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Stochastic Freight Rate Modeling and Application to Value-at-Risk

Predictive Power and Limitations of

Stochastic Models to Forecasting Freight Rates

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Abstract

The purpose of this paper is to investigate the dynamics of freight rates in the dry bulk shipping market from the maritime literature point of view. Based on this theoretical insight the aim is to introduce two stochastic models that reflect one or more of the stylized facts inherent in spot freight rates. Using Monte Carlo simulations these models are applied to the concept of value at risk.

First, from maritime economics and empirical research freight rates are found to exhibit mean-reverting behavior. Second, in situations where the vessel supply becomes almost perfectly inelastic, freight rates become highly volatile and sudden price jumps are likely to occur as a result of temporary bottlenecks. Third, due to cycles in certain commodity trade flows, the derived demand for freight displays seasonal patterns.

The application of the discussed stochastic price processes to the concept of Value-at-Risk reveals that the mean-reverting process produces more accurate results. That is, the chosen VaR threshold is exceeded consistently more in line with what the model suggests using a mean-reverting process as compare to a Geometric Brownian Motion.

1. Introduction

The freight market belongs to the most volatile ones in tradable asset markets. Hence, it is highly interesting to explore its price formation and dynamics in more detail. The fascination to analyze freight rates arises from the complexity of and interdependencies between relevant price influencing factors. On the one hand, the supply and demand fundamentals of every dry bulk commodity play an important role in understanding the global trade flows and the corresponding freight demand. While commodity flows are subject to high fluctuations (e.g. seasonality, macro-economic variables etc.), the supply of vessels to meet the transportation needs is relatively stable and unresponsive in the short-run due to capacity and mobility constraints. Hence, short-term supply and demand imbalances might lead to sudden abrupt price changes. On the other hand, freight markets are exposed to sentiment driven behavior of market participants such as shipowners and operators/charterers based on their expectations about future price developments.

The aim is to model certain key statistical properties inherent in the spot freight rates using common stochastic models used by market practitioners. Spot freight rates exhibit price characteristics that are similar to those observed in in commodity markets: High fluctuations, volatility clustering, seasonality, cyclicality, mean reversion and dependence on global commodity and financial markets (Stopford, 1997; Koekebakker et al., 2006; Nomikos & Doctor, 2012). An understanding of these price dynamics is of great importance for risk management applications, derivatives pricing and freight trading strategies.

2. Research Questions:

1) What are the main theoretical freight rate dynamics derived from the maritime economics literature?

2) What are the striking statistical features inherent in the Baltic Capesize 4TC Spot Index returns?

3) To what extent different stochastic models contain predictive qualities when applied to the Baltic Capesize 4TC Spot Index? What are the major limitations?

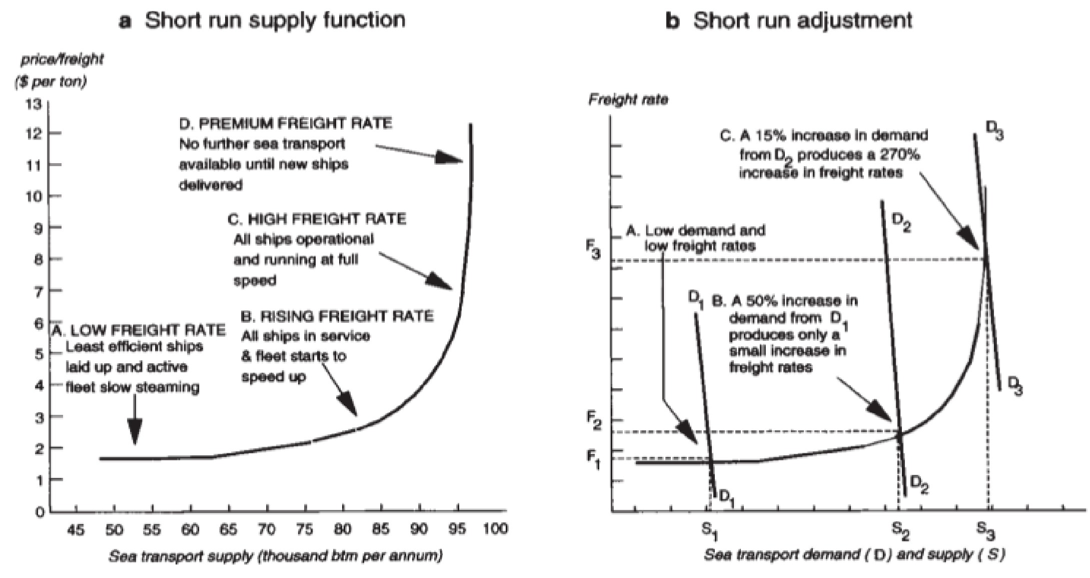
4) How does Monte Carlo VaR differ with respect to different underlying stochastic processes?

3. Review of Freight Market Fundamentals

3.1 Spot Freight Rate Formation

In the diagram below the short-term supply and demand functions in accordance with the classic static equilibrium theory in maritime economics (Stopford, 1997; Alizadeh & Nomikos, 2009) are presented.

Figure 1: Short-run supply and demand equilibrium



Source: Stopford (1997)

Panel a of figure 1 depicts the short-run supply function for freight service. Assuming the freight market in dry bulk shipping is characterized by a perfectly competitive market structure (see Koekebakker et al., 2006), the freight rate is determined by the marginal costs of the marginal vessel that is required to meet the demand for transportation. In the short-run the supply function reflects the shipowners' decision whether to move ships in or out of service in response to prevailing freight rates. In the maritime economic literature, the short-run supply curve is distinguished by two regimes depending on whether the fleet is fully employed or tonnage is unemployed (Koopmans, 1939).

The freight market is cleared where the supply and demand curves cross. At this point the equilibrium freight rate is determined and the market is balanced. Alizadeh & Nomikos (2009) state that spot freight rates at any point in time reflect the balance between supply and demand for transportation services. According to Stopford (1997) the market forms an equilibrium price depending on the time period that owners and charterers face in order to adjust their market positions.

Firstly, in the very short-run the freight price is negotiated for prompt shipments (momentary equilibrium). The momentary state of the freight market is highly fragmented, that is, the market is driven by regional supply and demand fundamentals. Most importantly, the ratio of tonnage available and cargos to be lifted determine the specific freight rate in the region under consideration. If more vessels are available than cargoes, shipowners will desperately offer attractive rates to charterers in order to secure vessel employment, which ultimately pushes rates down. In an overtonnaged region, shipowners face the alternative of fixing the vessel at a lower rate or earning nothing. Those shipowners that remain unemployed might wait until the daily hire rate is getting more favorable or dislocate to other ports where more cargo is expected. Within a short time frame the state of the market can turn into a situation where more cargoes are available to be shipped. Consequently, charterers bid against each other to secure their transportation needs. Eventually, this drives up shipowner's earnings. Freight rates are very volatile in the momentary equilibrium. Many short-term factors might impact spot rates to a larger or lesser extent. Port congestion, port/railway maintenance, infrastructure disruptions, port stocks and weather can heavily influence the momentary equilibrium price.

Secondly, the short-run equilibrium forms under the circumstances where there is some time needed to adjust for supply shortages by reactivating vessels from layup or ballasting. With increasing freight rates owners decide to move vessels out from layup and begin to increase the fleet productivity. At a certain point, the supply curve becomes perfectly inelastic, as the supply cannot react to increased freight rates (see figure 1). Only in the long-run, newly delivered vessels increase the supply. Thus, the sensitivity of freight rates becomes increasingly high with a constrained short-term vessel supply.

