in the EWMA figure illustrates the trend in the sample volatility, and the black lines in the Rolling Window illustrate a 99% confidence interval of the historical volatility.*

The TC5 FFA EWMA yearly volatility shows lower levels of volatility than the volatility estimate for the spot freight rate. It also tends to be less volatile with lower peaks from the middle of 2007, which might be explained by the surplus capacity in the tanker market. This is supported by the results in Table 8 where the volatility of the volatility for the TC5 FFA is reduced from over 10% to less than 5% in the last periods. The volatility is evidently stochastic due to clear jumps in the volatility and the narrow 99% confidence interval, which is clearly exceeded.

	Volatility of the volatility			
	SPOT daily	**SPOT annually**	**FFA daily**	**FFA annually**
2004 - 2012	0.69 %	13.11 %	0.76 %	14.53 %
2004 - 2005	0.44 %	8.45 %	0.62 %	11.89 %
2006 - 2007	0.53 %	10.09 %	0.56 %	10.62 %
2008 - 2009	0.75 %	14.30 %	0.24 %	4.50 %
2010 - 2011	0.38 %	7.34 %	0.21 %	4.09 %
2011 - 2012	0.31 %	5.96 %	0.19 %	3.67 %

Table 8: *Volatility of the 90-days Rolling Window volatility for various* periods for TC5 spot and TC5 FFA

5.3 TD3

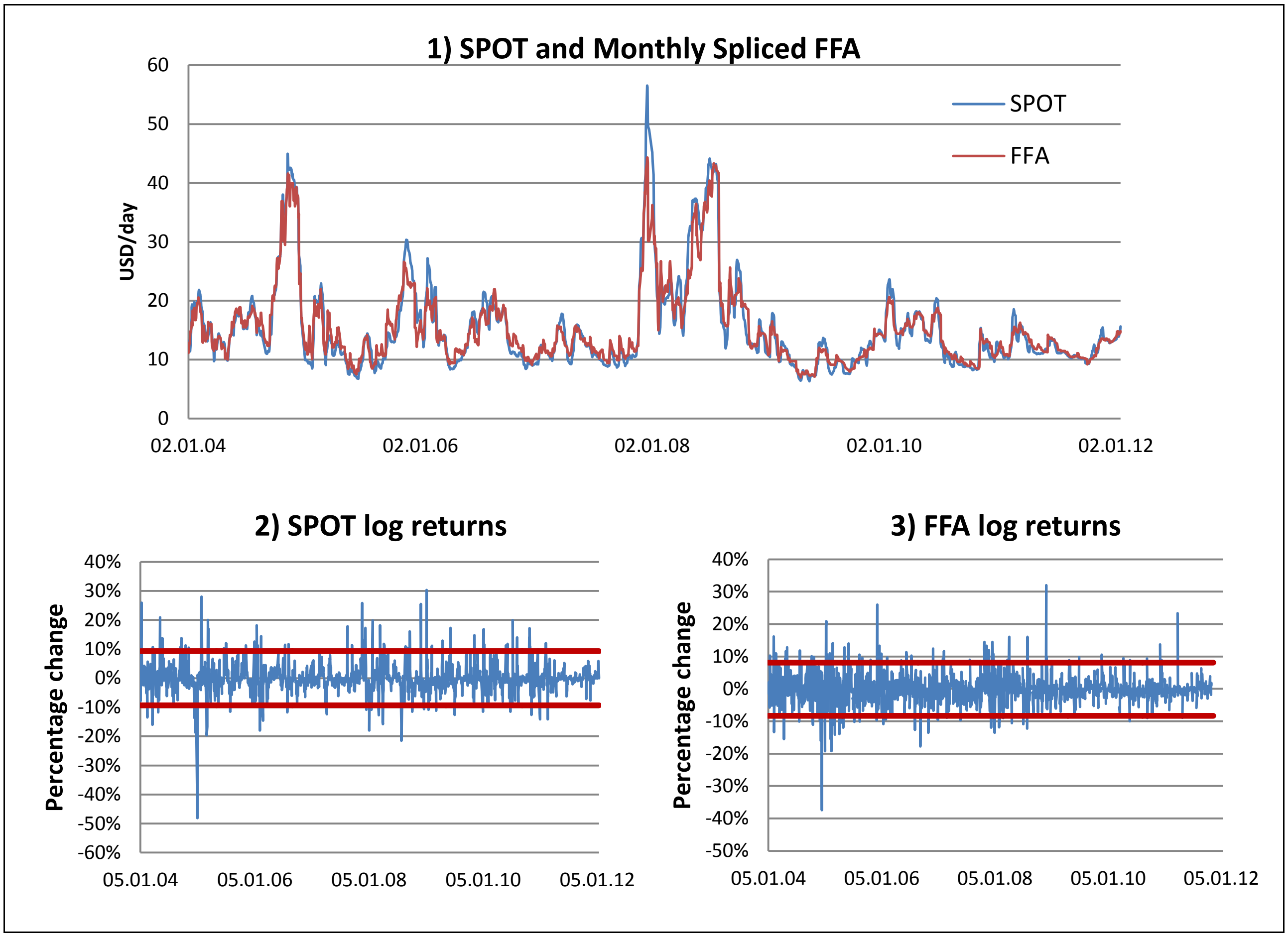


Figure 19: *1) TD3 spot and spliced FFA prices from 2004 to January 2012. 2) Spot log-returns for the same period. 3) Log returns for TC2 FFA for the same period. Red lines illustrate a 95% confidence interval around the mean return of the sample.*

TD3 is a VLCC route, transporting crude oil from the Middle East to the Far East. The indicative route is Ras Tenura in the Middle East gulf to Chiba in Japan. VLCCs are the largest vessels in the shipping industry, and the risks linked to these vessels are known to be large due to the limited number of harbours capable of servicing them. Hence, VLCCs offer lower flexibility than smaller vessels. The historical plot shows several peaks in the TD3 freight rate over the period. However, recent years show considerably lower peaks than the period prior to the financial crisis. As for TC5, we had expected an impact from the tsunami in Japan March 2011 on the TD3 freight rate but our data does not show any distinct price drop due to the tsunami. The plot of the TD3 fright rate illustrates that TD3 spot seems to have peaks a bit higher than the spliced TD3 FFA. This is natural since the settlement price of the FFA is based on an arithmetic average of the delivery period for the underlying spot. It also appears that TD3 spot and FFA follow the empirically proven seasonality in the shipping market.

5.3.1 Distributions

	SPOT	FFA		SPOT	FFA
Number of obs.	2008	1912	Mean	0.01 %	-0.06 %
Skewness	0.24	0.22	Median	-0.25 %	0.00 %
Kurtosis	10.40	8.63	Max return	30.32 %	32.05 %
Jarque-Bera	9066.77	5946.92	Min return	-48.09 %	-37.48 %

Table 9: *Descriptive statistics for TD3 spot and TD3 FFA*

The kurtosis indicates that the distribution has a high peak, which is illustrated in Figure 20. TD3 has a bit more extreme returns than TC2 and TC5, but the tails of the spot distribution do not seem to be fatter compared to the Gaussian distribution than the tails of TC2 and TC5. This is because TD3 consequently also has a higher constant standard deviation in the period compared to TC2 and TC5. Subsequently, the JB-statistic confirms with a significance level of 99% that the TD3 spot distribution does not follow the Gaussian distribution.

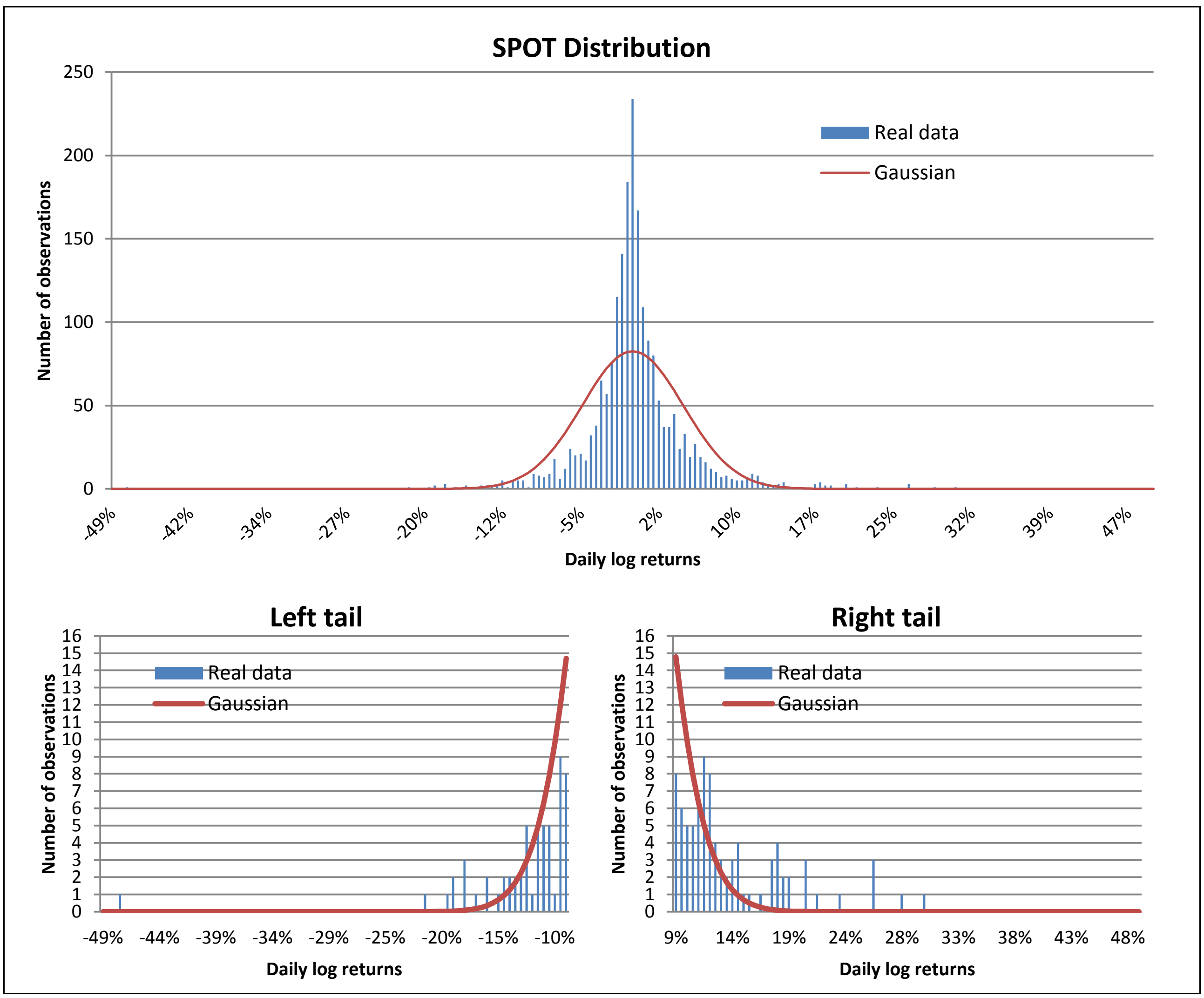


Figure 20: *Distribution for TD3 spot (blue bars), compared to Gaussian distribution (red line). The figures at the bottom are zoomed in on the left and right tail of the distribution*

The distribution for TD3 FFA differs from the TD3 spot distribution due to the approximately 480 zero returns. We assume that the high number of zero returns is caused by the same reasons as explained for TC2 FFA. Both the left and right tail figures illustrate the presence of fat tails. The fluctuations in the TD3 FFA are also greater than the fluctuations in the FFAs for the clean tanker routes. JB-statistic corroborates the non-normality of the spliced FFAs distribution.

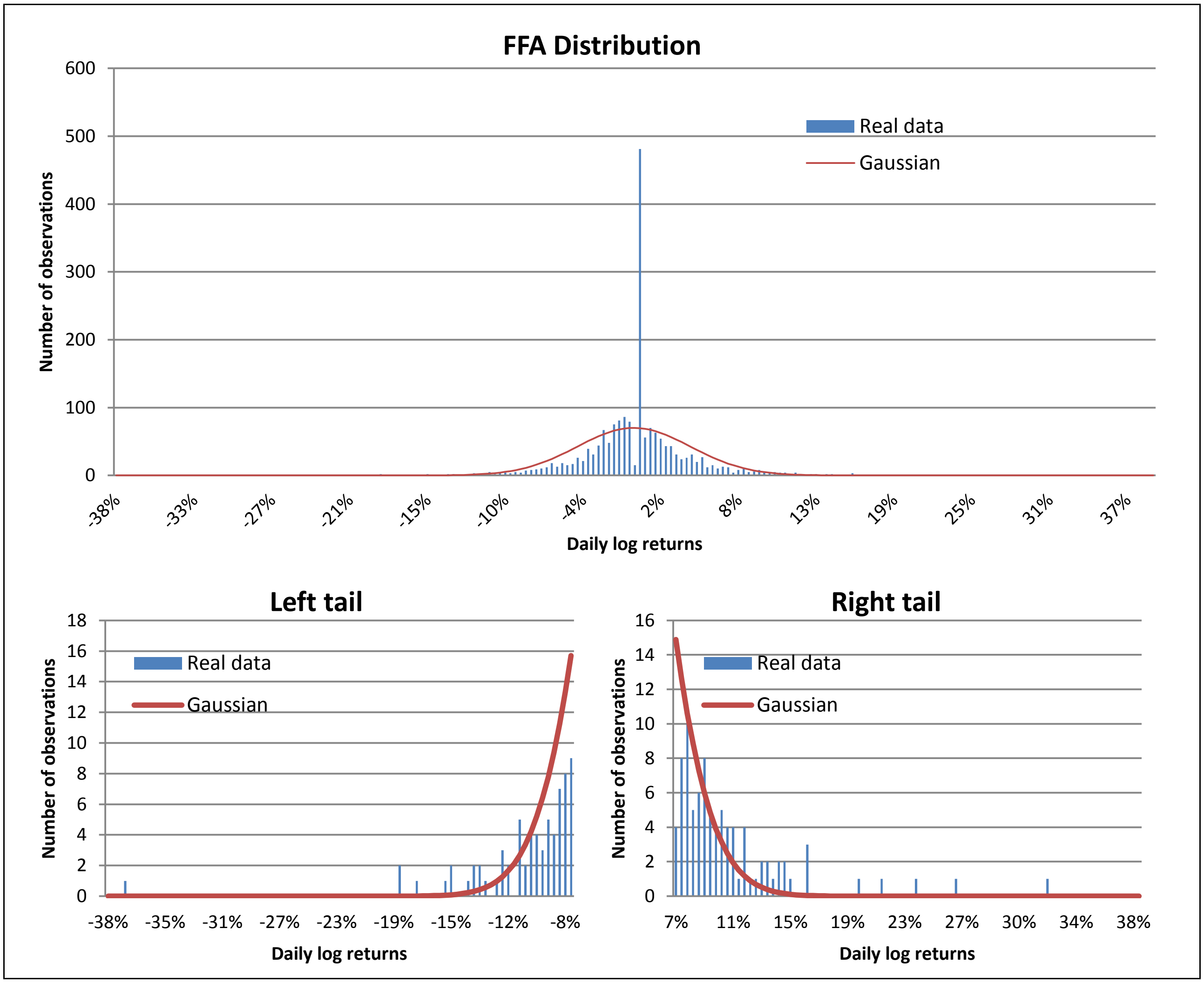


Figure 21: *Distribution for TD3 FFA (blue bars), compared to Gaussian distribution (red line). The figures at the bottom are zoomed in on the left and right tail of the distribution*

5.3.2 Volatility

As Figure 22 illustrates, the TD3 spot EWMA volatility is considerably higher than the previous routes, varying from 250% to under 50%. The Rolling Window shows naturally the same trends as the EWMA, however the peaks are not as high as for the EWMA. These results are also congruent with the theory of high volatility for VLCC routes. Furthermore, Figure 22 shows that the TD3 spot Rolling Window volatility frequently varies outside the 99% confidence interval. This implies that the stochastic volatility is not caused by sampling errors.

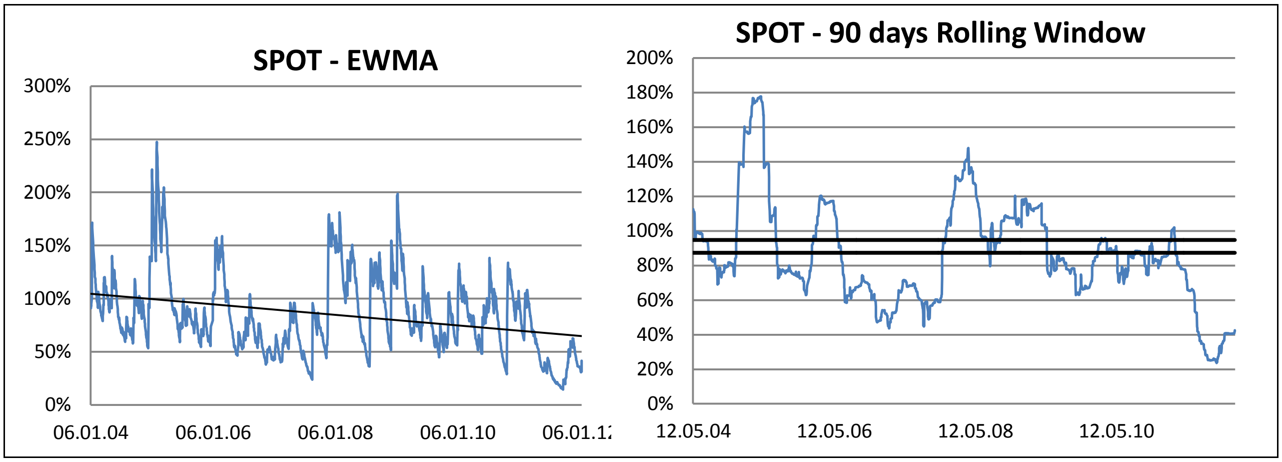


Figure 22: *Yearly volatility calculated with EWMA and 90-days Rolling Window for TD3 spot from 2004 to January 2012. The black line in the EWMA figure illustrates the trend in the sample volatility, and the black lines in the Rolling Window illustrate a 99% confidence interval of the historical volatility*

It also appears to be a declining trend in the volatility in the sample period, which might be caused by the surplus capacity in the tanker market, since the peaks in freight rates often appear in periods with limited capacity. Further on, it seems like several of the peaks in the volatility of TD3 are caused by jumps in the freight rate over the Christmas holidays.

