

INVESTMENT AND CHARTER UNDER MARKET AND REGULATORY
UNCERTAINTY: REAL OPTIONS-BASED STUDIES IN
INTERNATIONAL CONTAINER SHIPPING

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*To my parents, my sister, and Kathi
for their love and support.*

ABSTRACT

This dissertation investigates capacity and technology choice decisions in maritime container shipping under demand and regulatory uncertainty. In an introductory overview, we¹ discuss the industry and the challenges that complicate investment decisions in shipping: e. g., the multitude of decisions, market volatility, excess capacities and the trend of new environmental regulation.

Real option valuation methods can account for strategic options and the uncertainties in capacity decisions in shipping. To assess the impact of chartering on maritime investment, we analyze investment and charter options individually in a continuous-time model. We combine both in a discrete-time approach taking into account key features of the industry: investment with time to build, divestment, chartering, an endogenous charter rate, layup, and demand uncertainty. While we find demand volatility to increase optimal capacities if only investment with time to build is possible, chartering reduces this effect. It adds value to the overall project, should be mainly applied to compensate unexpected capacity shortages and needs to be considered in decision-making.

Uncertainty about future eco-regulation is a further challenge for the industry. In an approximate dynamic programming model extension, we account for a stochastic introduction of operating cost-increasing regulation to assess optimal capacity choice under regulatory uncertainty. Regulation can allow for grandfathering, affecting only newly acquired vessels. We find uncertainty about future regulation *with* grandfathering to induce heavy up-front investment to secure a low cost base even in regulated markets. Such uncertainty may increase excess capacities and industry emissions. Uncertainty *without* grandfathering, however, reduces overall investment and emissions. In this case, the market may contract as investors resort to chartering until uncertainty is resolved.

To also assess technology choice in light of uncertain future regulation, we develop a two-phase regime-switching model. We derive analytical solutions and study the effects of regulatory uncertainty on technology choice in a numerical extension that relaxes restrictive assumptions. We find that such uncertainty can increase optimal capacities and that a single-technology strategy is preferable over a fleet of mixed technologies in most cases. We further extend the model and compare the effectiveness of two different regimes—an emissions cap and an emissions tax. Results suggest that an emissions cap is more effective at reducing overall emissions while a tax causes lower regulation cost. The regime choice also determines the optimal technological fleet composition.

The main implication is that chartering and regulatory uncertainty have a strong effect on optimal investment in shipping and should be considered in project valuation. Further, regulatory uncertainty can lead to unintended investment behavior that undermines regulatory goals. Lastly, regulatory regimes are not equally effective/efficient in reducing the environmental footprint of shipping and constitute varying incentives for investing in eco-friendly technology.

¹The term “we” refers to the authors of the respective chapters as denoted at the beginning of each chapter. For the abstract, this refers to the authors of Haehl and Spinler (2017a,b,c).

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ACRONYMS

ADP	Approximate dynamic programming
CO₂	Carbon dioxide
DCF	Discounted cash flow
DP	Dynamic programming
ECA	Emission control area
EEDI	Energy Efficiency Design Index
EU	European Union
HFO	Heavy fuel oil
IMO	International Maritime Organization
LHS	Left-hand side
LNG	Liquefied natural gas
MARPOL	International Convention for the Prevention of Marine Pollution from Ships
MDO	Marine diesel oil
NPV	Net present value
NO_x	Nitrogen oxide
RHS	Right-hand side
SCFI	Shanghai Containerized Freight Index
SEEMP	Ship Energy Efficiency Management Plan
SO_x	Sulfur oxide
SO₂	Sulfur dioxide
SO₃	Sulfur trioxide
TEU	Twenty-foot equivalent unit
USD	US dollar



INTRODUCTION

*Quand tu veux construire un bateau, ne commence pas
par rassembler du bois, couper des planches et distribuer du travail,
mais reveille au sein des hommes le desir de la mer grande et large.*

—Antoine de Saint Exupéry

1.1 THE CONTAINER SHIPPING INDUSTRY

Ships and the sea have exerted a magic attraction on humans for generations as a means of travel and trade. With its origins in Asia, trade on sailing vessels has developed from regional routes in trade networks like the Hanseatic League to trading across continents after the discoveries of explorers like Christopher Columbus. In these times and up until the middle of the 19th century, sailing vessels were the predominant means of sea transport before they were replaced by steam shipping and later diesel-powered engines. The physically hard work on board ships and in port handling as well as the resulting high personnel intensity limited the growth of the industry until the breakthrough of containerized freight. Since the 1950s, during which the American shipper Malcolm McLean has introduced intermodal transportation of containers to maritime shipping (World Shipping Council 2017), the industry has seen immense growth. Today it is a truly global trading network, in which ever-increasing container vessels, liner services, and continuous efficiency increases also in shore-based operations allow the transportation of unconceivable volumes of cargo around the world. In 2015, world seaborne trade totaled 53.6 billion ton-miles across all trade lanes and vessel types. An overwhelming majority of general cargoes is now transported in standard containers, leaving container shipping with a contribution of about 16% of ton-miles. Total yearly volumes of containerized trade are estimated at 175 million twenty-foot equivalent units (TEU), which is the standardized size of a twenty foot container used as a measurement unit in the industry. (United Nations Conference on Trade and Development 2016)

This logistical achievement is accomplished by a fleet of 6,000 container vessels with a total capacity of 20.6 million TEU, which has been strongly growing over the past years. (Alphaliner 2017) The growth in fleet size is driven by ship orders but also the growing average size of new-built vessels, which has risen more than 130% between 2009 and 2015 in a race for economies of scale. (United Nations Conference on Trade and Development 2016) Container ships with capacities exceeding 10,000 TEU have become common and the largest container vessel ever launched is currently Maersk Line's "Madrid Maersk"— a ship of the so called "Triple E Mark II class" with a capacity of 20,568 TEU. (Hand 05/02/2017) Further vessels with capacities in excess of 21,000 TEU are

already on order. Figure 1.1 showcases how the worldwide fleet of container vessels and average vessel sizes have grown since the year 1996.

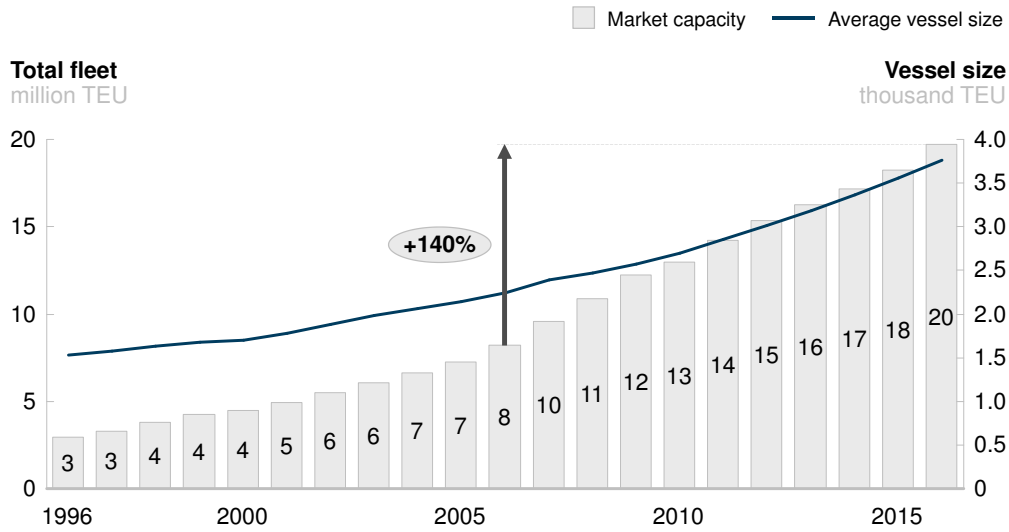


Figure 1.1: Global container vessel fleet and average vessel size. Source: Clarksons (2016d).

Although maritime shipping has been a leading enabler of globalization and has grown immensely over the past decades, the industry has been in difficult waters since the world financial crisis in 2009. Shipping companies face a multitude of challenges ranging from extensive excess capacities in the market, depressed freight and charter rates, and fierce competition, to upcoming regulation that targets the environmental footprint of the industry. The challenging decision-making in this highly capital intensive industry under significant uncertainty—especially from potential regulation—is the focus of this dissertation.

1.2 INVESTMENT CHALLENGES IN MARITIME SHIPPING

There are ship investments that have created significant wealth for investors and shipping companies, but at the same time such investments entail substantial risks due to the complexity and volatility of the industry. Especially in the ongoing shipping crisis, many investors and shippers are facing scarce financial resources, diminishing profits or heavy losses, significant uncertainties and a market consolidation due to bankruptcies and takeovers. The largest bankruptcy occurred in 2016 when Hanjin Shipping Co., Ltd., one of the world's largest container shipping lines with more than 140 vessels, went bankrupt and finally seized operations in early 2017. (The Guardian 09/02/2016) Investment decisions in such a market environment are complex and need special decision support tools for an appropriate project valuation. The following sections aim to give a brief overview of the key challenges faced by maritime investors.

1.2.1 *Multitude of Decisions*

At any point in time, ship investors and operators have a large variety of options for action. First, carriers need to adapt their available capacities to market conditions. This can be done through ordering new ships that will be delivered after a building period that fluctuates with the demand for new-built vessels. Alternatively, used vessels can be acquired or sold on the second-hand market to adapt transportation capacities more quickly. Apart from owning the shipping fleet, investors can additionally resort to chartering vessels either based on long-term contracts or spontaneously for short durations from the charter spot market. Second, based on available capacities and current market conditions, shippers need to define the trading lanes they want to serve and at what frequency. This decision is not only driven by transportation demand on this route, but also by price elasticity, competition and how the trade lane fits into the carrier's remaining network. Third, carriers need to determine the freight rate at which they offer transport services. This choice is strongly driven by market dynamics: especially in times of large capacities in the market, carriers oftentimes are forced to lower their rates to undercut the market rate. Only then are they able to reach sufficient utilization of their vessels to cover fixed operating costs. Lastly, and among many more detailed decisions, ship operators can choose to leave vessels idle in so-called layup. In these cases, it is cheaper for the vessel to wait without cargo for more attractive market conditions instead of operating with low utilization, realizing even higher operating losses. In all choices discussed, there is also an inherent technological component. Both in capacity choices and deployment, it is vital to employ appropriate vessel technology to ensure regulatory compliance and cost efficiency also in the future.

1.2.2 *Uncertainty and Market Volatility*

Shipping companies operate in a volatile industry with many sources of uncertainty that should be taken into account in investment and operating decisions. The first uncertainty to cope with are volatile vessel prices in the new-building, second-hand and charter markets. Overall investment success oftentimes not only depends on successful operations but also on adequate and optimal investment timing. Vessel prices are mainly driven by the ratio between total capacity in the market and transportation demand as well as state funded subsidies granted to shipyards. In times of high excess capacities, it is generally cheaper to expand capacities, while in times of booming markets, high utilization rates and capacity shortages, additional ships can be acquired only at sky-rocketing prices. (Stopford 2009) The fact that there is a considerable time lag (e. g., 2 - 3 years) between the ordering of a new-built vessel and its delivery further adds volatility to investment costs. It can also lead to situations in which carriers are willing to pay higher prices for second-hand vessels than for new-builds to be able to operate the ship already in a potential peak demand. Such a situation can be observed for the year 2005 in Figure 1.2, which shows indices for new and 10 year old second-hand container vessel prices. It also illustrates the volatility in vessel prices over time.



Figure 1.2: Vessel price index for new-built and second-hand container vessels. Source: Clarksons (2016a,b).

Freight rates are the market price that container carriers gain for shipping one container from a port of origin to a destination. They are therefore the source of income that should cover for the operator's expenses including operating costs. Like ship prices, freight rates are also volatile and depend both on market demand for and supply of transportation services. In recent years since the financial crisis in 2009, such rates have not only been volatile but also remained on low levels, sometimes falling short of operating cost. (United Nations Conference on Trade and Development 2013) High freight rate volatility is also documented in Figure 1.3 by the Shanghai Containerized Freight Index (SCFI), an industry index of freight rates.

Apart from asset prices and charter and freight rates, operating costs are volatile, mainly due to the fluctuating oil price. Most vessels today operate on heavy fuel oil (HFO), which is a residual fuel that remains from the distillation process of producing petrol and distillate diesel oils. There are also cleaner, distillate fuels available and in use—such as marine diesel oil (MDO)—mainly within certain geographical areas in which higher environmental standards apply. All fuel prices however depend on the uncertain oil price and as such complicate investment valuation and decisions in maritime shipping.

Last but not least, uncertainties about future (mainly environmental) regulation have strong effects on investment decisions and technology choice in this industry. We¹ devote a separate introductory section (Section 1.3) to this topic as it is a main focus of this dissertation.

¹The term “we” refers to the authors of the respective chapters as denoted at the beginning of each chapter. For the introduction, this refers to the authors of Haehl and Spinler (2017a,b,c).

1.2.3 *Curse of Excess Capacities*

A key challenge for the industry is to avoid the buildup of large amounts of excess capacity in the market. Especially since the financial crisis in 2009, shipping companies suffer from high capacities that exert downward pressure on freight and charter rates. Industry experts have often referred to this as the vicious circle of container shipping (Merk 04/16/2016): freight rates drop as a result of an initial stagnation or recession of transportation demand. To operate profitably despite low freight rates, carriers order larger container ships hoping to reduce the total cost base per container shipped by realizing economies of scale. The simultaneous ordering leads to an increase of total market capacities that exceed demand and are therefore barely utilized. As fixed costs of vessels are high, carriers need to offer lower freight rates to attract cargo that can cover operating costs. This fuels an intense price competition with low returns. Such a situation is again an incentive to invest in even larger vessels with alleged additional economies of scale. Such investment behavior of an entire industry has led to significant excess capacities as can be seen from the layup pool shown in Figure 1.3.

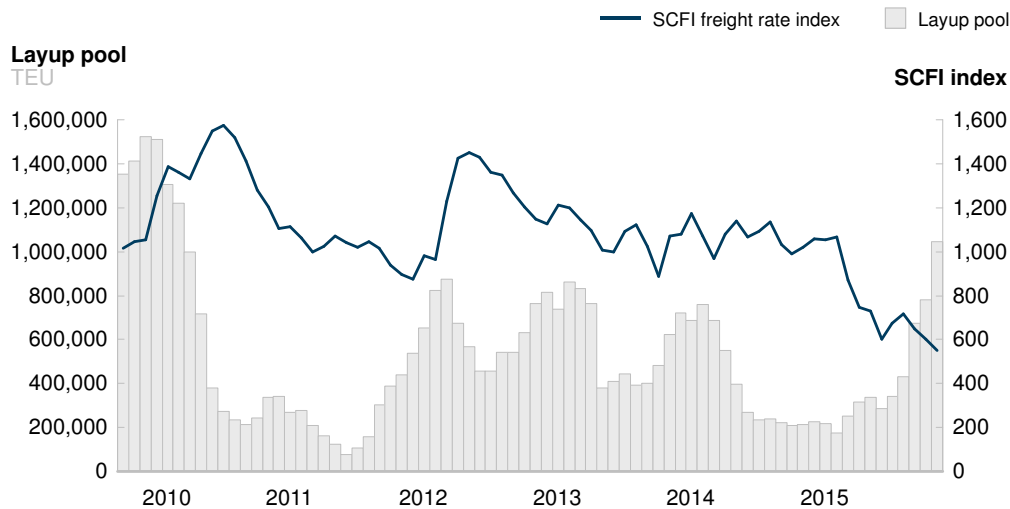


Figure 1.3: Container vessel layup pool and Shanghai Containerized Freight Index (SCFI). Source: Alphaliner (2012, 2015, 2016), Clarksons (2016c).

In addition to this vicious circle, there is also evidence in other shipping classes that behavioral aspects contribute to over-investment Greenwood and Hanson (2015) find for bulk shipping markets that firms overextrapolate positive demand shocks. In such demand peaks, firms have heavily invested into new capacity, which was only delivered when the market had ended its rally. The resulting excess capacities have led in lower freight rates and investment returns than it was expected by shipping companies.

While such behavioral arguments likely explain much of the buildup of excess capacities, there may also be market features such as regulatory uncertainty, that can induce carriers to (rationally) build up more capacity². Such

²Such effects have also been shown in other real options models. Refer to e. g., Aguerrevere (2003), Sarkar (2009)

effects have been observed also in the models proposed in this dissertation and will be discussed in the subsequent sections. It is important to note, however, that excess capacities are costly for the industry and—while small excess capacities may be rational to be able to cope with unexpected demand peaks—should be avoided in the extent as observed over the past years.

1.3 ECO-REGULATION AND COMPLIANCE

Emerging environmental regulation and compliance is a major trend in container shipping and the maritime industry in general. Regulating bodies for the sector can be individual states for their territorial waters (i. e., the United States or the European Union) and the IMO on an international level. As a specialized agency of the United Nations, the IMO sets global standards regarding the safety, security and environmental requirements for maritime shipping. It is composed of representatives from 172 seafaring nations that develop, negotiate and pass resolutions. (International Maritime Organization 2017a) Proposals for a resolution can be submitted by any contracting government and are subsequently discussed, amended and adopted in the IMO's committees. After the adoption of a resolution it cannot enter into force before sufficient IMO member states have accepted and ratified the resolution. (International Maritime Organization 2017b) Both, the negotiation process within the IMO as well as the ratification of conventions by member states can be lengthy processes of previously unknown duration. The complexity of regulating such an international industry with many governments involved and the lengthy ratification process imply fundamental uncertainties for shipping companies as to what regulations they need to comply with in the future.

In recent years, the IMO has increased the focus on reducing the environmental impact of maritime shipping. While shipping remains the most ecologically friendly means of transport per ton-mile, the sheer dimensions of the industry make it a major contributor to worldwide greenhouse gas and other polluting emissions. According to an IMO study, it contributes about 3% to global carbon dioxide (CO₂), 12% to sulfur oxide (SO_x) and 13% to nitrogen oxide (NO_x) emissions. With the exception of SO_x emissions, all three pollutants are also expected to significantly increase in a business as usual scenario until 2050 as shown in Figure 1.4. The expected reduction of SO_x emissions can be attributed to new abatement regulation introduced by the IMO. (International Maritime Organization 2014) In accordance with environmental efforts in other sectors, the IMO aims to reduce greenhouse gas emissions of the industry by 20% by the year 2020 compared to 1990 levels. (Helfre and Boot 2013)

With a new focus on reducing the industry's environmental footprint, the IMO has started to adopt and enact several new conventions, of which the following policies are an excerpt: the new Energy Efficiency Design Index (EEDI) requires new-buildings of seagoing vessels to comply with numerous design principles that promote the energy efficiency of the new vessel. While new vessels are required to comply, this policy does not apply to the existent fleet³. In contrast to the EEDI, which aims for energy efficient vessel design, the new Ship

³Except if existing vessels undergo significant constructional changes.

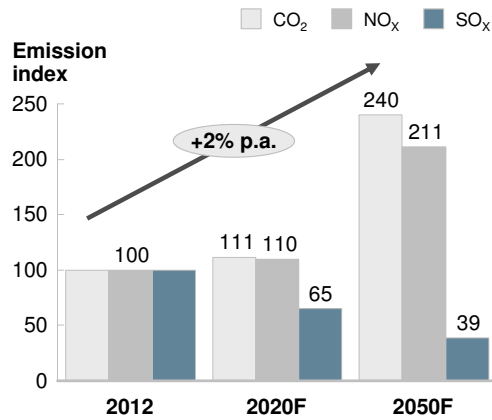
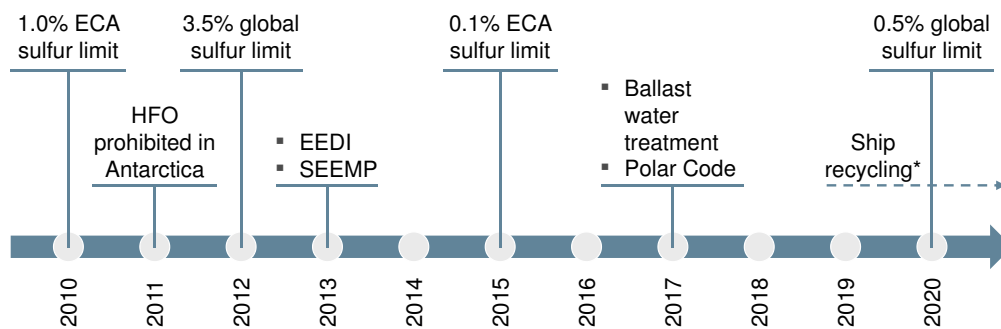


Figure 1.4: Expected development of shipping emissions until 2050. Numbers refer to an index based on 2012 emission levels (= 100). Source: International Maritime Organization (2014).

Energy Efficiency Management Plan (SEEMP) requires carriers to develop operating plans that promote energy efficient operating procedures and adequate monitoring. This measure targets both old and new vessels. New ship recycling rules limit the use of hazardous materials in ship-building and require shipyards to build vessels in a way that allows materials to be recycled upon their demolition at the end of the lifetime. This regulation also monitors that recycling of old vessels is performed by certified recycling companies. While adopted by the IMO, this convention has not yet been ratified by its member states. Rules on ballast water treatment will enter into force in 2017 and prevent micro-organisms from being transported in ships’ ballast water tanks from one habitat to another, where they could damage the local ecosystem. (International Maritime Organization 2017c) A selection of effective dates of IMO regulations is displayed in Figure 1.5.



* Convention adopted by IMO, ratification by member states pending

Figure 1.5: Overview of effective dates of IMO regulations. Adapted from Det Norske Veritas (2012).

One of the most significant new regulations introduced is the International Convention for the Prevention of Marine Pollution from Ships (MARPOL) Annex VI, which targets the reduction of sulfur emission levels. To achieve a significant reduction, the IMO has adopted a staged approach of reducing the permissible

sulfur content in shipping fuels. Additionally, so called emission control areas (ECAs) were defined, in which the reduction proceeds significantly faster with lower sulfur limits. Examples of ECAs are the North and Baltic Seas, the Mediterranean Sea, or the United States coastlines. Note that Annex VI does not directly define SO_x emission limits but rather an admissible sulfur content in the fuel. However, carriers can comply with this regulation also by limiting their SO_x emissions to a level that corresponds to the respective sulfur content in the fuel. Ship operators therefore have three main options for compliance that come at high cost and pose challenge to carriers (Ryan Sept/Oct 2014): They can resort to a fuel-switching strategy in which vessels operate on HFO fuels with higher sulfur content in international waters and switch to more expensive low sulfur MDO fuels when entering an ECA. Alternatively, they can install exhaust gas cleaning systems (so called scrubbers). This allows continued operations using cheaper HFO fuels but requires an investment of up to 13 million USD for the installation or retrofit of a scrubber depending on engine size (Den Boer and Hoen 2015). Lastly, vessels could be retrofitted with liquefied natural gas (LNG) propulsion, which currently is expensive and rarely used. (Lloyd's Register 2015) Uncertainty about SO_x emission regulation will serve as a practical example for the application of the investment valuation models under regulatory uncertainty presented in Chapters 3 and 4.

From the most recent IMO policy actions and the ambitious reduction targets, it can be expected that the industry will face more new environmental regulation (The Economist March 30, 2013). The unknown content of future regulation as well as the unpredictable duration of the legislative process introduce fundamental regulatory uncertainty to the market that further complicates the investment decision in maritime shipping. Uncertainty about future regulation and technological compliance will be one of the most prominent challenges for the industry in the foreseeable future and is a key focus of this dissertation. (Forum For the Future May 2011)

1.4 REAL OPTIONS: A METHOD FOR VALUATION UNDER UNCERTAINTY

It has become clear from the previous sections, that investment decisions in maritime shipping are connected to high levels of uncertainty about the future that need to be taken into account. At the same time, ship operators possess considerable flexibility to react to changed market conditions and can therefore follow different strategies after uncertainty has resolved. The investment modeling presented in this dissertation is based on real options theory, which is well suited for such valuations and is shortly presented here⁴.

Traditional finance theory teaches that investments should be valued using discounted cash flow (DCF) methods. Using this approach, an investor discounts expected cash flows from the project and invests if they exceed the investment cost. The net present value (NPV) is said to be positive. This approach has two drawbacks which real options theory aims to solve. First, DCF comes short of business reality as it does not take into account management's possibility to

⁴Helpful overviews of real option approaches can be found e. g., in Chevalier-Roignant et al. (2011), Dixit and Pindyck (1994), Schwartz (2013).

react to unexpected events: The approach requires to form an expectation on future earnings which typically are dependent on an overall state of the future (e. g., demand for sea transportation). While future states are uncertain, the DCF method assumes a single realization and ignores the fact that management can react to market conditions after the investment has been triggered. In reality, management can react to the realization of unexpected future states to optimize project payoff based on the new situation. Real options analysis aims to consider management's flexibility to change strategies after uncertainty is resolved (Bendall and Stent 2003).

As Dixit and Pindyck (1994) point out, the second shortcoming of the DCF approach is its assumption of investment reversibility. DCF requires that investments are reversible in a sense that costs can be recovered in case market conditions do not turn out as well as anticipated. If reversibility is not met, DCF alternatively assumes that the investment is a now or never opportunity. Most real world investments, however, do not meet either of these conditions (Dixit and Pindyck 1995). Consider investing into a container ship. If market conditions deteriorate and the investor cannot earn the profits originally anticipated, he cannot undo the investment. Neither will it be possible to sell the ship at its original cost because other shippers will have the same difficulty of achieving the anticipated profit in deteriorated market conditions. Selling will therefore only be possible at a discount, rendering parts of the investment a sunk cost. At the same time, investing into container ships is not a now or never decision. If the investor does not invest today, the option to invest remains available in the future as well.

Real options theory addresses these two shortcomings of traditional DCF methods by taking into account the value of options that the investor owns during the investment period. There are various types of options that can be considered. One of the most frequently used options is the option to defer. Here it is assumed that an investor has the option to invest over a certain period of time (American call option). Once the investor buys the project, he gives up the option to invest. Instead of investing today, the investment can be deferred over the lifetime of the option. Such an option changes the investment rule compared to DCF so that discounted future earnings need to offset not only the investment cost but also the value of the call option that is executed. The rule becomes: invest, if

$$\text{Discounted earnings} \geq \text{Investment cost} + \text{Value of option to invest.}$$

Other types of options that can be modeled are options to expand, contract or abandon the project and to choose between various possible strategies such as employing a ship on a different route or chartering it out. (Bendall and Stent 2003) The models and analyses presented in this dissertation are based on real option methods to specifically take into account the most important uncertainties in focus as well as the carrier's options to react. While many real option models can be solved for an exact solution, some can exceed available computing power. Such models can be solved using approximate dynamic programming (ADP) methods⁵ that we will apply in Chapter 3.

⁵For an overview of such methods, please refer to Powell (2009, 2011, 2012).

1.5 CONTRIBUTIONS OF THIS WORK

In the following chapters of this thesis, we⁶ aim to analyze optimal capacity and technology choice under regulatory uncertainty in the container shipping industry. It was shown in the previous sections, that this industry is characterized by various sources of uncertainty, that—together with immense capital intensity—complicate optimal decision making. By developing quantitative valuation models with different foci, we aim to support decision-making, which practitioners oftentimes consider an irrational race for ever-increasing vessels. We primarily focus on regulatory uncertainty as it is a major influencing factor and trend for the industry and that—despite its importance—has found little attention in the quantitative decision support literature. We base our modeling approaches on real option methods that are well suited to value investment projects and their inherent management options under uncertain market conditions.

To lay the foundation, in Chapter 2 we propose a multi-period real option model for valuing investments in the container shipping industry and add a charter option to the framework. The model is used to analyze the effect of chartering on optimal decision making and the results serve as the basis for the model in the next chapter. In Chapter 3, we add the potential introduction of environmental regulation to the valuation approach. We specifically analyze the effects of regulatory uncertainty on optimal investment choice - both for regulation that allows the grandfathering of existing capacities (i. e., existing capacities do not have to comply) and for regulation targeting both old and new vessels. In Chapter 4, we develop a two phase regime switching model to focus on technology choice for complying with uncertain future regulation. In detail, the three main chapters evolve as follows:

- In Chapter 2, we analyze the effect of chartering on optimal investment decisions in the context of international container shipping. Based on a continuous-time real options model, we show that long-term chartering alone does not exhibit the capacity increasing effects in volatile markets typically observed in investment-only models. We present a discrete-time real options model that combines investment into and (long-term or short-term) chartering of capacities at the same time. The model allows for important market characteristics such as time to build, operating flexibility, divestment and an endogenous charter rate. We calibrate the model to the international container shipping industry and analyze optimal capacity choice with investment and chartering. We find that chartering increases the investment project's value and dampens the capacity-increasing effect of investments' time to build. At the same time, chartering can increase optimal total capacities in volatile markets as it allows spontaneous capacity additions in times of unexpected demand peaks. As chartering can be used to offset spontaneous capacity shortages, it reduces the optimal level of owned capacities. Overall, our model shows that the charter option

⁶The term "We" refers to the authors of the respective chapters as noted at the beginning of each chapter.

changes the dynamics of optimal investment and thus should be taken into account in decision-making.

- In Chapter 3, we present a real options model for capacity expansion that introduces uncertainty about potential future regulation (regulatory uncertainty) and four key characteristics of capacity decisions: investment with time to build, divestment, the option to charter, and operating flexibility. Regulatory uncertainty is modeled as a possible upward jump in operating, investment, and charter costs during the simulation horizon. Our model distinguishes between regulation with and without the grandfathering of existing capacity, where grandfathering is the exemption of the extant fleet from regulatory compliance. Although the model is developed as a dynamic program, we solve it for near-optimal decisions using approximate dynamic programming. By applying our model to the international container shipping industry, we derive insights regarding optimal capacity choices under regulatory uncertainty. We find that uncertainty about regulation *with* grandfathering may promote so much up-front investment that current operational needs are exceeded, leading to excess capacity and increased emissions. However, regulatory uncertainty *without* grandfathering reduces investment and emissions and leads investors to adopt more flexible capacity options, such as chartering.
- In Chapter 4 we present a real options approach to evaluating technology and capacity choices under potential future regulation (i. e., regulatory uncertainty). Our two-phase, regime-switching model includes the option of investing in different technologies as well as a charter option and a layup option. From a base-case version of this model, we derive an analytical solution before studying the effect of regulatory uncertainty in a numerical extension that relaxes certain restrictive assumptions. We then describe two regulation regimes, an emissions cap and an emissions tax, and compare how effectively each reduces emissions. Applying the model to maritime container shipping, we develop insights on the optimal technology choice for reducing SO_x emissions. We find that regulatory uncertainty can increase not only project values but also owned capacity. From a regulatory perspective, an emissions cap reduces emissions more effectively whereas an emissions tax reduces the cost of regulation. Finally, we show that setting the emissions cap level—or deciding on the level above which an emissions tax applies—is critical because total industry emissions are reduced in a noncontinuous manner.

Chapter 5 summarizes the dissertation and presents the condensed managerial implications of the three main chapters. Potential avenues for relevant future research are also discussed.

We contribute to existing shipping literature by proposing quantitative real option models as a decision support for investments in the volatile container shipping industry. The models presented in this thesis help to better understand optimal investment strategies and how, specifically, the availability of chartering and the uncertainties induced by volatile market demand and potential future regulation influence optimal capacity and technology choice. Find-

ings and implications derived are relevant for investors, operators and regulators in the (container) shipping markets. Our models help investors to better understand optimal investment strategies in general, the choice between owning and chartering capacities, the influence of potential regulation on optimal investment and rules for optimal technology choice for regulatory compliance. Regulators need to understand the immediate and long-lasting effects of different regulatory approaches and the uncertainty created by the legislative process. Specifically, our models help regulators to evaluate the expected reaction of market participants to regulatory uncertainty (both with and without grandfathering) and the effectiveness of different regulatory regimes in reducing industry emissions at a low regulation cost.

THE IMPACT OF CHARTERING ON INVESTMENT UNDER MARKET UNCERTAINTY: A REAL OPTIONS STUDY IN INTERNATIONAL CONTAINER SHIPPING

The following chapter is based on Haehl and Spinler (2017c).

2.1 INTRODUCTION

Excess capacities are a recurring challenge to the sea transport industry, regularly forcing companies out of business. Especially during times of economic downturn, excess capacities exert additional downward pressure on freight and charter rates, which sometimes can fall below operating cost levels. While there are theories to explain such investments from a behavioral standpoint (Greenwood and Hanson 2015), real options theory has contributed explanations based on optimal investment for profit maximization. Aguerrevere (2003) explains excess capacities seen in investment under market uncertainty as the result of time to build (capacity is not delivered immediately upon ordering) and operating flexibility. He finds that the possibility to leave capacity idle offers a protection against negative market developments and together with time to build can increase optimal capacity buildup especially in volatile markets.

However, existing approaches to investment under uncertainty focus only on investment into own production capacity. In real markets, however, businesses also have the option to enter long- and short-term leasing or charter contracts. While chartered capacity can also be left unused in unattractive market environments (operating flexibility), it is delivered without a time lag. It therefore can be expected, that flexible chartering reduces incentives to build up high capacities because it compensates the characteristic time to build of the investment option. To evaluate how effective real options methods are as an explanation of high levels of capacities in volatile markets, it is necessary to take chartering into account as well.

International container shipping with its problem of excess capacities is an interesting industry to apply such an investment model. As a volatile industry, shipping is exposed to various uncertainties, one of which is high volatility in asset prices (see for example Kavussanos (1997), Tsolakis et al. (2003)). Such volatility makes investment timing crucial for earning an attractive return. Secondly, the transport market itself features highly cyclical time charter and freight rates that can be very attractive in times of scarce transport capacity but even below operating cost in times of economic downturn (United Nations Conference on Trade and Development 2013). The market outcome of such investment decisions in shipping is oftentimes a situation of excess capacity. The industry has repeatedly found itself ordering large volumes of additional capacity in times of economic upswing with deliveries arriving only during market downturns. This has led to extensive excess capacities and ship opera-

tor bankruptcies when the market was already suffering from depressed charter and freight rates. It is often assumed, even by industry practitioners, that players invest irrationally in a race for ever larger ships and economies of scale. Real options literature, such as Aguerrevere (2003) offer an explanation why such investment may be optimal despite periodic excess capacities. This paper aims to analyze the effect of chartering on overall capacity decisions to evaluate whether or not previous findings hold true even in markets where investment and chartering co-exist.

In this paper, we adapt the real options investment model of Aguerrevere (2003) that features market uncertainty, time to build and operational flexibility, to the container shipping industry to serve as a base case for comparison. We show, using the same analytical approach, that chartering - on its own - does not lead to the same capacity increasing effects in volatile markets, making the interaction of investment and charter an exciting field of study. To study whether capacity implications hold true in environments, where investment and chartering co-exist, we develop a discrete-time binomial lattice model of ship investment and charter under market uncertainty and with time to build, operating flexibility and divestment. With this paper, we contribute to real options literature in three ways. First, based on an adapted model from Aguerrevere (2003), we confirm that time to build and operating flexibility for owned capacities lead to increased investment, but find that chartering alone leads to less capacity in volatile markets. Secondly, we combine the options to invest and charter in a new discrete-time dynamic programming model extending Fontes (2008) by introducing time to build and the additional charter option. We show that even if investment is joined by flexible chartering, the effects of owned capacity dominate: time to build and volatility can increase optimal capacities in volatile markets. Thirdly, we find that chartering is not employed to build base capacity but mainly used to offset unforeseen capacity shortages in sudden demand peaks. Finally, our model can also be applied to leasing production capacities or the sourcing of subcomponents from a third party. This, for example, is the case in semiconductor manufacturing where the contracting with silicon foundries would correspond closely to chartering in our model.

The remainder of the paper is organized as follows. Section 2.2 gives an overview of existing literature on real options analysis in general and as an application to the shipping industry. In Section 2.3 we adapt a real options model proposed by Aguerrevere (2003) to determine either optimal investment or the optimal amount of chartered container shipping capacity. We combine both investment and long-term charter options in a discrete-time model in Section 2.4 to analyze the interplay between these two capacity sources. In Section 2.5 we extend the discrete model by divestment and highly flexible short-term chartering to confirm that the findings hold true even in a model that allows for more flexibility. Section 2.6 concludes.