Lastly, the long-run equilibrium is formed by pricing in market activities in the S&P market, newbuilding market and demolition market. Obviously, the supply side of the equation can only adjust with a considerable time lag to the demand which lays out the foundation of shipping market cycles (Stopfod, 1997)[1]

3.2 Spot Freight Rate Dynamics

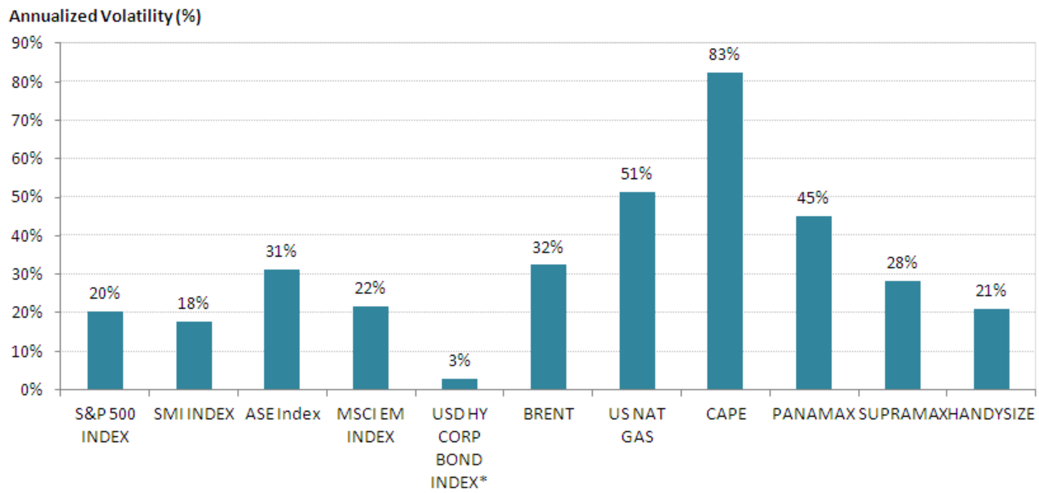
Based on the before fundamentals of maritime economics, the 2 main dynamics of spot freight rates are derived and elaborated: Mean-reversion and volatility/price jumps.

Mean-reversion of prices is referring to the tendency of prices to gravitate towards a long-run value. Extremely high or low freight rates are considered as not sustainable due to the potential for short-term supply adjustments (Adland, 2003). Thus, prices exhibit a probable tendency to revert back to the long-run average or the so-called mean-reversion level. The equilibrium price towards which exploding or collapsing prices gravitate over time is usually governed by the cost of production and level of demand (Blanco & Soronow, 2001).
The theory of spot freight rate formation can explain the tendency of mean-reversion and with it the cyclicality. Koekebakker et al. (2006) concludes based on basic maritime economics that freight rates are expected to display mean-reverting dynamics. Also, empirical findings support the idea that freight rates display the tendency to revert back to a long-run equilibrium price. Adland (2000) proves that mean-reversion becomes significant if the freight rates exceed a certain threshold level (e.g. USD 35'000 per day for Capesize vessels) and provides an explanation that the drift rate is decreasing with high freight rates in order to prevent rates to explode. The mean-reverting property in the shipping market has been dominant in the literature since quite a while (see Zannetos, 1966, Strandenes, 1984 and Tevedt, 1997).

[1] Shipowners tend to base investment on the current state of the market—they order more ships when freight rates are high and fewer when freight rates are low. The delay in delivering these ships means, however, that demand may have changed by the time the ships are delivered, so any cyclical tendency is amplified (Cobweb theorem). See Stopford (1997) and Hampton (1991).

The freight market belongs to one of the most volatile markets amongst tradable assets. Among the equity indices the Athens Stock Index (ASE Index) is the most volatility with an annualized volatility of 31%, higher than the MSCI Emerging Markets Index (22%). The notoriously volatile natural gas market in the US displays a volatility of 51%. With a volatility of 83%, the Capesize freight rates are clearly the most risky ones compared to other asset classes and amongst its peers of the dry bulk freight market.

Figure 2: Comparison of volatilities of different tradable assets



** Data only available since 1/4/2010*

Source: The Baltic Exchange (2014) and Bloomberg (2015). The figure presents a comparison of annualized daily volatilities of different commodities and financial assets estimated over a time horizon of 10 years (1/3/2005 - 12/31/2014).

The main fundamental reason for the significant volatility in the freight market can be explained by the non-storability of a freight service. Globally the dry bulk fleet is operating in the main trading routes where shipowners can maximize their revenues. Accordingly, certain regions of the world attract a glut of vessels which eventually will lead to a regional oversupply. In turn, other regions can potentially not attract enough tonnage for the time being due to less attractive return prospects. However, freight rates in this particular region can suddenly jump if the freight demand is firming up as a result of a higher crop outlook just to name one example
Therefore, volatility and sudden price jumps arise due to geographical fleet dislocations causing temporary supply bottlenecks (see inelastic short-term supply explained earlier).

The non-storability argument comes into play by the fact that a temporary shortage of vessel supply in a certain region cannot be covered by drawing from inventories. Once shipowners decide to relocate to a more attractive region in terms of potential revenues, the tonnage in that region is "gone" and cannot be carried forward as inventory to absorb positive demand shocks. Hence, a shortage of tonnage in the Atlantic for instance, can only be resolved by more vessels ballasting from the Indian Ocean/Pacific to the Atlantic. As a consequence, prices for freight can react very abruptly to a situation where suddenly more cargoes are offered in the market while tonnage is currently insufficient. Increased volatility and occasional price spikes cause shipowners and charterers to send vessels into the shortage region in order to resolve the bottlenecks. Eventually, freight rates tend to drift towards a more sustainable price level. As the uncertainty about a shortage of vessel supply vanishes, the volatility decreases.

4. Application of Common Stochastic Models to Spot Freight Rates

The first step in stochastic modeling is to choose a suitable process that mirrors one or multiple stylized facts of the empirical spot freight rates. For this purpose, two distinct theoretical price processes will be introduced. Firstly, the Geometric Brownian Motion (GBM) will be introduced. This model is the most known stochastic price process and forms the basis for many risk management applications and option valuation. For instance, the famous Black-Scholes option pricing model is based on the assumption that the underlying asset prices follow a GBM. Secondly, the mean-reverting stochastic process introduced by Vasicek (also known as Ornstein-Uhlenbeck process) will be discussed.

According to Geman (2005) the stochastic models should satisfy the following conditions in order to be appropriate:

(1) The simulated price paths should generate a probability distribution that resembles the one observed in the empirical time series (e.g the statistical moments must coincide with the empirical moments)
(2) The simulated prices should be (qualitatively) consistent with the observed dynamics (e.g. the generated price paths should look like the observed ones from a trajectorial standpoint)

Once the stochastic models have been chosen, the parameters involved in the models (e.g. volatility, mean-reversion rate etc.) have to be estimated. The price models will then be simulated using Monte Carlo simulations with the objective to obtain possible price paths that will then be further used in the Value-at-Risk application (see chapter 5).

4.1 Geometric Brownian Motion

Simulated price paths over a period of 252 days following a GBM is shown in the chart below. The drift is assumed to be 4% and the annualized volatility is assumed to be constant at 90%. If S is the spot freight rate, the change ΔS is described as follows:

$$\Delta S = \mu S\Delta t + \sigma S \varepsilon\sqrt{\Delta t}$$

To simulate random prices according to a GBM, the expected volatility over the simulation horizon (e.g. 1 year or 252 trading days) has to be estimated. Either the volatility is estimated based on historical observations (historical volatility) or is implied from option prices (implied volatility). Here, the volatility shall be estimated based on historical observations and is calculated based on a 50day rolling window, commonly referred to as the rolling window approach (see Alexander, 2008). First, the estimation window based on which the model parameters are estimated is fixed at, say 50 days. Second, by keeping the length of the window constant, it is constantly rolled forward by one day.

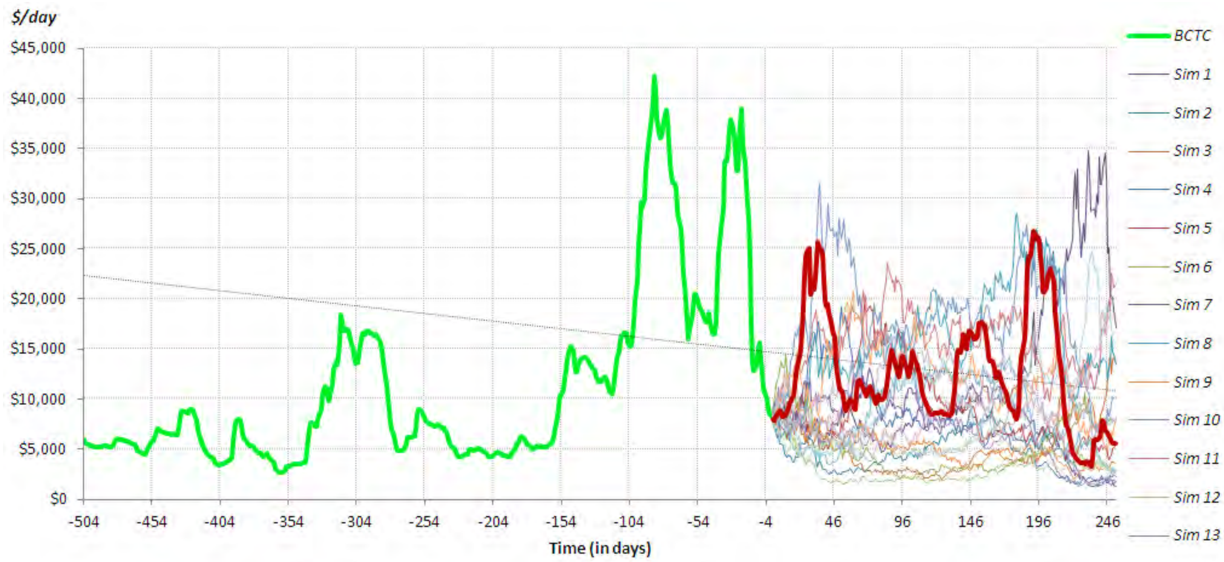
The initial sample window constitutes the log-return observations from 11/15/2013 to 1/31/2014 (50 daily returns). Note that for now all observations obtain the same weights. Additionally, to simulate the GBM the drift term $\mu S\Delta t$ is estimated either by looking backwards (using the slope of the regression/trend line over the estimation window) or by relying on growth projections for global trade growth or industrial production for the year ahead published by official sources such as WTO, OECD, IMF, World Bank or private institutions such as banks and consultancy firms.