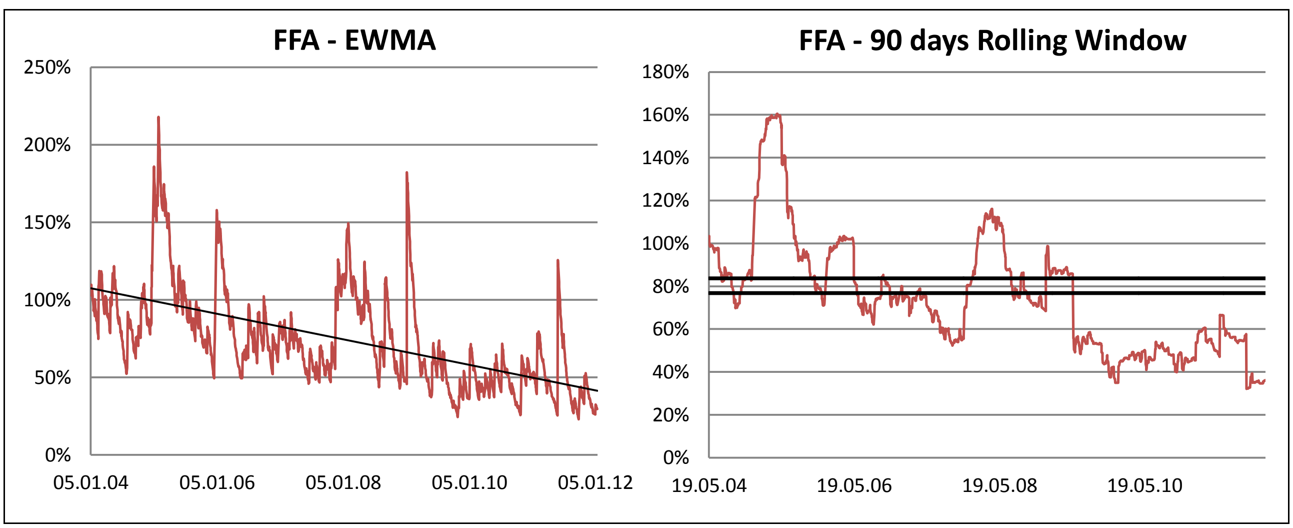


Figure 23: *Yearly volatility calculated with EWMA and 90-days Rolling Window for TD3 FFA from 2004 to January 2012. The black line in the EWMA figure illustrates the trend in the sample volatility, and the black lines in the Rolling Window illustrate a 99% confidence interval of the historical volatility*

TD3 FFA EWMA shows the same declining trend and also approximately the same volatility level as the TD3 spot. However, it looks like the variations in the FFA volatility have been a bit less, at least in the last years of the sample period. If we look at the results in Table 10, it illustrates the same, because it looks like the volatility of the volatility to TD3 FFA has been lower compared to the spot in the last years of the sample period. Further on, the 90-days Rolling Window figure illustrates that the volatility of the FFA is clearly stochastic. The estimated Rolling Window volatility exceeds the 99% confidence interval most of the time of the sample period. Hence, sampling errors do not cause the stochastic volatility.

	Volatility of the volatility			
	SPOT daily	SPOT annually	FFA daily	FFA annually
2004 - 2012	1.55 %	29.62 %	1.43 %	27.25 %
2004 - 2005	1.85 %	35.36 %	1.51 %	28.94 %
2006 - 2007	1.12 %	21.33 %	0.73 %	14.01 %
2008 - 2009	1.09 %	20.91 %	1.14 %	21.75 %
2010 - 2011	1.22 %	23.39 %	0.39 %	7.39 %
2011 - 2012	1.32 %	25.20 %	0.52 %	9.85 %

Table 10: *Volatility of the 90-days Rolling Window volatility for various* periods for TD3 spot and TD3 FFA

5.4 TD5

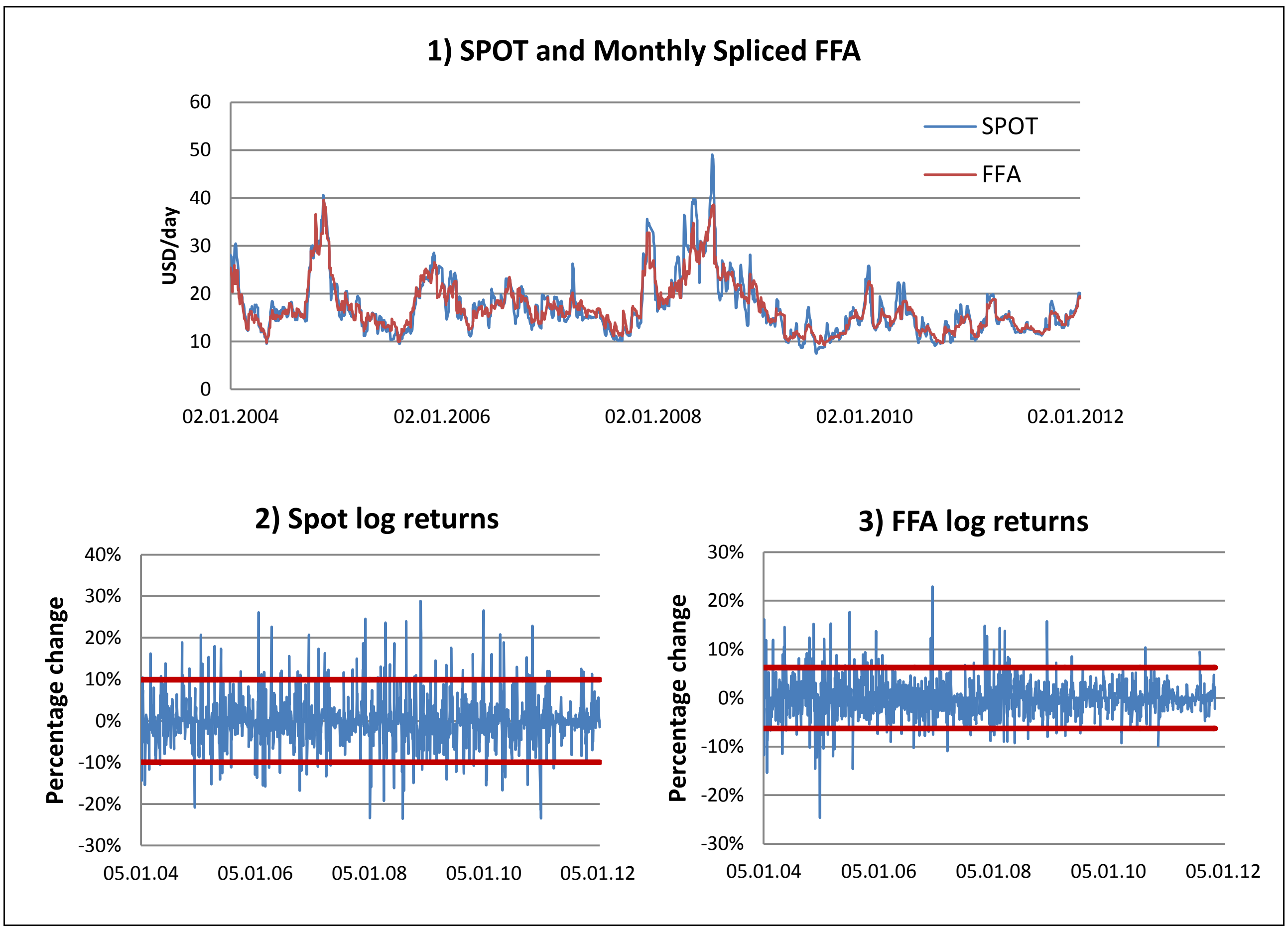


Figure 24: *1) TD5 spot and spliced FFA prices from 2004 to January 2012. 2) Spot log returns for the same period. 3) Log returns for TC2 FFA for the same period. Red lines illustrate a 95% confidence interval around the mean return of the sample.*

TD5 is a Suezmax (130,000mt) route for crude oil between West Africa and the US Atlantic Coast. The indicative route is between Bonny (Nigeria) to Philadelphia. It is worth to mention that Sunoco Inc. recently announced that would shut its oil refinery in Philadelphia if it is not sold by July 2012. This may result in lower liquidity in TD5 in the future.

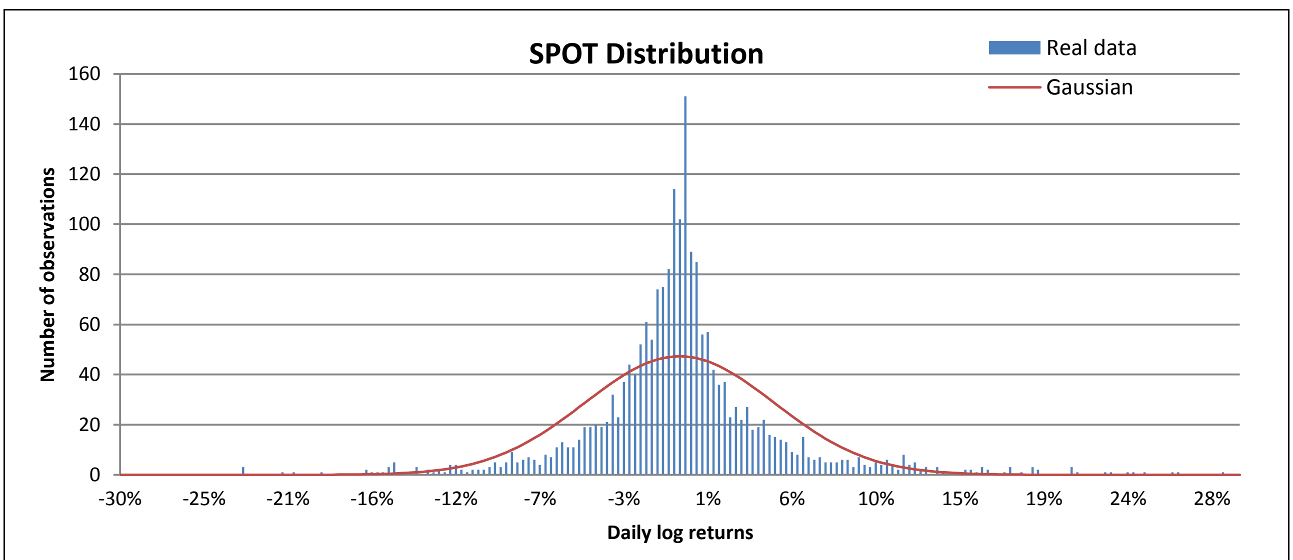
TD5 seems to follow the same major trends as TD3, with the same characteristics of seasonality and high peaks in the freight rate. Recent years appear to have had less dramatic fluctuations compared to earlier years in the sample period. This trend may be caused by the surplus capacity in the tanker market. As for the previous routes, the TD5 spot has greater fluctuations compared to the spliced FFA contracts. TD5 spot had some extreme daily returns in the past, which might indicate jumps in the time-series. In the plot of TD5 spot and FFA prices, the spot frequently peaks at higher levels than the FFA. This is natural considering the settlement calculation of the FFA contracts.

5.4.1 Distributions

	SPOT	FFA		SPOT	FFA
Number of obs.	2008	1912	Mean	-0.02 %	-0.01 %
Skewness	0.61	0.42	Median	-0.19 %	0.00 %
Kurtosis	5.07	7.59	Max return	28.88 %	22.93 %
Jarque-Bera	2 271	4 651	Min return	-23.52 %	-24.62 %

Table 11: *Descriptive statistics for TD5 spot and TD5 FFA*

The TD5 spot distribution is clearly peaked, which is supported with a high kurtosis. Figure 25 evidently indicates that the TD5 spot distribution differs from the Gaussian distribution, which is also confirmed by the JB-statistic. The tail figures show the presence of fat-tails and it seems like the right tail is a bit heavier than the left, corresponding to the trend from the other routes.



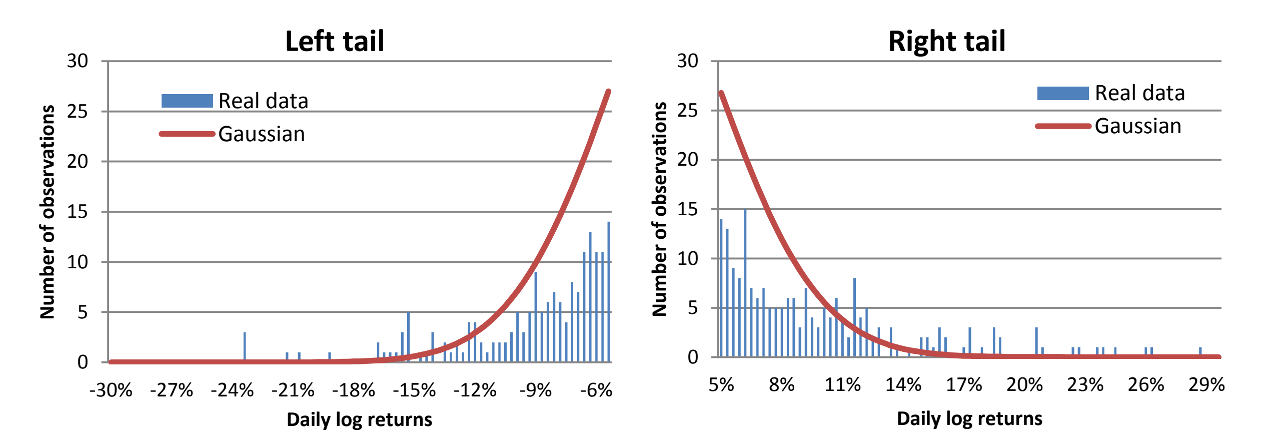
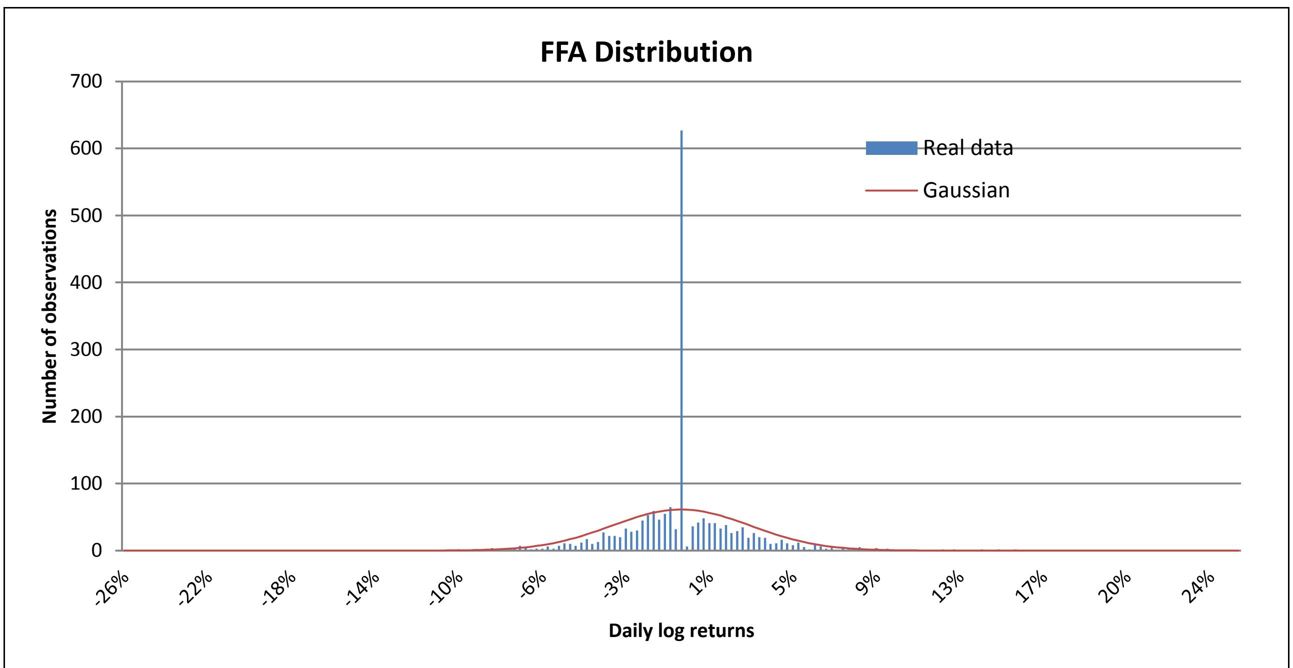


Figure 25: *Distribution for TD5 spot (blue bars), compared to Gaussian distribution (red line). The figures at the bottom are zoomed in on the left and right tail of the distribution.*

Figure 26 illustrates the TD5 FFA distribution which is characterized by over 500 zero returns. Hence, the figures clearly indicate high peaks of zero returns and the occurrence of fat tails. The JB-statistic also states that the TD5 FFA distribution is not normally distributed. Like the TD5 spot distribution, TD5 FFA distribution appears to have a right tail heavier than the left tail. However, the returns are less extreme for the FFA. The maximum and minimum return of the FFA compared to the spot shows the same result. This might indicate that the volatility is at a lower level for the FFA than for the spot.



