



Switching Options in Tanker Shipping Markets

A New Approach to Product Tanker Valuation

David Hansson & Levin von der Wense

Supervisor: Roar Adland

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Abstract

The thesis investigates the value of a switching option for an LR2 product tanker, which can switch between dirty and clean freight markets, using a real option valuation model based on a stochastic freight rate differential between the two markets along with the optimal switching policy. The parameters have been estimated based on empirical methods of the freight rates from two resembling routes in the time interval of January 1997 to November 2015. The authors find that the flexibility may add value to owners engaging in switching strategies, especially at the end of the time series, when the freight rate differential is in favor of the dirty market.

However, the value of the option and the optimal switching policy is highly dependent on the parameters. This is indicated in the sensitivity analysis and rolling window estimation. The sensitivity analysis shows how some of the parameters affect the value and optimal switching policy. Meanwhile, the rolling window estimation indicates that the model's assumptions regarding constant parameters seem to be unrealistic over time, thus the model may not be suitable to use when valuating the option and finding the optimal switching strategy. Furthermore it indicates that the sample used to estimate parameters has a large impact on the value of the option.

Finally, the general limitations of the model are discussed and how these may lead an unrealistic valuation.

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1. Introduction

1.1 Aim of the Thesis

Tanker freight rates have a highly volatile and cyclical nature. High capital investments are required to enter the market. For these reasons risk management and managerial flexibility are key in increasing profits or mitigating losses for shipowners. Risk management tools can consist of forward or future agreements of different kinds, but can also be embedded in the real asset (i.e. the vessels themselves). This managerial flexibility depends on the specifications of the vessel. It will be the aim of this paper to investigate the value of such real asset flexibilities in the product tanker market.

The tanker shipping industry distinguishes between two submarkets; the dirty market, including crude and dirty refined products, and the clean product market. While we will investigate the characteristics of these in detail later on, let's for now say that there are dirty oil products and clean oil products, which cannot be transported by the same vessel. Dirty products might lead to pollution of clean ones, while clean products may lead corrosion of tanks if not equipped with the correct coating. This has led to different ship types serving the two markets. On one hand there are classical crude oil tankers of different sizes, which transport crude oil and its dirty derivatives around the world. On the other there are product tankers, which are used for transporting clean refined oil derivatives. While a crude oil tanker is generally not able to serve the clean product market, due to its tank characteristics and risk of contamination after transportation of dirty products, a product tanker would be able to switch between markets. Intuitively a rational, risk-taking shipowner would like to exploit arbitrage opportunities whenever the spread between the two markets allows.

The relevance of such an option to switch becomes apparent when looking at the Clean – Dirty TCE spread between Clarksons routes over the course of 1997 till today, see Figure 1.1. Both routes range from the Middle East to the Singapore/Japan region and are operated with tankers of Aframax or LR2 size with 80,000/75,000 dwt cargo intake.

While in a period from 1997 till 2003q3 the higher newbuilding price of a product tanker was generally rewarded with a freight rate premium, since then the market seems to have shifted from clean dominance to dirty dominance. It looks like two markets have been going through

different phases of integration. The varying volatility and persistence of shocks to the differential depicts possible gains from switching between markets.

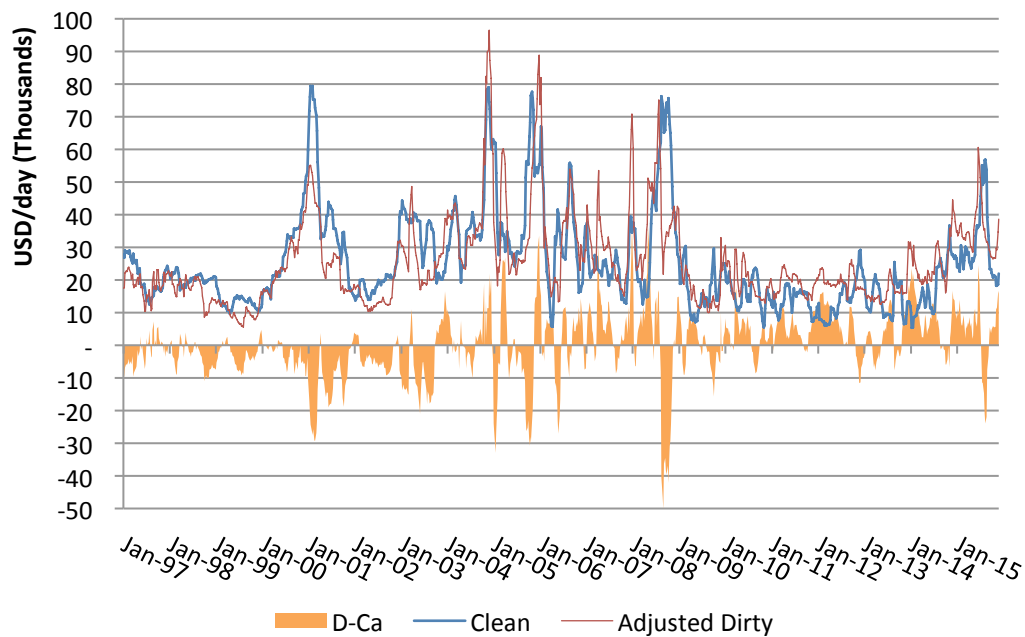


Figure 1.1 Earnings Spread Clean – Dirty (adjusted) (\$/day), weekly 3. Jan. 1997 – 27. Nov. 2015; Source: (Clarksons Research Ltd, 2015c)

Switches between transport of clean and dirty products have recently gained a lot of media attention, see for instance Mohindru and Wang (2015) and Papachristou (2014). However such switches seem to be influenced by variety of other factors than just the freight rate differential, such as segregation between upstream and downstream operations in large, integrated oil companies and the requirement for outperformance of one market over the other for a long period of time (Poten & Partners, 2014). While some shipowners are already engaging in switching, there is to the authors' knowledge no previous academic research on market switching between clean and dirty.

Switching product tankers could serve as the integrator of the two. Hence, the motivation for the thesis is to test whether the switching of markets is coherent with economic theory, to establish to what extent there is any value of such flexibilities and if so what the optimal switching policy is. The aim is to extend the empirical research on real options, switching options specifically. Through the process we are able to investigate market integration between dirty and clean freight rates. Additionally, we are contributing to theory on product tanker valuation.

More precisely, the thesis will investigate the following problem:

An owner of a LR2 product tanker has the option to let it operate in the clean or in the dirty market. The tanker is travelling between Middle East and Singapore/Japan over the time frame 1997 to 2015. The value of this option is determined by the differential in freight rate between the two markets and the active switching policy of the owner. On the contrary, the alternative passive strategy would be to let the tanker run in the freight market for clean products only.

The aims for the thesis will be accomplished by building a mathematical exit-entry model under uncertainty mainly based on two academic papers; Sødal et al. (2008; 2009). The model applies an Ornstein-Uhlenbeck process to model the freight rate differential to calculate the value and optimal strategy of the real option given certain parameter estimates. A sensitivity analysis will describe if and how the estimated parameters affect the value of the option. Finally, we will test for stability of parameters and model outcomes.

1.2 Literature review

An intensive search on existing empirical literature did not lead to directly related academic work in the field of product tanker market switching. This works as additional motivation to dive into and elaborate on the topic. Nevertheless, there is a series of academic papers, which provides us with the relevant theoretical framework for our analysis. Another set of literature is of empirical nature, thereby applying this theory to problems largely different from ours. However these practical applications work as a guideline for our research process.

Modeling Freight Markets

The extensive literature for modeling freight market is divided into two main schools: *the classical school*, focusing on supply and demand models for transport, and *the modern school*, modeling freight rates as stochastic processes.

One of the earliest efforts in the classical school was the model for freight markets by Tinbergen (1934) presenting the sensitivity of freight rate following movements in demand and supply. Similarly Koopmans (1939) examined the determinants for supply and demand in the spot markets for tanker freight rates. The classical school later divided into two approaches of modeling the freight markets; firstly by using static supply and demand models

(see e.g. Zannetos (1964)); secondly by using dynamic econometric models (see e.g. Beenstock and Vergottis (1989)).

The modern school, on the other hand, has modeled freight rates as stochastic processes of various types, typically including mean reversion to account for stationarity in freight rates. Bjerksund and Ekern (1997) modeled freight rates as a mean-reverting stochastic process, using an Ornstein-Uhlenbeck process. Meanwhile other mean reverting processes have also been used. See Tvedt (1997) presenting a geometric mean reverting process to model the freight rates, which in contrast to the Ornstein-Uhlenbeck process does not allow negative freight rates. Other papers, such as Adland & Cullinane (2006) and Adland & Koekebakker (2007), use a non-parametric stochastic process to model freight rates. Finally, there is research merging desirable features of the two schools together in so-called stochastic partial equilibrium models, see Tvedt (1996; 2003), Adland & Strandenes (2004).

Entry-Exit Literature

The problem above describes an option to switch under uncertainty. As the switch is reversible, there is an entry and an exit to markets. Mossin (1968) was the first to set up such a model for combined exit-entry decision by describing a rule for optimal decision policy regarding the lay-up and reentry for vessels. A general real option framework for an exit-entry model was later developed in Brennan and Schwartz (1985) and Dixit (1989). The two works present a general valuation framework for highly uncertain prices with slightly different degrees of complexity of the setting. All three works point out certain price thresholds to drive the decisions; one upper threshold, which should trigger an entry decision, and one lower threshold, which should trigger an exit decision. The triggers are in turn dependent on the nature of the stochastic price process and the costs of switching.

Several theoretical contributions to the entry-exit model have been made since, extending the literature with slightly different approaches. Brekke and Øksendal (1994) considered scenario where a resource is extracted taking into account the depletion of the resource. Bar-Ilan and Strange (1996) implements investment lags, i.e. the time between when the decision is made and when revenues change to that of the new mode. Sødal (2006) proposed simplified versions of works mentioned in this paragraph along with some other by applying the discount factor approach from Dixit et al. (1999).

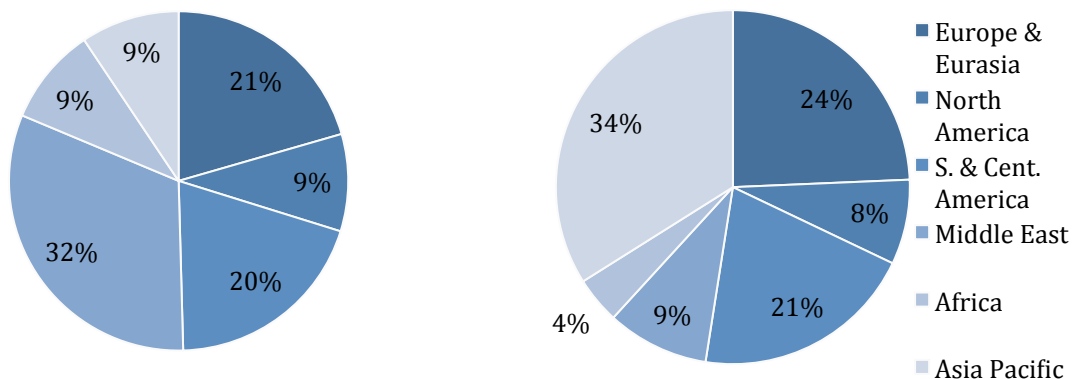
While there is some theoretical research for exit-entry decisions the empirical research is scarce. Sødal et al. (2008; 2009) serve as empirical research. The former paper investigates the value of switching between wet and dry cargo using a combination carrier. The latter paper discusses switching between the same markets using an asset play strategy where tankers and dry vessels are acquired and sold whenever the freight rate spread allows. Bjerknes and Herje (2013) consider a similar scenario where the flexibility stems from the mobility of dry bulks by doing geographical switching between the Atlantic basin and the Pacific basin. Considering the similarities in flexibility and industrial setting between this thesis and three mentioned works our thesis will to an extent share the intuition and mathematical models.

2. Seaborne Transport of Crude Oil and Oil Products

To understand the model presented in later chapters it is important to have some knowledge about the practical properties of transport of crude oil and oil derivatives. This segment will provide a fundament for understanding of the trade and seaborne transport of crude oil and oil products.

2.1.1 Geography of Crude Oil and Oil Products

The demand for crude oil and oil derivatives is widespread across the world. Meanwhile, the distribution between the supply sources and the demand is uneven. Figure 2.1 shows the production and consumption of oil. Note that Asia Pacific produces very little, while the consumption is the highest. Similarly, the reversed relationship can be seen for Middle East. The production and consumption is almost the same in size, thus indicating that the mentioned regions can be seen as the biggest net importer and net exporter respectively.



2.1 Oil Production (left) and Oil Consumption (right) in 2014; Source (BP, 2015)

Figure 2.2 shows the density of tanker routes in 2014. A lighter color indicates a higher density of tanker routing through the area. Some of the more notable areas with a high density are Middle East, the Mediterranean, Cape of Good Hope, the US Gulf, East Asia and Western Europe. The density comes either from a high demand, high supply or the geographical restrictions of oil freight. In the case of the Middle East it is reasonable to think that the high density is based on the high supply of crude oil, whereas in the case of East Asia a high demand drives the high density, which makes routes between these two regions

particularly interesting. The high density tankers at the Cape of Good Hope is no less than the geographical limitations of transporting oil from the Middle East to the Americas and to some extent to Europe (due to the draught restrictions of the Suez Canal) via other routes.

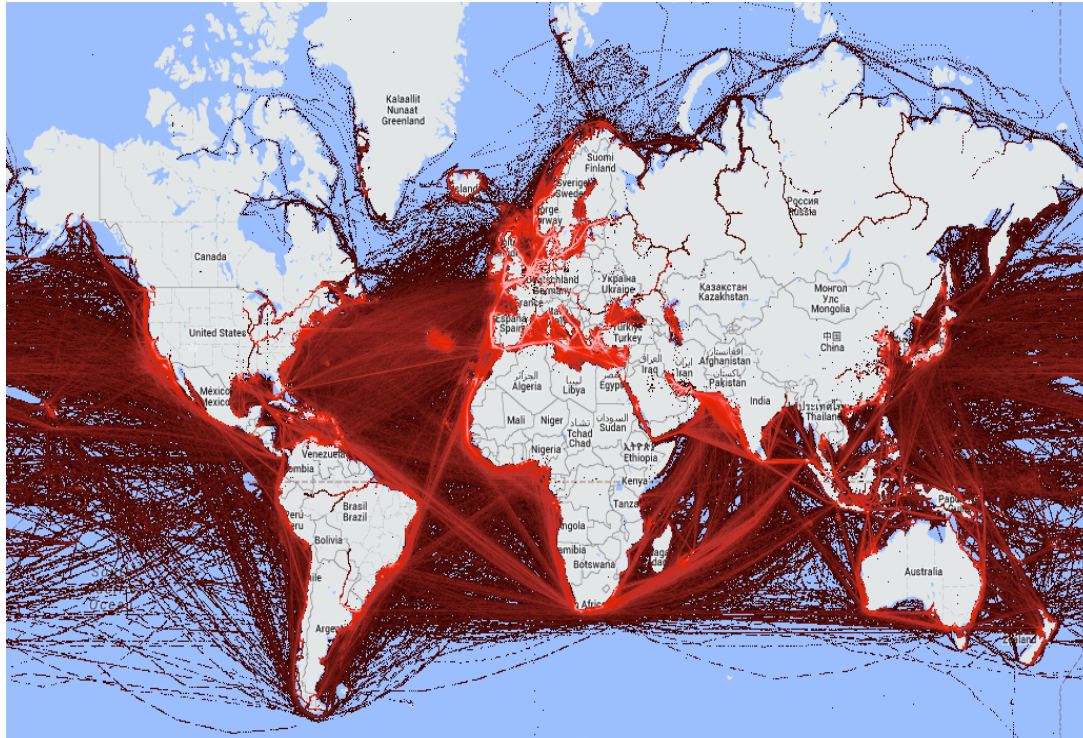


Figure 2.2 Density map for tanker voyages in 2014; Source: (MarineTraffic, 2015)

2.1.2 Tanker - A Liquid Bulk Vessel

As a consequence of the high demand for oil, transport from the sources to the consumer has risen. The means for transporting oil is via pipelines, ships, and to some extent railways. The seaborne transport is conducted via *tankers*. Tankers take an active part of the value chain for oil-based energy. Firstly they transport crude oil from the oil wells to the refineries; secondly they transport the oil products from the refineries to the market. Thereby they are the mean to reduce geographical imbalance between demand and supply of oil and its derivatives.

The concept of seaborne oil transport may initially seem simple. This is to a great extent true for crude carriers, but the activity becomes more complex when oil derivatives are included. Stopford (2009) describes two important factors, in which crude oil and oil products can differ from a transport viewpoint; *specific gravity* and *standards of cleanliness needed to transport it*. Table 2.1 illustrates that the heavy fuel oils, i.e. the fuel oils with a higher specific gravity, typically are referred to as *dirty cargoes*. On the other side of the scale for

specific gravity we find the light fuel oils, these are referred to as *clean cargoes*. The implication of cargoes being ‘clean’ is that these products are sensitive to chemical reactions with the traces of previous cargoes, whereas ‘dirty’ products are less sensitive. Gas oil is categorized as ‘mainly clean’ because it is neither very sensitive nor polluting. It can thus be used as a transitional product to “clean up” the tanks after having carried dirty cargoes.