The log-returns of the Cape 4TC Index of the sample window display a historical (annualized) volatility of 94%. Importantly, the return distribution over that estimation window reveals that the returns are heavy tailed with a kurtosis of 7.6. A skewness of 0.3 implies that the distribution might be considered as relatively symmetric. The drift term is estimated by relying on the latest global trade growth projections issued by WTO. According to their press release, world trade growth for 2015 was cut to 4% from 5.3% previously (WTO, 2014). According to IMF's latest

World Economic Outlook (WEO), the annual growth of world industrial production was around 3% as per August, 2014 (IMF, 2014).

The figure below extends the historical Cape 4TC Index (green line) by the 20 GBM simulations. On the x-axis the negative numbers indicate that the corresponding y-values are historical data points used for the volatility estimation. As explained above, the initial estimation window is rolled one day ahead after every point estimation of the volatility. The repetition of rolling the sample window forward, allows to simulate price paths using the GBM simulation approach. One can see that at the end of the forecasting period which was set at 252 days or 1 year (see x-axis), the simulated price paths open up a range of possible y-values that vary between $ 1,200 and $ 21,000 with a mean value at $ 8,000.

Figure 1: 20 simulated price paths based on GBM



Source: Own calculation

In order to validate if the GBM model satisfies the accuracy conditions outlined above, the average distribution properties over the 20 simulations/paths and the distribution parameters from the empirical price series are summarized in the model "cockpit" below (figure 4). The objective is to evaluate if the outcome of the simulations accurately reflects the empirical return distribution of the Cape 4TC spot freight rates. The bold red line in figure 3 is the Cape spot price evolution as it has actually occurred (backtesting). The backtesting horizon here corresponds to the forecasting horizon of 252 trading days and ranges from 2/3/2014 to 2/4/2015. The comparison between the sample price paths and the real price evolution reveals that the real price evolves essentially within the possibilities generated by the simulations.

Figure 2: Model result output

Model Parameter	
Spot Freight Rate at t=0	$8,263
Time (T) in year(s)	1
Number of Days (N)	252
Delta t	0.004
Drift rate (growth rate p.a.)	4%
Avg. Annualized Volatility (% p.a.)	50d Rolling

Model Description

$$\Delta S = \underbrace{\mu S\Delta t}_{\text{Drift rate}} + \underbrace{\sigma S \varepsilon\sqrt{\Delta t}}_{\text{Stochastic term}}$$

Main Model Assumptions

Rolling Volatility

Normal Distribution

Simulation Summary	
Average Mean Return of all Sim	-0.23%
Average ann. Vol of all Sim	105.96%
Average Skew of all Sim	-0.31
Average Kurtosis of all Sim	0.96
Min/Max/Average of Sim Prices	$1,214/ $21,462/ $8,038

Empirical Return Statistics	*Regime 3*
Mean Return	-0.11%
Annualized Volatility	93.68%
Skewness	0.27
Kurtosis	4.64

Source: Own calculation as per description

Following the conditions to measure the model performance introduced at the beginning of this chapter, several striking conclusions can be drawn when comparing the "Simulation Summary" and the "Empirical Return Statistics" (see figure 4).

(1) Probability Distribution

a. The mean return of the simulations slightly differs from the empirical mean returns. This deviation occurs purely due to sampling variation. With many drawings the mean would converge toward zero, as imposed in the underlying model.

b. The average volatility of the simulations is higher than the empirical volatility (106% vs. 94%). The deviation is arising from the fact that the simulations are based on a rolling volatility estimation, whereas the empirical volatility of is a point estimation (estimation over one particular estimation window). The average 50d rolling volatility of the actual/empirical freight rates over the backtesting period is 109%, thus gets closer to the simulated volatility.

c. The simulated price paths on average exhibit almost no heavy tails (excess kurtosis of 1) as is implied by the theoretical normal distribution. However, the empirical freight rate returns over the particular estimation period are heavy tailed (excess kurtosis of 4.6)

(2) Freight Rate Dynamics

a. The dynamics inherent to the simulated price paths are consistent with the historical price evolution. Hence, from a purely trajectorial viewpoint Cape spot freight rates can be regarded as a random price path following a GBM.

b. In accordance with the stylized facts of freight rate returns, the simulated paths display short cycles and pronounced price spikes as does the real freight price evolution. Though, the drift of the actual rates over the particular backtesting horizon turned out to be negative (see smooth line in figure 3).

Although the price paths simulated on the basis of a simple GBM model resemble some characteristics of the empirical freight prices, the GBM process is too simplistic to be considered as accurate. First, modeling freight rates using a GBM fails to accommodate for heavy tailed returns. With more realistic assumptions with respect to the return distribution, such as the student's t distribution, heavy tails can to some extent be incorporated in the GBM model. Second, a commonly observed feature in freight rates is the tendency to revert to the mean. In its most basic form the GBM does not account for mean-reversion. A stochastic process that exhibits mean-reversion was introduced in 1977 by Vasicek and was originally used to model interest rates (Vasicek, 1977). In the recent literature on commodity price modeling, mean-reversion has been systematically incorporated.

4.2 Mean Reverting Processes

The maritime economics literature and several relevant research papers dealing with stochastic freight rate modeling state that spot freight rates exhibit mean-reverting behavior. Koekebakker et al. (2006) conclude that due to the existence of a lower and upper bound to the spot freight rate, rates cannot exhibit an explosive behavior. Hence, a counter-balancing effect causes freight rates to gravitate towards a mean value.

The objective of this chapter is to introduce a particular stochastic price model that accommodates mean-reversion. Below, the mean-reverting Vasicek model is presented. It resembles the above discussed GBM price process, while introducing the mean-reversion property with a given long-term gravitation level, denoted by *S**.

$$S_{t+1} - S_t = \alpha\left(S^* - S_t\right) + \sigma\,\varepsilon_t$$

where σ is the annualized volatility of spot freight rates, α indicates the speed at which prices tend to revert to the long-term mean level and ε is the normally distributed random shock to the price system. This price model is popular because it captures several stylized facts as discussed earlier. That is, stochastic behavior of spot freight rates, positivity and mean-reversion. Compared to the GBM model the drift term is now replaced by the tendency of prices to revert to a certain long-term mean value. If S_t is greater than S^* the expected change (S_{t+1} - S_t) is negative and vice versa. This creates the mean-reversion property of the simulations where prices tend to return to a mean level.

To calibrate the Vasicek model, three parameters need to be estimated: the volatility, the mean-reversion speed and the mean-reversion level. The volatility is estimated the same way as for the GBM process discussed earlier by using a 50d rolling estimation window giving equal weight to the past return observations. The mean-reversion speed is commonly estimated by either applying least-square regression (OLS) or maximum likelihood estimation techniques. According to Blanco&Soronow (2001), estimating the mean-reversion speed by using the OLS technique yields relatively robust results. The estimated parameters might be considered as robust/accurate if the estimates are unbiased and the standard deviation of estimates is low. Importantly, different estimation methodologies yield slightly different results and vary with respect to the estimation quality. For the present purpose only the OLS estimation approach is applied in order to estimate the mean-reversion speed.

