Market organization in natural resource industries: Empirical analysis of salmon aquaculture

by

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Preface

This thesis is submitted in fulfillment of the requirements for the degree of Doctor of Philosophy (PhD) at the University of Stavanger (UiS), Faculty of Science and Technology, Norway. The research work has been carried out between March 2017 and March 2019. In addition, part of my studies were carried out at the University of Florida (UF) as a visiting scholar at the Institute for Sustainable Food Systems, from September 2018 to May 2019.The compulsory courses were given and attended at UiS, the Norwegian School of Economics (NHH), and Barcelona Graduate School of Economics (GSE).

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Thanks to all my colleagues at UiS for sharing this process with me. Particularly, many thanks to Ana, Viktoria, and Sindre for your conversations and guidance through the highs and lows. I am particularly grateful for Grecia and Luis, without their support this endeavor would not have taken place. Finally, I want to thank my family and friends that always provided support from the distance.

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List of Papers

1 Introduction

This thesis aims to contribute to a better understanding of the intricacies of market organization in a renewable natural resource industry: The Norwegian salmon industry. Natural resource industries are of special interest because they depend on the interactions between environmental/biological conditions, firms, and institutions (Van Der Ploeg & Poelhekke, 2017; Van der Ploeg & Venables, 2011). In particular, due to the public interest in managing natural resources, industries that rely on them face heavy regulations everywhere; often, the effects of these regulations on natural resources and their related industries may determine if the possession of such resources is a blessing or a curse (Arezki & van der Ploeg, 2007; Van der Ploeg, 2011).

The Norwegian salmon aquaculture sector serves as a useful case in market organization for four main reasons: 1) the sector is relatively young (about 50 years), which allows observing the evolution of several stages of industrialization and how firm structure evolved. 2) Within the industrialization process, which in particular has taken place during the last three decades, the sector has experienced different types of regulation aimed at controlling market concentration, production levels, and environmental problems. Especially, the salmon aquaculture sector has been subject to increased scrutiny and regulation due to biological and environmental problems related to fish diseases, effects on stocks of wild salmonid fish, and other emissions from farms. 3) The sector serves a global market with a persistent high demand rarely observed in other industries. 4) At the aggregate level there are a few producing countries with similar production technologies - being Norway the main producer- which allows extending the analysis to other competing countries.

These particular conditions and the availability of firm-level data on production and costs for the last 20-30 years, makes the Norwegian salmon sector and ideal candidate to empirically evaluate four aspects pertaining market organization: Evolution of a) production costs, b) productivity and productivity dispersion, c) regulations effects on production costs, and d) price relationship with input shocks. A careful analysis of these aspects is required to solve the puzzle of what factors can incentivize or deter the growth and sustainability of the sector in the future. The thesis consists of four papers treating the aspects mentioned above. All of them are empirical applications using firm-level data that covers the period 2001-2016 except for paper number four that covers the period 2000-2019. The rest of this chapter presents (2) the background of the salmon market, (3) research design and methods, (4) summary of the four papers, and (5) contributions and limitations of the thesis.

2 Background

Salmon aquaculture is an example of farmed species with high retail price and a complex market structure, which extends through all the supply chain, from agents directly involved in the production process to suppliers of capital equipment, feed, pharmaceuticals, and consultancy services, and also through multinational salmon companies that operate in several countries. Salmon is produced in several countries with appropriate biophysical conditions, which reduces to sufficient sheltered coastal zones and appropriate sea temperatures through the year.

Salmon is produced mainly in Norway, Chile, Canada, Scotland, USA, and the Faroe Islands. Although similar technology is used across countries, production volumes and production growth rates vastly differ between them. To some extent, this can be explained by biophysical conditions. However, different regulatory regimes may have played a significant role in explaining countries' different salmon aquaculture growth trajectories. Although salmon may end up as differentiated final consumer product, exported farmed salmon products can be characterized as a commodity as it is difficult to differentiate the attributes of whole salmon or salmon fillets for companies and countries. Salmon farming companies in different countries compete in many export markets, and price formation is global. Therefore, the supply quantity and market shares of salmon from different companies and countries are largely determined by government regulation, firms' productivity, production costs, and environmental conditions (Iversen, Asche, Hermansen, & Nystøyl, 2020).

Norway has the largest coast in Europe (58,133 km) and it has been dependent on fishing through its history. The introduction of aquaculture for salmon in the country dates back to the 1970s as a policy measure for providing a new income source to coastal towns (Liu, Olaussen, & Skonhoft, 2011). The sector is internationally oriented with the majority of production being exported; as it can be seen on figure 1, monthly export volumes grew by a factor of five between 2001 and 2019 with a consequent increase in production value, going from around 17 bn NOK in 2001 to 58 bn NOK in 2018. Currently, farmed salmon is the second most exported product from Norway behind the oil and gas exports; producers are located through all the coastal zone covering 10 regions and employing directly around 7000 people in 2016 with a 30% increase from 2007 as it can be seen in figure 2[1].

