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## **Preface**

The following thesis is the final work after five years of study at the University of Stavanger (UiS). According to the Norwegian Ministry of Education and Research, every master's candidate is required to write a thesis during the last year or final semester of their study. It is stated that the thesis shall be based on actual problems in industry, society, or research and development. We decided to write this thesis about the Norwegian salmonid aquaculture during our final semester of our master's program.

Norway has a long history of exploiting the vast resources of its long coastline with regards to fishing, aquaculture, and oil and gas. In modern days, the export of salmon from aquaculture has a significant impact on the Norwegian trade economy. In the future, it is expected that the salmonid aquaculture industry will further develop and may be accompanied by onshore and offshore fish farming, as well as new methods to tackle sea lice infestations. It is safe to say that the Norwegian coast has had a critical role in the Norwegian economy and will continue to do so in the future.

This thesis builds on previous work done by Jay Abolofia and James E. Wilen from the University of California, and Frank Asche from the University of Florida. Their research has proved to be critical to perform our analysis.

We would like to give a special mention to the Norwegian Directorate of Fisheries for allowing us to use their production and biomass data from Norwegian farming sites. This has been a deciding factor for reaching the conclusions in this study, as well as strengthened the validity of the thesis.

We would also like to thank our supervisor, Bård Misund, and Ragnar Tveterås from UiS Business School, for their contributions and guidance throughout the process.

Finally, we hope the findings in this thesis can give valuable information and insights on the salmonid aquaculture industry in Norway and elsewhere.

Enjoy your reading,

Ole Kaldheim and Sondre Nordbotn

Stavanger, Norway

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## **Abstract**

The salmonid aquaculture industry is facing significant environmental and biological challenges, limiting the industry's ability to grow. One of the most critical challenges is the prevalence of sea lice. Parasitic sea lice negatively affect the biological growth rate of farm biomass and, as such, contribute to loss of revenues and lowered fish welfare. As a result of this, the utilization of chemical and mechanical delousing are popular measures used to combat lice infestations. For some time, there has been a suspicion that such measures adversely impact the biological growth rate of farmed salmonids. This study is the first of its kind to investigate this suspicion in detail. The main objective of this study is to provide an updated estimation of the industry-wide costs related to lice, while simultaneously measuring the effect of lice treatment on biological growth rate. The analysis performed in this thesis is enabled through the utilization of a rich data set containing information on biophysical variables, lice counts, and treatment applications for all Norwegian farms in the period from 2012 to 2017. Using this data set, we empirically investigate the biological and economic impacts of observed levels of sea lice and their associated mitigation efforts.

Our results suggest that lice treatments negatively affect biological growth rate and contribute to a higher loss of revenue compared to sea lice alone. From our marginal effects estimation, both bath and mechanical treatments reduce growth rate. Bath treatments reduce growth rate between 0.92% to 1.21%, while mechanical treatments reduce the growth rate between 1.73% to 2.14%, depending on geographical location. Additionally, our analysis shows that the total cost of lice is equivalent to 14.21% of revenues or 7.63 NOK per kg produced fish, which corresponds to an industry-wide cost of 11.2 billion NOK in 2017.

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## **List of Abbreviations**

AB – Ancillary Biomass  
AIC – Akaike’s Information Criterion  
BPLM – Breusch-Pagan Lagrange Multiplier  
CI – Confidence Interval  
EBIT – Earnings Before Interest and Taxes  
FCR – Feed Conversion Ratio  
FE – Fixed-Effects  
FTE – Full-time equivalent  
GWE – Gutted Weight Equivalent  
MAB – Maximum Allowable Biomass  
MBE – Marginal Bath Effect  
MLE – Marginal Lice Effect  
MLEM – Marginal Lice Effect at Means  
MLR – Multiple Linear Regression  
MME – Marginal Mechanical Effect  
NOK – Norwegian Crowns  
OLS – Ordinary Least Squares  
PD – Panel Data  
RE – Random Effects  
UiS – University of Stavanger  
WFE – Whole Fish Equivalent



# 1. Introduction

Norway is the world's largest producer of farmed salmon, supplying 37.5% of the total production volume in 2017 (FAO, 2019a). The industry is an integral part of Norwegian export, having a production value of 64 billion NOK in 2017 (Statistics Norway, 2018). Biological welfare in animal production processes have become progressively more critical as animal density, and process efficiency have increased. Prevention and mitigation of diseases and parasites are especially crucial as the high density of animals provides an environment where diseases and parasites can spread aggressively and potentially inflict substantial economic losses. Salmonid aquaculture is no exception, experiencing several diseases and biological challenges that, through government regulations, limit the industry's ability to grow (Vedeler, 2017). Today, parasitic sea lice are a substantial concern for salmonid farmers as the parasite hinders growth and may cause increased mortality (Torrissen et al., 2011). Increased density of salmon farms has fundamentally changed the number and distribution of potential sea lice hosts, increasing the risk of severe lice infestations both on farmed and wild stocks (Jansen et al., 2012).

The last decade has seen a drastic change in the way salmon farmers combat sea lice. Mechanical and biological methods have mainly replaced chemical delousing (bath and in-feed). At the same time, reports suggest escalating production costs, in part due to substantial problems with sea lice, particularly during the period from 2014 to 2016. Moreover, in 2013, new limits were set on the allowable amount of sea lice on farmed salmon. According to the new regulations, farmed salmon can at maximum be the host of, on average, 0.5 adult female lice (0.2 during the spring). Hence, there are two separate mechanisms potentially affecting the personal cost of lice for fish farmers: Change in treatment and change in regulation. One purpose of the thesis and our empirical analysis is to disentangle these two effects, which, to the best of our knowledge, have not been previously studied.

Detailed data for the entire salmonid aquaculture industry is readily available because of strict government regulations and requirements. However, only a few attempts have been made to assess the economic impact of sea lice. Understanding the aggregated implications of sea lice for the industry as a whole is essential to evaluate, and prioritize mitigation efforts, justify regulations and assess the viability of production processes where sea lice are eliminated. This is the motivation for the following thesis research question:

*How large are the aggregated economic losses associated with sea lice in Norwegian salmonid aquaculture?*

Through our research question, we intend to quantify the impact of sea lice and sea lice mitigation efforts on the biological growth rate of farm biomass and utilize our results to provide recommendations and implications for government regulations. In what follows, we use a rich panel data set that measures farm-level input and production data, biophysical variables, lice counts, and lice treatment applications for all actively producing Norwegian salmon farms over a 72-month period. Specifically, it allows us to conduct an empirical investigation of the biological and economic impacts of lice infestations and lice treatments. We also attempt to separate the parasite-inflicted growth impacts from the growth impacts inflicted by the application of chemical and mechanical delousing treatments. Our bio-econometric model of fish biomass growth incorporates productive and biophysical inputs (e.g., feed use, fish weight, water temperature, and stocking density) and harmful inputs, such as, sea lice and sea lice treatment applications.

Using our model, we estimate marginal damages imposed by sea lice and delousing treatments, and econometrically simulate the impact of common infestation scenarios over typical production cycles. Previous studies have focused exclusively on the adverse effects of increased sea lice population. However, there is reason to suspect that the treatment application itself may adversely affect the biological growth rate. Our model facilitates the exploration of such a hypothesis by incorporating chemical and mechanical delousing treatments as independent variables. The model also provides insights into important biological and behavioral factors that influence the costs associated with sea lice, including the influence of water temperature, stocking and harvesting patterns, pen density, and treatments.

The scope of this paper is limited to the Norwegian salmon aquaculture industry. Satisfactory data is, at the time of writing, only accessible for Norway. The socio-economic impacts of sea lice are commonly divided into two groups: Negative externalities and private economic losses for salmonid farmers. This paper will focus on only the private economic losses of sea lice by examining fish farmer profits. Negative externalities associated with sea lice are not examined in this paper. However, these externalities are expected to be of high significance, considering sea lice is the most critical limiting factor to industry growth.

Our analysis of the economic implication of sea lice is focused on the national and regional industry as a whole, not on individual companies or farms. The reasoning behind this decision

is to provide interesting and valuable information for the industry and its stakeholders at a general level, rather than focusing on the individual challenges faced by specific companies. Our results are therefore of interest to regulators such as the Norwegian Directorate of Fisheries and the Norwegian Ministry of Trade, as well as advising research institutions such as the Institute of Marine Research and the Norwegian Food Safety Authority. The findings will also be of interest to salmon farming companies.

The paper will first present a literature review with insights on essential areas relevant for the following analysis. Then, Chapter Three provides an overview of the salmonid aquaculture production process and identifies important process input factors. An introduction to the sea lice parasite and an overview of available sea lice mitigation efforts are presented to provide the reader with useful insights that further support the understanding of our empirical model and analysis later in the paper.

Chapter Four contains detailed information about our data set, as well as the data acquisition and preparation process. We also highlight significant trends and features of our data set, which offer the reader useful information about the development and structure of the salmonid farming industry today.

The fifth chapter outlines the methodology used throughout the thesis. It is meant to provide a solid theoretical foundation for researching the defined problem. First, we present the model for the private cost of lice, which includes costs associated with lost biomass growth. Then, we introduce the bio-econometric model used to estimate the biological growth rate before an overview of the different panel data estimators is presented.

Chapter Six includes the presentation and analysis of all empirical results, with a numerical answer to our research question. We also present useful insights on the effect of lice and lice treatments on biological growth rate and provide results that showcase the regional differences along the Norwegian coastline.

In Chapter Seven, we discuss our results and highlight the strengths and weaknesses of our framework. Implications for government regulations discovered by the results are also presented, together with an overview of new technology being developed to combat sea lice.

Finally, concluding remarks are made, presenting the most important findings and suggestions for further research and possible extensions of the utilized methodology.

## 2. Literature Review

As a result of Norway being the world's largest producer of farmed salmon, extensive research has been conducted on Norwegian salmonid aquaculture. The industry has recently faced many new challenges, such as increased production costs, stagnation in growth, and outbreaks of viral diseases and parasites. These challenges are of interest to researchers that seek to improve industry efficiency and sustainability. Thus, negative externalities, sea lice biology, and epidemiology and profitability are among the topics that have been extensively examined.

Negative externalities that have been studied include genetic interaction and escape, disease, pollution and emissions, area utilization, feed and feed resources (Christiansen, 2013). Specifically, the influence of sea lice abundance on wild stocks has been a prevalent topic as it is the main factor dictating government regulation of the industry. Such studies have shown that the introduction of salmon aquaculture negatively impacts existing wild salmon stocks, especially when wild smolts migrate from freshwater to the sea (Costello, 2009b; Krkošek et al., 2007; Nekouei et al., 2018). Krkosek, Lewis, and Volpe (2005) found that the infection pressure imposed by a single farm was four orders of magnitude greater than ambient levels. There also exists evidence that increased density of salmonid farms increases the risk of lice infestation transmission between closely situated farms (Aldrin et al., 2013; Jansen et al., 2012; Kristoffersen et al., 2014). Furthermore, the prevalence of chemical delousing has been a source for concern since the beginning of the 1970s, particularly the effects these chemicals might have on non-target species. Since then, direct mortalities, as well as sub-lethal effects, have been detected in species that live in the proximity of production areas (Urbina et al., 2019).

Studies on the biology of sea lice (*Lepeophtheirus salmonis*) have provided valuable information on how to best combat the parasite. Important factors that affect sea lice growth and development are salinity and water temperature (Bricknell et al., 2006; Groner et al., 2016; Heuch et al., 2009). Adult female lice represent the most significant risk to salmonid welfare, as an abundance of adult female lice will result in an exponential increase in the release of new eggs and further intensify infestation severity (Helgesen & Kristoffersen, 2018). Sea lice host responses are primarily reduced appetite and growth. Also, hosts experience increased susceptibility to secondary infections of viral or bacterial diseases as a cause of external wounds, as well as increased stress and reduced vitality (Abolofia, Asche, & Wilen, 2017; Dill et al., 2009). Sea lice infestations are rarely observed to induce host mortality, but secondary health impacts resulting from infestation may increase mortality (Pike & Wadsworth, 1999).

The socio-economic impact of sea lice is, as previously mentioned, commonly divided into two groups: Negative externalities and the private economic cost for fish farmers. The private economic costs for fish farmers are further divided into direct and indirect costs. Direct costs comprise cost related to lice mitigation, prevention, and monitoring, while indirect costs represent the costs inflicted by sea lice in the form of reduced biological growth rates and increased mortality. As the problems surrounding sea lice have risen in recent decades, multiple studies have examined the negative externalities of salmonid aquaculture (e.g., the influence of increased infection pressure on wild salmon stocks and chemical pollution from lice treatments) and the direct costs for salmon farmers. The Norwegian research institute Nofima has published two reports focusing on the direct costs associated with sea lice, and report a total yearly industry cost of 3 billion NOK in 2015 and 4.5 billion NOK in 2017 (Iversen et al., 2015; Iversen et al., 2017).

Few efforts to quantify the indirect costs associated with sea lice have been made, but a study by Abolofia et al. (2017) estimates the total cost (indirect and direct) of lice by utilizing an econometric panel data model which estimates the effects of lice and lice mitigation efforts on biological growth rate. This study is the first of its kind to use a rich data set and present an empirical study incorporating the indirect economic losses caused by sea lice in Norway. Through this research, a total yearly cost of 2.564 billion NOK in 2011 is reported, which is equivalent to 3.040 billion NOK in 2019 (Abolofia et al., 2017). A similar study by Costello (2009a) estimated an industry-wide cost of 1.058 billion NOK in 2006, which equates to 1.390 billion NOK in 2019.

It is expected that the total cost of lice has increased significantly considering the recent escalation in problems related to sea lice, particularly from 2014 to 2016. Also, estimates by Abolofia et al. (2017) are based on a data set from 2005-2011. The aquaculture industry has undergone substantial changes to lice mitigation efforts, government regulation, and production inputs (e.g., production cycle length, feed quality and infrastructure) since then. This provides motivation to produce new and updated estimates for the private cost of lice using a more recent data set, better reflecting the current industry situation.

All animal protein production processes are affected by challenges related to parasites. A comparison between the economic impact of sea lice and parasitic challenges in other animal protein production indicates that the severity of sea lice infestations is unparalleled. Kumar et al. (2013) assert that parasitic diseases inflict large economic losses on the livestock industry and adversely affect animal welfare. The total cost of parasites in Australian beef production is

reported to be AUS\$348.3 million annually (Meat & Livestock Australia, 2015). In the poultry industry, the economic impacts of coccidiosis are estimated to be 4.54% of gross revenues (Williams, 1999). The economic impact of parasitic disease in beef and poultry production is of minor significance when compared to recent estimates of the cost of sea lice, especially considering the relative size and production value of these industries.

### 3. Theory and Background

In this chapter, we will provide some background as to why it is important to quantify the economic effects of sea lice infestations in salmonid aquaculture. First, we describe the development of the salmonid farming industry, comparing its expansion to other seafood industries such as fisheries. Then, we present the production process for farmed Atlantic salmon, examine key factors affecting salmonid production and present the general cost structure for salmonid farmers. Next, we provide an overview of the biology and life cycle of parasitic sea lice. Finally, the most common sea lice mitigation efforts and treatments are described in detail, along with their associated costs.

#### 3.1 Salmonid Aquaculture Industry

The global production of aquaculture and capture is a large-scale industry totaling over 200 million tonnes of harvested volume in 2016. Historically, capture fisheries have been the primary source of harvested fish volumes, accounting for 90% of supply in 1978. The aquaculture industry has grown significantly over the past 40 years and managed to surpass the output volumes from capture fisheries for the first time in 2013, illustrated in Figure 3-1 (FAO, 2019b).

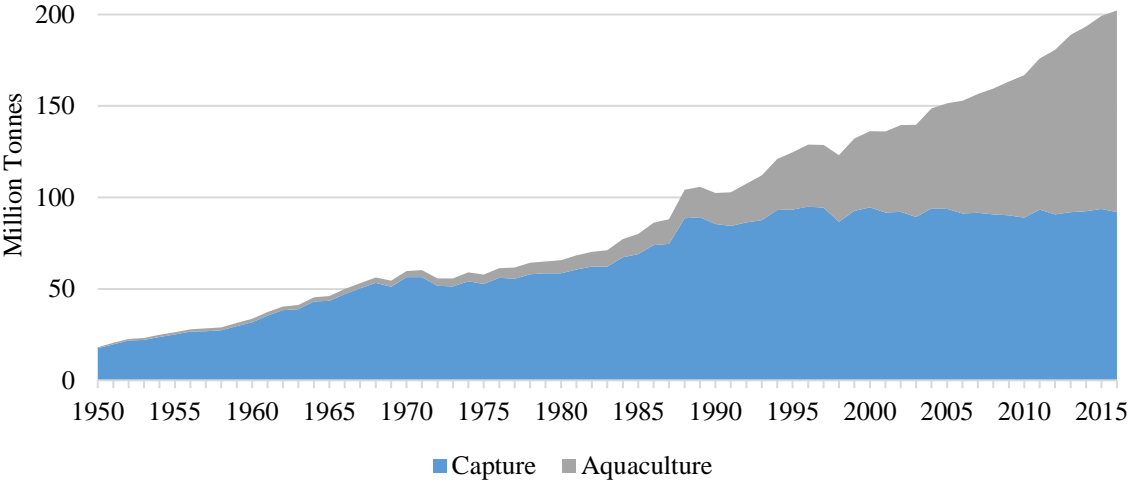


Figure 3-1: Total Global Production of Aquaculture and Capture from 1950 to 2016. Source: (FAO, 2019a, 2019b)

Salmonid aquaculture is a worldwide industry with approximately 3.3 million tonnes of whole fish equivalent (WFE) harvested in 2016. Norway and Chile are the two largest contributors to farmed fish volumes from salmonid aquaculture. In addition, wild salmonid capture varies between 0.8 and 1.0 million tonnes harvested each year. As illustrated by Figure 3-2, Norway

is the largest producer of farmed salmonids; others include Chile, Scotland, Faroe Islands, and Canada. Salmonid aquaculture only comprises a small fraction of the total production volume. In 2016, farmed salmonid accounted for 3% of the entire global aquaculture production volume, and the industry accounted for 7.9% of the total value generated from aquaculture (FAO, 2019a).

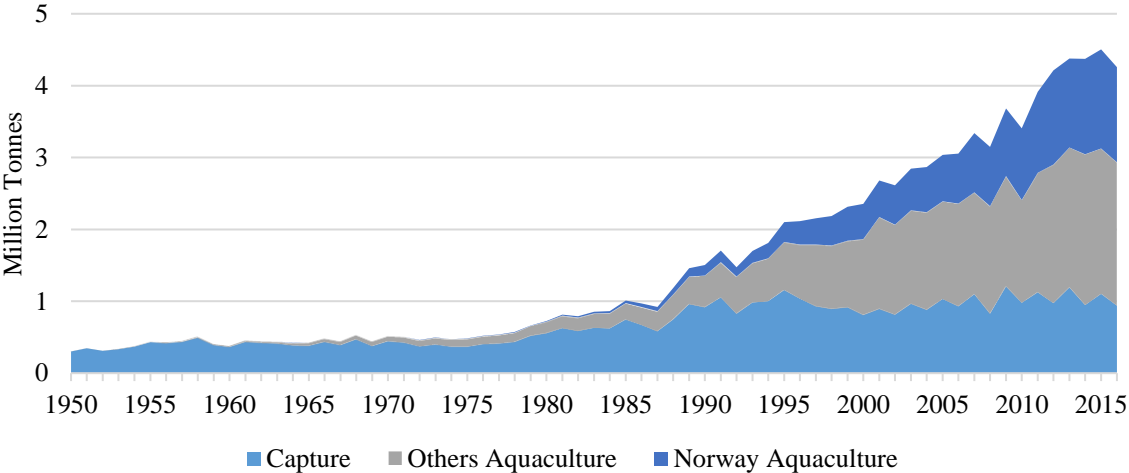


Figure 3-2: Global Salmonid Production from Aquaculture and Capture from 1950 to 2016. Source: (FAO, 2019a, 2019b)

The common salmonids that are being farmed globally are Atlantic salmon, small trout, large trout, Coho and Chinook. Atlantic salmon is the most abundant species by quantity, but due to biological constraints, seawater temperature, salinity levels, and other natural constraints, the production of farmed salmonids is limited to a few regions. Salmonids are cold-blooded animals (ectotherm); thus, they depend on ambient temperature to regulate their body temperature. The optimal temperature for Atlantic salmon aquaculture ranges from 8 to 14 degrees Celsius, as can be viewed on the red-shaded area in Figure 3-3. This figure also depicts the average monthly seawater temperatures in five different countries/regions, indicating the ideal locations for salmonid farming.



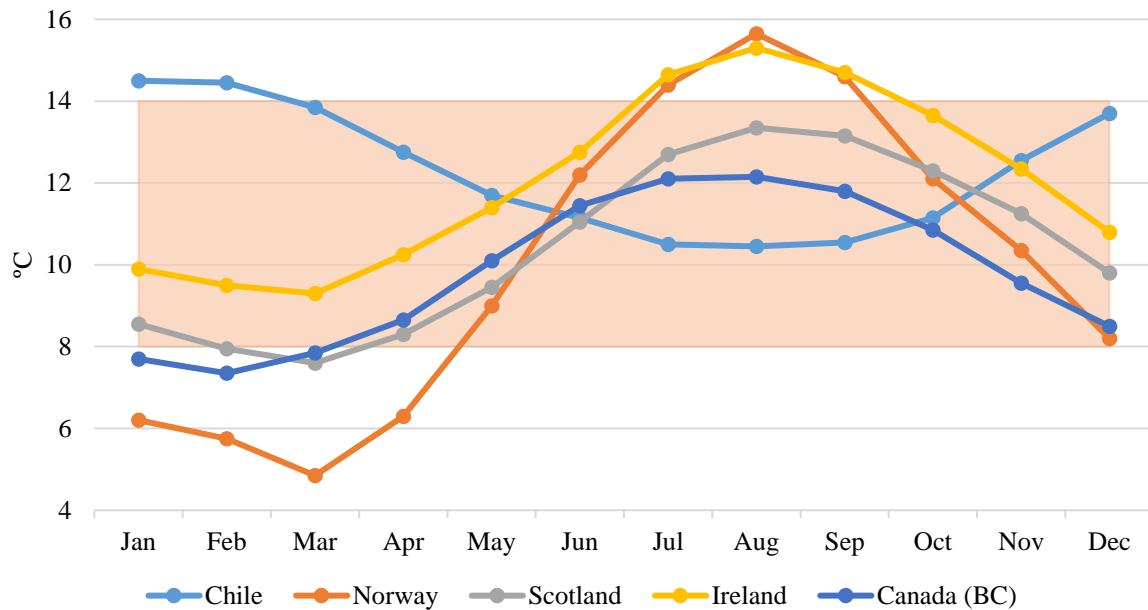


Figure 3-3: Average Monthly Sea Water Temperatures (°C) for Selected Countries with the Optimal Temperature Range for Salmonid Aquaculture. Source: (Marine Harvest, 2018b; World Sea Temperature, 2019)

The initial efforts to culture Atlantic salmon began in 19<sup>th</sup> century UK in freshwater with the intention of stocking waters with parr to improve wild returns for anglers. Norway was the first country to utilize sea cages to raise Atlantic salmon to a marketable size in the early 1970s. The success in Norway encouraged the development of salmon farming in Scotland, Ireland, the Faroe Islands, Canada, Chile, and Tasmania. Due to the inherent biology of the salmon, major production areas are located within latitudes 40-70° in the Northern Hemisphere, and 40-50° in the Southern Hemisphere (Towers, 2010).

The Norwegian salmonid farming industry was a great success due to exceptional conditions such as favorable hydrographic environment (stable salinity levels and temperature), excellent availability of deep sheltered sites, natural salmon strains with late maturity, and heavy governmental investment and support. The Norwegian salmon strain has been widely used for crossbreeding with other native salmonid cultures. This has been done mainly to increase the time to maturity, which results in an increased value of the fish as they reach marketable size. Thus, hybrid strains are now common in most production areas (Towers, 2010).

The Norwegian salmonid industry began to face many challenges by the end of the 1980s, after having had a steady growth during the 1970s and early 1980s (Vedeler, 2017). Falling salmon prices occurred as a result of increased international competition and rapid growth in production (Aarset & Jakobsen, 2004; Towers, 2010). In 1996, the authorities enforced feed-quotas which effectively set a restriction on the amount of feed that may be used for one permit in a year.

This led to slower growth of the industry, which is apparent as the annual Norwegian production of salmon almost tripled from 1992 to 1997, but only increased by 13% from 1999 to 2002 (Aarset & Jakobsen, 2004). In the period from 2002 to 2011, the production increased by 30%, which resulted in a significant price reduction in 2012. The Maximum Allowed Biomass (MAB) replaced the feed-quota system in 2005, which sets a limit on the volume of fish a company can hold at sea at all times.

In 2018, Norway harvested 1.3 million tonnes of farmed salmonids, in which Atlantic salmon accounted for 95% of the volume as illustrated in Figure 3-4. This is a significant increase in comparison to the production of 8,000 tonnes in 1980. Today, the aquaculture industry is experiencing a stagnation in growth, primarily due to the increased presence of sea lice (Norsk Industri, 2017). The aquaculture industry is looking to embrace new technology and treatment options in an attempt to tackle the lice problem and resume growth to reach the government’s goal of 5 million tonnes of production by 2050. Among the potential solutions are offshore- and land-based fish farming, and utilization of mechanical treatments and cleaner fish (SalMar, 2017; Thomsen, 2019; Tvette, 2016).

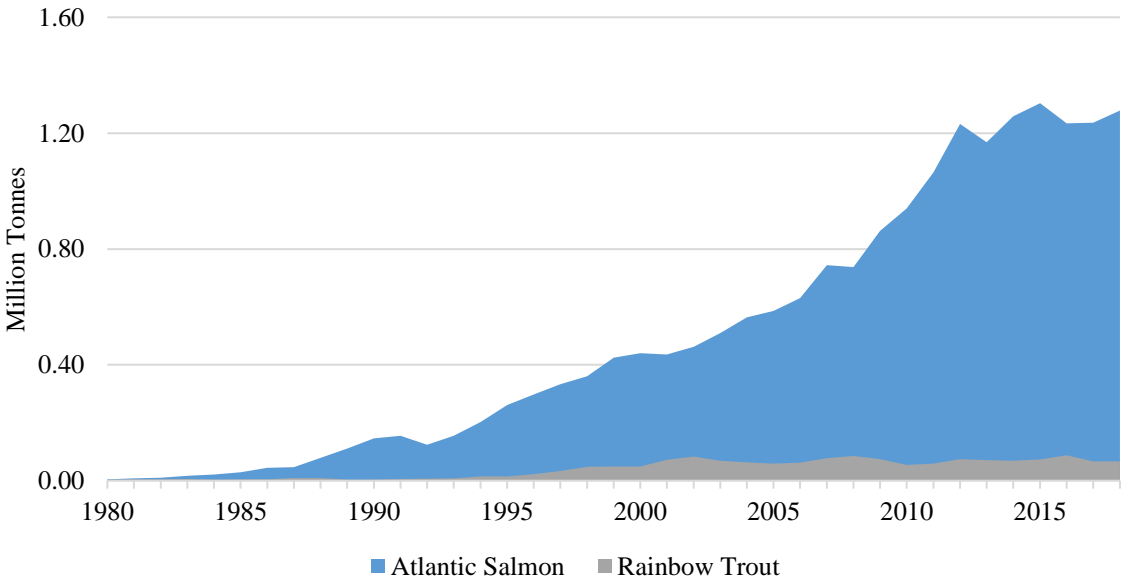


Figure 3-4: Norwegian Production of Atlantic Salmon and Rainbow Trout from 1980 to 2018. Source: (FAO, 2019a; Norwegian Directorate of Fisheries, 2019)

The global demand for salmon has and is expected to grow rapidly. Several factors contribute to this. First, the global population is growing, resulting in an overall increased global demand for food. Also, as more people in the developing world make the leap from poverty into the middle class, the demand for high-quality protein is expected to increase further (EY, 2017).

Finally, the health benefits and higher resource efficiency of salmon compared to other animal protein sources is increasingly being promoted by global health authorities (Marine Harvest, 2018b).