Regressing absolute price changes on the previous price levels yields a reversion speed of 51%. In fact, the speed is determined by the negative of the regression slope. The mean-reversion level can simply be calculated by estimating the average freight rate over the estimation window, which is yielding $ 12,869 (Blanco & Soronow, 2001). Besides estimating model parameters solely based on statistical techniques it is of importance also to validate these values with what makes (qualitatively) sense from a practical point of view. The mean-reversion level in the commodity space is often referred to as the cost of production (e.g. Geman, 2005, Blanco & Soronow, 2001). In the context of shipping freight rates, the mean-reversion level shall be referred to as the daily vessel operating costs. The daily operating costs as per 2011 for a Capesize vessel were reported at $ 7,876 (UNCTAD, 2012).

The figure below (figure 5) extends the historical Cape 4TC Index by the 20 Vasicek process simulations over a period of 252 trading days. One can see that at the end of the forecasting window, the simulated price paths vary between $ 1,700 and $ 24,000 with a mean value at $ 8,000. The tendency of over- or undershooting prices before gravitating towards the mean-reversion level at $ 8,000 becomes somewhat observable, however, there is admittedly no striking difference compared to the GBM simulation outcome. If the mean-reversion speed is assumed to be much higher (e.g. 200%), a considerably narrower range of possible prices is resulting (figure 6). Besides the volatility, the mean-reversion speed is a crucial variable that influences the accuracy to model freight rates based on the Vasicek price process. The model output in figure 7 compares the simulation outcome (with high and low mean-reversion speed) and the empirical distribution properties.

Figure 5: 20 simulated price paths with slow mean-reversion speed

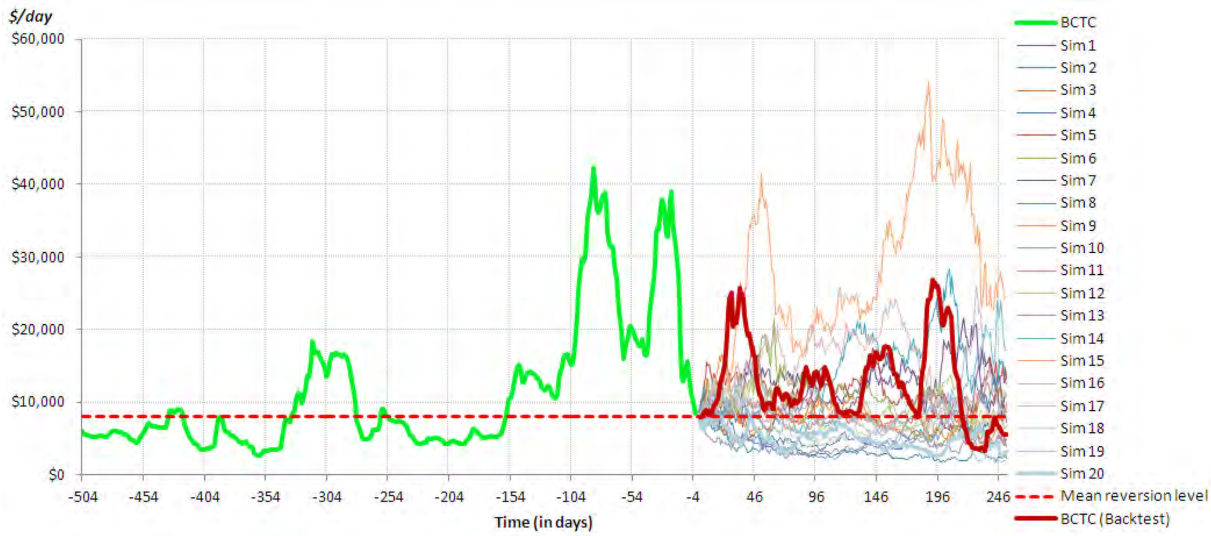


Figure 6: 20 simulated price paths with high mean-reversion speed

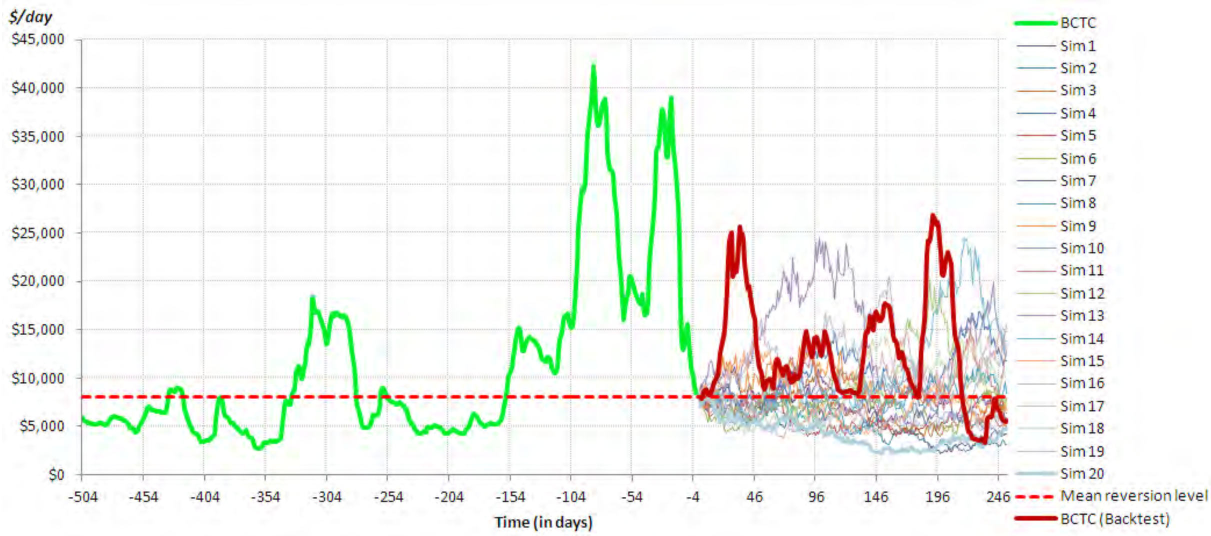


Figure 7: Model result output

Model Parameter	High Speed	Low Speed	
Spot Freight Rate at t=0	\$8,263	\$8,263	
Time (T) in year(s)	1	1	
Number of Days (N)	252	252	
Delta t	0.004	0.004	
Drift rate (growth rate p.a.)	4%	4%	
Annualized Volatility (% p.a.)	50d Rolling	50d Rolling	
Mean reversion speed	200.0%	51.2%	negative of the slope from the regression
Mean reversion level	\$8,000	\$8,000	Daily vessel operating costs according to UNCTAD (2012)

Model Description

$$S_{t+1} - S_t = \underbrace{\alpha\,(s^* - s_t)}_{\text{Mean reversion}} + \underbrace{\sigma\,\varepsilon_t}_{\text{Stochastic term}}$$

Main Model Assumptions

Rolling Volatility, mean reversion speed and level

Normal Distribution

Simulation Summary	High Speed	Low Speed
Average Mean Return of all Sim	-0.03%	-0.04%
Average ann. Vol of all Sim	91.65%	109.24%
Average Skew of all Sim	-0.13	-0.36
Average Kurtosis of all Sim	-0.08	1.12
Min/Max/Average of Sim Prices	\$3'082/ \$15'480/ \$8'459	\$1'668/ \$24'446/ \$8'386

Empirical Return Statistics	Regime 3
Mean Return	-0.11%
Annualized Volatility	93.68%
Skewness	0.27
Kurtosis	4.64

Source: Own calculation as per description

Comparing the "Simulation Summary" and the "Empirical Return Statistics", 2 striking conclusions can be drawn:

(1) Probability Distribution

a. The average annualized volatility of the 20 simulated price paths is closer to the empirical volatility when the reversion speed is set higher.

b. The range of possible price outcomes is narrower assuming a higher reversion speed. The lowest price forecast is more realistic at \$ 3,100 as compared to \$ 1'700 using a slow reversion speed. Recently, the Cape spot freight rates hit a multi-year low at \$ 3,315 on 1/9/2015. An accurate price model should prevent rates to drop to unrealistically low levels.

c. Similarly to the GBM, the simulated price paths based on a mean-reverting process on average exhibit almost no heavy tails, as is implied by the theoretical normal distribution.

(2) Freight Rate Dynamics

a. The dynamics obtained by simulating prices following the Vasicek model with a high mean-reversion speed (see figure 6) are displaying a channeling behavior towards the end of the forecasting horizon. That is, the price paths converge towards the long-term mean level assumed in the underlying stochastic process.

b. The actual freight rates (bold red line) effectively reverted back to the mean around \$ 8000 after prices spiked. This real behavior is corresponding to what the model is intended to capture. Compared to the simulated price paths, the freight rates, however, are characterized by short and pronounced price cycles with a high reversion speed.