[1] Source: Norwegian Statistical Bureau SSB. https://www.ssb.no/en/jord-skog-jakt-og-fiskeri/artikler-og-publikasjoner/growing-numbers-working-in-fish-farming

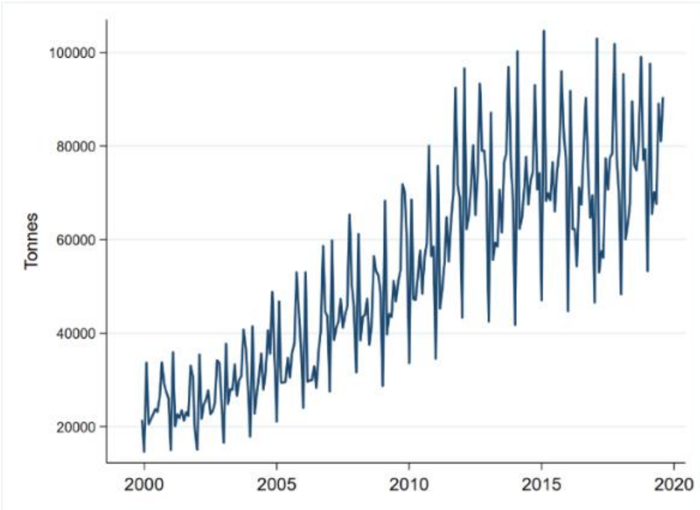

Figure 1 - Monthly export volume of salmon 2000-2019

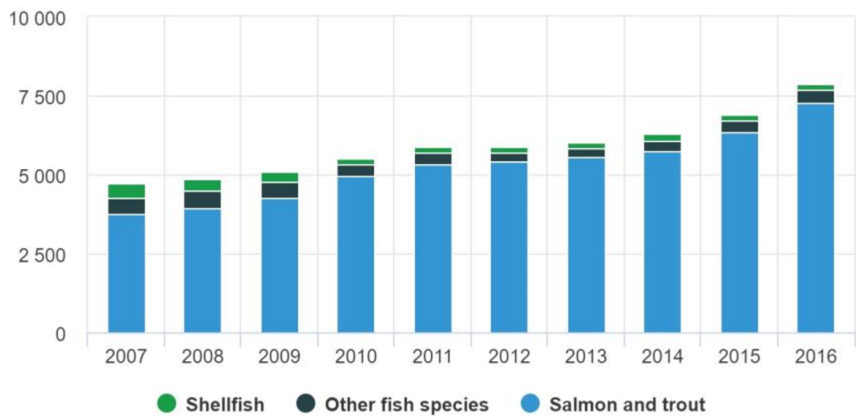

Figure 2 - Number of workers by production in farming of fish and shellfish

The observed situation of increased production and increased value suggests that global demand is growing faster than supply; this mismatch between demand and supply can be observed on the price evolution in figure 3, in 2000 the average price was 25 NOK/kg while in 2018 the average price was 60 NOK/kg, representing a growth of 140% on price. The rise in price is not only attributed to higher demand but also to supply-side factors like increases in production costs, negative supply shocks caused by diseases in the main producing countries (Chile, Faroe Islands, and Norway), and government regulations that constrain production growth.

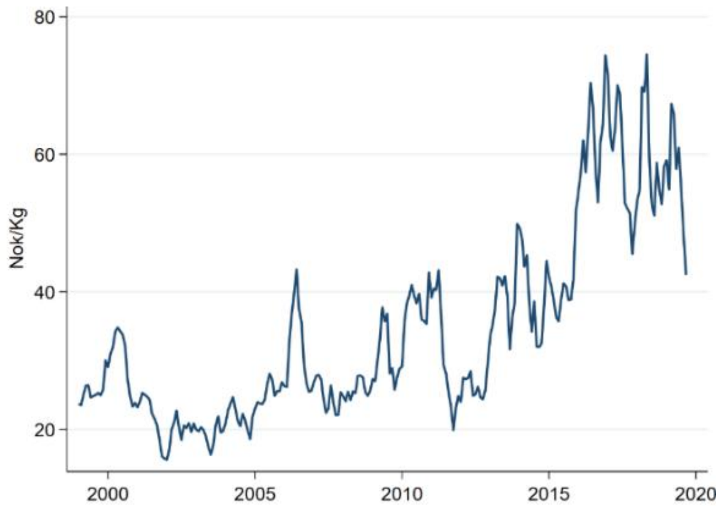

Figure 3 - Monthly salmon spot price 1999-2019

<u>Productivity and Costs in Salmon aquaculture</u>

The expansion of production at the early stages of the industry during the 1980s and 1990s was driven mainly by productivity improvements, learning by doing, and scale economies. High productivity growth at every level of the supply chain, from improvements on feed to better distribution channels, resulted in lower production costs and lower prices

(Asche, Bjørndal, & Sissener, 2003; Asche, Guttormsen, & Tveterås, 1999; Asche & Roll, 2013; Asche, Roll, & Tveteras, 2016; Tveteras, 2002; Tveterås & Heshmati, 1999). However, a change in the trend occurs around 2005 when production costs start increasing, coinciding with a change in production regulations. From that date, evidence show a slowdown in productivity growth, a fact that is attributed to a maturing of the industry, negative biological shocks, and to some extent government regulations (Asche, Roll, & Tveteras, 2009; Rocha Aponte & Tveterås, 2019; Vassdal & Sørensen Holst, 2011).