At this point, it is not certain whether the suppliers of salmon will be able to obtain the required growth opportunities to meet future demands. Salmonid fisheries are almost fully exploited, with heavy government regulations limiting industry growth. The supply of farmed salmon has limited potential to grow unless sustainable solutions to current problems are discovered (Marine Harvest, 2018b).

### **3.2 Production Cycle of Salmonids**

Salmonids are anadromous fish, which means that they spawn, hatch, and have their first growth stage in freshwater before they eventually migrate to seawater. The transformation process of the juveniles before they migrate is called smoltification. Wild salmonids will return to the same river where they were born to spawn at 1-4 years of age (Vøllestad, 2018). The production cycle of farmed salmonids mimics that of wild salmonids and lasts for 2-3 years from fertilization to harvest. The biological process from egg to farmed fish consists of four steps: Production of broodstock and roe, production of fry, production of smolts, and production of farmed fish (Asche & Bjørndal, 2011). The following section describes each step in more detail.

#### **Production of Broodstock and Roe**

Eggs are stripped from the female, fertilized and transported to a hatchery where they are incubated for two months until the yolk-sack larvae are hatched. Today, eggs come from a broodstock which has been domesticated over time. Norway has systematically been breeding salmon since 1972 (Asche & Bjørndal, 2011).

#### **Production of Fry**

After hatching, the larvae feed on the contents of the yolk-sack for a few weeks before initial feeding is started. This transition is considered one of the most delicate stages of salmonid production and is often associated with high mortality rates. As the fry reach a weight of about 5 grams, they start to take on the distinct characteristics of a salmonid (Asche & Bjørndal, 2011).

#### **Production of Smolt**

When the fry has grown to an approximate weight of 100-150 grams, the process of smoltification takes place. In this process, the fry are adapted to saltwater and are prepared for

seawater transfer (Marine Harvest, 2018b). In the wild, Atlantic salmon smoltify 16 months after being hatched. Through breeding, the industry has developed smolts that grow more rapidly to better utilize hatchery capacity. Because of the faster growth, smolts can be released into sea pens after only eight months in the hatchery. Since the hatching of larvae typically is done in January, smolts are now being released as early as September the same year, and as late as May the following year (Asche & Bjørndal, 2011). In Norway, salmonids are typically released in sea pens during two distinct periods each year; fall release (Aug. – Oct.) and spring release (Apr. – May). This creates two separate seawater production cycles (fall and spring release) with different durations, growth patterns, harvesting weights, temperature variations, lice infection levels and treatment patterns (Abolofia et al., 2017). This has resulted in a smoother production cycle and supply as there are always at least two cohorts of salmonids in the sea.

### **Production of Farmed Fish**

After the smoltification process, the smolt is released into seawater cages where it is grown to a marketable size before harvest. The average weight at harvest is generally between four and five kilograms (Marine Harvest, 2018b). The duration of the seawater grow-out stage varies between 12 and 24 months and is primarily determined by the time of release. The fall release cycles last 16 months on average, while the spring release cycles last 20 months on average (Abolofia et al., 2017). There are many factors influencing the production cycle duration, with the most important ones being diseases, parasitic infections, average fish weight, and smolt availability. After a location is harvested, the fish is transported to a processing facility for slaughtering and gutting. Most of the salmon is then sold whole by weight (GWE). After harvesting, the respective location is fallowed between two and six months. This results in a two-year cycle of smolt release at each site, although many locations contain several different cohorts at once (Marine Harvest, 2018b). The production of farmed fish in sea pens is what is normally thought of as salmonid aquaculture. This part of the production cycle takes the most time and is where most market-relevant decisions are made (Asche & Bjørndal, 2011). Sea lice only affect salmonids during the seawater grow-out phase; therefore, the predominant focus of this paper is on this part of the production cycle.

### **3.3 Key Factors Influencing Salmonid Production**

In the following section, we introduce the most important factors influencing the production process of salmonids in the grow-out stage.

#### **Fish Growth**

Fish growth is an important factor related to salmonid production. Fish growth directly influences revenues, and a lower growth rate will either result in a longer production process duration or lower average fish weight at harvest. Important factors that affect fish growth can be divided into abiotic and biotic factors. Abiotic factors refer to the non-living parts of the environment that affects an ecosystem. Time, light, and temperature are the most important abiotic factors concerning salmonid aquaculture (Aunsmo et al., 2014). Abiotic factors cannot be controlled for in traditional salmonid aquaculture since the fish is held in open sea pens subjected to natural variations in these factors. Biotic factors are related to the living organisms of an ecosystem. This includes diseases, parasites, and the fish itself. Sea lice abundance is an important biotic factor that inhibits fish growth (Abolofia et al., 2017).

The influence of sea lice on fish growth is discussed extensively throughout this thesis. Several companies in the industry have on-going projects developing closed systems (on- and off-shore) where abiotic and biotic factors to a larger extent can be controlled. This would allow for the optimization of fish growth and the elimination of disease and sea lice infection risk. Another effort to optimize fish growth is the systematic breeding of salmonids. Through breeding, the efficiency of salmonid production has increased immensely. According to Gjedrem (1993), important factors dictating breeding include growth rate, feed use, sexual maturation, meat quality, and resistance to diseases and parasites.

#### **Government Regulation**

The majority of salmonid producing nations around the world have adopted production controlling regimes that limit either standing biomass and/or density of a farming site. In Norway, the Aquaculture Act (2005) and the Food Safety Act (2003) are the most important laws regulating salmonid aquaculture. Production limitations are regulated as “maximum allowed biomass” (MAB), which is defined as the maximum volume of fish that can be held at any time. One license typically has a MAB of 780 tonnes (945 tonnes in the counties of Troms and Finnmark). The sum of the MAB for each license held in a specific production region specifies the given company’s total allowed biomass in this region. Generally, individual sites have a MAB between 2,340 and 4,680 tonnes (Marine Harvest, 2018b).

In 2013, new regulations regarding sea lice abundance were implemented. These regulations require that every individual farming location reports the average lice count for their facility every week at water temperatures above four degrees Celsius and every other week at temperatures below four degrees Celsius. The upper limit for the average number of adult female lice is set to 0.5 adult female lice per fish during most of the year. In the late spring and early summer, when wild salmonid smolt migrates from freshwater to seawater, the upper lice limit is set to 0.2 adult female lice per fish. Due to weather and climate differences, the time of smolt migration is slightly delayed in the northern part of the country. Therefore, the lice limits vary based on geographical location. Figure 3-5 presents the lice limits for the different counties of Norway. When the lice limit is 0.5 lice per fish farmers are required to count the lice of at least ten fish from each net pen and then report the average number of lice per fish. In periods where the lice limits are 0.2 lice per fish, a minimum of 20 fish must be counted from each net pen. Even though the lice limit only concerns the number of adult female lice, it is also required to count the other mobile lice and attached lice (Forskrift om lakselusbekjempelse, 2012). The different stages of lice development and the life cycle are described in more detail in section 3.5.

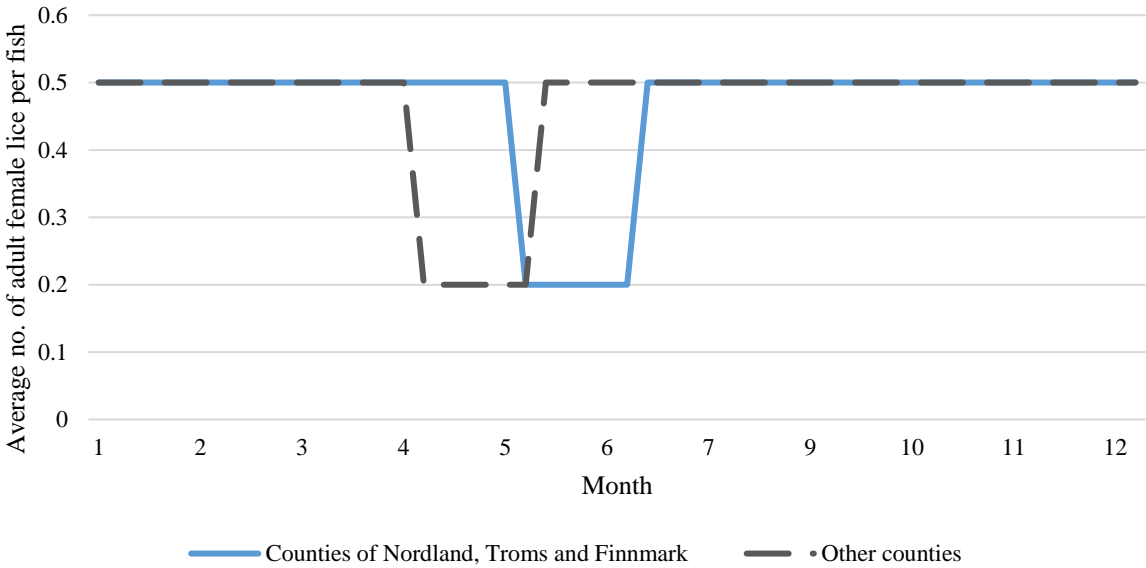


Figure 3-5: Lice Limits throughout the Year for Norwegian Salmonid Farmers. Source: (Forskrift om lakselusbekjempelse, 2012)

In 2017, the Norwegian coast was divided into 13 geographical production regions. Each region is also assigned an indicator for sea lice levels, which determine whether the total MAB for each region should increase, stay the same, or decrease. Figure 3-6 presents a map showing the different production regions and their associated traffic light classification as of May 2019. Regions classified as green will have their total MAB increased by two percent each year, while red regions will suffer penalties by having their total MAB reduced. In yellow regions, the total MAB will stay constant and have the lice situation closely monitored. In addition to these geographical classifications, individual farms are awarded a six percent increase in total MAB if average lice levels are below 0.1 lice per fish (Norwegian Directorate of Fisheries, 2018c). These regulations provide an incentive for fish farmers to keep lice levels low, as their opportunities to grow depends on it.

In addition to the above regulations, salmon farmers also must perform sediment tests to determine the biological impact of the farm on the local ecosystem. These tests are called B- or C- tests. B-tests are performed near the immediate vicinity of the farm at set intervals, and results are reported to the Norwegian Directorate of Fisheries. C-tests, on the other hand, measure trends in the biological impact on the local ecosystem. Both B- and C- tests measure sediment composition (grain size, total organic carbon, and amount of heavy metals) and water quality (salinity, oxygen saturation, and temperature). Based on the results from these investigations, each farm receives a classification which determines the biological state of the farm and the interval between successive tests (Norwegian Directorate of Fisheries, 2018a).

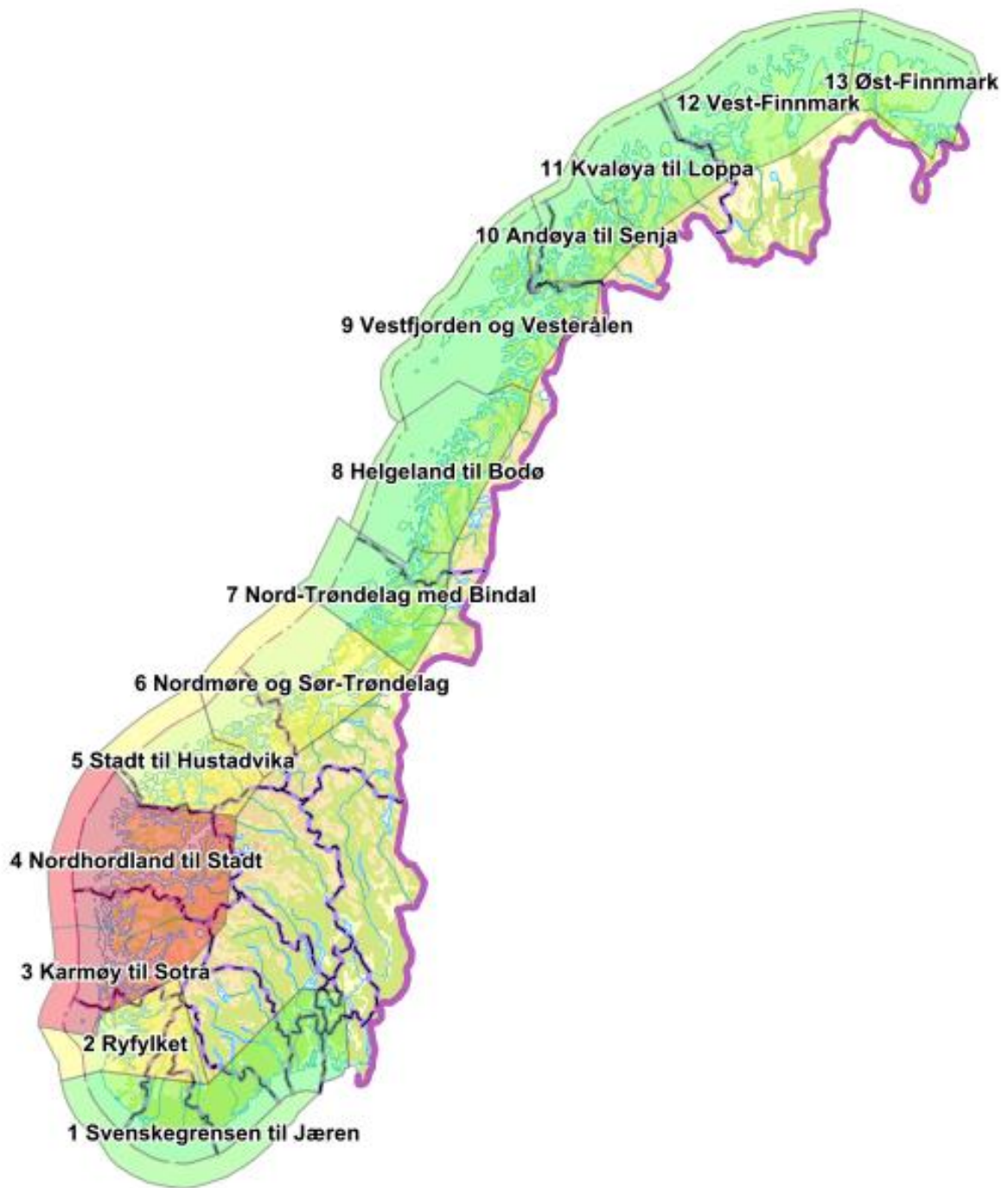


Figure 3-6: Norwegian Production Regions and Their Associated Traffic Light Classification as of May 2019. Source: (Norwegian Directorate of Fisheries, 2019)



**Feed**

The effectiveness of animal production is typically measured by the feed conversion ratio (FCR) of the operation. The FCR is the ratio between feed input and product output, usually measured as the amount of feed (kg) required to increase output by one unit (kg). Salmonid aquaculture is one of the most effective farming operations compared to other important protein sources such as beef, pork, and poultry (Marine Harvest, 2018b). A wide variety of feed types are available for salmonid farmers, each with different cost, pellet size and proportions of nutrients. Fish feed producers typically offer different feeds for each specific stage of the production cycle, as well as medical feeds, which are used to combat diseases and parasitic infections (Skretting, 2015).

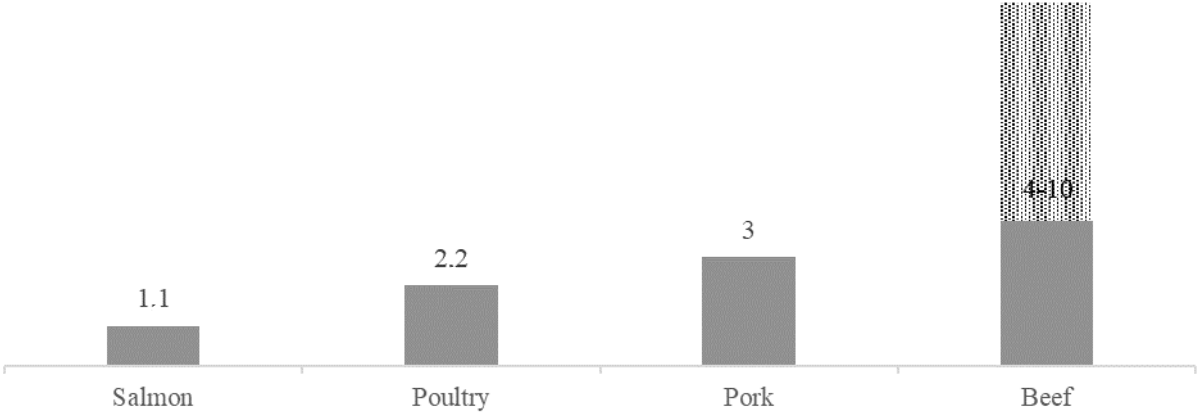


Figure 3-7: Feed Conversion Ratio for Selected Animal Protein Sources. Source: (Marine Harvest, 2018b)

### 3.4 Salmonid Aquaculture Cost Structure

Later in this paper, cost inputs are used to estimate the economic losses associated with sea lice in the Norwegian aquaculture industry. Therefore, it is useful to provide an overview of the industry's cost structure and terminology used later in this thesis. Iversen et al. (2015) have previously grouped production costs of salmon aquaculture into seven categories: Smolt costs, feed costs, labor costs, insurance costs, other operating costs, harvest costs, and well-boat costs, in addition to costs associated with yield loss.

Figure 3-8 illustrates the yearly salmon price and total production cost from 2012 to 2017. The production cost has gradually increased over the period from 25.93 NOK/kg in 2012 to 35.53 NOK/kg in 2017, which is equivalent to a 37% increase. The salmon price has had significant growth in the period from 27.02 NOK/kg in 2012 to 52.82 NOK/kg in 2017, which is a 95% increase. One factor contributing to the large spike in salmon price from 2015 to 2016 is the algae bloom crisis which occurred in Chile in early 2016.

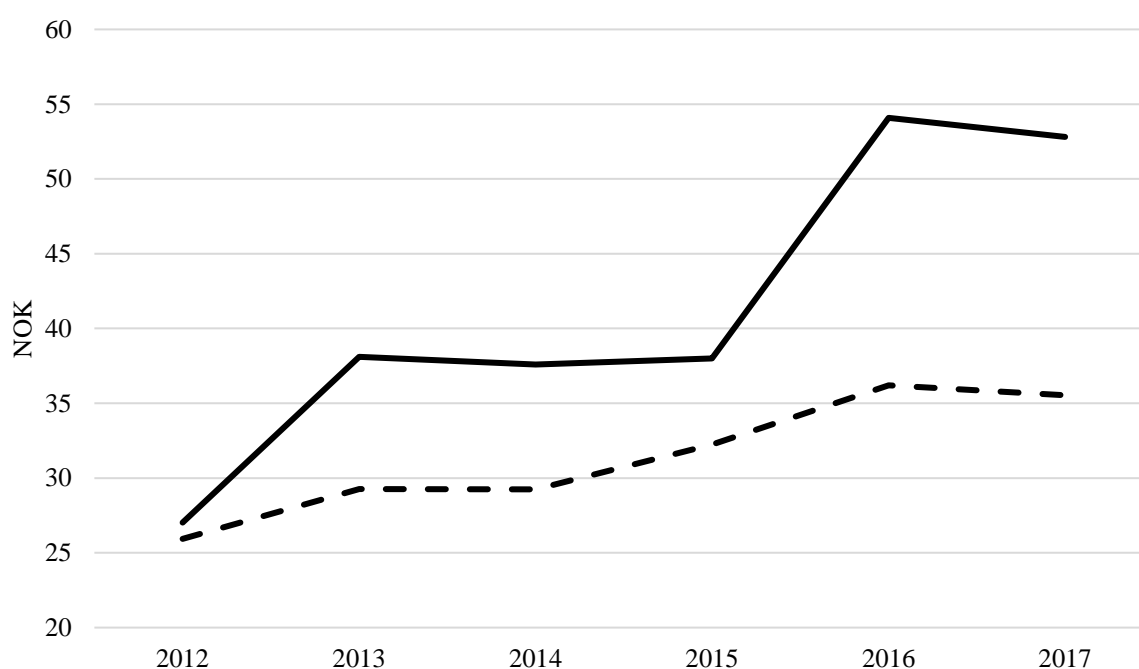


Figure 3-8: Yearly Salmon Price (solid) and Total Production Cost (dashed) per kg from 2012 to 2017. Source: (Norwegian Directorate of Fisheries, 2018b)

Note: Numbers are inflation-adjusted for 2019.

### **Smolt Cost**

Smolt costs vary based on several factors dependent on its production process. Key factors are the smolt size (which affects the accumulated feed costs), the efficiency of the hatchery (energy consumption and production duration) and transportation. Larger smolt will have a higher cost but are more resilient to external factors such as lice, disease, and temperature when released into net pens (Iversen et al., 2015).

### **Feed Cost**

Feed cost is the largest cost factor; hence, it greatly impacts the cost structure of salmonid farmers. The main two factors influencing feed costs are feed price and feed conversion ratio. Feed costs have increased from 12.80 NOK/kg in 2012 to 15.10 NOK/kg in 2017 (Norwegian Directorate of Fisheries, 2018b). Since feed costs represent roughly 50% of the total production cost, profits will be relatively sensitive to increased feed prices (Marine Harvest, 2018b). Feed conversion ratio also varies based on external factors such as temperature, water quality, lice infection, and diseases.

### **Labor Cost**

Since the beginning of salmonid aquaculture, the requirements for labor have changed significantly. Rapid technological development has brought more automation and better control of important factors affecting efficiency. The need for workers to perform labor-intensive tasks has been reduced considerably (Asche & Bjørndal, 2011). Despite a two-fold increase in production volume from 2004 to 2012, the use of labor only increased by about ten percent (Henriksen, 2014). Henriksen (2014) also asserts that the use of labor in other industries connected to salmon aquaculture has seen significant growth. This indicates that labor-intensive activities at farming sites increasingly are outsourced to other companies, reducing the demand for labor in the industry, but increasing labor demand in supporting industries (e.g., companies specializing in lice treatments, well-boat services, and net pen maintenance).

### **Insurance Cost**

Several different types of insurance are available to salmonid farmers, some of them being algae blooms, biomass, and environmental pollution. Biomass insurance typically covers three types of potential losses: Theft, mortalities, and escapes (Vedeler, 2017). Insurance costs are relatively small compared to other production costs, but insurance payouts are important for the fish farmer, dictating implications of lice outbreaks. Insurance premiums are calculated monthly based on reported biomass, average weight, and other relevant factors.

**Other Operating Costs**

Other operating costs include maintenance of infrastructure and equipment, acquisition of new equipment and health costs. Direct costs associated with sea lice fall into this category as they are considered a health cost. Section 3.6 provides a detailed description of the components comprising direct costs of sea lice and sea lice mitigation efforts.

**Harvesting and Well Boat Transportation**

When harvesting the fish, well-boats are used to transport the fish from the sea pens to a slaughtering facility. Costs associated with transportation and slaughtering will depend on the specific firm’s capacity and transportation distance. In periods of full capacity, utilization firms often hire external well-boats or expand their processing capacity using external capital (Vedeler, 2017).

**Cost Breakdown**

Figure 3-9 gives an overview of the components of the yearly production costs, which is shown by the dashed line of Figure 3-8. The feed cost is by far the largest component, followed by other operating costs, smolt cost, harvesting and transportation costs, labor cost, and depreciation, respectively. Insurance cost is not included in Figure 3-9 as it is very small.

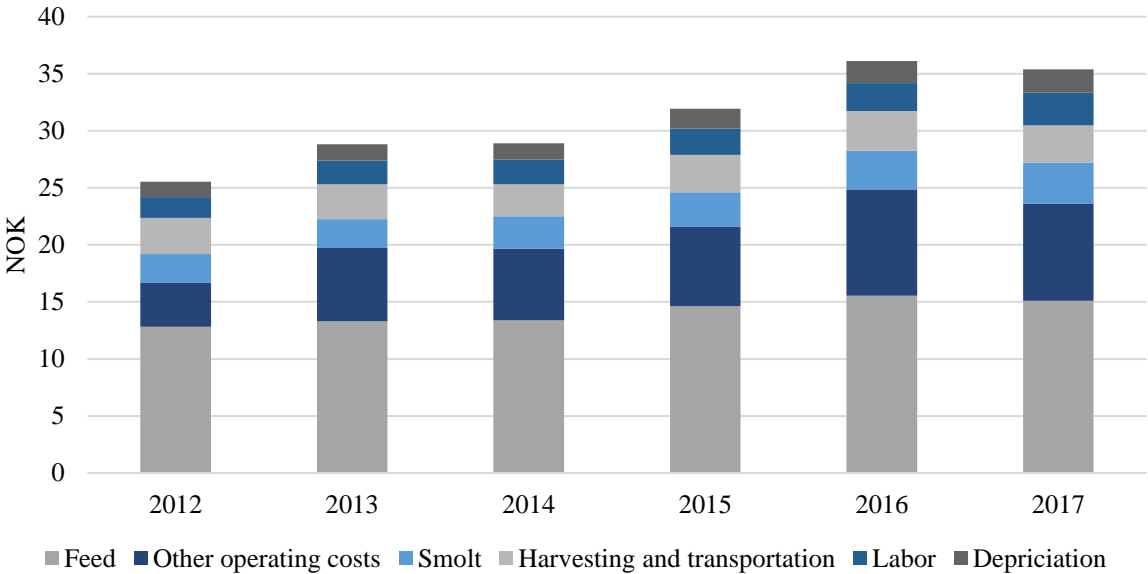


Figure 3-9: Breakdown of Yearly Total Production Cost Elements per kg Produced Fish from 2012 to 2017. Source: (Norwegian Directorate of Fisheries, 2018b)

## Yield Loss

For all production processes, there is some degree of yield loss. In the salmonid aquaculture industry, yield loss refers to the discrepancy between live fish weight (biomass) and marketable fish weight (gutted weight equivalent). Table 3-1 shows the typical yield loss for salmon in Norway. Since fish farmers sell most of their fish by gutted weight (GWE), the yield loss for the farmer is on average 16% (Marine Harvest, 2018b).

Table 3-1: Yield Loss for Salmonid Aquaculture Production. Source: (Marine Harvest, 2018b)

	Yield/ yield loss
Live fish	100%
Loss of blood/starvation	7%
Harvest weight / Round bled fish (WFE)	93%
Offal	9%
Gutted fish, approximate (GWT)	84%
Head, approximate	7%
Head off, gutted	77%
Fillet (skin on)	56 – 64%
C-trim (skin on)	60%
Fillet (skin off)	47 – 56%

## 3.5 Sea Lice

The parasite *Lepeophtheirus salmonis*, commonly known as sea- or salmon lice is one of the major challenges faced by the Norwegian salmonid aquaculture industry today. The parasite attaches to the skin of salmonids and feeds on their skin, blood, and mucus. Increased capacity and density of fish farms in later years have increased infection pressure, both on farmed and wild stocks.

### Sea Lice Life Cycle

Sea lice have simple life cycles that consist of ten separate stages: Three free-swimming, four parasitic, and three mobile stages illustrated in Figure 3-11. When the lice are in their free-swimming stages, they move with sea currents and are mostly only able to maneuver vertically in the sea. Thus, infection pressure is mainly influenced by sea current and wind conditions, as well as the positioning of the farms in relation to one another. In the parasitic stages, the lice can attach to a host. They do this using a prehensile antenna and maxillipeds, followed by a

more durable connection via frontal filament. After attaching to a host, the lice feed on the fish until they are fully developed and gain the ability to move about on the host. These fully-grown lice are commonly referred to as mobile lice. Mobile lice represent the largest threat to fish welfare because of their size and ability to reproduce. Adult female lice produce two egg strings that can contain up to 1000 eggs per string (Abolofia et al., 2017). The eggs are then released, and the lifecycle is completed. Consequently, adult female lice pose the greatest threat to increased infection levels. One adult female lice can produce 6-11 broods in its lifespan of about seven months (Costello, 2006).