With respect to the return distribution of the simulations, the Vasicek model in its most basic form has the same major shortcoming as the GBM. The model does not accommodate for fat tails that are observed in historical freight rate returns. The mean-reversion speed has great influence on the model outcome. The example above has shown, that the statistical estimation of the reversion speed using a regression is not yielding very realistic results. Clearly, the estimation of the reversion speed is dependent on the estimation window, and hence subject to sampling variation. A low reversion speed causes prices to persist for longer either on very low or high levels, whereas the higher imposed speed produced more accurate results when compared to the empirical statistics and actual freight rate dynamics.

4.3 Main Shortcomings of Stochastic Models

Using stochastic models to predict possible price evolutions is only of so much value as one is aware of their shortcomings. The analysis above has shown that mirroring one or several stylized features of historical price observations is subject to estimation error. This implies that the choice for one model or the other is a deliberate simplification of the reality in order to reflect specific empirical properties. Clearly, the more complex a price model is, the closer it might reflect the reality. In turn, the practical applicability, however, is becoming complicated due to the complexity of the model calibration. Hence, the choice of a specific model for a specific purpose is a balancing act between over-simplification and over-complexity. To conclude this chapter, the main shortcomings of stochastic models in general are discussed.

4.3.1 Model distribution assumptions

Every stochastic model is based on specific assumptions about the expectation of the future dynamics of freight rate returns. As discussed, the normality assumption of log-returns has its clear advantages in order to simplify the practical usage of price models such as the GBM or the Vasicek model. The empirical analysis of spot freight rates, however, has shown that the normality assumption is a limitation. Large positive and negative returns contained in the tails of the distribution are in reality more frequently observed than what the normal distribution implies. These extreme price variations are not captured accurately using a model that relies on normally distributed shocks imposed on the price system. The awareness of this shortcoming is of relevance for risk management applications and option pricing because the inherent risk of a freight market position is systematically underestimated.

4.3.2 Model parameter assumptions

Every stochastic model requires estimating the (future) volatility. In the performed analysis the volatility was estimated based on a 50 days rolling window. It was shown that the volatility can vary widely. Hence, the prediction of the future volatility based on historical observations is clearly a simplification. An accurate volatility estimation is highly complex due to its various properties that are highly dynamic (e.g. volatility clusters). More sophisticated risk management models take these empirical facts into consideration for estimating the model parameters (e.g. GARCH models).

The time-varying nature of model parameters applies not only to the volatility but also to other model parameters such as the mean-reversion speed. In the basic model setting as applied in this chapter, the average mean-reversion speed was derived from the OLS regression over a specific estimation window and assumed to be constant over time. Realistically, however, prices tend to revert back to a 'normal' level much faster after an incurred pronounced price spike than after a small price shock. More complex models incorporate a mean-reversion speed dependent on the magnitude of a price shock. Furthermore, the cause of a price jump might also affect the reversion speed. If freight rates spike due to short-term disruptions to the supply chain (e.g. maintenance) or weather disruptions, the prices might revert faster than if the prices spike due to a structural vessel deficit in one crucial loading area.

4.3.3 Model parameter estimation

In the analysis performed the model was entirely calibrated based on historical data samples. A direct consequence is that the user of such a model assumes that history is repeating itself and that history is the 'best' estimate for the future. For instance, if the data set used to estimate the volatility is exceptionally volatile, the estimated volatility will be potentially too high to reflect the future. Nevertheless, history provides the necessary information about dynamics and behaviors one might project forward. A more forward looking estimation approach is to use forward market or options market information. The forward volatility curve for instance reflects the expectation of market participants regarding the future price fluctuations. This market information might be used complementary to historical data in order to achieve a more accurate model calibration.

5. Application and Backtesting Value-at-Risk

This final chapter is applying the concept of Value-at-Risk based on Monte Carlo simulations using the Geometric Brownian Motion and the Vasicek mean-reverting model. The first objective is to compare these two models with respect to their accuracy to measure the inherent risk in a freight market trading position. The resulting VaR assuming either a GBM or the mean-reverting model is backtested by measuring the effective amount of exceedences of the VaR threshold versus the theoretical implied exceedences. The second objective is to test the GBM model when the volatility estimation is performed on the basis of EWMA (exponentially weighted moving average) weighting scheme using different lambda factors. Again, the accuracy is measured by comparing the effective count of exceedences versus the theoretical implied exceedences.

5.1 Backtesting Methodology

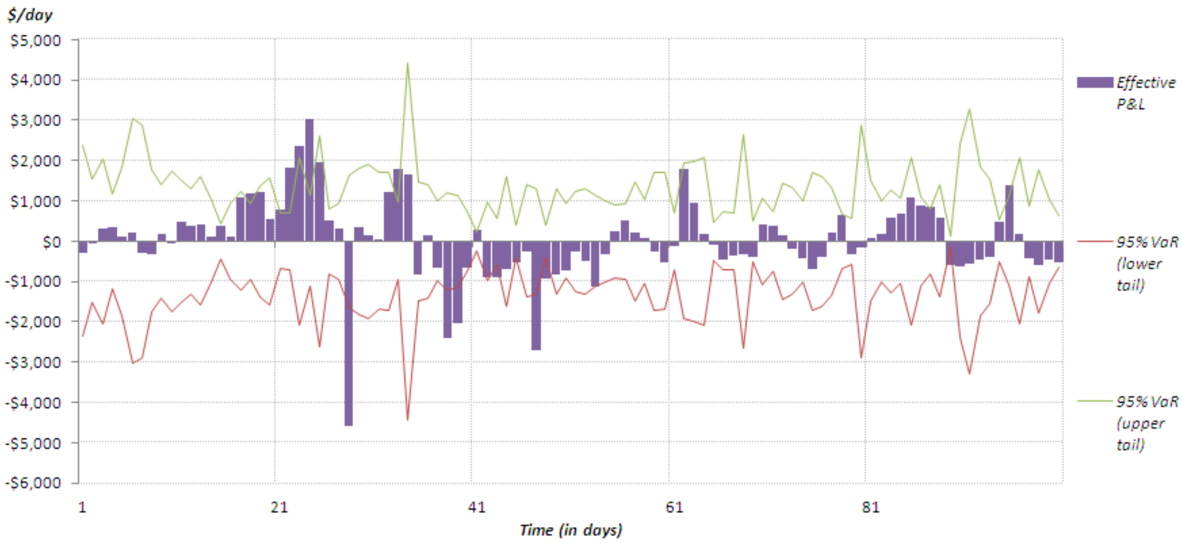
To systematically backtest a VaR model involves comparing the estimated VaR at time t with the subsequent daily P&L of a market position at time $t+1$ (Jorion, 2007, and McNeil et al., 2005). If the calculated VaR based on a specific stochastic model is compared to the realized P&L over a certain backtesting horizon, the probability that the VaR is exceeded is expected to be on average $1\text{-}\alpha$. That is, assuming a 95% confidence level, the VaR is expected to be exceeded by 5% of the realized P&L. If the actual daily P&L exceeds the VaR more than the 5% of the observations used as a backtesting horizon implies that the VaR is underestimating the inherent market risk. Clearly, due to sampling error it is highly unlikely that the actual amount of expected exceedences is exactly matching the theoretical implied exceedences from the model specifications (Alexander, 2008). Backtesting provides necessary information to improve the calibration of a VaR model and it gives indications of the predictive power of an underlying stochastic model (model quality).

The applied backtesting shall be based on a 100 day period. That is, the VaR is calculated for a period of 100 days ahead. The daily VaR is expressing the amount of loss that will not be exceeded at a specific confidence level over a one day period (see chapter 4 for theoretical background). The effective P&L from daily spot freight rate earnings is then compared to the VaR measure. The amount of time the effective P&L exceeds the VaR serves as a sort of quality measure as it indicates how accurate a stochastic model underlying the VaR calculation is able to reflect the risk in a freight market position. Note that the parameter estimation for the applied stochastic models to VaR is in accordance with the previous discussions.

