

INVESTMENT INTO OCEAN FREIGHT CAPACITY: DEVELOPMENT OF
A REAL OPTIONS INVESTMENT MODEL IN OLIGOPOLISTIC
COMPETITION TO EVALUATE INVESTMENT DECISIONS IN
SHIPPING

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Philipp Wilhelm Josef Rau : *Investment into ocean freight capacity: Development of a real options investment model in oligopolistic competition to evaluate investment decisions in shipping*, © March, 2017

Abstract

This dissertation assesses investment decisions in container shipping. To understand the current state of the industry, key characteristics and challenges, such as overcapacity, eroding margins due to low freight rates, long investment lead times, and frequent changes in alliance structure are introduced.

The nature of the industry motivates the application of real options, hence a real options investment model in oligopolistic competition is presented. An analytic solution in continuous time as well as a dynamic programming solution in discrete time are derived. The model takes into account an endogenous price function, fuel-efficient investment, endogenous lead times, and endogenous price formation in the secondary vessel market. This allows to study the impact of competitive intensity, number of players, volatility, fuel-efficiency, lead time, and variable cost on optimal capacity. An investigation of optimal investment policies shows that strategic action increases firm value and strategic alliances might help alleviate some of the industry's challenges.

Since the container shipping market is characterized by frequent alliance changes, the performance of the real options model in the context of a cooperative shipping game is assessed. Extending the coalition structure value concept it can be shown that, compared with discounted cash flow, the real options trigger performs better, especially in light of high competitive intensity and freight rate volatility while not exhibiting substantial disadvantages in other settings. A further assessment of a number of drivers for alliance instability finds that alliance complexity cost, freight rate volatility, and competitive intensity increase alliance changes.

To verify the investment approach, a characterization of the container freight rate is provided with an empirical Autoregressive Integrated Moving Average (ARIMA) model. It can be observed that the freight rate exhibits a negative relationship with capacity deployment; hence the oligopoly price function is confirmed. Based on the freight rate characterization, a back testing of the real options investment approach is provided. It shows that if players had applied the presented approach, capacities would have decreased and rates improved. A number of limitations of the real options approach are identified, i.e. substantial impact of volatility expectation, potentially induced cyclicity from trigger approaches, and the timing impact of investment and divestment lead times.

The implications of this research are that strategic action in the container shipping industry is worthwhile and understanding the market specifics (such as competitive intensity, volatility, and freight rate characterization) is very important. Container carriers should add a real options approach to their investment toolkit and keep an eye on potential overcapacity. Finally, entering strategic alliances is suggested, but complexity should be avoided.

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Acronyms

ACF	Autocorrelation Function
AIC	Akaike Information Criterion
AICc	Akaike Information Criterion for small sample sizes
AMM	Alphaliner Monthly Monitor
APL	American President Lines
ARIMA	Autoregressive Integrated Moving Average
BCO	Beneficial Cargo Owner
BDI	Baltic Dry Index
BIC	Bayesian Information Criterion
CCFI	China Containerized Freight Index
CO₂	Carbon Dioxide
COSCO	China Ocean Shipping Company
COSCOCS	China COSCO Container Lines
CS	Coalition Structure
CSCL	China Shipping Container Lines
DCF	Discounted Cash Flow
ECA	Emission Control Area
GBM	Geometric Brownian Motion
GDP	Gross Domestic Product
GRI	General Rate Increase
HHI	Herfindahl-Hirschman Index
IMO	International Maritime Organization
LNG	Liquefied Natural Gas
LP	Linear Programming
MAPE	Mean Absolute Percentage Error
MCDM	Multicriteria Decision Making
MOL	Mitsui Osaka Shosen Kaisha Lines

MSC	Mediterranean Shipping Company
NOL	Neptune Orient Lines
NO_x	Mono-Nitrogen Oxides
NPV	Net Present Value
NYK	Nippon Yusen Kabushiki Kaisha
OOCL	Orient Overseas Container Line
PACF	Partial Autocorrelation Function
PCF	Process of Coalition Formation
ROA	Real Options Analysis
SCFI	Shanghai Containerized Freight Index
SFI	Ship Finance International
SO₂	Sulfur Dioxide
SSE	Shanghai Shipping Exchange
TC	Time Charter
TEU	Twenty-Foot Equivalent Unit
UASC	United Arab Shipping Company
VSA	Vessel Sharing Agreement
WACC	Weighted Average Cost of Capital

Introduction

1.1 MOTIVATION

An obsession with scale to drive down costs and the defense of market share, rather than a focus on the bottom line, drive the desire for ever larger, more fuel efficient vessels.

—Odell (2012) Financial Times

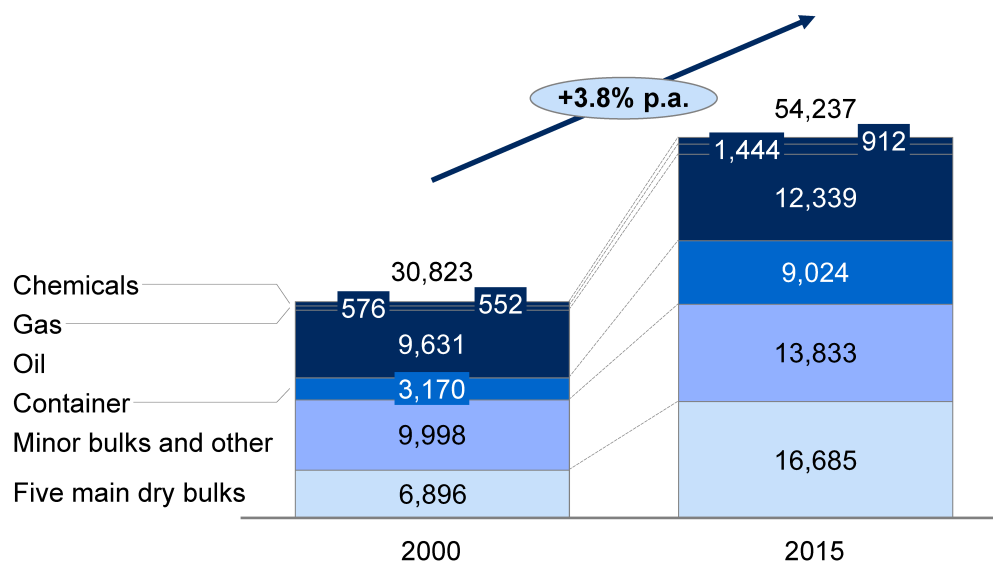
1.1.1 Industry perspective

The shipping industry is an industry of superlatives. Container, bulk, and tanker vessels are an integral part of global supply chains, transporting raw materials and finished goods that are necessary for daily life across the world. In 2015 alone, world seaborne trade amounts to 54 trillion cargo ton-miles.

Figure 1.1: World seaborne trade

World seaborne trade

Cargo-ton miles by cargo type, billions of ton-miles



Source: UNCTAD (2015), 2015 numbers are a forecast

Figure 1.1 shows that world seaborne trade has grown by 3.8 percent in the past 15 years. The container share has drastically increased over the years (2000: 10.3 percent; 2015: 16.6 percent), in terms of cargo-ton miles it has almost tripled.

As of April 2016, there are 5,173 cellular containerships (Alphaliner 2016) and the world's largest containership, the "Mediterranean Shipping Company (MSC) Oscar", has a nominal capacity of 19,224 Twenty-Foot Equivalent Units (TEU). This container vessel is 395.4 meters long and 59 meters wide; it corresponds to the size of more than 3 soccer fields (Stackhouse 2016).

Despite the impressive superlatives, players in the shipping industry have suffered from a number of challenges and have been under constant pressure in the past years. The world financial crisis in 2009 has shown how closely the fate of the shipping industry is tied to economic growth. And even before that, the industry had experienced market cycles of different length and size (Stopford 2010). From a regulatory perspective, a number of challenges are ahead: Carbon Dioxide (CO₂), ballast water, and local air pollution requirements are to be introduced by governments and the International Maritime Organization (IMO).

All of that combined with capital-intensive, long-term investments make it a very challenging situation to form rational and sustainable investment decisions. Especially since freight rate indices have only been introduced to container shipping in the 21st century, market participants are still trying to find the right approaches to use market intelligence to support their decision processes. As a consequence, decision making in the industry has not been purely rational. This has led to a mismatch of supply and demand, and finally an immense amount overcapacity (Bendall 2010, Rousos and Lee 2012, Scarsi 2007).

The Financial Times (Odell 2012) provides an appropriate summary of the situation: players in the industry are literally "obsessed" with scale and market share; strategic, rational investment decisions can only be observed to a limited extent. Therefore, it is obvious that this is an extremely interesting industry; and given the outlined situation and characteristics, it is an ideal basis for further research with respect to investment methods.

1.1.2 *Personal perspective*

As a management consultant, I worked on several engagements within the logistics industry. Personally, I think the projects with players within the container shipping industry were most challenging and most rewarding. I am enthusiastic about the industry and have been overwhelmed by the sheer size of container vessels which I have come across during my visits to the ports of Hamburg, Hong Kong, Singapore, and Antwerp.

Discussions at a number of research conferences as well as frequent talks with practitioners, researchers, and consultants familiar with container shipping have encouraged me that this is a relevant and exciting topic.

I believe there are a lot of highly interesting and relevant questions to be asked within the spectrum from network design, port operations, fleet deployment, all the way across to shipping investment. With this thesis, I want to contribute a model theoretic, empirical, and strategic perspective to this industry.

1.1.3 *Desired impact*

The key motivation for this dissertation is to have impact on research and management. In this work, I aim to fulfill the following objectives:

- Understand the current situation of the shipping industry and which challenges market participants are facing
- Characterize investment decisions and which financial and non-financial factors are relevant
- Develop a real options model for shipping investment
- Model investment decisions in the presence of dynamic coalition structure
- Assess the nature of the container freight rate
- Test the validity of the investment model empirically

The key contribution is that researchers can build on the insights (e.g. the continuous-time and discrete-time real options investment game models or the ARIMA freight rate characterization) to create further investment models in shipping or unrelated industries. Managers can add the models or parts thereof to their investment toolkits to make better, more informed investment decisions.

1.2 THE CONTAINER SHIPPING INDUSTRY

The objective of this Section is to embed this dissertation into the broader context of the shipping industry. I provide an overview of the value chain in shipping, present key figures, and add a regulatory perspective.

1.2.1 *Value chain*

In this work, I consider ship yards, ship owners, ship operators, freight forwarders, Beneficial Cargo Owners (BCOs), and regulators as key participants of the shipping investment value chain (Figure 1.2). The BCO as end customer wants to ship goods from an origin to a specified destination. This can be achieved by short or long-term contracts with a freight forwarder, or, for large volumes, directly with a ship operator. The freight forwarders may be characterized as the interface between BCOs and carriers. They handle most of the administrative tasks related to the shipments but can go as far as to organize door to door service, e.g. by providing further inland transport. The cost for the shipping service is determined by the freight rate. The China Containerized Freight Index (CCFI) which was introduced in 2003 and Shanghai Containerized Freight Index (SCFI) (introduced in 2009) are industry-wide accepted freight rate indices. BCOs and freight forwarders represent the demand side of the container shipping market.

On the supply side, ship operators (so-called carriers) provide the shipping service. In liner shipping, schedules are published in advance and carriers operate vessels on network strings. For example, a network string “Asia-Europe

(AE1) by Maersk connects Kobe in Japan with Bremerhaven in Germany. It has 10 additional port calls in Japan, China, Hong Kong, Malaysia, Egypt, UK, and the Netherlands. This is complemented with a feeder service, for example to allow transshipment from Thailand or transshipment to other ports in the UK. This particular string is operated with comparatively small vessels of the S Type with 8,500 TEU capacity (Maersk 2016a).

Figure 1.2: Value chain in container shipping



Vessel operators usually manage a portfolio of owned and chartered vessels. An owned vessel is on the operator's balance sheet and can be characterized as a long-term investment. In the case of chartering, a ship owner finances a vessel and makes a short or long-term charter contract with an operator. Charter contracts can have durations of variable length. In order to fulfill peak demands, vessels may be chartered for only a few months. For example, Maersk secured a 5,576 TEU vessel from Diana Containerships for 6 to 9 months at a charter rate of 14,750 USD per day (Alphaliner 2015a). New ultra-large vessels are normally chartered on a long-term basis. For example, the "YM WELLNESS", a 14,080 TEU vessel was ordered by ship owner Seaspan and chartered to the shipping operator Yang Ming on a 10 year contract (Alphaliner 2015e). An indicator of the current charter prices is represented in the various Time Charter (TC) rates, for example as provided by Clarksons (2013c).

Ship owners or owner-operators place orders with ship yards. Since vessels are a high involvement, long-term, expensive investment, ship owners normally codevelop ship classes with ship yards and buy a number of ships of the same design. An example is the Maersk Triple-E class which has been built 20 times from 2012 to 2015 and specifically designed for cutting CO₂ emissions, greater fuel efficiency, and improved vessel recycling (Maersk 2016b).

Finally, the container shipping industry is overseen by the IMO and individual countries' regulators. The IMO is continuing to provide new regulation

with respect to air pollution from ships, ballast water management, and ship recycling (c.f. Section 1.2.3).

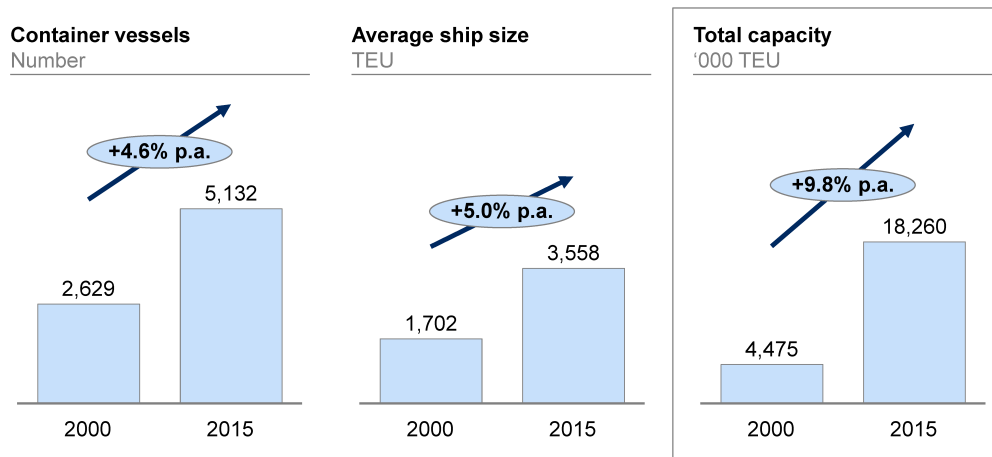
In this thesis, the focus is on the investment decision made by operator-owners of container vessels. The decision of whether to charter or to own a vessel is not considered.

1.2.2 Key figures

Capacity

Despite a number of economic crises, the container shipping industry has exhibited steady growth throughout the first 15 years of the 21st century. In the years 2000 to 2015, the number of container ships has almost doubled (Figure 1.3). As of 2015, Clarksons (2016) counts 5,132 registered containerships.

Figure 1.3: Container shipping capacity development 2000-2015



Source: Clarksons (2016)

At the same time, the average ship size in the market has significantly increased, from 1,702 TEU in 2000 to 3,558 TEU in 2015; hence it has more than doubled within 15 years. This is mainly driven by the ultra-large container-ships which have been put into service in the recent years in an attempt to gain economies of scale (c.f. Section 1.1.1).

The combination of more ships and higher average capacity has led to a more than four-fold increase in total market capacity; in 2015 total container shipping capacity amounted to 18.2 million TEU.

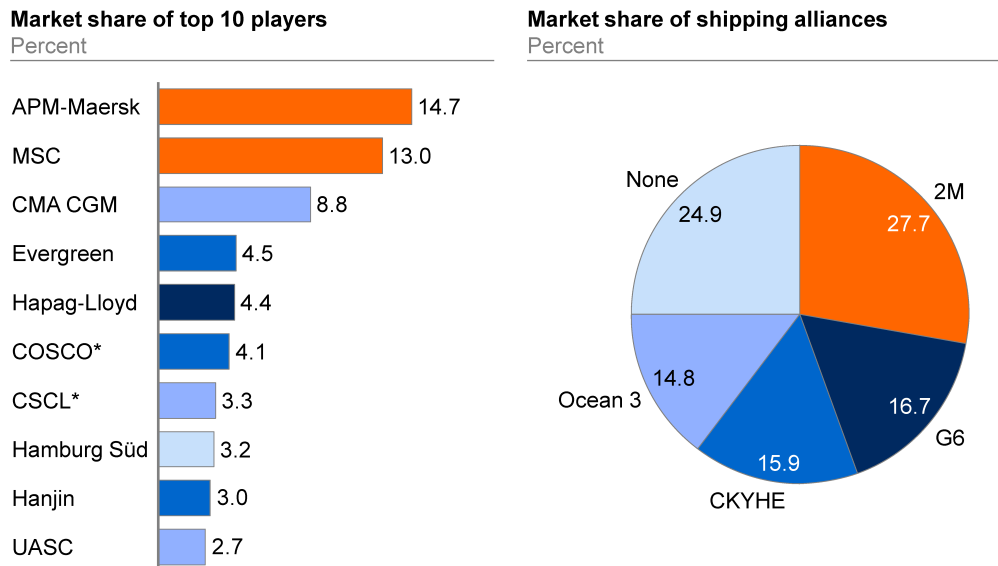
Market share

In terms of market share, the container shipping industry is concentrated. As shown in Figure 1.4, the top 10 players control more 61.7 percent of the market share¹. Furthermore, all top 10 players - except for Hamburg Süd - are

¹Note that this number assumes that assets of the recent merger between CSCL and COSCO have not been pooled yet.

organized in different shipping alliances. Shipping alliances are a collaboration between players in the industry. The standard definition is a joint service offering based on vessel sharing agreements, but it can also take on a less strong collaboration, such as slot charter agreements (Slack et al. 1996).

Figure 1.4: Container shipping market shares



*Fleets have been consolidated under COSCON, however, they remain under separate alliance agreements.

Source: Alphaliner (2016)

The two largest players in the industry, APM-Maersk and MSC, are currently operating jointly as the 2M alliance and achieve a combined market share of 27.7 percent. The G6 alliance with a 16.7 percent market share consists of Hapag-Lloyd, Orient Overseas Container Line (OOCL), Mitsui Osaka Shosen Kaisha Lines (MOL), American President Lines (APL), Nippon Yusen Kabushiki Kaisha (NYK), and Hyundai. CKYHE with 15.9 percent stands for the first letters of China Ocean Shipping Company (COSCO), K Line, Yang Ming, Hanjin, and Evergreen. Finally, the Ocean 3 alliance with 14.8 percent consists of CMA CGM, China Shipping Container Lines (CSCL), and United Arab Shipping Company (UASC). In summary, more than 75 percent of the global container shipping capacity is in the hands of 4 major alliances.

1.2.3 Regulatory perspective

Container shipping has a strong impact on the environment and as a consequence, especially the IMO as well as the EU and the USA have introduced and intend to introduce further regulations.

The polar code is a set of safety and environmental guidelines with respect to Arctic and Antarctic shipping. To ensure safe navigation in potentially dangerous waters as well as protect the remote environment from pollution, the polar

code has been adopted by the IMO. It is put into effect for newbuildings from January 2017, for existing ships from January 2018.

Furthermore, there are a number of guidelines with regards to ship design and operational measures to avoid CO₂, Sulfur Dioxide (SO₂), and Mono-Nitrogen Oxides (NO_x). For example, the share of sulphur in bunker fuel needs to be reduced to 0.5 percent until 2020. In Emission Control Areas (ECAs), such as the Baltic Sea, there are even stricter restrictions (2015: 0.1 percent).

For large vessels, it is common to use ballast water tanks in order to ensure stable sailing conditions. However, this is a threat to the ocean's ecosystem since non-native organisms can be introduced into different parts of the world. Hence, there are a number of IMO regulations that aim at avoiding transferring aquatic organisms across regions (UNCTAD 2015).

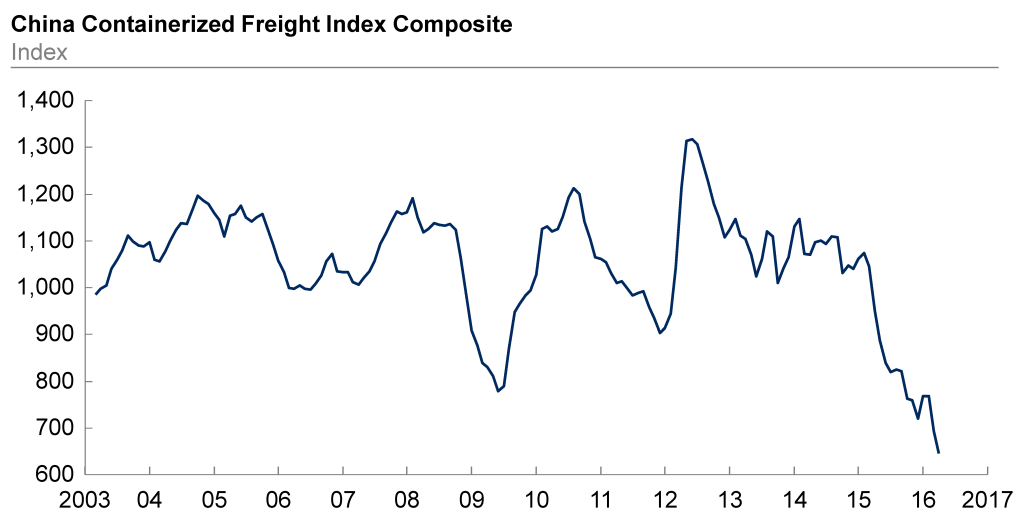
1.3 INDUSTRY DYNAMICS

Since the financial crisis of 2009, the situation of the container shipping industry has further deteriorated. In this section I explore the additional challenges of the industry, describe the reactions of players, and explain how this has affected the industry as a whole.

1.3.1 *Overcapacity and low freight rates*

While world container trade in cargo ton-miles has been growing on average by 7.2 percent per year (Figure 1.1), total container capacity has grown by 9.8 percent per year (Figure 1.3). These highly aggregated figures are a first indicator that container shipping players have built up overcapacity in the past 15 years.

Figure 1.5: Development of CCFI



Source: SSE (2016)

Taking a closer look at one of the leading market indices, the CCFI, it becomes apparent that overcapacity - in combination with low demand resulting from a

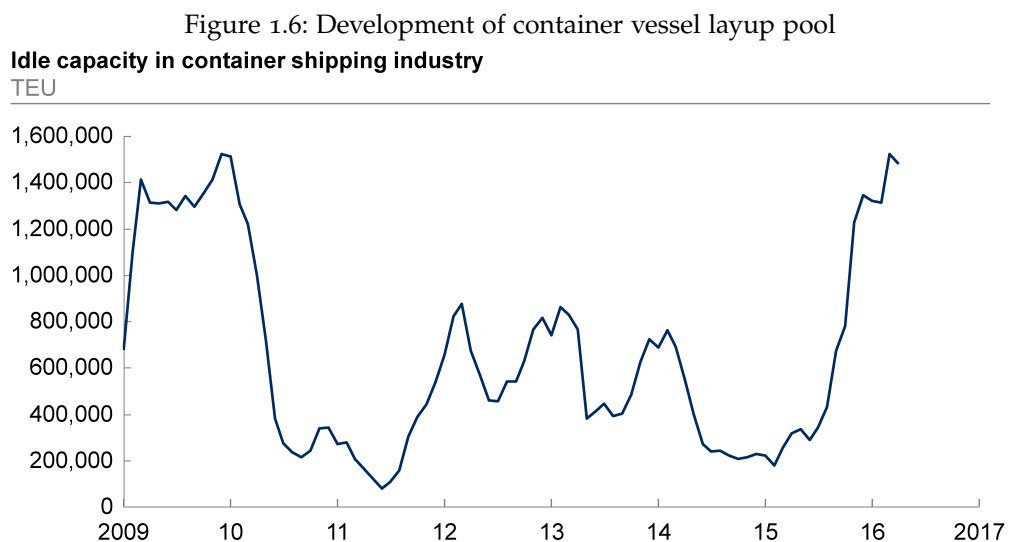
number of economic crises - has led to historically low freight rates. Figure 1.5 shows that after its introduction in 2003 with a value of 1,000 the CCFI exhibited a number of cycles before hitting values of less than 800 in the aftermath of the 2009 financial crisis. It seemed to recover through 2010 and 2011 but remained much more volatile. After a short period of stability in 2014 and 2015, it hit its all-time low in the beginning of 2016 with no signs of recovery yet.

1.3.2 Reactions of players

At prevailing freight rate levels, it is impossible for shipping companies to operate profitably in the market. Hence, players have chosen to cope with overcapacity and low freight rates in three ways: (1) slow steaming to improve fuel consumption and keep utilization of vessels high, (2) improve fuel efficiency of vessels, and (3) lay up additional vessels to reduce active market capacity.

Slow steaming is motivated by the fact that the fuel consumption rate of oceangoing vessels increases exponentially with vessel speed. Hence, when facing high bunker fuel cost, low demand, and low freight rates shipping players employ slow steaming. Due to higher transit times, available supply is reduced and can alleviate overcapacity. Due to the exponential relationship between speed and fuel consumption, vessel operators can reduce their operating cost substantially (Meyer et al. 2012). There is also an environmentally friendly side effect. Cariou (2011) shows that slow steaming has cut emissions by about 11 percent over the years 2008 to 2010.

The challenging market environment has boosted the research and development of so-called “eco-ships”. Those vessels have newer generations of engines, improved hull designs, and innovative coatings. At low steaming speeds, newer generations of ships can achieve combined fuel reductions of up to 30 percent (Lomar 2012, Notteboom and Cariou 2009, Visser 2011).



Source: Alphaliner (2012, 2014b, 2015b,c, 2016)

Finally, shipping players have reduced the amount of deployed vessels or even canceled entire strings on their networks. This has led to high amounts of idle capacity. Figure 1.6 shows the development of the layup pool over time. Currently, the layup pool is again at levels comparable to the 2009 financial crisis. As of April 2016, there is 1.48 million TEU idle capacity which corresponds to 7.4 percent of the worldwide cellular fleet (Alphaliner 2016).

1.3.3 *Effects*

This situation has had adverse effects on the shipping companies and several players were facing bankruptcy (Barnato 2016). It resulted in government bailouts and further consolidation, both in terms of mergers and acquisitions and in terms of container shipping alliances.

Hapag-Lloyd had to be bailed out by the German government in 2009 with a 1.2 billion EUR loan guarantee due to significant losses resulting from overcapacity (CityAM 2009). Neptune Orient Lines (NOL) was acquired by CMA CGM in 2015 (Shingleton 2016); COSCO and CSCL announced their merger in 2015 (Alphaliner 2016). According to Notteboom (2016), this will impact container shipping alliances once more: Ocean alliance (CMA CGM, China COSCO Container Lines (COSCOCS), OOCL, and Evergreen) and THE alliance (Hanjin, MOL, K Line, Yang Ming, NYK, and Hapag-Lloyd) are expected to start operations in 2017 while only 2M (Maersk and MSC) will remain in its current state.

In summary, the container shipping industry moved further away from perfect competition (bulk shipping as described by Pirrong (1992)) to a more oligopolistic market with a few, dominant players. This is an ideal setting to work with real options investment games in cooperative and non-cooperative markets with an endogenous oligopoly price function.

1.4 STRUCTURE OF THE DISSERTATION

Chapter 2 discusses that the container shipping industry is challenging due to market cycles, capital-intensive investments, supply-demand imbalances, and market concentration. This has led to overcapacity and margin erosion. Investment decisions are not solely driven by true intrinsic value, but also by fuel efficiency, networks, funding sources, regulation, vessel sizes, and asset prices. A container industry-specific real options investment model in oligopolistic competition is developed. It takes into account an endogenous price function, fuel-efficient investment, endogenous lead times, and endogenous price formation in the secondary vessel market. I provide an assessment on how optimal capacity is influenced by competitive intensity, number of players, volatility, fuel-efficiency, lead time, and variable cost. Moreover, I investigate optimal investment policies. It turns out that strategic action increases firm value and that it is worthwhile to consider alliances. Additionally, players in the market should consider retrofitting old vessels for fuel economy in economic downturns and using new, fuel-efficient vessels for capacity expansion in market upswings.

In Chapter 3, I discuss the role of container shipping alliances and their changing composition over the past years. With the intent of examining the merits of a real options trigger approach in light of a cooperative industry, I extend the coalition structure value concept. Compared with discounted cash flow the real options trigger performs best, especially in light of high competitive intensity and freight rate volatility. It does not exhibit substantial disadvantages in other market scenarios and has no substantial negative impact on coalition stability or market concentration. I quantify impact of competitive intensity, lead time, alliance complexity cost, and freight rate volatility on industry capacity, cash flow to players, alliance stability, and industry concentration. As consequence, I encourage shipping players to apply real options trigger approaches to strategic capacity investments.

Chapter 4 provides an empirical characterization of the container freight rate for the Asia to Europe trade lane with an ARIMA model. It can be shown that the freight rate has autoregressive properties and there is a negative relationship between capacity deployment and freight rate. This confirms the assumption of an endogenous oligopoly price function for the container shipping market. I further test the empirical performance of a real options investment approach. For the time period 2012 to 2016 I find that capacity would have declined and rates improved, had shipping carriers applied a real options framework. The real options approach, however, potentially induces cyclical-ity and is strongly dependent on the assumption of forward-looking market volatility. In summary, the application of the real options trigger is beneficial from an empirical perspective, albeit one needs to keep in mind that the market needs to be small enough to allow for signaling or needs a capacity regulator.

Chapter 5 summarizes the dissertation and reflects on the objectives presented in Section 1.1.3. Managerial implications as a consequence of the three main chapters as well as an outlook on future research are presented.

Investment into container shipping capacity: A real options approach in oligopolistic competition¹

2.1 INTRODUCTION

“Rough seas ahead for container shipping industry” was the title of a CNBC news item that aired in April 2015. It seems the container shipping industry was indeed facing historical challenges. Several players were facing bankruptcy and struggled to make money with transportation services (Barnato 2016). One year later, however, the situation has even further deteriorated: the SCFI has hit his all-time low since introduction in 2009 (414 USD/TEU in March 2016) while capacity in the market has continued to rise (SSE 2016).

Facing challenges to this large extent, players in the industry need to draw more attention to their capacity investments. They should assess the viability of strategic investment, assess optimal capacity and how it is influenced and finally design optimal investment policies over time. The intention of this research is to shed light on these issues and show how - by consideration of a real options investment model in oligopolistic competition - investment policy can be improved.

2.1.1 *Challenges of the shipping industry*

The shipping industry is a challenging environment, because players are exposed to market cycles, the high capital intensity of investments, supply-demand imbalances and market concentration.

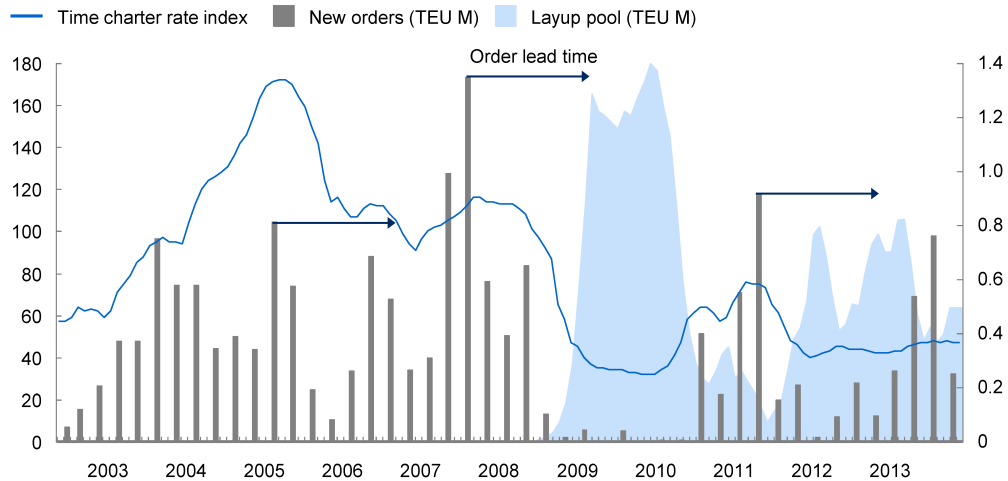
The ocean freight market has experienced market cycles since the start of modern sea trade; in the past decades, however, these cycles have varied significantly in terms of length and amplitude (Stopford 2010). Investments into freight vessel capacity are capital-intensive and have a long-term horizon of 20-30 years. These investments are usually undertaken by shipowners with the backing of long-term charter contracts. For example, the Vicente Pinzon (4,800 TEU) was recently put into service by Alianca de Navegacao (part of the Oetker group among Hamburg-Süd and others). It had originally been ordered by Ship Finance International (SFI) for 57.5 million USD, backed by a seven year charter contract with Hamburg Süd (26,250 USD per day). After delivery delays, however, SFI walked away from the contract and Hamburg-Süd assumed direct ownership of the vessel (Alphaliner 2014f).