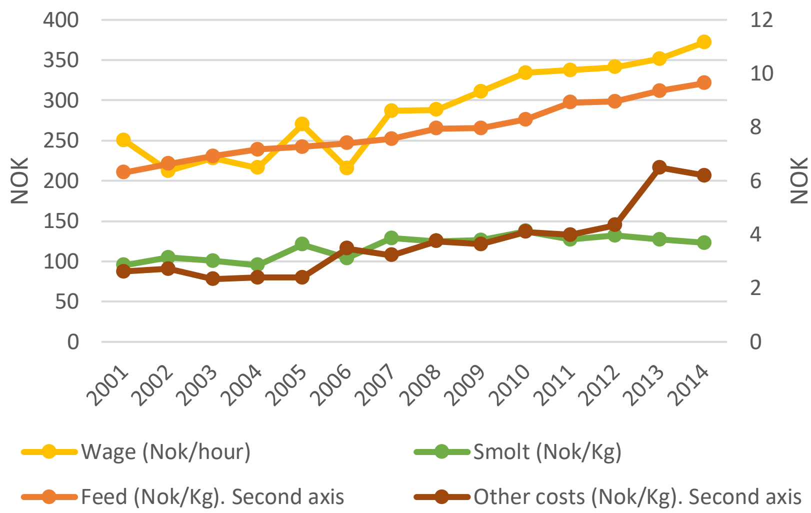

Figure 4 - Average unit evolution of production costs by input 2001-2014

Figure 4 shows the evolution of production costs in the sector disaggregate by the main inputs in production (Feed, wages, smolt, and other costs). The biggest growth is observed on Feed and other costs; particularly, other costs went from representing 19% of variable costs in

2001 to 28% in 2014. Feed represents the main input with around 50% of total production costs, while wages and smolt represent 10% and 15% respectively.

Regulations in the Norwegian Salmon aquaculture

Salmon aquaculture firms have been allocated coastal farm locations and licenses to produce through different mechanisms by the government over time. The first type of regulation on the industry was the limitation of the type of firms that were allowed to produce; by issuing production licenses only to single farmers, the government aimed at supporting coastal towns and provide a new income source for small farmers (Liu et al., 2011). Then, in the 1980s with the First Farming License Act, each producing plant was regulated by limiting the volume of the pens where salmon grows. The main objective was to achieve a regional allocation of farms through all the Norwegian coast and to avoid industry concentration (Salvanes, 1993). Greater flexibility was introduced during the 1990s to allow companies to grow and profit from scale economies, at the same time, a feed quota was introduced to constrain production but was proven to be unsuccessful as producers changed to higher protein content feeds (Guttormsen, 2002).

In 2005, a regulation limiting the biomass of live salmon in the sea – and thus production at the farm, regional, and national level – was introduced. The stock of farmed salmon in the sea is restricted by the government from the national level to the site level. Individual firms need licenses for maximum allowed biomass (MTB), which limits the maximum biomass of live salmon in the cages at any point in time during the year. Furthermore, firms need a location license to operate a farm at a particular coastal site, which is public property. The government also limit MTB for each licensed farm location, based on an assessment of the biological carrying capacity of the site. Each salmon producer can have several MTB licenses and licensed sites and can move their MTB around to their sites. Most firms have several producing farm sites at any given time, and some large firms produce in several regions along the coast. Thus, by controlling the MTB, the government is also controlling how much each region can grow; as it can be seen in figure 5, the regions of Trøndelag, Finnmark, and Troms are the ones with the highest growth in produced biomass. These regions were the special focus of new licenses in the rounds of 2006 and 2009 (Hersoug, Mikkelsen, & Karlsen, 2019).

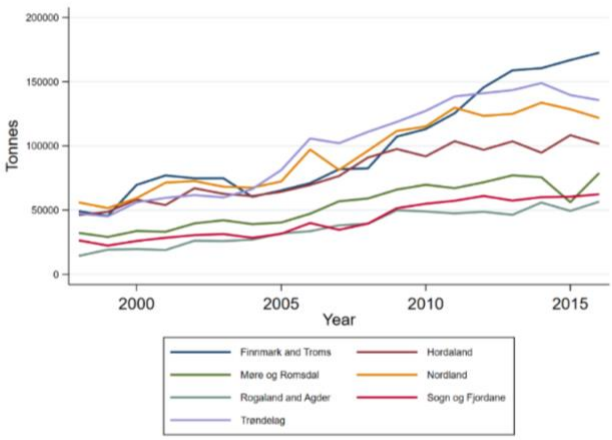

Figure 5 - Maximum Allowable Biomass per region 1999-2016

Biological and environmental conditions

The biological production process in salmon farming is basically one where salmon feed is converted to salmon biomass through growth. The total production cycle from egg to ready to harvest adult salmon lasts between 24 to 36 months and its divided in the following three stages: Fist, eggs are bred on fresh water until they become salmonids and they are transferred to open cages, and rely on inflows of clean water with appropriate salinity, oxygen content, and temperature. The flow of water also transports nutrients and feces away from the cages, contributing to a healthy living environment for the salmon. Like other farm animals, salmon will not realize its potential in terms of feed digestion, growth, and survival rates without an environment that provides sufficiently high levels of animal welfare. Finally, the fish is harvested, slaughtered and packed/processed for distribution.