2.2 LITERATURE REVIEW

Discounted cash flow (DCF) has been the method of choice in investment appraisal but it features two important drawbacks: As Bendall and Stent (2003)

point out, DCF does not account for management's valuable options to react to unexpected events. Further, DCF assumes investment opportunities to be either reversible or else a now or never opportunity (Dixit and Pindyck 1994). Neither is usually the case for capacity investments. Real option methods address these shortcomings by valuing irreversible investments with options for action such as deferral, expansion, contraction or abandoning of the project once uncertainty is resolved.

In their seminal work, Dixit and Pindyck (1994) have treated real options from a mainly methodological standpoint giving an overview of methods available. Other authors have suggested extensions building on the same basic theory. A few model extensions should give an overview of the real options literature. Building on the basic model, Bar-Ilan and Strange (1996) have analyzed investment lags as a feature that is important for the shipping industry. Others such as Mossin (1968) and Brennan and Schwartz (1985) have considered operational flexibility, allowing to suspend operations at unattractive market price levels. Instead of only taking into account a single investor, some models focus on strategic interaction. Sødal (2006) suggests an entry-exit model analyzing market entry of new players and exit of incumbents. A slightly different direction is followed by Williams (1993) and Grenadier (2002), who combine real options and game theory by reflecting strategic interaction between market players. Like our paper, most real options literature assumes a risk-neutral investor. Chronopoulos et al. (2011) relax this assumption and introduce risk aversion instead. While most publications are based on European or American options, Driouchi et al. (2010) introduce path-dependent Asian options to decide on overall capacity based on average demand development. Martzoukos and Trigeorgis (2002) relax the common assumption of normally distributed uncertainties in real option models and propose a jump-diffusion process with multiple sources of rare events such as innovation, political or regulatory risks. Chronopoulos et al. (2016) compare lumpy investment strategies with stepwise investment options with the investor able to choose the timing and size of investment. Chevalier-Roignant et al. (2011) review recent developments on real options, including models of incremental investment relevant for this paper.

Apart from methodological contributions, there are also applications to the energy or real estate markets and to a lesser extent in the shipping industry. For example, the market entry-exit model was applied to shipping by Sødal (2006). Sødal et al. (2008) use real options to model the decision to switch between the dry bulk and wet bulk markets with combination carriers. Efficiency in these markets is analyzed by Sødal et al. (2009) using a similar model. Bendall and Stent (2007) use real options to value investment into an additional ship on top of an existing fleet. Management options here include to operate the ship, charter it to a third party or to use it as a replacement for an older existing ship. In another paper, Bendall and Stent (2005) compare the value of ship investment with predefined liner service to flexible strategies that can be adapted over time. They show that management's options increase the project value. Rau and Spinler (2016) analyze strategic interaction in oligopolistic container shipping. They show that a high number of market players leads to deteriorating firm values and identify vessel sharing agreements or the formation of alliances

as potential countermeasures. Gkochari (2015) use real options to optimize investment timing in dry bulk shipping.

Outside of real options literature, Greenwood and Hanson (2015) have used a behavioral approach to explain perceived over-investment in the dry bulk shipping market. They conclude that excess capacities originate from over-extrapolation of external demand surges while not taking into account investment decisions of competitors. Kalouptsidi (2014) studies investment and market entry and exit under various types of time to build. She finds that time to build is negatively correlated with fleet size and volatility.

We contribute to the literature in the following ways: (1) The continuous-time approach allows us to identify key differences of optimal capacity buildup between the investment and charter options separately. (2) Our discrete-time model incorporates novel features to ensure applicability to the container shipping market: We jointly study the option to invest or divest and the option to charter. We further allow for time to build and layup of excess capacities. (3) Based on the two models, we study the sensitivity of investment choice with respect to the pertinent parameters and derive managerial implications for capacity choice with investment and chartering.

2.3 ANALYTICAL INVESTMENT-ONLY AND CHARTER-ONLY MODEL

In this section, we extend the model proposed by Aguerrevere (2003) by incorporating chartering of ships. From separate investment and charter models, we confirm that, in the investment case, time to build and operating flexibility lead to increased capacity buildup in volatile markets. By contrast, when only chartering is possible, total capacities are relatively smaller in volatile environments. These findings will be the basis for developing our model of combined investment and charter in Section 2.4. For ease of comparability, we adopt notation from Aguerrevere (2003).

2.3.1 *Model Derivation - Investment Model*

We model a monopolistic market, in which the investor (the ship operator) can expand his shipping capacity by incremental investment. While competition in container shipping is oligopolistic, the monopoly assumption allows us to combine more features of interest and still analyze their individual influences. Features in the discrete-time models of Sections 2.4 and 2.5 include simultaneous investment, divestment and charter options as well as endogenous charter cost, time to build and operating flexibility. The fact that Aguerrevere (2003) finds the same capacity effects in oligopolistic competition as in a monopolistic market (though more pronounced in an oligopoly), gives us confidence that the monopoly assumption does not restrict the validity of directional findings derived from our model. Where relevant, we will point out how we expect the outcomes to differ in oligopolistic competition.

As an important market feature, we incorporate time to build between order and delivery of new capacity before it can be used in operations. We also allow for operating flexibility, letting the shipping company reduce operations in

market downturns by sending ships to layup. While in layup, capacity does not generate turnover but incurs lower cost: specifically fixed costs that still apply even if the ship is not operated¹.

The market for ocean freight transport and its price level are defined by the inverse demand function

$$P(t) = Y(t)q^{\frac{1}{\gamma}}, \quad (2.1)$$

where $P(t)$ denotes the market output price at time t for one container moved, q the level of transport capacity operated and γ the price elasticity of demand with $\gamma < 0^2$. The term $Y(t)$ is a stochastic demand shock and includes market influences such as the general economic development, import and export needs and overall transportation demand. This shock term evolves according to a Geometric Brownian Motion

$$dY(t) = \mu Y(t)dt + \sigma Y(t)dZ(t), \quad (2.2)$$

where μ and σ are the rate of demand growth per period and volatility, respectively.

The shipping company is assumed to operate capacity on a round-trip route. Capacities are measured in twenty-foot equivalent units (TEU), which refers to the twenty foot containers. All capacities and transportation output are measured on a TEU per year basis on one leg of the round-trip route. If, for example, we consider a 12,000 TEU ship that completes 6 round-trips per year at a utilization of 80%, the vessel has a yearly capacity of 115,200 TEU. The shipping company can choose to expand capacity and how much of available capacity to operate at any time, leaving the remainder in layup. In this continuous-time model, investment, operations and layup can be chosen incrementally. As a more realistic assumption, we introduce lumpy investment in our discrete model in Section 2.4. Ordered capacity is paid for directly, but takes time to build before it is delivered and operational. We distinguish between two types of capacity: Operational capacity $O(t)$ has been delivered and can be deployed in operations. By contrast, we define as committed capacity $K(t)$ those units that will be available after the time to build. $K(t)$ includes both operational capacity $O(t)$ as well as those units that have been ordered but not yet delivered.

Eq. (2.3) defines the firm's cost of operations: Cost components c_1 and c_2 refer to operating cost. Together, they reflect operating expenses such as fuel, crewing, port charges and regular maintenance cost. At any time, the ship operator can decide how much of available capacity to operate in the market. Depending on market demand, it may be optimal to leave capacity idle in layup at cost c_3 which applies only to the $\max(O(t) - q, 0)$ units of capacity in layup. Cost parameter c_3 can also be interpreted as the fixed part of operating costs c_1 that applies even if the capacity remains unused³. Lastly, financing costs apply to the capital invested. A percentage financing cost c_4 thus applies to in-

¹We consider warm layup, where ships remain ready to be reactivated with short notice. During layup, ships therefore are manned and maintained but do not incur fuel cost.

²For easier reference, Appendix A.1 lists and explains all variables used within this paper.

³Especially for cold layup, deactivation and reactivation of capacity can produce one time costs. As we treat warm layup (where such one time costs are less relevant) and in order not to unnecessarily increase model complexity, we do not consider one time deactivation or reactivation costs.

vestment cost k per unit of committed capacity $K(t)$. The overall cost function is:

$$C(q) = c_1 q + 0.5c_2 q^2 + \max(O(t) - q, 0)c_3 + K(t)kc_4. \quad (2.3)$$

Due to the layup option, the shipping company can choose to operate any capacity from none to total available operational capacity $O(t)$ depending on the current market price. This reflects in the company's profit function:

$$\begin{aligned} \pi(O(t), K(t), Y(t)) = \\ \max_{0 \leq q \leq O(t)} \left[Y(t)q^{1+\frac{1}{\gamma}} - c_1 q - 0.5c_2 q^2 - \max(O(t) - q, 0)c_3 - K(t)kc_4 \right]. \end{aligned} \quad (2.4)$$

The shipping company can expand by ordering new capacity, which is like holding a real option to invest. As we utilize the model's results as a base case for comparison, we refer to Aguerrevere (2003) for the derivation of the option value. Details for our model with the adapted profit function in Eq. (2.4) can be found in Appendix A.2.

As the model treats incremental investment, the shipping company can increase capacities at any time and as often as it is optimal. We can thus value the real option to invest like a perpetual American call option. Let $F_I(K, Y)$ denote the value of the option to buy an additional unit of committed capacity at a certain level of committed capacity $K(t)$ and demand $Y(t)$. The option to invest can be exercised for an investment cost k per unit of capacity. We can construct a risk-free portfolio and equate its expected rate of return to the risk-free rate of interest r by applying the no-arbitrage condition (Dixit and Pindyck 1994). This leads us to the following differential equation:

$$\frac{\sigma^2}{2} Y^2 F_I'' + \mu Y F_I' - r F_I = 0. \quad (2.5)$$

This equation can be solved as outlined in Appendix A.2 to derive the condition for optimal capacity choice. We define $K(Y)$ as the optimal committed capacity from investment dependent on market demand Y .

$$\beta [G_I(K(Y), Y, h) - k] - Y G_I'(K(Y), Y, h) = 0. \quad (2.6)$$

In this condition, β is the positive root to the characteristic quadratic equation, h is the time to build in years, G_I is the marginal value of an additional unit of committed capacity and G_I' is its derivative with respect to Y .

2.3.2 Model Derivation - Charter Model

We set up an analogous model, in which only chartering is possible. The definition of the overall market remains unchanged to the investment model. The ship operator can now expand by chartering new capacity, which is available immediately for deployment, without time to build. The assumption in this model, that charter contracts run until the end of the time horizon, will be relaxed in the discrete-time version in Section 2.5. The cost function only changes slightly: While operational and layup costs remain unchanged, we introduce

chartering cost c_5 which applies to all chartered capacity. The new cost function reads:

$$C(q) = c_1 q + 0.5c_2 q^2 + \max(O(t) - q, 0)c_3 + O(t)c_5. \quad (2.7)$$

The valuation of the option to charter is performed analogously to the investment option above and is outlined in Appendix A.3. The main difference is that chartering comes without time to build so that the replicating portfolio for the option to charter can be set up one step earlier. As before, the conditions of the resulting differential equation (see Eq. (A.13) in Appendix A.3) allow us to derive the optimal charter capacity $O(Y)$ as a function of demand shock Y :

$$\beta H_C(O(Y), Y) - YH'_C(O(Y), Y) = 0, \quad (2.8)$$

where H_C denotes the value of a marginal unit of chartered capacity and H'_C is its derivative with respect to demand shock Y .

2.3.3 Model Calibration

After setting up the separate investment and charter models, we simulate and interpret their results. While applicable to many markets, we calibrate them to the container shipping industry which is well reflected with characteristics of time to build and operational flexibility. Especially the combination with an option to charter is typical of this industry. This approach lets us better understand the difficult investment and charter decisions in shipping, which frequently suffers under excess capacities. Even though a monopolistic model, it lets us derive directional implications for optimal investment in shipping.

Table 2.1: Model parameters as used in base case scenario in all models if not specified otherwise.

Para- meter	Value	Description	Para- meter	Value	Description
γ	-1.4	Demand elasticity	c_1	700	Operating cost (\$/TEU)
μ	0.01	Market growth	c_2	0.00008	Operating cost (\$/TEU)
σ	0.2	Market volatility	c_3	28	Layup cost (\$/TEU)
r	0.06	Interest rate	c_4	0.02	Financing cost
k	1,000	Investment cost (\$/TEU)	c_5	120	Charter cost (\$/TEU)
k_s	100	Divestment price (\$/TEU)			

To derive cost parameters, we refer to AECOM (2012), who identify typical cost structures for a Neo Panamax container vessel of 12,000 TEU capacity. This vessel class is expected to gain importance with the expansion of the Panama Canal and is therefore used as basis for our model. The vessel is assumed to complete 6 round-trips between the United States and Asia per year, carrying

a total of 115,200 TEU per year at a utilization of 80%. Investment cost for the vessel is estimated at about 120 million US dollar (USD). On a per TEU basis (calculating with 115,200 TEU), we set investment cost at $k = 1,000$ USD per TEU. For operating costs we consider yearly bunkering, personnel and maintenance cost of 89 million USD, leading to a cost of 772 USD per TEU and year. Operational cost is split between cost factors c_1 and c_2 , where we assign only a small portion to c_2 which lets costs grow with increasing capacities. This is to reflect that economies of scale play an important role in shipping and that increasing marginal costs only become relevant at high levels of capacity. We thus set $c_1 = 700$ and $c_2 = 0.00008$. During layup, we assume only fixed parts (personnel and maintenance) of the 89 million USD operating costs to apply, while there are no variable costs for bunkering. This leads to a cost of $c_3 = 28$ USD per TEU for warm layup. For financing cost c_4 we assume an interest rate of 8% on a debt financing volume of 25% of invested capital for owned capacity. The remainder we assume to be financed by equity. Seen on the overall investment volume, this results in a financing interest rate of $c_4 = 2\%$ per year. Demand elasticity is assumed at $\gamma = -1.4$ (Rau and Spinler 2016), market drift at $\mu = 0.01$ and the risk-less interest rate r at 6% in our base case simulations. Table 2.1 gives an overview of the base case parameters just derived.

For the chartering model, we also need to set charter cost c_5 . Because the charter market for 12,000 TEU ships is narrow and nontransparent, we estimate charter cost from the New ConTex index published by the Association of Hamburg ship brokers (VHSS Vereinigung Hamburger Schiffsmakler und Schiffsagenten e.V. 2015). At the time of writing, a 4,250 TEU ship had a daily time charter rate of approximately 16,000 USD. Scaling to a 12,000 TEU ship results in yearly charter cost per TEU of 142 USD. For a like-for-like comparison with the investment model we remove personnel and maintenance cost from the charter rate⁴ as they are included in operating costs c_1 and c_2 . We thus reduce charter cost to $c_5 = 120$ USD per TEU and year.

2.3.4 Numerical Study

We now analyze optimal capacity choice resulting from the separate investment and charter models. The optimal capacity choice in the investment model results from Eq. (2.6). Because Eq. (2.6) cannot be solved analytically, we apply a numerical Brent root-finding algorithm that combines section search with parabolic interpolation (Brent 2002). Fig. 2.1a shows the optimal choice of committed capacity $K(Y)$ as a function of demand Y for different levels of demand volatility σ . To serve as benchmark, this figure is based on a scenario without time to build ($h = 0$). Without time to build, the ship operator prefers lower committed capacity K for increasing volatility σ in a riskier market. This effect can be observed because, as in Aguerrevere (2003), there is a cost of excess capacity (unnecessary initial investment and layup cost) in case of a market downturn. Bullish markets, however, can be taken advantage of immediately

⁴Time charter rates typically include manning and regular maintenance of the chartered vessel. Bunkering cost, tolls and harbor fees are paid by the charterer.

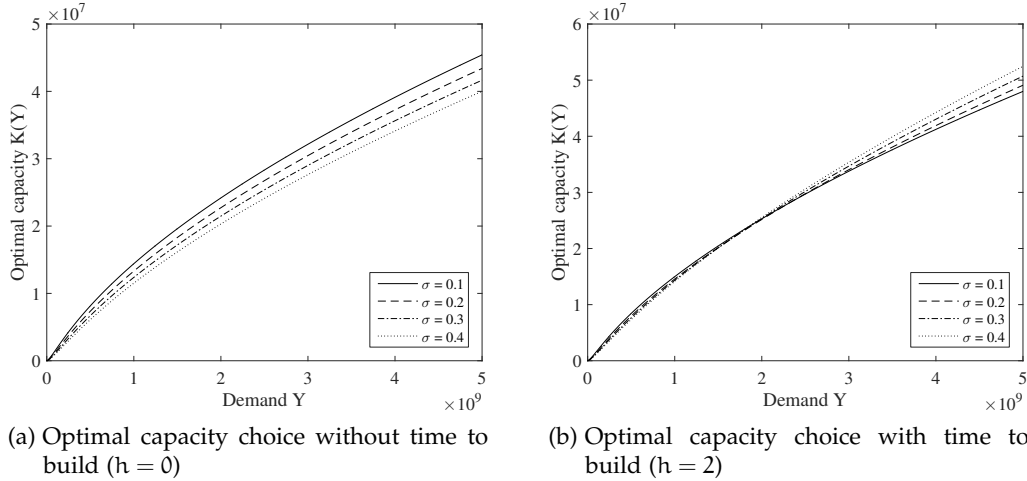


Figure 2.1: Optimal capacity choice as a function of demand Y for varying demand volatility. Parameters are defined as: $\gamma = -1.4$, $\mu = 0.01$, $r = 0.06$, $c_1 = 700$, $c_2 = 0.00008$, $c_3 = 28$, $c_4 = 0.02$, $k = 1,000$.

as additional capacity is available without delay. This leads to more hesitant investment in volatile markets.

The situation changes if time to build of $h = 2$ is introduced (Fig. 2.1b). This feature leads to a mixed effect of high demand volatility. At low demand, the ship operator acts as before, building up less capacity in riskier markets. For high demand however, we see increased investment in volatile markets, which is consistent with effects seen in Aguerrevere (2003), Bar-Ilan and Strange (1996), and Bar-Ilan et al. (2002). While this effect may seem surprising, Aguerrevere (2003) offers two opposing effects of volatility as economic rationale. In case of falling demand and excess capacity, the ship operator has to bear layup and financing cost while not generating any revenue. This effect incentivizes the ship operator to invest less. The opposing effect is the opportunity cost of profits forgone if the ship operator runs into a capacity shortage. Depending on which effect dominates, the ship operator will tend to under- or over-invest. Based on model parameters and the level of demand, the shipping market can range in either of the two regions identified in Fig. 2.1b. As an important implication from this model, time to build induces ship operators to build up more capacity in volatile markets with high demand, which can lead to excess capacities. Note however that the direction of this effect is ambiguous and depends on the level of demand.

A second effect of time to build needs to be taken into account: Fig. 2.2 shows increased investment for longer times to build, irrespective of the level of demand in the market. This effect supports large capacity orders in already overheated markets with long time to build.

From the investment-only model we can derive the following findings: First, longer time to build leads to increased optimal capacity for any level and volatility of demand. Second, higher demand volatility can in certain situations lead to capacity expansion if investors face time to build. Market characteristics of international container shipping may therefore be an incentive for companies to increase transportation capacities to levels where they run the risk of facing

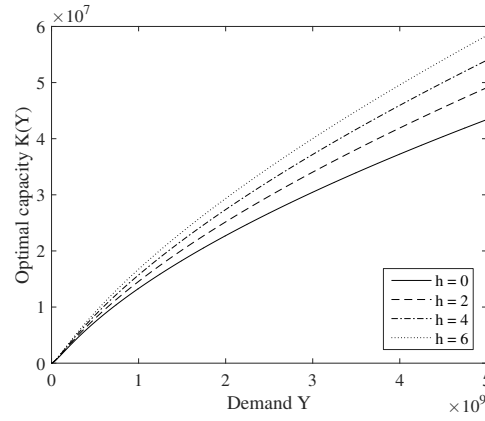


Figure 2.2: Optimal capacity choice as a function of demand Y for varying time to build. Parameters are defined as: $\gamma = -1.4$, $\mu = 0.01$, $\sigma = 0.2$, $r = 0.06$, $c_1 = 700$, $c_2 = 0.00008$, $c_3 = 28$, $c_4 = 0.02$, $k = 1,000$.

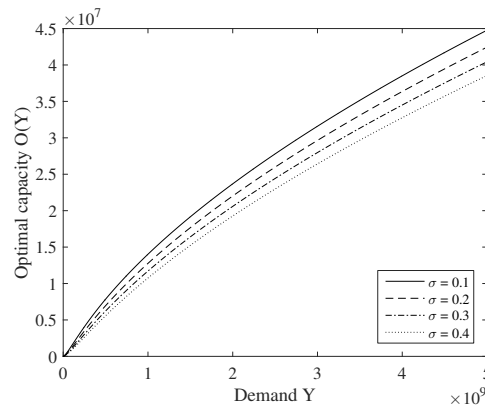


Figure 2.3: Optimal capacity choice as a function of demand Y for varying volatility. Parameters are defined as: $\gamma = -1.4$, $\mu = 0.01$, $r = 0.06$, $c_1 = 700$, $c_2 = 0.00008$, $c_3 = 28$, $c_5 = 120$.

excess capacities. In such situations, opportunity costs of capacity shortages are large enough to outweigh potential costs of excess capacity. A limitation to these findings is that we base our analysis on a monopolistic model while the container shipping market is of oligopolistic nature. Because Aguerrevere (2003) finds the discussed effects and optimal capacities to be even larger in oligopolistic or perfect competition, we are confident that results from our monopolistic model (that we extend over the course of this paper) lets us derive directional implications, even if their extent may be underestimated. Other limitations are addressed in the following models by taking into account lumpy investment and the option of chartering.

Results change significantly in the charter-only model as displayed in Fig. 2.3. Here, ship operators strictly charter less for increased demand volatility. This effect is expected from an economic perspective. Chartering little capacity reduces the risk of carrying costly excess capacity, while for demand increases, the shipping company can charter without delay. The cost of excess capacity effect thus outweighs the potential opportunity cost of a capacity shortage, which the investor cannot run into without time to build.

This said, we do not find the same capacity increasing effects of volatility as we have seen in the investment model. The question to be solved in Sections 2.4 and 2.5 will be whether or not the effects seen from investment will be noticeable also in a market where investment and chartering are available within the same model.

2.4 COMBINED INVEST AND LONG-TERM CHARTER MODEL

In the previous section, we have treated investment and charter separately. We showed that for the option to invest, there are relevant effects that can help explain high investment levels in shipping, which are non-existent in the charter-only model. Next, we combine both options into one model to analyze the resulting capacity choice. While for now we treat long-term investment and chartering, we will introduce more flexibility in Section 2.5 by allowing divestment and short-term charting with contract durations of one time period only. As combining both options in continuous time appears overly complex, we use a discrete-time binomial lattice model. The next two sections extend an approach by Fontes (2008) by adding time to build and the swing option between investment and chartering to the model.

2.4.1 Model Derivation

In this discrete-time model, the shipping company has two simultaneous choices to make in each time period t . After observing stochastic demand Y_t , the firm decides on shipping capacity and optimal transportation output for this period. The capacity choice can take three forms. First, the firm can invest into new owned ships that will be delivered h periods after ordering. Second, shipping capacity can be instantaneously increased by chartering additional vessels that can be used already in the current period. Lastly, the company can choose to leave capacity levels unchanged. A simultaneous expansion of owned and chartered capacity is not allowed. For now, we also assume that built-up capacities (owned and chartered) cannot be reduced. In parallel to the capacity decision, the investor determines the period's optimal transportation output to maximize period profits.

The state variables and state space, as shown in Table 2.2, describe all states of the world the firm can find itself in. We treat time as a discrete variable that is also represented by a subscript t in other variables that depend on it. One period corresponds to a time step of one year. The Geometric Brownian Motion of demand Y_t with drift μ and volatility σ is approximated in a binomial lattice approach as developed by Cox et al. (1979), where demand can increase or decrease each period. The up and down multiplication factors u and d as well as the risk-neutral probability p of an up- and $(1 - p)$ of a down-movement are defined as

$$u = e^{\mu\Delta T + \sigma\sqrt{\Delta T}}, \quad d = e^{\mu\Delta T - \sigma\sqrt{\Delta T}}, \quad \text{and} \quad p = \frac{e^{r\Delta T} - d}{u - d}. \quad (2.9)$$

Table 2.2: Definition of state variables and state space for model with time to build $h = 2$.

State space	Description
$t \in T = \{0, 1, 2, 3, \dots, T-1, T\}$	Time period
$Y_t \in Y = \{Y_0, uY_0, dY_0, u^2Y_0, udY_0, d^2Y_0, \dots\}$	Demand in time period t
$OC_t \in OC = \{24,000z \mid z \in \mathbb{N} \cup 0\}$	Operational capacity from chartering in t
$OI_t \in OI = \{24,000z \mid z \in \mathbb{N} \cup 0\}$	Operational owned capacity in t
$PI_t \in OI = \{24,000z \mid z \in \mathbb{N} \cup 0\}$	Pipeline of ordered ships: operational capacity in next period $t + 1$

Besides time period t and demand level Y_t , the state space comprises operational capacity from chartering OC_t at the beginning of each time period. Similarly, OI_t describes available operational capacity from investment (owned capacities). To anticipate future project values, it is necessary to know the expected capacity ramp-up from orders not yet delivered. Pipeline PI_t denotes operational capacity from investment in period $t + 1$, which includes OI_t and the capacity in pipeline for delivery in $t + 1$. In contrast to the previous sections, this model treats lumpy investment. To keep computing times manageable, we allow investment in 24,000 TEU intervals, corresponding to one fully loaded round-trip of a container ship as we use it for our parameter calibration.

Table 2.3: Definition of decision variables and decision space.

Decision space	Description
$charter_t \in OC = \{24,000z \geq OC_t \mid z \in \mathbb{N} \cup 0\}$	Additional capacity chartered in t
$invest_t \in OI = \{24,000z \geq PI_t \mid z \in \mathbb{N} \cup 0\}$	Additional owned capacity ordered in t
$q_t \in Q = \{24,000z \leq OC_t + charter_t + OI_t \mid z \in \mathbb{N} \cup 0\}$	Transportation output level in t

Table 2.3 defines the decision space available to the investor in each period. The firm can increase chartered capacity immediately by choosing $charter_t$ new units. Alternatively, a number of $invest_t$ new units of owned capacity can be ordered that will be delivered in period $t + h$ due to time to build. While chartered and own capacity cannot be increased in the same period, the investor can choose not to expand capacities at all ($invest_t = charter_t = 0$). q_t describes the transportation output chosen. Any capacity not operated is sent to layup and incurs cost c_3 per period. Both, capacity choice and output quantities can be set to multiples of 24,000 TEU. An extension to this model is to allow the firm to also divest existing capacity, which we introduce in Section 2.5.

The profit function is unchanged from the previous sections, except that owned and chartered capacities are combined:

$$\begin{aligned}\pi_t(Y_t, q_t, OC_t, OI_t, PI_t) &= Y_t q_t^{1+\frac{1}{\gamma}} - c_1 q_t - 0.5c_2 q_t^2 \\ &\quad - \max(OC_t + OI_t - q_t, 0)c_3 \\ &\quad - PI_t k c_4 - OC_t c_5.\end{aligned}\tag{2.10}$$

This profit function allows us to define the reward function of the dynamic program. It describes the project value in each state of the world depending on which actions are taken. We can define the project value as the greater of two elements: the project value of the most profitable charter expansion strategy VC_t and the value of the most profitable expansion strategy through investment VI_t :

$$V_t(Y_t, OC_t, OI_t, PI_t) = \max\{VC_t, VI_t\},$$

where

$$\begin{aligned}VC_t &= \max_{0 \leq \text{charter}_t \leq OC_{\max} - OC_t} \left\{ \max_{0 \leq q_t \leq (OC_t + \text{charter}_t + OI_t)} \left\{ \begin{aligned} &\pi_t(Y_t, q_t, OC_t + \text{charter}_t, OI_t, PI_t) \\ &+ e^{-r \, dT} \mathbb{E}[V_{t+1}(Y_{t+1}, OC_{t+1}, OI_{t+1}, PI_{t+1})] \end{aligned} \right\} \right\}, \\ VI_t &= \max_{0 \leq \text{invest}_t \leq OI_{\max} - PI_t} \left\{ \max_{0 \leq q_t \leq (OC_t + OI_t)} \left\{ \begin{aligned} &\pi_t(Y_t, q_t, OC_t, OI_t, PI_t + \text{invest}_t) \\ &+ e^{-r \, dT} \mathbb{E}[V_{t+1}(Y_{t+1}, OC_{t+1}, OI_{t+1}, PI_{t+1})] \end{aligned} \right\} - k \, \text{invest}_t \right\}.\end{aligned}\tag{2.11}$$

Note that we maximize over all possible charter and output choices for VC_t and investment capacity expansion and output possibilities for VI_t . The value consists of period profits π_t , the discounted expected value $e^{-r \, dT} \mathbb{E}[V_{t+1}]$ of the project in the next period and cash outflow for new-orders in the investment case. We solve the optimal value function recursively, starting with a terminal value in the last period and solving backwards until we reach period $t = 0$ (Bellman 1957). To do so, we define terminal values in period $T + 1$ assuming that existing capacities will be used infinitely⁵:

$$V_{T+1} = \max_{0 \leq q_{T+1} \leq OC_{T+1} + OI_{T+1}} \left\{ \frac{\pi_{T+1}(Y_{T+1}, q_{T+1}, OC_{T+1}, OI_{T+1}, PI_{T+1})(1 + \mu)}{r - \mu} \right\}.\tag{2.12}$$

⁵Total capacity choice remains largely unchanged if we consider a limited lifespan after the end of the simulation horizon (e. g., 15 years). Shortening the lifespan, however, changes the final capacity mix towards chartered capacity as investment cost of owned capacities has less time to amortize.

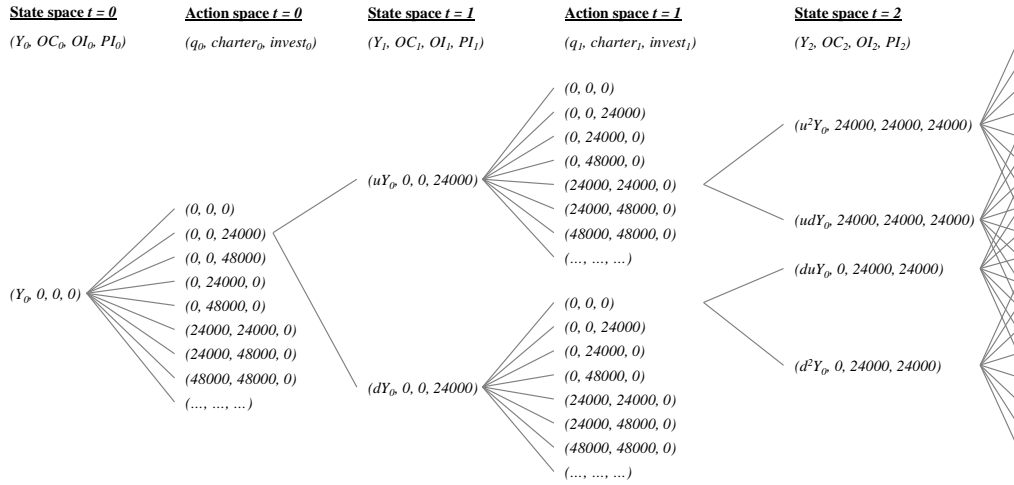


Figure 2.4: Schematic 2-dimensional representation of the lattice approach.

From here on, the model folds back through time. The state space is updated from period to period depending on decisions taken and defined by the following transition functions:

$$Y_{t+1} = \begin{cases} uY_t & \text{for "up" movement} \\ dY_t & \text{for "down" movement,} \end{cases} \quad (2.13)$$

$$OC_{t+1} = OC_t + charter_t, \quad (2.14)$$

$$OI_{t+1} = PI_t, \quad (2.15)$$

$$PI_{t+1} = PI_t + invest_t. \quad (2.16)$$

Fig. 2.4 depicts the model schematically in a binomial tree. In time period $t = 0$, the state space describes the investor's world. Based on perceived market demand Y_0 , the ship operator decides whether to expand capacity through chartering or investing or to leave it unchanged. In parallel, the optimal output quantity for this period is selected. Given a choice, the investor can be in one of two states of the world in time period $t = 1$, depending on whether stochastic demand Y moves up or down. Once demand Y_1 is known, the next combination of capacity and output choice is made. While the tree is set up from starting time period $t = 0$ to the final period $t = T$, it is solved recursively from the last period backwards. At every node the dynamic program chooses the best action assuming that all future choices will be taken optimally.

2.4.2 Numerical Study

We now turn to analyzing model results from simulations in three different model variants: The first variant is our full model described above allowing investment at time to build $h = 2$ years and instantaneous chartering. The second variant allows investment with a time to build of $h = 1$ year and chartering and our third variant is an investment-only model at time to build $h = 2$ years. We gain insights from these model variants in two ways. First, we compare

project values to derive the value added by the long-term charter option. This allows us to better understand when chartering is a valuable on-top option. Secondly, we investigate optimal total capacity choice and the split between investment and chartering in different parameter and market scenarios. In these scenarios, we vary market drift μ , market volatility σ and risk-free interest rate r and leave remaining parameters unchanged compared to the models of the previous section.

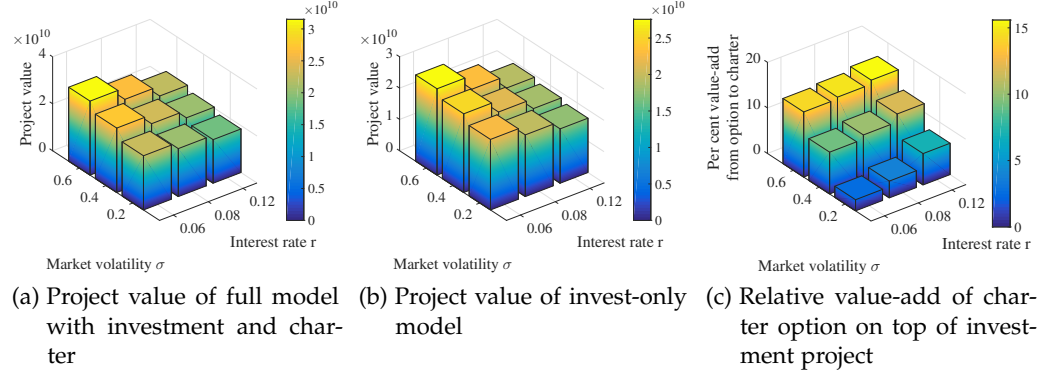


Figure 2.5: Project values of full model and investment-only model and resulting relative value-add provided by option to charter. Parameters are defined as: $\gamma = -1.4$, $\mu = 0.01$, $c_1 = 700$, $c_2 = 0.00008$, $c_3 = 28$, $c_4 = 0.02$, $c_5 = 120$, $k = 1,000$, $h = 2$, $OI_0 = 144,000$.

We first analyze project values of the full charter and investment model with time to build $h = 2$ and the investment-only model. Fig. 2.5a shows the project value at different market volatilities σ and interest rates r for the full model. The value of the project decreases for higher interest rates because the market benchmark of a risk-free alternative investment becomes more attractive. For increased market volatility σ we find larger project values. Given a positive market drift μ , higher volatility makes demand surges more likely, in which the shipping company can realize improved profits. The same effects are observed in Fig. 2.5b, which shows the project values for the investment-only project without chartering. Of special interest is what additional value is created by granting the ship operator a charter option on top of investment. This added value matches the value difference between the full and the investment-only projects. It is difficult, however, to analyze the effect of parameter changes on the value of the charter option in absolute terms as both the values of the full and investment-only projects change at the same time. In Fig. 2.5c we thus introduce a relative value-add from the charter option, which is calculated as:

$$\text{Relative value-add} = \frac{\text{Value of full project} - \text{Value of invest-only project}}{\text{Value of invest-only project}}.$$

It expresses the value added to the investment project by the charter option in per cent of the investment-only project's value.