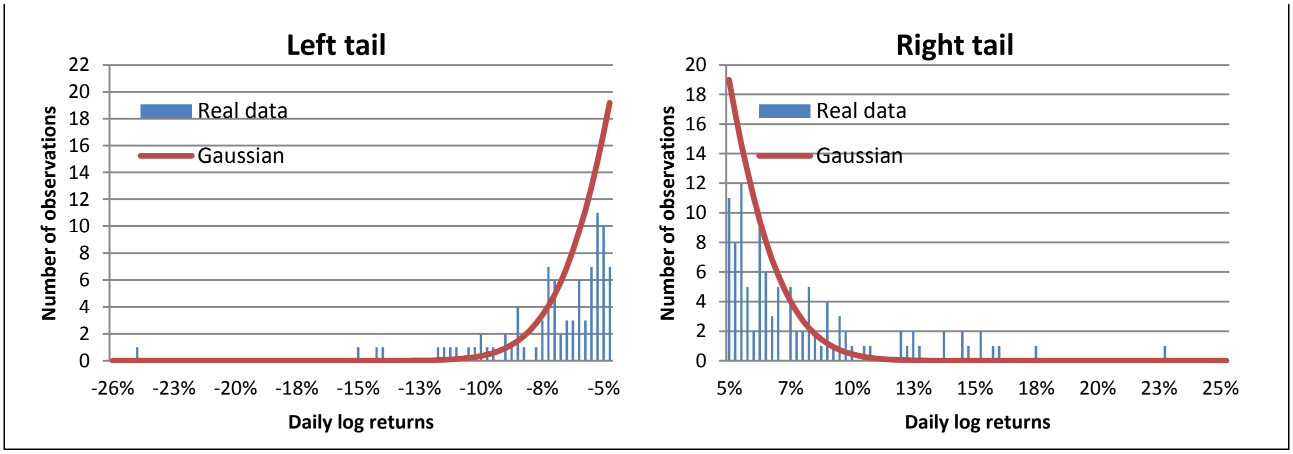


Figure 26: *Distribution for TD5 FFA (blue bars), compared to Gaussian distribution (red line). The figures at the bottom are zoomed in on the left and right tail of the distribution.*

5.4.2 Volatility

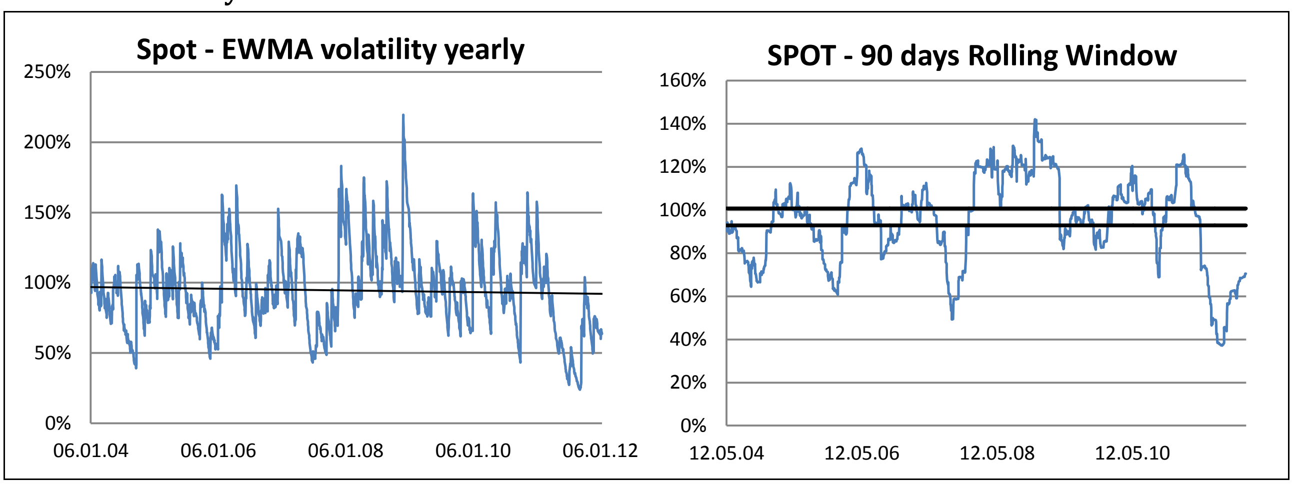


Figure 27: *Yearly volatility calculated with EWMA and 90-days Rolling Window for TD5 spot from 2004 to mid-January 2012.The black line in the EWMA figure illustrates the trend in the sample volatility, and the black lines in the Rolling Window illustrate a 99% confidence interval of the historical volatility*

The chart for TD5 spot in Figure 27 illustrates a high and varying volatility, and the EWMA volatility varies from over 200% to less than 35%, and is indicating stochastic volatility. The many peaks in the EWMA plot are caused by the weighting of each day's volatility in the EWMA calculation, and are another indication of stochastic volatility. The Rolling Window volatility also varies with time, and the volatility is frequently exceeding the limits of the 99% confidence interval, which implies that the volatility is stochastic. As we can see from the TD5 spot EWMA plot there has been a slightly declining trend in the volatility, however, the trend for TD5 is less significant compared to the TD3.

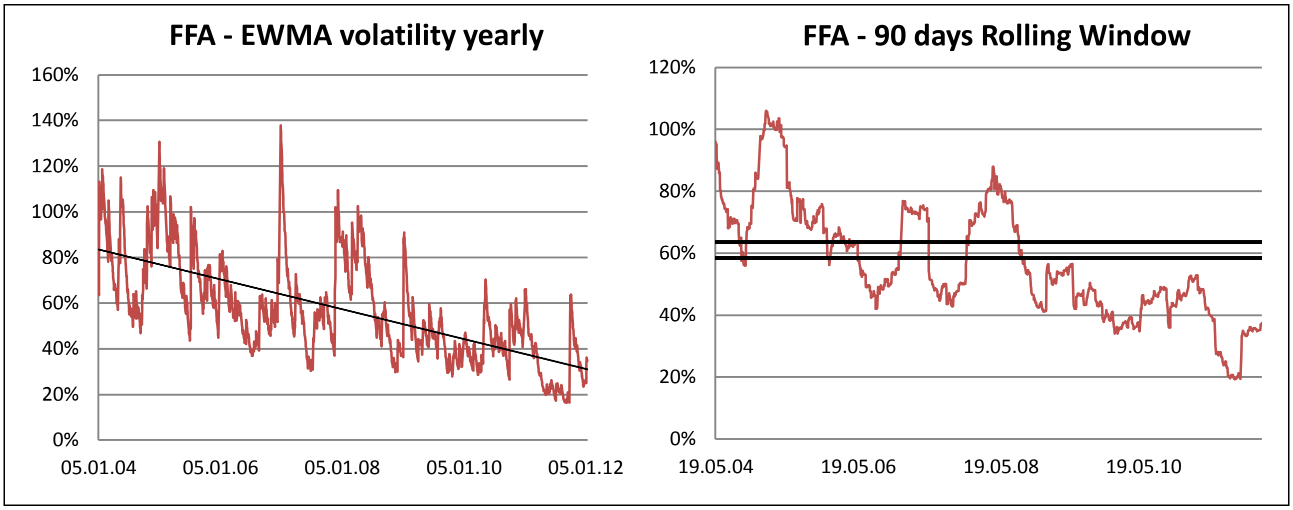


Figure 28: *Yearly volatility calculated with EWMA and 90-days Rolling Window for TD5 FFA from 2004 to January 2012. The black line in the EWMA figure illustrates the trend in the sample volatility, and the black lines in the Rolling Window illustrate a 99% confidence interval of the historical volatility*

Figure 28 indicates a stochastic volatility for the TD5 FFA, and the volatility levels are high considering that this is a FFA contract. However, the levels are significantly lower compared to the spot, which is expected since the settlement price is calculated as an arithmetic average of the delivery period for the FFA contract. The confidence intervals imply that the excessive volatility is not caused by sampling errors and can therefore be interpreted as stochastic volatility. The volatility trend for TD5 FFA over the last eight years is declining way significantly more than the TD5 spot trend; hence the volatility in TD5 FFA is at a considerably lower level now than in 2004.

	Volatility of the volatility			
	SPOT daily	**SPOT annually**	**FFA daily**	**FFA annually**
2004 - 2012	1.09 %	20.74 %	0.96 %	18.30 %
2004 - 2005	0.68 %	12.93 %	0.71 %	13.47 %
2006 - 2007	0.93 %	17.74 %	0.54 %	10.37 %
2008 - 2009	0.81 %	15.39 %	0.76 %	14.48 %
2010 - 2011	1.31 %	25.07 %	0.48 %	9.20 %
2011 - 2012	1.50 %	28.64 %	0.57 %	10.80 %

Table 12: *Volatility of the 90-days Rolling Window volatility for various* periods for TD5 spot and TD5 FFA

Table 12 provides supportive calculations to the volatility analyses and also indicates that the volatility changes over time. There appears to be an increasing trend for the volatility of the volatility in the TD5 spot.

5.5 TD7

TD7 is a tanker route for the transport of crude oil from the North Sea to Continent. The indicative route is from the Sullom Voe terminal in the Shetland Islands of Scotland to Wilhelmshaven in the north west of Germany. Furthermore the TD7 route is an Aframax route, meaning the transportation of 80,000mt.

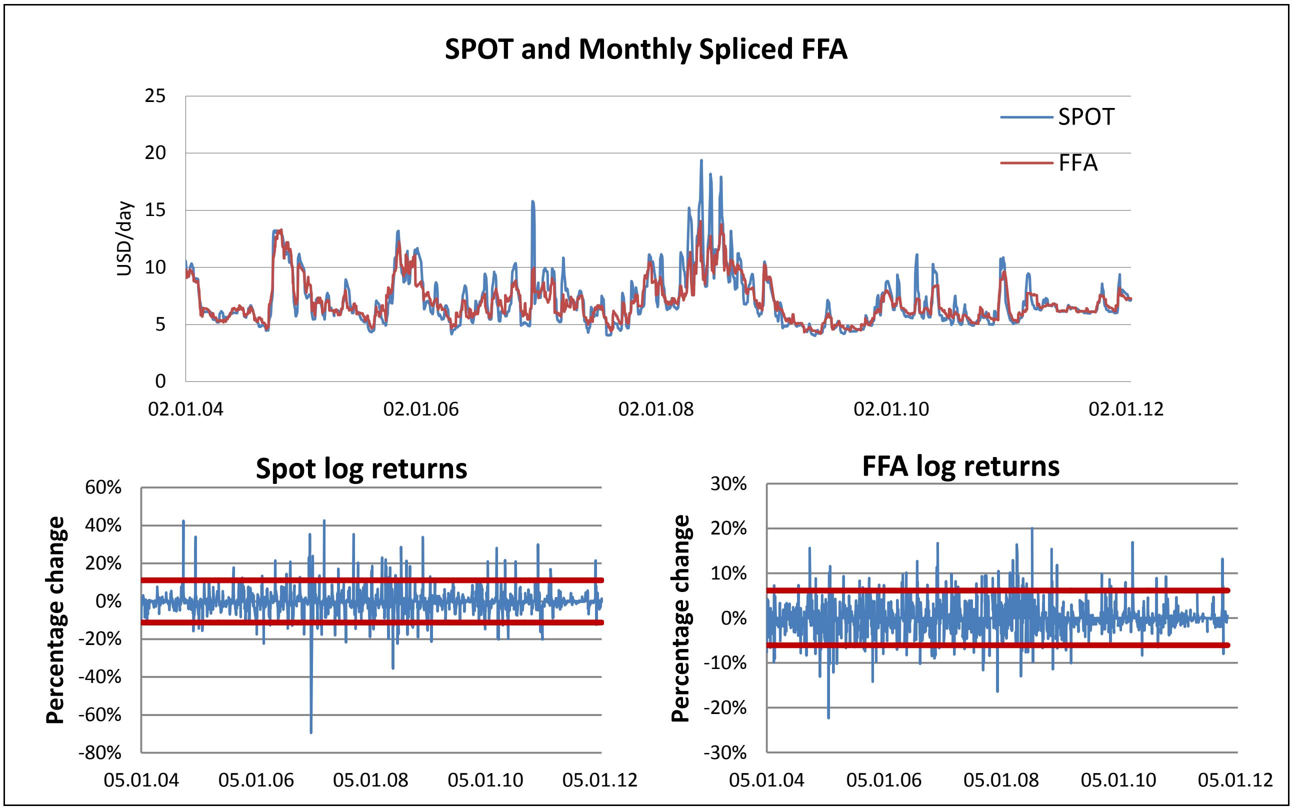


Figure 29: *1) TD7 spot and spliced FFA prices from 2004 to January 2012. 2) Spot log returns for the same period. 3) Log returns for TC2 FFA for the same period. Red lines illustrate a 95% confidence interval around the mean return of the sample.*

We can see from the plot of the TD7 spot and TD7 FFA in Figure 29, that the freight rate has been varying from approximately 5 USD/mt per day for both the spot and the FFA to nearly 20 USD/mt per day for the spot and close to 15 USD/mt per day for the FFA. Some of the peaks in the TD7 freight rate might be explained by seasonality. It also seems that the spot has higher peaks than the FFA. This might be explained by the contract specifications for the FFA contract. Hence, smaller fluctuations in the FFA than the spot are natural. From the plot figures of the daily log returns, we can see that the fluctuations have been greater for the spot than for the FFA in the sample period. The figures also illustrate that the returns have exceeded a 95% confidence interval around the mean return on several occasions. The TD7 freight rate seems to follow the same major trends as the other dirty routes, and after the financial crisis the TD7 freight rate has stabilised at a level between 5 USD/mt per day and 10 USD/mt per day the last couple of years for both spot and FFA. The lower peaks in the fright rate in this period might be explained by the surplus capacity in the tanker market.

5.5.1 Distribution

	SPOT	FFA		SPOT	FFA
Number of obs.	2008	1912	Mean	-0.02 %	0.05 %
Skewness	0.24	0.39	Median	-0.16 %	0.00 %
Kurtosis	20.76	7.02	Max return	42.70 %	20.07 %
Jarque-Bera	36 083	3 974	Min return	-69.54 %	-22.31 %

Table 13: *Descriptive statistics for TD7 spot and TD7 FFA*

Figure 30 illustrates that the spot distribution is clearly leptokurtic, with a high peak and fat-tails. This is also confirmed by and the JB-statistic, which clearly states that the TD7 spot distribution is not equal to the Gaussian distribution. The maximum and minimum return also shows that there have been some extreme daily fluctuations in past, which are also more extreme than the returns for the other tanker routes in this thesis. This might indicate that there is considerable volatility in the TD7 spot. Further on, the right tail seems to be a bit fatter than the left. However, both tail plots illustrate that there are several returns that are more extreme than the Gaussian distribution.

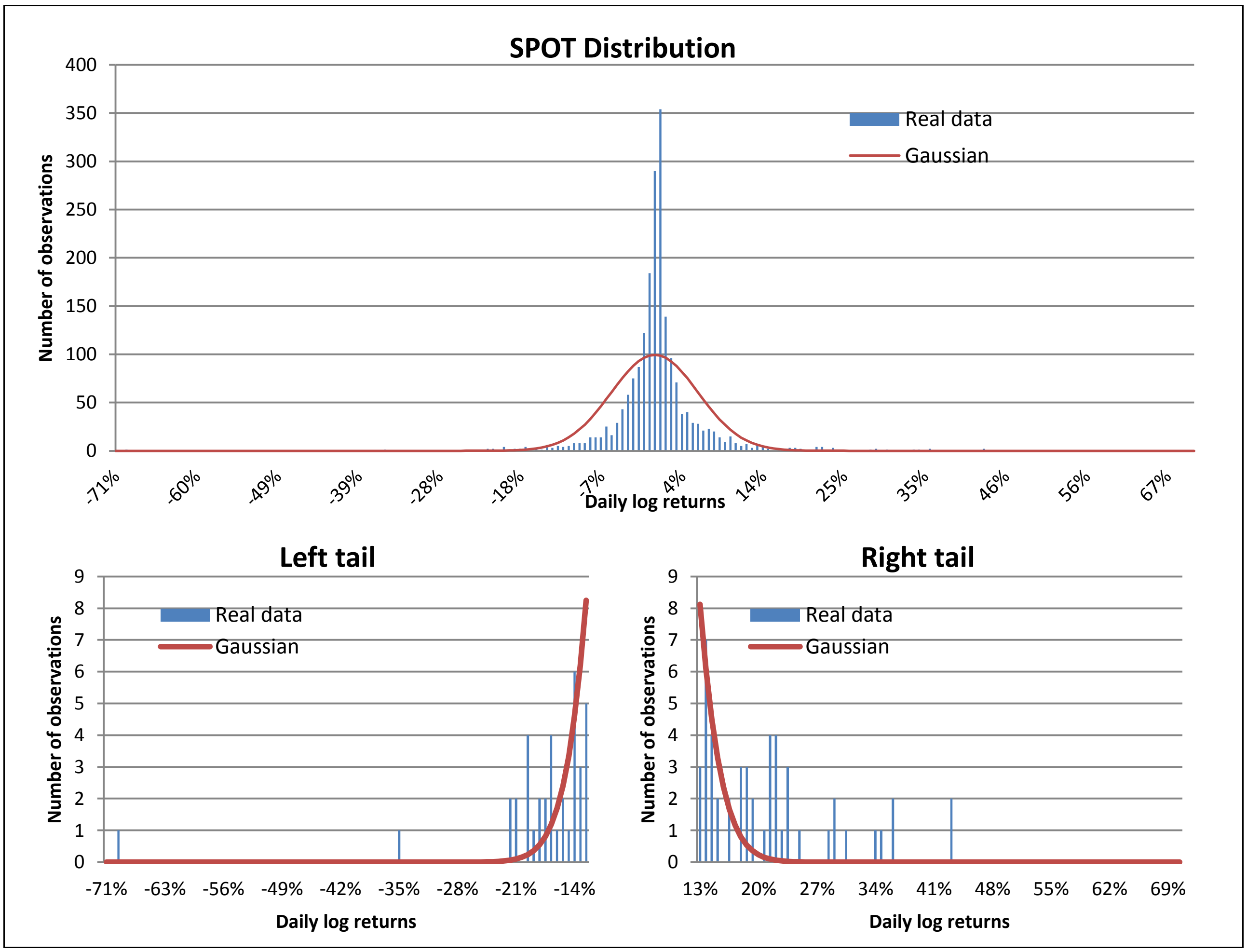


Figure 30: *Distribution for TD7 spot (blue bars), compared to Gaussian distribution (red line). The figures at the bottom are zoomed in on the left and right tail of the distribution.*

The TD7 FFA distribution differs from the spot distribution due to over 750 zero-returns, and the fluctuations in the FFA are also less extreme than the spot. This might be explained by the time to maturity and that the FFA is based on the arithmetic average of the spot in the delivery period. Nevertheless, the tail-figures show the presence of fat-tails for the TD7 FFA. The distribution is slightly positively skewed and has a smaller kurtosis than the spot distribution. However, there is no doubt that the distribution does not follow the assumptions of the Gaussian distribution. This is confirmed by the JB-statistic.