	Specific gravity (at 15°C)	Cargo type	Special characteristics	Typical cargo size (tons)	Stowage/ton (M³)
Heavy fuel oil	0.98	Dirty	Cargo heating	50-80.000	0.93
Heavy crude oil	0.95	Dirty	Cargo heating	60-300.000	0.95
Diesel oil	0.86	Dirty		40.000	1.05
Light crude oil	0.85	Dirty		60-300.000	1.07
Gas oil (light fuel oil)	0.83	Mainly clean		30.000	1.09
Paraffin	0.80	Clean	Clean tanks	30.000	1.14
Petrol	0.74	Clean	Clean tanks	30.000	1.22
Aviation spirit	0.71	Clean	Clean tanks	30.000	1.28
Naphtha	0.69	Clean	Clean tanks	30.000	1.31

Table 2.1 Characteristics of and requirements for some oil products; Source: (Stopford, 2009)

The categorization into clean and dirty products also has an impact on the vessels used. Firstly, the typical parcel sizes for the dirty products tend to be higher. For this reason the tankers used for clean products are either smaller, or contain more tanks for different products. Secondly, vessels carrying clean products have coated tanks to facilitate the cleaning process and prevent corrosion. Usually they are equipped with special pumping systems to enable separate loading and unloading of different products (Kegl, 2015). Dirty products can generally be shipped in conventional tankers (Stopford, 2009). These vessels are carrying more viscous products, which requires a heating coil in the cargo tank to prevent the liquid from becoming too viscous. Hence, the vessels built for carrying clean products have to uphold higher requirements and may carry both clean and dirty products. Vessels built for dirty products may only carry dirty products, unless it has never carried dirty cargo or the tank is coated at a later stage. A clean tanker will hence be able to switch between the two markets.

2.1.3 Size Matters – Segmentation Across Vessel Size

Apart from the segmentation with regards to the product transported, segmentation can arise from size differences of the vessels. Vessels of different sizes engage in different types of transport over different regions for reasons of economies of scale. However, scaling up the size of vessels may have adverse effects on the flexibility of the vessel, diseconomies of scale.

Kavussanos (2003) suggests that the volatility level of the freight rates generally increases along with the size of the vessel. However, there are some common forces driving volatilities of freight rates for different sizes in the same direction after an external shock, typically higher freight rate levels imply higher volatility. Meanwhile, there are also idiosyncratic factors making volatility unique for different sizes.

While there are several ways to define the size of tanker vessels we use the definitions presented in Table 2.2.

Product Tankers		Crude Carriers	
Name	Size Interval	Name	Size Interval
MR	40,000-55,000 dwt	Panamax	55,000-85,000 dwt
LR1	55,000-80,000 dwt	Aframax	85,000-120,000 dwt
LR2	80,000-120,000 dwt	Suezmax	120,000-200,000 dwt
-	-	VLCC	200,000+ dwt

Table 2.2 Product and Crude Carrier Size Categories; Source: (Scorpio Tankers, 2015)

2.1.4 Charter contracts

The two specific charter contracts relevant in this thesis are: *voyage charter* and *time charter*. In a *Voyage charter* a specific cargo is transported from one specified port to another specified port within a pre-specified time. A voyage charter contract is typically agreed upon in the spot market, and the charterer only pays a fixed freight rate on an USD/ton-basis. The freight rates in the tanker market are based on Worldscale (WS), instead of USD/ton (Alizadeh & Nomikos, 2009).

Time charter contracts give the charterer the operational control over the ship for a specified period of time. Under time charter contracts, the shipowner continues to pay capital costs and operational costs (crewing, maintenance, etc.), while the charterer pays the voyage costs (bunker, port charges and canal dues). Unlike voyage charter rates, time charter rates are

denoted in USD/day. Voyage charter freight rates and time charter freight rates can be compared through TCE (time-charter equivalent), see formula in appendix 1.

2.1.5 Shipping economics

Supply and Demand

To refresh the understanding of freight rate dynamics this section will describe some of its mechanisms. This foundation is important for building the model presented in the methodological chapter 3. Note that this will be an overview of and may thus contain simplifications in order to facilitate the modeling. Stopford (2009) singles out the five most important variables affecting the demand and supply for seaborne transport, respectively. These variables are noted in Table 2.3 and will be further investigated in this section. For a detailed discussion of the factors see Stopford (2009).

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 2.3 Demand and supply variables; Source: (Stopford, 2009)

The *shippers* are central players of demand for seaborne transport. Shippers constitute the entity that wants to ship a cargo from one place to another. These can for example be oil companies wanting to take crude oil from the drilling site to the refineries. The shippers are typically big companies shipping large quantities of the commodity each year. There are few alternatives to shipping when transporting large quantities of bulk cargoes efficiently. Furthermore, the shipping costs constitute a small proportion of the total cost of the end product, that the demand side is relatively inelastic. Shippers are not always the ones renting the vessel. Vessels are rented by charterers, who might be operators or other players taking the shipping order from the shipper.

On the supply side, the central players are the shipowners. However, other players such as shippers/charterers, financiers and authorities, may also force building or scrapping of vessels. The supply of ships is by nature slow in responding to an increased demand, due to the time lag of about 1-4 years (depending on the orderbook) between the order and the

delivery of a vessel. Similarly, vessels have a physical life of about 15-30 years, making it difficult to respond to rapidly decreasing demand. As a consequence the tanker markets are often characterized by longer periods of oversupply followed by shorter periods of undersupply. Norman (1980) argues that this pattern is a sign of that the tanker market is functioning efficiently, based on the relatively low cost of oversupply as opposed to the costs incurred if the oil company would be unable to find a transport. In the following segment the supply variables as described by Stopford (2009) will be discussed.

Supply is by nature relatively fixed in the short-run, compared to the dynamically fluctuating demand. These factors create a market with extreme volatility and with self-reinforcing cycles. Furthermore, supply is greatly influenced due to behavioral traits when forecasting the demand before making decisions for investing or divesting in vessels, which makes the markets even more unpredictable. The following section will more closely examine how freight rates are determined, through the relationship between supply and demand.

The freight rate mechanism

The freight rate mechanism is an adjustment mechanism of supply and demand. In practice, shipowners and charterers negotiate the freight rate. The final price reflects the balance of ships and cargoes available. The freight rate mechanism here will be based on a model for perfect competition, since the tanker market inhibits many of the features characterizing perfect competition. There are three core concepts in the model: the *supply function*, the *demand function* and the *equilibrium price*, the latter of the three will be described below.

The point at which the demand curve intersects with the aggregate supply defines the *equilibrium prices*. This is the point where the shipowner and charterer agree on a price acceptable to them both. This is however not a complete description of how freight rates are formed. Stopford (2009) points out a time dimension, which also plays a central role in the formation of freight rates. The time dimension can in turn be decomposed into three time periods: the *momentary equilibrium*, the *short-run equilibrium* and the *long-run equilibrium*.

The *momentary equilibrium* describes the freight rates negotiated for an immediate deal, i.e. when vessels are available for instant loading of awaiting cargo. Due to the tight time frame the market is highly fragmented by geographic locations. Hence, regional shortages and surpluses can build up, causing temporary peaks and troughs. Once a vessel is in the region it must decide whether to make a deal or wait and lose money. Figure 2.4 illustrates how the

momentary equilibrium works. When the demand for the vessels is relatively low, as shown by D1, the shipowners will compete with low freight rates. The equilibrium will hence give a freight rate at the marginal costs of the least efficient operating vessel, illustrated by E1. However, when the demand for freight is higher than the supply, as illustrated by D2, the charterers will compete about paying the higher freight rates. This will, as shown by E2, create equilibrium at a higher level than in E1, the exact level is given by the marginal shippers willingness to pay.

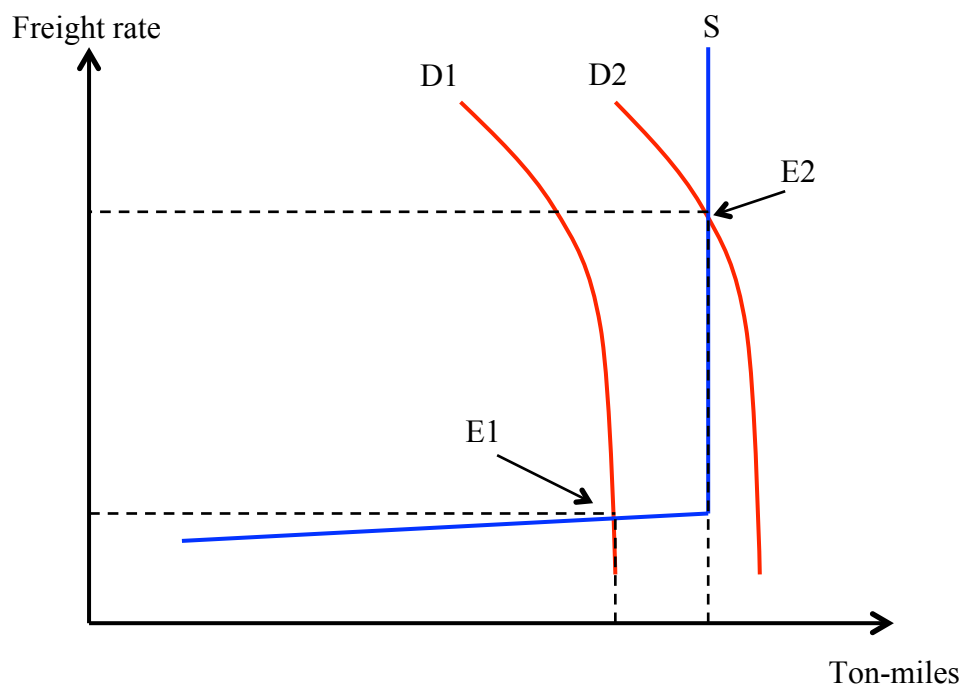


Figure 2.4 Momentary equilibriums; Source: (Stopford, 2009)

The curvature of the demand indicates that shippers will chose not to freight at very high freight rates, this does however not mean that the price inelasticity of demand does not exist in a momentary situation. The curvature reflects that the shipper can wait until the freight rate becomes cheaper. As has been implied the freight-rate spread between the two situations can be sizable, although the demand and supply does not change very much. For this reason the short-term volatility of freight rates can become high.

The *short-run equilibrium* allows shipowners and charterers to adjust for price changes through productivity measures. In the short run the supply curve is J-shaped. The curve starts at the point where the most efficient vessel starts operating and continues to increase as more vessels can follow and as the vessels speed up until the maximum capacity is reached and no

further supply can be provided by increasing the productivity. Figure 2.5 describes the short-term freight rate mechanism given three scenarios with different demand levels: D1, D2 and D3. In the first scenario, D1, the demand is quite low, thus setting a low freight rate at the short-term equilibrium in point A. As demand increases to scenario D2, the freight rate increases, but quite slowly, as more ships breaking lay-up still start operating in the market. However, when the demand shifts to D3, the level of the freight rate jumps, this is because the oldest, least efficient vessels in the fleet become the marginal vessel. Since no more capacity is available in the market the charterers will bid against one another thus pushing up the freight rates even further.

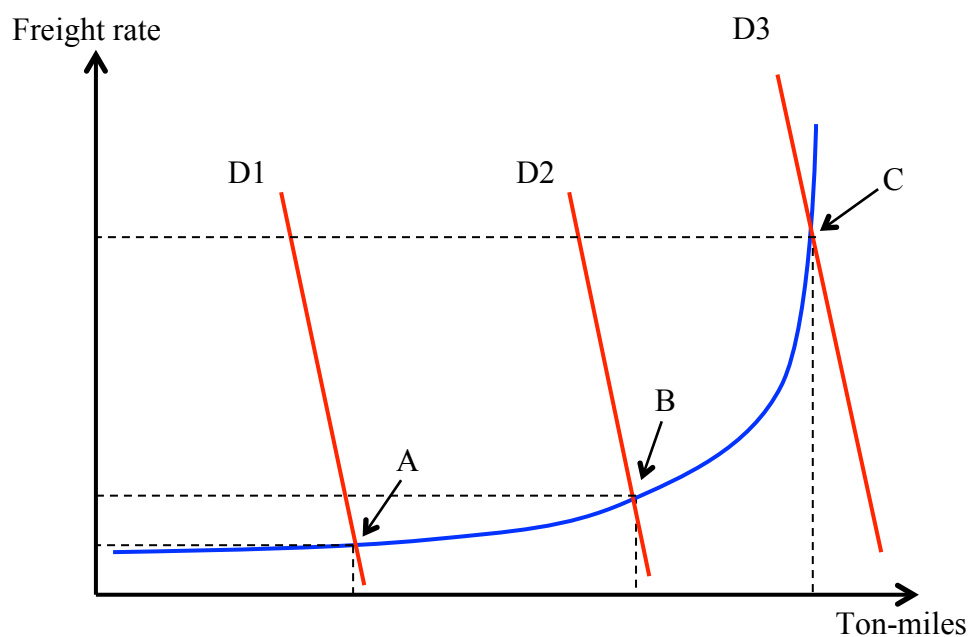


Figure 2.5 Short-run equilibriums; Source: (Stopford, 2009)

The third and last time-dependent equilibrium is the *long-run equilibrium*. In the long run the shipowner has several tools in response with the market conditions. These responses can involve scrapping, second-hand purchases and newbuilding, which gradually will create shifts in the supply curve. This implies that the adjustment mechanism also balances supply and demand via other markets than the freight market. These are the three markets briefly described in a previous chapter: the *shipbuilding market*, the *sales and purchase market* and the *demolition market*. As freight rates fall in a recession, the profitability of ships falls. As profitability falls, the second-hand value of vessels falls as the expected future cash flow decreases. Eventually, the second-hand value of the least efficient ship has fallen to the

demolition value and is hence sold for scrapping. As the vessel is scrapped the capacity it provided is permanently removed from the market.

On the other hand, in a market with shortage on vessels freight rates will increase. Thus, have a positive effect on the value of second-hand vessels. Furthermore, such increase will eventually drive shipowners to expand their fleet through newbuildings, which will lead to an increase of supply a few years into the future. At the time when the fleet has started to grow the demand may already have declined. Thus, such an order backlog may come to depress the future freight market even more. Figure 2.6 illustrates the intuition behind this. D1 and S1 is demand and supply respectively today, whereas D2 and S2 is demand and supply when the vessels are delivered at a future point. Notice that the long-term equilibrium is set by the intercept between D2 and S2, which is well below the intercept between D1 and S2, which in turn would have been the case if the demand were fixed in the long run.

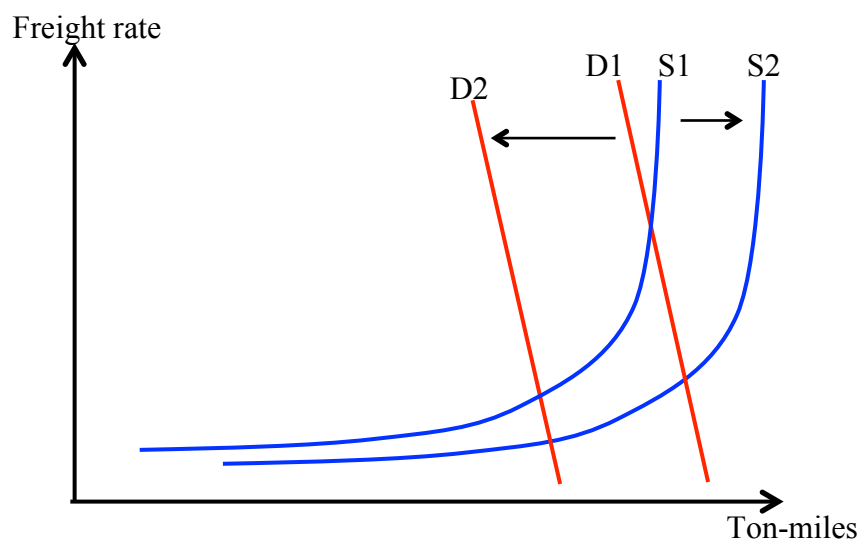


Figure 2.6 Long-run equilibriums; Source: (Stopford, 2009)

The concept behind long-term equilibrium is to illustrate how shipping cycles work. However, there is reason to question the concept of long-term freight rates. In a market with the described supply and demand dynamics it is reasonable to assume that steady earnings cannot be expected over several years, hence it is uncertain whether the average freight rate level will be high enough to pay for the vessel.

3. Theory and Methodology

This chapter will explain the economic theory and methodology upon which the analysis is based. Firstly, an introduction to fundamental theoretical concepts will be given. In the latter part of the chapter the model used in the analysis will be presented and explained.

3.1 Option theory

This segment will explain the general function of how options work and how their inherent value may benefit their holder. Followed by a more thorough discussion of the switching option analyzed in this thesis. Finally, some real option pricing methods will be presented and discussed.

3.1.1 Introduction to option theory

There are two categories of options. Financial options are standardized financial products traded in international financial markets in large quantities. The owner has either the right or the obligation to buy or sell a certain underlying at a prespecified price at a prespecified point(s) in time. The other category of options is real options. Similarly to financial options, real options offer a right – but not an obligation – to make a business decision. However, real options are related to the real, physical, often unique assets and are hence not standardized. Every real option is unique and can thus not be traded in financial markets. Consequently, a synthetic portfolio cannot replicate them (McDonald, 2013). There are several types of real options, such as options to switch (input or output), abandon or expand. Real options can be embedded in contracts or can stem from flexibility of an asset. In shipping, embedded real options can be discovered as optionality to order more vessels from shipyards or as period time-charter extension options. On the other hand, real options may arise from the flexibility of the asset itself. For example, a vessel may have the ability to switch markets by switching cargo or geographical location¹.

Since options can be said to defer the business decision to a future point in time, they give the holder flexibility, which reduces the uncertainty of the investment and thus the risk. According to standard economic theory reduced risk increases the value. Real options may be

¹ For more examples of real options in the shipping industry see Bendall (2010) or Alizadeh & Nomikos (2009).

of substantial value for shipowners, due to the volatility and time lags described in previous chapters. Despite significant value that real options may add, their explicit valuation is seldom, possibly since there is no straightforward method. (McDonald, 2013).

3.1.2 Switching options

A switching option is a type of real option that derives from a real asset's ability to switch between input, output, contract types, markets, etc. A switching option grants the holder the flexibility to exploit temporal arbitrage opportunities. Switching options are referred to as a combination of several entry and exit decisions and have been generalized in a real option model in academic papers². A modified version of this real option model will be described and used in later sections of this paper.