5.2 VaR Using Different underlying Stochastic Price Models

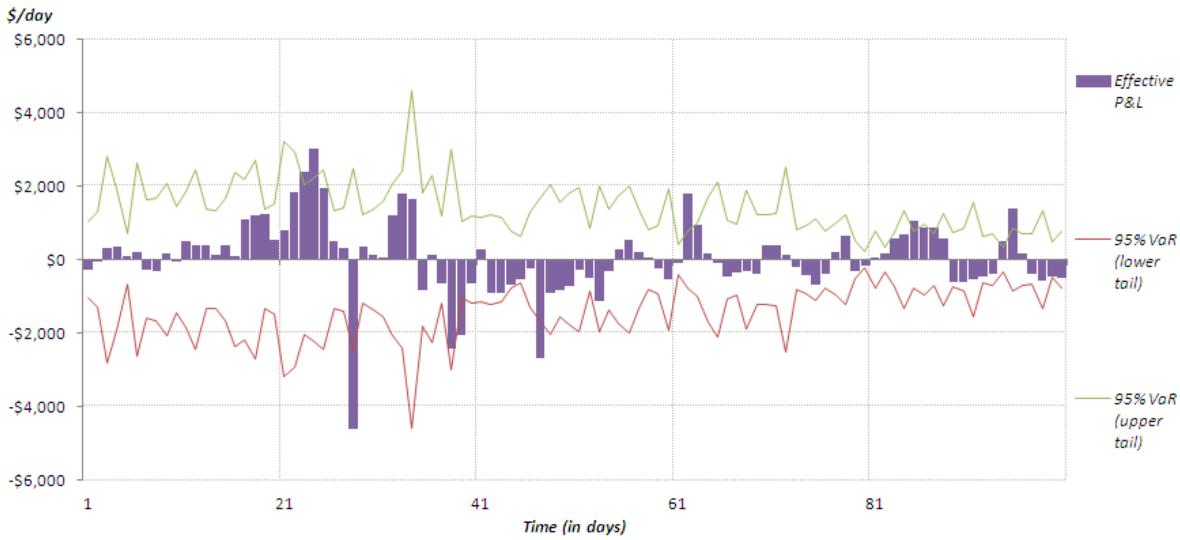
The first comparison is to investigate if the VaR differs with respect to different underlying stochastic processes outlined previously. VaR is calculated as the percentile (95% and 99%) of the performed Monte Carlo simulations. The backtesting results over a 100 days period are presented in the figure below, comparing the VaR outcome based on a GBM process and based on a mean-reverting Vasicek process.

Figure 8: VaR based on Geometric Brownian Motion



Source: Own calculation based on description

Figure 9: VaR based on mean-reverting price process



Source: Own calculation based on description

Figure 10: VaR Model Output and Comparison

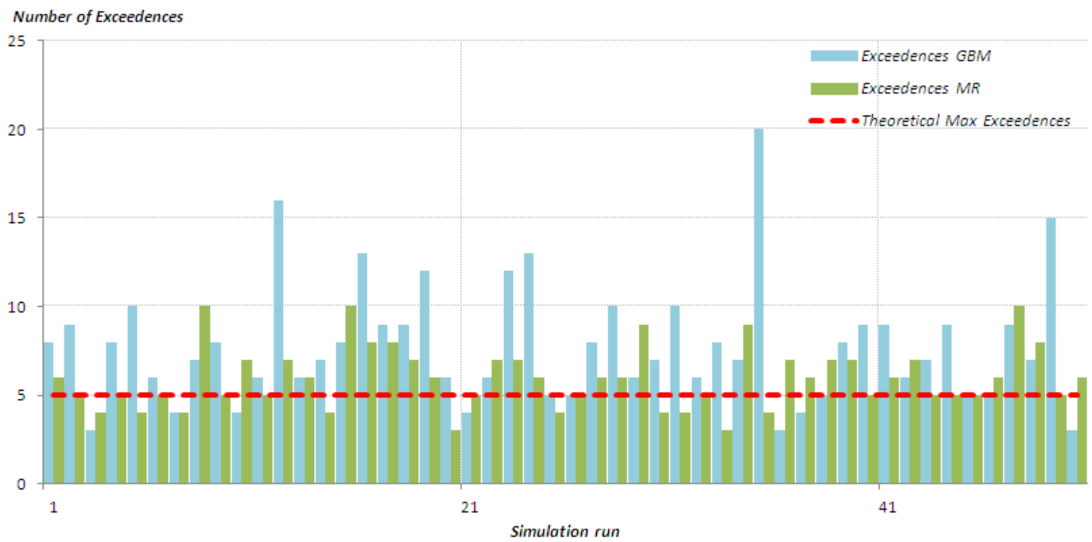
Geometric Brownian Motion			
Value at Risk Backtest Results		*Value at Risk Backtest Results*	
Backtesting Horizon	100	*Backtesting Horizon*	100
VaR Confidence Level	95%	*VaR Confidence Level*	99%
Theoretical Exceedences	5	*Theoretical Exceedences*	1
Effective Count of Exceedences	8	*Effective Count of Exceedences*	7
Mean-Reverting Process			
Value at Risk Backtest Results		*Value at Risk Backtest Results*	
Backtesting Horizon	100	*Backtesting Horizon*	100
VaR Confidence Level	95%	*VaR Confidence Level*	99%
Theoretical Exceedences	5	*Theoretical Exceedences*	1
Effective Count of Exceedences	3	*Effective Count of Exceedences*	2

Source: Own calculation

The results reveal that by underlying a mean-reverting process to simulate the VaR, the model accuracy is higher than by using a GBM process. Given a 95% confidence level and 100 days of observations, VaR should not be exceeded in more than 5 instances. In the present context negative exceedences are considered. The effective P&L (purple bars) are exceeding the VaR (red line in figure 9) using a mean-reverting process only 3 times whereas in the case of a GBM the VaR is exceeded 8 times. Given a 99% confidence interval and the same amount of observations the P&L should not exceed the VaR by more than 1 instance. For the 99% VaR, it is recommended to include much more observations in order to get a measure with more informative power.

Importantly, one cannot draw a final conclusion from above observations. By running the Monte Carlo simulations several times, the outcome is always different. Only after recalculating the results a sufficient amount of time, systematic differences between the two models might be detected. The figure below compares the VaR exceedences for 50 simulation runs and reveals that using a mean-reverting process to simulate VaR is systematically more accurate than underlying a simple GBM price process. Over 50 simulations, the GBM produces an average exceedence of 8 versus a theoretical maximum of 5. Using a mean-reverting process the average exceedences is 6, which is considerably closer to the theoretical maximum of the exceedences. In conclusion, the GBM process underestimates the inherent risk in a spot freight market position systematically in more instances as compared to the mean-reverting process. In addition, as figure 11 shows, calculating the VaR using a GBM process, the risk is underestimated by far higher amounts as compared to the mean-reverting process.

Figure 11: Comparison of VaR Exceedences



Source: Own calculation based on description

5.3 VaR Using Different Volatility Estimation Techniques

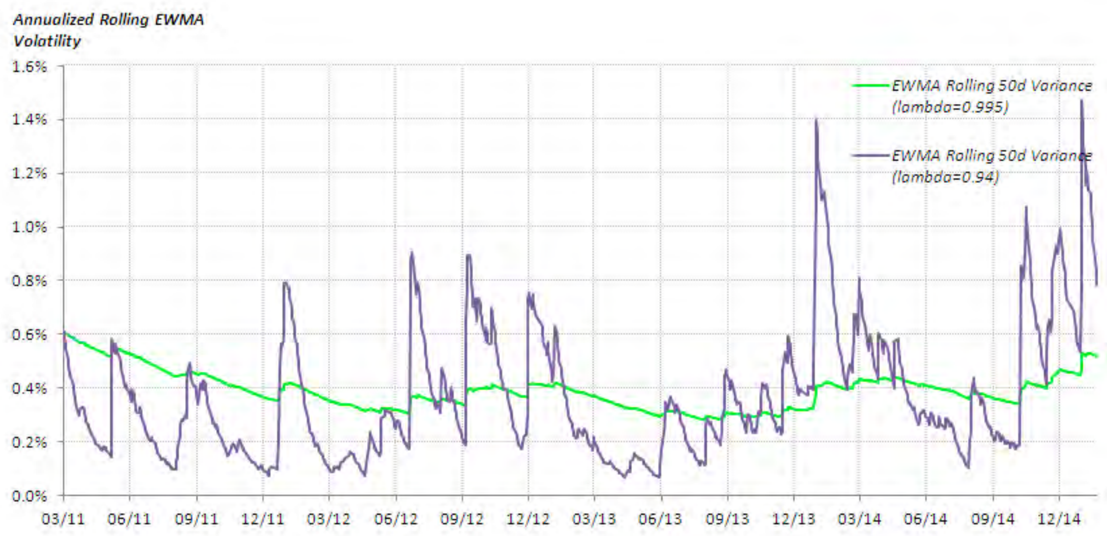
The second comparison is intended to draw a conclusion how different volatility estimation techniques influence the accuracy of the VaR measure. Again, the accuracy of a particular VaR measure is assessed following the backtesting procedure outlined earlier.