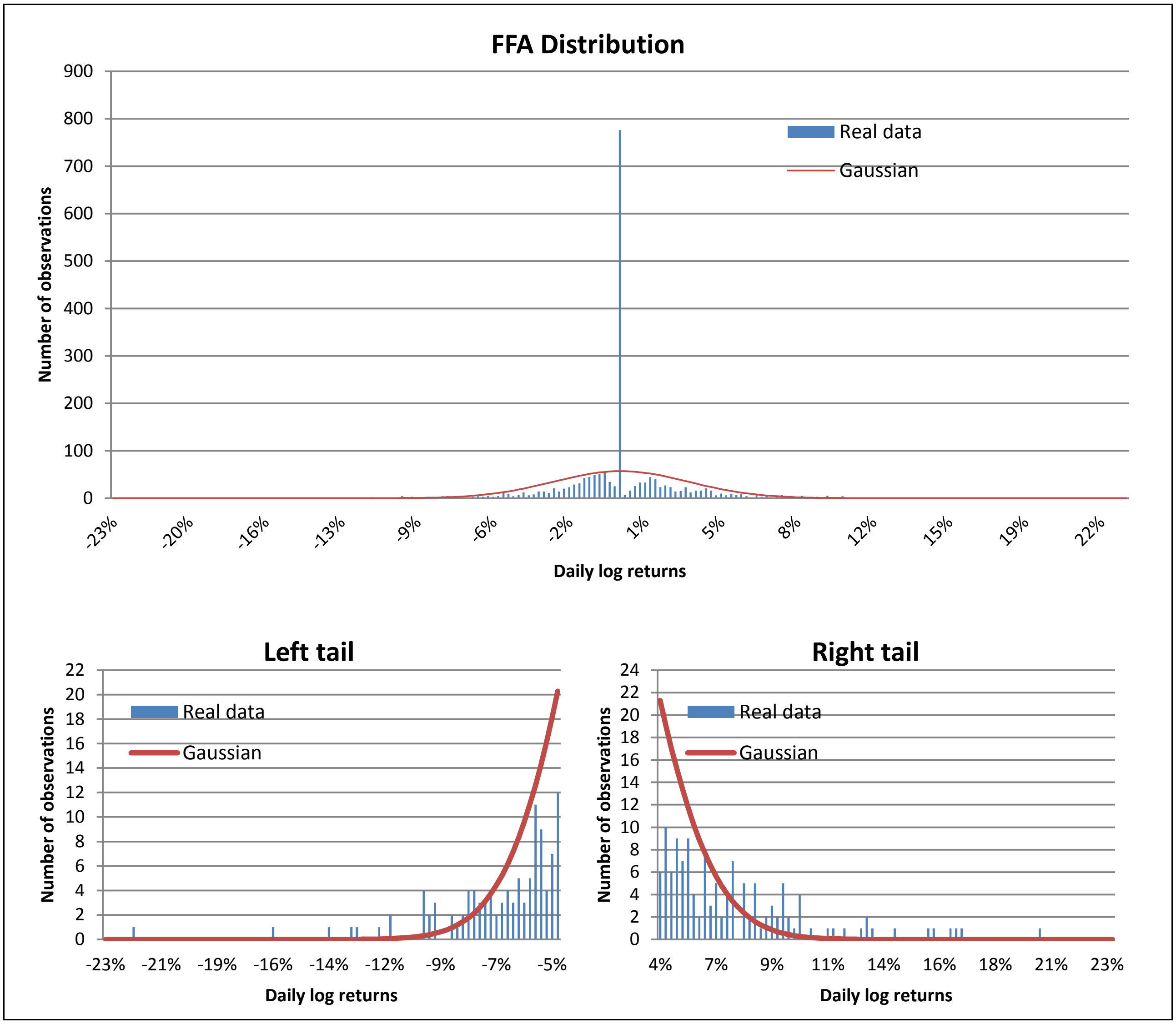


Figure 31: *Distribution for TD7 FFA (blue bars), compared to Gaussian distribution (red line). The figures at the bottom are zoomed in on the left and right tail of the distribution.*

5.5.2 Volatility

As expected, considering the TD7 spot distribution, the spot volatility figures reveal considerable volatility in the spot market of TD7. Both the 90-days Rolling Window and the EWMA plot naturally show the same trends. The EWMA plot varies from approximately 15% yearly volatility in August 2011 to over 350% yearly volatility at the beginning of January 2007. The 90-days Rolling Window, naturally, do not have the same distinct peaks as the EWMA. However, it shows that the Rolling Window volatility for TD7 spot has been varying between approximately 20% yearly volatility in August 2011 to about 225% in January 2007. Further on, the historical standard deviation of the sample of TD7 spot is 108.53%, and as we can see from the 99% confidence interval displayed in the 90-days Rolling Window figure, the volatility estimated in the period clearly exceeds the limits of the interval. We can therefore state that the stochastic volatility of TD7 spot is not caused by sampling errors.

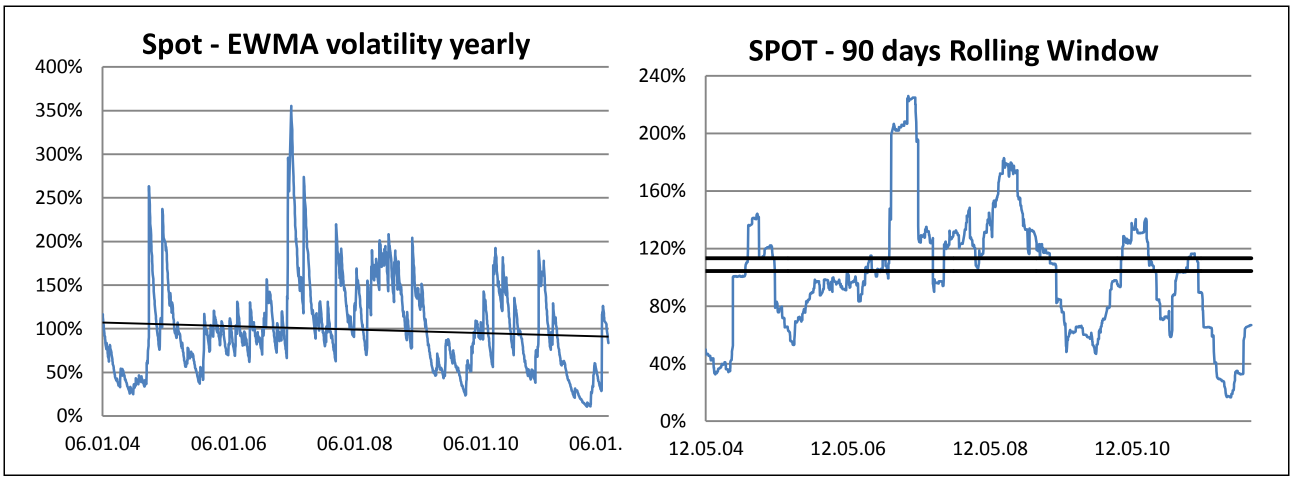


Figure 32: *Yearly volatility calculated with EWMA and 90-days Rolling Window for TD5 spot from 2004 to mid-January 2012.The black line in the EWMA figure illustrates the trend in the sample volatility, and the black lines in the Rolling Window illustrate a 99% confidence interval of the historical volatility*

The TD7 FFA is following the same major trends as the spot. However, the volatility for the FFA is at a considerably lower level than the spot. Figure 8 illustrates that the volatility of the FFA has been varying between approximately 15% yearly volatility to about 130% in the EWMA plot and between 15% to about 100% for the Rolling Window volatility. The FFA volatility appears to have been at a bit lower level since the summer of 2009. There is no clear trend in the volatility. However the volatility levels appear to be a bit lower in recent years compared to the period from 2006 to 2008.

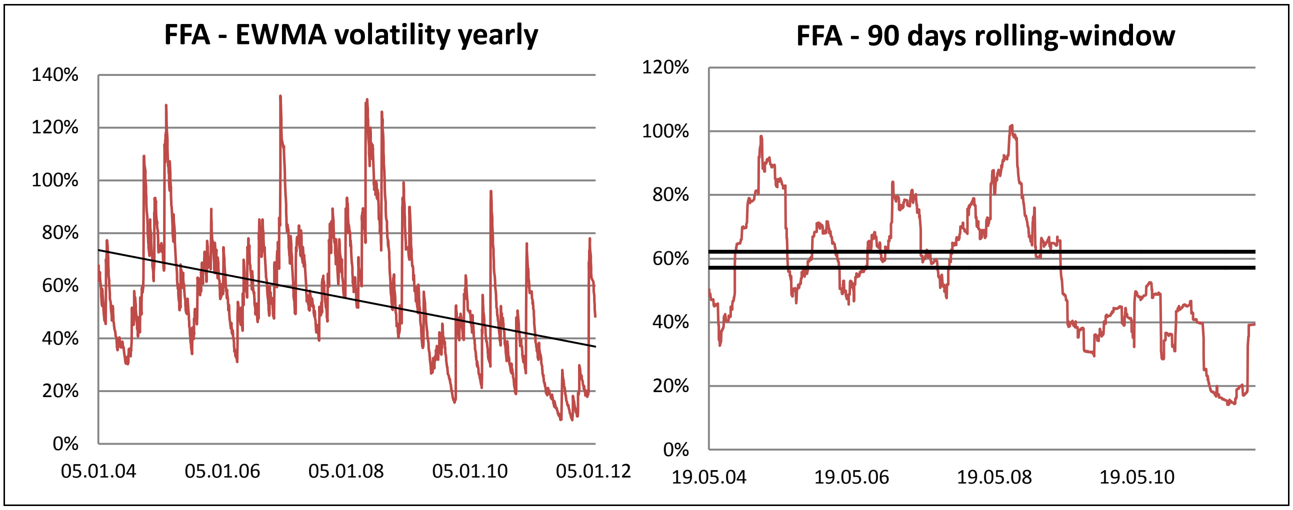


Figure 33: *Yearly volatility calculated with EWMA and 90-days Rolling Window for TD5 FFA from 2004 to mid-January 2012.The black line in the EWMA figure illustrates the trend in the sample volatility, and the black lines in the Rolling Window illustrate a 99% confidence interval of the historical volatility.*

Table 14 indicates that the volatility of the volatility has been higher for the spot than the FFA, which is not surprising considering the volatility figures of the TD7 spot and FFA. The volatility of the volatility also varies with different periods. The historical standard deviation for the FFA is 59.55%, and as for the spot the 90-days Rolling Window volatility for the FFA clearly exceeds the 99% confidence interval, hence the volatility is stochastic. Table 14 indicates higher volatility of the volatility for TD7 spot compared to TD7 FFA.

	Volatility of the volatility			
	SPOT daily	**SPOT annually**	**FFA daily**	**FFA annually**
2004 - 2012	2.22 %	42.49 %	1.05 %	19.98 %
2004 - 2005	1.67 %	31.86 %	0.90 %	17.19 %
2006 - 2007	2.19 %	41.93 %	0.48 %	9.09 %
2008 - 2009	2.12 %	40.55 %	1.08 %	20.72 %
2010 - 2011	1.89 %	36.14 %	0.66 %	12.59 %
2011 - 2012	1.82 %	34.77 %	0.63 %	12.06 %

Table 14: *Volatility to the 90-days Rolling Window volatility for various* periods for TD7 *spot and TD7 FFA*

5.6 Value-at-Risk

5.6.1 Impact of the distribution

To test for tail risks we have backtested the Model-Building Approach, based on the Gaussian distribution and the historical standard deviation of the freight rates. We have tested for spot and spliced FFA with and without splice returns. We have tested for both a long and a short position. The VaR estimation for a long position reflects the risk attached to the left tail of the distribution, while a short position reflects the risk of the right tail of the distribution.

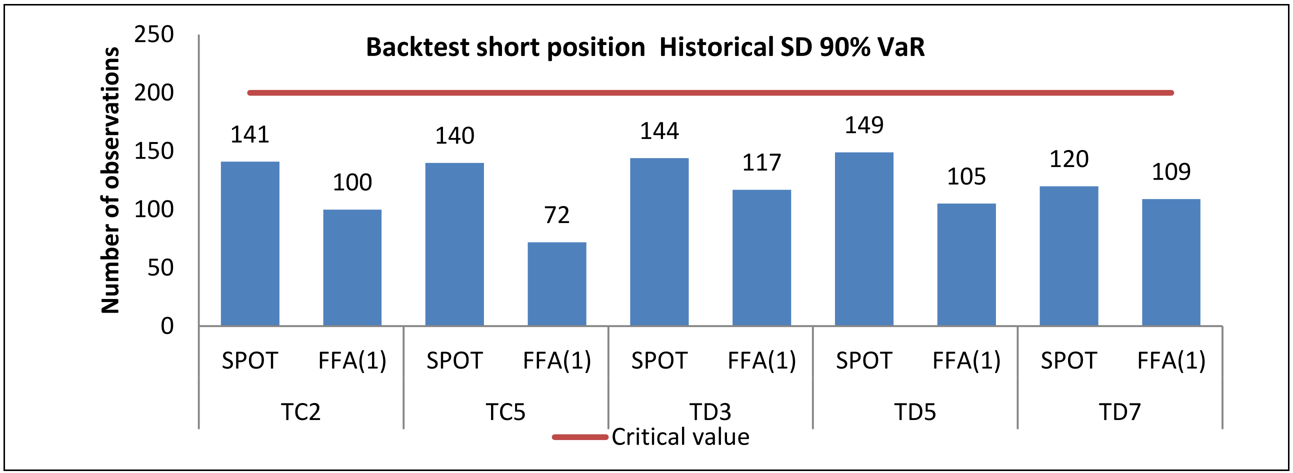


Figure 34: *Backtest of MBA using historical standard deviation. The critical values are the expected number of observations greater than the 90% VaR estimate if the historical returns were normally distributed. The numbers on the top of the bars are the actual historical numbers of observations greater than the 90% VaR estimate from the MBA. FFA(1) Is with the returns from the splicing dates.*

Consider a short position in the freight rates. Figure 34 and Figure 35 show that the MBA has historically overestimated the 90% VaR. Neither the spot or the FFA with (FFA(1)) or without (FFA(2)) the returns from the splice date exceeds the limit of the critical values.

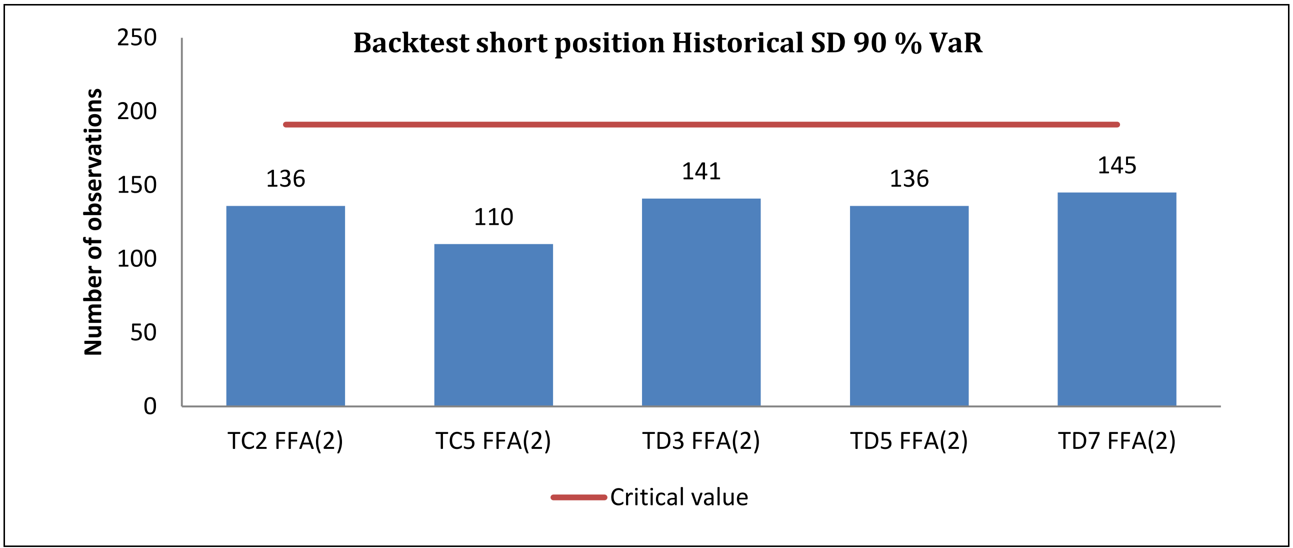


Figure 35: *Backtest of MBA using historical standard deviation. The critical values are the expected number of observations greater than the 99% VaR estimate based on a sample containing 1,908 observations. The numbers on the top of the bars are the actual historical numbers of observations greater than the 90% VaR estimate from the MBA. FFA(2) Is without the returns from the splicing dates.*

The 99% VaR backtest indicates a completely different trend. As we can see from Figure 36 and Figure 37, the MBA historically underestimates the 99% VaR. These results illustrate the risk associated with the right tail of the distribution. The results in Appendix 8.6 reveal fat tail for TC2 spot and TD5 spot at 95% VaR.