The switching option considered in this thesis is the flexibility to switch between clean and dirty market. Bendall (2010) points out that in an industry, characterized by high uncertainty (with regards to both freight rates and second-hand price of vessels) and high capital intensity, flexibilities carry substantial value. To switch from transporting clean products to transporting dirty products the shipowner would have to expect higher freight rates over a certain time frame for dirty products, which offset the switching costs due to the cleaning process before switching back to clean (involves cost to clean tank, off-hire and up to three discounted voyages). Additionally, the shipowner incurs an opportunity cost of commitment to the other market for a certain period. A possible change of the freight rate differential in favor of the exited market might lead to forgone revenues. To illustrate this we assume that T_{clean} and T_{dirty} is the present value of expected earnings for transport of clean and dirty respectively. SC is the switching cost, which also could be interpreted as the exercise price. A rational investor would exercise the option, in this case switch from clean to dirty, when the expected earnings for transporting dirty products exceeds the expected earnings for transporting clean products and the switching cost. If otherwise, the switch would not occur and the payoff is zero. The payoff structure can be expressed as follows:

$$Payoff = \max[0, T_{dirty} - T_{clean} - SC] \quad (3.1)$$

There are two important factors to whether switching would or would not occur; the *spread between expected earnings of the two operation modes* and the *switching cost*. Alizadeh and

² See for instance Brennan & Schwartz (1985) and Dixit (1989).

Nomikos (2009) point out that Equation 3.1 is true for a scenario where only one switch can be made. However, in cases when the company has the option to switch forth and back between the modes the equation would have to be extended to take into account certain dynamics that may influence the decision, such as additional costs in switching between the modes. An important influence to the decision to switch markets is the relative cost of switching. It is generally much more expensive to switch from dirty to clean than the other way around. Meanwhile the earnings for a clean vessel are expected to be on average higher than those of a dirty vessel. The option to switch back and forth between the modes is essentially a portfolio with an infinite amount of American put and call options. These enable the entry and exit of the market at any point in time.

3.1.3 Real option pricing methods

Real options are in many ways more complex and less concrete than financial options, thus more variables will have to be considered for valuation. Nevertheless, financial option pricing theory is a good basis for real option valuation.

Discounted cash flow (DCF) is a conventional method used by companies to evaluate investments and projects. However, DCF is not an appropriate method for taking uncertainty and adaption of a started project into account since it is maximizing the value based on a static nature of cash flows. Due to the previously discussed nature of shipping, DCF is possibly inadequate for giving a fair value to an investment in a vessel since it does not allow for managerial flexibility (Bendall, 2010).

To price real options other methods would have to be considered. Three prominent pricing techniques in academic works are: *Monte Carlo simulations*, *binominal trees* or *closed-form solutions* (McDonald, 2013). The typical way of conducting option valuation via Monte Carlo simulations is to run large numbers of simulations given a set of uncertainty variables affecting their value, the simulations are then used to determine the average path of payoffs, which is discounted to find the net present value of the option. Binominal trees are an iterative method in which a tree of potential payoffs is built given two states, up and down state, in discrete time. The final value at each option node is then found and calculated back to the initial node, which is then value of the option. Closed-form solution is a method in which a stochastic, continuous-time process is used to model the future price given certain

market dynamics. Whereas the real path of the future price is unknown initially, a stochastic differential equation is here used to represent the unknown function.

In this thesis a closed-form solution is used to find the value of the switching option.

3.2 Stochastic processes

As described in the literature review, the functioning of freight markets and modeling spot freight rates have been subjects to much academic research starting with Koopmans (1939). Whereas the classic literature has focused on modeling demand and supply, similar to the framework presented in chapter 2.3, a more recent development has focused on modeling freight rates in stochastic models (Adland & Strandenes, 2004). This section will describe the intuition behind stochastic processes.

Stochastic processes are sets of random variables indexed by time (McDonald, 2013). The future value of a stochastic variable is uncertain but conforms to a probabilistic distribution. Although the variable depends on a probabilistic distribution it develops randomly, hence follows a stochastic process. The variable can be either discrete (variable has certain, fixed value points) or continuous (variables has infinitely small increments between two discrete value points there is an infinite amount of other values points). Discrete approaches are simpler to present and interpret. However, continuous approaches are more useful for more complex scenarios through increased accuracy. While there are several types of stochastic processes with slight differences in the mathematical this thesis will focus on a mean-reverting Ornstein-Uhlenbeck process.

3.2.1 Markov Processes

In a *Markov process* the current value of a variable is the only relevant factor for predicting future developments of the variable. Hence, historical developments in the variable are irrelevant for the probability distribution of a stochastic process with Markov properties (Hull, 2009). For this reason, Markov processes are consistent with theory for weak market efficiency, where future prices cannot be forecasted by analyzing historical prices. Future prices are not carried by patterns reflected by historical data, but follow a random walk. The reason is that competition ensures that the current value of the variable fully reflects the historical development in the variable.

3.2.2 Wiener Processes

Wiener process (or *Brownian motion*) is a special type of a Markov process. The Wiener has two properties, which distinguish it from the broader Markov process definition (Dixit & Pindyck, 1994). The first property of the Wiener process is *independent increments*, which means that the probability distribution is independent of other non-overlapping time intervals. The second property is that for any finite time interval the process is normally distributed and its variance increases proportionally to time.

The properties can also be expressed formally, where z is a variable following a Wiener process if the following conditions are satisfied (Hull, 2009; Dixit & Pindyck, 1994):

Property 1: The change in Δz in a short period of time Δt is given by:

$$\Delta z = \epsilon_t \sqrt{\Delta t} \quad (3.2)$$

where ϵ_t is a normally distributed variable with a mean of 0 and a standard deviation of 1.

Property 2: The random variable ϵ_t is serially uncorrelated; $E[\epsilon_t \epsilon_s] = 0$ for $t \neq s$. Hence, the values of Δz for two different time intervals will be independent.

Consequently, these two properties implies that the change in a variable, Δz , following a Wiener process has a normal distribution, with a mean of 0 and a variance of Δt , in each of the short time periods Δt . Hence, the variance will grow linearly as time progress. By making Δt infinitely small, i.e. let $\Delta t \rightarrow 0$, the increments of the Wiener process, dz , can be expressed in continuous time as $dz = \epsilon_t \sqrt{dt}$.

3.2.3 Itô Processes

An *Itô process* is a generalized Wiener process, in which there are two parameters a and b . Parameter a represents the instantaneous drift rate and parameter b represents the instantaneous variance rate. Both parameters are functions of x , which is following a Markov process with independent increments, and t , time. Hence, they can be expressed as $a(x, t)$ and $b(x, t)$. The Itô process is formalized through the following formula (Dixit & Pindyck, 1994):

$$dx = a(x, t)dt + b(x, t)dz \quad (3.3)$$

where $b(x, t)dz$ represents the amount of added variability and $a(x, t)dt$ is the expected drift rate of per unit of time (Hull, 2009). Hence, the strength of using an Itô process is that it allows for adjusting the model for developments of the variables that affect decisions.

3.2.4 Mean-Reverting Processes

Non-stationary stochastic processes may only be realistic with regards to the behavior of some economic variables, such as stock prices. However, other economic variables may have long-term means to which they revert after a random shock; hence following so-called *mean-reverting processes*. Examples of economic variables usually exhibiting such behaviors are freight rates, (renewable) commodity prices and interest rates (McDonald, 2013). Ornstein-Uhlenbeck process is a process that allows for mean reversion, which is mathematically formulated as follows (Dixit & Pindyck, 1994):

$$dx = \mu(\bar{x} - x)dt + \sigma dz \quad (3.4)$$

Where, μ is the rate at which the variable reverts back towards mean (the speed of mean reversion), and \bar{x} is the level to which x tends to revert. The σ represents the standard deviation (error term). By making dt infinitely small, i.e. let $dt \rightarrow 0$, the increments of the Ornstein-Uhlenbeck process, dz , can be expressed in continuous time as $dz = \epsilon_t \sqrt{dt}$. Equation 3.4 indicates that the bigger the difference between \bar{x} and x , the more rapidly will the reversion occur.

Since the difference between x and \bar{x} affects the development of the variable in the next time interval, the process does not satisfy the property of independent increments of a Wiener process. It does, however, satisfy the property of a Markov process by using the current value as the predictor of the future value. In cases with two integrated, competitive markets a stationary relationship can be expected, hence the use of mean-reverting processes seems reasonable. Testing for unit roots of the freight rate differential process later in this text will statistically confirm the mean reversion characteristic.

3.3 The Theoretical Entry-Exit Model

As stated in the literature review, the technical foundation of this thesis is based on the entry-exit model developed by Dixit (1989), further adapted to a more appropriate approach for switching options in bulk segments by Sødal et al. (2008) and by Sødal, et al. (2009). The latter serves as the main foundation for the theoretical model described here. The theoretical model shares many similarities with Bjerknes and Herje (2013), which are also based on the papers previously mentioned.

3.3.1 Discount Factor Approach – An Introduction

The objective of the discount factor approach is to calculate the net present value of a real option to switch between two markets. The possible added value of the flexibility stems from the size and persistence of freight rate differential between the two markets. The value of the flexibility is also affected by switching cost – i.e. switching will only happen when the expected net present value of the freight rate differential exceeds expected net present value of the switching cost.

The switching will occur when the freight rate differential hits one upper and one lower threshold value, set by an optimal switching policy.

3.3.2 General model

Suppose a shipowner has a product tanker operating in the clean market. At time t the freight rate in the clean market is $p_c(t)$, similarly the freight rate in the dirty market is $p_d(t)$. Hence, the freight rate differential can be formalized as $p(t) = p_d(t) - p_c(t)$. Now assume that the freight rate differential follows an Ornstein-Uhlenbeck process:

$$dp(t) = \mu(m - p(t))dt + \sigma dB(t) \quad (3.5)$$

where m is the long-run mean of the freight rate differential, $\mu (>0)$ is a constant parameter for the speed of the mean reversion, and $\sigma (>0)$ is the constant measure of volatility, dt is the time increment and $dB(t)$ is the increment of the standard Wiener process. A high μ suggests that the deviation from the long-run mean of the freight rate differential will revert back quickly. This implies that the higher the parameter for the mean-reverting speed, the higher the integration of the markets. Consequently, as the μ approaches zero, there is no force

pulling the two rates together, hence indicating that the markets are independent of each other.

The future cash flows are discounted at a constant discount rate ρ (>0). The discount rate itself is the sum of a real interest rate, r , a depreciation rate, λ , and possibly a risk adjustment. The depreciation rate encompasses all considerations of the vessel's lifetime, such as the risk that the vessel sinks; see Sødal et al. (2008) for a more detailed discussion.

As noted previously, the switching cost is an important consideration. Let B be the fixed switching cost when the vessel switches from carrying clean products to dirty products, and correspondingly let F be the fixed switching cost when the vessel switches back. The model assumes that the switching costs are constant, this may not be a realistic as the required cleaning process depends on several factors, such as degree of tank contamination.

Assume, for now, that only one more switch can be made and let the expected, discounted value of future freight rate differentials at time t be denoted V_t , which gives:

$$V_t = E \left[\int_t^{\infty} p_s e^{-\rho s} ds \right] = \left[\int_t^{\infty} (m + (p_s - m)e^{-\mu s}) e^{(-\rho s)} ds \right] = \frac{p_t}{\rho + \mu} + \frac{\mu m}{\rho(\rho + \mu)} \quad (3.6)$$

where, $E[\cdot]$ represents the expectations operator and p_t is the current freight rate differential. Since the only variable in Equation 3.6 is p_t , the expected net present value V_t will be a linear function of that variable. Sødal, et al. (2009) points out that V_t follows the Ornstein-Uhlenbeck process by Itô's Lemma:

$$dV = \mu(\tilde{m} - P)dt + \tilde{\sigma}dz \quad (3.7)$$

where, $\tilde{m} = m/\rho$ and $\tilde{\sigma} = \sigma/(\rho + \mu)$. Furthermore, the time scripts have been omitted since the parameters for drift, μ_t , and volatility, σ_t , do not explicitly depend on time but may depend on p_t (Sødal, Koekebakker, & Adland, 2008).

3.3.3 Optimal Switching Policy

To determine the optimal switching policy of a vessel a value function has to be defined. The expected net present value is then maximized, when switching happens according to the lower and upper freight rate thresholds. Assume that the vessel already operating with clean cargo. It will switch to carrying dirty, as soon as the freight rate differential hits a certain

value. The upper threshold, p_H , is a positive differential value and indicates when the vessel should switch from carrying clean to carrying dirty products. Conversely, the lower threshold, p_L , is a negative differential value and represents the point at which the vessel should switch back from carrying dirty to clean products. Intuitively, there will be no switch if the differential remains in between the two triggers. The value function can be expressed as (Dixit et al., 1999)³

$$W_0 = \frac{Q(p_0, p_H)(V_D - B - Q(p_H, p_L)(F + V_C))}{1 - Q(p_L, p_H)Q(p_H, p_L)} \quad (3.8)$$

where, p_0 ($< p_H$) represents the current freight rate differential, while V_D and V_C represents the expected net present values of future earnings given at the trigger points. The $Q(x, y)$ are discount factor functions, in which the motion of a current freight rate x is applied to the motion of another to another freight rate y . Consequently, $Q(x, y) = 1$ when $x = y$ and $0 \leq Q(x, y) < 1$ when $x \neq y$. Due to the instantaneous switching process of the model, the value function W_0 requires $B + F \geq 0$. So the maximum value cannot be obtained by switching continuously, thus creating an infinite profit under the maximization (Bjerknes & Herje, 2013).

The discount factor functions are specific to the type of stochastic process⁴. The discount factor functions for the Ornstein-Uhlenbeck process can be represented as (Sødal, Koekebakker, & Adland, 2009):

$$Q(p_L, p_H) = \frac{M(p_L) + U(p_L)}{M(p_H) + U(p_H)} \quad (3.9)$$

$$Q(p_H, p_L) = \frac{M(p_H) - U(p_H)}{M(p_L) - U(p_L)} \quad (3.10)$$

where, $B_D > B_C$ and $M(\cdot)$ and $U(\cdot)$ are given by:

$$M(p_x) = H\left(\frac{\rho}{2\mu}, \frac{1}{2}, \frac{\mu}{\sigma^2}(p_x - m)^2\right) \quad (3.11)$$

³ For a detailed explanation of the value function see Bjerknes & Herje (2013)

⁴ Compare for example the discount factor functions in Sødal et al. (2009) with the corresponding in Sødal (2006).

$$U(p_x) = \frac{2(p_x - m)\sqrt{\mu}\Gamma\left(\left(\frac{1}{2}\right) + \left(\frac{\rho}{2\mu}\right)\right)}{\sigma\Gamma\left(\frac{\rho}{2\mu}\right)} * H\left(\frac{1}{2} + \frac{\rho}{2\mu}, \frac{3}{2}, \frac{\mu}{\sigma^2}(p_x - m)^2\right) \quad (3.12)$$

where, $\Gamma(\cdot)$ is the Gamma function and $H(\cdot)$ is Kummer's confluent hypergeometric function. The Kummer function can be represented as found in Sødal et al. (2009):

$$H(a, b, x) = 1 + \frac{a}{b}x + \frac{a(a+1)x^2}{b(b+1)2!} + \frac{a(a+1)(a+2)x^3}{b(b+1)(b+2)3!} + \dots \quad (3.13)$$

These equations presented in this chapter represent the framework for valuing the switching option with the discount factor approach, using an Ornstein-Uhlenbeck process. The optimal switching policy is found by maximizing the value function given two thresholds. The optimization problem will be solved in later chapters by iterating possible values for the thresholds in Matlab.

Unlike Ilan & Strange (1996) the decision to switch will be assumed to be instantaneous. The chartering process generally assumes vessel deliveries about one month after the charter party was fixed (except for prompt tonnage). As such vessels operating in the spot market of one geographical region only, can be considered to instantaneously profit from changes in rates. Rates are being monitored on a continuous basis and as soon as they get near trigger values, shipowners can aim at fixing the next charter party in the opposite market. The switch is done as soon as the new charter party hire is mutually agreed on and not at the laycan. Hence as long as the vessel is not committed to a long-term charter or far away from the load port, the only time lag would be between decision to switch and the signed charter party. Negotiations usually do not take long in the case of high differential (as vessels are needed). As will be shown in the next chapter, the data consists of round voyage routes, where the vessels ballast back to load port. Such ballast time could also be used for cleaning, supporting the instantaneous switch assumption. The data consists of weekly estimations, which allows for one week of negotiations/travelling to load port without changes in freight rate. On the other hand high rate differentials are usually a sign of prompt tonnage demand in at least one segment.

4. Clean and Dirty Market – A Data Discussion

4.1 Data Description

To accurately estimate spread between the dirty in clean product market we had to find the TCE on comparable, representative routes in both of the markets over a sufficient time frame. Clarksons Research Ltd (2015) was used for data collection

The data ranges from 3. January 1997 till 27. November 2015 in weekly increments of TCE (\$ per day) quotations, totaling 987 observations. Due to age of the benchmark vessels in January 2009 new vessel benchmarks were set.. The two routes are well comparable, since both have the same load port. Additionally, both routes have comparable cargo sizes. An overview of the relevant route specifics is given in Appendix 2 (Clarksons Reserach Ltd, 2015c).

One would assume that problems might arise from the difference in distance. The longer distance to Chiba leads to a lower port sea ratio for this route. The port charges, which can be assumed to be similar for both are divided over less voyage days for the route to Singapore. Hence the TCE is lower, than justified. Other possible flaws are the differences in consumption and speed of the vessels on the two routes. The differences in bunker consumption are sometimes more than 40 percent. Together with the increased route distance, bunker costs are likely to become the main cost of operations.