An analysis of time charter rates, new orders as well as idle fleet in the container shipping sector (Figure 2.1) shows that strong ordering during time charter rate hikes has - repeatedly - led to high capacity delivery in low rate

¹Rau and Spinler (2016b): Rau, P., Spinler, S. (2016). Investment into container shipping capacity: A real options approach in oligopolistic competition. Transportation Research Part E: Logistics and Transportation Review, 93, 130-47. Presented at EURO 2015 Conference, Glasgow.

environments. As of September 2014, idle capacity for container ships has dropped to 1.3 % of total fleet (vs. 3.9 % in September 2013). However, with the start of the winter period, more empty sailings are expected to occur and the amount of idle capacity is expected to increase (Alphaliner 2014d).

Figure 2.1: Analysis of time charter rates, new ordering and idle fleet



Sources: Alphaliner (2014c), Clarksons (2013b,c)

It can be argued that under- and over-supply situations occur frequently in shipping markets due to non-optimal investment timing. For example, the boom years from 2001 to 2008, when daily earnings increased strongly, led to supply demand imbalances in the 2009 recession (Syriopoulos 2010). One reason for non-optimal investment timing is shortcomings in current methods to evaluate sea freight capacity investments; for example, current Discounted Cash Flow (DCF) methodologies do not capture flexibility in investment timing. Non-optimal investment timing and sizing has resulted in strong growth in the capacity market (Bendall 2010). At the end of 2013, there were 5,115 container vessels (+4.9 % p.a. since 1999) with an average capacity of 3,349 TEU (+5.0 % p.a. since 1999) (Clarksons 2013c).

In contrast to the bulk shipping market, which is characterized by perfect competition (Pirrong 1992), container shipping is much more concentrated: the top 10 operators control more than 60 % of worldwide TEU capacity (Alphaliner 2014g). Hence, the actions of single companies do matter in terms of price and market share. Moreover, price adjustments (up and down) are not always in line with supply-demand fundamentals; at the same time, the price elasticity of long-distance container shipping demand is very low since no substitutes are available at a comparable cost.

2.1.2 Investment decisions in shipping

Investment decisions in shipping are driven by a number of factors. On the one hand, the true intrinsic value of a project - based on time charter or freight rate earnings and lifetime of a ship, along with potential embedded real options - is

relevant and drives decisions. On the other hand, factors such as fuel efficiency, network considerations, sources of funding, regulation, vessel sizes, and asset prices also play an important role.

First, new generations of ships offer substantial fuel savings of up to 30 % which mostly benefit the carriers. Hence, substantial operational cost advantages allow carriers to replace ships earlier and to gain a competitive advantage from operating newer ships. Second, carriers serve customers in networks. For example, the CMA CGM "French Asia Line 16" runs from Kaohsiung via Shanghai, Tanjung Pelepas, and other ports to Hamburg. The 13,800 TEU ships sail on a published weekly schedule and need 57 days for a round trip. The 10 vessels associated with the string are operated by CMA CGM's strategic partner Evergreen (CMA-CGM 2014). This means that a minimum number of ships needs to be deployed to serve a network string; it also means that, in case of vessel sharing agreements or alliance membership, investment decisions need to be aligned with strategic partners. Third, since the financial crisis and bankruptcies of shipping funds, sources of financing have changed. KG funding (closed-end shipping funds in Germany) is almost nonexistent and large shipping banks are reducing exposure; this makes financing vessel purchases more difficult and forces ship buyers to rely more on equity and debt capital markets as well as private equity investment. Fourth, substantial regulatory changes are expected: ballast water, air pollution, and overall CO₂ targets are expected to change in the decades to come, calling for retrofitting and new investment. Fifth, in terms of vessel sizes, the Panama canal expansion, the building of the Nicaragua canal and increased port sizes around the world are changing size requirements. This will favor investment into larger ships, while Panamax ships (4,000-5,099 TEU, about 20 % of total capacity) will be increasingly scrapped. Currently, one of the largest container ship designs is the Maersk Triple E class with a capacity of 18,340 TEU. These very large ships are optimized for slow steaming and provide significant fuel efficiency savings - when fully utilized. They are deployed on Asia-Europe routes since the volumes are sufficient and their size still allows them to cross the Suez Canal. Finally, new and secondary market prices are currently at historic lows and drive vessel purchases contrary to supply-demand fundamentals (expert interviews conducted in 2013 and 2014, Alphaliner (2013b, 2014g), Clarksons (2013a)).

2.1.3 *Research questions*

The objective of this paper is to develop a real options investment model in oligopolistic competition to evaluate investment decisions in shipping. The research questions that guide this research are:

- Under what conditions is strategic behavior in the container shipping industry beneficial?
- What is the optimal capacity in an oligopolistic shipping market and how is it influenced by factors such as competitive intensity, number of competitors, freight rate volatility, fuel efficiency, lead time, and variable cost?

- What are optimal policies for undertaking investments in the container shipping industry over time?

The structure of the paper is as follows. Section 2.2 reviews existing real options literature on maritime investment and oligopoly models and details the contribution of this research. Section 2.3 introduces a continuous-time model and shows general insights. Section 2.4 presents the detailed, discrete-time model and shows results. Section 2.5 is a discussion of managerial implications from the model results and Section 2.6 concludes the paper as well as suggests areas of future research.

2.2 LITERATURE REVIEW

The DCF methodology has been considered the standard approach to maritime investment appraisal (Evans 1984, Gardner et al. 1984). However, since there is substantial freight rate volatility as well as a need to capture the value of managerial flexibility, we choose to apply Real Options Analysis (ROA) in this paper. Several contributions to maritime shipping (Bendall and Stent 2003, Bendall 2010, Bendall and Stent 2005, 2007, Dixit and Pindyck 1994, Goncalves 1992) have successfully applied ROA to liner and bulk shipping investment problems. The motivation is that the nature of shipping investment decisions - irreversibility of investment, uncertainty about future cash flows, and managerial flexibility - can be represented more accurately in a ROA context. We hence outline literature on real options application to shipping as well as on real options in game-theoretic oligopoly.

There are a number of related, very interesting approaches to shipping investment and deployment decisions. From a more macro-level perspective, Alizadeh and Nomikos (2007) look at shipping investment strategies on the basis of trading rules and fundamental analysis. They find that, especially for bigger used ships, strategies based on earnings-price ratios perform better than buy and hold strategies. A similar approach is taken by Cullinane (1995) who applies financial market concepts (Markowitz portfolio theory) to dry bulk shipping. He finds that shipping investment analysis should take a portfolio perspective and incorporate the respective risk measures. From a more micro-level perspective, Mossin (1968) derives a decision rule with respect to when vessels should be put into layup or put back into operation. Under the assumption of stationary, stochastic revenues, the author derives critical freight rate values that depend on cost of operation, cost of layup, and switching cost. Ng (2015) studies the actual vessel deployment decision of carriers in light of demand uncertainty. The model considers dependencies between shipping demands on different routes.

2.2.1 *Real options application to shipping*

One of the first applications of real options to a shipping investment problem is presented by Goncalves (1992). Goncalves (1992) shows a methodology for real options valuation in the bulk shipping industry, which is considered to be characterized by perfect competition, and uses both a continuous-time

and a discrete-time model to derive optimal chartering investment policies for shipowners. Dixit and Pindyck (1994) build upon that and apply real options theory for entry and exit decisions in the tanker industry.

Bendall and Stent (2003) introduce a real options framework to evaluate the additional value of flexibility in a capacity expansion decision at a shipping company. The authors later extend their 2001 short sea shipping model (Bendall and Stent 2001) to capture the flexibility of the real options inherent in the shipping operations. They model a two-port feeder service with four vessels which has the option to buy a fifth ship. Using both DCF and real options models, they show how real options analysis can capture the additional flexibility of the shipping operations, i.e., the option to charter the fifth ship out in case the market deteriorates (Bendall and Stent 2005). In a later step, Bendall and Stent (2007) assess the value of a portfolio of real options and find that a higher volatility of underlying projects increases real options values, that a higher number of alternative strategies increases the value added of the options, and that the higher the correlation between the underlying assets, the less net value is added by a single option in the portfolio.

Pires et al. (2012) apply the concept of real options to the valuation of an abandonment option, answering the question of whether to own or charter a vessel. Dikos (2008) creates an equilibrium model covering aggregate investment behavior in the tanker new building market and proves the validity of the "option value multiple" hypothesis, i.e. that the real options value of an investment project is an adequate statistic to describe aggregate investment decisions. Further Dikos and Thomakos (2012) empirically show that investors in oil tanker capacity systematically assign value in waiting. Jørgensen and De Giovanni (2010) present a valuation method for different styles of time charter contracts with purchase options, so-called TC-POPs. They propose a single-factor continuous-time model on which the spot freight rate is the only source of uncertainty. Based on this model they apply contingent claims valuation to price TC-POPs of European, American, and Bermudan style by deducting either closed-form valuation formulas or, for the more complex option styles, by applying numerical methods.

2.2.2 *Real options in game-theoretic oligopoly*

Chevalier-Roignant et al. (2011) synthesize strategic investment under uncertainty and provide a comprehensive overview of relevant real options models. They subdivide the research streams into lumpy investment decisions, incremental capacity expansion, and complex investment decisions under uncertainty and competition. In terms of modeling competitive activity, the authors point out that - when it comes to explaining the incentives of firms facing market entry decisions - game-theoretic, endogenous approaches are more appropriate than models that assume anticipated or random Poisson arrivals of competitors. Azevedo and Paxson (2014) provide an overview of the evolution of real option game models. They argue that while many problems have been addressed with real options games, there is a need for consideration of multiple sources of uncertainty. Further, they suggest - in an effort to avoid overcomplex-

ity - a distinction between micro (from company perspective) and macro (from policy maker perspective) level models.

With regards to game theory in real options investment, Williams (1993) develops a game-theoretic model for more than two players and derives a Nash equilibrium for real estate investment. He finds that - with increasing competition - options are exercised earlier. Leahy (1993) shows that the introduction of competition into irreversible investment models does not necessarily affect the timing. He shows that a myopic firm faces the same investment trigger as a firm that correctly anticipates competitive action; however, the size of the investment will be different. Baldursson (1998) develops a game-theoretic real options investment model to study the price of a perishable commodity in an oligopolistic industry. He considers different initial sizes of firms and provides a numerical solution. Grenadier (2002) is one of the first to present a real options investment model with an in-depth analysis of competitive action. The author finds that competition has a significant impact on a firm's exercise strategies, since a higher degree of competition leads firms to invest earlier because of fear of pre-emption. Hence, the value of the option to wait in a real options framework decreases when there are more competitors in the model. Gkochari (2015) estimates the competitive dynamic equilibrium in the dry bulk shipping market on the basis of the Grenadier (2002) model and finds that a reduction of order lead time reduces the investment trigger value.

Aguerrevere (2003) extends the aforementioned model of irreversible investment (Grenadier 2002) by introducing a utilization factor and allowing firms to handle their usage of the assets in a flexible way, i.e., units of capacity can be shut down at no cost. Additionally, he considers variable cost. He finds that more uncertainty as well as increasing construction lags incentivize firms to install more capacity. Moreover, he discovers that firms might invest in additional capacity even if their current assets are underutilized. Based on this previous work, Aguerrevere (2009) uses a real options model to explain how companies' investment decisions impact their asset returns. He finds that the asset returns of firms in competitive industries are more volatile in low demand scenarios, while firms in markets with a higher concentration will have riskier returns with high demand. In his explanation, this divergence results from the effects of competition on the value of growth options. Armada et al. (2011) develop a model that consists of strategic players and hidden competitors. The strategic players are in a leader-follower setting while the hidden rivals increase the level of competition in the market. The authors find that the presence of hidden rivals has a significant impact on value functions and optimal triggers of the strategic players. Ruiz-Aliseda and Wu (2012) model entry and exit decisions in cyclical markets and show how entry and exit patterns are different from those obtained by the assumption of a geometric Brownian motion. An application of this model to the shipping context can be found in Balliauw (2015).

2.2.3 *Research contributions*

Our research can be positioned at the intersection of two well developed streams in the literature which we outline in the previous Subsections. On the one

hand, there is real options theory in (container) shipping where either the assumption of perfect competition needs to be made or competitive interaction is modeled via random Poisson arrival. On the other hand, there is a research stream related to real options investment models in oligopolistic competition in related industries, such as real estate or bulk shipping. The key differences between bulk and container shipping are that for liner shipping, demand is infinitely divisible (to the size of single containers) and carriers adhere to published schedules, hence the assumption of perfect competition does not hold. For bulk shipping, demand is indivisible and the market is more competitive (Pirrong 1992).

Our work is partially in response to Chevalier-Roignant et al. (2011) who call for research efforts based on discrete-time approaches that allow to better take into account industry characteristics. This is particularly important since investment decisions in the container shipping industry are driven by a number of unique characteristics such as oligopolistic competition with an endogenous price function, regulation and fuel efficiency, endogenous lead times as well as correlated secondary markets. Those factors are currently not captured well by established investment appraisal methods. The assumption of oligopolistic competition (as opposed to perfect competition) is of paramount importance because it introduces strategic action into the framework (an individual player can actually influence price formation with capacity decisions). Fuel efficiency impact is of high importance due to two reasons: regulatory uncertainty and bunker fuel considerations. While the former is driven by CO₂ targets and IMO regulations in the next decades, bunker fuel cost are likely to impact running costs of container shipping carriers already today. Finally, the different shipping markets are correlated, i.e. production lead times for new vessels tend to increase in times of high order pipelines, and secondary market prices decrease in times of low freight rates.

We thus argue that the design of a novel modeling framework for investment in the container shipping industry is necessary, especially since this framework allows us to take into account oligopolistic competition as well as address container shipping industry specifics (endogenous price function, fuel-efficient investment alternatives, endogenous lead times, endogenous price formation in the secondary market for ships). The necessity for a fresh look at container shipping investment has been also pointed out by Lau et al. (2013) who call for increased research efforts to explain and counter excess capacity and persistent overinvestment.

Based on this gap in research, we contribute a better understanding of the investment dynamics in the container shipping industry by drawing on two real options investment models: one approach in continuous-time and one approach in discrete time. The continuous-time approach extends previous research by incorporating variable cost in the investment trigger and allows us to generate insights on optimal investment timing under the assumption of order lead times. It further allows to compare different scenarios of competitive intensity, number of players, volatility, and variable cost. Our discrete-time approach is the first to combine an endogenous oligopoly price function, fuel-efficient investment alternatives, endogenous lead times as well as an endogenous secondary market for ships.

Our valuation framework for the container shipping industry permits us to perform the following analyses: first, we test whether strategic action (as opposed to being a myopic player²) increases firm value. Second, we study in detail how competitive intensity, variable cost, and different fuel efficiency rates impact optimal capacities and respective investment timing. Third, we assess to what extent fuel-efficient investment is beneficial in different market scenarios and how it relates to retrofitting.

2.3 CONTINUOUS-TIME MODEL

By making a number of assumptions (e.g. infinitely divisible output, endogenous price function) it is possible to derive first insights into the investment decision in shipping in continuous-time; especially with respect to the impact of number of firms, competitive intensity, variable cost, and volatility on the investment trigger (and, hence the timing of investment).

Continuous-time investment models have been developed in the bulk shipping context by Goncalves (1992) and Gkochari (2015). The approach taken by Gkochari (2015) builds on Baldursson (1998), Grenadier (2002), and Leahy (1993), uses the real options approach to investment under uncertainty and has been used to prove the approach's validity for bulk shipping. The disadvantage of the continuous-time approach is that in order to retain a closed-form investment trigger solution, the number of extensions and considerations of specific shipping industry characteristics is limited. A discrete-time approach allows to incorporate shipping industry characteristics such as fuel efficiency, layup pool, divestment including a secondary market, and endogenous lead time in a straightforward manner.

Our objective is to explore both approaches. Since the continuous-time approach has been extensively studied by Gkochari (2015), we introduce the approach and derive implications for our research questions, especially with regards to the changes of the investment trigger with respect to different levels of competition, variable cost, and volatility. In a second step we formulate an investment model in discrete time and solve it via Dynamic Programming. The exploration of both approaches allows us to derive synthesized managerial recommendations from two modeling perspectives.

Due to oligopolistic competition, the payoff from option exercise is endogenous, hence the starting point is an endogenous price process which is driven by a Geometric Brownian Motion (GBM) $X(t)$ and the industry supply $Q(t) = \sum_{i=1}^n q_i(t)$; defined as

$$p(t) = X(t)Q(t)^{-\frac{1}{\gamma}}, \quad (2.1)$$

where γ is the elasticity parameter, n is the number of players and q_i is the capacity of an individual player.

Under the assumption of infinitely divisible output and full capacity utilization, it is possible to derive a firm value in Nash equilibrium. This means that

²According to Leahy (1993), a myopic firm will assume that the industry capital stock remains fixed forever. It will only optimize within its own action and state space based on its own Bellman equation.

each firm chooses its output process to maximize its value given the strategies of competitors. As a consequence of the myopic firm principle³ (Leahy 1993) it is possible to simplify accordingly. The optimal policy can be shown to be a trigger policy (Grenadier 2002). To introduce lead time into the model, we need to define committed capacity as $Q(t) = C(t) + N(t)$, where $C(t)$ is current installed capacity and $N(t)$ is the capacity under construction. Applying a demand curve transformation to satisfy the oligopoly assumptions the investment trigger becomes

$$X^* = v_\kappa e^{(r-\mu)\kappa} Q^{\frac{1}{\gamma}}, \quad (2.2)$$

where κ is the lead time, Q denotes total industry capacity, γ is the competitive intensity, μ is the drift term of the geometric Brownian motion and r is the risk-free rate. The term v_κ is given by

$$v_\kappa = \left[\left(\frac{\beta}{\beta-1} \right) \left(\frac{n\gamma}{n\gamma-1} \right) (r-\mu) \left(\eta + c e^{-r\kappa} \frac{1}{r} \right) \right], \quad (2.3)$$

where β is the fundamental quadratic, n is the number of players, η are investment cost and c is the variable cost component. The optimal policy is given by the investment trigger, hence we deem it insightful to find the first order derivations of the trigger with respect to elasticity γ , number of players n , volatility σ , and variable cost c . We find that the investment trigger decreases with a higher number of firms but increases with increasing competitive intensity, increasing variable cost, and increasing volatility (Appendix A.1).

2.4 DISCRETE-TIME MODEL

2.4.1 Model assumptions

In the following paragraphs we describe the discrete-time model assumptions in detail. Please refer to Table 2.1 for a full list of parameter values.

Market regime and capacity

In the discrete-time model we assume that three firms interact in a strategic oligopoly to allow for computational efficiency. From a practical perspective, this can be considered a focus on the top three container operators in the market: APM-Maersk, MSC, and CMA-CGM. They achieve a 37.1 % combined market share (Alphaliner 2014g). Industry capacity Q is defined as the sum of the 3 firms' individual capacities q_1, q_2, q_3 in TEU terms. We assume an average ship size of 12,000 TEU; for calculation of cash flows we assume that one ship's capacity can be sold every two months, i.e. implementing a round-trip time of 60 days. We allow for a capacity bandwidth between three and ten vessels per player in the market model. We refer to Cullinane and Khanna (1999) for an account of economies of scale and variable cost. They show that for

³Leahy (1993) shows that the introduction of competition into irreversible investment models does not necessarily affect the timing. He shows that a myopic firm faces the same investment trigger as a firm with correct anticipation of competitive action, however, the extent of the investment will be different.

larger ships 300 USD per TEU can be assumed on the Europe-Far East market. Since we choose to look at round trip voyages, we assume variable cost of 600 USD including backhaul.

Table 2.1: Discrete-time model assumptions

Parameter	Value
Number of time periods	$T = 15$
Delivery interval	$\kappa = 6$ months
Volatility of underlying GBM	$\sigma = 0.3$
Drift of underlying GBM	$\mu = 0.05$
Time step	$dt = 1/6$ years
Starting freight rate	$p = 1,500$ USD
Interest rate	$r = 0.1$
Gross Domestic Product (GDP) factor	$\omega = 1.1$
GDP expectation	$G = 1.04$
Variable cost	$c = 600$ USD
Layup cost	$c_l = 240$ USD
Investment cost conventional	$\eta_{conv} = 70m$ USD
Investment cost fuel efficient	$\eta_{fe} = 80m$ USD
Scrap value of divestment function	$B = 8m$ USD
Midpoint of divestment function	$p_0 = 1,500$ USD
Ceiling of divestment function	$D = 32m$ USD
Steepness of divestment function	$k = 0.01$
Fuel efficiency gain	$\epsilon = 0.3$

Price function

The players in the market are subject to an endogenous, constant-elasticity price function $p(t) = XQ^{-\frac{1}{\gamma}}\omega G$, that depends on the capacity deployed in the market Q (assuming an elasticity factor γ), a random shock term X , a GDP factor ω , and the GDP expectation G . As a starting point, we assume an all-in rate of $p = 1,500$ USD per TEU including backhaul⁴. Container shipping lines can only change capacity in the long run, due to published schedules. Hence, lines strive to fill their capacity even if they have to offer substantial discounts. During an economic downturn (low GDP expectation), this leads to enormous pressure on prices, which can translate into operational losses (Fakhr-Eldin and Notteboom 2012). The random shock term is governed by a geometric Brownian motion (drift, interest rate, and volatility are detailed in Table 2.1); this is in line with previous shipping industry-related work by Adland and Cullinane (2006), Adland and Strandenes (2007), Bendall and Stent (2005, 2007), Gkochari (2015),

⁴We refer to the SCFI (SSE 2016). Its long-run headhaul average is about 1,000 USD, we assume that 50 percent of the rate can be achieved on backhaul, hence all-in rate of 1,500 USD.

Goncalves (1992), Koekebakker et al. (2007), Sødal et al. (2008). Possible alternatives are geometric mean reversion (Tvedt 1997, 2003), the Ornstein-Uhlenbeck process (Bjerksund and Ekern 1995), or the assumption of stochastically cyclical markets (Balliauw 2015, Ruiz-Aliseda and Wu 2012). Note that a positive drift in the GBM is an assumption from a long-term perspective; a full calibration to the past five years of freight or time charter rates could also justify a zero percent drift assumption. We have tested our model with a zero percent drift assumption and find consistent firm value and policy results, albeit results in absolute terms are lower due to the more pessimistic GBM assumption. We further assume that GDP expectations have a linear impact on the freight rate given by parameters G and ω .

Information asymmetry

In the strategic oligopoly, we assume that current installed capacity is known to all market participants since this information is widely available through information providers such as Alphaliner or Clarksons Shipping Intelligence Network. We assume that order pipeline and idle capacity are private information. This is somewhat of an abstraction from reality since some information providers publish order books and track idle fleet. However, for simplicity and since carriers can better control information dissemination for these items (e.g. financing structure through private equity), we choose to keep it private.

Investment

We further assume that there is an investment opportunity to buy either fuel efficient or conventional vessels. The purchase of a fuel efficient vessel will be associated with an investment cost markup and an operating cost benefit (30 percent). For example, the UASC paid a 10 % markup on vessels with the ability to burn liquefied natural gas (Alphaliner 2013d). Fuel efficient ships are so-called "eco-ships" with newer engines, improved hull design and innovative coatings (Lomar 2012, Notteboom and Cariou 2009, Visser 2011). These features can lead to combined fuel savings of up to 30 % at 18 knots steaming speed (Bergmann 2012, Hoifodt 2011). Conventional investment can refer to ships of older design or simply to used assets that do not provide the fuel efficiency savings. In this calibration, we assume a purchase price of 70 million USD for conventional vessels and 80 million USD for fuel-efficient vessels. We assume that buying in larger quantities will lead to a discount on all units purchased, i.e. a 10 or 30 percent discount for 2 or 3 ships, respectively.

Lead time

In order to model the delivery time of roughly 1.5 years (Alphaliner 2014e), we assume that one third of the outstanding order pipeline will be delivered every six months. Since, in reality, the lead time is endogenous and depends on the orderbook (Adland and Strandenes 2007), we implement delivery delays in case the order pipeline of a single player exceeds 8 vessels.

Layup and divestment

We assume that vessels can be put into layup. The carrier will incur layup cost which are a share of the variable cost (40 percent). Those laid up units can also be sold in a secondary market which is dependent on the freight rate. We express the functional relationship by a sigmoid function

$$\lambda = \frac{D}{1 + e^{-k(p-p_0)}} + B \quad (2.4)$$

where B is the scrap value (8 million USD), the sum of D and B is the maximum attainable secondary market value (40 million USD), p is the current freight rate in USD per TEU, p₀ defines the midpoint of the function (1,500 USD per TEU) and k = 0.01 is the steepness of the curve. The intuition here is that since freight rates and asset prices are correlated, sales prices in tough market environments will be under strong pressure (Luo and Fan 2011).

2.4.2 *Model formulation*

The discrete-time model evaluates the actions of three strategic firms. The model considers 15 time increments (each represents 2 months) with a salvage value which assumes that operations will remain unchanged forever, assuming discounting. Thus, once every 2 months investment decisions are made on the basis of the prevailing freight rate expectations. This is plausible since from a charter perspective, a two-month contract is normally the shortest duration possible. Due to the dimensionality of the model, we restrict the analysis to 2.5 years. The focus of our analysis is the optimal investment policy and its impact via delivery of units on capacity and firm values. Since we can observe decision and delivery within 18 months, we argue that the analysis time window of 2.5 years is sufficient.

Figure 2.2 illustrates the model setup. This covers all eight dimensions of the real options tree, a summary of the profit functions, a graphical representation of the optimal policy Nash equilibrium as well as the recursive dynamic programming equations.

Every period, each of the firms observes the random shock term which is governed by a geometric Brownian motion. The state update for the demand shock shall be approximated with a binomial, discrete-time process based on the options valuation logic by Cox et al. (1979) (for details, refer to Appendix A.2). We choose a discrete-time approach for modeling the stochastic underlying since the continuous-time approach introduced in the previous chapter cannot accommodate all the necessary characteristics of the investment opportunities. A Monte Carlo option pricing model as introduced by Boyle (1977) would be a valid alternative, since it would provide us with even more flexibility with regards to design of the investment decision; however, in this case we would consider the additional computation time needed not worth the additional flexibility. The salvage value is defined as the perpetuity of operating income

$$J_{1T}(X, q_1, q_2, q_3, L_1, P_{conv1}, P_{fe1}, f) = \frac{\pi_{ops} - \pi_{layup}}{r - \mu} \quad (2.5)$$

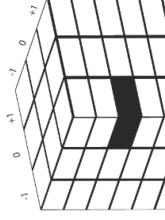
Figure 2.2: Model formulation

(1) Build up 8-dimensional tree

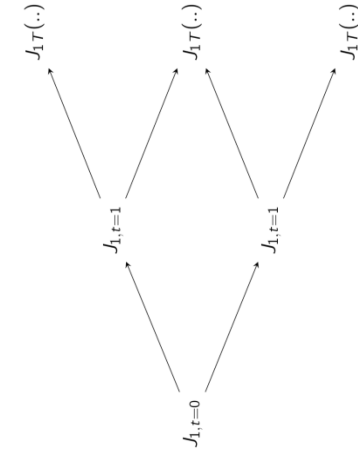
q_1, q_2, q_3	Number of ships for firms 1,2,3
f	Number of fuel-efficient vessels
X	Shock term governed by GBM $X_{t+1} = pX_t u + (1-p)X_t d$ with $u = e^{\sigma\sqrt{\Delta t}}$, $d = e^{-\sigma\sqrt{\Delta t}}$, $ud = 1$ and $p = \frac{e^{r\Delta t} - d}{u - d}$
L_1	Layup pool $L_t = L_{t-1} + \frac{P_{conv_{t-1}} + P_{fe_{t-1}}}{3}$, $\forall t = 6, 12, 18$
P_{conv_1}	Conventional pipeline $P_{conv_t} = P_{conv_{t-1}} - \frac{P_{conv_{t-1}}}{3}$, $\forall t = 6, 12, 18$
P_{fe_1}	Fuel-efficient pipeline $P_{fe_t} = P_{fe_{t-1}} - \frac{P_{fe_{t-1}}}{3}$, $\forall t = 6, 12, 18$

(2) Calculate profits

Profit operations	$\pi_{ops_1} = q_1(XQ^{-\frac{1}{7}}\omega G - \max(q_1 - f, 0)c_1 - \min(f, q_1)c_1(1 - \epsilon))$
Layup cost	$\pi_{layup_1} = (L_t + I_{layup_1})c_l$
Investment cost	$\pi_{inv_1} = \eta_{conv}\theta I_{P_{conv_1}} + \eta_{fe}\theta I_{P_{fe_1}}$
Divestment cost	$\pi_{div_1} = -\min(\lambda I_{cap_1}, 0)$

(3) Find optimal policy

- Profit calculation for 10 strategies given observable competitive action
- Identification of Nash equilibrium
- Derivation of optimal strategy's impact on capacity, layup pool, and pipelines $I_{cap}, I_{layup}, I_{P_{conv}}, I_{P_{fe}}$

(4) Solve by recursive dynamic programming**Salvage value**

$$J_{1,T}(X, q_1, q_2, q_3, L_1, P_{conv_1}, P_{fe_1}, f) = \frac{\pi_{ops} - \pi_{layup}}{r - \mu}$$

Bellman equation

$$J_{1,t}(X, q_1, q_2, q_3, L_1, P_{conv_1}, P_{fe_1}, f) = \max_{I_{cap}, I_{layup}, I_{P_{conv}}, I_{P_{fe}}} \mathbb{E} \left[\pi_{ops_1} - \pi_{layup_1} - \pi_{inv_1} + \pi_{div_1} + \alpha J_{1,t+1}(X, q_1, q_2, q_3, L_1, P_{conv_1}, P_{fe_1}, f) \right]$$

where L is the current Layup pool, P is the current pipeline, f the number of fuel efficient ships, π_{ops} the operating profit and π_{layup} the layup cost.

Each firm observes its current capacity and it knows its current layup pool and pipeline which can be impacted by deliveries of outstanding orders. The firm has the potential to order either conventional or fuel efficient vessels. Delivery occurs every six months while always one third of the capacity on order is delivered and automatically put into layup (from where it can be put into service). The current conventional vessel pipeline P_{conv_t} , fuel efficient vessel pipeline P_{fe_t} , and layup pool L_t are hence defined by

$$P_{conv_t} = P_{conv_{t-1}} - \frac{P_{conv_{t-1}}}{3}, \forall t = 6, 12, 18 \quad (2.6)$$

$$P_{fe_t} = P_{fe_{t-1}} - \frac{P_{fe_{t-1}}}{3}, \forall t = 6, 12, 18 \quad (2.7)$$

$$L_t = L_{t-1} + \frac{P_{conv_{t-1}} + P_{fe_{t-1}}}{3}, \forall t = 6, 12, 18, \quad (2.8)$$

subject to constraints set by the model, such as maximum allowable layup capacity and delivery delays dependent on the order pipeline. Each firm then has the choice of ten different courses of action given the actions of the competition (Table A.1). The resulting profit function for each period translates into the following Bellman equation

$$\begin{aligned} J_{1_t}(X, q_1, q_2, q_3, L_1, P_{conv_1}, P_{fe_1}, f) = \\ \max_{I_{cap}, I_{layup}, I_{P_{conv}}, I_{P_{fe}}} \mathbb{E} \left[\pi_{ops_1} - \pi_{layup_1} - \pi_{inv_1} + \pi_{div_1} \right. \\ \left. + \alpha J_{1_{t+1}}(X, q_1, q_2, q_3, L_1, P_{conv_1}, P_{fe_1}, f) \right] \end{aligned} \quad (2.9)$$

where α is the period discount factor, I is the decision variable, and I_{cap} , I_{layup} , $I_{P_{conv}}$ and $I_{P_{fe}}$ define its impact on current capacity, layup pool and the two order pipelines, respectively. π_{inv} and π_{div} denote in- and outflows from investment and divestment, respectively. Profit from operations is given by

$$\pi_{ops_1} = q_1(XQ^{-\frac{1}{\gamma}}\omega G - \max(q_1 - f, 0)c_1 - \min(f, q_1)c_1(1 - \epsilon)) \quad (2.10)$$

with $Q = q_1 + q_2 + q_3$, $q_1 = q_{1_{t-1}} + I_{cap_1}$, $q_2 = q_{2_{t-1}} + D_2$ and $q_3 = q_{3_{t-1}} + D_3$ where D_2 and D_3 stand for possible capacity decisions of firms 2 and 3, namely add one unit (+1), do nothing (0) or sell one unit (-1). The number of active fuel efficient ships is defined by f and the fuel efficiency gain in operating cost is given by ϵ . Layup cost is defined as

$$\pi_{layup_1} = (L_t + I_{layup_1})c_l \quad (2.11)$$

where c_l is the cost of having one unit in the layup pool during one time period. Investment cost are defined as

$$\pi_{inv_1} = \eta_{conv}\theta I_{P_{conv_1}} + \eta_{fe}\theta I_{P_{fe_1}} \quad (2.12)$$

with purchasing price η dependent on whether a vessel is fuel efficient and θ as a factor that considers economies of scale in purchasing vessels. Divestment costs depend on the proceeds from sales of units λ in the secondary market given by the Sigmoid function in Equation (2.4) and are defined as

$$\pi_{div_1} = -\min(\lambda I_{cap_1}, 0). \tag{2.13}$$

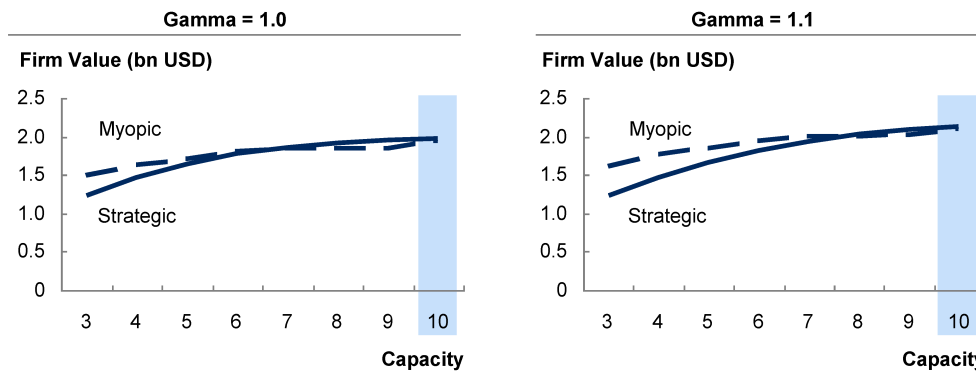
Technically, the discrete-time model is implemented in Matlab using backward induction. Every time period, the value of all ten strategies is calculated given the competitive action that can be observed, namely addition, removal, or keeping of capacity. The resulting Nash equilibrium is identified within a three-dimensional investment game and then applied to the detailed strategies of each firm. The firm values as well as the resulting optimal policies are stored in an array for every period.