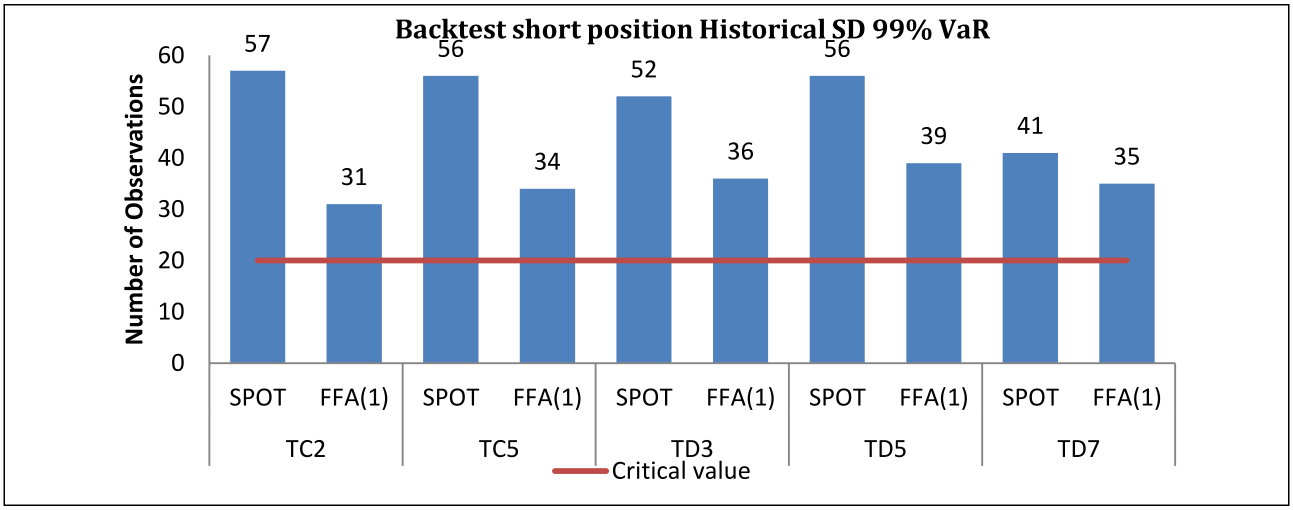


Figure 36: *Backtest of MBA using historical standard deviation. The critical values are the expected number of observations greater than the 99% VaR estimate based on a sample containing 2,000 observations. The numbers on the top of the bars are the actual historical numbers of observations greater than the 99% VaR estimate from the MBA. FFA(1) Is with the returns from the splicing dates.*

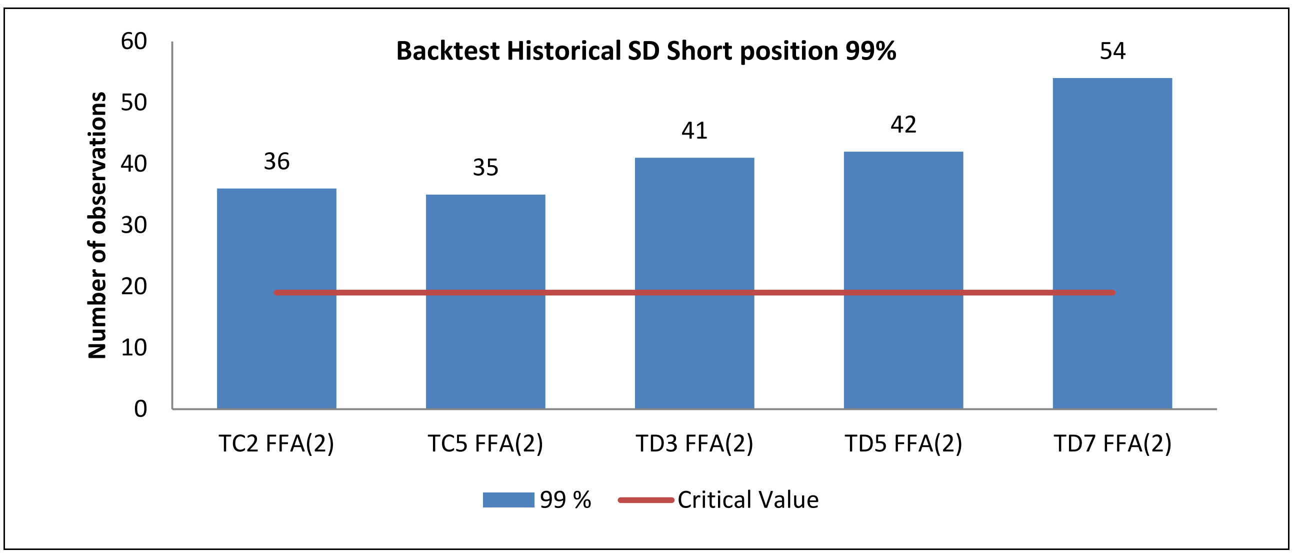


Figure 37 *Backtest of MBA using historical standard deviation. The critical values are the expected number of observations greater than the 99% VaR estimate based on a sample containing 1,908 observations. The numbers on the top of the bars are the actual historical numbers of observations greater than the 99% VaR estimate from the MBA. FFA(2) is without the returns from the splicing dates.*

The results also indicate that the right tail is fatter for the FFA without the returns of the splicing compared to the FFA results including the returns. This might be explained by a higher historical standard deviation for the FFA with the splicing returns. Hence, the Gaussian distribution will become wider. However there is no doubt that the MBA historically has failed to estimate the VaR.

The difference between the VaR results in the following tables illustrates the historical overestimation and underestimation of the MBA VaR for a short position of 1,000,000 USD. Comparing Table 15 and Table 16 we can see that the 99% VaR results are higher for the HS than the MBA. The opposite trend is found for the 90% VaR. The results also reveal the right tail for TC2 and TD5 spot at 95% VaR. The VaR results clearly illustrate the considerable historical risk of not taking the tail events into account. Furthermore, it is a higher risk in the dirty routes compared to the clean routes.

VaR HS short position				
		90 %	*95 %*	*99 %*
	SPOT	$29 816	$48 241	$100 992
TC2	FFA(1)	$27 974	$45 810	$104 044
	FFA(2)	$24 349	$40 822	$74 877
	SPOT	$22 473	$37 041	$75 223
TC5	FFA(1)	$22 100	$37 271	$107 642
	FFA(2)	$19 343	$29 230	$63 058
	SPOT	$47 914	$75 175	$168 386
TD3	FFA(1)	$49 393	$80 969	$183 923
	FFA(2)	$45 120	$67 558	$127 833
	SPOT	$51 287	$88 432	$173 504
TD5	FFA(1)	$35 994	$58 998	$146 982
	FFA(2)	$32 790	$49 227	$103 436
	SPOT	$49 944	$81 133	$211 007
TD7	FFA(1)	$36 905	$61 875	$142 921
	FFA(2)	$33 523	$51 432	$101 096

Table 15: *Value-at-Risk results when using the Historical Simulation method.*

VaR MBA				
		90 %	*95 %*	*99 %*
	SPOT	$37 230	$47 784	$67 582
TC2	FFA(1)	$45 629	$58 564	$82 828
	FFA(2)	$32 216	$41 349	$58 480
	SPOT	$29 476	$37 832	$53 506
TC5	FFA(1)	$46 288	$59 410	$84 025
	FFA(2)	$26 390	$33 872	$47 905
	SPOT	$60 455	$77 594	$109 742
TD3	FFA(1)	$74 931	$96 173	$136 019
	FFA(2)	$53 712	$68 938	$97 501
	SPOT	$64 735	$83 087	$117 511
TD5	FFA(1)	$56 226	$72 165	$102 064
	FFA(2)	$40 850	$52 431	$74 153
	SPOT	$72 886	$93 548	$132 307
TD7	FFA(1)	$56 744	$72 830	$103 005
	FFA(2)	$39 948	$51 272	$72 515

Table 16: *Value-at-Risk results estimated with the Model-Building Approach with a historical standard deviation. These results naturally represent both tails.*

The results from the distribution analyses indicate that the left tail seems to be less fat compared to the right tail. If so, the results from the backtest of a long position should reveal the same result. Figure 38 graphically illustrates the results of the 90% VaR. The results show that the MBA historically has overestimated the 90% VaR. Furthermore, the difference between the long and short position is greater for the spot than the FFA.

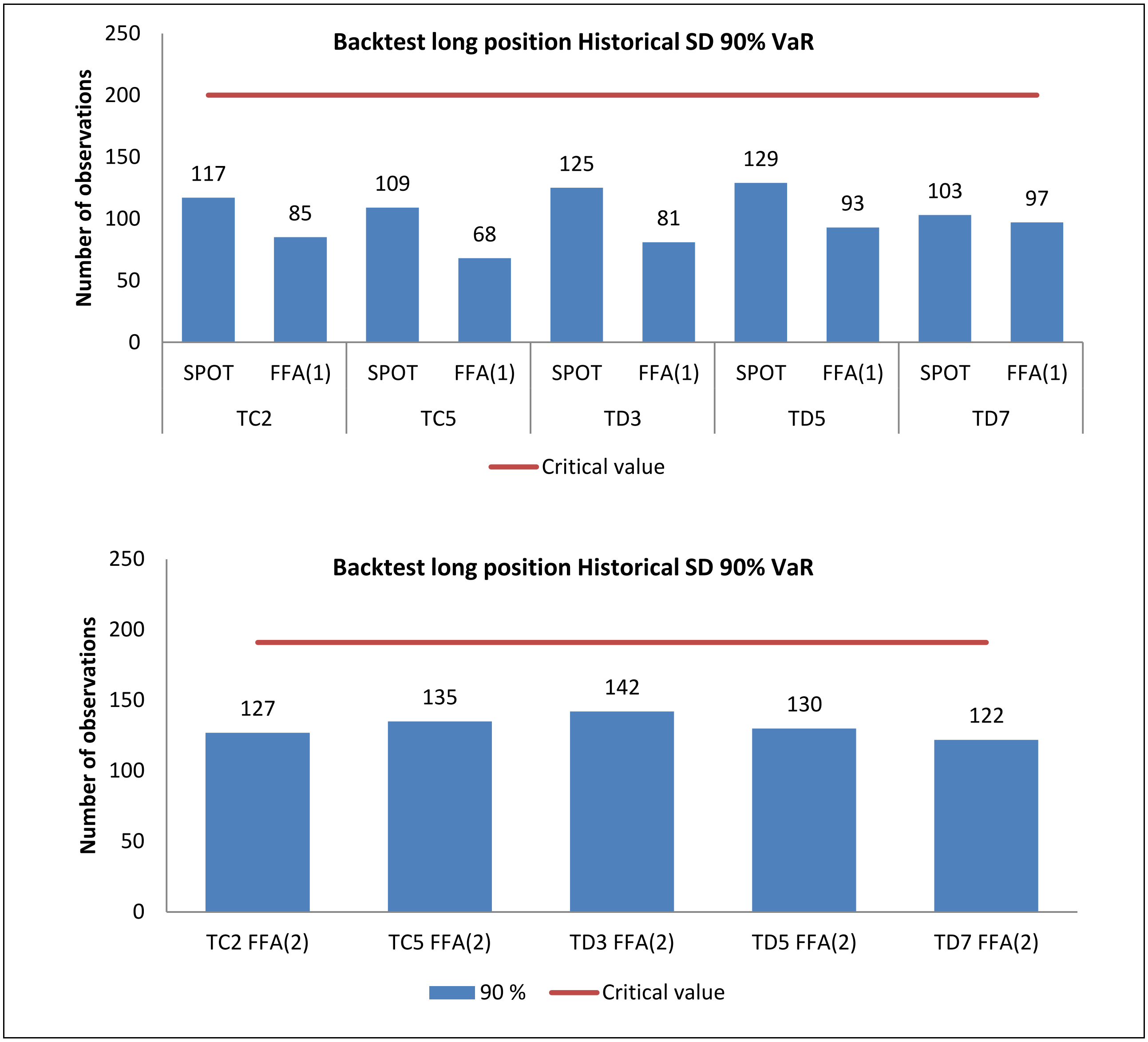


Figure 38: *Backtest of MBA using historical standard deviation. The critical values are the expected number of observations greater than the 99% VaR estimate based on a sample containing 2,000 observations for spot and FFA(1), and 1,908 observations for the FFA(2). The numbers on the top of the bars are the actual historical numbers of observations greater than the VaR estimate form the MBA. FFA(1) is with the returns from the splicing dates and FFA(2) is without.*

The results in Figure 39 indicate that the tail of TC2 spot is not very fat, and the MBA 99% VaR estimate actual performs well historically. This illustrates that the tail risk of a long position in TC2 spot has not been very high. However, this does not mean that there have not been large negative fluctuations in the past, the tails are however not revealed by the 99% VaR estimate. The backtest reveals that the MBA historically has underestimated the left tail risk for the other routes.

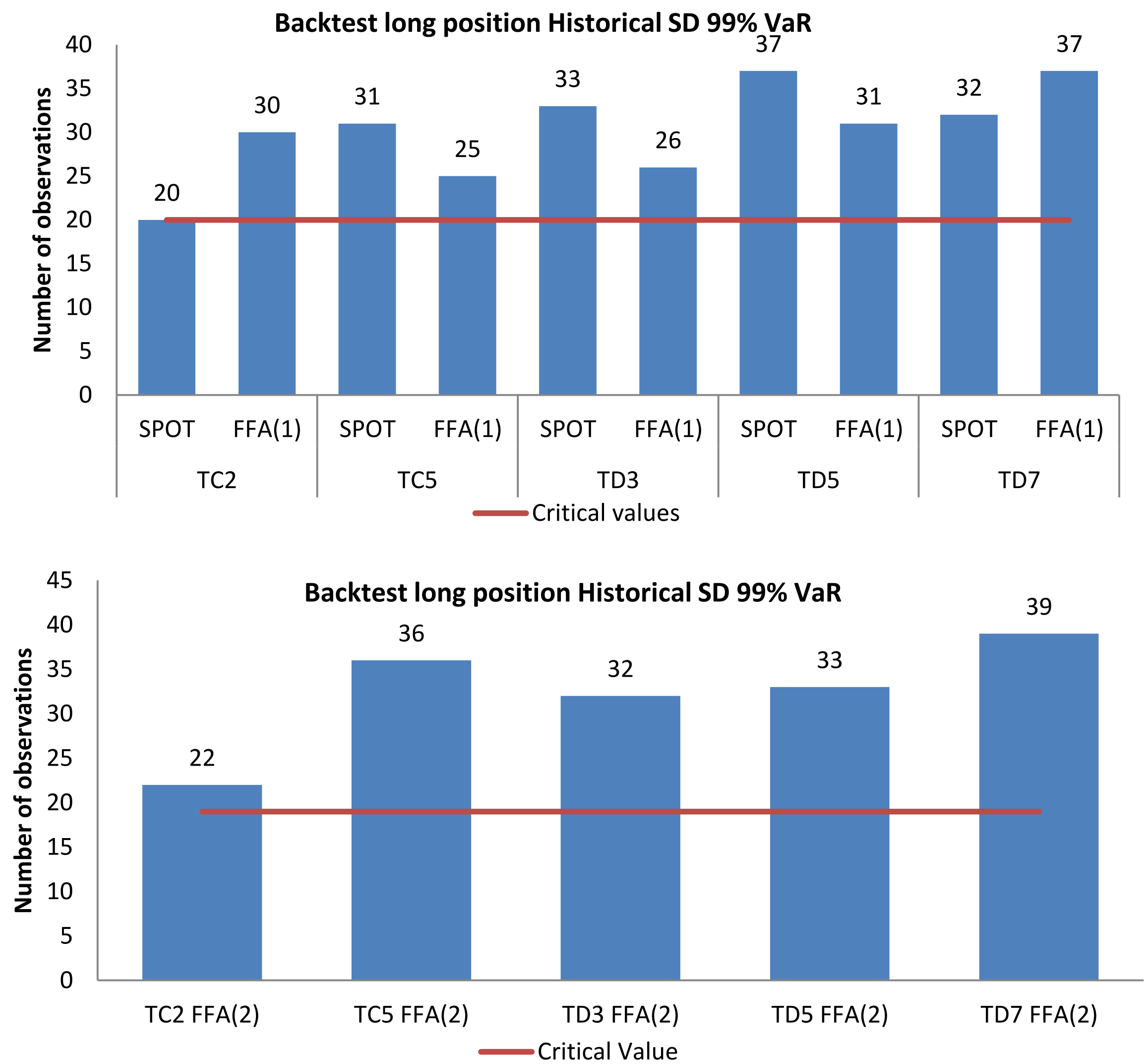


Figure 39: *Backtest of MBA using historical standard deviation. The critical values are the expected number of observations greater than the 99% VaR estimate based on a sample containing 2,000 observations for Spot and FFA(1), and 1,908 observations for the FFA(2). The numbers on the top of the bars are the actual historical numbers of observations greater than the VaR estimate form the MBA. FFA(2) Is without returns from the splicing dates.*

Figure 39 Figure 39 also indicates that the splice returns of the FFA decreases the left tail of the FFA distribution for four of the routes. Which we assume is caused by a higher historical standard deviation for the FFA distributions without the splice returns. A comparison of the backtests of the long and the short positions indicates that the right tail is fatter than the left for the spot freight rates. The difference is however not that evident for the FFAs.

Furthermore, the VaR results for a long position of $1,000,000 reveal considerable risk. However, the risk is substantially higher for the dirty routes when compared to the clean routes. The risk is higher for the spots when compared to the FFAs without the splice returns, and the results also indicate that the splice returns increase the risk. If we compare the results in Table 17 with the results from Table 15, the difference in VaR results illustrates the dissimilar risks of the tails, which clearly indicates that the tail risk is higher for a short position when compared to a long position. The MBA VaR results for a long and short position is naturally identical. The tail risk is revealed at 99% VaR for all the routes, however there is little tail risk revealed for TC2 spot and FFA without the splice returns. Table 15 and Table 17 show that TD7 has the highest spot VaR and that TD3 has the highest FFA VaR for both a long and a short position.

VaR HS long position				
		90 %	*95 %*	*99 %*
TC2	SPOT	$27 277	$40 705	$68 287
	FFA(1)	$25 891	$38 583	$103 797
	FFA(2)	$25 553	$36 368	$61 187
TC5	SPOT	$21 506	$30 772	$65 083
	FFA(1)	$21 391	$35 718	$103 696
	FFA(2)	$20 203	$31 749	$57 158
TD3	SPOT	$43 492	$67 911	$128 288
	FFA(1)	$41 964	$65 751	$152 016
	FFA(2)	$43 485	$64 539	$115 832
TD5	SPOT	$50 111	$74 509	$149 250
	FFA(1)	$32 790	$50 772	$119 801
	FFA(2)	$33 523	$47 253	$89 612
TD7	SPOT	$46 540	$75 834	$163 501
	FFA(1)	$31 045	$54 488	$140 822
	FFA(2)	$28 710	$47 253	$90 151

Table 17: *Value-at-Risk results when using the Historical Simulation method.*

5.6.2 Impact of the volatility

As we know from the volatility results, the volatility is not constant. Hence, the VaR results from the HS and FHS will often not be equal or close to equal. HS implicitly states that the volatility is stochastic, which we have proved for the tanker routes. FHS on the other hand, tries to transform the historical distribution to the current volatility level by using time-varying or stochastic volatility models. This means that the difference between HS and FHS to a large extent is caused by the differing assumptions concerning the volatility. The calculated results for a long position of 1,000,000 USD for the spot are shown in Table 18.

Route	VaR method	EWMA vol. 18.01.12	90% VaR	95% VaR	99% VaR
TC2 spot	HS		$27 728	$42 505	$73 393
	FHS	6,11 %	$65 515	$98 621	$208 108
TC5 spot	HS		$21 741	$31 651	$67 618
	FHS	1,04 %	$12 042	$16 460	$31 494
TD3 spot	HS		$44 144	$71 120	$136 271
	FHS	2,24 %	$21 890	$32 850	$71 018
TD5 spot	HS		$51 889	$82 520	$167 016
	FHS	3,11 %	$32 183	$50 658	$100 051
TD7 spot	HS		$48 502	$81 053	$170 956
	FHS	3,98 %	$37 178	$61 990	$123 205

Table 18 *Value-at-Risk results using HS and FHS. The daily volatility of 18.01.12 is estimated using the EWMA model.*

The large difference between the calculated HS VaR and FHS VaR clearly illustrates the problem concerning volatility assumptions for all freight rates. The HS VaR estimates are higher compared to the FHS VaR for all routes except the TC2. HS predicts a considerably lower risk in the TC2 than FHS because of a relatively high EWMA volatility estimate for 18.01.2012 for TC2 spot. If we look at Figure 11 and Figure 12 in section 5.1.2, we can see an actual peak in both the TC2 spot and TC2 FFA volatility. This peak is caused by large fluctuations in the TC2 freight rate in January 2012. These fluctuations are not found in the other routes, which seemed to operate at relatively low levels of volatility in the middle of January 2012 compared to historical volatility levels of the sample.