Until now, salmon has been farmed in the coastal zone which is sheltered from the open ocean waves and winds. Through innovations which have led to more robust cages and other capital equipment, salmon farms have gradually moved to farm sites more exposed to waves and winds, but also with greater water exchange and carrying capacity. The natural characteristics of water flows, sea temperatures, and topographical conditions below the water surface influence the carrying capacity of a farm location, in terms of the total salmon biomass and production at the farms site, and the densities of salmon in the cages.

The higher concentration and density in production sites have led to several negative environmental externalities related to disease transmission. Particularly, sea lice contagion has been the main problem in the salmon aquaculture industry, with both direct and indirect effects on production costs via treatment costs, lower fish growth, and higher mortality rates (Samsing, Johnsen, Dempster, Oppedal, & Treml, 2017). Moreover, these type of negatives externalities may extent to wild populations of salmon and trout, affecting the livestock of such species and harming recreational fishing.

3 Research design and Methods

As explained above, the current policy objective of the Norwegian government is to allow 'sustainable growth' of salmon aquaculture and therefore there is a need to provide an adequate picture of market organization in the salmon market so it is possible to understand what possibilities/challenges the sector face and what measures can be taken – policy wise – to maintain growth. Thus, this thesis covers topics related to regulations, production costs, productivity, and price evolution by posing the following questions:

Table 1 - Research questions and approaches

#	Question	Approach	Market side approach	Agents
1	What are the main drivers of costs increases? Are those factors internal/external to the production process?	Analyze production costs at the firm level by using a flexible cost function that allows capturing the effects of scale economies, productivity growth, and input prices.	Supply	Firms
2	How quantity regulations affect production costs? Are any differential effects of the regulations	Estimate the effect of public policies on quantity restrictions via the license system on production costs and firm heterogeneity in the sector.	Supply	Firms Government Regulatory Authorities

#	Question	Approach	Market side approach	Agents
	according to firm size?			
3	What factors explain productivity dispersion? Are those factors demand specific?	Estimate Total Factor Productivity indexes and estimate regressions to find down the sources of total factor productivity dispersion on technical inefficiency and firm fundamentals.	Supply Demand	Firms Clients/Buyers
4	Do input feed prices have explanatory power over salmon prices? Are they useful when forecasting monthly prices?	Model a system of endogenous variables via VAR models and time varying VAR models with stochastic volatility.	Demand Supply	N/A

Each numeral is analyzed per paper, covering all questions in four papers. The following subsection describes briefly the methods applied in search for answers to the research questions.

Flexible costs functions

Flexible cost functions are generally suitable to describe industries that experiment rapid technical change. They have typically been used in empirical work on industries that transition from public control to privatization or deregulation[2]. A very popular version is the translog function (Christensen, Jorgenson, & Lau, 1973) which is a flexible second order function that does not impose any assumptions on the production technology (Baltagi et al., 1995; Kumbhakar, 2004). A general translog cost function can be described as:

$$\begin{aligned}\ln C_{it} = {} & \alpha_0 + \sum_{i} \lambda_i D_i + \sum_{t} \beta_{it} D_t + \beta_y \ln Y_{it} + \beta_k \ln K_{it} + \sum_{\alpha} \beta_\alpha \ln w_{\alpha it} \\ & + 0.5 \sum_{\alpha} \sum_{l} \beta_{\alpha l} \ln w_{\alpha it} \ln w_{lit} + \sum_{\alpha} \beta_{\alpha k} \ln K_{it} \ln w_{\alpha it} \\ & + \sum_{\alpha} \beta_{\alpha y} \ln Y_{it} \ln w_{\alpha it} + \sum_{\alpha} \sum_{t} \beta_{\alpha t} \ln w_{\alpha it} D_t + \beta_{yk} \ln Y_{it} \ln K_{it} \\ & + 0.5\, \beta_{yy} \ln Y_{it}^2 + 0.5\, \beta_{kk} \ln K_{it}^2 + \sum_{t} \beta_{yt} \ln Y_{it} D_t \\ & + \sum_{t} \beta_{kt} \ln K_{it} D_t + u_{it}\end{aligned} \tag{1}$$

where i, t are firm and time subscripts respectively. D_i are dummies that capture firm-specific differences, C is total costs, Y is the corresponding output, W_α is a vector of input prices, K is fixed costs (capital, equipment, other), D_t are time dummies that capture technical change, and, finally, u_{it} is an *i.i.d.* zero mean random error.