*Figure 3-10: Adult Female Lice with Egg Strings (top), Adult Female Lice without Egg Strings (middle) and Pre-Adult Lice (bottom). Source: (Bjørkan, 2009)*

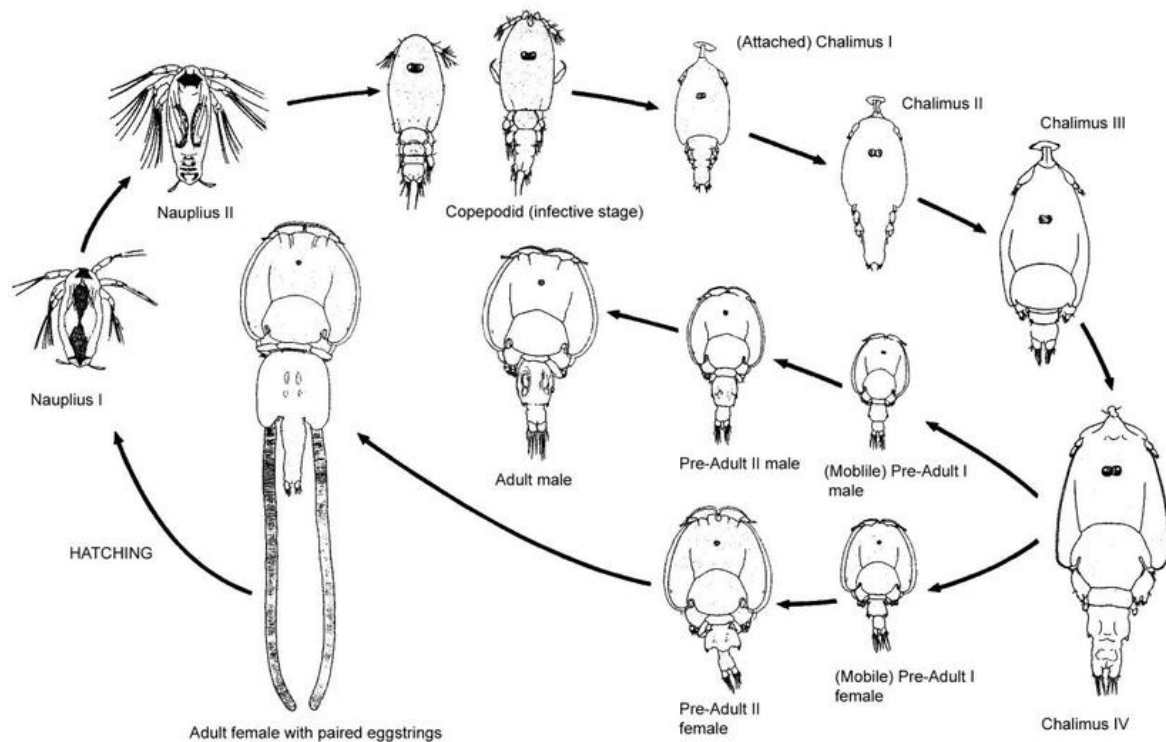


Figure 3-11: Sea Lice Life Cycle and the Different Growth Stages. Source: (Whelan, 2010)

The increased density of fish farms and increased density of fish in each farm contribute to increased infection rates. Several studies have shown that salinity and water temperature significantly affect lice development (Bricknell et al., 2006; Groner et al., 2016; Heuch et al., 2009); therefore, infection risk varies throughout the year. Warmer water temperatures decrease lice development time, increasing infection risk through increased release of lice eggs in the sea. Several common lice mitigation efforts take advantage of the parasite's inability to adapt to sudden changes in temperature or salinity. The most common lice mitigation efforts will be discussed in the following section.

### 3.6 Sea Lice Mitigation Efforts and Treatment Options

This section will cover the most current commercialized lice mitigation efforts, how mitigation preferences have changed in recent years, and give an overview of benefits and drawbacks for the different options. Cost estimates for the various treatment options are based on (Iversen et al., 2017). Figure 3-12 presents the prevalence of different mitigation efforts from 2012 through 2017.

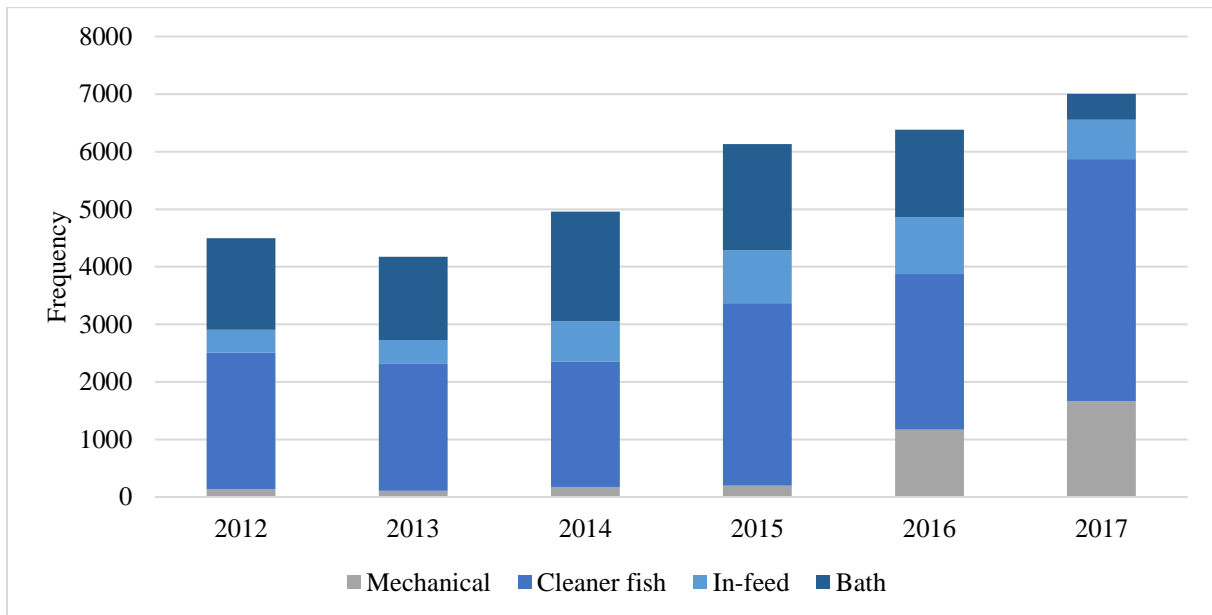


Figure 3-12: Prevalence of Lice Mitigation Efforts for 2012 -2017. Source: (BarentsWatch, 2019)

#### In-feed Treatment

For in-feed treatments, farmers use a specifically formulated feed which promotes optimum fish health. Such feeds contain ingredients that help salmon fight off sea lice in two key ways. First, the feed can help alter sea lice development and growth, reduce the fish's immune suppression caused by sea lice, as well as inhibiting sea lice ability to attach to fish. Secondly, they support natural fish defenses by strengthening the fish's external barriers through thickening protective mucus layers on their skin and boosting the immune and inflammatory responses of the fish (MSD Animal Health, 2012). Mortality rates associated with in-feed treatments are generally low. These treatments are typically administered as a preventive measure to reduce lice infection pressure and increase fish resilience. In-feed treatments are especially useful for younger, more fragile fish, where other mitigation efforts can cause high mortality rates. The fish is starved for about a week prior to and post-treatment, which will cause reduced growth and potential revenue loss. Besides the indirect cost of starving, in-feed treatment costs are low compared to other mitigation efforts and are determined by the



discrepancy between the cost of treatment feed and regular feed. Figure 3-13 [A] indicates that fish farmers tend to administer this type of treatment to the entire farm rather than treating individual net pens. Figure 3-13 [B] depicts the total number of treatments, as well as the use of different chemicals. The industry’s reports of severe lice outbreaks and costs related to lice in the period 2014-2016 is well reflected by both graphs.

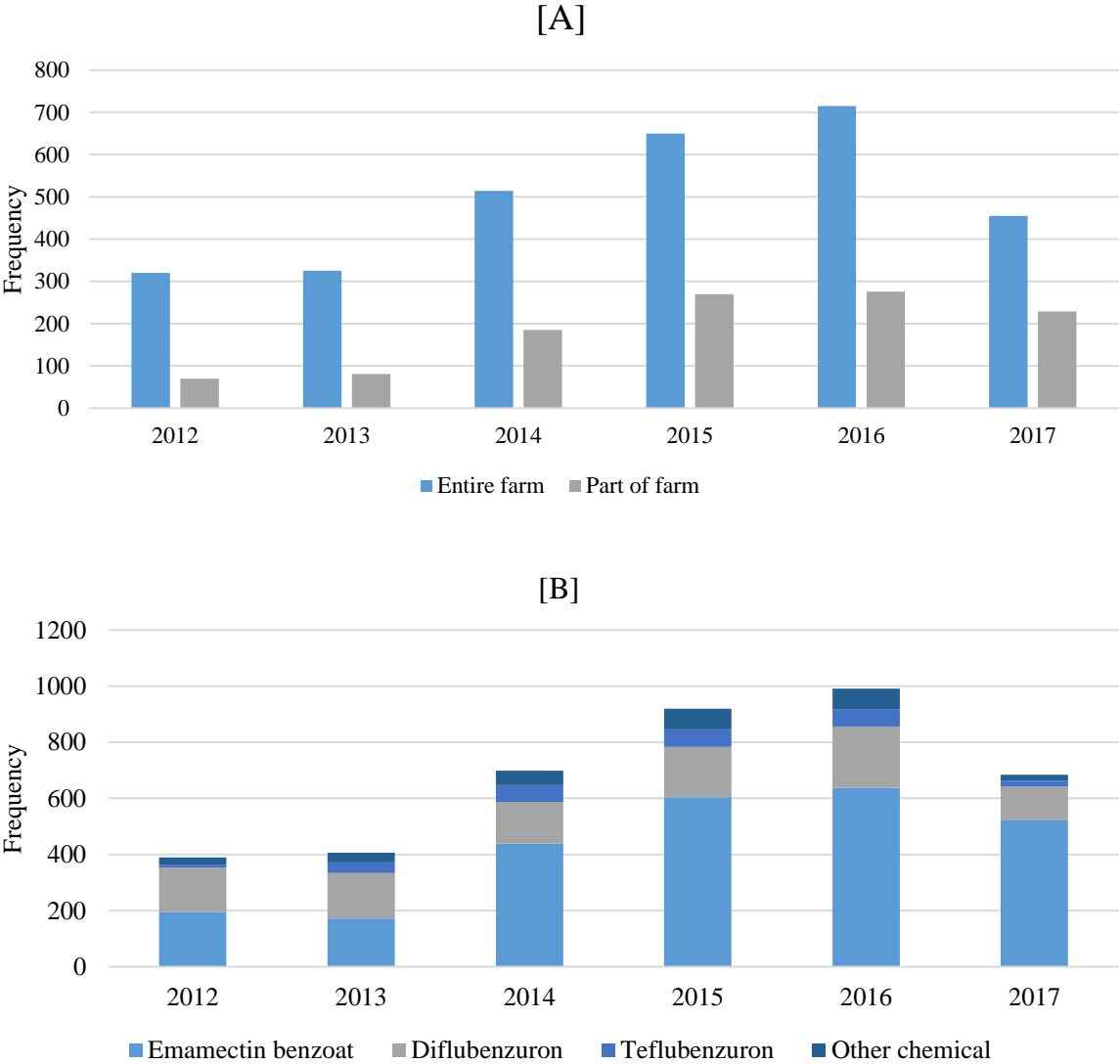


Figure 3-13: In-Feed Treatment Preferences for Scope of Treatment [A] and Chemical Use [B]. Source: (BarentsWatch, 2019)

## **Bath Treatment**

Bath treatments confine the fish to a closed system, either using a well-boat or a watertight tarp to enclose the sea pens. The desired chemical is then applied to kill off most of the lice (Lusedata, 2010). This type of treatment has seen a steep decline in recent years, which is caused by several factors. Most importantly, the sea lice have been observed to have an increased resistance towards treatment, reducing efficacy. Increased stress and mortality in fish stocks have also been reported after repeated treatments (Norwegian Food Safety Authority, 2016). In addition, bath treatments are also very resource-intensive, with high cost of labor, vessels, and chemicals. As mentioned before, the concerns of adverse spillover effects of bath treatments on surrounding ecosystems have been confirmed, further lowering the appeal of these types of treatments.

The efficiency of bath treatments varies based on the number of previous treatments and chemical concentration, among others. In this paper, we will distinguish between the use of hydrogen peroxide ( $H_2O_2$ ) and traditional chemicals (Azamethiphos, Deltamethrin, Cypermethrin) in bath treatments, as the cost and mortality rates are significantly different for the two; the mortality rates for hydrogen peroxide and traditional chemicals are 1% and 0.5%, respectively (Iversen et al., 2017). The decrease in these medical treatments in recent years suggests that these types of treatments are used more as an emergency measure when sea lice levels reach critical levels to avoid forced harvest or high mortalities. Figure 3-14 [A] indicates that bath treatments often are performed on individual net pens to immediately relieve lice infection pressure and reduce the risk of infecting nearby pens or farms. Both figures show the abrupt decline in frequency from 2016 to 2017. Figure 3-14 [B] also shows a clear increase in the use of hydrogen peroxide in the period from 2014 to 2016.

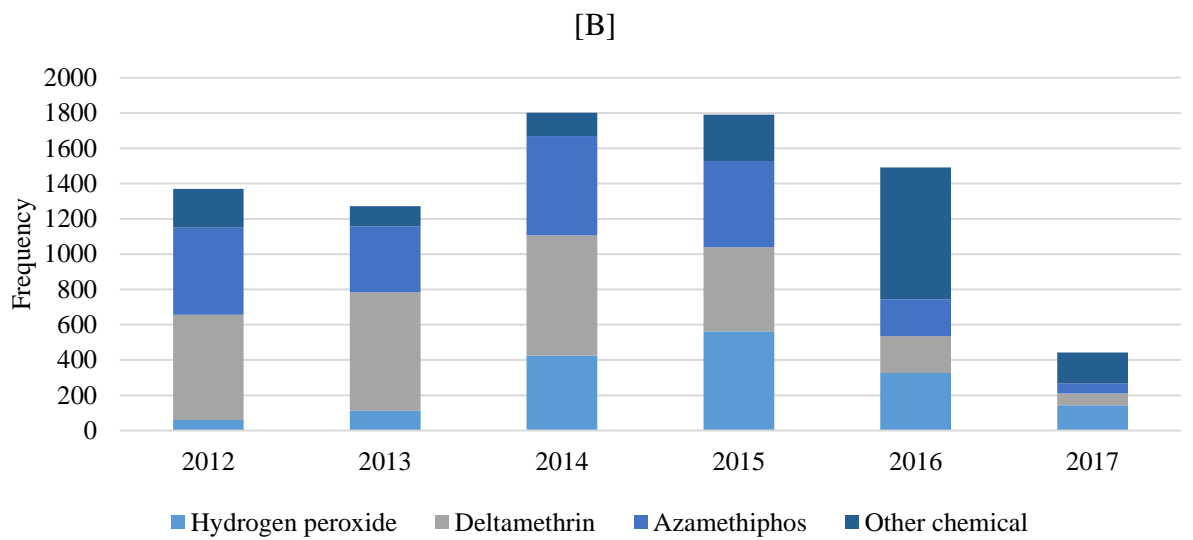
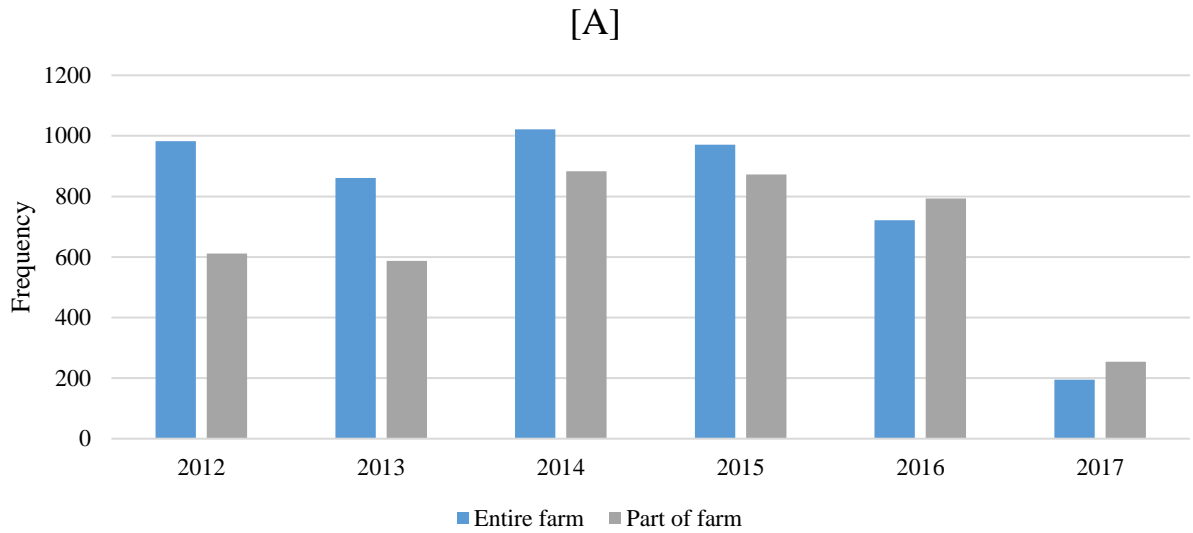


Figure 3-14: Bath Treatment Preferences for Scope of Treatment [A] and Chemical Use [B]. Source: (BarentsWatch, 2019)

## **Mechanical Treatment**

In recent years, mechanical delousing has emerged as a viable alternative to other treatment methods. There are many different options for mechanical lice removal, the most popular methods being thermal, pressure, and brush treatments. Even though the reported mortality rates for these types of delousing treatments are low, these numbers do not account for lost biomass growth and delayed mortalities due to higher stress levels from treatment. When the fish is subjected to mechanical delousing treatments it can trigger a strong flight-response. This induces higher stress levels and reduced overall fish welfare. In recent years, a new disease called cardiomyopathy syndrome (CMS) has emerged as a potential threat to fish welfare. CMS is a disease that weakens the fish's heart, making it more vulnerable to stress and physical strain. Although diseases are outside the scope of this thesis, it is vital to highlight the connection between CMS and mechanical lice treatments. Because of high stress levels and increased physical strain when mechanical lice treatments are used, these treatments act as a catalyst to trigger CMS-induced mortalities (Norwegian Veterinary Institute, 2013).

Thermal treatments use a specialized well-boat to pump the fish through a system containing tepid water, which will cause the lice to release from the fish (Gjerve et al., 2015). Gjerve et al. (2015) also state that the efficiency of thermal treatments using the Thermolicer® was between 75-100%, with an approximate 0.5% spike in mortality rates the week following treatment.

Pressure treatment systems such as the FLS-de-licing-system and the Hydrolicer use pressurized water (0.2- 0.8 bar) to force the lice to release from the fish. This process has shown the efficiency of about 89% (Fish Farmer Magazine, 2018) and a mortality rate of 0.25% (Iversen et al., 2017). Treatments using brushing to remove lice have a similar cost structure and process, which is why pressure and brush treatments are aggregated for the purpose of this thesis.

Figure 3-15 [A] highlight a preference in fish farmers to delouse individual net pens rather than the entire location. As mechanical delousing can be relatively labor-intensive, farmers often prioritize treatment of pens where lice levels are highest. Panel [B] of Figure 3-15 shows that the most prevalent mechanical delousing method is the use of thermal treatments, with pressure and freshwater treatments following. Several new treatment methods are in development at the time of writing and have not yet been commercialized. In section 7.3, some space is devoted to discussing a few of the most promising new treatments.

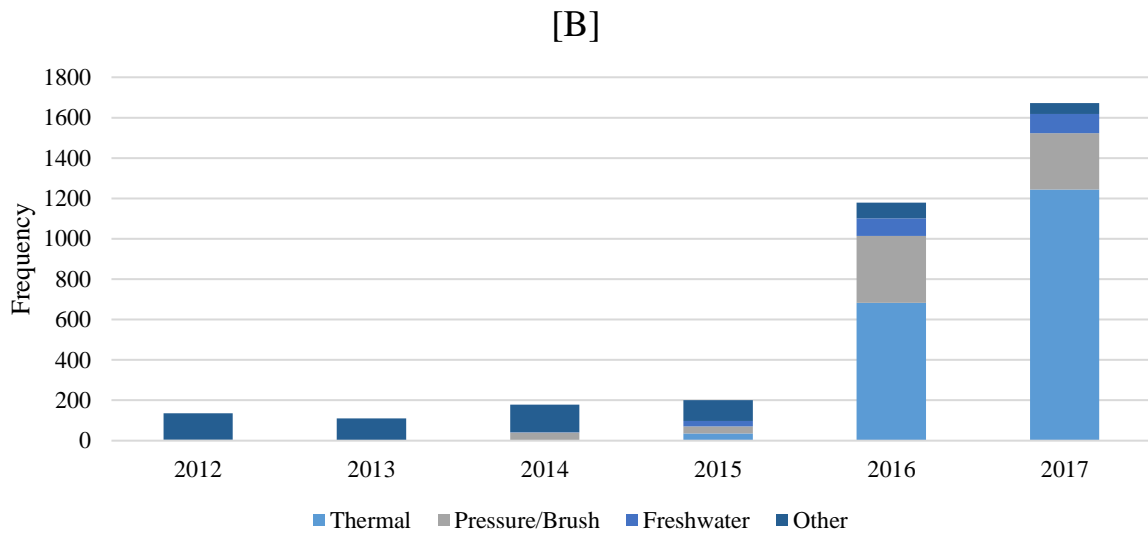
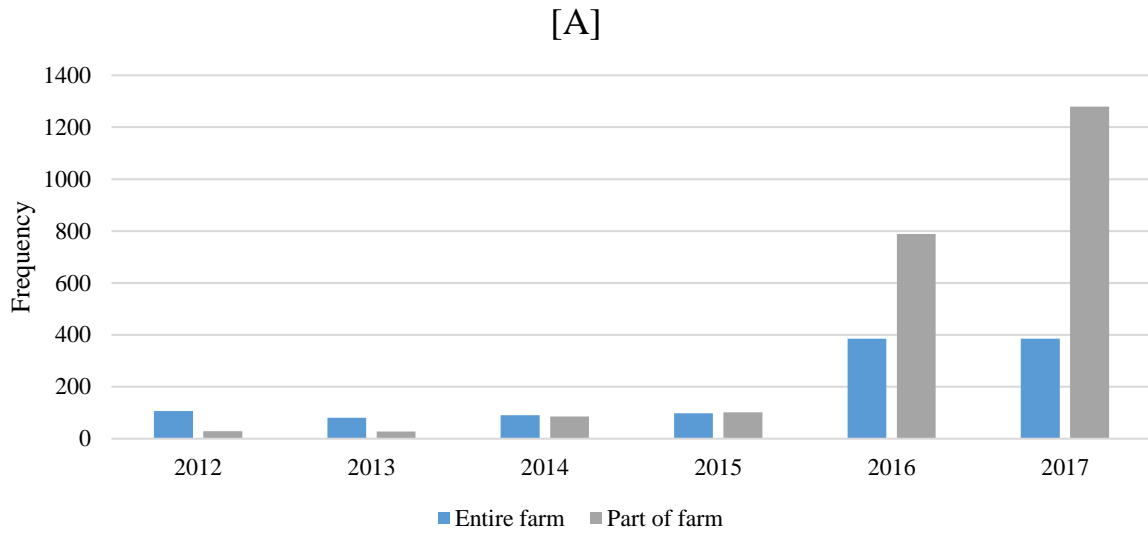


Figure 3-15: Mechanical Treatment Preferences for Scope of Treatment [A] and Treatment Method [B]. Source: (BarentsWatch, 2019; Norwegian Veterinary Institute, 2018)

## Cleaner Fish

Cleaner fish are fish of the “wrasse” family. They are typically released amongst the salmon in the net pens to feed on sea lice, thus keeping sea lice levels in control. The use of cleaner fish has increased in frequency in recent years, with companies reporting that as many as 78% of farming sites utilize cleaner fish to combat sea lice (Marine Harvest, 2018a). With the industry facing problems of chemical resistance and potentially fatal consequences associated with a major lice infection, cleaner fish have become a popular preventive method for keeping lice levels low. The efficiency of cleaner fish depends on factors such as temperature, access to other feed, overall wellbeing, and proportion of cleaner fish to salmonid individuals. The proportion of cleaner fish is typically between 5-15% (Misund, 2018). The cost characteristic of this treatment method is different from the others, as there is a significant maintenance cost associated with feeding and cleaning of the hiding spots which cleaner fish require to thrive in the sea pens. This makes an estimation of cleaner fish costs complicated. Cleaner fish are usually released from late July to late September and remain in the net pens until the salmon is slaughtered.

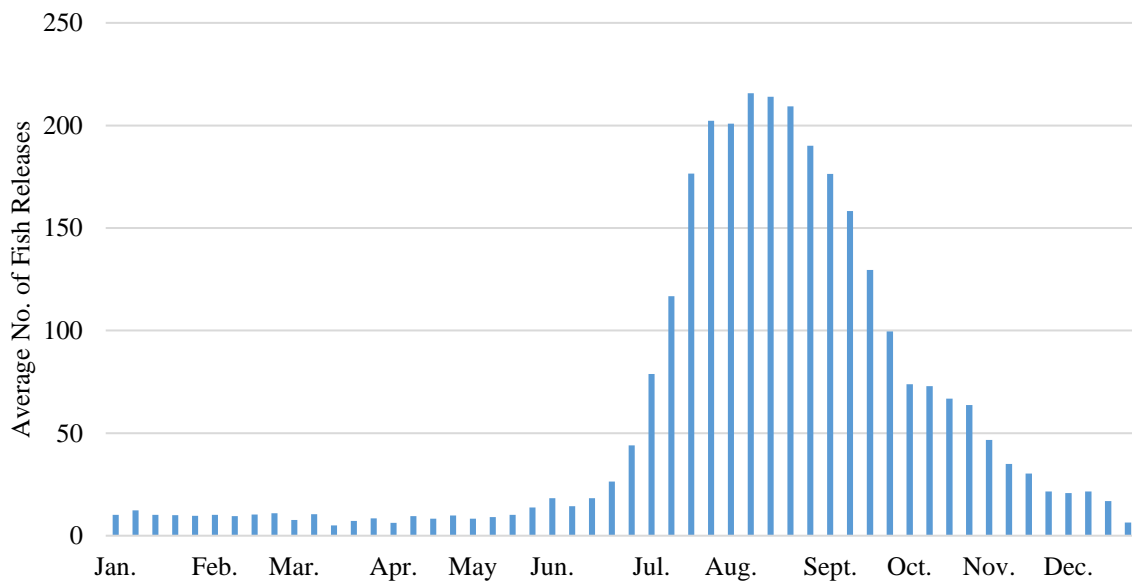


Figure 3-16: Frequency of Cleaner Fish Releases by Month. Source: (BarentsWatch, 2019)

### Lice Skirts and Special Net Pens

The main function of a lice skirt or special net pen is to restrict or stop lice from being able to enter the net pen. Sea lice are present only in depths less than 5 – 10 meters; these preventive methods take advantage of that. A lice skirt made of a special fabric is placed around the net pen in the top layer, and this fabric can either be water permeable or block water flow completely. A common feature of both types is that they prevent lice from passing through, thus reducing lice pressure (Iversen et al., 2015). Other types of special net pens work in the same manner by restricting water flow in the top layer of the net pen. Figure 3-17 illustrates (from left to right) how lice skirts, snorkel net pens, and submerged pens work.

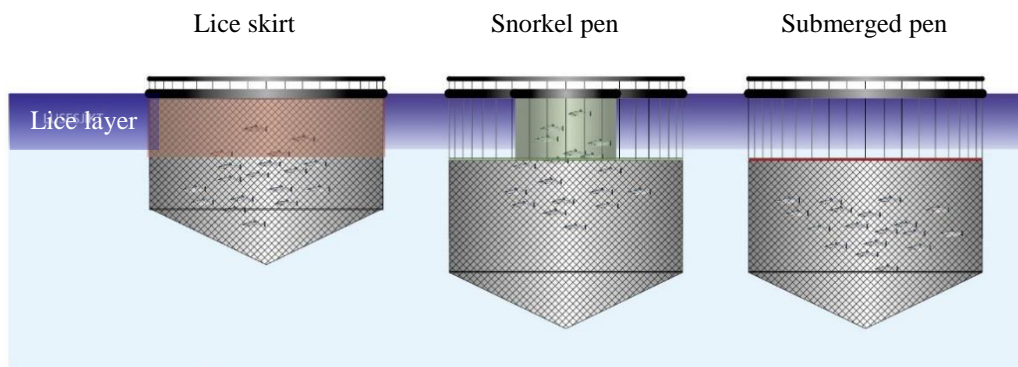


Figure 3-17: Illustration of Lice Skirts, Snorkel Pens and Submerged Pens. Source: (Iversen et al., 2017)

The industry is in a state of constant technological innovation, with new net pen concepts that more effectively combat industry problems being continually developed. The Aquatraz system developed by Seafarming Systems AS and Midt-Norsk Havbruk AS is an example of a new net pen that possesses significant advantages over traditional net pens. The Aquatraz system is entirely closed in the upper layers of the sea and open at the bottom. This effectively prevents lice from entering the pen while simultaneously reducing the risk of net pen damage that can lead to fish escapes (Inventas, 2018). Because of the semi-closed construction of the pen, it requires additional water circulation to ensure satisfactory water quality for the fish. Other advantages include better stability and resilience to harsh weather, easier maintenance, and lower labor requirements (Midt-Norsk Havbruk AS, 2018).