Route	VaR method	EWMA vol. 18.01.12	90% VaR	95% VaR	99% VaR
TC2 FFA	HS(1)		$27 652	$40 822	$106 972
	FHS(1)	5,36 %	$49 219	$75 050	$223 006
	HS(2)		$27 974	$42 212	$103 797
	FHS(2)	5,42 %	$47 687	$73 634	$187 796
TC5 FFA	HS(1)		$23 218	$40 274	$108 096
	FHS(1)	4,22 %	$29 167	$48 021	$152 801
	HS(2)		$21 277	$37 740	$108 096
	FHS(2)	1,07 %	$7 352	$13 060	$36 713
TD3 FFA	HS(1)		$46 189	$67 823	$156 452
	FHS(1)	1,88 %	$15 153	$21 964	$60 568
	HS(2)		$44 452	$67 823	$156 452
	FHS(2)	1,90 %	$14 668	$22 405	$59 032
TD5 FFA	HS(1)		$36 368	$55 152	$122 218
	FHS(1)	2,89 %	$24 767	$39 797	$87 041
	HS(2)		$35 091	$52 368	$124 053
	FHS(2)	3,00 %	$25 559	$39 649	$91 402
TD7 FFA	HS(1)		$33 523	$60 625	$152 469
	FHS(1)	2,79 %	$23 511	$40 857	$104 909
	HS(2)		$33 398	$57 158	$164 303
	FHS(2)	2,72 %	$23 201	$38 385	$105 001

Table 19 *Value-at-Risk results for spliced FFAs based on HS and FHS. The splicing returns are included in the calculations. The volatility at 18.01.12 is estimated using the EWMA model*

The same trend is found in the spliced FFA contracts (see Table 19). The HS method is estimating a higher VaR than the FHS method for all freight rates except TC2. However, the TC5 FFA displays different results depending on if the returns of the splicing date are included in the VaR estimate. This is also illustrated by the difference in the EWMA volatility estimates for TC5 FFA the 18.01.2012. The data shows that there has been a large return on the last splicing date, which explains the difference in the EWMA volatility estimate for TC5.The dirty routes do not show the same trend as TC2 FFA, and HS estimates a higher VaR compared to FHS for the FFAs. The FFAs for the dirty routes appears to have a relatively low EWMA volatility in January 2012 compared to historical volatility levels of the sample. This explains why the FHS calculates lower VaR results than the HS.

The MBA can be adjusted with time-varying or stochastic volatility models. Figure 40 displays the results of a backtest on the MBA based on the estimated EWMA volatility for the spot freight rates. The results show that the adjustment does not improve the MBA. Historically it has actually performed worse compared to the MBA based on the historical standard deviation of the sample for a 99% VaR. The same results are found for the FFA with or without the splice returns (see Appendix 8.8). The results also illustrate the problem of trying to predict the future volatility.

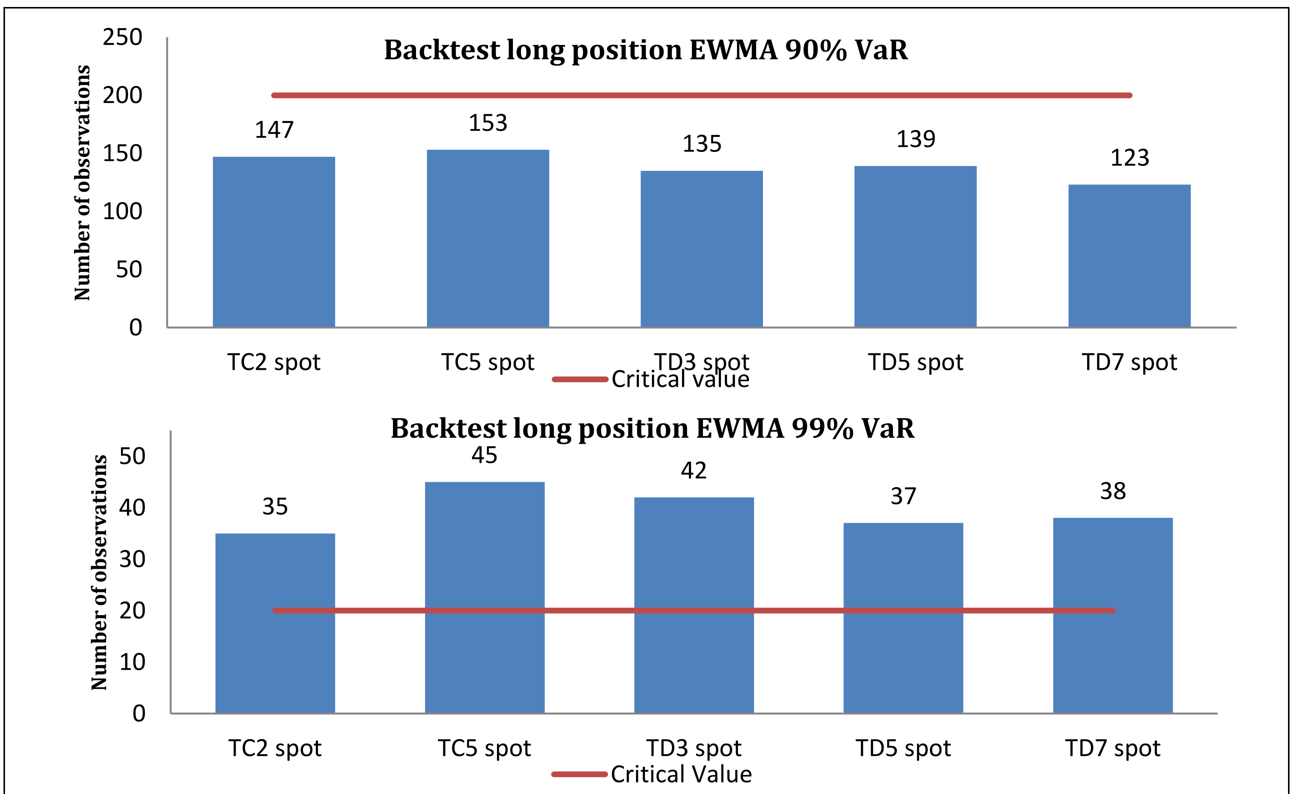


Figure 40: *Backtest of MBA based on EWMA volatility. The critical values are the expected number of observations greater than the 99% VaR estimate based on a sample containing 2,000 observations. The numbers on the top of the bars are the actual historical numbers of observations greater than the VaR estimate form the MBA.*

Intuitively one could expect the FHS method to perform superior to the simple HS method, since FHS allow for the current level of volatility or at least try to. There might of course be other VaR methods or volatility models that are better suited than the EWMA model to estimate VaR for freight rates. However, findings earlier in this thesis prove that the freight rate volatility is stochastic, and extreme returns are not easy to foresee (Taleb 2010). It is therefore maybe not surprising that Angelidis and Skiadopolous (2008) found that the simple non-parametric VaR methods like HS outperforms more complex methods for freight rates. This may indicate that when the volatility is stochastic there is a high degree of uncertainty in the VaR results. Methods that attempt to adjust for the volatility will often fail because they are not able to predict extreme events. In this thesis we have estimated one-day VaR for a single asset with results displaying large differences in the VaR estimates, and the uncertainty in the VaR estimates will naturally increase if they were to consider hundreds of variables and a longer timeframe.

6 CONCLUSION

Financial models and methods often assume that the returns of an asset follow the normal distribution. However, this is usually not the case in reality. Research has revealed that the distribution of the returns of an asset is often leptokurtic, with high peaks and fat tails compared to the Gaussian distribution. This may lead to considerable miscalculations and Haug (2007b) and Taleb (2010) claims that fat tails or extreme events is one of the most important topics in financial economics. The first objective of this thesis is therefore to compare the historical distribution of five different tanker routes. The findings reveal:

- Historical distributions do not follow the assumption of normality.
- Historical distributions reveals fat tails for all the freight rates, and the right tail appears to be heavier compared to the left tail. This indicates higher right tail risk compared to left tail risk.
- Spot distributions are leptokurtic. However, TC5 is significantly different from the other tanker routes, due to several zero returns in the sample period.
- Spliced FFA contracts are characterised by a high amount of zero returns. However, the results still reveal the presences of fat tails.

The findings are congruent with findings from other markets and assets, and the results from Kavussanos and Dimitrakopoulos (2011). The presence of fat tails for both the spot and FFA for all routes might lead to implications in the risk management process.

Several financial models and applications also assume constant volatility. This is usually a simplification of the reality, since the volatility normally varies over time and different assets will not have the same volatility variations. Actors in the tanker shipping market have also claimed that volatility has been reduced in the tanker market over the last couple of years. Hence, our next objective was to examine the volatility of the tanker freight rates. The findings conclude that:

- The volatility for all tanker freight rates, both spot and FFA, is stochastic.
- The freight rates in the tanker market have considerable volatility in the sample period.
- The dirty routes have higher levels of freight rate volatility compared to the clean routes.
- There appears to be a decreasing volatility in the sample period for the FFAs.

- The TC2 spot trend indicates an increasing volatility in the sample period. However, for some of the freight rates, there seems to be a bit lower volatility levels at the end of the sample period.
- Generally it is higher volatility in the spot freight rates than the FFAs.

The volatility results are congruent with findings from earlier periods by Kavussanos and Dimitrakopoulos (2011). Decreasing volatility for FFAs is also congruent with statements from market actors claiming lower volatility levels in recent years. However, the spot volatilities do not clearly indicate the same trend.

Assumptions concerning the distributions and volatility may have a considerable impact on risk management decisions, Value-at-Risk, valuations of derivatives and hedging. We wanted to see if this was the case for the freight rates in the tanker market. Our final objective was to illuminate problems concerning the distributions and the volatility in Value-at-Risk estimations for freight rates in the tanker market. Considering the distributions of the freight rates, the results indicate:

- Assuming that the returns of the freight rates follow the Gaussian distribution, they will often result in an underestimation of the tail risk for all routes. However, we found no left tail risk using VaR for TC2 spot.
- The right tail risk is higher for all spot freight rates and FFAs, except TC5 FFA without splice returns.
- Higher VaR for the dirty routes compared to the clean routes.

When considering the impact of the volatility, the results imply:

- The VaR results are highly affected by the choice of method, based on different assumptions concerning the volatility.
- The MBA based on EWMA volatility has historically failed to estimate the actual tail risks for the freight rates, implying that time-varying or stochastic volatility models do not necessarily improve the VaR estimates.

Considering these results we are not surprised that Angelidis and Skiadopoulos (2008) found that simple non-parametric VaR methods like HS are best suited for the freight rate market since HS anticipates stochastic volatility.

With the uncertainty associated to the VaR estimates, we would therefore suggest testing other methods for measuring freight rate risk, which might be better suited to capture the tail risk. Further on, we have examined five tanker routes and it would be interesting to analyse the other tanker routes as well. As far as we know, there is no published research on hedge effectiveness of the FFAs from the last couple of years, which also would be interesting to look into.

7 LITERATURE

Alizadeh, A. H. & N. K. Nomikos. 2009. *Shipping Derivatives and Risk Management*. London: Palgrave Macmillan.

Andreou, E. & E. Ghysels (2002) Rolling-Sample Volatility Estimators. *Journal of Business & Economic Statistics,* 20**,** 363-376.

Angelidis, T. & G. S. Skiadopoulos (2008) Measuring the Market Risk of Freight Rates: A Value-at-RIsk Approach. *international Journal of Theoretical and Applied Finance,* 11**,** 447-469.

Barone-Adesi, G., K. Giannopoulos & L. Vosper (1999) VaR Without Correlations for Nonlinear Portfolios. *Journal of Futures Markets,* April**,** 583-602.

Bodie, Z., A. Kane & A. J. Marcus. 2009. *Investments*. New York: Mc Graw Hill.

Bollerslev, T. (1986) Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics,* 31**,** 307-327.

Bonett, D. G. & E. Seier (2002) A test of normality with high uniform power. *Computational Statistics & Data Analysis***,** 435 – 445.

Bookstaber, R. M. & S. Pomerantz (1989) An Information-Based Model of Market Volatility. *Financial Analysts Journal,* 45**,** 37-46.

Bowman, K. O. & L. R. Shenton (1975) Omnibus test contours for departures from normality based on ,àöb1 and b2. *Biometrika,* 62**,** 243-250.

Brooks, C. 2008. *Introductory Econometrics for Finance*. Cambridge: Cambridge University Press.

Chan, N., M. Getmansky, S. M. Haas & A. W. Lo (2005) Systemic Risk and Hedge Funds. *NBER Working Papers*.

Christoffersen, P. F. 2003. *Elements of Financial Risk Management*. McGill University and CIRANO: Academic Press.

D'Agostino, R. B., A. Belanger & R. B. D'Agostino, Jr. (1990) A Suggestion for Using Powerful and Informative Tests of Normality. *The American Statistician,* 44**,** 316-321.

Dowd, K. 2005. *Measuring Market Risk*. Chichester: John Wiley & Sons Ltd.

Engle, R. F. (1982) Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation. *Econometrica,* 50**,** 987-1007.

Fama, E. F. & J. D. MacBeth (1973) Risk, return, and equilibrium: Empirical tests. *The Journal of Political Economy,* 81**,** 607-636.

French, K. R., G. W. Schwert & R. F. Stambaugh (1987) Expected stock returns and volatility. *Journal of Financial Economics,* 19**,** 3-29.

Froot, K. A., D. S. Scharfstein & J. C. Stein (1993) Risk Management: Coordinating Corporate Investment and Financing Policies. *The Journal of Finance,* 48**,** 1629-1658.

Gel, Y. R. & J. L. Gastwirth (2008) A robust modification of the Jarque–Bera test of normality. *Economics Letters,* 99**,** 30-32.

Gel, Y. R., W. Miao & J. L. Gastwirth (2007) Robust directed tests of normality against heavy-tailed alternatives. *Computational Statistics & Data Analysis,* 51**,** 2734-2746.

Hagan, P. S., D. Kumar, A. S. Lesniewski & D. E. Woodward (2002) Managing Smile Risk. *WILMOTT Magazine***,** 84-108.

Harrington, S. E. & G. R. Niehaus. 2004. *Risk Management and Insurance*. New York: McGraw Hill.

Haug, E. G. 2007a. *The Complete Guide to Option Pricing Formulas*. New York: The Mcgraw-Hill Companies, Inc.

---. 2007b. *Derivatives - Models on Models*. Chichester, West Sussex, England: John Wiley & Sons Ltd.

Heston, S. (1993) A closed-form solution for options with stochastic volatility with applications to bond and currency options. *Review of Financial Studies,* 6**,** 327-343.

Hoffman, J., J. M. Rubiato & A. Miroux. 2011. Review of Maritime Transport. ed. United Nations. New York and Geneva: United Nations,.

Hull, J. C. 2012. *Options, Futures, And Other Derivatives*. Harlow: Pearson Education Limited.

Jarque, C. M. & A. K. Bera (1980) Efficient tests for normality, homoscedasticity and serial independence of regression residuals. *Economics Letters,* 6**,** 255-259.

Jorion, P. 2006. *Value at Risk: The New Benchmark for Managing Financial Risk*. New York: McGraw-Hill.

Jorion, P. & N. N. Taleb. 1997. The Jorion-Taleb Debate. http://www.derivativesstrategy.com.

Kavussanos, M. G. & D. N. Dimitrakopoulos (2011) Market risk model selection and medium-term risk with limited data: Application to ocean tanker freight markets. *International Review of Financial Analysis,* 20**,** 258-268.

Klein, B. (1977) The Demand for Quality-adjusted Cash Balances: Price Uncertainty in the US Demand for Money Function. *Journal of Political Economy,* 85**,** 692-715.

Kolman, J., M. Onak, P. Jorion, N. N. Taleb, E. Derman, B. Putnam, R. Sandor, S. Jonas, R. Dembo, G. Holt, R. Tanenbaum, W. Margrabe, D. Mudge, J. Lam & J. Rozsypa (1998) Roundtable the limits of VAR. *http://www.derivativesstrategy.com,* 3.

Linsmeier, T. J. & N. D. Pearson. 1996. Risk measurement: an introduction to value at risk.

Mandelbrot, B. (1963) The Variation of Certain Speculative Prices. *The Journal of Business,* 36**,** 394-419.

Mantalos, P. 2010a. Robust Critical Values For The Jarque-Bera Test For Normality. Jönköping International Business School.

---. 2010b. Three Different Measures of Sample Skewness and Kurtosis and their Effects on the Jarque-Bera Test for Normality. Jönköping International Business School.

Miller, M. H. & F. Modigliani (1958) The Cost of Capital, Corporation Finance and the Theory of Investment. *The American Economic Review,* 48**,** 261-29.

Mills, F. C. (1927) The Behaviour of Prices. *National Bureau of Economic Research*

Oliver, M. (1926) Les Nombres indices de la variation des prix. *Paris doctoral dissertation*.

Pearson, K. (1895) Contributions to the Mathematical Theory of Evolution. II. Skew Variation in Homogeneous Material. *Philosophical Transactions of the Royal Society of London. (A.),* 186**,** 343-414.

--- (1905) Das Fehlergesetz und Seine Verallgemeinerungen Durch Fechner und Pearson. A Rejoinder. *Biometrika,* Vol. 4, No. 1/2**,** pp. 169-212.

Rajan, R. G. (2006) Has Finance Made the World Riskier? *European Financial Management,* 12**,** 499-533.

Ruppert, D. (1987) What Is Kurtosis?: An Influence Function Approach. *The American Statistician,* 41**,** 1-5.

Skjetne, R. A. 2005. Applied Financial Risk Management for the Shipping Industry using IMAREX Derivatives. Bergen: Norwegian School of Economics and Business Administration (NHH).

Stopford, M. 2009. *Maritime Economics*. Oxon: Routledge.

Supervision, B. C. o. B. 2012. Fundamental review of the trading book. Basel: Bank for International Settlements.

Taleb, N. N. 1997. The World According to Nassim Taleb. In http://www.derivativesstrategy.com.

Taleb, N. N. 2010. *The Black Swan: The Impact of the Highly Improbable*. New York: Random House Trade.