Equation 1 requires the imposition of homogeneity and symmetry restrictions required by duality theory. Equations 2 and 3 describe the linear homogeneity and symmetry restrictions. These restrictions are

[2] See for example Baltagi, Griffin, and Rich (1995), Salvanes (1993), Bjørndal and Salvanes (1995) and Feng and Serletis (2010).

also necessary for the theoretical monotonicity and regularity assumptions of the cost function (Diewert, 1982).

$$\sum_{a} \beta_a = 1 \; ; \; \beta_{al} = \beta_{la} \tag{2}$$

$$\sum_{a} \beta_{al} = \sum_{a} \beta_{ay} = \sum_{a} \beta_{ak} = \sum_{a} \beta_{at} = 0 \tag{3}$$

Shephard's lemma allows obtaining input shares as:

$$S_{\alpha} = \frac{\delta lnVC}{\delta lnW_a} = \beta_a + \sum_{l} \beta_{\alpha l} lnW_l + \beta_{\alpha y} lnY + \beta_{\alpha k} lnK + \beta_{\alpha t} D_t \tag{4}$$

The cost function in equation 1 is estimated simultaneously with the input share equations by using the seemingly unrelated regression technique (SUR) (Zellner & Huang, 1962). Once estimated, the system contains all the necessary information to obtain input and output elasticities (equations 5 to 8), and technical change (equation 9) measures as follows:

$$\epsilon_{ii} = \frac{\beta_{ii} + S_i^2 - S_i}{S_i} \tag{5}$$

$$\epsilon_{ij} = \frac{\beta_{ij} + S_i \, S_j}{S_i} \tag{6}$$

$$\theta_t = \frac{\delta lnVC}{\delta lnY} = \beta_y + \beta_{yy} lnY + \sum_{a} \beta_{ay} lnW_a + \beta_{yk} lnK + \beta_{yt} D_t \tag{7}$$

$$\epsilon k_t = \frac{\delta lnVC}{\delta lnK} = \beta_k + \beta_{kk} lnK + \sum_{a} \beta_{ak} lnW_a + \beta_{yk} lnY + \beta_{kt} D_t \tag{8}$$

$$Tech.\text{change} = -[(\beta_t - B_{t-1}) + (\beta_{yt} - \beta_{yt-1})lnY + \sum_a (\beta_{at} - \beta_{at-1})lnW_a + (\beta_{kt} - \beta_{kt-1})lnK] \quad (9)$$

To analyze the effects described above any estimation of a cost or a production function needs to satisfy the theoretical regularity conditions - a set of conditions that matches economic theory with the empirical applications and make the results coherent - next subsection provides a description of such conditions.

Theoretical Regularity

Under a neoclassical economics framework, costs or production functions can describe equally well the technology of a given firm/industry given certain conditions (Diewert, 1974, 1982; Diewert & Wales, 1987). Such conditions are denominated the theoretical regularity and their presence is a necessary and sufficient condition to make the duality theory valid. In a cost function setting, the chosen function must satisfy four conditions: linear homogeneity, positivity, curvature, and monotonicity. Linear homogeneity is described in equations 2 and 3 and relates to the underlying production function by ensuring that any increase in inputs use will increase the production quantity accordingly. Positivity ensures that the estimated costs are always positive as long as the production level is positive, this can be expressed as:

$$\hat{C}(w, Y, t, K) > 0; \quad (10)$$

Monotonicity ensures that any increase in input prices will make the minimum cost of producing any output to rise accordingly. Monotonicity requires the estimated input share equations (equation 4) to be positive. Finally, curvature requires the cost function to be a concave function of input prices, the curvature constraint is analyzed by checking the following matrix to be negative semidefinite (Diewert & Wales, 1987):

$$\Phi = B - S + ss' \tag{11}$$

Where B is a matrix with elements $\beta_{\alpha j}$, s is the vector of input shares, and S is diagonal matrix with the share vector s on the diagonal.

Satisfying such conditions in empirical applications is rare as there is a tradeoff between the regularity conditions and the flexibility of the estimated function (Barnett, 2002); the more flexible the function the less likely it will satisfy the regularity conditions. Thus, practitioners need to sacrifice one for the other depending on the objective of their research. There are different approaches to impose regularity on flexible cost functions (See Serletis and Feng (2015)). In this thesis, the focus is on the Bayesian approach since it allows the translog cost function to remain flexible, while also providing the option to impose regularity conditions over a reasonable region.

Bayesian econometrics

The Bayesian approach to econometric estimation is based on the Bayes' rule. Consider two random variables B, Y, then Bayes' rule states that:

$$p(\beta|Y) = \frac{p(Y|\beta)p(\beta)}{p(Y)} \tag{12}$$

Bayes' rule helps to understand the probability of an event based on previous knowledge of the conditions. In an econometric context, it allows the probability of the estimated coefficients to take certain values conditional on the data the researcher is using. In equation 12, consider that β is a vector of parameters of interest and Y is the dataset; then, we can simplify Bayes' rule to relate only to the elements including β as follows:

$$p(\beta|Y) \propto p(Y|\beta)p(\beta) \tag{13}$$

Equation 13 states that the posterior density $p(\beta|Y)$ is proportional to the likelihood function $p(Y|\beta)$ times the prior $p(\beta)$. The prior contains all the information about the parameters that is not dependent on the data set. For example, in the context of the duality theory explained above, the prior could include the necessary restrictions on the parameters that satisfy the regularity conditions. On the other hand, the likelihood function is the density of the data conditional on the parameters (Koop, Poirier, & Tobias, 2007). Finally, the posterior combines both the data and the prior "believes" to produce distributions that show parameter values that maximize the chance of observing the data.