## Lice Removal Using Laser

Laser removal is a passive mitigation effort that is relatively new. Special units fitted with a detector and laser are placed into the sea pens. When a parasite is detected, a short laser beam is ejected, killing the lice. This laser beam does not harm the fish since the fish's mucus is reflective. There is no increase in mortality rate related to this treatment method. Laser treatment efficiency will depend on how many units are placed in each sea pen and is hard to estimate because the system is passive (Iversen et al., 2017).

## Direct Cost Estimates for Lice Mitigation Efforts

Table 3-2 presents unit treatment costs reported by Iversen et al. (2017). These cost estimates form the basis for the treatment costs used in section 6.4 to estimate the total economic losses associated with sea lice.

Table 3-2: Unit Costs of Key Lice Mitigation Efforts. Source: (Iversen et al., 2017)

Treatment	Cost (NOK/kg)	Notes
Bath (traditional chemicals)	0.46	
Bath (hydrogen peroxide)	0.72	Unit cost for treatment of entire farm
Thermal	0.45	(4,000 tonnes)
Brush/ pressure	0.38	
Cleaner fish	1.25	Unit cost for a single farm over a single
Lice skirts	0.08	production cycle

To effectively combat sea lice proper monitoring and reporting are essential to maintain an overview of the current sea lice situation and infection pressure. Continuous counting and reporting of sea lice levels are therefore mandated by law. In a report by Iversen et al. (2017), estimates are based on the assumption that each farm requires two people one day each week to count lice. The average number of producing farms is 600, which results in 240 full-time employee equivalents and a total cost of 180 million NOK or 0.15 NOK/kg.



## 4. Data

To be able to perform an empirical analysis of the cost associated with sea lice, historical data on production, biophysical variables, lice counts, and lice treatment applications for all producing Norwegian salmon farms are required. Extensive data regarding lice counts and treatment applications were acquired on BarentsWatch, which is an institution with the objective to collect, develop, and share information regarding Norwegian coast and sea areas (BarentsWatch, 2018). The Norwegian Directorate of Fisheries stores data on production and biophysical variables of salmonid aquaculture on farm-level. However, such information is branded sensitive and, as such, is not publicly available. To access this information, an application for data for research purposes was required. Following approval of the application, an agreement of confidentiality and liability had to be signed by the dean of UiS Business School before data could be received.

The panel data set covers 72 monthly reports, from January 2012 to December 2017, of all farmed salmonids in Norway. In total, 1,044 distinct producing farms with 43,558 non-zero biomass observations are included in the data set. Farm-level summary statistics for the data set are shown in Table 4-1. The data set provides information on fish stocks, farm production activities, lice prevalence, and geographical location. A detailed description of all the variables included in the data set is presented in Table 4-2. The average number of adult female lice per fish is 0.18 with a standard deviation of 0.41, indicating that lice levels are on average below lice limits, but that farms experience lice outbreaks where lice levels are well above the specified lice limits. The average harvested fish weight is 4.90, with a standard deviation of 1.29. When comparing our data set to the data set presented by Abolofia et al. (2017), we notice several important differences. The average fish weight has decreased from 2.31 kg to 2.24 kg, and the average standing biomass has increased from 870,963 kg to 1,190,266 kg, indicating that the fish is on average smaller when released into the net pens and that farm size has increased considerably in recent years.

Following research by Abolofia et al. (2017) and Jansen et al. (2012), we group farms into three distinct geographical regions by latitude. We use these regions to report spatial differences in our empirical results later in the paper. Specifically, the central region consists of all farm between latitudes  $62^{\circ}$  35 minutes and  $67^{\circ}$ . The north and south regions consequently are comprised of all farms of latitudes above  $67^{\circ}$  and below  $62^{\circ}$  35 minutes, respectively. A map presenting the different geographical regions is provided in Figure 4-2. In our data set, 27% of

farms are situated in the northern region, 29% in the central region and 43% in the southern region.

Figure 4-1 provides a graphical presentation of mean values for key time series and highlights the seasonality and regional heterogeneity of farm and company operations, water temperatures, standing farm biomass, lice counts, and the use of lice treatments. Graphs [A-C] illustrate: (1) the importance of water temperature on lice counts across all regions, (2) that bath treatments are used primarily as a method of post-infestation control, (3) the recent decline in utilization of bath treatments and increase in use of mechanical treatments and (4) the recent decrease in peak lice infestations across all regions. Graphs [D-F] illustrate the stagnation in the production of Atlantic salmon in Norway, caused by stagnation in both the number of producing farms and average standing farm biomass levels. From this figure, it is also evident that farms in the south are on average smaller, but more abundant, and that farms in the central region are largest.

Our model requires a variable that measures the age of the fish (number of months in the sea). Since our data sets did not contain such a variable, an imperfect proxy variable was created. This variable will be referred to as months at sea. Since fish farmers sometimes have different cohorts of salmonids at the same farm at the same time, this variable is not perfect and serves as an estimate for fish age. The months at sea variable is used to define distinct production cycles and production cycle characteristics later in the thesis. The mean value for months at sea in our data set is 9.06 with 5<sup>th</sup> and 95<sup>th</sup> percentiles at 1 and 19 months at sea respectively. These numbers suggest that most production cycles last less than 19 months.

Table 4-1: Summary Statistics (2012-2017).

Variable	Observations	Farms	Mean	Std. Dev.	P5 <sup>a</sup>	P95 <sup>a</sup>
Total number of producing farms	43,558	1,044	496.29	285.25	43	939
Months at sea	43,558	1,044	9.51	5.84	1	19
Water temperature (°C)	43,207	1,031	9.06	3.50	3.95	15.15
Number of fish released <sup>b</sup>	5,746	986	413,882.40	343,641.60	26,000	1,088,069
Number of fish	43,558	1,044	664,782.90	483,687.50	0	1,557,858
Average fish weight (kg) <sup>b</sup>	40,733	1,039	2.24	1.82	0.15	5.50
Fish biomass (kg)	43,558	1,044	1,190,266	1,149,306	0	3,449,047
Feed use (tonnes)	43,558	1,044	226.99	219.04	2.47	668.94
Number of fish mortalities <sup>b</sup>	42,827	1,041	6,017.51	15,042.69	166	23,069
Number of fish removals <sup>b</sup>	8,620	822	2,383.58	6,829.09	43	9,528
Number of fish escapes <sup>b</sup>	50	43	16,608.92	28,118.83	2	68,009
Number of miscellaneous fish losses <sup>b</sup>	14,461	1,003	637.59	15,388.14	-14,908 <sup>e</sup>	15,423
Number of fish harvested <sup>b</sup>	11,063	977	143,103.70	125,146.20	17,115	385,110
Average harvested fish weight (kg) <sup>b</sup>	11,063	977	4.90	1.29	3.33	6.66
Harvested fish biomass (kg) <sup>b</sup>	11,060	976	691,190.50	608,581.40	81,092.31	1,912,739.00
Adult female lice (avg. number/fish)	42,791	1,044	0.18	0.41	0	0.70
Other mobile lice (avg. number/fish) <sup>c</sup>	42,791	1,044	0.79	1.46	0	3.16
Total mobile lice (avg. number/fish) <sup>d</sup>	42,761	1,044	0.96	1.60	0	3.80
Number of bath treatments	43,558	1,044	0.20	0.61	0	2
Number of mechanical treat.	43,558	1,044	0.08	0.36	0	1
Number of cleaner fish releases	43,558	1,044	0.39	1.38	0	3
Number of cleaner fish released <sup>b</sup>	5,657	671	22,062.80	25,617.47	1,000	71,000
Atlantic salmon (dummy)	43,558	1,044	0.91	0.29	0	1
Rainbow trout (dummy)	43,558	1,044	0.09	0.29	0	1
Latitude	43,530	1,038	63.92	3.75	59.29	70.21
Longitude	43,530	1,038	10.41	5.77	4.97	22.90
Northern region (dummy)	43,558	1,044	0.27	0.45	0	1
Central region (dummy)	43,558	1,044	0.29	0.46	0	1
Southern region (dummy)	43,558	1,044	0.43	0.50	0	1

<sup>a</sup> P5 and P95 are the 5<sup>th</sup> and 95<sup>th</sup> percentiles of the data.

<sup>b</sup> Non-zero observations only.

<sup>c</sup> Pre-adult mobiles and adult male lice.

<sup>d</sup> Adult females plus other mobile lice.

<sup>e</sup> This variable is used by farmers to correct wrongly estimated fish numbers and therefore contains negative values.

Source: Norwegian Directorate of Fisheries (2019); BarentsWatch (2019)

Table 4-2: Description of all variables presented in Table 4-1.

Variable	Description
Total number of producing farms	All farms that have been operational in the period of the data set.
Months at sea <sup>a</sup>	An imperfect proxy variable for fish age. The procedure for generation of this variable is explained in more detail in Table 4-4.
Water temperature	Average monthly water temperature in degrees Celsius throughout the period.
Number of fish released	The total number of fish released during a specific month including released smolt and relocated fish.
Number of fish	Total amount of fish in a farm.
Average fish weight <sup>a</sup>	Total fish biomass divided by total number of fish.
Fish biomass	Total amount of live fish biomass in kilograms.
Feed use	Quantity of feed used in tonnes.
Number of fish mortalities	Total amount of fish mortalities.
Number of fish removals	Total amount of fish removals.
Number of fish escapes	Total amount of fish escapes.
Number of miscellaneous losses	Total amount of miscellaneous losses. This variable is often used by fish farmers to correct erroneous fish numbers reported in previous months, hence it may contain negative values.
Number of fish harvested	Total amount of fish harvested.
Average harvested fish weight <sup>a</sup>	Total harvested fish biomass divided by total number of fish harvested.
Harvested fish biomass	Total amount of harvested fish biomass in kilograms.
Adult female lice	Average amount of adult female lice per fish.
Other mobile lice	Average amount of other mobile (male adult/pre-adult) lice per fish.
Total mobile lice <sup>a</sup>	Sum of adult female lice and other mobile lice.
Number of bath treatments	Total amount of bath treatment performed.
Number of mechanical treatments	Total amount of mechanical treatment performed.
Number of cleaner fish releases	Total number of cleaner fish releases.
Number of cleaner fish released	Total amount of individual cleaner fish released.
Atlantic salmon	Dummy variable indicating the presence of Atlantic salmon.
Rainbow trout	Dummy variable indicating the presence of Rainbow trout.
Latitude	Coordinate farm location.
Longitude	Coordinate farm location.
Northern region <sup>a</sup>	Dummy variable indicating a farm location above latitude 67°.
Central region <sup>a</sup>	Dummy variable indicating a farm location between latitude 62° 35 minutes and 67°.
Southern region <sup>a</sup>	Dummy variable indicating a farm location below 62° 35 minutes.

<sup>a</sup> These variables were created by the authors, using a combination of existing variables from the given data.

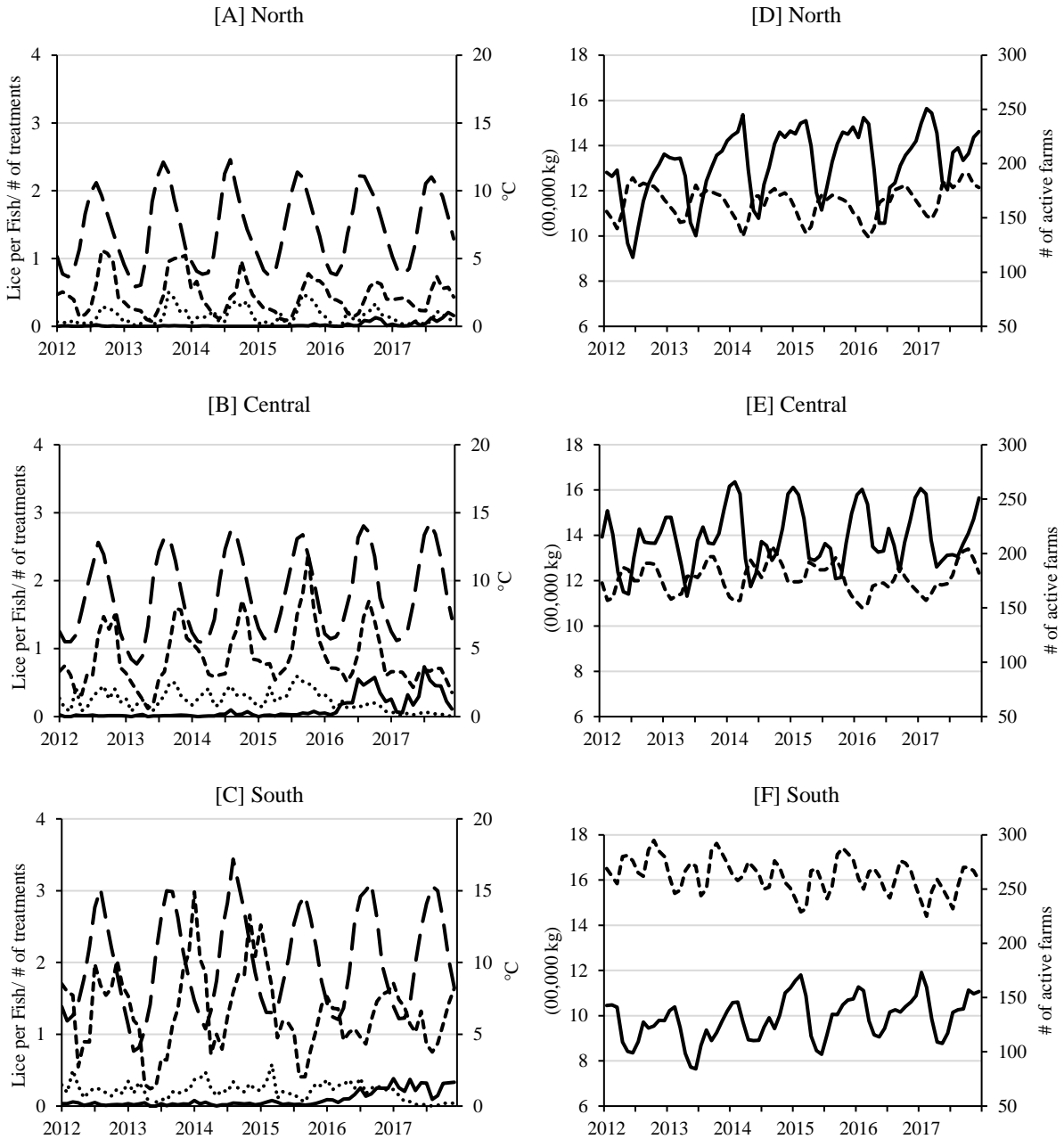
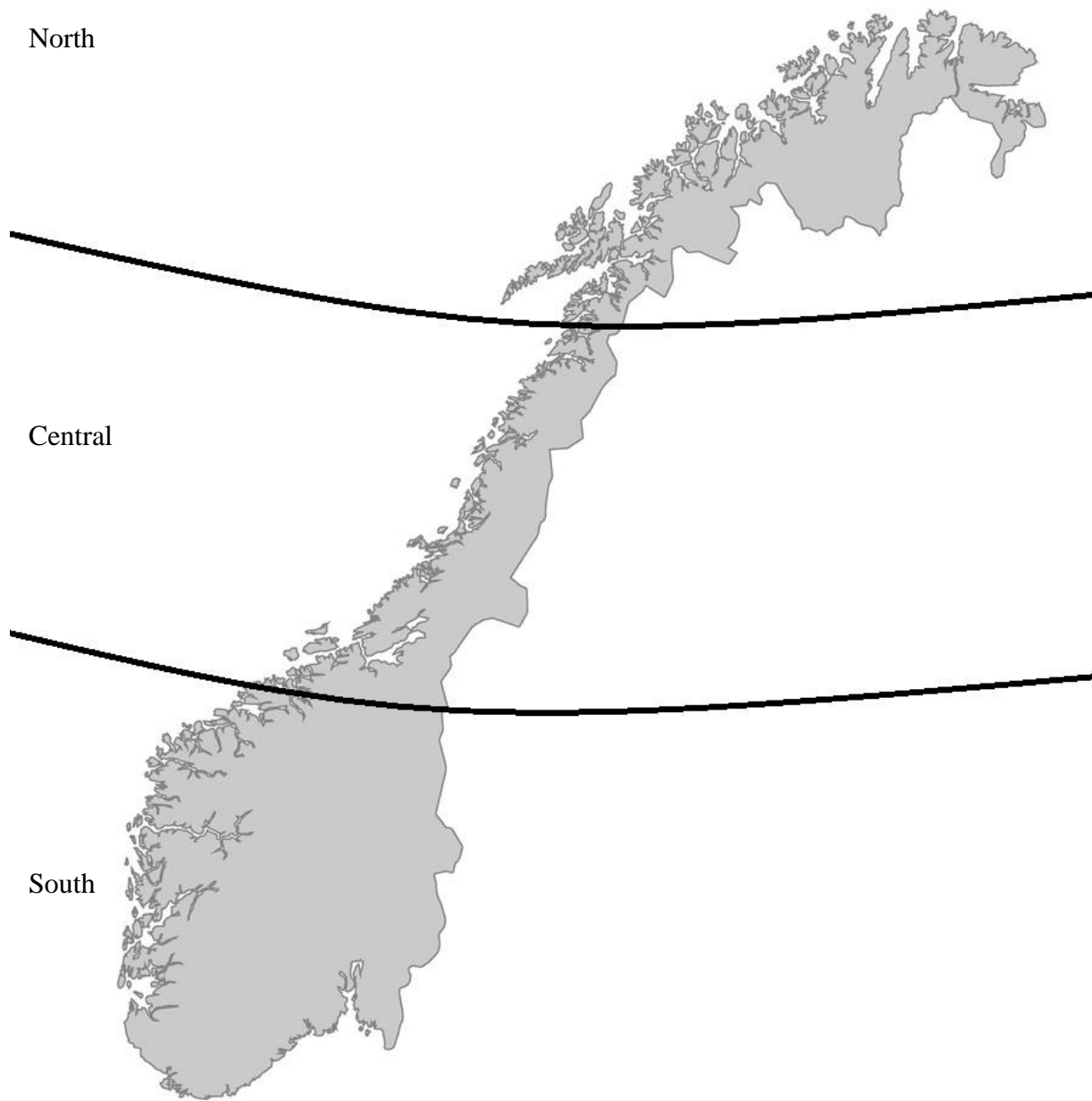


Figure 4-1: [A-C] Monthly Average Water Temperature (long dash), Average Total Mobile Lice per Fish (dash), Average Number of Bath Treatments (dot) and Average Number of Mechanical Treatments (solid) by Region. [D-F] Monthly Total Number of Producing Farms (dash) and Average Standing Farm Biomass (solid) by Region.



*Figure 4-2: Division of Geographical Regions.*

## **Data Preparation**

Before the acquired data set could be used in an econometric model, several steps were undertaken to combine the two raw data sets into one. Table 4-3 contains information on all the steps undergone to merge the two data sets.

The data set containing lice counts and lice treatment information has weekly reported data. On the other hand, the data set containing biophysical and production information has monthly reported data. This limits the analysis of our data to a monthly basis. All variables from the data set acquired from BarentsWatch were therefore transformed from weekly to monthly data. The data sets were then merged based on farm specific number, year, and month. Any farms only present in one of the data sets were omitted. These farms were mainly onshore farms which are not subjected to lice infestation and therefore do not have an obligation to report such numbers.

Due to variation in lice and biomass reporting requirements and possible erroneous reporting, removal of highly improbable values and imputations of missing values were performed. Table 4-4 provides detailed information on all imputed and omitted data points.

Table 4-3: Steps Undertaken to Merge Biomass and Lice Data Sets.

Step	Data set	Number of obs. before	Number of obs. after	Notes
Grouping to monthly from weekly data, grouped by farm, year and month.	Lice and treatment	478,847	107,959 <sup>1</sup>	-Lice and temperature calculated as averages of all weeks in a given month. -Treatment variables were summed for all weeks in a given month. -Time invariant variables were left unaltered.
Grouping of data points of the same farm, year and month	Biomass	50,684	44,354	-Summed all time-dependent biophysical variables for data points corresponding to the same farm, year, and month. -Time invariant variables were left unaltered.
Merging of the two data sets	Final data set	-	43,558	-Biomass data set was used as the primary data set, and data points from lice and treatment data set corresponding to biomass data points were merged. -Biomass data for land-based farms were omitted, as these farms are not subjected to sea lice.
Adding proxy variable for fish age, months at sea (mas)	Final data set	43,558	43,558	-An imperfect proxy variable created using the variables cohort year, biomass and number of smolt released. These variables determine in conjunction if a new production cycle started or ended, which again was used to fill in the months at sea variable. -Production cycles that were determined to have started before January 2012 and ended in the data set were handled in the following way; After identifying the given cycle's end month, it was assigned the median value (18) for production cycle lengths (determined by all the complete cycles in the data set). All data points before this were imputed by referencing the end of the production cycle. For the purpose of calculating average cycle lengths, only complete cycles (starting and ending in the data set were used).

<sup>1</sup> Lice and treatment data set contained data points for all weeks/months for all farms despite many of them being empty, which is the reason for the high number of observations.



Table 4-4: Value Imputations and Removals.

Variable	Number of obs. removed	Number of obs. imputed	% of observations	Notes
Total mobile lice	-	952	2.22%	-All missing total mobile lice values at the start of any cycle were imputed as 0. It is reasonable to assume that the fish is free of lice when first released into the sea.
Total mobile lice	-	1,265	2.96%	-All missing total mobile lice values at the end of any cycle were imputed as the previous month's value. -Farmers are not obligated to report lice numbers when they are very close to harvesting; this does not mean that no lice are present.
Total mobile lice	30	-	0.0007%	-Any values of total mobile lice higher than 20 were removed as these values were deemed highly improbable and possibly a result of erroneous reporting.
Average water temperature	-	1,508	3.57%	-Missing water temperature values were imputed by taking the average water temperature of the same farm and the same month for the other years in the data set. If no temperature data was present for the farm in the given month, no value was entered.
Average water temperature	125	-	0.29%	-Water temperatures lower than 2 °C were removed as these values were regarded as highly improbable and unsuitable for salmonid aquaculture.
Average fish size	384	-	0.009%	-Average fish sizes over 10 kg were removed. The average harvest size is 4-5 kg; therefore, any fish sizes over 10 kg were deemed improbable.
Dependent variable <sup>2</sup> ; $\ln\left(\frac{Biomass_{it} - AB_{it}}{Biomass_{it-1}}\right)$	166	-	0.41%	-All dependent variable values corresponding to a biomass loss of more than 80% or a growth over 200% were removed. Such growth rates were determined to be highly improbable or impossible.

<sup>2</sup> The dependent variable used in our regression model is introduced in section 5.1.

## 5. Methodology

In this chapter, we describe the strategy and fundamental model theory necessary to estimate the biological and economic impacts sea lice and separate the individual effects of treatment and lice on the biological growth of farm biomass. First, we present a conceptual model to calculate the private cost of lice, which includes both indirect and direct cost components. Next, an approach to create an empirical model to estimate the biological growth rate of farm biomass is elaborated. Finally, we present the various panel data estimators and their distinct differences.

### 5.1 Conceptual and Empirical Models

The goal of this paper is to measure both the indirect and direct costs associated with sea lice infestation. To be able to answer the research statement, a conceptual model of the private costs of lice and an empirical model of fish biomass growth, both based on Abolofia et al. (2017) is utilized. For the models to fit the research to be conducted in this paper, they must be modified. Changes to each of the models will be described in detail throughout this section.

#### Model of the Private Cost of Lice

The model of the private cost of lice can be constructed by accounting for factors that impact a farmer's profit. Through the reasoning described in Abolofia et al. (2017), the farmer's discounted profits,  $\Pi(T)$ , become:

$$\begin{aligned} \Pi(T) = P(T) \cdot \left( B_0 + \int_0^T \dot{B}(t, L(t)) \cdot dt \right) \cdot e^{-rT} - C_f \int_0^T FCR \cdot \dot{B}(t, L(t)) \cdot e^{-rt} \\ \cdot dt - C_b \sum_{n=1}^{N^b} e^{-rT_n} - C_m \sum_{n=1}^{N^m} e^{-rT_n} \end{aligned} \quad \text{Eq. 5-1}$$

where  $T$  is harvest time,  $P(T)$  is the price per kilogram of fish,  $B_0$  is the initial biomass stock which is free of lice,  $\dot{B}(\cdot)$  is fish biomass growth, and  $L(t)$  is lice per fish at time  $t$ . Moreover,  $C_f$  is the unit feed price,  $FCR$  is the feed conversion ratio,  $r$  is the farmer's discount rate,  $C_b$  is the unit bath treatment cost,  $C_m$  is the unit mechanical treatment cost,  $N^b$  is the total number of bath treatments,  $N^m$  is the total number of mechanical treatments, and  $T_n$  is the time when treatment  $n \in [1, N]$  occurs.

We extend the original model developed by Abolofia et al. (2017), where the difference is the inclusion of mechanical treatment cost. Since the original formula was based on biomass data from 2005 through 2011, the use of mechanical treatment had not yet become very prominent in the industry and as such chemical delousing treatments were still the main form of treatment. Because the data in this paper range from 2012 through 2017, it is deemed reasonable to include mechanical treatment cost as a term in the equation as this treatment option started to be utilized with a higher frequency in 2016. In addition to this, sea lice regulations were changed in 2013, placing further restrictions on lice abundance. This has likely also increased the necessity for farmers to perform lice treatments.

Eq. 5-1 can be used to measure the economic impact of a specific sea lice infestation scenario on discounted farm profits over a single production cycle of fixed length. This enables the possibility to estimate the economic impact of sea lice infestation by taking the difference in discounted net revenues of a scenario with and without lice. Thus, the private economic cost becomes:

$$\begin{aligned}
 \Pi(T)^{no\text{lice}} - \Pi(T)^{lice} = & \underbrace{e^{-rT} \cdot P(T) \sum_{i=1}^I \int_{t_{i-1}}^{t_i} (\dot{B}(t,0) - \dot{B}(t,L(t))) dt}_{\text{Revenue loss}} - \underbrace{C_f \cdot FCR \sum_{i=1}^I \int_{t_{i-1}}^{t_i} (\dot{B}(t,0) - \dot{B}(t,L(t))) e^{-rt} \cdot dt}_{\text{Feed cost savings}} \\
 & + \underbrace{C_b \sum_{n=1}^N e^{-rT_n}}_{\text{Bath treatment cost}} + \underbrace{C_m \sum_{n=1}^N e^{-rT_n}}_{\text{Mechanical treatment cost}}
 \end{aligned} \tag{Eq. 5-2}$$

Eq. 5-2 is composed of four different parts: Lice infestation results in harvesting a lower amount of biomass because of the negative effect of lice on fish growth, which is captured in the revenue loss term. The farmer's lower expenditure on feed from the reduced appetite of their fish is captured in the feed cost savings term. The bath treatment cost captures the total cost of performing  $N$  total bath treatments, and the mechanical treatment cost captures the total cost of performing  $N$  total mechanical treatments.

To provide an estimate of the difference in profits in Eq. 5-2, it is necessary to establish an empirical model of fish biomass growth that is dependent on the level of sea lice and every other exogenous factor affecting the level of fish growth in the current period.