There are two main findings to be drawn from Fig. 2.5c that showcase the value proposition of chartering compared to investing. First, the relative value created by the charter option increases with the risk-free rate of interest. The

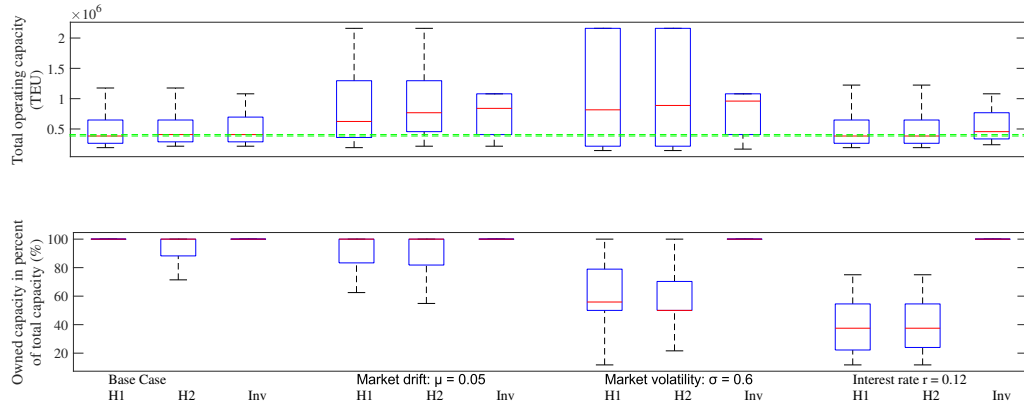


Figure 2.6: Simulation of total capacity and investment vs. charter split for different market scenarios in model with investment and long-term charter. Base case parameters are defined as: $\gamma = -1.4$, $\mu = 0.01$, $\sigma = 0.2$, $r = 0.06$, $c_1 = 700$, $c_2 = 0.00008$, $c_3 = 28$, $c_4 = 0.02$, $c_5 = 120$, $k = 1,000$, $OI_0 = 144,000$. Deviating parameter values are labeled in the respective scenario.

economic intuition lies in the discounting of future cash flows: At high interest rates, it is especially advantageous to postpone costs to later periods and to realize revenue as early as possible. Compared to investment, chartering postpones costs evenly over the time horizon. In high interest rate markets it is thus advisable for ship operators to make increased use of chartering. The second finding from Fig. 2.5c is the increased value of the charter option in highly volatile markets. With high market volatility σ , demand surges become more likely. In such markets, chartering offers the ship operator increased flexibility by spontaneously providing capacity without time to build. It thereby allows to both avoid unnecessary costs for excess capacity (layup cost) and to benefit from sudden upward movements of demand. With these two findings, Fig. 2.5c clearly shows the main sources of value creation from chartering.

We now simulate the model to assess capacity choices in different market situations and how chartering vs. investment are used. We run all model variants for different parameter scenarios with $N = 20,000$ simulations each to generate reliable results. Where not indicated otherwise, we analyze capacity results in the last period $T = 15$ of our simulation.

Fig. 2.6 displays simulation results for our base case (where our focus parameters are $\mu = 0.01$, $\sigma = 0.2$ and $r = 0.06$) and three scenarios where one of the focus parameters is increased. Results are shown in groups of three box plots, representing the full model with time to build $h = 1$, the full model with time to build $h = 2$ and the investment-only model with time to build $h = 2$, labeled as H1, H2 and Inv respectively. The upper pane displays total capacities recorded during 20,000 simulations, while the lower pane shows owned capacity as a percentage of total capacity. The box plots describe the distribution of data with the red line marking the median, the outer blue edges the 25th and 75th percentiles and the whiskers indicating the most extreme data points that have not been considered outliers. In the figure, we see that the ship operator invests into slightly more capacity when market growth μ is increased compared to the base case scenario and slightly less for higher interest rates r . Let us follow up on the effect of volatility and time to build. In the continu-

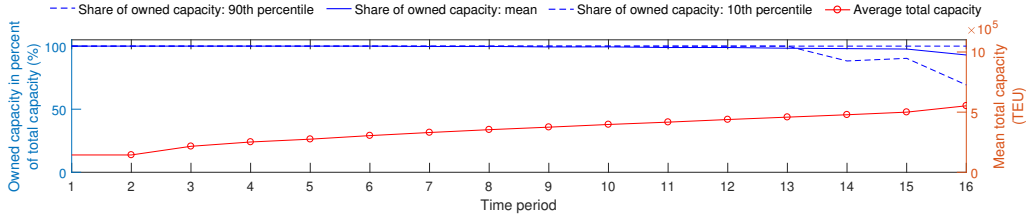
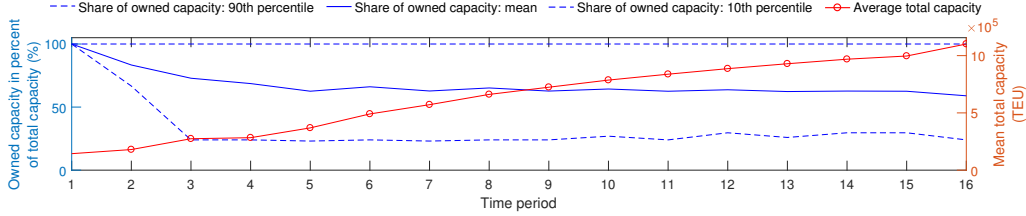
(a) Base case with volatility $\sigma = 0.2$ (b) Increased market volatility scenario with $\sigma = 0.6$

Figure 2.7: Owned capacity share and total capacity build-up over time in base case and high market volatility scenario. Results are based on H_2 model with investment at time to build of 2 periods and long-term charter. Remaining parameters are $\gamma = -1.4$, $\mu = 0.01$, $r = 0.06$, $c_1 = 700$, $c_2 = 0.00008$, $c_3 = 28$, $c_4 = 0.02$, $c_5 = 120$, $k = 1,000$, $OI_0 = 144,000$.

ous investment model of Section 2.3, we have seen that increased time to build leads to higher optimal capacity and that increased market volatility with time to build can lead to a further capacity expansion. We find these results confirmed in the discrete model as shown in Fig. 2.6. The capacity-increasing effect of time to build can be observed by comparing resulting capacities of the H1 and H2 model variants, where we see (slight) increases of capacity for higher time to build throughout all parameter scenarios. Compared to the investment-only model of Section 2.3, this effect is still observable, though dampened by the charter option. The second effect, where resulting capacities are increased by a combination of time to build and increased market volatility is also present in our discrete model. This can be observed by comparing the base case and high volatility market scenarios where we find strongly increased capacities for higher demand volatility. The capacity increasing effect of high volatility is even stronger in the full model with long-term chartering. Chartering allows to increase capacities spontaneously in unforeseen demand spikes, which leads to even higher capacities compared to the investment-only model. This intuition is supported by increased total capacity compared to the investment-only case and the larger share of chartered capacity at high volatility compared to the base case scenario.

Taken together, the results suggest that time to build can increase optimal capacities in volatile markets, although the long-term charter option dampens this effect. At the same time, chartering increases total optimal capacity in volatile markets as it allows for spontaneous capacity additions in bullish markets.

Interesting for practitioners are also observations derived from the model regarding the use of long-term charter. We have already seen from Fig. 2.5c that the option to charter adds most value to the investment project when interest rates are high and/or demand is volatile. Chartering should thus be

considered an alternative especially when high interest rates make it attractive to postpone costs and when high market volatility leads to unforeseen demand surges. Fig. 2.7 details the build-up of capacity over time and displays the mean share of owned out of total installed capacity. In Fig. 2.7a, the base case is shown at low market volatility of $\sigma = 0.2$, where the ship operator relies almost entirely on own capacity as the cheaper alternative. Fig. 2.7b shows the capacity split for higher volatility at $\sigma = 0.6$, where more chartering is used compared to the base case. Taken together, chartering is more expensive so that investment is preferred in smooth and predictable market environments. In volatile markets, chartering becomes an attractive option to skim demand in sudden upward movements of demand. Chartering is thus used to either compensate unforeseen demand peaks or to build up capacity in high interest rate environments. In the latter case, postponing costs can partially offset the general cost disadvantage of chartering.

Overall, our discrete model of investment and long-term charter supports the effects found in the continuous investment model in Section 2.3. Time to build and high market volatility can lead to increased investment with a risk of building up excess capacities even with a charter option available. The long-term charter option's flexibility even increases the capacity increasing effect of volatility as demand surges can be taken advantage of. In this section, we have combined the investment and long-term charter options as seen in the continuous model. As real markets allow divestment of owned capacities and also more flexible short-term chartering with contracts that expire, the question remains whether the effects are still relevant in a more realistic market. To address this question, we extend our model to allow divestment and highly flexible chartering with one year contracts in Section 2.5.

2.5 COMBINED INVEST AND SHORT-TERM CHARTER MODEL WITH DIVESTMENT OPTION

In this section, we further adapt the model to the actual market by implementing three changes: First, we allow divestment of owned capacities. Second, we implement short-term chartering with a contract duration of one year. As short-term charters are more dependent on the current market environment, we also introduce an endogenous charter rate. Third and last, all decisions (invest, divest and charter) can now be taken simultaneously in each time period. With this setup, we introduce a high degree of flexibility to the model and use simulations to analyze the effect of chartering on overall capacity choice and to assess whether findings from previous sections also hold in even more flexible and realistic model setups.

2.5.1 *Model Derivation*

Compared to the model in Section 2.4, we now allow for simultaneous invest, divest and charter decisions. This leads to one common value function in which we do not need to differentiate between charter and investment strategies anymore. While investment does not change, divestment of owned capacity OI_t is

possible at sales price k_s . We assume divestments to be implemented only in the next time period and therefore discount divestment proceeds in the value function. In this new model, we let chartering be a myopic decision in each time period as contracts expire after one year. With this change, chartered capacity OC_t drops out of the state space and $charter_t$ represents the capacity chartered in period t . The new value function is:

$$\begin{aligned}
V_t(Y_t, OI_t, PI_t) = & \\
& \max_{0 \leq \text{invest}_t \leq OI_{\max} - PI_t} \left\{ \max_{0 \leq \text{divest}_t \leq OI_t} \left\{ \max_{0 \leq \text{charter}_t \leq OC_{\max}} \left\{ \right. \right. \right. \\
& \max_{0 \leq q_t \leq (\text{charter}_t + OI_t)} \left. \left. \left. \left\{ \pi_t(Y_t, q_t, \text{charter}_t, OI_t, PI_t + \text{invest}_t) \right\} \right\} \right\} \right. \\
& \left. + e^{-r \, dT} \mathbb{E} [V_{t+1}(Y_{t+1}, OI_{t+1}, PI_{t+1})] - k \text{invest}_t + e^{-r \, dT} k_s \text{divest}_t \right\}. \tag{2.17}
\end{aligned}$$

Note how V_t is not dependent anymore on chartered capacity, as OC_t drops out of the state space. We now optimize over all investment, divestment, charter and operating output options possible depending on the state of the system. The value again is comprised of period profit π_t , the discounted expected project value in the next period $e^{-r \, dT} \mathbb{E}[V_{t+1}]$, cash outflow from investment and discounted cash inflows from divestment realized in the next time period. To reflect the new workings of the model, the transition functions need to be adapted. While we drop the transition function for chartered capacity, we refer to Eq. (2.13) for the transition of demand and define the remaining transitions as:

$$OI_{t+1} = PI_t - \text{divest}_t, \tag{2.18}$$

$$PI_{t+1} = PI_t + \text{invest}_t - \text{divest}_t. \tag{2.19}$$

The state space of this model is smaller and simpler than in the previous section. However, with investment, divestment and chartering available simultaneously at each time step, the number of possible actions that need to be iterated by the program increase significantly.

To more closely represent real charter markets, we also introduce an endogenous charter rate $c_{5,t}$. We assume demand to not only increase freight rates (the market price) but also the charter rate that applies for chartering vessels. Such a feature is realistic as market participants' need to charter additional capacities increases in periods of attractive market prices for transportation services. We thus define endogenous charter cost as

$$c_{5,t} = c_5((Y_t/Y_0 - 1)\omega + 1), \tag{2.20}$$

where $\omega \geq 0$ denotes the portion of demand growth passed on to charter cost growth. With $\omega = 0$, for example, charter costs are fixed and independent from demand while $\omega = 1$ would result in an equal percentage growth or contraction of demand and charter rate $c_{5,t}$. With chartering as a myopic decision and the

charter rate being defined endogenously, the slightly adapted profit function now reads:

$$\begin{aligned} \pi_t(Y_t, q_t, \text{charter}_t, \text{OI}_t, \text{PI}_t) = & Y_t q_t^{1+\frac{1}{\gamma}} - c_1 q_t - 0.5c_2 q_t^2 \\ & - \max(\text{charter}_t + \text{OI}_t - q_t, 0)c_3 \\ & - \text{PI}_t k c_4 - \text{charter}_t c_{5,t}. \end{aligned} \quad (2.21)$$

2.5.2 Numerical Study

We simulate the investment and short-term charter model with the same cost parameters that we have applied in the previous sections. The only cost parameter added is the selling price applicable for divested capacities k_s . We assume the operator to be able to sell owned operational capacities at a low price of $k_s = 100$.

Model with constant charter rate: We first analyze simulation results for $\omega = 0$, which reflects static charter cost c_5 as in the previous sections. Fig. 2.8 shows simulation results for the base case and for increases of our focus cost parameters. The model changes compared to Section 2.4 lead to increased flexibility both for owned and chartered capacities. While it is now possible to divest owned ships, chartered capacity is chosen spontaneously every period after market demand is observed. These changes not only affect total capacities, but also the choice between investment and chartering. Compared to the investment and long-term charter model (Fig. 2.6), we see that optimal decisions in the more flexible model (Fig. 2.8) result in a higher investment share of total capacity. This reflects that, even though chartering has become more flexible as well, the investment option became disproportionately more attractive as divestment is now possible.

With the shift of capacity sourcing in mind, we now analyze resulting total capacities and the effect of time to build and volatility. As seen in previous

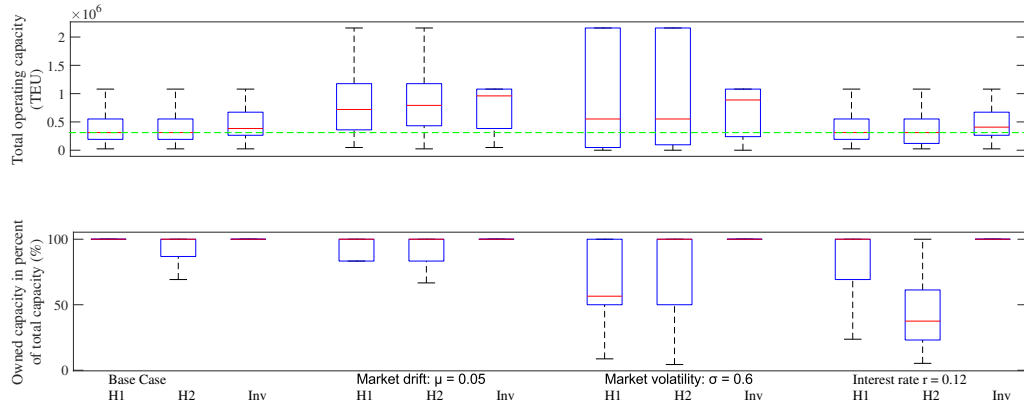


Figure 2.8: Simulation of total capacity and investment vs. charter split for different market scenarios in model with divestment, short-term charter and static charter rate. Base case parameters are defined as: $\gamma = -1.4$, $\mu = 0.01$, $\sigma = 0.2$, $r = 0.06$, $c_1 = 700$, $c_2 = 0.00008$, $c_3 = 28$, $c_4 = 0.02$, $c_5 = 120$, $\omega = 0$, $k = 1,000$, $k_s = 100$. Deviating parameter values are labeled in the respective scenario.

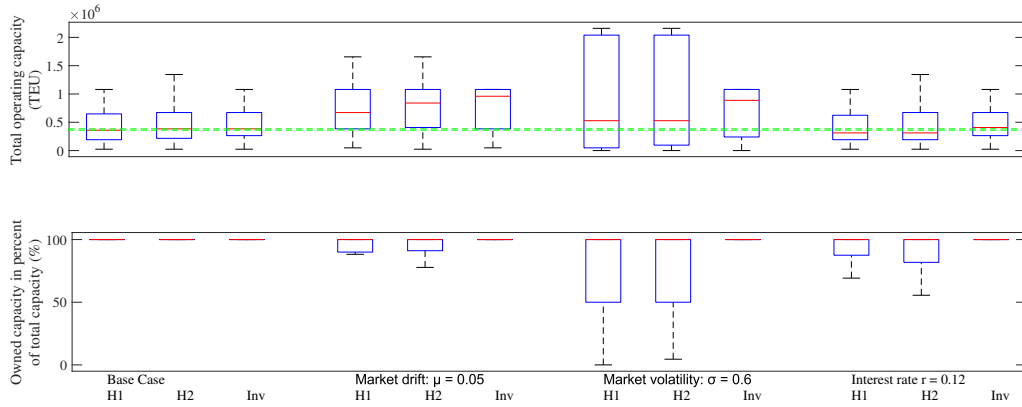


Figure 2.9: Simulation of total capacity and investment vs. charter split for different market scenarios in model with divestment, short-term charter and endogenous charter rate. Base case parameters are defined as: $\gamma = -1.4$, $\mu = 0.01$, $\sigma = 0.2$, $r = 0.06$, $c_1 = 700$, $c_2 = 0.00008$, $c_3 = 28$, $c_4 = 0.02$, $c_5 = 120$, $\omega = 0.2$, $k = 1,000$, $k_s = 100$. Deviating parameter values are labeled in the respective scenario.

sections, higher time to build leads to increased total capacities. This can be confirmed by comparing the full model variant with investment, chartering and time to build of $h = 2$ to the full model with time to build of $h = 1$. Similarly, we also see a strong increase in capacity buildup for the high volatility scenario. We can thus confirm that time to build alone, and high volatility in combination with time to build lead to an increase in capacities even in our flexible model with divestment and short-term charter. Interestingly, the median of resulting capacities in the high volatility scenario is slightly lower in our flexible model as compared to Fig. 2.6 in Section 2.4. This shows that the effects of time to build and high volatility are dampened by increased flexibility and the possibility to also reduce capacity through divestment and expiring charter contracts. Overall, this model shows that highly volatile markets in combination with time to build can lead investors to rationally expand capacities, which frequently results in excess capacities.

Model with endogenous charter rate: To resemble real shipping markets more closely, Fig. 2.9 shows simulation results for the investment and short-term charter model with an endogenous charter rate at $\omega = 0.2$ (i. e., 20% of demand growth or contraction is passed on to the charter rate). As expected, we find that short-term chartering - though highly flexible - only accounts for relatively small parts of total capacity and is used mainly in volatile markets. Endogenous charter rates make chartering less attractive as it becomes expensive in the very market environments in which chartering is needed most: during demand peaks for which the shipping company has not built up enough owned capacity. We still find that time to build increases total capacities. The effect of increased volatility is not as high anymore as in our previous models. This can be explained by the fact that the short-term charter option is not as attractive anymore during demand peaks.

Overall, we see that short-term chartering offers increased flexibility to the ship operator, which has two opposing effects. On the one hand, the absence of time to build for chartered capacities reduces the incentive for operators to

build up capacities in advance of possible demand surges in volatile markets. At the same time, it offers the option to increase capacities on short notice if there is not enough owned capacity to serve demand. This second effect leads to increases of total capacities, especially in high volatility scenarios. Which of these effects dominates strongly depends on the question how charter rates develop in times of bullish markets, as this feature determines the attractiveness of the charter option. While the capacity increasing effects of time to build and volatility, as also found in Aguerrevere (2003), remain intact overall, their intensity is strongly influenced by available charter options. It is therefore important to account for chartering in optimal capacity decisions. While investment behavior and high capacities in practice may also (and jointly) be driven by other considerations such as behavioral motivations (Greenwood and Hanson 2015) or by financial constraints (Drobotz et al. 2016), the effects found in this paper contribute to high capacity levels in international shipping.

2.6 CONCLUSION AND IMPLICATIONS FOR FUTURE RESEARCH

In this paper, we include charter options in capacity expansion models. By extending a continuous-time incremental investment model by Aguerrevere (2003) to reflect charter decisions, we show that chartering does not exhibit the same capacity-increasing incentives as investment. While time to build and volatility increase optimal capacity choice in investment-only projects, the opposite is the case if only chartering is allowed in the model. To analyze the effects of chartering on investment and total capacity decisions, we combine both investment and long-term charter options in a discrete-time model based on a binomial lattice approach. In an extension, we introduce divestment and short-term instead of long-term chartering at an endogenous charter rate to the model for more flexible decision-making. We thus contribute to the real options literature by incorporating the key characteristics of capacity expansion decisions in many industries: time to build, operating flexibility at a certain cost, divestment and most importantly the fundamental decision between owning and (long-term vs. short-term) chartering of capacities. We further add to existing maritime logistics literature by applying the investment and charter real option models to capacity expansion decisions in the container shipping industry, thereby deepening the understanding of optimal capacity choice in this cyclical and volatile market. Additionally, the presented model set-up also applies to other industries with similar characteristics such as electricity markets or the semiconductor industry.

The main findings are the following: First, we find that an additional charter option offers significant added value to a ship investment project especially in situations of high interest rates and/or high demand volatility. Chartering allows to postpone costs to later time periods and to spontaneously react to unforeseen demand peaks, enabling ship operators to offset capacity shortages from investment. Second, chartering appears to be the more expensive way to expand capacities, making it an optimal instrument for short-term capacity corrections while not being used for build-up of base capacity. Third, we present evidence that the existence of time to build leads to an increase of optimal

capacity choice even with the opposing effects of chartering as an alternative capacity source. This is a result of opportunity costs of unforeseen capacity shortages outweighing expected costs of potential excess capacities. Fourth, we show that in certain market situations and with time to build, an increase in market volatility can lead to higher optimal capacities for the investor. Fifth and lastly, we see that chartering - while generally dampening incentives to build up large capacities - also contributes to high capacity buildup in situations of peak demand if insufficient owned capacity is available. Overall, time to build of owned ships together with volatility can increase optimal capacities despite the charter option's opposite effect. This opposing effect can even be dominated by the charter option's flexibility, allowing ship operators to quickly increase capacities in bullish markets.

Future research could test our results empirically against observed capacity outcomes in real markets. Specifically, it would be interesting to test what portions of observed investment can be attributed to effects as seen in this paper and to other explanations such as behavioral effects. Further relevant extensions of our model are to analyze oligopolistic competition or to consider other sources of uncertainty such as stochasticity of operating costs, asset price uncertainty or so far neglected regulatory uncertainty.

Uncertainty about the timing and intensity of future environmental regulation is a key challenge for the container shipping industry. It further complicates capacity and investment decisions in this volatile and capital intensive industry. The focus of the next chapter is to account for uncertain future eco-regulation that can significantly increase the operating cost base for the operator. We will use this modeling to assess the impact of regulatory uncertainty on optimal fleet size, investment vs. charter mix and resulting industry emissions.

CAPACITY EXPANSION UNDER REGULATORY UNCERTAINTY: A REAL OPTIONS–BASED STUDY IN INTERNATIONAL CONTAINER SHIPPING

The following chapter is based on Haehl and Spinler (2017a). This manuscript is currently under revision after a “revise and resubmit” decision from Transportation Research Part E: Logistics and Transportation Review.

3.1 INTRODUCTION

In the past, international maritime shipping has been largely excluded from environmental regulation efforts that forced other industries to reduce their ecological footprints. Although such shipping is the most ecologically friendly means of transport, the industry’s sheer size makes it a major contributor to worldwide emissions and pollution with a total contribution of 3% to global carbon dioxide (CO₂), 13% of nitrogen oxide (NO_x) and 12% to sulfur oxide (SO_x) emissions (International Maritime Organization 2014). This fact has attracted the interest of such regulators as the International Maritime Organization (IMO), the European Union (EU), and the United States, thus the industry will increasingly be subject to regulation. With the target of reducing greenhouse gas emissions by 20% below 1990 levels by 2020 (Helfre and Boot 2013), one such policy is the stepwise reduction of SO_x emission limits from 4.5% to 0.5% globally and even 0.1% in specially designated areas. Even before these new regulatory efforts, ship investors and operators faced an investment decision complicated by its high capital intensity and by several sources of uncertainty, such as volatility in charter and freight rates. Regulator actions introduce a new risk, and firms must account for both the content and timing of prospective regulation. The main reason for timing uncertainty is the process by which the IMO, as a representative of seafaring nations within the United Nations, passes new legislation: no new convention is in effect until enough member states have ratified it. Because that process can be a lengthy one, there is uncertainty about the exact content and timing of future regulation.

Given their effect on operational costs, regulations (and their associated uncertainty) must be considered when evaluating any opportunity owing to their influence on investment success (Forum For the Future May 2011). Traditional discounted cash flow (DCF) valuation methods are not well suited to capture uncertainties and stochasticity (Dixit and Pindyck 1994); in contrast, real options models can be successfully used to analyze the effect of regulatory uncertainty.

This paper presents a real options model for precisely that purpose. In a numerical study, we investigate the effects of uncertain regulation by applying our model to the container shipping industry. We also assess whether there is a significant difference between expected regulatory action that allows for the so-called grandfathering of current capacity and regulation that affects all ships

(i. e., regardless of when purchased). For that purpose, we formulate a real options investment model in a dynamic programming (DP) framework. Thus we extend the capacity investment model of Fontes (2008) by introducing time to build, adding an option to charter, and incorporating regulatory uncertainty. Finally, we use approximate dynamic programming (ADP) to solve this computationally intensive model and to overcome the “curses of dimensionality” (Powell 2011) in real-world-sized instances.

Our paper contributes to research in four ways. First, we extend the methodological literature by proposing an approach to consider regulatory uncertainty via an investment model applicable to many industries. Second, we employ a novel ADP variation that approximates the additional value created by investment—that is, above the lower boundary established by a strictly myopic strategy. Third, by fitting our model to the shipping industry, we contribute to research on shipping through the insights we derive on optimal decisions—from the investor’s perspective—under regulatory uncertainty. Fourth, though we do not focus on optimal policy making from the viewpoint of a regulator, we do help regulators better understand how legislative processes that induce uncertainty affect the investment decisions of market participants and resulting industry emissions.

The rest of the paper proceeds as follows. Section 3.2 reviews the existing literature on real options in general and in the shipping industry; it also introduces the existing literature on regulatory uncertainty. In Section 3.3, we use DP to develop a formal real options model for regulation with or without grandfathering. Section 3.4 introduces our ADP approach to solving the computationally intractable DP model. In Section 3.5, this latter method is used to present our findings from a numerical study tailored to the container shipping industry. Section 3.6 concludes.

3.2 LITERATURE REVIEW

Uncertainty can be defined as “perceived inability to predict” an organization’s future external environment (Milliken 1987). We adopt that definition and focus on state uncertainty, where the organizational environment’s future states are uncertain owing to, for example, unforeseeable regulatory action. Uncertainty due to emerging eco-regulation is acknowledged to be a growing concern for businesses in many industries (Marcus et al. 2011). While Lister et al. (2015) find that maritime shipping is lagging behind in terms of reducing its environmental footprint, both Lister et al. (2015) and Poulsen et al. (2016) detect significant regulatory uncertainty regarding content and timing of upcoming regulation as the IMO is accelerating its regulatory efforts. For example, IMO regulations require member ratification—a lengthy process that can last “a decade or longer” and so is clearly problematic for shippers’ investment decisions (Lister et al. 2015). Forum For the Future (May 2011) expects regulatory uncertainty, and its adverse effect on investment decisions, to be one of the industry’s key future challenges. The IMO has discussed (and, in many cases, implemented) ecological measures that target energy efficiency in ship design and operational procedures, ship recycling, ballast water management, and ship exhaust emissions

of carbon dioxide, sulfur, and particulate matter. While regulation in other sectors such as power generation mostly allows the grandfathering of previously existing capacity, this is not always the case in shipping. While, for example, requirements for energy efficient ship design only target newly built vessels, lower sulfur emission levels or the requirement to develop operational measures for increased fuel efficiency are mandatory for both new and existing ships. (International Maritime Organization 2016a)

Research on the effects of regulatory uncertainty has mainly focused on whether or not it leads to a deferral of investment. A majority of researchers has argued that investment is dampened: Reinelt and Keith (2007), for example, model replacement decisions for coal-fired power plants. They account for the introduction of regulation as a stochastic increase of carbon emission costs where both timing and the new cost level are uncertain. They find that such uncertainty increases social costs of abatement and dampens investment incentives if abatement options are expensive. Similarly Fuss et al. (2009) analyze capacity investment in the energy sector under regulatory uncertainty represented by stochastic carbon emission prices. They also find that increased volatility in emission prices defers the adoption of less emission intensive but more expensive technologies. Providing regulatory certainty is also demanded by Blyth et al. (2007), who find in their real option model for the energy sector that this would incentivize adoption of low carbon technologies. Ritzenhofen and Spinler (2016) find deferred or even withdrawn capacity investment in a real options framework if feed-in tariff support schemes are withdrawn, creating regulatory uncertainty. Several empirical studies also support the view that investment is deferred by such uncertainty. Fabrizio (2013) finds reduced investment incentives in the US renewable energy sector in states with greater uncertainty. Similarly, Gulen and Ion (2015) show the same in an empirical study across multiple US industries.

Opposing views are held by Hoffmann et al. (2009), who use a resource-based view of the firm to argue that regulatory uncertainty can promote investment, if it can be used to build up a competitive advantage or alleviate societal pressure. From a real options perspective, Hassett and Metcalf (1999) find that if uncertain tax policy is modeled as a discrete jump process (which is more realistic than a continuous time random walk), investment is carried out earlier with more capital invested. Boomsma et al. (2012) focus on the energy sector and find both effects: uncertainty regarding the potential change of support schemes leads to investment deferral, while uncertainty from renewable certificate trading leads to the opposite effect. Baumann and Friehe (2012) find in an options model that uncertainty from potential market liberalization can increase incentives for market entry but reduces investment by incumbent players.

Adopting a similar approach to model regulatory uncertainty as Reinelt and Keith (2007), we extend research on investment under regulatory uncertainty to the maritime shipping industry. We will also show that, whether such uncertainty has positive or negative effects on investment crucially depends on the policy's design: in our case whether or not regulation allows grandfathering of old capacities is pivotal.

Real options methods are well suited to value investment under various uncertainties. While Dixit and Pindyck (1994) give an invaluable overview of methods available, there are several contributions that feature model characteristics also relevant to our model: Bar-Ilan and Strange (1996) are credited with introducing investment *lags* (or time to build) that we also consider; both Mossin (1968) and Brennan and Schwartz (1985) examine operational flexibility by allowing investors to suspend operations if market prices fall to untenable levels. A significant extension to path-dependent Asian options is detailed by Driouchi et al. (2010). Martzoukos and Trigeorgis (2002) relax the assumption of normally distributed uncertainties and allow for jump-diffusion processes with multiple sources of rare events. This is particularly relevant for modeling uncertainty from potential regulation.

In the field of shipping, real options have been used to analyze switching between dry and wet bulk shipping (Sødal et al. 2008) and to assess the efficiency of these markets (Sødal et al. 2009). Bendall and Stent (2005) show that real options capture the value of management flexibility and lead to better decisions under uncertainty (as compared to those based on DCF). Bendall and Stent (2007) review fleet capacity extension with various usage options for new ships. Acciaro (2014) combines a focus on regulation and shipping, by using real options to compare technologies for regulatory compliance. They find that deferring investment into LNG powered vessels to gain better insight into future fuel markets may be optimal. Patricksson et al. (2015) develop a fleet renewal model that accounts for emission control areas (ECAs) and multiple technologies available for regulatory compliance.

This paper's real options-based methodology uses both dynamic programming and approximate dynamic programming in order to derive the optimal solution. The paper thereby expands on Fontes (2008), who uses a DP approach to compare systems with fixed versus flexible production capacity. We extend that model by incorporating time to build and a charter option and also by adding regulatory uncertainty as a second stochastic process.

3.3 MODEL FORMULATION AS A DYNAMIC PROGRAM

In this section, we formulate the real options model using methods of exact DP as introduced by Bellman (1957). Because the resulting DP model is complex and computationally intractable for large instances, we propose an ADP in Section 3.4 that allows us to solve the model approximately. Our model incorporates the following characteristics: the option to invest with time to build, the option to divest and to charter, operating flexibility (layup option), and uncertainty regarding market demand and the introduction of regulation affecting investment and operating costs.

We model a monopolistic market with an investor or shipper who operates available transportation capacity. While the container shipping market is of oligopolistic nature, we make use of the monopoly assumption to be able to combine the multiple market features presented in this model: investment, divestment, charter, a layup option and regulatory uncertainty. This assumption allows us to include and analyze the market characteristics most in focus for the

paper presented. Findings in Aguerrevere (2003) suggest that capacity effects in oligopolistic and monopolistic markets may differ in size but not direction. We are thus confident that this assumption does not restrict the validity of directional findings implied from our model. The transport market is defined by the inverse demand function

$$P_t = \tilde{Y}_t q_t^{1/\gamma}. \quad (3.1)$$

Here P_t is the market price to transport one twenty-foot equivalent unit (TEU) in time period t ; \tilde{Y}_t is the exogenous market demand; q_t is the output or transportation quantity; and $\gamma < 0$ is the market's price elasticity. The exogenous demand shock \tilde{Y}_t follows a geometric Brownian motion with market drift μ and volatility σ . We approximate demand development in a binomial lattice (Cox et al. 1979) with a relative up-movement (u) or down-movement (d),

$$u = e^{\mu dT + \sigma\sqrt{dT}} \quad \text{or} \quad d = e^{\mu dT - \sigma\sqrt{dT}}, \quad (3.2)$$

in each time period with probability

$$p = \frac{e^{r dT} - d}{u - d} \quad (3.3)$$

for an up-movement and probability $1 - p$ for a down-movement. We use dT to signify the time-step-size (in years). See Table B.1 in Appendix B.1 for a descriptive list of variables used.

Before introducing the model's detailed workings, we explain the overall sequence of decisions. This is displayed in Figure 3.1 in a two-dimensional representation of the resulting DP lattice. In each time period the shipper has investment, divestment, charter and layup options available for use. In each period, the shipper observes her available capacities and the current market characteristics including overall demand and whether the market is unregulated or regulated. Depending on this information, she then chooses how much new capacity to order (to be delivered with a time lag due to time to build), to sell and how many units to charter from the market. She additionally decides what parts of the available capacity to operate in the market, thereby influencing the market price. Subsequently, the random events of the model are drawn for the next time period. These consist of the new market demand and a regulatory signal, which - after having arrived twice - leaves the market regulated with higher operating costs. The level of operating cost in the regulated market is previously uncertain and drawn from a separate stochastic process. It is only revealed once the market becomes regulated. Then, the process of decision-making is initiated again.

Capacity decisions are made in steps of 24,000 TEU, which corresponds to a single round-trip of a 12,000-TEU ship that we also use to derive cost parameters. Ordered ships are delivered following a two-period time to build, whereafter they increase operational capacity from investment OI_t . Prior to delivery, ordered ships are considered to be in the pipeline PI_t , which comprises total capacity from investment (i. e., irrespective of whether delivery has already occurred). The pipeline includes OI_t and also undelivered orders from period

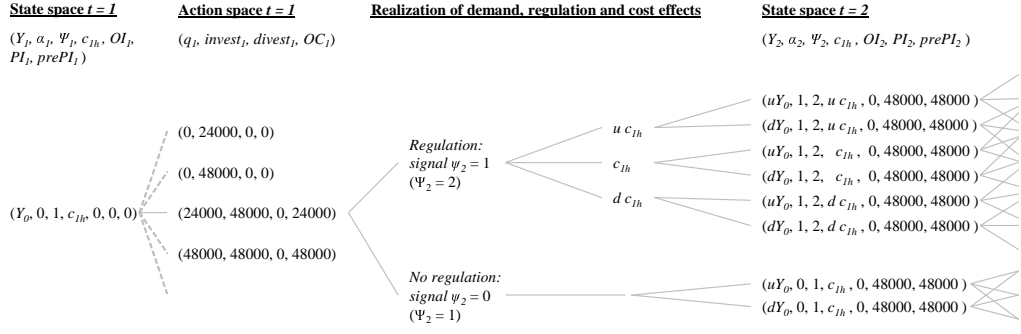


Figure 3.1: Two-dimensional representation of binomial tree structure in the dynamic programming approach. Note that, to be able to display the effect of regulation, we assume a regulatory signal ψ_1 to have arrived in the transition from period $t = 0$ to $t = 1$.