It is important to notice that in the Bayesian approach, the estimated coefficients are random variables; therefore, the posterior shows probability distributions about where the "true" value of the parameters may lie. As parameters are treated as random variables, credible intervals (similar to traditional confidence intervals) can be exactly estimated with a probability level given apriori (Bolstad & Curran, 2016). This brings an advantage when interpreting such intervals, as its analysis is more intuitive than the frequentist approach. For instance, a 95% credible interval means that there is a 95% chance that the value will lie inside the specified interval. In contrast, with the frequentist approach, the interpretation of confidence interval is cause of confusion as it means that if the estimation were performed a large number of times with similar population samples, then in 95% of the estimations the values will lie inside the interval.

Formally, let B be the parameter space, and C a subspace of β. The probability that β belongs to space C is:

$$p(\beta \epsilon C|Y) = \int_{c}^{C} p(\beta|Y) d\beta = 1 - \alpha \qquad (14)$$

With $0 < \alpha < 1$ and C is considered de Bayesian credible region. The smallest credible region C^* for a certain α level – called highest posterior density (HPD) – is the one where the following conditions hold:

$$p(\beta \in C^*|Y) = 1 - \alpha \qquad (15)$$

And for $\beta_1 \in C^*$ and $\beta_2 \notin C^*$

$$p(\beta_1|Y) \geq p(\beta_2|Y) \qquad (16)$$

The estimation of such intervals, allow the inclusion of past information via priors, which have been shown to produce more efficient estimates (Grzenda, 2015).

In sum, the Bayesian approach to estimate economic models brings three main advantages: 1) It allows the inclusion of previous information and economic theory via the priors, 2) Makes the interpretation of credible intervals and effects from the parameters (like price elasticities, scale economies, input elasticities) more intuitive, and 3) Allows to update the findings as new information comes in (Koop et al., 2007).

In many cases, the likelihood and/or the joint posterior distribution do not have a closed analytical form and therefore the parameters cannot be estimated directly. To circumvent this situation it is usual to recur to posterior simulation methods based on Markov Chain Monte Carlo techniques (MCMC). MCMC estimates the properties of any distribution by extracting random samples from that distribution (Monte Carlo) given that a sequential process (Markov Chain) generates such random samples (Van Ravenzwaaij, Cassey, & Brown, 2018). The extended details of the Bayesian methodology are provided in paper number three of this thesis. We now turn to total factor productivity, which is a measure of overall productivity in a productive unit (i.e., firm, industry, country).

Total Factor Productivity

The literature on total factor productivity is large and, for example, discussions about measurement techniques, issues and, advantages can be found on Haltiwanger, Kulick, and Syverson (2018) and Syverson (2014). In this thesis, I focus on index numbers techniques that can be used with the data where both firm-level quantities and prices are available. Additionally, cost-share TFP indexes are generally robust measures of productivity (Syverson, 2014) and can be expressed as:

$$tfp_{it} = y_{it} - \sum_{j} \alpha_j w_{it} \tag{17}$$

where tfp is the total factor productivity, i is a firm index for $i = 1, \dots, n$ and t is a time index for $t = 1, \dots, T.$, y is output produced, α_j is the cost share on input j and w is the quantity of input j used. Lower case letters indicate logarithms of variables. This measure is the physical total factor productivity (TFPQ). A second index that includes demand effects on productivity is the revenue total factor productivity (TFPR) and is described as follows:

$$TFPR = TFPQ \cdot Price \tag{18}$$

TFPR is useful to investigate demand effects on productivity change and dispersion in the sector. A typical isoelastic demand is used to obtain price elasticity estimates, this is done by using instrumental variables (IV) techniques controlling for prices with supply-side instruments. This demand estimation allows retrieving the idiosyncratic component for each firm. Then, as in Haltiwanger et al. (2018) the TFPR variance is estimated and decomposed into demand effect, inefficiency effect, and misallocation (distortions) effects. In this thesis, the TFP measures and the estimation methods discussed above have been used to analyze aspects of productivity, costs, and regulation in salmon aquaculture. However, the next method to be discussed, vector autoregressive models, was primarily used to model salmon prices and the factors that have influenced it.

Vector Autoregressive models (VAR)

Vector autoregressive (VAR) models are the extension of single ARMA models when there are multiple series and there is a lack of belief that any of the variables are exogenous. VAR models are suitable for analyzing supply and demand variables that affect each other by current and past realizations (Enders, 2008).VAR models can be summarized as follows:

$$Ay_t = F_0 + F_1 y_{t-1} + \cdots + F_p y_{t-p} + u_t \tag{19}$$

Where y_t is a vector of observed time series, u_t are uncorrelated white noise disturbances with standard deviation vector σ. The vectors A and F are matrices of coefficients with A containing the instant relationship of the variables as follows:

$$\mathrm{A} = \begin{pmatrix} 1 & 0 & \cdots & 0 \\ a_{21} & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ a_{k1} & \cdots & a_{k,k-1} & 1 \end{pmatrix} \tag{20}$$

The VAR model can be used to examine the interaction between the variables in the system via the impulse response functions (IRF). Consider the moving average (MA) representation of the VAR system in equation 21[3]:

$$y_t = \mu + \sum_{i=0}^{\infty} \phi_i u_{t-i} \tag{21}$$

[3] For a detailed derivation of the MA representation of a VAR system refer to (Enders, 2008).