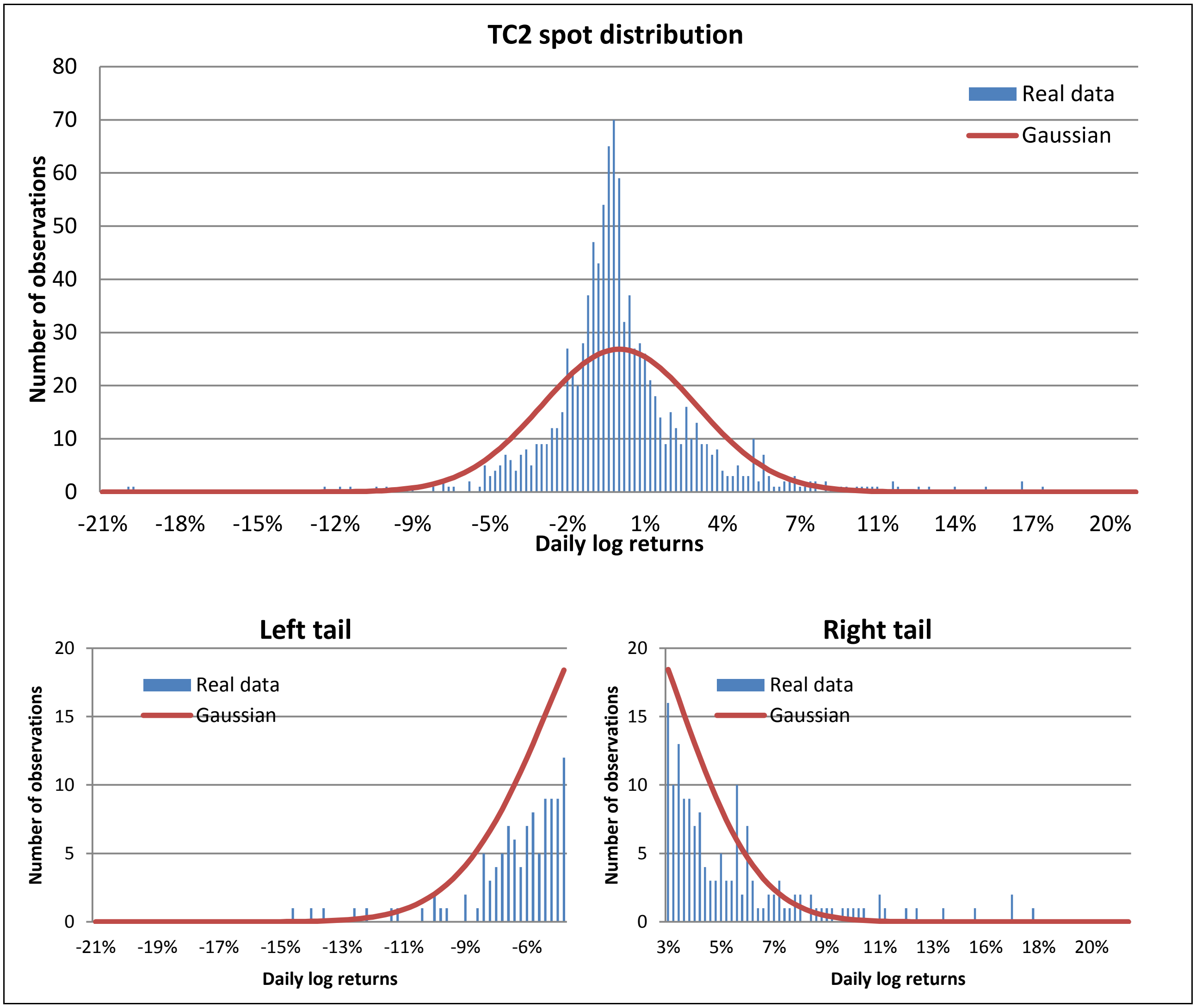
Thadewald, T. & H. Böning (2007) Jarque–Bera Test and its Competitors for Testing Normality – A Power Comparison. *Journal of Applied Statistics,* 34**,** 87-105.

Tirole, J. 2006. *The Theory of Corporate Finance*. Princeton: Princeton University Press.

Urzúa, C. M. (1996) On the correct use of omnibus tests for normality. *Economics Letters,* 53**,** 247-251.

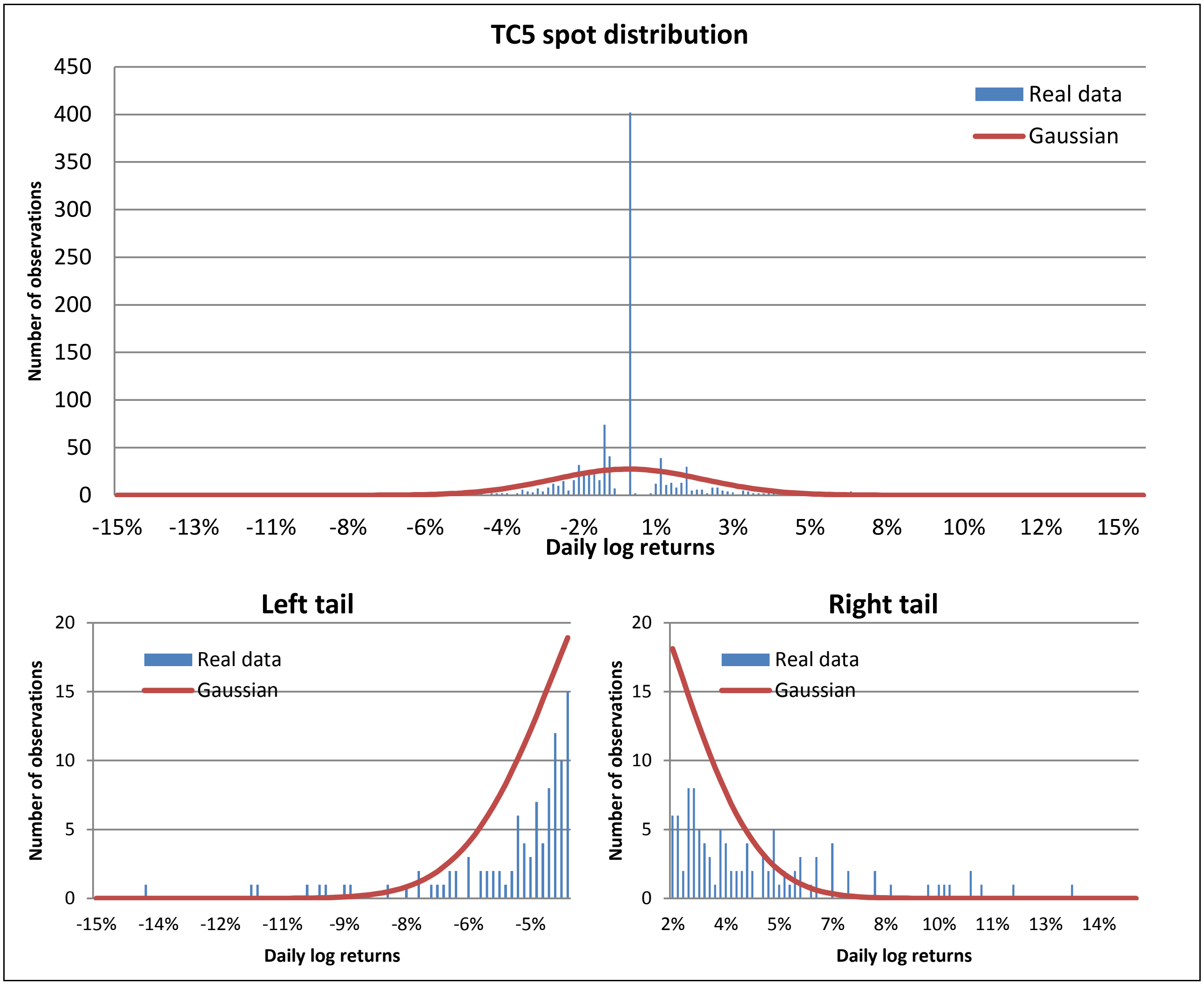
8 APPENDIXES

8.1 TC2 spot distribution 2008 - 2012



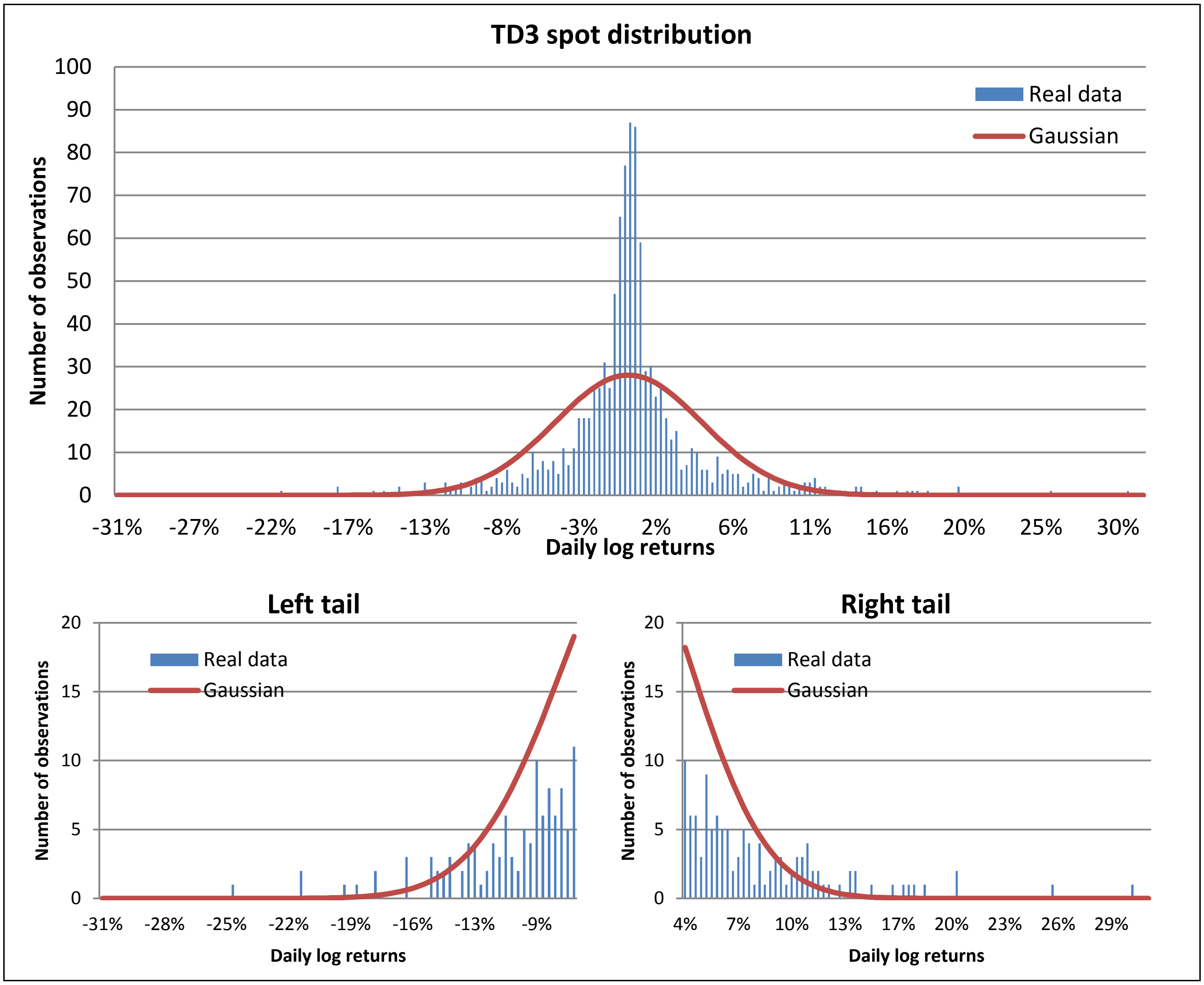
Distribution for TC2 spot (blue bars), compared to Gaussian distribution (red line) for the period 2.1.2008 to 17.1.2012. The figures at the bottom are zoomed in on the left and right tail of the distribution.

8.2 TC5 spot distribution 2008 – 2012



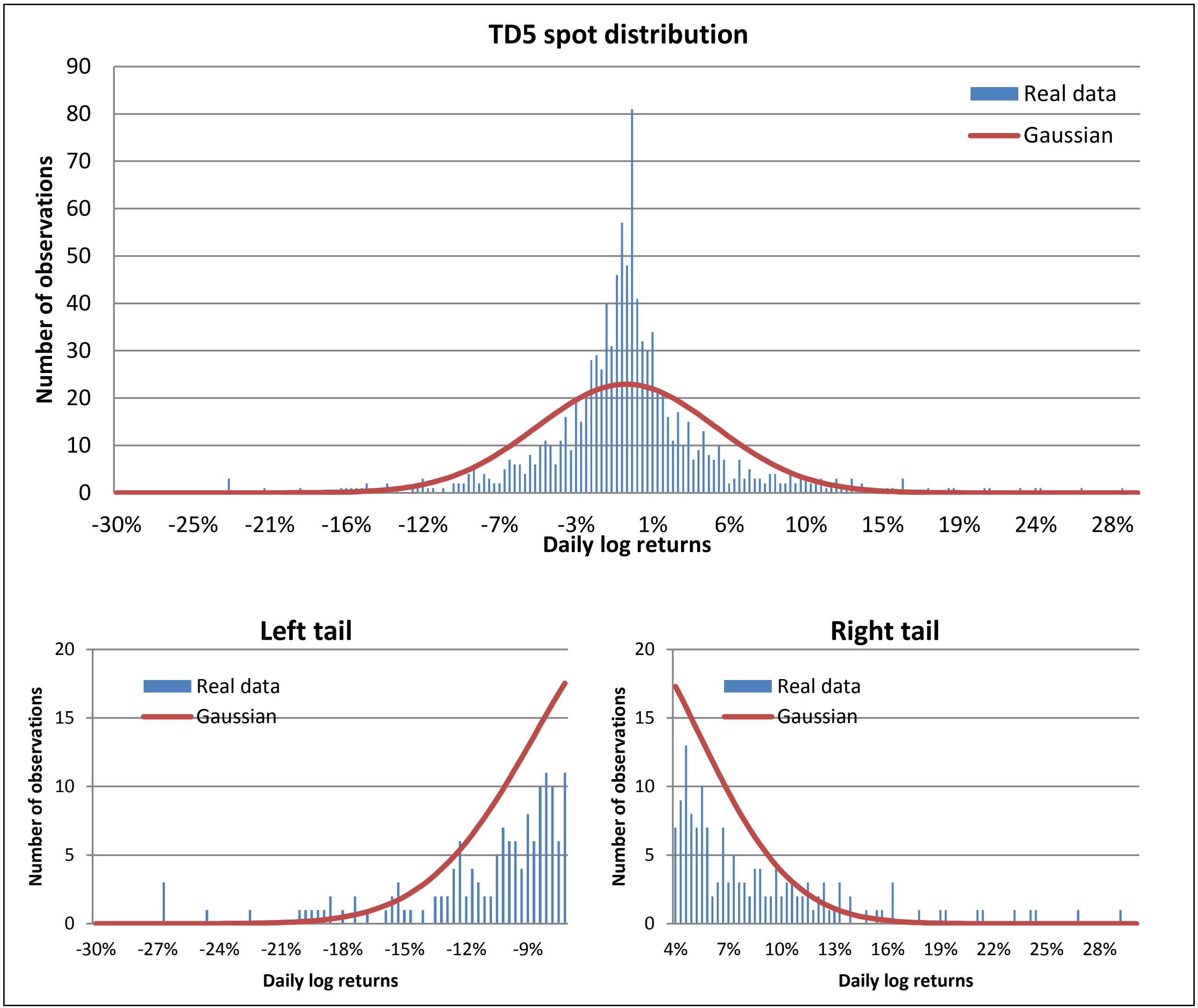
Distribution for TC5 spot (blue bars), compared to Gaussian distribution (red line) for the period 2.1.2008 to 17.1.2012. The figures at the bottom are zoomed in on the left and right tail of the distribution

8.3 TD3 spot distribution 2008 – 2012



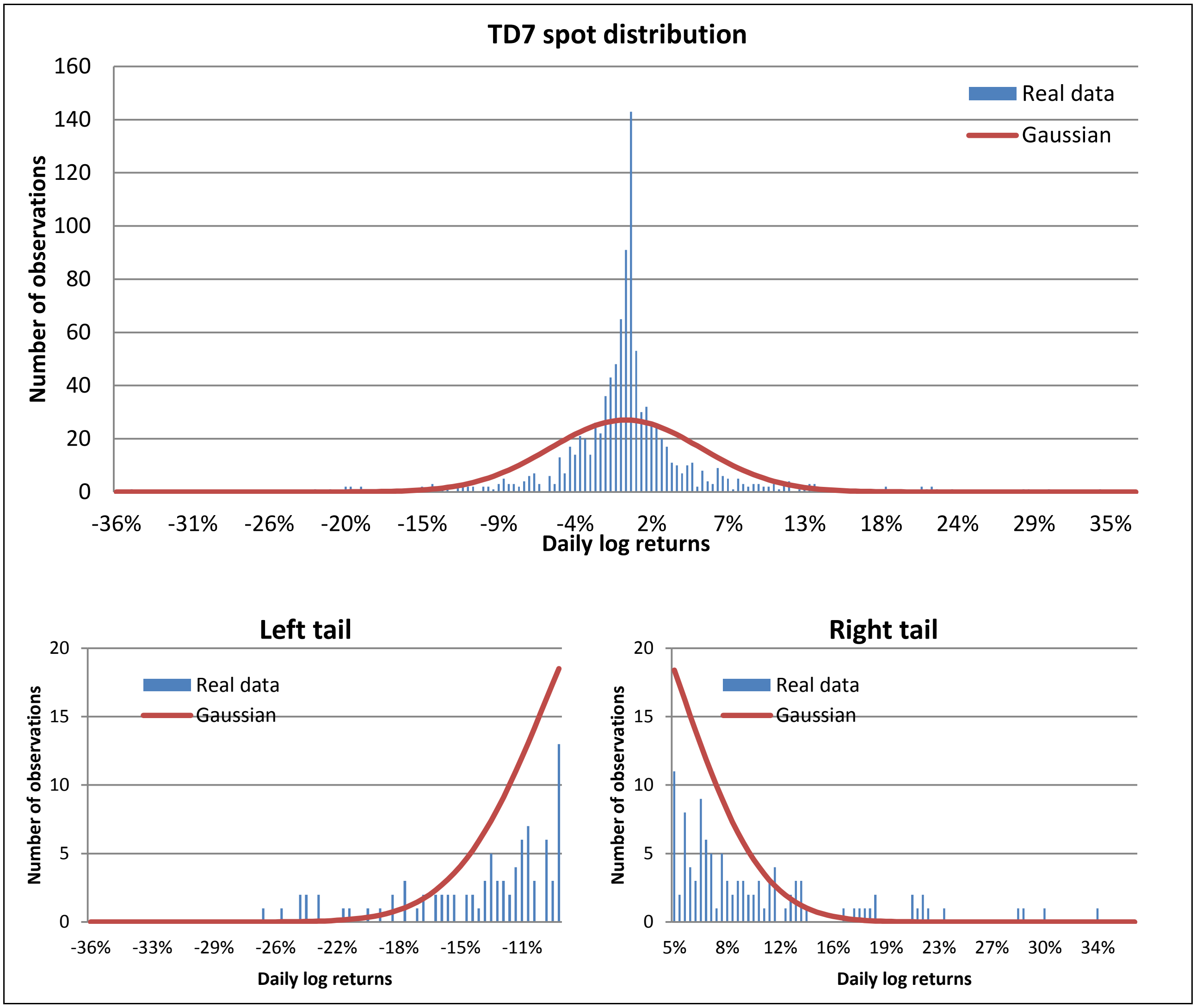
Distribution for TD3 spot (blue bars), compared to Gaussian distribution (red line) for the period 2.1.2008 to 17.1.2012. The figures at the bottom are zoomed in on the left and right tail of the distribution