Accordingly, it is necessary to adjust for the differences in vessel specifications. When the product tanker specified above would switch to the dirty market between Ras Tanura and Singapore the net earnings per day are likely to be lower due to differences in bunker costs. We calculated the dirty TCE back to a dollar per ton basis using the TCE formula (see appendix 1) and information regarding the TCE calculation provided by Clarksons (2015b). As such, we added current bunker costs, estimated port charges and commission back to the net profit per round voyage and divided the result by the cargo size. As data of port charges was not readily available we assumed fixed port charges of 14,048 dollars in Ras Tanura and of 25,000 dollar in Singapore for the entire sample (Platts McGraw Hill Financial, 2014; McQuilling Partners Inc., 2015). The bunker prices were benchmarked at Fujairah weekly fixtures, extracted from Clarksons Research Ltd (2015). The LR2 was assumed to be able to carry the same amount of crude oil an Aframax tanker could, namely 80,000 metric tons.

From the calculated dollar per ton rate, we converted back to the TCE, but using the product tanker specifics given in Appendix 2 and in Clarksons (2015b). This resulted in a mixed picture of positive and negative adjustments of the dirty freight rate.

The adjustment process assumes that bunker consumption and vessel speed do not change when switching. This might in light of the necessity to heat dirty cargo to keep it liquid, inherit some remaining flaws. Additionally, port charges are not likely to be constant over time. These fluctuating differences in OPEX and port costs are tough to account for in a mathematical model, as the data is not readily available.

The data is compiled of weekly estimates from surveys sent around H. Clarkson & Co. brokers and are hence based on the estimations of few individuals. This can lead to market sentiment being driven by emotion and overreactions to information flows. However, as the shipping industry does not have market-monitoring instruments like the financial industry, we have to rely on information of market makers such as Clarksons (Clarksons Research Ltd, 2015b).

The time-series of the two routes and their differential is presented in Figure 4.1 below. Based on graphical assessment implying that there are different dynamics characterizing different periods, we can divide the time series into three broad subsamples:

	From	To
Full Sample	03.01.97	27.11.15
Period 1	03.01.97	26.09.03
Period 2	03.10.03	14.11.08
Period 3	15.11.08	27.11.15

Table 4.1 Subsample Periods

From January 1997 to September 2003 the clean market almost continuously outperformed the dirty market, shown by the negative spread value in the figure above. In the following period from October 2003 until the outbreak of the financial crisis in December 2008 there was high volatility in the spread between the two markets. Since January 2009 the two markets seem to be characterized by a higher integration, which is expressed by less volatility.

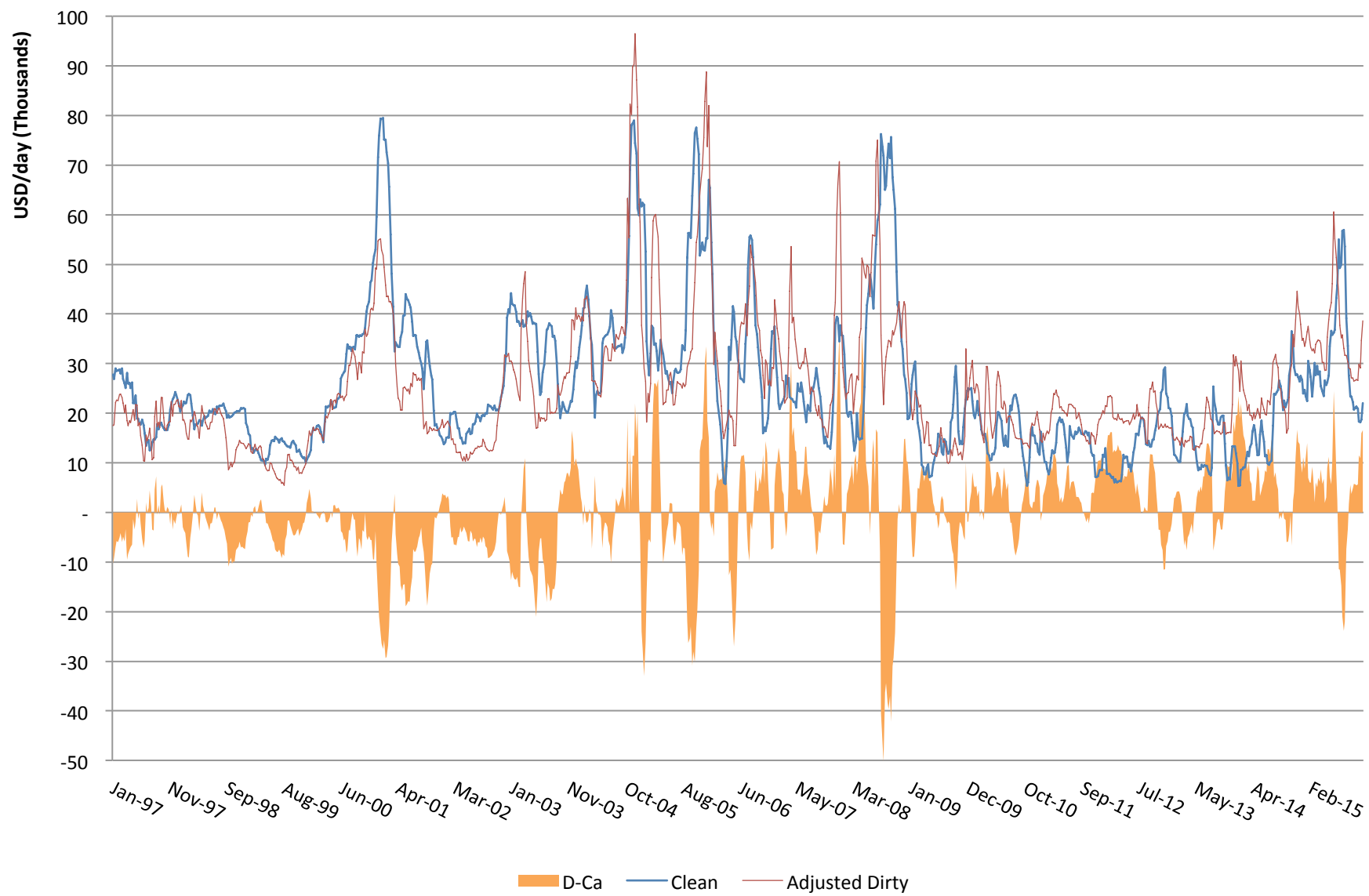


Figure 4.1 Freight rate differential Clean-Dirty, 3. Jan. 1997 - 27. Nov. 2015; Source: (Clarksons, 2015c)

The value of the option to switch derives from a higher dirty freight rate than clean rate, the size of this outperformance and its persistence. Accordingly, we expect the option to have a rather small value in the first period and increasing value from period two onwards. A look at the below descriptive statistics of the series in table 4.2 supports the claim. We have to understand that the option value derives from being able to exploit outperformance of dirty market over the clean market, the difference between Dirty and Clean (D-C).

Variable	#obs	min	mean	max	std.dev
Clean	987	5334	25249	79448	14583
Adjusted Dirty	987	5481.8	25260	96442	13257
D-Ca	987	-50156	10.358	36378	10335
D-Ca (Period 1)	352	-29308	-5185.5	10899	6359.5
D-Ca (Period 2)	268	-50156	1108.4	36378	14470
D-Ca (Period 3)	367	-23883	4192	24431	7162.4

Table 4.2 Descriptive statistics of the freight rate differential

While high volatility in period 2 has led to massive spikes in the data, the mean is in favor of the dirty market. It is the persistence of positive differentials in period 3 that leads to clear outperformance of the clean market. One would intuitively expect the option to have the highest value in the third period since the mean is largely in favor of the dirty market.

4.2 Mean Reversion – Intuition and Test

The graphical appearance of the freight rate differential, see Figure 4.1, indicates that the momentary differential can deviate vastly from long term average through demand and supply dynamics in either market, as described in Chapter 2.3. However, as time progresses it seems like the series reverts to a stationary differential level. To validate the choice of using a mean reverting stochastic process (Ornstein-Uhlenbeck) to model freight rates, the stationary hypothesis have to be tested.

This means that the process has to be reverting to a constant mean with a constant finite variance. To fulfill this condition the coefficients have to be within unity ($-1 < \beta < 1$). Following a random shock the process will now revert to its long run mean instead of exploding (Li, 2015). An Augmented Dickey Fuller (ADF) test is applied to test the stationary condition. A graphical assessment of the freight rate differential, see Figure 4.1, implies that it has no deterministic trend. Hence no a trend has to be included.

The ADF takes the following nature:

$$\Delta(p) = \alpha + r(p)_{t-1} + \sum_{i=1}^p \beta_i \Delta(p)_{t-i} + \varepsilon_t \quad (4.1)$$

With the following hypotheses:

$$H_0: r = 0, \text{ the series is non-stationary}$$

$$H_1: r < 0 \text{ the series is stationary with a non-zero mean}$$

After careful evaluation of AIC and SBC a lag length of 2 lags was chosen, which proved the series to be stationary with a constant mean (Test statistic: -9.90 < CV: -2.57) at a 99 percent confidence level (Hill, Griffiths, & Lim, 2012; Li, 2015).

Hence it is appropriate to use a mean-reverting process. Furthermore, the results seem intuitive given the fairly high degree of integration between the two markets.

In a perfect market without any frictions, the amount of vessels switching would bring the differential to the long-run average differential. This would correspond to the discounted premium cash flow on the additional investment cost of an LR2 relative to an Aframax. This is an unrealistic assumption, which will be discussed in this segment. In order to understand the speed of mean reversion one has to understand the frictions and rigidities affecting the premises for switching and thus the speed of mean reversion. The rigidities relate to the dynamics of the relatively static supply relative to a dynamic, inelastic demand functions.

In the short run, the product tankers can switch from clean to dirty easily, thus lowering supply in the clean while increasing supply in the dirty market, which leads to mean reversion of the freight rate. The switch back from dirty to clean may require a bit of time lag, due to a screening regarding the ‘three last cargoes’. An alternative solution is converting Aframaxes to LR2’s by coating the cargo tank, doing this would however decrease the supply of Aframaxes and increase the supply of LR2’s, which eventually will bring the freight rate differential to the stationary point. In the long run, a relative undersupply or oversupply of either vessel type will be leveled out by shipbuilding or scrapping. Hence, the time lag will affect the speed of mean reversion, by delaying the opportunity switch, especially from dirty to clean.

Despite the theory described, rates do not seem to be perfectly integrated. While a negative differential can only be served by newbuildings, as crude carriers cannot switch to the clean market in the short run; the positive differential in recent years should have not occurred in such persistence, if product tankers would have switched over to the dirty market. Not all LR2 shipowners may be willing to engage in switching strategies, thus leaving room for deviation from the average long-run freight rate differential for longer periods of time. One reason is the uncertainty in whether the differential will remain beneficial over a sufficient period of time so that the switch will generate a profit. Furthermore, the switching strategy is a self-depleting business, meaning that the switching itself will increase the supply in the other market thus bringing the differential closer to the long-run mean. Note that the value of the option depends on only a few shipowners engaging in an active switching strategy. Furthermore, shipowners may have to fill a certain quota of cargo transported, stipulated by contracts. Other reasons include a missing institutional framework giving legal background to the switching process. No measure for contamination and cleanliness of tanks exists (Johnson, 2011). Little is known about the actual cost of switching. Risk and return are difficult to assess under such uncertainty.

4.3 The Clean and Dirty Market in a Historical Context

Following the first oil crisis in 1973 the tanker shipping market was not able to recover until China joined the WTO in 2001 (see Figure 4.1). The following years' rates were characterized by high volatility. In November 2003 the market shifted from close integration of clean and dirty with a negative differential mean to a floating less integrated market with a positive mean.. When the global financial crisis, falling demand for crude and oil products hit a massive order backlog in 2008, rates plummeted (Lun et al., 2013). The effect of a demand decrease first affected dirty market, before clean rates were falling too (see figure 4.1). Higher volatility led to more extreme differentials. The volatility in this period, same as for the full sample, derives in large parts from strong seasonality of the freight rate differential discussed in the following section. Other reasons are shocks in oil supply such as the announcement of increased production by the OPEC in September 2007, which immediately led to a spike in rates (Shi et al., 2013).

After the financial crisis, markets stabilized again. In spite of the clean market's better adaptation to the order backlog, from this point onwards it was outperformed by the dirty

(Clarksons Research Ltd, 2015a). This might be a regional development, though. When comparing the micro development above to that of the worldwide clean and dirty market the picture looks different.

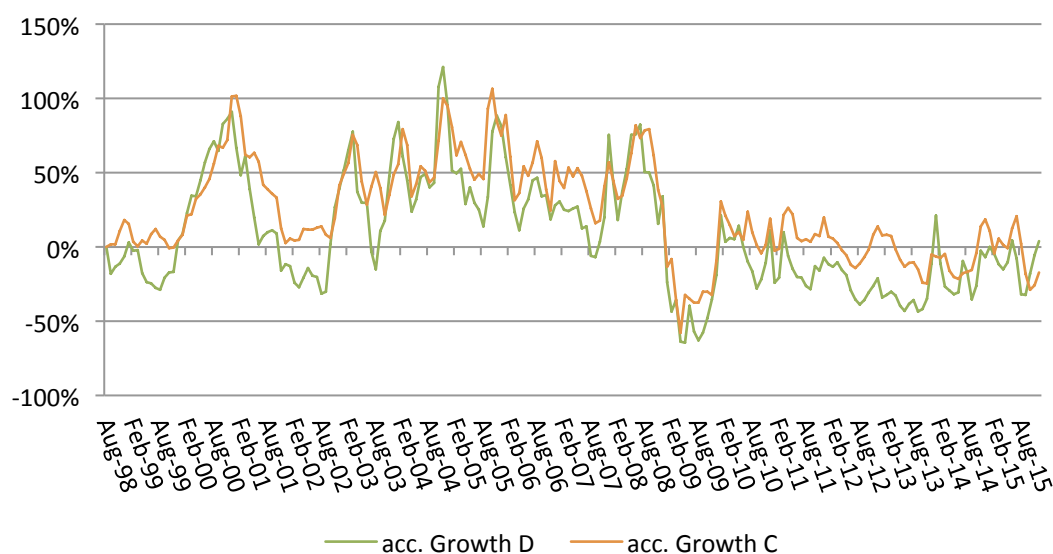


Figure 4.2 Accumulated Growth of Clean and Dirty, Aug. 1998 - Nov 2015; Source: (Clarksons, 2015)

Figure 4.2 shows the accumulated growth development of the Baltic Clean and Dirty Tanker Index between August 1998 and today. Assuming relatively similar levels in August 1998, the performance of each market since then has been largely better for the clean. Nevertheless, today the clean market is worse off than in 1998 and both markets have not been able to recover from the financial crisis yet. Lun et al. (2013) correctly claim that in capital-intensive industries booms based on bubbles are usually followed by bust that bring market down to a level, which is worse than pre-boom. Since the financial crisis freight rates have remained rather low and fairly integrated until a recent shift with decreasing oil price since mid 2014. Even though world economy has been able to recover, the vast overinvestment in the tanker shipping industry previous to the financial crisis has hindered sustained increase in freight rates. In revenue terms however, shipowners have largely been able to recover through increased effort towards profitability (Lun et al., 2013).

We have calculated that the correlation coefficient has decreased over the three subperiods (from 0.99 to 0.35), which may indicate that the integration has decreased. Beta coefficients and mean reversion parameters over the subsamples in chapter 5.1 oppose this claim. However, later testing for parameter stability in chapter 6.4 will show, that this averaging over samples is superficial.

After looking at the freight rate differential in a historical context the next chapter will investigate which factors distinguish the movement of the tanker freight market from the other shipping markets.

4.4 Qualitative Discussion of the Freight Rate Differential

The petroleum industry can be divided into upstream, defined as exploration, development and production, midstream as trading and transportation and downstream as oil refining and marketing. Consequently the transportation of crude oil is part of the midstream operations, while the transportation of oil products, the clean market, belongs to the downstream (Inkpen & Moffett, 2011). Oil transportation demand is derived from the demand for crude oil. Tankers reduce the regional imbalances between demand and supply for oil and oil products (Shi et al., 2013).

The distance between markets and their corresponding demand drive international demand for tankers. While the dirty market links production with refineries, the clean market connects refineries and consumers. It is more efficient to transport crude oil to refineries than refined products to end consumers, which has led to a refinery structure close to the main consuming markets of the US, Europe and Japan. Recently however there has been a shift in refinery industry with large refinery capacity building up in the Middle East. This will increase the *average haul*. The average haul is the average distance a tanker travels in one voyage. If it increases, more vessels are needed to serve the same market. This will hence increase demand while decreasing supply. This comes in favor of the clean market as experts forecast (Roussanoglou, 2015).

The link between clean and dirty markets is the refineries. The refinery margin is referred to as the *crack spread*. The crack spread is the difference in price of crude oil and that of oil products (Inkpen & Moffett, 2011). The disintegration of prices for crude oil and its main refined products heating oil and unleaded gasoline leads not only to high variations in crack spread, but also the clean and dirty product market (Chicago Mercantile Exchange, 2013). If prices reflect the supply and demand relationship in each market, then the refinery margin should intuitively be a good indicator for the freight rate differential of clean and dirty. Graphical comparison of movements in the Singapore Medium Hydrosourcracking spread

and clean and dirty rate, show close correlation of the three up until the financial crisis. Thereafter they behave very disintegrated (see Appendix 3).

The Chicago Mercantile Exchange (2013) lists factors, which are influencing the crack spread. A number of these are likely to affect the freight rate differential, too. As already mentioned in the Chapter 2 *geopolitics* are highly important for the world economy and formation and demand of oil prices; hence also for the freight rate differential. Slow *economic growth* will first affect the demand for refined products and hence lead to a reduction in differential. The opposite is the case for an economic boom.

