Decision making under uncertainty in fisheries management:
capital adjustment, fishermen behavior and stochasticity in fish stocks

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Chapter 1

Introduction

1.1 The state of world fisheries

According to the 2012 FAO report on the state of world fisheries (FAO, 2012), the world's marine fisheries have in recent years been characterized by declining global catch, together with an increase in overexploited fish stocks, where overexploitation is generally understood as fishing the stock to below the size that is associated with maximum fish stock growth. Management actions have been successful in reducing exploitation rates in some areas, but a large number of stocks will stay collapsed unless exploitation rates are further reduced. In many areas, effective management is still required (Worm et al., 2009). The 2012 FAO report (FAO, 2012: p12) concludes with the following statement:

> 'The state of world marine fisheries is worsening...To increase the contribution of marine fisheries to the food security, economies and wellbeing of the coastal communities, effective management plans must be put in place to rebuild overexploited stocks.'

Overfishing is the act of catching with such a high intensity that the fish cannot reproduce sufficiently to support and replace the population. The economic factors that are fundamental to overfishing, as a result of absent or weak management, have been generally understood since the 1950s (Gordon, 1954; Scott, 1955; Beddington et al., 2007). In fact, already in 1911 Jens Warming pleaded for private and common-properties to be subjected to governmental management policies (Warming, 1911). Common property holds when 'the management group has a right to exclude nonmembers, and nonmembers have a duty to abide by exclusion' (Bromley, 1991). This is different from open access, under which 'no defined group of users or owners and benefit stream is available to anyone' (Bromley, 1991). Through the introduction of the exclusive economic zone (EEZ) in the 1970s, which gives coastal states up to 200 nautical miles of exclusive exploration rights and use rights, fishing populations in these zones have been converted from being open access resources to common property resources. In the EEZ, fish populations are examples of common-property resources that tend to become overexploited over time through a process known as 'the tragedy of the commons' (Hardin, 1968), if they are not well managed. In his study, Hardin (1968) concluded that 'freedom in the commons brings ruin to all,' but that the tragedy could be avoided by privatizing the commons or maintaining them as public property with government control on entry and use. In the high seas, fisheries can still be regarded as open access because everybody is entitled to fish, unless excluded or regulated by a legally binding international treaty.

An important threat to survival of many fish species and fisheries is the increase in fishing fleet capacity, caused by economic incentives of fishermen under open-access and poor management. The worldwide crisis in marine fisheries has even been summarized by Clark (2006b) as 'too many boats chasing too few fish.' The resulting overcapacity prevents fisheries from becoming profitable (Pauly et al., 2002). As there is too much fleet capacity, it is necessary to reduce this in order to recuperate profits and to prevent fish stocks from becoming overexploited.

The success of a management system is specified in terms of biological, economic, social and political objectives of the fishing industry and the management authority. Balancing these objectives makes the implementation of policies one of the main challenges in fisheries management. To prevent overfishing, different measures have been set that limit catch and/or the fleet capacity. Yet, many management systems have failed to prevent overfishing and have often resulted in an increase in investments in the fleet capacity, causing overcapacity. The root to both overfishing and overcapacity can in fact be traced back to the economic behavior of fishermen (Clark, 2006a; Beddington et al., 2007). Therefore, central to understanding the development, enforcement and compliance of management systems is the analysis of behavior and incentives of the fishing industry and the management authority (Beddington et al., 2007). When behavior and incentives are understood, the solution to overcapacity is to adjust the management approach, that is used to maintain and allocate fishery resources, accordingly.

1.1.1 Fisheries management in the world

Fisheries policies can be broadly categorized as output measures and input measures. Output measures are direct limits on the amount of fish caught from a fishery in a period of time and input measures are restrictions on the intensity, i.e. the use of vessels and gear, of fishing. The most common output measure is total allowable catch (TAC), which is a system that sets a maximum to the allowable exploitation of fish stocks. TACs can be operated through incentive-based approaches, which are individually allocated quotas that provide quota holders with a fixed share of the TAC, individual fishery quotas (IFQs) that are not transferable to other quota holders and individual transferable quotas (ITQs) that are transferable to other quota holders.

Management systems, such as the TAC and technical measures like gear restrictions, have originally been developed for single species. Many fisheries, however, impact multiple species simultaneously. For example, fishermen may continue harvesting once the TAC of one of their target species is fully fished. Or, fishermen may redirect their fishing activities to an area with a high abundance of the more valuable target species. Multi-species fisheries, where several species are caught jointly, present the challenge of understanding spatial patterns in fishermen behavior as they try to balance profitable catch target species while avoiding fish species with low catch limits. Fisheries that harvest multiple species are therefore more difficult and costly to manage effectively than single-species fisheries and have resulted in high bycatch and discard rates. Bycatch is inevitable in many multi-species fisheries and economic incentives of fishermen are important when they determine the amount of bycatch. ITQ programs help to address this problem by providing fishermen with economic incentives to take on a quota portfolio that better fits their expected catches (Sanchirico et al., 2006).

Output measures come with several challenges, such as non-compliance of regulation. For example, fishermen can be economically tempted to land more fish than their quota allocations allow, they may report one species as another species, or they may report a species as coming from another management area. This can affect trust in the management system and distort catch statistics, which are the basis for future catch limits (Rijnsdorp et al., 2007). Quota systems are also prone to discarding. Fishermen discard bycatch, which is part of the catch that may be over-quota, undersized fish or less economically valuable. The latest development on discard reduction in the European Union is the plan to reduce discards to 7% of total catch by the year 2019. This should be compared to current discard rates in the European Union, which range between 5% and 95%, depending on the type of fishing and the fishing area (European Commission, 2012b).

Inputs in fisheries include e.g. labor, vessels, nets, sonar gear, storage capacity and motor capacity.

Input measures refer to restrictions on the number of vessels, fishing time or motor capacity. The number and size of fishing vessels may be restricted through licenses or permits. A limited-entry system is an example of limiting the total fleet size by means of a cap on the number of tradable or non-tradable permits that give the right to participate in a fishery. Fishing time may be restricted through Vessel Day Schemes (Havice, 2010), which put a limit on the number of fishing days at sea or on the use of capacity (Cochrane and Garcia, 2009; European Commission, 2012a). The motor capacity can be restricted by setting a limit on the engine power. One of the challenges of input measures includes the increase in technical efficiency over time, which enables fishermen to catch a greater proportion of the available fish stock. Restricting investment in engine size by effort management makes technical improvement in vessel efficiency even more likely. Another challenge concerns licenses that specify engine power. After certification of a license requirement, fishermen may be tempted to upgrade the engine power without permission (Cochrane and Garcia, 2009).

Besides the difficulty of understanding economic incentives of fishermen, another challenge of input and output controls is that the management process is highly dependent on uncertainty about current fish stock levels, their dynamics, the impact of human activity and environmental variability. Attempts to reduce fleet capacity include removing vessels from the fleet by means of vessel buy-back programs. These subsidies have shown to be inefficient because only the least efficient vessels are removed and then replaced by new and more efficient ones that add to the problem of overcapacity and overexploitation (Clark, 2006a).

In order to deal with uncertainty in fisheries systems and to account for incomplete knowledge, a precautionary approach has been adopted in the 1990s with the objective of managing fish stocks within safe biological limits. Predetermined biological reference points and fish stock status are translated into harvest control rules such as constant catch, constant effort and constant escapement, where escapement is the number of fish that escapes the fishery. All rules are based on keeping landings, fish mortality or survivors constant (Zhang et al., 2013) and form the basis for output measures such as TACs. It is common practice to use single-species models where each species is considered in isolation from the rest of the ecosystem. The harvest control rule that keeps fish mortality constant has been shown to be most robust to uncertainty in fish stock dynamics and is therefore the most common rule for setting output measures (Zhang et al., 2013).

The next two sections zoom in on examples of problems in fisheries management in the European Union and Alaska. These are further studied in Chapters 2-5.

1.1.2 Fisheries management in the European Union

In the European Union, fisheries policies are authorized by the Common Fisheries Policy (CFP) and enforced by the member states (Mora et al., 2009). The CFP has to account for biological conservation and environmental, political and socio-economic structures such as the institutional organization and behavior of fishermen, policy instruments, monitoring and enforcement. During the 1992 review of the CFP it became obvious that ill-defined policies had lead to the incentive of fishermen to 'race to fish' (Costello et al., 2008), to invest in more fishing capacity and to harvest more intensively. The result was overinvestment and overexploitation, with the consequence of decreasing catches. In addition, fish stocks are dynamic, uncertain and not well understood by policy makers. It is thus difficult for managers to estimate biological reference points and to set policies at the right level in order to prevent overexploitation and overcapitalization. Determination of policies also requires high management costs in terms of obtaining information and negotiations between experts and policy makers. The costs of operating the quota management system have been estimated at 78 million euro per year for 13 European countries (European Advisory System Evaluation, 2007). A major reform of the CFP took place in 2002: among other things, a commitment was made to develop recovery and multiannual management plans for fish stocks and to reduce high management costs, which include costs for meetings between policy makers and scientists. Despite the new measures, the CFP failed to tackle problems of overcapacity and overexploitation, and profits continued to drop. These shortcomings were identified and published in 2009, in a Green Paper on the Reform of the Common Fisheries Policy (European Commission, 2009b). In 2011, fishermen organizations demanded that economic, social and environmental sustainability be combined in the 2012 reform of the Common Fisheries Policy. This was in contrast to the up to then prevailing opinion that the primary focus of the CFP was the population biology. Eventually, in February 2013 the reform was adopted with amendments concerning multiannual management plans and a gradual elimination of discards in order to reduce overcapacity and overfishing and improve the economic performance of the fishing industry.

1.1.3 Fisheries management in Alaska

In the state of Alaska, a limited entry system was introduced in 1974 for salmon fisheries, classified by gear and harvesting area (Clark, 2006b). The limited entry system is regulated by the Commercial Fisheries Entry Commission (CFEC) by restricting the number of operators, but allowing for permits to be traded. Essential to this limited entry system is that there is a maximum on the number of entry permits. An entry permit grants the right to participate in the fishery, but it does not guarantee a catch or quota (Hilborn et al., 2005). To be able to participate, entry permits need to be renewed annually, but when a fishermen sells his entry permit, he loses the right to fish. Although this tradable permit system has contributed to high earnings and catch since the 1970s, ex-vessel prices of some salmon species have fluctuated greatly and have resulted in unstable earnings for fishermen. Since the early 2000s, participation in the fishery has fluctuated and a substantial number of permit holders has left the fishery, but returned a few years. Still, by the late 2000s, a large number of fishing permits remained unused.

1.2 Fisheries economics literature

Already in 1911, a plea was made for open access resources to be subjected to governmental management policies (Warming, 1911). The economic theory of open access and sole ownership in fisheries was further developed by natural resource economists Gordon (1954) and Scott (1955). The most common objective in fisheries management is that catch should be as large as possible, yet sustainable in the long run. The maximum sustainable yield (MSY) aims to maintain the size of the fish stock at the point of maximum growth rate, by harvesting the fish that would be added to the fish stock, allowing the stock to continue to be productive indefinitely: ‘Any species each year produces a harvestable surplus, and if you take that much, and no more, you can go on getting it forever and ever’ (Larkin, 1977: p1). Fishing the stock to below the size associated with MSY has been a traditional interpretation of biological overexploitation and is therefore an integral part of most fisheries management, in concept and/or in practice. Gordon (1954) showed that when the marginal costs of fishing are equal to the marginal revenues, the resource rents that can be obtained from the fishery are maximized and this maximum economic yield (MEY) always gives higher resource rents than the MSY. That is, at the MEY, resource rents are highest at effort and harvest levels that are lower than at the MSY. The maximum economic yield, however, is only recently becoming more of an accepted and implemented target in fisheries management (Grafton et al., 2010).

On one hand, in an open-access fishery, fishermen receive resource rents from harvesting the fish stock, where resource rents are defined as the difference between revenues from harvesting a fish stock and costs of the corresponding fishing effort. More fishermen continue to access the fishery as long as they anticipate receiving resource rents. Eventually, this often leads to overexploited fish stocks or even a collapse. On the other hand, in a fishery with a sole owner, this sole owner has the exclusive right of access to a fishery and his objective is to choose the harvest level that maximizes the present value of the resource rents.

1.2.1 Bio-economic models

Based on the work of Gordon (1954), an extensive number of models have been developed that integrate biological and economic aspects, in order to analyze fisheries management systems and the interactions between biological and economic subsystems. Next an overview is presented of characteristics and assumptions of biological submodels and economic submodels. This is followed by a description of how uncertainty and different fisheries management systems are incorporated in bio-economic models.

Biological submodels

In many bio-economic fisheries models, the biological submodel is simplified with density-dependent growth of fish stock. The functional form that was first applied in bio-economic models is the logistic growth function, which states the growth rate as a function of fish stock, the carrying capacity and the intrinsic growth rate. It is a commonly used functional form in theoretical models (Sethi et al., 2005; Albornoz and Canales, 2006; Clark, 2006b; Singh et al., 2006; Braverman and Braverman, 2009; Da Rocha and Gutiérrez, 2012). Another density-dependent growth function is the non-linear Ricker spawner-recruitment function (Ricker, 1954; Marsden et al., 2009), which is used for species with non-overlapping generations (Clark, 2006b). Alternatively, the density-dependent Beverton-Holt stock-recruitment function (Beverton and Holt, 1957) explicitly distinguishes multiple cohorts (Tang et al., 2006; Kulmala et al., 2007; Kim et al., 2008). Logistic growth does not specify which population processes are affected in case of overfishing. Harvesting of different age groups can be analyzed with age-structured fish population models, such as the Beverton-Holt stock-recruitment function (Kulmala et al., 2008; Tahvonen, 2009; Link et al., 2011; Rocha et al., 2012; Gourguet et al., 2013; Quaas et al., 2013). When the analysis concerns a multi-species population, which has biological interactions, dynamics can be described using predator-prey models (Flaaten, 1998).

Economic submodels

In the fisheries economics literature, it is common to assume that the bio-economic objective of a policy maker is to set a policy that maximizes the discounted net present value of resource rents (Arnason, 2009). The planning horizon is commonly assumed to be long-term, which in modeling terms is translated into an infinite planning horizon (Bjørndal et al., 2000; Singh et al., 2006; Kulmala et al., 2008). Short-term planning horizons have been studied to a lesser extent (Mardle and Pascoe, 2002).

A decision-making unit often consists of a number of agents with each a different objective (Arnason, 2009). That is, fishermen may have a different objective than a policy maker. Behavior of fishermen has been considered in the literature with different assumptions. Long-term harvest behavior, where fishermen seek a long-term sustainable fish stock when deciding on the harvest level, has been assumed in Clark et al. (2005), Daníelsson (2005), Singh et al. (2006), Kulmala et al. (2008) and Nøstbakken (2009). Fishermen reveal short-term harvest behavior when they do not consider the effect of their harvest decision on the future fish stock, i.e. it is assumed that the future looks the same as the present. This has been considered in Hämäläinen et al. (1990), Sandal and Steinshamn (2004) and Olaussen and Skonhoft (2008). Investment behavior is frequently assumed to be a long-term decision (Eisenack et al., 2006; Singh et al., 2006). Both short and medium-term planning horizons are considered in Link et al. (2011). Although it has been posed in Karagiannakos (1996), Grafton et al.

(2006) and European Commission (2009a) that short-term harvest behavior is not far off from true fishermen behavior, there seems to be no general consensus about whether fishermen operate with a short or long planning horizon.

The process of harvesting has a number of characteristics that should be captured in a harvest function. The input for harvesting includes effort, which may include fishing gear, a vessel and labor, and the fish stock. The output is the harvest level. Different functional forms make different assumptions about the relation between the input and output and the choice of functional form may depend on the specific fish species that is studied. A standard harvest function in fisheries economics is the Schaefer model, which represents harvest as a function of fish stock and effort (Schaefer, 1954; Clark et al., 2005; Homans and Wilen, 2005; Marsden et al., 2009; Da-Rocha et al., 2011; Link et al., 2011). This function assumes that catch per unit of effort is proportional to the level of fish stock (Clark, 1990). A critical assumption of this model is that in any one year the harvest is a linear function of effort, so that the catch per unit of effort is constant for a given fish stock size. The effort can be indefinitely applied in the short run and harvest increases at a constant rate. In a discrete-time analysis, the consequence of setting the catch per unit of effort at the beginning of the period and assuming a constant catch per unit of effort for the following period is that the fish stock will go extinct if the effort level is not restricted. The Spence harvest function incorporates, in a discrete-time analysis, that within one period the fish stock reduces as the fishing effort increases. That is, the catch per unit of effort decreases. Characteristic to the Spence function, therefore, is that the fish stock will not go extinct, unless the effort level is infinitely large (Spence, 1973; Reed, 1979; Nøstbakken, 2008).

Because of the problem of overfishing, the impact of capital adjustment has become an important issue in fisheries economics (Clark et al., 1979; Eisenack et al., 2006). In the literature this is represented by a system of dynamically interacting fish stock and capital stock. A standard investment function in fisheries economics is one where the physical capital investment is determined by the given capital stock, which depreciates over time (Clark et al., 1979). This capital stock becomes a limit on the effort level. An overview of capital adjustment in the fisheries economics literature is given in (Nøstbakken et al., 2011).

1.2.2 Uncertainty in bio-economic models

In statistics, uncertainty is defined as the estimated amount or percentage by which an observed or calculated value may differ from the true value. Many types of uncertainty play a role in fisheries management, such as environmental variability and uncertainty in fish stock growth, but also measurement uncertainty, economic uncertainty and scientific uncertainty. When management decisions are to be based on quantitative estimates from fisheries models, it is desirable that the uncertainty is quantified. Bio-economic fishery models have considered uncertainty in fish stock dynamics, the price of fish, or both. Environmental variability often explains why fish stock dynamics are uncertain. Many studies assume environmental variability (Li, 1998; McDonald et al., 2002; Saphores, 2003; Singh et al., 2006; Nøstbakken, 2008; Sarkar, 2009; Da Rocha and Gutiérrez, 2012), where the uncertainty is often incorporated by means of a random variable that is multiplied with the fish stock growth function (Singh et al., 2006; Nøstbakken, 2008; Da Rocha and Gutiérrez, 2012). Carson et al. (2009) take a different approach, namely a periodically oscillating growth function. Compared to a random variable, with this approach there are bad and good years. The effect of an uncertain price of fish on the optimal harvest level has been studied in Maza (2004); Murillas and Chamorro (2006); Nøstbakken (2006). Few studies look at the effects of several sources of uncertainty on optimal management. In Sethi et al. (2005), uncertainty on fish stock growth, fish stock measurement and harvest have been accounted for and in Nøstbakken (2006) both fish stock growth and price uncertainty are incorporated.

1.2.3 Modeling fisheries management

In the fisheries economics literature different fisheries management systems have been studied with bio-economic models. For example, the total allowable catch (TAC) is usually determined through a decision maker's objective of determining the quota that maximize resource rents. The optimal quota is then set at a level such that the fish stock will remain at an efficient level, i.e. to have the stock at optimal health and productivity, while at the same time a profit can be made from harvesting. Individual transferable quotas (ITQs) represent a harvesting right to the TAC, which fishermen are then free to use or trade. First the TAC is set and then quotas are tradable on the quota market. There will be a tendency for only the most efficient fishermen to operate in the fishery, where the quota price acts as a restraint to harvesting. The less efficient ones will sell their quota and leave the fishery. The objective of the policy maker therefore is to maximize the quota price along the maximization of resource rents. By setting the appropriate TAC, the policy maker can control the ITQ price and ensure optimal utilization of the fish stock. Similar models, incorporating ITQ prices, have been developed in Arnason (1990); Batstone and Sharp (2003); Arnason (2009); Little et al. (2009). Input measures such as limited entry fisheries imply that participation is limited to a given number of fishermen, who each determine their own harvest level or fleet size as a function of fish stock, fleet capacity and possibly a quota and season length (Clark, 1976, 2006b).

Bycatch and discards are often analyzed in a bio-economic setting of multiple fish stocks and have been incorporated, among others, in quota and tax optimization (Androkovich and Stollery, 1994), harvest or effort optimization (Turner, 1997; Pascoe, 2000; Herrera, 2005; Abbott and Wilen, 2009; Singh and Weninger, 2009) and bycatch penalty optimization (Abbott and Wilen, 2009). For example, Pascoe (2000) includes a discard variable in his static analysis, Herrera (2005) includes a random bycatch parameter and Abbott and Wilen (2009) incorporate a harvest bycatch function. There has been substantial progress in multi-species fisheries models, ranging from predator-prey bio-economic models (Singh and Weninger, 2009) to elaborate ecosystem models and size-based models (Pinnegar et al., 2008; Punt et al., 2011). For other subjects than bycatch, the generalized model is a two-species model where the objective of the decision maker is to determine the harvest levels of both species that maximize resource rents, while anticipating on the dynamics of both fish stocks (Chaudhuri, 1986; Fleming and Alexander, 2003; Clark, 2006b). Few multi-species models have actually been used to provide fisheries advice and to set quotas. It is still difficult for fisheries scientists to predict with certainty what impact harvesting one species may have on other parts of the ecosystem.

1.3 Objectives and research questions

The overall objective of this thesis is to study the impact of different fisheries management systems on resource rents, investment and stochastic fish stocks. To achieve this objective, the following research questions are addressed:

1. How can we model the interaction between the quota decision of a policy maker and fishermen behavior in a model that accounts for dynamics in the biological system and dynamics in economic behavior? And, how can we exploit model characteristics in order to derive the optimal quota in a deterministic and a stochastic setting?

2. What is the effect of multiannual adjustment of fish quota on quota fluctuation and resource rents, considering uncertainty in fish stock growth, investment in the fleet capacity and management costs?

3. What is the effect of a quota adjustment restriction on resource rents, overcapacity and fish stock in the long run and during recovery from a downward external shock on the fish stock?

4. How can we model entry and exit decisions of fishermen under uncertainty about the ex-vessel price of fish? And, at what ex-vessel price is it optimal for fishermen to enter Alaska's limited entry salmon fishery, at what price is it optimal to lay-up and at what price is it optimal to permanently exit the fishery?

1.4 Methodology

In this thesis three methodologies are applied. Stochastic dynamic programming (Howard, 1960; Puterman, 1994) and simulations are used to solve research questions 1-3. The real options theory (Dixit and Pindyck, 1994) is used to address research question 4.

1.4.1 Stochastic dynamic programming

Stochastic dynamic programming (SDP) is a framework for modeling decision making under uncertainty (Bellman, 1957; Howard, 1960). It is a technique for solving sequential decision problems with respect to finite and infinite horizon optimization problems. The optimal policy of a finite-horizon SDP model may be non-stationary, because of the finiteness of the horizon and/or because parameter values may be dependent on a time index. In infinite-horizon SDP models one either optimizes the sum of discounted contributions, or the average contribution. Value function iteration is stochastic dynamic programming with an infinite horizon and with a stopping criterion based on fixed point theorems (Puterman, 1994).

In fisheries management, when setting fish quota, policy makers deal with uncertainty due to e.g. environmental variability, monitoring problems, uncertainty in fish stock growth and economic uncertainty. Several studies have used SDP to deal with policy questions in the domain of fisheries economics (Sethi et al., 2005; Singh et al., 2006; Da Rocha and Gutiérrez, 2012).

1.4.2 Simulation

Results from the SDP model, as described above, typically provide an optimal decision for each feasible state. It does not give an insight into what decisions are made over time, e.g. on the long run and on the short run when the fish stock is subject to an external environmental shock. Dynamic behavior of the modeled system can be studied with a simulation. That is, the bio-economic system is imitated to study the dynamic behavior of the system when it is controlled by an optimal policy. Simulation is commonly applied to evaluate the effect of experimental factors on performance measures of a system and to compare policies with each other (Law and Kelton, 2000; Robinson, 2004). Haijema et al. (2007), Hendrix and Toth (2010), Haijema et al. (2012) and Haijema (2013) are some recent studies where simulation is used to analyze the structure of complex dynamic control policies.

Three dimensions can be used to categorize simulation models. First, a distinction can be made between static simulations and dynamic simulations; static simulations imitate systems at a moment in time and dynamic simulations are systems that develop over time. Second, a distinction can be made between deterministic simulations and stochastic simulations; deterministic simulations do not include probabilities, while stochastic simulations include a random component. Third, there are continuous-time simulations and discrete-time simulations; continuous-time simulations imitate systems who's states develop continuously over time and discrete-time simulations imitate systems who's states develop instantaneously over time (Law and Kelton, 2000). Stochastic simulations are based on sampling, where a sample refers to a value or a set of values that is selected from a distribution (or population), i.e. a value from this distribution is sampled. A single sample may be informative, but it does not give statistical information about the accuracy of the simulation. From multiple samples, statistical information can be obtained about the spread of the data points from the mean, i.e. the variance between samples.

To get insight into annual changes in state variables and decisions in a stochastic and dynamic model, a simulation of a single sample over multiple years may be desired. When the focus is on long-term averages of states and decisions, it may be preferred to take the average over multiple samples and multiple years. The larger the sample size, the more accurate the long-term average will be. This can be done by taking the average over an increased number of years or by drawing more samples per year. Important in a simulation are initial values of the state variables. It depends on these initial values how long the 'warm-up period' is before reaching a steady state (in the case of a deterministic setting) or a long-term average (in the case of a stochastic setting and multiple samples). In fisheries, fish stocks change over time and they are often subject to environmental variability. In the literature it is therefore common to perform stochastic and dynamic simulations (Kell et al., 2005, 2006; Kulmala et al., 2008). It is also common to base simulations on discrete time steps (Guyader, 2002; Kulmala et al., 2007, 2008), especially if on beforehand an SDP model is solved using discrete time steps (Kulmala et al., 2008), and to take multiple samples to study long-term averages (Kulmala et al., 2007, 2008; Haijema et al., 2012).

1.4.3 Real options theory

Many investment decisions in natural resources are irreversible. Moreover, they are often carried out in an uncertain environment and they can be postponed to get more information about future alternatives. Irreversible investments require up-front analysis, because once an investment is made it cannot be reversed without losing some or all of its value. The decision to invest or to wait is based on the price or revenues from the natural resource. Once the investment is made, the option to abandon the project and recover the invested capital is lost. It is therefore important to analyze other available options, including the temporary suspension of operations, reactivation and permanent exit. Real Options (RO) theory can be used to analyze investment and disinvestment decisions, by incorporating uncertainty and the value of holding on to an option to (dis)invest (Dixit and Pindyck, 1994).

The uncertain environment is often characterized by a price, revenues or even dynamics in the natural resource. Different assumptions can be made about the stochastic process. First, the stochastic variable can follow a geometric Brownian motion (GBM). A Brownian motion is a stochastic process, where each random variable is independent from the previous realization, each random variable has an identical distribution that is normal and it is a continuous process. Geometric means that we are looking at the percentage change in the stochastic variable, which is the same as the change in the log of the stochastic variable. A more complex process is a geometric Brownian motion with drift, which indicates in which direction the stochastic variable grows. In a geometric Brownian motion with random walk, the direction and/or size of each step is taken randomly. Second, the stochastic process can be mean-reverting, which has the underlying assumption that high and low values of the stochastic variable are temporary and that the value will move to an average over time. Typically, this implies the incorporation of a speed of reversion and a value of the stochastic variable to which it reverts in the long run. Third, the stochastic process may be a jump process. The stochastic variable makes discrete and infrequent jumps, which can be of fixed or random size.

A geometric Brownian motion is the most simple and commonly used model of stock price behavior. A number of arguments can be made to describe the dynamics of a price as a geometric Brownian motion. A GBM process and stock prices have similar paths, both stock prices and GBM assume positive values and a GBM allows for relatively easy calculations. Disadvantages of the GBM include that the distribution may not always be realistic. Literature that applies Real Options theory to fisheries often assumes a geometric Brownian motion with drift, representing the stochastic process of the fish price or the fish stock dynamics (Li, 1998; Saphores, 2003; Nøstbakken, 2006; Sarkar, 2009).

1.4.4 Methods related to the research questions

In this thesis, research questions 1, 2 and 3 are addressed using stochastic dynamic programming and simulations, and research question 4 uses the Real Options theory in the following manner.

To answer research question 1, an elaboration is provided on model characteristics of the bi-level SDP model and on the implementation of the solution procedure. The bi-level model is considered with discrete time steps. The assumptions of a single-species fishery and a deterministic setting allows one to analytically shed light on model characteristics. In the elaboration on the numerical implementation, also a stochastic setting is considered, namely stochastic fish stock dynamics. At level one, the policy maker's quota decision is an optimization problem that is based on value function iteration. The objective of the policy maker is to determine the quota that maximizes resource rents, while considering deterministic or stochastic fish stock dynamics and capital stock dynamics and anticipating on fishermen behavior. At level two, fishermen reveal short-term behavior, that is, harvest and investment decisions are based on current levels of fish stock and capital stock. This allows one to determine harvest and investment decisions analytically. The two levels are connected by the quota that is set by the policy maker at level one and becomes a restriction for fishermen at level two. Deterministic and stochastic dynamic behavior of the fish stock dynamics is studied with a simulation, using discrete time steps, multiple samples and considering different initial values of fish stock. The model is applied to a stylized setting of North Sea plaice. This is one of the main commercially exploited flatfish species in the North Sea of which growth has changed over the years, partly due to activities of the fishing industry. Biological data were obtained from the International Council for the Exploration of the Sea (ICES) (Rijnsdorp and Millner, 1996; Grift et al., 2003; Kell and Bromley, 2004; Pilling et al., 2008; ICES, 2009; for the Exploration of the Sea, 2011). Economic data were obtained from Van Balsfoort (2006), European Commission (2007) and Taal et al. (2009).

To answer research question 2, the bi-level model is extended to introduce the management system of multiannual quota, where quota are fixed for multiple years. At level one, the quota is no longer adjusted on an annual basis. Instead, it is assumed that the quota is optimized at the beginning of a new quota period and consequently fixed during the remaining years of the quota period. The policy maker incorporates the management costs, which are reduced because they are spread over the number of years for which the quota is fixed. At level two, fishermen still reveal short-term behavior with respect to harvest and investment and the two levels are still linked by the quota. To study the fish stock and quota and investment decisions over time, stochastic dynamic simulations are performed with discrete time steps and a single sample. Multiple samples are used to examine long-term averages of resource rents, overcapacity and quota. North Sea place is used as an illustrative example.

To answer research question 3, the bi-level model is extended to introduce the management system of a quota adjustment restriction. This implies that, with respect to the quota in the previous period, the current quota can at most be adjusted upward or downward by a specified percentage. At level one, the quota decision of the policy maker becomes a function of stochastic fish stock dynamics, capital stock dynamics and the quota of the previous period. In addition, the policy maker anticipates fishermen behavior. At level two, fishermen reveal short-term harvest behavior and assume that the fish stock and quota do not change over time. Their investment, on the other hand, is a long-term decision and is solved with dynamic programming. The two levels are still linked by the quota, which is set by the policy maker at level one and becomes a restriction for fishermen at level two. The effect of an external environmental shock on the fish stock is studied with a stochastic dynamic simulation. A single sample is used to study quota and multiple samples are used to study long-term averages of resource rents, overcapacity, quota, harvest and fish stock, when recovering from an external environmental shock. North Sea place is used as an illustrative example.

To answer research question 4, Real Options theory is used, namely an optimal switching model. A setting is presented in which fishermen can be either operating, laid-up (temporarily suspending operations) or inactive. The model then determines at what ex-vessel prices it is optimal for fishermen to switch between operation, lay-up and exit. Specifically, threshold prices are determined for switching from an inactive state to entry, from an operating state to lay-up and exit, and from lay-up to reactivation. Uncertainty is characterized as coming through the ex-vessel price of fish, where the ex-vessel price follows a geometric Brownian motion with drift. The model is applied to the sockeye salmon gillnet fishery in the Bristol Bay area, in Alaska. The ex-vessel price of sockeye salmon has been estimated and reported by the Commercial Fisheries Entry Commission (CFEC) and by the Department of Fish and Game (ADFG) (Schelle et al., 2004; ADFG, Alaska Department of Fish and Game, 2010). These data are used for the ex-vessel price and uncertainty. With respect to cost data, reports are used from the CFEC, which contain estimated data of costs, revenues and investment (Carlson, 2002; Schelle et al., 2004).

1.5 Contribution of this research

The novelty of this study is that different models are used that deal with decision making under uncertainty. With stochastic dynamic programming and simulations, questions are addressed concerning how much fishermen harvest and invest when they are restricted by a quota. For that, the following specific contributions are distinguished. First, the commonly applied setting of a single decision maker is extended to a setting of multiple decision makers, namely policy makers and fishermen. Second, by dealing with each decision maker separately, light is shed on model characteristics, which is of great value when interpreting dynamics and optimal strategies. In addition, the reader is taken step-by-step through the implementation of the solution procedure, which facilitates the reproduction of similar problems. Third, the bi-level SDP model is a basic model that can be extended to study different management systems and fishermen behavior. Fourth, besides studying long-term levels of fish stock and overcapacity, an analysis is provided of the recovery of the bioeconomic system after an external environmental shock that reduces the fish stock temporarily to an extremely low level. Finally, thus far multiannual management plans have been studied for their biological effects (Kell et al., 1999; Roel et al., 2004; Kell et al., 2006). In light of the 2013 reform of the Common Fisheries Policy, which explicitly points out the importance of reducing overfishing and overcapacity with multiannual management plans, the bi-level SDP is useful to study both biological and economic impacts of multiannual management plans.

Real Options theory deals with the question at what ex-vessel prices it is optimal to invest and disinvest in the fishery. This gives the following specific contributions. First, it is common in the literature to use Real Options theory to determine optimal harvest policies (Li, 1998; Saphores, 2003; Nøstbakken, 2006; Sarkar, 2009). Real Options theory is less often used to determine at what ex-vessel prices it is optimal to change between different states of operation. Second, with this analysis the management of the Bristol Bay salmon fishery is provided with an improved understanding of investment decisions of fishermen when they are confronted with uncertainty in the ex-vessel price.