The strategic firm 3 can be defined to be a myopic firm. In this case, the firm will assume that the industry capital stock remains fixed forever. It will only optimize within its own action and state space based on its own Bellman equation (Leahy 1993). We, however, derive the resulting payoffs in the competitive equilibrium separately.

2.4.3 Strategic vs. myopic behavior

Based on Leahy (1993) a myopic firm is defined as a player that assumes industry capital stock to be fixed forever. Naturally, the myopic player’s objective function will not be impacted by competitive investment. Hence, we find that the myopic player’s perceived firm value is monotonically increasing in capacity installed, that is the player would always want to increase capacity irrespective of competitive action.

Figure 2.3: Firm value in oligopoly (3 players) vs. duopoly + myopic firm



If we derive the resulting payoffs, however, depending on the capacity, the two players perform differently (Figure 2.3). At $\gamma = 1.0$ and an optimal capacity of 10 units, the strategic firm will be valued higher. The myopic firm’s better performance in cases below optimal capacity is a consequence of the myopic player’s constant desire to increase capacity in contrast to the strategic nature of the other players. Hence, if from an economical perspective a strong increase

of capacity is necessary, complete ignorance of competitive action leads to a slightly faster capacity adjustment. If competitive intensity is lower, i.e. $\gamma = 1.1$, we see a similar effect. We conclude that strategic action pays off as long as firms operate near optimal capacity.

2.4.4 *Impact of competition: intensity and number of players*

We consider competition from two perspectives: the intensity (or elasticity) γ and the number of players n . The demand elasticity γ has a substantial impact on the propensity to invest. The price function is defined as $p(t) = X(t)Q(t)^{-\frac{1}{\gamma}}\omega G(t)$, hence it is a constant-elasticity demand function. If additional investment has a too strong negative effect on the price, firms will choose not to undertake investment at all.

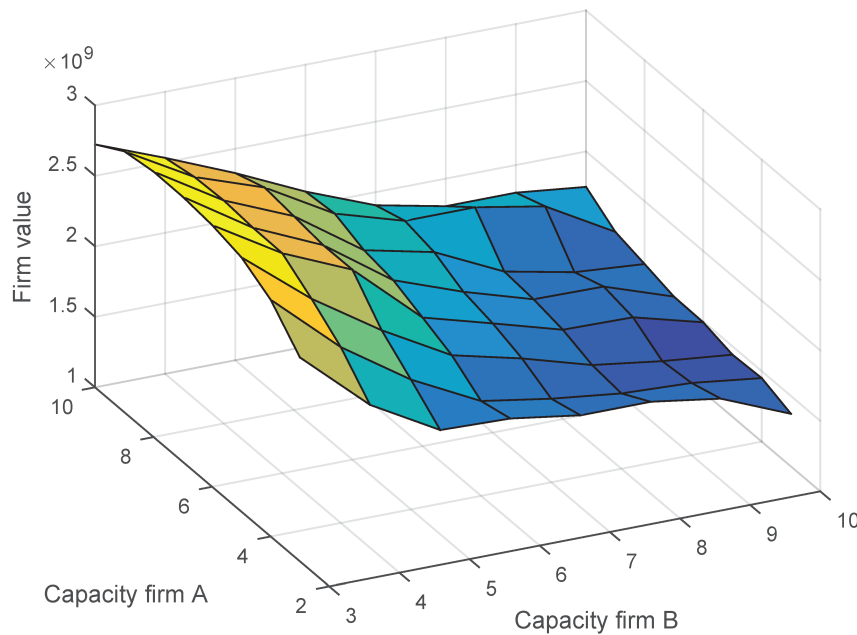
In previous literature, we find a relatively broad bandwidth of γ values in constant elasticity inverse demand models. In an analysis of economies of scale in an imperfect competition setting, Perry (1984) uses elasticity values between 0.5 and 2.0. In an analysis of road pricing, Santos et al. (2000) work with elasticities between 0.2 and 0.7. In his time-to-build real options model, Grenadier (2000) uses an elasticity value of 1.2 while in the option exercise games contribution, Grenadier (2002) uses an elasticity value of 1.5. In line with the mentioned work we have calibrated our model with values for γ between 1.0 and 1.4. Restricting the analysis to this range of parameter values allows us, additionally, to understand the differences with respect to Grenadier (2000) who uses $\gamma = 1.2$.

In order to check for anomalies in the results for different γ and σ combinations, we show the value of optimal capacity in Table A.2. We find that, for the most part, firm values are monotonically increasing in σ and γ . Hence, we illustrate that our calibration with γ values between 1.0 and 1.4 delivers consistent results within the volatility bounds.

We calibrate the discrete-time model with parameters set in Table 2.1. To derive implications regarding the impact of the number of players we study a number of market settings, namely monopoly, duopoly, 3-firm oligopoly as well as duopoly plus a myopic firm. For all regimes, a relevant capacity bandwidth between three and ten ships is assumed. We choose this bandwidth to achieve effective computation times while still being able to illustrate all relevant investment decisions and capacity evolutions in the state space of the model.

The main results for the discrete-time model are the solutions of the Bellman equation and optimal strategy maps given different evolutions of the stochastic shock term X . Figure 2.4 shows the duopoly value of firm 1 given different capacities of firm 2. In general, we find a plane that shows the highest firm values for a low firm 2 capacity. There is a maximum for firm 1 capacity (if firm 2 has 3 ships, it turns out to be 8 ships) which does not remain constant when increasing firm 2 capacity. From a graphical perspective, firm value decreases and optimal capacity increases when capacity of firm 2 increases. The optimal capacity for firm 1 (given firm 2 has 10 ships) is hence also 10 ships, because

Figure 2.4: Firm value of duopoly firm 1 given different capacities of firm 2



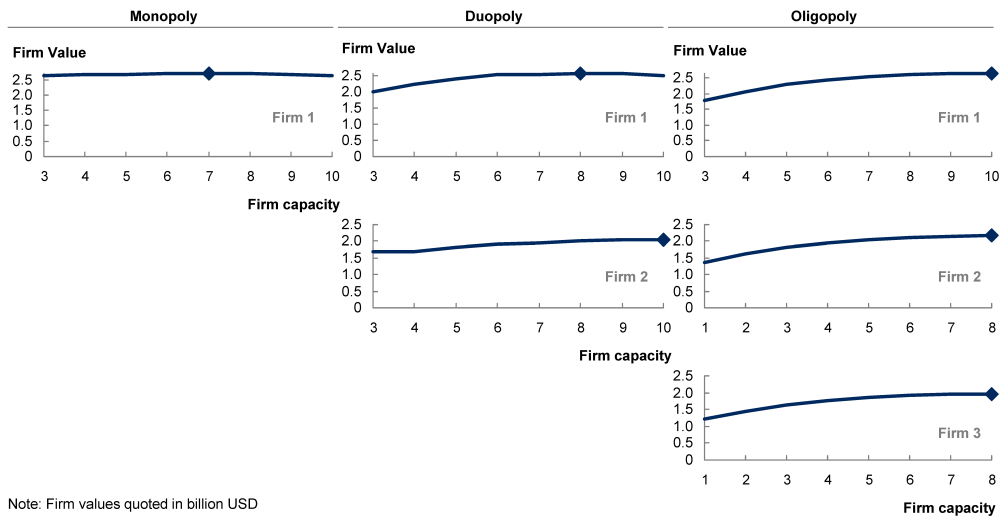
firm 2's higher capacity affects the industry price through the endogenous price function.

The discrete-time model illustrates that a higher number of competitors leads to higher optimal capacity. Figure 2.5 shows that when moving from a monopoly regime to a 3-firm oligopoly, optimal capacity rises substantially. For elasticity values of $\gamma = 1.0$ we find an optimal monopoly capacity of 7 ships, which corresponds to a firm value of 2.70. If we move into the duopoly regime with standard capacities of 6 and 4 ships for firm 1 and 2, respectively, we find that the optimal capacities are 8 and 10 ships and would be valued at 2.58 and 2.04. In the oligopoly case with standard capacities of 6, 4, and 3 ships the optimal capacities are always 10 ships with firm values of 2.64, 2.17, and 1.97. Even if we were to assume the lowest possible capacities, optimal capacities would sum up to 7 in the monopoly, 17 in the duopoly, and 27 in the oligopoly.

An analysis of the duopoly results for robustness with regards to investment cost and divestment revenue reveals that changes in these factors do affect the firm value results. Figure 2.6 shows the firm value for different sets of investment cost and divestment revenue. Apart from the base case calibration, we define a best case with 10 percent lower investment cost (and 10 percent lower divestment revenue factors B and D to ensure consistency). We further define two less favorable sets with 10 and 20 percent increase, respectively.

We find that the most favorable set (Set 1) leads to the highest firm value, albeit not statistically significant. Overall, the differences are not substantial, however, if we compare capacities and respective firm values at optimal capacity across the four sets. The intuition here is that a change in investment and divestment parameters may shift the firm's value function to higher or lower values but does impact optimal capacity only to a small extent. This leads us to conclude that the model is robust to changes in investment and divestment

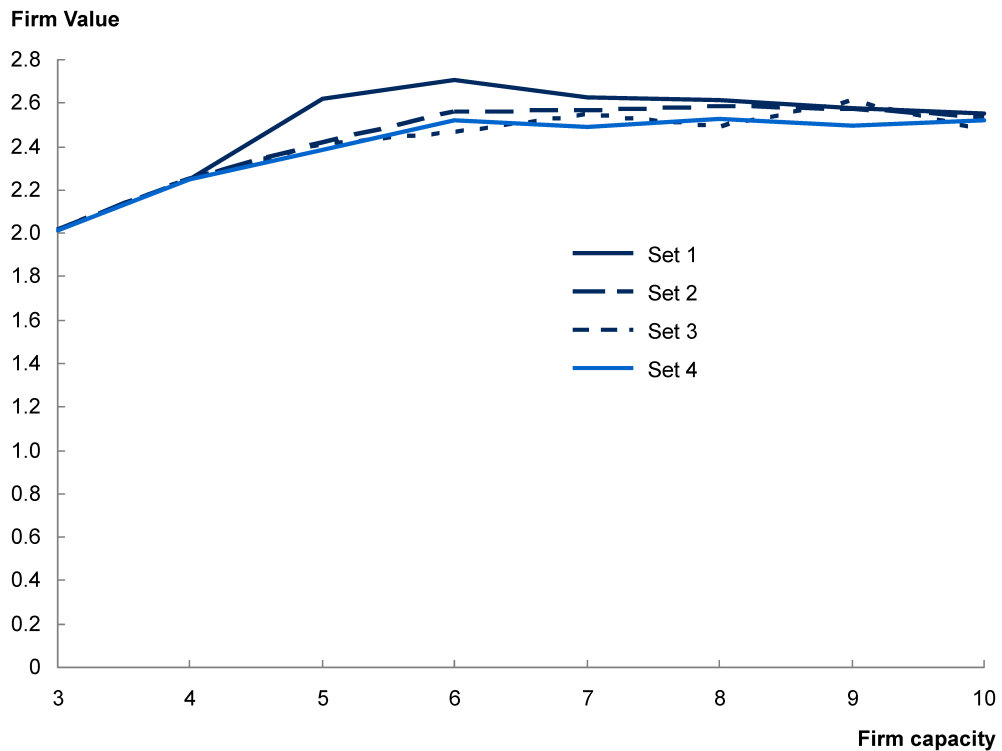
Figure 2.5: Firm values for different market settings at t=1



Note: Firm values quoted in billion USD

Calibration with $\gamma = 1.0$

Figure 2.6: Firm value of duopoly firm 1 for different investment cost and divestment revenue



Set 1, 2, 3, and 4: $\eta_{conv} = 63, 70, 77, 84$ m USD; $\eta_{fe} = 72, 80, 88, 96$ m USD; $B = 7.2, 8.0, 8.8, 9.6$ m USD; $D = 28.8, 32.0, 35.2, 38.4$ m USD

parameters. From Figure 2.6 we further learn that the slope of the value curves - even for varying investment and divestment parameters - is relatively flat and hence the penalty for misalignment (not acquiring the optimal capacity) is low, i.e. the average penalty for 1 ship deviation from optimal capacity amounts to 3.2 percent, 0.6 percent, 5.0 percent, and 1.4 percent, for Sets 1,2,3, and 4, respectively.

2.4.5 Duopolistic capacity and firm values

To capture the effect of changes in variables to the key results of the model, the optimal capacity and associated firm value, we employ a two-level factorial design based on Box et al. (2005). The output measures are the optimal capacity of firms 1 and 2, Y_1 and Y_2 , as well as the associated values F_1 and F_2 . The two firms have the same cost structure, but we derive the optimal capacity and value of firm 1 given that firm 2 has a capacity of 4 ships. For the values of firm 2 we assume a capacity of 6 ships at firm 1. The independent variables chosen are volatility X_σ ($\sigma_+ = 0.5, \sigma_- = 0.2$), fuel efficiency impact X_ϵ ($\epsilon_+ = 0.4, \epsilon_- = 0.2$), elasticity X_γ ($\gamma_+ = 1.1, \gamma_- = 1.0$) and variable cost X_c ($c_+ = 500, c_- = 700$). We choose a relatively narrow bandwidth of γ values since the impact of elasticity on the results is very strong. For higher γ values, the optimal capacity results would surpass the allowed capacity bandwidth of three to ten ships. Table A.3 shows the experimental matrix for the 2^n factorial design.

Given the different parameter settings, we find the optimal capacity and associated values of firms 1 and 2 for each of the 16 factorial model runs. It turns out that, due to relatively high variety, in some cases optimal capacity will reach ten, which is the capacity bandwidth constraint. We assume that the five highest order interactions (123, 124, 134, 234, 1234) are due to noise and use them as a reference set to derive the standard error. We adopt this logic from Box et al. (2005). The intuition here is the sparsity-of-effects principle. Using this principle, it can be argued that only main effects and low-order interactions have a significant impact on factorial design experiments. Hence, in experiments without a reference set, the highest-order interactions most likely have no explanatory power, but represent random noise. We can calculate the standard error by averaging the 5 squared highest-order interactions. The standard errors turn out to be $SE(Y_1) = 0.40$, $SE(Y_2) = 0.25$, $SE(F_1) = 24.72$ and $SE(F_2) = 24.98$ (firm values quoted in USD million). We perform a t-test at 90 % confidence level and five degrees of freedom. Table A.4 provides the estimated effects and the standard error for the four dependent variables σ (1), ϵ (2), γ (3) and c (4).

We find that higher volatility ($\sigma = 0.5$) increases optimal capacity and respective value for both firms, however, it is only statistically significant for Y_2, F_1 , and F_2 . For the fuel efficiency impact, the results with regards to optimal capacity and firm value are not significant. Assume a player that is at or near optimal capacity. The incentive to invest into fuel efficient capacity would be rather low, since additional investment would drive down prices by adding to industry capacity. If a player's current capacity, however, is significantly lower than the optimum, the fuel efficiency impact becomes more pronounced since

additional investment is worthwhile and even more profitable if fuel efficient capacity is chosen. This is why in the optimal strategy maps, fuel efficiency savings will actually drive the investment behavior of the players, especially if they are far away from the optimum. The impact of the elasticity γ is positive on capacities, hence a higher γ value leads to higher optimal capacity (statistically significant for Y_1). Directionally, higher γ values do also increase firm values, however, we cannot identify statistical significance (positive effect for F_1 , very close to zero for F_2). With regards to variable cost, we find that a more favorable variable cost position increases optimal capacity and increases the respective firm value with statistical significance.

In terms of combination effects, we find that high volatility in combination with higher fuel efficiency gains decreases optimal capacity for firm 2. We also find that high γ along with high volatility increases firm 1 capacity significantly. Moreover, high volatility with low variable cost drives down firm 2 capacity significantly. For firm 2 we also find a combination effect in which low variable cost with high fuel efficiency decreases firm value, but in combination with high γ it actually increases firm value. We furthermore find that the combination of high elasticity and low variable cost decreases firm 1 value significantly.

2.4.6 *Optimal investment policies*

In order to evaluate optimal investment policies resulting from the discrete-time model, we create so-called optimal strategy maps. The strategy maps show the optimal firm policy over time for all possible evolutions of the shock term X . The optimal strategy maps are created by keeping all parameters in the Bellman equation (see Equation (2.9)) constant except for the shock term and then simulating optimal action going forward. The optimal strategy maps take into account path dependencies, such as order pipelines or layup pool.

Lemma 2.4.1 *High competitive intensity (low γ) leads to replacement investment while low competitive intensity (high γ) drives expansion.*

The optimal strategy map (Figure 2.7) shows that with a low γ value (high elasticity), firms will not invest in positive market scenarios but only make replacement investments to safeguard profitability in the downside cases (e.g. order 2 or 3 fuel efficient units in periods 2 or 3 and sell old vessels upon delivery of the new fleet in case the rate development is not positive). At a γ value of 1.2 we find that "do nothing" becomes optimal since upstate investments are hindered by the price effect but overall higher profitability does not justify investment in the down states. Hence, we observe only late-stage investment from period 8 on. When γ is increased to 1.4, investment in the upside scenarios becomes more likely.

Lemma 2.4.2 *Minimum level of efficiency gains required to consider the fuel efficient investment alternative*

In Figure 2.8 we find that for a rather low level of efficiency impact, the shipping player should only invest in conventional capacity. Only if the efficiency impact is larger than 30 percent, the fuel efficient alternative can be justified.

Lemma 2.4.3 *Higher fuel efficiency effect can trigger strategy difference between replacement and capacity expansion*

From Figure 2.8 we further learn that if the fuel efficiency impact is at 30 percent, replacement investment is worthwhile, i.e. ordering fuel efficient ships in negative market scenarios and use them as replacement to safeguard cost. If the efficiency impact is substantial, however, we find that also early capacity expansion in positive market developments can be justified.

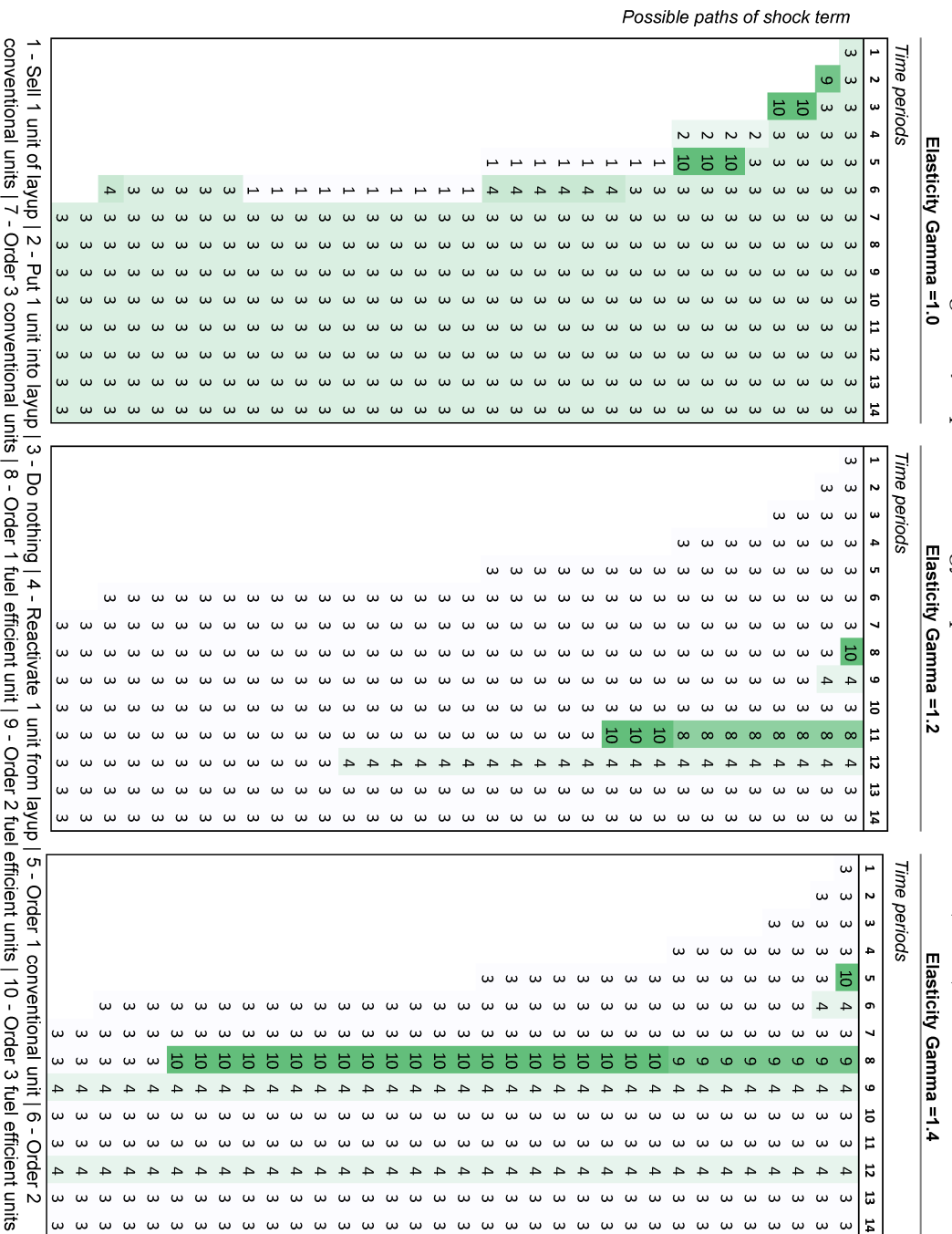
We assume that the mentioned fuel efficiency savings can be achieved by three main factors: engine technology, hull design, and innovative paints. New engines are more efficient in general and can better accommodate today's relatively low steaming speeds of about 20 knots (conventional vessels were designed for steaming speeds above 20 knots (Alphaliner 2013c, Notteboom and Cariou 2009)). For an analysis of economic considerations with regards to ocean vessel speed, refer to Magirou et al. (2015). This also holds true for hull design, which has become more aerodynamic (Bergmann 2012, Lomar 2012). Innovative paints can help smooth the hull of ships and further reduce water resistance (Visser 2011). The overall impact of the measures can be an up to 30 % reduction of fuel consumption (Hoifodt 2011). To a certain extent, ships can also be retrofitted to be more fuel efficient, especially with regards to paints and potentially engines. Even changes in hull are possible but may be limited due to sleek hull forms originally designed for higher speeds (Alphaliner 2013a).

2.5 MANAGERIAL IMPLICATIONS

We find that two competition-relevant measures impact optimal capacity, firm values, and the investment trigger: Those measures are the number of players n and the intensity of competition (elasticity) γ . The results we derive are as follows: an increasing number of players n (going from monopoly to oligopoly) leads to higher optimal capacities, lower individual firm values as well as earlier investment. An increase in intensity of competition γ , however, decreases optimal capacity while also decreasing firm value. Note that in the former case, the sheer presence of more players in the market drives the optimal capacity upward. The fear of preemption leads players to try to capture an advantage from being a first mover in capacity addition. In this case, the steeper slope of the demand function decreases optimal capacities. The implication of this is that a shipping player's objectives with regards to the two dimensions of competition should be to keep n low while trying to increase γ .

Minimizing n could not only be achieved by preventing new entry, but also by entering - in accordance with anti-trust laws - vessel sharing agreements and alliances. This should include joint investment and deployment decisions on selected routes (especially with strong price reaction to capacity) and could help to reduce overall capacity in the market and create more value for the players. Improving the γ of the industry and/or selected trade lanes demands two steps. Firstly, market players should understand the concept of elasticity well and use tools for regular measurement. This would include the weekly tracking of competitive investment and vessel deployment on a trade lane level. Using that information, firms can better anticipate competitive activity and investment

Figure 2.7: Optimal strategy maps for different elasticities (firm 2)



impact on freight rates. An analysis of supply-demand gap and elasticity on a trade lane basis should be carried out to develop fleet sizing strategies. In markets with strong price reaction it might make sense to delay investment in order to safeguard profitability, whereas in markets with less pronounced price reaction, preemptive investment may be worthwhile. In a second step, players can work on actually improving γ . Since container shipping is a commodity market, differentiation is difficult. However, frequency of service and access to ports are factors that can potentially impact γ . The introduction of "Daily Maersk" is an example of differentiation by increased frequency (Zhang and Lam 2015).

From the discrete-time model we can learn that if the price markup of fuel efficient vessels is justified by sufficient operating cost advantages, firms should start investing into fuel efficient capacity. When the fuel efficiency impact is rather low, replacement investment should be preferred; when the fuel efficiency impact is very substantial, new investment should be considered. This implies that from a strategic point of view, investment into fuel efficient capacity should always be preferred as long as prices are justified. Players should retrofit vessels in economic downturns, since retrofitting can bring some fuel efficiency savings without changing the overall capacity and impacting market prices, especially in low γ markets. If very substantial fuel efficiency savings can be achieved, for example with the introduction of completely redesigned hull and engine combinations, players should invest in new capacity, especially if freight rates are expected to increase. Overall, a higher flexibility in capacity decisions is required to have enough action space in economic downturns. In the light of this model we refer to the option of ending charter contracts at short notice, moving vessels to alternative markets, or taking vessels out of active capacity to conduct fuel efficiency retrofits. The mentioned investment strategy would help to maintain cost-competitiveness while complying with regulatory standards.

An individual firm can benefit from higher volatility if it is sufficiently flexible in its capacity decisions, i.e., if it is able to sell units at reasonable prices. Of course, overall unnecessary volatility in the market should be avoided, for example by carefully studying price effects of new investment or by avoiding unnecessary General Rate Increases (GRIs) without supply-demand justification. Nevertheless, players should make sure that they are able to cope with increased freight rate volatility, e.g. they should use flexible charter contracts for peak capacity.

A lower variable cost position leads to higher optimal capacity as well as higher overall firm values. In addition to fuel efficiency savings, players should constantly monitor their variable cost position and find levers for improvement. From a ship owner's perspective (without considering bunker fuel) this mostly includes personnel, maintenance, insurance, and operating supplies.

Finally - and most importantly - from a comparison of myopic and strategic firms in discrete-time we find that - if operating near optimal capacity - it is financially advantageous to be strategic. Hence, players in the shipping industry should behave strategically and we strongly recommend that they focus on the above-mentioned recommendations with respect to the number of players n and the intensity of competition γ .

2.6 CONCLUSION

The shipping industry is characterized by cyclicality, and strong ordering has created oversupply in a market with eroding margins. This paper shows that existing oligopolistic competition models can be used to model investment decisions in the shipping industry with embedded real options. Discussing the analytic model by Grenadier (2002) and running a detailed discrete-time model, we generate new insights regarding firm values, investment triggers, and optimal strategy maps. We find that a higher number of competitors leads to lower firm values but more investment, and conclude that players should enter into vessel sharing agreements and/or alliances. Further, we find that the impact of elasticity - the price reaction to new capacity - is substantial and should be part of investment decisions. We show that fuel efficiency retrofitting can help in negative market developments while substantial innovations should be used for capacity expansion. Individual firms can benefit from freight rate volatility if their fleet-sizing approach is sufficiently flexible. Firms should work on their variable cost position to remain competitive in the market. Finally, we find that it is financially advantageous to be strategic, and that understanding the market and monitoring competition are key.

From this approach in a non-cooperative game-theoretic oligopoly, we can draw very relevant insights. Since we observe that the liner shipping industry is currently in a phase of strong consolidation with the extensive use of shipping alliances, a logical next step would be to investigate investment decisions from the perspective of cooperative game theory. It would be highly interesting to study how the consolidation of the industry into alliances impacts competition, investment behavior, service levels, and freight rates. Moreover, it would be desirable to extend current investment models in continuous-time and discrete-time to incorporate stochastic variable cost and stochastic fuel prices.

Alliance formation in a cooperative container shipping game: performance of a real options investment approach¹

3.1 INTRODUCTION

In their battle to safeguard profitability in a market characterized by overcapacity and eroding margins, container shipping players have been increasingly seeking to establish cooperation in the form of strategic alliances. This process led to a point where 71.8 percent of global shipping capacity would have been in the hands of 3 large alliances (P3, G6, and CKYHE) - had the Chinese Ministry of Commerce not stepped in²; prohibiting the formation of the P3 alliance by Maersk, MSC, and CMA-CGM which would have had a global market share of about 37 percent (Alphaliner 2014a, MOFCOM 2014).

Not only from a regulatory perspective, but even more from an investment standpoint, players and policymakers in the shipping industry need to ask themselves a number of questions: How stable is the current alliance structure in the industry? When, and for which reasons is it appropriate to seek new partners? How should investment be evaluated in light of a dynamic coalition structure? To what extent should and can we collaborate on capacity investments? We intend to shed light on a number of those questions with this research effort.

3.1.1 *Challenges of the shipping industry*

Players in the container shipping industry are operating in a challenging market environment. They face market cycles (Stopford 2010), supply-demand imbalances (Rau and Spinler 2016b, Syriopoulos 2010), high capital intensity of investments, and market concentration (Alphaliner 2014g) - in contrast to bulk shipping which can be characterized by perfect competition (Pirrong 1992).

A possible explanation for non-optimal investment timing and sizing is shortcomings in investment evaluation methods (Bendall 2010). The DCF methodology is seen as the primary tool for ocean freight capacity investment (Evans 1984, Gardner et al. 1984), even though it fails to take into account uncertainty and managerial flexibility (Bendall 2010). One possible alternative is ROA (Bendall 2010, Rau and Spinler 2016b). Its merits are to be outlined in this research effort.

¹Rau and Spinler (2016a): Rau, P., Spinler, S. (2016). Alliance formation in a cooperative container shipping game: performance of a real options investment approach. Unpublished Working Paper. Presented at INFORMS 2015 Annual Meeting, Philadelphia.

²Extract from official statement (MOFCOM 2014): "Upon review, the Ministry of Commerce believes that the establishment of the network center may lead to the formation of a compact association by Maersk, MSC and CMA CGM, and have effects of excluding or restricting competition on the container liner shipping market for the Asia-Europe route. Therefore, the Ministry of Commerce has decided to prohibit the concentration of undertakings."

From the beginnings of sea trade, carriers chose to cope with their situation by forming conferences, alliances, or other means of cooperation. The Calcutta conference in 1875 was a starting point and further conferences on the most important trade routes were soon to be established. A liner shipping conference can be defined as an agreement between a number of shipping companies that provides for a fixed transportation service on a specific route with joint pricing. Conferences had been under legal scrutiny for antitrust reasons; with the Ocean Shipping Reform Act of 1998 they ceased existing (Sjostrom 2010, Thanopoulou et al. 1999).