$t - 1$. Divestments reduce owned capacity but with a time lag of one period (the time required to close a deal). Chartered capacity OC_t is available immediately and expires at the end of the period. Thus a shipper has considerable flexibility when determining each period's chartered capacity.

The firm's cost structure in an unregulated market, as formalized in Eq. (3.4), consists of operating, layup, financing, and chartering costs. Costs that are at low levels in an unregulated market are marked by a subscript l . Operating costs c_{1l} and c_2 apply to the transportation quantity offered, q_t , and cover such expenses as fuel, crewing, and maintenance. When demand is low, unneeded capacity (i. e., operational capacity *minus* output q_t) can be laid up at cost c_3 . Owned capacity can be ordered at cost k_l per TEU; in doing so, however, the shipper incurs financing cost c_4 on the capital invested $k_l PI_t$. Because we assume that vessels must be paid for when ordered, the financing cost applies to all capacity PI_t . Finally, chartered capacity incurs a per-period charter cost of c_{5l} :

$$C_t = c_{1l}q_t + 0.5c_2q_t^2 + \max\{OI_t + OC_t - q_t, 0\}c_3 + PI_tk_lc_4 + OC_tc_{5l}. \quad (3.4)$$

The market simulated by our model is unregulated in time period $t = 0$. In every period, there is some risk that a regulation process is started or (later) completed with a new environmental regulation coming into force that increases future operating costs. We model a regulatory signal $\psi_t \in \{0, 1\}$ that arrives with probability ξ in each period and is observable by the shipper ($\Pr(\psi_t = 1) = \xi$). Once the signal has arrived twice, the market becomes regulated. The first signal can thus be interpreted as the start of political efforts towards regulation and the second signal as its enactment. We count the signals received up to and including time period t in the variable denoted Ψ_t . Our dummy variable α_t indicates whether the market is unregulated ($\alpha_t = 0$ if $\Psi_t < 2$) or regulated ($\alpha_t = 1$ if $\Psi_t \geq 2$). We assume regulation to be irreversible and so, once regulated, a market will remain regulated.

In what follows, we finalize the model by way of adding one of two different properties: with and without grandfathering. In the first case, existing capacity is not affected by regulation; this case is detailed in Section 3.3.1. A model with-

out grandfathering—under which all capacity, whenever ordered or activated, must comply with the new standards—is developed in Section 3.3.2.

3.3.1 Regulatory Uncertainty with Grandfathering

In this section we assume that regulation allows the existing fleet to be grandfathered, which means that new standards apply only to capacity ordered or chartered since the regulation's effective date¹. Because eco-regulation usually requires market participants to install more advanced technology and/or use less polluting fuels, we assume that such regulation entails an increase in investment, charter, and operating costs for new capacity (as marked by the subscript h , for higher costs). Under grandfathering, operating costs are defined as

$$c_1 = \begin{cases} c_{1l} & \text{if } \alpha_t = 0, \\ c_{1l} & \text{if } \alpha_t = 1 \text{ (for capacity ordered pre-regulation),} \\ \tilde{c}_{1h} & \text{if } \alpha_t = 1 \text{ (for capacity ordered post-regulation).} \end{cases} \quad (3.5)$$

Operating costs are at relatively low levels c_{1l} in unregulated markets. Even when new laws are passed, old capacity is exempt and can still be operated at low cost. Now, however, new capacity incurs higher costs \tilde{c}_{1h} that are unknown before regulation is introduced. This reflects that the sizing of new regulation and resulting compliance cost are uncertain. We let \tilde{c}_{1h} be normally distributed with $\tilde{c}_{1h} \sim N(\mu_{c_{1h}}, \sigma_{c_{1h}})$ around an expected new cost level. Once realized, \tilde{c}_{1h} remains constant until the simulation's last period ($t = T$). To fit our discrete dynamic programming model approach, we approximate this distribution as a trinomial lattice (Haug 2007), where

$$\tilde{c}_{1h} = \begin{cases} \mu_{c_{1h}} e^{\sigma_{c_{1h}} \sqrt{2dT}} & \text{with probability } p_u, \\ \mu_{c_{1h}} & \text{with probability } p_m = 1 - (p_u + p_d), \\ \mu_{c_{1h}} e^{-\sigma_{c_{1h}} \sqrt{2dT}} & \text{with probability } p_d. \end{cases} \quad (3.6)$$

We define the probabilities p_u of an up-movement and p_d of a down-movement as

$$p_u = \left(\frac{e^{(r dT)/2} - e^{-\sigma_{c_{1h}} \sqrt{dT/2}}}{e^{\sigma_{c_{1h}} \sqrt{dT/2}} - e^{-\sigma_{c_{1h}} \sqrt{dT/2}}} \right)^2 \quad (3.7)$$

and

$$p_d = \left(\frac{e^{\sigma_{c_{1h}} \sqrt{dT/2}} - e^{(r dT)/2}}{e^{\sigma_{c_{1h}} \sqrt{dT/2}} - e^{-\sigma_{c_{1h}} \sqrt{dT/2}}} \right)^2. \quad (3.8)$$

¹In both models, it is assumed to be public information whether or not potential regulation will allow grandfathering of existing capacities.

Regulation also affects investment costs k and chartering costs c_5 , since newly acquired capacity is not covered by grandfathering and so must comport with any new regulation:

$$k = \begin{cases} k_l & \text{if } \alpha_t = 0, \\ k_h & \text{if } \alpha_t = 1; \end{cases} \quad c_5 = \begin{cases} c_{5l} & \text{if } \alpha_t = 0, \\ c_{5h} & \text{if } \alpha_t = 1. \end{cases} \quad (3.9)$$

We now distinguish unregulated from regulated markets in the cost function in Eq. (3.10). In a regulated market with grandfathering, own operational capacity ordered pre-regulation (preOI_t) incurs lower operating costs and is used first in operations. The first line of Eq. (3.10)'s Right-hand side (RHS) represents operating costs in a regulated market, where the shipper operates old capacity when it is sufficient ($I_{[q_t \leq \text{preOI}_t]} = 1$) and fills the gap with expensive new capacity at cost \tilde{c}_{1h} if the output quantity exceeds pre-regulation capacity preOI_t ($I_{[q_t \leq \text{preOI}_t]} = 0$). The second line shows operating cost in the unregulated market. Layup costs c_3 (third line) apply to all unused capacity. In the fourth line, the financing cost applies to all invested capital. However, ships purchased pre-regulation incur a lower capital outlay because the cost per TEU is low (k_l) whereas post-regulation capacity is more expensive. We therefore define prePI_t as owned capacity ordered pre-regulation, for which financing costs apply to low levels of invested capital ($k_l \text{prePI}_t$). Capacity purchased post-regulation ($\text{PI}_t - \text{prePI}_t$) incurs financing costs on a higher level of capital invested (a consequence of the higher purchasing cost k_h). The two terms in the last line stand for chartering costs in the regulated market and those in the unregulated market. Thus we write

$$\begin{aligned} C_t(\alpha_t, \tilde{c}_{1h}, q_t, \text{OC}_t, \text{OI}_t, \text{PI}_t, \text{prePI}_t) &= \alpha_t (I_{[q_t \leq \text{preOI}_t]} c_{1l} q_t + (1 - I_{[q_t \leq \text{preOI}_t]})(c_{1l} \text{preOI}_t + \tilde{c}_{1h}(q_t - \text{preOI}_t))) \\ &+ (1 - \alpha_t) c_{1l} q_t + 0.5 c_2 q_t^2 \\ &+ \max\{\text{OI}_t + \text{OC}_t - q_t, 0\} c_3 \\ &+ \text{prePI}_t k_l c_4 + (\text{PI}_t - \text{prePI}_t) k_h c_4 \\ &+ \alpha_t (\text{OC}_t c_{5h}) + (1 - \alpha_t) (\text{OC}_t c_{5l}), \end{aligned} \quad (3.10)$$

where

$$I_{[q_t \leq \text{preOI}_t]} = \begin{cases} 1 & \text{if } q_t \leq \text{preOI}_t, \\ 0 & \text{otherwise;} \end{cases} \quad \text{and} \quad \text{preOI}_t = \min\{\text{OI}_t, \text{prePI}_t\}. \quad (3.11)$$

Note that operational owned capacity ordered pre-regulation, preOI_t , is the *lesser* of the pre-regulation pipeline (prePI_t) and the available operational capacity from investment (OI_t). In an unregulated market, only OI_t is both operational and ordered pre-regulation and thus always lower than prePI_t . Once the market is regulated, preOI_t is defined by the *lower* of operational (already delivered) and ordered pre-regulation capacity.

Table 3.1: Definition of state variables and state space.

State space	Description
$t \in T = \{0, 1, 2, 3, \dots, T-1, T\}$	Time period
$\tilde{Y}_t \in Y = \{Y_0, uY_0, dY_0, u^2Y_0, udY_0, d^2Y_0, \dots\}$	Demand in time period t
$\alpha_t \in \{0, 1\}$	Indicator for whether or not regulation has been introduced
$\Psi_t \in \mathbb{N}_0$	Sum of regulatory signals received up to and including time period t
$\tilde{c}_{1h} \in \{\mu_{c_{1h}} e^{-\sigma_{c_{1h}} \sqrt{2d\bar{T}}}, \mu_{c_{1h}}, \mu_{c_{1h}} e^{\sigma_{c_{1h}} \sqrt{2d\bar{T}}}\}$	Stochastic component of operational cost in regulated market
$OI_t \in OI = \{24,000z \mid z \in \mathbb{N} \cup 0\}$	Operational capacity from investment in time period t in steps of 24,000 TEU
$PI_t \in OI = \{24,000z \mid z \in \mathbb{N} \cup 0\}$	Pipeline of ordered ships: operational capacity in next period $t+1$
$prePI_t \in OI = \{24,000z \mid z \in \mathbb{N} \cup 0\}$	Part of pipeline ordered pre-regulation

The profit function can be established by subtracting all costs from the revenue realized:

$$\begin{aligned} \pi_t(\tilde{Y}_t, \alpha_t, \tilde{c}_{1h}, q_t, OC_t, OI_t, PI_t, prePI_t) \\ = \tilde{Y}_t q_t^{1+1/\gamma} - C_t(\alpha_t, \tilde{c}_{1h}, q_t, OC_t, OI_t, PI_t, prePI_t). \end{aligned} \quad (3.12)$$

Having defined all the variables, we can summarize in Table 3.1 the state variables and state space of our model. The time period, demand level, state of regulation, sum of received regulatory signals and level of post-regulatory operating costs—together with the three capacity levels (OI_t , PI_t , $prePI_t$)—are sufficient to characterize all the states in which a firm can find itself.

We now focus on the decision options available to the investor. In each time period, the shipper makes three interrelated decisions. Given the observed market state, its first choice involves setting the output quantity q_t so as to maximize same-period profits. When capacity overruns demand, the excess is stored as layup. Second, the output quantity is used to determine how much capacity OC_t should be chartered for this period in case of a capacity shortage. Finally, the shipper decides about expanding or contracting the owned fleet by (respectively) investing or divesting. Investment is possible at cost of k_l or k_h per unit and with a time to build of two periods; divestment is also possible, with sales proceeds of k_s per TEU, and is realized in the following time period. We label the units of capacity ordered as $invest_t$ and those sold as $divest_t$. Table 3.2 lists our decision variables and their respective action spaces.

Table 3.2: Definition of decision variables and action spaces.

Action space	Description
$OC_t \in OC = \{24,000z \mid z \in \mathbb{N} \cup 0\}$	Chartered capacity available for operation in current time period t
$invest_t \in OI = \{24,000z \leq OI_{\max} - PI_t \mid z \in \mathbb{N} \cup 0\}$	Units of capacity from investment ordered in time period t
$divest_t \in OI = \{24,000z \leq OI_t \mid z \in \mathbb{N} \cup 0\}$	Units of capacity from investment sold in time period t
$q_t \in Q = \{24,000z \leq OC_t + OI_t \mid z \in \mathbb{N} \cup 0\}$	Transportation output in period t

The state transfer from one period to the next is described by Eqs. (3.13)–(3.18). Demand and regulation evolve as described previously. The sum of regulatory signals Ψ_{t+1} is increased by the most recent signal. New pipeline capacity is increased by investment decisions and reduced by divestment decisions. To update operational capacity OI , pipeline PI_t becomes operational and is reduced by the capacity sold in period t . In an unregulated market, pre-regulation capacity $prePI_t$ is affected by investment and divestment. When selling capacity in a regulated market *with* grandfathering, post-regulation capacity is sold first because of its higher operating costs. According to Eq. (3.18), $prePI_t$ will be reduced by divestment *only* if there is no post-regulation capacity to be sold. At the same time, investment does not increase $prePI$ in a regulated market:

$$\tilde{Y}_{t+1} = \begin{cases} u\tilde{Y}_t & \text{for an "up" movement,} \\ d\tilde{Y}_t & \text{for a "down" movement;} \end{cases} \quad (3.13)$$

$$\alpha_{t+1} = \begin{cases} 1 & \text{if } \Psi_{t+1} \geq 2, \\ 0 & \text{otherwise;} \end{cases} \quad (3.14)$$

$$\Psi_{t+1} = \Psi_t + \tilde{\Psi}_{t+1} \quad (3.15)$$

$$PI_{t+1} = PI_t - divest_t + invest_t; \quad (3.16)$$

$$OI_{t+1} = PI_t - divest_t; \quad (3.17)$$

$$prePI_{t+1} = \begin{cases} prePI_t - divest_t + invest_t & \text{if } \alpha_t = 0, \\ \min\{prePI_t, PI_{t+1}\} & \text{if } \alpha_t = 1. \end{cases} \quad (3.18)$$

We can now set up the DP's reward function, which consists of same-period profits, the project's discounted expected future value, and the cash flow CI_t from investment and divestment. Observe that the firm maximizes profit π_t by choosing the optimal charter capacity and output. Transportation output can

range between zero and the total operational capacity available, $OI_t + OC_t$, reflecting the model's layup option. Chartered capacity can be freely chosen up to the maximum charter capacity of OC_{\max} . By making optimal investment and divestment choices, the firm maximizes not only the project's discounted future value ($e^{-r \text{d}T} \mathbb{E}[V_{t+1}]$) but also the cash flow CI_t from investment and divestment. The shipper can divest by selling any owned and available operational capacity, and it can invest up to the maximum capacity OI_{\max} . Formally, we have the following value function:

$$\begin{aligned}
& V_t(\tilde{Y}_t, \alpha_t, \tilde{c}_{1h}, OI_t, PI_t, \text{pre}PI_t) \\
&= \max_{0 \leq \text{invest}_t \leq OI_{\max} - PI_t} \left\{ \max_{0 \leq \text{divest}_t \leq OI_t} \left\{ \max_{0 \leq OC_t \leq OC_{\max}} \left\{ \max_{0 \leq q_t \leq (OI_t + OC_t)} \left\{ \right. \right. \right. \right. \\
&\quad \left. \left. \left. \pi_t(\tilde{Y}_t, \alpha_t, \tilde{c}_{1h}, q_t, OC_t, OI_t, PI_t + \text{invest}_t, \text{pre}PI_t + (1 - \alpha)(\text{invest}_t)) \right\} \right\} \right\} \\
&\quad + e^{-r \text{d}T} \mathbb{E}[V_{t+1}(\tilde{Y}_{t+1}, \alpha_{t+1}, \tilde{c}_{1h}, OI_{t+1}, PI_{t+1}, \text{pre}PI_{t+1})] \\
&\quad \left. \left. \left. + CI(\alpha_t, \text{invest}_t, \text{divest}_t) \right\} \right\}, \tag{3.19}
\end{aligned}$$

where

$$CI(\alpha_t, \text{invest}_t, \text{divest}_t) = -\text{invest}_t(\alpha_t k_h + (1 - \alpha_t)k_l) + e^{-r \text{d}T}(\text{divest}_t k_s). \tag{3.20}$$

3.3.2 Regulatory Uncertainty without Grandfathering

In Section 3.3.1 we developed a model of investing that accounts for regulatory uncertainty with grandfathering. However, many regulations target all capacity regardless of when it was purchased. So in this section we adapt our model to the case without grandfathering.

The model's basic logic, including the decision options available, remains unchanged. However, apart from introducing a new cost parameter, we also need to adapt the cost and profit functions as well as a transition function due to a new merit order of operations. New regulation now targets both legacy capacity and new vessels acquired after legislation is passed. Hence new capacity operates at the high cost level \tilde{c}_{1h} . For old capacity we assume an additional cost c_{old} , since the same standards must be met but with older technology:

$$c_1 = \begin{cases} c_{1l} & \text{if } \alpha_t = 0; \\ \tilde{c}_{1h} + c_{old} & \text{if } \alpha_t = 1 \text{ for capacity ordered pre-regulation,} \\ \tilde{c}_{1h} & \text{if } \alpha_t = 1 \text{ for capacity ordered post-regulation.} \end{cases} \tag{3.21}$$

Note that now, in a regulated market without grandfathering, it is more attractive to operate a new fleet, which changes the merit order of operations. Investment and charter costs remain unchanged from the grandfathering case

and so are still defined by Eq. (3.9). Hence our profit function for the no-grandfathering case changes as follows:

$$\begin{aligned}
\pi_t(\tilde{Y}_t, \alpha_t, \tilde{c}_{1h}, q_t, OC_t, OI_t, PI_t, OC_t, \text{pre}PI_t) \\
&= \tilde{Y}_t q_t^{1+1/\gamma} - \alpha_t (I_{[q_t \leq \text{post}O_t]} \tilde{c}_{1h} q_t \\
&\quad + (1 - I_{[q_t \leq \text{post}O_t]}) (\tilde{c}_{1h} \text{post}O_t + (q_t - \text{post}O_t) (\tilde{c}_{1h} + c_{old}))) \\
&\quad - (1 - \alpha_t) c_{1l} q_t - 0.5 c_2 q_t^2 \\
&\quad - \max\{OI_t + OC_t - q_t, 0\} c_3 \\
&\quad - \text{pre}PI_t k_l c_4 - (PI_t - \text{pre}PI_t) k_h c_4 \\
&\quad - \alpha_t (OC_t c_{5h}) - (1 - \alpha_t) (OC_t c_{5l}),
\end{aligned} \tag{3.22}$$

where

$$\text{post}O_t = OI_t + OC_t - \text{pre}OI_t \quad \text{and} \quad I_{[q_t \leq \text{post}O_t]} = \begin{cases} 1 & \text{if } q_t \leq \text{post}O_t, \\ 0 & \text{otherwise.} \end{cases} \tag{3.23}$$

In comparison with Eq. (3.10), the post-regulation operating cost (in the first line of the RHS) has changed. In the regulated market, new post-regulation capacity (regardless of whether owned or chartered) is cheaper to operate than old capacity and is therefore the preferred method of meeting output demand. We define $\text{post}O_t$ as operational capacity acquired or chartered post-regulation; it consists of all operational capacity *except* vessels ordered pre-regulation. With enough post-regulation capacity $\text{post}O_t$ to meet output, a shipper can operate at the medium-level price \tilde{c}_{1h} . All transportation services exceeding post-regulation capacity ($q_t > \text{post}O_t$) are provided at higher cost, $\tilde{c}_{1h} + c_{old}$.

The transition functions that apply to operational owned capacity OI_{t+1} and the pipeline PI_{t+1} remain unchanged. Yet when divesting in a market without grandfathering, the shipper prefers to sell pre-regulation capacity first because of its higher operating cost ($\tilde{c}_{1h} + c_{old}$) as compared with post-regulation capacity. Hence the transition function now becomes

$$\text{pre}PI_{t+1} = \begin{cases} \text{pre}PI_t - \text{divest}_t + \text{invest}_t & \text{if } \alpha_t = 0, \\ \min\{\text{pre}PI_t - \text{divest}_t, 0\} & \text{if } \alpha_t = 1. \end{cases} \tag{3.24}$$

The DP's value function is unchanged from that in Section 3.3.1 because the choices available to the shipper are identical in both cases. We can therefore again use Eqs. (3.19) and (3.20).

3.4 SOLUTION APPROACH: APPROXIMATE DYNAMIC PROGRAMMING

When applied to real-world problems, dynamic programming models quickly reach limits owing to three ‘‘curses of dimensionality’’ (Powell 2011): the exponentially growing size in the state, outcome, and action spaces that can make DP models computationally intractable. To meet this challenge, we employ approximate dynamic programming. In particular, we adapt a policy iteration

algorithm for finite-horizon problems to our purposes, combining that algorithm with a basis function–derived approximation. In this approach we follow Powell (2011), who provides an invaluable overview of the current state of ADP and methods available.

In traditional DP, the solving algorithm visits every state S of the problem, calculates the optimal action a to be taken, and thereby recursively deduces the project value in every possible state of the model. This program requires that one solve the classical recursive value function:

$$\begin{aligned} V_t(S_t) &= \max_{a_t \in \mathcal{A}_t} \{C(S_t, a_t) + \gamma \mathbb{E}[V_{t+1}(S_{t+1}) \mid S_t]\} \\ &= \max_{a_t \in \mathcal{A}_t} \left\{ C(S_t, a_t) + \gamma \sum_{S_{t+1} \in \mathcal{S}} \Pr(S_{t+1} \mid S_t, a_t) V_{t+1}(S_{t+1}) \right\}. \end{aligned} \quad (3.25)$$

Calculating the expected project value in period $t + 1$ rapidly becomes computationally burdensome. We substantially reduce the calculation demands by using ADP, adopting a basis function approach to approximate the post-decision state value. Thus we obtain—as explained more thoroughly in what follows—the value function

$$\bar{V}_t(S_t) = \max_{a_t \in \mathcal{A}_t} \{C(S_t, a_t) + \gamma \bar{V}_{t+1}(S^{M,a}(S_t, a_t))\} \quad (3.26)$$

$$= \max_{a_t \in \mathcal{A}_t} \left\{ C(S_t, a_t) + \gamma \sum_f \theta_{tf} \phi_f(S^{M,a}(S_t, a_t)) \right\}. \quad (3.27)$$

Instead of calculating the project value recursively, the program is now simulated from time period $t = 0$ to the last period $t = T$. In every iteration, the algorithm collects data on actions taken and the resulting value; these data are used to improve the next iteration’s value function approximation. Although we cannot calculate the exact solution in this way, ADP allows us to derive near-optimal results with significantly less calculation effort even for larger-sized problems. This approach has similarities to least squares Monte Carlo simulation as proposed in Longstaff and Schwartz (2001). However, the approach based on Powell (2011) and used in our paper applies a recursive estimation of the approximation parameters after every iteration. It therefore learns with each simulation and can use the improved knowledge for better results immediately.

3.4.1 Post-Decision State

Approximate dynamic programming reduces computation requirements by estimating the expected value of the project in time period $t + 1$. To facilitate this approximation, its value is estimated based not on the pre-decision state (in period t) but rather on the post-decision state. Whereas the pre-decision state is the one prevailing before any action is taken, the post-decision state reflects the world immediately after decision a_t has been made in state S_t but *before* the random event w_t is drawn. Therefore, reaching the post-decision state requires only the transition functions defined in Eqs. (3.16) and (3.17) together with Eq. (3.18) in the grandfathering case and Eq. (3.24) in the no-grandfathering

case. The functions that describe the realization of stochastic events w_t (demand and regulation) then lead from the post-decision state to the next pre-decision state in period $t + 1$, but they are not needed to describe the post-decision state.

3.4.2 Basis Function Approach

To approximate the value of a post-decision state, we take a basis function approach that produces value estimates using linear least-squares regression. Instead of valuing all possible states S_{t+1} in the next time period, we approximate this expected value based on information already known in the post-decision state S_t^a . In regression analysis, a typical model has the form

$$y = \theta_0 + \sum_{i=1}^I \theta_i x_i + \varepsilon,$$

where the x_i are the independent variables and the θ_i are the regression coefficients. In our model we use a similar approach but make use of the ADP naming convention.

We start by defining a basis function $\phi_f(S_t^a)$, where $f \in F$ is a feature of the post-decision state S_t^a . Basis functions extract—from the post-decision state—the information relevant for estimating the project value in period $t + 1$. We then use this information to define the value approximation as

$$\bar{V}_t(S_t^a | \theta_t) = \sum_{f \in F} \theta_{tf} \phi_f(S_t^a). \quad (3.28)$$

We remark that, because the model is time-dependent, it incorporates regression coefficients θ_{tf} that vary with each time period t . These coefficients are initialized at the beginning of the ADP algorithm; in each subsequent iteration, they are recursively fitted to the observed data.

Because our model allows for flexible short-term chartering, large portions of a project's value can be realized without any investment. Chartered capacity can be acquired for the current period without affecting future project values, so increasing capacity *solely* by chartering can be viewed as a myopic decision. To identify more clearly the value added by long-term investment, we split up the value approximation into the value ($\bar{V}_t^m(S_t^a)$) due to the myopic strategy and the approximate value added (\bar{V}_t^{av}) due to owning investment capacity:

$$\bar{V}_t(S_t^a | \theta_t) = \bar{V}_t^m(S_t^a) + \bar{V}_t^{av}(S_t^a | \theta_t). \quad (3.29)$$

Because the value of a purely myopic charter-only strategy does not factor in to long-term investment choices, we can safely ignore it when seeking the optimal decision policy. Our novel approach is to focus solely on the value added in the post-decision state (i. e., that in excess of value from adopting the myopic strategy) and to approximate it as follows:

$$\bar{V}_t^{av}(S_t^a | \theta_t) = \sum_{f \in F} \theta_{tf} \phi_f(S_t^a). \quad (3.30)$$

3.4.3 ADP Algorithm

In dynamic programming, the state and action spaces are fully iterated recursively to derive the exact solution. Because this process is computationally expensive, approximate dynamic programming uses simulations. For a sufficient number of iterations M , the algorithm simulates the model from period $t = 0$ to the final period $t = T$. In each iteration, the algorithm observes the value created by the decisions taken and uses this information to update the estimation coefficients of the basis functions. By iterating sufficiently often, the algorithm produces an increasingly exact approximation of the value function, from which better decisions will follow. The algorithm is reproduced as Figure B.1 in Appendix B.2.

A key challenge in ADP is discovering optimal choices. Decisions depend on a value approximation that may well be far from accurate in the early iterations. As a result, the algorithm may choose suboptimal actions because it has not yet internalized the value of alternatives. We address this problem by augmenting the algorithm with a mixture of exploitation and exploration. Here *exploitation* refers to choosing the value-maximizing response a_t based on the approximation, and *exploration* amounts to randomly choosing actions and thus helping the algorithm discover values that are, at first, hidden. We incorporate exploration into our model by choosing random actions during the algorithm's first 1,000 iterations. For subsequent iterations, an ϵ -greedy approach determines whether to explore in the iteration—as will occur if a randomly drawn number $e \sim U[0, 1]$ is smaller than ϵ/m , where m is the iteration counter. In this approach, the likelihood of pursuing exploration decreases over time.

3.4.4 Value Function Approximation

One cannot approximate the post-decision state value without first selecting suitable basis functions. To derive these, we implemented a DP version of our model after reducing its state and action spaces enough to enable iterating the entire state–action space. For this purpose we limited the model to $T = 9$ time periods and set the maximum investment and charter capacity to the low levels of 360,000 TEU. This “toy” model was used to generate data on optimal decision making so we could evaluate and compare the effectiveness of potential basis functions.

The basis functions that in the statistical analysis seemed to be most promising for use were subsequently tested for their performance in the ADP algorithm. The final basis functions were selected based on performance with respect to two criteria. First, in an ADP with the same parameters as the DP “toy” model, the basis functions presented below (excluding ϕ_2^2) have led to a close replication of capacity decisions as seen in the DP “toy” model's exact and optimal results. The second criterion was the value added in the full ADP model as compared with a myopic (charter-only) project. Here we compared the average of actual project values achieved in 10,000 simulations with the average project

² ϕ_2 contains a threshold that needs to be set individually for a specific calibration of the model. As the threshold is not the same in the “toy” and full models, ϕ_2 could not be tested in the “toy” model.

value achieved in a myopic version of the ADP model—that is, one in which no investment is possible. In this reference model the shipper—after perceiving demand and the regulatory state of the market—can choose charter and output capacity in each period. That flexibility makes the myopic model a highly challenging benchmark against which to compare our ADP model.

Of all the basis functions tested, the best performance was delivered by the following:

$$\begin{aligned}
 \phi_1 &= \tilde{Y}_t, & \phi_5 &= I_{[\Psi_t=1]}PI_t, & \phi_9 &= OI_t^2, \\
 \phi_2 &= \max\{\tilde{Y}_t - \text{threshold} \times (1 + \mu)^t, 0\}, & \phi_6 &= I_{[\Psi_t=2]}PI_t, & \phi_{10} &= PI_t^2. \\
 \phi_3 &= \tilde{Y}_t OI_t & \phi_7 &= I_{[\Psi_t=1]}prePI_t, & & \\
 \phi_4 &= \tilde{Y}_t PI_t, & \phi_8 &= I_{[\Psi_t=2]}prePI_t, & & (3.31)
 \end{aligned}$$

In these basis functions, market demand is reflected in ϕ_1 ; interaction terms between demand and capacities OI and PI are reflected in ϕ_3 and ϕ_4 , respectively; ϕ_5 and ϕ_6 capture the effect of pipeline PI in a market with one regulatory signal received ($\Psi_t = 1$) and in the regulated market ($\Psi_t \geq 2$) and ϕ_7 and ϕ_8 the effect of pre-regulation capacity prePI in these markets. In ϕ_9 and ϕ_{10} , the squared versions of (respectively) operational capacity OI and pipeline capacity PI introduce curvature to the approximated value function and thereby prevent the model from always choosing extreme capacities. Basis function ϕ_2 considers demand above a certain threshold. This helps us approximate option-like payoffs in the value function, and we increase the threshold each period by market drift μ . We set a threshold of 29m in our expression for ϕ_2 , but we omit this basis function in simulations *without* regulatory uncertainty.

3.5 INVESTMENT BEHAVIOR UNDER REGULATORY UNCERTAINTY

In this section we calibrate our model to the container shipping industry toward the end of developing insight into optimal investment levels and strategy under regulatory uncertainty. We use the reduction in allowed limits of sulfur oxide emissions as an example test case, but the model can be adapted to address the effects of other regulations also.

3.5.1 Regulation of Sulfur Emissions in Maritime Shipping

The IMO has acknowledged that shipping is a major contributor to global emissions of SO_x (i. e., sulfur dioxide (SO_2), sulfur trioxide (SO_3), and many other compounds containing both sulfur and oxygen), and it has begun to lower the permissible levels of emissions. In Annex VI of the International Convention for the Prevention of Marine Pollution from Ships (MARPOL), the IMO laid out a staged approach to reducing sulfur emissions worldwide and also in special emission control areas (ECAs) like the Baltic and North Seas and the English Channel. The limits posted in Table 3.3 show the gradual lowering of admissible SO_x emissions. Because the strictest MARPOL limits are still 100 times higher than those allowed in vehicular road traffic (Brynnolf et al. 2014), the future almost certainly holds further regulatory action on this front.

Table 3.3: Sulfur oxide emission limits.

Outside an ECA	Inside an ECA
4.5% m/m prior to 1 January 2012	1.5% m/m prior to 1 July 2010
3.5% m/m on and after 1 January 2012	1.0% m/m on and after 1 July 2010
0.5% m/m on and after 1 January 2020	0.1% m/m on and after 1 January 2015

Adapted from International Maritime Organization (2016b). ECA = emission control area; m/m = mass per mass (i. e., percentage mass of sulfur oxide gases in the total mass of the emission).

There are two main technological approaches available for compliance with MARPOL Annex VI: shippers can either shift to low-sulfur fuels or clean contaminated exhausts using “scrubbers”. Using low-sulfur fuels requires little investment, but it does raise operating costs significantly because such fuels are 60%–70% more expensive (Schinas and Stefanakos 2012). Installing a scrubber requires sizeable investment, especially as a retrofit, and also increases operational costs slightly because of reduced fuel efficiency (Lindstad and Eskeland 2016). Retrofitting a ship of the size used in our calibration would cost about 13 million US dollars (USD) (200 USD/kW engine power) in investment cost (Den Boer and Hoen 2015) and about 3 million USD of additional yearly operating costs for maintenance, operating materials and reduced fuel efficiency (Lindstad et al. 2015, Van Rynbach et al. 2015). The IMO’s efforts to reduce sulfur emissions pose financial challenges to the shipping industry, and they offer fertile ground for our numerical analysis. For this we consider the reduction of the worldwide SO_x emission limit from 3.5% to 0.5% sulfur content and assume that vessels ordered or chartered in a regulated market are equipped with scrubber technology. Vessels ordered before the introduction are assumed to comply with regulation by switching to low-sulfur fuels if they are not protected by grandfathering.

3.5.2 Model Calibration

Our numerical study uses the financial parameters listed in Table 3.4; the indicated values are derived from AECOM (2012), a document that reports on the cost structure of a 12,000-TEU Neo Panamax container vessel. This vessel class is used as the basis for our study, in part because we expect it to gain in importance following expansion of the Panama Canal. We assume that a vessel completes six round-trips between Asia and the United States each year. Given an average utilization of 80%, this vessel’s yearly capacity is 115,200 TEU. If the market is unregulated then we assume that a newly built ship costs about 105 million (all monetary values are given in US dollars), or a per-TEU investment amount k_I of roughly 900. Divestments of owned capacity can be executed at a sales price of $k_S = 300$ per TEU.

Operating costs for bunkering (i. e., fueling), personnel, and regular maintenance amount to some 89 million each year and are split between the cost

Table 3.4: Base-case parameters used in all models (unless indicated otherwise).

Parameter	Value	Parameter	Value
T	15 (years)	c_2	0.00008 (USD)
γ	-1.4	c_3	28 (USD)
μ	0.03	c_4	0.02
σ	0.1	c_{5l}	140 (USD)
r	0.06	c_{5h}	160 (USD)
ξ	0.3	k_l	900 (USD)
c_{1l}	700 (USD)	k_h	1,000 (USD)
$\mathbb{E}[\tilde{c}_{1h}]$	800 (USD)	k_s	300 (USD)
$\sigma_{\tilde{c}_{1h}}$	0.05	OI & OC	$0 \leq x \leq 1,080,000$ (TEU)
c_{1ot}	20 (USD)	Y_0	18,000,000

parameters $c_{1l} = 700$ and $c_2 = 0.00008$ —values that allow unit costs to grow slowly with rising capacity. We adopt this approach to reflect the importance of economies of scale and also because increasing marginal costs are irrelevant except at high levels of capacity. If the ship is not operated then no bunkering is needed; in that case, the vessel incurs lower layup costs of $c_3 = 28$ per TEU. For acquired ships, we assume that 25% of the investment cost was financed using debt at an interest rate of 8%. Spread across the overall investment volume, financing costs amount to 2% ($c_4 = 0.02$).

We assume that in each period there is a constant risk ($\xi = 0.3$) of a regulation signal, while regulation is enacted once the second signal has been received. Once the market is regulated, we let the investment cost rise to $k_h = 1,000$, reflecting the additional cost of about 13 million USD for a scrubber. Operating costs in the regulated market are normally distributed with a mean expected value of $\mathbb{E}[\tilde{c}_{1h}] = 800$ and a standard deviation of $\sigma_{\tilde{c}_{1h}} = 0.05$, representing the additional operating cost mainly driven by a loss of fuel efficiency. Once the post-regulation cost is unveiled, it remains constant until the simulation's last period. In a regulated market without grandfathering, old capacity must be operated on low sulfur marine diesel oil (MDO) which is more expensive than using a scrubber. The cost disadvantage of capacity based on old technology is fixed at a low value of $c_{old} = 20$.