1.6 Outline of the thesis

Chapters 2-5 of this thesis address the research questions as outlined in Section 1.3. Chapter 2 analyzes a fishery policy along a bi-level stochastic dynamic programming algorithm. The interaction is modeled between the quota decision of a policy maker and fishermen behavior in a model that accounts for stochastic dynamics in the biological system and dynamics in the behavior of the policy maker. The reader is taken step-by-step through the implementation of the solution procedure in a deterministic and stochastic setting. Chapter 3 extends the bi-level SDP model to analyze the effect of multiannual quota on quota fluctuation and resource rents, while accounting for management costs. Chapter 4 extends the bi-level SDP model to analyze the effect of a quota adjustment restriction on resource rents, overcapacity and fish stock in the long run and short-run, when the fish stock is recovering from an external environmental shock. Chapter 5 applies an optimal switching model based on Real Options theory to determine the ex-vessel prices at which it is optimal to switch between three states of operation: operation, lay-up and exit. Uncertainty in this chapter is characterized as coming from the ex-vessel price of fish. Finally, Chapter 6 provides an overview of the main findings in this thesis and draws conclusions from each of Chapters 2-5. This chapter also discusses limitations and suggestions for future research.

Chapter 2

On solving a bi-level stochastic dynamic programming model for analyzing fisheries policies: fishermen behavior and optimal fish quota*

Stochastic dynamic programming (SDP) is a useful tool for analyzing policy questions in fisheries management. In order to understand and reproduce solution procedures such as value function iteration, an analytic elaboration of the problem and model characteristics is required. Because of the increased use of numerical techniques, our aim is to improve the understanding of mathematical properties of the solution procedure and to give more insight into their practical implementation by means of a specific case that uses value function iteration. We provide an analytic description of model characteristics and analyze the solution procedure of a bi-level SDP model to study fisheries policies. At the first level, a policy maker decides on the fish quota to be imposed, keeping in mind fish stock dynamics, capital stock dynamics, long-term resource rents and anticipating fishermen behavior. At the second level, fishermen reveal short-term behavior by reacting on this quota and on current states of fish stock and capital stock by deciding on their investments and fishing effort. An analysis of the behavior of the model is given and a method is elaborated to obtain optimum strategies based on value function iteration. Bi-level decision making enables us to present the model in an understandable manner, and serves as a basis for extension to more complex settings.

*This chapter is based on the paper: Diana van Dijk, Eligius M.T. Hendrix, Rene Haijema, Rolf A. Groeneveld, Ekko C. van Ierland. On solving a bi-level stochastic dynamic programming model for analyzing fisheries policies: fishermen behavior and optimal fish quota. Accepted for publication in Ecological Modelling.

2.1 Introduction

Policy makers in fisheries management face uncertainty related to dynamics in fish stock due to environmental variability. Moreover, policy makers consider human behavior when setting policies. Quota are not only based on known or unknown dynamics in fish stock and fleet capacity of the fishery sector, but also based on how fishermen behave in an unregulated setting. The implementation of these interactions in a model is a challenge, because policy makers and fishermen make their decisions on different scale levels and hence face different incentives. Policy makers can be assumed to seek a long-term sustainable fish stock and maximization of resource rents for the whole of society. Fishermen, on the other hand, are caught in a classical Prisoner's Dilemma: whatever the actions of other fishermen, an individual fisherman can improve his individual payoffs at the expense of others, by increasing his individual catch (Clark, 1990). There is thus a need to account for fishermen behavior in the quota decision making process.

Fisheries policies are analyzed in the literature in a setting of dynamic optimization, where a sole owner determines optimal harvest and investment levels for a specific fishery (Boyce, 1995; McDonald et al., 2002; Sethi et al., 2005; Singh et al., 2006). Such models have been developed in deterministic and stochastic settings, assuming uncertainty in fish stock dynamics due to environmental variability. The assumption of sole ownership, however, ignores behavior of fishermen and the effect of a policy on this behavior. Models that do incorporate behavior of different decision makers may be presented with a multi-stage approach. Actors make a decision at stage one that is independent of the other actors behavior. At stage two, each actor uses decisions from stage one to decide on the best strategy (Ruseski, 1998; Kronbak and Lindroos, 2006). Fisheries models are often sequential decision-making problems, i.e. actors make decisions one after another. The setting typically consists of two sectors, regions or countries that compete for a single species(Hannesson, 1995; Laukkanen, 2003; van Dijk et al., 2013a) or multiple species (Munro, 2009; Wang and Ewald, 2010; Mullon and Nagurney, 2012). For example, in Laukkanen (2003) two fleets harvest a single species that migrates between two areas. Laukkanen (2003) builds on the deterministic model in Hannesson (1995), by incorporating stochastic recruitment. In van Dijk et al. (2013a) a policy maker decides on the quota of a single species with stochastic growth and is followed by the quota-restricted harvest and investment decisions of fishermen. In Wang and Ewald (2010), a number of fisheries harvest two stochastically interacting species. The assumption of uncertainty makes such models complex, which in turn makes the interpretation of bio-economic dynamics not straightforward. In these studies, policy questions are analyzed with numerical solution methods such as stochastic dynamic programming and may be solved using the numerical procedure of value function iteration (Sethi et al., 2005; Singh et al., 2006; Wang and Ewald, 2010; Da Rocha and Gutiérrez, 2012; van Dijk et al., 2013a). An elaboration of model characteristics and implementation of the solution procedure, however, is often not provided in the literature. Complex stochastic dynamic models are therefore not easily understood and reproduced.

We intend to fill a gap in the literature by showing in detail how numerical solution methods can be used to solve a problem in a practical application. For a specific case of a deterministic and stochastic dynamic programming model with multiple actors, the reader is taken step-wise through the model and solution procedure of value function iteration. The following research questions are investigated. How can we model the interaction between the quota decision of a policy maker and fishermen behavior in a model that accounts for dynamics in the biological system and dynamics in the behavior of the policy maker? And, how can we exploit model characteristics in order to derive the optimal quota in a deterministic and stochastic setting?

We develop a model setting in which the objective of a policy maker is to determine levels of quota that maximize long-term resource rents, while incorporating dynamics in fish stock and capital stock and anticipating behavior of fishermen. We study a single-species fishery, where fish stock growth is considered stochastic. From this perspective, it is useful to analyze fisheries policies in a framework of stochastic dynamic programming. In this model, fishermen reveal short-term behavior with respect to harvest and investment decisions, i.e. they base their decisions on current levels of fish stock and capital stock and do not consider the effect of their decisions on the future fish stock. We call this a bi-level model (Amouzegar and Moshirvaziri, 2001): at the first level of the bi-level stochastic dynamic programming model, the policy maker determines the optimal quota for known values of fish stock and capital stock. At the second level, fishermen make their harvest and investment decisions, where they are restricted by available fish stock, capital stock and the quota set by the policy maker at level one. Bi-level decision making enables us to present the model in a simple manner such that it can be reproduced. We show how the model can be solved by means of value function iteration in order to find the optimal strategy for determining the quota. We analyze how the model performs under increased uncertainty and what the impact is of a continuous versus a discrete decision space, i.e. a grid-search procedure.

2.2 Methods

We develop a bi-level model where at level 1 a policy maker sets a quota that maximizes long-term resource rents, while incorporating dynamics in fish stock and capital stock, fishermen behavior and uncertainty about the future fish stock. At level 2, fishermen reveal short-term behavior with respect to their harvest and investment decisions: their decisions are based on currently observed levels of fish stock, capital stock and the quota that is set by the policy maker at level 1 and becomes a restriction at level 2. Fishermen thereby do not consider the effect of their decisions on the future fish stock, i.e. assume that the future looks the same as the present. In what follows, the model first describes dynamics of a biological system that interacts with dynamics of economic behavior. We describe the biological submodel, the economic submodel and optimization. Then the optimization model is presented with fishermen's harvest and investment decisions at level 2 and the policy makers quota decision at level 1. In the used symbols, we distinguish between model parameters (exogenous in lower case letters) and decision variables (capitals) that include direct decision variables, dependent variables and stock variables. The dynamics are modeled in discrete time using an index t.

2.2.1 Biological submodel

The development of one species of fish is based on the Gordon-Schaeffer model (Gordon, 1954; Schaefer, 1954). Parameters used are the carrying capacity of the species in kton m, the intrinsic growth rate r and a lognormally distributed random variable ξ with cumulative distribution function $G(\xi)$. The distribution function is based on parameters μ and σ, with $\mu + \frac{1}{2}\sigma^2 = 0$, so that $\mathbb{E}(\xi) = 1$.

The random variable describes a random multiplicative effect. A lognormal distribution is commonly assumed in fisheries economics literature. Let the stock variable be fish stock X_t in kton and H_t harvest in kton. Then dynamics of fish stock is given by

$$X_{t+1} = X_t + \xi r X_t \left(1 - \frac{X_t}{m}\right) - H_t. \tag{2.1}$$

2.2.2 Economic submodel

The economic part of the model includes capital stock dynamics depending on investment in fleet equipment and all costs to harvest fish. Effort and capital are measured in terms of engine capacity of vessels and number of days at sea, expressed in millions of horse power days, mln hpd. Capital is thereby a cap on the effort. Parameters used are the fixed selling price p in euro per kton of fish, euro/kton, the cost of effort c^e in euro/mln hpd, the investment cost c^i in euro/mln hpd and the crew receives a share of the revenues, so that the crew cost c^s is expressed in euro/euro. The catchability coefficient q in the harvest function and the yearly depreciation rate of capital γ.

Let K_t describe capital stock and I_t investment. Then following neoclassical investment theory we have

$$K_{t+1} = K_t(1-\gamma) + I_t, \tag{2.2}$$

where investment costs in the fishery are $c^i I_t$.

To describe cost of harvesting, a decision variable E_t representing fishing effort (intensity) is introduced that makes harvest H_t in fact a dependent variable. The variable E_t is expressed in horse-power-days (hpd). The relation between harvest H_t and effort E_t is one of the elements where the two sub-models are linked. Harvest not only depends on effort, but also on the size of the fish population. We assume a Spence harvest function (Spence, 1973)

$$H_t = X_t\left(1 - e^{-qE_t}\right) \rightarrow E(X_t, H_t) = \frac{1}{q}\ln\frac{X_t}{X_t - H_t}. \tag{2.3}$$

Effort is limited by capital

$$E_t \leq K_t \rightarrow H_t \leq X_t\left(1 - e^{-qK_t}\right), \tag{2.4}$$

which implies that, for a finite effort, harvest is always less than fish stock:

$$H_t < X_t. \tag{2.5}$$

Profit of the fishery sector is sales from harvest, pH_t, minus effort cost, $c^e E_t$, and crew cost, $c^s pH_t$. Effort cost $c^e E_t$ can be expressed in the harvest function, H_t, by substituting variable E_t: $c^e E_t = \frac{c^e}{q}\ln\frac{X_t}{X_t - H_t}$. Direct profit for the fishery sector,

$$\pi_2(Q_t, X_t, K_t) = pH_t - c^s pH_t - \frac{c^e}{q}\ln\frac{X_t}{X_t - H_t},$$

depends on harvest decision $H_t = H(Q_t, X_t, K_t)$ and, via (2.4), on the investment decision $I_t = I(Q_t, X_t, K_t)$ taken by the fishery sector as described in Section 2.2.3.

2.2.3 Optimization model

Objectives to be optimized depend on the actors such as different groups of fishing companies and authorities like countries and the European Union. In this paper, we focus on a policy maker (EU authority) that sets a quota in order to maximize the discounted stream of future resource rents, given levels of fish stock X_t and capital stock K_t. The fishery sector reacts on that by deciding on investment level $I(Q_t, X_t, K_t)$ and harvest $H(Q_t, X_t, K_t)$, given levels of fish stock, capital stock and quota decision Q_t.

Decisions at level 2

At the second level, it is assumed that fishermen are homogeneous, where each individual fisherman maximizes his own profits. It is furthermore assumed that the entire fishing fleet operates under a quota system, i.e. a quota is assigned to all fishermen. Implicitly, we assume that the quota is distributed over the fishermen as such that in the end the requirements of the quota are met. Fishermen will only leave the fishery when marginal costs of fishing exceed marginal benefits (Conrad and Clark, 1987). The harvest decision is thus restricted by quota Q_t, capital stock via Equation (2.4) and the marginal cost of harvesting. Harvest is set to zero if the effort cost $\frac{c^e}{q}\ln\frac{X_t}{X_t-H_t}$ is higher than the return $(1-c^s)pH_t$. The fish stock at which $\frac{c^e}{q}\ln\frac{X_t}{X_t-H_t} > (1-c^s)pH_t$, is in fact the level below which it is not profitable to harvest. Profit for the fishery sector, given quota Q_t and stock levels X_t and K_t, is

$$\pi_2(Q_t,X_t,K_t) = \max_H \left\{ pH - c^s pH - \frac{c^e}{q}\ln\frac{X_t}{X_t-H} \right\}, \tag{2.6}$$

subject to $0 \leq H \leq Q_t$ and $H \leq X_t\left(1-e^{-qK_t}\right)$. If the optimization problem in Equation (2.6) has an interior solution, the analytical expression follows from the first order condition

$$\frac{d}{dH}\left\{ pH - c^s pH - \frac{c^e}{q}\ln\frac{X_t}{X_t-H} \right\} = 0. \tag{2.7}$$

Given upper and lower bounds in (2.6), the solution is given by

$$H(Q_t,X_t,K_t) = \min\left\{ \left(X_t - \frac{c^e}{pq(1-c^s)}\right)^+, Q_t, X_t\left(1-e^{-qK_t}\right) \right\}, \tag{2.8}$$

where the operator y^+ stands for $\max\{0,y\}$ and where $\frac{c^e}{pq}$ has been identified in Conrad and Clark (1987) as the bioeconomic equilibrium escapement in the Spence model.

With respect to the investment decision, it is assumed that the fishery sector observes the desired harvest level

$$\hat{h}(Q_t,X_t) = \min\left\{ \left(X_t - \frac{c^e}{pq(1-c^s)}\right)^+, Q_t \right\}, \tag{2.9}$$

and adjusts its capital stock for next year to have sufficient capital to reach $\hat{h}$

$$K_{t+1} \geq E\left(X_t, \hat{h}(Q_t,X_t)\right) \tag{2.10}$$

Given dynamics of capital stock K_t in (2.2) and assuming nonnegative investment, this leads to the investment function

$$I(Q_t,X_t,K_t) = \left(\frac{1}{q}\ln\frac{X_t}{X_t-\hat{h}_t(Q_t,X_t)} - K_t(1-\gamma)\right)^+. \tag{2.11}$$

Decisions at level 1

At the first level, we have

$$\max_{Q(X,K)} \mathbb{E}\left\{ \sum_{t=0}^{\infty} \frac{\pi_1(Q(X_t,K_t),X_t,K_t)}{(1+\rho)^t} \right\}, \tag{2.12}$$

where ρ is the discount rate,

$$\pi_1(Q,X,K) = \pi_2(Q_t,X_t,K_t) - c^i I(Q_t,X_t,K_t). \tag{2.13}$$

Typically the investment cost $c^i I(Q_t,X_t,K_t)$ is only accounted for at level 1. Decision $Q_t = Q(X_t,K_t)$ depends on dynamics of fish stock in Equation (2.1) and capital stock in Equation (2.2). Note that this model deals with a stationary system, which means that the optimum strategy consists of a decision rule that tells the policy maker what quota $Q(X,K)$ to set given fish stock X and capital stock K. Furthermore, the optimum strategy depends on behavior of the fishery sector at the second level.

2.3 Model analysis for the deterministic case

In this section we address the question what are characteristics of the model that can be used in the solution procedure of value function iteration. We first look at model characteristics that are used to define implicit bounds of decision variables. We then derive steady state values that are later used in the value iteration approach to verify long-term behavior of the system.

2.3.1 Bounding decision values

Let $\hat{x}$ denote the long-term level of fish stock below which it is not profitable to harvest:

$$\hat{x} = \frac{c^e}{pq(1-c^s)}. \tag{2.14}$$

The long-term fish stock does not fall below $\hat{x}$, but the initial level could be lower. Hence, we set $H_t = 0$ if $X_t < \hat{x}$. In that case, a positive quota is not binding in the decision on the harvest level H_t. We consider the minimum level of harvest to be chosen in case Q_t has alternative solutions. Often this means that $Q_t = H_t$.

Fish stock as described in Equation (2.1) increases up to carrying capacity m and decreases if fish stock, would exceed that level. Due to fishing behavior it is also known that for $X_t < \hat{x}$ no fishing takes place and growth is always positive. On one side, $\hat{x}$ is a lower bound on fish stock X_t if initial stock $X_0 > \hat{x}$. On the other side, if the initial stock is higher than the carrying capacity, $X_0 > m$, the stock can only go down from that level. Given an initial stock X_0,

$$X_t \in \left[\min\left\{X_0, \hat{x}\right\}, \max\left\{X_0, m\right\}\right]. \tag{2.15}$$

This means that the interesting range for harvest H_t and quota Q_t is $[0, \max\{X_0, m\} - \hat{x}]$. This range also provides corresponding values for capital stock K_t and investment I_t. Due to investment cost and depreciation, the level of capital should not exceed what is required to catch the desired level, as specified by Equation (2.10)

$$K_t, I_t \in \left[0, \max\left\{\frac{1}{q}\ln\left(\frac{m}{\hat{x}}\right), K_0\right\}\right].$$

2.3.2 Steady state values

In a stationary system, X_t, K_t, H_t, I_t, Q_t are constant over time with steady state values $\bar{X}$, $\bar{K}$, $\bar{H}$, $\bar{I}$, $\bar{Q}$. Harvest is a constant fraction of fish stock in Equation (2.1), so that $X_{t+1} = X_t = \bar{X}$. If for the steady state value $\bar{X}$, $\hat{x} \le \bar{X} \le m$, it can be found that

$$\bar{H} = r\bar{X}\left(1 - \frac{\bar{X}}{m}\right) \to \bar{X} = \frac{rm + \sqrt{(rm)^2 - 4rm\bar{H}}}{2r}. \tag{2.16}$$

Otherwise, if $\bar{X} < \hat{x}$, no harvest takes place. In the long run, capital, quota and harvest converge to the same level, so that $\bar{Q} = \bar{H}$, $\bar{K} = \frac{1}{q}\ln\frac{\bar{X}}{\bar{X}-\bar{H}}$, and $\bar{I} = d\bar{K} = \frac{d}{q}\ln\frac{\bar{X}}{\bar{X}-\bar{H}}$. The policy maker at level 1 tries to keep stationary resource rents π_1 as high as possible, whereas harvest equals growth;

$$\max_{\bar{H}}\left\{\bar{\pi}_1 = p\bar{H} - c^s p\bar{H} - \frac{c^e + \gamma c^i}{q}\ln\frac{\bar{X}}{\bar{X}-\bar{H}}\right\}, \tag{2.17}$$

subject to

$$\bar{H} = r\bar{X}\left(1 - \frac{\bar{X}}{m}\right).$$

Substitution of growth in the (constant over time) resource rents function gives

$$\bar{\pi}_1 = r(1-c^s)p\bar{X}\left(1-\frac{\bar{X}}{m}\right) + \frac{c^e+\gamma c^i}{q}\ln\left((1-r)+\frac{r}{m}\bar{X}\right). \tag{2.18}$$

For an interior optimum, $\hat{x} < \bar{X} < m$, the first order condition $\frac{d\pi_1}{dX} = 0$ leads to the equilibrium value

$$\bar{X} = \frac{3m}{4} - \frac{m}{2r}\left(1-\frac{1}{2}\sqrt{(r-2)^2+\frac{8r(c^e+\gamma c^i)}{q(1-c^s)mp}}\right). \tag{2.19}$$

Note that the static optimization problem in (2.17) leads to the same steady state as in the dynamic optimization problem in (2.12) if and only if the discount rate is zero, i.e. $\rho = 0$.

2.4 Model analysis for the stochastic case

Now that we are familiar with characteristics of the model and how these characteristics are used to determine steady state values, we next explain the value function iteration approach and are concerned with the question how value function iteration is implemented in a deterministic and stochastic setting.

In the literature, the Stochastic Dynamic Programming (SDP) solution follows the Bellman equation (Puterman, 1994) and takes for our setting the following general notation

$$\begin{aligned} V_t(X_t,K_t) = \max_{Q_t} \{ & \pi_2(Q_t,X_t,K_t) - c^i I(Q_t,X_t,K_t) \\ & + \delta \mathbb{E} V_{t+1}(X_{t+1},K_{t+1}) \}, \end{aligned} \tag{2.20}$$

where V_t is the value function that represents the maximized value of the objective function from time t onwards. The expectations operator $\mathbb{E}$ holds the transition probabilities of moving from a given current state of fish stock X_t, to next period's fish stock X_{t+1}.

In our specific model, we are dealing with a system that is stationary and that is subject to discounting. This means that a function V exists such that the optimal solution fulfills the Bellman equation. Behavior of the system depends on the optimum quota rule $Q(X_t,K_t)$ that solves (2.12), maximizing discounted future resource rents

$$V(X_t,K_t) = \max_{Q} \{\pi_2(Q,X_t,K_t) - c^i I(Q,X_t,K_t) + \delta \mathbb{E} V(X_{t+1},K_{t+1})\}, \tag{2.21}$$

where X_{t+1} and K_{t+1} follow from dynamic Equations (2.1) and (2.2), i.e. they depend on values for Q_t, X_t and K_t and the fishermen behavior $H(Q_t,X_t,K_t)$ and $I(Q_t,X_t,K_t)$.

2.4.1 Value function iteration of the deterministic case

Optimum $Q(X_t,K_t)$ can be found by a value function iteration approach that iteratively approximates the value function V by a function V_1. In this approach the system starts with an arbitrary choice of function V_1 and determines V_2 iteratively. The iterative process of repeating $V_1 = V_2$ continues until $V_2(X,K) - V_1(X,K)$ converges to an arbitrarily small convergence accuracy ε, for all state values (X,K). This works with a discretization of state space of (X,K) with vectors x,k, repeating for each grid point the iteration

$$V_2(X_t,K_t) = \max_{Q} \{\pi_2(Q,X_t,K_t) - c^i I(Q,X_t,K_t) + \delta V_1(X_{t+1},K_{t+1})\}, \tag{2.22}$$

Algorithm 1 :Pseudo code value function iteration

Funct data, x,k vectors, ε; Q,V matrices

1. $V_1 = 0$ matrix
2. **for** all i,j
3. solve (2.22) for $X_t = x_i, K_t = k_j$
4. **if** $\max_{ij}(V_2(i,j) - V_1(i,j)) - \min_{ij}(V_2(i,j) - V_1(i,j)) > \varepsilon$
5. $V_1 = V_2$ and go to step 2

with X_{t+1}, K_{t+1} following from the dynamics and fishermen behavior. Iteratively, we set $V_1 = V_2$. We first outline the approach for a deterministic setting (Judd, 1998), i.e. random variable $\xi = 1$, and illustrate the results of a base case. We show how steady state values are reached if the system starts at arbitrary levels of states of fish stock and capital stock.

Using $X_t \in \{x_1, x_2, \ldots, x_i, \ldots, x_{max}\}$ and $K_t \in \{k_1, k_2, \ldots, k_j, \ldots, k_{max}\}$ in fact discretizes the state space, such that function $V(X,K)$ is approximated by the matrix $F(i,j) = V(x_i, k_j)$. For each matrix entry (i,j), iteratively the minimum over Q is found of a function

$$f_{ij}(Q) = \pi_2(Q, x_i, k_j) - c^i I(Q, x_i, k_j) + \delta V_1(X_{t+1}, K_{t+1}), \tag{2.23}$$

where V_1 is approximated by a matrix F. As a result of the dynamics and decision, X_{t+1} and K_{t+1}, may not be on the grid defined by x,k. The usual approach is to interpolate $V_1(X_{t+1}, K_{t+1})$ from matrix $F(i,j)$. Iterative minimisation of $f_{ij}(Q)$ over Q in (2.23) can be done by using a grid on a range of $[0, Q_{max}]$, or by using a one-dimensional minimisation algorithm.

The implementation requires considering first appropriate boundaries x_1, x_{max} and k_1, k_{max} of the system and whether all combinations x_i, k_j are feasible. As discussed in Section 2.3.1, fish stock values $X_t < \hat{x}$ are not considered, as harvest is then zero and quota can be set at $Q_t = 0$. Upper bound x_{max} depends on the possibility of considering starting values $X_0 > m$. We can take $[x_1, x_{max}] = [\hat{x}, \max\{X_0, m\}]$. Following the reasoning in Section 2.3.1, it is appropriate to take $[k_1, k_{max}] = [0, \frac{1}{q}\ln(\frac{m}{\hat{x}})]$. Grid points x_i and k_j are not necessarily equidistant in their corresponding ranges. A more refined grid, i.e. using more grid points, results in a better approximation of value function $V(X,K)$ and policy decision $Q(X,K)$.

Example 1

We introduce a base case with data taken from van Dijk et al. (2013a), a study on North Sea plaice. This species is one of the main commercially exploited flatfish in the North Sea and is subject to increasing fishing pressure (Kell and Bromley, 2004). We express fish stock X and harvest H in kton, while capital stock K and effort E are expressed in million horsepower days, mln hpd. We use the following parameter values: $m = 460$ kton, $r = 0.74\%$, $\xi = 1$, $q = 0.0139$ mln hpd^{-1}, $\gamma = 0.1\%$, $\delta = 0.95$, $p = 1.83 * 10^6$ €/kton, $c^i = 2.1 * 10^6$ €/mln hpd, $c^s = 0.25\%$, $c^e = 3.54 * 10^6$ €/mln hpd. For this base case, given above parameter values and (2.14), fishing is not profitable below $\hat{x} = 185.6$ kton. According to (2.19), the stationary value of fish stock is $X = 349.5$ kton.

The value function iteration algorithm is run with $x_1 = 170, x_{max} = 500, k_1 = 4, k_{max} = 70$ and taking 23 equidistant points x_i and k_j on each axis. So the distance between the grid points is 15 for X_t and 3 for K_t. Iterative minimisation of Q is done by a one-dimensional minimisation algorithm FMINBND of MATLAB. For the matrices V_1 and V_2 in the algorithm, we have that $\max_{ij}(V_2 - V_1) - \min_{ij}(V_2 - V_1)$ becomes smaller than $\varepsilon = 0.1$ within 20 iterations, indicating that the policy $Q(X,K)$

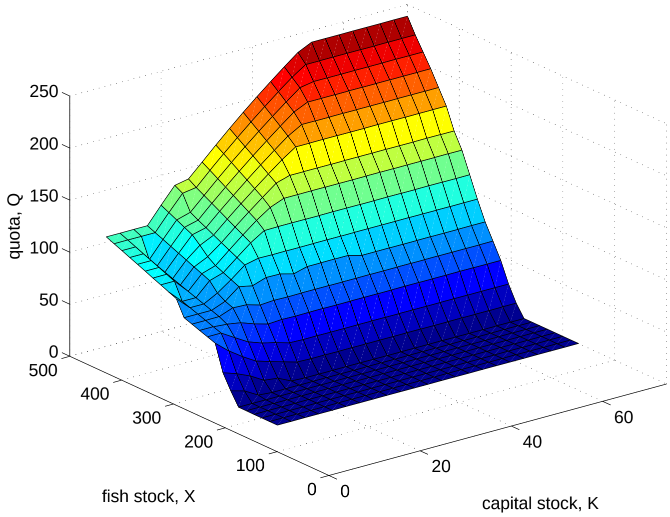

Figure 2.1. Optimal quota function Q for each combination of fish stock X and capital stock K, found by value function iteration in the deterministic model.

found at iteration 20 is optimal. Resulting values of $Q(X,K)$ are depicted in Figure 2.1.

The behavior of the system is sketched in Figure 2.2 by simulation for four different starting values of the fish stock X_0 and initial capital stock of $K_0 = 9$. The system converges after 7 time steps to the steady state. Stable dynamics of fish stock, due to Equation (2.1), are determined by fishing behavior. For low values of fish stock, no fishing takes place and for values higher than carrying capacity m, harvesting reduces the stock due to low effort cost. The policy maker helps to reach the stable situation. For instance for $X_t = 200, K_t = 9$, the fishery sector would harvest about 14 kton. Notice that the policy maker sets quota at zero, preventing harvest, in order to promote recovery of the fish stock and keeping in mind long term resource rents.

2.4.2 Value function iteration of the stochastic case

Now consider the model in a stochastic setting (Judd, 1998). We show how the system behaves when random variable ξ has a variation. We look at stability of the system, deviations of long term average states and how fast the system reacts to deviations from stationary values.

When random variable ξ has a variation, the necessary condition (Bellman equation) for an optimal Q needs to be adjusted, i.e. expected value and probabilities come into play. The Bellman equation (2.21) for an optimum solution $Q(X_t, K_t)$ is that there exists a value function V such that

$$V(X_t, K_t) = \max_{Q} \left(\pi_2 (Q, X_t, K_t) - c^i I_t (Q, X_t, K_t) \right. \\ \left. + \delta \mathbb{E}_{\xi} \left[V \left(X_{t+1}, K_{t+1} \right) \right] \right), \tag{2.24}$$

where expected value $\mathbb{E}_{\xi}$ is taken over future resource rents.

Different methods exist to compute the expectations (Miranda and Fackler, 2002). For the use of the algorithm here, the distribution of ξ is discretized, which can be done in several practical ways. One way is to iterate over all possible grid points x_i, k_j for V_1 and assign probabilities to these outcomes given decision Q. This approach is quite cumbersome as it requires re-calculation of V_1 for many values of quota and associated probabilities. A more usual approach is to discretize the space of possible outcomes of stochastic variable ξ. This can be done in several ways. For example,

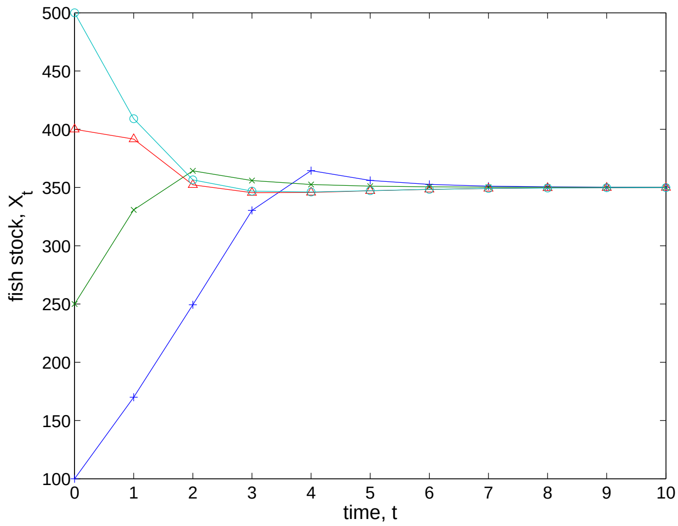

Figure 2.2. Convergence of fish stock X_t to steady state in the deterministic model, with starting values $K_0 = 9$, $X_0 = 100, 250, 400, 500$.

a non-uniform grid such as a Chebychev discretization may be used according to the idea that the distance between points can be larger when the value function is less nonlinear. In order to be able to present the value function in a three-dimensional figure and without loss of efficiency, this model uses a uniform grid by using quantiles of the lognormal distribution. A more usual approach is to discretize the space of possible outcomes of stochastic variable ξ. A way to do this is by using quantiles of the lognormal distribution. An equidistant grid is taken over probability range $[0,1]$ with a step p_ξ and generating a discrete outcome space $\{\theta_1, \theta_2, \ldots, \theta_n\} = \{G^{-1}(p_\xi), G^{-1}(2p_\xi), G^{-1}(3p_\xi), \ldots, G^{-1}(1 - p_\xi)\}$. The consequence of this operation is that the outcome space is truncated by the p_ξ-quantiles and each outcome has the same probability of occurrence. Equation (2.24) is iteratively approximated by using in the algorithm

$$\begin{aligned} \mathbb{E}_\xi V_1(X_{t+1}, K_{t+1}) \approx p_\xi \sum_{i=1}^{n} V_1 \left(X_t + \theta_i r X_t \left(1 - \frac{X_t}{m} \right) \right. \\ \left. - H(Q, X_t, K_t), K_{t+1} \right), \end{aligned} \tag{2.25}$$

where $H(Q, X_t, K_t)$ is the harvest level chosen by the fishing sector on level 2. Interpolation is required in the state space to valuate V_1 for every possible outcome θ_i of the growth multiplier. Ranges for state variables do not change compared to the deterministic model since possible outcomes θ_i are always positive. This means that for $X_t < \hat{x}$, growth is positive and for $X_t > m$ growth is negative, so the same bounds can be used as in the deterministic case. Calculation time for the value function iteration increases as for each evaluation of a suggested quota Q_t, now n values of the value function are interpolated.

Example 2

In this example, variable ξ is lognormal distributed with parameters $\sigma = 0.159$ and $\mu = -0.0126$. Distributing $n = 40$ points over the outcome space with $p_\xi = 0.025$ we have $\{\theta_1, \theta_2, \ldots, \theta_n\} = \{0.596, 0.716, \ldots, 1.593\}$. We run the value function iteration by solving (2.24) with (2.25). $\|V_1 - V_2\| < \varepsilon$ is obtained after 15 iterations. The behavior of the system is sketched for 4 different starting values X_0 and $K_0 = 9$ in Figure 2.4, showing 10 realizations of sample paths that follow the optimum strategy.