The winter *seasonality*'s increased demand for distillates is hence likely to increase demand for product tankers, even though figure 4.3 below results suggest a time lead on the clean markets reaction. Summer seasonality has a similar effect as it increases the demand for gasoline. Picking up on the seasonality aspect of the freight rate differential we present below the average monthly freight rate differential over the full sample:

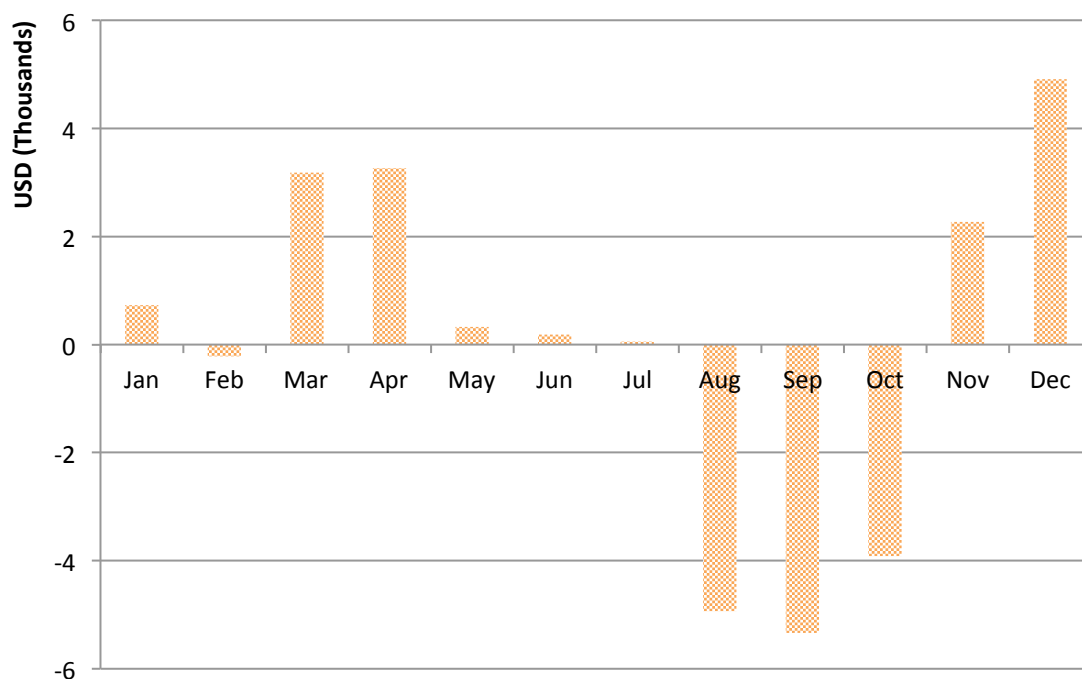


Figure 4.3 Average freight rate differential per month 3.Jan. 1997 - 27. Nov. 2015; Source: (Clarksons, 2015c)

The above suggested seasonality was tested in a regression and months March, April, August till October and December were found to have significant effect on the freight rate differential with 99 percent confidence. November effect was significant on a 95 percent confidence level (see appendix 4). The overall explanatory power of the model was at 10

percent. This strong seasonal effect suggests switching between markets on a pre-specified yearly pattern; staying in the clean market for August till October, before switching to the dirty market for the month of November till July. Such strategy would be interesting to discuss in detail in another paper.

Non-USD *Currency weakness* will increase the price for crude oil, thereby reducing demand and hence reduce the clean and dirty freight rates. A time lag in effect is likely to increase the differential (Chicago Mercantile Exchange, 2013).

Another important factor in the model is production of oil and its derivatives. Oil is considered a non-renewable finite asset. Accordingly one could say it is a supply driven market. Regardless of an increase in demand, supply behaves in limits of natural capacity. In this relationship demand for oil transportation is only going to rise if more oil or oil products have to be transported. Shi et al. (2013) finds that if there is a non-supply shock to the oil market, freight rates remain unaffected, as a higher demand, if not met by supply is not going to lead to more demand in transportation. On the other hand a negative supply shock is going to decrease freight rates. Meanwhile, a positive supply shock is going to increase demand for transportation, as more oil needs to be transported (Shi et al., 2013). The problem with this argument is that in reality capacity for oil production is far exceeding oil demand, as can be seen in the current market floating strategy of the OPEC. Hence increased demand for oil products in an oversupplied market is likely to find supply and is hence going to have a positive effect on freight rates.

Lastly, the *refinery lead time* should play a role in the behavior of the freight rate differential. Crude oil is worthless until it is refined (Inkpen & Moffett, 2011). Hence all crude oil produced is going into the refinery process. Accordingly, an increase in freight rates of dirty tankers should be followed by an increase in product tanker freight rates after the increased amount of oil transported to the refineries is ready to hit the market. This time lag, equal to the lead time of refineries, could work as an indicator of differential movements.

5. Parameter Specifications

5.1 Long-run Mean, Mean Reversion and Volatility

As described above the freight rate differential follows a stationary process. It is hence not only fitting the underlying processes of the model, but also eligible for the modeling through an ARMA model. To estimate the parameters for our model we need to econometrically model the O-U process. We followed Sødal et al. (2008) and built autoregressive AR (1) models of the following form:

$$p_t = C + Ap_{t-1} + \varepsilon_t \quad (5.1)$$

Clearly observable here, C is the constant term, A is the coefficient of p_t 's own lagged value and ε_t represents the error term following a stochastic process. The parameters C and A as well as the standard deviation of the residuals (S) of the models were estimated through OLS regression for the full and the previously defined subsamples resulting in the below numbers (Table 5.1). The significance of the coefficients is given by the p-values. The N is the number of observations.

	A	p-value	C	p-value	S	N
Full Sample	0.9100	0.0000	26.6589	0.8459	4305.00	986
Period 1	0.9089	0.0000	-444.7370	0.0158	2660.13	351
Period 2	0.8917	0.0000	107.5170	0.7906	6588.60	267
Period 3	0.8880	0.0000	506.5750	0.013	3355.04	366

Table 5.1 Results AR(1) Model

The estimation results are in line with the descriptive statistics above. It is worth noting that the constant parameter C lacks significance in all but the first period subsample, where it is significantly different from zero on a 95 percent confidence level. This indicates high uncertainty about the parameter. Contrary, the estimates of A are all significantly different from zero with 99 percent confidence. Progressing in the subsamples the parameter is decreasing. The closer A is to one, the lower the speed of mean reversion, the less integrated are the markets of clean and dirty, the more the differential follows a random walk. With A approaching zero, the mean reversion increases and the market integration increases. This is contrary to our correlation analysis in chapter 4.3.

These estimations could now be used for the calculation of the model inputs. These are the mean reversion (μ), the long-run mean (m) and the volatility parameter (σ) using the three functions found in Sødal et al. (2008):

$$\mu = \frac{-\ln(A)}{\Delta t} \quad (5.2)$$

$$m = \frac{C}{1 - e^{-\mu\Delta t}} \quad (5.3)$$

$$\sigma = \sqrt{S^2 \frac{2\mu}{1 - e^{-2\mu\Delta t}}} \quad (5.4)$$

The time increment of our data is represented by Δt , which in our case of weekly data corresponds to 1/52. Calculations of the parameters for all our samples led to:

	μ	m	σ
Full Sample	4.9070	155.0017	32,520
Period 1	4.9651	-2,558.3272	20,105
Period 2	5.9629	524.6159	50,260
Period 3	6.1787	2,394.9883	25,644

Table 5.2 Parameter Results

The sigma reflects the volatility of the sample period, which was already discussed in the descriptive statistics. The long term mean is a product the interrelation of constant C and mean reversion. A slower mean reversion and more extreme constant C will lead to a more skewed long-term mean. According to the parameters one expects the option value to be lowest in period one and be higher in the following two periods.

One surprising observation from the above table is that the full sample mean reversion is the lowest amongst the samples. One would assume it to resemble the weighted average of the three subsamples. The explanation lies in the use of the O-U process. The regression line is a

difference equation with one lag and will approach a fixed positive value from below. The speed of this approach for the whole sample is interdependent with, but not the average of the subsamples.

Although we assume the parameters to be constant in our model, the estimations among subsamples show that there is variation over time. The above equations show that running a sensitivity analysis on these parameters will lead to spurious results as they are interrelated. An increase in speed of mean reversion will lead to a decrease in absolute value of the long-run mean, as the denominator in equation 5.3 will increase. Meanwhile, a decrease will lead to the opposite. The effect on the volatility is similar. An increase in speed of mean reversion (μ) will increase the numerator in equation 5.4 and increase in the denominator. Hence an increase in mean reversion has a multidirectional effect on volatility. The direction depends on the power of nominator in relation to denominator. This power is higher for the nominator part as with speed of mean reversion approaching infinity the denominator will approach one, while the nominator will approach infinity. Hence the volatility will increase along with increasing speed of mean reversion.

One could assume m to only to change by a movement in C and σ to change only through a development in S . However, this would mean running sensitivity analyses on S and C instead of m and σ . Instead, we will focus our efforts on rolling window estimation to test the stability of the parameters later in this paper.

5.2 Benchmark Value

An approach to the benchmark value is presented in Sødal et al. (2008), where the value of the option is compared to the initial investment premium. This is set as the newbuilding price differential. If one wants acquire the option to switch, one needs to invest in a more expensive LR2 product tanker, instead of the standard Aframax vessel. This initial investment has to be deducted from the W_0 to acquire the investments return.

Unfortunately there was no reliable data on the newbuilding price differential of LR2s and Aframaxes for the full time period. The average differential of a 113-115k dwt Aframax and a 113-115k dwt LR2 from June 2013 till November 2015 found at Clarksons is a 2.09 million dollar premium for the LR2. We assume this to be relatively stable over time. Estimates for the additional cost of coating were set at 1.5 to 3 million by industry expert Alexander

Donger (2015). Hence we will set the newbuilding benchmark (B2) to a constant 2.5 million dollars.

5.3 Switching Costs

Switching costs can be divided into two categories: switching from *dirty to clean* and *clean to dirty*. The switch from clean to dirty is quite a simple process. As described in Energy Institute (2009) thorough draining of the tanks, necessary to avoid chemical reactions, has to be conducted even when switching from clean to dirty. This is the minimum cleaning that has to be done in any case of cargo change. Hence it is as a sunk cost (Energy Institute, 2009). Industry Expert Ulf Bäcklund (2015) described the cost of switching from clean to dirty as virtually zero. We will follow this suggestion.

However, theory on the challenges and cost of switching from dirty to clean is scarce and circumstantial. Tanks and pipes have to be thoroughly cleaned to avoid pollution of the next cargo. This cleaning process takes time and chemicals. Thereafter, charterers usually demand three voyages with ‘mainly clean’ products to assure an inerrant transition process (Stopford, 2009). As this restricts the cargo menu, these three voyages are expected to be rewarded at a discount. Therefore cost of switching resembles from expenses for cleaning, opportunity cost of cleaning, a possible difference in the cost of operations and a possible opportunity cost incurred by restrictions on cargo after the cleaning process.

In contact with industry experts, estimations for switching costs were ranging widely. Ulf Bäcklund, head of Stena Bulk in Singapore, estimated the total cost of the switching process to be around 500,000 to a million dollars for an LR2 (Bäcklund, 2015). Platts reports quoted another insider on cleaning costs of 350,000 dollars plus 250,000 dollars in discount on follow-up voyages. The cleaning time ranged from seven days to three weeks (Wang & Mohindru 2015a, 2015b)

Two articles by Johnson (2010, 2011) gave valuable insight into the cleaning process, its prerequisites, measurements of cargo contamination and actual estimation of cleaning costs. He shows that especially for modern product tankers the difficulties and costs of a switch from dirty to clean seem to be overestimated through historical bias. He argues that costs of cleaning could be significantly reduced and proposes, a more risk affine behavior of owners in switching negotiations with charterers could be of significant benefit.

Johnson (2011) comes up with concrete estimates for the cleaning cost of a 75k dwt DNV ETC (Easy Tank Cleaning) classified product tanker. The report argues that the cleaning process is often overestimated, and hence too much time, effort and resources are dedicated to it. He estimates that costs of a conventional cleaning process (not including the discount on follow-up voyages) to be about 137,000 dollars. Taking into account the marginal benefit of cleaning and the degree of dilution when refilling the cargo tanks these costs could be reduced to only about 76,000 dollars for the same tanker specifications. Additionally, the current legislation states that the owner is responsible for the cleaning of the tanks and hence fully responsible in case of pollution or loss of the cargo. Consequently, if experience would show that tank-cleaning effort could be reduced at no danger of polluting the cargo, the owner might well be willing to take that risk. Moreover, it is estimated that one voyage with “mainly clean” cargo would be sufficient to fully assure an inerrant transition process (Johnson, 2011). Assuming that cleaning costs are proportional to size of the vessel, the cleaning costs for in Aframax vessel of 115k dwt would have to be about 1.5 times higher.

Industry experts, such as Alexander Donger (2015) from the Tanker Department of Hanseatic Unity Chartering estimate the difference in cost of operations to a few hundred dollars (Donger, 2015). Sødal et al. (2008) stated that the differences in operating cost are already reflected in the net freight rate. Regardless of this, applying a net freight rate to a different vessel, as done in our case might lead to flaws. As we assume these to be negligible however, we set the difference on operating costs to zero.

The discount on following the voyages after the switch from dirty to clean stems from transitional cargos, which have to be transported to assure a clean voyage history of the vessel. Charterers are hesitant to accept a vessel in the clean market if the last three cargos have not been clean or ‘mainly clean’. Hence after the cleaning process three voyages with ‘mainly clean’ cargos, such as fuel oil have to be done. These are likely to be rewarded at a discount. The size of that discount is tough to measure. Logical estimation however leads us to believe that the rate attained for the first three voyages after cleaning will not be lower than the dirty rate.

On the basis of this rather ambiguous information, we will perform a sensitivity analysis on the switching cost. We will take the different estimates as possible scenarios, showing the effect on option value. These cost scenarios are shown in Table 5.3. In the base case we assume a cleaning cost according to Wang & Mohindru (2015) of 350,000 dollars and an

additional discount of 250,000 dollars. In the two Johnson cases, we adjusted for the difference in size plus a discount on three voyages for the high case and a discount of one voyage in the low case⁵. The range up to a million is based on the spread of the other sources we encountered.

Cleaning Costs	Scenario	Total Cost
Full Sample	Base Case	600,000
	Johnson High	460,000
	Johnson Low	200,000
	High	1,000,000

Table 5.3 Cleaning Cost Scenarios

5.4 Miscellaneous

The base case discount rate is set at 10 percent per annum, which corresponds to estimations in previous academic literature of Sødal et al. (2008) and Bjerknes & Herje (2013). This rate is based on an estimated expected return of 5 percent and an expected depreciation rate of 5 percent applying to an expected lifetime of the vessel of 20 years. The discount rate is highly cyclical which is why we decided to apply different scenarios from 5 percent till 15 percent in 2.5 percent increment steps to the full sample to picture the effect of the discount rate.

The value of the current differential p_0 is set at the long-run mean of the sample, as the expected freight rate differential at any point in time is its long-run mean.

⁵ $High = 137000 * \frac{115}{75} + 250000$; $Low = 75000 * \frac{115}{75} + \frac{250000}{3}$

6. Model Results and Numerical Experiments

After having decided upon the parameter values, we can now step over to run our model for the different scenarios and discuss the results. Matlab was used to calculate the value of the option and the thresholds of the optimal switching policy. The code for the model was based on Bjerknes and Herje (2013), however included iterations to calculate several scenarios at once; the code can be found in appendix 5.

6.1 Base Case Results

To start out observe the results for the option value and thresholds for the base case scenarios, as shown in the table 6.1 below.

Base Cases	Total Cost	m	sigma	Value	Investment Profit	P _H	P _L
Full Sample	600,000	155	32,520	6,689,986	4,189,986	12,345	-12,345
Period 1	600,000	-2,558	20,105	421,353	-2,078,647	12,540	-6,680
Period 2	600,000	525	50,260	10,739,539	8,239,539	16,260	-16,540
Period 3	600,000	2,395	25,644	8,065,868	5,565,868	8,600	-14,040

Table 6.1 Estimation Results - Base Case

The value of the option (V_0) is about 6,7 million over the whole sampling period. The graph in Appendix 6 illustrates the chosen values for p_H and p_L for the full sample would have led to a total number of 14 switches when beginning in the clean market. Note however, that such strategy would imply that the shipowner would have perfect information about the future development of the differential, which is not a realistic assumption.

Referring back to the hypothesis presented in the graphical and descriptive analysis of the freight rate differential, the results in the three subperiods meet our expectations. In period one, where the clean market was generally outperforming the dirty the value from switching is very low. In period two, which was characterized by high volatility, the option value is the highest and in period three, where dirty and clean market seemed more integrated the value decreases, but is still above that of the full sample. Deducting the newbuilding price differential shows a positive return over the course of the whole sample. In period one the option value is too small to justify the increased investment. The following periods however clearly exhibit environments, where gains are to be made from switching between markets.

The trigger values behave according to long-run mean and volatility. The more positive the long-run mean, the more skewed they are to the positive side and vice versa. The higher the volatility the further they drift apart, conversely the smaller the sigma, the smaller the range between the trigger values.

6.2 Parameter influence on Option Value

Now we examine the influence of long-run mean, speed of mean reversion and volatility on the option value over the three subsamples. The following graphics do not show the isolated effect of these parameters, as they are all interdependent. Rather, they serve as a basis to obtain information on which parameter is correlated closest with the development of the option value.