This paper so far has estimated the volatility of a particular stochastic process based on a simple rolling window approach, where all observations included in this window obtain equal weight. Boudoukh et al. (1998) suggest a modification to the standard VaR calculation based on equally weighted volatility estimation. The proposition is to assign more weight to more recent return observations to better reflect the current volatility environment. This estimation approach is referred to as exponentially-weighted moving average (EWMA) (see Hull, 2010). As a result, distant observations are not causing jumps in current volatilities as soon as they drop out of the estimation window (ghost effects). VaR based on EWMA volatility is more responsive to recently occurred large fluctuations. The EWMA model assigns a weight to each past return using a specific decay factor, denoted by λ, that determines the rate at which the weights decay as the returns become more distant. According to Hull (2010) the respective weights are assigned as follows:

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

where the volatility estimate for day n is denoted by $\sigma^2 n$ and $r^2 n\text{-}1$ is the most recently observed daily return. From the formula above it becomes apparent that the lower the factor λ, the higher the weight given to the most recent return observation. Hence, an occurring market shock causes the EWMA volatility estimates to spike instantly when using a low lambda-factor, and also to decline rapidly. The EWMA volatilities based on a high and a low decay factor is presented in the figure below (λ=0.998 and λ=0.94[2]).

Figure 12: EWMA volatilities using different decay factors



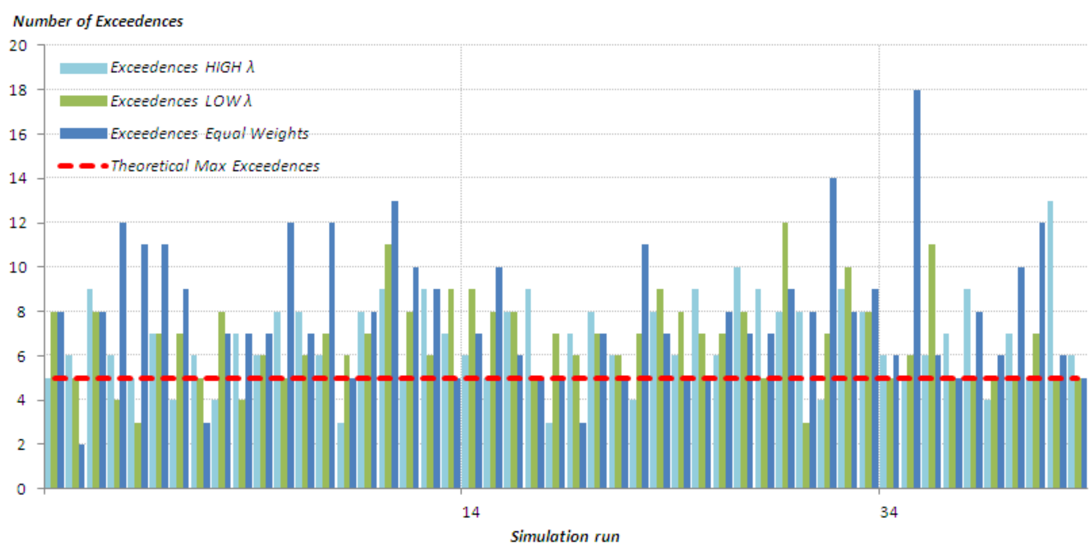
Source: Own calculation

Using these volatility estimates, the Monte Carlo VaR is calculated by underlying a simple GBM process. The backtesting results reveal that using a low lambda-factor, the VaR adjusts

[2] The RiskMetrics database created by J.P. Morgan uses the EWMA model with a decay factor of 0.94.

more reactively to sudden volatility increases, however, no systematic outperformance over the other models (high lambda-factor or equally weighted volatility estimation) is observed. The chart below summarizes this finding by performing 50 simulation runs. Clearly, 50 simulation runs are still subject to sampling variation. From the comparison, one can conclude that using a high or a low decay factor does not systematically improve the model quality. Given a 95% confidence interval, the exceedences average 7 for both models using either a high or a low decay factor. The VaR calculated based on the GBM using equally weighted volatility estimates performs slightly worse, with on average 8 exceedences and the highest absolute exceedences in comparison. However, this slight difference does not permit to systematically disqualify the equally weighted volatility estimation. In conclusion, using EWMA volatilities with high reactivity to the current environment might capture empirical return characteristics such as volatility jumps and volatility clusters more accurately. However, these models risk to over- or undershoot as the reaction to a sudden price jump is only incorporated in the estimated volatility the day after a market shock. From a theoretical point of view, however, applying the EWMA estimation approach is advantageous for markets that are characterized by frequent volatility clusters.

Figure 13: EWMA volatilities using different decay factors



Source: Own calculation

6. Results

The present research paper has covered the topic of stochastic modeling with a special focus on the characteristic dynamics of freight rates and the application to Value-at-Risk. The answers to the research questions outlined at the beginning of this paper have revealed nuanced results. In the following, these will be briefly summarized.

This paper has shown that freight rates exhibit cycles, different volatility environments and mean-reversion, all of which can be explained from a maritime economics literature point of view. Freight rates on a short-term basis are highly reactive to the vessel supply elasticity, which in turn is dependent on the current fleet employment rate. The market price is built by constantly reflecting the cargo/vessel ratio in a specific region. Moreover, different short-term and longer-term supply and demand factors have been discussed how they might affect freight rates (e.g. macro-economic variables, political factors etc.).

In the context of the data analysis, the Baltic Capesize 4TC Spot Index was investigated with respect to its statistical features. The spot returns are exhibiting fat tails and volatility clusters. Nevertheless, the returns for the ease of modeling are assumed to follow the normal distribution. Based on the different volatility environments, regimes were set up in order to account for the variability of the volatility.

Using Monte Carlo simulations, the paper has shown that modeling freight rates based on the Geometric Brownian motion and the Vasicek mean-reverting price process, achieve to mirror certain empirical freight rate characteristics, however both fail to account for fat-tailed returns. The predictive qualities of more complex models (e.g. jump-diffusion models) might be increased but on the cost of the higher complexity with respect to its practical implementation. In general, the limitations of stochastic models are their simplifying assumptions about the return distribution. Additionally, the model quality is largely dependent on the parameter estimation, which again is an abstraction of the reality.

Applying the two most commonly used processes the concept of Value-at-Risk reveals that the mean-reverting process systematically produces a more accurate risk assessment in terms of VaR threshold exceedences. By varying the volatility estimation technique it was found that using the Exponentially Weighted Moving Average (EWMA) approach, the risk is measured slightly more accurately as compared to the equally weighted volatility estimation. Putting more weight on recent observations to estimate the volatility allows to better capturing volatility jumps and clusters. The paper, however, has shown that models calibrated with EWMA volatilities are not systematically revealing much better results.

7. Final Remarks

This paper concludes that stochastic modeling is a useful tool in order to mirror empirical dynamics of spot freight rates. To choose a specific model, it is of great importance to first have a sound understanding of the behavior of empirical freight rate returns and its economic rationale. Applying a stochastic model is tied to the clear intention to reflect one or more stylized facts inherent to freight rates. It is therefore crucial to test a specific model with respect to its predictive qualities from a quantitative and a qualitative point of view. The aim is not only to match the empirical distribution properties with the simulation outcome, but also to recognize the imposed dynamics and patterns.

The choice of a stochastic model is a decision that involves a classical trade-off. On the one hand, the objective is to replicate the reality most accurately. On the other hand, in practice a model only gains acceptance if its practical implementation is limited in its complexity. Most importantly, however, is that the shortcomings of the models in risk management application are clearly understood. A stochastic price model – regardless of its degree of complexity – remains an abstraction of the reality and is based on certain assumptions.

References

Adland, R. O. (2003). *The stochastic behavior of spot freight rates and the risk premium in bulk shipping*. Massachusetts Institute of Technology. Dissertation. February 2003.

Adland, R. O. & Cullinane, K. (2005). *A Time-Varying Risk Premium in the Term Structure of Bulk Shipping Freight Rates*. Journal of Transport Economics and Policy. Volume 39. Part 2. May 2005, pp. 191-208.

Alexander, C. (2008). *Value-at-Risk Models*. Market Risk Analysis Volume IV. New Jersey: John Wiley & Sons Ltd.

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

Blanco, C., Choi, S. & Soronow, D. (2001). *Energy Price Processes Used for Derivatives Pricing & Risk Management.* Commodities Now. March 2001.