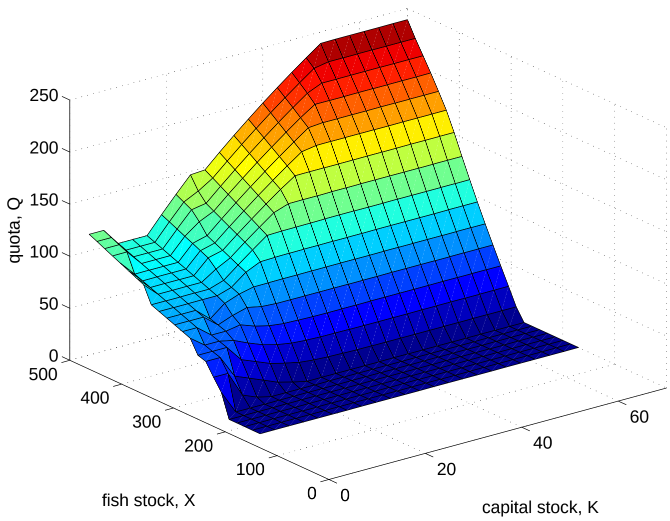

Figure 2.3. Optimal quota function Q for each combination of fish stock X and capital stock K, found by value function iteration and using continuous optimization with FMINBND in the stochastic model.

2.5 Sensitivity analysis

So far illustrations show that the model leads to stable paths. There may be robustness-performance and efficiency trade-offs concerning parameter uncertainty (Schapaugh and Tyre, 2013) and the choice of solution procedure.

With respect to parameter uncertainty in this model, variability of fish stock is difficult to assess. We therefore analyze whether higher variability reduces stability and if it leads to a different long term average solution. Experiments are shown in Section 5.4.3.

The suggested solution procedure of dynamic programming enhances an iterative nonlinear optimization step for each matrix element F_{ij}. Alternative to this continuous search of the optimal quota is a grid-search (Hendrix and Toth, 2010), where possible quota values are limited to rounded values and where the solution procedure is evaluated for a grid of possible quota values. In Section 2.5.2 we analyze the quality of the solution of the grid-search and the impact for efficiency of the procedure.

2.5.1 Impact of variability on model outcomes

Because stock growth is unknown, we investigate whether the described solution method is robust with respect to higher or lower variability in the model, what the impact is on the optimum solution and if the long term average depends on variability σ. Experiments are based on varying variability $\sigma \in \{0.05, 0.16, 0.5\}$ and corresponding $\mu \in \{-0.0013, -0.0126, -0.125\}$ to have an average growth of 1. Besides the base case of $\sigma = 0.159$ (van Dijk et al., 2013a), we now look at scenarios of low variability and high variability. For the SDP procedure this means that the range of multiplication factors ranges between $[\theta_1, \theta_n] = [0.85, 1.16]$ for the scenario of low variability and $[\theta_1, \theta_n] = [0.2, 3.66]$ for high variability.

The consequence for the solution procedure is that the high growth possibility in the high variability scenario may lead to fish stock values that exceed the $x_{max} = 500$ value used in the ranges of the algorithm. We know, however, that stock levels exceeding carrying capacity imply a decrease in stock in the next year. In that case, setting a quota is not necessary as harvest is limited by the size of capital stock. Running the algorithm for the three scenarios gives in all cases a convergence of the value function within 20 iterations.

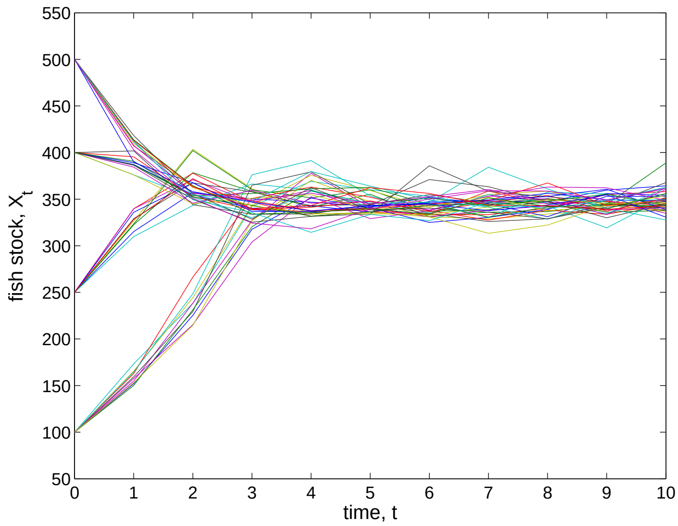

Figure 2.4. Realizations of stochastic paths of fish stock X_t, with starting values $K_0 = 9$, $X_0 = 100, 250, 400, 500$.

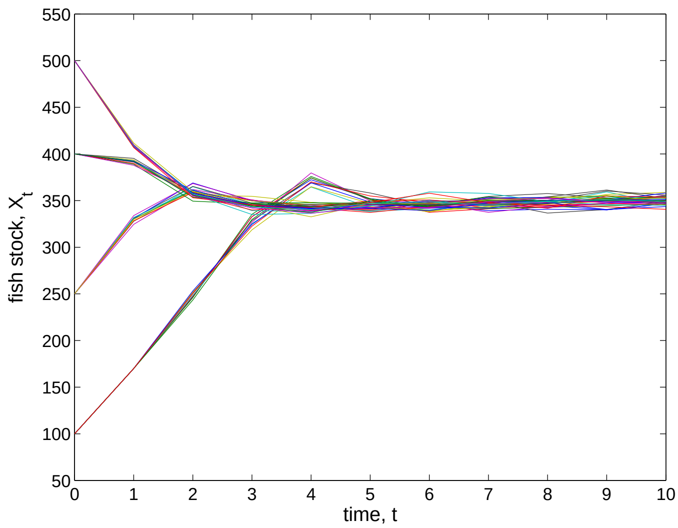

Figure 2.5. Realizations of stochastic paths of fish stock X_t under low variability.

We now examine the impact on behavior of the system. So far, the model shows stable behavior towards the long term average. It is expected to observe higher and lower variability in fish stock when feeding the optimum strategy to the system. This is illustrated in Figures 2.5 and 2.6 for 10 sample paths from 4 different starting values of X_t. We are interested in finding out whether the long term average is influenced by variability and whether fish stock and corresponding harvest are higher or lower with increasing variability. We simulate the system for a period of 10,000 years based on the same random numbers for all scenarios, where realizations of the growth factor are calculated by transforming normal pseudo-random numbers to lognormal random numbers with specified variability and expected value. When measuring long term average, median, 5% and 95% percentiles, it can be observed that the interpercentile-range increases with variability, but the average value slightly changes downward. Results are given in Table 2.1. The distribution of X_t becomes more skewed with increasing variability; the median value starts to deviate from the mean.

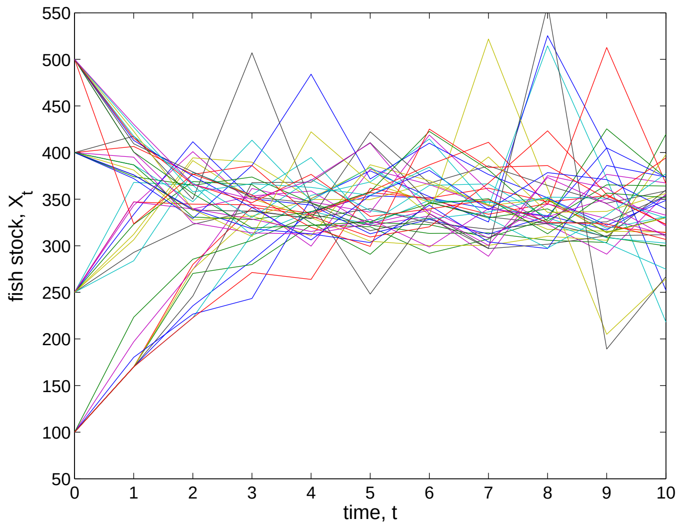

Figure 2.6. Realizations of stochastic paths of fish stock X_t under high variability.

Table 2.1. Stock X_t distribution for varying variability and optimal quota

σ	0.05	0.16	0.5
Mean	349.4	348.3	347.5
$Perc(5\%)$	343.3	331.1	302.4
Median	349.4	348.0	344.1
$Perc(95\%)$	355.6	367.1	405.9

2.5.2 Impact of grid-search on the solution procedure

For the base case, we use standard one-dimensional nonlinear optimization to derive iteratively for every grid point (x_i, k_j) the optimum of $f_{ij}(Q_t)$ in equation (2.23). Quota are determined in terms of rounded numbers, e.g. $Q \in \mathbb{Q} = \{0, 10, 20, \ldots, 270\}$. The grid-search procedure selects the best value of $\mathbb{Q}$ and generates the value function V with that. We evaluate *effectiveness*, i.e. whether the procedure generates accurate results, and *efficiency*, i.e. the impact on computing time.

With respect to efficiency, evaluating $|\mathbb{Q}| = 28$ values at each minimization step requires slightly more time than using the standard FMINBND procedure of MATLAB; 400 seconds versus 360. Using a more accurate grid with 55 points doubles computing time. Despite that, in a grid-search procedure the approximate value of Q_t converges faster due to being fixed to a grid point. The number of iterations up to convergence is similar in both procedures.

As for effectiveness, the best values of quota are sketched in Figure 2.7. They are in fact rounded values of the continuous optimization. The impact on discounted welfare is more difficult to assess in an SDP context. We consider the value of $f_{ij}(Q_t)$ around deterministic stationary states of the base case, $x_{13} = 350$ and $k_{15} = 46$, with the same matrix V found after convergence. It appears that the optimal (continuous) value of $Q_t(350, 46) = 77.6$ provides the same value as using the value $Q_t = 80$ found by the grid search. The objective function is rather flat at the optimum value, which means that one could use rounded numbers for quota instead.

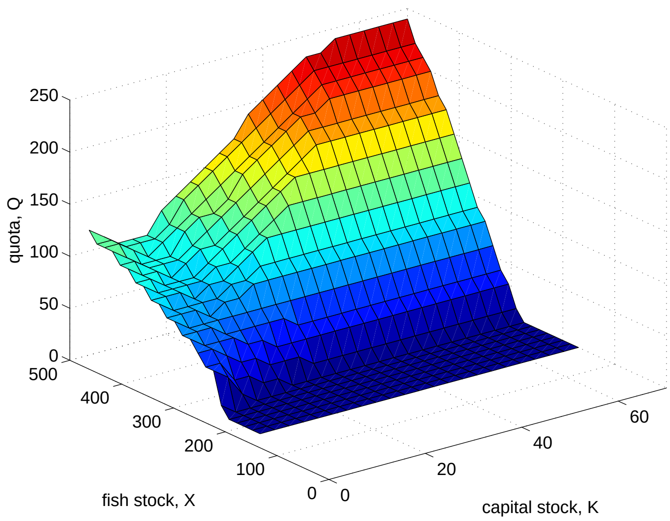

Figure 2.7. Optimal quota function Q for each combination of fish stock X and capital stock K, found by using iterative grid search, with grid size 10.

2.6 Conclusions

This chapter investigated how the interaction between the quota decision of a policy maker and fishermen behavior can be studied in a model that accounts for dynamics in the biological system and dynamics in the behavior of the policy maker, and, how model characteristics can be exploited in order to derive the optimal quota in a deterministic and stochastic setting.

Stochastic dynamic programming models have shown to be a useful modeling tool to analyze questions in fisheries management (Singh et al., 2006; Kulmala et al., 2008; van Dijk et al., 2013a). In order to understand and reproduce such models, we modeled the interaction between the quota decision of a policy maker and fishermen behavior, while accounting for dynamics in the biological system and dynamics in the behavior of the policy maker. We showed how model characteristics and the solution procedure are implemented in a deterministic and a stochastic setting. Robustness of the model was assessed with respect to higher variability and with respect to the search procedure of the optimal policy.

In our specific case, we studied fisheries policies with a bi-level stochastic dynamic programming model that describes dynamics in fish stock and capital stock. At the first level, a policy maker decides on quota to be fished, keeping in mind long-term resource rents. At the second level, fishermen react on this quota and on current states of fish stock and capital stock by deciding on their investments and fishing effort.

We found that fish stock dynamics provide stability to the model, with a tendency to converge to a long-term steady state. The assumption that the policy maker sets the quota after incorporating environmental variability in the decision making process, may explain this stability. More realistically, however, policy makers are not always able to perfectly quantify the impact of environmental variability on the fish stock.

For the derivation of the optimal quota, a careful assessment of boundaries of the system was required to analyze those states that have a high probability of occurrence. Given this analysis, a stochastic dynamic programming approach based on value function iteration is a feasible option to derive the optimal quota.

The procedure is robust with respect to parameter variation of the model, but its convergence is sensitive with respect to exact boundaries used in the implementation. Furthermore, the optimal solution is robust with respect to variability in the model. Moreover, we found that the quota is optimal for both a continuous solution procedure and a grid-search procedure.

The bi-level set up of the model allowed us to analytically derive boundary values for state and action spaces and steady states, which is a useful, but not always taken step before proceeding to implementation of the solution procedure. In solving the problem, we can make efficient use of standard techniques after having a good understanding of the problem structure. These insights are obtained from a mathematical analysis and numerical experimentation, starting with a simpler version of the problem. The model we studied can be extended in several directions, for example to study multi-annual quota adjustment, longer-term behavior of fishermen and by increasing the number of actors. The literature discusses some of the implications of heterogeneous fishermen, e.g. Sumaila (1997) on optimal harvest cooperation with shared resource rents between efficient and less efficient fishermen and Merino et al. (2007) on optimal effort cooperation between multiple vessels. In further studies the model will be used to answer questions on feasibility of such extensions.

Chapter 3

Fluctuating quota and management costs under multiannual adjustment of fish quota[*]

North Sea fisheries are managed by the European Union (EU) through a system of annual quota. Due to uncertainty about future fish stocks, yearly revisions of these policies lead to fluctuation in quota, which in turn affects harvest and investment decisions of fishermen. Determination of quota requires high management costs in terms of obtaining information and negotiations between experts and policy makers. To reduce both quota fluctuation and management costs, the EU has proposed a system of multiannual quota. In this paper we study the effect of multiannual quota on quota volatility and resource rents, while accounting for management costs. We develop a bi-level stochastic dynamic programming model, where at level one, the EU determines the quota that maximizes resource rents. At level two, fishermen decide myopically on their harvest and investment levels, subject to the quota. Results show that policy makers can reduce quota volatility and improve resource rents from the fishery with multiannual quota. Important trade-offs are involved in the accomplishment of these objectives: fish stock and investments become more volatile, which leads to more overcapacity.

[*]This chapter is based on Diana van Dijk, Rene Haijema, Rolf A. Groeneveld, Ekko C. van Ierland (2013). Fluctuating quota and management costs under multiannual adjustment of fish quota. Ecological Modelling 265, 230-238.

3.1 Introduction

Total Allowable Catches (TACs) of North Sea fish species are established on an annual basis as new catch and biological survey data become available. Annual adjustment of quota results in overcapacity for fishermen (Eisenack et al., 2006) and high management costs for the EU (Arnason, 2009).

Natural fluctuation in fish stock growth provides a challenge to management of fish species, often resulting in sub-optimal adjustment and annually fluctuating quota (Daw and Gray, 2005). Fishermen in return are confronted with unstable quota. As capital adjustment is costly, adjusting capital stock each year to the new required level is cumbersome. Due to irreversibility of investment in capital stock and with fishermen revealing short-term behavior, the result is often volatile investment (Charles, 1983) or even overcapacity (Eisenack et al., 2006).

Management costs, i.e. the costs of operating the quota management system, have been estimated at 78 million euro per year for 13 European countries (European Advisory System Evaluation, 2007). Studies that derive management costs on a country or species basis show that these costs range from 2.5% of harvest value, for North Sea herring, to 25% of harvest value for Iceland, Newfoundland and Norway (Hatcher and Pascoe, 1998; Millazo, 1998; Arnason et al., 2000; Wallis and Flaaten, 2003; Simmonds, 2007). Discussions about whether these management costs are relatively small compared to benefits (Arnason et al., 2000) or whether they represent a net economic loss (Arnason, 2009) are ongoing. This implies that management costs should not be ignored when adjusting quota such that they maximize resource rents (Arnason, 2009), where resource rents are defined as the difference between revenues from harvesting a fish stock and costs of the corresponding fishing effort. To the best of our knowledge, management costs have not been fully accounted for in the literature on optimal policies, meaning that there may be a sub-optimal balance between economic and biological objectives.

In the 2002 reform of the Common Fisheries Policy, a first step towards multiannual management plans was proposed to reduce the problem of fluctuating quota and high management costs. Given biological targets such as obtaining a specific reduced fishing mortality rate, annual changes in quota and effort are not to exceed a certain percentage (European Commission, 2009a). Besides setting quota, multiannual management plans also provide measures such as closed areas, mesh size, gear, inspections, monitoring and effort management.

Let us consider one of the measures under multiannual management plans. This is a management system where the policy is to keep quota constant for multiple years, i.e. multiannual quota. On one hand, this allows fishermen to reduce capital volatility. In addition, fewer meetings between policy makers and scientists are required, which reduces management costs and potentially increases resource rents. On the other hand, policy makers are restricted in their options to adjust quota to new developments in the fish stock.

Studies that evaluate multiannual management plans include Karagiannakos (1996), Kell et al. (1999), Roel et al. (2004) and Kell et al. (2006). Kell et al. (1999) examine whether the fish stock remains above the assigned precautionary limit of biomass. It shows that multiannual management is more likely to speed-up recovery in the stock than annual management, which in turn may lead to less restricted harvest levels. The authors, however, provide no reason for this finding. A counter-argument is raised in Roel et al. (2004), who argue that multiannual management is less effective because of the higher risk of falling below the precautionary level. Another counter-argument in Roel et al. (2004) states that due to uncertainty in the future fish stock, it is impossible to achieve interannual stability of quota. Unless quota are kept at very conservative levels, fixation may be done at the cost of reducing sustainability of fish species (Kell et al., 2006). The consequence may be even greater fluctuation of quota and greater volatility in investment (Karagiannakos, 1996). While these studies are based on landing data (Kell et al., 1999) or stock and landing data (Roel et al., 2004; Kell et al., 2006), it remains unknown to what extent quota fluctuate between periods under multiannual management plans and whether results of the above mentioned studies hold when uncertainty and dynamics in biological and economic factors are incorporated. Also the reduction in variable management costs, which include costs for meetings between policy makers and scientists, needs to be accounted for. If investment costs increase because of greater volatility in quota, this may be offset by reduced management costs and may even have a positive effect on resource rents. To the best of our knowledge, there are no studies that look at the effect of multiannual management plans, including reduced management costs, on resource rents.

With respect to the objective of multiannual management plans to reduce quota fluctuation and management costs, we formulate two research questions: (i) do multiannual quota reduce fluctuation in quota? And (ii) do multiannual quota improve resource rents? With respect to fishermen, the subquestion that follows is whether investment becomes more or less volatile and if overcapacity is reduced or increased under multiannual quota.

We address these questions with a bi-level dynamic model that includes stochastic dynamics of the fish stock and dynamics of capital stock. At the first level, the EU determines the quota that maximizes resource rents. At the second level, fishermen operate under a system of restricted open access, which means that their harvest and investment decisions are subject to the quota that the EU determines at level one. We assume that fishermen behave myopically in their decisions on harvesting and adjusting the capital stock. The problem is written in a stochastic dynamic programming (SDP) framework and is solved with Value Function Iteration.

While Kell et al. (1999, 2006) and (Roel et al., 2004) only study biological effects of multiannual quota and while Arnason et al. (2000) and Arnason (2009) question the implication of high management costs on resource rents, the contribution of this paper to the literature is that the problems of fluctuating quota and high management costs are addressed simultaneously. For illustration we apply the model to North Sea plaice, which is one of the main commercially exploited flatfish in the North Sea.

3.2 Methods

We present a bi-level stochastic dynamic programming (SDP) model that includes stochastic dynamics of the fish stock and dynamics of capital stock (van Dijk et al., 2013b) (Chapter 2 of this thesis). At the first level, the EU determines the quota that maximizes resource rents. Quota may be fixed for multiple years, which are called multiannual quota. At the second level, myopic fishermen are subject to this quota and decide on their annual harvest and investment levels correspondingly.

3.2.1 Fishermen: myopic harvest and dynamic investment behavior under restricted open access

We first present the decisions at level two, i.e. fishermen behavior with respect to harvest and investment. The importance of accounting for fishermen behavior has been pointed out in Wise et al. (2012). In this model, it is assumed that fishermen are homogeneous and that they operate under restricted open access. This means that the fishery sector is restricted by a quota, while each individual fisherman maximizes his own profits. Fishermen will only stop fishing when rents have dissipated (Homans and Wilen, 1997). In our model, a Spence harvest function describes the interaction between harvest and effort: $h_t = x_t(1 - e^{-qE_t})$, where q is a catchability coefficient (Spence, 1973). Hence, the effort E_t needed to harvest h_t depends on fish stock x_t:

$$E(x_t,h_t) = \frac{1}{q} ln\left(\frac{x_t}{x_t - h_t}\right). \tag{3.1}$$

The open access fish stock, i.e. the level of fish stock below which it is not profitable to harvest (Clark, 2006b), is derived by equating revenues ph_t and costs $C_t = c_E E_t + c_R R_t$ and then solving for $\hat{x} = x_t$. Here, p is a fixed price, c_E is the cost per unit of effort and c_R is the cost per unit of revenue that represents crew costs:

$$\hat{x} = \frac{c_E}{pq(1-c_R)}. \tag{3.2}$$

In Conrad and Clark (1987), $\frac{c_E}{pq}$ has been identified as the bioeconomic equilibrium escapement in the Spence model. At fish stock levels below $\hat{x}$ harvest is zero, so that in such a case a positive quota is not binding. We therefore assume that $h_t = 0$ if $x_t < \hat{x}$.

Under pure open access, harvest takes place for a fish stock $x_t > \hat{x}$. In that case, the level of harvest is given by $h_t = (x_t - \hat{x})^+$, where the operator $(y)^+ = \max\{0,y\}$. In restricted open access, however, fishermen are also confronted with quota Q_t, such that fishermen tend to harvest

$$\hat{h}_t = \min\{(x_t - \hat{x})^+, Q_t\}. \tag{3.3}$$

Harvest is also determined by the available capital stock, k_t. This means that fishermen cannot harvest more than what their capital stock allows. Given the Spence harvest function and substituting capital stock k_t for effort E_t, provides the following myopic harvest rule:

$$h_t = min\{\hat{h}_t, x_t(1-e^{-qk_t})\}. \tag{3.4}$$

Based on similar assumptions as above, myopic investment behavior is determined by currently available and desired capital stock. The investment in period t becomes available in the next period, $t+1$. The capital stock is set to the effort level required to harvest $\hat{h}_t$, so that $k_{t+1} = E(x_t, \hat{h}_t)$. Given the available depreciated capital stock, $(1-\gamma)k_t$, fishermen invest the difference with k_{t+1} so that the investment rule looks as follows:

$$i_t = max\{0, k_{t+1} - (1-\gamma)k_t\}. \tag{3.5}$$

3.2.2 The EU: a discrete-time stochastic dynamic programming model

At level one, the EU decides on the quota that maximizes the expected discounted resource rents, while considering stochastic fish stock dynamics and capital stock dynamics. We first present the bio-economic model for optimal quota adjustment and then describe the solution method of stochastic dynamic programming in terms of all its components.

Bio-economic model for optimal quota adjustment

At level one, the objective of the EU is to find, every f years, the quota that maximizes the expected discounted resource rents given observed levels of fish stock and capital stock of fishermen. The quota will hold for f years, where the value of f is preset. Resource rents, π_t, in any period t are:

$$\pi(x_t,k_t,Q_t) = (1-c_R)ph_t - c_E E_t - c_i i_t - \frac{c_{mc}}{f}, \tag{3.6}$$

where harvest h_t, effort E_t and investment i_t are fishermen's decisions at level two, determined by state variables fish stock x_t and capital stock k_t and by the decision variable of the EU, quota Q_t. The cost per unit of investment is c_i and the management cost that the EU faces for adjustment of quota is c_{mc}. Here we refer to variable management costs that are reduced by spreading them over the number of years for which the quota is fixed, f. The remaining fixed management costs do not change in f and are therefore excluded. From here on we refer to f as the fixed quota period. Compared to yearly adjustment of quota, annual management costs reduce to a half when the fixed quota period consists of 2 year, they reduce to a third when the the fixed quota period consists of 3 years, and so on. The objective of the EU is then to determine the quota Q_t that maximizes expected discounted resource rents:

$$\max_{Q_t} \mathbb{E}\left\{\sum_{t=0}^{\infty} \frac{\pi(x_t, k_t, Q_t)}{(1+\rho)^t}\right\}, \tag{3.7}$$

where decision Q_t is subject to

$$\begin{cases} 0 \leq Q_t \leq Q_{max} & \text{if } t \text{ is a multiple of } f \\ Q_t = Q_{t-1} & \text{otherwise} \end{cases} \tag{3.8}$$

In Equation (3.7), $\mathbb{E}$ stands for the expectation we take over current values of state variables fish stock x_t and capital stock k_t. The discount rate is ρ. In order to maintain a sustainable fish stock and a profitable fishery, the decision of Q_t is also based on dynamics in fish stock x_t and fishermen behavior in terms of harvest and investment decisions, embedded in the dynamics of capital stock k_t:

$$x_{t+1} = x_t + z_t G_t - h_t \tag{3.9}$$

$$k_{t+1} = (1-\gamma)k_t + i_t. \tag{3.10}$$

Fish stock x_{t+1} in period $t+1$, depends on the previous stock x_t stochastic growth $z_t G_t$ and harvest h_t. We assume density-dependent growth $G_t = r x_t(1 - \frac{x_t}{M})$, where r is the intrinsic growth rate and M is the carrying capacity. The growth shock z_t is a multiplicative i.i.d. random variable with known distribution. Capital stock k_{t+1} is determined by its previous value k_t, diminished by a deterministic vessel depreciation rate γ and by capital investment i_t. The quota decision of the EU is based on knowledge of harvest and investment levels of fishermen. Furthermore, the EU optimizes the quota at the beginning of each fixed quota period. If a fixed quota period consists of one year, $f = 1$, the quota is optimized in each year t and we have annual quota adjustment. If a fixed quota period consists of two years, $f = 2$, the quota is optimized in $t = 0, 2, 4, ...$ and it is fixed in $t = 1, 3, 5, ...$ at the level of $t = 0, 2, 4, ...$, respectively. A fixed quota period of more than one year thus represents multiannual quota.

Solution method: stochastic dynamic programming

The model for setting the quota can be solved numerically by stochastic dynamic programming (SDP). We assume an infinite horizon problem with discrete time steps equal to 1 year. In years $t = 0, f, 2f$, etc. the quota can be adjusted. In the years in between, the quota is fixed to the level of last year Q_{t-1}. Following the literature on stochastic dynamic programming (Howard, 1960; Puterman, 1994; Judd, 1998), we discuss the state (space), decision (space), state transition (probabilities), the contribution and the Bellman equation. In particular we pay attention to implementation aspects.

State and state space: The states is the state of fish stock x_t and capital stock k_t at the start of year. In years in which a new quota Q_t may be set, i.e. at $t = 0, f, 2f$, etc., the state is (x_t, k_t). In years in which the quota is unchanged, the state is (x_t, k_t, Q_{t-1}). The state space is continuous, as fish stock x_t, capital k_t and last year's quota Q_{t-1} are continuous. For numerical calculations a grid is chosen with n_x levels of x, n_k levels of k, and n_Q levels of quota. The grid consists of $n_x \times n_k \times n_Q$ states. To simplify notations, the state is denoted as (x_t, k_t, Q_{t-1}) irrespective of the value of t. When implementing the SDP model one should keep in mind that Q_{t-1} is redundant for $t = 0, f, 2f$, etc.

Decision and decision space: The decision is Q_t, the quota that holds for year t. The decision space is continuous and does not require a grid, for reasons explained below. In years in which the quota may not be changed the decision space consists of a single element: $\{Q_{t-1}\}$. Note that the quota period f is a fixed value that does not change between periods and therefore is not a decision in the SDP model.

Transition and transition probabilities: State transitions from (x_t, k_t, Q_{t-1}) to (x_{t+1}, k_{t+1}, Q_t) follow Equations (3.9) and (3.10). In (3.9), z_t is a continuous stochastic variable, which has been discretized into 100 levels: the percentiles of the underlying probability distribution. For evaluating a decision in a particular state, we consider thus one hundred transitions with equal probability 0.01. Although transitions will be considered from all states (x_t, k_t, Q_{t-1}) on the grid, the resulting states (x_{t+1}, k_{t+1}, Q_t) usually are not on the grid. In discussing the Bellman equation we explain how we deal with this issue.

Contribution: The objective function (3.7) is separable in contributions per period in (3.6).

Bellman equation: The objective function for a fixed value of f can be defined recursively:

$$V_t(x_t, k_t, Q_{t-1}) = \begin{cases} \max\limits_{Q_t} \{(\pi(x_t, k_t, Q_t) + \delta \mathbb{E}[V_{t+1}(x_{t+1}, k_{t+1}, Q_t)])\} \\ \text{if } t \text{ is a multiple of } f \\ \\ \pi(x_t, k_t, Q_{t-1}) + \delta \mathbb{E}[V_{t+1}(x_{t+1}, k_{t+1} Q_{t-1})] \\ \text{if } t \text{ is not a multiple of } f \end{cases} \tag{3.11}$$

V_t is the value function that represents the maximized value of the objective function from time t onwards, $\delta < 1$ is the discount factor and $\mathbb{E}$ is the expectations operator that holds the transition probabilities of moving from a given current state of fish stock x_t to next period's fish stock x_{t+1}. Assuming a long horizon of T years, we can solve the maximization problem recursively, starting with $V_T(x_T, k_T, Q_{T-1}) = 0$, for all $n_x \times n_k \times n_Q$ states on the grid. Next, successively $V_{T-1}, V_{T-2}, \ldots, V_1, V_0$ are computed for all states on the grid. For states that are not on the grid, the state values are derived by interpolation.

The numerical procedure of (3.11) is also known as Value Function Iteration. For a description of the value iteration process see Puterman (1994), and on its implementation see van Dijk et al. (2013b) (Chapter 2 of this thesis).

3.2.3 Application of the model to North Sea plaice

As an illustration, we apply the model to North Sea plaice, which is one of the main commercially exploited flatfish in the North Sea. Growth of North Sea plaice has changed over the years and the fishing industry has played a role in this. We use ICES data on North Sea plaice in this study (Rijnsdorp and Millner, 1996; Grift et al., 2003; Kell and Bromley, 2004; Pilling et al., 2008) and we measure fish stock, harvest and quota in kton. The intrinsic growth rate of plaice r is set to 0.74 and the carrying capacity M is 460 kton, which is twice the maximum sustainable yield (for the Exploration of the Sea, 2011). The multiplicative i.i.d. random variable on fish stock growth z_t is based on a timeseries of North Sea plaice over the period 1957-2009 (ICES, 2009). For this timeseries a lognormal distribution fits well (Gillis et al., 2008; Pilling et al., 2008) with $\mu = -0.0126$ and $\sigma = 0.159$, so that $\mu + \frac{1}{2}\sigma^2 = 0$ and the average multiplicative shock on growth is 1. Although a fish stock may depend on last year and also on the year before, we follow biological dynamics as described in the fisheries economics literature and we assume a first-order Markovian process.

Economic data, for level one and two, are obtained from Van Balsfoort (2006), Taal et al. (2009), and the European Commission (2007). We use data on the Netherlands as representative for the remaining EU countries that exploit plaice in the North Sea. Effort and capital are measured in terms of engine capacity of vessels and number of days at sea, expressed in millions of horse power days, mln hpd.

We assume a per unit investment cost c_i of €$2.1 \cdot 10^6$ per mln hpd. A management cost c_{mc} of €$5.29 \cdot 10^6$ is derived from Hatcher and Pascoe (1998), Millazo (1998), Arnason et al. (2000), Wallis and Flaaten (2003) and Simmonds (2007). We finally apply a discount factor δ of 0.95. We use a fixed fish price p of €$1.83 \cdot 10^6$ per kton, a per unit effort cost c_E of €$3.54 \cdot 10^6$ per mln hpd, a per unit revenue cost c_R of 0.25%, and a vessel depreciation rate of $\gamma = 10\%$. Now we can derive open access fish stock, $\hat{x} = 185.6$ kton.

For the bounds of the state space of fish stock, we have $x_t \in [\hat{x}, M]$. Because of the assumption that $h_t = 0$ if $x_t < \hat{x}$, we do not consider values below $\hat{x}$. From this assumption follows that a reasonable range for optimal quota is $Q_t \in [0, M - \hat{x}]$. Finally, for the bounds of the state space of capital stock we have $k_t \in [0, 74]$. The grid of the state space has $n_x = 23$, $n_k = 23$, and $n_Q = 28$ equidistant levels for x_t, k_t, respectively Q_{t-1}. The years in which quota are not adjusted, the state space consists of $n_x \cdot n_k \cdot n_Q = 14,812$ states. The years in which quota are revised, i.e. at $t = 0, f, 2f$, the state space consists of $n_x \cdot n_k = 529$ states, etc.; for each state (x_t, k_t) a nonlinear search procedure is applied, in which interpolation is used to estimate state values.

3.3 Results

With respect to the research question whether multiannual quota reduce fluctuation in quota, we first present results on quota volatility. Then the research question is addressed whether multiannual quota improve resource rents. In light of the problem of overcapacity under annual quota adjustment, we also study the effect of multiannual quota on capital volatility and overcapacity. A sensitivity analysis concludes this section.

3.3.1 Quota volatility

Let us consider in Figures 3.1-3.4 the optimal quota Q_t as a function of capital stock k and fish stock x, for a fixed quota period $f = 2, 3, 4, 5$. The Figures show that harvest increases in fish stock x and capital stock k, which agrees with Singh et al. (2006). Comparing low fish stock levels to high levels, two observations can be made. First, at low fish stock levels the quota increases with f. Second, at high fish stock levels the quota declines with f. The intuition behind this result is as follows. When the fish stock is high, i.e. when $x > \hat{x}_t$, we know from the growth function that growth is low. In order to maintain a sustainable stock in all future periods, the EU needs to be conservative when assigning a quota. This conservative behavior is enforced as the quota is fixed for a longer period of time. With an increasing fixed quota period f, the EU has to anticipate the fish stock over a longer period of time. When we consider low fish stock levels, i.e. when $x < \hat{x}_t$, the EU knows that growth is high, so if a positive quota is assigned today the fish stock will recuperate in the future. We therefore observe a positive quota that increases in f and a quota that becomes positive at lower levels of fish stock as f increases. The optimal quota clearly depends on the fixed quota period f. But if $x_t < \hat{x}_t$, harvest and investment are unaffected by f or by the quota. Because we assume that at $x_t < \hat{x}_t$, harvest is zero, and as a result of myopic investment behavior, investment is zero.