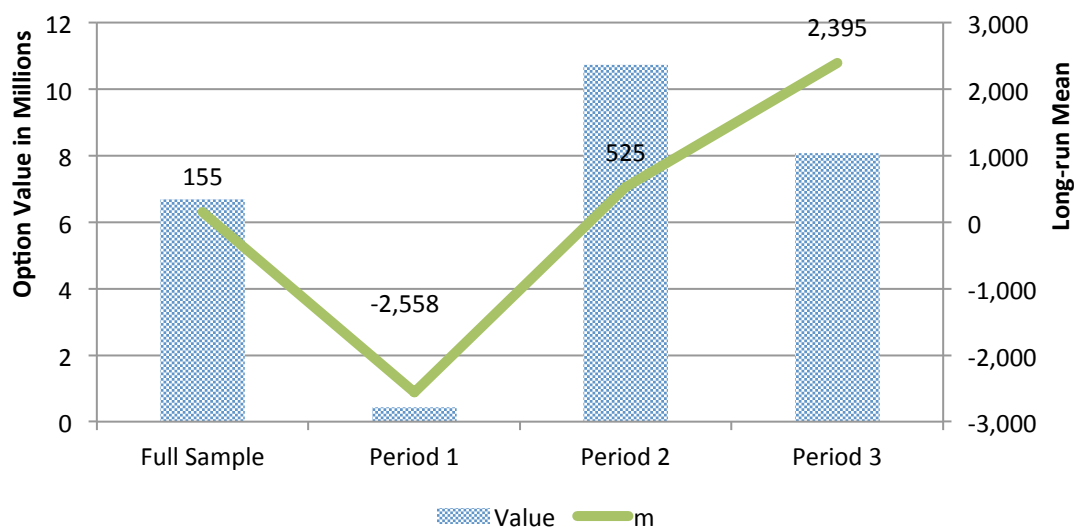


Figure 6.1 Influence of long-run mean on option value

A negative long-run mean resembles a long-term premium for the clean market over the dirty. The closer this mean comes to zero the lesser the premium. If it becomes positive as in period three, the dirty market is expected to on average outperform the clean. Intuitively one would expect the value of the option to rise the more positive the long-run mean becomes, since the product tanker would be able to exploit this market shift. From figure 6.1 one can observe that the value of the option increases, the closer the long-run mean is to zero. This makes sense, as an active strategy will benefit from frequent switches in differential direction. The closer the differentials long run mean is to zero, the more likely is a switch from positive to negative and vice versa.

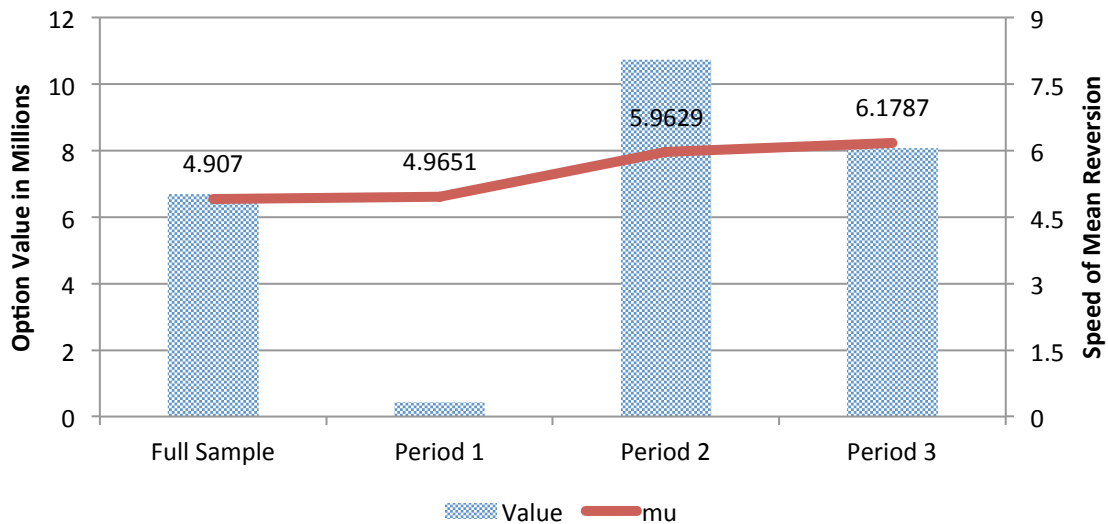


Figure 6.2 Influence of speed of mean reversion on option value

Next up is the influence of speed of mean reversion on the option value among the base cases in whole sample and its subsamples, as shown above. The speed of mean reversion is increasing over the course of the full sample, indicating a higher cointegration of clean and dirty market. An increase in speed of mean reversion leads to less persistent shocks and deviations from the long-run mean. Hence one expects the option value to decrease with increased speed of mean reversion. This is to some extent depicted in the figure above.

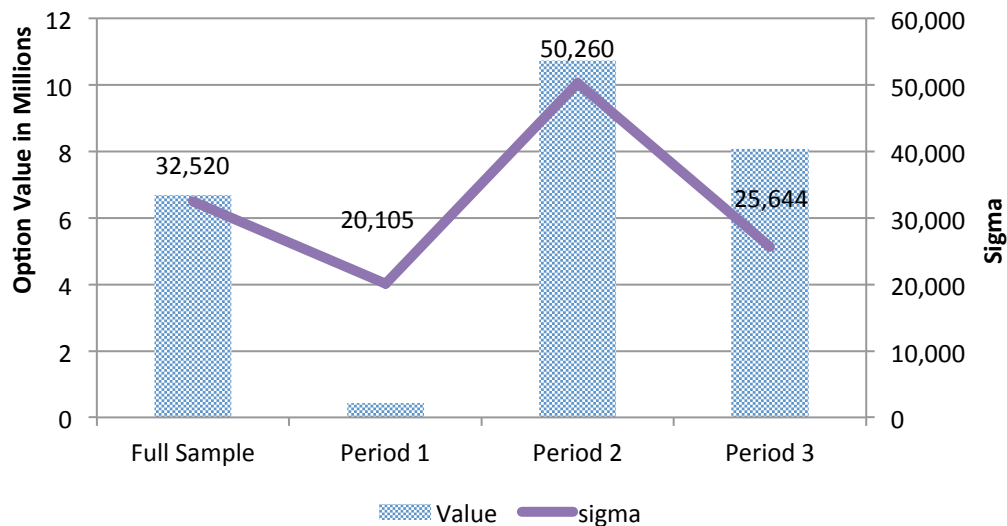


Figure 6.3 Influence of volatility on option value

The figure above shows how the change in volatility influences the option value. The graphical depiction shows very close correlation of option value and volatility, which

confirms the intuitive expectations. Higher volatility leads to more and higher extremes in the freight differential. An active switching policy is able to capture and exploit these deviations from the mean and hence has increased value. Volatility seems to be the most influential factor for the option value.

6.3 Sensitivity Analysis

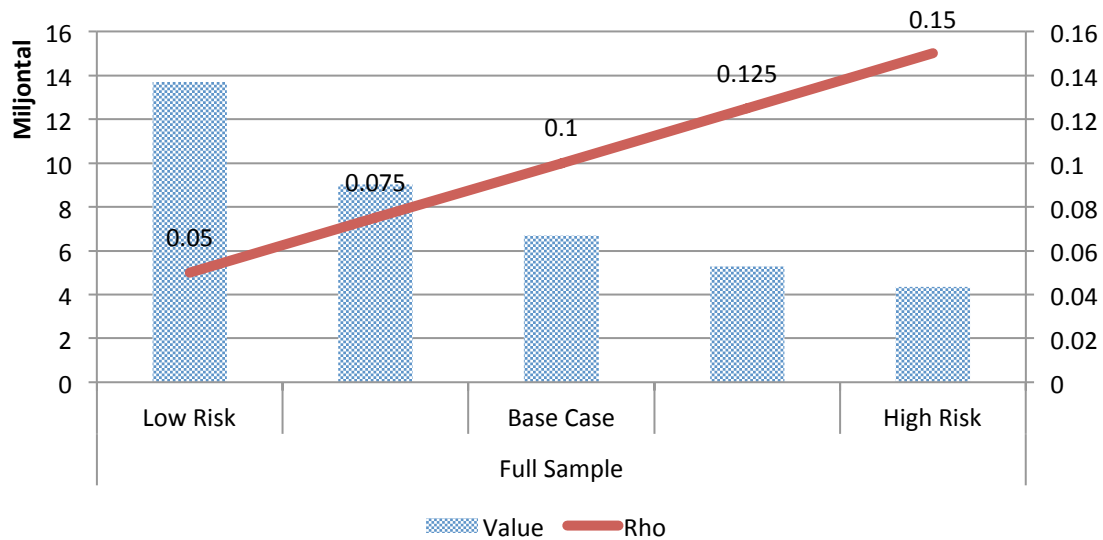


Figure 6.4 Influence of discount rate on option value

As the graph above clearly shows, an increase in discount rate decreases option value. This happens at a marginally decreasing rate. An increase from 5 percent to 7.5 percent will reduce option value by about a third, a step from 7.5 to 10 percent on only by about a fourth and the next step to 12.5 percent will leave a decreasing effect of about a fifth.

Discount Factor		p	Value	p _H	p _L
Full Sample	Low Risk	0.05	13,683.569	12,340	-12,400
		0.075	9,020,720	12,400	-12,360
	Base Case	0.1	6,689,986	12,435	-12,345
		0.125	5,292,090	12,480	-12,320
	High Risk	0.15	4,360,616	12,540	-12,280

Table 6.2 Estimation results - Sensitivity analysis on discount rate

During these increases in discount rate the trigger values remain almost completely stable, but drift apart and into positivity slightly with increasing discount rate, meaning that the optimal switching policy remains almost unaffected (see table 6.2). The model is based on a

mean reverting process in perpetuity. Hence there will be no trend in freight rate development and unlike an exhaustible resource there will be no advantage in shipping more cargo at an earlier point in time, if the discount rate increases. Hence there is no possibility to adapt to increasing discount rates by changing the switching policy. Trigger values drift apart and to positivity to account for unequal effect of discount rate on switching cost and revenues. The switching cost is discounted at the beginning of the switch, while revenues, which have to overcome costs are discounted weekly. In perpetuity the effect is marginal, but to account for higher costs in relation to lower revenues the trigger values shift apart.

Table 6.3 shows the effect of a change in current freight rate differential p_0 . The effect on the value is very small and the switching policy remains unaffected, as long as the trigger values do not get hit and no instantaneous switch is provoked. Such a switch at p_0 might take a long time for reversion as can be seen in appendix 6. Sødal et al. (2008) point out that the effect could affect the initial investment decision for a product or a crude tanker.

Current Freight Rate Diff		p_0	Value	P_H	P_L
Full Sample	Actual	-10,670	6,565,589	12,345	-12,345
	Base Case	155	6,689,986	12,345	-12,345
	Positive	10,670	6,979,581	12,345	-12,345

Table 6.3 Estimation results - Sensitivity analysis on current freight rate differential

Different switching cost scenarios and their corresponding option values are depicted in Figure 6.5 and Table 6.4 below.

Figure 6.5 indicates an inverse relationship between the switching costs and the option value. The relationship is very intuitive as increased switching costs, everything else kept fixed, naturally will have an inverse effect on profits. The effect of switching cost seems to be persistent across all periods including the full sample. The cost increase has constant marginal effect. An increase of 400k from 200k to 600k reduces the option value by about a third. An increase of another 400k to one million results in reduction of another third.

Table 6.4 shows that the switching thresholds diverge along with the switching costs. This is consistent with theory, as a more extreme negative or positive differential would be needed to profit from the switch as the switching costs increase.

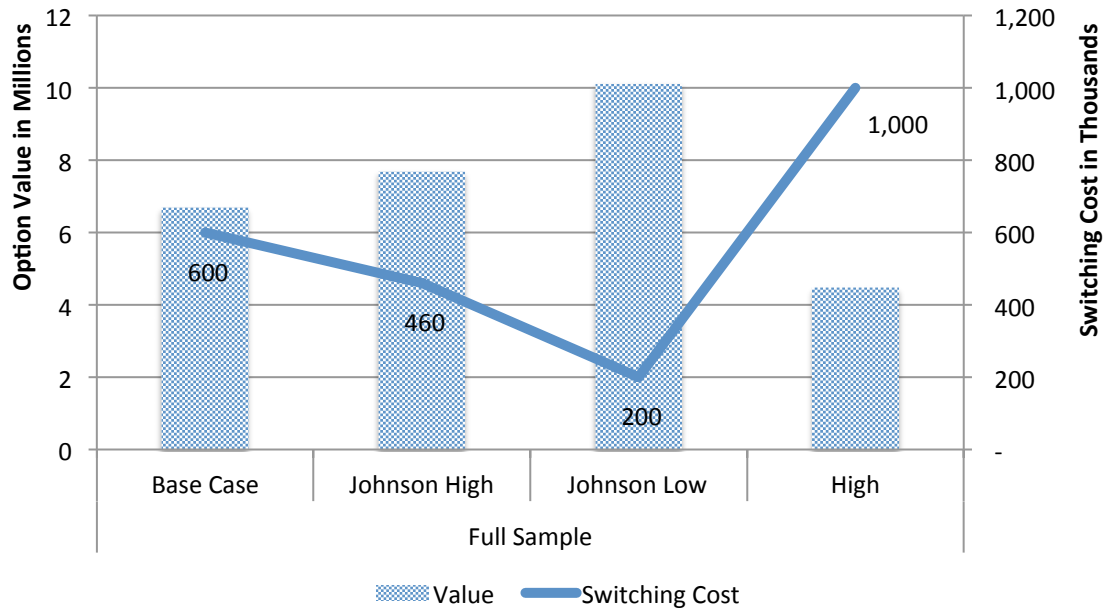


Figure 6.5 Influence of switching costs on option value

Cleaning Costs		Total Cost	Value	P_H	P_L
Full Sample	Base Case	600,000	6,689,986	12,345	-12,345
	Johnson High	460,000	7,690,714	11,175	-11,130
	Johnson Low	200,000	10,115,726	8,175	-8,160
	High	1,000,000	4,480,563	15,500	-15,200

Table 6.4 Estimation results - Sensitivity analysis on switching costs

6.4 Testing for Parameter Stability

As described in the methodology, our model assumes constant parameters over time. We already mentioned that this is not very realistic. To test the model on actual data we applied the switching policy estimated from period one to period two. It would have resulted in a net loss of 13.263 million; applying that of period two to period three would result in a net profit of 1.677 million (compare to expected results in table 6.1). Both values are compared to a passive policy of only operating in the clean market and are not net of investment cost. Of course this comparison is superficial, as the time horizon in the model is unlimited, while finite here, but it shows how far off estimations are from reality.

To investigate how the values of speed of mean reversion, long-run mean, volatility and ultimately option value and trigger values change over time, we used rolling window estimation for the O-U process.

A rolling window estimation involves choosing a fixed sample window which rolls along the time series in a fixed step size, running an operation at each step; in this case the OLS regression of the AR(1) model. We chose a step size of one i.e. one week. For significance of the results the freight rate in each window still had to follow a stationary process. The window size was set at three years, as this assured that the lion's share of the samples fulfilled the stationary condition (see appendix 7). Additionally, it is worth taking a shipowner's perspective. How far would he look back to properly assess the situation and make a decision on whether to switch or not?

Choosing the window size is a tradeoff between beta variability (accuracy) and sampling error (reliability) (Dunis et al., 2003). Narrowing down the window size makes the results more sensitive to changes to depict the dynamics more accurately, but reduces significance as the sample size reduces. As we see later there might be problems of non-stationarity due to too small window size. An increased window size will also lead to a higher loss of observations, as estimation can only start at the end of the first window to not incur missing values.

From the estimated regression coefficients, the model parameters were calculated again and plotted against the freight rate differential. The timeframe now starts 156 weeks after the first observation at the 24th of December 1999 and still ends on 27th of November 2015.

An immediately striking insight is the behavior of speed of mean reversion at points where the freight rate does not follow a stationary process (see appendix 7). Then μ not only has values extremely close to zero but also negative observations. A speed of mean reversion parameter of zero would imply an explosion of the O-U process, which actually has to fulfill the stationary condition. The cause is the behavior of the beta coefficient λ (see equation 5.2). When plotting both over time we can clearly see the inverse relationship.

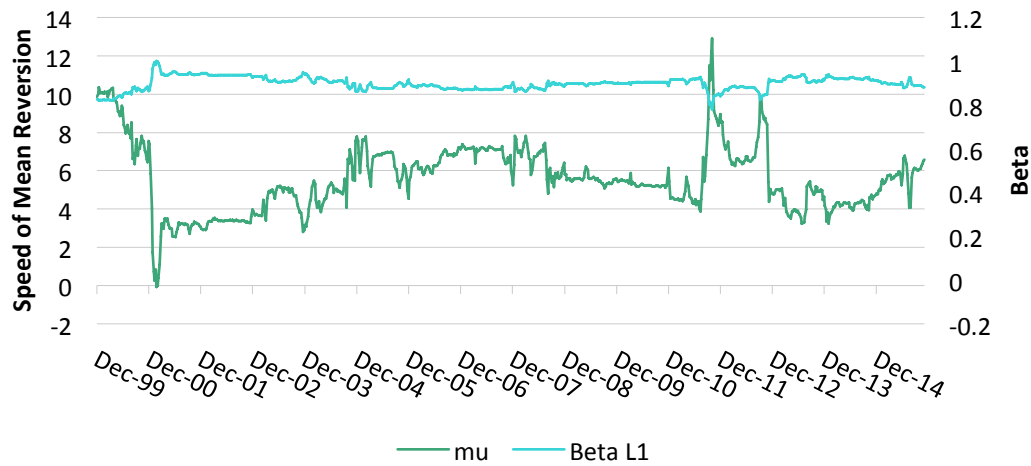


Figure 6.6 Rolling window estimation results – Speed of mean reversion & coefficient A

Comparing the graph above directly to the development of the long run mean shows the effect of negative speed of mean reversion. If the beta approaches 1, then the mean reversion will approach 0 and the long run mean will explode. As soon as beta exceeds 1 the mean reversion will approach $-\infty$ and the long-run mean will approach zero. Referring back to the parameter equations above: If A becomes 1, then speed of mean reversion becomes zero, which result in the denominator of equation 5.3 to become 0, which in turn leads to an unreal answer. This problem arises from the differential in that particular period not following a stationary process and hence not fulfilling the conditions of the O-U process. This shows on one hand the limitations of the O-U process and on the other a possibly too small window size. These extremes have to be treated as outliers and were hence excluded from the data set and thus further analysis. Luckily, with a window size of three years these are just four observations. This is a good tradeoff.