Blanco, C. & Soronow, D. (2001). *Mean Reverting Processes. Energy Price Processes Used For Derivatives Pricing & Risk Management*. Commodities Now. June 2001.

Blanco, C. & Soronow, D. (2001). Jump Diffusion Processes. *Energy Price Processes Used For Derivatives Pricing & Risk Management*. Commodities Now. September 2001.

Boudoukh, J., Richardson, M. & Whitelaw, R.F. (1998). *The Best of Both Worlds : A Hybrid Approach to Calculating Value at Risk*. Risk, May, pp. 64-67.

Denning, K. C., Riley, W. B. & Delooze J. P. (1994). *Baltic Freight Futures: Random Walk or Seasonally Predictable?* International Review of Economics and Finance. 3(4), pp. 399-428. JAI Press, Inc.

Dowd, K. (2005). *Measuring market risk*. 2nd ed. New Jersey: John Wiley & Sons Ltd.

Geman, H. (2005). Commodities and Commodity Derivatives. Modeling and Pricing for Agriculturals, Metals and Energy. John Wiley & Sons Ltd.

Hampton, M. (1991). *Long and Short Shipping Cycles: The Rhythms and Psychology of Shipping Markets.* 3rd Edition. Cambridge Academy of Transport Cambridge, March 1991.

Hendricks, D. (1996). Evaluation of Value-at-Risk Models Using Historical Data. Federal Reserve Bank of New York Economic Policy Review (April). In: Grayling, S. (1997), editor. *VaR: Understanding and Applying Value-at Risk*. London: Risk, pp. 151-171.

Hopper, G. (1996). Value at Risk: A New Methodology for Measuring Portfolio Risk. Federal Reserve Bank of Philadelphia Business Review (September-October). In: Grayling, S. (1997), editor. *VaR: Understanding and Applying Value-at Risk*. London: Risk, pp. 141-149.

Hull, J. (2010). *Risk Management and Financial Institutions*. 2nd ed. Boston: Pearson Education Inc.

IMF (2014). World Economic Outlook. October 2014. Retrieved from: http://www.imf.org/external/pubs/ft/weo/2014/02/pdf/text.pdf

IMO (2012). *International Shipping Facts and Figures – Information Resources on Trade, Safety, Security, Environment.* Maritime Knowledge Centre: March 2012. Retrieved from: http://www.imo.org/KnowledgeCentre/ShipsAndShippingFactsAndFigures/TheRoleandImportanceofInternationalShipping/Documents/International%20Shipping%20-%20Facts%20and%20Figures.pdf

Jackson, P., Maude, D.J. & Perraudin, W. (1997). *Bank Capital and Value-at-Risk*. The Journal of Derivatives. Vol. 4 (Spring), No. 3, pp. 73-90.

Jetzer, G. (2012). *Value-at-Risk in Portfolio Risk Management*. Explanatory Power and Limitations to Market Risk Measurement. Master thesis at the University of St.Gallen, written under the supervision of Professor P. Gantenbein. May 2012.

Jordan, J. V. & Mackay, R. J. (1996). *Assessing Value-at-Risk for Equity Portfolios: Implementing Alternative Techniques*. Working Paper. Center for Study of Futures and Options Markets. Virginia Polytechnic Institute.

Jorion, P. (1996). Risk^2*: Measuring the Risk in Value-at-Risk.* Financial Analyst Journal. Vol. 52 (Nov/Dec), No. 6, pp. 47-56.

Jorion, P. (2007). Value *at Risk: The New Benchmark for Managing Financial Risk*. 3rd ed. New York: McGraw-Hill.

Jorion, P. (2011). *Financial Risk Manager Handbook: FRM Part I/Part II*. 6th ed. New Jersey: John Wiley & Sons Inc.

JP Morgan (1996). *RiskMetrics - Technical Document*. 4th ed. New York: JP Morgan.

Kavussanos, M. G. & Alizadeh, A. H. (2001). *Seasonality patterns in dry bulk shipping spot and time charter freight rates*. Transportation Research. Part E 37 (2001), pp. 443-467.

Kavussanos, M. G. & I. D. Visvikis (2006). *Derivatives and Risk Management in Shipping*. Witherby Shipping Business.

Khindanova, I. N. & Rachev, S. T. (2000). *Value at Risk: Recent Advances*. University of California, Santa Barbara and University of Karlsruhe, Germany.

Klovland, J.T. (2002). *Business cycles, commodity prices and shipping freight rates*. Some evidence from the pre-WWI period. SNF Report No. 48/02.

Koekebakker, S., Adland, R. & Sødal, S. (2006). Are spot Rates Stationary? Journal of Transport Economics and Policy. Volume 40, Part 3, September 2006, pp. 449-472.

Koopmans, T. (1939). *Tanker freight rates and tankship building*. De Erven F. Bohn: Haarlem, Netherlands.

Leong, K. (1996). The Right Approach. In: Grayling, S. (1997), editor. *VaR: Understanding and Applying Value-at Risk*. London: Risk, pp. 41-46.

Markowitz, H. (1952). *Portfolio Selection.* The Journal of Finance, Vol. 7, No. 1., pp. 77-91.

McNeil, A.J., Frey, R. & Embrechts, P. (2005). *Quantitative Risk Management: Concepts, Techniques, and Tools*. Princeton and Oxford: Princeton University Press.

Merton, R. (1976). *Option pricing when underlying stock returns are discountinuous.* Journal of Financial Economics. 3 (1976), pp. 125-144.

Nomikos, N. K. & Doctor, K. (2012). *Economic significance of market timing rules in the Forward Freight Agreement markets.* Transportation Research. Part E 52 (2013), pp. 77-93. Elsevier Ltd.

Nomikos, N. K. (n.a.). *Freight Modelling Workshop*. Cass Business School. Retrieved from: https://www.balticexchange.com/dyn/_assets/_pdfs/media/Nikos_Nomikos_London_FFABA_final.pdf

Norman, V.D. (1979). *Economics of Bulk Shipping*. Institute for Shipping Research, Norwegian School of Economics and Business Administration, Bergen.

Pirrong, C. (2014). *The Economics of Commodity Trading Firms*. Trafigura. White Paper.

Pritsker, M. (1996). *Evaluating Value-at-Risk Methodologies: Accuracy versus Computational Time.* Wharton Financial Institutions Center Working Paper Series, Working Paper 96-48.

Pyndyck, R. S. & Rubinfeld, D. L. (1998). *Econometric Models and Econometric Forecasts.* 4th Edition. Irwin McGraw-Hill.

Reed, N. (1996). Variations on a Theme. *In: Grayling, S. (1997), editor. VaR: Understanding and Applying Value-at Risk. London: Risk,* pp. 23-26.

Simons, K. (1996). Value at Risk – New Approach to Risk Management. In: Grayling, S. (1997), editor. *VaR: Understanding and Applying Value-at Risk*. London: Risk, pp. 134-140.

Stopford, M. (1997). *Maritime Economics*. 2nd Ed. London and New York: Routledge.

Strandenes, S. P. (1984). *Price Determination in the Time Charter and Second Hand Markets. Center for Applied Research*. Norwegian School of Economics and Business Administration. Working paper MU 06.

Tevdt, J. (1997). *Valuation of VLCCs under income uncertainty*. Maritime Policy and Management. 24(2), pp. 159-147.

UNCTAD (2012). Review of Maritime Transport 2012. Report by the UNCTAD secretariat. Chapter 3. United Nations. New York and Geneva. Retrieved from: http://unctad.org/en/PublicationChapters/Chapter%203.pdf

Vasicek, O. (1977). An equilibrium characterization of the term structure. Journal of Financial Economics. 5, pp. 177-188.

Veenstra, A. & Van Dalen,J. (2011): Fixtures-based freight rate indices, and their impact on freight rate modeling in the shipping industry. In: Cullinane, K. (2011). *International Handbook of Maritime Economics*. Edward Elgar. pp.63ff.

WTO (2014): WTO lowers forecast after sub-par trade growth in first half of 2014. Press Release / 722. 23 September 2014. Retrieved from: http://www.wto.org/english/news_e/pres14_e/pr722_e.htm

Zannetos, Z. S. (1966). *The theory of oil tankship rates*. Cambridge, M.A.: MIT Press.

Price Databases:

Bloomberg (2015). Asset class prices used for the calculations of annualized volatilities (figure 2). Company subscription.

The Baltic Exchange (2014). Daily rate assessment reports and prices used for calculations. Company subscription.