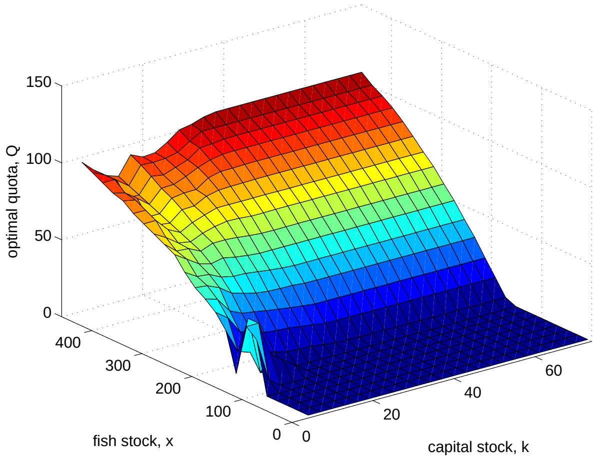

Figure 3.1. Optimal quota Q for each combination of fish stock x and capital stock k, for fixed quota period $f = 2$.

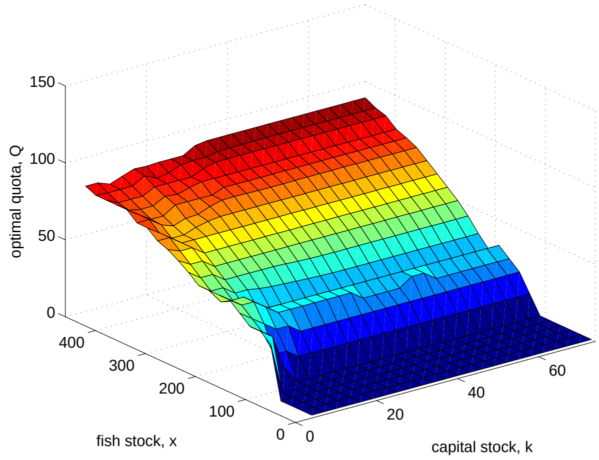

Figure 3.2. Optimal quota Q for each combination of fish stock x and capital stock k, for fixed quota period $f = 3$.

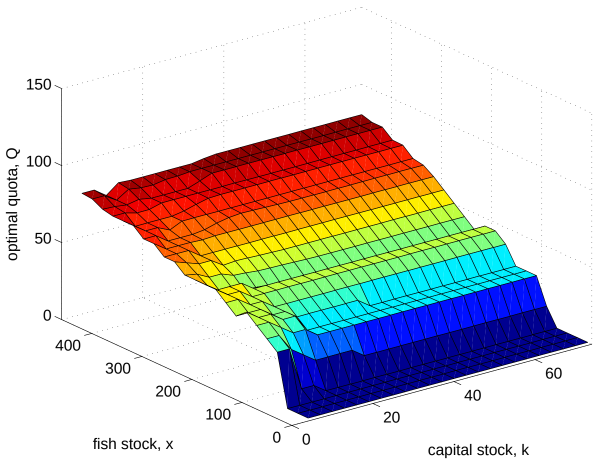

Figure 3.3. Optimal quota Q for each combination of fish stock x and capital stock k, for fixed quota period $f = 4$.

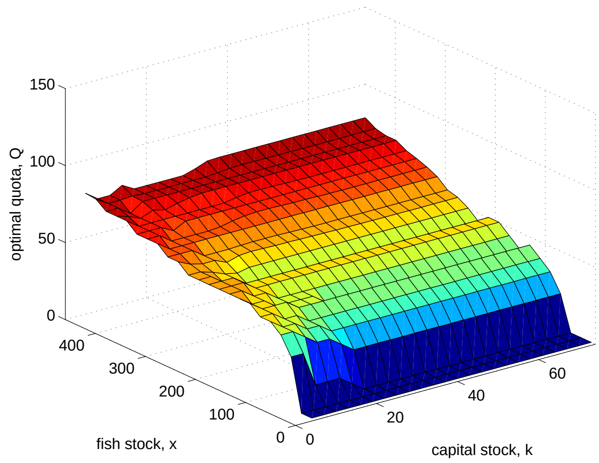

Figure 3.4. Optimal quota Q for each combination of fish stock x and capital stock k, for fixed quota period $f = 5$.

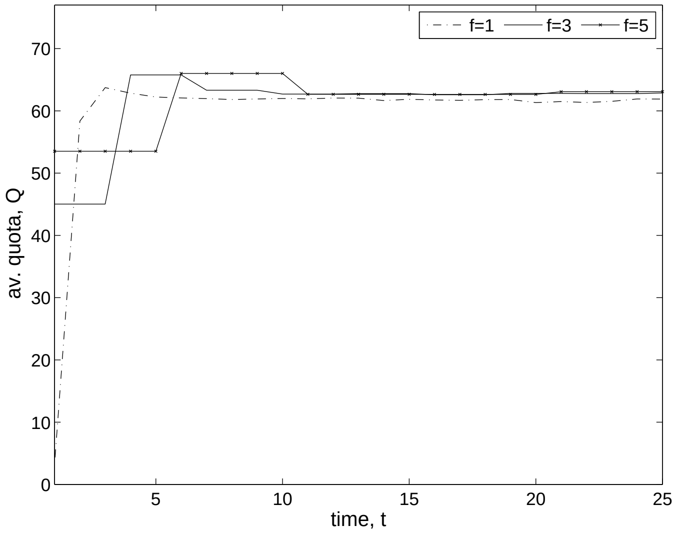

Figure 3.5. Average quota Q_t over 1,000 sample paths of 25 years each, for fixed quota period $f = 1,3,5$.

The dynamic behavior of the model can be studied with a simulation (Rogers et al., 2010). Using optimal quota as input, Figure 3.5 shows an average over 1,000 sample paths of 25 years each. Given initial stock values $x_0 = 250$ and $k_0 = 9.7$, the average long-term quota increases slightly in f. The time to reach the long-term average also increases in f, which is a consequence of decreasing flexibility in quota adjustment. Note that these long-term averages are reached for all combinations of x_0, k_0, and, the further away these initial values are from long-term averages, the longer it takes to arrive there. Long-term averages of quota for fixed quota periods $f = 1,3,5$ are $Q_t = 61.8, 62.8, 63$, with a corresponding reduced average standard deviation $\bar{\sigma}_Q = 0.097, 0.048, 0.047$, respectively. The increase in long-term average quota is observed in Figure 3.6, which illustrates differences in quota fluctuation for three sample paths of 100 years, for $f = 1,3,5$. Considering the research question whether quota fluctuation decreases under multiannual quota, we first look at annual quota $f = 1$. We observe strong fluctuation in annual quota, with quota values ranging between $Q = 52.8$ and $Q = 68.7$. Comparing this policy with multiannual quota for periods $f = 3$ and $f = 5$, we see that fixing quota for multiple years leads to less fluctuation; for a period of $f = 3$, quota values range between $Q = 59.7$ and $Q = 68.1$, and for $f = 5$ between $Q = 61.2$ and $Q = 66.2$. Two factors contribute to this decrease in quota fluctuation, which are both related to the anticipation of future levels of fish stock. The EU (i) has to anticipate the future fish stock over a longer period of time and (ii) deals with a longer recovery period of the fish stock, i.e. the quota is adjusted less to extremely low fish stock values than what we observe under annual quota.

Assuming that fishermen show myopic behavior, they respond to higher quota by increasing their harvest level so that the long-term average fish stock reduces in f. The effect of higher quota on the fish stock is observed in Figure 3.7, which illustrates differences in fish stock fluctuation for three sample paths of 100 years, for $f = 1,3,5$. Fluctuation in the fish stock increases under multiannual quota with an average standard deviation of $\bar{\sigma}_x = 0.52, 0.53, 0.63$ for $f = 1,3,5$, respectively.

3.3.2 Resource rents

To investigate the question whether multiannual quota improve resource rents from the fishery, we look at the effect of management costs on resource rents. Figure 3.8 shows long-term average resource rents π_t for fixed quota periods $f = 1,2,3,4,5$. The figure shows that with the reduction of

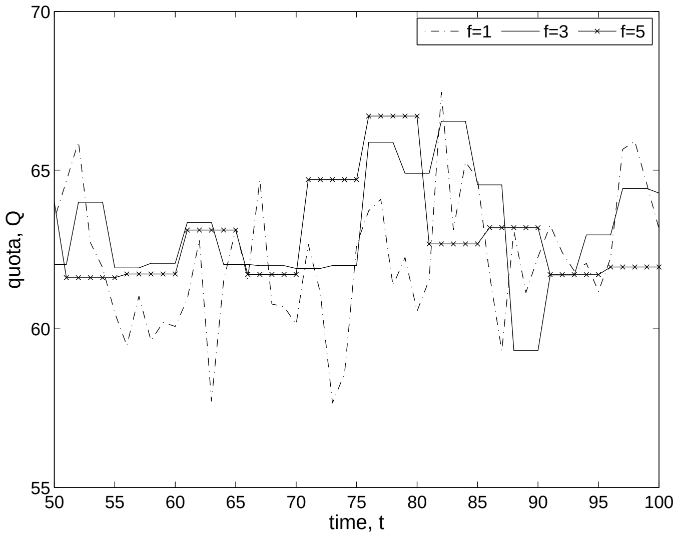

Figure 3.6. Sample path of quota Q_t of 50 years, for fixed quota period $f = 1,3,5$.

management costs in f, resource rents increase. The increase of quota in f is followed by higher effort and higher investment levels. The result is an increase in effort costs, crew costs and investment costs. The increase in costs is less than the reduction in management costs. This can be observed in Figure 3.9, which shows long-term averages of each cost component as a fraction of revenues ph_t. Between $f = 1$ and $f = 5$, the effort cost increases with 5%, the crew cost with 0%, the investment cost with 2% and the management cost reduces with 80%. As a proportion of total costs, and reported as average over all considered fixed quota periods, the effort cost makes up 60%, the crew cost 34%, the investment cost 4% and the management cost is 3% of total costs. As a proportion of revenues for $f = 1$, the management cost makes up 6%, which is at the lower end within the range of 2.5%-25% that has been reported in the literature (Hatcher and Pascoe, 1998; Millazo, 1998; Arnason et al., 2000; Wallis and Flaaten, 2003; Simmonds, 2007). Finally, management costs directly enter the resource rents function, so that a reduction has a direct effect.

3.3.3 Capital volatility and overcapacity

We now investigate whether a reduction in quota volatility also leads to less volatile investment i_t and less overcapacity $k_t - E_t$ when we increase the fixed quota period f. Figure 3.10 illustrates a 25 year sample path of investment i_t for $f = 1,3,5$ and shows that investment fluctuates more under multiannual quota. Measured over 1,000 samples and 25 years, the standard deviation is $\bar{\sigma}_i = 0.003, 0.02, 0.02$ for $f = 1,3,5$, respectively. The model assumes that myopic fishermen will always try to fully harvest the quota, but the investment in period t only becomes available in period $t+1$. The current capital stock therefore does not always meet the desired capacity and so harvest is either restricted by the quota or by capital stock. With the increase of quota in f, not only effort and investment increase, also the discrepancy between required effort $E(x_t, \hat{h}_t)$ and available capital stock k_t is enforced, i.e. capital stock is on average more often restrictive than the quota. This explains that long-term average overcapacity in Figure 3.11 increases in f.

3.3.4 Sensitivity analysis

To explore implications of alterations in parameter values, we conducted a sensitivity analysis. Table 3.1 shows the effect of changes in economic and biological parameters on long-term average values

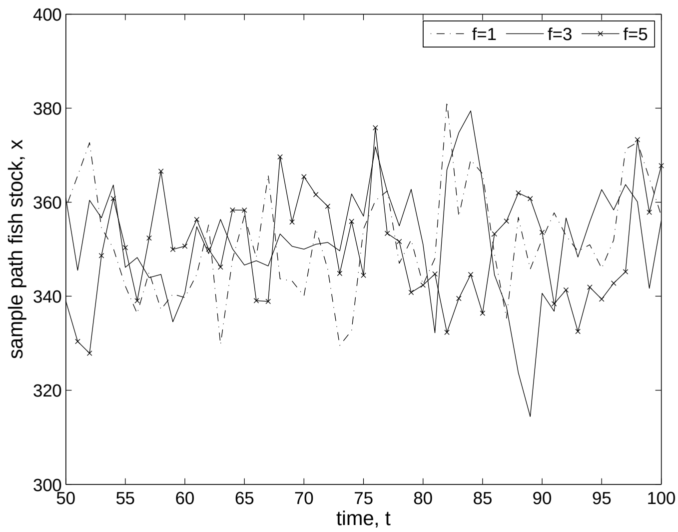

Figure 3.7. Sample path of fish stock x_t of 50 years, for fixed quota period $f = 1,3,5$.

of quota Q_t and resource rents π_t. We measure this for fixed quota periods $f = 1,3,5$.

Table 3.1. Effect of changes in economic and biological parameters on quota Q_t and resource rents π_t, for $f = 1,3,5$.

			1	*2*	*3*	*4*
	Parameter changes	f	Quota, Q_t	99% CI	Resource rents, π_t	99% CI
1	Baseline	1	61.83	[61.80, 61.85]	27.09	[27.06, 27.12]
		3	62.85	[62.81, 62.88]	30.54	[30.51, 30.56]
		5	62.89	[62.86, 62.91]	31.21	[31.19, 31.22]
2	crew cost, c_R	1	52.79	[52.60, 52.98]	13.72	[13.66, 13.77]
		3	54.07	[54.07, 54.09]	17.22	[17.19, 17.24]
		5	53.87	[53.85, 53.88]	17.90	[17.89, 17.92]
3	effort cost, c_E	1	41.39	[39.40, 43.36]	7.52	[6.83, 8.22]
		3	41.75	[41.26, 42.25]	10.98	[10.64, 11.32]
		5	41.72	[41.60, 41.84]	11.69	[11.43, 11.94]
4	investment cost, c_i	1	61.78	[61.75, 61.81]	25.60	[25.67, 25.64]
		3	62.12	[62.10, 62.14]	29.05	[29.02, 29.07]
		5	62.40	[62.38, 62.42]	29.73	[29.71, 29.75]
5	management cost, c_{mc}	1	64.96	[64.89, 65.03]	5.85	[5.81, 5.89]
		3	64.21	[64.17, 64.25]	23.44	[23.40, 23.53]
		5	63.91	[63.88, 63.93]	26.94	[26.88, 27.01]
6	intrinsic growth rate, r	1	54.15	[54.10, 54.20]	21.74	[21.70, 21.77]
		3	53.99	[53.96, 54.04]	25.25	[25.10, 25.40]
		5	54.05	[54.02, 54.08]	25.92	[25.81, 26.03]

The baseline, in row 1, holds values that result from the illustrated case of North Sea plaice. With respect to the long-term average value of quota in column 1, it has been shown that the increase of quota Q_t in fixed quota period f is a consequence of the combined effect of having to anticipate the future fish stock over a longer period of time and having a longer recovery period of the fish stock, which allows the fish stock to grow and to recover faster than under annual quota. With respect to long-term average values of resource rents in column 3, the increase of resource rents π_t in fixed quota period f has been shown to be a result from the reduction in annual management costs.

In rows 2, 3 and 4 costs per unit of revenue, which represent crew costs c_R, effort c_E and investment c_i, were each increased by 50%. Long-term average values of quota and resource rents increase

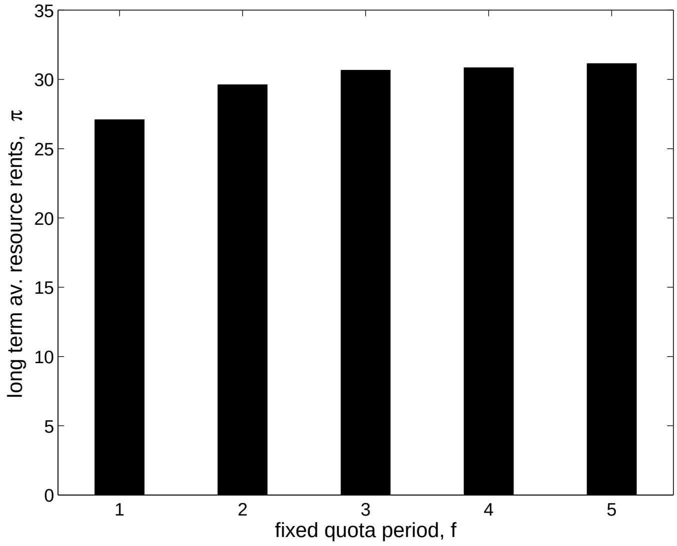

Figure 3.8. Long-term average resource rents π for fixed quota period $f = 1,2,3,4,5$.

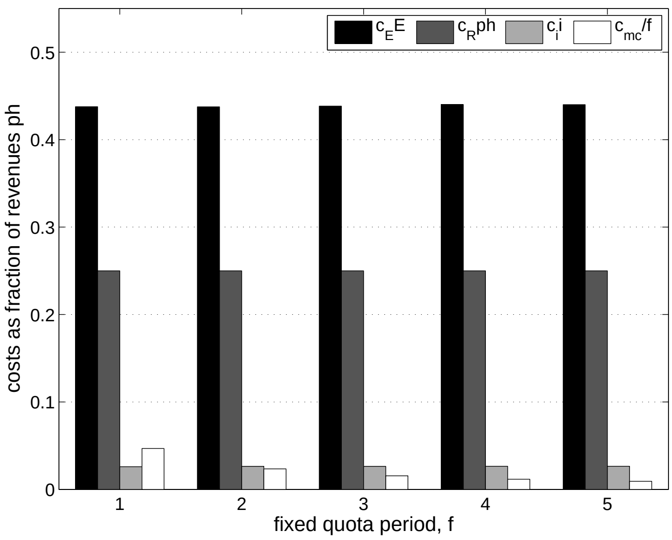

Figure 3.9. Long-term averages of effort costs $c_E E$, crew costs $c_R ph$, investment costs $c_i i$ and management costs $\frac{c_{mc}}{f}$, as a fraction of revenues ph, for fixed quota period $f = 1,2,3,4,5$.

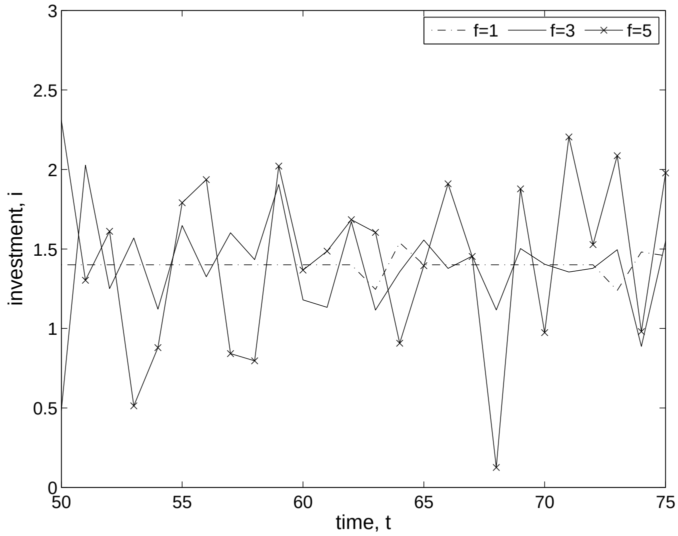

Figure 3.10. Sample path of investment i_t of 25 years, for fixed quota period $f = 1,3,5$.

in f, but they are lower than in the baseline, where the extent of reduction depends on the proportion of each cost factor in resource rents. Effort costs $c_E E_t$ in fact make up for the largest proportion of resource rents in the baseline. This explains why an increase in c_E has a larger downward impact on quota than an increase of c_R and c_i.

The impact of management costs on decisions, and on corresponding costs, is relatively small in the baseline. Management costs directly enter into resource rents, where resource rents increase in fixed quota period f. We consider in row 5 of Table 3.1 a value for c_{mc} that makes up 25% of revenues, which corresponds to the management costs estimated by Hatcher and Pascoe (1998), Millazo (1998), Arnason et al. (2000), Wallis and Flaaten (2003) and Simmonds (2007), under $f = 1$; c_{mc} is five times the baseline value. Model characteristics show that fishermen's decisions are almost not affected by management costs. This holds for a c_{mc} that is at the upper end of the range of management costs as a percentage of harvest value. Similarly, resource rents π_t are reduced, although substantially more due to higher costs. Finally, in row 6 a lower intrinsic growth rate of the fish stock, $r = 0.6$, is considered. Relative to the baseline, a lower growth rate allows the fish stock to recover slower, with the result that the long-term average quota and resource rents decrease.

Because it is difficult to assess fish stock uncertainty (Schapaugh and Tyre, 2013), Figure 3.12 shows the long-term average quota for different levels of stochasticity of fish stock growth, for $f = 1,2,3,4,5$. We consider $\sigma \in \{0.05, 0.10, 0.15, 0.20\}$, as well as the deterministic case. Note that in the deterministic case the quota does not depend on fixed quota period f. In the stochastic case, if $f = 1$, the EU only accounts for uncertainty in growth. This leads to conservative decisions and thus a lower long-term average quota as uncertainty increases. If $f > 2$, the EU also has to anticipate the future fish stock over a longer period of time. In terms of a sample path of quota, like in Figure 3.6, the effect of having to account for both uncertainty and a fixed quota period leads to even fewer low values of quota. In terms of the long-term average quota, as in Figure 3.5, the quota increases because it does not have to be adjusted to levels as low as under annual quota. This is enhanced as σ increases.

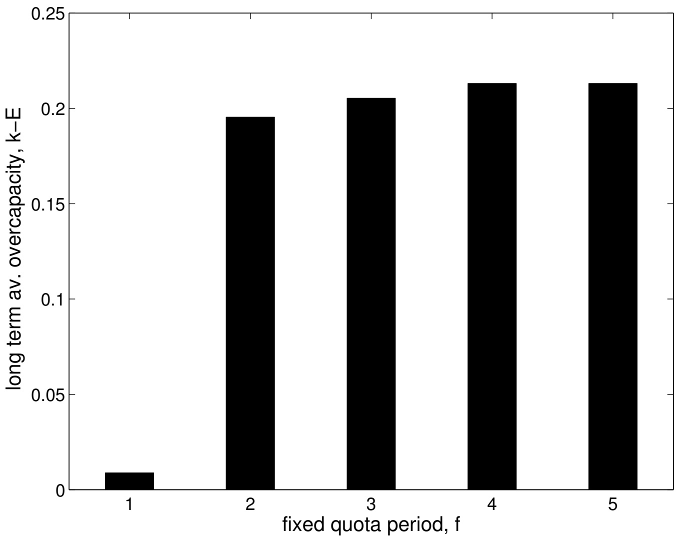

Figure 3.11. Long-term average overcapacity $k-E$, for fixed quota period $f = 1,2,3,4,5$.

3.4 Discussion

Our results suggest that multiannual quota reduce fluctuation in quota, while they increase the long-term average quota. In a setting with myopic behavior of fishermen, two factors contribute to this that are related to the anticipation of future fish stock levels. First, the EU anticipates the future fish stock over a longer period of time, which leads to more conservative quota adjustment and less fluctuation. Second, the EU accounts for a longer recovery period of the fish stock, which ensures a high fish stock in the future. With this anticipation, the EU sets a higher quota.

Nevertheless, with an increased fixed quota period it takes longer to reach a steady long-term average quota. Even though this reduces the long-term average fish stock, we show that stability of quota under multiannual quota is obtained at the cost of more volatility in the fish stock. On one hand, the result of reduced quota volatility disagrees with the argument in Roel et al. (2004) that, because of uncertainty in the future fish stock, it is impossible to achieve interannual stability of quota. On the other hand, with the result of increased fluctuation in the fish stock we agree with Roel et al. (2004) in that multiannual quota are less effective because of the higher risk of falling below the precautionary level. As pointed out in Kell et al. (2006), if quota were kept at more conservative levels, the risk of reducing sustainability would be lower. Our finding of a longer recovery period of fish stock contrasts the finding in Kell et al. (1999), where it is shown that multiannual quota are more likely to speed up fish stock recovery than annual quota. Quota in our model, as mechanism to steer harvest and investment, becomes steady once the fish stock and capital stock have become steady. A longer fixed quota period implies more time to reach a steady long-term average quota and that way, it also takes longer to reach steady long-term average values of fish stock and capital stock. Hence, a reduction in quota volatility does not imply a reduction in fish stock volatility. It rather reflects the expectation that the EU has over future fish stock levels, given their knowledge about the growth of fish and accounting for uncertainty.

According to our study, multiannual quota improve resource rents from the fishery, where highest resource rents are generated when the quota is fixed for the largest fixed quota period considered in this study, which is five years. Although reduced management costs contribute to this improvement, model characteristics show that the reduction hardly affects decisions of the EU and fishermen. Due to the small impact of multiannual quota on revenues and costs, the positive effect on resource rents is small when management costs are at the lower end of the range of reported costs in the literature.

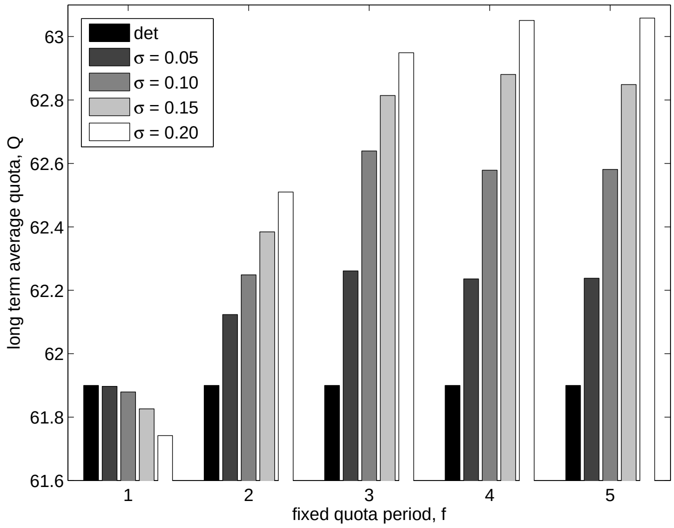

Figure 3.12. Effect of different values of σ on long-term average quota Q, for fixed quota period $f = 1,2,3,4,5$.

Results agree with Arnason et al. (2000) in that these costs make up a relatively small percentage of revenues. When we consider management costs at the higher end of the reported range, multiannual management has a substantial positive effect on resource rents. Given that the exact level of the costs remains unknown, it is important for the resource rents maximizing EU to account for management costs.

Reduced quota fluctuation also comes at the cost of more volatile investment and more overcapacity for fishermen. Due to the myopic behavior of fishermen in the model, higher multiannual quota induce more investment, but with the one year lag in availability of investment there is always a discrepancy between available and required capital.

Naturally, the reported results are subject to a number of assumptions and should be interpreted within the context of the SDP model. Although the assumption of myopic behavior may be considered a simplification, it is not far off from true fishermen behavior according to Grafton et al. (2006) and the European Commission (2009a). Alternatively, fishermen may have a longer planning horizon or they may change their behavior when they know that the quota is fixed for multiple years. The maximum on the fixed quota period of five years suffices to address the research questions on fluctuating quota and management costs. It may be unlikely that the EU will opt for a larger fixed quota period, even if the value of the fishery is higher. It is further assumed that the source of uncertainty comes from fish stock growth alone. This assumption ignores that the observed stock may not be the true stock. This is another, potentially more important source of uncertainty. Finally, we assumed a first-order Markovian process of fish stock. The fish stock may depend on last year, but also on the year before.

3.5 Conclusions

Uncertainty in fish stock growth provides an important challenge to deci-sion-makers. Yearly revisions of fisheries policies lead to fluctuation in quota, which results in overcapacity for fishermen. It is therefore unlikely that the current system of annual quota is optimal. Another phenomenon in yearly quota adjustment is the high management costs involved. Therefore, decision-makers are developing new policies with which they hope to improve both biological sustainability and resource rents.

In this context, the EU has proposed a system of multiannual quota for North Sea fish species.

One of the objectives of this system is to reduce annual fluctuation in quota, so that fishermen will be subject to less capital volatility and less overcapacity. In addition, it reduces management costs as fewer meetings are required between policy makers and scientists. Because it remains unclear whether this policy, compared to annual quota, indeed reduces quota volatility and increases resource rents, we investigated these questions with a bi-level stochastic dynamic programming model.

Our results suggest that policy makers can reduce quota volatility and improve resource rents with multiannual quota. The accomplishment of these objectives come with important trade-offs that may be equally or more important. Multiannual quota increase volatility in the fish stock, they increase volatility in investments of fishermen and they lead to more overcapacity. This indicates that objectives of the EU and fishermen cannot be jointly achieved with this policy and that the fish stock is more sensitive to reaching an unsustainable level under multiannual quota. In future work, the model will be extended to account for alternative forms of fishermen behavior and different management schemes. For example, fishermen may have a longer planning horizon or they may even change their behavior when they anticipate a quota that is fixed for multiple years. A deeper understanding may help to find ways to reduce overcapacity as well as ensuring sustainable levels of fish stock.

Chapter 4

An adjustment restriction on fish quota: resource rents, overcapacity and recovery of fish stock*

Management objectives of the European Union (EU) for North Sea fish stocks are shifting towards considering both biological sustainability and economic benefits. As part of multiannual management plans, an adjustment restriction on fish quota has been introduced. Its objective is to obtain an efficient fish stock and to reduce overcapacity for the fishing industry. We develop and apply a bi-level stochastic dynamic programming model to study the effect of a quota adjustment restriction on the net present value of resource rents, overcapacity and fish stock, when the system is recovering from a downward environmental shock. At level one, a policy maker sets the quota, considering fishermen behavior, stochastic fish stock dynamics, capital stock dynamics and a quota adjustment restriction. At level two, fishermen harvest myopically and make long-term investment decisions, assuming that fish stock and quota do not change over time. The two levels are linked by the quota, which is optimized by the policy maker at level one and becomes a restriction for myopic harvest and long-term investment decisions of fishermen at level two. Our analysis suggests that in the long run, overcapacity can be reduced by 54% at modest costs, namely at a 1% reduction in the net present value of resource rents. Long and short run sustainability of the fish stock is not affected.

*This chapter is based on the paper: Diana van Dijk, Eligius M.T. Hendrix, Rene Haijema, Rolf A. Groeneveld, Ekko C. van Ierland. An adjustment restriction on fish quota: resource rents, overcapacity and recovery of fish stock. Submitted.

4.1 Introduction

Management objectives of the European Union (EU) for North Sea fish stocks have traditionally focussed on biological sustainability. Natural fluctuation in fish stocks is a challenge for policy makers when adjusting quota on an annual basis (Carson et al., 2009). Fluctuation in fish stocks leads to annual quota volatility (Daw and Gray, 2005), which in turn affects fishermen in their ability to make long-term investment plans (Kell et al., 2006). Adjustment of fleet capacity is costly and overcapacity exists in EU fishing fleets (Guyader, 2002).

Objectives of policy makers have been shifted towards considering economic benefits and biological sustainability. In the 2013 reform of the Common Fisheries Policy, multiannual management plans have been proposed to reduce annual quota volatility. The objective of these plans is to obtain both efficient fish stocks in the long run and to provide greater stability for the fishing industry by enabling operators to plan ahead. Stability is to be provided by restricting the annual change in quota, but besides setting quota, multiannual management plans also provide measures such as closed areas, mesh size, gear, inspections, monitoring and effort management.

One of the measures under multiannual management plans is a quota adjustment restriction. This measure restricts annual quota volatility in the sense that quota can at most be adjusted upward or downward by 15% with respect to the previous quota. There are, however, potential challenges with this quota adjustment restriction. First, if quota adjustment is restricted, the quota may not be reduced sufficiently in years of low recruitment and this can delay fish stock recovery (Kell et al., 2005). The quota also cannot increase by more than 15%, which prevents benefiting from years of increased recruitment levels (Butterworth, 2007). Second, Bennear and Stavins (2007) have shown that a restriction on the policy instrument causes the policy maker to make sub-optimal decisions and that this has a negative impact on the net present value of resource rents. van Dijk et al. (2013a) (Chapter 3 of this thesis) show that when the quota are free of any restriction, and the policy maker accounts for dynamics in fish stock and capital stock, sustainability of the fish stock is realized, however at the cost of maintaining some overcapacity. This overcapacity is the result of fishermen not being able to adjust their capital stock to changes in the quota. While it is optimal according to the policy maker to maintain overcapacity, it can lead to a dissatisfied fishing industry and turn up the pressure to reduce fluctuation in quota. It implies that, with the current objective of the policy maker to obtain both an efficient fish stock and to reduce overcapacity, a quota adjustment restriction may lead to a reduction in resource rents and a delay in fish stock recovery or an increase in overcapacity. In this respect it is the political ambition of keeping fishermen content, as well as obtaining an efficient fish stock, that drives the policy maker to introduce a quota restriction at the cost of lower resource rents.

Studies on the quota adjustment restriction have made an attempt at understanding the effect of this rule on sustainability of fish stocks (Kell et al., 2005, 2006). They show that in the short run, the effect of the restriction depends on the starting condition of the fish stock, while in the medium and long run, the restriction hardly affects harvest and sustainability of the fish stock. The more restrictive the quota adjustment restriction, the stronger its impact. A quota adjustment restriction between 20% and 40% hardly affects harvest and sustainability of fish stock, while a 10% quota adjustment restriction leads to large changes in the stock size and affects the ability to achieve management targets.