The charter rate is determined based on information from VHSS Vereinigung Hamburger Schiffsmakler und Schiffsgagenten e.V. (2015), a publisher of rates for different classes of vessel. We use the rate for the largest published vessel class and then scale it to a 12,000-TEU vessel; this results in a charter cost of $c_{5l} = 140$, which rises to $c_{5h} = 160$ when the market is regulated. The markup in the regulated market represents the cost of installing a scrubber that the owner charges to the charterer with an assumed amortization period of 5 years.

The remaining market parameters are set as follows. The model runs over $T = 15$ time periods, the price elasticity is $\gamma = -1.4$, the market drift is $\mu = 0.03$, the standard deviation of demand is $\sigma = 0.1$, and the risk-free interest rate is set at $r = 0.06$ in the base-case scenario.

In the numerical study, we also calculate the regulation's impact on yearly emission levels. For this purpose we assume ships in the unregulated market to operate on heavy fuel oil (HFO) with 3.5% m/m sulfur content. In the regulated market, all vessels that need to comply with the new regulation are assumed to be using scrubbers or low-sulfur fuels that reduce the sulfur emissions to the equivalent of 0.5% sulfur. Based on the distance between Asia and the United States, we assume the vessel to consume 0.6 tons of fuel per TEU transported on the one-way route. Multiplying this assumed fuel consumption with the sulfur content yields the resulting SO_x emissions.

3.5.3 Numerical Study

We now simulate the ADP model—using the parameters previously stipulated—to analyze the effect of regulatory uncertainty on optimal investment in the shipping industry. Toward that end, we start by simulating a comparison scenario without regulation; we then compare it to a model with regulatory uncertainty and assess its effects on capacity outcomes. Finally, we present a scenario with increased post-regulation costs to better understand the impact of high regulatory uncertainty in this market. To obtain a sufficiently large set of data, we simulate each model 10,000 times and derive implications based on average simulation results. Model runs are performed with the following tuning parameters, which yield reasonable outcomes. We iterate the model $M = 15,000$ times, incorporate exploration for the first 1,000 iterations, and use $\epsilon = 10$ for the ϵ -greedy exploration thereafter. With regard to the step-size, we set $\delta_1 = 0.4$ and $\delta_2 = 0.8$. A sensitivity analysis, in which we assess the variation in project values induced by changes in the most relevant model parameters is shown in Table B.2 in Appendix B.3. Relative changes of project values are small in all cases, which highlights the robustness of the proposed model. Note also, that there is only little difference in resulting project value variations between the models with and without grandfathering. As a limitation, the model does not generate added value—on top of the ambitious benchmark established by the flexible myopic strategy³—when market volatility exceeds $\sigma = 0.2$. This, however, does not restrict the model's application to the shipping industry: with a 7.0% standard deviation of yearly container shipping demand between 2009 and 2016 on the trade lane analyzed (Far East to United States), there is a solid buffer for the model to be applicable even if the industry should become more volatile. (Alphaliner 2012, 2015, 2017) Additionally to demand uncertainty, the model allows for volatility from potential market regulation and cost uncertainty.

The simulation outcomes with (resp., without) regulation are plotted in Figure 3.2 as solid black (resp., dashed red) lines; under both conditions we use the base-case parameters from Table 3.4. The lines plot mean values based on 10,000 simulations, while the “whiskers” indicate standard deviations. Results in markets where regulation features grandfathering are displayed in the figure's left column, and the no-grandfathering results are shown in its right column.

³As chartering is chosen after uncertainty is resolved, the shipper can always choose the optimal capacity and has no risk of incurring a loss.

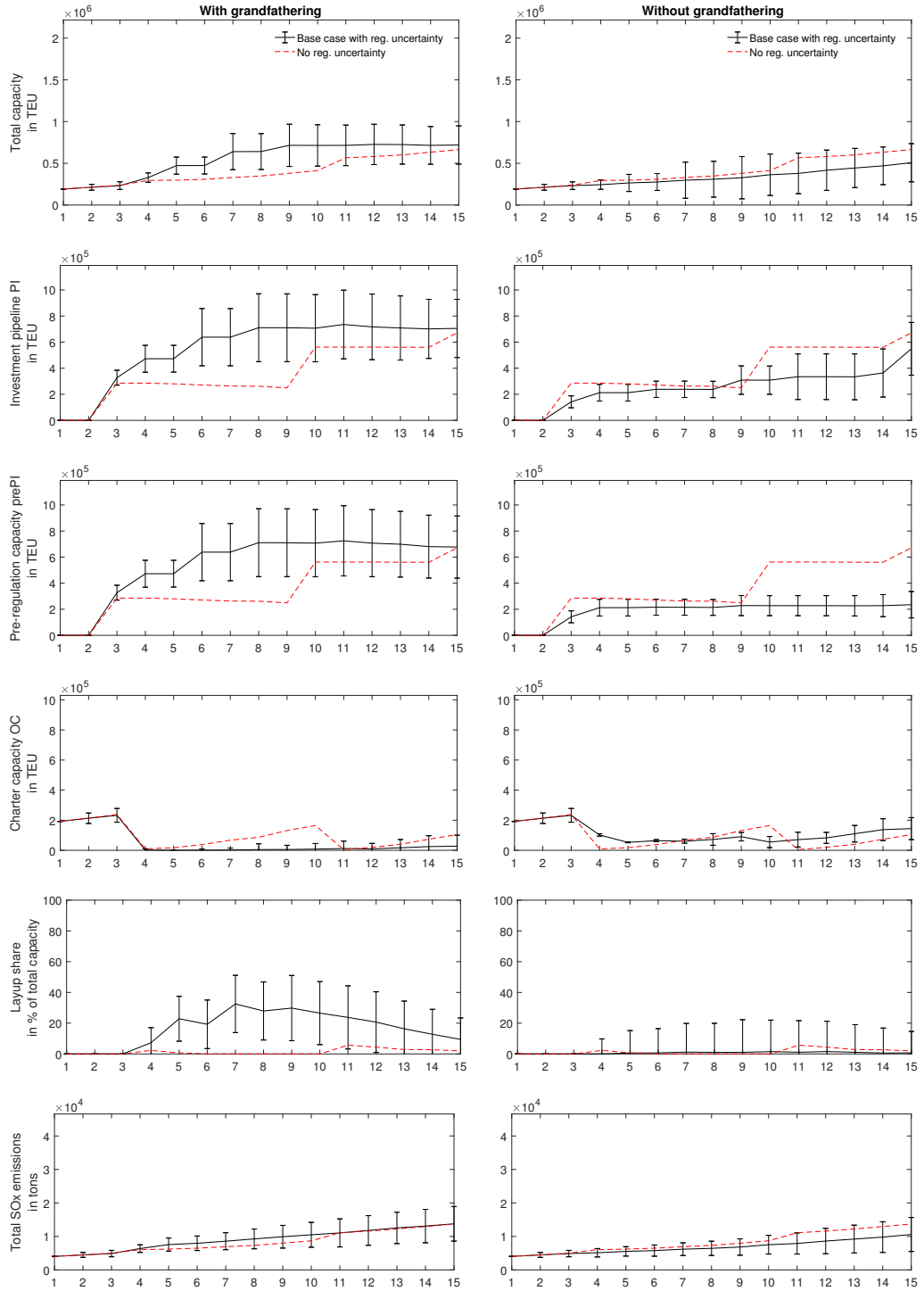


Figure 3.2: Results for simulations without regulatory uncertainty (red) and the base-case model with regulatory uncertainty (black). Base-case parameters, as listed in Table 3.4, apply with the following exception: the model without regulatory uncertainty (red) is calculated with probability of regulation $\xi = 0$. All calculations are performed with $M = 15,000$ ADP iterations.

In the market without regulation risk, investment behavior is driven solely by stochastic demand. Absent regulation, there is no need (or way) to distinguish between cases with or without grandfathering. Total capacity, including

owned and chartered ships, increases in a fairly stable manner. We can see also that owned capacity makes up a large part of total capacity and that chartering is used mainly to compensate for unexpected changes in demand. Use of the layup option is observed even in this simulation without regulatory uncertainty. Excess capacity may be parked in layup as a consequence of two opposed effects that are relevant to identifying optimal capacity (Aguerrevere 2003). On the one hand, the cost of excess capacity (in the form of layup and financing costs) argues for a relatively conservative choice of capacity. On the other hand, capacity shortages during periods of strong demand amount to an opportunity cost of profits forgone; this latter dynamic argues for a relatively aggressive capacity decision. Which of these two effects dominates, as well as the amount of excess capacity observed, depends on both market volatility and the cost parameters. The results from this model without regulatory uncertainty can serve as a base case for comparison.

Next, we extend the model by adding the possibility of new regulation being introduced. The market is unregulated in the first time period but, with probability $\xi = 0.3$, regulatory signals can arrive in any of the following periods. In a market with regulatory uncertainty but without grandfathering (black lines in graphs on the right side of Figure 3.2), we derive two main results. First, compared to our no-regulation model, optimal investment in own capacity declines—which, in turn, reduces total capacity. Potential regulation increases operating, investment, and charter costs, which means that freight rates would also have to rise to keep operating capacity stable. Since demand is no different than in our no-regulation scenario, the shipper must reduce capacity to maximize its profits. Regulation *without* grandfathering thus leads to reduced market capacity, which results from an increased cost base for ships acquired (i. e., both pre- and post-regulation).

Our second main result from the market *without* grandfathering is that, despite reduced investment, chartering remains stable and even increases in the later periods. This finding underscores the charter option's attractiveness: the shipper can observe market conditions *before* determining its optimal charter capacity, and the charter contracts run for just a single time period. Chartering is a slightly more expensive yet extremely flexible source of capacity. Especially in volatile markets with regulatory uncertainty, it is preferable to rely more on chartering—and to refrain from investing heavily in owned capacity—until that uncertainty is resolved.

The overall investment and operating behavior in markets *without* grandfathering is also reflected in the resulting emission levels. On average, total emissions are reduced compared to the base case without regulatory risk. Note that the reason for the seemingly small reduction in overall emissions is a result of simulations in which the market becomes regulated during the time horizon considered and simulations in which the market remains without regulation.

In the scenario *with* grandfathering (left side of Figure 3.2), the anticipated regulation excludes any capacity ordered before that regulation takes effect. That exception fundamentally changes the market's economics: whereas new ships are cheaper to operate in the no-grandfathering case, old capacity is more attractive in the grandfathering case. This claim is supported by three key takeaways from our simulations. First, as compared with the no-regulation scenario,

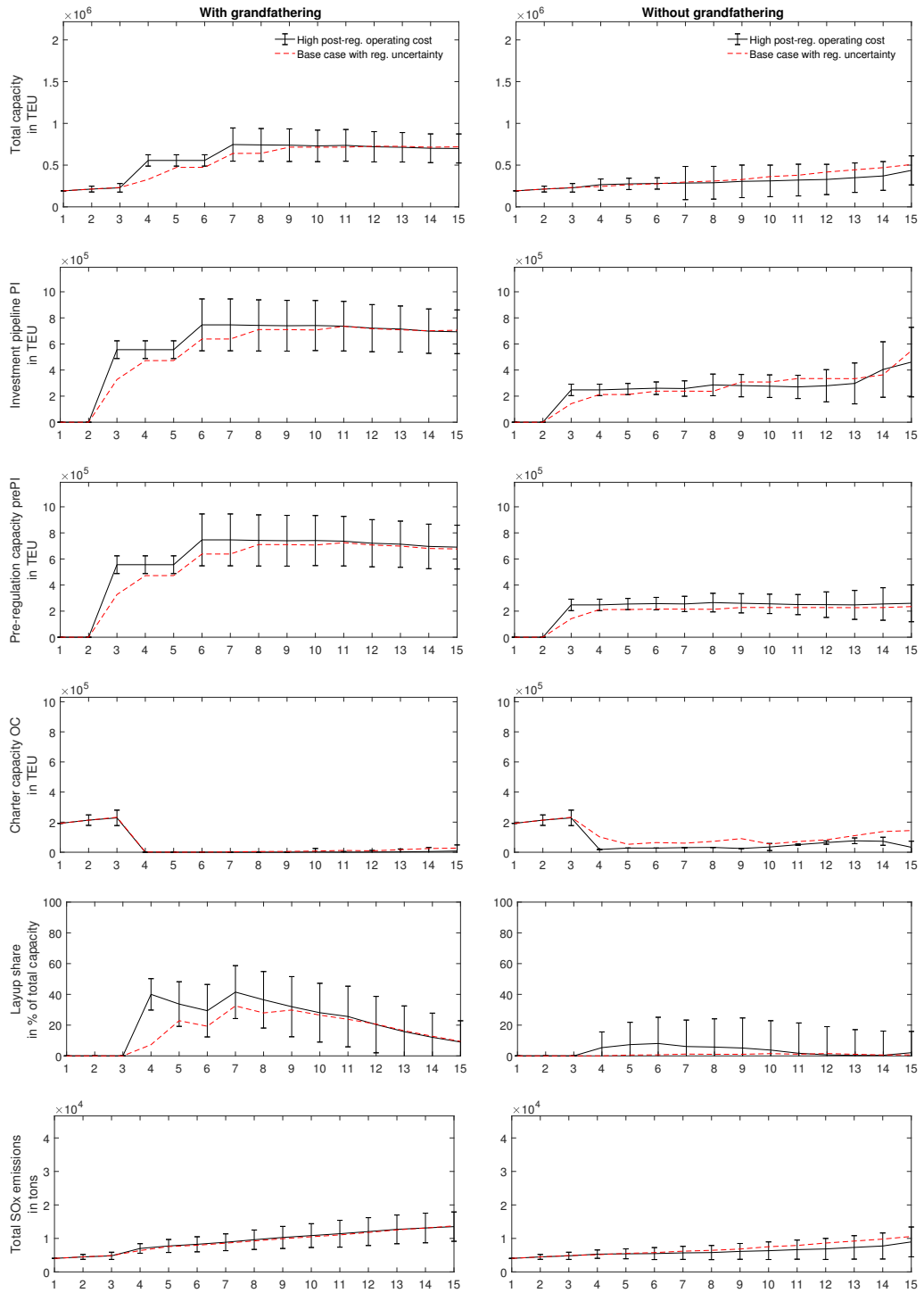


Figure 3.3: Results for simulations with regulatory uncertainty (red) and with increased post-regulation operating costs (black). Base-case parameters, as listed in Table 3.4, apply with the following exception: the model with increased post-regulation cost (black) is calculated with $\mathbb{E}[\tilde{c}_{1h}] = 1,000$. All calculations are performed with $M = 15,000$ ADP iterations.

we find higher levels of total capacity—especially during the early time periods. Note that this increased capacity is driven by the owned capacity ordered prior to regulation being introduced. The pre-regulation investment capacity prePI

is built up to secure a low-operating cost base for the possibly regulated future. Our second finding is that, under regulation, chartering is cut back severely and replaced with investment. Such behavior confirms that, in a regulated market, old owned capacity is cheaper to operate than either chartered or newly ordered ships. Since the chartering in our model is contracted on a yearly basis, it follows that chartered capacity is always affected by regulation. Third, the share of total capacity in layup increases significantly as compared with the no-regulation scenario. In this example, optimal outcomes result from up-front investment in excess of operational needs; value is generated not by making myopic decisions but by accounting for the repercussions of today's decision on future profits.

The upfront investment also leads to repercussions on the emission levels resulting from operations. As shippers heavily invest into old technologies that are cheap to operate, the environmental regulation even leads to a slight increase in total emissions. Apart from having created uncertainty for shippers, the policy has counteracted the original goal of reducing environmental pollution. While this is a transitional effect, it will take many years until old vessels protected by grandfathering are nearing the end of their lifetime and are replaced by ships that need to comply with the new emission limits.

Overall, then, it is optimal—in a market with regulatory uncertainty and grandfathering—to boost investment *before* regulation is enacted and thereby to lock in a low-cost base. This conclusion is relevant to shippers, who can improve their odds of long-term success by investing pre-regulation (in the grandfathering case), and even more relevant to regulators. By creating uncertainty about the details of future regulation (when grandfathering is expected), regulators unwittingly encourage current investment with two adverse effects. First, the new orders are probably still equipped with technologies targeted for replacement by new regulation. This uncertainty can therefore even increase total emissions for a long transitional period and thereby undermine regulatory targets. Second, regulatory uncertainty with grandfathering can lead to additional build-up of excess capacity. That outcome can hasten deteriorating market conditions in an industry that repeatedly suffers from excess capacity and hence from depressed freight and charter rates. While excess capacities exert downward pressure on market prices, they do not reduce the transportation output by the shipper. An increase of emissions can therefore be expected, which counteracts the regulatory objective. It is therefore imperative that the regulator minimize the duration of uncertainty, especially if grandfathering is likely.

In Figure 3.3 we analyze how the possibility of more drastic regulation affects capacity decisions. Dashed red lines plot the market with regulatory uncertainty and base-case parameters from Table 3.4, while the black lines plot a comparable scenario but with expected post-regulation operational costs increased to $\mathbb{E}[\tilde{c}_{1h}] = 1,000$. The results accord with those displayed by, and discussed with reference to, Figure 3.2: the risk of tighter regulations promotes up-front investment with an *increase* in total emissions *provided that* regulation allows for grandfathering. Without grandfathering, however, increased regulatory risk reduces investment in own capacity and also charter capacity; in this case, the market runs the risk of contracting. Therefore, regulators must remain

cognizant of how uncertainty-inducing legislative processes can adversely affect the real economics of the industry. There are two main limitations to the findings derived from this model. First, we have assumed a monopolistic market structure which we believe would only change the size of the effects found but not the qualitative findings. Second, the proposed model is an approximate dynamic program, which means that solutions obtained are believed to be near-optimal strategies. It is possible, however, that there exist better strategies than the ones found by this approximative algorithm. When applied to other settings, the model needs to be re-calibrated to deliver reliable results.

3.6 CONCLUSION AND IMPLICATIONS FOR FUTURE RESEARCH

This paper proposes a real options model to analyze optimal investment under regulatory uncertainty. We employ both dynamic and approximate dynamic programming to implement and solve the model computationally. To derive insights concerning the effect of regulatory uncertainty on investment decisions, we apply the proposed approach to international maritime shipping. This industry is characterized by extremely capital-intensive projects, the need to make foresighted decisions (a consequence of time required to build and the durability of ships), and a recent trend toward regularization that has burdened the market with another source of uncertainty. Our proposed investment model contributes to the real options literature by combining the characteristics of many capacity decisions—an investment and divestment option, time to build, an alternative charter option, and operational flexibility—that are relevant to the real-world setting examined here. We believe that this is the first paper to combine these factors with regulatory uncertainty when analyzing the latter's effects on optimal investment. We contribute also to maritime shipping research by raising awareness for, and by analyzing the influence of, regulatory uncertainty. We establish some directional findings with respect to optimal investment under regulatory uncertainty, and in so doing we identify another possible source of continued excess capacity in this market.

We derive two principal results from simulating the model. First, we find that uncertainty about future regulation with grandfathering leads to a significant increase of investment in capacity and an increase of industry emissions. According to the model, shippers should deliberately build up capacity before regulation is introduced to secure sustained low operating cost levels. In fact, we show that capacity rises above expected operational needs and so ends up significantly increasing the market's excess capacity. Regulators would do well to focus on this result, since it indicates that regulatory uncertainty (with grandfathering) incentivizes market participants to invest in more old capacity than is currently needed—a dynamic that is clearly at odds with the regulator's mandate to reduce the negative environmental effects of the industry.

Second, in a market with regulatory uncertainty but without grandfathering, we find that the uncertainty discourages investment and reduces overall emissions. More specifically, shippers spend less on developing their own capacity and focus more on chartered capacity. Yet the increase in chartering in later periods does not entirely compensate for capacity contraction on the

investment side, so total market capacity shrinks. Without grandfathering, regulatory uncertainty puts markets in a “waiting” mode where chartering—the more flexible capacity—is preferred until uncertainty is resolved. In real markets, the reduction of total capacity may become even more pronounced if the availability of chartered capacity is limited.

In short: regulatory uncertainty has a strong effect on the investment decisions made by maritime shippers, and investors as well as regulators should be well aware of its likely repercussions. Furthermore, it is not just the regulation itself but also the preceding uncertainty that amounts to an “intervention” that can move markets in sometimes unexpected or unwanted directions. Intriguing topics for future research are to test these findings empirically or to expand the analytical model so that it offers investors a technology choice when facing regulatory uncertainty.

This last question is especially relevant as investors need to build a fleet of vessels that is able to comply with upcoming regulation at the lowest cost possible. To this end, they will have to decide about what vessel technologies to invest in. Such technology choice when facing uncertain future regulation is the focus of the next chapter, in which we both the effects of regulatory uncertainty on optimal technology choice and the effectiveness of different regulatory regimes in reducing the environmental footprint of maritime shipping.

TECHNOLOGY CHOICE UNDER EMISSION REGULATION UNCERTAINTY IN INTERNATIONAL CONTAINER SHIPPING

The following chapter is based on Haehl and Spinler (2017b). This manuscript is currently under revision after a “revise and resubmit” decision from the European Journal of Operational Research (EJOR).

4.1 INTRODUCTION

Uncertainty concerning environmental regulation affects capacity decisions and technology choice decisions in many industries, and it is of growing importance especially in ocean shipping. International container shipping is the most efficient means of transport, yet it contributes significantly to worldwide emissions owing to the sheer size of the industry. Moreover, environmental regulation has focused less on maritime shipping than it has on land-based sectors (Lister et al. 2015). Hence most such shipping still operates on “residual” fuels and other technologies that contribute to worldwide pollution and the emission of greenhouse gases, and there are strong barriers to the adoption of ameliorating technological innovation. These barriers include cost and capital expenditure factors, industry practices, and problems of a principal–agent nature (Acciaro et al. 2013). The maritime shipping sector is a major contributor to worldwide emissions: it accounts for (approximately) 3% of global carbon dioxide (CO₂) emissions, 13% of nitrogen oxide (NO_x) emissions, and 12% of sulfur oxide (SO_x) emissions (International Maritime Organization 2014).¹ In recent years, the International Maritime Organization (IMO) has become increasingly active in introducing regulations that aim to reduce the industry’s ecological footprint. Among the new rules, most prominent are the limits on sulfur oxide emission introduced by Annex VI of the International Convention for the Prevention of Marine Pollution from Ships (MARPOL). Under this ruling, the IMO sets maximum permitted fuel sulfur content and maximum levels of the resulting SO_x emissions depending on whether ships operate on the high seas or within specified emission control areas (ECAs), where lower limits apply. Those emission limits will be further reduced in a staged approach, eventually forcing ship operators to adopt various costly abatement options—for example, switching to more expensive distillate fuels, installing exhaust gas–cleaning systems, or operating on liquefied natural gas.

The increase in regulatory activities by institutions (such as the IMO) and individual member states causes uncertainty for ship operators about the future regulatory environment, which fundamentally affects investment economics. Regulatory compliance is widely acknowledged as a factor that drives capacity

¹Here NO_x denotes nitric oxide (NO) and nitrogen dioxide (NO₂); similarly, we use SO_x as shorthand for sulfur monoxide (SO), sulfur dioxide (SO₂), sulfur trioxide (SO₃), and so forth as well as for other, more complex sulfur compounds such as S₂O₂, S₆O₂, and S₇O₂.

decisions in general and, more specifically, investment in emission abatement technology (Acciaro 2014). Since regulatory compliance has become so important, it follows that accounting for expected regulations, the resulting uncertainty, and available technology options are all key to successful investment decisions in shipping and also in other industries.

Our paper presents an investment model that allows for identifying the optimal technology and capacity choices under regulatory uncertainty. Both analytically and in a numerical study, we investigate optimal decision making—from the ship operator’s perspective—as a function of market conditions and the regulatory uncertainty that shippers face. We also analyze different regulation methods while adopting the perspective of a regulator seeking to achieve targeted emission levels in a cost-effective manner. To address these issues, we develop a regime-switching investment model via a two-phase approach. This real options model accommodates the possible introduction of environmental regulation, with the result that both operating costs and emission levels are stochastic; in addition, it incorporates an option to invest in capacity offered by different technologies, the alternative of chartering, and a layup option for excess capacity. Our approach extends the model of Drake et al. (2016) by adding a charter option, modeling an endogenous price function as well as the possibility of switching from an unregulated to a regulated market, and accounting for emissions more explicitly.

This paper contributes to the literature in three ways. First, we present an extended model that enables one to consider investment decisions under regulatory uncertainty, which is characteristic of many industries. Second, by adopting the investor’s viewpoint we are better able to explain the optimal technology choice—that is, the choice that maximizes profit while ensuring regulatory compliance. Third, we help regulators understand the outcomes and effectiveness of two different regulation approaches: a strict cap on emissions and a penalty (via taxation) for failing to meet emission targets. Both scenarios are analyzed in detail so that we can better explicate the trade-offs that arise when deciding on a regulatory approach.

The paper proceeds as follows. Section 4.2 reviews the extant research on investment under uncertainty and on regulatory uncertainty both within and outside the shipping industry. In Section 4.3, we start by taking regulatory uncertainty as given and develop—under some basic assumptions—the analytical model for technology investment; we then examine the results that follow from this approach. Next we relax those assumptions by way of a numerical extension of the model and detail its implications for optimal investment behavior. Section 4.4 adopts the regulator’s perspective and compares the cost effectiveness of two alternative regulatory regimes at achieving emission targets. In Section 4.5 we discuss what the proposed models imply for optimal investment decisions by ship operators and also for efficient market regulation. Section 4.6 concludes.

4.2 LITERATURE REVIEW

Our proposed model is related to several strands of existing literature, which are briefly reviewed here. In particular, that research addresses real options methods for investment appraisal under various types of uncertainty, regulatory uncertainty per se, and choosing technology with an eye toward both profit maximization and regulatory compliance.

Real options methods are well known to be appropriate for valuing investments under uncertainty (Copeland and Antikarov 2001, Dixit and Pindyck 1994). Scholars have applied this approach to project valuation under operational flexibility (Brennan and Schwartz 1985, Mossin 1968), with investment lags (Aguerrevere 2003, Bar-Ilan and Strange 1996), and in oligopolistic markets featuring strategic interaction (Aguerrevere 2009, Grenadier 2002, Sødal 2006, Williams 1993). Such approaches have also been applied to the industry of maritime shipping, where Bendall and Stent (2003) show that real options better capture—than do traditional discounted-cash flow methods—the value of various options for deploying purchased ships. Bendall and Stent (2005) value the introduction of a new express liner service with flexible employment strategies, and Bendall and Stent (2007) allow new shipping capacities to be used as expansion or replacement assets. Sødal (2006) uses options to analyze market entry and exit decisions in an oligopolistic shipping market. The dry and wet bulk markets are examined with regard to market efficiency and to the switching between these markets by combination carriers in Sødal et al. (2009), and the value added due to the flexibility of switching (between wet and dry bulk markets) by combination carriers is evaluated in Sødal et al. (2008). Rau and Spinler (2016) develop a container shipping-specific real options model with strategic interaction and find that strategic interaction increases firm value. Their argument for alliance formation is addressed in a follow-up study by Rau and Spinler (2017), who show that real options methods outperform alternative methods even in a competitive setting with deliberate formation of alliances.

Regulatory uncertainty and its effect on optimal investment decisions have been debated in empirical work and also in research employing real options approaches—especially as regards the energy production sector. Most studies in the real options literature posit that regulatory uncertainty reduces or at least delays investment. For example, Reinelt and Keith (2007) analyze the cost of regulatory uncertainty for a technology choice investment problem in energy production. They find that regulatory uncertainty increases the social cost of emission abatement, and delays investment in new gas-fired power plants, if gas prices are expected to be high. Fuss et al. (2009) likewise find that the transition to renewables is postponed when the trading prices for SO_x emissions are volatile; yet they also find that periodic jumps in emission price reduce investment less than do policies that change in a more continuous fashion. Blyth et al. (2007) accordingly recommend that regulators reduce long-term policy uncertainty if they wish to promote investment in energy-efficient technologies. Ritzenhofen and Spinler (2016) find only a limited effect of regulatory uncertainty under a regime of feed-in tariffs on investment, but they argue that this result reflects particular modeling assumptions; they expect that optimal investment levels would be lower if regulators were allowed to modify

support regimes retroactively. The claim that uncertainty has a negative effect on investment incentives is supported also by some empirical studies on this subject. Both Fabrizio (2013) and Gulen and Ion (2015) find that regulatory uncertainty reduces investment in the energy sector and also in a US sample spanning multiple industries. The results reported by Gulen and Ion suggest that this effect is even stronger when investment is irreversible or when firms are heavily dependent on government spending.

The other side of this debate usually adopts a resource-based view of the firm. With regard to power generators in Germany, Hoffmann et al. (2009) argue that policy uncertainty does not postpone investment by firms able to secure a competitive resource, leverage complementary resources, or alleviate institutional pressure—as may occur when societal pressure induces the firm to behave in an environmentally responsible manner. Rodriguez Lopez et al. (2017) conduct a survey of 250 participants in the European Union's Emissions Trading System and find that regulation-induced uncertainty (e. g., about abatement costs) makes a firm *more* likely to invest. Those empirical findings are seemingly confirmed by a real options analysis of uncertain tax policy offered by Hassett and Metcalf (1999). The authors find that, although firm-level investment may be delayed if cost follows a continuous-time random walk, the opposite dynamic may prevail if tax policy follows a stationary and discrete jump process. These results are in accord with the findings in Fuss et al. (2009) just mentioned. Boomsma et al. (2012) also document both deferral and promotion of investment for increased policy uncertainty in the energy sector, where the outcome varies as a function of the regulator's chosen support scheme(s).

The third related line of research is the modeling of technology choice. In the non-shipping literature, the aforementioned model of Reinelt and Keith (2007) also treats technology choice and offers the power generation firm various options, including gas-fired plants, for the replacement of an old coal-fired plant. Fuss et al. (2009) also allow for investment in fossil-fuel technology, with and without carbon capture, as well as in alternative renewable energy sources. They find that—under SO_x emission price uncertainty—firms prefer to invest in coal-fired power plants, to retrofit carbon capture technology when that approach is dictated by the economics of SO_x penalties, and to make the transition to renewable energies only as a last resort. This behavior pattern reflects the anticipated benefit of waiting until uncertainty is resolved. Kettunen et al. (2011) provide another example of using real options approaches to study technology choice in the energy business. With regard to shipping, Acciaro (2014) uses real options to compare different means of complying with the limits established for emission control areas. He finds that immediate retrofitting of liquefied natural gas (LNG) propulsion is less profitable than switching to low-sulfur fuels, despite the latter approach's high cost. The advisability of deferring investment in an LNG retrofit depends on the price difference between high- and low-sulfur fuels. Patricksson et al. (2015) establish a fleet renewal model in which a fleet's ships can either switch fuel when entering ECAs, avoid ECAs altogether, or be retrofitted with so-called scrubber systems; the second stage of this model incorporates allocation of capacity to different trade lanes. These authors show that considering new regulation and technology choices are crucial elements of maritime investment decision making.

The model that we propose combines a capacity investment problem with technology choice under regulatory uncertainty. We extend the model of Drake et al. (2016), who analyze the effects of an emissions tax regime and an emissions cap-and-trade regime on technology choice in a two-stage model. In particular, we incorporate the following new features: an endogenous price function, a stochastic introduction of regulation that increases operating costs, and an additional charter option. These features render the model suitable for the analysis of shipping markets and of the possibility that emissions will be regulated. We also model explicitly the environmental effect of regulation on emissions in order to compare the effectiveness of two different regulatory policies: a *cap* versus a *tax* on emissions.

4.3 INVESTMENT UNDER REGULATORY UNCERTAINTY

In this section we formulate a two-stage, regime-switching real options model for technology choice under regulatory uncertainty, thereby extending a model proposed by Drake et al. (2016). Our model—in all its forms—presupposes a monopolistic market setting. Even though the container shipping sector more closely resembles an oligopoly, the monopoly assumption makes it easier to analyze how regulatory uncertainty affects the firm's choice of technology. This assumption also allows us to incorporate more features of the market being considered and facilitates isolating their impact on optimal decision making. We are confident that the effects of market characteristics are qualitatively similar in monopolistic and oligopolistic settings, as Aguerrevere (2003) has shown. Because we aim to identify the directional effects of regulatory uncertainty and are not concerned with the precise sizing of markets, we have adopted the assumption that this setting is a monopolistic one.

We begin by deriving an analytical market model that yields general analytical results. Yet because this version of the model requires strict assumptions that need not apply in practice, we shall later relax those assumptions and derive implications by way of a numerical study in which the model is calibrated to the container shipping industry.

4.3.1 *Analytical Model of the Shipping Market*

The analytical investment model introduced next forms the basis for all extensions developed later in the paper. After presenting this model in Section 4.3.1.1, we derive analytical results in Section 4.3.1.2. A numerical extension with less strict assumptions then follows in Section 4.3.2.

4.3.1.1 *Investment under Market and Regulatory Uncertainty*

We consider a monopolistic ship investor/operator in a stochastic model with two phases: an investment phase and an operating phase. In the first of these phases, the investor may acquire shipping capacity based on various technologies that feature different investment costs, operating costs, and levels of environmentally damaging emissions. At the time of investment, the shipping firm faces uncertainty about future demand and about whether (or not) the market

will be regulated. These uncertainties are resolved after phase 1. In phase 2, the investor can operate the “owned capacity” acquired in phase 1 and can also resort to chartering should demand exceed that shipping capacity. The shipper is free to decide whether or not owned capacity is employed in phase 2 as well as which technology is employed first.

The model can be more easily understood if we first consider phase 2, the operating phase. In a monopolistic market, container transport can be offered at market price $p = \beta D^\gamma$; thus the freight rate depends on demand D and the “tuning” parameters β and γ . Demand in our model is a stochastic parameter, but uncertainty is resolved before the second phase and so demand is a known quantity at that point. Both the market price p and demand D refer to one container being transported one way on a round-trip. Transportation demand can be served by the shipper using its owned capacity acquired in phase 1. Such capacity can be based on different technologies, which we label using the subscript i . Equation (4.1) formalizes the total costs incurred by a ship’s operator, in phase 2, as a function of the transported quantity q_i . Our model explicitly accommodates the stochastic risk that regulation will be introduced in the market. The parameter α indicates whether the market is unregulated ($\alpha = 0$) or regulated ($\alpha = 1$) in the operating phase.

In an *unregulated* market, we assume that capacity enabled by any particular technology can be operated in its standard configuration (i.e., as it has been delivered to the shipper). Then the owned capacity employing technology i can be operated at cost $c_i^{o, \text{std}}$ per twenty-foot equivalent unit (TEU) transported. In a *regulated* market, compliance requires that the shipper’s vessels be retrofitted; the result is a higher operating cost, $c_i^{o, \text{ret}}$, for a unit of capacity based on retrofitted technology i .

Instead of operating its owned capacity, the shipper also has what is known as the layup option. A shipper that chooses to operate less than its available shipping capacity, K_i , incurs a layup cost of c^l . Note that both fixed and flexible costs are included in the operating cost c_i^o , which applies to all capacity operated in the market. Ships in layup do not incur this cost; instead they incur the lower layup cost c^l , which represents only the fixed part of operating costs (i.e., crewing and maintenance). Finally, the shipper incurs a debt financing cost on invested capital. While K_i denotes the units of owned capacity, k_i denotes the price per unit of capacity in which the firm invested during phase 1. The term c^f stands for the debt financing cost as a percentage of total invested capital. Thus the overall cost function C is expressed formally as

$$C = \sum_i [((1 - \alpha)c_i^{o, \text{std}} + \alpha c_i^{o, \text{ret}})q_i + \max\{K_i - q_i, 0\}c^l + K_i k_i c^f] + ((1 - \alpha)c_c^{o, \text{std}} + \alpha c_c^{o, \text{ret}} + c^c)q_c, \quad (4.1)$$

where

$$q_c = \max\left\{D - \sum_i K_i, 0\right\}.$$

When stochastic demand D exceeds available owned capacity $\sum_i K_i$, the shipper can bridge that capacity gap by accessing the charter market, thus offering transportation via chartered capacity q_c . Like owned ships, chartered capacity

can be operated at a standard operating cost $c_c^{o, \text{std}}$ in an unregulated market ($\alpha = 0$) or at a higher cost $c_c^{o, \text{ret}}$ in a regulated market that requires ships to be retrofitted. Moreover, a charter rate c^c is added for every unit of chartered capacity. We remark that capacity is chartered only if doing so is profitable—that is, only if the market price exceeds operating and chartering costs.