In the 1990s, the shipping industry went through a paradigm shift as the first strategic alliances - Grand Alliance and Global Alliance - were established (Midoro and Pitto 2000). In the past 20 years, however, the formation of alliances has been very unstable and various studies show that up to 80 percent of alliances fail (Song and Panayides 2002). Even during the years 2011 to 2015, there have been several changes to the alliance setup in container shipping. Figure 3.1 shows that in 2011, there were three major alliances, namely CKYH (11.3 percent market share), Grand Alliance (9.2 percent), and The New World Alliance (8.5 percent). 2014 would see a consolidation of 71.8 percent of the market to only three alliances, i.e. P3 (37.1 percent), G6 (18.0 percent), and CKYHE (16.7 percent). Since this structure had been rejected by Chinese authorities (though approved by the Federal Maritime Commission), as of 2015, there were four alliances, which are 2M (18.4 percent), Ocean 3 (14.7 percent), G6 (18.4 percent), and CKYHE (17.0 percent). Throughout 2016, the alliance structure has remained unchanged so far despite the merger of COSCO and CACL. The 2016 acquisition of NOL (APL) by CMA-CGM will, however, lead to further changes since the European Commission's approval of the merger is conditional on NOL (APL) leaving the G6 alliance (Shingleton 2016).

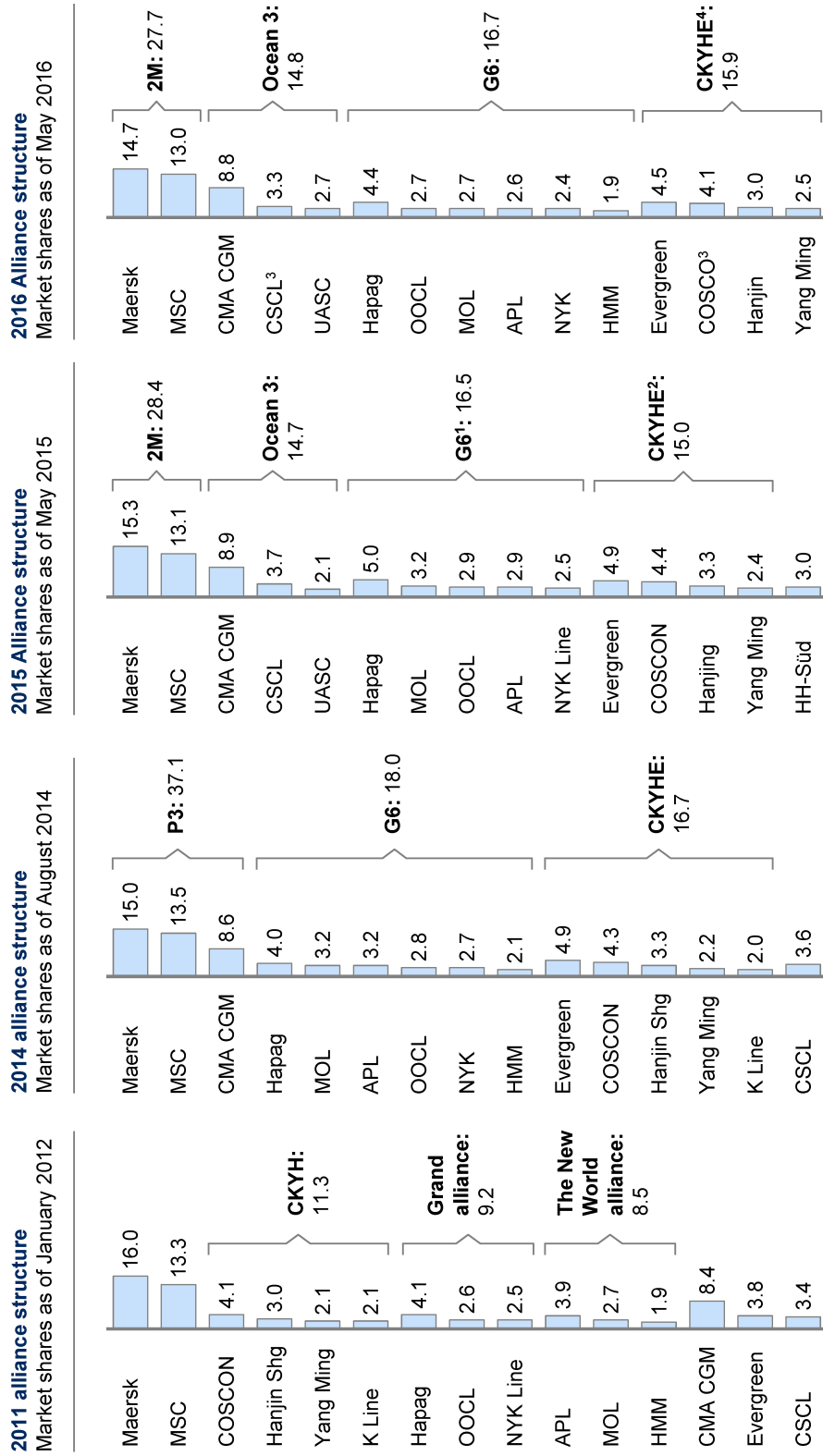
Investment decisions in shipping are not only driven by intrinsic values, but also by fuel efficiency, network considerations, funding sources, regulation, vessel sizes, and asset prices (Rau and Spinler 2016b). The changing nature of coalition structures in today's shipping market adds another layer of complexity to the investment decision.

3.1.2 *Resulting market dynamics*

As the substantial consolidation in the market is still relatively new, the effects on the market dynamics have not yet completely materialized. Leach (2015) argues that some beneficial cargo owners expect prices to rise due to more tightly managed capacity, integrated services and networks. This, in turn, will have an effect on ports. Smaller ports might have to accommodate larger ships while typical hubs might experience significantly more traffic.

Midoro and Pitto (2000) conclude that alliance formation has been relatively unstable in the end of the 19th century; from Figure 3.1 we argue that this has remained valid until today. Hence, from a carrier perspective, it will be critical to keep alliances stable. Ways to improve stability are creation of mutual trust (Lu et al. 2006) or reduction of organizational complexity by reducing number

Figure 3.1: Analysis of alliance changes in the past 5 years



1 Excluding HMM (1.9 percent); 2 Excluding K Line (2.0 percent); 3 Fleets have been consolidated under COSCON, however, they remain under separate alliance agreements. Capacity split estimated based on 2015 capacity figures; 4 Excluding K Line (1.8 percent)
Source: Alphaliner

of partners, differentiating roles and contributions, and coordinating sales and marketing (Midoro and Pitto 2000).

3.1.3 *Research objectives*

The literature on shipping has provided a comprehensive account of (1) how the characteristics of the shipping industry have favored alliance formation, (2) what the general motivation and drivers are for entering an alliance; (3) that collaboration in the shipping industry is necessary; (4) and that challenges in investment decisions can be addressed by real options methods. However, the performance of investment approaches in a cooperative market setting has - to our best knowledge - neither been model-theoretically evaluated nor empirically been tested. From a managerial perspective it is essential to make investment decisions that do not only take into account the inherent characteristics of the shipping industry, but also the changing coalition structure.

Our model uses cooperative game theory to reflect crucial aspects of the container shipping industry. It allows for a choice in terms of investment approach, i.e. real options trigger, individual DCF, and collective DCF approach. Our main hypothesis is that a real options trigger investment approach performs comparatively best, especially in light of high competitive intensity and high freight rate volatility. It does not affect coalition stability and market concentration negatively or exhibit disadvantages in other market scenarios. We quantify the impact of competitive intensity, lead time, alliance complexity cost, and freight rate volatility on average industry capacity, cash flow to players, alliance stability, and industry concentration.

The structure of the paper is as follows. Section 3.2 reviews existing literature on shipping alliances, game theory in shipping, and optimal coalition structure as well as details the contribution of this research. Section 3.3 introduces our simulation model and Section 3.4 develops hypotheses. In Section 3.5 we show the results and discuss them from a managerial perspective. Section 3.6 concludes the paper and suggests areas of future research.

3.2 LITERATURE REVIEW

3.2.1 *Shipping alliances*

Collaboration in the shipping industry has a long tradition: Sjostrom (2010) presents an account of shipping alliance history from historic conferences up to today's strategic alliances and extends to liner shipping competition practices: predatory pricing (prevent entry), loyalty contracts with shippers, price discrimination, as well as price and output fixing. An account of the recent situation of the industry is given by Panayides and Wiedmer (2011) who present a review and integration into literature of liner shipping structure, types of alliances, objectives, stability, and success as well as discuss the structure and services of liner shipping companies as well as global strategic alliances.

Glaister and Buckley (1996) assess the motivation for alliances. They define alliances as (equity) joint ventures with strategic and operational coordination

and provide a comprehensive literature review on reasons for alliances: risk sharing, economies of scale, technology transfer, shaping competition, government policy, international expansion, vertical integration, and consolidation of market position. They further identify alliance likelihood drivers in a factor model, i.e. partner size, location of alliance, contractual form, industry group, and nationality of partner. Lu et al. (2006) evaluate the CKYH alliance with the Delphi method and find that business niches, service coverage extensions, and more service frequency are key drivers for alliances. They again find that mutual trust is the most important basis for collaboration and conclude that the importance of alliances in the shipping industry will continue to rise. Agarwal (2007) lists motivations for alliance formation: (i) consolidation of manufacturing sector, (ii) capital intensity, (iii) larger ships, (iv) low product differentiation, (v) high frequency of service due to just in time production, (vi) increasing global reach, and (vii) defending "home turf". Zhang and Lam (2015) study the effect of "Daily Maersk" (offering absolute reliability along with late fees) on other shipping players. They find that the most promising mitigation action taken by other players is the formation of further alliances to increase service frequencies.

A more critical view is suggested by Alix et al. (1999) who present a case study on CP ships who performed well as a focused niche market player and focused on growth through acquisition instead of playing "the alliance game". Midoro and Pitto (2000) assess alliance stability and argue that alliance formation has been a very unstable, repeated process so far. They identify organizational complexity as key driver for instability and suggest to reduce the number of partners, differentiate roles and contributions, and coordinate sales and marketing.

The impact of alliances is studied by Cariou (2002) who finds that alliance effects are mainly economies of scale (bigger vessels), operational synergies (better allocation of vessels), and market control. Slack et al. (2002) conduct an empirical examination of developments in liner shipping with regards to alliances and consider 3 features: transformation of services, evolution of fleet, and port calls. They find that alliances increase uniformity in the industry (service number and frequencies, largest ships in joint alliance services, and more port calls to "important" ports). Moreover they find pooling of assets and higher service integration. Houghtalen et al. (2011) create a microeconomic model to analyze the impact of strategic alliances. They find that the alliance benefits increase with network size and fleet capacity.

Adding an anti-trust perspective, Lam et al. (2007) conduct a structure, conduct and performance analysis in the liner shipping industry and find that even though high market concentration is present (top 10 players have a greater than 60 percent market share), no abuse of market power can be observed. They rather call the collaboration a "joint effort to survive".

3.2.2 *Game theory in shipping alliances*

From the perspective of core theory, it is possible to argue that some form of collusion is necessary in industries that do not have a competitive equilibrium.

These industries are characterized by divisible and stochastic demand, fixed supply in large increments and cost of having idle assets (Bittlingmayer 1982, Telser 1985, Zhao 2007).

Specifically for the shipping industry, Sjostrom (1989) argues that price and output fixing can solve the empty core problem. He finds that core theory is more valid than cartel theory in shipping; market settings that appear to be cartels are sometimes rather an empty core solution. Pirrong (1992) distinguishes between bulk and liner shipping. He finds that bulk shipping is characterized by perfect competition while he can explain collusion in liner shipping with core theory due to indivisible cost but divisible demand. More recently, Yang et al. (2011) assess stability of alliances with core theory. They consider new phenomena such as joint service through pooling and mega ships and find that it is necessary to collude in order to avoid overcapacity, react to market changes more flexibly, and earn higher profits. They further find that if a sub-alliance is more profitable than an alliance, alliances will be unstable due to an empty core.

There is another literature stream around resource allocation in shipping alliances. Doi et al. (2000) create a linear program for resource allocation with the objective of overall alliance profit. The author argues that incentives are necessary to encourage alliance-conform behavior but assumes distribution of incentives without central decision maker. Agarwal (2007) provides a further Linear Programming (LP) algorithm to allocate alliance benefits in the core. Moreover, Agarwal and Ergun (2010) formulate a service network design LP model to motivate collaboration. Among other results, they find that complementary partners are more likely to form stable alliances, e.g. freight forwarder and carrier.

More conceptually, Song and Panayides (2002) apply a cooperative game theory framework to liner shipping alliances. They provide an overall game theory basis as well as liner shipping examples and conclude that the goal to achieve a stable core is almost impossible in the shipping industry.

3.2.3 *Optimal coalition structure*

Cooperative game theory aims at optimal allocation of profits to alliance members. With the solution concepts Shapley value and core, for example, the optimal payoff structure can be derived. Based on that, Shenoy (1979) presents a game-theoretic approach on coalition formation from a static perspective.

Owen (1977) introduces the Coalition Structure (CS) value as a modification to the Shapley value, arguing that a priori collaboration might impact the optimal coalition outcome. Hart and Kurz (1983) build on that to consider endogenous formation of coalitions. They argue that a two-step approach is needed to solve the coalition structure problem: first, it is necessary to find the optimal outcome among coalitions, then within each of the coalitions. They apply the CS value, namely evaluate the players' prospects and find stable coalitions by looking at the concept of "strong equilibrium". The concept of CS value has been implemented to solve various problems in research. Rothkopf et al. (1998) apply the concept to combinational auctions, e.g. FCC radio spectrum auctions.

They develop an algorithm to solve the CS value for a large number of possible combinations. Sandholm et al. (1999) argue that finding the optimal coalition structure is NP-complete and present a further algorithm that performs better. Rahwan (2007) provides a helpful overview over coalition generation algorithms.

Konishi and Ray (2003) introduce a dynamic Process of Coalition Formation (PCF) with creation, change, and liquidation of coalitions. They assume that the future value of coalitions is endogenous and study equilibrium PCFs.

3.2.4 *Contribution of this research*

Our contribution is the examination of the real options trigger approach in an industry characterized by alliances that are subject to frequent changes. Earlier contributions focus on investment in (static) competitive markets or exclude the investment problem from the analysis (i.e. focus on alliance motivation, drivers, or stability). We incorporate the component of dynamic coalition formation in our analysis and provide further support for the merits of the real options trigger approach by comparing its performance with the currently established investment appraisal method: DCF.

Our cooperative game theory model further allows for consideration of different volatility, intensity of competition, alliance complexity cost, and order lead time scenarios. We can draw relevant insights on capacity, cash flow, industry concentration, and alliance stability. From a managerial perspective, we show that our investment approach not only leads to a lower industry capacity (and hence can help alleviate the problem of overcapacity in the industry) but also to higher cash flows for the players.

3.3 MODEL FORMULATION

We develop a cooperative shipping game with up to seven players. By taking on the perspective of the individual container ship carriers in the industry, we can apply straightforward rules on investment, alliance formation, and operational items. We build the system up from the single agent perspective to then derive implications on the whole simulated container shipping market. This is an analogy to agent-based modeling and simulation where sophisticated systems are modeled by looking at characteristics and behaviors of individual agents (Macal and North 2010). The simulation model is a market simulation with 120 increments (every 2 months) and hence covers 20 years. It consists of 4 main parts: initialization/state update, the coalition formation process, investment decisions, and earnings realization.

3.3.1 *Assumptions*

Trade lane and capacity

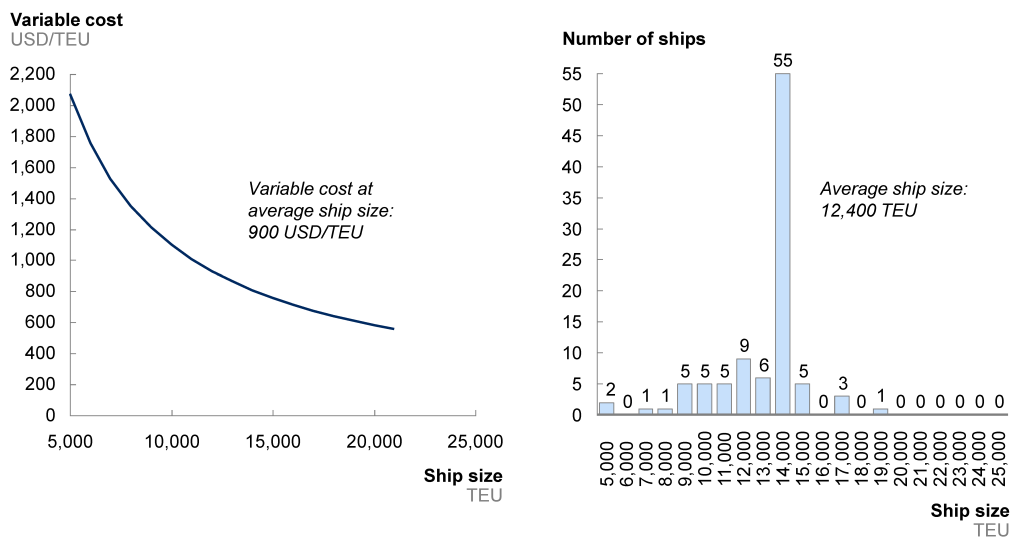
The basis of our simulation model is a specific shipping trade lane, i.e. Shanghai to Rotterdam with up to seven carriers who may decide on how much capacity

to offer and on whether to enter an alliance. In terms of capacity, we look at all departures for June and July 2015 for the route Shanghai to Rotterdam, due to an average round trip time of 2 months this corresponds to the bimonthly increments (Table B.1).

Freight rate and variable cost

The freight rate in the market model is endogenous, i.e. dependent on the capacity available in the market. The uncertainty of the freight rate process is driven by a geometric Brownian motion. As a starting point, we assume a long-run freight rate of USD 2,000 per TEU including backhaul based on the Shanghai Containerized Freight Index (SSE 2016).

Figure 3.2: Variable cost and ship size distribution for Shanghai-Rotterdam sailings



Source: <http://www.jocsailings.com>, own analysis

We assume variable cost to be dependent on ship size and set the break-even rate to 900 USD at average ship size on the considered route which turns out to be 12,400 TEU (Cullinane and Khanna 1999, Gkonis and Psaraftis 2009, Richter 2015) (Figure 3.2). We assume that ships can be temporarily laid up to reduce operating expenses to 320 USD/TEU (Howley and McCabe 2009).

Investment opportunity

For the investment opportunity we assume an investment cost of 8,250 USD per TEU which is in line with recent orders: Seaspan 10,000 TEU ships ordered in April 2015 for 90 million USD each and CMA CGM, OOCL and MOL 20,000 TEU ships ordered in February and April 2015 for 150 million USD each (Alphaliner 2015d). Ship purchases are assumed to be financed with a mix of debt and equity. There is an equity requirement dependent on alliance status and a geometric debt depression by 5 percent. We also assume that with more players in an alliance, larger ships will be ordered (Table B.2).

Table 3.1: Model parameters

Symbol	Parameter	Value
β	Fundamental quadratic	
γ	Elasticity	1.8
Δt	Time step	1/6 years
ϵ	Scaling factor	0.1
η	Calibration parameter	
κ	Inv. lead time	18 months
μ	Drift term	0.05 p.a.
σ	Volatility	15 percent p.a.
τ	Time index in forecast model	
ϕ	Norm. dist. random number	
A	Stirling number	
a	Number of players in coalition	
c	Variable cost	
C_a	Alliance complexity cost	600,000 USD per period
C_d	Debt service payment	
C_I	Equity part of investment cost	
C_l	Layup cost	320 USD per TEU
C_r	Interest cost	
CS	Coalition structure	
d	Debt service	0.05 p.a.
f	Number of ships ordered	
g	Variable cost parameter	900,000
h	Variable cost parameter	-2,700,000
I	Investment cost	8,250 USD per TEU
i	Number of coalitions	
M	All possible coalition structures	
n	No. of players	5
NPV	Net present value	
p_0	Starting freight rate	2,000 USD
Q_t	Capacity	
q	Player capacity	
r	Interest rate	0.10 p.a.
s	Average ship size	
T	Willingness to switch threshold	3 periods
V	Value	
X_t	Random shock term	
X^*	Investment threshold	
Z	Coalitions per player	

Alliance formation

Players may choose to enter a container shipping alliance with one or more players. The optimal alliance status is based on an alliance prospects forecast that depends on investment pipeline, freight rate forecast, alliance complexity cost, alliance benefits as well as current capacity and variable cost. The freight rate forecast consists of a linear trend forecast plus an alliance markup due to higher flexibility and network penetration. The membership in an alliance is expected to improve pricing due to sales and marketing coordination and improved schedules (Lu et al. 2006, Zhang and Lam 2015). Once there has been a deviation from the optimal alliance status for 3 consecutive time periods, new alliances will form. There are coordination costs that increase linearly with the number of players in an alliance as the organizational complexity is expected to increase (Midoro and Pitto 2000).

3.3.2 *Initialization/state update*

To initialize the model, we first generate a random GBM path for the following 120 periods. The return of the GBM per period is given by

$$\frac{X_t}{X_{t-1}} = \mu\Delta t + \sigma\phi\sqrt{\Delta t}, \quad (3.1)$$

where μ is the drift³, Δt is the time step, σ is the volatility, and ϕ a normally distributed random number. Note that σ , r , and μ are converted to correspond to bimonthly terms.

In all periods (except for the first period in each simulation run) we perform a state update. The order pipelines are updated based on investments in the previous period. Furthermore, deliveries are added to the current capacity of players. The final available capacity for the period is derived by applying changes in the layup pool. With that, the freight rate for the period can be realized as

$$p_t = X_t Q_t^{\frac{-1}{\gamma}}, \quad (3.2)$$

where Q_t is total industry capacity, X_t is the random shock term driven by Equation (3.1), and γ measures competitive intensity.

3.3.3 *Coalition formation process*

Key element of the simulation model is the coalition formation process. Since we apply the coalition structure value (Hart and Kurz 1983, Rahwan 2007, Rothkopf et al. 1998), we first need to create all possible coalition structures.

³Note that the 5 percent drift assumption (c.f. Table 3.1) might be considered comparatively optimistic given that freight rates have constantly decreased in the past years. For the freight rate process in this article we rely on an oligopoly price function (negative relationship between fleet size and freight rate). Hence, when estimating the drift term, we need to correct for the increase in fleet size and can justify a positive drift term. We have tested our model for different drift terms ($\mu = 0.075, 0.05, 0.025, 0, -0.025$) and find that the structure of the results remains consistent.

According to Sandholm et al. (1999), the number of coalition structures is the Stirling number of the second kind

$$A = \sum_{i=1}^n Z(n, i), \quad (3.3)$$

where $Z(n, i) = iZ(n-1, i) + Z(n-1, i-1)$, $Z(n, n) = Z(n, 1) = 1$; n is the number of players and i is the number of coalitions. Hence, in order to create a full enumeration it is necessary to (1) count the number of coalition structures by adding the new player to each of the existing coalitions and (2) add the new player into a coalition of its own. Using the full enumeration of possible coalition structures, we solve for the optimal coalition structure

$$CS^* = \arg \max_{CS \in M} V(CS) \quad (3.4)$$

where M are all possible coalition structures and $V(CS)$ is the value of a coalition structure CS and defined by

$$V(CS) = \sum_{\tau=1}^{20} \left[p(\tau, CS) - c(\tau, CS) \right] q(\tau, CS) - C_a(\tau, CS) - C_l(\tau, CS) - C_r(\tau, CS) \quad (3.5)$$

where c is variable cost, q is individual player capacity, C_a is alliance complexity cost, C_l is layup cost, and C_r is interest cost. τ is the time index in the forecast period of 20 periods and the freight rate is given by

$$p(\tau, CS) = \left[\frac{p_t - p_0}{t} \tau \epsilon + p(t) \right] \left[1 + 0.1(1 - e^{-a(CS)}) \right], \quad (3.6)$$

where t is the time step, p_0 is the model starting rate, ϵ is a scaling factor, and the term on the right hand side is an alliance markup dependent on the number of players a in the respective coalition structure CS . The intuition here is that alliance membership can improve pricing due to higher flexibility, network penetration, and coordination (c.f. Section 3.3.1). The size of the improvement, however, shows decreasing returns to scale. Variable cost are given by

$$c(\tau, CS) = \frac{g \ln(s(\tau, CS)) - h}{s(\tau, CS)} \quad (3.7)$$

where g, h are constants and $s(\tau, CS)$ is the average ship size of the coalition.

The capacity $q(\tau, CS)$ is forecasted by taking into account current pipelines, alliance complexity cost $C_a(\tau, CS)$ are increasing linearly with the number of players a , layup cost $C_l(\tau, CS)$ depend on the layup pool at $\tau = 0$, and interest cost $C_r(\tau, CS)$ are calculated on outstanding debt (geometric debt repayment). We assume that - even though CS^* can change rather rapidly - in reality, players will be reluctant to switch to different alliances every other period. Hence, we implement a threshold for the willingness to switch alliance membership; that means players will only change their alliance membership if the alliance setup has been non-optimal for three periods.

3.3.4 Investment decisions

Shipping players in our model have the opportunity to order 1, 2, or 3 ships in each period. To shed light on the impact of investment appraisal choice, we study three different investment approaches: a real options trigger policy, an individual DCF model, and an alliance-based, collective DCF model.

Even though the DCF approach is still considered the standard approach in maritime investment, it fails to incorporate industry characteristics, such as freight rate uncertainty, managerial flexibility, and the oligopoly nature of the shipping industry (Bendall 2010, Rau and Spinler 2016b). We hence propose the introduction of a continuous-time real options investment trigger policy in a discretized form. This approach accounts for freight rate volatility, lead time, the number of players, and competitive intensity. Real options analysis has been successfully applied to maritime investment in earlier studies (Bendall 2010, Bendall and Stent 2007, Gkochari 2015, Goncalves 1992, Rau and Spinler 2016b).

3.3.4.1 Trigger policy

The real options investment trigger can be derived by assuming an endogenous freight rate driven by a geometric Brownian motion and finding the firm value in Nash equilibrium. For further details refer to Gkochari (2015), Grenadier (2002), Rau and Spinler (2016b). The investment trigger is

$$X^* = v_\kappa e^{(r-\mu)\kappa} Q^{\frac{1}{\gamma}} \quad (3.8)$$

where κ is the lead time, Q denotes total industry capacity, γ is the competitive intensity, μ is the drift term of the geometric Brownian motion and r is the risk-free rate. The term v_κ is given by

$$v_\kappa = \left[\left(\frac{\beta}{\beta-1} \right) \left(\frac{n\gamma}{n\gamma-1} \right) (r-\mu) \left(\eta + c e^{-r\kappa} \frac{1}{r} \right) \right], \quad (3.9)$$

where β is the fundamental quadratic, n is the number of players, η are investment cost and c is the variable cost component. To fit into our discrete-time framework, we assume that once the freight rate exceeds the threshold, new investment will be triggered. Investment into two or three ships requires the freight rate to surpass the threshold by 10 and 20 percent, respectively. Note that σ , r , and μ are converted to correspond to bimonthly terms.

3.3.4.2 Individual DCF model

The first formal expression of the DCF methodology dates back to the time after the stock market crash in 1929 (Edwards and Williams 1939, Fisher 1930). The main assumptions are that the value of a project can be calculated by estimation of future cash flows and discounting with an appropriate Weighted Average Cost of Capital (WACC). By subtracting investment, the Net Present Value (NPV) can be attained. Generally, a positive NPV implies investment into a project would be worthwhile; a negative NPV leads to rejection of the

investment opportunity. The individual DCF model solves the following optimization problem:

$$NPV^* = \arg \max_{f \in \{0,1,2,3\}} \sum_{i=1}^{60} \frac{CF_i(CS, f)}{(1 + WACC)^i} - I(f) \quad (3.10)$$

where f is the number of ships to be purchased and WACC denotes the weighted average cost of capital. The cash flow of each period i is defined as

$$CF_i = [p(i, CS) - c(i, CS, q)]q(i, CS, f). \quad (3.11)$$

Freight rate and variable cost going forward are calculated according to Equations 3.6 and 3.7.

3.3.4.3 Collective DCF model

As we argue that the alliance status has an impact on investment decisions, we allow a joint DCF investment approach as a third potential investment method in our simulation model. The key assumption here is that - rather than estimating future cash flows from an individual firm perspective - in the collective approach, firms add their prospective cash flows and make a joint investment decision based on NPV. The ordered ships are allocated to the players based on their current capacity. The mechanics of the DCF approach are analogous to Equations 3.10 and 3.11, however, cash flows of the alliance partners are added and the maximum investment considered is 3 units per player.

3.3.5 Realization of earnings and operational impact

Before realizing period earnings, we assess whether required equity is available and adjust respective investment decisions. The required equity depends on alliance size and is depicted in Table B.2. The intuition is that ships are financed with a mix of debt and equity. The equity requirement is the share of investment cost that needs to be paid from retained cash flows. We assume that the larger the coalition, the stronger the negotiation power towards banks. Hence, the equity requirement decreases with more alliance partners. We further allow firms to move 1 unit per period into layup in case variable cost are greater than the sum of freight rate and layup cost (and vice versa). Realized earnings (cash flow perspective) are given by

$$CF(\tau, CS) = [p(\tau, CS) - c(\tau, CS)]q(\tau, CS) - C_a(\tau, CS) - C_l(\tau, CS) - C_r(\tau, CS) - C_I(\tau, CS) - C_d(\tau, CS), \quad (3.12)$$

where C_I are investment cost (equity part) and C_d are debt service payments (geometric debt schedule).

3.4 HYPOTHESES

The input parameters we vary are competitive intensity, order lead time, alliance complexity cost, and freight rate volatility. We measure four output

variables: (1) the average capacity over the measurement period of 120 periods, (2) the sum of cash flows to the players during the measurement period, (3) the number of changes in the coalition structure during the measurement period, and (4) the industry concentration measured by the Herfindahl-Hirschman Index (HHI) at the end of the measurement period. We run the simulation model with all possible parameter settings and - in combination with an extensive literature survey - identify the following main hypotheses.

3.4.1 *Independent variable variation*

Competitive intensity

Due to the application of an oligopolistic price function (Gkochari 2015, Grenadier 2002, Rau and Spinler 2016b) the competitive intensity described by γ has an impact on the endogenous freight rate rate as well as on the propensity to invest. For a competitive shipping market it can be shown that a higher γ value (lower intensity of competition) increases optimal market capacity and firm values (Rau and Spinler 2016b). We further expect that higher competitive intensity will trigger players to consider alliance changes more often. We hence believe that this will lead to greater instability. This view is in line with Midoro and Pitto (2000) who show that (1) higher intra-alliance competition and (2) a higher degree of competition in the surrounding environment lead to instability of alliances. This view is also supported by Lu et al. (2006) who identify competition between partners as a driver for alliance instability.

Hypothesis 1: *Lower competitive intensity reduces the number of alliance changes.*

Lead time

As container ships are built to order, delivery times are around 1.5 years⁴. Typically, the lead time is endogenous and depends on the order volume at the shipyards (Adland and Strandenes 2007). We hypothesize about the lead time impact on HHI. We have not come across previous research that explores the lead time or construction time impact on industry concentration. There are, however, two related studies: Lijesen (2004) shows that airlines with shorter flight times achieve higher market shares; Hendricks and Singhal (1997) show that delays in new product introduction have a negative effect on firm values. Along with that, we argue that increasing lead time is likely to lead to lower industry concentration.

Hypothesis 2: *Increasing lead time reduces market concentration.*

⁴For example, ten ultra-large container ships had been ordered by Enesel in July 2012 from Hyundai Heavy Industries and delivered between September 2013 and October 2014, achieving an average delivery time of 20 months (Alphaliner 2014e).

Alliance complexity cost

Midoro and Pitto (2000) argue that a key factor driving instability of liner shipping alliances may be organizational complexity. They suggest that it is important to build alliances that are “simple enough to be manageable”. We introduce this complexity argument as alliance complexity cost in the simulation model. In line with Midoro and Pitto (2000) we expect alliance complexity costs to increase changes in alliance composition.

Hypothesis 3: *Increasing alliance complexity cost increases the number of alliance changes.*

Freight rate volatility

The simulation model’s assumption of a geometric Brownian motion shock driving the freight rate implies that volatility has a strong impact on rate realizations. Since it is possible to consider investment from a real options perspective (cf. Section 3.3.4.1) we expect deferred investment for higher volatilities which will in turn lead to lower capacity. This view is in line with Grenadier (2002) who shows that the real options investment trigger increases with volatility, i.e. asking for a higher freight rate in order to justify investment. Aguerrevere (2003) further shows that optimal capacity is actually decreasing in volatility. Rau and Spinler (2016b) show that in an oligopoly market, firm values are increasing in volatility. From a real options perspective, Bendall and Stent (2007) show that the value of the real option is increasing in volatility.

We hypothesize that in a more volatile market, alliance composition will be less stable as well. With respect to volatility impact, Midoro and Pitto (2000) argue that in light of “environmental uncertainty surrounding the activities of the alliance” stability is likely to suffer.