These studies have a number of limitations. First, they perform simulations of historical data of quota and fish stock, while accounting for the quota adjustment restriction. This means that the simulated quota may be sub-optimal. Second, capital stock and revenues and costs from harvesting are not considered. It is therefore unknown what the economic impact is of the adjustment restriction on quota. Third, Kell et al. (2005, 2006) focus on the path towards a long-term average, while it remains unknown what the effect is on the system when the fish stock deviates from this path, e.g. after a shock. Analysis of long-term values in a system with a quota adjustment restriction does not provide sufficient insight in the effect of such a restriction on recovery of fish stocks and on overcapacity. The effect of a quota adjustment restriction is better measured for system states that deviate from long-term stability. Finally, although the objective of the quota adjustment restriction is to address both recovery of fish stocks and overcapacity, fishermen behavior in terms of planning and adjusting fleet capacity is not incorporated in the studies of Kell et al. (2005, 2006). This is a limitation, because the policy maker makes assumptions about harvest and investment behavior when setting the quota.

There exists extensive theoretical literature on investment behavior of fishermen, but because of limited data availability there are few empirical studies that analyze investment in fisheries (Tsitsika and Maravelias, 2008). To the best of our knowledge, there is no general agreement or evidence from data that fishermen operate with a short-time view, i.e. they act myopically, or that they have a long planning horizon when they make harvest and investment decisions. Harvest behavior has been modeled with an infinite planning horizon (Clark et al., 2005; Daníelsson, 2005; Singh et al., 2006; Kulmala et al., 2008), as well as myopically (Hämäläinen et al., 1990; Sandal and Steinshamn, 2004; Olaussen and Skonhoft, 2008; van Dijk et al., 2013a). It has been suggested that myopic harvest is not far off from true fishermen behavior (Karagiannakos, 1996; Grafton et al., 2006; European Commission, 2009a).

The objective of this paper is to study the effect of a quota adjustment restriction on the net present value of resource rents, overcapacity and recovery of fish stock, while considering biological and economic variables. We first look at the long-term effect of different levels of quota adjustment restriction and then introduce a downward environmental shock on the fish stock. To compare with Kell et al. (2005, 2006), we study the effect of different levels of quota adjustment restriction, including 30%, 15%, 10% and 5% restrictions. The analysis is based on a bi-level stochastic dynamic programming (SDP) model. A deterministic bi-level framework is developed in Homans and Wilen (1997) to study the combined implementation of a quota and season length, which are each determined at a different level. This model is extended in Anderson (2000) to account for disaggregated vessel level behavior and to allow for political intervention. A stochastic extension of the model is presented in Da Rocha and Gutiérrez (2012), by assuming unknown current levels of fish stock. Characteristic to the bi-level model in our study is that decisions of the policy maker and fishermen are made at their first and second level, respectively. At level one, the policy makers determines the quota by maximizing the net present value of resource rents, while anticipating fishermen behavior, stochastic fish stock dynamics, capital stock dynamics and a quota adjustment restriction. At level two, fishermen make myopic harvest and long-term investment decisions, for which it is assumed that fish stock and quota do not change over time. The two levels are linked by the optimal quota that is derived at level one and becomes a restriction at level two. With the quota, the policy maker protects fishermen from too optimistic investment decisions.

The contribution of this paper is threefold. First, where Kell et al. (2005, 2006) determine quota through simulations of historical data, we optimize the quota with an adjustment restriction. This optimal quota is consequently used in a simulation to study the effect of the adjustment restriction on the net present value of resource rents, overcapacity and recovery of fish stock. And, while Homans and Wilen (1997), Anderson (2000) and Da Rocha and Gutiérrez (2012) study fisheries policies with a similar bi-level framework, they do not focus on the problem of overcapacity. Second, in order to study fish stock recovery and overcapacity, dynamics in both fish stock and capital stock are considered when determining the optimal quota. Finally, resource rents are compared for the case of a quota without adjustment restriction and a quota with adjustment restriction.

4.2 The model

We present a bi-level stochastic dynamic programming (SDP) model, where at level one, the policy maker determines the quota that maximizes resource rents, while anticipating fishermen behavior, stochastic fish stock dynamics, capital stock dynamics and a quota adjustment restriction. At level two, fishermen decide on their myopic harvest and long-term investment levels. For this long-term investment fishermen assume that the fish stock and quota will remain at the current levels. The two levels are linked by the quota that is derived at level one and becomes a restriction for fishermen at level two.

4.2.1 Fishermen decisions

We first present the decisions at level two, i.e. fishermen behavior with respect to harvest and investment. Harvest behavior is myopic, reacting on current costs, revenues from harvesting, on restrictions set by the policy maker and on current fleet capacity. The investment is considered a long-term decision, based on current levels of fish stock, capital stock and quota. Table 4.1 provides an overview of the model variables, parameters and their definition.

Myopic harvest behavior

In the literature on fisheries economics, harvest behavior has been modeled with different assumptions concerning the planning horizon. It is common to assume either an infinite planning horizon (Clark et al., 2005; Singh et al., 2006; Kulmala et al., 2008) or a short planning horizon (Hämäläinen et al., 1990; Sandal and Steinshamn, 2004; Olaussen and Skonhoft, 2008; van Dijk et al., 2013a). Nevertheless, myopic harvest has been considered to be close to true fishermen behavior (Karagiannakos, 1996; Grafton et al., 2006; European Commission, 2009a). We specify harvest behavior based on current fish, capital and quota levels.

In this model, fishermen react on costs and revenues from harvesting, depending on the experienced level of fish stock x_t and on restrictions due to capital stock k_t and quota Q_t. This quota is determined by the policy maker. A Spence harvest function is used to represent the relation between harvest h_t, fish stock x_t and effort E_t (Spence, 1973):

$$h_t = x_t\left(1 - e^{-qE_t}\right) \rightarrow E(x_t, h_t) = \frac{1}{q}\ln\left(\frac{x_t}{x_t - h_t}\right). \tag{4.1}$$

Harvest h_t and fish stock x_t are expressed in kton, while effort E_t is expressed in million horse power days, mln hpd, and the catchability coefficient q is expressed in mln hpd^{-1}. In Conrad and Clark (1987), $\frac{c}{pq}$ has been identified as the bioeconomic equilibrium escapement, where c stands for the cost per unit of effort and p is the unit price of fish. This is in fact the fish stock below which the marginal unit of harvest is no longer profitable. This is usually called the open access fish stock. In this model we incorporate the cost per unit of effort c_E, which includes maintenance, haul-in, haul-out and storage. Crew costs are included separately as the cost per unit of revenue c_R, so that the open access fish stock $\hat{x}$ is

$$\hat{x} = \frac{c_E}{pq(1 - c_R)}. \tag{4.2}$$

Under pure open access, harvest takes place for a fish stock $x_t > \hat{x}$. In that case, the open access harvest level is $\tilde{h}(x_t) = (x_t - \hat{x})^+$, where the operator $(y)^+ = \max\{0, y\}$. In restricted open access, fishermen are also confronted with quota Q_t, expressed in kton, so that the harvest is

$$\hat{h}(x_t, Q_t) = \min\left\{\tilde{h}(x_t), Q_t\right\}. \tag{4.3}$$

The effort is restricted by the fleet size k_t expressed in the same units, $E_t \leq k_t$. This means that fishermen cannot harvest more than what their capital stock allows. The maximum possible harvest given the available capital stock is $h(x_t, k_t) = x_t(1 - e^{-qk_t})$. This gives the following myopic harvest rule:

$$h(x_t, k_t, Q_t) = \min\left\{\hat{h}(x_t, Q_t), x_t\left(1 - e^{-qk_t}\right)\right\} \tag{4.4}$$

Long-term investment behavior

We now develop a long-term investment rule for fishermen. Although the length of the planning horizon is subject to considerable debate (Link et al., 2011), it is common to assume that fishermen decide over the long-term (Eisenack et al., 2006; Singh et al., 2006; Kulmala et al., 2008). In Eisenack et al. (2006) long-term investment decisions are determined for a multiple number of identical fishing firms, while in Singh et al. (2006) it concerns the investment decision of a sole owner. In both studies, decisions are based on known dynamics in fish stock and capital stock. It is thereby ignored that fisheries are often managed by a resource manager, where each party may have different knowledge about fish stock dynamics. In fact, it is unlikely that fishermen have the same knowledge about fish stock growth and future values of fish stock as a policy maker.

In this model we assume that fishermen have no information about fish stock dynamics. They consider the current observed fish stock to be constant during the planning horizon. Similarly, it is assumed that fishermen have no knowledge about future quota. They therefore consider the current quota as the future one in their investment decision. That is, the long-term investment decision is based on observed levels of current fish stock x_t, capital stock k_t and quota Q_t, where the latter is set by the policy maker. The objective of fishermen is to choose a future investment path $i_{t+j},\ j = 0, \ldots, \infty$ such that the sum of the discounted future profits is maximized:

$$\max_{i_{t+j}} \left\{ \sum_{j=0}^{\infty} \frac{\pi(x_t, k_{t+j}, Q_t, i_{t+j})}{(1+\rho)^j} \right\} \tag{4.5}$$

with

$$\pi(x, k, Q, i) = (1 - c_R)ph(x, k, Q) - c_E E(x, k, Q) - c_i i \tag{4.6}$$

where ρ is the discount rate and where the fleet is foreseen to develop according to

$$k_{t+j+1} = (1-\gamma)k_{t+j} + i_{t+j}. \tag{4.7}$$

The discounted future profit in (4.5) are based on revenues from harvest ph minus effort costs $c_E E$, crew costs $c_R ph$ and investment costs $c_i i$. As in Elliston and Cao (2006), we include crew costs as a constant share per unit of revenue. Decisions $h_{t+j}, E_{t+j}, i_{t+j}$ are determined by current observed fish stock x_t, capital stock k_{t+j} and by the decision of the policy maker, quota Q_t. Decision E_{t+j} follows from $h_{t+j} = h(x_t, k_{t+j}, Q_t)$. A constraint is included, namely fishermen assume for all years $t + j$ that both fish stock x_t and quota Q_t remain constant at levels x_t and Q_t.

A good approximation of the optimum investment level i_t of problem (4.5), (4.6), (4.7) can be derived from the following reasoning. Consider that fishermen invest such that the investment extends in one period directly to the capital level corresponding to long-run harvest $\overline{h}$, given fish stock x and quota Q. Investment is zero if the capital stock exceeds this level:

$$i(x, k, Q) = \left\{\frac{1}{q}\ln\left(\frac{x}{x - \overline{h}}\right) - (1-\gamma)k\right\}^{+} \tag{4.8}$$

with

$$\overline{h} = \min\{x - \frac{c_E + c_i\gamma}{pq(1-c_R)}, Q\}. \tag{4.9}$$

For a derivation see the appendix.

4.2.2 The policy maker

At level one, a policy maker sets the quota, considering fishermen behavior, stochastic fish stock dynamics, capital stock dynamics and a quota adjustment restriction. We first present the bio-economic model for optimal quota adjustment and then describe the solution method of stochastic dynamic programming in terms of all its components.

Bio-economic model for annual quota adjustment

At level one, the policy maker determines the annual quota for the fishing industry. The objective of the policy maker is to determine the quota Q_t that maximizes the net present value of resource rents π_t,

$$\max_{Q_t} \mathbb{E}\left\{\sum_{t=0}^{\infty} \frac{\pi(x_t, k_t, Q_t, i(x_t, k_t, Q_t))}{(1+\rho)^t}\right\}, \tag{4.10}$$

with resource rents π_t according to (4.6). We incorporate a quota adjustment restriction by means of a restriction on the change in the quota:

$$A \leq Q_t \leq B, \tag{4.11}$$

where $A = Q_{t-1}(1-\alpha)$ and $B = Q_{t-1}(1+\alpha)$, and where $Q_{t-1}(1-\alpha) \leq Q_t \leq Q_{t-1}(1+\alpha)$ states that the quota cannot deviate more than α from the previous quota Q_{t-1}.

Harvest h_t in (4.4) and investment i_t in (4.8) are fishermen decisions at level two, that are determined by fish stock x_t, capital stock k_t and the quota decision Q_t of the policy maker. This means that the policy maker anticipates harvest and investment decisions of fishermen, which coincide with the harvest and investment rules in (4.4) and (4.8). The difference is that the policy maker has information about future, stochastic fish stock development and uses this information to protect the fishery from overinvestment and overfishing. In the objective function of the policy maker the notation $\mathbb{E}$ therefore represents the expectation taken over possible outcomes of fish stock x_t and capital stock k_t. Fish dynamics are modeled as

$$x_{t+1} = x_t + z_t r x_t\left(1 - \frac{x_t}{M}\right) - h_t, \tag{4.12}$$

where stochastic fish stock growth is represented by an i.i.d. random variable z_t that is lognormally distributed. The fleet develops according to

$$k_{t+1} = (1-\gamma)k_t + i_t. \tag{4.13}$$

Solution method: stochastic dynamic programming

The model for setting the quota can be solved numerically using stochastic dynamic programming. We assume an infinite horizon problem with discrete time steps. In each year, the quota can at most be adjusted upward or downward by a specified percentage with respect to the quota in the previous period. Following the literature on stochastic dynamic programming (Howard, 1960; Puterman, 1994; Judd, 1998), we discuss the state (space), decision (space), state transition (probabilities), the contribution, the Bellman equation and computational complexity. In particular we pay attention to the implementation of the solution method.

State and state space: The state is the state of fish stock x_t and capital stock k_t at the start of year and the quota from the previous period Q_{t-1}, because each year the quota decision Q_t can at most be adjusted upward or downward by a specified percentage with respect to Q_{t-1}; the state is (x_t, k_t, Q_{t-1}). The state space is continuous, as fish stock x_t, capital k_t and last year's quota Q_{t-1} are continuous. For numerical calculations a grid is chosen with n_x levels of x, n_k levels of k, and n_Q levels of quota. The grid consists of $n_x \times n_k \times n_Q$ states. To simplify notations, the state is denoted as (x_t, k_t, Q_{t-1}) irrespective of the value of t.

Decision and decision space: The decision is Q_t, the quota that holds for year t. The decision space is continuous and does not require a grid, for reasons explained below.

Transition and transition probabilities: State transitions from (x_t, k_t, Q_{t-1}) to (x_{t+1}, k_{t+1}, Q_t) follow Equations (4.12) and (4.13). In (4.12), z_t is a continuous stochastic variable, which has been discretized into 40 quantiles of the underlying probability distribution. For evaluating a decision in a particular state, we consider thus forty transitions with equal probability 0.025. Although transitions will be considered from all states (x_t, k_t, Q_{t-1}) on the grid, the resulting states (x_{t+1}, k_{t+1}, Q_t) usually are not on the grid. In discussing the Bellman equation we explain how we deal with this issue.

Contribution: The objective function (4.10) is separable in contributions per period in (4.6).

Bellman equation: The objective function can be defined recursively:

$$V(x_t, k_t, Q_{t-1}) = \max_{A \leq Q_t \leq B} \{\pi(x_t, k_t, Q_t, i(x_t, k_t, Q_t)) + \delta \mathbb{E}[V(x_{t+1}, k_{t+1}, Q_t)]\}. \quad (4.14)$$

V_t is the value function that represents the maximized value of the objective function from time t onwards, $\delta < 1$ is the discount factor and $\mathbb{E}$ is the expectations operator that holds the transition probabilities of moving from a given current state of fish stock x_t to next period's fish stock x_{t+1}. Restrictions on quota Q_t are given by A and B in (4.11). Assuming a long horizon of T years, we can solve the maximization problem recursively, starting with $V_T(x_T, k_T, Q_{T-1}) = 0$, for all $n_x \times n_k \times n_Q$ states on the grid. Next, successively $V_{T-1}, V_{T-2}, \ldots, V_2, V_1$ are computed for all states on the grid. For states that are not on the grid, the state values are derived by interpolation.

Computational complexity: For the bounds of the state space of fish stock, we have $x_t \in [\hat{x}, M]$. Because of the assumption that $h_t = 0$ if $x_t < \hat{x}$, we do not consider values below $\hat{x}$. From this assumption follows that a reasonable range for optimal quota is $Q_t \in [0, M - \hat{x}]$. Finally, for the bounds of the state space of capital stock we have $k_t \in [0, 74]$. The grid of the state space has $n_x = 23$, $n_k = 23$, and $n_Q = 28$ equidistant levels for x_t, k_t and Q_{t-1}, respectively. For each state (x_t, k_t, Q_{t-1}) a nonlinear search procedure is applied, in which interpolation is used to estimate state values.

The numerical procedure of (4.14) is also known as Value Function Iteration. For a description of the value iteration process see Puterman (1994), and on its implementation see van Dijk et al. (2013b) (Chapter 2 of this thesis).

4.3 Results

The model is applied to a stylized setting for the management of North Sea plaice, for which parameter values have been derived in van Dijk et al. (2013a) (Chapter 3 of this thesis). Table 4.1 gives an overview of parameter and variable values. We first look at the effect of a quota restriction on long-term quota fluctuation. We then introduce a downward environmental shock in the system and study the effect of the quota adjustment restriction on resource rents, overcapacity and recovery of fish stock.

Table 4.1. Parameter and variable values from van Dijk et al. (2013a) (Chapter 3 of this thesis)

Symbol	Definition	Value	Unit
Biological	**parameters**		
$\hat{x}$	open access stock of North Sea plaice	185.6	$kton$
r	intrinsic growth rate of North Sea plaice	0.74	%
M	carrying capacity of North Sea plaice	460	$kton$
α	quota restriction	± 15	%
μ	mean of the lognormally distributed z_t	-0.0126	
σ	standard deviation of random variable z_t	0.16	
Economic	**parameters**		
p	price	$1.83 * 10^6$	$\varepsilon/kton$
q	catchability coefficient	0.0139	$mln\ hpd^{-1}$
c_E	effort cost	$3.54 * 10^6$	$\varepsilon/mln\ hpd$
c_R	crew cost	0.25	%
c_i	investment cost	$2.1 * 10^6$	$\varepsilon/mln\ hpd$
δ	discount factor	0.95	
γ	vessel depreciation rate	10	%
Biological	**variables**		
x_t	stock size of North Sea plaice	$\in [\hat{x}, M]$	$kton$
h_t	harvest of North Sea plaice	$\in [0, Q_t]$	$kton$
Q_t	quota for North Sea plaice	$\in [0, M - \hat{x}]$	$kton$
z_t	i.i.d. random variable	$\sim logn(\mu, \sigma)$	
Economic	**variables**		
k_t	fleet capacity of North Sea plaice fishery	$\in [0, \frac{1}{q} ln \frac{M}{\hat{x}}]$	$mln\ hpd$
i_t	investment in capital stock	$\in [0, \infty]$	$mln\ hpd$
E_t	fleet effort North Sea plaice	$\in [0, k]$	$mln\ hpd$
π_t	net present value of resource rents		$mln\ \varepsilon$

4.3.1 Long-term effect of a quota adjustment restriction

Let us first consider the effect of a quota adjustment restriction on quota fluctuation. Based on a simulation of one run with a sample path of 200 years and given initial stock values $x_0 = 350, k_0 = 14$, Figure 4.1 illustrates the relative annual change in quota $(Q_t - Q_{t-1})/Q_{t-1}$, when the quota is not restricted. The relative annual change in quota ranges from -0.17 to 0.37 and has a standard deviation of $\sigma = 0.08$. That is, the volatility in quota change is large and results in overcapacity. When a 5% quota adjustment restriction is applied to the quota, the relative annual change in quota is illustrated in Figure 4.2, with given initial stock values $x_0 = 350, k_0 = 14, Q_0 = 65$. The relative annual change in quota ranges from -0.04 to 0.05, with a lower volatility of $\sigma = 0.02$.

We use the optimal quota Q_t, derived from Equation (4.14), to study the effect of a quota adjustment restriction on long-term average discounted resource rents, overcapacity and fish stock. Table 4.2 shows results for different levels of quota adjustment restriction, i.e. $30\%, 15\%, 10\%, 5\%$. Average values of long-term discounted resource rents π_t, overcapacity $k_t - E_t$, capital stock k_t, effort E_t, quota Q_t, harvest h_t and fish stock x_t are based on 5,000 sample paths over 100 years each. Furthermore, an estimate is given of the number of years where harvest is bounded by capital stock and quota, i.e. $E_t = k_t$ and $h_t = Q_t$ respectively.

Long-term averages of resource rents π_t, quota Q_t, harvest h_t and fish stock x_t are little or not affected by a 30% and 15% quota adjustment restriction. Overcapacity $k_t - E_t$ is slightly lower under a 30% adjustment restriction and continues to reduce as the system becomes more restrictive. As has been put forward in Bennear and Stavins (2007), here we observe what is to be expected from a restriction, namely sub-optimal decisions lead to a reduction in the net present value of resource rents. Compared to a quota without adjustment restriction, however, under a 5% quota adjustment restriction resource rents are reduced by 1% while overcapacity is reduced by 54%. Less overca-

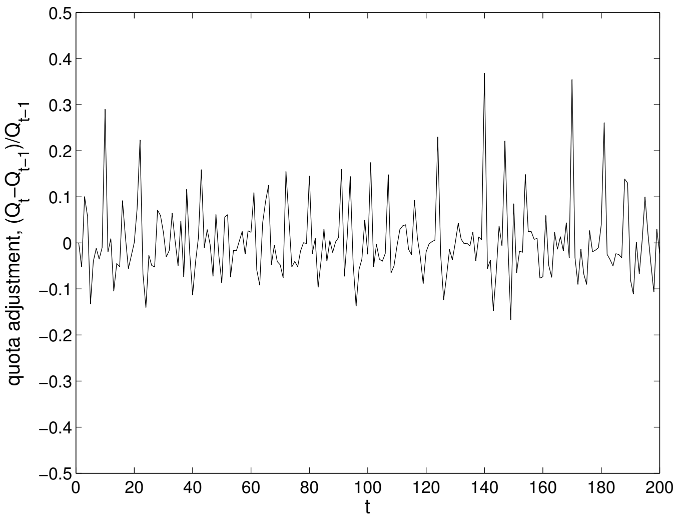

Figure 4.1. A 200 year sample path of relative annual quota change $(Q_t - Q_{t-1})/Q_{t-1}$, with given initial stock values $x_0 = 350, k_0 = 14$; no quota adjustment restriction.

pacity here, i.e. from 0.28 to 0.13, is due to keeping a lower capital stock and a lower effort level. This is the reaction of fishermen to a lower long-term quota. Because the policy maker is limited in the adjustment of quota, a lower level is maintained so that uncertain levels of future fish stock, as a consequence of stochastic growth, are anticipated. At the same time, characteristics of the Spence harvest function prevent the fish stock from going extinct (Reed, 1979; Nøstbakken, 2008). In this model, the Spence harvest function ensures that the fish stock always exceeds the open access fish stock $\hat{x}$. Fishermen therefore do not fully harvest the quota. On one hand, the policy maker tailors the quota to the investment behavior of fishermen, affecting thereby harvest and investment decisions. On the other hand, fishermen assume fixed levels of fish stock and quota over the entire investment planning horizon. Eventually, the effect of the policy and the response of fishermen are observed in the long-term fish stock. With less capital input under a 5% quota adjustment restriction, harvest decreases as well and the long-term average fish stock increases by 1%.

How often capital stock $E_t = k_t$ and quota $h_t = Q_t$ are binding, is shown by the percentages over all 500,000 simulated years. Without quota adjustment restriction, capital is binding 31% of the simulated years. This percentage increases to 48% as the system becomes more restrictive. This can be explained by fishermen choosing an effort level that follows the capital stock more closely, where this effort reaches the level of the available capital stock more often. Without an adjustment restriction, the quota is binding 69% of the time and this reduces to 52% as we consider a more restrictive quota adjustment. With fishermen reducing overcapacity, it is the capital stock that becomes more often the binding factor, while the quota is less frequently the binding factor.

4.3.2 Recovery from an external shock

We now turn to the case where the fish stock is temporarily reduced due to an external environmental shock that is not anticipated by the policy maker when setting the quota. This means, the external shock is in addition to the assumption of stochastic growth. The difference is that stochastic growth is anticipated by the policy maker, whereas a shock is an event to which the quota is adjusted at the moment of occurring. With reference to the double objective of the policy maker, i.e. to obtain an efficient fish stock and to reduce overcapacity, we are concerned with the following question. After a downward external shock, what is the effect of a quota adjustment restriction on resource rents,

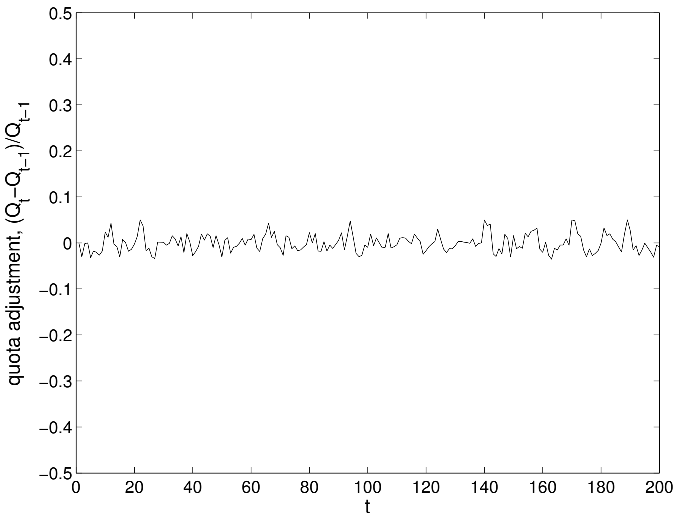

Figure 4.2. A 200 year sample path of relative annual quota change $(Q_t - Q_{t-1})/Q_{t-1}$, with given initial stock values $x_0 = 350, k_0 = 14, Q_0 = 65$; 5% quota adjustment restriction.

overcapacity and fish stock recovery?

To investigate this question, we simulate the system, where the fish stock reduces instantaneously, but temporarily to $x_t = 200$ in year $t = 20$. Table 4.3 shows long-term and short-term discounted resource rents $\pi_t/(1+\rho)^t$, as well as overcapacity $k_t - E_t$, capital stock k_t, effort E_t, quota Q_t and harvest h_t over a 5 year recovery period, i.e. between $t = 20$ and $t = 24$. Fish stock recovery $|x_{24} - x_{100}|$ is measured as the absolute difference between the fish stock in $t = 24$ and its long-term average in $t = 100$. Again, we consider different levels of quota adjustment restriction, i.e. $30\%, 15\%, 10\%, 5\%$. Reported values are averages over 5,000 sample paths. Long-term resource rents are taken over a period of 80 years.

The long-run analysis suggests that a restrictive system provides a reduction in overcapacity in exchange for lower resource rents. Table 4.3 shows that the long-term effect, including recovery from a downward external shock, i.e. the period $t = 20$ to $t = 100$, provides a similar conclusion with respect to resource rent reduction. Compared to a quota without adjustment restriction, long-term resource rents can be reduced by 3% under a 5% quota adjustment restriction. This is because in the short-term with an adjustment restriction, the policy maker can bring down the quota only by a small amount. During the 5 year recovery period, restricting quota adjustment by more than 30% has little effect on resource rents. Compared to a quota without restriction, each adjustment restriction provides a 10-11% decrease in resource rents, regardless of its size. During the same period, overcapacity can be reduced by 38-50%, again independently of the size of the restriction. This is realized by keeping lower levels of capital stock and higher levels of effort as a result of setting the cumulative quota higher as the system becomes more restrictive. Higher effort also explains the increased cumulative harvest during recovery and a fish stock that, in year $t = 24$, is further away from the long-term average.

Figure 4.3 shows the levels of quota during recovery. Without adjustment restriction, the quota reduces to zero in $t = 20$, after which it can be adjusted according to fish stock recovery. Introducing and increasing the level of quota adjustment restriction gives that the quota in $t = 20$ is set at a higher level because the adjustment restriction sets a lower bound on the quota. With restriction, the harvest is actually limited by the open access fish stock in $t = 20$. This means that on average, the quota in this year is not binding and thereby does not affect the effort level, effort costs and resource rents.

Figure 4.4 shows how often capital stock is binding, i.e. $E_t = k_t$, during the 1,000 simulations for

Table 4.2. Long-term average discounted resource rents $\pi_t/(1+\rho)^t$, overcapacity $k_t - E_t$, capital stock k_t, effort E_t, quota Q_t, harvest h_t and fish stock x_t; no adjustment restriction versus $30\%, 15\%, 10\%, 5\%$ adjustment restrictions. Reported values are averages over 5,000 sample paths for 100 years each, given initial stock values $x_0 = 350, k_0 = 14, Q_0 = 65$. Furthermore, the number of years that capital stock k_t and quota Q_t bound harvest, $E_t = k_t$ and $h_t = Q_t$, is provided as percentages of the total number of simulations and years that fleet capacity and quota are binding.

Quota adjustment	Resource Rents $\sum_{t=0}^{100} \frac{\pi_t}{(1+\rho)^t}$	Over-capacity $k_t - E_t$	Capital Stock k_t	Effort E_t	Quota Q_t	Harvest h_t	Fish Stock x_t	Binding Capital[a] $E_t = k_t$	Binding Quota[b] $h_t = Q_t$
No restriction	643	0.28	14.5	14.2	63.5	62.3	348.5	31%	69%
30%	643	0.27	14.4	14.1	63.3	62.2	348.8	33%	67%
15%	643	0.21	14.3	14.1	62.8	62.0	349.3	39%	61%
10%	640	0.13	13.4	13.2	60.2	59.7	355.0	43%	57%
5%	638	0.13	13.0	12.9	59.0	58.5	357.9	48%	52%

[a]the fraction of years in which capital is binding, that is, the percentage of 5,000*100 simulated years in which effort is limited by the fleet capacity.

[b]the fraction of years in which the quota is binding, that is, the percentage of 5,000*100 simulated years in which harvest is limited by the quota.

Table 4.3. Long and short-term discounted resource rents $\pi_t/(1+\rho)^{(t-20)}$, overcapacity $k_t - E_t$, capital stock k_t, effort E_t, quota Q_t, harvest h_t and fish stock x_t after an external shock where the fish stock drops to $x_t = 200$. We consider different levels of quota adjustment restriction, i.e. $30\%, 15\%, 10\%, 5\%$. Reported values are averages over 5,000 sample paths.

Quota adjustment	Long-term Resource Rents $\sum_{t=20}^{100} \frac{\pi_t}{(1+\rho)^{(t-20)}}$	Short-term Resource Rents $\sum_{t=20}^{24} \frac{\pi_t}{(1+\rho)^{(t-20)}}$	Over-capacity $\sum_{t=20}^{24} (k_t - E_t)$	Capital $\sum_{t=20}^{24} k_t$	Effort $\sum_{t=20}^{24} E_t$	Quota $\sum_{t=20}^{24} Q_t$	Harvest $\sum_{t=20}^{24} h_t$	Short-term recovery Fish Stock $\lvert x_{24} - x_{100} \rvert$
No restriction	575	84.4	20.8	67.8	47.0	215.2	202.9	2.8
30%	568	75.2	12.9	62.8	49.9	241.4	200.3	9.9
15%	566	76.2	10.6	65.7	55.1	258.9	214.3	0.2
10%	562	75.7	10.5	65.8	55.3	263.7	215.5	7.6
5%	559	74.8	11.8	67.8	56.0	272.2	217.5	12.7

each of the years $t = 20$ up to $t = 40$. In $t = 20$ the fish stock reduces to a level at which the capital stock cannot be fully used. The capital stock therefore does not limit effort and harvest under any considered quota adjustment restriction. With fishermen assuming that the fish stock remains at this level throughout the investment planning horizon, the investment level drops to zero and in $t = 21$ the capital stock reduces with the fleet depreciation. While the capital stock reduces in $t = 21$, the fish stock increases rapidly, causing desired harvest and effort levels to hit the fleet capacity. This occurs in most of the simulations, i.e. 89-100%, under 15%, 10% and 5% quota adjustment restrictions. If quota adjustment is limited to 30% or not limited at all, the number of times that the full capacity is reached remains low, i.e. 4-5%, as it is the quota that limits the harvest. Due to the large investment under 15%, 10% and 5% quota adjustment restrictions, in $t = 22$ a large fleet capacity becomes available. A 30% quota adjustment restriction, or no restriction, causes investment to be small in $t = 21$ such that the fleet capacity becomes more restrictive in $t = 22$, i.e. 26-98%. In the following years, the difference fades out because the fish stock approaches its long-term average.

Figure 4.5 shows how often quota is binding $h_t = Q_t$ during the years $t = 20$ up to $t = 40$. In the year of the shock, only a restriction-free system can follow the downward movement of the harvest in 100% of the simulations. With an adjustment restriction, the quota cannot follow and is not binding. Although the fish stock is able to increase rapidly at a zero quota, it is still in recovery in $t = 21$, such that harvest is limited by quota in a large number of the simulations, i.e. 96%. The 30% and 15%

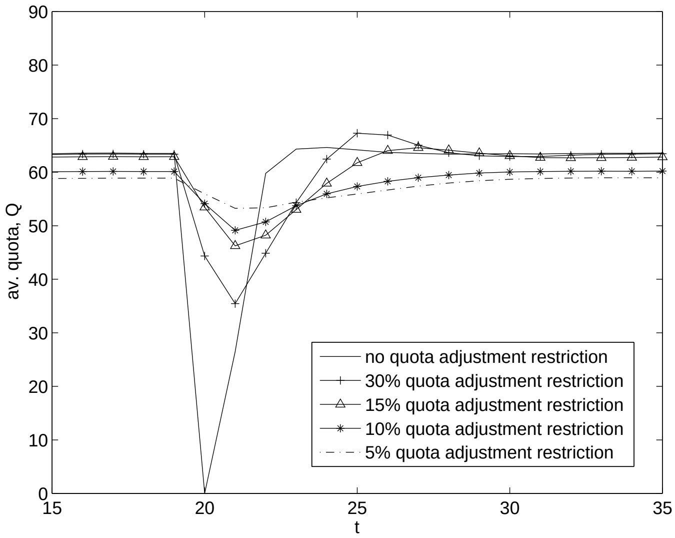

Figure 4.3. Average quota Q_t over 5,000 sample paths of 20 years each, without and with different levels of quota adjustment restriction, i.e. $30\%, 15\%, 10\%, 5\%$, and given a downward shock in $t = 20$.

quota adjustment restrictions provide the same tendency. The investment in year $t = 21$ increases, especially in a system with no adjustment restriction because of the zero quota and zero investment in the previous year. Consequently, in $t = 22$ the desired open access harvest $\tilde{h}(x_t) = (x_t - \hat{x})^+$ exceeds the quota. This provides a large number of simulations, i.e. 99-100%, of harvest being limited by the quota under a 15% 10% and 5% adjustment restriction. In the following years, the system recovers from the shock and returns to its long-term state where a quota with adjustment restriction is less limiting for harvest than a quota without restriction.