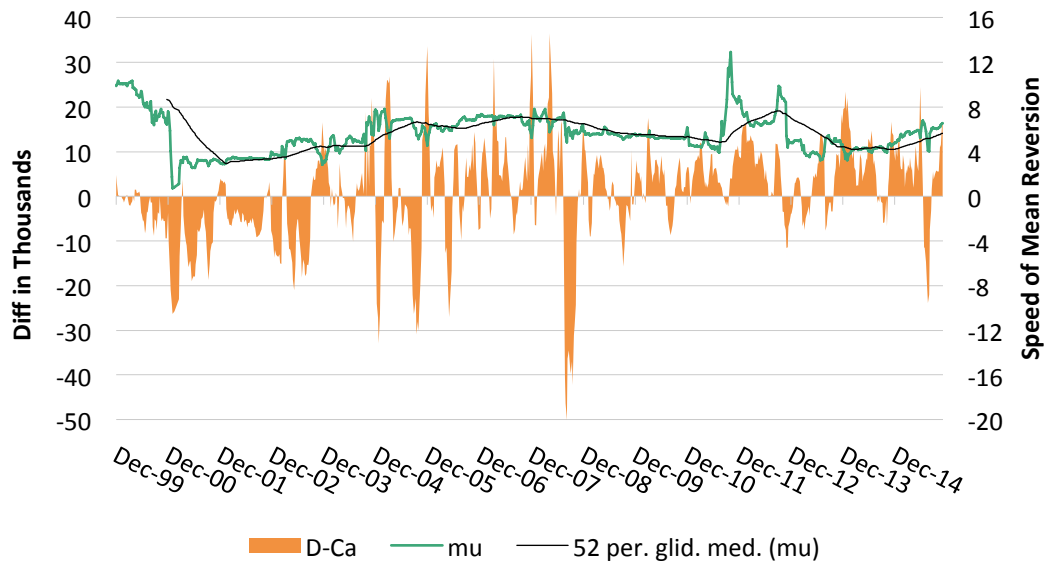


Figure 6.7 Rolling window estimation results - Speed of mean reversion

The graph above pictures the development of the mean reversion parameter over time in relation to the freight rate differential. As proven in earlier chapters, high mean reversion is indicating high integration of the two markets and vice versa. Contrary to subsample interpretations in 4.3 and 5.1, markets have not become less integrated over time but have gone through different phases, with integration increasing again recently. There is high variation from 0.72 on 26th of January 2001 to 12.24 on 21st of October 2010. Speed of mean reversion has largely been floating between four and 8 with spikes in October 2011 and September 2012. Since then the speed of mean reversion has been fairly stable around 4 with some recent fluctuation in summer 2015. If mean reversion becomes particularly low, high spikes in freight rate differential occur. Overall we can conclude that while there is significant volatility in the speed of mean reversion, over certain time frames of one to four years it seems to be relatively stable.

Pictured below in figure 6.8 is the long run mean together with the freight rate differential over time. The figure reveals a trend in long term mean from negativity to positivity, as already seen over the course of the subsamples in previous analysis. This trend is almost linear between 2001 and 2015. Within this period however there are four subperiods: from 2001 till mid 2008, till end 2011, till mid 2015, till today. The differential has risen substantially before falling back, during each of them. Nevertheless the upward trend is undeniable.

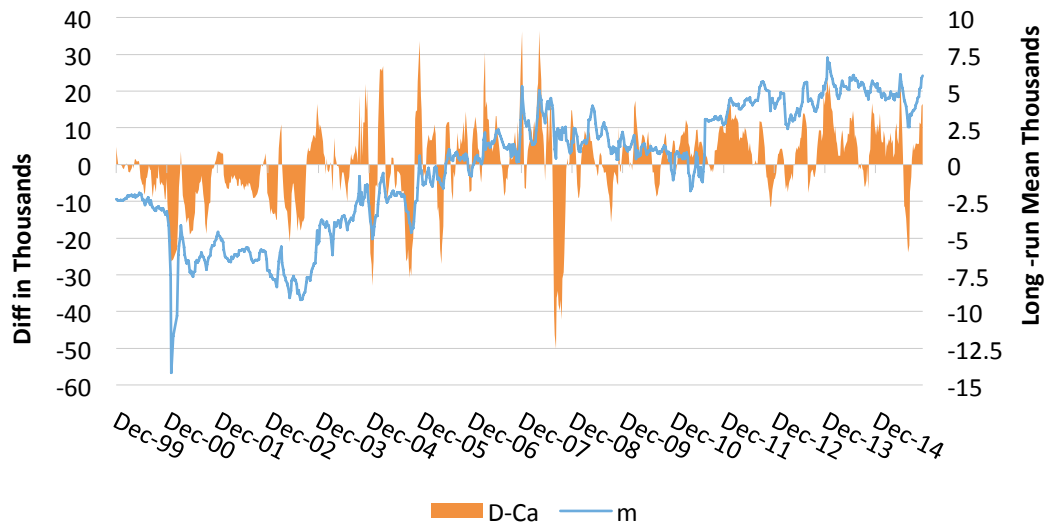


Figure 6.8 Rolling window estimation results - Long-run mean

The result is interesting for several reasons, firstly the additional investment of an LR2 as opposed to an Aframax is approximately in the range of USD 1.5-3 million (Donger, 2015). Assuming that long-run mean of the differential is approaching zero, or even becoming positive, there is will be no premium for a LR2 hence it seems irrational to pay for coating. Secondly, the picture may indicate that the two markets are not very integrated after all since the LR2 owners do not seem to take advantage of the higher freight rates in the dirty market. Thirdly, the estimated long-run mean varies over time, which implies that the model's assumption regarding a constant long-run mean may not be very appropriate.

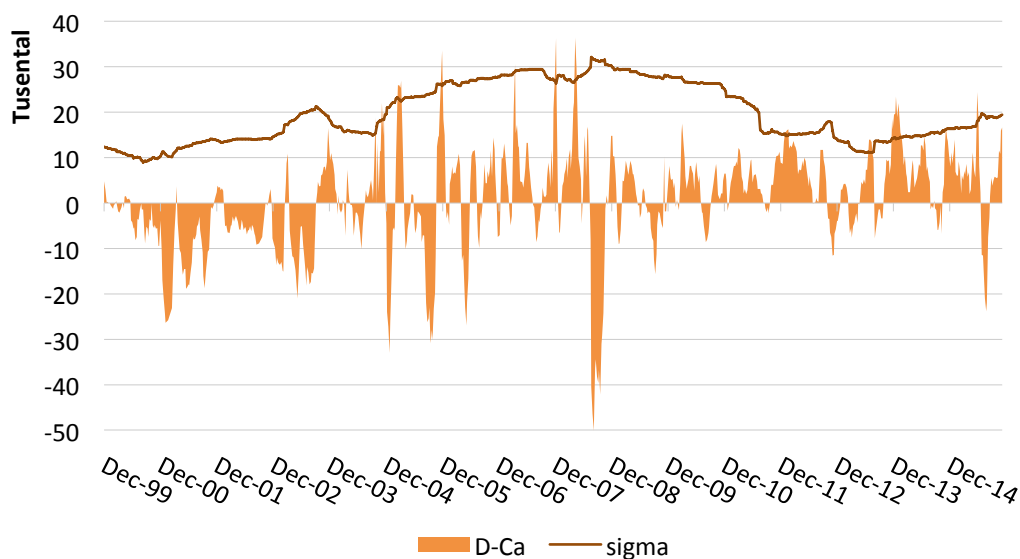


Figure 6.9 Rolling window estimation results - Volatility

Finally, we have plotted the development of sigma against the differential over time in figure 6.9. The analysis shows the high variation in volatility. There are however some trends to be captured. Over time volatility of the differential went from low to high to low and has recently been increasing again. This can possibly be related to the increase in volatility of the underlying freight rates in periods with high levels of the freight rates (Kavussanos, 2003).

6.5 Testing for Option and Trigger Value Stability

Using the parameter values from rolling window estimation, we computed the option value and the corresponding trigger values. From a managerial viewpoint the expected option value was estimated each week, with data from the past three years. The result is shown in figure 6.10 below.

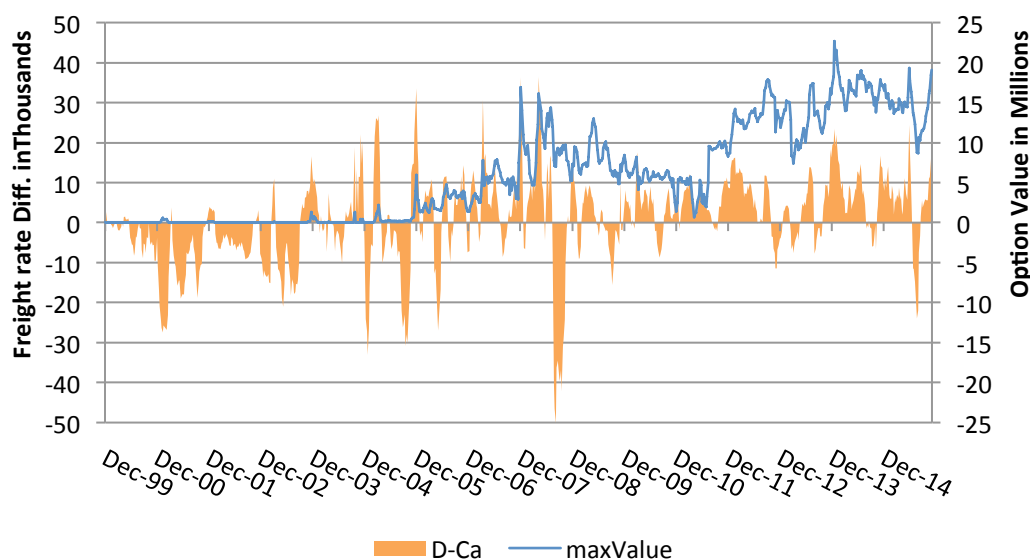


Figure 6.10 Rolling window estimation results - Option value

As expected from the high variation in parameters the option value is highly volatile. It reacts according to our microanalysis in chapter 6.2. The long-run mean and speed of mean reversion of the sample has high influence on the option value (compare Figure 6.10 to 6.7 and 6.8). Especially the correlation between long run mean and option value is strong. The volatility positively affects the option value. The high variation over time shows that the model clearly reacts to parameter changes and that the estimations are highly dependent on weekly market changes and sample choice. Option value, which directly derives from market disintegration, is found to be almost zero up until 2003. Then disintegration of clean and dirty

market lets the value of flexibility increase following a linear trend till the financial crisis, after which a period of less higher speed of mean reversion till September 2011 reduces option value sharply. Beginning a climb in August 2011 with the shift in differential to favor of dirty market the expected option value has been high until the recent drop in oil price especially in summer 2015. Since then it has actually increased again.

The lesson to be learned is that option value is highly dependent in disintegration of clean and dirty market, a shift in favor of the dirty market and the persistency of such a shift. Over time option value has increased substantially. The expected value cannot be considered constant, but has to be reassessed continuously. A larger window would lead to a more evened out result and might give a more accurate long-run fit of the expected option value. This would however make the model less responsive to structural changes in the market.

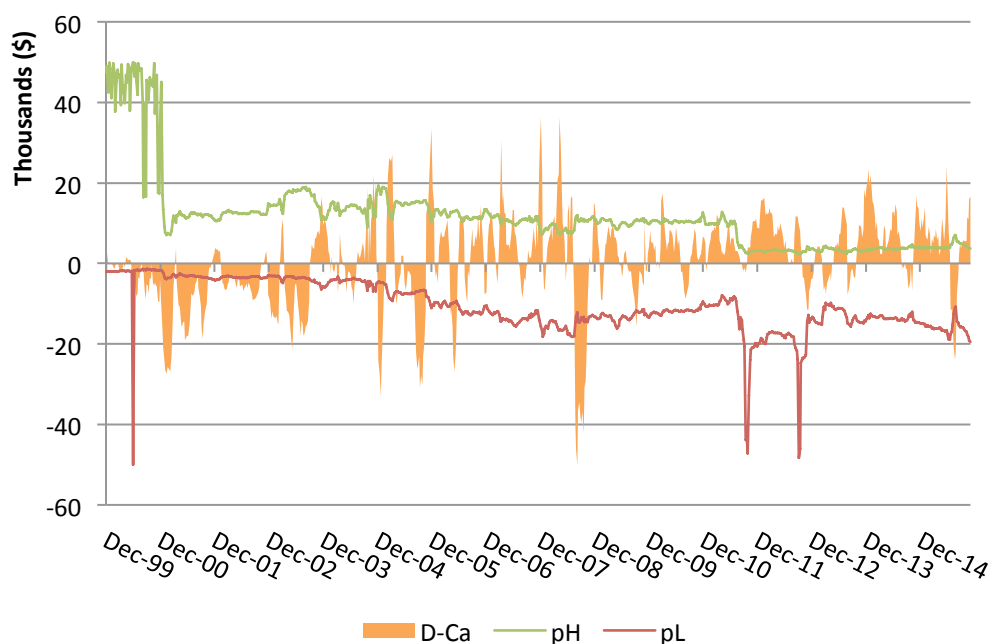


Figure 6.11 Rolling window estimation results - Trigger values

As can be seen in figure 6.11, the trigger values are also unstable. High volatility of the freight rate differential lets them drift apart, while in periods of stability they approach each other. If the freight rate differential is positive the triggers are negatively skewed and vice versa. Assuming an initial position in the clean market, the first switch would have happened in December 2003, reversed barely a year later in January 2005. Until the first switch markets have been relatively efficient.

As the model regards the parameters and trigger values as constant over time and models the option value over an infinite period, it does not seem to be well able to capture the volatility of the tanker market.

7. Limitations

When modeling markets some simplifications make the process manageable. These affect the accuracy of the results of the research.. There are several limitations to the research conducted in this thesis, some of which deserve a description. This chapter will reflect some of the assumptions that may have had an adverse effect on the accuracy of the results presented.

Firstly, the model is too static. Although the parameters move over time, they are assumed to remain at a constant level in the model. The parameters have a significant impact on the option value; see for instance volatility of freight rates, switching costs and the discount rate in the sensitivity analysis 6.2 and following. Such parameter rigidity may lead to inaccurate valuation results, especially when implemented for a real asset investment typically stretching over more than 20 years. In fact, the parameters may themselves follow stochastic processes. However, implementing such features would make the model less tractable, which in our case is less desirable. The lack of dynamics caused by constant parameters was investigated by the sensitivity analysis and the rolling window estimations.

The models assumption of lifetime perpetuity of the asset is a problem. It should account for additional investment costs every 15 to 25 years, to model newbuildings. A simple way to do so would be altering the freight rate accordingly at expected newbuilding dates. Unfortunately this fixes the decision instead of giving the owner the option to either build another LR2 or switch to the dirty market completely by investing in an Aframax tanker.

Moreover the model does not account for the possibility of Aframax switching to the clean market. In cases where newbuilt vessels are still completely clean, Aframax are well able to carry clean products, which simply leads to corrosion at the tank covers, which may have to be replaced after some years, as industry expert Dr. Kurt Klemme (2015), CEO of Reederei Nord Group, points out. Modern Aframax tankers are usually coated too, which would enable switching (Wang W. , 2015).

Furthermore, the arithmetic Ornstein-Uhlenbeck process unrealistically allows the future underlying freight rates to become negative (Sødal et al., 2008). Intuitively, freight rates will not become negative in a market with rational shipowners. However, Sødal et al. (2008)

points out that the process can still serve as a good approximation of the freight rate differential.

The switching process is assumed to happen instantaneously when the threshold is reached; in reality there is a time lag between the exercise and when revenue from the strategy starts coming in. The effect of the time lag is however unclear since fixtures are negotiated in advance, hence the spot market is not necessarily the same as prompt tonnage. It may however have a greater effect on the following fixtures in a case where all fixtures were for prompt tonnage or fixed shortly before loading. Our model could overestimate the value of the option, since time for cleaning would not be accounted for when switching from dirty to clean. As noted in 4.2, speed of mean reversion may also be asymmetric between the two markets due to the difference in cleaning time, conversion of vessel and newbuildings.

The model is highly dependent on long-run mean. As such period three in our subsamples had the highest value. However if dirty market constantly outperforms clean, a shipowner might be able to achieve higher profit by simply investing in an Aframax vessel. The model does not account for this. Accurate benchmarking and a higher emphasis on continuous change of differential direction is needed.

Another limitation is caused by the data, which is collected from two different routes sharing only one port and having slight differences in cargo intake. Although the data has been extrapolated to account for such deviations, this may cause an inaccurate option value. Furthermore, in a more realistic scenario the shipowner would be more flexible by being able to switch between several different routes. Due to the tractability of the model this cannot easily be taken into account.

When running the Matlab model we have used increments of \$15 to \$20, for the base case and sensitivity analysis, and \$50, for the rolling window and recursive estimations, instead of increments of \$1 when running the model through the 1001*1001 matrix. The alternative would have been to run the \$1 increments through a larger grid. The reason for choosing not to increase the matrix is the increased processing time for completing the calculations, which grows exponentially with the matrix. The consequence of higher increments is the likelihood of barriers deviate from the actual value.