## Biological Growth Model

The information in our data set enables the possibility to measure the impact of lice on the biological growth of farm biomass by incorporating all changes to standing biomass levels within months. This includes stocking, harvesting, mortalities, removals, escapes, and miscellaneous losses. In order to devise the expression for the biological growth rate of farm biomass, it is necessary to define the net growth in ancillary biomass ( $AB_{it}$ ) of each farm in each period as follows (Abolofia et al., 2017):

$$AB_{it} = (Stocking_{it} - Harvesting_{it} - Mortalities_{it} - Removals_{it} - Escapes_{it} - Misc. Losses_{it})$$

Each term in the equation above is expressed in units of biomass<sup>3</sup>. With this definition, the biological growth rate of farm biomass can be expressed as:

$$r_{it} = \frac{(Biomass_{it} - AB_{it}) - Biomass_{it-1}}{Biomass_{it-1}} \quad \text{Eq. 5-3}$$

where  $i$  is the  $i^{th}$  farm, and  $t$  is the  $t^{th}$  of  $T$  months in a fixed production cycle on a specific farm  $i$ .<sup>4</sup>

To measure the effect of lice on the biological growth rate of farm biomass,  $r_{it}$  from Eq. 5-3 is expressed as a non-linear (logarithmic) function of a vector of explanatory variables that are time-dependent. Explicitly,  $\ln(1 + r_{it}) = x'_{it}\beta$ , where  $x'_{it}$  is a vector comprising the explanatory variables available that affect growth rate, and  $\beta$  is the corresponding vector of parameters to be estimated. Also allowing for time-specific effects  $\delta_t$  to capture seasonality effects, farm-specific effects  $c_i$ , and an idiosyncratic error term,  $u_{it}$ , the model for farm  $i$  at time period  $t$  becomes (Abolofia et al., 2017):

$$\ln\left(\frac{Biomass_{it} - AB_{it}}{Biomass_{it-1}}\right) = x'_{it}\beta + \delta_t + c_i + u_{it} \quad \text{Eq. 5-4}$$

---

<sup>3</sup> Because only  $Harvesting_{it}$  is reported in units of biomass, we construct the remainder of  $AB_{it}$  using the product of reported fish numbers and average fish weights. For stocking numbers, we use the average fish weight from the current month of stocking since our data does not report stocked weight. For the remaining variables, we use the average fish weight from current and previous months to account for the fact that all biophysical variables are reported at the end of each month.

<sup>4</sup> Importantly, this setup limits the possibility to investigate lice-induced mortalities, since all mortalities in our data are compiled into one variable.

In Eq. 5-4, the choice of panel estimator depends on the treatment of  $c_i$ . The model parameters may be consistently estimated using either a fixed-effects or random-effects analysis method; however, this must be determined by the Durbin-Wu-Hausman test. Additionally, a series of econometric testing must be run in order to check and potentially correct for serial correlation and heteroskedasticity. Econometric testing and correction will be carefully elaborated in the analysis and results section of this paper.

The empirical model given in Eq. 5-4 is similar to the model devised by Abolofia et al. (2017), with a distinct difference in the vector of explanatory variables  $x'_{it}$ . The original analysis performed by Abolofia et al. (2017) focused strictly on the negative impact of sea lice infestation; however, there is reason to believe that treatment itself may have an impact on biomass growth as well. The model in this paper takes this suspicion into account and adds bath- and mechanical treatment as independent explanatory variables in the regression model. By doing this, it is possible to quantify the impact of treatment on biological growth rate while also observing the impact of lice infestation. The overall hypothesis is that both treatment and lice will have a negative impact on the biological growth rate, but if treatment is performed, the negative impact of lice will decrease. The results and potential confirmation or rejection of this hypothesis will be presented in Chapter 6.

### **Estimation of Marginal Effects**

When interpreting complex econometric models with multiple explanatory variables, including interaction terms, it is useful to estimate the marginal effects of certain variables. The marginal effects indicate a specific variable's impact on the dependent variable in a *ceteris paribus* setting. In section 6.2, we estimate the marginal effects of key model covariates evaluated at region-specific means. The following procedure was employed to estimate these marginal effects:

$$\frac{\partial \hat{y}_{it}}{\partial x} = \frac{\partial (x'_{it}\hat{\beta} + \hat{\delta}_t + \hat{c}_i)}{\partial x} \quad \text{Eq. 5-5}$$

where  $\hat{y}_{it}$  is the estimated dependent variable,  $x$  is a specific variable of interest,  $x'_{it}$  is the vector of explanatory variables, and  $\hat{\beta}$  is the corresponding vector of estimated coefficients. Moreover,  $\hat{\delta}_t$  is the estimated time-specific effects, and  $\hat{c}_i$  is the estimated farm-specific effects.

In order to obtain estimates of the region-specific marginal effects, we evaluate Eq. 5-5 by fixing all model covariates at their region-specific means. The marginal effects can be interpreted as the

change in biological growth rate with a unit increase (from the mean) in the specific variable of interest.

## 5.2 Panel Data

After sorting and merging the data sets, a unique panel data set was created. Panel data (longitudinal data) is a combination of time series data and cross-sectional data. The panel consists of 1,044 groups (farms) measured over a 72-month period. The panel data set enables an empirical study of the private economic and biological impacts of observed levels of sea lice. It facilitates the possibility to estimate the impact of sea lice and the effectiveness of lice control measures on farmed salmon stocks in a quasi-natural experiment setting. A modified bio-econometric model based on the model by Abolofia et al. (2017) will be used to estimate the marginal damages due to infective sea lice (Abolofia et al., 2017). However, before panel data regression can be performed, it is necessary to understand the mechanisms behind panel estimators and analysis techniques.

The following theory regarding multiple linear regression and the corresponding assumptions are based on the paper of Schmidheiny (2018).

The foundation for the choice of panel estimator starts with the multiple linear regression model  $i = 1, \dots, N$  who is observed at time periods  $t = 1, \dots, T$

$$y_{it} = \alpha + x'_{it}\beta + z'_i\gamma + c_i + u_{it} \quad \text{Eq. 5-6}$$

where  $y_{it}$  is the dependent variable,  $x'_{it}$  is a vector of time-varying explanatory variables with the corresponding vector of parameters  $\beta$ ,  $z'_i$  is a vector of time-invariant explanatory variables with the corresponding vector of parameters  $\gamma$ ,  $\alpha$  is the intercept,  $c_i$  is an individual-specific effect and  $u_{it}$  is an idiosyncratic error term.

Multiple linear regression is only appropriate when the following conditions are satisfied:

*PD1: Linearity*

$$y_{it} = \alpha + x'_{it}\beta + z'_i\gamma + c_i + u_{it} \text{ where } E[u_{it}] = 0 \text{ and } E[c_i] = 0$$

The model is required to be linear in parameters  $\alpha$ ,  $\beta$ ,  $\gamma$ , effect  $c_i$  and error  $u_{it}$ .

*PD2: Independence*

$$[X_i, z_i, y_i]_{i=1}^N \text{ i.i.d. (independent and identically distributed)}$$

All the observations are independent across individuals but do not necessarily have to be independent across time.

*PD3: Strict exogeneity*

$$E[u_{it}|X_i, z_i, c_i] = 0 \text{ (mean independent)}$$

The error term  $u_{it}$ , is considered to be uncorrelated with the explanatory variables for all time periods of the same individual.

*PD4: Error variance*

1.  $Var[u_i|X_i, z_i, c_i] = \sigma_u^2 I, \sigma_u^2 > 0$  and finite (homoscedastic and no serial correlation)

2.  $Var[u_{it}|X_i, z_i, c_i] = \sigma_{u,it}^2 > 0$ , finite and

$$Cov[u_{it}, u_{is}|X_i, z_i, c_i] = 0 \forall s \neq t \text{ (no serial correlation)}$$

3.  $Var[u_i|X_i, z_i, c_i] = \Omega_{u,i}(X_i, z_i)$  is p.d. and finite

There are two analytical techniques that can be utilized to analyze panel data; fixed-effects and random-effects.

### **Fixed Effects Model**

Fixed effects (FE) analysis method is appropriate when the impact of variables that vary over time is of interest. This method measures the relationship between the explanatory variables and the dependent variables within an entity (country, company, farm, etc.). The explanatory variables may or may not be influenced by the individual characteristics of each entity. The utilization of FE is based on the assumption that something within the individual may impact or bias the explanatory-

or dependent variables which need to be controlled for. This is the basis behind the assumption of the correlation between an entity's error term and the explanatory variables (Torres-Reyna, 2007).

FE eliminates the effect of the time-invariant characteristics, and as a result, enables the assessment of the net effect of the explanatory variables on the dependent variable. A critical assumption of the FE framework is that the time-invariant characteristics are unique to each individual and should not be correlated with any other individual characteristics. The entity's error term and the constant should not be correlated with the others due to the inherent differences of each entity. If there exists a correlation between the error terms, then FE is not appropriate because inferences may not be precise. Such a relationship must be modeled using other frameworks such as the random-effects model and the related Hausman test, which will be described in more detail in the following sections (Torres-Reyna, 2007).

Taking the above reasoning into account, Eq. 5-6 is reduced to the equation for the fixed effects model:

$$y_{it} = x'_{it}\beta + c_i + u_{it} \quad \text{Eq. 5-7}$$

Performing the fixed effects transformation by subtracting Eq. 5-7 with the average over time of the same equation yields the first-difference model:

$$\dot{y}_{it} = \dot{x}'_{it}\beta + \dot{u}_{it} \quad \text{Eq. 5-8}$$

where the two dots represent the first-difference factor. The important thing about Eq. 5-8 is that the unobserved effect,  $c_i$ , has disappeared. This suggests that Eq. 5-8 should be estimated by utilizing pooled OLS. A pooled OLS estimator that is based on this equation is called the fixed effects estimator (Wooldridge, 2014).



## Random Effects Model

The random effects (RE) analysis method, as opposed to fixed-effects analysis, assumes variation across entities to be uncorrelated and random with the explanatory variables or predictor included in the model. If there is reason to suspect that differences across entities may have an impact on the dependent variable, then random effects should be utilized. A great advantage of the random-effects method is that it allows the inclusion of time-invariant variables. In contrary to the fixed-effects model, these time-invariant variables are captured by the intercept (Torres-Reyna, 2007).

Due to the elaborated rationale above, the random-effects model becomes:

$$y_{it} = \alpha + x'_{it}\beta + z'_i\gamma + c_i + u_{it} \quad \text{Eq. 5-9}$$

which is the same as the original equation for multiple linear regression. The goal is, as opposed to fixed-effects analysis, not to eliminate  $c_i$  because this will result in inefficient estimators due to  $c_i$  being uncorrelated with each explanatory variable for all time periods (Wooldridge, 2014).

To find the most efficient estimator, the first step is to define an equation with the composite error term as  $v_{it} = c_i + u_{it}$ , thus Eq. 5-9 becomes:

$$y_{it} = \alpha + x'_{it}\beta + z'_i\gamma + v_{it} \quad \text{Eq. 5-10}$$

Since  $c_i$  is a part of the composite error term in every time period, the  $v_{it}$  are serially correlated across time. This can be seen under the random-effects assumption:

$$\text{Corr}(v_{it}, v_{is}) = \frac{\sigma_c^2}{(\sigma_c^2 + \sigma_u^2)}, t \neq s$$

where  $\sigma_c^2 = \text{Var}(c_i)$  and  $\sigma_u^2 = \text{Var}(u_{it})$ . The positive serial correlation in the error term can potentially be quite large, and, because pooled OLS standard errors disregard this correlation, they will be incorrect (Wooldridge, 2014). To be able to solve the problem of autoregressive serial correlation, GLS can be used. First, define:

$$\theta = 1 - \sqrt{\frac{\sigma_u^2}{(\sigma_u^2 + T\sigma_c^2)}} \quad \text{Eq. 5-11}$$

which is between 0 and 1. Then the transformation becomes:

$$y_{it} - \theta \bar{y}_i = (1 - \theta)\alpha + (x'_{it} - \theta \bar{x}'_i)\beta + (z'_i - \theta \bar{z}'_i)\gamma + (v_{it} - \theta \bar{v}_i) \quad \text{Eq. 5-12}$$

where the time averages are denoted by the overbars. The GLS estimator is basically the pooled OLS estimator of Eq. 5-12. This transformation allows for time-invariant variables which is favorable compared to fixed-effects estimation (Wooldridge, 2014).

### **Time Fixed Effects Model**

In many cases, there are also reasons to suspect that there are time-specific effects  $\delta_t$  which will affect all individuals in the same way. The model can then be extended to include this time-specific effects term:

$$y_{it} = \alpha + x'_{it}\beta + z'_i\gamma + \delta_t + c_i + u_{it} \quad \text{Eq. 5-13}$$

This extended model can be estimated by including a dummy variable for each time period (Schmidheiny, 2018). The model makes it possible to eliminate bias from unobservables that change over time but are constant over individuals, and it controls for factors that vary across individuals but are constant over time (Arnold et al., 2019). By utilizing such a model, seasonality can be captured.

## 6. Analysis and Results

In this chapter, the regression results for the biological growth model and our estimate of the indirect and direct costs of sea lice are presented. Initially, the final fixed-effects regression model for the growth rate is presented along with a table describing all covariates. Then, a thorough description of all the testing procedures that have been done to construct the fixed-effects model is explained, this includes the Breusch-Pagan test for pooled OLS vs. random-effects and Hausman test for random-effects vs. fixed-effects. Next, the marginal effects of lice and delousing treatments are presented in order to measure their impact on the biological growth rate in the different regions. Finally, we utilize a parametrized version of the model of the private cost of sea lice presented in section 5.1 to estimate the indirect and direct costs on an aggregate level.

### 6.1 Econometric Testing and Correction of Empirical Model

In order to produce the most efficient and consistent estimators, it is necessary to perform a series of econometric tests on the empirical model to be studied. First, a simple pooled OLS model was estimated, before increasingly more complex model specifications were added based on econometric test results. For the ease of reading, we only present the equation for the final regression model (Model C in Table 6-2)<sup>5</sup>, given by Eq. 6-1:

$$\begin{aligned}
 lngrowth_{it} = & \alpha + \beta_1 months\ at\ sea_{it} + \beta_2 feeduse_{it} + \beta_3 feeduse_{it}^2 \\
 & + \beta_4 fishweight_{it-1} + \beta_5 nfish_{it-1} + \beta_6 seatemp_{it-1} \\
 & + \beta_7 seatemp_{it-1}^2 + \beta_8 bathtreat_{it} + \beta_9 mechtreat_{it} + \beta_{10} lice_{it-1} \\
 & + \beta_{11} lice_{it-1}^2 + \beta_{12} lice_{it-1} \cdot fishweight_{it-2} + \beta_{13} lice_{it-1} \\
 & \cdot seatemp_{it-1} + \beta_{14} lice_{it-1} \cdot mechtreat_{it} + \beta_{15} lice_{it-1} \\
 & \cdot bathtreat_{it} + \delta_t + c_i + u_{it}
 \end{aligned} \tag{Eq. 6-1}$$

This is the expanded model of Eq. 5-4 devised in the methodology, where  $lngrowth_{it} = \ln\left(\frac{Biomass_{it}-AB_{it}}{Biomass_{it-1}}\right)$ . Table 6-1 provides a detailed description of all model covariates included in Eq. 6-1.

<sup>5</sup> Other model specifications are reported in Table 6-2.

Table 6-1: Explanation of Variables in the Final Model Given in Eq. 6-1.

Variable	Notes
$lngrowth_{it}$	The dependent variable. The logarithm of the biological growth rate of farm biomass.
$months\ at\ sea_{it}$	Proxy for fish age, it is expected that the biological growth rate will vary depending on fish age/ number of months since initial stocking.
$feeduse_{it}$	Quantity of feed used will affect the biological growth rate.
$feeduse_{it}^2$	Feed use squared enters the model to capture the diminishing effects of increased feed use.
$fishweight_{it-1}$	We expect that the biological growth rate will depend on the average fish weight at the end of the previous month. Therefore, fish weight enters with a one-month lag.
$nfish_{it-1}$	Fish density is expected to affect biological growth rate; it enters with a one-month lag because most of our variables are reported at the end of every month.
$seatemp_{it-1}$	Water temperature will affect the biological growth rate.
$seatemp_{it-1}^2$	Water temperature is expected to have diminishing returns at higher values.
$bath\ treat_{it}$	The number of bath treatments performed in the current month is expected to have a negative impact on the growth rate.
$mech\ treat_{it}$	The number of mechanical treatments performed in the current month is expected to have a negative impact on the growth rate.
$lice_{it-1}$	Lice infestation level in the previous month is expected to have a negative impact on the biological growth rate.
$lice_{it-1}^2$	We expect a diminishing effect of lice infestations at higher lice levels.
$lice_{it-1} \cdot fishweight_{it-2}$	We include an interaction term between lice and fish weight to capture the connection between fish size and vulnerability to lice. Here fish weight enters with a two-month lag as lice infestation level enters with a one-month lag.
$lice_{it-1} \cdot seatemp_{it-1}$	It is expected that lice infestation damages will intensify at higher water temperatures.
$lice_{it-1} \cdot mech\ treat_{it}^a$	Mechanical treatments are expected to instantaneously reduce lice infestation levels and therefore, will reduce the impact of lice on biological growth rate.
$lice_{it-1} \cdot bath\ treat_{it}^a$	Bath treatments are expected to instantaneously reduce lice infestation levels and therefore, will reduce the impact of lice on biological growth rate.

<sup>a</sup> The impact of the regulatory change in lice limits is captured in the empirical model as interaction terms, which facilitates a comparison between the positive effect of a reduction in lice levels to the inherent negative effects of lice treatments.

Initially, a Breusch-Pagan Lagrange multiplier test is used to determine whether a pooled OLS or random-effects model produces the most efficient estimators. The next step is to perform a Hausman test to decide whether a fixed-effects or random-effects model is the most appropriate analysis method. In the following section, a detailed explanation of all testing and evaluation procedures is elaborated.

### **Breusch-Pagan Lagrange Multiplier Test**

Firstly, the Breusch-Pagan Lagrange multiplier (BPLM) test for random effects is used to determine whether a pooled OLS or random-effects model is most appropriate. In other words, the test indicates if the model can be efficiently estimated using multiple linear regression (MLR) or if panel data analysis is needed to achieve the most efficient estimators.

According to StataCorp (2013c), Stata uses the following model to calculate the Lagrangian multiplier:

$$y_{it} = \alpha + x'_{it}\beta + u_{it} \quad \text{Eq. 6-2}$$

This model is fit through OLS, and then the Lagrangian multiplier is calculated by:

$$\lambda_{LM} = \frac{(n\bar{T})^2}{2} \left( \frac{A_1^2}{(\sum_i T_i^2) - n\bar{T}} \right) \quad \text{Eq. 6-3}$$

where  $A_1 = 1 - \frac{\sum_{i=1}^n (\sum_{t=1}^{T_i} u_{it})^2}{\sum_i \sum_t u_{it}^2}$ .

Under the null hypothesis, the Lagrangian multiplier is distributed asymptotically as  $\chi^2$  (Wooldridge, 2014), and variance across entities is zero (Torres-Reyna, 2007),  $Var(u_{it}) = 0$  (homoskedasticity). If this is true, then there are no random effects, and the model can be efficiently estimated using pooled OLS. However, if the result is significant ( $H_0$  is rejected),  $Var(u_{it}) > 0$ , then there exist random effects and random-effects estimation is a better approach (K. Baum, 2007).

Using Stata to test Eq. 6-1 yields a  $\chi^2$  of 328.77, which suggests strong significant differences across farms and the null hypothesis is rejected, thus pooled OLS is not an optimal approach.

### Durbin-Wu-Hausman Test

Since the BPLM test concluded that a random-effects model is preferred over pooled OLS, the next step is to determine which is the preferred panel estimator between random and fixed-effects. To verify which is the most efficient panel estimator, a (Durbin-Wu) Hausman test can be performed. The foundational basis of this test is that it compares an estimator  $\hat{\theta}_1$ , which is known to be consistent with another estimator,  $\hat{\theta}_2$ , that is efficient under the assumption being tested. Under the null hypothesis, the estimator  $\hat{\theta}_2$  is undeniably an efficient and consistent estimator of the true parameters. Were this to be the case, then there should not be any systematic difference between the two estimators. However, if there is a systematic difference in the estimates, then there is reason to doubt the assumptions for which the efficient estimator is based on (StataCorp, 2013b).

This means that under the null hypothesis, the random-effects model is preferred over the fixed-effects model. In all simplicity, it tests whether the idiosyncratic errors,  $u_{it}$ , are correlated with the explanatory variables, and under the null hypothesis, they are uncorrelated (Torres-Reyna, 2007). In the methodology, it was explained that this depends on the assumptions and treatment of the individual-specific effect term,  $c_i$ . With this reasoning, the equation for the Hausman test, according to StataCorp (2013b) is given by:

$$H = (\beta_c - \beta_e)'(V_c - V_e)^{-1}(\beta_c - \beta_e) \quad \text{Eq. 6-4}$$

where  $\beta_c$  ( $\beta_e$ ) is the coefficient vector from the consistent (efficient) estimator and  $V_c$  ( $V_e$ ) is the covariance matrix of the consistent (efficient) estimator.

Stata software is used to perform this Hausman test. Initially, it is assumed that the random-effects model is appropriate (due to the result of the BPLM test) for farm-level effects in our model, then a fixed-effects model is fitted which will capture all temporally constant farm-level effects. The assumption is that this model is consistent for the true parameters. The next step is to fit a random-effects model as a completely efficient specification of the individual farm effects. By using the “hausman” command in Stata, the software is able to compare the fixed-effects and random-effects model with each other and produce a test statistic (StataCorp, 2013b). The Hausman test yields a  $\chi^2$  distributed statistic of 108.72 for Eq. 6-1, and as such resoundingly rejects the initial hypothesis that a random-effects model sufficiently models the farm-level effects. Thus, the optimal panel estimation method is fixed-effects analysis.

## Modified Wald Test

In fixed-effects regression analysis, an OLS estimator is applied for interval and point estimates under the classical MLR assumptions that the error process is independently and identically distributed (i.i.d). However, these assumptions may be violated in many ways in panel data context (C. F. Baum, 2001).

The errors may be homoscedastic within each cross-sectional unit, but its variance can be different across units; a phenomenon called group-wise heteroskedasticity. In order to check for this, a modified Wald statistic for group-wise heteroskedasticity in the residuals of the fixed-effects regression model can be calculated. Under the null hypothesis, it is specified that  $\sigma_i^2 = \sigma^2$  for  $i = 1, \dots, N_g$ , where  $N_g$  is the number of cross-sectional units. Next, let  $\hat{\sigma}_i^2 = T_i^{-1} \sum_{t=1}^{T_i} u_{it}^2$  be the estimator of the  $i^{th}$  cross-sectional unit's error variance which is based on the  $T_i$  residuals  $u_{it}$  available for that unit (C. F. Baum, 2001).

Based on the reasoning above, the estimated variance of  $\hat{\sigma}_i^2$  can be defined as:

$$V_i = T_i^{-1}(T_i - 1)^{-1} \sum_{t=1}^{T_i} (u_{it}^2 - \hat{\sigma}_i^2)^2 \quad \text{Eq. 6-5}$$

Thus, the modified Wald test statistic can be defined as:

$$W = \sum_{i=1}^{N_g} \frac{(\hat{\sigma}_i^2 - \hat{\sigma}^2)^2}{V_i} \quad \text{Eq. 6-6}$$

The Wald test statistic will be distributed as  $\chi^2(N_g)$  under the null hypothesis. Stata is used to obtain this test statistic through the “xttest3” command. The modified Wald test yields a  $\chi^2(1017)$  distributed statistic of 47,424.90 for Eq. 6-1, which decisively rejects the null and the errors exhibit group-wise heteroskedasticity.

## Wooldridge Test

Serial correlation affects linear panel data models by biasing the standard errors, which causes the results to be less efficient; hence it is necessary to identify serial correlation in the idiosyncratic error term in panel data estimation. There exist several different methods for this, and the Wooldridge test from 2002 will be utilized here due to the simplicity of few assumptions needed in order to implement the test (Drukker, 2003).

The Wooldridge method uses the residuals from the regression of the first-differences. This model is described in the methodology under fixed-effects model and given by Eq. 5-8. The test procedure begins by estimating the parameters  $\beta$  by regressing  $\dot{y}_{it}$  on  $\dot{x}'_{it}$  and acquiring the residuals  $\hat{u}_{it}$ . The core of this method is Wooldridge's remark that, if the idiosyncratic errors  $u_{it}$  are not serially correlated, then  $Corr(\dot{u}_{it}, \dot{u}_{it-1}) = -0.5$ . With this observation, the procedure runs a regression of the residuals  $\hat{u}_{it}$  from the regression with the first-differenced variables on their corresponding lags and then tests that the coefficient on the lagged residuals is equal to  $-0.5$ . In order to account for the within-panel correlation in the regression of  $\hat{u}_{it}$  on  $\hat{u}_{it-1}$ , the variance-covariance estimator (VCE) is adjusted for clustering at the panel-level. Since clustering also implies robust, this test is thus robust against heteroskedasticity (Drukker, 2003).

By running the command “xtserial” in Stata with the model at hand, the result yields an  $F(1, 989)$  statistic of 116.25. Since the null hypothesis implies no serial correlation, this is strongly rejected, and as such, the model exhibits serial correlation. Because this test method utilizes VCE, which accounts and corrects for serial correlation and heteroskedasticity, the VCE will be further used in our analysis to correct for the mentioned phenomenon.

## Akaike's Information Criterion

Akaike's information criterion (AIC) can be used to compare the quality of a set of statistical regression models to each other (Anderson & Burnham, 2002). In this paper, it is of interest to study which and how variables contribute to the biological growth rate. To ensure that the model given by Eq. 6-1 is, in fact, the most optimal model, a total of 4 different model specifications are created and presented in Table 6-2. By running regression on each of the specifications and calculating the corresponding AIC value, we are able to rank the models from best to worst based on the AIC scoring criterion, where the model with the lowest AIC score is preferred.



Stata is used to calculate the AIC value for each of the models using the following formula:

$$AIC = 2k - 2 \ln(\hat{L}) \quad \text{Eq. 6-7}$$

where  $k$  is the number of explanatory variables in the model, including the intercept, and  $\hat{L}$  is the maximum value of the likelihood function for the model (StataCorp, 2013a).

The AIC value for each model specification is given on the last row in Table 6-2. The pooled OLS regression model without interaction terms is by the logic of this test the worst model relative to the others, and it can be seen that the model gradually becomes better by the inclusion of interaction terms and time fixed-effects.

## 6.2 Regression Results

Table 6-2 reports estimation results for several iterations of the model with progressively more complex specifications. All the estimated parameters are statistically significant. In models B and C, some of the variables enter non-linearly, the marginal effects of these variables are therefore reported separately and are evaluated at the means of all covariates. Our results are comparable to those reported by Abolofia et al. (2017), with corresponding model covariates exhibiting the same sign and order of magnitude. For every model specification, the marginal effect of lice is negative and statistically significant at greater than the 1% level. Our results, therefore, suggest that in a *ceteris paribus* setting, farms with a higher monthly average lice count will experience lower biomass growth. The marginal effects of both of the lice treatment options included in our model are also negative and statistically significant at the 1% level. Thus, our results suggest that farms undergoing either bath or mechanical treatments will experience lower levels of biomass growth.

Table 6-2: Biological Growth Model Results.