Hypothesis 4: *Increasing freight rate volatility increases the number of alliance changes.*

3.4.2 *Selection of investment approaches*

Our goal is to assess whether the application of a real options trigger policy has advantages over individual and collective DCF approaches. Overall, our guiding hypothesis is that a real options trigger approach performs comparatively best in comparison with DCF approaches, especially in light of high competitive intensity and high freight rate volatility; while not exhibiting substantial disadvantages when it comes to other market scenarios as well as in terms of coalition stability and industry concentration. As the real options approach takes into account industry characteristics such as freight rate uncertainty and managerial flexibility (c.f. Section 3.3.4), we expect that its financial performance will be better than the two DCF approaches.

Due to the option nature of the trigger policy (and the way it has been derived according to industry specifications), we expect its performance to be even better in environments of high competitive intensity, long lead times, and

high volatility. In high competitive intensity settings we expect the trigger to perform better due to the fact that it specifically takes into account an endogenous oligopoly price function (Gkochari 2015, Grenadier 2002, Rau and Spinler 2016b).

Hypothesis A: *The real options trigger policy leads to higher cash flow, particularly for high competitive intensity.*

In settings of long lead times, we expect the real options trigger to perform better than the other approaches as it specifically takes lead time into account (parameter κ).

Hypothesis B: *The real options trigger policy leads to higher cash flow, particularly for long lead times.*

Finally, due to its financial option nature, we expect that the real options trigger is most suitable to accommodate high freight rate volatility.

Hypothesis C: *The real options trigger policy leads to higher cash flow, particularly for high volatility.*

3.5 RESULTS AND DISCUSSION

To study the hypotheses about parameter impact and investment approach selection we construct a base case to make all three investment approaches comparable in terms of final capacity at the end of the measurement period. We then conduct a number of analyses with respect to competitive intensity, lead time, alliance complexity cost, freight rate volatility, and investment approach selection. The simulation model covers 120 periods which corresponds to a measurement period of 20 years. We find convergence for 5,000 iterations.

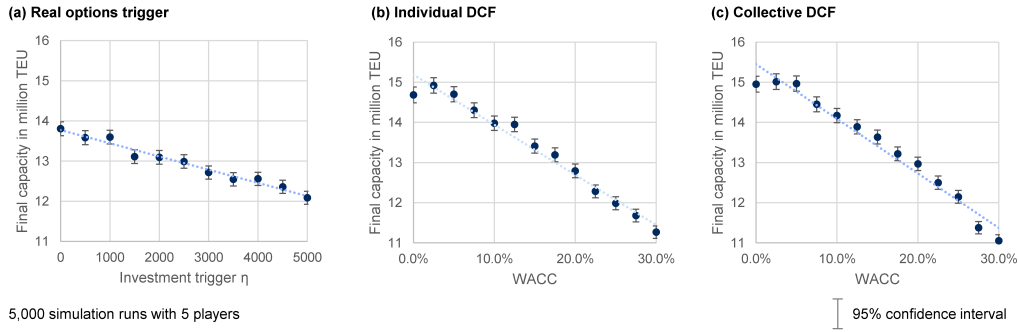
3.5.1 Base case

The assumptions for the fictitious market model (outlined in Section 3.3.1) lay the foundation for our base case scenario. In order to allow for relative comparison of the three investment approaches, we aim to calibrate them in a way that will produce equivalent final capacity at the end of the measurement period, namely 13.6 million TEU. We explicitly choose not to use financial impact as a base case measure because the financial outputs of the models show a greater variance than capacity outputs. The calibration parameters are the fictitious investment cost η for the real options trigger approach and the respective WACC values for the two DCF approaches.

Figure 3.3 shows final capacity of the three approaches for different values of the calibration parameters. Capacity is decreasing in both η and WACC and by a linear regression of the means we are able to derive the following base case parameter values:

- $\eta = 528.31$ USD

Figure 3.3: Base case final capacities for different η (investment trigger) and WACC (DCF approaches) values



- $WACC_{ind} = 12.75\%$
- $WACC_{col} = 13.60\%$

Table B.3 shows industry WACC data as of January, 2016. We observe that, depending on the country, WACC rates for “Shipbuilding and Marine” range from 4.88 percent (Japan) to 11.38 percent (India) (Damodaran 2016). Our WACC values are comparatively high, however, we argue that given the risky nature of the shipping industry, those values are appropriate to answer our research questions. Note that the base case calibration assumes a very stable market, i.e. competitive intensity is assumed to be $\gamma = 1.8$ and volatility is set to a value of $\sigma = 0.15$. This allows us to show that all three investment appraisal methods can produce equal results. To derive meaningful and still consistent results for the container shipping industry we, however, adjust these values for the analysis section that follows. We choose a higher competitive intensity $\gamma = 1.5$ which is in line with previous research (Rau and Spinler 2016b). We further assume a $\sigma = 0.25$ freight rate volatility which is consistent with historical data of the SCFI Composite (SSE 2016).

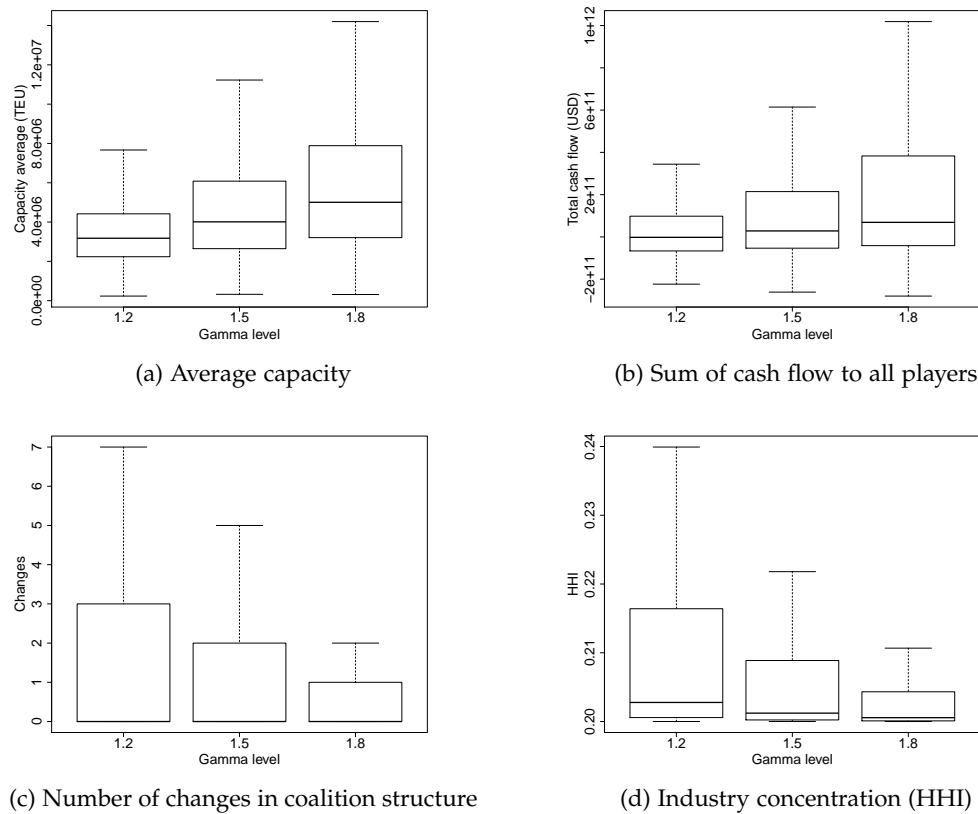
3.5.2 Independent variable variation

We use the simulation model to study the hypotheses outlined in Section 3.4.1 by changing independent variables. For this analysis, we choose to apply only the real options trigger investment approach because it is the focus of our study. In Section 3.5.3 we apply all three investment approaches to our cooperative game to study parameter impact and to compare the approaches. We vary competitive intensity ($\gamma_{low} = 1.2; \gamma_{medium} = 1.5; \gamma_{high} = 1.8$), lead time ($\kappa_{low} = 3; \kappa_{medium} = 9; \kappa_{high} = 15$ periods), alliance complexity cost ($C_{low} = 400,000; C_{medium} = 600,000; C_{high} = 800,000$ USD), and freight rate volatility ($\sigma_{low} = 0.15; \sigma_{medium} = 0.25; \sigma_{high1} = 0.35; \sigma_{high2} = 0.45; \sigma_{high3} = 0.55$).

Competitive intensity

We show the model output for different γ elasticity values in Figure 3.4. We observe that average capacity and its variance are increasing in γ (Figure 3.5a). We further see a γ -independent capacity floor. The increase in average capacity is driven by the endogenous price function, since in a high γ setting, additional investment has a less detrimental effect on the freight rate. The increase in variance - especially in the upside variance - might be driven by the fact that in very high freight rate settings, a low competition intensity will enable earlier investment which can in turn lead to higher capacities in later periods. The capacity floor implies that there is a competition-independent minimum capacity in the market. The cash flow results are consistent with the capacity observations (Figure 3.5b). γ has a positive effect on cash flow and its (upside) variance due to the endogenous price function and early investment.

Figure 3.4: Independent variable variation results for different elasticity values γ



With respect to the number of changes and the HHI (Figures 3.5c and 3.5d), we find a decrease in γ . The lower the impact of capacity on the price function, the more stability we observe (both in terms of absolute changes and their variance). This is most likely caused by the fact that the incentive to deviate from an alliance becomes less strong with lower intensity of competition. From an HHI perspective it seems that in light of high competitive intensity, players or alliances can make better use of operating cost advantages through ship size, hence the industry is more concentrated. We can hence confirm that with lower competitive intensity, alliances are likely to be more stable and accept

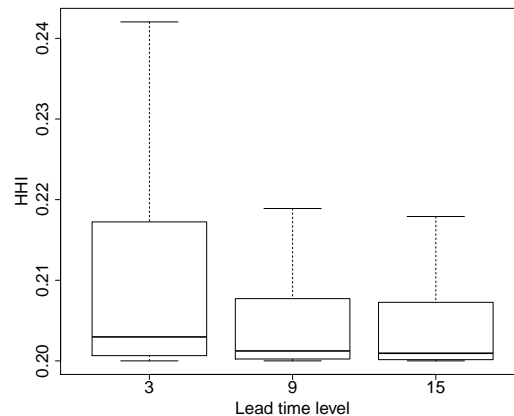
Hypothesis 1. Note that the Median HHI approaches 0.20 in the $\gamma = 1.8$ setting which implies an almost fully balanced industry structure at the end of the measurement period, even though initial capacities are different (c.f. Table B.1).

In summary, we find that in situations of higher competitive intensity, capacity is lower and alliances are less stable. From a managerial perspective choosing the right capacity (i.e. by applying a more appropriate investment approach such as a real options investment methodology) becomes even more important. Further, when considering alliances - especially if related to a certain trade lane with high competitive intensity - the higher tendency for instability needs to be kept in mind when negotiating an alliance.

Lead time

With respect to the lead time effect (Figure 3.5) on industry concentration, we make the observation that starting from a very short lead time (3 periods) towards a medium lead time (9 periods), we find a slight decrease in industry concentration. We hence find support for Hypothesis 2. We also observe a decrease in variance of HHI values. This is most likely caused by the loss of flexibility from longer lead times.

Figure 3.5: Industry concentration (HHI) for different lead times



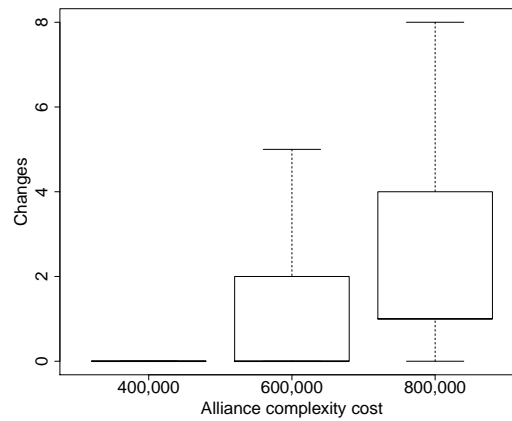
As a consequence, with shorter lead times players can improve their competitive position. One way to secure a competitive advantage in the shipping industry could be to secure delivery slots at shipyards or a higher focus on chartering vs. own investment.

Alliance complexity cost

From Figure 3.6 we further learn that alliance complexity cost are a driver for alliance instability. The alliance complexity cost increase linearly with the number of players in an alliance. The incentive to leave or change an alliance rises with higher alliance complexity cost. Hence, the more complex the collaboration (number of players, location, network complexity), the higher the instability. We accept Hypothesis 3.

From a managerial perspective, alliance complexity cost play an important role for alliance stability. Hence, the following factors need to be considered

Figure 3.6: Number of changes in the coalition structure for different values of alliance complexity cost

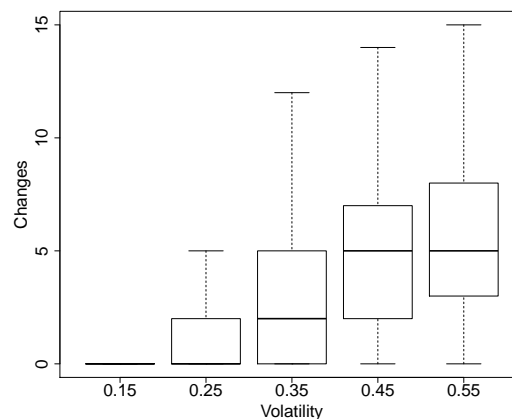


when forming new alliances: “scope of alliance activities; environmental uncertainty surrounding these activities; and adequacy of skills and competencies within the alliance” (Midoro and Pitto 2000).

Freight rate volatility

With respect to freight rate volatility, Figure 3.7 shows clear evidence that alliances are likely to change more often in light of higher volatility and hence we accept Hypothesis 4. Note that when moving to extreme volatility parameter values, we observe that the extent of the median increase becomes less. This is most likely due to the fact that there is a maximum number of manageable alliance changes, even for extremely volatile markets.

Figure 3.7: Number of changes in the coalition structure for different volatility levels



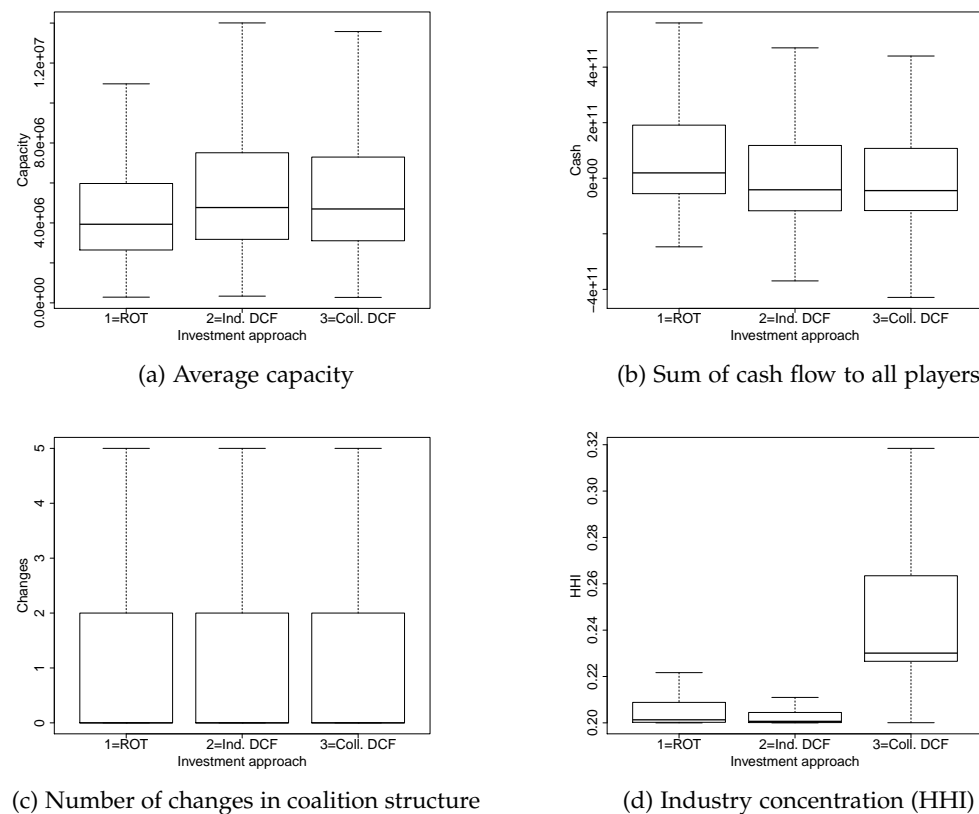
In volatile market environments, the right choice of alliance membership becomes paramount since the incentive to leave an existing alliance is likely to become much stronger if it is not well aligned with the expectations of the player.

3.5.3 Selection of investment approaches

We can address Hypotheses A-C by comparing outputs for the three different investment approaches. We observe that the resulting distributions are skewed but similar across investment approaches. We choose to apply the Mann-Whitney test instead of a t-test to evaluate the statistical significance of the results. If we assume that the distributions of the different results are similar and there is only a shift in location, this test can be described as corresponding to a test of the difference in medians (Hart 2001).

From Figure 3.8 we observe⁵ that the real options trigger approach leads to lowest average capacity (Figure 3.9a), a higher cash flow to the players (Figure 3.9b) and no observable difference in number of alliance changes (Figure 3.9c). Both the real options trigger and the individual DCF approaches deliver a similar level of industry concentration; the collective DCF approach, however, leads to a strong increase in HHI (Figure 3.9d). The increase in HHI can be explained by the fact that - in the collective DCF investment approach - firms form an investment decision together, have more relaxed equity constraints, and share the resulting fleet after delivery.

Figure 3.8: Investment approach comparison (1=Real options trigger, 2=Individual DCF, 3=Collective DCF)



⁵Note that both Figure 3.8 and the statistical tests in Table B.4 are based on a simulation run with standard parameters, i.e. $\gamma=1.8$, $\kappa=9$, and $\sigma=0.25$.

The statistical test (Table B.4) finds significance for all values. Note that even though the median changes are zero, the mean rank of the real options trigger approach is higher. This means that the distribution of alliance changes across all 5,000 model iterations is on a higher level. Hence, the real options trigger exhibits a higher number of changes.

In terms of cash flow impact (Figure 3.9) we find that the real options trigger approach performs well across the board, but is better in markets with high competitive intensity (Figure 3.10a). Hence, we accept Hypothesis A. For short lead times, the real options trigger approach performs extremely well, but for long lead times (Figure 3.10b) the difference between the approaches becomes smaller. That means we need to reject Hypothesis B. However, it should be noted that even when approaching longer lead times, the real options investment trigger approach still performs better than the other approaches. Finally, we find support for Hypothesis C since the real options trigger cash flow to the players is substantially increasing in volatility (Figure 3.10c). The differences between the results from the investment trigger vs. the individual DCF approach are statistically significant (Tables B.5, B.6, and B.7).

The real options trigger approach performs well across the board and has distinctive advantages in volatile and competitive markets. Hence, the more volatile and competitive a market, the stronger we encourage alternative investment approaches, such as the proposed real options trigger approach or other approaches that can capture the shipping industry-specific characteristics, namely freight rate uncertainty and competitive intensity.

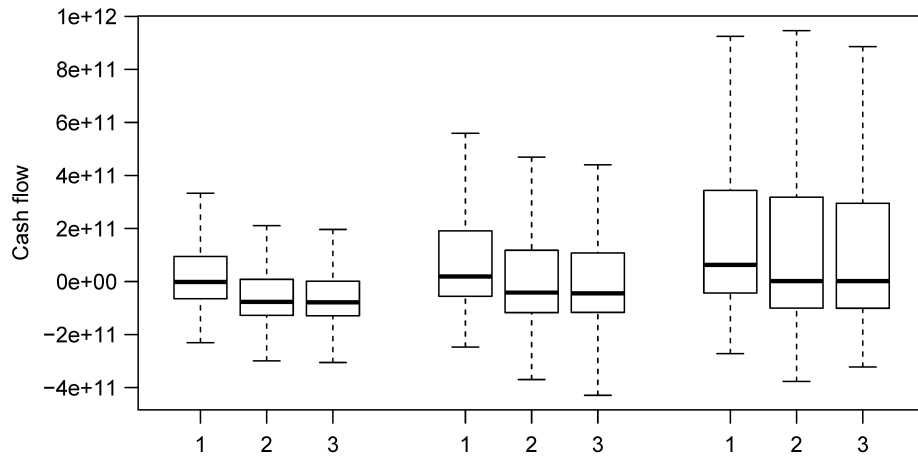
3.6 CONCLUSION

With this research effort, we address some of the questions that arise in light of the challenges of the shipping industry: overcapacity and eroding margins, repeatedly changing strategic alliances, and non-trivial investment decisions. We propose a cooperative game theory simulation model that allows us to compare different investment approaches in light of varying competitive intensity, lead time, alliance complexity cost, and freight rate volatility. We confirm that competitive intensity, alliance complexity cost, and freight rate volatility are drivers for alliance changes.

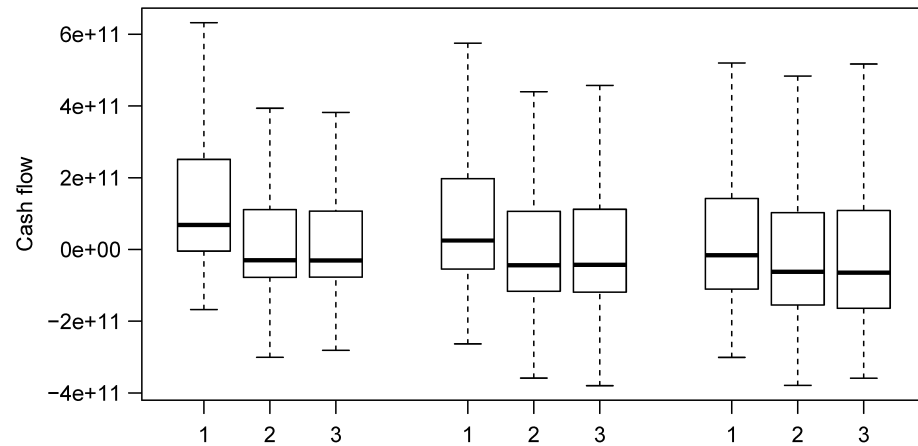
Overall, we find that - especially in light of high volatility and high competitive intensity - the choice of investment approach is key. The proposed real options investment approach by Gkochari (2015), Grenadier (2002), Rau and Spinler (2016b) offers a substantial financial advantage that increases with volatility and competitive intensity; while only slightly increasing alliance stability in comparison with traditional DCF approaches.

Avenues for further research could be an empirical back testing of the real options investment approach with a long timeframe of industry data. We also suggest the further exploration of the effect of lead time on industry concentration.

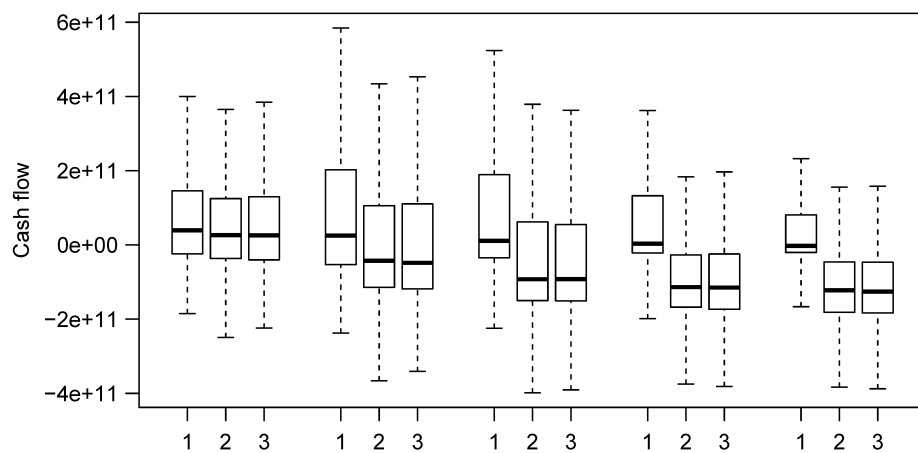
Figure 3.9: Investment approach comparison cash flow (1=Real options trigger, 2=Individual DCF, 3=Collective DCF)



(a) Different elasticity (gamma) levels: 1.2, 1.5, and 1.8



(b) Different lead time levels: 3, 9, and 15 time periods



(c) Different volatility levels: 0.15, 0.25, 0.35, 0.45, and 0.55

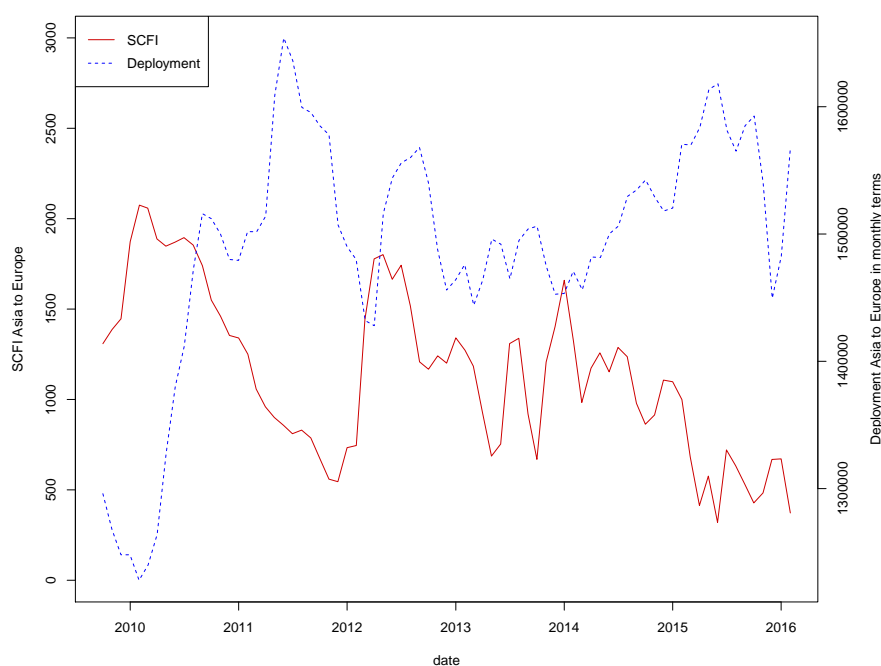
Real options investment in container shipping: An empirical view on capacity and rate development¹

4.1 INTRODUCTION

4.1.1 Container freight rates at historical low

Operating in the container shipping industry has never been particularly easy. Freight operators have ever since faced changing market cycles (Stopford 2010), highly capital-intensive investments (Rau and Spinler 2016b), supply-demand imbalances (Syriopoulos 2010), and a market that is far from perfect competition (Pirrong 1992). Since the beginning of the year 2015, the rates on the SCFI have dropped significantly and are currently at historically low levels. In March 2016, the SCFI Composite Index has dropped to the lowest value since introduction, namely 414 USD per twenty-foot equivalent unit (TEU) (SSE 2016).

Figure 4.1: SCFI and deployment for Asia to Europe over time



Source: Alphaliner (2012, 2014b, 2015b,c, 2016), SSE (2016)

Looking at rates and capacity deployment for the popular Shanghai to Europe route in Figure 4.1, the decrease in rates is even more pronounced. One

¹Rau and Spinler (2016c): Rau, P., Spinler, S. (2016). Real options investment in container shipping: An empirical view on capacity and rate development. Unpublished Working Paper. Presented at INFORMS 2016 International Conference, Waikoloa.

TEU freight from Shanghai to Europe is currently sold at a rate of of 271 USD (April 22nd, 2016). Part of this drop may be attributed to lower fuel prices since SCFI values are quoted including Bunker Adjustment Factor (SSE 2016). However, even with the usage of very large vessels, it is close to impossible to even cover variable cost for this sort of voyage.

From Figure 4.1 we further find that in line with decreasing freight rates, capacity deployment has been increasing. This data suggests two hypotheses that we want to explore in detail: (1) the oligopoly price function which states that the higher the capacity, the lower the rate (Rau and Spinler 2016b) holds for container shipping, and (2) the container shipping industry is suffering from overcapacity.

4.1.2 *Impact on container shipping industry*

The deteriorating market situation influences behavior in the container shipping industry in 3 ways. First, it has been reported that liner shipping companies are facing bankruptcy since - despite a recovery in the world economy - players are suffering from high amounts of debt and excess capacity as a result of ordering booms in the past years. Some players even had to shed non-core assets to ensure sufficient liquidity (Barnato 2016). Second, capital expenditures for container vessels have significantly declined, especially when it comes to smaller market participants (Barnato 2016). Third, the industry is in the middle of a strong trend towards consolidation. In the past years, strategic alliances have evolved drastically (Rau and Spinler 2016a) and further consolidation has been driven by mergers and acquisitions. For example, in April 2016, the European Commission approved the acquisition of NOL by CMA CGM. This will not only impact services but lead to a new alliance composition. As part of the merger, NOL needs to leave the G6 alliance (Shingleton 2016).

4.1.3 *Research objectives*

A number of authors argue that non-optimal investment methods and/or timing have triggered overcapacity in the shipping industry and container shipping in particular (Bendall 2010, Lau et al. 2013, Rousos and Lee 2012, Scarsi 2007). Gkochari (2015) shows that a real options trigger approach performs well for bulk shipping. Rau and Spinler (2016a) show with simulations that this approach is valid for container shipping as well and argue that it should be preferred over the traditional DCF approaches. So far, the validity of the real options trigger approach has not been shown in container shipping from an empirical perspective. We aim to provide new insights on container freight rates and real options investment in container shipping by asking the following research questions:

- How can an oligopoly container freight rate be empirically characterized?
- To what extent does the oligopoly price function hold for container shipping?

- How would shipping players have performed in the past five years if they had utilized a real options approach for their investment projects?

The structure of this paper is as follows: Section 4.2 reviews existing literature on empirical research in shipping, capacity investment in shipping, and the real options trigger approach as well as explains the contribution of this research. Section 4.3 introduces the empirical ARIMA model to characterize the container freight rate and Section 4.4 shows the industry back testing of the real options approach. In Section 4.5 we provide a discussion of the results. Section 4.6 concludes with managerial recommendations and suggests areas for further research.

4.2 LITERATURE REVIEW

We position our research into existing literature and reflect on previous contributions with respect to investment decisions in shipping, empirical research in bulk and liner shipping, and the development of real options investment models in shipping. Moreover, we explain how our econometric model and industry back testing fills a gap in research as well as detail the contribution of this article. A comprehensive overview of the current state of research is provided by Lee and Song (2016). The authors argue that overcapacity and low freight rate, among others, present challenges for the container shipping industry and call for further research in container shipping.

4.2.1 *Investment decisions in shipping*

A number of research contributions have argued that investment decisions in shipping are biased and the still prevalent DCF methodology might not capture the nature of the investment problem accordingly. Scarsi (2007) argue that in the bulk shipping business shipowners ignore or underestimate market trends and follow their intuition, hence do not exhibit rational behavior. In some cases, players imitate competitors' strategy. The authors list as potential reasons lack of experience, managerial culture, decision making attitude, and company structure. Bendall (2010) argues that the traditional DCF analysis does not take into account managerial flexibility. In the container shipping context, this may lead to a misinterpretation of the investment opportunity, for example since the investor might have the option to expand the number of ships on a specific route or - depending on income development - discontinue service on a given route or in a region altogether. Rousos and Lee (2012) argue that besides monetary factors, there are other, non-financial determinants for shipping investment. They apply analytical hierarchy process and Multicriteria Decision Making (MCDM) to create an investment proposal model that accepts non-financial and financial inputs. They argue that decision making in shipping is biased since there are non-financial inputs. They show that MCDM indeed works and find that an optimal tradeoff between net present value, internal rate of return, risk profile, and the decision maker's psychology can explain shipping investment adequately. In a meta analysis of 282 papers on container shipping published between 1967 and 2012, Lau et al. (2013) find that so far,

research was focused around three key topics: (1) the East-West transport axis, (2) practical, daily shipping activities, and (3) quantitative analysis even though it is hard to obtain reliable data. The authors call for a change in the research to focus on well-being of the world community as well as increase research efforts to explain and counter excess capacity and persistent overinvestment in the container shipping industry.

4.2.2 *Empirical research in bulk shipping*

With respect to bulk shipping investment, Alizadeh and Nomikos (2007) evaluate the performance of trading strategies in sale and purchase for dry bulk ships. They use price and charter ratios from 1976 to 2004 and estimate a price earnings ratio as investment decision criterion. They find that price-earnings-ratio strategies outperform buy and hold strategies due to high volatility in the large vessel markets. Gkochari (2015) tests the real options approach by Grenadier (2002) in the dry bulk shipping industry. By estimating the competitive dynamic equilibrium in the market she explains boom-and-bust cycles in shipping and finds that a reduction of order lead time reduces the investment trigger value.