The coefficients ϕ_i can then be used to generate the effects of u_{t-i} on the paths of the variables. The accumulated effects of the impulses (one unit shock of u_{t-i}) of series p on series q is the Impulse response function, such sequences is expressed as:

$$\sum_{i=0}^{n} \phi_{pq}(i) \tag{22}$$

IRF is a valuable tool to analyze how shocks in one variable transmit to the other variables in the system, which provides useful information on the connectedness of the system. The VAR model can be used also for multi equation forecasting. By using equation 19 it is straightforward to obtain one-step ahead forecasts using the coefficients of the system. Then again, recursively, the forecast can be performed for two, three, and n steps ahead. However, when the system is large in the number of variables and the number of coefficients, the forecast procedure can become computationally intensive as the number of coefficients increases rapidly. To overcome this burden one can impose restrictions on the coefficients by using economic theory on what is denominated structural VAR, or by using Bayesian approaches to impose prior beliefs on the estimated VAR model (Koop, 2013; Koop & Korobilis, 2018; Koop et al., 2007).

The methods summarized on this section allow us to cover different aspects of the Norwegian salmon aquaculture sector that allows to cover the different problematics described in table 1. The next section will provide a brief summary of the papers of the thesis.

4 Summary of the papers

On the drivers of cost changes in the Norwegian salmon aquaculture sector: A decomposition of a flexible cost function from 2001 to 2014

Co-authored with *Sigbjørn Tveterås*[a]

Published in *Aquaculture economics & Management* **23**, 276-291 (2019*)*

a) Department of Economics, safety, and planning. University of Stavanger, Stavanger 4036, Norway.

Abstract: Since 2005, Norwegian salmon farmers have experienced increasing unit costs, contrasting pre-2005 trends characterized by innovations, rapid productivity growth, and diminishing unit costs. This article investigates these cost changes using a panel of salmon producers. The drivers behind cost changes in the industry are identified for the period of 2001–2014 using a flexible cost function. In particular, it is explored how cost changes can be attributable to scale economies, negative productivity shocks, production expansion, and input prices. The results indicate that cost increases in the sector are affected by external factors out of the control of individual firms such as input prices and environmental conditions like sea lice.

Effects of regulations on quantity in natural resource industries: A Bayesian estimation on the Norwegian salmon aquaculture.

Co-authored with $Frank\ Asche^{a}$ and $Ragnar\ Tveter$ås^{b}

Submitted to Journal of Environmental Economics and Management

a) Institute for Sustainable Food Systems and School of Forest Resources and Conservation. University of Florida, Gainesville, Flo 32611-0180, USA.

b) Business school. University of Stavanger, Stavanger 4036, Norway

Abstract: In this paper, we estimate the effects of regulations and quantity restrictions on production costs in natural resource industries with high firm heterogeneity. To obtain such effects and to calculate their shadow price we use a Bayesian methodology to estimate a cost function that satisfies the theoretical regularity conditions. We apply this approach to the Norwegian salmon aquaculture sector as a suitable example of a regulated industry - by production quantities - with high firm dispersion. We found that the regulation system constrains salmon firms from benefiting from scale economies, as they cannot increase their production levels beyond the physical limits imposed. Therefore, such regulations have an increasing cost effect on small and medium-size firms. Since regulations on the production capacity of firms are important in other industries, the methodology applied on this paper has broad application.

Firm dispersion and total factor productivity: Are Norwegian salmon producers less efficient over time?

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Abstract: The Norwegian salmon farming sector has experienced an increase in industry concentration for the last 20 years attributed to agglomeration externalities and scale economies; big firms increase their size and market share while small firms remain operating at the minimum level. However, small firms have higher profitability ratios than their bigger counterparts, a fact that contradicts economic theory as less efficient firms (and less profitable) will not grow and eventually will disappear. This paper quantifies the role of idiosyncratic demand and distortions on observed productivity differences across Norwegian salmon producers from 2001 to 2016. By using a data set that measures directly firm-level quantities, prices and sales, it is possible to break down the sources of total factor productivity dispersion on technical inefficiency and firm fundamentals. The understanding of total factor productivity (TFP) dispersion is useful as micro-productivity changes can point out aggregate productivity movements that matter on industrial and macroeconomic policies.

Salmon Price Forecasting with a Market in Flux.

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The salmon market is in transition due to rapid changes in regulations, production technology, and environmental conditions. This paper models and forecasts salmon prices via a time-varying parameter VAR model (TVP-VAR) that deals with structural changes as it allows for both smooth and structural changes on the estimated coefficients and the volatility structure. Using monthly data that span 2000-2019, the model considers supply-side fundamentals such as input prices, exchange rates, and available supply. The results showed that the TVP-VAR models predict the direction of price changes accurately 8 out of 12 months. The TVP-VAR model better captures the changes in market conditions, such as structural changes in regulation, the volatility of input prices (soybean and fishmeal), and models the seasonality present in salmon prices.

5 Contributions and limitations

This section describes the main contributions of each paper; the contributions are both methodological and empirical.