Variable	Pooled OLS	FE (Model A)	FE (Model B)	FE (Model C)
Months at sea <sup>a</sup>	-0.0053** (0.0003)	-0.0056** (0.0003)	-0.0055** (0.0004)	-0.0063** (0.0004)
Feed use <sub>t</sub> ('00,000 kg) <sup>b</sup>	0.0130** (0.0006)	0.0134** (0.0006)	0.0273** (0.0023)	0.0243** (0.0025)
x feed use <sub>t</sub>	-	-	-0.0012** (0.0002)	-0.0012** (0.0003)
Average fish size <sub>t-1</sub> (kg)	-0.0411** (0.0011)	-0.0412** (0.0013)	-0.0480** (0.0015)	-0.0435** (0.0015)
Number of fish <sub>t-1</sub> ('00,000s)	-0.0030** (0.0004)	-0.0032** (0.0006)	-0.0067** (0.0007)	-0.0054** (0.0007)
Average water temp <sub>t-1</sub> (°C)	0.0115** (0.0003)	0.0117** (0.0003)	0.0277** (0.0012)	0.0199** (0.0017)
x avg. water temp <sub>t-1</sub>	-	-	-0.0008** (0.0001)	-0.0008** (0.0001)
Number of mechanical treatments <sub>t</sub>	-0.0203** (0.0016)	-0.0196** (0.0016)	-0.0213** (0.0023)	-0.0236** (0.0023)
Number of bath treatments <sub>t</sub>	-0.0090** (0.0010)	-0.0097** (0.0009)	-0.0134** (0.0011)	-0.0137** (0.0011)
Lice <sub>t-1</sub> (avg. number/fish) <sup>c</sup>	-0.0070** (0.0006)	-0.0068** (0.0006)	-0.0104** (0.0023)	-0.0050* (0.0023)
x lice <sub>t-1</sub>	-	-	0.0005** (0.0001)	0.0003** (0.0001)
x avg. fish size <sub>t-2</sub> <sup>d</sup>	-	-	0.0054** (0.0005)	0.0047** (0.0004)
x avg. water temp <sub>t-1</sub>	-	-	-0.0019** (0.0002)	-0.0019** (0.0002)
x num. of mech. treatments <sub>t</sub> <sup>e</sup>	-	-	0.0045** (0.0010)	0.0047** (0.0010)
x num. of bath treatments <sub>t</sub> <sup>e</sup>	-	-	0.0033** (0.0005)	0.0034** (0.0004)
Year fixed effects <sup>f</sup>	YES (F = 2.40*)	YES (F = 3.08**)	YES (F = 7.56**)	YES (F = 3.41**)
Farm fixed effects	NO	YES (F = 1.82**)	YES (F = 1.88**)	YES (F = 1.95**)
Month fixed effects <sup>g</sup>	NO	NO	NO	YES (F = 52.70**)
<b>Marginal effects</b>				
Feed use <sub>t</sub>	0.0130** (0.0006)	0.0134** (0.0006)	0.0211** (0.0011)	0.0182** (0.0012)
Average water temp <sub>t-1</sub>	0.0115** (0.0003)	0.0117** (0.0003)	0.0106** (0.0003)	0.0043** (0.0007)
Lice <sub>t-1</sub> (avg. number/fish)	-0.0070** (0.0006)	-0.0068** (0.0006)	-0.0151** (0.0010)	-0.0111** (0.0009)
Number of mech. treatments <sub>t</sub>	-0.0203** (0.0016)	-0.0196** (0.0016)	-0.0170** (0.0017)	-0.0192** (0.0017)
Number of bath treatments <sub>t</sub>	-0.0090** (0.0010)	-0.0097** (0.0009)	-0.0102** (0.0009)	-0.0105** (0.0009)
Observations	38,687	38,687	35,648	35,648
Number of farms	1,024	1,024	1,017	1,017
Avg. observations per farm	37.8	37.8	35.1	35.1
R <sup>2</sup> (within/overall)	(-/0.39)	(0.39/0.39)	(0.43/0.43)	(0.44/0.44)
Hausman test	-	$\chi^2(13) = 46.54^{**}$	$\chi^2(20) = 67.73^{**}$	$\chi^2(31) = 108.72^{**}$
AIC	-44,340	-46,209	-48,504	-49,383

Rogers (1993) standard errors in parentheses; \*p-value < 0.05; \*\*p-value < 0.01

<sup>a</sup> Months at sea is the number of months since initial stocking and is a proxy for fish age.

<sup>b</sup> Feed use enters without lag since it a cumulative measure of the amount of feed used in month *t*.

<sup>c</sup> Total number of mobile lice per fish.

<sup>d</sup> Since fish size is reported at the end of each month, a two-month lag is used.

<sup>e</sup> Treatment performed in the current month is expected to have an immediate effect on adult lice counts and biological growth rate, as such mitigating damages from an infestation in the previous month and reducing the growth rate in month *t*.

<sup>f</sup> Year fixed effects capture technological change.

<sup>g</sup> Month fixed effects capture non-temperature related seasonality variations.

When accounting for farm fixed effects, monthly fixed effect (which capture seasonality), yearly fixed effect (which captures technological advancement) and other important biological factors and interaction terms the overall fit ( $R^2$ ) of the model is increased from 0.39 to 0.44. Such an overall fit is quite good when considering the micro-nature of our data. The overall  $R^2$  of Model C in Table 6-2 is significantly higher than the overall  $R^2$  reported for the corresponding model by Abolofia et al. (2017). This increase may be a result of the inclusion of independent treatment variables in our model. It is also possible that our decision to remove extreme values from our data set has contributed to a significantly better fit. However, this is difficult to evaluate since Abolofia et al. (2017) do not provide details regarding removed/imputed values. The lice interaction terms suggest that the marginal effects of lice on biomass growth will decay at higher levels of lice, fish size, number of mechanical treatments and number of bath treatments, and intensify at higher water temperatures. Our model also suggests that the marginal effects of both treatment options on biomass growth will decay at higher levels of lice. In the following section, the marginal effects of lice and lice treatments will be explored further.

### **Marginal Effects of Lice on Biomass Growth**

In this section, similar terminology to Abolofia et al. (2017) will be used. We refer to the marginal effect of lice on fish biomass growth as the marginal lice effect (MLE) and report the rate of farm biomass growth as opposed to the MLE level. Therefore, we must transform our parameter estimates to produce marginal effects measured in units of live weight of lost biomass growth and percent change in the rate of biomass growth. Importantly, the effectiveness of delousing treatments at reducing lice levels is accounted for in the MLE, but the negative effect of delousing treatments on biomass growth is not accounted for in the MLE. Therefore, marginal bath treatment effect (MBE) and marginal mechanical treatment effect (MME) are also reported. Table 6-3 presents the MLE, MBE, and MME at the means of all covariates by geographical region. Column 4 of Table 6-3 shows the percent change in fish biomass growth with an instantaneous unit increase in the given variable, with all other model covariates fixed at their respective region-specific means. Since farms in the southern region on average are smaller, more abundant and have higher lice counts, the percent change in lost biomass growth is highest for this region, at -1.272%. On the other hand, in the northern region farms are larger and relatively sparse with low amounts of lice, which results in a lower lost biomass growth of -0.856%. The fifth column of Table 6-3 presents the lost biomass growth in units of live weight. According to our model, the central region

experiences the largest losses in live weight biomass growth due to farms having a high average standing biomass and experiencing higher lice infection pressure than the north region. Moreover, the north region experiences the lowest live weight biomass growth despite having on average, the highest standing biomass of any region.

Table 6-3 also presents the marginal effects of lice treatments on biomass growth. For both treatment options, the north region has the highest percentage loss in biomass growth. Since lice levels are lower for the northern region, treatments are also often performed at lower lice levels compared to the other regions, which could be a factor contributing to higher values. The same argument applies to the central region when compared to the south region. Treatments are also performed less frequently in the northern region compared to the other regions, which result in less overall damages from treatment over a full production cycle. These figures are also further enhanced in column 5 due to regional differences in farm size. Importantly, our results show that performing these types of lice treatments adversely affect biomass growth and will result in significant revenue loss.

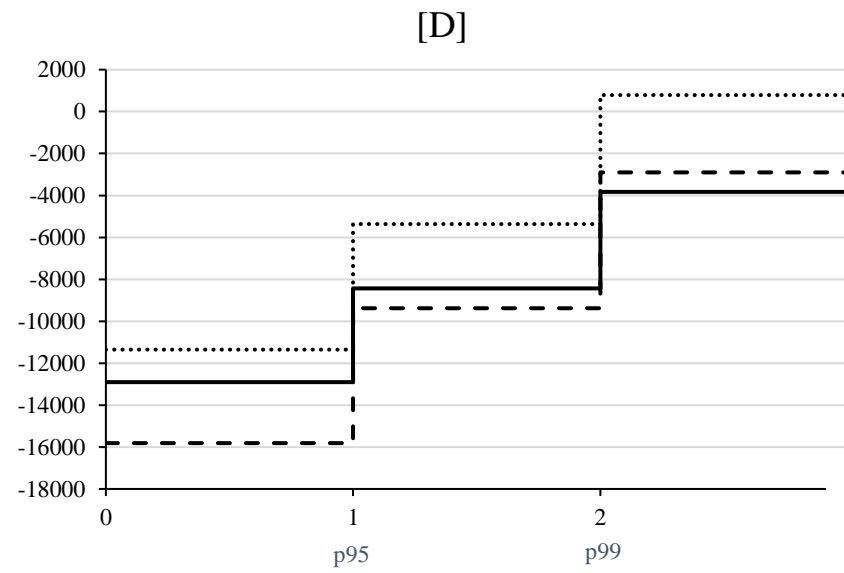
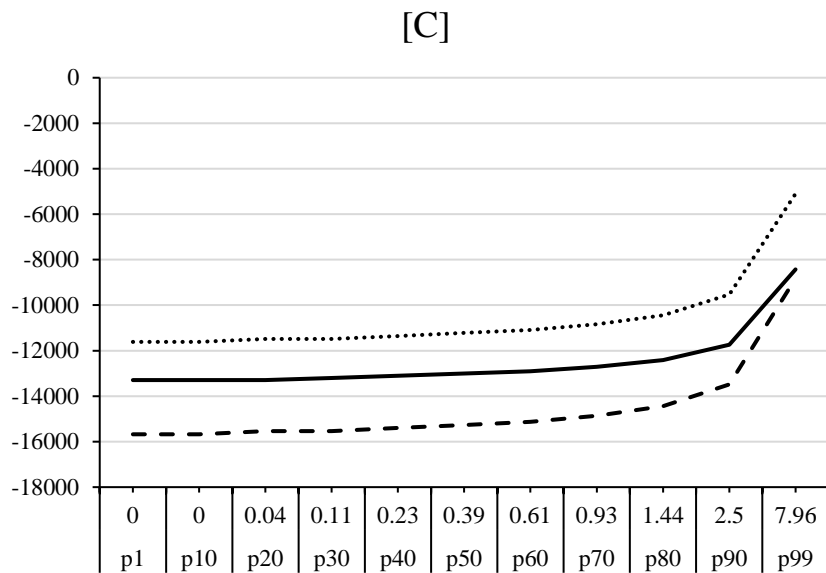
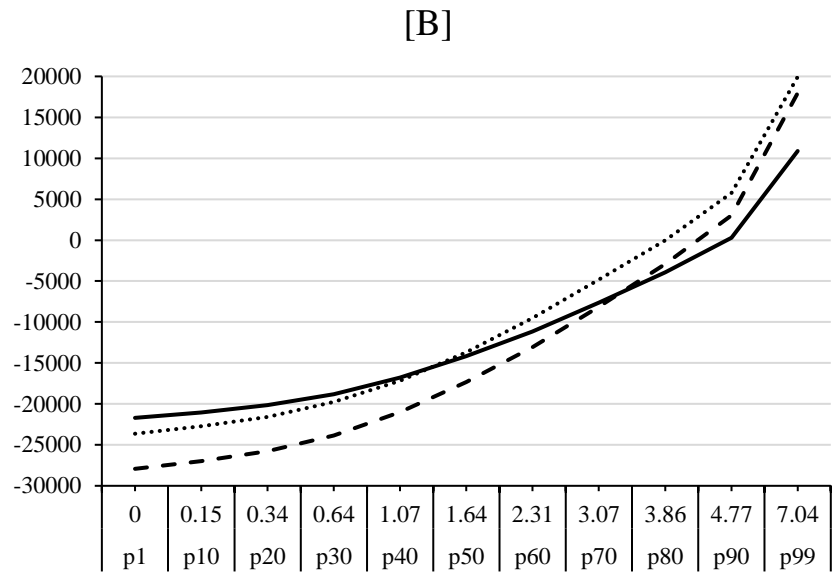
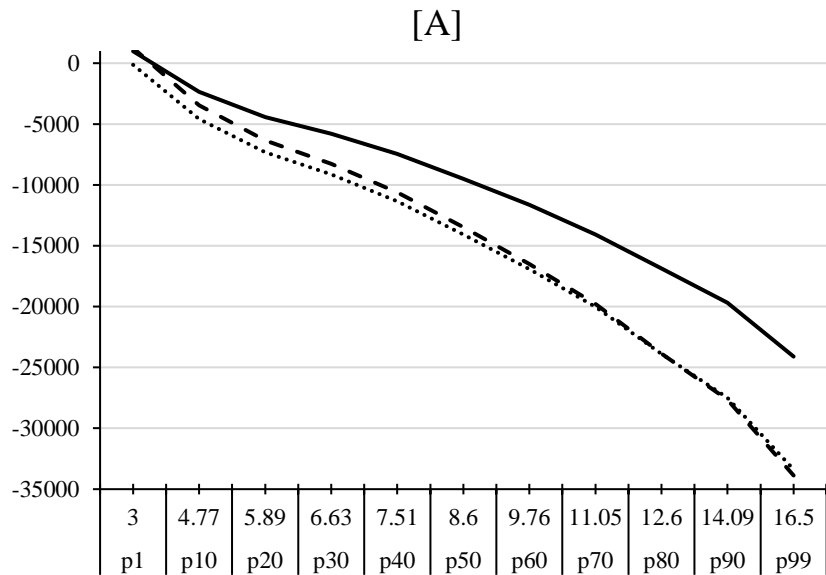
Table 6-3: Regional Marginal Effects of Selected Model Variables.

Variable	Region	Marginal effect	Percentage change <sup>a</sup>	Mean biomass loss (kg)
Lice <sub>t-1</sub>	North	-0.0086** (0.0011)	-0.856%	-11,220.6
	Central	-0.0108** (0.0010)	-1.074%	-14,853.6
	South	-0.0128** (0.0010)	-1.272%	-12,517.9
Mechanical treatment <sub>t</sub>	North	-0.0216** (0.0020)	-2.137%	-28,012.2
	Central	-0.0197** (0.0018)	-1.951%	-26,982.6
	South	-0.0174** (0.0016)	-1.725%	-16,975.9
Bath treatment <sub>t</sub>	North	-0.0122** (0.0010)	-1.213%	-15,900.2
	Central	-0.0108** (0.0010)	-1.074%	-14,853.6
	South	-0.0092** (0.0010)	-0.916%	-9,014.4

Rogers (1993) standard errors in parentheses; \*\* p-value < 0.01

<sup>a</sup> To obtain percentage change in biomass growth a simple log-transformation was used;  $exp^{(Marginal\ effect - 1)}$ .

Figure 6-1 presents the variation in the marginal lice effect at means (MLEM) as a function of different important model covariates. Panel [A] in Figure 6-1 shows that the MLEM is relatively sensitive to water temperature and fish size, implying that higher temperatures and smaller fish intensify the loss in biomass growth due to lice. Panel [B] highlights the vulnerability to lice of smaller salmon; the MLEM decreases as fish size increases. Panel [C] indicates that the MLEM is relatively insensitive to number of lice, meaning that one additional louse will have roughly the same negative impact on growth rate regardless of how many lice are present at the farm already. It is only at very high levels of lice (7.96 average total mobile lice per fish) that the damaging effect of one additional louse will start to diminish. The MLEM as a function of treatment effects is shown as step functions in Panel [D] and [E] as these variables only take integer values. It is important to note that the MLEM only reflects the effect that lice directly will have on the biomass growth. Therefore, the MLEM will decline as lice treatments increase since lice treatments lower the level of lice. The MLEM does not account for the loss in biomass growth resulted from treatments.



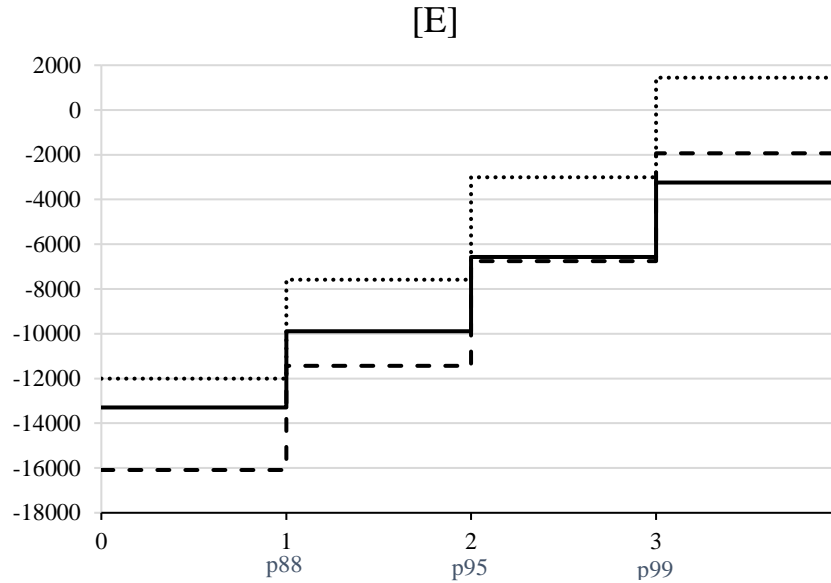


Figure 6-1: Variation in MLEM in kg by: [A] avg. water temp<sub>t-1</sub>, [B] avg. fish size<sub>t-2</sub>, [C] avg. lice per fish<sub>t-1</sub>, [D] number of mechanical treatments<sub>t</sub>, and [E] number of bath treatments.  
 Note: Values denoted with the letter p represent percentiles of the data. The decimal numbers represent actual numerical values corresponding to the percentiles. All other covariates are fixed at region-specific means. The different regions are represented by North (dotted), Central (dashed), and South (solid).

Figure 6-2 presents the average growth rate ( $\hat{r}_{it}$ ) as a function of lice and mechanical treatments (Panel [A]) and lice and bath treatments (Panel [B]). Lice numbers in parentheses are the corresponding adult female lice counts. The marginal effects reported in Table 6-3 are not sufficient to present the combined influence of lice and lice treatments on biological growth rate. We, therefore, present surface plots that showcase how the growth rate changes for combined values of lice and lice treatments. We report these numbers to later relate our results to the lice and lice counting regulations and politic implications and possible conflicts of interest. These graphs suggest that mechanical and bath treatments will have a negative impact on growth rate for lice counts under 5.00 average total mobile lice per fish (0.84 average adult female lice per fish) and 4.5 average total mobile lice per fish (0.69 average adult female lice per fish) respectively (indicated by the dark lines on the surface plot). Our research indicates that there is no economic incentive for farmers to keep lice levels below the government lice limits, as performing these treatments when lice levels are at or below the lice limit will result in a lower growth rate than if no treatment was performed.

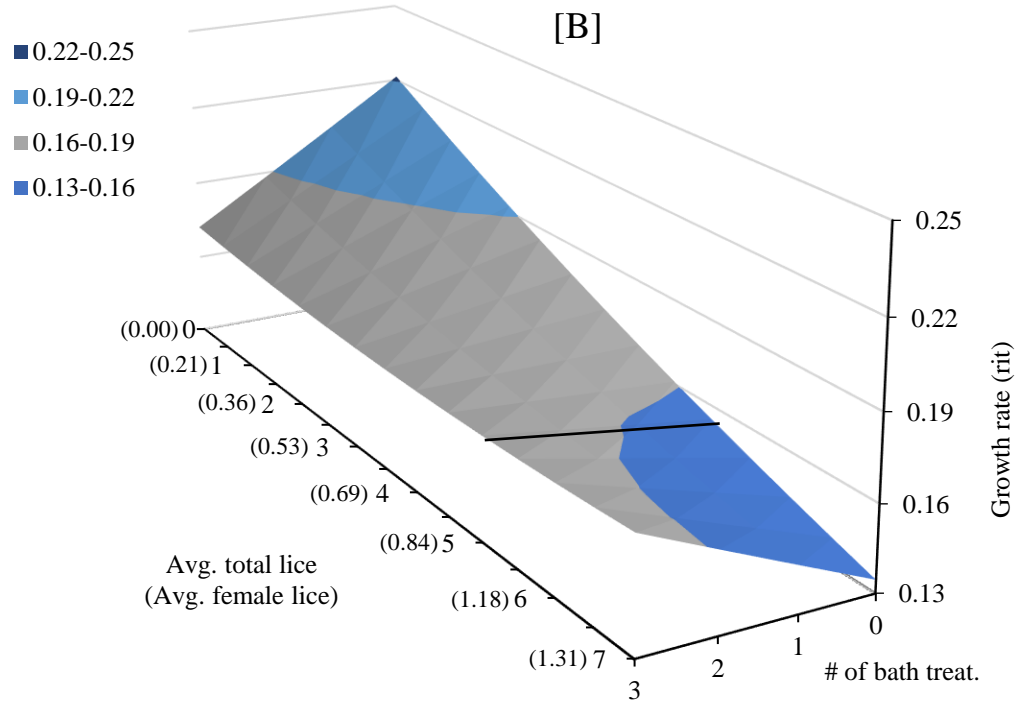
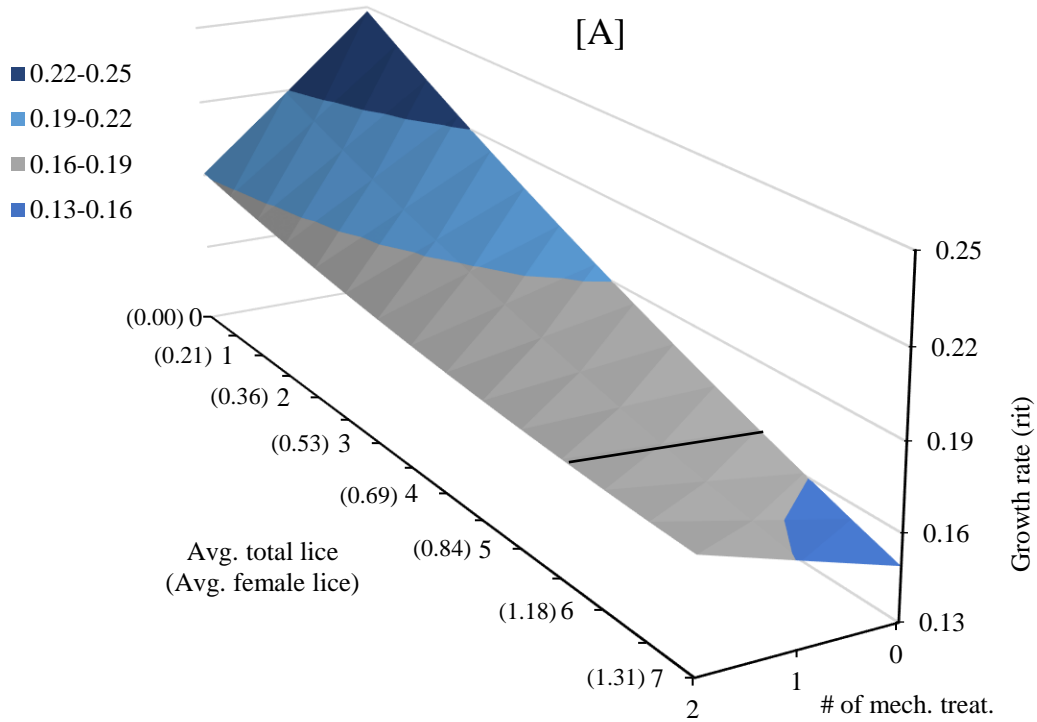


Figure 6-2: Surface Plots of Predicted Growth Rate as a Function of Lice and Mechanical Treatment [A] and Lice and Bath Treatment [B].

Note: Values in parentheses represent the average number of adult female lice.



### 6.3 Lost Biomass Growth for Typical Production Cycles

To be able to estimate the cost of lice, it is first necessary to find the difference in biomass growth for a typical lice infestation scenario and a perfect scenario with no lice or lice treatments. Hence, we construct a data set where all model variables are fixed at their region-specific means, and one data set where all lice and lice treatment variables are set to zero and all other variables are fixed at region-specific means. Model C in Table 6-2 is then used to obtain predicted values for all data points in both data sets. The predicted values with no lice are subtracted from the corresponding predicted values with lice. To obtain estimates reported in kg of biomass growth ( $\hat{g}_{it}$ ), we transform the predicted values of our original model as follows;  $\hat{g}_{it} = [\exp(\hat{y}_{it}) - 1] \cdot biomass_{it-1}$ . This prediction remains consistent in the face of the log-transformational bias. The following expression was used to calculate the difference in predicted biomass growth for the two scenarios.

$$\Delta \hat{g}_{t+1} = \hat{g}_{t+1}^{nolice} - \hat{g}_{t+1}^{lice} \quad \text{Eq. 6-8}$$

To get an understanding of the inter-region heterogeneity, we calculate the average  $\Delta \hat{g}_{t+1}$  for different distinct production cycles. In our data, the average length of a production cycle is 18 months. Contrary to Abolofia et al. (2017), we find no significant difference in spring and fall release cycle lengths. Considering technological advancement, possible preference changes in fish farmers, and a recent report by Garshol et al. (2018), the change in average production cycle length is reasonable. In Figure 6-3, we present typical grow out cycles featuring the means of key model covariates as well as lice and lice treatment numbers. The figure presents important elements of the inter-region heterogeneity. In the south and central regions, the fish grow faster and have higher lice counts than farms in the north. The difference in temperature is also evident, and lice counts are clearly correlated with temperature, but with a lag. The average standing biomass tends to decrease towards the end of the production cycles, indicating that harvesting often is performed over several months, rather than all at once.

Figure 6-4 presents the estimated lost biomass growth for each month for typical production cycles. The lost biomass growth is reported as a percentage of average MAB in the specific region. Thus, we account for regional differences in farm size and can directly compare the impact of lice in the three regions. There is a clear visual difference between spring and fall release, with spring release cycles having two distinct peaks in  $\Delta \hat{g}_{t+1}$  and fall release cycles only having one. The lost biomass growth in the central and south region are similar, with a peak loss of approximately 2.9% of the MAB in month 14 of the fall production cycle.

Moreover, the north region only experiences a peak loss of roughly 1.1% of the MAB in month 18 of the spring production cycle. Figure 10-1 in appendix 10.1 presents the lost biomass growth in metric tonnes.

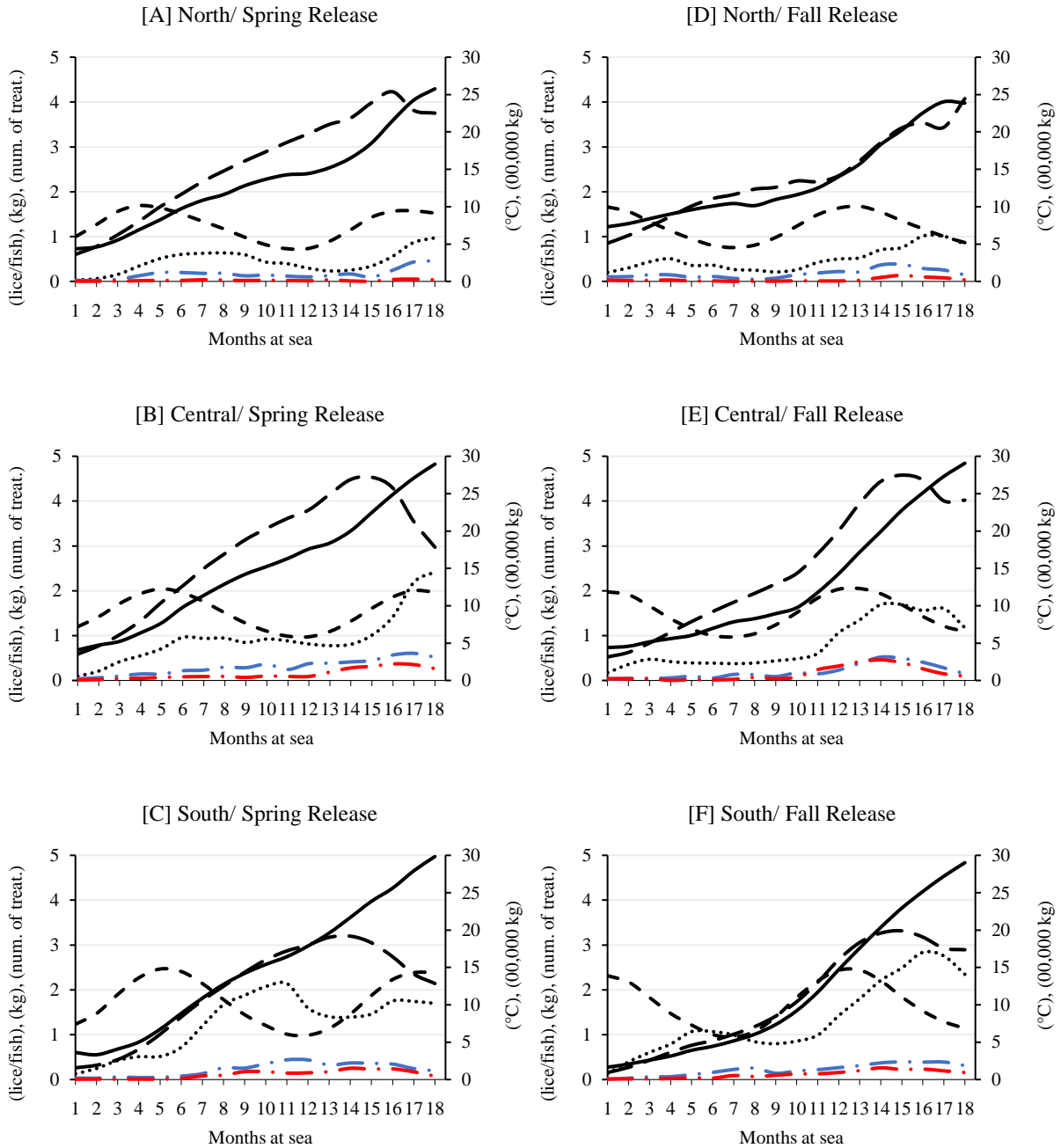


Figure 6-3: Typical Spring-Release [A-C] and Fall-Release [D-F] Production Cycles Represented by Region and Season of Release.