In terms of freight rate, Xu et al. (2011) study the relationship between time-varying volatility and change in supply fleet. They find that change in fleet size positively affects freight rate volatility, but in a nonlinear way. The methods employed are AR-GARCH and GMM regression. Alizadeh (2013) investigate the relationship between price volatility and trading volume in the shipping forward freight market from 2007 to 2011. Applying VaR and GARCH methods, they find a momentum effect in which higher capital gains in the market lead to more transactions. Alizadeh and Muradoglu (2014) find by regression analysis that changes in freight rates can predict stock index returns for the United States because they carry information. They name three key reasons: (1) freight rates take on an international and hence more comprehensive view, (2) the data is available instantly, and (3) shipping demand leads production and hence has a timing advantage. Dai et al. (2015) apply a multivariate GARCH model to capture volatility spillover effects across vessel and freight markets. They confirm the existence of volatility spillovers between the markets.

4.2.3 *Empirical research in liner shipping*

With respect to liner shipping freight rates, Cariou and Wolff (2006) find that there is a Granger causal relationship between average bunker price and bunker adjustment factor. They further find that the time charter rate has a causal effect on the average freight rate. This relationship can, however, only be found for Westbound rates. The effect on Eastbound rates is not significant due to trade imbalances. Luo et al. (2009) run an econometric model for the container shipping market. They analyze freight rates, demand, and capacity. Under the assumption of a freight rate governed by demand and capacity interactions, exogenous trade, and endogenous capacity (increased by orders proportional to profits) they are able to replicate market fluctuation for 1980-2008 and provide

a prediction. They use a Cobweb model for market clearing and can explain more than 90 percent of the variations in fleet capacity and freight rate.

Hsiao et al. (2013) assess return lead-lag and volatility transmission effects in bulk and container shipping markets. They compare the Baltic Dry Index (BDI) with the CCFI with the goal to gain insights that can be used to hedge. They mention three important differences between the markets: (1) type of goods transported, (2) contract duration, and (3) price formation, i.e. perfect competition vs. oligopoly. They conduct cointegration and Granger causality tests and split their data into pre, during, and post 2008 financial crisis datasets. They find that there is no significant relationship before the crisis. During the crisis, the BDI is ahead of the CCFI, most likely from market pressure due to high competition. After the crisis, the CCFI is ahead of BDI which might be explained by a better and quicker response to the economic recovery due to the “sticky-up” nature of container freight rates.

Lun et al. (2013) apply demand chain management to liner shipping. They mention three shipping industry specifics: (1) high fixed cost, (2) low service differentiation, and (3) a concentrated number of players. With a 1996-2007 Clarksons dataset, they use structural equation modeling to test a number of relationships between demand, fleet size, rate, newbuilding price, secondary market price, and scrap price. The results confirm expectations; for example increasing fleet size puts pressure on rates. Nielsen et al. (2014) add a perspective to forecasting container freight rates since they argue the limited number of previous studies have two main shortcomings, i.e. capacity cannot react fast enough and only world-aggregated rates are taken into account. They develop an econometric container freight rate forecast model by looking at the relationship of individual company rates vs. global market rates. They consider demand, capacity, seasonality, GRIs, and the SCFI as explanatory variables, partly with time lags. Their forecast model performs well and achieves the objective of 5 percent Mean Absolute Percentage Error (MAPE) within a 6 weeks forecast period.

In terms of (excess) capacity, Cullinane and Khanna (1999) develop a cost model for container ships to assess the tradeoff between economies of scale at sea from large ships and diseconomies of scale in ports due to higher handling effort. They find that economies of scale in container shipping are highly dependent on port productivity and argue that the optimal ship size is 8,000 TEU. Fusillo (2003) argue that container shipping is close to a natural monopoly and that as a result of core theory, excess capacity is an issue due to lumpy investment, especially if there is no form of cooperation. As reasons for why excess capacity has improved very little over the past decades, they isolate strategic entry deterrence for the top four players and, more importantly, lumpiness of investment. Yip et al. (2012) apply a structure, conduct and performance framework to liner shipping and develop a functional specification of the relationship between capacity and market share as an S-Curve. For the period from 1997 to 2008, they find evidence for scale economies and diseconomies.

With respect to investment, Fan and Luo (2013) analyze ship investment and choice behavior for liners with binary choice and nested logit models from 1999 to 2009. They find that - for small players - expansion decisions are mostly driven by the market, i.e. high demand, high demand growth, or high TC rates.

At the same time, large players tend to use expansion as a means of maintaining market share. They further find that companies who do more chartering tend to expand less frequently. Bragoudakis et al. (2013) find that the shipping crisis (low rates and layup) has strong impact on the Greek economy and shipping due to the slow response of supply. They find that anticyclicity in investment declined after 2006.

4.2.4 *Real options models for shipping investment*

Real options analysis can better incorporate shipping industry specifics, such as irreversibility of investment, cash flow uncertainty, and flexibility in decision making; hence a research stream has emerged. A detailed literature review of real options in shipping and game-theoretic real options models can be found in Rau and Spinler (2016b); we provide a summary here.

Goncalves (1992) is the first to apply real options analysis to bulk shipping. Dixit and Pindyck (1994) extend this work to assess tanker industry decisions. Bendall and Stent (2007) contribute a number of articles with respect to real options analysis in short sea container shipping and find that real options models can capture ship investment better. Dikos (2008) shows the validity of the real options hypothesis and Pires et al. (2012) apply real options analysis to the decision on whether to own or charter. Gkochari (2015) finds that a real options game based on Grenadier (2002) can successfully be applied to bulk shipping. Rau and Spinler (2016b) develop a real options game model in continuous and discrete time and (Rau and Spinler 2016a) test its validity in a simulation. They find that the real options trigger approach performs comparatively better than a DCF approach, especially if volatility and competitive intensity are high.

4.2.5 *Literature gap and contribution*

We believe there is a gap in research due to a number of reasons. First, several authors have pointed out that the (container) shipping industry suffers from shortcomings in investment methods and overcapacity (Bendall 2010, Rousos and Lee 2012, Scarsi 2007) and call for additional research efforts in this particular area (Lau et al. 2013, Lee and Song 2016). Second, a lot of research has focused on bulk and tanker shipping, in part due to better availability of time series data. However, with the introduction of the CCFI and SCFI indices (SSE 2016), data availability has improved and opened new avenues of research. Third, during our extensive literature survey, we have not come across any articles that analyze how fleet or capacity deployment impact autoregressive freight rates or empirically test real options game approaches within the context of container shipping.

We argue that with this research effort, we are able to contribute a deeper understanding of the container freight rate and its dependency on fleet deployment by conducting an ARIMA regression model on SCFI with deployment data from the past 5 years. Another contribution to the literature stream for real options shipping investment is the empirical verification of a proposed investment approach as well as the identification of prerequisites and limitations

of the approach: for example the substantial impact of volatility expectation, potentially induced cyclicalities from trigger approaches, and the timing impact of investment lead times.

Our research has clear implications for practitioners. We foster a better understanding of container freight rates and how players can work to improve their situation. With the real options trigger approach and the industry back testing, we present a ready-to-use investment approach that can be added to a shipping player's investment decision toolkit.

4.3 EMPIRICAL CHARACTERIZATION OF THE FREIGHT RATE

With this Section, we aim to empirically characterize the container freight rate for the trade lane Asia to Europe. Even though data availability for container shipping remains comparatively low, we present relevant data sources, explain the motivation for ARIMA modeling, as well as present an ARIMA model with and without regressors.

4.3.1 *Data*

To characterize the freight rate empirically we rely on time series data that captures freight rates, capacity deployment, and shipping demand. In the following, we present an overview of the available sources. For our analysis, we choose the SCFI for the Asia to Europe trade lane in monthly increments to represent the freight rate since it has the largest panel and is suitable for the trade lane under investigation. In terms of capacity, we choose to work with the capacity deployment for the Asia to Europe trade lane as published by Alphaliner. For a cross-check for demand impact, we rely on weekly shipping demand on the trade lane provided by Alphaliner.

4.3.1.1 *Freight rate data*

The SCFI was introduced in 2009 and is a widely accepted freight index. For example, it is used for publications of the United Nations Conference on Trade and Development, such as the Review of Maritime Transport (UNCTAD 2015). This index reflects the actual spot rate in USD per TEU for 15 trade lanes originating in Shanghai on a weekly basis. The index panel includes 22 liner shipping companies as well as 17 shippers and freight forwarders (SSE 2016).

A possible alternative is the CCFI which has been first published with a starting value of 1,000 in 1998. The index contains of 14 trade lanes originating in China and data is provided by a freight rate formulation committee which is made up of 22 Chinese and foreign shipping companies (SSE 2016). Current index values for SCFI and CCFI can be obtained from the Shanghai Shipping Exchange (SSE) website while a full time series with up to weekly granularity can be obtained from several data providers. Clarksons SIN, for example, provides weekly data from October 2009 (SCFI) or March 2003 (CCFI) until today.

Shipping rates for a multitude of origin-destination pairs can also be obtained from Drewry Container Freight Rate Insight (Drewry 2016). However, in contrast to SCFI and CCFI, rates are only available on a subscription basis,

are usually available on a bimonthly basis only and tend to rather show a long-term development of rates as opposed to SCFI and CCFI, which are linked to short-term market developments, such as demand and capacity deployed.

4.3.1.2 Capacity data

The weekly capacity deployment on the trade lanes Far East to Europe, Far East to North America, and Europe to North America, is reported in the Alphaliner Monthly Monitors (Alphaliner 2012, 2014b, 2015b,c, 2016). It is based on the nominal vessel capacity and estimated on the first of every month. Slow steaming is not captured in the analysis. A full dataset is not available for purchase, however, it is possible to gather the actual figures from January 2011 until today from several Alphaliner Monthly Monitor reports. Data points from January 2009 until December 2010 are only available in charts, hence we extract those graphically.

Alternatively, Clarksons Shipping Intelligence Network (SIN) publishes the total fleet development by number of ships, total capacity, and total deadweight tonnage. Monthly data points are available from January 1996. The data is based on registered container ships and does not allow for a segmentation by trade lane or region (Clarksons 2016).

4.3.1.3 Demand data

Alphaliner provides monthly demand data for both Far East to Europe and Far East to US trades. Data from January 2009 until today can be collected from a number of Alphaliner Monthly Monitors (Alphaliner 2012, 2014b, 2015b,c, 2016). An alternative would be demand data by Global Insight or a regression between demand and GDP of importing countries.

4.3.2 Model selection

The goal for our research is to characterize the freight rate price function by estimating an econometric model to assess factor importance on freight rate (e.g. fleet size, deployment, demand). As a starting point, we take the oligopoly price function

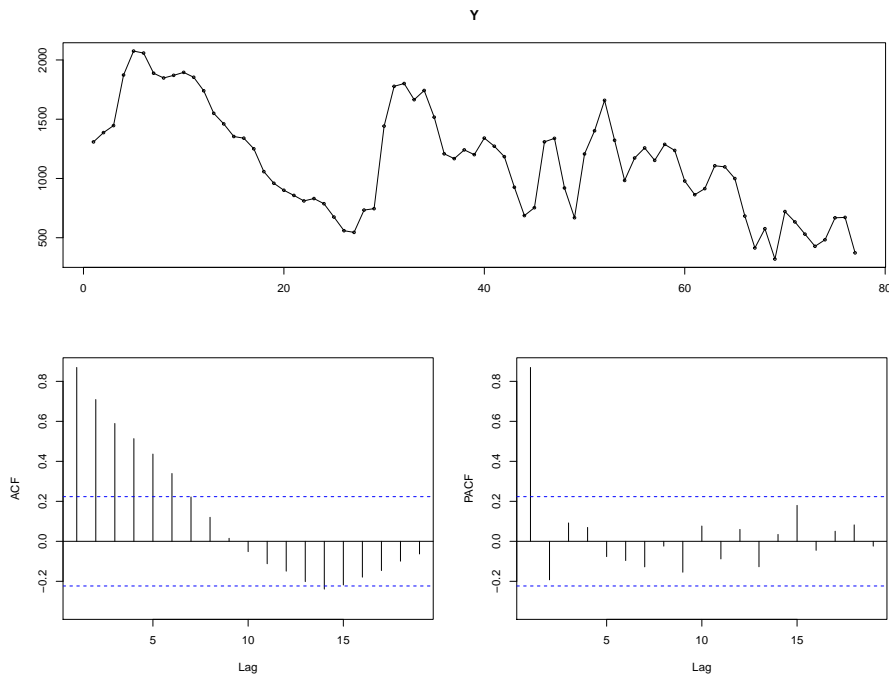
$$p_t = Q_t^{-\gamma} X_t \quad (4.1)$$

where p_t is the current freight rate, Q_t is the current deployed capacity, γ is the elasticity (intensity of competition), and X_t is a random shock term.

After evaluating a number of options, we select an ARIMA model to capture the autoregressive part of the SCFI with Asia to Europe Deployment as a regressor within the time frame October 2009 until February 2016, i.e. 77 data points². A descriptive time series analysis in Figure 4.2 reveals non-stationarity of SCFI data as well as a significant autocorrelation. Linear regression methods

²Note that an ARIMA model on the CCFI Asia to Europe index with Deployment as regressor would be a viable alternative. We have conducted a full-scale ARIMA analysis and found that while in this case, the ARIMA terms would be significant, we cannot establish a significant relationship between deployment and freight rate.

Figure 4.2: Time series chart of SCFI Shanghai to Europe



Source: SSE (2016)

would not be able to capture those effects, hence we apply an ARIMA model. ARIMA stands for Autoregressive integrated moving average, it is a class of time series models. ARIMA(p,d,q) classifies the model: p refers to the order of the autoregressive model, d to the degree of differencing to achieve stationarity, and q refers to the order of the moving average model (Asteriou and Hall 2007, Box et al. 1976, Nau 2016). Decisive advantages of the ARIMA model are that it captures the autocorrelation of the time series well and the regressor is significant. However, the increased complexity, especially in contrast to straightforward regression models, may be seen as a disadvantage.

Naturally, there are other options as well. A correlation analysis with a number of potential freight rate drivers such as bunker fuel price, layup capacity, total fleet, secondary market vessel prices, newbuilding vessel prices, time charter rates, GDP, demand, deployment, and purchasing manager index would be straightforward in the analysis and can help identify freight rate drivers³. However, this approach would not capture the autoregressive part of the SCFI time series and the isolation of an elasticity γ would be difficult. Lun et al. (2009) have conducted such an analysis for the container shipping market, albeit with a limited number of drivers.

A multiple regression model with five significant factors (secondary market vessel prices, new built vessel prices, demand, purchasing manager index, deployment) from October 2009 to May 2015 would show the relevant drivers for

³We have conducted this analysis for the timeframe October 2009 until May 2015 and found that, among others, layup pool and time charter rates are negatively correlated, total fleet and GDP are highly positively correlated, bunker price does not have significant correlations, and freight rates and deployment are negatively correlated.

the freight rate and present a straightforward methodology. However, it does not capture the autoregressive part of SCFI data and the adjusted R^2 would not exceed 0.50.

An ARIMA model with a longer timeframe to capture the CCFI global index with total fleet as regressor (March 2003 to October 2015) would still capture the autocorrelation of CCFI data well, but in addition to the ARIMA complexity, the fleet regressor is not significant and a trade lane focus is not possible.

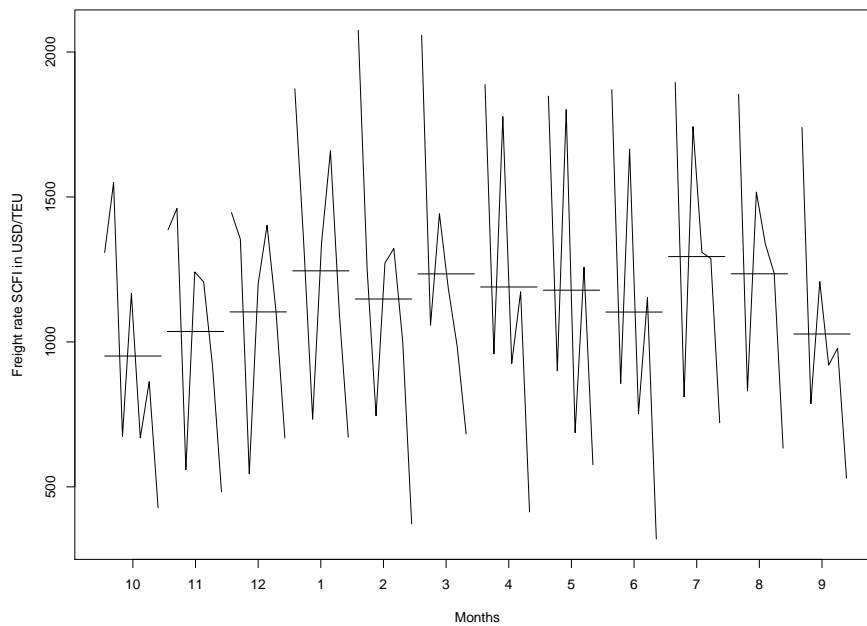
4.3.3 ARIMA analysis

We conduct a full-scale ARIMA analysis with the SCFI Shanghai to Europe for the time period October 2009 to February 2016. We check for seasonality, take natural log and first differences to achieve stationarity, and estimate the model. We compare different models for fit, identify remaining crosscorrelations of error terms and finally estimate an ARIMA (0,1,3) model with monthly capacity deployment on the Asia to Europe trade lane as regressor.

4.3.3.1 Seasonality

Within the SCFI data we do not see a strong sign of seasonality. The monthly subplot in Figure 4.3 shows a large bandwidth of index values for the respective months, but there is no clear indication of seasonality. Directionally, we find that there seem to be slightly higher rates in the first months of the year as well as in July and August. Based on those observations, we choose to not control for seasonality in the ARIMA model.

Figure 4.3: Monthly subplot of SCFI Shanghai to Europe

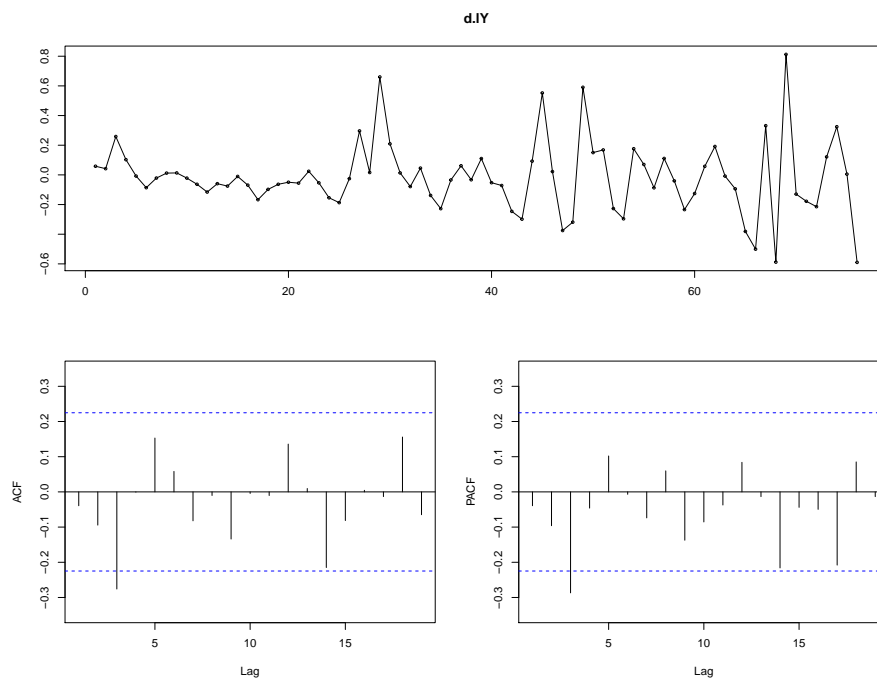


Source: SSE (2016)

4.3.3.2 Stationarity

In order to be consistent with the structure of the oligopoly price function, we translate the time series into natural log terms. This transformation alone does not lead to stationarity since we see a significant negative trend in the series. Stationarity is achieved when mean, variance, and covariances are constant over time (Asteriou and Hall 2007). Figure 4.4 is the first difference of the time series and fulfills the three characteristics required for stationarity⁴. Further differencing does not improve the level of stationarity.

Figure 4.4: Time series chart of SCFI Shanghai to Europe, natural log terms, first difference



Source: SSE (2016)

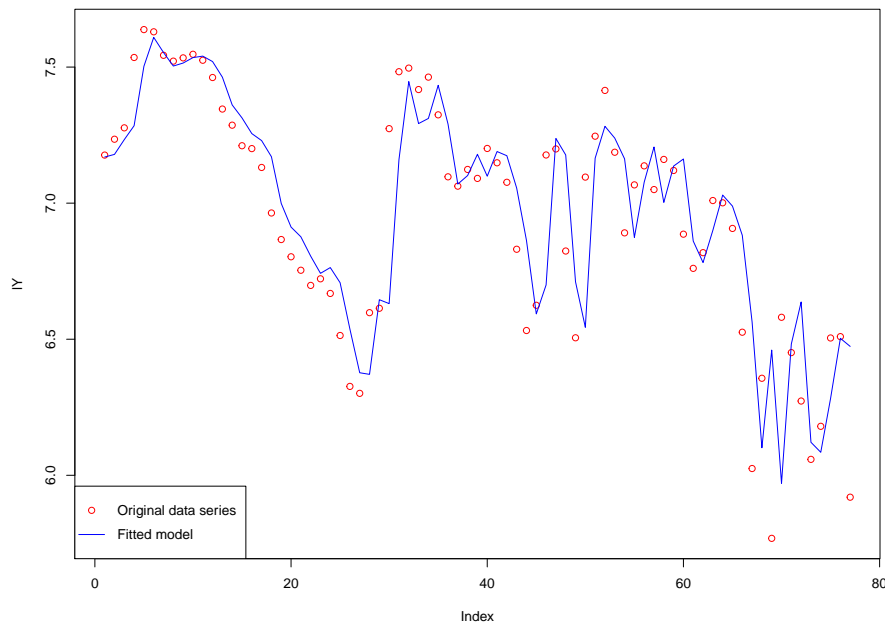
4.3.3.3 Estimate ARIMA model

From Figure 4.4 we conclude that a potential starting point would be a moving average model with 3 coefficients, i.e. an ARIMA (0,1,3) model. The Autocorrelation Function (ACF) has a clear spike at lag 3, hence we need to include 3 coefficients. Furthermore, we see a gradual decay in the Partial Autocorrelation Function (PACF) which indicates a moving average process (Asteriou and Hall 2007).

The fitted model is depicted in Figure 4.5. A first graphical observation leads to the conclusion that the moving average model performs very well in the first two thirds of the time series. For the last part - which is characterized by significantly higher volatility - there is a stronger deviation between fitted

⁴Note that the SCFI Asia to Europe is highly volatile, hence also higher degrees of differencing cannot fully eliminate the increasing variance over time.

Figure 4.5: Fitted ARIMA(0,1,3) model of SCFI Shanghai to Europe



Source: SSE (2016)

model and original time series. The coefficients, standard error and goodness of fit statistics are given in Table C.1. We find that the freight rate estimate depends on the past 3 forecast errors, in negative terms, albeit only θ_3 (moving average term third order) is statistically significant. The R^2 value - here defined as the squared correlation between fitted model and original data series - is 0.73.

4.3.3.4 Model performance

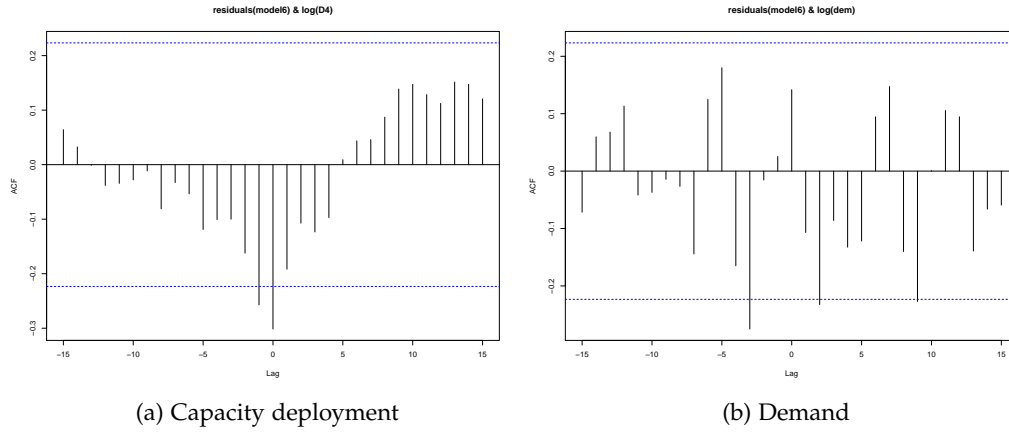
A good ARIMA fit can be established by performing 4 checks: (1) the parameter of the longest lag is significant, (2) ACF and PACF of remaining forecast errors are all insignificant, (3) the performance in key goodness of fit measures is good compared to other potential models, and (4) there are no remaining cross-correlations (Asteriou and Hall 2007, Box et al. 1976, Nau 2016).

Table C.1 shows that the coefficient for the longest lag θ_3 is significant, hence a reduction of coefficients is not feasible. The ACF and PACF of the remaining forecast errors are - except for the very high lag 14 - not significant. A comparison of the 4 key goodness of fit measures⁵ across 10 possible model settings reveals that the ARIMA (0,1,3) and the ARIMA (3,1,0) models perform comparatively best (Table C.2). The second difference models do not perform very well. A crosscorrelation analysis between error terms of the model with

⁵We consider the Akaike Information Criterion (AIC), the Akaike Information Criterion for small sample sizes (AICc), the Bayesian Information Criterion (BIC) and the squared correlation between fitted model and original data series (R^2). For AIC, AICc, and BIC a lower number indicates a better fit while a higher R^2 indicates a better fit.

deployed capacity and demand on the Asia to Europe trade lane in monthly terms (Figures 4.7a and 4.7b) reveals that while demand seems to not have a significant influence on the errors, capacity deployment should be considered as a regressor for the ARIMA model.

Figure 4.6: Crosscorrelation of ARIMA(0,1,3) residuals



Source: SSE (2016)

4.3.3.5 ARIMA with deployment as regressor

Entering capacity deployment on the Asia to Europe trade lane as regressor into the ARIMA (0,1,3) model improves model fit. Figure 4.7 shows the original data series with the fitted model. We find a statistically significant negative relationship between deployment and freight rate (c.f. Table C.3). All of the goodness of fit measures have improved as well.

With respect to the model checks, the highest lag remains significant and also ACF and PACF or remaining forecast errors are - except for the high lag 14 - insignificant. In comparison with other candidate models, the ARIMA (0,1,3) and ARIMA (3,1,0) models still perform best as shown in Table C.4. We cannot find a significant remaining crosscorrelation with demand on the selected trade lane. We conclude that the ARIMA (0,1,3) model with deployed capacity as a regressor, in monthly terms, is the appropriate characterization of the SCFI Asia to Europe freight rate process.

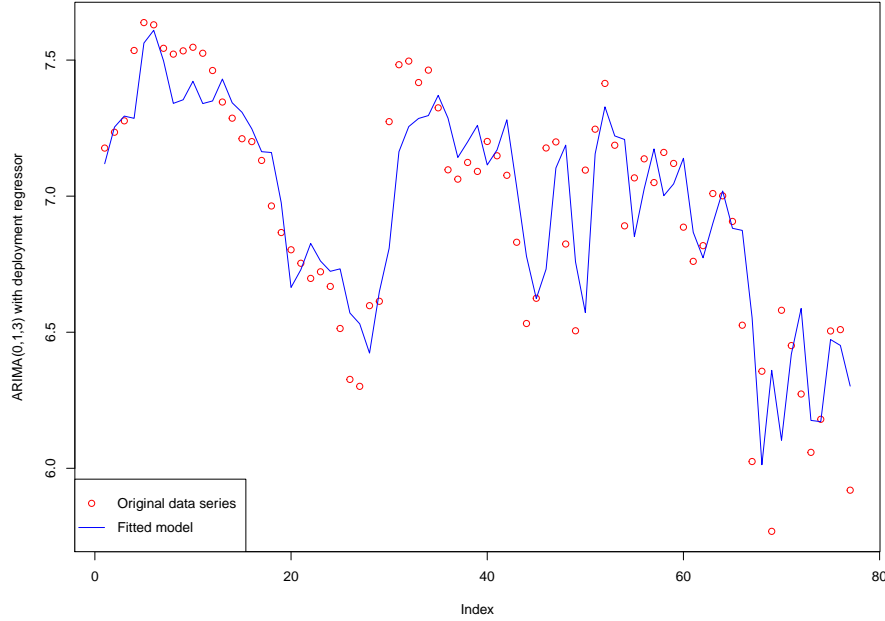
4.3.4 Derivation of freight rate formula

In order to apply the insights from the ARIMA analysis, we need to derive the respective freight rate formula in the following. We are using an ARIMA(0,1,3) model and the general characterization is

$$\Delta^1 \ln y_t = \theta_1 u_{t-1} + \theta_2 u_{t-2} + \theta_3 u_{t-3} + \psi \Delta^1 \ln Q_t + \ln \epsilon_t \tag{4.2}$$

where y_t is the freight rate for period t , Δ^1 is the first difference operator, u_{t-i} is the forecast error from period $t - i$, θ_i is the moving average coefficient for

Figure 4.7: Fitted ARIMA(0,1,3) model with capacity deployment as regressor



Source: SSE (2016)

the respective lag i , ψ is the regression coefficient, Q_t is the capacity deployed in period t , and ϵ_t is the iid error term.

Denoting \hat{y}_t as freight rate forecast, this can be simplified to

$$y_t = y_{t-1} \left(\frac{y_{t-1}}{\hat{y}_{t-1}} \right)^{\theta_1} \left(\frac{y_{t-2}}{\hat{y}_{t-2}} \right)^{\theta_2} \left(\frac{y_{t-3}}{\hat{y}_{t-3}} \right)^{\theta_3} \left(\frac{Q_t}{Q_{t-1}} \right)^{\psi} \epsilon_t. \quad (4.3)$$

If we define $\epsilon_t = X_{real,t}$, $y_t = p_t$, and $\psi = -\frac{1}{\gamma}$, the price function can be expressed as

$$p_t = Q_t^{-\frac{1}{\gamma}} X_{real,t} p_{t-1} \left(\frac{p_{t-1}}{\hat{p}_{t-1}} \right)^{\theta_1} \left(\frac{p_{t-2}}{\hat{p}_{t-2}} \right)^{\theta_2} \left(\frac{p_{t-3}}{\hat{p}_{t-3}} \right)^{\theta_3} \left(\frac{1}{Q_{t-1}} \right)^{-\frac{1}{\gamma}}. \quad (4.4)$$

The intuition behind this empirical characterization in Equation (4.4) is that, in contrast to the originally hypothesized freight rate process from Equation (4.1), the freight rate is also driven by last period's freight rate, the forecast errors from the last 3 periods and last period's deployed capacity on the trade lane.

4.4 INDUSTRY BACK TESTING OF REAL OPTIONS APPROACH

Our goal is to assess the effect of an innovative investment approach on deployed capacity and realized freight rate for a container shipping trade lane. We develop an industry back testing model that covers the time period from January 1st, 2012 until April 1st, 2016. Based on the observed starting capacity in the market, we formulate investment and divestment decisions with the

continuous-time real options investment model by Rau and Spinler (2016b). We calibrate the real options investment trigger from an individual player perspective, taking into account the variables (e.g. interest rate, deployed capacity) at the time of decision making. We estimate realized freight rate with the ARIMA model we obtain in Section 4.3.

4.4.1 Real options trigger

The real options investment model is outlined in Rau and Spinler (2016b). It follows the continuous-time real options approach to investment under uncertainty by Gkochari (2015), Baldursson (1998), Leahy (1993), and Grenadier (2002). The key assumptions are infinitely divisible output, an endogenous oligopoly price function, and full capacity utilization. A geometric Brownian motion (GBM) X_t and the industry supply $Q_t = \sum_{i=1}^n q_{i,t}$ drive the endogenous price process

$$p_t = X_t Q_t^{-\frac{1}{\gamma}}, \quad (4.5)$$

where γ is the elasticity parameter, n is the number of players and q_i is the capacity of an individual player.

It is possible to derive a firm value in Nash equilibrium, i.e. each player chooses capacity given the potential strategies of others. Applying the myopic firm principle (Leahy 1993), it is possible to show that the optimal policy is a trigger policy. The trigger policy⁶ is characterized by

$$X^* = v_\kappa e^{(r-\mu)\kappa} Q^{\frac{1}{\gamma}}, \quad (4.6)$$

where κ is lead time, μ the drift term of the geometric Brownian motion, and r the risk-free rate. The term v_κ is given by

$$v_\kappa = \left[\left(\frac{\beta}{\beta-1} \right) \left(\frac{n\gamma}{n\gamma-1} \right) (r-\mu) \left(\eta + c e^{-r\kappa} \frac{1}{r} \right) \right], \quad (4.7)$$

where n is the number of players, η are investment cost and c is the variable cost component. β is the fundamental quadratic

$$\beta = \frac{-(\mu - \frac{1}{2}\sigma^2) + \sqrt{(\mu - \frac{1}{2}\sigma^2)^2 + 2\sigma^2 r}}{\sigma^2} \quad (4.8)$$

with freight rate volatility σ . The trigger solution can be applied to investment and divestment. To capture the difference in investment cost and lead times, we hence define η_{inv} and η_{div} as well as κ_{inv} and κ_{div} .