The cost function can now be used to establish a formula characterizing firm profits. The ship operator will maximize those profits by identifying the optimal transportation quantities q_i . Here the operator has two options. First, the shipper can decide to leave capacity idle in layup if operation would be unprofitable; this option is reflected by the $(\cdot)^+$ formulation for both owned and chartered capacity. Second, the shipper retains “dispatch flexibility” and can therefore choose which type of available capacity to employ (i. e., which technology is used first to serve demand). The constraints on this profit maximization problem are that transportation volume must be nonnegative and, in the case of owned ships, cannot exceed available capacity. Neither can transportation volume exceed market demand D . Hence we can write

$$\begin{aligned} \pi(D, \alpha, K_i) = \max_{q_i} & \sum_i (p - (1 - \alpha)c_i^{o, \text{std}} + \alpha c_i^{o, \text{ret}} + c^l)^+ q_i \\ & + (p - (1 - \alpha)c_c^{o, \text{std}} - \alpha c_c^{o, \text{ret}} - c^c)^+ q_c - \sum_i K_i (k_i c^f + c^l) \quad (4.2) \\ \text{s.t.} & \quad 0 \leq q_i \leq K_i, \quad q_c \geq 0, \quad \sum_i q_i + q_c \leq D. \end{aligned}$$

As in Drake et al. (2016), we use a *merit-ordering* approach to solve phase 1’s profit maximization problem. This approach requires the following two basic assumptions: (i) all capacity can be operated profitably for all possible realizations of stochastic demand and the resulting freight rate; and (ii) the merit ordering of technologies is already known in the investment phase. Assumption (ii) implies that, in the analytical solution, there cannot be two different merit orders in a regulated and an unregulated market. We use a sorting function to rank owned capacity in terms of decreasing marginal profit; thus $\Omega(j) = \arg \max_{i \in N \setminus \Omega(\{1, \dots, j-1\})} \partial \pi / \partial q_i$. This function returns which technology i ranks in j th place as regards the marginal profit merit order of technologies. For simplicity and comparability, we adopt the notation used in Drake et al. and abbreviate as follows: $[i] = \Omega(i)$; thus subscript $[i]$ refers to the technology in i th place of the merit order. Hence merit ordering allows us to establish that the shipper will first use the most profitable owned capacity available to serve demand. If demand exceeds the capacity of the most profitable technology, then the second most profitable technology will be employed to fill as much of the remaining demand for which capacity is available. The optimal transportation quantities $q_{[i]}^*$ can thus be formulated as the minimum of (a) available capacity and (b) the remaining demand yet to be served:

$$q_{[i]}^* = \min \left\{ K_{[i]}, \left(D - \sum_{i=1}^{i-1} K_{[i]} \right)^+ \right\}. \quad (4.3)$$

Having solved the model's second phase, we can now work backwards to examine the transition between the investment and operation phases. Between these phases, all uncertainty addressed by the model is resolved. In our analytic model, we consider both demand \tilde{D} and regulation $\tilde{\alpha}$ to be *uncertain*; however, we do not further specify the stochastic distribution of either parameter. We only assume that stochastic demand $\tilde{D} > 0$ and that $\tilde{\alpha} \in \{0, 1\}$, where the market is regulated (in phase 2) with probability ξ .

Next we analyze investment during phase 1. At this stage, demand is unknown and it is also unknown whether the market will be regulated in phase 2. Given these uncertainties, the shipper must decide how much total capacity to acquire and from which technology to source that capacity. Of course, not all ordered ships must employ the same technology. Each unit of capacity can be acquired at an investment cost k_i . Thus the investor attempts to optimize the investment project's expected value, which consists of the expected profits from phase 2 *minus* the investment cost from phase 1. The optimization is constrained only by the requirement that ordered capacity may not be negative:

$$V(\tilde{D}, \tilde{\alpha}, K_i) = \max_{K_i} \mathbb{E}[\pi(\tilde{D}, \tilde{\alpha}, K_i)] - \sum_i k_i K_i \quad \text{s.t. } K_i \geq 0 \quad \forall i. \quad (4.4)$$

To be able to derive an analytical solution, we solve this maximization problem for a scenario in which there are two technologies that can be ordered. For our purposes in this paper, technology 1 is defined as an old technology that incurs high operating costs in both unregulated and regulated markets yet is relatively inexpensive to procure. Technology 2 is ecologically friendly but requires high levels of investment; however it incurs lower operating costs in both unregulated and regulated markets. Maximizing the value function for these two capacity types yields the optimal investment described by Proposition 1. See Appendix C.2 for a proof that solving Eq. (4.4) yields the optimal capacity choice; our model's variables are all listed and defined in Appendix C.1.

Proposition 1. *Under demand and regulatory uncertainty, assume that the merit order is known ex ante. Then, provided that phase 2's marginal profits are positive, optimal capacity $K_{[1]}^*$ and $K_{[2]}^*$ are given by:*

$$K_{[1]}^* = \begin{cases} 0 & \text{if } \bar{c}_c^o + c^c \leq k_{[2]} + k_{[2]}c^f + \bar{c}_{[2]}^o, \\ \hat{K}_{[1]} & \text{if } \frac{k_{[1]} + k_{[1]}c^f - k_{[2]} - k_{[2]}c^f}{\bar{c}_{[2]}^o - \bar{c}_{[1]}^o} \leq \frac{k_{[2]} + k_{[2]}c^f + c^l}{\bar{c}_c^o - \bar{c}_{[2]}^o + c^c + c^l} \\ & \wedge \bar{c}_c^o + c^c > k_{[2]} + k_{[2]}c^f + \bar{c}_{[2]}^o, \\ 0 & \text{if } \bar{c}_{[1]}^o + k_{[1]} + k_{[1]}c^f \geq \bar{c}_{[2]}^o + k_{[2]} + k_{[2]}c^f \\ & \wedge \bar{c}_c^o + c^c > k_{[2]} + k_{[2]}c^f + \bar{c}_{[2]}^o, \\ F_D^{-1} \left(1 - \frac{k_{[1]} + k_{[1]}c^f - k_{[2]} - k_{[2]}c^f}{\bar{c}_{[2]}^o - \bar{c}_{[1]}^o} \right) & \text{otherwise;} \end{cases}$$

$$K_{[2]}^* = \begin{cases} 0 & \text{if } \bar{c}_c^o + c^c \leq k_{[2]} + k_{[2]}c^f + \bar{c}_{[2]}^o, \\ 0 & \text{if } \frac{k_{[1]} + k_{[1]}c^f - k_{[2]} - k_{[2]}c^f}{\bar{c}_{[2]}^o - \bar{c}_{[1]}^o} \leq \frac{k_{[2]} + k_{[2]}c^f + c^l}{\bar{c}_c^o - \bar{c}_{[2]}^o + c^c + c^l} \\ & \wedge \bar{c}_c^o + c^c > k_{[2]} + k_{[2]}c^f + \bar{c}_{[2]}^o, \\ \hat{K}_{[2]} & \text{if } \bar{c}_{[1]}^o + k_{[1]} + k_{[1]}c^f \geq \bar{c}_{[2]}^o + k_{[2]} + k_{[2]}c^f \\ & \wedge \bar{c}_c^o + c^c > k_{[2]} + k_{[2]}c^f + \bar{c}_{[2]}^o, \\ \hat{K}_{[2]} - K_{[1]}^* & \text{otherwise.} \end{cases}$$

Here

$$\hat{K}_{[i]} = F_D^{-1} \left(1 - \frac{k_{[i]} + k_{[i]}c^f + c^l}{\bar{c}_c^o + c^c - \bar{c}_{[i]}^o + c^l} \right),$$

$$\bar{c}_{[i]}^o = (1 - \xi)c_{[i]}^o + \xi c_{[i]}^o, \quad \bar{c}_c^o = (1 - \xi)c_c^o + \xi c_c^o.$$

This proposition reveals that there exists a range of strategies that include making no investment at all, effecting a “portfolio solution”, and adopting the “corner solution” of investing in just one technology. It is optimal for the shipper *not* to invest if, after investment cost is accounted for, the total costs of chartered capacity are lower than those of owned technology. Under this approach, the shipper waits until phase 2 and then makes a myopic decision about the optimal charter and transportation quantities depending on perceived demand and the shipper’s belief about the likelihood of future market regulation.

However, if chartering is—as would normally be expected—more expensive, then a corner solution involving a single-technology investment strategy is optimal in the two cases described next. (i) If the second condition in the set of optimal solutions holds, the investor builds up capacity using only technology [1] (here, the clean technology) and has a higher operating margin. This may occur if the sum of the investment cost and the fixed (i. e., layup) cost of dirty technology [2] is not low enough to compensate for [2]’s operating margin disadvantage as compared with technology [1]. The left-hand side (LHS) of the condition gives the additional investment in [1] needed for every dollar of gain in the operating margin versus technology [2]. If that ratio is smaller than the additional investment in [2] needed for every dollar of gain in the operating margin versus chartering, then it is optimal to invest only in technology [1], for which operating profits are achievable at the lowest relative investment cost. (ii) If the investment and fixed costs of dirty technology [2] are low enough to compensate for its operating margin disadvantage, then [2] becomes the more profitable technology overall. In this case, the outcome is a single-technology strategy with investment only in $K_{[2]}$ despite the lower operating margin. In both single-technology strategies, the amount of investment is defined by the upper bound of $\hat{K}_{[i]}$ that is derived by setting the other technology’s capacity to zero: $K_{[-i]} = 0$. This statement follows because the value function is concave in capacity K_1 and also in capacity K_2 (see Appendix C.2 for details) and because the cross partial derivative is negative (see Eq. (C.8)).

Finally, a portfolio solution consisting of both technologies is optimal in all other cases. This solution obtains if owning vessels is cheaper overall than char-

tering and if neither technology clearly outperforms the other. Under those circumstances, the most certain part of stochastic demand is served with clean and profitable technology [1], which typically requires a greater investment and likely involves more risk. The least certain peaks of demand are served with the operationally less profitable dirty technology [2], for which both investment cost and risk are lower. These results for the optimal capacity and technology choices are similar to those reported in Drake et al. (2016). The main difference stems from the additional charter option included in our model, which must be considered when assessing the trade-offs of investing in either of the two technologies.

4.3.1.2 Implications for Optimal Investment

We now explore how regulatory uncertainty affects the optimal choice of capacity and technology in this analytical model; we also show how the charter option contributes value to the overall investment project, especially under regulatory uncertainty. Regulatory uncertainty in our model is proxied by the possible introduction of new environmental policy that requires retrofitting extant capacity for compliance purposes. Depending on the technology of ships purchased, retrofitting may entail either a small or a large additional cost. The following corollary shows how total capacity changes as new regulations become more likely to be enacted (i. e., as ξ increases).

Corollary 1. *Suppose the market is characterized by regulatory uncertainty. Assume that the merit order is known ex ante and that positive marginal profits are generated in phase 2. Then total owned capacity*

$$K_{[1]}^* + K_{[2]}^* \begin{cases} \text{increases with } \xi, & \text{if } (c_c^{o,\text{ret}} - c_c^{o,\text{std}})/(c_{[2]}^{o,\text{ret}} - c_{[2]}^{o,\text{std}}) > 1, \\ \text{decreases with } \xi, & \text{if } (c_c^{o,\text{ret}} - c_c^{o,\text{std}})/(c_{[2]}^{o,\text{ret}} - c_{[2]}^{o,\text{std}}) < 1. \end{cases}$$

The displayed statements are true provided that $c_c^o + c^c > k_{[2]} + k_{[2]}c^f + c_{[2]}^o$ holds; otherwise, investment remains at $K_{[1]}^ + K_{[2]}^* = 0$ per Proposition 1.*

For an increase in regulation probability ξ , total capacity increases if the operating cost of chartered capacity rises more—in response to the change from an unregulated to a regulated market—than does owned (dirty) capacity [2]. Otherwise, total investment declines. Note that total owned capacity is driven by the operating cost of [2], the *less* profitable technology. Because increasing owned capacity would replace chartered ships in the operation phase, the relative size of their marginal operating profits determines the overall effect of regulation on investment.

Corollary 2. *Let the market be characterized by regulatory uncertainty, let the merit order be known ex ante, and suppose that phase 2 yields positive marginal profits. Then the choice of technology changes with an increase in regulation probability ξ , depending on which case of the optimal solution (described in Proposition 1) applies:*

- (a) $K_{[1]}^*$ and $K_{[2]}^*$ remain unchanged ($K_{[1]}^* = K_{[2]}^* = 0$).

- (b) $K_{[1]}^* \begin{cases} \text{increases with } \xi, & \text{if } (c_c^{o,\text{ret}} - c_c^{o,\text{std}})/(c_{[1]}^{o,\text{ret}} - c_{[1]}^{o,\text{std}}) > 1 \\ \text{decreases with } \xi, & \text{if } (c_c^{o,\text{ret}} - c_c^{o,\text{std}})/(c_{[1]}^{o,\text{ret}} - c_{[1]}^{o,\text{std}}) < 1 \end{cases}$
 $K_{[2]}^*$ remains unchanged.
- (c) $K_{[1]}^*$ remains unchanged;
 $K_{[2]}^* \begin{cases} \text{increases with } \xi, & \text{if } (c_c^{o,\text{ret}} - c_c^{o,\text{std}})/(c_{[2]}^{o,\text{ret}} - c_{[2]}^{o,\text{std}}) > 1 \\ \text{decreases with } \xi, & \text{if } (c_c^{o,\text{ret}} - c_c^{o,\text{std}})/(c_{[2]}^{o,\text{ret}} - c_{[2]}^{o,\text{std}}) < 1 \end{cases}$
- (d) $K_{[1]}^* \begin{cases} \text{increases with } \xi, & \text{if } (k_{[1]} + k_{[1]}c^f - k_{[2]} - k_{[2]}c^f) \\ & \times (c_{[2]}^{o,\text{ret}} - c_{[2]}^{o,\text{std}} + c_{[1]}^{o,\text{std}} - c_{[1]}^{o,\text{ret}}) > 0 \\ \text{decreases with } \xi, & \text{otherwise.} \end{cases}$
Change of $K_{[2]}^*$ is unclear.

If chartering is so cheap that no investments are made, then a change in the likelihood of regulation does not alter investment behavior in phase 1. In both cases of a single-technology solution, the same logic holds as for total owned capacity. If the operating costs of owned ships increase less under new regulation than do the costs of chartering vessels, then the optimal amount of investment in that single technology increases. The portfolio solution case is more complicated. Although one cannot know in advance how new regulation affects capacity $K_{[2]}$, investment in the more profitable [1]-based capacity increases: (i) if such capacity has a higher investment cost $k_{[1]}$ yet its operating cost increases less under regulation than does the operating cost of technology [2]; or (ii) if [1]-based capacity suffers more than does [2]-based capacity from increased post-regulation operating costs yet has a lower investment cost. In a portfolio solution with technologies as specified previously, scenario (i) is most likely when clean capacity [1] requires more investment—but is less affected by tighter regulation—than [2]. Then it becomes more likely that the firm invests in clean technology.

Thus we have demonstrated that the charter option has a significant effect not only on total capacity but also on the choice of technology—since ordering more owned vessels reduces the likelihood of chartering. Corollary 3 details when the charter option contributes to the overall investment project value.

Corollary 3. *Let the merit order be known ex ante, and suppose as before that phase 2 generates positive marginal profitability. Then, under regulatory uncertainty, chartering adds value to the portfolio solution of the investment project provided that $\Pr(\tilde{D} > K_{[1]}^* + K_{[2]}^*) > 0$. These inequalities hold if*

$$\bar{c}_c^o + c^c > \bar{c}_{[2]}^o - c^l.$$

The displayed condition is satisfied for all cases in Proposition 1 that result in the firm investing in accordance with either the single-technology or portfolio solution. When the condition does *not* hold, a charter-only solution is optimal—

in which case chartering is the sole contributor to project value. For all other cases in Proposition 1, there is always a positive probability that demand will exceed owned transportation capacity and so chartering will contribute to the project's overall expected value.

4.3.2 Numerical Extension: Relaxing the Assumptions

The analytical model presented in previous sections is based on two key assumptions: first, that all shipping capacity (whether owned or chartered) can be operated profitably in both unregulated and regulated markets; second, that the merit order is already known in the investment phase. Yet real-world regulation can alter the merit order of technologies and in some cases can even render technologies unprofitable. Therefore, in this section we relax both assumptions and solve the model numerically for a scenario in which merit ordering occurs instead during the operation phase. In order to derive the expected value of future profits, as presented in Eq. (4.4), we perform a Monte Carlo simulation of 50,000 stochastic demand and regulation realizations—thereby ensuring convergence to the true expected value. To solve the phase-1 optimization problem we employ MATLAB's pattern search algorithm (from its Global Optimization Toolbox) for constrained, derivative-free optimization. Our insights are then derived by simulating and solving the model for different parameter settings that are based on a calibration to the international container shipping industry.

4.3.2.1 Model Calibration

For the numerical experiments, we calibrate the model to international container shipping and the industry's exposure to regulations aimed at reducing sulfur (SO_x) emissions. With its revision of the International Convention for the Prevention of Marine Pollution from Ships (MARPOL) Annex VI, the IMO introduced a staged approach to reducing such emissions both worldwide and in special emission control areas. The sulfur content allowed in shipping fuels is summarized in Table 4.1. The actual date upon which a worldwide limit of 0.5% m/m was to become official had been substantially delayed pending a review, but that date has recently been confirmed to be 2020. Ship operators have three main options for complying with the new regulation. The compliance option in widest use is fuel switching. On worldwide trade routes, ships mostly operate on heavy fuel oil (HFO)—a residual fuel whose sulfur content is normally 3.5%. The MARPOL revision dictates that ships entering ECAs, and ships sailing anywhere after 2020, must reduce their emissions. Such reduction can be achieved by switching to (more expensive) low-sulfur distillate fuels, such as marine diesel oil (MDO), or by retrofitting or building ships to operate on liquefied natural gas. The latter option is expensive and so is rarely used. The most popular method (after fuel switching) used to reduce emissions is the retrofitting of exhaust gas-cleaning systems or *scrubbers*. When fitted with scrubbers, ships can continue operating on cheaper HFOs because the scrubber captures SO_x particles from the exhaust (Den Boer and Hoen 2015, Lloyd's Register 2015).

Table 4.1: Sulfur oxide emission limits defined by MARPOL.

Outside an ECA	Inside an ECA
4.5% m/m prior to 1 January 2012	1.5% m/m prior to 1 July 2010
3.5% m/m on and after 1 January 2012	1.0% m/m on and after 1 July 2010
0.5% m/m on and after 1 January 2020	0.1% m/m on and after 1 January 2015

Note: ECA = emission control area; m/m = mass per mass (i.e., percentage mass of sulfur oxide gases in the total mass of the emission).

Source: Adapted from International Maritime Organization (2016b).

In the following analyses, our model takes the introduction of a worldwide 0.5% SO_x limit as the change in regulatory regime faced by shippers. A shipping firm can invest in a standard ship (technology 1) that operates on HFO in an unregulated market but must switch to more expensive MDO if SO_x limits are reduced. As technology 2, we consider an “eco-friendly” ship equipped with a scrubber.² We shall assume that all available chartered vessels must also resort to fuel switching.

As summarized in Table 4.2, the model parameters have been set as follows. We consider the trade lane between Asia and the US West Coast, for which the yearly transport volume is about 13 million TEU (Alphaliner 2016). We assume that demand is drawn from a truncated normal distribution (Botev 2017) centered at $\mu = 13$ million and with volatility $\sigma = 0.2$. The distribution’s lower boundary is truncated at zero because we require that demand be strictly positive. The freight rate (p) at the time of writing was about \$850 (US) from Shanghai to Los Angeles and \$340 for the return trip (World Freight Rates 2017). We set that price function’s tuning parameters to $\beta = 0.15$ and $\gamma = 0.5$ to reach a representative market price when demand is 13 million TEU per year.

Table 4.2: Base-case parameters used in all models (unless specified otherwise).

Market parameters					
$\beta = 0.15$	$\mu = 13 \text{ mn}$	$c^f = 0.02$	$\xi = 0.25$	$\tau = 3,500$	
$\gamma = 0.5$	$\sigma = 0.2$	$c^l = 28$	$\bar{e} = 0.6$	$\hat{\chi} = 0.005$	
Techn. 1: Fuel switch		Techn. 2: Scrubber		Chartering	
$k_1 = 70$		$k_2 = 80$		$c^c = 85$	
$c_1^{o,\text{std}} = 350$	$\chi_1^{\text{std}} = 0.035$	$c_2^{o,\text{std}} = 355$	$\chi_2^{\text{std}} = 0.035$	$c_c^{o,\text{std}} = 350$	$\chi_c^{\text{std}} = 0.035$
$c_1^{o,\text{ret}} = 450$	$\chi_1^{\text{ret}} = 0.005$	$c_2^{o,\text{ret}} = 380$	$\chi_2^{\text{ret}} = 0.001$	$c_c^{o,\text{ret}} = 450$	$\chi_c^{\text{ret}} = 0.005$

²We focus exclusively on the vessel’s SO_x impact. However, some have objected that scrubbers are not environmentally beneficial because they reduce fuel efficiency and because vessels that continue to operate on HFOs still emit—that is, even with scrubbers—high levels of other emissions (e.g., particulate matter). See Lindstad and Eskeland (2016).

For all ship-specific parameters, we assume a neo-Panamax container vessel with a capacity of 12,000 TEU. Because we are interested in yearly costs, we assume that the ship completes six round-trips on the Asia–US route with an average utilization of 80%, yielding a yearly capacity of 115,200 TEU. According to a study on vessel operating costs AECOM (2012), the standard 12,000-TEU ship costs about \$120 million; hence $k_1 = \$70$ on an annual per-TEU basis—assuming that the vessel has an economic lifetime of 15 years. A technology-1 (fuel-switching) ship has a standard operating cost of $c_1^{o, \text{std}} = \$350/\text{TEU}$ when operating on HFO. This figure is based on annual maintenance and personnel costs of \$3.3 million (AECOM 2012) and an HFO price of \$300/ton (Ship & Bunker 2017). In a regulated market, operating costs increase because the MDO fuel cost is \$400/ton (Ship & Bunker 2017); thus $c_1^{o, \text{ret}} = \$450/\text{TEU}$.

It is also possible to order technology-2 ships (here, those equipped with a scrubber) but at a higher investment cost of $k_2 = \$80/\text{TEU}$. This figure is based on a price of \$15 million—or \$200 per kilowatt of engine power—for installation of a scrubber (Den Boer and Hoen 2015), where the typical engine size is 75,000 kW (MAN Diesel & Turbo 2013). The ship with scrubber can be operated at $c_2^{o, \text{std}} = \$355/\text{TEU}$, which includes a small cost premium for scrubber maintenance (although we assume that the scrubber is deactivated in an unregulated market). In a regulated market, the scrubber is activated while the ship continues to operate on HFO. The scrubber technology entails an additional annual cost of about \$3 million due to maintenance, operating materials, and the vessel’s consequent reduced fuel efficiency (Lindstad et al. 2015, Van Rynbach et al. 2015). In a regulated market, then, a technology-2-based ship’s operating cost is $c_2^{o, \text{ret}} = \$380/\text{TEU}$. Irrespective of their technology base, owned ships can be laid up at a cost of $c^l = \$28/\text{TEU}$, a figure that incorporates a vessel’s fixed costs of \$3.3 million per year for maintenance and personnel. When laid up, ships are assumed to incur no fuel cost. Unless otherwise indicated, we assume a regulation probability of $\xi = 0.25$.

Chartered ships have the same operating cost as do owned ships that rely on fuel switching (technology 1). Additionally, a charter cost of $c^c = \$85/\text{TEU}$ applies. This figure reflects daily charter costs of \$10,000 for a 4,250-TEU vessel, which we have scaled up to the standard 12,000-TEU ship and converted to the corresponding TEU volume on an annual capacity basis (VHSS Vereinigung Hamburger Schiffsmakler und Schiffsbagenten e.V. 2015). The emission parameters given in Table 4.2 will be discussed in Section 4.4.

4.3.2.2 *Implications for Optimal Investment*

We now take a numerical approach to analyzing technology choice and the influence of regulatory uncertainty. Figure 4.1 plots total owned capacity and its composition (by technology) for the base-case parameters as a function of the regulation probability ξ . The graph shows that it is always optimal, under these parameters, to adopt a single-technology strategy. There exist very few combinations of other parameter values for which a portfolio solution would be optimal. Figure 4.1 also reveals the switching point between strategies: whereas a fuel-switching strategy based on standard container ship technology (i. e., technology 1) is optimal at low regulation probabilities, technology-2 ships with

scrubbers become more attractive at $\xi \geq 0.3$. Note that this result holds even though—unlike our specification for the analytical model—the merit order of technologies 1 and 2 is not known ex ante. If the market remains unregulated (resp., becomes regulated), then fuel-switching ships will be cheaper (resp., more expensive) to operate.

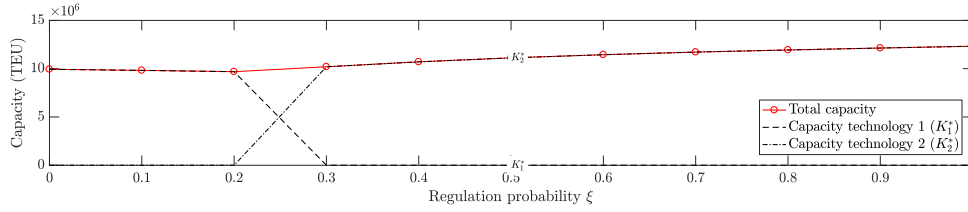


Figure 4.1: Optimal total owned capacity and technology choice for different regulation probabilities ξ .

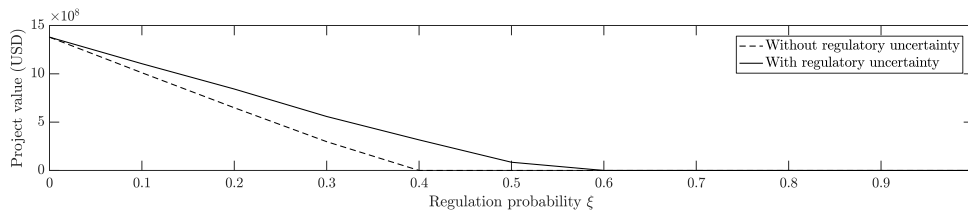
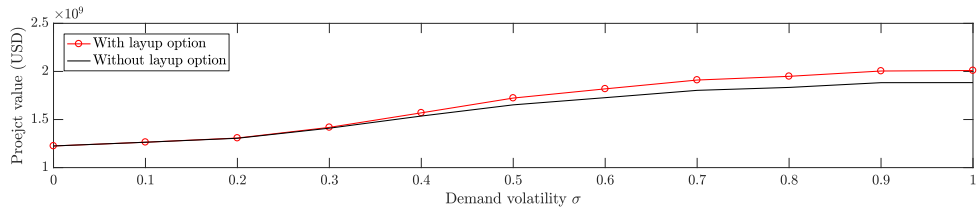


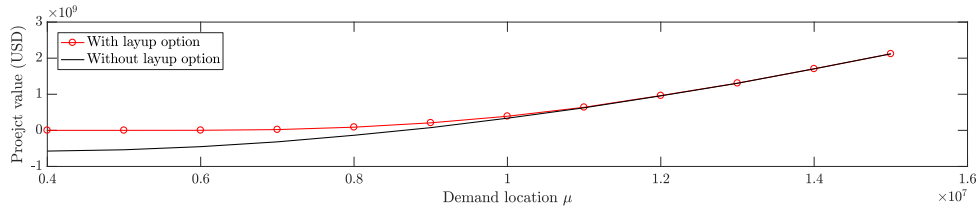
Figure 4.2: Total expected project value for investment projects with and without regulatory uncertainty as a function of the regulation probability ξ . *Note:* Operating cost in the scenario without regulatory uncertainty assumed to equal the expected operating cost in the scenario with regulatory uncertainty.

Although the model identifies a single-technology strategy as optimal, regulatory uncertainty does increase the investment project’s value. Figure 4.2 compares project values in a regime where operating costs are deterministic with values in a regime where the possibility of regulation renders those costs stochastic. For a fair comparison, we assume that capacity in the no-regulation scenario can be handled at the average expected operating cost that applies when future regulation is uncertain. Two results are clearly evident. First, increases in the likelihood of regulation reduce the investment project’s value: despite the unchanged operating costs in regulated and unregulated markets, a higher regulation probability increases expected cost. Second, under regulation uncertainty the project has greater value because of the shipper’s available options in responding to potential regulation. In particular, both the option to charter and the layup option (for unprofitable technologies) limit the shipper’s investment risk.

Figure 4.3 details one of these sources of value: the layup option. In Figure 4.3a we can see that project values—across all levels of demand volatility σ —are no less with the layup option than without it. The option of laying up unprofitable vessels is especially attractive at high levels of demand volatility, where it is more likely that the prices a shipper can charge will fall to such low levels that it is no longer possible to cover operating expenses. Similarly, the layup option can limit firm losses when expected demand \bar{D} is low; that dynamic is evident in Figure 4.3b. Thus the layup option, the charter option, and the flexibility to employ the most profitable technology all lead to increased



(a) Project value with and without the layup option for different values of demand volatility σ



(b) Project value with and without layup option for different demand locations μ

Figure 4.3: Value added due to the layup option under various scenarios.

project values under regulatory uncertainty as compared to the case of shippers facing a deterministic operating cost that equals the *expected* value under uncertainty.

4.4 EVALUATING EMISSION REGULATION REGIMES

We have heretofore treated potential regulation as the source of a stochastic increase in operating costs. Next we extend the model to reflect two specific environmental policy regimes. We also now grant shippers the flexibility to decide whether their vessels should be retrofitted (i.e., operated at a higher cost) for compliance purposes. This approach allows us to adopt the perspective of a regulator, who must be cognizant of the effects that different regulatory regimes have—on market participants' investment and operating behavior—when devising a regime intended to achieve regulation targets efficiently. We shall examine outcomes under two different regimes, a emissions cap and an emissions tax, and then compare how those regimes affect a shipper's optimal strategies.

4.4.1 Emissions Cap Regime

The regulatory regime we discuss first is one that strictly prohibits the operation of vessels that exceed a predefined emissions cap. This regime matches the actual SO_x regulation as passed by the IMO, which allows the operation of only those vessels that can meet the prevailing SO_x limit—either by switching fuels, installing a scrubber, or employing LNG propulsion. To adapt the model previously developed to this new policy regime, we define \bar{e} as the average fuel consumption required for transporting 1 TEU on the trade route between Asia and the United States. Furthermore, we let χ_i^{std} denote the SO_x emissions level of technology i in its standard configuration and let χ_i^{ret} denote that level in the retrofitted configuration (i.e., operating on MDO fuel or with an activated

scrubber). The term $\hat{\chi}$ represents the maximum allowable SO_x emission level in the regulated market. Given these parameters, we can express the adapted profit function. Again we assume that the market can be either unregulated (in which case the old emissions cap of 3.5% SO_x applies) or regulated (where the limit is lowered to 0.5%). We allow the shipper to decide, in light of particular regulatory demands, whether it wants to employ technologies in their standard or retrofitted configurations. Hence the profit function can change because, for each technology i , the shipper will choose the more profitable configuration (standard vs. retrofit) that complies with the emissions cap. If a configuration of technology i achieves regulatory compliance, the indicator function used in the following definition of firm profits becomes $I_{[\alpha\chi_i^{\text{std/ret}} \leq \hat{\chi}]} = 1$. The same function applies to chartered capacity, where the shipper can also choose the standard or retrofitted configurations provided that the emission requirements are satisfied:

$$\begin{aligned} \pi = & \max_{q_i} \left\{ \sum_i \left(\max\{(\beta\tilde{D}^\gamma - c_{[i]}^{\text{o, std}} + c^l)I_{[\alpha\chi_i^{\text{std}} \leq \hat{\chi}]}, (\beta\tilde{D}^\gamma - c_{[i]}^{\text{o, ret}} + c^l)I_{[\alpha\chi_i^{\text{ret}} \leq \hat{\chi}]} \}^+ q_i \right) \right. \\ & + \max\{(\beta\tilde{D}^\gamma - c_{[c]}^{\text{o, std}} - c^c)I_{[\alpha\chi_c^{\text{std}} \leq \hat{\chi}]}, (\beta\tilde{D}^\gamma - c_{[c]}^{\text{o, ret}} - c^c)I_{[\alpha\chi_c^{\text{ret}} \leq \hat{\chi}]} \}^+ \\ & \times \left(\tilde{D} - \sum_i K_{[i]} \right)^+ - \sum_i K_{[i]}(k_{[i]}c^f + c^l) \left. \right\} \\ & \text{s.t. } 0 \leq q_i \leq K_i \text{ and } \sum_i q_i \leq D \quad \forall i. \end{aligned} \tag{4.5}$$

It is worth noting that, in this version of our model, there is considerable flexibility in setting the emission parameters of the legal cap and also of the individual technologies affected. Whereas the assumption in previous sections was that the retrofitted configurations of all technologies fulfill the requirements of a regulated market, it is now possible to analyze situations in which some technologies cannot be employed at all—that is, not even when retrofitted—after regulation has been introduced. Conversely, however, some technologies can be supposed to “overachieve” with respect to new emission targets. So if the standard configuration of a sufficiently eco-friendly technology fulfills even the regulated market’s requirements, then the shipper now can use the standard (i. e., not retrofitted) configuration in that market.

So that we can analyze the resulting impact on industry emissions, we define total emissions based on the capacities operated in the market; here q^{std} and q^{ret} refer to the transportation quantities available from using (respectively) standard or retrofitted technology. These variables are further marked with the subscript i or c to indicate owned technologies and chartered capacity:

$$E = \sum_i (\chi_i^{\text{std}} q_i^{\text{std}} + \chi_i^{\text{ret}} q_i^{\text{ret}}) \bar{e} + (\chi_c^{\text{std}} q_c^{\text{std}} + \chi_c^{\text{ret}} q_c^{\text{ret}}) \bar{e}. \tag{4.6}$$

4.4.2 Emissions Tax Regime

The second regulatory regime to be analyzed is an emissions tax, which is assessed on all emissions that exceed a predefined threshold. In this regime, the regulator sets both the emissions threshold $\hat{\chi}$ and the tax rate τ that applies to any emissions in excess of $\hat{\chi}$. Much as in the emissions cap regime, the shipper can decide which technologies and configurations thereof to employ. Depending on the cost parameters, it may be optimal to employ a technology in standard configuration with high emissions and simply pay the penalty tax. Yet it might also be more profitable to adopt the cleaner retrofitted configuration, which would have a higher operating cost but would be charged a lower (or no) emissions tax. In the adapted profit function, we thus introduce a minimization between the costs of the standard and retrofitted configurations for each technology. Note that the tax applies only if the market is regulated ($\alpha = 1$) and the emission limit is exceeded ($\chi^{\text{std/ret}} > \hat{\chi}$); furthermore, it applies to the excess $(\chi - \hat{\chi})^+ \bar{e}$ emitted per operated unit. The new profit function is thus written as follows:

$$\begin{aligned} \pi = & \\ & \max_{q_i} \left\{ \sum_i [(p + c^l - \min\{c_i^{\text{o,std}} + \alpha(\chi_i^{\text{std}} - \hat{\chi})^+ \bar{e}\tau, c_i^{\text{o,ret}} + \alpha(\chi_i^{\text{ret}} - \hat{\chi})^+ \bar{e}\tau\})^+ q_i] \right. \\ & + (p - c^c - \min\{c_c^{\text{o,std}} + \alpha(\chi_c^{\text{std}} - \hat{\chi})^+ \bar{e}\tau, c_c^{\text{o,ret}} + \alpha(\chi_c^{\text{ret}} - \hat{\chi})^+ \bar{e}\tau\})^+ q_c \\ & \left. - \sum_i K_i(k_i c^f + c^l) \right\} \\ & \text{s.t. } 0 \leq q_i \leq K_i \text{ and } \sum_i q_i \leq D \quad \forall i. \end{aligned} \tag{4.7}$$

The emissions tax regime grants great flexibility to the shipper, who can freely choose which technology and configuration to employ toward the end of maximizing its profit. Total emissions resulting from operations can be determined as shown in the emissions cap setting formalized in Eq. (4.6).