8.4 TD5 spot distribution 2008 – 2012



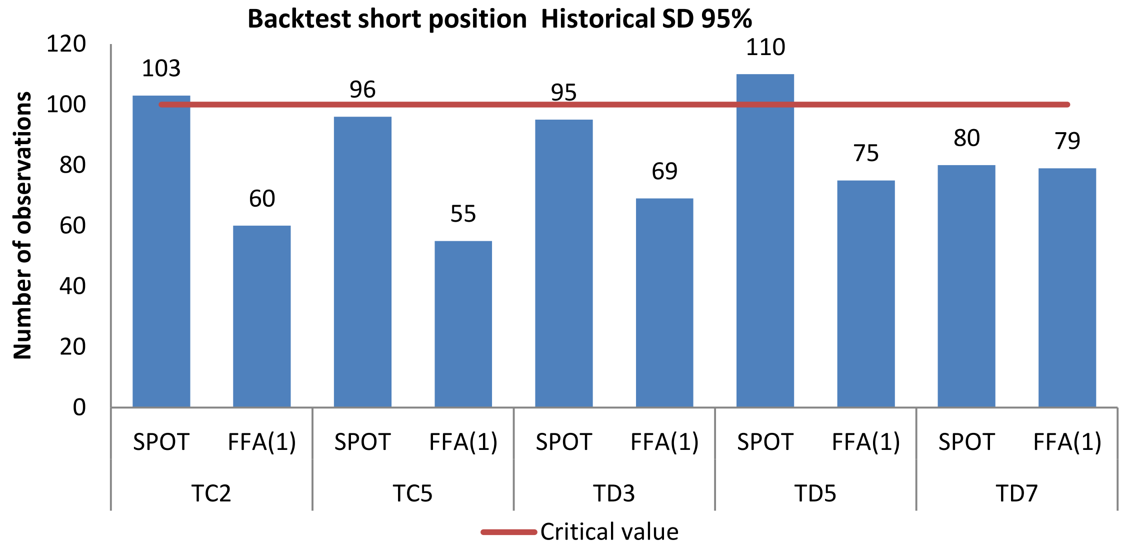
Distribution for TD5 spot (blue bars), compared to Gaussian distribution (red line) for the period 2.1.2008 to 17.1.2012. The figures at the bottom are zoomed in on the left and right tail of the distribution.

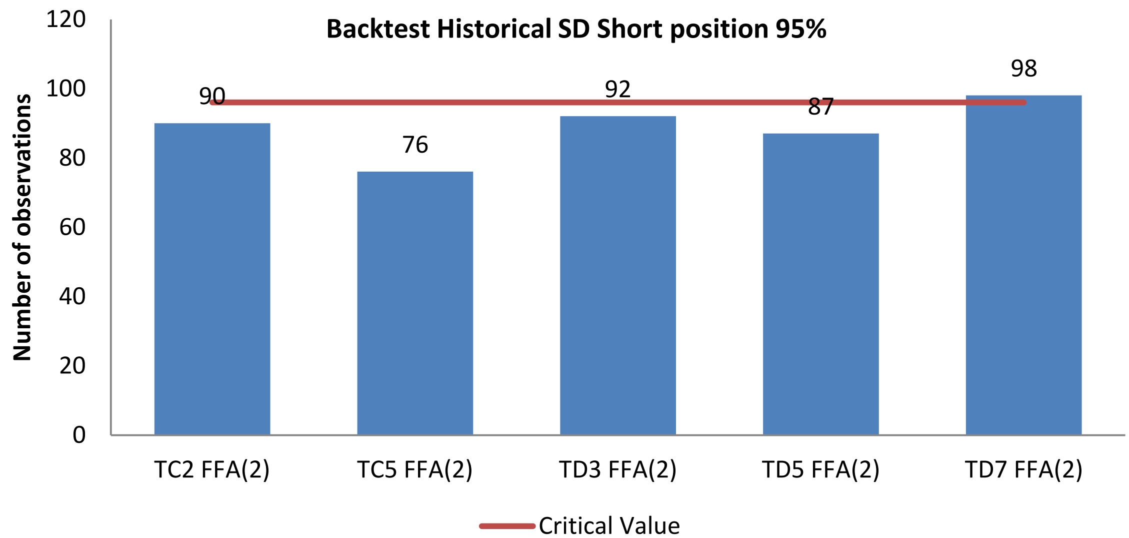
8.5 TD7 spot distribution 2008 - 2012



Distribution for TD7 spot (blue bars), compared to Gaussian distribution (red line) for the period 2.1.2008 to 17.1.2012. The figures at the bottom are zoomed in on the left and right tail of the distribution

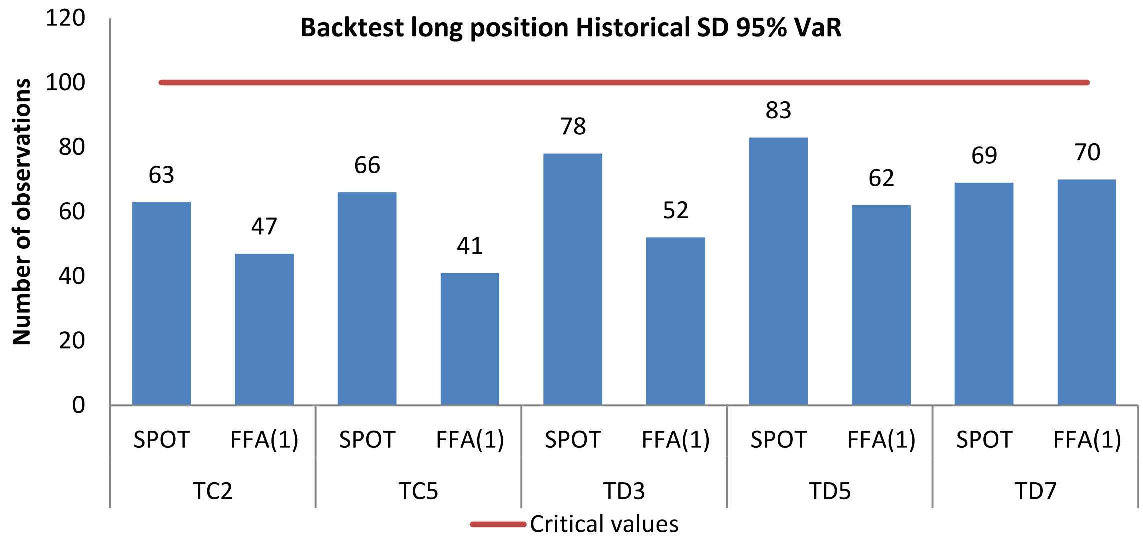
8.6 Backtest MBA 95% VaR Short position

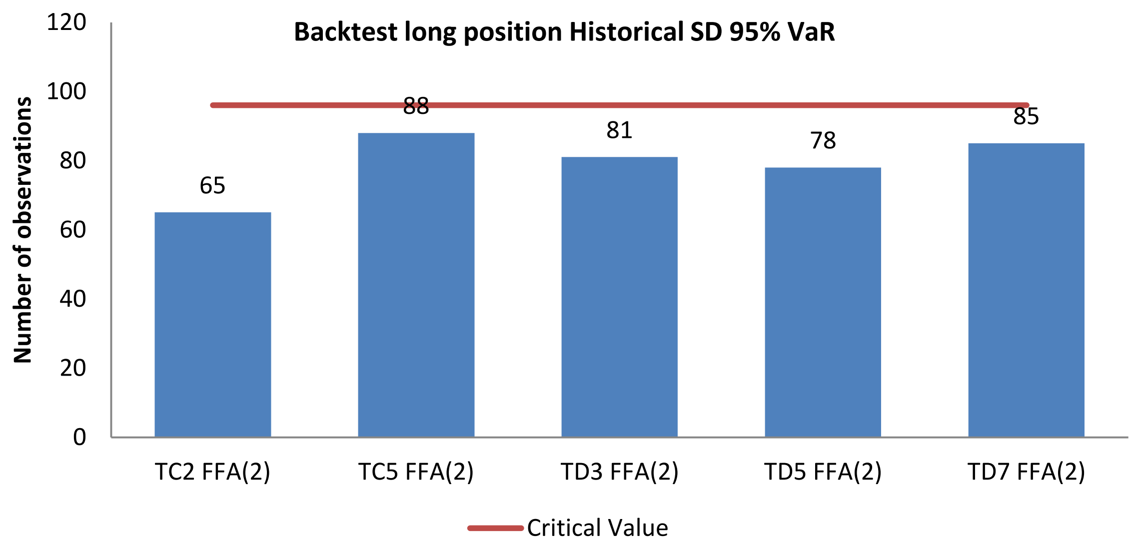




Backtest of MBA using historical standard deviation. The critical values are the expected number of observations greater than the 95% VaR estimate based on a sample containing 2,000 observations for Spot and FFA(1), and 1,908 observations for the FFA(2). The numbers on the top of the bars are the actual historical numbers of observations greater than the VaR estimate form the MBA. FFA(1) Is with the returns from the splicing dates and FFA(2) is without

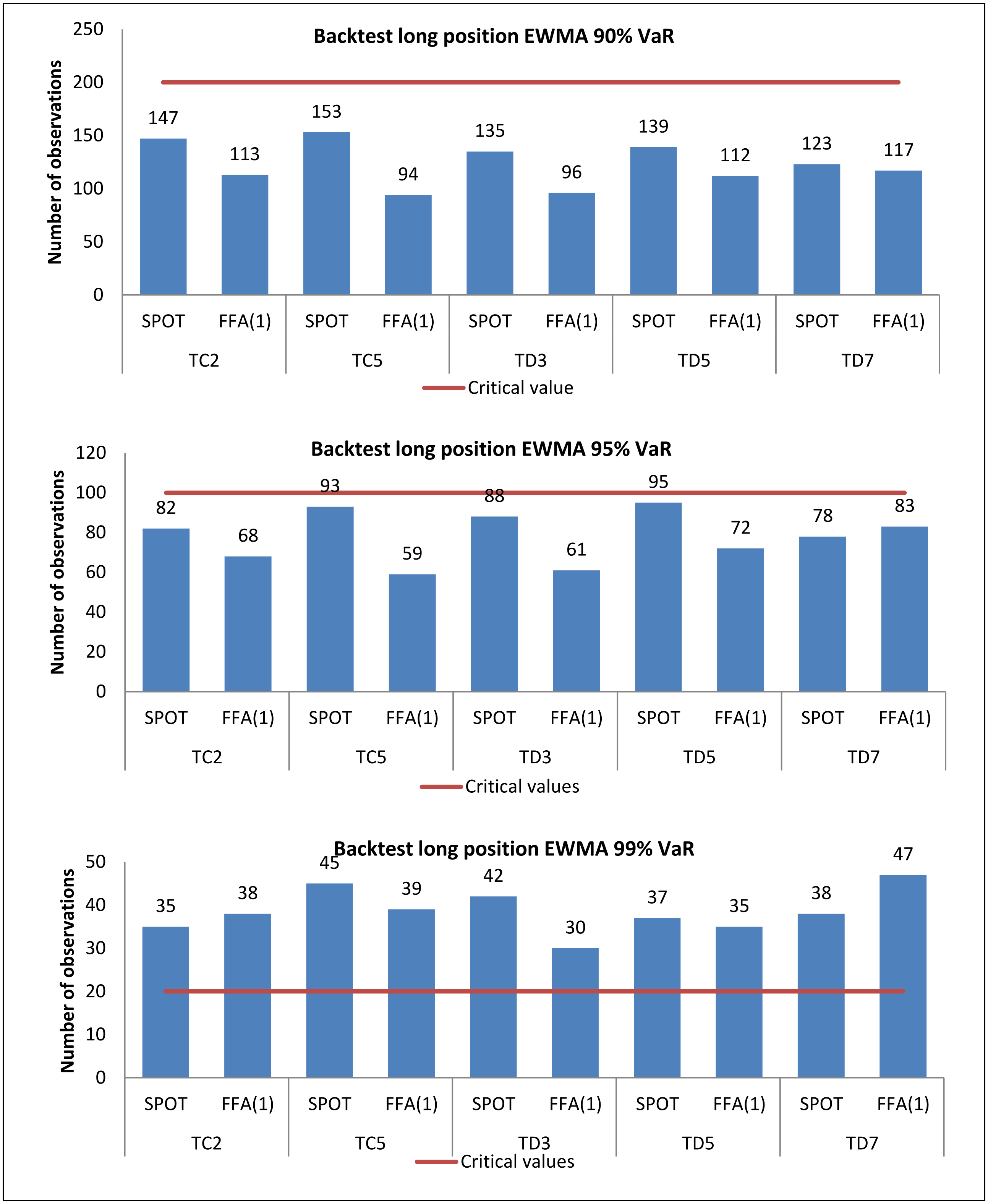
8.7 Backtest MBA 95% VaR long position



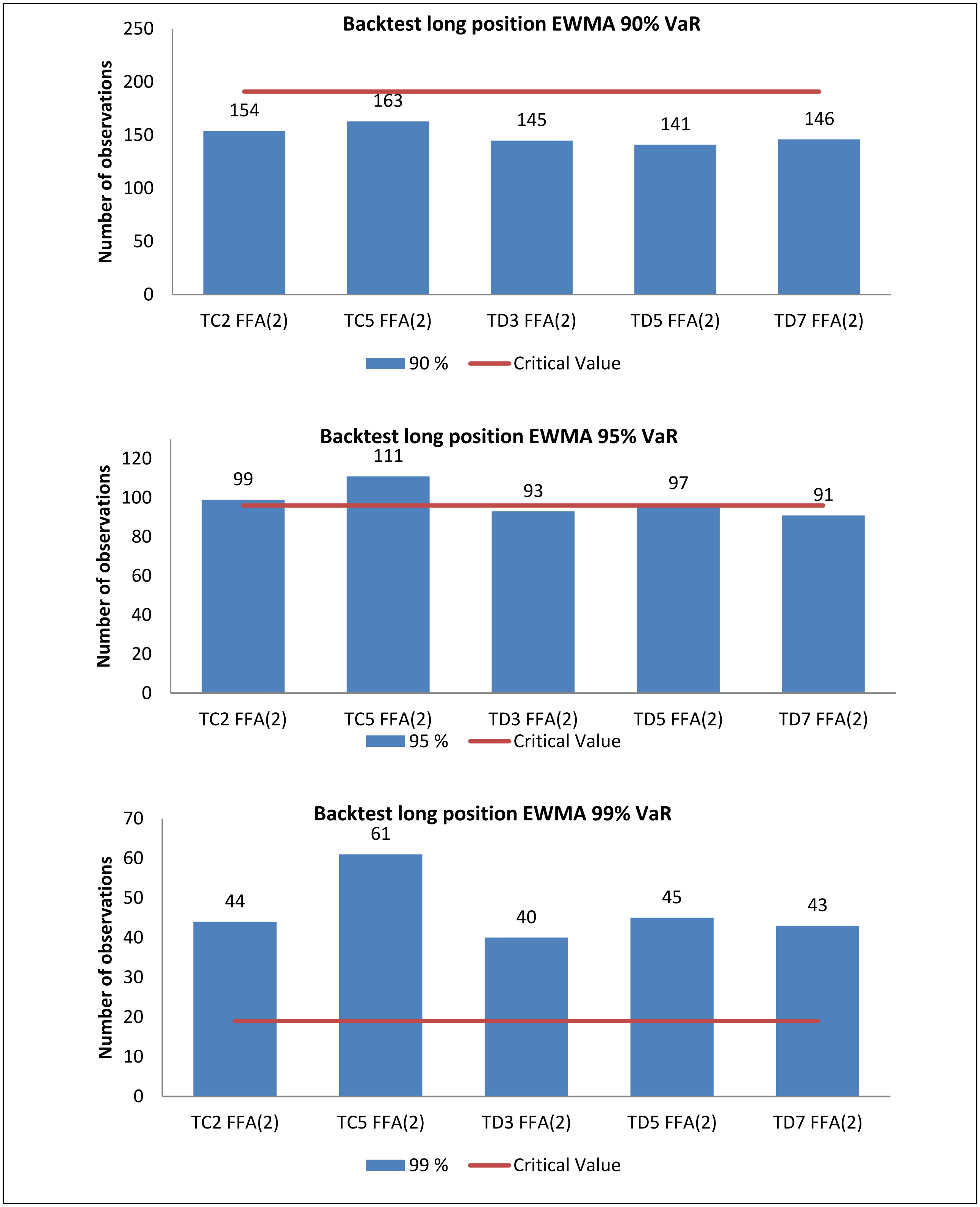


Backtest of MBA using historical standard deviation. The critical values are the expected number of observations greater than the 95% VaR estimate based on a sample containing 2,000 observations for Spot and FFA(1), and 1,908 observations for the FFA(2). The numbers on the top of the bars are the actual historical numbers of observations greater than the VaR estimate form the MBA. FFA(1) Is with the returns from the splicing dates and FFA(2) is without

8.8 Backtest MBA long position EWMA volatility



Backtest of MBA using EWMA volatility. The critical values are the expected number of observations greater than the 90%, 95% and 99% VaR estimate based on a sample containing 2,000 observations. The numbers on the top of the bars are the actual historical numbers of observations greater than the 90% VaR estimate from the MBA. FFA(2) Is without the returns from the splicing dates.



Backtest of MBA using EWMA volatility. The critical values are the expected number of observations greater than the 90%, 95% and 99% VaR estimate based on a sample containing 1,908 observations. The numbers on the top of the bars are the actual historical numbers of observations greater than the 90% VaR estimate from the MBA. FFA(2) Is without the returns from the splicing dates.