4.4.2 Calibration assumptions

To formulate investment decisions, we calibrate the real options trigger with Equations (4.6), (4.7), and (4.8). Table 4.1 shows a complete list of parameters. We provide details and explanations in the following subsections.

⁶Note that the trigger policy changes over time. For better readability we, however, omit subscript t in the following formulaic expressions

Table 4.1: Overview of parameters and assumptions

Symbol	Parameter	Value at t = 1	Assumption/source
β	Fundamental quadratic		Real options model
$\hat{\gamma}$	Elasticity	0.3247	Regression analysis
γ	Elasticity	0.2801	ARIMA model
Δ^i	Difference operator		ARIMA model
ϵ_t	iid error term		ARIMA model
η_{inv}	Inv. cost	19,099 USD	Cost of 1 TEU per month
η_{div}	Div. cost	12,348 USD	Proceeds from 1 TEU p.m.
θ_1	Moving average	-0.1527	ARIMA model
θ_2	Moving average	0.0548	ARIMA model
θ_3	Moving average	-0.2714	ARIMA model
κ_{inv}	Inv. lead time	19 months	Alphaliner (2013c)
κ_{div}	Div. lead time	6 months	Schedule announcement
μ	Drift term	0	ARIMA assumption
ν_κ	Part of trigger		Real options model
ξ_i	Capacity factor		AMM
σ	Volatility	5 percent	Base case assumption
ψ	Regression coefficient		ARIMA model
a	Variable cost parameter	357,595.63	Economies of scale
b	Variable cost parameter	-2,700,000	Economies of scale
c_1	Variable cost	659.7 USD	10 percent margin
$E_{c,i,t}$	pre-2012 capacity		Delivery ordered pre-2012
$E_{s,i,t}$	pre-2012 ships		Deletion decided pre-2012
$N_{i,t}$	Nominal capacity		AMM
n	No. of players	20	2012 market structure
$o_{i,t}$	Orders and removals		Real options model
p_t	Price process	733 USD	Oligopoly price function
Q_t	Deployed cap.	1,489,960 TEU	Monthly revenue terms
$q_{i,t}$	Individual player capacity		Monthly revenue terms
r_1	Interest rate	0.14 percent	ECB (2016)
$s_{i,t}$	Average ship size		AMM
s_{new}	New capacity	15,000 TEU	Assumption
u_t	Forecast error		ARIMA model
$v_{i,t}$	Number of ships		AMM
$X_{real,t}$	Rate realization shock	1.19	ARIMA model
$X_{dec,t}$	Decision making shock	7.6 E21	Oligopoly price function
$X_{div,i,t}^*$	Divestment threshold		Real options model
$X_{inv,i,t}^*$	Investment threshold		Real options model
y_t	Price process		ARIMA model

All values in monthly terms unless otherwise indicated

4.4.2.1 Capacity

We segment the total $n = 20$ players on the Asia to Europe container shipping trade lane into 7 strategic players and 13 non-strategic players which are summarized as “other”⁷ (Figure 4.8). We identify the total nominal capacity by player $N_{i,t}$ from Alphaliner Monthly Monitor (AMM) reports “Main Carriers - Breakdown of Capacity Operated by Trade” (Alphaliner 2012, 2014b, 2015b,c, 2016). The total number of ships $v_{i,t}$ is obtained from AMM “Global Capacity Deployment Breakdown by Trade” and the carrier split is estimated by cross-referencing with the container ship register (Clarksons 2012). We further identify weekly deployed capacity $q_{i,t}$ and Q_t from AMM “East-West Trade Deployment”.

The capacity factor ξ_i shown in Figure 4.8 is carrier-specific. It is the conversion factor from nominal, installed capacity to weekly capacity offered on the trade lane. A low value means that with a given nominal capacity, a carrier can achieve a higher weekly capacity offering. We assume this to be a strategic characteristic of the individual player and keep it constant over the time period of the analysis.

4.4.2.2 Investment

We assume that there is an investment opportunity to purchase up to three additional vessels per month based on the investment trigger solution (Section 4.4.1). We discretize the investment trigger solution as follow: if the shock term surpasses the investment threshold by up to ten percent, one vessel will be ordered; for up to 20 percent and more than 20 percent, 2 or 3 ships will be ordered, respectively. We represent this by the parameter $o_{i,t}$ which takes positive values for investment and negative values for divestment.

The ship size for new investment is $s_{new} = 15,000$ TEU and we assume an investment lead time of 19 months. Due to the lead time, the investment decisions based on the real options model impact market capacity only at the end of 2013. We, therefore, consider realized capacity additions ($E_{c_{i,t}}$ for TEU capacity and $E_{s_{i,t}}$ for number of ships) based on pre-2012 investment decisions for the first 19 months of our back testing model. We derive this by comparing carrier nominal capacity⁸ between January 1st, 2012 and August 1st, 2013. We assume capacity additions to be linearly distributed across the 19 months.

We further assume that investment cost η_{inv} is the cost of supplying one TEU of monthly revenue capacity. To derive the investment cost, we consider recent orders by Seaspam and CMA CGM (10,000 TEU for 90 million USD and 20,000 TEU for 150 million USD) (Alphaliner 2015d) to derive investment cost of 8,250 USD per nominal TEU. We apply the average capacity factor of $\xi = 9.26$ (Figure 4.8) which results in 76,395 USD per weekly TEU. Dividing by 4, we can represent monthly revenue capacity with 19,099 USD per TEU.

⁷For the “other” players, we assume the actual capacity development that has been observed in the market; we do not model real options investment decisions.

⁸Based on weekly AMM deployment, capacity factor ξ_i (weekly to nominal) assumed to be fixed.

Figure 4.8: Capacity starting point as of January 1st, 2012

$N_{i,t}$ Total nominal capacity deployed on ASEU TEU	$V_{i,t}$ Ships	ξ_i Capacity factor TEU to weekly deployment	$q_{i,t}$ Total weekly capacity TEU	$S_{i,t}$ Average ship size TEU
MSC	82	14.7	56,989	10,208
APM-Maersk	81	8.7	85,880	9,194
CMA	62	12.2	48,068	9,487
COSCON	30	11.3	23,857	8,953
CSCL	19	10.4	17,976	9,836
Hanjin	12	6.7	13,799	7,713
APL	10	6.2	12,457	7,783
Other ¹	86	5.8	113,464	7,554
Overall	382	9.26	372,490	9,030

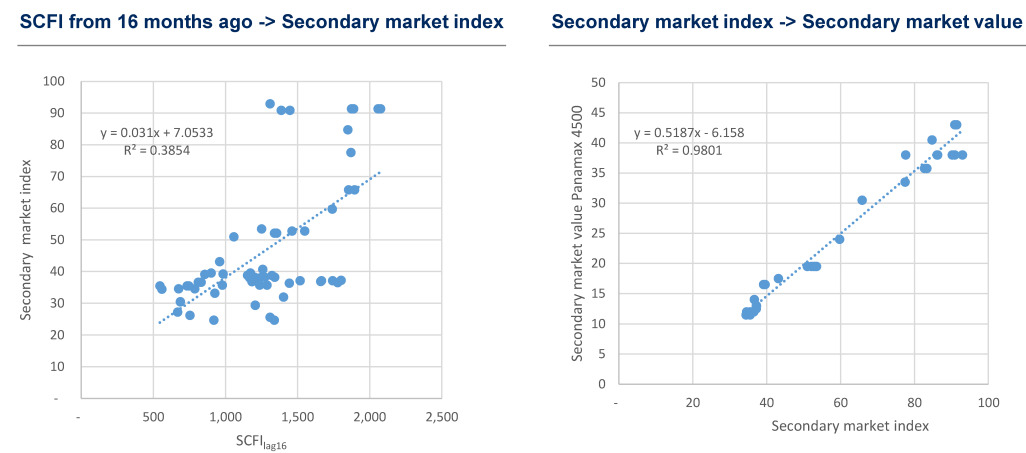
¹ Hapag-Lloyd, Evergreen, MOL, OOCL, NYK, CSAV, Yang Ming, K Line, Zim, HMM, PIL, UASC, Wan Hai

Source: Alphaliner (2012, 2014b, 2015b,c, 2016), Clarksons (2012)

4.4.2.3 *Divestment*

We discretize the divestment opportunity as follows: if the shock term surpasses the investment threshold by up to 20 percent, one vessel will be removed. If it surpasses the trigger by more than 20 percent, two vessels will be sold. The inherent logic is that every 6 months, a full string (8 ships with weekly service, 60 round trip days) can be removed. That means, on average, 1.33 ships per month are removed from the market throughout a longer time of suboptimal market conditions. The ship size for divestment corresponds to the average player capacity. We assume a divestment lead time of 6 months due to announcement of schedules. We consider realized ship removals for the first 6 months of 2012 (analogous to Section 4.4.2.2).

Figure 4.9: Two-step regression for endogenous secondary market



We further assume that players can sell all their assets and exit the container shipping market on the considered trade lane. They can later re-enter the market with the investment opportunity outlined in Section 4.4.2.2.

For divestment income η_{div} , we assume that it is the gain of removing one TEU of monthly revenue capacity. The conversion between nominal and monthly revenue capacity is analogous to Section 4.4.2.2. However, we assume an endogenous secondary market. The secondary market value is taken from Clarksons (2016) and represents 10 year old Panamax vessels. We estimate its value in a two-step regression (Figure 4.9): First, $SCFI_{lag16}$ explains the secondary market index from Clarksons. We find in a cross-correlation analysis that lags above 10 months are significant and achieve the highest R^2 (0.39) at lag 16. This may be attributed to the lead time from realizing low freight rates to putting capacity up for sale and finally an even later reflection on the secondary market values. Second, the secondary market index and secondary market prices are highly correlated, hence we can extrapolate Panamax values from our estimated freight rates. Values for η_{div} range between 3,944 and 32,714 USD per TEU per month.

4.4.2.4 Variable cost

We model variable cost following Rau and Spinler (2016a) and assume a cost function that decreases in ship size

$$c = \frac{a \ln(s) - b}{s}, \quad (4.9)$$

where s denotes the average ship size and a, b are parameters that determine the shape of the curve. We calibrate the parameters to result in a 10 percent profit margin at average ship size of 9,030 TEU. Based on an SCFI rate of 733 USD per TEU on January 1st, 2012, this amounts to $c = 659.7$ USD.

4.4.2.5 Drivers of geometric Brownian motion

We assume the European Central Bank marginal lending facility as variable interest rate throughout the back testing period (ECB 2016). The drift of the geometric Brownian motion underlying the investment trigger is zero, since stationarity implies that the process is reverting to a constant mean (Asteriou and Hall 2007).

4.4.2.6 Competitive intensity

To measure competitive intensity, we assume that the oligopoly price function (Equation (4.1)) holds. The parameter $\hat{\gamma}$ can be estimated with a linear regression

$$\ln p_t = -\frac{1}{\hat{\gamma}_t} \ln Q_t + \ln X_{dec,t}, \quad (4.10)$$

where p_t is the value of the SCFI Asia to Europe, Q_t is the deployed capacity according to Alphaliner, $X_{dec,t}$ is the random decision making shock term. The regression data is shown in Figure 4.10 and we find a value for $\hat{\gamma} = 0.32$. Since this is calculated from a player perspective, we consider freight rate and deployment data from October 1st, 2009 (SCFI introduction) until January 1st, 2012 (starting point of back testing model). This market is much more competitive than previously assumed markets (cf. Gkochari (2015), Grenadier (2002), Rau and Spinler (2016a,b)), however, according to shipping practitioners this trade lane is one of the most competitive markets in the container shipping industry.

4.4.2.7 Freight rate volatility

Freight rate volatility in container shipping has been considerably high in the past years. Figure 4.11 shows a comparison of the volatility of returns for the major container freight indices. It is a volatility measurement on a rolling basis, i.e. the value depicted for October 1st, 2011 is the standard deviation of the past 24 monthly returns. On average since October 2011, monthly volatility is between 4.4 percent (CCFI composite index) and 28.8 percent (SCFI Asia to Europe). This corresponds to annualized values from 15.2 to 99.7 percent.

As a consequence, an endogenous modeling of the SCFI Asia to Europe volatility is not feasible. Therefore, we run a base case analysis with a $\sigma = 5$

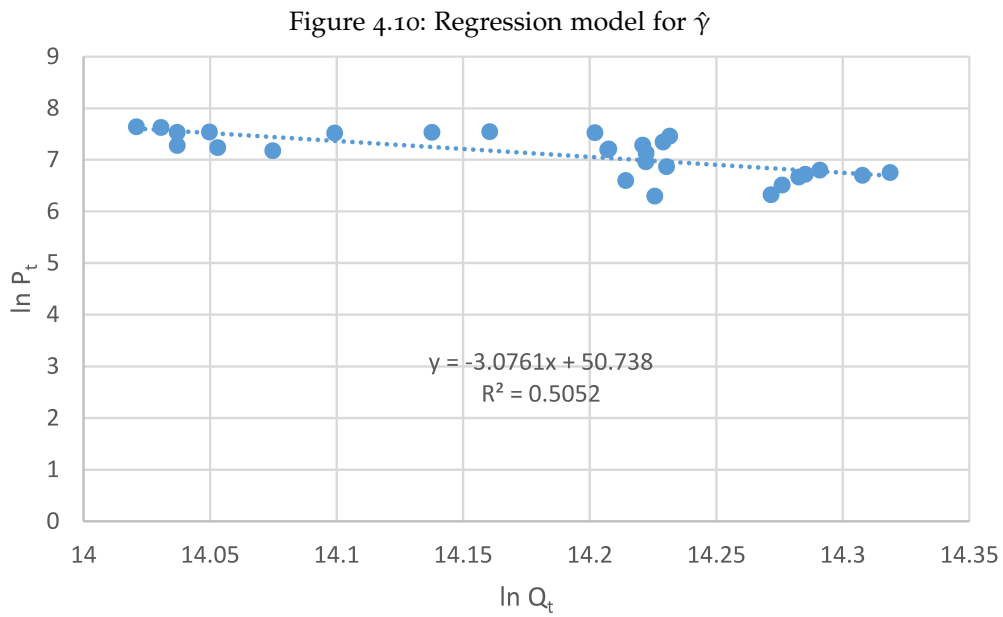
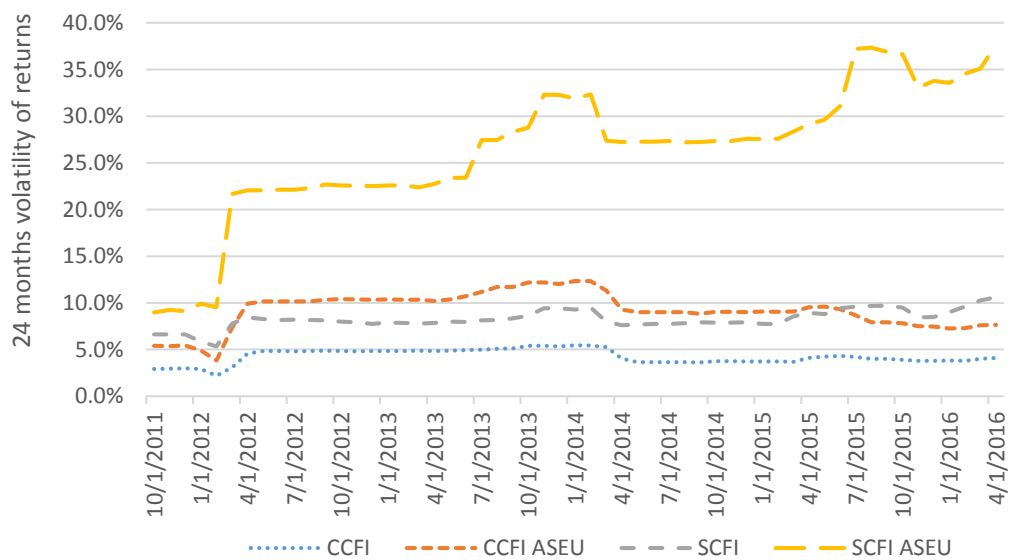


Figure 4.11: Volatility analysis for major container freight indices: rolling 24 months volatility of returns



percent monthly volatility and add a sensitivity analysis to show the model performance on different volatility levels.

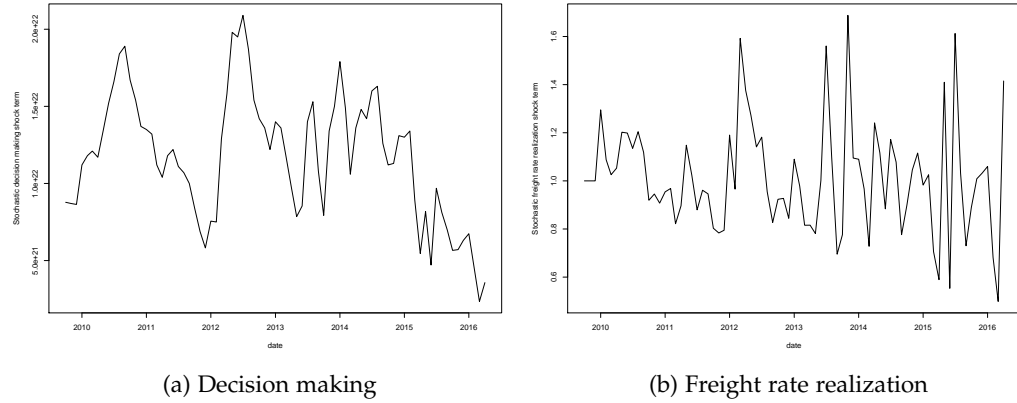
4.4.3 Shock terms

We can differentiate between two different shock terms: (1) the decision making shock term $X_{dec,t}$ and (2) the freight rate realization shock term $X_{real,t}$. The decision making shock term $X_{dec,t}$ is estimated by the regression outlined in Section 4.4.2.6 from a player perspective. The formulaic expression is as follows:

$$X_{dec,t} = \frac{p_t}{Q_t^{-\frac{1}{\gamma}}} \quad (4.11)$$

We assume it is calculated from a player perspective, i.e. assuming no prior knowledge of the ARIMA nature and its parameters but rather taken the oligopoly price function (Rau and Spinler 2016b) as given. In the back testing model, this shock term is compared with the investment and divestment thresholds $X_{inv_i,t}^*$ and $X_{div_i,t}^*$. Its evolution is depicted in Figure 4.13a.

Figure 4.12: Stochastic shock terms



The freight rate realization shock term $X_{real,t}$ is shown in Figure 4.13b. It represents the uncertainty in the market which cannot be explained by the ARIMA model:

$$X_{real,t} = \frac{p_t}{Q_t^{-\frac{1}{\gamma}} p_{t-1} \left(\frac{p_{t-1}}{\hat{p}_{t-1}}\right)^{\theta_1} \left(\frac{p_{t-2}}{\hat{p}_{t-2}}\right)^{\theta_2} \left(\frac{p_{t-3}}{\hat{p}_{t-3}}\right)^{\theta_3} \left(\frac{1}{Q_{t-1}}\right)^{-\frac{1}{\gamma}}} \quad (4.12)$$

When estimating freight rates based on real options trigger capacity decisions, we apply the value of $X_{real,t}$ to Equation 4.4.

4.4.4 Model structure

The back testing model has 4 key calculation steps for every monthly decision making interval. It covers the time period from January 1st, 2012 until February

1st, 2016. The 4 steps are: (1) initialization, (2) estimation of real options trigger, (3) investment decisions, and (4) state update.

4.4.4.1 Initialization

Nominal capacity $N_{i,t}$ and number of vessels $v_{i,t}$ are initialized based on last period's state update (for $t=1$ starting values from Figure 4.8 are used). Deployed industry capacity is calculated by

$$Q_t = \sum_{i=1}^n (N_{i,t} \xi_i). \quad (4.13)$$

Average ship size is calculated by $s_{i,t} = \frac{q_{i,t}}{v_{i,t}}$. The realized freight rate can be estimated by Equation (4.4).

4.4.4.2 Estimation of real options trigger

The real options investment and divestment triggers $X_{inv_{i,t}}^*$ and $X_{div_{i,t}}^*$ can be estimated by Equations (4.6), (4.7), and (4.8). The variables that change over time within the trigger equations are Q_t , η_{div_t} , and $c_{i,t}$. η_{div_t} is defined by the 2-step regression in Figure 4.9 while the variable cost follow

$$c_{i,t} = \frac{a \ln(s_{i,t}) - b}{s_{i,t}}. \quad (4.14)$$

4.4.4.3 Investment decisions

We compare investment triggers with the decision making shock term X_{dec_t} to make optimal investment decisions. The decision making shock term is calculated with Equation (4.11). In line with the assumptions in Section 4.4.2.2, we derive values for $o_{i,t}$ depending on the distance to the trigger.

4.4.4.4 State update

Finally, nominal capacity $N_{i,t}$ and number of ships $v_{i,t}$ are updated to reflect capacity changes:

$$N_{i,t+1} = (o_{i,t-\kappa_{inv}})^+ s_{new} + (o_{i,t-\kappa_{div}})^- s_{i,t} + E_{c_{i,t}} + N_{i,t} \quad (4.15)$$

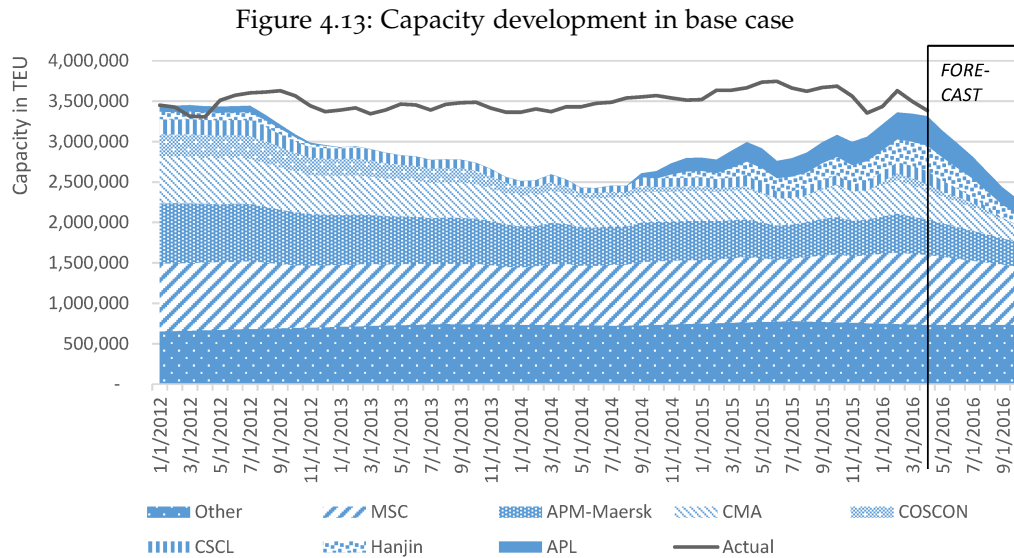
$$v_{i,t+1} = (o_{i,t-\kappa_{inv}})^+ + (o_{i,t-\kappa_{div}})^- + E_{s_{i,t}} + v_{i,t}. \quad (4.16)$$

4.5 RESULTS AND DISCUSSION

4.5.1 Base case

In our base case analysis we assume a constant volatility of $\sigma = 5$ percent in monthly terms (annualized: 17.3 percent). Figure 4.13 shows the nominal capacity development of the back testing model in comparison with actual total nominal capacity on the Asia to Europe trade lane. The back testing model

results are segmented into the seven strategic players and the total of the 13 non-strategic players. Note that the back testing model covers the time period until April 1st, 2016. The following data points are a forecast based on investment and divestment decisions as well as the ARIMA freight rate characterization but without consideration of the stochastic shock term $X_{\text{real}t}$.

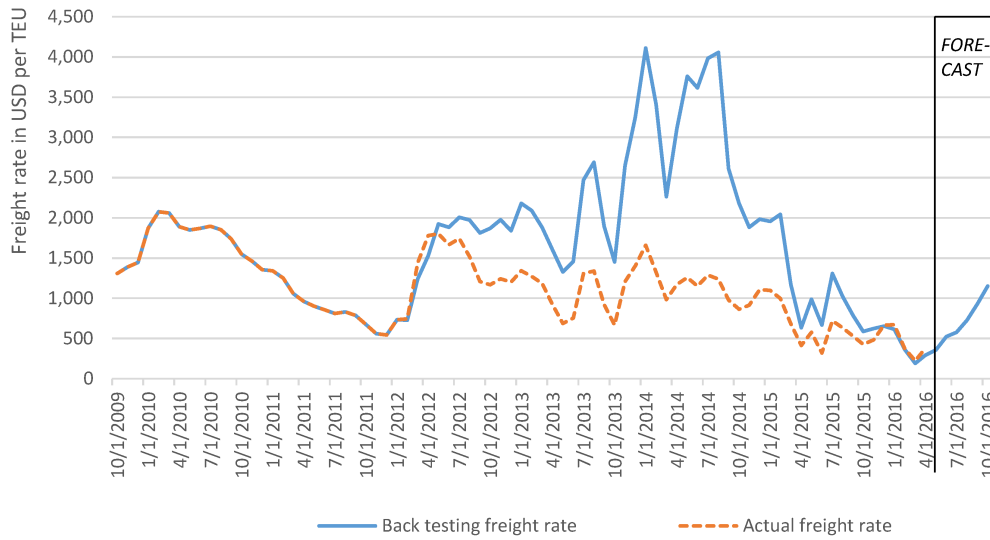


The application of the real options trigger would see all players' capacities to drop significantly since the real options trigger's optimal capacity level is lower than 2012 market capacity. Furthermore, large players and players with low variable cost dominate the market while very small players would completely exit the trade lane. Since we allow for reentry with a better variable cost position ($s_{\text{new}} = 15,000$ TEU), small players would re-enter and build up significant capacity by the end of 2015. The first minimum capacity of 2.4 million TEU nominal is realized in June 2014 and at this point freight rates have recovered to an extent that new investment is triggered. This new investment is delivered throughout 2015 and 2016. It seems that a cyclicity is introduced into the capacity developments. This may result from the different lead time levels for investment and divestment.

With respect to freight rates, we find that the decrease in capacity driven by the real options investment trigger would have had a positive effect on rates (back testing freight rate), even in the suboptimal market environment of 2014 and 2015. Given the high competitive intensity ($\gamma = 0.28$) the capacity reduction effect is substantial and leads to very freight rate levels up to 4,000 USD per TEU. While this may appear extreme at first sight, the intuition is as follows: in periods of overcapacity, competition leads to low freight rates near or below variable cost. In terms of scarcity of capacity, however, freight rates are oriented at the shippers' willingness to pay.

The induced cyclicity in the capacity market is also reflected in freight rates. We find that rates would return to low levels in the middle of 2015 again. Reducing capacity throughout 2016 could lead to another increase in rates, albeit the impact of potential random shocks cannot be part of the forecast.

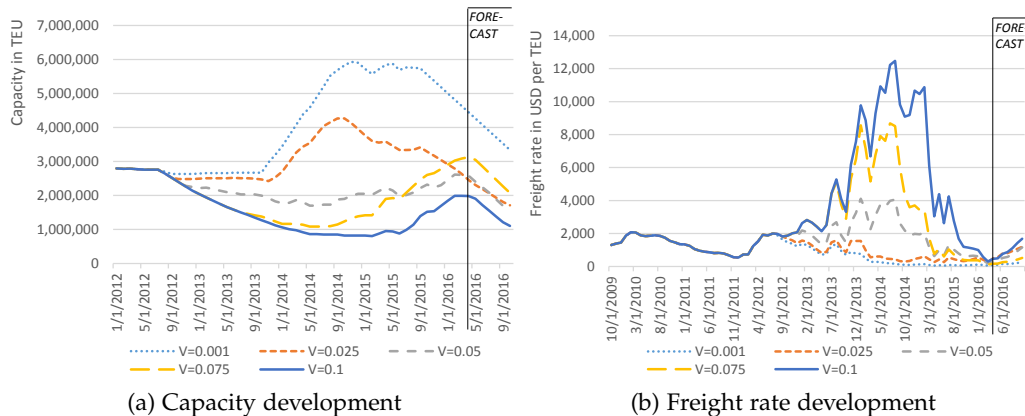
Figure 4.14: Freight rate development in base case



4.5.2 Sensitivity analysis for different volatilities

From a sensitivity analysis with different volatilities (Figure 4.16a) we learn that capacity development is highly dependent on the volatility assumption. For a σ close to zero ($V = 0.001$), the real options approach would suggest a strong increase in capacity to almost twice the starting capacity. In a predictable market where the oligopoly price function of Equation (4.1) holds, this could be a valid approach. In the highly competitive and volatility ARIMA market of the Asia to Europe trade lane, this is not feasible. The opposite extreme - a monthly volatility of $\sigma = 10$ percent - would see a constant reduction of capacity for the first 3 years before any kind of investment would appear in nominal or deployed capacity.

Figure 4.15: Capacity and freight rates for different volatilities



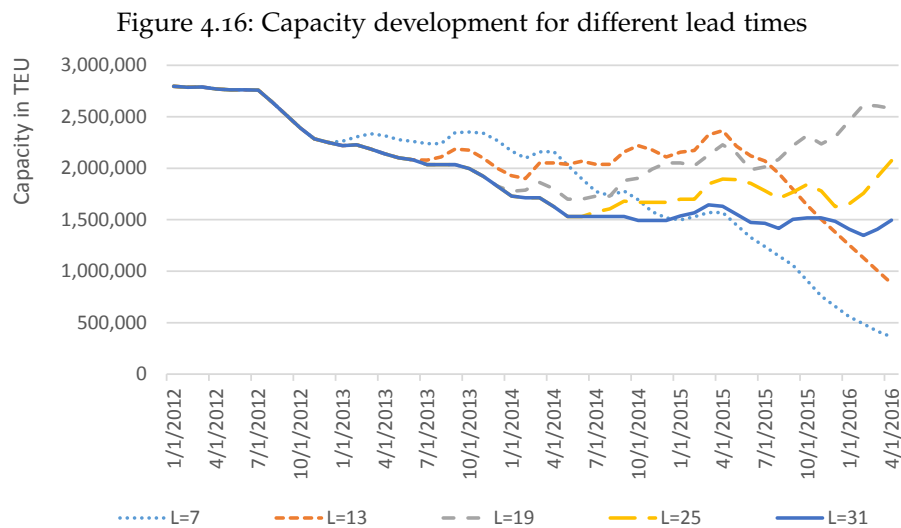
Note: Capacity depicted is the sum of all strategic players' nominal capacity, "other" players not included.

The $V=0.075$ case shows an interesting development: the very strong capacity reduction in the first months allows players to trigger comparatively early investment (vs. the less volatile base case with $V=0.05$). This illustrates the advantage of the real options trigger in adjusting flexibly to changing market circumstances.

The effect on freight rates is shown in Figure 4.16b. The freight market is a clear reflection on the capacity development over time. While a strong decrease in capacity would see rates go to excessive levels, the low volatility cases and associated overinvestment would create pressure on freight rates.

4.5.3 Sensitivity analysis for different lead times

A sensitivity analysis with respect to investment lead time is shown in Figure 4.16. For very long lead times ($L = 31$, solid line) we find that for the most part, only a capacity reduction can be observed. A slight increase in capacity is shown in 2015. Moving to shorter lead times, we find that the timing of the first realized capacity addition is 6 months earlier for every lead time difference of 6 months. Looking at the evolution of strategic capacities (other capacity is not considered in Figure 4.16), we find that if investment and divestment lead time are similar, strategic capacity is strongly reduced in 2016. This is driven by a decrease in the decision making shock term (c.f. Figure 4.13a). For the long lead time scenarios, investment pipelines compensate the reduction triggered by the low shock term in 2016. In summary, the longer the lead time or the mismatch between lead times for investment and divestment, the more difficult to appropriately adjust to changing market situations.



Note: Capacity depicted is the sum of all strategic players' nominal capacity, "other" players not included.

4.6 CONCLUSION AND MANAGERIAL RECOMMENDATIONS

In conclusion, we find that the container freight rate has autoregressive properties and vessel capacity (deployment on a trade lane) has a significant impact on the container freight rate. Consequently, the oligopoly price function assumed by Rau and Spinler (2016b) holds from an empirical perspective, albeit correctly characterized by an ARIMA(0,1,3) model with deployment as regressor. The implication is that models to capture freight rates require methods that can capture autocorrelation. Capacity deployment decisions directly affect rates; hence capacity reduction can help safeguard margins for container shipping lines.

Given the real options investment approach outlined in Section 4.4.1, container market capacity on the Asia to Europe trade lane is significantly too high. The application of a real options trigger approach to investment and divestment would have seen capacities strongly decline and freight rates recover. Hence, players in this market should consider to significantly remove capacity. This decision could be supported by an analysis of value destruction of layup vs. freight rate loss due to overcapacity deployed. The real options approach should further be added to the investment decision toolkit at liner shipping companies.