8. Conclusion

Product tankers have the flexibility to serve the clean and the dirty freight markets. However, clean and dirty tanker shipping markets are not perfectly integrated and efficient since the newbuilding price premium on a product tanker is not accurately reflected in the freight rate differential. Since 1997 there has been a shift in the differential from a premium for clean to a premium for dirty tonnage, which leads to arbitrage opportunities. The substantial value to be gained is tied to flexibility of letting an LR2 tanker switch between clean and dirty market under the assumption we made. This suggests reevaluation of common product tanker valuation models. The development in freight rates suggests that the value of an active switching policy has grown from period one to period three.

However there is a high degree of uncertainty involved. Model parameters cannot be considered stable over time, which makes results sensitive to situational dynamics. The instability has been shown in rolling window estimation, to indicate how the maximal option value shifts along with shifts in the parameters. When using the model based on a rolling window there is a trade off between realistic assumptions regarding the parameters and the responsiveness to changing market conditions. A larger window size will make the managerial decisions less responsive to the conditions, while shorter may cause overvaluation in certain periods.

The model needs better adaptation to market reality and rolling backtesting on actual market data would be of high value. Seasonality in the differential suggests the investigation of alternative approaches to trigger value models. Additionally, the factors specifically influencing the freight rate differential need more attention. They are suspected to be economic boom or bust, oil production, seasonality, refinery margin and average haul. Future research should investigate their relationship to the freight rate differential to derive clear trading rules for product tanker market switching. Furthermore, no clear legislation exists to regulate switches. This leaves charterers and shipowners vulnerable to capriciousness of the opponent party. There needs to be clear rules for division of responsibility and a common measure for contamination of cargo. The risk of contamination needs to be investigated and be compared to the return of an active switching policy. It might well be that the profit does not justify the risk.

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10. Appendix

10.1 Time-charter Equivalent formula

$$TCE = \frac{VR * t - FC - PC - CD}{T}$$

where:

VR = Voyage freight rate

t = Cargo size on tons

FC = Total fuel costs

PC = Total port costs

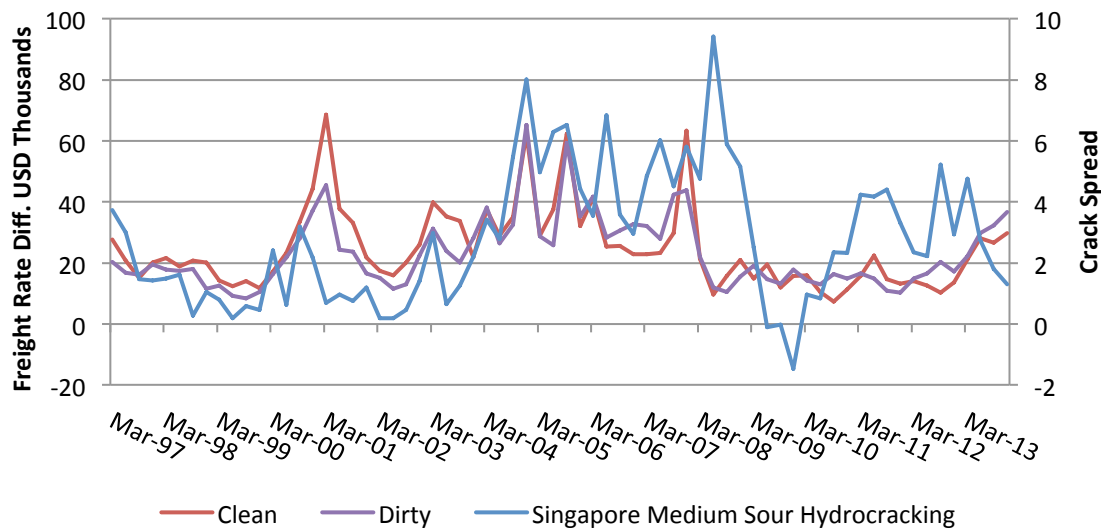
CD = Canal dues

T = Total voyage time (including time in port and time sailing ballast and laden)

10.2 Route and Vessel Specifics

			Round Voyage Specs						
Time	Code	Cargo	Load Port	Dis Port	Total Distance in nm	Total Voyage Time in days	Cargo Size (dwt)	Vessel Size (dwt)	YoB
1997-2003	T52	Dirty	Ras Tanura	Singapore	7404	27,2	80000	89636	1990/91
	T72	Clean	Ras Tanura	Chiba	13210	42,5	75000	106000	late 90s
2004-2008	T52	Dirty	Ras Tanura	Singapore	7404	28	80000	96000	1990/91
	T72	Clean	Ras Tanura	Chiba	13210	43,9	75000	106000	late 90s
2009-today	T181	Dirty	Ras Tanura	Singapore	7404	29,5	80000	115000	2010
	T72	Clean	Ras Tanura	Chiba	13308	49,8	75000	115000	2010
			Speed		Consumption at Sea t/day			Consumption in Port t (gross)	
Time	Code	Cargo	Laden	Ballast	CST380		MDO	CST380	MDO
					Laden	Ballast			
1997-2003	T52	Dirty	13,5	14,5	39	39	2,5	106	0
	T72	Clean	15	15	50	50	5	20	6
2004-2008	T52	Dirty	13,5	13,5	41	39	0	80	18
	T72	Clean	14,5	14,5	50	50	0	67	0
2009-today	T181	Dirty	13,5	12	52	30	0	115	0
	T72	Clean	13,5	12	42	30	0	100	0

10.3 Crack Spread Correlation



Source: (Clarksons & BP, 2015)

10.4 Seasonality Regression Results

	<i>Coefficients</i>	<i>Standard Error</i>	<i>t Stat</i>	<i>P-value</i>
Jan	727,43	1074,47	0,68	0,50
Feb	-223,33	1128,90	-0,20	0,84
Mar	3184,90	1087,33	2,93	0,00
Apr	3260,31	1100,68	2,96	0,00
May	321,96	1074,47	0,30	0,76
Jun	189,54	1100,68	0,17	0,86
Jul	56,73	1080,84	0,05	0,96
Aug	-4927,85	1074,47	-4,59	0,00
Sep	-5333,33	1107,53	-4,82	0,00
Oct	-3915,95	1068,20	-3,67	0,00
Nov	2275,08	1100,68	2,07	0,04
Dec	4907,55	1114,52	4,40	0,00

10.5 Matlab Code

The code for this thesis is based on the code written in Bjerknes and Herje (2013). However, some code has been revised to facilitate iterations of the model used for the sensitivity analysis. The code is composed of one script and three functions, which will be presented below.

10.5.1 Loop.m

This script calculates the value function using the parameters specified, and calls the other scripts that will be presented later in this appendix segment. The first part of the script specifies the fixed parameters used in the when running the model, i.e. the parameters that are expected to remain constant throughout the whole iteration grid:

```
% Fixed Parameters
```

```
rho=0.10;
```

```
B=600000;
```

```
F=0;
```

```
p0=0;
```

The second part of the script determines the grid through which the barriers are optimized. The variables determinines the starting points of the matrix that is being assessed, at what rate the increments are increasing and how many increment steps are required (note that small increments will give a more precise valuation, however will need an increased number of increments which in turn will require more processor power):

```
% Start of iteration
```

```
pHStart=0;
```

```
pLStart=0;
```

```
pIncrementSize=1;
```

```
pNumberOfIncrements=10000;
```

The third part empties the tables where the output of the value function calculations are stored:

```
% Empty tables
```

```
Low=zeros();
```

```
High=zeros();
```

```
Val=zeros();
```

The fourth and last part is the function describing the iteration process of the value function and the parameters that have been reestimated over time using the rolling window and

recursive estimation. Firstly the script starts with initiating the for-loop which updates the number of steps in the specified range 1:n, where n = the number of data observations for each parameter:

```
% for loop used to iterate the formula change (1:n) to  
appropriate range  
for i=1:n
```

After the for-loop has been specified the floating parameters are specified to be collected from tables my, mean and stdev at the position decided by the chronological order and number of iterations:

```
% Floating Parameters  
mu=my(i);  
m=mean(i);  
sigma=stdev(i);
```

Then the value function is formalized and calls for the DiscountFactorCalculation-function, where the specified parameters are used as input.

```
% Value function  
[maxValue, pH, pL] = DiscountFactorCalculation(rho, mu, m, B,  
F,...  
    sigma, p0, pLStart, pHStart, pIncrementSize,  
pNumberOfIncrements);
```

Lastly, the output of the maximum value of the function and the optimal barriers are plotted into three tables and the for-loop is ended:

```
% Used to store output in a table  
Low(i)=pL;  
High(i)=pH;  
Val(i)=maxValue;  
end
```

10.5.2 DiscountFactorCalculation.m

As noted in Loop.m the value function calls the DiscountFactorCalculation.m. That function will be discussed here. Firstly, the function is specified with the parameters denoted within the parenthesis:

```
function [maxValue, pH, pL] = DiscountFactorCalculation(rho,  
mu, m, B, F, sigma, p0, pLStart, pHStart, pIncrementSize,  
pNumberOfIncrements)
```

Secondly, the function defines and empties the matrix in which the barriers will be typed out later:

```
valueMatrix =  
zeros(pNumberOfIncrements+1,pNumberOfIncrements+1);
```

Thirdly, a sequence of loops is conducted which calculates the value, given the upper threshold and lower threshold for each pH and pL in the grid, given the increment size and start levels of the grid, see pHStart and pLStart in Loop.m. Note that the loop calls the function DiscountFactorApproach, this function will be described in the next segment. The loop then plots the results for W, pH and pL in the matrix defined before:

```
for pHIndex = 0:pNumberOfIncrements  
    pHValue = pHStart + (pHIndex * pIncrementSize);  
    for pLIndex = 0:pNumberOfIncrements  
        pLValue = pLStart - (pLIndex * pIncrementSize);  
        W = DiscountFactorApproach(rho, mu, m, B,  
            F, sigma, p0, pHValue, pLValue);  
        valueMatrix(pHIndex + 1, pLIndex + 1) = W;  
    end  
end
```

Finally, the output of the maximum value of the grid and it's the optimal switching policy (pH and pL) is plotted into the corresponding rows and columns. The column and row indices are subtracted with one since the index-loops starts at zero. Finally, the DiscountFactor-

Calculation.m is ended:

```
[maxValue, linearIndex] = max(valueMatrix(:));
[rowIndex, columnIndex] =
ind2sub(size(valueMatrix),linearIndex);
pH = pHStart + ((rowIndex - 1) * pIncrementSize);
pL = pLStart - ((columnIndex - 1) * pIncrementSize);
end
```

10.5.3 DiscountFactorApproach.m

In the previous segment, a function DiscountFactorApproach is called. This function represents the mathematical calculation of the value of the option, W, at given pH and pL levels.

First, the value function W is specified given the parameters denoted in parenthesis:

```
function W = DiscountFactorApproach(rho, mu, m, B, F, sigma,
p0, pH, pL)
```

Secondly the equations 3.11-3.12 [kummer functions in theory/methodology] are defined for p0, pH and pL. Note that similar to previous function these functions contain a third function, kummer:

```
MpH = kummer(rho/(2*mu),1/2,(mu/sigma^2)*(pH-m)^2);
MpL = kummer(rho/(2*mu),1/2,(mu/sigma^2)*(pL-m)^2);
Mp0 = kummer(rho/(2*mu),1/2,(mu/sigma^2)*(p0-m)^2);

UpL = ((2*(pL-m)*sqrt(mu)*gamma(1/2 + rho/(2*mu)))...
/(sigma*gamma(rho/(2*mu))))...
*kummer((1/2)+(rho/(2*mu)),3/2,((mu/sigma^2)*(pL-m)^2));
UpH = ((2*(pH-m)*sqrt(mu)*gamma(1/2 + rho/(2*mu)))...
/(sigma*gamma(rho/(2*mu))))...
*kummer((1/2)+(rho/(2*mu)),3/2,((mu/sigma^2)*(pH-m)^2));
Up0 = ((2*(p0-m)*sqrt(mu)*gamma(1/2 + rho/(2*mu)))...
/(sigma*gamma(rho/(2*mu))))...
*kummer((1/2)+(rho/(2*mu)),3/2,(mu/sigma^2)*(p0-m)^2);
```

Third and finally, the value function W described in equation X.X calculated using the definitions described earlier, before the function is ended.


```

W    = (Mp0+Up0)/(MpH+UpH)*((pH*330)/(rho+mu)+(mu*m*330)...
      /(rho*(rho+mu))-B-(MpH-UpH)/(MpL-UpL)...
      *(F+(pL*330)/(rho+mu) + (mu*m*330)/(rho*(rho+mu)))...
      /(1-(MpL+UpL)/(MpH+UpH)*(MpH-UpH)/(MpL-UpL));

```

```
end
```

10.5.4 Kummer.m

The last function required is the kummer function. Similar to Bjerknes and Herje (2013), the code used in this thesis was created by Mousaw (2011), and then uploaded on the user-based community forum for MathWorks. The function will be presented in its entirety, including the terms of use along with the copyright statement below.

```

function f = kummer(a,b,x)
% fprintf('Calling kummer with arguments: a=%f, b=%f, x=%f\n',
a, b, x);
% This function estimates the Kummer function with the
specified tolerance
% the generalized hypergeometric series, noted below. This
solves Kummer's
% differential equation:
%
%      x*g''(x) + (b - x)*g'(x) - a*g(x) = 0
% Default tolerance is tol = 1e-10. Feel free to change this
as needed
tol = 1e-10;

% Estimates the value by summing powers of the generalized
% hypergeometric series:
%
%
%      sum(n=0-->Inf)[(a)_n*x^n/{(b)_n*n!}
%
% until the specified tolerance is acheived. %
%a=
%b=
%x=
term=x*a/b;
f=1 + term;
n=1;
an=a;
bn=b;
nmin=10;
while(n < nmin || max(abs(term) > tol))
    n = n + 1;
    an = an + 1;
    bn = bn + 1;

```

```
term = x.*term*an/bn/n;  
f = f + term;  
end  
end
```

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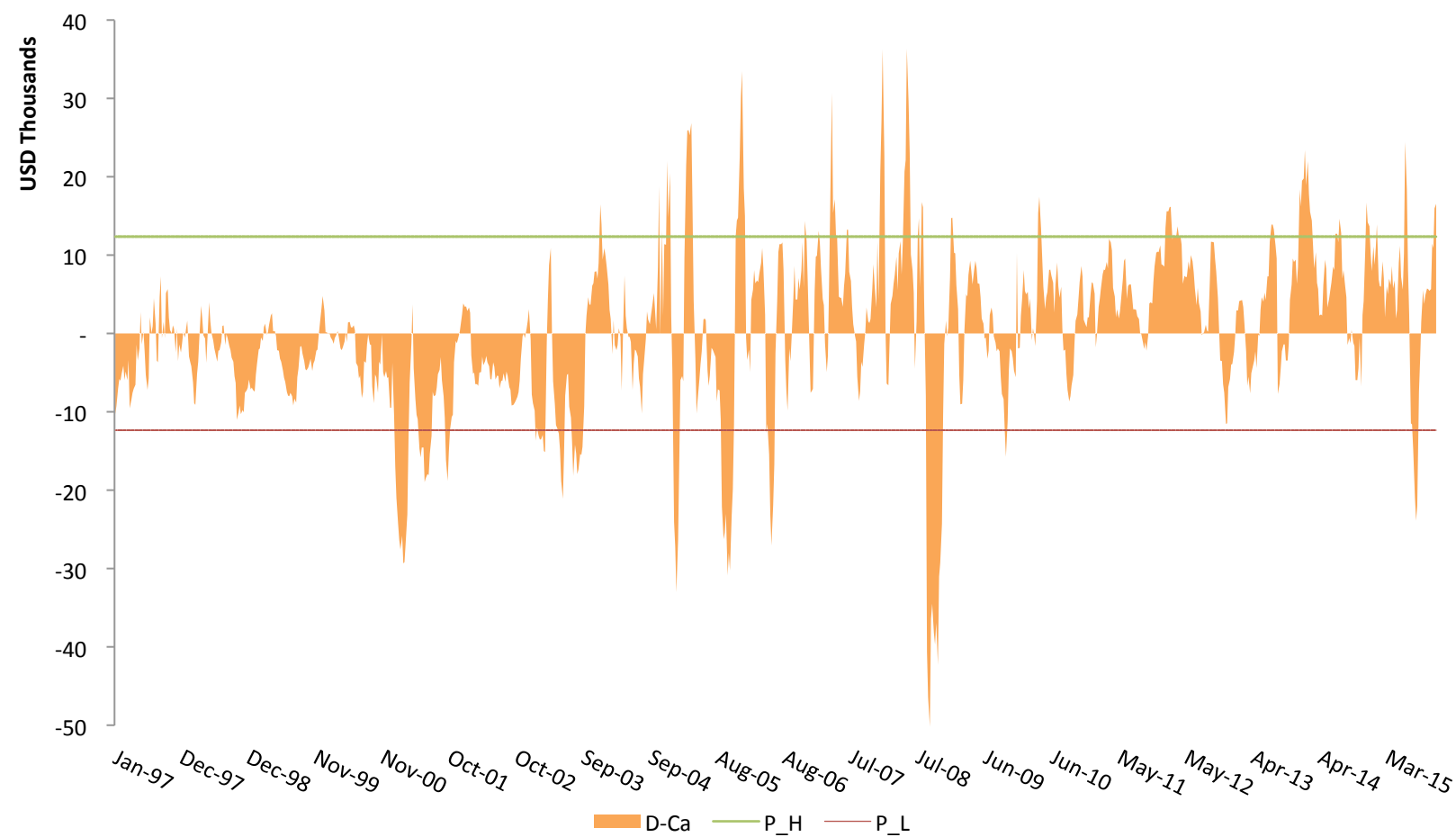
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10.6 Trigger Value Depiction



10.7 Rolling Window ADF-test (two lag) Results