4.4 Summary and conclusions

The European Union has introduced an adjustment restriction on fish quota, as part of multiannual management plans, to obtain an efficient fish stock and to reduce overcapacity in the fishing industry. We studied the effect of a quota adjustment restriction on the net present value of resource rents, overcapacity and fish stock using a bi-level stochastic dynamic programming model. At level one, the policy maker determines the quota that maximizes expected discounted resource rents, while anticipating fishermen behavior, stochastic fish stock dynamics, capital stock dynamics and a quota adjustment restriction. At level two, fishermen harvest myopically and show long-term investment behavior. For the long-term investment, fishermen assume that fish stock and quota remain at their current states. The two levels are linked by the quota that is derived at level one and becomes a restriction for fishermen at level two.

For the long run, our results suggest that a quota adjustment restriction realizes both an efficient fish stock and reduces overcapacity for the fishing industry. By anticipating uncertain future values of fish stock, the policy maker becomes more conservative and sets the quota at a somewhat lower level than without quota adjustment restriction. Fishermen follow this quota by reducing their effort level and by adjusting their capital stock downward, such that they are less often bounded by quota and they are able to realize a large reduction in overcapacity. Under a high level of quota adjustment restriction a 54% reduction in overcapacity can be realized at a 1% loss in resource rents. Fish stock increases thereby with 1%, so that long-run efficiency of the fish stock is not affected.

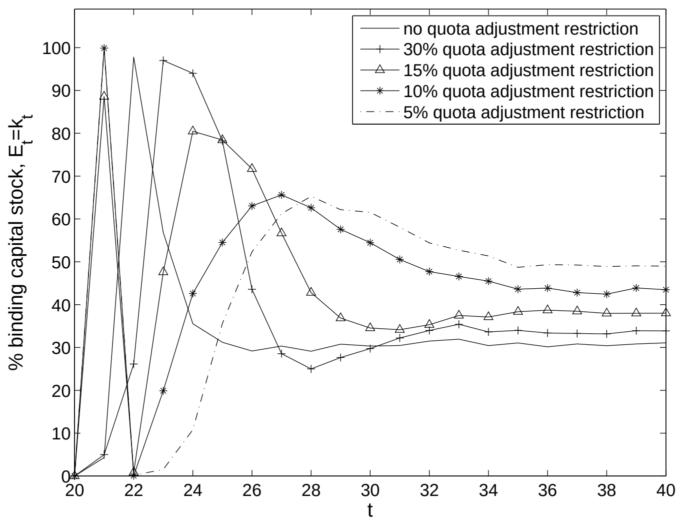

Figure 4.4. Binding capital stock $E_t = k_t$ as a percentage of 5,000 simulations in the 20 year period after the shock.

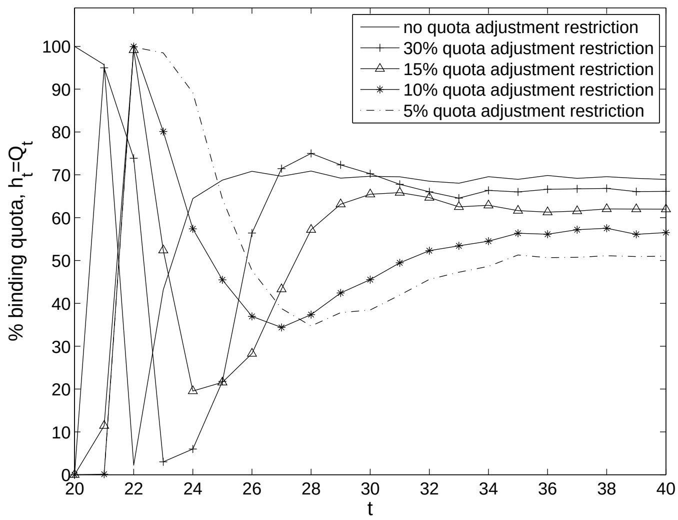

Figure 4.5. Binding quota $h_t = Q_t$ as a percentage of 5,000 simulations in the 20 year period after the shock.

We also studied the behavior of the system after a downward environmental shock, where the fish stock reduces temporarily to an extremely low level due to an external factor that was not taken into account. The analysis shows that long-term resource rents reduce with the introduction and increase of the level of quota adjustment restriction. Due to a restricted decrease in quota, it is the fish stock and capital stock that limit harvest of fishermen during the first years of recovery. The quota only becomes limiting after the capital stock is adjusted to higher levels and the fish stock approaches its long-term average. This holds for all considered quota adjustment restrictions. Over a 5 year recovery period, therefore, all considered quota adjustment restrictions lead to a 10-11% loss in resource rents as compared to the maximized resource rents when adjustment is unrestricted. Hence, also during recovery from an external shock the reduction in overcapacity comes at the cost of a reduction in expected discounted resource rents.

Compared to no restriction, a quota adjustment restriction provides a 38-50% reduction in overcapacity. Although the external shock reduces the fish stock to an extremely low level, the Spence harvest function assumes that the fish stock cannot be fully harvested. In addition, the quota steers harvest and investment such that, after a shock, the fish stock increases and stabilizes at its long-term average. Although we agree with Kell et al. (2005) that a quota adjustment restriction delays fish stock recovery, the delay appears to be small and the long-term efficiency is not affected under any restriction. In the long-run, the objective of both obtaining an efficient fish stock and reducing overcapacity for fishermen is realized with a quota adjustment restriction.

These results are based on a number of assumptions that may be relaxed in future work. For example, fishermen assume a long-term investment planning horizon, where levels of fish stock and quota do not change over time. In an alternative model different planning horizons may be considered, as well as investment behavior where fishermen do have some knowledge about fish stock dynamics. It may also be more realistic to incorporate an uncertain future quota. Finally, we assume that the policy maker knows fishermen's decisions. This may be extended to a setting in which information about fishermen's decisions is imperfect.

Appendix

When fishermen decide on the long-term investment, they consider depreciation of capital stock γ and investment costs $c_i i$, leading to the fishermen profit function (4.6). Profit π depends on revenues from harvest ph, costs from effort, crew and investment $c_E E + c_R ph + c_i i$. In (4.5)-(4.7), fishermen are free to adapt the fleet size in one period to a long-term desired level in case its capacity is insufficient to catch the profit maximizing harvest, which depends on the quota Q and fish stock x. After adaptation, effort and the capital stock are at the same constant level $E = k$ and investment i is equal to the depreciated capital stock γk. Let us first denote fishermen profit:

$$\pi = (1 - c_R)ph - c_E E - c_i i \tag{4.15}$$

The model uses a Spence harvest function so that effort $E = \frac{1}{q}\ln\left(\frac{x}{x-h}\right)$. We have

$$i = \gamma k = \gamma E = \frac{\gamma}{q}\ln\left(\frac{x}{x-h}\right), \tag{4.16}$$

and profit function (4.15) can be rewritten as

$$\pi = (1 - c_R)ph - \frac{(c_E + c_i\gamma)}{q}\ln\left(\frac{x}{x-h}\right). \tag{4.17}$$

The maximum of π in (4.17) with respect to harvest h can be derived from the first-order condition that should also take into account that profit is non-negative. This provides us with a harvest level $h = (x - \bar{x})^+$ where

$$\bar{x} = \frac{c_E + c_i\gamma}{pq(1 - c_R)p}. \tag{4.18}$$

However, harvest is also constrained by quota Q, such that the optimum harvest level is

$$h = \min\left\{x - \frac{c_E + c_i\gamma}{pq(1 - c_R)}, Q\right\}. \tag{4.19}$$

If the current fleet size is not sufficient for the long-run desired effort level $\bar{E} = \frac{1}{q}\ln\left(\frac{x}{x-\bar{h}}\right)$, fishermen can directly, i.e. in one year, arrive at the desired capital stock by investing the difference between desired effort $\bar{E}$ and the depreciated capital stock $(1-\gamma)k$. If the capital stock exceeds that level in the next period, no investment needs to be made. This gives the following investment decision

$$i = \left\{\frac{1}{q}\ln\left(\frac{x}{x-\bar{h}}\right) - (1-\gamma)k\right\}^+. \tag{4.20}$$

Chapter 5

Limited entry fisheries and Real Options theory*

Natural resources, including fisheries, provide a significant source of income in the state of Alaska. Salmon fisheries in Alaska are managed through a limited entry system, which places an overall limit on the number of commercial vessels in the fishery. Permits are tradable, but somewhat counterintuitively, a high proportion of the permits sit latent in any given year while permit values are often high. We argue that the option value of permits may explain this phenomenon. In the face of uncertainty about future resource rents, fishermen are faced with the challenge of determining at which ex-vessel price they should invest and disinvest in the fishery. We characterize the uncertainty as coming through the ex-vessel price and develop an optimal switching model that determines at what threshold prices fishermen switch between three states of operation: active, lay-up and exit. The model is applied to permit holders in the Bristol Bay sockeye salmon drift gillnet fishery. Results show that optimal threshold prices depend on the cost profile of the fisherman. It may also be appealing for fishermen to hold on to a permit because they expect the ex-vessel price and the market value of the entry permit to recover to their historically high levels.

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*This chapter is based on the paper: Diana van Dijk, Rolf A. Groeneveld, Ekko C. van Ierland. Limited entry fisheries and Real Options theory. Submitted.

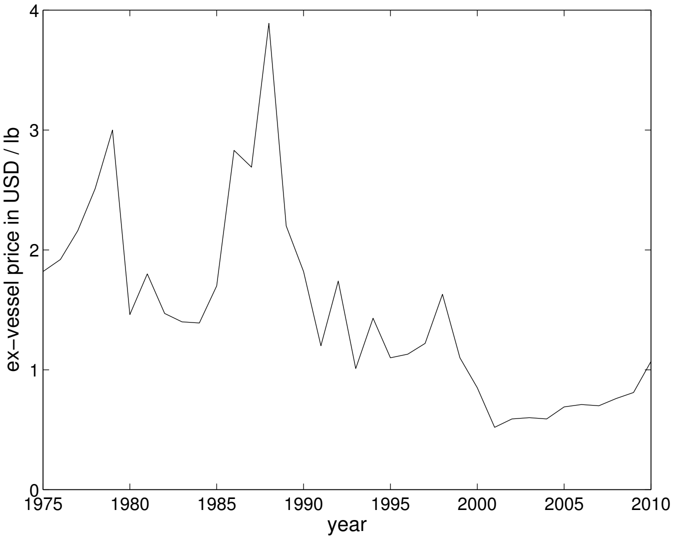

Figure 5.1. Ex-vessel price of Bristol Bay sockeye salmon in USD/lb, over the period 1975-2010, in real 2010 values.

5.1 Introduction

A common form of managing fisheries is limited entry. Most limited entry fisheries set an overall cap on the number of fishing permits. Fishermen are then allowed to trade these permits. If the constraint on the number of permits is binding, the market value of a permit can be high. Surprisingly, however, in some fisheries the permit value remains high despite a high proportion of unused permits.

In the Bristol Bay commercial salmon fishery, management areas are operated by the Alaska Department of Fish and Game (ADFG) through a limited entry system. Entry permits were first issued in 1974 for salmon fisheries, classified by gear type and harvesting area (Clark, 2006b). The system has a number of characteristics that determine the rules of the game for fishermen. First, an entry permit gives the right to participate in the fishery. It limits the total fleet size, but it does not assure a quota (Adasiak, 1979; Hilborn et al., 2005). A maximum number of entry permits has been established for the fishery, where the number of permits is regulated by the Commercial Fisheries Entry Commission (CFEC). Second, in order to remain active, a permit holder has to renew his entry permit annually. Third, entry permits are tradable and once a fisherman has sold his entry permit, he looses the right to fish. Finally, a permit holder is allowed to own entry permits for different fish species, but no one may own more than one entry permit for any given fishery (Huppert et al., 1996). For more details, the reader is referred to the 2012-2013 Bristol Bay commercial salmon fishing regulations (ADFG, 2012).

The limited entry system has been recognized as a well established program that has contributed to high earnings and catch since the 1970s (Hilborn et al., 2003). Nevertheless, as is depicted in Figure 5.1, the ex-vessel price of sockeye salmon has fluctuated greatly. As a result of these fluctuations, annual earnings have been volatile. Figure 5.2 shows that average annual gross earnings per entry permit have ranged between 25,486 USD and 210,626 USD over the period 1975-2010. Also the market value of a permit can be high and has ranged between 24,632 USD and 451,333 USD over the period 1978-2010. Average annual profits per permit holder have ranged between -9,642 USD and 78,912 USD over the reported period 1983-2003 (Schelle et al., 2004).

With considerable volatility in resource rents there is uncertainty regarding future earnings for fishermen and this is expected to affect investment decisions. Although this uncertainty likely stems from several sources, e.g. ex-vessel prices, run/stock size, environmental uncertainties and manage-

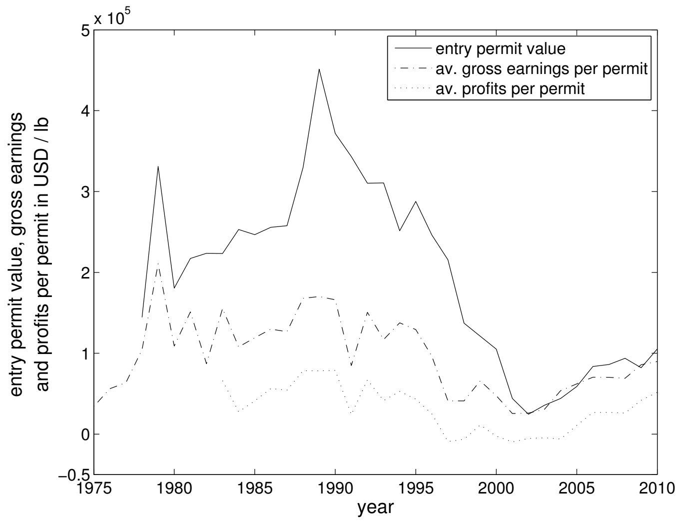

Figure 5.2. Entry permit value of sockeye salmon, average gross earnings and average profits per permit in USD/lb, over the period 1975-2010, in real 2010 values.

ment uncertainty, in this paper we focus on uncertainty in one variable: the ex-vessel price. Volatility in the ex-vessel price of sockeye salmon can be explained by a combination of natural processes and market developments.

With respect to natural processes, Bristol Bay sockeye production is sensitive to climate variability (Hilborn et al., 2003), which has seen positive and negative effects on run size since catch was first estimated in the 1970s. The run size here can be described as the number of adult fish in spawning areas of coastal rivers. The run size is also believed to be sensitive to climate changes (Ruggerone et al., 2007). In the late 1970s, the fish stock was subject to favorable climatic circumstances so that run sizes and catch increased substantially (Hilborn et al., 2003). The result of higher earnings induced investment in the fishery, namely the total number of entry permits increased from 1,721 to 1,837 in the period 1976-1988 (Commercial Fisheries Entry Commission, 2012). In the 1990s, run sizes declined. A reduction of 13 million sockeye salmon in 1997 had a great impact on catch and earnings. A net loss of earnings for all fishermen followed in 1997 and remained throughout the early 2000s.

Market changes have also contributed to volatility in the ex-vessel price. The increasing demand for sockeye salmon in the 1970s and 1980s, mainly due to Japanese demand for frozen sockeye salmon (Steiner et al., 2011; Vukina and Anderson, 1994), drove up the ex-vessel price from 1.82 USD/lb to 3.89 USD/lb in the period 1975-1988. Investment in the fishery followed. In the 1990s, however, increased supply of salmon by farms and hatcheries had a negative effect on the ex-vessel price (Steiner et al., 2011; Valderrama and Anderson, 2010; Eagle et al., 2004). In the period 1985-2000, supply from world farm salmon increased from 6% to 58% of world salmon production and supply from Alaska hatchery fish increased from 2% to 20% of Alaska salmon landings (Eagle et al., 2004). Competition from mainly rainbow trout and Chilean export of farmed Atlantic salmon kept the ex-vessel price relatively low (Steiner et al., 2011). This may partially explain why earnings and investment increased less than in the previous two decades, despite increases in the run size.

Although the catch dropped, the number of permits was held steady by the regulator and some permit holders temporarily suspended their activities, i.e. they laid-up. Figure 5.3 shows that the proportion of used permits reduced from 99% in 1997 to 63% in 2002 and the ex-vessel price reached a record low level of 0.52 USD/lb in 2001. In 2003, the fishing area experienced an increase in run size. The catch, ex-vessel price and the proportion of used permits picked up again. The proportion

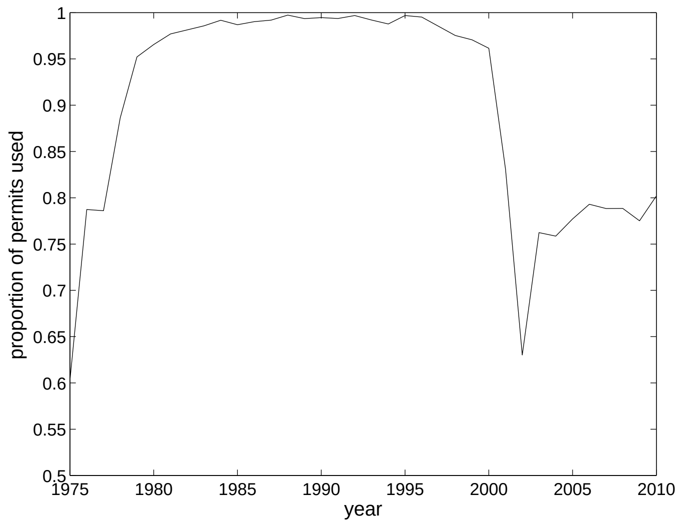

Figure 5.3. Used permits as proportion of total number of permit holdings, over the period 1975-2010.

of used permits remained stable at around 77%. Given the large range between profits and net losses between 1975-2010, it is unclear why many fishermen did not either use or sell their entry permits. We argue that the reluctance of fishermen to sell their entry permits is at least partly due to the option value of holding on to the entry permit. If a fisherman sells his entry permit, he looses the option to start fishing again, which can only be regained by buying a new entry permit. This option gives an incentive to hold on to the entry permit, even if it is not used.

Optimal timing of entry and exit can be analyzed in a framework of Real Options theory (RO) (Dixit and Pindyck, 1994). This theory models investment options, which can be exercised or postponed, and estimates threshold prices at which it is optimal to exercise each option. Real Options theory proves to be a robust technique for problems that are subject to uncertain environments (Lin and Huang, 2010). Although the method originates from financial economics, it enables dealing with the flexible nature of natural resources and has therefore been a popular method in the natural resources literature, e.g. in climate change (Balikcioglu et al., 2011), mining (Sabour, 2001), energy (Lin et al., 2007; Schmit et al., 2009; Lin and Huang, 2010), nuclear waste (Louberge et al., 2002) and fisheries (Karpoff, 1989; Li, 1998; Saphores, 2003; Nøstbakken, 2006; Sarkar, 2009). Nøstbakken (2006), Sarkar (2009), Li (1998) and Saphores (2003) optimize the harvest policy that maximizes discounted net benefits. The RO theory is applied in these studies in order to come up with a harvest trigger or harvest policy under switching costs and uncertainty in fish stock and market prices. Schmit et al. (2009) study for ethanol plant investment the optimal time of entry and exit under price uncertainty. Karpoff (1989) studies a limited entry fishery and suggests that holding a permit in limited entry is similar to holding an option on future increases in resource rents. Consequently, a license valuation model is developed with which the entry option is analyzed.

Our objective is to get insight into fishermen's decisions to invest and disinvest in Bristol Bay's sockeye salmon drift gillnet fishery. We formulate the following research question. At what ex-vessel price is it optimal to invest in the fishery, to lay-up and to permanently exit the fishery? We address this question with a Real Options model, using the contingent claims method.

The contribution to the literature is twofold. Where Li (1998), Saphores (2003), Nøstbakken (2006) and Sarkar (2009) determine optimal harvest policies, we look at the ex-vessel prices at which it is optimal to change between different states of operation. In addition, while Karpoff (1989) studies the option to enter a limited entry fishery, we also consider options to lay-up, reactivate and exit. Second, the management of the Bristol Bay salmon fishery is provided with an improved understanding of investment decisions of fishermen when they are subject to price volatility.

5.2 The Real Options model

In this section the Real Options model is described. We explain simplified solutions of each part of the model. For a detailed exposition and the theoretical background of Real Options theory, the reader is referred to Dixit and Pindyck (1994).

5.2.1 Costs and price uncertainty

Three states of operation are considered in this model, including inactive, active and lay-up. For each state we determine the threshold prices at which fishermen it is optimal to switch from one state of operation to another. Threshold prices are determined for entry P_H from an inactive state, lay-up P_M and exit P_S from an operating state and reactivation P_R from lay-up. These prices are determined by the uncertain ex-vessel price of salmon P and by known and fixed cost parameters that correspond to changing from one state to another. In order to enter the fishery from a state of inactivity, a sunk investment cost I is made. Then, as long as the fisherman is in operation, an operating cost C is incurred. For permanent exit from a state of operation, there is sunk exit cost E_s. Upon exit, however, fishery equipment may remain valuable, which implies that the investment cost I is only partially sunk. An operating fisherman also has the option to lay-up. Going from operation to lay-up is possible at a sunk lay-up cost E_m and as long as the fisherman is laid-up, a maintenance cost M keeps the option open to reactivate business in the future without having to invest again. Finally, reactivation from lay-up comes at a sunk reactivation cost R. The ex-vessel price, threshold prices and costs are expressed in USD/lb.

For lay-up to be a realistic option, the operating cost exceeds the lay-up maintenance cost, $M < C$, and the investment cost exceeds the reactivation cost, $R < I$. With $R < I$, also the entry threshold price is higher than the reactivation threshold price, so we expect that $P_S < P_M < P_R < P_H$. For the uncertain ex-vessel price of salmon we assume a stochastic process, where price P follows a geometric Brownian motion with drift:

$$dP = \mu P dt + \sigma P dz. \tag{5.1}$$

The drift rate of price μ is the rate at which the mean price changes, volatility of price is given by σ and $dz = \varepsilon_t \sqrt{dt}$ is the increment of a Wiener process, where ε_t is a standard normal iid random variable. We follow standard Real Options literature, where it is assumed that the stochastic price specification P is a process that is lognormally distributed (Dixit and Pindyck, 1994; Schmit et al., 2009).

The geometric Brownian motion process has gained wide acceptance in the natural resources literature as a valid model for the growth in price or resource rents from a stock over time. It provides a relatively simple analytical evaluation and allows closed form solutions to many different problems (Marathe and Ryan, 2005; Postali and Picchetti, 2006).

5.2.2 The options to enter, lay-up, reactivate and exit the fishery

Let us first explain the elements that determine the value of being in a specific state of operation. The value V is a function of the stochastic ex-vessel price P, the state which the fisherman is in and the value of the option to switch to another state. We denote the three states by inactive (0), active (1) and lay-up (m). Let $V_0(P)$ be the value of being inactive, $V_1(P)$ the value of being active and $V_m(P)$ the value of being laid-up.

Entry

When a fisherman is inactive, he does not generate a cash flow, but he holds the option to invest in the fishery. This option has a value. To determine the value of the inactive state V_0 a differential equation is solved, applying Ito's Lemma:

$$dV_0(P) = V_0'(P)dP + \frac{1}{2}V_0''(P)dP^2. \tag{5.2}$$

We assume risk-neutrality, which means that a rational investor wants to be rewarded for risk by receiving a return on the investment:

$$\mathbb{E}[dV_0(P)] = \delta V_0(P)dt. \tag{5.3}$$

The expected change in value $\mathbb{E}[dV_0(P)]$ is equal to the interest rate that an investing fisherman would receive on $V_0(P)$. Therefore, $\delta V_0(P)dt$ is the return on the investment, with δ as the discount rate. It is further required that $\delta > \mu$, because when the value of the project increases faster than the discount rate, it is always better to postpone investment indefinitely; on the bank the value of money increases more than when this money is invested elsewhere.

The contingent claims method allows for the incorporation of a risk-adjusted discount rate, which may be preferred to an arbitrary assumption of the discount rate. We agree with Karpoff (1989) that it is difficult to determine the appropriate risk-adjusted discount rate for resource rents in a limited entry fishery. In this study we therefore do not adjust for risk, which makes δ a risk-free discount rate. Substituting equation (5.2) in (5.3) gives a differential equation:

$$\delta V_0(P)dt = \mathbb{E}\left[V_0'dP + \frac{1}{2}V_0''(P)dP^2\right]. \tag{5.4}$$

Given the geometric Brownian motion in (5.1), only dz is stochastic. We therefore have that $\mathbb{E}[dt] = dt$, $\mathbb{E}[dz] = 0$, $\mathbb{E}[dz^2] = dt$ and $\mathbb{E}[dP^2] = \sigma^2 P^2 dt$. Equation (5.4) can be rewritten to the following differential equation:

$$\frac{1}{2}\sigma^2 P^2 V_0''(P) + \mu P V_0'(P) - \delta V_0(P) = 0, \tag{5.5}$$

which gives the general solution for the value of being inactive V_0, i.e. the value of the option to invest:

$$V_0(P) = A_1 V^{\beta_1} + A_2 V^{\beta_2}. \tag{5.6}$$

A_1, A_2 are constants that need to be determined and the values for β_1 and β_2 are roots of the quadratic equation, a positive and a negative root: $\beta_1 = 1/2 - \mu/\sigma^2 + \sqrt{(\mu/\sigma^2 - 1/2)^2 + 2\delta/\sigma^2} > 1$ and $\beta_2 = 1/2 - \mu/\sigma^2 - \sqrt{(\mu/\sigma^2 - 1/2)^2 + 2\delta/\sigma^2} < 0$ (Dixit and Pindyck, 1994).

When we evaluate $V_0(P) = 0$, it can be verified that $A_1 V^{\beta_1} = 0$, because of $\beta_1 > 1$, and $A_2 V^{\beta_2} = +\infty$, because of $\beta_2 < 0$. Therefore, A_2 has to be equal to zero and (5.6) simplifies to:

$$V_0(P) = A_1 V^{\beta_1}. \tag{5.7}$$

For $V_0(P)$ holds that it is optimal for a fisherman to remain inactive as long as the price P lies within the interval $(0, P_H)$, where P_H is the price at which it is optimal to exercise to option to invest. In order to find the values of the unknowns A_1 and P_H, we need a set of boundary conditions, which specify values of a function or its derivatives:

$$V_0(P_H) = V_1(P_H) - I \qquad V_0'(P_H) = V_1'(P_H). \tag{5.8}$$

$V_0(P_H)$ is the value of being inactive at the investment threshold price P_H, i.e. the price at which it is optimal to exercise to option to invest. The first boundary condition, the value-matching condition, says that the value of being inactive at the investment threshold price $V_0(P_H)$ equals the value of being active at the investment threshold price minus the investment cost $V_1(P_H) - I$, because upon investing at $V_0(P_H)$ a net pay-off of $V_1(P_H) - I$ is received. This condition ensures that the two functions V_0, V_1 connect. The second boundary condition, the smooth-pasting condition, says that the slopes of the value functions V_0, V_1 are the same. This ensures that there is only one value at which it is optimal to invest. If this condition is not met, a fisherman may be better off exercising the option at a different point.

Lay-up

When a fisherman is active, he has a cash flow of $(P - C)dt$, namely the active fisherman pays an operating cost C to receive ex-vessel price P. Now, he holds the option to lay-up and he has a running business that generates a cash flow. The value of the active state V_1 is determined from the differential equation, which includes an adapted notation for risk-neutrality:

$$\mathbb{E}[dV_1(P)] = \delta V_1(P)dt + (P - C)dt. \tag{5.9}$$

The expected change in value is the same as the return on the investment plus the cash flow from being active. Substituting (5.2), which is adjusted with V_1, in (5.9) gives the following differential equation:

$$\frac{1}{2}\sigma^2 P^2 V_1''(P) + \mu P V_1'(P) - \delta V_1(P) + P - C = 0, \tag{5.10}$$

which solves for the value of being active, i.e. the value of the fisherman's running business plus holding the option to lay-up:

$$V_1(P) = B_2 P^{\beta_2} + \frac{P}{(\delta - \mu)} - \frac{C}{\delta}. \tag{5.11}$$

$B_2 P^{\beta_2}$ is the value of the option to lay-up, where B_2 is a constant that needs to be determined. $P/(\delta - \mu) - C/\delta$ is the expected value of remaining active forever. A fisherman remains active within the interval (P_M, ∞). Finally, we incorporate the boundary conditions:

$$V_1(P_M) = V_m(P_M) - E_M \qquad\qquad V_1'(P_M) = V_m'(P_M). \tag{5.12}$$

$V_1(P_M)$ is the value of being active at the lay-up threshold price P_M, i.e. the price at which it is optimal to exercise to option to lay-up. The interpretations of the value-matching and the smooth-pasting conditions in (5.12) are similar to the ones given for (5.8). Now, when laying-up at $V_1(P_M)$ a net pay-off of $V_m(P_M) - E_M$ is received, where $V_m(P_M)$ is the value of being laid-up at the lay-up threshold price P_M and E_M is a lay-up cost.

Reactivation and exit

When a fisherman is laid-up, he holds the options to reactivate and exit, but he also pays a lay-up maintenance cost M for being in that state. We solve for the value of lay-up V_m in a similar way as above, where the expected change in value now is equal to the return on the investment minus the maintenance cost that is incurred while being laid-up:

$$\mathbb{E}[dV_m(P)] = \delta V_m(P)dt - M. \tag{5.13}$$

The differential equation becomes:

$$\frac{1}{2}\sigma^2 P^2 V_m''(P) + \mu P V_m'(P) - \delta V_m(P) - M = 0 \tag{5.14}$$

and solves for the value of being laid-up $V_m(P)$:

$$V_m(P) = D_1 P^{\beta_1} + D_2 P^{\beta_2} - \frac{M}{\delta}. \tag{5.15}$$

D_1 and D_2 are constants to be determined, $D_1 P^{\beta_1}$ is the value of the option to reactivate, $D_2 P^{\beta_2}$ is the value of the option to exit and M/δ is the maintenance cost when the fishermen stays laid-up, even if it is more convenient to reactivate or exit. The fisherman remains laid-up as long as the price falls between the exit and reactivation threshold prices, (P_S, P_R). Boundary conditions are incorporated for reactivation and exit:

$$V_m(P_R) = V_1(P_R) - R \qquad V_m'(P_R) = V_1'(P_R), \tag{5.16}$$

$$V_m(P_S) = V_0(P_S) - E_S \qquad V_m'(P_S) = V_0'(P_S). \tag{5.17}$$

$V_m(P_R)$ is the value of being laid-up at the reactivation threshold price P_R and $V_m(P_S)$ is the value of being laid-up at the exit threshold price P_S. In (5.16), when reactivating at $V_m(P_R)$, a net pay-off of $V_1(P_R) - R$ is received, where R is a reactivation cost. In (5.17), when exiting at $V_m(P_S)$ a net pay-off of $V_0(P_S) - E_S$ is received, where E_S is an exit cost.

5.2.3 Deriving threshold prices

By substituting the value functions (5.7), (5.11) and (5.15) in the value matching and smooth pasting conditions in (5.8), (5.12), (5.16) and (5.17), a system of eight equations is formed. We solve this for the thresholds P_H, P_R, P_M, and P_S, as well as for the unknown coefficients A_1, B_2, D_1 and D_2. The interaction between lay-up E_m and reactivation R is given by

$$-D_1 P_R^{\beta_1} + (B_2 - D_2) P_R^{\beta_2} + \frac{P_R}{(\delta - \mu)} - \frac{(C - M)}{\delta} = R, \tag{5.18}$$

$$-\beta_1 D_1 P_R^{\beta_1 - 1} + \beta_2 (B_2 - D_2) P_R^{\beta_2 - 1} + \frac{1}{(\delta - \mu)} = 0, \tag{5.19}$$

$$-D_1 P_M^{\beta_1} + (B_2 - D_2) P_M^{\beta_2} + \frac{P_M}{(\delta - \mu)} - \frac{(C - M)}{\delta} = -E_m, \tag{5.20}$$

$$-\beta_1 D_1 P_M^{\beta_1 - 1} + \beta_2 (B_2 - D_2) P_M^{\beta_2 - 1} + \frac{1}{(\delta - \mu)} = 0, \tag{5.21}$$

and the interaction between investment I and exit E_s is given by

$$-A_1 P_H^{\beta_1} + B_2 P_H^{\beta_2} + \frac{P_H}{(\delta - \mu)} - \frac{C}{\delta} = I, \tag{5.22}$$

$$-\beta_1 A_1 P_H^{\beta_1 - 1} + \beta_2 B_2 P_H^{\beta_2 - 1} + \frac{1}{(\delta - \mu)} = 0, \tag{5.23}$$

$$(D_1 - A_1) P_S^{\beta_1} + D_2 P_S^{\beta_2} - \frac{M}{\delta} = -E_s, \tag{5.24}$$

$$\beta_1 (D_1 - A_1) P_S^{\beta_1 - 1} + \beta_2 D_2 P_S^{\beta_2 - 1} = 0. \tag{5.25}$$

The model is nonlinear and can only be solved numerically. We determine the threshold values P_H, P_R, P_M, P_S, using MATLAB's algorithm for nonlinear systems of equations, FSOLVE.