Note: The lines are sea month specific mean values of standing farm biomass (long dash), fish size in kg (solid), water temperature (dash), lice per fish (dot), number of mechanical treatments (red dash-dot) and number of bath treatments (blue dash-dot).

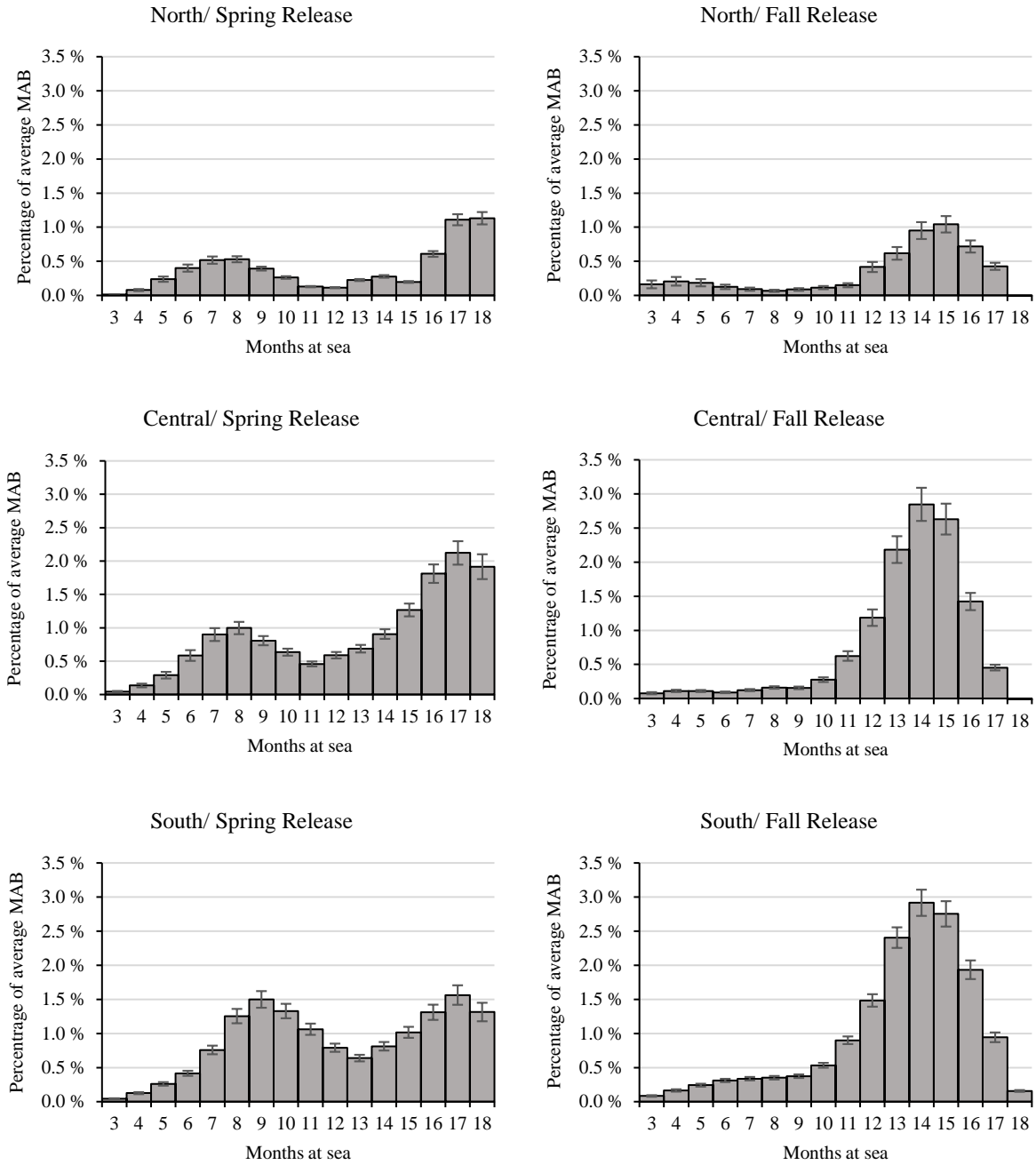


Figure 6-4: Predicted Monthly Loss of Biomass Growth ( $\Delta\hat{g}_{it+1}$ ) From Average Lice Infestation and Treatment Scenarios With 95% CIs.

Note: In this figure  $\Delta\hat{g}_{it+1}$  is displayed as a percentage of the region-specific average MAB. Hence, we are able to directly compare the biomass loss across the different regions since we adjust for regional differences in farm size. Estimates for  $\Delta\hat{g}_{it+1}$  reported in metric tonnes can be found in Figure 10-1 in appendix 10.1.

## 6.4 The Private Cost of Lice

To calculate the private cost of lice, we utilize a parametrized version of Eq. 5-2. By applying this equation to the different distinct production cycles, we are able to quantify the cost of lice over typical production cycles. Then, we use harvesting data from our data set to calculate the average revenue of a production cycle and standardize the cost of lice as a percentage of the revenue. Eq. 6-9 is a parametrized adaptation of Eq. 5-2 and combines the indirect costs associated with revenue loss and feed cost savings with the direct costs associated with lice treatments.

$$\frac{P}{(1+r)^T} \underbrace{\sum_{t=1}^T (\Delta \hat{g}_{t+1})}_{\text{Revenue loss}} - \underbrace{\sum_{t=1}^T \frac{C_f \cdot FCR}{(1+r)^{t+1}} (\Delta \hat{g}_{t+1})}_{\text{Feed cost savings}} + \underbrace{\sum_{t=1}^T \frac{C_b \cdot N_{t+1}^b}{(1+r)^{t+1}}}_{\text{Bath treatment cost}} + \underbrace{\sum_{t=1}^T \frac{C_m \cdot N_{t+1}^m}{(1+r)^{t+1}}}_{\text{Mechanical treatment cost}} \quad \text{Eq. 6-9}$$

For our calculations, salmon price, feed price, feed conversion ratio (FCR<sup>6</sup>), bath treatment cost, and mechanical treatment cost were kept constant. Salmon price<sup>7</sup> and feed price<sup>8</sup> were set to the average prices over the data set duration and are not inflation-adjusted. Bath treatment cost and mechanical treatment cost were set to NOK 946,000 and NOK 627,000 respectively<sup>9</sup>. These costs were calculated using the unit cost for each treatment reported in Table 3-2, multiplied by the standing biomass at the specific month for each farm where a treatment occurred. The sensitivity analysis performed in section 6.5 indicates that this assumption has little impact on our results.

Table 6-4 presents estimates for revenue loss, feed cost savings, bath treatment cost, and mechanical treatment costs for typical production cycles. All numbers reported in Table 6-4 and Table 6-5 are estimated using Eq. 6-9. As expected, the central and south regions experience the largest average treatment costs for typical production cycles since lice infestations are larger and more prevalent. The northern region experiences very low costs associated with mechanical treatment, about 25% of the cost compared to the other regions. There are also significant regional differences in bath treatment costs, with the central region spring cycles having an average cost of 4.93 million NOK and the north region fall cycles having an average cost of only 2.78 million NOK. Table 6-4 also emphasizes our models focus on indirect costs

<sup>6</sup> Feed conversion ratio is set to 1.15 as reported by Marine Harvest (2018b)

<sup>7</sup> The salmon price is set to 45.43 NOK/kg, which is the average weekly spot price from 2012-2017. Source: (Fish Pool, 2019).

<sup>8</sup> A feed price of 11.80 NOK/kg is used. This price is reported by Iversen et al. (2017) and does not account for medical feed price.

<sup>9</sup> Treatment costs are reported in 2017-values and are not inflation-adjusted.

associated with lost biomass growth (revenue loss and feed cost savings). We report confidence intervals for these cost components as they are dependent on our model estimations reported in Figure 6-4.

Table 6-5 presents the cost of lice for the different production cycles in our data set. Column 4 in Table 6-5 reports the cost per kilogram of harvested fish; these numbers were obtained by dividing the total private economic costs per cycle by the average harvested biomass of that cycle. Column 5 in Table 6-5 reports the cost of lice as a percentage of the average revenue of a single production cycle. The conversion to percentage of revenue is especially useful when expressing the aggregated cost for the entire industry over a specific period. For example, a typical fall release cycle in the northern region will experience an economic loss of NOK 9.6 million, equivalent to NOK 4.53 per kg of harvested biomass or 9.07% of total revenues. A typical fall release cycle in the southern region, on the other hand, will experience an economic loss of NOK 21.7 million, equivalent to NOK 11.53 per kg of harvested biomass or 20.24% of revenues. Our estimates suggest that typical infestation and treatment regimes are 2 to 2.5 more costly in the south and central region compared to the north region. Column 6 in Table 6-5 presents the distribution of the different production cycles in our data set. Only 8.14% of the complete production cycles identified in our data set were classified as fall releases in the north region. On the other hand, 24.78% of the production cycles were identified as fall release in the south region. Our distributions of the different types of production cycles are similar to the numbers reported by (Garshol et al., 2018).

Table 6-4: Individual Cost Elements of Average Lice Infestation and Treatment Scenarios Evaluated Using Eq. 6-9 ( $r = 0$ ).

Region	Release	Revenue Loss (NOK)	Feed Cost Savings (NOK)	Bath Treatment Cost (NOK)	Mechanical Treatment Cost (NOK)
North	Spring	10,939,993 [10,004,125, 11,875,861]	3,267,910 [2,988,354, 3,547,465]	2,809,194	250,275
Central	Spring	26,918,966 [24,466,136, 29,371,797]	8,041,025 [7,308,334, 8,773,715]	4,930,061	1,535,061
South	Spring	21,464,731 [19,643,826, 23,285,637]	6,411,778 [5,867,851, 6,955,705]	3,723,196	1,272,667
North	Fall	9,405,155 [7,872,889, 10,937,421]	2,809,435 [2,351,728, 3,267,141]	2,780,435	298,341
Central	Fall	23,677,489 [21,443,933, 25,911,045]	7,072,756 [6,405,565, 7,739,946]	3,038,724	1,502,547
South	Fall	24,026,414 [22,387,294, 25,665,535]	7,176,984 [6,687,359, 7,666,609]	3,653,405	1,261,716

Table 6-5: Cost of Average Lice Infestation and Treatment Scenarios ( $r = 0$ ).

Region	Release	Total Cost of Lice (NOK)	Cost/kg of Lice (NOK)	% of Revenue	Distribution of Cycles (%)
North	Spring	10,731,553 [10,075,240, 11,387,865]	4.16 [3.91, 4.41]	8.39 [7.92, 8.86]	15.33
Central	Spring	25,343,063 [23,622,923, 27,063,203]	6.50 [6.06, 6.94]	12.51 [11.76, 13.25]	17.42
South	Spring	20,048,816 [18,771,837, 21,325,794]	7.78 [7.28, 8.27]	14.62 [13.81, 15.40]	22.40
North	Fall	9,674,496 [8,699,936, 10,749,056]	4.53 [4.03, 5.04]	9.07 [8.15, 9.98]	8.14
Central	Fall	21,146,005 [19,579,639, 22,712,370]	7.65 [7.08, 8.21]	14.41 [13.49, 15.31]	11.94
South	Fall	21,764,596 [20,615,101, 22,914,091]	11.53 [10.92, 12.14]	20.24 [19.38, 21.09]	24.78

Note: Confidence intervals for Table 6-4 and Table 6-5 are obtained by using the upper and lower limits of the CIs reported in Figure 6-4.

To calculate the cost of lice for the industry on a yearly basis, we calculate the aggregated revenue loss by weighting the revenue losses from the different production cycles on the distribution of cycles in our data set. This results in an aggregated average revenue loss of 14.21%, and an average yearly cost of lice of 8.2 billion NOK. Figure 6-5 presents the estimates for the cost of lice in specific years together with the monthly average salmon price. To obtain specific year costs, the total production volume for the given year was multiplied with the average salmon price for that year, which was then multiplied by the aggregated percentage revenue loss. It is important to note the strong connection between salmon price and cost of lice. Since our model of the private cost of lice mostly is comprised of the lost biomass growth, the lost revenues from this part of the equation affect the costs greatly. In section 7.2, we further elaborate on the implications of the lost biomass growth for salmon price and supply. Figure 6-6 presents a comparison between the average EBIT for the industry and the average cost of lice. Numbers are reported as a percentage of total revenue and show that the cost of lice corresponds to approximately 50% of industry EBIT, further emphasizing the severity of sea lice prevalence.

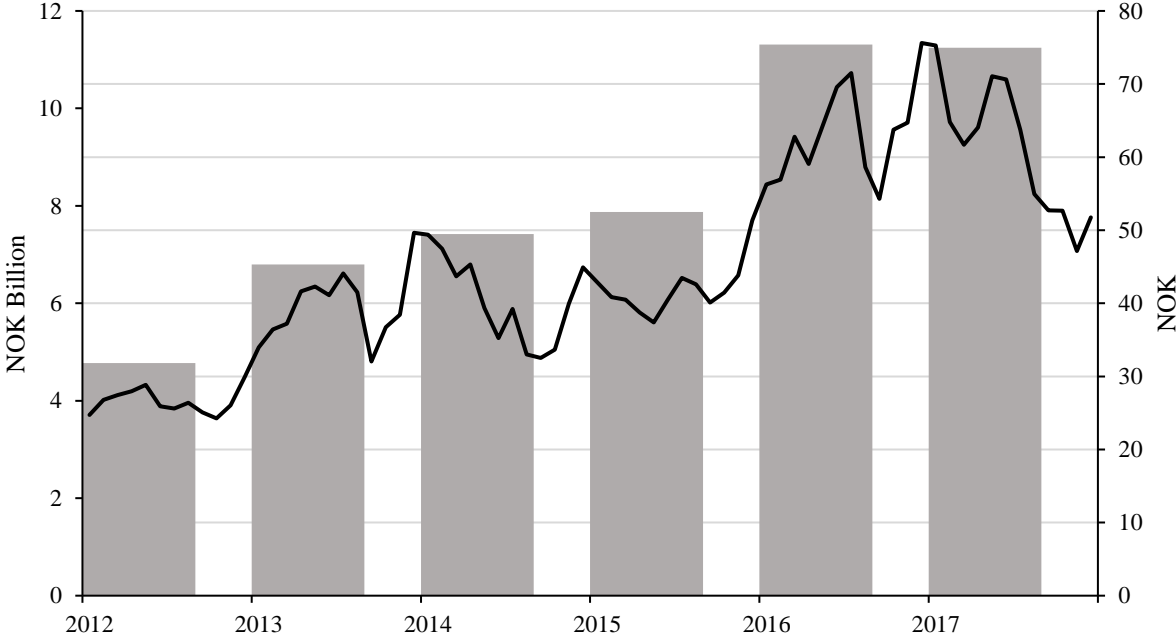


Figure 6-5: Predicted Economic Loss Due to Lice and Average Monthly Salmon Price. Source: (Fish Pool, 2019)  
 Note: Here, the cost of lice is the product of the estimated revenue loss (14.21%), annual production quantity and annual average salmon price.

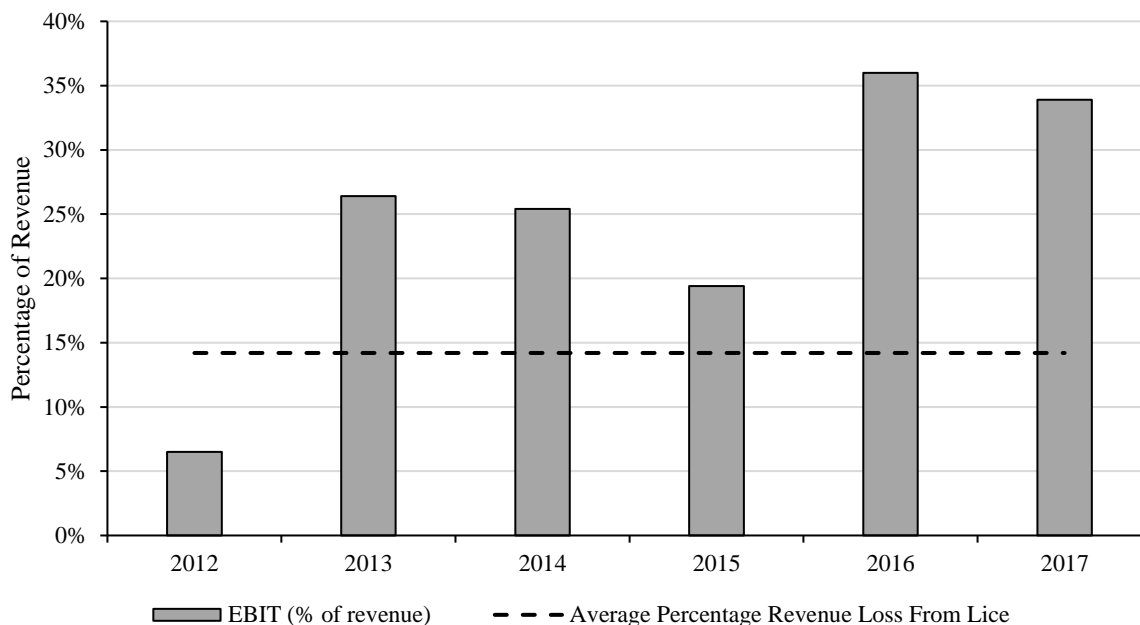


Figure 6-6: Average Yearly EBIT and Cost of Lice Displayed As a Percentage of Total Revenue. Source: (Norwegian Directorate of Fisheries, 2018b)

## 6.5 Sensitivity Analysis

To highlight the strengths and limitations of our model and estimations, it is important to investigate how our results change, as different variables change. The excel add-in *@TopRank* was used to create graphical illustrations of the different variables' sensitivity. Figure 6-7 shows how the percentage revenue loss change as key variable values are varied. For the purpose of simplicity and comparison, all variables are varied from -50% to +50% of their initial values. Feed price is the most important factor determining the percentage revenue loss from lice as a higher feed price will increase feed cost savings and reduce the percentage loss of revenue. If feed price increases by 50%, from 11.80 NOK to 17.70 NOK, the percentage of revenue lost will go down from 14.21% to 12.40%. Should the feed price decrease, the feed cost savings would drop, increasing revenue loss. For the percentage revenue loss, the salmon price has relatively little impact; this is because the revenue itself and the cost associated with loss of biomass growth will move together as the salmon price changes. An important note considering the sensitivity of percentage revenue loss on changes in bath treatment cost is that the utilization of this treatment method has declined rapidly in recent years. Thus, using more recent data to perform a similar analysis would likely not yield the same sensitivity to bath treatment cost. As expected, the salmon price has a great impact on the total cost of lice (not the percentage revenue loss) as the salmon price determines the revenue and therefore also the lost revenue from lost biomass growth.



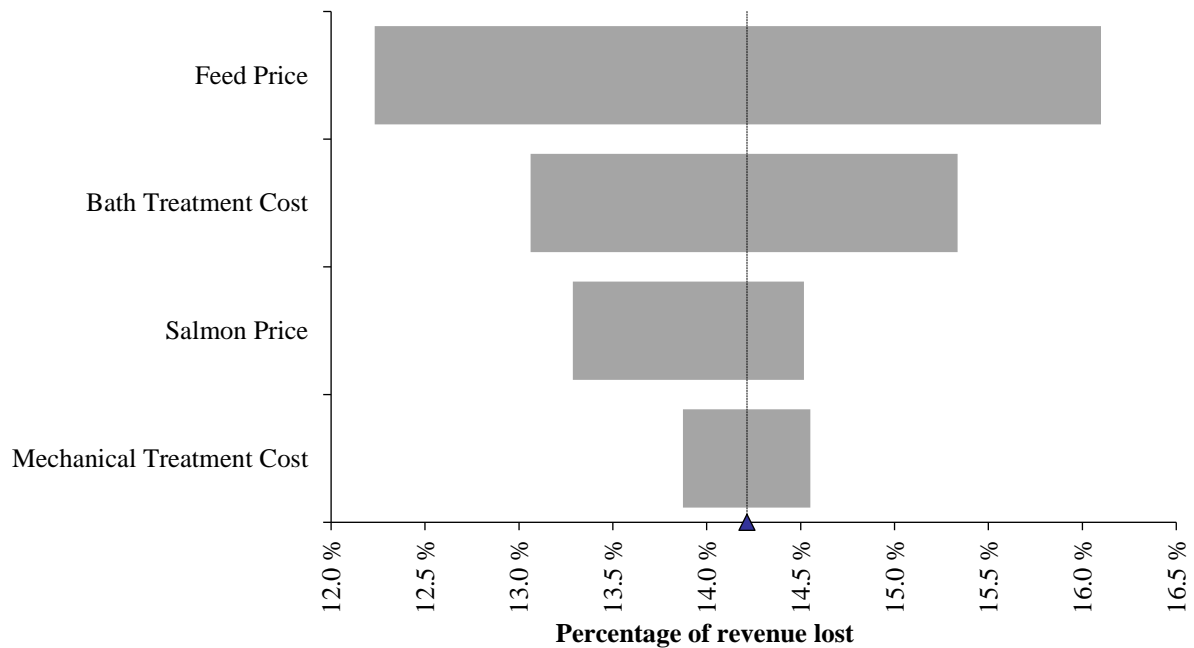


Figure 6-7: Tornado Graph Presenting the Sensitivity of Percentage Revenue Lost Due to Lice, Conditional on Key Model Variables.

### Price Sensitivity of Increased Supply

Based on the estimated loss in biomass growth reported in section 6.3, we calculate the potential increase in supplied quantity in a perfect scenario with no lice. The average loss in biomass growth for each month at sea, presented in Figure 10-1, are summed for each of the six individual production cycles. Then, the percentage of lost production quantity is calculated using average harvest numbers for these cycles. These percentage changes in quantity are then weighted using the distribution of cycles in our data set, creating an aggregate percentage supply increase of 18.7%. This number reflects the estimated increase in production volume from the current lice situation to a perfect scenario with no lice. Using a price elasticity of demand of -1.1, as reported by Capia (2019), the corresponding price decrease would be 16.5%. Accounting for the price decrease, the average annual cost estimation of 8.2 billion NOK is reduced to 6.8 billion NOK. The possible implications of this price correction are discussed in section 7.2.

## **7. Discussion**

In this chapter, we first discuss important limitations and sources of error regarding our data and analysis. Then we elaborate on the possible impact of increased supply on the price of salmon. Next, we highlight the importance of research and development of new technologies concerning sea lice mitigation and control. Lastly, we provide some reflecting thoughts on current government regulations and conflicts of interest.

### **7.1 Limitations and Sources of Error**

One limitation of our model is the absence of variables describing the effects of cleaner fish and in-feed chemical treatments. Information on these mitigation efforts was deemed insufficient in providing valuable estimations on their influence on biological growth rate. For example, the presence of cleaner fish at individual farms is unknown, only information about the release of new cleaner fish is provided. For in-feed chemical treatments, no information concerning the duration of treatment and starvation period is present. Additionally, the transformation from weekly to monthly data imposed further censoring of treatment variables. There exist several studies on the direct cost associated with cleaner fish and in-feed chemical treatments. Detailed estimates reported by Iversen et al. (2017) is presented in Appendix 10.4. The effects of these treatment options can easily be incorporated into our model if more detailed data becomes available in the future.

As the industry is in a state of constant technological development, there exist significant changes in treatment preferences, production cycle length, and other important factors in our data set that may interfere with our results. For example, in 2012, almost no mechanical treatments were performed as the technology was yet not commercially available. Therefore, bath treatments were much more prevalent then, compared to 2017, where mechanical treatments replaced a large portion of bath treatments.

Our data only distinguishes between whether the entire farm or part of the farm was subjected to delousing treatments. Thus, an assumption on the average amount of biomass being treated when a treatment was performed on only part of the farm had to be made. Most data points indicating that part of the farm was treated contained two or more treatments. This suggests that less than 50% of the farm biomass was treated during each treatment procedure; otherwise, the data point would report that the entire farm was treated. The assumption is that a treatment on part of the farm, on average, would be equivalent to 25% of the standing biomass being treated.

This assumption affects the average direct cost of treatment, causing our treatment cost estimates in Table 6-4 to potentially be biased. When considering the relative insensitivity of percentage revenue loss to direct treatment costs, illustrated in Figure 6-7, this possible bias is not a significant cause of concern.

## **7.2 Impact of Increased Supply on Salmon Price**

The most important factors contributing to higher prices are stagnation in supply growth, mostly due to lice and lice regulations, and increasing demand for salmon as Norway's export market is growing (Norges Sjømatråd, 2019). This surge in salmon prices have increased farmers' margins and compensated for increased production costs. Since our estimates of lost biomass growth due to lice are of a significant magnitude, the total salmon supplied to the market would be significantly higher in a scenario with no lice. By our estimations, the supplied quantity would increase by 18.7%. In this scenario, the price of salmon would decrease by 16.5%, significantly lowering farmer margins. It can, therefore, be argued that the difference in profits between the current scenario and the no lice scenario reported in this paper is slightly overestimated. Even if new technology can contribute to reduce lost biomass growth due to lice, the decrease in price resulted from a higher supply will also decrease the costs of lice, since the salmon price is used to estimate the revenue loss from lost biomass. The recent high salmon prices may also blind salmon farmers in their decision-making for long-term lice control, not prioritizing research and development to increase efficiency and sustainability. If production costs continue to increase, there will come a time where salmon aquaculture is no longer profitable. In the following section, we focus on how new technology can contribute to industry growth and sea lice mitigation.

## **7.3 New Technology**

If the industry is to be successful in reaching its production goal of 5 million tonnes by 2050, new solutions that solve the major environmental challenges must be developed and implemented. This will require the major companies in the industry to provide the necessary capital to fund research, development, innovation, piloting, and commercializing of the new solutions. Current net pen aquaculture along the Norwegian coast and fjords is very effective, but because there exists no barrier between farmed fish and the existing ecosystem it is also very high risk. Thus, there has been an increased focus on developing closed farming facilities in recent years. Such closed farms include onshore farms, submerged net pens, and closed sea

pens. The potential for further industry growth likely relies on the success of these aquaculture concepts.

According to Norsk Industri (2017), traditional net pens will likely be placed further out at sea in the future. This will reduce the environmental impact on wild salmon and fjord/coast ecosystems. The lice infection risk will also decrease since the farms can be placed at greater distances from one another, potentially reducing the use of lice treatments. Although offshore farms may be a great solution, they still entail significant technological challenges such as extreme weather, supply of feed and personnel and anchoring. It is important to emphasize the government's role in issuing research and development licenses for new technologies so that they can be implemented as fast as possible.

These new aquaculture farming solutions may have a different cost structure than traditional net pens. Closed pens typically have additional costs associated with water filtering, construction costs, among others. Since these solutions eliminate the sea lice problems, we can use the cost of lice to provide valuable information on how large the additional costs of closed system salmon farming can be to make this type of production favorable to traditional farming. Considering the recent development in the production cost of traditionally farmed salmon (see Figure 3-8), it is possible that new production systems quickly will become favorable to traditional farming, especially when bearing in mind their major advantages.

Several new lice mitigation efforts in development are showing promising results, for example, ultrasound treatments and net pen vacuum systems. The ultrasound treatment dislodges and eliminates sea lice without disturbing the fish, similar to laser treatments (discussed in section 3.6). Vacuum systems consist of a pump that processes large amounts of seawater through a filter and gathers sea lice in all development stages. Importantly, these measures are environmentally friendly and have a low negative impact on fish welfare (Global Salmon Initiative, 2017; Prado, 2016; Salmon Business, 2019).