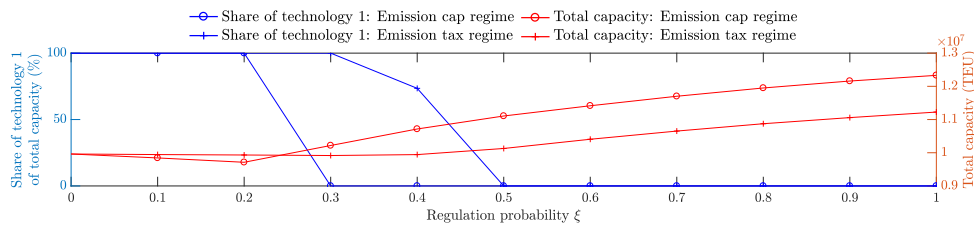
4.4.3 Model Calibration

In addition to the parameters already defined in Section 4.3.2.1, we now calibrate the remaining emissions-related parameters necessary for the regulatory regime extensions just described. Recall that the investor can order owned ships of two technologies: the market standard is technology 1, which requires switching to expensive MDO fuels in order to reach low SO_x emission levels; technology 2 is more expensive to order but is equipped with a SO_x scrubber. Chartered vessels rely on the fuel-switching technology 1 (refer to Table 4.2 for the respective cost parameters). To calculate emission levels, we assume a fuel consumption of $\bar{e} = 0.6$ tons per one-way trip; this figure is based on a typical 12,000-TEU ship's consumption of 450 tons per day and a voyage duration of 13 days (AECOM 2012). Both technology-1 capacity and chartered capacity run on HFO in the standard configuration and emit the HFO-typical 3.5% SO_x per ton of fuel. These statements apply also in the case of technology 2's stan-

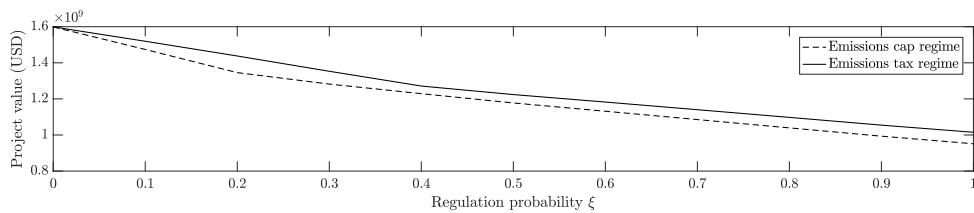
standard configuration, under which the ship operates on HFO and with an idle scrubber. We therefore set all standard emission levels to $\chi_i^{\text{std}} = \chi_c^{\text{std}} = 0.035$. In a retrofitted configuration, both technology-1 vessels and chartered vessels operate on low-sulfur MDO fuel and have emission levels of no more than 0.5% SO_x ($\chi_1^{\text{ret}} = \chi_c^{\text{ret}} = 0.005$). The scrubber retrofitting in technology 2 is even more effective; when activated, it results in emission levels as low as 0.01% (and so $\chi_2^{\text{ret}} = 0.001$). For our numerical analyses we use a tax rate of $\tau = \$3,500$ per extra ton of SO_x emitted. This value is a hypothetical one given that the regulator can set the tax rate at any level. Yet our analyses indicate that a tax rate near this value would be high enough to reduce emissions significantly but also low enough that shipping capacity of lower emission efficiency would not necessarily be excluded. After all, such exclusion would render the emissions tax regime no different than the emissions cap regime.

4.4.4 Performance Comparison

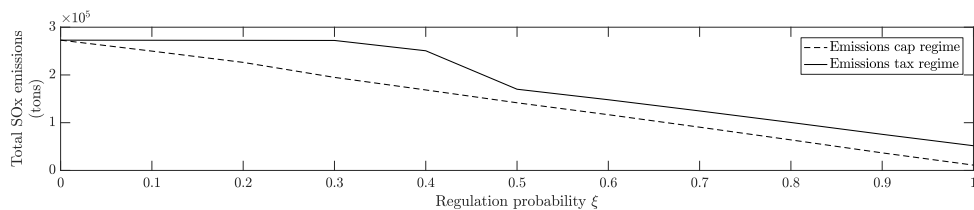
Prior to evaluating the effectiveness of our two proposed policy regimes, we analyze and compare their respective investment levels, project values, and SO_x emissions. These outcomes are illustrated in Figure 4.4. The figure clearly confirms our intuition that an emissions cap regime is the more challenging policy approach because it allows shippers less flexibility. Figure 4.4b documents the consistently lower project values under an emissions cap regime.



(a) Optimal total capacity and choice of technology



(b) Expected project value



(c) Expected total SO_x emissions

Figure 4.4: Comparison of regulatory regimes under various regulation probabilities ξ .

Although regulation via taxes reduces the project value to a lesser extent than does regulation via caps, the shipper's capacity choices differ significantly. Figure 4.4a plots total owned capacity (red lines) and the respective shares of investment in the fuel-switching technology 1 for the emissions cap (circular markers) and the emissions tax (cross marks). The two main findings with regard to technology choice are that, first of all, investing in a single-technology portfolio is the optimal strategy in most cases. Only in a small bandwidth of regulation probabilities do we find a mixture of technologies to be the optimal approach under an emissions tax regime. Second, we see that the stricter regulation associated with an emissions cap regime incentivizes shippers to invest in the eco-friendly technology 2 (scrubbers) even when the likelihood of regulation is low. Thus new technologies are promoted more by capping emissions than by taxing them.

There also are two main results with regard to total owned capacity. The first is that, at low regulation probabilities, more investment in own capacity is observed in the tax regime than in the cap regime. The intuition here is that if regulation is unlikely and emissions are addressed via taxation, then the shipper can still operate technology 1 vessels in standard configuration (burning HFO) by paying an emissions tax that is less than would be the additional cost of switching to MDO fuel. In the cap regime, however, that approach is not an option and so the firm reduces own capacity to lower its investment risk. Then, if more capacity is needed, it makes more sense to secure that by chartering. The second main result is that, once a shipper switches to scrubber technology in the emissions cap regime, it builds up more own capacity than it would in the emissions tax regime. The explanation for this finding is that, if regulation is extremely probable, then the profits from adopting the scrubber technology are much greater than those from chartering. However, a shipper that is short on capacity will be forced to resort to expensive chartered vessels, which can comply with regulation only by using expensive MDO fuel. Because profitability would then decline, the shipper prefers to ensure enough capacity for which policy compliance is relatively inexpensive.

The investment behavior just discussed can also be seen in the SO_x emissions, plotted in Figure 4.4c that result from operations. As expected, the stricter emissions cap regime consistently leads to lower overall emissions. At the same time, the emissions curve of the tax regime clearly shows the points at which an investor would switch technologies. The emissions tax does not have a favorable effect until the regulation probability reaches 30%; only then does the transition to more efficient technologies become optimal—that is, since doing so avoids a profit-reducing tax burden. These technology switches explain the curvature of expected emissions in the tax regime.

We now address the question of how effectively the two considered regimes reduce total emission levels at an acceptable cost. Figure 4.5 shows in a compact way the particular emissions caps and thresholds needed, in each regulation regime, to achieve a certain level of total industry SO_x emissions—and at what cost to the shipper. The graph can be read as follows. If the emission level in a cap regime is to be lowered, then the targeted level of overall industry emissions in tons is given on the x-axis. Moving upward to the blue line with round markers, one can read off the required emissions cap $\hat{\chi}$ on the *left*

y-axis; the total cost of regulating the market can be identified by moving upward to the solid red line and then reading the cost of regulation from the *right* y-axis. The same procedure can be followed with regard to the emissions tax regime. So identifying the nearest cross mark on the blue line lets one read off the required emission threshold $\hat{\chi}$ above which the emissions tax applies. Then, moving upward to the nearest cross on the dashed red line reveals the regulation cost incurred by the shipper. In this tax regime, however, the shipper's regulation cost differs from the overall economic cost of regulation. For the latter, taxes paid are not considered a cost from the perspective of an entire economy; that economic cost is plotted by the figure's "dash-dotted" red line. When interpreting this graph, one must bear in mind that it is impossible to achieve an emission level of (say) 1.5×10^{-5} tons: lowering the emissions cap to below 3.5% immediately reduces total emissions to levels far lower than one would expect as there is only technology available at very high and very low emission efficiency levels. In contrast, lowering the emission threshold in the tax regime to below 3.5% has no effect on total emissions until that threshold falls below 1.6%. At this point, the shipper switches technology and total emissions are reduced instantly because eco-friendly operations become less expensive than paying the emissions tax. It is therefore important to consider only those values that are marked on the graph.

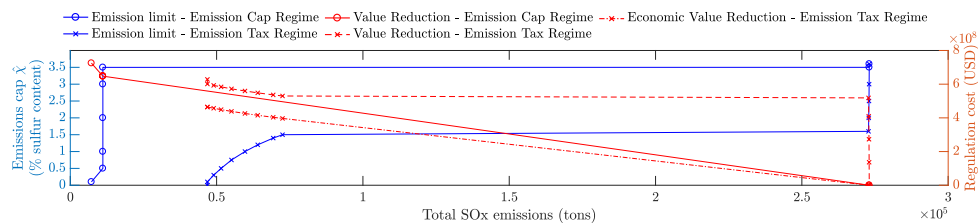


Figure 4.5: Comparison of regulatory regimes: Emission limits and costs associated with achieving mandated emission levels. *Note:* Regulation cost is defined as the difference in project value between an unregulated market ($\xi = 0$) and a market in which regulation is certain ($\xi = 1$).

Four principal findings follow from Figure 4.5. First, a given emissions limit can lead to very different overall emission outcomes in the two regimes. Under an emissions tax regime, outcomes can be further affected by modifying the tax rate per ton of SO_x emitted. Increasing the tax rate (τ) shifts the cross-marked blue emission line of the tax regime to the left. At the currently assumed tax rate of $\tau = \$3,500$ per ton, it is not possible to achieve the same overall reduction in emissions as in the emissions cap regime—that is, regardless of how low a regulator sets the threshold. To achieve the same results, the tax rate would have to be raised. Second, lowering emission limits can sometimes lead to large reductions in overall emissions yet can sometimes have no effect at all. Hence it is essential that the regulator be aware of these “tipping points” if the aim is to design an effective policy. Third, the overall economic cost of a tax regime is significantly less than the profit loss incurred by market participants. In such a regime, then, the regulator reaps some of the shipper profits. Fourth, a tax regime is less costly to implement. The shipper's costs are also lower than in the emissions cap scenario, though with less effectiveness in reducing overall

emissions. Although it is (slightly) more expensive for the shipper, an emissions cap regime achieves significantly lower total emissions.

4.5 IMPLICATIONS FOR OPTIMAL INVESTMENT AND REGULATORY DECISIONS

The results derived from our analytical and numerical approaches described in previous sections bear important implications for optimal investment under regulatory uncertainty from the investor's perspective and also for optimal regulatory design from a legislative viewpoint. Although the model was calibrated for international container shipping, it could easily be adapted to other regulatory and industry settings. Therefore, the implications for investors and regulators should be of interest to a broader audience.

There are four main implications for optimal investment. First, despite the analytical model showing that portfolio solutions of multiple technologies are possible, the numerical study suggests that these are rather unlikely. In our calibration for the shipping industry, a portfolio solution is optimal only in a narrow band of regulation probabilities; in all other cases, a single-technology strategy maximizes expected project value. One caveat to this conclusion is that the two-period model we propose does not account for developments over a longer time span. It seems reasonable to suppose that accounting for additional time periods would increase the attractiveness of a portfolio solution, since in that case the fleet would need to function at optimal levels across periods characterized by a greater variety of trading conditions. The second main implication of our findings is that, as the likelihood of regulation increases, it may be optimal to increase owned capacity. This dynamic applies when the profitability of own technologies are less compromised by a new policy than is the alternative of chartering additional capacity. It follows that if regulation is expected then a careful analysis of predicted cost effects is in order, especially since it may not be immediately self-evident that a shipper's own capacity should be expanded in response to more likely regulation. Third, the wisdom of changing technologies when the regulation probability increases depends on how adversely a technology—as compared with alternative methods of compliance—is affected by new policies. This paper has established that a technology's relative attractiveness can be either heightened or diminished by regulation effects. Finally, we have seen that regulatory uncertainty can increase the expected value of the investment project. Here we must distinguish between two effects. If we compare an unregulated market with one that faces potential regulation, we find that a project's value *decreases* as the average cost of operations increases. However, if we compare a market with a deterministic operating cost that is comparable to the probability-weighted expected operating cost of a market with regulatory uncertainty, then we find that uncertainty *increases* that project's value. This increase in value is explained by the various strategic options (layup option, charter option, dispatch flexibility) available to the shipping firm, which enable an optimal response to market conditions. Those options serve to protect investors against potential losses. Paradoxically,

then, investor payoffs may be greater in a relatively uncertain than in a relatively certain market (provided there is no increase in expected costs).

The numerical study presented in Section 4.4 yields three primary implications relevant to the optimal *design* of regulations. First, a strict emissions cap prohibiting the operation of vessels that do not meet mandated emission standards will reduce overall industry emissions more effectively than an emissions tax regime. Such a cap can also promote more investment in clean technologies that may even overachieve vis-à-vis defined emission targets. Nevertheless, the second implication of our numerical study is that an emissions tax regime—which levies a tax on all emissions above a certain threshold—gives the investor more operational flexibility regarding technology choice. When that flexibility is exploited to maximize profits, an emissions tax regime may end up costing the shipper less even though its operational profits must be shared with tax-levying agencies. These two implications underscore the necessity of regulators having a clear view of their priorities: if the main goal is to minimize emissions and promote clean technology, then an emissions cap is preferable; but if the main goal is to reduce emissions—albeit while minimizing the regulatory effect on profits—then an emissions tax is preferable. The third main implication for regulatory design is illustrated in Figure 4.5. Namely, selecting the emission limit is crucial in both of the regimes examined here. The effect, on overall industry emissions, of lowering that limit is neither linear nor continuous. Regulators should therefore analyze in considerable detail all the technologies available for achieving compliance; only then will the chosen emission limits be likely to have their intended effect.

The findings and implications stemming from our model were derived with reference to container shipping, but the main results should be valid also for other industries. The model itself can likewise be calibrated to fit other industries and regulatory settings. There are, naturally enough, some limitations of the model we develop. For instance, it presupposes a monopolistic market to enable our focus on the main characteristics relevant to this study; notwithstanding our confidence that the results derived here are qualitatively applicable to oligopolistic settings, their quantitative magnitude may well vary. Also, this paper's focus on a change in regulatory regime led us to design a two-phase model. Taking more time periods into account could modify our results and/or yield additional findings of interest.

4.6 CONCLUSION AND IMPLICATIONS FOR FUTURE RESEARCH

This paper proposes a real options regime-switching model that can be used to identify optimal investment and technology choices under regulatory uncertainty. We employ a two-phase modeling approach and characterize both market demand and the introduction of environmental regulation as stochastic components. In order to derive insights regarding the optimal choice of technology, we devise and solve a basic version of the model analytically. By then calibrating the model to international container shipping and solving it numerically, we can drop some of the analytical model's restrictive assump-

tions. Finally, we adopt the perspective of a regulator and compare the costs and effectiveness of two different regulatory regimes.

The proposed investment model contributes to the real options literature by accounting for the most relevant features of investment in an era that has become increasingly affected by ecological awareness and regulation. Thus our model incorporates the option to invest in transportation capacity based on different technologies, the possibility that new regulations could increase operating costs, a layup option, and the option to charter additional capacity during the model's second (operating) phase. We also account specifically for the emission characteristics of those technologies considered, which allows us to assess the effect of various technology investment strategies on overall industry emissions. This paper contributes to the literature on investment appraisal by presenting a model that can be usefully adapted to multiple industries, and it contributes to the maritime literature by offering insights based on our calibration of that model to the shipping industry. Finally, we contribute by enabling a better understanding by regulators of the relative effectiveness of common regulatory policies.

In short, we have demonstrated that regulation uncertainty can strongly influence investment patterns and the choice of technology for operations. Our paper is therefore relevant not only to maritime shipping but also to any industry in which regulatory uncertainty can affect the appraisal of investments. Fruitful avenues for future research include analyzing technology choices under regulatory uncertainty in other market settings as well as expanding the time horizon considered. Another aspect worthy of consideration in future modeling efforts is the "time to build", which is extremely important also in the shipping industry.

SUMMARY AND OUTLOOK

5.1 SUMMARY

Maritime container shipping has been in stormy weather since the 2009 financial crisis despite the immense growth the industry has seen over the past decades. High volatility in asset prices, freight and charter rates as well as fundamental uncertainty as to future regulatory conditions are key challenges for capacity and technology decisions in this highly capital intensive industry. In a quest for economies of scale, past capacity choices have resulted in a race for ever-increasing vessels and a capacity supply that fundamentally exceeds transportation demand. The induced price competition has led to such low levels of freight and charter rates that it has become difficult to operate profitably—also resulting in bankruptcies¹ and a market consolidation. In light of past investment decision making that has frequently been considered irrational by practitioners, there is a need for decision support tools to better understand optimal capacity and technology choice in this challenging industry. An increasing focus by the IMO on reducing the industry’s environmental footprint will be one of the key challenges for the industry going forward that further complicates capacity decisions. Therefore, there is also a need to analyze the impact of characteristic uncertainties and challenges of the shipping market on optimal capacity and technology choice.

This dissertation aims to contribute to a better understanding of optimal capacity choice in maritime container shipping. To this end, we² develop quantitative valuation models that let us analyze the effects of selected market features. We first lay the foundation by evaluating how an additional charter option changes the optimal investment outcome under demand uncertainty (Chapter 2). We build on these findings by introducing regulatory uncertainty in the form of a stochastic introduction of new regulation that increases the cost of compliance (Chapter 3). This model helps ship investors and regulators to better understand how uncertainty about future regulation can change market economics and optimal decision-making. Lastly, we shift the focus to technology choice under such regulatory uncertainty (Chapter 4). In a regime-switching model we analyze optimal compliance strategies in different regimes of environmental regulation. Findings help investors make better decisions on how to build up capacity that is compliant with regulation in a cost-effective way. They also contribute to regulators’ understanding of how effective different regulation regimes are in reducing emission levels and doing so at as little cost as possible.

In Chapter 2, we explore the effect that the availability of chartering has on optimal investment decisions. In a continuous-time real options model, we

¹See, for example, the bankruptcy of Hanjin Shipping Co., Ltd. (The Guardian 09/02/2016)

²The term “we” refers to the authors of the respective chapters as denoted at the beginning of each chapter. For the conclusion, this refers to the authors of Haehl and Spinler (2017a,b,c).

show that increased demand uncertainty can be an incentive to rationally expand own capacities if these are delivered only after a time to build. In a similar model, in which only chartering is possible (i. e., without time to build), we do not find this capacity-increasing effect of market volatility. To create a better understanding of the interaction of these two individual effects, we present a discrete-time real options model that allows investment and (long-term or short-term) chartering at the same time under market uncertainty. The shipping industry is reflected in additional model features such as time to build, operating flexibility, a divestment option and an endogenous charter rate. Results show that the availability of chartering increases project values and reduces the incentive of time to build to preventively increase capacities in volatile markets. In demand peaks, however, chartering can lead to increased capacity levels as it allows to reap profits from unexpected demand surges by immediately increasing capacities. Overall, the level of owned capacity should be reduced. While carriers can bridge resulting capacity shortages with short-term charter, chartering does not appear to be optimal for a buildup of base capacity. Findings from this chapter are relevant to ship operators, who can further their understanding of optimal capacity choice and investment vs. charter split.

In Chapter 3, we focus on the effect of regulatory uncertainty on optimal capacity choice. To this end, we include a stochastic introduction of new environmental regulation in the model that increases operating costs in a regulated market to a previously unknown level. We differentiate two models, one in which the grandfathering³ of old capacities is allowed and one in which all capacities are affected by new regulation. The model is formulated in a dynamic programming (DP) approach that allows for time to build, divestment, (short-term) charter and operating flexibility. As a full iteration of this discrete-time model is intractable, we resort to approximate dynamic programming (ADP) methods to solve for near-optimal solutions. From an investor's perspective, we find that regulatory uncertainty *with* grandfathering can lead to excessive upfront investment to secure a low operating cost base even if the market should become regulated in the future. A capacity buildup well beyond current operational needs may be optimal from an individual investor's point of view. In an oligopolistic market, this could well lead to significant excess capacities and pronounced price competition. The case is different if investors expect regulation *not* to allow grandfathering. In this case, investors should invest conservatively and rely more on chartering until uncertainty is resolved. From a regulator's perspective, these findings are also highly relevant, as both situations of uncertainty come with unwanted side-effects. Uncertainty about regulation *with* grandfathering can plunge the already beaten market into even more severe excess capacities, while uncertainty about regulation *without* can impede investment altogether and slow down the market. It also turns out that, if grandfathering is allowed, investors build up capacities of cheap, old technology. This can even increase total industry emissions above the level in a completely unregulated market without any uncertainty about future regulation. This is not the case if grandfathering is not allowed: here, emissions are reduced already before new policies are introduced. Regulators should there-

³If regulation allows for grandfathering, only vessels built after the effective date of the policy need to comply.

fore keep uncertainty regarding the legislative process low to avoid unwanted effects of excess capacities, increases of total emissions or a slow-down of market activity due to reduced investment.

In Chapter 4, we shift focus to explicitly modeling and analyzing technology choice for compliance under regulatory uncertainty. We present a two-phase regime-switching model in which the ship operator can invest into two different technologies, a “clean” and a “dirty” technology in phase 1. In the second phase, there is a chance of the market being regulated, which increases operating costs. In this phase the carrier can additionally charter vessels and makes the decision how many vessels of which technology to deploy in operations. We first solve the model analytically and subsequently relax basic assumptions by finding optimal solutions numerically. Model results suggest that—while portfolio solutions of both technologies are possible—they are optimal only in few cases under restricted conditions. In most cases, a single-technology strategy is the better and more profitable choice. We further find that, if owned capacity is hurt less by regulation than chartered vessels, it can be optimal to increase the owned fleet in light of regulatory uncertainty. Interestingly, regulatory uncertainty can further increase the overall project value. This is a result of the options embedded in the model: the chartering and the layup options provide a protection against potential losses in unattractive markets (low demand and/or regulated market) and at the same time allow to reap profits from unexpectedly positive market environments. While these findings are highly relevant to investors, we also take on a regulator’s perspective by introducing and comparing two different regulation regimes—an emissions cap and an emissions tax regime. While an emissions cap regime is more effective at reducing overall industry emissions, the tax regime leaves more operational flexibility to the ship operator. This impairs the emission reduction potential but leads to lower cost caused by regulating the market. An important takeaway for regulators is also that total emissions are not reduced in a linear or even continuous fashion with a reduction of the emissions limit (i. e., the emissions cap or the limit above which an emissions tax applies). It is therefore essential for regulators to study the technologies available for compliance in sufficient detail to identify the relevant thresholds.

There are three main limitations to the findings presented in this dissertation. First, we have assumed a monopolistic market setting in all models of this thesis while the container shipping market is of oligopolistic nature. This choice was made deliberately as it has allowed to include in the model the numerous features relevant to the shipping industry, such as investment and divestment options, time to build, a charter option, a layup option, demand uncertainty and regulatory uncertainty. As other research has found the same capacity effects under market uncertainty in monopolistic and oligopolistic settings (see Aguerrevere (2003)), we are confident that our assumption influences only the quantitative extent but not the direction of effects found. The second limitation affects only findings presented in Chapter 3, where we solve the real options model using ADP methods. While we have ensured the algorithm’s performance versus a challenging benchmark, it remains an approximation of optimal strategies. The last limitation concerns the regime-switching model in Chapter 4. While the other models presented span multiple time periods, the

regime-switching model with which we analyze technology choice under regulatory uncertainty focuses on two phases—an investment and an operating phase. Including more time periods could, for example, make portfolio options more attractive than they appear when analyzing two time periods only.

With this dissertation, we contribute both to methodological real option literature by analyzing the effect of chartering on investment choice, by proposing an ADP-based method for valuing investment and charter projects under regulatory uncertainty and by analyzing technology choice in a framework that can be adapted to different regulatory regimes. All models presented can be modified and calibrated to other industries than shipping as well. We further contribute to maritime shipping investment literature and present relevant insights both for ship investor-operators and regulators. Operators can benefit from an advanced understanding of optimal investment vs. charter split, of capacity choice under regulatory uncertainty with and without grandfathering and of optimal technology choice under regulatory uncertainty depending on different policy regimes. Regulators can learn about expected market reactions from uncertainty about future regulation, about the effectiveness of two different regulation regimes and about potential unexpected pitfalls, such as an increase of emission levels despite the desire to introduce emission-lowering policies.

5.2 OUTLOOK

This dissertation focused on optimal capacity and technology choice in container shipping under market and regulatory uncertainty. While the models proposed deliver many interesting and valuable findings, such research also leads to new questions and avenues for future research to be addressed.

The models presented in this dissertation were calibrated to the maritime shipping industry by applying typical market and cost parameters. It would be interesting to test the findings from these models empirically against the actual shipping markets. Such empirical testing could be attempted for example by analyzing capacity and technology choice effects before and after the introduction of SO_x regulations by the IMO. This could not only confirm the directional findings proposed here, but also attempt a sizing of the relevant effects.

Apart from this empirical approach, there are also exciting fields for further research in the real options space. As mentioned above, we have chosen to apply a monopoly assumption to be able to include the relevant market characteristics in focus. It would be an exciting challenge to push valuation methods further to be able to include these features also in an oligopolistic setting with competition between ocean carriers. Such an advancement of methods could potentially also allow combining the features that we have analyzed in separate modeling approaches into a single model. With this, the interaction between chartering, endogenous charter cost, regulatory uncertainty, and technology choice could be analyzed and evaluated for reinforcing or canceling effects.

We have discussed in Section 1, that shipping is characterized by a multitude of uncertainties. In our modeling, we have focused on demand and regulatory uncertainty (leading to uncertain cost levels). Future research could also take

into account cost uncertainty from oil prices as well as asset price uncertainty, which we have not included. Especially studying asset price uncertainty is believed to be an interesting field as there are players in the market that generate their profits almost entirely from an asset play.

Lastly, we have focused our analyses on the operations on a specific trade lane. Future research could add value by integrating our research into an overarching strategic game, in which the operator can choose on which trade lanes to compete. Such a feature could take into account network effects to integrate optimal decision making from the initial investment decision, to the choice of trade lanes, and finally the choice of transportation supply offered on each lane.

In conclusion, investment decisions in maritime shipping remain a complex optimization problem. There are plenty of aspects remaining for further research, of which the ones presented above are the ones closest related to this dissertation. We therefore believe that there is a promising research agenda at the crossing point of real options valuation methods and the international shipping industry.

A.1 DEFINITION OF MODEL VARIABLES

Table A.1: Definition of variables used in continuous-time models.

Variable	Description
γ	Price elasticity of demand with $\gamma < 0$
μ	Drift rate of demand $Y(t)$ in Geometric Brownian Motion
π	Firm profit (USD)
σ	Standard deviation of demand Y in Geometric Brownian Motion
$C(q)$	Firm total cost function (USD)
c_1	Operating cost: personnel, bunker, maintenance (USD/TEU)
c_2	Operating cost: personnel, bunker, maintenance (USD/TEU)
c_3	Layup cost factor (USD/TEU)
c_4	Cost factor for financing cost of owned capacity
c_5	Charter rate per unit of chartered capacity (USD/TEU)
$dZ(t)$	Increment of a standard Wiener process
$F_C(O, Y)$	Value of the option to charter (USD)
$F_I(K, Y)$	Value of the option to invest (USD)
$G_I(K, Y, h)$	Value of incremental unit of committed capacity from investment (USD)
h	Time to build before ordered capacity is delivered (years)
$H_C(O, Y)$	Value incremental unit of chartered operational capacity (USD)
$H_I(O, Y)$	Value of incremental unit of invested operational capacity from investment (USD)
k	Investment cost per unit of capacity (USD/TEU)
$K(t)$	Committed capacity reflecting both operational capacity as well as capacity ordered but not yet delivered (TEU)
$O(t)$	Operational capacity, reflecting those transport capacities delivered to the investor and are ready for operation (TEU)
O_0	Initial capacity at $t = 0$ (TEU)
$P(t)$	Market price at time t (USD/TEU)
q	Output quantity (TEU)
r	Risk-free rate of interest
$Y(t)$	Market demand signal, (Geometric Brownian Motion)

Table A.2: Definition of additional variables used in discrete-time models

Variable	Description
ω	Portion of demand growth/contraction passed on to the endogenous charter rate $c_{5,t}$
charter_t	Additional charter capacity chartered in t (TEU)
d	Percentage change of demand per period for a down-movement
divest_t	Divestment in period t (TEU)
invest_t	Investment / new-orders in period t (TEU)
k_s	Divestment price (USD/TEU)
OC_t	Operational capacity from charter at beginning of time period t (TEU)
OI_t	Operational capacity from investment in time period t (TEU)
p	Risk-neutral probability of an up-movement
PI_t	Pipeline of investment capacity in time period t including capacity delivered in period $t + 1$ (TEU)
t	Time period of 1 year
u	Percentage change of demand per period for an up-movement

A.2 VALUATION OF OPTION TO INVEST

In this appendix, we derive the value of the option to invest of Section 2.3. We follow an approach as outlined in Aguerrevere (2003), extending it with layup cost c_3 and financing cost c_4 .

We start by deriving H_I , the value of an additional unit of operational capacity O based on Eq. (2.4). At a given level of operational capacity O , an additional unit of operational capacity creates marginal profits of

$$\Delta\pi(O, Y(t)) = \max \left[\left(1 + \frac{1}{\gamma}\right) Y(t) O^{\frac{1}{\gamma}} - c_1 - c_2 O - kc_4, -c_3 - kc_4 \right]. \quad (\text{A.1})$$

To value an additional unit of operational capacity H_I , we use methods based on contingent claims analysis as detailed in Dixit and Pindyck (1994). The approach is to construct a risk-less portfolio and to equate its expected rate of return to the risk-free rate of interest r by applying the no-arbitrage condition¹:

$$\frac{1}{2} \sigma^2 Y^2 H_I''(Y) + \mu Y H_I'(Y) - r H_I(Y) + \pi(Y) = 0. \quad (\text{A.2})$$

¹The assumption is that capital markets are complete and arbitrage-free because asset prices adapt so that assets with the same expected rate of return have the same market value. Hence, a risk-less portfolio must pay the risk-free interest r .

By solving differential Eq. (A.2), we receive the value of the marginal unit of operational capacity:

$$H_I(O, Y) = \begin{cases} A(O)Y^\alpha + \frac{(1+\frac{1}{\gamma})YO^{\frac{1}{\gamma}}}{r-\mu} \\ \frac{-c_1+c_2O+kc_4}{r} \end{cases} \quad \text{for } Y \geq \left(1 + \frac{1}{\gamma}\right)^{-1} O^{-\frac{1}{\gamma}}(c_1 + c_2O - c_3)$$

$$\begin{cases} B(O)Y^\beta - \frac{c_3+kc_4}{r} \end{cases} \quad \text{for } Y < \left(1 + \frac{1}{\gamma}\right)^{-1} O^{-\frac{1}{\gamma}}(c_1 + c_2O - c_3)$$
(A.3)

with

$$A(O) = \frac{\left(1 + \frac{1}{\gamma}\right)^\alpha O^{\frac{\alpha}{\gamma}}(c_1 + c_2O - c_3)^{1-\alpha}}{(\beta - \alpha)} \left(\frac{\beta}{r} - \frac{\beta - 1}{r - \mu}\right)$$

$$B(O) = \frac{\left(1 + \frac{1}{\gamma}\right)^\beta O^{\frac{\beta}{\gamma}}(c_1 + c_2O - c_3)^{1-\beta}}{(\beta - \alpha)} \left(\frac{\alpha}{r} - \frac{\alpha - 1}{r - \mu}\right). \quad (A.4)$$

The exponents α and β are the negative and positive roots to the characteristic quadratic equation respectively:

$$\alpha = \frac{1}{2} - \frac{\mu}{\sigma^2} - \sqrt{\left(\frac{\mu}{\sigma^2} - \frac{1}{2}\right)^2 + 2\frac{r}{\sigma^2}}, \quad \beta = \frac{1}{2} - \frac{\mu}{\sigma^2} + \sqrt{\left(\frac{\mu}{\sigma^2} - \frac{1}{2}\right)^2 + 2\frac{r}{\sigma^2}}.$$
(A.5)

Having valued an additional unit of operational capacity today, we consider time to build h to derive the value of the marginal unit of committed capacity $G_I(K, Y, h)$ at the time of ordering:

$$G_I(K(t), Y(t), h) = E \left[\int_h^\infty e^{-rt} \Delta\pi(K(t), Y(t)) dt \mid Y(t) \right]$$

$$= e^{-rh} E \left[\int_0^\infty e^{-rt} \Delta\pi(K(t), Y(t)) dt \mid Y(t) \right]$$

$$= e^{-rh} E [H_I(K(t), Y(t+h)) \mid Y(t)] \quad (A.6)$$

We derive the expectation analogous to Aguerrevere (2003) and refer to his Appendix B for mathematical details. We specify the value of an additional unit of committed capacity as

$$G_I(K, Y, h) = (1 - \Phi(v - \alpha\sigma\sqrt{h}))A(K)Y^\alpha$$

$$+ (1 - \Phi(v - \sigma\sqrt{h})) \frac{\left(1 + \frac{1}{\gamma}\right) K^{\frac{1}{\gamma}} Y e^{-(r-\mu)h}}{r - \mu}$$

$$- (1 - \Phi(v)) \frac{c_1 + c_2K + kc_4}{r} e^{-rh} + \Phi(v - \beta\sigma\sqrt{h})B(K)Y^\beta$$

$$- \Phi(v) \frac{c_3 + kc_4}{r} e^{-rh} \quad (A.7)$$

where Φ is the cumulative distribution function of the standard normal distribution and v is defined as

$$v = v(K, Y, h) = \frac{\log \left[\left(1 + \frac{1}{\gamma}\right)^{-1} K^{-\frac{1}{\gamma}} (c_1 + c_2 K - c_3) \right] - \log Y - \left(\mu - \frac{\sigma^2}{2}\right) h}{\sigma\sqrt{h}}.$$

Based on the value of an additional unit of committed capacity G_I , we value the option to invest into this additional capacity. The option can be valued like a perpetual American call option. Let $F_I(K, Y)$ denote the value of the option to buy an additional unit of committed capacity at given committed capacity K and demand Y . We establish a risk-less portfolio, determine its return and equate it to the risk-free rate of interest, yielding the differential equation

$$\frac{\sigma^2}{2} Y^2 F_I'' + \mu Y F_I' - r F_I = 0 \quad (\text{A.8})$$

with three boundary conditions that describe the option value in a situation of demand $Y = 0$, the investment threshold and the smooth-pasting condition respectively:

$$\begin{aligned} F_I(K, 0) &= 0 \\ F_I(K, Y(K)) &= G_I(K, Y(K), h) - k \\ F_I'(K, Y(K)) &= G_I'(K, Y(K), h) \end{aligned} \quad (\text{A.9})$$

Using the second and third boundary conditions, we can derive the equality condition for optimal choice of committed capacity $K(Y)$ dependent on observed demand Y :

$$\beta[G_I(K(Y), Y, h) - k] - Y G_I'(K(Y), Y, h) = 0 \quad (\text{A.10})$$

where G_I' is defined as

$$\begin{aligned} G_I'(K, Y, h) &= (1 - \Phi(v - \alpha\sigma\sqrt{h}))\alpha A(K)Y^{\alpha-1} + \frac{\Phi(v - \alpha\sigma\sqrt{h})}{Y\sigma\sqrt{h}} A(K)Y^\alpha \\ &+ (1 - \Phi(v - \sigma\sqrt{h})) \frac{\left(1 + \frac{1}{\gamma}\right) K^{\frac{1}{\gamma}} e^{-(r-\mu)h}}{r - \mu} \\ &+ \frac{\Phi(v - \sigma\sqrt{h})}{\sigma\sqrt{h}} \frac{\left(1 + \frac{1}{\gamma}\right) K^{\frac{1}{\gamma}} e^{-(r-\mu)h}}{r - \mu} \\ &- \frac{\Phi(v)(c_1 + c_2 K + kc_4)e^{-rh}}{rY\sigma\sqrt{h}} + \Phi(v - \beta\sigma\sqrt{h})\beta B(K)Y^{\beta-1} \\ &- \frac{\Phi(v - \beta\sigma\sqrt{h})}{Y\sigma\sqrt{h}} B(K)Y^\beta + \frac{\Phi(v)}{Y\sigma\sqrt{h}} \frac{c_3 + kc_4}{r} e^{-rh}. \end{aligned} \quad (\text{A.11})$$

A.3 VALUATION OF OPTION TO CHARTER

To value the charter option, we determine the value of an additional unit of chartered capacity $H_C(O, Y)$ based on the adapted cost function in Eq. (2.7):

$$\Delta\pi(O, Y(t)) = \max \left[\left(1 + \frac{1}{\gamma} \right) Y(t) O^{\frac{1}{\gamma}} - c_1 - c_2 O - c_5, -c_3 - c_5 \right]. \quad (\text{A.12})$$

Using contingent claims analysis, a risk-less portfolio can be constructed. The following differential equation can be derived for the change in portfolio value, where $H_C(Y)$ denotes the value of a marginal unit of chartered capacity and $H'_C(Y)$ and $H''_C(Y)$ are the first and second partial derivatives with respect to demand shock Y :

$$\frac{1}{2} \sigma^2 Y^2 H''_C(Y) + \mu Y H'_C(Y) - r H_C(Y) + \pi(Y) = 0. \quad (\text{A.13})$$

The solution to this equation is the value of an added unit of chartered capacity H_C :

$$H_C(O, Y) = \begin{cases} A(O) Y^\alpha + \frac{(1 + \frac{1}{\gamma}) Y O^{\frac{1}{\gamma}}}{r - \mu} \\ \quad - \frac{c_1 + c_2 O + c_5}{r} & \text{for } Y \geq \left(1 + \frac{1}{\gamma} \right)^{-1} O^{-\frac{1}{\gamma}} (c_1 + c_2 O - c_3) \\ B(O) Y^\beta - \frac{c_3 + c_5}{r} & \text{for } Y < \left(1 + \frac{1}{\gamma} \right)^{-1} O^{-\frac{1}{\gamma}} (c_1 + c_2 O - c_3), \end{cases} \quad (\text{A.14})$$

with $A(O)$ and $B(O)$ defined as seen in Eq. (A.4) and α and β being the negative and positive roots to the characteristic quadratic equation respectively (see Eq. (A.5)).