5.3 Data of the Bristol Bay sockeye salmon drift gillnet fishery

The optimal switching model is applied to the Bristol Bay sockeye salmon drift gillnet fishery. Ex-vessel price and cost data have been estimated and reported by the Alaska Department of Fish and Game (ADFG) and the Alaska Commercial Fisheries Entry Commission (CFEC). From ex-vessel price data we derive the drift rate and volatility. From cost data we estimate the operating, lay-up, maintenance, reactivation and exit costs.

5.3.1 Ex-vessel price and uncertainty

As a first step, we focus on the uncertainty in the ex-vessel price. The ex-vessel price P in USD/lb has been estimated and reported by Schelle et al. (2004) and the ADFG, Alaska Department of Fish and Game (2010) over the periods 1975-2003 and 1984-2010, respectively. Following standard real options literature, price changes are lognormally distributed (Dixit and Pindyck, 1994; Schmit et al., 2009) so that the log change in permit price is used to derive a volatility of $\sigma = 0.30$. Between 1988 and 2001 there has been a downward trend in the ex-vessel price, but from 2002 onwards there has been an upward trend. To prevent results from being influenced by a trend, and assuming that the price of Alaska sockeye salmon does not influence the world market price of salmon, we assume that the drift $\mu = 0$ (Trigeorgis, 1996). Finally, a discount rate δ of 5% is applied.

5.3.2 Costs

The CFEC has estimated cost data for permit holders in the Bristol Bay salmon drift gillnet fishery over the period 1983-2003 (Schelle et al., 2004). In addition, in 2002 the CFEC conducted a survey, with the specific objective of obtaining data over the year 2001 on costs, resource rents and investment in vessels (Carlson, 2002). In order to be in line with reported ex-vessel price and resource rents, we conducted a forecast[†] of costs over the period 2004-2010 in order to account for the average over the period 1983-2010.

In Schelle et al. (2004) and Carlson (2002), operating costs include food, fuel, crew shares, maintenance, gear, insurance, taxes, transportation, license fees, administrative services, vessel depreciation and opportunity costs. This gives an average operating cost C of 1.07 USD per pound of fish, i.e. USD/lb, per permit holder. For the sunk investment cost I we take the average vessel purchase value and the average permit value of 4.92 USD/lb per permit holder. The average lay-up cost E_m of 0.03 USD/lb per permit holder is a sunk cost that is made up of moorage, gear storage and haul-out. For the lay-up maintenance cost M of 0.16 USD/lb per permit holder we include maintenance costs, insurance, property tax, administrative services, permit and license fees and vessel depreciation. These are in fact fixed costs that are incurred as long as a fisherman remains in business. The reactivation cost R is another sunk cost, i.e. the reported haul-out cost, which is incurred when reactivating the temporarily suspended project. Because moorage, storage and haul-out are compiled under one cost, we assume for convenience that haul-out is one third of this reported value, giving an average reactivation cost of 0.01 USD/lb per permit holder. Finally, when exiting the fishery, the entry permit is sold at its average market value. This gives an average exit cost E_s of -2.69 USD/lb per permit holder. This makes the investment cost I a partially sunk cost. We are aware that, upon exiting, some fishermen may be able to sell their boat, while others will scrap.

[†]In the forecast process, first, the GARCHFIT algorithm in MATLAB was used to model an observed univariate return series as a constant. This was followed by a forecast of the conditional mean of the univariate return series, using the GARCHPRED algorithm, and the standard deviation of the realizations 7 periods into the future, i.e. the forecast time horizon, from 2004 to 2010. Finally, the presample observations were used by the GARCHSIM algorithm to simulate the outputs.

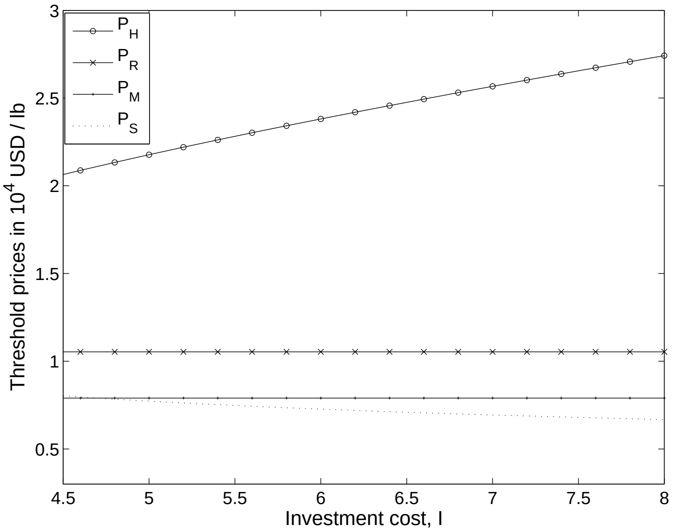

Figure 5.4. Threshold prices for different values of investment cost I. Other costs are at their default values of $C = 1.07$, $E_m = 0.03$, $M = 0.16$, $R = 0.01$, $E_s = -2.69$.

5.4 Results

In order to get insight into fishermen's decisions to invest and disinvest in the fishery, we determine the ex-vessel prices at which it is optimal to invest, to lay-up and exit. We first consider, for each cost parameter, different cost profiles so as to understand how they affect threshold prices. We then study threshold prices for the derived cost profile in Section 5.3, along the historic development of the ex-vessel price and the number of permit holdings.

5.4.1 Threshold prices for different values of costs

Fishermen may not all have similar profiles in terms of costs. For example, one fisherman may operate more efficiently than another. We therefore determine in Figures 5.4-5.9 the threshold prices of entry P_H, lay-up P_M, reactivation P_R and exit P_S for different costs of investment I, lay-up E_m, maintenance M, reactivation R, operation C and exit E_s. All prices and costs are expressed in terms of USD per pound of fish, i.e. USD/lb, per permit holder.

Consider first in Figure 5.4 the threshold prices as a function of the investment cost I. It can be observed that the entry threshold price P_H increases in investment cost I, while the exit threshold price P_S decreases in I. The intuition behind this is that a higher investment cost makes fishermen wait longer before investing in the fishery. Similarly, the waiting period to exit the fishery becomes longer because investing again after exiting is more costly. Reactivation P_R and lay-up P_M threshold prices are unaffected by I, but below the critical limit of $I = 4.5$ the exit threshold price P_S exceeds the lay-up threshold price P_M. This means that either the reactivation cost R or the maintenance cost M is too high, or both. It further implies that under these circumstances of such a low investment cost, it is not interesting to lay-up.

Figure 5.5 shows threshold prices as a function of the lay-up cost E_m. Increasing E_m has the strongest, but still a modest effect on the reactivation threshold price P_R and on the lay-up threshold price P_M. With a higher cost to lay-up, activities are laid-up at a somewhat lower threshold price. And, reactivation from a state of lay-up is delayed because laying-up again after reactivation is costly. Reactivation therefore takes place at a slightly higher threshold price.

Next consider in Figure 5.6 threshold prices as a function of maintenance cost M. The exit thresh-

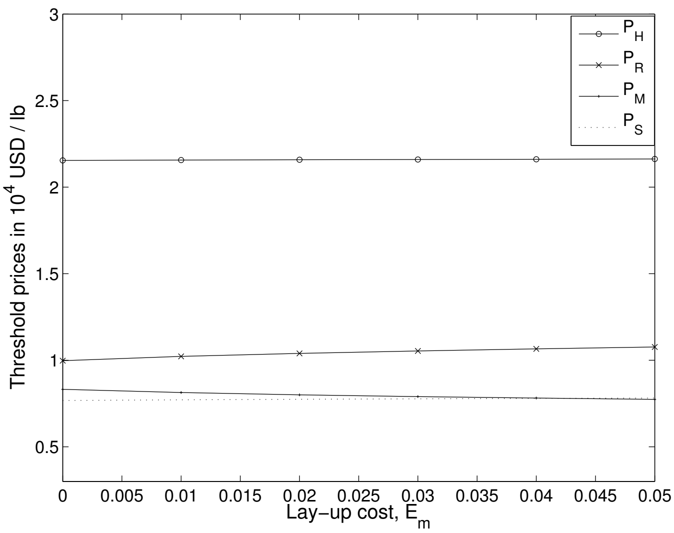

Figure 5.5. Threshold prices for different values of lay-up cost E_m. Other costs are at their default values of $C = 1.07$, $I = 4.92$, $M = 0.16$, $R = 0.01$ and $E_s = -2.69$.

old price P_S increases in M, whereas the reactivation threshold price P_R and lay-up threshold price P_M decrease in M. The entry threshold price P_H is not affected. Even though the maintenance cost increases, the exit threshold price P_S increases. At the same time, a fisherman who is laid-up and faces a higher maintenance cost will execute the option to reactivate at a lower threshold price P_R. The reverse holds for an active fisherman. From a state of operation, the lay-up threshold price P_M decreases in M. Note that beyond the critical limit of $M = 0.18$, exit is a first choice because the maintenance cost is too high to consider the option to lay-up.

Figure 5.7 shows threshold prices as a function of reactivation cost R. Entry and exit threshold prices are hardly affected by R. Note that the difference between the lay-up and exit threshold prices is small and that this difference decreases because the lay-up threshold price P_M decreases slightly in R. The critical limit is reached at $R = 0.02$, beyond which the option to lay-up becomes irrelevant.

Threshold prices for different values of operation cost C are shown in Figure 5.8. As C increases, the drop in resource rents causes an inactive fisherman to wait longer to make an initial investment. That is, the entry threshold price P_H increases in C. An active fisherman will exit the fishery at a higher price. To prevent resource rents from dropping further, the option to exit will be exercised at a higher exit threshold price P_S. Similarly, from a state of lay-up, the option to reactivate will be exercised at a higher threshold price P_R as the operation cost increases. The limit of C is therefore critical on the lower end, at $C = 1$, while at the higher end the wedge between entry and exit only increases in C.

Finally, Figure 5.9 shows the threshold prices for different values of exit cost E_s. A higher exit cost makes fishermen wait longer before investing in the fishery because exiting again after becoming active becomes more costly. The entry threshold price P_H therefore increases in E_s. Also, as it becomes more costly to exit the fishery, this option will be delayed. The exit price decreases in E_s. The reactivation P_R and lay-up P_M threshold prices are unaffected by the exit cost, but below the critical limit of $E_s = -2.8$, where $P_S > P_M$, lay-up has no economic sense.

5.4.2 Optimal threshold prices for a given cost profile

In order to understand historic investment and disinvestment decisions, we study threshold prices along the historic development of the ex-vessel price and the number of permit holdings. Threshold

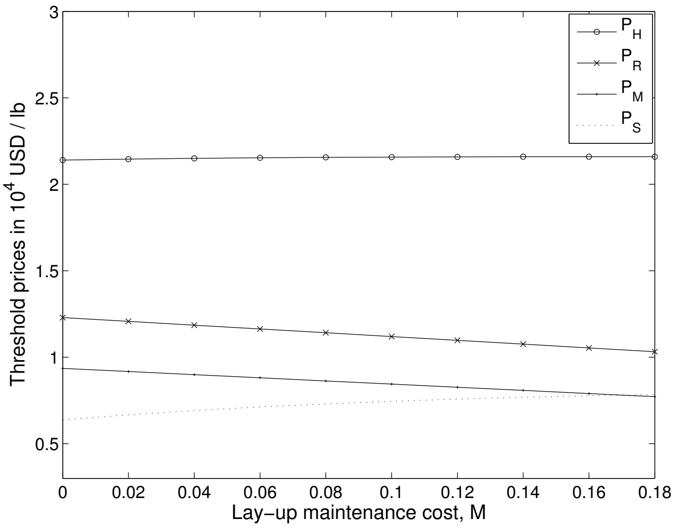

Figure 5.6. Threshold prices for different values of lay-up maintenance cost M. Other costs are at their default values of $C = 1.07$, $E_m = 0.03$, $I = 4.92$, $R = 0.01$, $E_s = -2.69$.

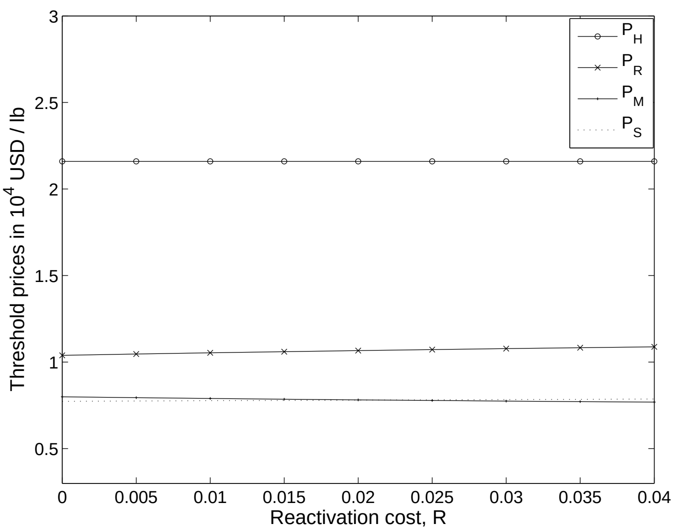

Figure 5.7. Threshold prices for different values of reactivation cost R. Other costs are at their default values of $C = 1.07$, $E_m = 0.03$, $I = 4.92$, $M = 0.16$, $E_s = -2.69$.

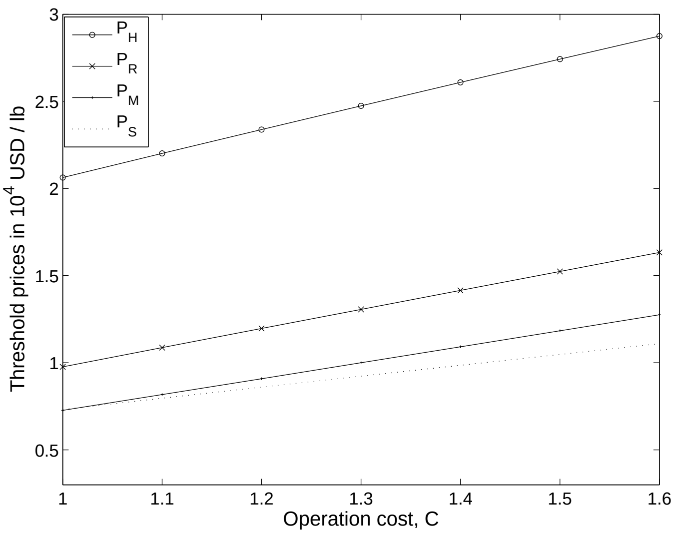

Figure 5.8. Threshold prices for different values of operation cost C. Other costs are at their default values of $E_m = 0.03$, $I = 4.92$, $M = 0.16$, $R = 0.01$, $E_s = -2.69$.

prices are based on the cost profile determined in Section 5.3. We find that the price at which entry to the fishery is optimal P_H, is 2.16 USD/lb per permit holder, while the optimal exit price P_S is 0.77 USD/lb. The reactivation threshold price P_R is 1.05 USD/lb and the lay-up threshold price P_M is 0.79 USD/lb. In Figure 5.10, these threshold prices are plotted together with the ex-vessel price and the number of permit holdings over the period 1975-2010.

Consider first the number of permit holdings. From 1975 to 1998, entrance to the fishery increases, which is followed by a decrease between 1998-2004 and a stabilization from 2004 onwards. With respect to the ex-vessel price P, it is known that within the interval $(0, P_H)$ it is optimal for an inactive fisherman to hold on to the option to invest. With relative stability in the number of permits in the periods 1980-1984 and 1990-2010, entrance to the fishery is in line with the development of the ex-vessel price and that fishermen indeed delay the option to invest.

In the periods that the ex-vessel price P exceeds the entry threshold price, it is optimal for an inactive fisherman to invest in the fishery. In the periods 1975-1980 and 1985-1990, $P \geq P_H$ and the number of permit holdings increase. That is, the option to invest is exercised. This is also confirmed when we look at the number of used permits as a proportion of total number of permit holdings, in Figure 5.3. In the period 1975-1980 the fraction of used permits increases from 0.6 to 0.95 and increases further to 0.99 in the year 1990. Note that these threshold prices are derived from surveys that provide estimates of average costs. Fishermen are heterogeneous with respect to costs and according to Carlson (2002), the value of a vessel depends on its attributes, so variability is high. A more expensive boat means that the investment cost is higher and a fisherman with such a cost profile will wait longer before investing in the fishery. The entry threshold price of this fisherman then exceeds that of a fisherman with a lower investment cost.

In the period 2001-2009, the ex-vessel price P drops below the exit threshold price P_S, making it optimal to exit. Fishermen exit in the first few years as a consequence of the loss of salmon in the year 1997, which is also shown by the steep decline in the number of used permits as a proportion of total permit holdings in Figure 5.3. From 2003, however, we see a slight increase in the number of used permits despite the low price. This may have been due to the large run in 2003. For the current cost profile it is assumed that upon exit, fishermen can sell the entry permit at the average market value. It may be that some fishermen are also able to sell their boat. This would reduce the exit cost and thereby the exit threshold price, so that fishermen remain active for a longer period of time. Or, if the

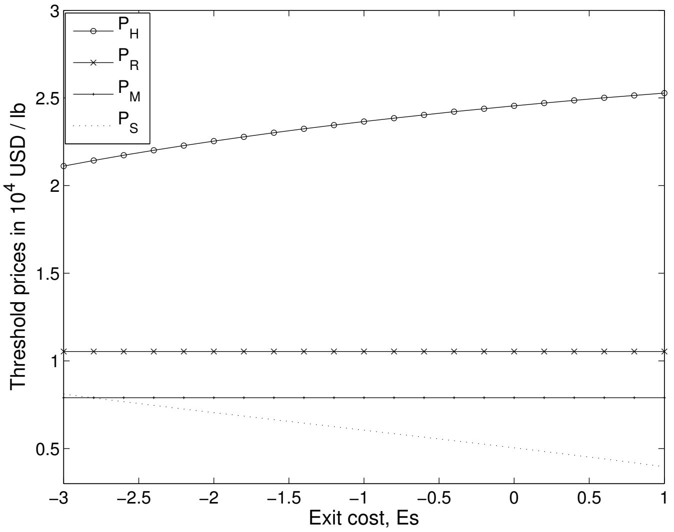

Figure 5.9. Threshold prices for different values of exit cost E_s. Other costs are at their default values of $C = 1.07$, $E_m = 0.03$, $I = 4.92$, $M = 0.16$, $R = 0.01$.

market value of an entry permit drops, the exit cost rises and a fisherman will exit later. In 2001, the market value of an entry permit dropped 140%. For this single year, the exit threshold price is higher, which is in line with the drop in the number of permits in that year. A similar argument holds for different values of the operating cost. This cost includes the fee for the annual renewal of the entry permit. Between 1983-2003 this fee has ranged between 142 USD and 850 USD. A fee at the higher end of the range would increase the operating cost and make fishermen exit the fishery at a higher exit threshold price. The reverse holds for a fee at the lower end of the range.

Finally, Figure 5.10 compares threshold prices of reactivation P_R and lay-up P_M with the proportion of used permits. With respect to the lay-up threshold price P_M, as long as the ex-vessel price P exceeds P_M, operating fishermen are expected to remain active. When the ex-vessel price reaches the lay-up threshold price, it is optimal for fishermen to lay-up and to remain laid up as long as the price stays above the exit threshold price P_S. As a result of a reduction of 13 million sockeye salmon in 1997, we observe a steep decline in the proportion of used permits between 1999 and 2002, from 0.96 to 0.61. This takes place in the period that the ex-vessel price P reaches the lay-up threshold price P_M, indicating that fishermen increasingly lay-up. With a continuing drop in the ex-vessel price, it is expected to observe a further decline or stagnation in the use of permits. But with the large run in 2003, harvesting opportunities are induced and the proportion of used permits increases again. The ex-vessel price, however, does not increase sufficiently for fishermen to stay in the fishery, i.e. the number of exits increases. And, as it is more costly to exit the fishery than to lay-up or to reactivate, the exit threshold price is pushed up towards the lay-up threshold price, such that the options to exit and lay-up can be exercised at almost the same price. This is confirmed in Figure 5.9, which illustrates that at the given exit cost E_s of -2.69 in the base case, the critical limit is almost reached. In the period 2004-2009 we observe again more reactivation than exit, although the lay-up and exit threshold prices are close to each other. In this period, fishermen may hold on to their entry permit because historically, the ex-vessel price and the market value of the entry permit have been high and are expected to recover. Note that the proximity of P_M and P_S depends on the cost profile. A higher investment cost or a higher exit cost will lead to a larger wedge between P_S and P_M.

When laid-up, between P_S and P_R, activities are expected to be resumed at reactivation threshold price P_R. The ex-vessel price only touches upon this threshold in the years 1993, 1999 and 2010, where only in the latter year the use of permits is resumed. In 1999 there is a steep decline in used

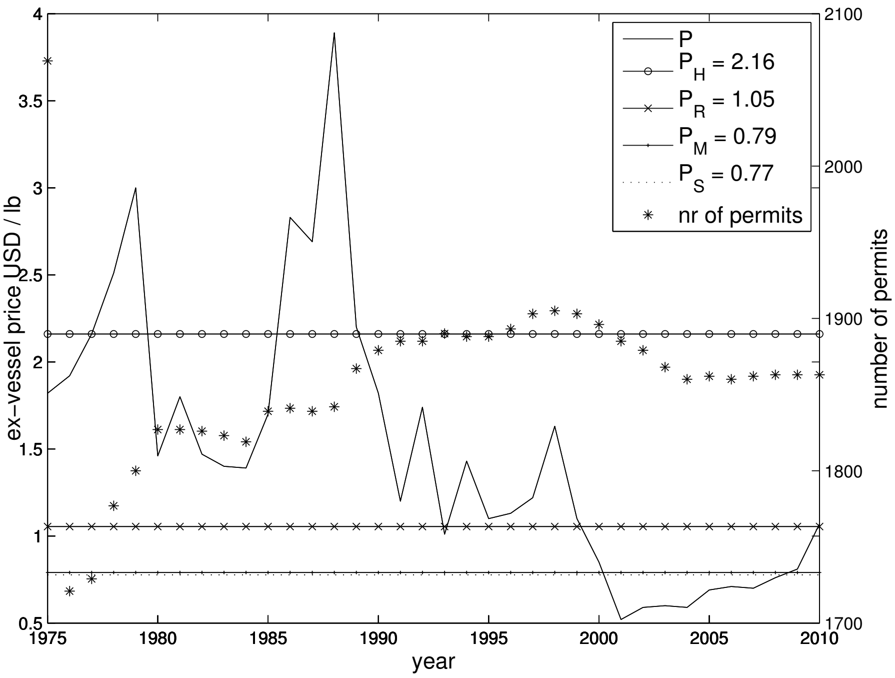

Figure 5.10. Ex-vessel price, threshold prices of permit holders and number of permits.

permits. In this period the reduced salmon stock influences the increased exit from the fishery. Here it seems that events that affect run size, may have a larger impact on entry and exit from the fishery than the ex-vessel price.

5.4.3 Increased volatility

The determination of volatility is subject to discussion. It is known that the Bristol Bay sockeye salmon production is sensitive to climate variability (Hilborn et al., 2003) and that volatility in the production is one of the factors that determine the ex-vessel price. This sensitivity makes it difficult to measure ex-vessel price volatility. In addition, fishermen may have different assumptions about volatility. It is therefore useful to consider several values of volatility and to study the effect on threshold prices.

Figure 5.11 shows the threshold prices P_H, P_R, P_M, P_S for different values of ex-vessel price volatility σ. It shows that the range between entry P_H en exit P_S threshold prices increases in volatility σ. Between $\sigma = 0.3$, from the base case, and $\sigma = 0.55$, the entry threshold price increase by 31.6% and the exit threshold price decreases by 24%. This can be explained by the more conservative behavior of fishermen as the future ex-vessel price becomes more uncertain. That is, fishermen wait longer to exercise the options to invest and exit. More conservative behavior also explains a 7.8% increase in the reactivation threshold price P_R and 6.5% decrease in the lay-up threshold price.

5.4.4 Downward trend in drift rate

In the base case a drift rate of $\mu = 0$ has been assumed, so that results are not influenced by a trend in the ex-vessel price. Over the period 1983-2010, however, there has been a downward trend in the price, giving a drift rate of $\mu = -0.015$. This small downward trend results in slightly higher entry and exit threshold prices; P_H increases by 2.3% and P_S increases by 3.6%. On one hand, if fishermen account for a downward trend in the ex-vessel price, they will enter the fishery at a higher

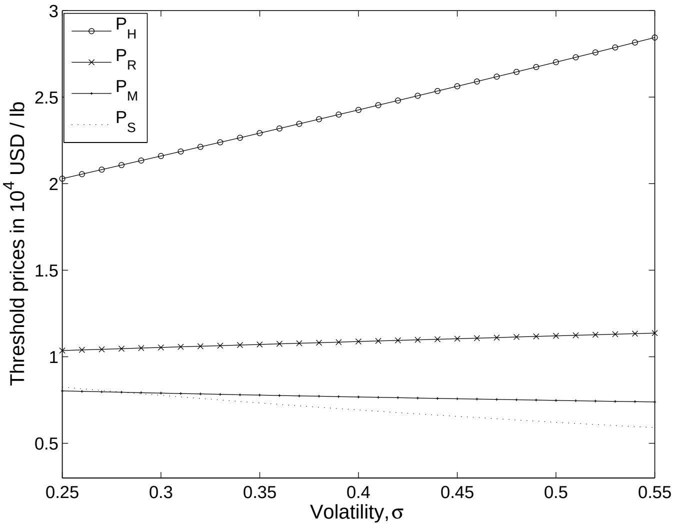

Figure 5.11. Threshold prices for different values of volatility σ.

entry threshold price. On the other hand, fishermen will exit the fishery at a higher exit threshold price. Reactivation and lay-up threshold prices are much less affected by a trend, they each increase by 0.2%.

5.5 Conclusions and discussion

We applied an optimal switching model to study investment and disinvestment decisions of fishermen in Bristol Bay's sockeye salmon drift gillnet fishery. Ex-vessel prices were derived at which it is optimal to enter, lay-up, reactivate and exit. We looked at the effect of different cost profiles of fishermen on these threshold prices and we studied whether historic decisions of fishermen are in line with derived threshold prices for a given cost profile.

Our results suggest that over the period 1975-2010, fishermen have followed the development of the ex-vessel price when making investment and disinvestment decisions. In years of extreme reductions in run size, it appears that it is not just the ex-vessel price that affect decisions of fishermen. Decisions are potentially more strongly affected by events in the run size.

Results show that different variables have an impact on the switching behavior of fishermen, where these variables differ between fishermen. For some it is appealing to remain active, while others prefer to be laid-up. These results are in line with Dixit and Pindyck (1994). Fishermen may also hold on to their entry permits because the ex-vessel price and the market value of the entry permit have been historically high and are expected to recover in the future. The model assumes a Markov process, but fishermen may think differently.

At higher volatility, the increase in the entry threshold price and the decrease in the exit threshold price are substantial. This has also been shown in Dixit and Pindyck (1994) and Schmit et al. (2009) and implies that when fishermen account for more volatility, they become more conservative in their decisions and will exercise the options to enter and exit the fishery at a higher ex-vessel price.

The model comes with a number of assumptions that may be relaxed in future research. First, we focused on the ex-vessel price and its uncertainty. Sockeye salmon production is notoriously volatile and difficult to predict. It may therefore be more realistic to account for multiple sources of uncertainty, including the run size and ex-vessel price, that can not be perfectly captured by a single variable. Second, the assumption of a risk-free discount rate may be relaxed in order to account for a risk-adjusted discount rate that is appropriate for fishing resource rents.

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Chapter 6

Discussion and conclusions

The overall objective of this thesis is to study the impact of different fisheries management systems on resource rents from the fishery, investment in the fleet capacity and stochastic fish stocks. In Chapters 2-4, a model is developed and analyzed that determines quota decisions of a policy maker and harvest and investment decisions of fishermen. Bi-level stochastic dynamic programming was used to study two management systems, which are part of multiannual management plans in the European Union: multiannual quota and a quota adjustment restriction. Chapter 5 studies investment and disinvestment options of fishermen in a limited entry fishery in Alaska. Real Options theory is used to determine the ex-vessel price at which it is optimal to invest and disinvest in the fishery. This chapter first discusses the research questions and findings. Then, the main conclusions are presented with respect to the methodology and policies. Finally, limitations and recommendations are provided for future research.

6.1 Research questions and overview of findings

1. How can we model the interaction between the quota decision of a policy maker and fishermen behavior in a model that accounts for dynamics in the biological system and dynamics in economic behavior? And, how can we exploit model characteristics in order to derive the optimal quota in a deterministic and a stochastic setting?

Chapter 2 developed a bi-level stochastic dynamic programming model in order to determine the levels of quota that maximize expected discounted resource rents. The characteristics of the model are divided over two levels. At level one, a policy maker decides on the quota that maximizes long-term resource rents, while accounting for stochastic fish stock dynamics, capital stock dynamics and fishermen behavior. At level two, fishermen react on current states of fish stock and capital stock when deciding on their harvest and investment. The two levels are linked by the quota decided at level one and restricting fishermen's harvest at level two. The optimal quota is obtained by using the iterative solution procedure of value function iteration. Numerical experiments were conducted for the annual optimization of quota for North Sea plaice.

Both in a deterministic and stochastic setting, the fish stock converges to a stable path in the long run. This may be explained by the assumption that the policy maker sets the quota after incorporating environmental variability in the decision making process; he quantifies the impact of variability on the fish stock. A number of observations were made concerning the behavior of the system. In the deterministic setting, when the fish stock is low, the policy maker sets the quota to zero so that the fish stock can recover to its long-term steady state. This may be a restriction for desired harvest levels of fishermen. When the fish stock is higher than the carrying capacity, negative growth of the fish stock reduces the fish stock and also the high harvest level reduces the fish stock because of low effort costs. The stationary value of fish stock is 349.5 million kton. In the stochastic setting, the effect of variability on long-term averages and stability was also studied. The long-term average fish stock slightly declines to 347.5 kton and at high variability the fish stock deviates more often from the average that at low variability.

2. What is the effect of multiannual adjustment of fish quota on quota fluctuation and resource rents, considering uncertainty in fish stock growth, investment in the fleet capacity and management costs?

Chapter 3 studied the management system of multiannual quota on North Sea plaice. Under this system, the quota is determined and consequently fixed for multiple years. The goal is to reduce capital volatility for fishermen and to reduce the management costs by having fewer meetings between policy makers and scientists. The bi-level stochastic dynamic programming model was extended to address the research question whether multiannual quota reduce fluctuation in quota and if they improve resource rents. At level one, a policy maker sets for several years the quota that maximizes resource rents, while anticipating on stochastic fish stock dynamics, capital stock dynamics and fishermen behavior. The investigated fixed quota periods range between one and five years. At level two, fishermen determine their harvest and investment levels based on current states of fish stock, capital stock and the quota. In this setting, it is assumed that fishermen base their harvest and investment decisions on current levels of fish stock and required capital stock, where the availability of the investment has a one-year lag.

Policy makers can reduce quota fluctuation and improve resource rents from the fishery with multiannual quota. This can be explained by two factors. First, when the quota is fixed for multiple years, the policy becomes more conservative as the future fish stock has to be anticipated over a longer period of time. Second, the policy maker has to account for a longer recovery period of the fish stock. The result is a less fluctuating quota and the quota is adjusted less to extremely low fish stock values than under annual quota. The long-term average quota is therefore set at a higher level than under annual quota. A reduction in quota fluctuation comes at the cost of more volatility in the fish stock. This results in a fish stock that becomes more often the binding factor for fishermen, while the quota becomes less limiting. A more volatile fish stock and an increased quota under multiannual quota hardly affect harvest and investment decisions of fishermen. The improvement in resource rents is therefore obtained by the reduction in management costs under multiannual quota. Besides increased volatility in the fish stock, the achievement of reduced quota fluctuation and improved resource rents comes at the cost of a higher quota under multiannual quota, and with the assumption that fishermen reacting myopically on more volatile fish stock, the investment level increases and becomes more volatile. At the same time, the discrepancy between available and required capital stock, due to the one-year lag in availability, increases and a larger fraction of fishing capacity remains unused.

3. What is the effect of a quota adjustment restriction on resource rents, overcapacity and fish stock in the long run and during recovery from a downward external shock on the fish stock?

Chapter 4 studied the management system of a quota adjustment restriction on North Sea plaice. Under this system, the quota can at most be adjusted upward and downward by a specific percentage, with respect to the previous quota. The goal is to obtain an efficient long-term fish stock, i.e. to bring stocks back to optimal health and productivity, and to provide greater stability for fishermen by enabling them to plan ahead. The bi-level stochastic dynamic programming model was extended to address the research question what the effect is of a quota adjustment restriction on resource rents, overcapacity and fish stock in the long run and during recovery from a downward external shock on the fish stock. At level one, the policy maker determines the quota that maximizes resource rents, while anticipating stochastic fish stock dynamics, capital stock dynamics, fishermen behavior and a quota adjustment restriction. Restriction adjustments of 30%, 15%, 10% and 5% at most were considered. At level two, fishermen reveal myopic harvest behavior and they make long-term investment decisions. For this long-term investment, fishermen assume that the fish stock and quota do not change over time. The two levels are linked by the quota that is decided at level one and becomes a restriction for fishermen at level two.

First, it is confirmed that volatility in quota change is large when the quota adjustment is unrestricted, which explains the problem of overcapacity. When quota adjustment is restricted, the volatility in quota change is lower and calls for a long and short-term analysis of overcapacity.