## **7.4 Implications of Government Regulation**

The results presented in this paper indicate that the use of lice treatments at, or below, the lice limits have a negative impact on biological growth rate. It also indicates that current lice regulations further exaggerate the revenue loss associated with lice through increased biomass loss when performing mechanical treatments at average lice levels below 0.84 adult female lice per fish (or bath treatments at average lice levels below 0.69 adult female lice per fish). Based on these findings, the question of whether the defined lice limits are too strict arises. On one

hand, increasing lice limits would by our analysis increase production efficiency and reduce loss in biomass growth due to excessive treatments. This increase in revenue could be applied to research and development of new lice fighting technologies that do not possess the negative effects on biomass growth. On the other hand, increasing lice limits further intensifies the risk of mass mortality and infection risk towards wild salmon stocks. The potential drawbacks of restricting lice abundance further are more frequent premature harvesting and increased loss of biomass growth.

The primary intention of government regulation is to ensure efficient and sustainable use of resources, and to provide the greatest benefit to society as a whole. The decision on the trade-off between increased efficiency and infection risk on wild salmon stocks is, therefore, dependent on the government's assessment of their relative importance. Since there is no inherent economic incentive for fish farmers to keep lice levels below the defined limits, the regulatory bodies must provide incentives for fish farmers to combat the lice problem. Current sea lice regulations in Norway accomplish this by awarding farmers that maintain low lice levels with increased MAB.

## 8. Concluding Remarks

The results presented in this study highlight the importance of parasitic sea lice in Norwegian salmonid aquaculture, and show that the impact of sea lice infestations and mitigation efforts on biological growth rates are severe. It is the first study to estimate the negative impact of delousing treatments on biological growth rate. The total yearly cost associated with sea lice in Norway is estimated to be 8.2 billion NOK from 2012-2017 or 14.21% of revenues. However, the recent increase in salmon price yield an estimated cost of 11.2 billion NOK in 2017. Comparing these results to previous estimates by Abolofia et al. (2017), who report the total cost of lice to be 2.5 billion NOK in 2011 (or 8.70% of revenues), our estimates are approximately four times larger. Iversen et al. (2017) report a direct cost of lice of 4.5 billion NOK in 2017, which is more in line with our estimates. The analysis consequently shows that the economic losses associated with sea lice infestation in Norwegian salmonid aquaculture are considerable and a major cause of concern for the industry. The cost estimates presented in this thesis represent the value of completely avoiding an average infestation scenario (i.e., maintaining a farm entirely free of lice) or the willingness-to-pay for a hypothetical vaccine for lice.

The study indicates that current lice mitigation efforts have a significant negative impact on the biological growth rate; consequently, efforts to minimize the use of such treatments should be prioritized, together with the development of new treatment and production methods. Our results provide an initial estimate of the point where delousing treatments have a positive effect on the growth rate, which is approximately 5 lice per fish for mechanical treatments and 4.5 lice per fish for bath treatments. Given that farms often conduct lice treatments when lice levels are well below specified limits (see Figure 6-3), our results suggest that either; (1) most of the economic benefit from treatment applications likely accumulate over the remainder of the production cycle, and/or (2) that treatments primarily are conducted due to government regulations.

Moreover, the estimates of the marginal effects of lice and lice treatments on biomass growth can provide additional information to farmers on the marginal cost of infective lice and the application of lice treatments. Such information may be used to improve decision making on when to apply delousing treatments or other lice mitigation efforts. Mechanical treatments, in particular, have a large negative impact on growth rate (marginal effects estimates indicate a reduction in growth rate between 1.73% and 2.14% depending on the geographical region),

which is in large attributed to increased stress and physical maneuvering of the fish during treatment.

Following our work, we suggest three possible extensions to the methodology applied in this thesis. An extension to include more lice mitigation efforts could be beneficial and produce more accurate estimations on the total cost of lice, provided more detailed data concerning these mitigation efforts become available. Specifically, the effect of cleaner fish presence on biological growth rate and lice levels are important factors that are not accounted for in our model mainly due to lack of data. Additionally, a simulation of hypothetical treatment patterns following a change in government regulation would be of interest. The utilization of more advanced simulation techniques such as Monte Carlo could facilitate estimation of the cost of lice in hypothetical scenarios with various lice regulations. This type of investigation could highlight the effect of regulation and answer important questions regarding the necessity and impact of treatment at different lice levels. Lastly, the methodology applied in this thesis could be extended to estimate the total cost of lice for other salmonid producing countries. The main barrier preventing analysis of other producers is the lack of transparent and detailed data.

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# 10. Appendices

## 10.1 Predicted Loss of Biomass Growth in Metric Tonnes

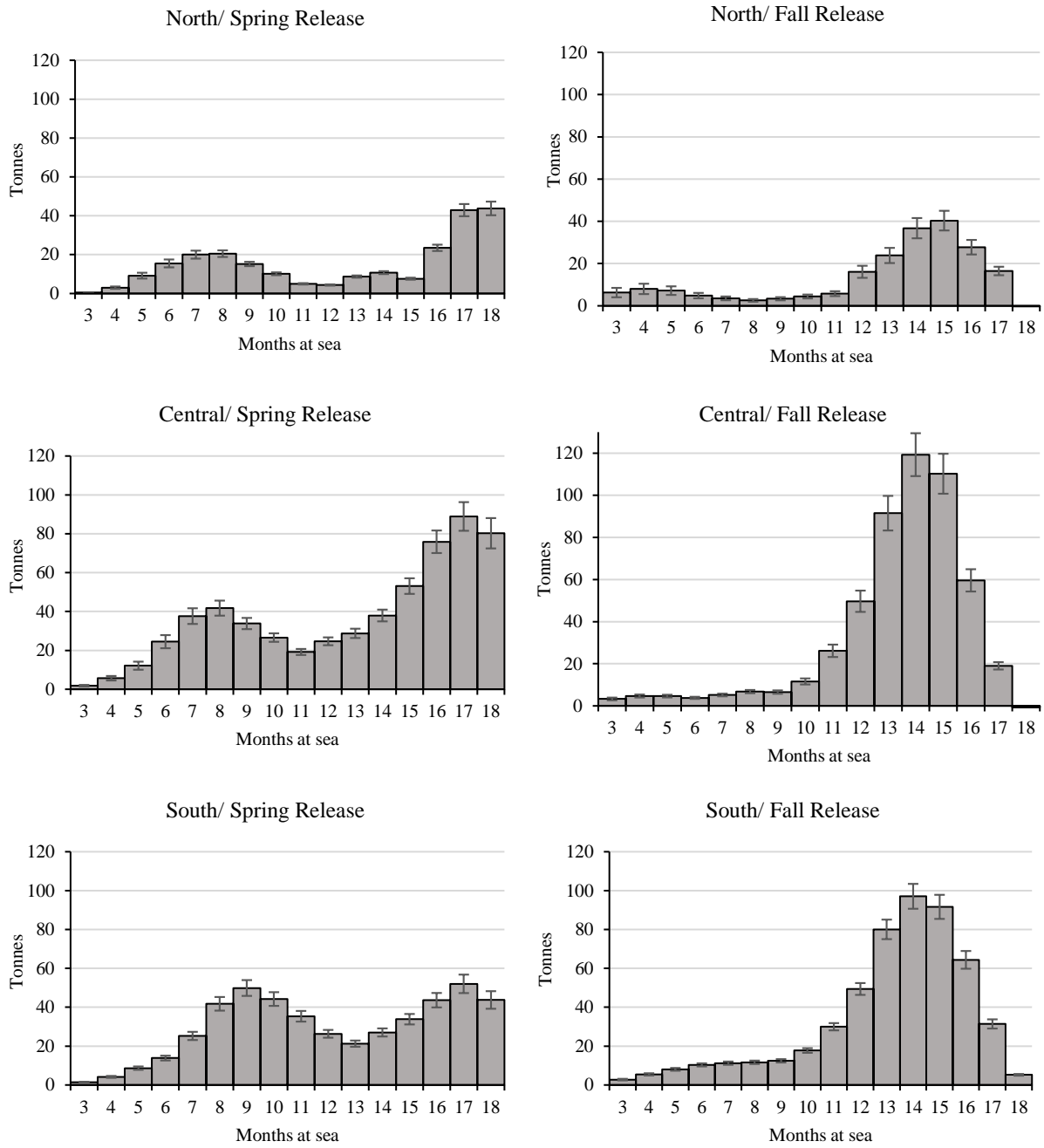


Figure 10-1: Predicted Monthly Loss of Biomass Growth ( $\Delta \hat{g}_{it+1}$ ) in Metric Tonnes from Average Lice Infestation and Treatment Scenarios with 95% CIs.

## 10.2 Stata Codes

### Codes for Data Preparation

```
*Load data set
use Dataset_modifiedweight.dta, clear

*Generating regional dummy variables
gen north = 1 if lat >67
replace north =0 if north ==.
gen south =1 if lat < 62.5833
replace south =0 if south ==.
gen central = 1 if north+south == 0
replace central= 0 if central ==.

*Creating monthly and yearly dummy variables to control for seasonality and
technological development
tabulate month
summarize i.month

tabulate year
summarize i.year

*Removing unrealistic growth rates
replace grwthmod =. if grwthmod >3
replace lngrowthmod =. if grwthmod ==.
replace grwthmod = . if grwthmod <0.2
replace lngrowthmod =. if grwthmod ==.
replace temp =. if temp <2

*Removing extreme lice counts
replace totlice =. if totlice >20

*Removing zero-values from loss variables
replace mortalities =. if mortalities ==0
replace escapes =. if escapes==0
replace removals =. if removals ==0
replace miscloss =. if miscloss==0
```

### Codes for Econometric Testing

```
*Load data set
use Dataset_modifiedweight.dta, clear

*Install test-packages
ssc install xttest3
ssc install xtserial

*Breusch-Pagan Lagrange Multiplier test for pooled OLS or random effects
xtreg lngrowthmod mas bath mech feeduse c.feeduse#c.feeduse l.avg_weightfish l.nfish
l.temp c.l.temp#c.l.temp l.totlice c.l.totlice#c.l.totlice c.l.totlice#c.l.temp
c.l.totlice#c.mech c.l.totlice#c.bath c.l.totlice#c.l2.avg_weightfish i.month
i.year, re
xttest0

*Durbin-Wu-Hausman test for random or fixed-effects
xtreg lngrowthmod mas bath mech feeduse c.feeduse#c.feeduse l.avg_weightfish l.nfish
l.temp c.l.temp#c.l.temp l.totlice c.l.totlice#c.l.totlice c.l.totlice#c.l.temp
c.l.totlice#c.mech c.l.totlice#c.bath c.l.totlice#c.l2.avg_weightfish i.month
i.year, fe

estimates store fixed

xtreg lngrowthmod mas bath mech feeduse c.feeduse#c.feeduse l.avg_weightfish l.nfish
l.temp c.l.temp#c.l.temp l.totlice c.l.totlice#c.l.totlice c.l.totlice#c.l.temp
c.l.totlice#c.mech c.l.totlice#c.bath c.l.totlice#c.l2.avg_weightfish i.month
i.year, re
```



```
hausman fixed ., sigmamore
```

```
*Testing for groupwise heteroskedasticity in panel data - Modified Wald test
xtreg lngrowthmod mas bath mech feeduse c.feeduse#c.feeduse l.avg_weightfish l.nfish
l.temp c.l.temp#c.l.temp l.totlice c.l.totlice#c.l.totlice c.l.totlice#c.l.temp
c.l.totlice#c.mech c.l.totlice#c.bath c.l.totlice#c.l2.avg_weightfish i.month
i.year, fe vce(cluster locnr)
xttest3
```

```
*Serial correlation test - Wooldridge test
gen feeduse2 = c.feeduse#c.feeduse
gen lagavg_weightfish = l.avg_weightfish
gen lagnfish = l.nfish
gen lagtemp = l.temp
gen lagtemp2 = c.l.temp#c.l.temp
gen lagtotlice = l.totlice
gen lagtotlice2 = c.l.totlice#c.l.totlice
gen lagtotlicexlagtemp = c.l.totlice#c.l.temp
gen lagtotlicexmech = c.l.totlice#c.mech
gen lagtotlicexbath = c.l.totlice#c.bath
gen lagtotlicexlag2avg_weightfish = c.l.totlice#c.l2.avg_weightfish
gen i2013 = year==2013
gen i2014 = year==2014
gen i2015 = year==2015
gen i2016 = year==2016
gen i2017 = year==2017
gen i2 = month==2
gen i3 = month==3
gen i4 = month==4
gen i5 = month==5
gen i6 = month==6
gen i7 = month==7
gen i8 = month==8
gen i9 = month==9
gen i10 = month==10
gen i11 = month==11
gen i12 = month==12
```

```
xtreg lngrowthmod mas bath mech feeduse feeduse2 lagavg_weightfish lagnfish lagtemp
lagtemp2 lagtotlice lagtotlice2 lagtotlicexlagtemp lagtotlicexmech lagtotlicexbath
lagtotlicexlag2avg_weightfish i2 i3 i4 i5 i6 i7 i8 i9 i10 i11 i12 i2013 i2014 i2015
i2016 i2017, fe vce(cluster locnr)
```

```
xtserial lngrowthmod mas bath mech feeduse feeduse2 lagavg_weightfish lagnfish
lagtemp lagtemp2 lagtotlice lagtotlice2 lagtotlicexlagtemp lagtotlicexmech
lagtotlicexbath lagtotlicexlag2avg_weightfish i2 i3 i4 i5 i6 i7 i8 i9 i10 i11 i12
i2013 i2014 i2015 i2016 i2017
```

```
*Find AIC
xtreg lngrowthmod mas bath mech feeduse c.feeduse#c.feeduse l.avg_weightfish l.nfish
l.temp c.l.temp#c.l.temp l.totlice c.l.totlice#c.l.totlice c.l.totlice#c.l.temp
c.l.totlice#c.mech c.l.totlice#c.bath c.l.totlice#c.l2.avg_weightfish i.month
i.year, fe vce(cluster locnr)
estat ic
```

## Codes for Regression

```
*Load data set
use Dataset_modifiedweight.dta, clear

*Pooled OLS regression
regress lngrowthmod mas feeduse bath mech l.avg_weightfish l.nfish l.temp l.totlice
i.year, vce(cluster locnr)

*Models without interaction terms (Model A)

*Fixed-effects
xtreg lngrowthmod mas feeduse bath mech l.avg_weightfish l.nfish l.temp l.totlice
i.year, fe vce(cluster locnr)

*Random effects
xtreg lngrowthmod mas feeduse bath mech l.avg_weightfish l.nfish l.temp l.totlice
i.year, re vce(cluster locnr)

*Models with interaction terms (Model B)

*Fixed-effects
xtreg lngrowthmod mas bath mech feeduse c.feeduse#c.feeduse l.avg_weightfish l.nfish
l.temp c.l.temp#c.l.temp l.totlice c.l.totlice#c.l.totlice c.l.totlice#c.l.temp
c.l.totlice#c.mech c.l.totlice#c.bath c.l.totlice#c.l2.avg_weightfish i.year, fe
vce(cluster locnr)

*Random effects
xtreg lngrowthmod mas bath mech feeduse c.feeduse#c.feeduse l.avg_weightfish l.nfish
l.temp c.l.temp#c.l.temp l.totlice c.l.totlice#c.l.totlice c.l.totlice#c.l.temp
c.l.totlice#c.mech c.l.totlice#c.bath c.l.totlice#c.l2.avg_weightfish i.year, re
vce(cluster locnr)

*Models with interaction terms and monthly fixed effects (Model C)

*Fixed-effects
xtreg lngrowthmod mas bath mech feeduse c.feeduse#c.feeduse l.avg_weightfish l.nfish
l.temp c.l.temp#c.l.temp l.totlice c.l.totlice#c.l.totlice c.l.totlice#c.l.temp
c.l.totlice#c.mech c.l.totlice#c.bath c.l.totlice#c.l2.avg_weightfish i.month
i.year, fe vce(cluster locnr)

*Random effects
xtreg lngrowthmod mas bath mech feeduse c.feeduse#c.feeduse l.avg_weightfish l.nfish
l.temp c.l.temp#c.l.temp l.totlice c.l.totlice#c.l.totlice c.totlice#c.l.temp
c.l.totlice#c.mech c.l.totlice#c.bath c.l.totlice#c.l2.avg_weightfish i.month
i.year, re vce(cluster locnr)
```

## Codes for Marginal Effects

\*Marginal effects (South Region)

```
xtreg lngrowthmod mas bath mech feeduse c.feeduse#c.feeduse l.avg_weightfish l.nfish  
l.temp c.l.temp#c.l.temp l.totlice c.l.totlice#c.l.totlice c.l.totlice#c.l.temp  
c.l.totlice#c.mech c.l.totlice#c.bath c.l.totlice#c.l2.avg_weightfish i.month  
i.year, fe vce(cluster locnr)  
margins if south, dydx(c.l.totlice bath mech) atmeans
```

\*Marginal effects (Central Region)

```
xtreg lngrowthmod mas bath mech feeduse c.feeduse#c.feeduse l.avg_weightfish l.nfish  
l.temp c.l.temp#c.l.temp l.totlice c.l.totlice#c.l.totlice c.l.totlice#c.l.temp  
c.l.totlice#c.mech c.l.totlice#c.bath c.l.totlice#c.l2.avg_weightfish i.month  
i.year, fe vce(cluster locnr)  
margins if central, dydx(c.l.totlice bath mech) atmeans
```

\*Marginal effects (North Region)

```
xtreg lngrowthmod mas bath mech feeduse c.feeduse#c.feeduse l.avg_weightfish l.nfish  
l.temp c.l.temp#c.l.temp l.totlice c.l.totlice#c.l.totlice c.l.totlice#c.l.temp  
c.l.totlice#c.mech c.l.totlice#c.bath c.l.totlice#c.l2.avg_weightfish i.month  
i.year, fe vce(cluster locnr)  
margins if north, dydx(c.l.totlice bath mech) atmeans
```

## Codes for Predicting Naïve Growth Estimator

\*Predict naïve growth estimator

```
use Dataset_modifiedweight.dta, clear  
xtset locnr id  
xtreg lngrowthmod mas bath mech feeduse c.feeduse#c.feeduse l.avg_weightfish l.nfish  
l.temp c.l.temp#c.l.temp l.totlice c.l.totlice#c.l.totlice c.l.totlice#c.l.temp  
c.l.totlice#c.mech c.l.totlice#c.bath c.l.totlice#c.l2.avg_weightfish i.month  
i.year, fe vce(cluster locnr)  
use Modifiedweight_v3.dta, clear  
xtset locnr id  
predict avggrwthlice  
predict uavggrwthlice, resid  
use Nolice_final.dta, clear  
xtset locnr id  
predict grwthnolice  
predict unolice, resid  
bysort locnr: gen git = (exp(avggrwthlice)-1)*l.biomass  
bysort locnr: gen git2 = (exp(grwthnolice)-1)*l.biomass  
gen deltagit = git2-git
```

## 10.3 Stata Regression Outputs

### Pooled OLS

```

Linear regression                               Number of obs   =   38,687
                                                F(13, 1023)    =   797.99
                                                Prob > F        =   0.0000
                                                R-squared       =   0.3920
                                                Root MSE       =   .1364
  
```

(Std. Err. adjusted for 1,024 clusters in locnr)

-----						
		Robust				
	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
-----						
lngrwth						
mas	-.005321	.0002841	-18.73	0.000	-.0058786	-.0047635
feeduse	.0130226	.0006255	20.82	0.000	.0117951	.0142501
bath	-.009	.0009578	-9.40	0.000	-.0108794	-.0071206
mech	-.0203369	.0016152	-12.59	0.000	-.0235064	-.0171674
avg_weightfish						
L1.	-.041112	.0010592	-38.81	0.000	-.0431904	-.0390336
nfish						
L1.	-.0029593	.0003501	-8.45	0.000	-.0036462	-.0022724
temp						
L1.	.0114765	.0003247	35.34	0.000	.0108393	.0121137
totlice						
L1.	-.006997	.0005638	-12.41	0.000	-.0081033	-.0058906
year						
2013	.0014988	.0031651	0.47	0.636	-.004712	.0077096
2014	-.0012077	.0025087	-0.48	0.630	-.0061304	.0037151
2015	-.00027	.0032356	-0.08	0.934	-.0066192	.0060791
2016	-.0063474	.0027259	-2.33	0.020	-.0116964	-.0009984
2017	-.0041347	.0030461	-1.36	0.175	-.010112	.0018426
_cons	.22973	.0053466	42.97	0.000	.2192384	.2402216



2017		-.0044051	.0033104	-1.33	0.184	-.0109011	.0020909
_cons		.230923	.0070549	32.73	0.000	.2170792	.2447668
-----+-----							
sigma_u		.04077307					
sigma_e		.13494209					
rho		.08365835	(fraction of variance due to u_i)				

---



-----+-----  
sigma\_u | .04498807

sigma\_e | .12429981

rho | .11582257 (fraction of variance due to u\_i)

---



## Fixed-Effects Model C

Fixed-effects (within) regression                      Number of obs        =     35,648

Group variable: locnr                                    Number of groups    =     1,017

R-sq:

within = 0.4449

between = 0.4287

overall = 0.4405

Obs per group:

min = 1

avg = 35.1

max = 62

F(31,1016) = 406.27

corr(u\_i, Xb) = -0.0399

Prob > F = 0.0000

(Std. Err. adjusted for 1,017 clusters in locnr)

-----						
		Robust				
	lngrwth	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
-----						
	mas	-.0063392	.0003782	-16.76	0.000	-.0070813    -.0055971
	bath	-.0137157	.0011439	-11.99	0.000	-.0159604    -.011471
	mech	-.0236242	.0023165	-10.20	0.000	-.0281699    -.0190785
	feeduse	.0243012	.0024569	9.89	0.000	.0194801    .0291222
	c.feeduse#c.feeduse	-.0011835	.0002676	-4.42	0.000	-.0017086    -.0006584
	avg_weightfish L1.	-.0434793	.0014905	-29.17	0.000	-.0464042    -.0405544
	nfish L1.	-.0053642	.0006806	-7.88	0.000	-.0066998    -.0040286
	temp L1.	.0199352	.0017286	11.53	0.000	.0165432    .0233273
	cL.temp#cL.temp	-.0007526	.0000748	-10.06	0.000	-.0008994    -.0006057
	totlice L1.	-.0049941	.0022708	-2.20	0.028	-.00945    -.0005381
	cL.totlice#cL.totlice	.0003138	.000107	2.93	0.003	.0001038    .0005238
	cL.totlice#cL.temp	-.0019057	.0001777	-10.73	0.000	-.0022544    -.0015571
	cL.totlice#c.mech	.0046526	.001044	4.46	0.000	.002604    .0067012
	cL.totlice#c.bath	.0034284	.0004494	7.63	0.000	.0025466    .0043102
	cL.totlice#cL2.avg_weightfish	.0047321	.000442	10.71	0.000	.0038648    .0055994
	month					
	2	-.0096478	.0027746	-3.48	0.001	-.0150925    -.0042032
	3	.0034856	.0033706	1.03	0.301	-.0031285    .0100997
	4	.0097263	.0034932	2.78	0.005	.0028715    .0165811
	5	.016828	.0037823	4.45	0.000	.009406    .02425
	6	.0251502	.0036143	6.96	0.000	.0180578    .0322425
	7	.0752472	.0043016	17.49	0.000	.0668061    .0836883

8		.0927023	.0053905	17.20	0.000	.0821244	.1032801
9		.0611972	.0060152	10.17	0.000	.0493936	.0730007
10		.0503015	.0055483	9.07	0.000	.0394141	.061189
11		.0293884	.004196	7.00	0.000	.0211545	.0376223
12		.0154884	.0033905	4.57	0.000	.0088352	.0221417
year							
2013		.0086993	.0034586	2.52	0.012	.0019126	.0154861
2014		.0073425	.0026808	2.74	0.006	.0020819	.0126031
2015		.0035999	.003517	1.02	0.306	-.0033015	.0105012
2016		.0001886	.0029164	0.06	0.948	-.0055342	.0059115
2017		.0032147	.0034452	0.93	0.351	-.0035457	.0099752
_cons		.2062924	.0125109	16.49	0.000	.1817422	.2308426

-----+-----

sigma\_u | .04519182

sigma\_e | .12275775

rho | .11935066 (fraction of variance due to u\_i)

---

## 10.4 Detailed Unit Treatment Costs

Table 10-1: Assumptions for Unit Cost of Bath Treatments Using Traditional Chemicals. Source: (Iversen et. al., 2017)

	Cost (NOK/kg)	Assumptions
Service boat	0.09	3 pcs, 15,000 NOK/day/pcs, 50,000 NOK/day
Labor	0.10	
Chemical cost	0.12	32 kg substance à 15,000 NOK/kg
Mortality	0.15	0.5% mortality rate, 29 NOK/kg
<b>Sum</b>	<b>0.46</b>	

Table 10-2: Assumptions for Unit Costs of Bath Treatments Using Hydrogen Peroxide. Source: (Iversen et. al., 2017)

	Cost (NOK/kg)	Assumptions
Service boat	0.11	3 pcs, 15,000 NOK/day/pcs, 50,000 NOK/day
Labor	0.11	
Chemical cost	0.20	25 tonnes substance/pen
Mortality	0.30	1% mortality rate, 29 NOK/kg
<b>Sum</b>	<b>0.72</b>	

Table 10-3: Assumptions for Unit Costs for Thermal Treatments. Source: (Iversen et. al., 2017)

	Cost (NOK/kg)	Assumptions
Depreciation	0.10	2 pcs, 30 mill NOK/pc, 4 year lifetime
Alternative cost	0.04	7.5%
Service boat	0.04	2 pcs, 15,000 NOK/day
Labor	0.11	21 FTEs for 150,000 tonnes
Electricity de-licing	0.03	11 kWh/ton, 2.5 NOK/kWh
Maintenance	-	Not estimated
Mortality	0.15	0.5% mortality rate, 29 NOK/kg
<b>Sum</b>	<b>0.45</b>	

Table 10-4: Assumptions for Unit Costs for Pressure/Brush Treatments. Source: (Iversen et. al., 2017)

	Cost (NOK/kg)	Assumptions
Depreciation	0.03	4 pcs, 5.5 mill NOK/pc, 4 year lifetime
Alternative cost	0.01	5%
Service boat	0.04	2 pcs, 15,000 NOK/day
Labor	0.13	24 FTEs for 150,000 tonnes
Fuel	0.01	1.5 liters/ton, 8 NOK/liter
Maintenance	Not estimated	
Mortality	0.15	0.25% mortality rate, 29 NOK/kg
Other	Not estimated	
<b>Sum</b>	<b>0.38</b>	

Table 10-5: Assumptions for Unit Costs for Cleaner Fish. Source: (Iversen et. al., 2017)

	Cost (NOK/kg)	Assumptions
Purchasing, fish	0.65	15% ratio (cleaner fish /salmonids), 16 NOK/fish
Transport	0.07	2 NOK/fish
Labor	0.27	1 FTE for the duration of production cycle
Feeding and hiding stations	0.02	35,000 NOK/pen
Feed cost	0.04	2% feeding,
Extra cleaning	0.19	6 times, 20,000/pen
<b>Sum</b>	<b>1.25</b>	

Table 10-6: Assumptions for Unit Costs for Laser Treatments. Source: (Iversen et. al., 2017)

	Cost (NOK/kg)	Assumptions
Depreciation	0.60	10 pcs./farm, 0.7 mill NOK/pcs, 5 year lifetime
Alternative cost	0.13	5%
Labor	0.03	3 month FTE for 18 month cycle
Maintenance and service	0.56	150,000 NOK/year
<b>Sum</b>	<b>1.32</b>	

Table 10-7: Assumptions for Unit Costs for Lice Skirts. Source: (Iversen et. al., 2017)

	Cost (NOK/kg)	Assumptions
Investment cost	0.05	1 skirt/ pen, 0.2 mill. NOK /skirt, 3 year lifespan
Alternative cost capital	0.01	5%
Labor	0.02	0.2 FTEs
Growth	-	Not estimated
<b>Sum</b>	<b>0.08</b>	