The steps performed so far are similar to the calculations for the option to invest. When chartering, however, new capacities are added immediately without time to build, so that we can directly value the option to charter, F_C , by solving the differential equation

$$\frac{\sigma^2}{2} Y^2 F''_C + \mu Y F'_C - r F_C = 0. \quad (\text{A.15})$$

Boundary conditions to this differential equation help to solve for the optimal operational capacity $O(Y)$. The first condition describes the option value at the absorbing barrier of demand $Y = 0$. The second condition defines the threshold at which an investor charters an additional unit of capacity. Thus the option to charter needs to be worth as much or less than the value of the added unit of chartered capacity. The third condition is the smooth-pasting condition:

$$\begin{aligned} F_C(O, 0) &= 0 \\ F_C(O, Y(O)) &= H_C(O, Y(O)) \\ F'_C(O, Y(O)) &= H'_C(O, Y(O)). \end{aligned} \quad (\text{A.16})$$

The first condition yields a general solution to the differential equation of the form $F_C(O, Y) = E(O)Y^\beta$ and from the second and third conditions we can derive the condition for the optimal charter capacity $O(Y)$ as a function of demand shock Y :

$$\beta H_C(O(Y), Y) - YH'_C(O(Y), Y) = 0. \quad (\text{A.17})$$

APPENDIX TO CHAPTER 3

B.1 DEFINITION OF MODEL VARIABLES

Table B.1 lists and describes all variables used in the dynamic and approximate dynamic programming models employed in the paper.

Table B.1: Definition of variables used in DP and ADP models.

Variable	Description
α_t	Indicator variable for whether the market is regulated ($\alpha_t = 1$) or not ($\alpha_t = 0$)
δ_1, δ_2	Tuning parameters in the step-size rule of the linear regression
ε	Tuning parameter in ε -greedy exploration
γ	Price elasticity ($\gamma < 0$)
μ	Expected market drift of demand \tilde{Y}_t
$\mu_{c_{1h}}$	Expected value of post-regulation operating cost \tilde{c}_{1h} (USD/TEU)
π_t	Period profit from operations (USD)
σ	Market volatility of demand \tilde{Y}_t
$\sigma_{c_{1h}}$	Standard deviation of post-regulation operating cost \tilde{c}_{1h}
θ_{tf}	Regression coefficients for feature f in period t
ξ	Probability of regulatory signal ($\tilde{\psi}_t = 1$) in each period
$\tilde{\psi}_t$	Stochastic regulatory signal $\in \{0, 1\}$ in time period t
Ψ_t	Sum of regulatory signals $\tilde{\psi}_t$ received before and including time period t
\tilde{c}_{1h}	Operating cost for regulated capacity (USD/TEU)
c_{1l}	Uncertain operating cost for unregulated capacity (USD/TEU)
c_2	Operating cost (USD/TEU)
c_3	Layup cost (USD/TEU)
c_4	Financing cost on capital invested
c_{5h}	Charter rate in regulated market (USD/TEU)
c_{5l}	Charter rate in unregulated market (USD/TEU)
c_{old}	Extra operating cost post-regulation for outdated technology (USD/TEU)
C_t	Period overall cost (USD)
k_h	Investment cost in regulated market (USD/TEU)
k_l	Investment cost in unregulated market (USD/TEU)

Table B.1: continued.

Variable	Description
k_s	Selling price for divested owned capacity (USD/TEU)
m, M	Iterations of ADP algorithm
OC_t	Operational capacity from chartering (TEU)
OI_t	Operational capacity from investment (TEU)
p	Risk-neutral probability of an up-movement of demand \tilde{Y}_t
P_t	Market price (USD/TEU)
p_d	Probability of down-movement of post-regulation operating cost \tilde{c}_{1h}
PI_t	Pipeline of operational capacity from investment available in period $t + 1$ (TEU)
$postO_t$	Operational capacity (invested and chartered) ordered post-regulation (TEU)
$preOI_t$	Operational capacity from investment ordered pre-regulation (TEU)
$prePI_t$	Pipeline of invested capacity ordered pre-regulation (TEU)
p_u	Probability of up-movement of post-regulation operating cost \tilde{c}_{1h}
q_t	Transportation quantity (TEU)
u	Percentage up-movement of demand \tilde{Y}_t
V_t	Project value (USD)
\tilde{Y}_t	Stochastic market demand

B.2 APPROXIMATE DYNAMIC PROGRAMMING ALGORITHM

Figure B.1 delineates the ADP algorithm used to find near-optimal solutions to the investment model presented in the paper.

In the first step of the algorithm, we define basis functions that extract the most relevant features of the post-decision state to approximate the value function. Regression coefficients are initialized for the first simulation ($\theta_{tf} = 0$) and updated at every iteration of the algorithm based on the sample data so far observed. Starting at a chosen initial state S_0^0 , we perform M iterations until the algorithm converges to (what is presumed to be) the true solution. For each iteration m , we draw a random set w^m of our stochastic variables: demand \tilde{Y}_t and regulatory signal $\tilde{\psi}_t$ (for all $t \in T$) and operational post-regulation costs \tilde{c}_{1h} . Starting at the initial state S_0^0 , we calculate the optimal decision a_t by maximizing the overall project value. Observe that this is where we employ the approximation of the value function. Given a chosen action a_t , the realization of random event w_t^m takes the system to the next state. This process is repeated until the last time period, $t = T$. Once we arrive at a state S_{T+1} , its value is initialized with a terminal value that assumes existing capacity can be used forever.

```

begin
  Define basis functions  $\phi_f(S)$ ;
  Initialize  $\theta_{tf}^0$  for all  $t$ ;
  Initialize recursive least-squares updating matrix  $B^0$ ;
  Choose initial state  $S^0$ ;
  for  $m = 1, 2, \dots, M$  do
    Choose sample path  $w^m$  for  $t = 0, 1, \dots, T + 1$ ;
    for  $t = 0, 1, \dots, T$  do
      if  $m \leq 1,000$  or  $\frac{\varepsilon}{m} > e$  then
        Choose random action  $a_t^m$ 
      else
        Compute optimal action:
          
$$a_t^m = \arg \max_{a_t \in \mathcal{A}_t^m} \left\{ \pi(S_t^m, a_t) + CI(a_t) + e^{r \, dT} \sum_f \theta_{tf}^{m-1} \phi_f(S^{M,a}(S_t^m, a_t)) \right\}$$

      end
      Compute next state in  $t + 1$ :
          
$$S_{t+1}^m = S^M(S_t^m, a_t^m, W_{t+1}(w^m))$$

    end
    Initialize terminal value  $\hat{v}_{T+1}^m = \pi(S_{T+1}^m) \frac{1+\mu}{r-\mu}$ ;
    for  $t = T, T-1, \dots, 0$  do
      Compute observed project value:
          
$$\hat{v}_t^m = \pi(S_t^m, a_t^m) + CI(a_t^m) + e^{-r \, dT} \hat{v}_{t+1}^m$$

    end
    Update approximation coefficients using recursive least-squares
    linear regression to obtain  $\theta_{tf}^m$  for all  $t \in T$  and  $f \in F$ :
          
$$\theta^m = \theta^{m-1} - H^m \phi^m \hat{\varepsilon}^m$$

  end
  Return regression coefficients  $\theta_t^M$  for all  $t \in T$ .
end

```

Figure B.1: Approximate dynamic programming algorithm used to solve real options model

Iterating backwards through time, the algorithm adds up profits and cash flows to derive the project value in each period. The values so obtained are specific to the realizations of stochastic variables w^m and to the decisions made during the iteration. Although the actions taken may not be optimal, they nonetheless reveal information that can be used to update the estimation coefficients. After that updating, we iterate until the algorithm converges.

The updating of the estimation coefficients is performed as follows: In contrast to empirical research, we have no batch data and instead obtain sample

data from our ADP model itself. Thus the first ADP iteration begins with initial values for the regression coefficients θ_{tf} , which can only be updated recursively as new observations are collected. That updating proceeds via a recursive least-squares approach for non-stationary data, as outlined by Powell (2011). The general recursive updating formula can be written in matrix notation as follows:

$$\theta^m = \theta^{m-1} - H^m \phi^m \hat{\varepsilon}^m; \quad (\text{B.1})$$

here H^m is a scaling matrix calculated as

$$H^m = \frac{1}{\gamma^m} B^{m-1}. \quad (\text{B.2})$$

The error term $\hat{\varepsilon}^m$ is the difference between the value estimate and the observed value \hat{v}^m :

$$\hat{\varepsilon}^m = \bar{V}_t^{\text{av}}(S_t^a | \theta_t^{m-1}) \hat{v}^m. \quad (\text{B.3})$$

As an $|F| \times |F|$ matrix, B^m has a row and column for each feature that is pulled from the state space by the basis functions. Formally, we have

$$B^m = \frac{1}{\lambda^m} \left(B^{m-1} - \frac{1}{\gamma^m} (B^{m-1} \phi^m (\phi^m)^T B^{m-1}) \right), \quad (\text{B.4})$$

where γ^m is a scalar:

$$\gamma^m = \lambda^m + (\phi^m)^T B^{m-1} \phi^m. \quad (\text{B.5})$$

In Eqs. (B.4) and (B.5), λ^m behaves like a typical step-size but in the opposite direction. A value of $\lambda^m = 1$ weights all observations equally while smaller values put more emphasis on recent observations. Although this parameter can be set statically, we achieve better results following an approach proposed by Powell (2011): define it as $\lambda^m = 1 - \delta_1/m^{\delta_2}$, where δ_1 and δ_2 are “tuning” parameters that we set to 0.4 and 0.8, respectively. Using this step-size rule, we achieve stable results by first allowing new observations to have a strong effect and subsequently weakening their impact.

B.3 SENSITIVITY ANALYSIS

Table B.2: Sensitivity analysis: Relative project values for selected parameter changes. The reference value of 100% refers to project values in a base case calibration according to Table 3.4 in the with and without grandfathering (GF) models.

Parameter	Parameter value	Relative project value		
		With GF	Without GF	
σ	-50%	0.05	97.0%	97.3%
	Base case	0.10	100.0%	100.0%
	+50%	0.15	102.6%	101.9%
μ	-20%	0.024	87.0%	87.1%
	Base case	0.03	100.0%	100.0%
	+20%	0.036	118.8%	118.9%
μ_{c1h}	-10%	720	100.2%	103.0%
	Base case	800	100.0%	100.0%
	+10%	880	99.8%	97.3%

B.4 MODEL VERIFICATION AND VALIDATION

This paper has proposed an approximate dynamic programming model to support and analyze capacity decisions in container shipping markets under demand and regulatory uncertainty. To ensure the model's credibility, we perform model verification and validation as described in Gass (1983) and Sargent (2013).

Model Verification

Model verification ensures the exact implementation of the mathematical model in the software. We assure this by applying several measures when programming.

- *Stepwise coding.* The model was programmed in a step-by-step manner, starting with a highly simplified version. Further variables were added only after expected and optimal performance had been assured at each step.
- *Documentation.* The programming code written for the technical implementation of the proposed model is commented wherever its intent is not entirely self-evident. In this way we improve the code's readability and make it easier for other researchers to understand.
- *Output verification.* To verify the model's correct functioning, we visualize model output for easier interpretation. Thus we run the model with

various sets of parameters to check its sensitivity to changes in input values. Finally, we perform a high number of simulations (as described in Section 3.5.3) to ensure that results are consistent.

Model Validation

We validate the model in the various ways described next.

- *Data validity.* We derive cost parameters by referring, whenever possible, to the detailed cost analyses in AECOM (2012). Chartering costs were estimated based on a publicly available charter cost index.
- *Extreme conditions test.* The model was tasked with delivering reasonable results even when running simulations that used extreme values of the parameters. For example, the no-regulation scenario and the scenario with heightened risk of regulation were used to test such extreme conditions.
- *Mathematical validity.* The mathematical model's detailed structure is explained in Section 3.3, and the solution approach using ADP is explained in Section 3.4. As further validation we present the ADP program's pseudocode in Figure B.1.
- *Sensitivity analysis.* We establish the robustness of our results by analyzing the model's sensitivity to different parameter assumptions. We performed sensitivity analyses for relevant input cost parameters; of these, the most interesting are presented in Section 3.5.3.

APPENDIX TO CHAPTER 4

C.1 DEFINITION OF MODEL VARIABLES

Table C.1: Definition of variables used

Variable	Description
$\tilde{\alpha}$	Indicator variable for whether or not the market is regulated
β	Scaling factor in the market price function
γ	Elasticity of demand
μ	Location of demand (TEU per year)
ξ	Probability of regulation
π	Firm profit (USD)
σ	Volatility of demand
$\hat{\chi}$	Emission cap in emissions cap regime; emission threshold in tax regime (% sulfur content)
$\chi_i^{\text{ret}}, \chi_c^{\text{ret}}$	Emission efficiency of retrofitted capacity (% sulfur content)
$\chi_i^{\text{std}}, \chi_c^{\text{std}}$	Emission efficiency of standard configuration capacity (% sulfur content)
c^c	Charter cost of chartered capacities (USD/TEU)
c^f	Financing cost of owned capacities (% of k_i)
c^l	Layup cost (USD/TEU)
$c_i^{\text{o,ret}}, c_c^{\text{o,ret}}$	Operating cost of technology i or of chartered capacity c in <i>regulated</i> market (USD/TEU)
$c_i^{\text{o,std}}, c_c^{\text{o,std}}$	Operating cost of technology i or of chartered capacity c in <i>unregulated</i> market (USD/TEU)
c_c^o	Operating cost of chartered capacity (USD/TEU)
\tilde{D}	Stochastic transportation demand (TEU)
\bar{e}	Typical fuel consumption (tons/TEU)
k_i	Investment cost of technology i (USD/TEU)
K_i	Capacity available of technology i (TEU)
\hat{K}_i	Maximum optimum capacity of technology i (TEU)
p	Freight rate (market price)(USD/TEU)
q_c	Transportation quantity using chartered capacity (TEU)
q_i	Transportation quantity using technology i (TEU)

C.2 PROOFS

Proof of Proposition 1. Inserting the phase-2 optimal output quantities from Eq. (4.3) into the value function of Eq. (4.4) yields

$$\begin{aligned}
V(\tilde{D}, \tilde{c}_i^o, c^c) = & \\
& \max_{K_1, K_2} \mathbb{E} \left[(\beta \tilde{D}^\gamma - (1 - \tilde{\alpha}) c_{[1]}^{o, \text{std}} - \tilde{\alpha} c_{[1]}^{o, \text{ret}} + c^l) \min\{K_{[1]}, \tilde{D}\} \right. \\
& \quad + (\beta \tilde{D}^\gamma - (1 - \tilde{\alpha}) c_{[2]}^{o, \text{std}} - \tilde{\alpha} c_{[2]}^{o, \text{ret}} + c^l) \min\{K_{[2]}, (\tilde{D} - K_{[1]})^+\} \\
& \quad \left. + (\beta \tilde{D}^\gamma - (1 - \tilde{\alpha}) c_c^{o, \text{std}} - \tilde{\alpha} c_c^{o, \text{ret}} - c^c) \left(\tilde{D} - \sum_i K_{[i]} \right)^+ \right] \\
& - \sum_i K_{[i]} (k_{[i]} + k_{[i]} c^f + c^l) \\
& \text{s.t. } K_{[i]} \geq 0 \quad \forall i.
\end{aligned} \tag{C.1}$$

The first derivatives with respect to $K_{[1]}$ and $K_{[2]}$ are, respectively,

$$\begin{aligned}
\frac{\partial V}{\partial K_{[1]}}(\tilde{D}, c_i^o, c^c) & \\
= & ((1 - \xi) c_{[1]}^{o, \text{std}} + \xi c_{[1]}^{o, \text{ret}} - (1 - \xi) c_{[2]}^{o, \text{std}} - \xi c_{[2]}^{o, \text{ret}}) F_{\tilde{D}}(K_{[1]}) \\
& + ((1 - \xi) c_{[2]}^{o, \text{std}} + \xi c_{[2]}^{o, \text{ret}} - (1 - \xi) c_c^{o, \text{std}} - \xi c_c^{o, \text{ret}} - c^c - c^l) F_{\tilde{D}}(K_{[1]} + K_{[2]}) \\
& - (1 - \xi) c_{[1]}^{o, \text{std}} - \xi c_{[1]}^{o, \text{ret}} + (1 - \xi) c_c^{o, \text{std}} + \xi c_c^{o, \text{ret}} + c^c - k_{[1]} - k_{[1]} c^f \quad (\text{C.2})
\end{aligned}$$

and

$$\begin{aligned}
\frac{\partial V}{\partial K_{[2]}}(\tilde{D}, c_i^o, c^c) & = ((1 - \xi) c_c^{o, \text{std}} + \xi c_c^{o, \text{ret}} - (1 - \xi) c_{[2]}^{o, \text{std}} - \xi c_{[2]}^{o, \text{ret}} + c^l + c^c) \\
& \times (1 - F_{\tilde{D}}(K_{[1]} + K_{[2]})) - (k_{[2]} + k_{[2]} c^f + c^l). \quad (\text{C.3})
\end{aligned}$$

Now setting Eq. (C.3) equal to zero, we obtain the optimal total capacity:

$$K_{[1]}^* + K_{[2]}^* = F_{\tilde{D}}^{-1} \left(1 - \frac{k_{[2]} + k_{[2]} c^f + c^l}{(1 - \xi) c_c^{o, \text{std}} + \xi c_c^{o, \text{ret}} - (1 - \xi) c_{[2]}^{o, \text{std}} - \xi c_{[2]}^{o, \text{ret}} + c^l + c^c} \right). \tag{C.4}$$

Setting Eq. (C.2) equal to zero and inserting the optimal total capacity from Eq. (C.4) then yields the optimal technology-[1] capacity

$$K_{[1]}^* = F_{\tilde{D}}^{-1} \left(1 - \frac{k_{[1]} + k_{[1]} c^f - k_{[2]} - k_{[2]} c^f}{(1 - \xi) c_{[2]}^{o, \text{std}} + \xi c_{[2]}^{o, \text{ret}} - (1 - \xi) c_{[1]}^{o, \text{std}} - \xi c_{[1]}^{o, \text{ret}}} \right). \tag{C.5}$$

Optimal investment in capacity $K_{[2]}$ is then derived by subtracting Eq. (C.5) from Eq. (C.4). The case differentiation in Proposition 1 follows because the arguments in Eq. (C.4) and Eq. (C.5)—as well as the difference between Eq. (C.4) and Eq. (C.5)—must all be nonnegative. \square

Proof of concavity in base case with regulatory uncertainty. To ensure that the optimum just calculated is indeed a maximum, we prove that the project value function V is concave. For this purpose we use the Hessian matrix

$$H(V) = \begin{bmatrix} \frac{\partial^2 V}{\partial K_{[1]}^2} & \frac{\partial^2 V}{\partial K_{[1]} \partial K_{[2]}} \\ \frac{\partial^2 V}{\partial K_{[1]} \partial K_{[2]}} & \frac{\partial^2 V}{\partial K_{[2]}^2} \end{bmatrix} \quad (C.6)$$

where

$$\begin{aligned} \frac{\partial^2 V}{\partial K_{[1]}^2} &= ((1 - \xi)c_{[1]}^{o, \text{std}} + \xi c_{[1]}^{o, \text{ret}} - (1 - \xi)c_{[2]}^{o, \text{std}} - \xi c_{[2]}^{o, \text{ret}}) f_{\bar{D}}(K_{[1]}) \\ &\quad + ((1 - \xi)c_{[2]}^{o, \text{std}} + \xi c_{[2]}^{o, \text{ret}} - (1 - \xi)c_c^{o, \text{std}} - \xi c_c^{o, \text{ret}} - c^l - c^c) \\ &\quad \times f_{\bar{D}}(K_{[1]} + K_{[2]}) \end{aligned} \quad (C.7)$$

and

$$\begin{aligned} \frac{\partial^2 V}{\partial K_{[2]}^2} &= \frac{\partial^2 V}{\partial K_{[1]} \partial K_{[2]}} = ((1 - \xi)c_{[2]}^{o, \text{std}} + \xi c_{[2]}^{o, \text{ret}} - (1 - \xi)c_c^{o, \text{std}} - \xi c_c^{o, \text{ret}} - c^l - c^c) \\ &\quad \times f_{\bar{D}}(K_{[1]} + K_{[2]}). \end{aligned} \quad (C.8)$$

The first-order leading principal is nonpositive because $\mathbb{E}[c_{[1]}^o] \leq \mathbb{E}[c_{[2]}^o]$, as follows from merit ordering and our assumption that the operating cost of all owned capacity is less than the operating and charter costs of chartered capacity: $\mathbb{E}[c_{[1]}^o] < \mathbb{E}[c_c^o] + c^c$. In fact, that leading principal is strictly negative when either $f_{\bar{D}}(K_{[1]})$ or $f_{\bar{D}}(K_{[1]} + K_{[2]}) > 0$. The Hessian's determinant (i.e., the second-order leading principal),

$$\begin{aligned} |H(V)| &= ((1 - \xi)c_{[1]}^{o, \text{std}} + \xi c_{[1]}^{o, \text{ret}} - (1 - \xi)c_{[2]}^{o, \text{std}} - \xi c_{[2]}^{o, \text{ret}}) f_{\bar{D}}(K_{[1]}) \\ &\quad \times ((1 - \xi)c_{[2]}^{o, \text{std}} + \xi c_{[2]}^{o, \text{ret}} - (1 - \xi)c_c^{o, \text{std}} - \xi c_c^{o, \text{ret}} - c^l - c^c) \\ &\quad \times f_{\bar{D}}(K_{[1]} + K_{[2]}), \end{aligned} \quad (C.9)$$

is strictly positive if both $f_{\bar{D}}(K_{[1]}) > 0$ and $f_{\bar{D}}(K_{[1]} + K_{[2]}) > 0$ —given that, by assumption, $(\mathbb{E}_{\bar{\alpha}}[c_{[1]}^o] - \mathbb{E}_{\bar{\alpha}}[c_{[2]}^o]) \leq 0$ and $\mathbb{E}_{\bar{\alpha}}[c_{[2]}^o] \leq \mathbb{E}_{\bar{\alpha}}[c_c^o] + c^l + c^c$. The Hessian is at least negative semi-definite, and it is negative definite whenever $f_{\bar{D}}(K_{[1]}) > 0$ and $f_{\bar{D}}(K_{[1]} + K_{[2]}) > 0$. Hence the value function V is concave in capacities $K_{[1]}$ and $K_{[2]}$ and is strictly concave provided that $f_{\bar{D}}(K_{[1]}) > 0$ and $f_{\bar{D}}(K_{[1]} + K_{[2]}) > 0$. \square

Proof of Corollary 1. In a market regime with regulatory uncertainty, with merit ordering that is known ex ante, and with positive marginal profits in phase 2, the total capacity changes with an increase of regulation risk ξ according to its first derivative:

$$\begin{aligned} &\frac{\partial K_{[1]}^* + K_{[2]}}{\partial \xi} \\ &= \frac{\partial}{\partial \xi} F_{\bar{D}}^{-1} \left(1 - \frac{k_{[2]} + k_{[2]} c^f + c^l}{(1 - \xi)c_c^{o, \text{std}} + \xi c_c^{o, \text{ret}} - (1 - \xi)c_{[2]}^{o, \text{std}} - \xi c_{[2]}^{o, \text{ret}} + c^l + c^c} \right) \end{aligned}$$

$$\begin{aligned}
&= \frac{(k_{[2]} + k_{[2]}c^f + c^l)(c_c^{o,\text{ret}} - c_c^{o,\text{std}} + c_{[2]}^{o,\text{std}} - c_{[2]}^{o,\text{ret}})}{f_{\bar{D}} \left(1 - \frac{k_{[2]} + k_{[2]}c^f + c^l}{\bar{c}_c^o - \bar{c}_{[2]}^o + c^l + c^c}\right) (\bar{c}_c^o - \bar{c}_{[2]}^o + c^l + c^c)^2} \\
&= \begin{cases} > 0 & \text{if } (c_c^{o,\text{ret}} - c_c^{o,\text{std}})/(c_{[2]}^{o,\text{ret}} - c_{[2]}^{o,\text{std}}) > 1, \\ < 0 & \text{if } (c_c^{o,\text{ret}} - c_c^{o,\text{std}})/(c_{[2]}^{o,\text{ret}} - c_{[2]}^{o,\text{std}}) < 1. \end{cases} \tag{C.10}
\end{aligned}$$

The reason is that both $f_{\bar{D}} \left(1 - \frac{k_{[2]} + k_{[2]}c^f + c^l}{\bar{c}_c^o - \bar{c}_{[2]}^o + c^l + c^c}\right) \geq 0$ and $(\bar{c}_c^o - \bar{c}_{[2]}^o + c^l + c^c)^2 \geq 0$ in the denominator and that $(k_{[2]} + k_{[2]}c^f + c^l) > 0$ in the numerator. \square

Proof of Corollary 2. To derive the influence of regulation probability on optimal capacities $K_{[1]}^*$ and $K_{[2]}^*$, we calculate the derivatives of the solution detailed in Proposition 1 for all four cases. *Case 1:*

$$\frac{\partial K_{[i]}}{\partial \xi} = 0. \tag{C.11}$$

Case 2:

$$\begin{aligned}
\frac{\partial K_{[1]}}{\partial \xi} &= \frac{\partial \hat{K}_{[1]}}{\partial \xi} = \frac{\partial}{\partial \xi} F_{\bar{D}}^{-1} \left(1 - \frac{k_{[1]} + k_{[1]}c^f + c^l}{\bar{c}_c^o + c^c - \bar{c}_{[1]}^o + c^l}\right) \\
&= \frac{(k_{[1]} + k_{[1]}c^f + c^l)(c_c^{o,\text{ret}} - c_c^{o,\text{std}} + c_{[1]}^{o,\text{std}} - c_{[1]}^{o,\text{ret}})}{f_{\bar{D}} \left(1 - \frac{k_{[1]} + k_{[1]}c^f + c^l}{\bar{c}_c^o + c^c - \bar{c}_{[1]}^o + c^l}\right) (\bar{c}_c^o + c^c - \bar{c}_{[1]}^o + c^l)^2} \\
&= \begin{cases} > 0 & \text{if } (c_c^{o,\text{ret}} - c_c^{o,\text{unreg}})/(c_{[1]}^{o,\text{ret}} - c_{[1]}^{o,\text{std}}) > 1, \\ < 0 & \text{if } (c_c^{o,\text{ret}} - c_c^{o,\text{unreg}})/(c_{[1]}^{o,\text{ret}} - c_{[1]}^{o,\text{std}}) < 1. \end{cases} \tag{C.12}
\end{aligned}$$

These equalities hold because the denominator in the second line is positive owing to the squared term and by definition of the probability density function. Also, $(k_{[1]} + k_{[1]}c^f + c^l) > 0$ and

$$\frac{\partial K_{[2]}}{\partial \xi} = 0. \tag{C.13}$$

Case 3:

$$\frac{\partial K_{[1]}}{\partial \xi} = 0 \tag{C.14}$$

and

$$\begin{aligned}
\frac{\partial K_{[2]}}{\partial \xi} &= \frac{\partial \hat{K}_{[2]}}{\partial \xi} = \frac{\partial}{\partial \xi} F_{\bar{D}}^{-1} \left(1 - \frac{k_{[2]} + k_{[2]}c^f + c^l}{\bar{c}_c^o + c^c - \bar{c}_{[2]}^o + c^l}\right) \\
&= \frac{(k_{[2]} + k_{[2]}c^f + c^l)(c_c^{o,\text{ret}} - c_c^{o,\text{std}} + c_{[2]}^{o,\text{std}} - c_{[2]}^{o,\text{ret}})}{f_{\bar{D}} \left(1 - \frac{k_{[2]} + k_{[2]}c^f + c^l}{\bar{c}_c^o + c^c - \bar{c}_{[2]}^o + c^l}\right) (\bar{c}_c^o + c^c - \bar{c}_{[2]}^o + c^l)^2} \\
&= \begin{cases} > 0 & \text{if } (c_c^{o,\text{ret}} - c_c^{o,\text{std}})/(c_{[2]}^{o,\text{ret}} - c_{[2]}^{o,\text{std}}) > 1, \\ < 0 & \text{if } (c_c^{o,\text{ret}} - c_c^{o,\text{std}})/(c_{[2]}^{o,\text{ret}} - c_{[2]}^{o,\text{std}}) < 1. \end{cases} \tag{C.15}
\end{aligned}$$

Here the same argument as in Case 2 applies—as does, accordingly, the inequality

$$(k_{[2]} + k_{[2]}c^f + c^l) > 0.$$

Case 4:

$$\begin{aligned} \frac{\partial K_{[1]}}{\partial \xi} &= \frac{\partial}{\partial \xi} F_{\bar{D}}^{-1} \left(1 - \frac{k_{[1]} + k_{[1]}c^f - k_{[2]} - k_{[2]}c^f}{\bar{c}_{[2]}^o - \bar{c}_{[1]}^o} \right) \\ &= \frac{(k_{[1]} + k_{[1]}c^f - k_{[2]} - k_{[2]}c^f)(c_{[2]}^{o,ret} - c_{[2]}^{o,std} + c_{[1]}^{o,std} - c_{[1]}^{o,ret})}{f_{\bar{D}} \left(1 - \frac{k_{[1]} + k_{[1]}c^f - k_{[2]} - k_{[2]}c^f}{\bar{c}_{[2]}^o - \bar{c}_{[1]}^o} \right) (\bar{c}_{[2]}^o - \bar{c}_{[1]}^o)^2} \\ &= \begin{cases} > 0 & \text{if } (k_{[1]} + k_{[1]}c^f - k_{[2]} - k_{[2]}c^f) > 0 \\ & \text{and } (c_{[2]}^{o,ret} - c_{[2]}^{o,std}) / (c_{[1]}^{o,ret} - c_{[1]}^{o,std}) > 1, \\ > 0 & \text{if } (k_{[1]} + k_{[1]}c^f - k_{[2]} - k_{[2]}c^f) < 0 \\ & \text{and } (c_{[2]}^{o,ret} - c_{[2]}^{o,std}) / (c_{[1]}^{o,ret} - c_{[1]}^{o,std}) < 1, \\ < 0 & \text{otherwise.} \end{cases} \end{aligned} \quad (C.16)$$

This result holds because the denominator is nonnegative due to the squared term and the definition of the probability density function. Finally,

$$\begin{aligned} \frac{\partial K_{[2]}}{\partial \xi} &= \frac{\partial}{\partial \xi} \left\{ F_{\bar{D}}^{-1} \left(1 - \frac{k_{[2]} + k_{[2]}c^f + c^l}{(1 - \xi)c_c^{o,std} + \xi c_c^{o,ret} - (1 - \xi)c_{[2]}^{o,std} - \xi c_{[2]}^{o,ret} + c^l + c^c} \right) \right. \\ &\quad \left. - F_{\bar{D}}^{-1} \left(1 - \frac{k_{[1]} + k_{[1]}c^f - k_{[2]} - k_{[2]}c^f}{(1 - \xi)c_{[2]}^{o,std} + \xi c_{[2]}^{o,ret} - (1 - \xi)c_{[1]}^{o,std} - \xi c_{[1]}^{o,ret}} \right) \right\} \\ &= \frac{(k_{[2]} + k_{[2]}c^f + c^l)(c_c^{o,ret} - c_c^{o,std} + c_{[2]}^{o,std} - c_{[2]}^{o,ret})}{f_{\bar{D}} \left(1 - \frac{k_{[2]} + k_{[2]}c^f + c^l}{\bar{c}_c^o - \bar{c}_{[2]}^o + c^l + c^c} \right) (\bar{c}_c^o - \bar{c}_{[2]}^o + c^l + c^c)^2} \\ &\quad - \frac{(k_{[1]} + k_{[1]}c^f - k_{[2]} - k_{[2]}c^f)(c_{[2]}^{o,ret} - c_{[2]}^{o,std} + c_{[1]}^{o,std} - c_{[1]}^{o,ret})}{f_{\bar{D}} \left(1 - \frac{k_{[1]} + k_{[1]}c^f - k_{[2]} - k_{[2]}c^f}{\bar{c}_{[2]}^o - \bar{c}_{[1]}^o} \right) (\bar{c}_{[2]}^o - \bar{c}_{[1]}^o)^2}. \end{aligned} \quad (C.17)$$

In this case, the direction of capacity change is unclear. \square

Proof of Corollary 3. Chartering adds value only if there is a positive probability that demand exceeds optimal capacity:

$$\begin{aligned} \Pr(\bar{D} > K_{[1]}^* + K_{[2]}^*) &> 0, \\ 1 - F_{\bar{D}}(K_{[1]}^* + K_{[2]}^*) &> 0. \end{aligned} \quad (C.18)$$

Inserting the solution of Eq. (C.4), we obtain

$$\begin{aligned}
 1 - \left(1 - \frac{k_{[2]} + k_{[2]}c^f + c^l}{(1 - \xi)c_c^{o, \text{std}} + \xi c_c^{o, \text{ret}} - (1 - \xi)c_{[2]}^{o, \text{std}} - \xi c_{[2]}^{o, \text{ret}} + c^l + c^c} \right) &> 0, \\
 \frac{k_{[2]} + k_{[2]}c^f + c^l}{\bar{c}_c^o - \bar{c}_{[2]}^o + c^l + c^c} &> 0, \\
 \bar{c}_c^o + c^c &> \bar{c}_{[2]}^o - c^l.
 \end{aligned} \tag{C.19}$$

□

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