In the long run, overcapacity can be reduced substantially at a small reduction in the net present value of resource rents and at a small increase in the fish stock. A restriction leads to sub-optimal decisions, so the observation of lower resource rents is in line with the expectation. With a restriction on quota adjustment, the policy maker becomes more conservative in order to account for uncertain levels of future fish stock. The quota is therefore set at a somewhat lower level. Fishermen follow this quota, due to their myopic harvest behavior, by choosing lower effort levels and maintaining a smaller fleet capacity. In exchange for a 1% reduction in the net present value of resource rents under a 5% quota adjustment restriction, the result is a 54% reduction in overcapacity.

In order to study the behavior of the system in the short run, a downward external shock on the fish stock was introduced. During recovery from this shock, fishermen are more often bounded by the fish stock and capital stock than by the quota. This is because the policy maker can reduce the quota only by a small amount. In the first years of recovery, investment levels are low so that the fleet capacity reduces by depreciation. At the same time, fishermen put in more effort because they are allowed to catch more than under a quota without adjustment restriction. The quota becomes restrictive again once the fish stock approaches its long-term average and the capital stock is re-adjusted to a higher level. With the introduction and increase of the level of quota adjustment restriction to 5%, resource rents are reduced by 11% in exchange for 50% less overcapacity and a small delay in fish stock recovery. Long and short-term efficiency of the fish stock is not affected under a 30%, 15%, 10% and 5% restriction.

4. How can we model entry and exit decisions of fishermen under uncertainty about the ex-vessel price of fish? And, at what ex-vessel price is it optimal for fishermen to enter Alaska's limited entry salmon fishery, at what price is it optimal to lay-up and at what price is it optimal to permanently exit the fishery?

Chapter 5 studied investment and disinvestment decisions of fishermen in the limited entry management system in the Bristol Bay salmon fishery in Alaska. It is questioned why many fishermen, in years of a low ex-vessel price, choose to lay-up instead of selling their entry permit. The hesitation of fishermen to sell their entry permits can at least be partly explained by the option value of holding on to them. Once an entry permit is sold, the option to fish again is lost and this option can only be recovered by buying a new entry permit. An optimal switching model based on Real Options theory was used to determine ex-vessel prices of fish at which it is optimal for inactive, active and laid-up fishermen to switch between these states of operation. Uncertainty about future resource rents was characterized through the ex-vessel price. By deriving threshold prices and comparing these with historic developments of the ex-vessel price, permit use and permit holdings, more insight can be gained into historic decisions of fishermen.

Different variables determine when it is optimal to invest, lay-up, reactivate and exit the fishery and these variables differ between fishermen. For example, one fisherman may operate less efficiently than another fisherman and may therefore have a higher operating cost and lower revenues. This causes the inactive fisherman to wait longer to invest in the fishery, which means that the entry threshold price increases. The same holds for a laid-up fisherman, while an active fisherman in this situation will exit the fishery sooner at a lower exit threshold price.

A specific cost profile was derived from two surveys that were conducted over the period 1983-2010 and 2002. Over the period 1975-2010, fishermen have followed the development of the ex-vessel price closely. In the years that the ex-vessel price exceeds the entry threshold price, it is optimal to exercise the option to invest and it can be observed that fishermen indeed increasingly entered the fishery. In years that the lay-up or exit threshold prices exceed the ex-vessel price, it is optimal to lay-up or exit the fishery. In some of the years of such a low ex-vessel price, it was not only the ex-vessel price that induced exit and lay-up, but it was also the reduction of 13 million salmon that explained increased exit and lay-up. In other years of a low ex-vessel price, a large run of salmon causes increased reactivation, while the number of permit holdings remained unchanged due to the low ex-vessel price. Events that affect the stock size may have had a larger impact on fishermen's decisions to switch between different states than the ex-vessel price. Nevertheless, in periods of a low ex-vessel price, fishermen may also hold on to their permit because historically, the ex-vessel price and permit value have been high and are expected to recover in the future.

6.2 Modeling conclusions

Stochastic dynamic programming is a useful tool to study decision making under uncertainty. In the context of fisheries management, it is a policy maker that decides on the optimal quota, while accounting for stochastic fish stock dynamics. The method has been widely applied in the fisheries economics literature, however often in a simplified setting of a single decision maker (Sethi et al., 2005; Singh et al., 2006) or in a complex game theoretic framework that is difficult to solve (Bailey et al., 2010; Wang and Ewald, 2010). In reality a policy maker also accounts for fishermen behavior when setting the quota. In view of that, a bi-level model was developed in Chapter 2 that allows for multiple decision makers and provides a setting where model characteristics can be derived analytically before implementing numerical experiments. In this Chapter, a number of assumptions are explained that improve the ability to reproduce such models. First, decisions are made sequentially at their corresponding first and second levels. The two levels are connected by the quota that is optimized at level one and becomes a restriction at level two. Second, fishermen reveal myopic harvest and investment behavior, i.e. their decisions are based on current levels of fish stock and capital stock. Finally, a single-species fishery is assumed for which quota are optimized on an annual basis.

The advantage of the basic bi-level stochastic dynamic programming model in Chapter 2 is that it can be extended to account for alternative management systems, such as multiannual quota in Chapter 3, a quota adjustment restriction in Chapter 4, or even a combination of annual quota and fishing periods as has been done in Da Rocha and Gutiérrez (2012). The management systems of multiannual quota and a quota adjustment restriction have been studied before in Kell et al. (1999), Roel et al. (2004) and Kell et al. (2005, 2006), by simulating landing and stock data. With the stochastic dynamic programming approach these management systems can be optimized, as well as simulated, while accounting for both biological and economic dynamics. Also different assumptions can be made about fishermen behavior. In Chapters 2 and 3, fishermen are assumed to reveal myopic harvest and investment behavior, while in Chapter 4, fishermen invest with a long-term view but harvest myopically.

Although the bi-level model proves to be robust with respect to the solution procedure and volatility of fish stock growth, it comes with a number of limitations. An important limitation of stochastic dynamic programming is the ‘curse of dimensionality’ (Bellman, 1957). This holds that when the number of state variables increases, the volume of the decision space increases exponentially and leads to slow convergence. To improve efficiency and to ease interpretation of the model, it is common to reduce the number of state variables. In Chapter 2, the problem has been kept to a two-dimensional problem of fish stock an capital stock. In Chapters 3 and 4, an additional state variable for quota was introduced in order to make the current quota a function of the previous quota. Other simplifications in this thesis include the assumptions by fishermen, in Chapter 4, that the quota remains constant throughout the entire investment planning horizon. In order to account for a more realistic setting of an uncertain future quota, the model would have to be extended with an additional stochastic variable. With respect to the biological sub-model, throughout the thesis a single-species fishery is assumed, with known values of current fish stock and logistic growth. Relaxing these assumptions would make the model more complex, namely a multi-species fishery and an uncertain current fish stock increase the dimensionality and many alternative growth functions do not provide a stable equilibrium of the fish stock, so that model characteristics can no longer be derived analytically. The choice of the Spence harvest function may be altered with the more conventional Schaefer harvest function (Schaefer, 1954), but it would require more strict boundary values, given that this harvest function assumes constant catch per unit of effort in discrete-time models and therefore allows for full depletion of the fish stock.

The optimal switching model in Chapter 5 was developed by Dixit and Pindyck (1994), who used both a dynamic programming approach and the contingent claims method to analyze investment and disinvestment decisions. Each solution procedure is based on the same concepts, except for one, the discount rate. Where the dynamic programming approach makes an arbitrary assumption on the discount rate, the contingent claims method uses an economic model to determine the risk-adjusted discount rate. Besides, the contingent claims method provides an easier interpretation of solutions properties. In light of that, the optimal switching model was solved with the contingent claims method. However, a number of simplifications were made. A single source of uncertainty was assumed, namely the ex-vessel price of fish. Results from the model showed that decisions are potentially more strongly affected by extreme events in the fish stock. It may therefore be more realistic to account for multiple sources of uncertainty. This would lead to a model similar to the one developed in Schmit et al. (2011) for ethanol plant investment decisions. The model set-up changes substantially and is solved using dynamic programming. Also a risk-free discount rate was assumed, which means that everything, including the market and the investment, is discounted at the same rate. This assumption does not simplify the shape of the solution and may therefore be relaxed once information is available about the risk-adjusted discount rate for fishing revenues.

6.3 Policy conclusions

The European Commision has stated in a report on the conservation and exploitation of fisheries resources under the Common Fisheries Policy that ‘multiannual plans are more effective in taking a long-term perspective in managing stocks than the annual quota decision-making’. A careful view should be taken on this, because according to the same report this conclusion is based on ‘an increase in the number of stocks for which no scientific advice is available’ (European Commission, 2011, Ch.2). In the face of uncertainty about fish stock dynamics, it remains unclear whether biological and economic objectives of policy makers can be achieved with multiannual management plans. This thesis focuses on two management systems that are part of multiannual plans: multiannual quota and a quota adjustment restriction. The following policy conclusions are drawn.

With multiannual quota the goal is to reduce fluctuation in quota and to reduce management costs. The reason for this is that under annual quota adjustment, volatility in fish stocks leads to high quota fluctuation and overcapacity for fishermen. The advantages of a reduction in management costs seem to exceed the disadvantages of a more restrictive management system. A reduction in management costs may improve resource rents. The analysis in Chapter 3 shows that objectives of the policy maker and fishermen cannot be jointly achieved with multiannual quota. The policy maker's objective of reducing quota volatility and improving resource rents is achieved, but in the setting of this model volatility in fish stock and investments increases and leads to more overcapacity in the fishing fleet. Although the reduction of overcapacity is one of the priorities in the 2013 reform of the Common Fisheries Policy, the importance of the trade-offs under multiannual quota will depend on the extent to which there is a political ambition to keep the fishing industry content by reducing overcapacity.

A quota adjustment restriction has been introduced to allow fishermen to make longer-term investment plans, namely 'the plans provide greater stability for the fishing industry and enable operators to plan ahead' (European Commission, 2009a, 2013b). Results presented in Chapter 4 suggest that in the long run, under a quota adjustment restriction, fishermen can reduce their overcapacity by 59% in exchange for a 1% reduction in resource rents. Similar results are found for the short term, when the fish stock is recovering from an environmental shock. Although this environmental shock leads to a small delay in the recovery of the fish stock, efficiency is not affected. The fish stock can even increase by 2% under a quota adjustment restriction. This is useful information for policy makers, given that the European Commission's conclusion of effective multiannual management plans (as a whole) is based on 'an increase in the number of stocks for which no scientific advice is available' (European Commission, 2011, Ch.2). Chapter 4 shows that there is a scientific link between effectiveness of a quota adjustment restriction and recovery of the fish stock, namely the quota adjustment restriction reduces overcapacity as compared to a setting without quota adjustment restriction and at the same time the long-term fish stock settles at a somewhat higher level. The more restrictive the quota, the lower the overcapacity and the more resource rents are foregone. However, also here the question can be raised what the political ambition is: how much resource rents are policy makers willing to give up to reduce overcapacity?

Chapter 5 deals with decision making under uncertainty in a different management system and a different management area, namely a limited-entry system in Alaska's Bristol Bay sockeye salmon drift gillnet fishery. In order to participate in the fishery an entry permit is required, which has to be renewed annually. A maximum number of entry permits has been established for the fishery in order to limit the total fleet size rather than setting a quota. Entry permits are tradable, but once an entry permit has been sold, the fisherman loses his right to fish. Although the limited-entry system has been recognized as a well-established program that has contributed to high earnings and catch, average annual profits of permit holders have been volatile and in some years economic losses have occurred. This is due to the costly investment and disinvestment decisions of fishermen to enter, lay-up and exit the fishery. Knowing that the ex-vessel price may be more volatile in years of extreme environmental events, policy makers are able to anticipate on how fishermen respond to these events in terms of investment and disinvestment decisions: at higher volatility, fishermen become more conservative in their decisions and wait to exercise the options to enter and exit the fishery until the ex-vessel price is higher. Also higher costs cause fishermen to hold on to the options to enter and exit until the ex-vessel price is higher. Policy makers may prevent this behavior and speed up entry and exit by lowering transaction costs. However, compensation through e.g. subsidies contribute to overcapitalization and are in conflict with conservation goals of limited entry systems.

6.4 Limitations and recommendations for future research

Chapters 3 and 4 focus on two management systems, namely multiannual quota and a quota adjustment restriction. Multiannual management plans include several more measures such as closed areas, mesh size, gear, inspections, monitoring and effort management. Conclusions should therefore be interpreted within the context of the modeled management systems and the assumptions of the behavior of the policy maker and fishermen.

In Chapter 3, it was assumed that fishermen behave myopically, that is, they determine their harvest and investment levels based on current states of fish stock and capital stock and do not consider the long-term consequences of their decisions. In Chapter 4, fishermen are assumed to reveal myopic harvest behavior but to make long-term investment decisions. For this long-term investment, it is assumed that the fish stock and quota do not change over time. There seems to be no consensus in the literature about true fishermen behavior and arguments have been provided for short and long-term behavior as well as for fishermen that anticipate on decisions of policy makers. For future research, it may be interesting to focus more on the effect of different types of fishermen behavior on quota volatility and resource rents.

Chapters 2, 3 and 4 assume that the source of uncertainty comes from fish stock growth alone. It was thereby ignored that the observed fish stock size may deviate from the actual stock size. Current decisions are based on an initial, uninformed belief system that does not change over time as new information becomes available. It may be more realistic to assume that information about fish stock is uncertain. In future work, learning about the uncertain fish stock may be incorporated using a framework of Bayesian updating. This shifts the research to questioning how learning affects quota decisions and to what extent updating information, which is costly and time consuming, is worthwhile instead of setting the quota based on unwarranted assumptions about the fish stock.

As a final note on the bi-level model, although it is a specified objective of the European Commission that multiannual management plans are to cover both single-species fisheries and multi-species fisheries (European Commission, 2013a), the bi-level model has only been developed for a single-species fishery. In future work, the model can be extended to incorporate multiple species.

Chapter 5 focused on the ex-vessel price and its uncertainty. It is known that the population size of sockeye salmon is volatile and difficult to predict. A sensitivity analysis was performed on this volatility, but in future research multiple sources of uncertainty may be accounted for, including the run size and ex-vessel price. Finally, in this Chapter a risk-free discount rate was assumed. This assumption may be relaxed in order to account for the appropriate risk-adjusted discount rate for revenues in a limited-entry fishery.

6.5 Closing remarks

Despite all the efforts all around the world to manage fisheries sustainably, it is still challenging to achieve goals of policy makers and fishermen simultaneously. Together, these goals include obtaining efficient fish stocks, resource rent maximization and less overcapacity in fishing fleets. Uncertainty about future fish stocks and ex-vessel prices makes it difficult for policy makers and fishermen to make the right decisions. On top of that, policies are based on anticipated fishermen behavior, on which there seems to be no general agreement.

This thesis has shown for input and output measures (limited entry and quota) that decisions of both policy makers and fishermen depend on their behavior, on conditions of the fish stock and the ex-vessel price and on expectations about their respective development. A more restrictive system comes with inevitable trade-offs, but it is up to policy makers to decide which objectives receive more weight. The challenge is to get an even better understanding of decision making under uncertainty and to find the behavioral and management conditions at which all goals can be achieved. The research methodology in this thesis provides a set-up with which other management systems and different fishermen behavior can be studied in order to further address problems of inefficient fish stocks, resource rents and investment decisions.

Summary

The world's marine fisheries are characterized by declining global catch, an increasing number of overexploited stocks and high natural variability in fish stocks. Policy makers are becoming more aware that effective management systems have to be implemented to rebuild overexploited fish stocks. The success of a management system is specified in terms of biological, economic, social and political objectives of policy makers and the fishing industry. However, the combination of these objectives makes the implementation of policies one of the main challenges in fisheries management. To prevent overfishing, different measures have been applied that limit catch and/or fleet capacity. Yet, the same management systems and economic behavior of fishermen may lead to an increase in investments in the fleet capacity, causing overcapacity. Decisions of policy makers and fishermen are made under uncertainty, such as uncertainty about fish stock dynamics and/or fish prices, and this can affect optimal management, investment decisions, healthy and productive fish stocks and resource rents. The objective of this thesis is to study the impact of different fisheries management systems on resource rents from the fishery, investment in the fleet capacity and fish stock under uncertainty about fish stock growth and the ex-vessel price of fish. Bi-level stochastic dynamic programming is used to model the interaction between the quota decision of a policy maker and fishermen behavior. The fisheries management systems of multiannual quota and a quota adjustment restriction are introduced and analyzed in terms of resource rents, overcapacity and fish stock. Real Options theory is used to determine for a fisheries management system of limited entry at what ex-vessel prices it is optimal for fishermen to make investment and disinvestment decisions.

Chapter 2 develops a bi-level stochastic dynamic programming model in order to determine optimal levels of quota. At level one, a policy maker decides on the quota that maximizes long-term resource rents, while considering stochastic fish stock dynamics, capital stock dynamics and fishermen behavior. At level two, individual fishermen behave as if they operate under open access within the restriction set at level one. They maximize their profits and will only stop fishing when marginal costs are equal to marginal revenues. This is translated in the model by fishermen reacting on current states of fish stock and capital stock when deciding on their harvest and investment. The two levels are linked by the quota that is derived at level one and becomes a restriction for fishermen at level two. The effect of more volatility in the fish stock is that the long-term average fish stock declines slightly and at high volatility the fish stock deviates more often from the average than at low volatility. This model provides a basis for studying different management systems and fishermen behavior.

Chapter 3 studies the management system of multiannual quota in a stylized application to North Sea plaice. Under this system, the quota is determined and consequently fixed for multiple years. The goal is to reduce capital volatility for fishermen and to reduce the management costs by having fewer meetings between policy makers and scientists. The bi-level stochastic dynamic programming model is extended to study whether multiannual quota reduce fluctuation in quota and if they improve resource rents. At level one, a policy maker decides on the quota that maximizes long-term resource rents, while considering stochastic fish stock dynamics, capital stock dynamics and fishermen behavior. At level two, it is assumed that fishermen behave myopically and that they determine their harvest and investment levels based on current states of fish stock, capital stock and the quota. Results show

that policy makers can reduce quota fluctuation and improve resource rents from the fishery with multiannual quota. The reduction in quota fluctuation however comes at the cost of more volatility in the fish stock, more volatile investment and more overcapacity.

Chapter 4 studies the management system of a quota adjustment restriction in a stylized application to North Sea plaice. Under this system, the quota can at most be adjusted upward and downward by a specific percentage, with respect to the previous quota. The goal is to obtain an efficient long-term fish stock and to provide greater stability for fishermen by enabling them to plan ahead. The bi-level stochastic dynamic programming model is extended to study the effect of a quota adjustment restriction on resource rents, overcapacity and fish stock in the long run and during recovery from a downward external shock on the fish stock. At level one, a policy maker decides on the quota that maximizes long-term resource rents, while considering stochastic fish stock dynamics, capital stock dynamics, fishermen behavior and a quota adjustment restriction. At level two, it is assumed that fishermen reveal myopic harvest behavior and in light of the policy maker's objective to enable fishermen to plan ahead, fishermen decide on the future investment path that maximizes long-term profits. For this long-term investment decision, fishermen assume that the fish stock and quota do not change over time. Results of the analysis suggest that in the long run, the introduction of a 5% quota adjustment restriction compared to a quota without adjustment restriction can lead to a 54% overcapacity reduction at a 1% reduction in the net present value of resource rents and a 1% increase in the fish stock. In the short run, when recovering from an downward external shock on the fish stock, fishermen are more often bounded by the fish stock and capital stock than by the quota. The quota becomes restrictive again once the fish stock approaches its long-term average and the capital stock is re-adjusted to a higher level. By setting the level of quota adjustment restriction to 5%, resource rents can be reduced by 11% in exchange for 50% less overcapacity. Long and short-term efficiency of the fish stock is not affected.

Chapter 5 studies investment and disinvestment decisions of fishermen in the limited entry management system in Alaska's Bristol Bay sockeye salmon fishery. An optimal switching model is used based on Real Options theory, to determine at what ex-vessel prices of fish it is optimal for fishermen to switch between being active, inactive or laid-up (i.e. temporarily suspending operations). Uncertainty about future revenues is characterized through the ex-vessel price. Fishermen may not all have similar cost profiles and results show that it is these cost profiles that determine when it is optimal to invest, lay-up, reactivate and exit the fishery. Over the period 1975-2010, given a specific derived cost profile, fishermen have followed the development of the ex-vessel price closely. However, events that have impacted the salmon stock may have had a larger impact on fishermen's decisions to switch between different states than the ex-vessel price. And, in periods of a low ex-vessel price, fishermen may also hold on to their permit because historically, the ex-vessel price and permit value have been high and are expected to recover in the future.

Three conclusions can be drawn from this thesis. First, according to the analysis of this thesis the policy maker achieves the objective of reducing quota volatility and improving resource rents with multiannual quota, by fixing the quota for multiple years and by reducing the management costs associated to the number of meetings between policy makers and scientists. Based on the bi-level stochastic dynamic programming model with assumptions of myopic harvest and investment behavior of fishermen, however, the fish stock becomes more volatile and fishermen have more overcapacity. Although the reduction of overcapacity is one of the priorities in the 2013 reform of the Common Fisheries Policy, the importance of resource rents versus overcapacity under multiannual quota will depend on the extent to which there is a political ambition to keep the fishing industry content by reducing overcapacity. Second, based on the bi-level model with assumptions of myopic harvest and long-term investment behavior of fishermen, a quota adjustment restriction reduces overcapacity as compared to a setting without quota adjustment restriction and at the same time the long-term fish stock settles at a somewhat higher level. This is realized at a small reduction in resource rents. Nevertheless, the political ambition determines how much resource rents policy makers are willing to give up to reduce overcapacity. Third, knowing that the ex-vessel price of sockeye salmon in the limited entry system of Alaska's Bristol Bay may be more volatile in years of extreme environmental events, policy makers in Alaska are able to anticipate on how fishermen respond to these events in terms of investment and disinvestment decisions: at higher volatility, fishermen become more conservative in their decisions and will exercise the options to enter and exit the Bristol Bay commercial fishery at a higher ex-vessel price of sockeye salmon.

Samenvatting

De zeevisvangst in de wereld wordt gekarakteriseerd door afnemende vangsten, toenemende overbevissing en grote natuurlijke variatie in visstanden. Beleidsmakers zijn er zich steeds meer van bewust dat effectieve managementsystemen moeten worden ingevoerd om uitgeputte visbestanden weer op te bouwen. Het succes van een managementsysteem wordt gespecificeerd in termen van biologische, economische, sociale en politieke doelstellingen van beleidsmakers en de visserij industrie. Echter, de combinatie van deze doelstellingen maakt het invoeren van beleid één van de belangrijkste uitdagingen. Om overbevissing te voorkomen zijn er verschillende maatregelen genomen om de vangst te beperken en/of de vlootcapaciteit te verminderen. Toch kunnen deze managementsystemen, als zij onvoldoende rekening houden met het economisch gedrag van vissers, leiden tot toenemende investeringen in vlootcapaciteit en mogelijk overcapaciteit veroorzaken. Beslissingen van beleidsmakers en vissers worden gemaakt op basis van onzekerheid over dynamiek in visstanden en/of visprijzen en dat kan invloed hebben op optimaal management, investeringsbeslissingen, gezonde en productieve visstanden en winsten. Het doel van dit proefschrift is om de invloed te bestuderen van verschillende visserijmanagementsystemen op winsten, investeringen in de vlootcapaciteit en visstanden onder onzekerheid over de groei van visbestanden en de prijs van vis. Een stochastisch dynamisch programmeringsmodel met twee niveaus is gebruikt om de interactie te modelleren tussen de quotabeslissing van een beleidsmaker en vissers. De visserijmanagementsystemen van meerjarenquota en een aanpassingsrestrictie voor quota zijn ingevoerd en bestudeerd in termen van winsten, overcapaciteit en visstand. De Reële Optie Theorie is gebruikt om te bepalen bij welke visprijzen het optimaal is voor vissers om investerings- en desinvesteringsbeslissingen te maken.

Hoofdstuk 2 ontwikkelt een stochastisch dynamisch programmeringsmodel met twee niveaus, met de bedoeling optimale quota te bepalen. Op het eerste niveau beslist een beleidsmaker over de quota die de lange termijn winsten maximaliseren, terwijl er rekening gehouden wordt met stochastiek in de dynamiek van de visstand, dynamiek in de kapitaalvoorraad en gedrag van vissers. Op het tweede niveau gedragen vissers zich myopisch, dat wil zeggen, ze houden geen rekening met de lange-termijngevolgen van de visserij. Ze maximaliseren hun winsten en zullen pas stoppen met vissen wanneer de marginale kosten gelijk zijn aan de marginale opbrengsten. Dit is vertaald in het model door vissers die reageren op de huidige standen van vis en vloot wanneer zij beslissen over hun vangst en investeringen. Vissers worden beperkt door een quotum, zodat de twee niveaus met elkaar zijn verbonden door het quotum dat is bepaald op het eerste niveau en vervolgens een beperking wordt voor vissers op niveau twee. Het effect van grotere schommelingen in de visstand is dat de lange termijn visstand gemiddeld genomen licht afneemt. Bij een grote schommeling wijkt de visstand meer af van het gemiddelde dan bij een kleine schommeling. Dit model verschaft een basis voor het bestuderen van verschillende managementsystemen en vissersgedrag.

Hoofdstuk 3 bestudeert het managementsysteem van meerjarenquota in een gestileerde toepassing op Noordzee schol. In dit systeem worden de quota bepaald en vervolgens vastgelegd voor meerdere jaren. Het doel is om schommelingen in kapitaal te verminderen en ook om de managementkosten terug te brengen door de frequentie van bijeenkomsten voor besluitvorming te beperken. Het stochastisch dynamisch programmeringsmodel met twee niveaus is uitgebreid met het doel te bestuderen of meerjarenquota de schommelingen in de quota kunnen verminderen en of zij winsten kunnen verbeteren. Op het eerste niveau beslist een beleidsmaker over de quota voor enkele jaren die de lange-termijnwinsten maximaliseren, terwijl er rekening gehouden wordt met stochastiek in de dynamiek van de visstand, dynamiek in de kapitaalvoorraad en gedrag van vissers. Het is aangenomen dat vissers myopisch gedrag vertonen en er wordt verondersteld dat zij hun vangst en investeringen bepalen op basis van de huidige visstand, kapitaalvoorraad en quota. De resultaten laten zien dat beleidsmakers via meerjarenquota schommelingen in de quota kunnen verminderen en tegelijkertijd winsten kunnen verbeteren. Het terugbrengen van quotaschommelingen brengt helaas meer fluctuatie in de visstand met zich mee, meer schommelende investeringen en meer overcapaciteit.

Hoofdstuk 4 bestudeert een managementsysteem met een aanpassingsrestrictie voor quota in een gestileerde toepassing op Noordzee schol. Onder dit systeem kan het quotum in de huidige periode, ten opzichte van het quotum in de vorige periode, maximaal naar boven en beneden aangepast worden met een vast percentage. Het doel is om een efficiënte visstand te verkrijgen en om een stabielere omgeving te creëren voor vissers door hen vooruit te laten plannen. Het stochastisch dynamisch programmeringsmodel met twee niveaus is uitgebreid om de effecten te bestuderen van een aanpassingsrestrictie voor quota op winsten, overcapaciteit en de visstand op de lange termijn, alsook tijdens herstel van een tijdelijk afgenomen visstand. Op het eerste niveau beslist een beleidsmaker over de quota die de lange termijn winsten maximaliseren, rekening houdend met stochastiek in de dynamiek van de visstand, dynamiek in de kapitaalvoorraad, vissersgedrag en een aanpassingsrestrictie voor quota. Op het tweede niveau is aangenomen dat vissers myopisch vangstgedrag vertonen en met het oog op het doel van de beleidsmaker om vissers vooruit te laten plannen, wordt de aanname gehanteerd dat vissers beslissen over de toekomstige investeringspaden die de lange-termijn winsten maximaliseren. Wat betreft deze lange-termijn investeringsbeslissingen, wordt er verondersteld dat vissers ervanuit gaan dat de visstand en quota niet over de tijd veranderen. Door quota zonder aanpassingsrestrictie te veranderen naar een 5% aanpassingsrestrictie voor quota, laten de resultaten zien dat op de lange termijn de overcapaciteit kan worden teruggebracht met 54% in ruil voor een 1% reductie in de winsten en een 1% verhoging in de visstand. Op de korte termijn, tijdens het herstel van een tijdelijk afgenomen visstand, zijn vissers vaker beperkt door de visstand en de kapitaalvoorraad dan door het quotum. Het quotum wordt weer beperkend als de visstand zijn lange-termijn gemiddelde bereikt en de kapitaalvoorraad naar boven wordt aangepast. Door de aanpassingsrestrictie voor quota in te stellen op 5%, kunnen de winsten worden gereduceerd met 11% in ruil voor 50% minder overcapaciteit. Dit heeft geen invloed op de korte- en lange-termijn efficiëntie van de visstand.

Hoofdstuk 5 bestudeert investerings- en desinvesteringsbeslissingen van vissers in het managementsysteem van beperkte toegang in Alaska's Bristol Bay sockeye zalmvisserij. Een optimaal schakelmodel is gebruikt, gebaseerd op de Reële Optie Theorie, om te bepalen bij welke visprijzen het optimaal is voor vissers om te wisselen tussen activiteit, inactiviteit of het tijdelijk opschorten van vissen. Onzekerheid over toekomstige inkomsten wordt gekarakteriseerd door de prijs. Niet alle vissers hebben hetzelfde profiel wat betreft de kosten en de resultaten laten zien dat de verschillende kostenprofielen bepalen wanneer het optimaal is om te investeren, tijdelijk activiteiten op te schorten, te reactiveren of de visserij te verlaten. Over de periode van 1975-2010 hebben vissers, gegeven een specifiek kostenprofiel, de ontwikkeling van de prijs nauwlettend gevolgd. Echter, gebeurtenissen die hebben geleid tot een groot verlies of tot een verhoging van de zalmstand, hebben mogelijk een grotere invloed gehad op de beslissingen van de vissers dan de prijs. En in tijden van een lage prijs is het ook mogelijk dat vissers vasthouden aan hun vergunning omdat historisch gezien de visprijs en vergunningswaarde hoog waren en er verwacht wordt dat deze in de toekomst zullen herstellen.

Er kunnen drie conclusies worden getrokken uit dit proefschrift. Ten eerste, volgens de analyse van dit proefschrift behalen beleidsmakers hun doel om de schommelingen in de kapitaalvoorraad te verminderen en om winsten van de visserij te verhogen met meerjaren quota, door de quota voor meerdere jaren vast te zetten en door managementkosten terug te brengen door de frequentie van bijeenkomsten voor besluitvorming te beperken. Echter, op basis van het stochastisch dynamisch programmeringsmodel met twee niveaus waarbij de aanname geldt dat vissers myopisch vangst- en investeringsgedrag vertonen, fluctueert de visstand meer en hebben vissers meer overcapaciteit. Hoewel de vermindering van overcapaciteit één van de prioriteiten is in de hervorming van de Common Fisheries Policy in 2013, zal het belang van winsten versus overcapacity onder meerjarenquota afhangen van de mate waarin er de politieke wil bestaat om de visserij industrie tevreden te houden door overcapaciteit te verminderen. Ten tweede, op basis van het model met twee niveaus waarbij er aangenomen wordt dat vissers myopisch vangstgedrag vertonen en lange-term investeringen maken, helpt een aanpassingsrestrictie voor quota de overcapaciteit te verminderen, vergeleken met quota zonder aanpassingsrestrictie. Tegelijkertijd komt de lange-termijn visstand op een iets hoger niveau te liggen. Dit wordt echter gerealiseerd in ruil voor een kleine afname in de winst. Niettemin bepaalt de politieke wil hoeveel winst beleidsmakers bereid zijn op te geven in ruil voor minder overcapaciteit. Ten derde, met de wetenschap dat de prijs van sockeye zalm in Alaska's Bristol Bay managementsysteem van beperkte toegang mogelijk meer zal schommelen in jaren van extreme omstandigheden, kunnen beleidsmakers in Alaska anticiperen op hoe vissers reageren op deze omstandigheden in termen van investerings- en desinvesteringsbeslissingen. Bij grotere schommelingen zijn vissers geneigd behoudendere beslissingen te nemen en zullen ze bij een hogere zalmprijs de opties uitvoeren om de Bristol Bay visserij toe te treden en te verlaten.

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Completed Training and Supervision Plan
Diana van Dijk
Wageningen School of Social Sciences (WASS)

Wageningen School of Social Sciences

Name of the activity	**Department/Institute**	**Year**	**ECTS (28 hrs)**
Project related competences			
PhD Research Proposal approval	WASS	2008	6
S020 Uncertainty Analysis	SENSE	2010	4
Advanced Micro Economics ECH 32306	WUR	2010	6
Advanced Macro Economics ENR 30806	WUR	2008	6
Econometrics	WUR	2009	6
Advanced Econometrics AEP 60306	WUR	2009	6
General research related competences			
Introduction course	WASS	2009	1.5
Techniques for Writing and Presenting A Scientific Paper	WGS	2009	1.2
Mansholt Multidisciplinary Seminar	WASS		1
Career related competences/personal development			
'Fluctuating quota and management costs under multiannual adjustment of fish quota'	19th Annual Conference of the European Association of Environmental and Resource Economics (EAERE) in Prague, Czech Republic.	2012	1
'Multiannual adjustment of fish quota'	International Institute for Fisheries Economics and Trade (IIFET) conference in Montpellier, France	2010	1
'Coping with stochasticity in fish stocks under costly capital adjustment and high information costs	IPOP Zee en Kustzones symposion	2009	1
Project & Time Management	WGS	2009	1.5
Teaching activities (ENR306): guide project group and assist in computer practical's	WUR	2009 & 2012	2
'Capturing the value of coastal ecosystem services for poverty allevation in East and Southern Africa'	Ecosystems Services for Poverty Alleviation (ESPa)	2010	
'Multiannual adjustment of fish quota'	University of California, Santa Barbara, USA	2010	
'Coping with stochasticity in fish stocks under costly capital adjustment and high information costs'	University of Almeria, Spain	2010	
TOTAL			**44.2**