The real options trigger model works for a bandwidth of different volatility values, but the impact on resulting capacity is substantial. From a practical perspective the estimation of a realistic market volatility is critical to the characterization of optimal investment and divestment policies. Furthermore, a mismatch between investment and divestment lead time or long lead times reduce the ability to react to changing market circumstances. It is therefore important to have access to short-term peak capacity to ensure that long-term pipelines do not lead to capacity additions at inappropriate times.

There are a number of potential concerns to keep in mind: First of all, the difference in investment and divestment lead times induces cyclicity in the results. Further, a joint reduction of capacity might only be possible if the market is either small enough to allow for signaling or a regulator steps in. If not, the industry will be facing a prisoner's dilemma situation. Finally, the alignment of incentives is potentially unclear: while shipping companies would clearly benefit from freight rates above variable cost, exporting economies might not since low freight rates may be considered an export stimulus.

Avenues of future research are the exploration of cyclicity effects due to different lead times in trigger policy solutions as well as the identification of potential countermeasures. The incorporation of the ARIMA price function in the real options framework would be an interesting extension. A further possible extension would allow for consideration of adjacent trade lanes to shift deployed capacity within a liner shipping company's network.

Summary and Outlook

Container shipping plays an existential role for global supply chains by enabling reliable transportation service at low cost. It turns out that this industry of superlatives - with vessels that can carry up to 20,000 TEU and total transported 9 trillion cargo-ton miles in a single year - is facing a number of unprecedented challenges.

The issues at hand are substantial overcapacity, low freight rates, regulatory pressure, capital-intensive investments with long horizon, market cycles, and consolidation. Combined with only early-stage market transparency, investment decision making has been far from rational and might have even contributed to further oversupply and deterioration of container freight rates.

In Chapter 1 I argue that this setting is an ideal basis for researching investment decisions and working with real options games in cooperative and non-cooperative markets with an endogenous price function. In this Section I provide the key insights to the six objectives of this research: (1) understand the industry and challenges, (2) characterize investment decisions, (3) develop a real options investment model, (4) model investment decisions in the presence of dynamic coalition structure, (5) assess the nature of freight rates, and (6) test the validity of the investment model. Further, I provide a summary of managerial recommendations and present avenues for further research.

5.1 CONCLUSION

5.1.1 *Understand situation and challenges of the container shipping industry*

One of the key challenges identified in this work is a mismatch of supply and demand in container shipping. This can be observed already from high-level figures where available capacity has increased stronger than actual cargo ton-miles. But also the reflection in TC and freight rates adds to this point. In Chapter 2 it shows that players tend to invest at TC rate peak times. Due to production lead times, however, capacity is delivered in times of low rates. Effects of the recent investments into ultra-large container ships are slow steaming and high idle capacity. As of 2016, the container layup pool is at 7.4 percent which corresponds to 2009 post-crisis levels.

Further, it turns out that freight rates are cyclical and heavily depend on global economic development. Long-term analyses of freight rates are not yet possible since transparent market indices have only been introduced with the CCFI in 2003 and the SCFI in 2009. The freight rate volatility has increased in the past years and reached extreme levels. Depending on index and trade lane, I observe historical 24-month values between 4.4 (CCFI Composite) and 28.8 (SCFI Asia to Europe) percent, in monthly terms. The freight rates are currently at historically low levels below variable cost.

From an investment perspective, the challenge is that vessels purchases are capital-intensive, long-term investments. A 20,000 TEU vessel can cost 150 million USD (Alphaliner 2015d). Investment into a container vessel usually has a horizon of more than 20 years; even charter contracts for new capacity are rarely shorter than ten years.

Increasing regulations endorsed by the IMO are with respect to air pollution, ballast water management, and specific guidelines on polar shipping. These regulations have and will have impact on shipping operations and vessel design.

Finally, shipping players operate in a concentrated market that has further consolidated in the past years. Currently, the top 10 players have a combined market share of more than 60 percent. Furthermore, alliance composition has been very unstable and numerous changes have led to today's situation where four alliances have a combined market share of more than 75 percent. Government bailouts, such as Hapag-Lloyd in 2009 and mergers and acquisitions have further reduced the number of players in the market, hence the container shipping market is close to being an oligopoly.

5.1.2 *Characterize investment decisions*

From literature review and expert discussions in Chapter 2 it follows that investment decisions in container shipping are first and foremost based on the intrinsic value of the project. The traditional means of investment appraisal is DCF. The classical approach that dates back to 1929 has a number of shortcomings: no consideration of flexibility in investment timing, future uncertainty, or investment lead time.

Due to regulatory pressure and the economic need for lower variable cost, fuel efficiency considerations play a more important role for investment decisions. So-called eco-ships have 3 key characteristics: newer engines that are optimized for lower steaming speeds and can burn different fuels, improved hull design, and innovative coatings that lead to efficiency improvements of up to 30 percent. However, the improved vessels come at a higher price, especially when equipped with dual-fuel engines that can burn Liquefied Natural Gas (LNG) in ECAs.

The changing nature of alliance composition adds another layer of complexity to the investment decision. If there are vessel sharing agreements in place, single players need to not only consider the effect of new investment on the jointly operated schedules, but also assess the effect on alliance stability.

Moreover, securing funding for vessel purchases has become more difficult. Since some of the shipping companies were close to bankruptcy, traditional banks have been reducing their exposure in the shipping markets. Also KG (closed-end shipping funds in Germany) funding is not existant any more. Consequently, some players had to sell non-core assets to improve their liquidity. Shipping investment currently relies more on equity and debt capital markets as well as private equity investment.

Vessel sizes have changed as well: due to the recent changes to the Panama canal, significantly larger ships can cross, hence the Panamax vessel size will be

increasingly scrapped. On feeder markets, Panamax ships are too large; on the global routes they cannot compete with the economies of scale of ultra-large container ships.

Finally, low asset prices can drive investment decisions because of investment timing considerations. Network considerations need to be kept in mind since a number of equally-sized ships is necessary to set up a network string.

5.1.3 *Develop a real options model for shipping investment*

In Chapter 2 I argue that real options analysis is very well suited to make investment decisions in container shipping, primarily due to its ability to capture freight rate volatility and managerial flexibility. The real options game model considers an endogenous oligopoly price function where capacity negatively impacts freight rates. It is possible to derive individual players' strategies in a non-cooperative Nash equilibrium. This investment model can be solved analytically in continuous time and it can be shown that the optimal solution takes on the form of a trigger policy.

In order to consider more shipping industry characteristics, the model is discretized. The discrete-time model additionally captures a fuel efficient investment alternative at a price markup, endogenous lead time, and an endogenous secondary market. The extended model can be solved with a recursive dynamic programming approach.

From a number of sensitivity analyses it becomes apparent that competition impacts shipping investment from two perspectives: first, a higher number of players leads to higher capacity, lower firm values, and earlier investment. Second, higher intensity of competition (given by the relationship between freight rate and capacity) decreases optimal capacity and firm values. Volatility can increase firm values if capacity decisions are sufficiently flexible.

With respect to fuel efficiency, optimal strategy over time suggests that for low savings potential, replacement investment is optimal while with high savings potential, even capacity expansion will be feasible. The intuition here is that the fuel efficiency savings can compensate the loss in freight rate resulting from additional market capacity.

Overall, from a comparison of strategic and myopic investment, I conclude that it is financially beneficial to make strategic investments, i.e. anticipate other shipping players' moves when making investment decisions.

5.1.4 *Model investment decisions in the presence of dynamic coalition structure*

From an extensive literature survey in Chapter 3, I learn that there are three main motivations for entering container shipping alliances: (1) a sharing aspect, (2) a size aspect, and (3) an external aspect. The sharing aspect evolves around sharing risks and capacity as well as transferring technology. Greater size allows for economies of scale, global reach, vertical integration, and a higher frequency of service. External motivations can be government policy and the need to defend market position in a market under consolidation.

An analysis of the alliance composition in the past 5 years shows that it has been a very unstable situation. This confirms previous research which had identified trust and complexity as key issues. From an anti-trust perspective, shipping alliances are not considered problematic; one author even points out that collaboration in shipping is necessary to survive. I further explore this issue by using the real options trigger solution from Chapter 2 in a cooperative game setup where players form expectations and decide on membership in dynamic coalitions.

The guiding hypothesis that the real options trigger performs better than DCF in terms of cash flow for players can be confirmed. It turns out that the real options approach performs especially well with high freight rate volatility and high competitive intensity while not exhibiting substantial disadvantages in other market scenarios and with respect to stability and concentration.

With regards to the stability argument, I find that increasing competitive intensity, alliance complexity cost, and freight rate volatility lead to higher instability of container shipping alliances. One interesting finding is also that the lower the investment lead time, the higher the industry concentration.

5.1.5 *Assess the nature of the container freight rate*

Compared to bulk shipping where I can find an abundance of empirical research, market transparency in container shipping (freight rates, deployed capacity, demand, and idle capacity) is still at an earlier stage. Since 2003, the CCFI serves a freight rate index and Clarksons provides data on container shipping, such as TC rates or total fleet on a global level. Alphaliner provides trade lane-specific data on capacity deployment and demand as well as measures the global layup pool.

Using this information an empirical characterization of the container freight rate is possible, albeit with a limited timeframe. It turns out that the freight rate has autoregressive properties and can appropriately be described with an ARIMA(0,1,3) model. Adding the capacity deployment as a regressor is statistically significant and improves model fit.

The relationship between capacity deployment and container freight rate is negative. This leads to the conclusion that the endogenous oligopoly price function assumed in Chapter 2 holds, but with autoregressive aspects.

5.1.6 *Test the validity of the investment model empirically*

To add an empirical perspective to the results from Chapter 3, I provide a backtesting model that assumes that shipping players would have applied the proposed real options trigger approach within the timeframe of January 2012 to April 2016. I find that the real options approach would suggest a substantial reduction of capacity within the analyzed timeframe.

Given the ARIMA freight rate characterization and considering the underlying stochastic shock term this would lead to a recovery of freight rates. Within the calibration of the investment approach, it turns out that one critical as-

sumption is the freight rate volatility going forward. The investment approach is appropriate for a bandwidth of volatility values.

There are 2 potential issues with the application of this investment approach: Firstly, in order to avoid a prisoners' dilemma situation when reducing capacity, one prerequisite is a small market that allows for signaling or a regulator who oversees capacity reduction. However, there might be an incentive problem between exporting economies and vessel operators. While governments might appreciate low freight rates as an export stimulus, shipping players might face difficult financial situations. Secondly, the approach potentially induces cyclical and long lead times can have a negative impact.

5.2 MANAGERIAL RECOMMENDATIONS

The biggest learning from this research effort is that strategic action in the container shipping industry is worthwhile. Strategic action can take on a number of different forms: understand the market, apply the right investment approach, tailor the investment strategy, use fuel efficiency improvements, and manage the market position.

Understanding the market requires a regular measurement of the relationship between the key variables on every major trade lane. This includes assessing the impact of capacity on freight rates with the elasticity parameter γ and using ARIMA or other appropriate autoregressive time series models to empirically characterize freight rates. The inherent volatility of freight rates needs to be measured as well as appropriately forecasted.

Based on this trade lane-specific understanding, a real options approach should be added to the container shipping investment toolkit. This approach provides a valuable perspective since it can capture managerial flexibility, explicitly consider lead time as well as use market intelligence (competitive intensity and volatility). This allows to improve investment timing and finding the optimal capacity.

Since the oligopoly price function holds, having the correct capacity has a substantial bottom line impact. The investment and deployment strategy should be tailored to trade lanes and consider supply-demand gap as well as competitive intensity. In situations of overcapacity, it is essential to assess the tradeoff between the cost of laying up vessels and the value destruction from overcapacity due to the oligopoly price function.

At this point in time, specifically, deployed capacity on the trade lane Asia to Europe should be reduced. The recently finished upgrade of the Panama canal could be a strategic opportunity to move larger ships to another trade since the new locks of the Panama canal are able to accommodate vessels with up to 13,000 TEU.

The development of fuel efficient ships is not only a means of complying with IMO regulations, but can also help to keep cost competitiveness in markets with high competitive intensity. Replacing conventional ships with fuel-efficient alternatives does not change market capacity and, consequently, does not impact freight rates, while it provides the operator with lower operating cost.

Finally, it is important to actively manage the market position. This can be achieved by creating barriers to entry or improving lead times by securing early delivery slots at ship yards. Most importantly, however, container operators should engage in alliances. Alliances are beneficial due to risk sharing, economies of scale, improved global networks, and a higher service frequency. Container shipping alliances can be very unstable, especially in markets with high competitive intensity and volatility, or when complexity cost are high.

Therefore, selective alliance contracts should be considered, for example by entering Vessel Sharing Agreements (VSAs) on selected routes. Furthermore, the organization of alliances should be lean; potentially with focus on a limited amount of partners. Finally, unnecessary volatility should be avoided by carefully managing GRIs. In very volatile markets, partner due diligence should be emphasized.

5.3 FUTURE RESEARCH

The real options investment model at hand should be extended to incorporate further container shipping industry specifics. For, example the consideration of stochastic fuel prices would be appropriate given that the oil price development, and hence bunker fuel, has exhibited significant uncertainty in recent years. Furthermore, given the increasing regulatory pressure, adding regulatory uncertainty into the investment model could help form optimal strategies with stricter emission goals or ballast water requirements. Moreover, adding an adjacent trade lane or even full network perspective with consideration of different vessel sizes would better address the fact that container ships are fungible. This could help to devise capacity hedging strategies across trade lanes.

The potentially induced cyclicalities due to a difference in investment and divestment lead times should be further explored. A potential remedy would be the consideration of an extended oligopoly price function, for example by using the ARIMA characterization that is presented in this work.

To address the topic of overcapacity and make even more practical decisions, an analytical model of the tradeoff between cost of idle capacity and value destruction from overcapacity could provide a new perspective on the layup decision.

Finally, a freight rate characterization for the major trade lanes, using specific carrier data, would provide an even clearer perspective on competitive intensity and volatility across different routes. On this basis, a trade lane-specific freight rate forecasting model that depends on deployed capacity could be developed.

In conclusion, this research effort has shown that a real options investment approach is appropriate for the container shipping industry. The trigger approach performs well: both from a simulation and an empirical perspective. It pays off to be strategic and players in the shipping industry should understand the competitive dynamics, anticipate competition, make strategic investments, and collaborate in shipping alliances.

Appendix 1

A.1 DERIVATIONS OF THE INVESTMENT TRIGGER

$$\frac{\partial X^*}{\partial \gamma} = X^* \frac{\gamma + (\gamma n - 1) \ln(Q)}{\gamma^2 - \gamma^3 n} < 0, \forall \gamma > \frac{1}{n} \quad (\text{A.1})$$

$$\frac{\partial X^*}{\partial n} = -X^* \frac{1}{n(\gamma n - 1)} < 0, \forall \gamma > \frac{1}{n}, \quad (\text{A.2})$$

$$\frac{\partial X^*}{\partial \sigma} = X^* \frac{2\sigma}{\sqrt{(\sigma^2 - 2\mu)^2 + 8r\sigma^2}} > 0, \quad (\text{A.3})$$

$$\frac{\partial X^*}{\partial c} = X^* \frac{1}{c + \eta r e^{k\tau}} > 0, \quad (\text{A.4})$$

A.2 COX-ROSS-RUBINSTEIN MODEL

$$X_{t+1} = pX_t u + (1-p)X_t d \text{ with } u = e^{\sigma\sqrt{\Delta t}}, d = e^{-\sigma\sqrt{\Delta t}}, ud = 1 \text{ and } p = \frac{e^{r\Delta t} - d}{u - d}.$$

A.3 TABLES

Table A.1: Decisions and their impact on capacity, layup and pipeline

ID	Decision	I _{cap}	I _{layup}	I _{P_{conv}}	I _{P_{fe}}
1	Sell 1 unit of layup	0	-1	0	0
2	Put 1 unit into layup	-1	1	0	0
3	Do nothing	0	0	0	0
4	Reactivate 1 unit from layup	1	-1	0	0
5	Order 1 conventional unit	0	0	1	0
6	Order 2 conventional units	0	0	2	0
7	Order 3 conventional units	0	0	3	0
8	Order 1 fuel efficient unit	0	0	0	1
9	Order 2 fuel efficient units	0	0	0	2
10	Order 3 fuel efficient units	0	0	0	3

Table A.2: Firm 1 duopoly value at optimal capacity (USD billion)

		σ			
		0.20	0.30	0.40	0.50
γ	1.0	2.67	2.58	2.54	2.65
	1.1	2.51	2.55	2.60	2.62
	1.2	2.60	2.64	2.65	2.71
	1.3	2.68	2.71	2.73	2.79
	1.4	2.77	2.79	2.80	2.85

Table A.3: Two-level factorial design with results for duopoly

Run	σ	ϵ	γ	c	Y_1	Y_2	F_1^{**}	F_2^{**}
1	-	-	-	-	8	7	2.3	1.9
2	+	-	-	-	6	9	2.4	2.0
3	-	+	-	-	7	8	2.4	2.0
4	+	+	-	-	7	9	2.4	2.1
5	-	-	+	-	6	7	2.4	1.8
6	+	-	+	-	8	10	2.5	2.0
7	-	+	+	-	7	8	2.4	1.9
8	+	+	+	-	9	10	2.5	2.0
9	-	-	-	+	8	8	2.8	2.3
10	+	-	-	+	8	10	2.8	2.4
11	-	+	-	+	9	10	2.7	2.2
12	+	+	-	+	7	9	2.9	2.4
13	-	-	+	+	10	9	2.8	2.3
14	+	-	+	+	10	10	2.9	2.5
15	-	+	+	+	10	9	2.8	2.4
16	+	+	+	+	10	9	2.9	2.4

*Or more, but limited due to capacity bandwidth; **USD billion

Table A.4: Estimation of the effects

	First order effects				Second order effects					
	σ	ϵ	γ	c	$\sigma\epsilon$	$\sigma\gamma$	σc	$\epsilon\gamma$	ϵc	γc
	1	2	3	4	12	13	14	23	24	34
Y_1	-	0.3	1.3	1.8	-	1.0	- 0.5	0.3	- 0.3	0.8
Y_2	1.3	0.3	0.3	0.8	- 0.8	0.3	- 0.8	- 0.3	- 0.3	- 0.3
F_1^*	82.5	8.8	47.0	392.5	8.1	11.0	- 17.6	- 9.1	- 7.6	- 14.5
F_2^*	103.9	34.3	- 2.4	391.2	- 26.9	- 0.8	- 4.9	4.8	- 50.7	88.8

Numbers in bold are significant at a 90 % confidence level; * USD million

Appendix 2

B.1 TABLES

Table B.1: Departures Shanghai-Rotterdam for June and July 2015

Operator	Capacity	Ships	Average Size
CMA-CGM	227,940	18	12,663
Hanjin	152,216	13	11,709
Cosco	141,565	11	12,870
Evergreen	100,738	9	11,193
MSC	89,462	7	12,780
China Shipping Group	87,392	7	12,485
Maersk	83,730	6	13,955
Hyundai	76,460	6	12,743
OOCL	66,040	5	13,208
Hapag-Lloyd	52,837	5	10,567
UASC	49,610	4	12,403
MOL	42,000	3	14,000
APL	41,900	3	13,967
CSAV	4,043	1	4,043
Grand Total	1,215,933	98	12,407

Source: <http://www.jocsailings.com>

Table B.2: Ship sizes and equity requirements

Alliance size	1	2	3	4	5
Ship size ordered	10,000	12,000	14,000	16,000	18,000
Equity requirement	0.20	0.15	0.12	0.10	0.09

Table B.3: Summary of values for WACC (percent) across different countries for container shipping-related industries

Country	Shipbuilding and Marine	Transportation
China	10.16	10.40
India	11.38	7.90
Japan	4.88	6.97
Europe	8.77	7.66
USA	7.07	8.69
Global	7.63	8.35

Source: Damodaran (2016)

Table B.4: Mann-Whitney test for significance

	Cap.		Change		Cash		HHI	
	Med.	Rank	Med.	Rank	Med.	Rank	Med.	Rank
1=ROT	3.9E+06	4,546	0	5,138	1.9E+10	5,576	0.2013	5,347
2= Ind. DCF	4.8E+06	5,455	0	4,863	-4.2E+10	4,425	0.2007	4,654
p value		2.2E-16		8.1E-09		2.20E-16		2.20E-16

Rank = Mean rank, Cap. = Capacity, Med. = Median

Table B.5: Mann-Whitney test for significance with respect to different elasticity levels

	$\gamma = 1.2$		$\gamma = 1.5$		$\gamma = 1.8$	
	Median	Rank*	Median	Rank*	Median	Rank*
1=ROT	-1.3E+09	5,908	1.9E+10	5,576	6.3E+10	5,378
2=Ind. DCF	-7.6E+10	4,093	-4.2E+10	4,425	1.4E+09	4,623
p value		2.2E-16		2.2E-16		2.20E-16

*Mean rank

Table B.6: Mann-Whitney test for significance with respect to different lead time levels

	$\kappa = 3$		$\kappa = 9$		$\kappa = 15$	
	Median	Rank*	Median	Rank*	Median	Rank*
1=ROT	6.8E+10	5,958	2.5E+10	5,638	-1.6E+10	5,368
2=Ind. DCF	-3.0E+10	4,043	-4.4E+10	4,363	-6.2E+10	4,633
p value		2.2E-16		2.2E-16		2.20E-16

*Mean rank

Table B.7: Mann-Whitney test for significance with respect to different volatility levels

	$\sigma = 0.15$		$\sigma = 0.25$		$\sigma = 0.35$	
	Median	Rank*	Median	Rank*	Median	Rank*
1=ROT	3.9E+10	5,164	2.5E+10	5,640	1.1E+10	6,071
2=Ind. DCF	2.6E+10	4,837	-4.3E+10	4,361	-9.3E+10	3,930
p value		1.4E-08		2.2E-16		2.20E-16

	$\sigma = 0.45$		$\sigma = 0.55$	
	Median	Rank*	Median	Rank*
1=ROT	3.4E+09	6,387	-2.5E+09	6,620
2=Ind. DCF	-1.1E+11	3,614	-1.2E+11	3,381
p value		2.2E-16		2.2E-16

*Mean rank

B.2 MODEL VERIFICATION AND VALIDATION

Throughout the development of the simulation model we conduct constant verification and validation following Gass (1983) and Sargent (2013). In order to ensure model verification, we constantly check how the conceptual model is coded in Matlab software. We run checks on several subsystems of the model such as coalition generation, coalition structure value assessment, or investment decisions before using the comprehensive simulation for insights generation. We calibrate the assumptions based on empirical data (c.f. Table 3.1) or clearly stated assumptions (c.f. Section 3.3.1).

We summarize the validation techniques in Table B.8 and Table B.9 and provide more details in the following subsections. The framework in which we present the validation is based on Ritzenhofen et al. (2014).

Figure B.1: Structure of the simulation model

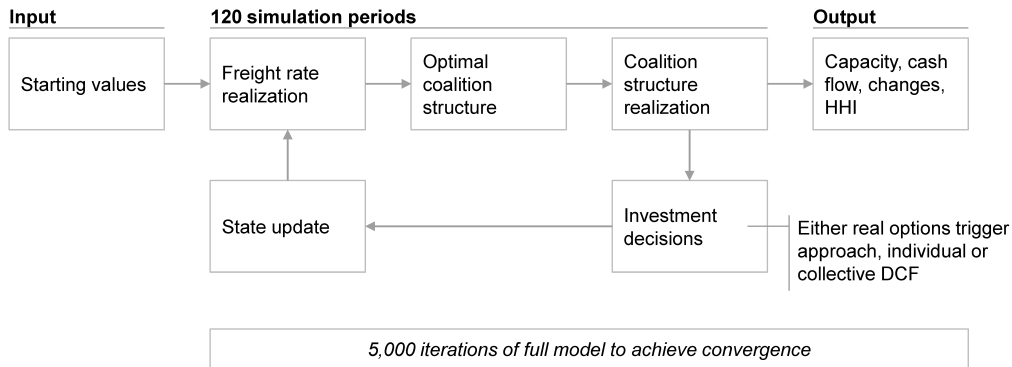


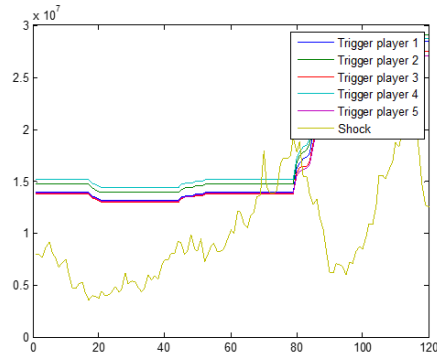
Table B.8: Technical validity of model

Type	Dimensions	Explanation
Conceptual model	Objectives	<ul style="list-style-type: none"> - Objectives of model outlined Section 3.1.3 - Assess performance of a real options investment approach - Quantify impact of competitive intensity, lead time, alliance complexity cost, and freight rate volatility on average industry capacity, cash flow to players, alliance stability, and industry concentration
	Appropriateness	<ul style="list-style-type: none"> - Model selected based on literature review: asset based simulation, coalition structure value, and real options trigger approach - Development of model consistent with objectives: integrated model with all 3 testable investment approaches
	Limitations	<ul style="list-style-type: none"> - Assumptions discussed in Section 3.3.1 - Limitations that are only implicitly mentioned through the assumptions: total number of players in the industry due to full enumeration of CS limited to 7, abstract straight-line forecasting of freight rates for CS calculation
	Documentation	<ul style="list-style-type: none"> - Structure of model explicitly documented in Section 3.3 - Illustration of model structure presented in Figure B.1
Logical/mathematical	Logic	<ul style="list-style-type: none"> - Transparent model logic and structure (c.f. Figure B.1) - Reflection of container shipping market based on literature and expert discussions from Rau and Spinler (2016b)
	Critical points	<ul style="list-style-type: none"> - Critical assumptions of the model: endogenous price function dependent on capacity in the market, GBM as driver for uncertainty in freight rate process, economies of scale in variable cost, linear alliance complexity cost and no switching cost
	Replication	<ul style="list-style-type: none"> - Convergence achieved with 5,000 model iterations - For 2 sample runs ($\sigma = 0.35$) with 5,000 iterations each: deviation of average capacity by less than 2 percent; deviation of total cash flow by less than 1 percent
Data	Documentation	<ul style="list-style-type: none"> - Documentation of input data in assumptions (Section 3.3.1) and in Table 3.1

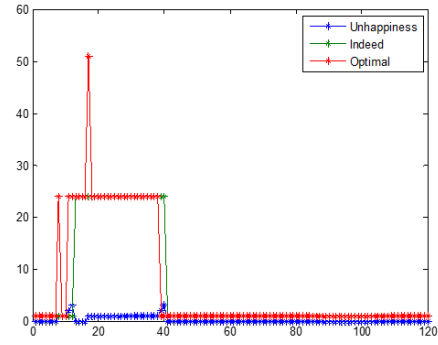
Table B.9: Operational validity of model

Type	Dimensions	Explanation
Results validation	Face validity	- Discussion of results with researchers from various backgrounds, practitioners in the industry, conference participants at INFORMS annual meeting, and management consultants
	Hypothesis tests	- Development of hypotheses (Section 3.4) - Testing of hypotheses (Section 3.5) with qualitative (box-plots) and quantitative tests (Mann-Whitney test)
	Operational graphics	- Assessment of (interim) results and through non-aggregated graphs (c.f. Figure B.2)
Experimental validation	Sensitivity analysis	- Sensitivity analyses for critical input parameters conducted: freight rate volatility, competitive intensity, lead time, alliance complexity cost, choice of investment appraisal method (c.f. Section 3.5)
Comparative validation	Comparison to other studies	- Discussion of other studies for hypothesis development (c.f. Section 3.4)
		- Higher degree of competition drives instability (Lu et al. 2006, Midoro and Pitto 2000)
		- Values are increasing in volatility (Bendall and Stent 2007, Rau and Spinler 2016b)
Policy impact validation	Comparison against public debate	- Research calls for innovative shipping investment approaches (Lau et al. 2013)
		- Overcapacity in shipping markets widely discussed in journals, magazines, and TV (Barnato 2016)

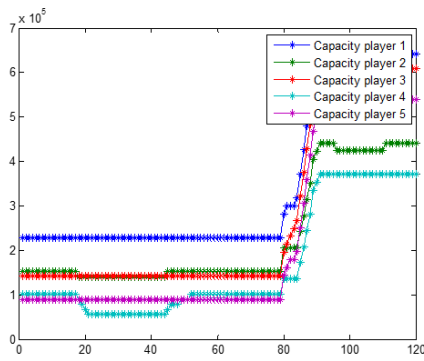
Figure B.2: Non-aggregated graphs created for each simulation run (illustrative only)



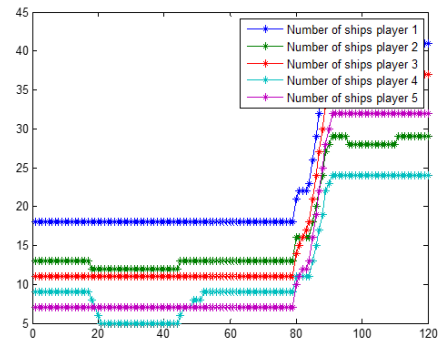
(a) Evolution of investment trigger



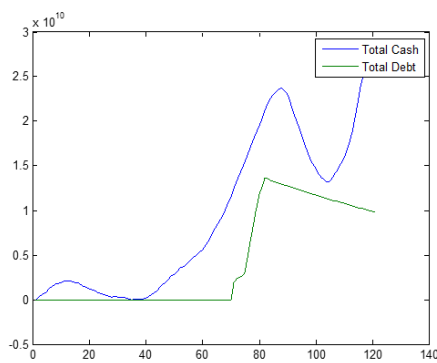
(b) Coalitions and willingness to switch



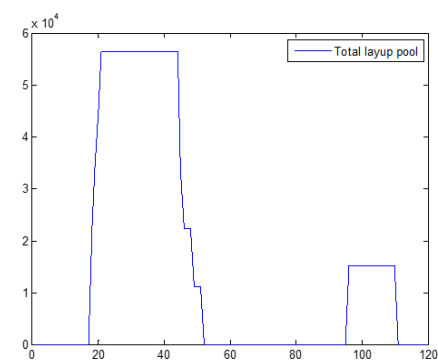
(c) Capacity of individual players



(d) Number of ships of individual players



(e) Evolution of total cash and debt



(f) Layup pool

Appendix 3

C.1 TABLES

Table C.1: Coefficients, error terms, and goodness of fit statistics for the ARIMA(0,1,3) model

	θ_1	θ_2	θ_3
Coefficient	-0.0749	-0.0329	-0.2947
Standard error	0.1108	0.1255	0.1189
p-value	0.4992	0.7931	0.0132

$$\text{AIC}=0.51 \quad \text{AICc}=1.07 \quad \text{BIC}=9.83 \quad \text{R}^2=0.73$$

Table C.2: Performance of different ARIMA models

ARIMA	AIC	AICc	BIC	R ²
(1,1,0)	3.25	3.25	7.75	0.71
(2,1,0)	4.40	4.73	11.39	0.71
(3,1,0)	(0.27)	0.29	9.05	0.73
(0,1,1)	3.05	3.22	7.72	0.71
(0,1,2)	3.66	3.99	10.65	0.71
(0,1,3)	0.51	1.07	9.83	0.73
(1,2,0)	38.16	38.33	42.80	0.65
(2,2,0)	37.51	37.85	44.47	0.65
(0,2,1)	8.17	8.34	12.81	0.73
(0,2,2)	10.10	10.44	17.06	0.73

Table C.3: Coefficients and error terms for the ARIMA(0,1,3) model with deployment as regressor

	θ_1	θ_2	θ_3	ln D4
Coefficient	-0.1527	0.0548	-0.2714	-3.5698
Standard error	0.1186	0.1473	0.1252	1.0770
p-value	0.1978	0.7099	0.0302	0.0009

$$\text{AIC}=-7.79 \quad \text{AICc}=-6.94 \quad \text{BIC}=3.86 \quad \text{R}^2=0.76$$

Table C.4: Performance of different ARIMA models with capacity deployment as regressor

ARIMA	AIC	AICc	BIC	R ²
(1,1,0)	-6.90	-6.90	-0.24	0.74
(2,1,0)	-5.27	-4.70	4.06	0.74
(3,1,0)	-7.00	-6.14	4.66	0.76
(0,1,1)	-7.23	-6.90	-0.24	0.74
(0,1,2)	-5.26	-4.69	4.07	0.74
(0,1,3)	-7.79	-6.94	3.86	0.76
(1,2,0)	24.51	24.85	31.47	0.69
(2,2,0)	23.33	23.90	32.60	0.70
(0,2,1)	-1.14	-0.80	5.81	0.75
(0,2,2)	0.38	0.95	9.65	0.75

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