In Paper 1, we found that operational costs increase could mainly be attributed to external factors out of control of producers. On one hand, salmon producers' feed demand is highly inelastic which make feed cost highly sensitive to changes in feed prices. As a result, shocks on feed prices resulting from increasing prices for protein meals and vegetable oils may be transmitted to salmon prices. On the other hand, the increase of other types of operational costs like disease treatment and prevention,s and the estimated negative productivity shocks indicate that external factors, linked to environmental conditions (diseases), have contributed to a shift from a decreasing trend to an increasing trend in costs in Norwegian salmon aquaculture before and after 2005.

Paper 2 has both methodological and empirical contributions. First, the methodological contribution is to use a Bayesian approach of imposing regularity and curvature conditions over a cost function to analyze regulations on salmon aquaculture. The Bayesian approach is not new, as it has been used to analyze efficiency and productivity growth in other industries. However, we took a different direction and show that this approach is suitable to analyze the effects of a frequently used policy instrument in natural resource industries: Quantity regulations in inputs and outputs. By imposing regularity, it is possible to evaluate the policy effects in a sector with high firm heterogeneity in size. We imposed the regularity conditions over a cost function that allows retrieving the effects on costs and the shadow price of the regulation at different levels of production.

Empirically, we analyze the effects of quantity restrictions in the Norwegian salmon aquaculture sector via the Maximum Total Biomass regulation (MTB). We found that such regulation creates cost inefficiencies that vary depending on firm size. Small firms face high costs increases (6%) while medium firms and big firms face low or no increase (2.8% and 0% respectively). The cost increase observed in a subset of the sample comes from two sources: 1) input misallocation mainly on labor and smolt use. More constrained firms (i.e., smaller ones) use these inputs more intensively when compared with medium and large ones. 2) Unused scale economies. Firms cannot fully profit from scale economies as their output level is constrained by the MTB system. We estimated the optimal production level for the industry – according to neoclassical economic theory – and found that 89% of the firms are below such optimum.

In paper 3, I analyzed the factors behind productivity dispersion in the salmon aquaculture sector. For several years, low productivity firms have survived alongside high productivity ones. In particular, small firms seem to be more profitable than large firms are which contradicts economic theory and previous empirical findings about the existence of scale economies in the sector. I used a dataset that allows observing firm-specific input and output prices to disentangle the effects of firm fundamentals, distortions (inefficiency and misallocation), and demand (via prices and inverse demand) on the observed productivity patterns. Small firms tend to have higher misallocation and technical inefficiency but profit from historical high spot prices. On the other side, big firms have higher allocative efficiency, but their firm-specific demand has a lower influence on revenue productivity than small and medium firms do. This could be explained by the fact that big firms are more likely to have long-term contracts with a fixed price scheme with their clients and thus they profit less from high spot prices.

Paper 4 focuses on modeling monthly salmon prices. We include a set of supply and demand-side variables that theoretically and empirically seem to have influenced salmon price behavior. We apply a TVP-VAR model that captures structural changes of the global salmon market on salmon prices via the stochastic volatility component. Our findings suggest that there is a diminishing effect of fishmeal shocks on salmon prices, which can be explained by the increasing share of vegetable protein ingredients used in the feed mix. In general, higher volatility of prices translates into higher volatility in revenues for the economic agents. The associated price risk is the reason why forecasting in the short and medium-term is important, as it gives better opportunities for more informed hedging decisions. We found that the TVP-VAR models predict the direction price changes accurately 8 out of 12 months and appears to capture well the seasonality present in salmon prices.

A limitation of all the four papers is data availability. The data used for the cost and productivity analyses come from a survey that the fisheries directorate realize about production costs. The directorate only provides data of the firms that deliver complete reports and thus the panel is unbalanced. This makes our sample to suffer from attrition. Since it is not possible to track which firms exit the market because their costs are too high (paper 1) or because of low productivity (paper 3) the extent of our analysis is limited. In addition, public information about M&A is very limited and the data available for diseases cannot be conciliated with the sample used. We circumvent these limitations by doing our analysis indirectly based on previous research, literature reviews, and economic theory.

Three main conclusions arrive from the findings of the papers on this thesis:

1) The era of high profits driven by cost decreases is approaching an end and the sustainability of the sector now depends on disruptive innovation. Therefore, incentives must be tailored to help players in the industry to invest in R&D that will materialize in the future.
2) Environmental externalities play a main role in inefficiency and production costs. Disease prevention and treatment require both individual and group incentives to make players internalize such costs in a profitable way and to drive the required innovation activity required to solve current challenges.

3) The MTB system seems to constrain firms to grow to their optimal long-run levels. However, the increase in production licenses must be balanced with the negative externalities – diseases – that may arrive because of higher production. There is a tradeoff between the profits from scale economies and the costs of negative environmental externalities.

A final reflection, market organization in natural resources sectors imply the interaction at multiple levels of institutions, environment, and market forces. Authorities must balance the complex tradeoff between production growth and environmental sustainability while providing the right incentives to economic agents to internalize the negative externalities and to create innovations that avoid them. One can argue that further sustainable growth in the Norwegian salmon production is possible with a properly designed policy regime that provides sufficient incentives to investments in research and innovation at different stages of the value chain. One aspect of the economic dimension is that capital and labor inputs are paid competitive wages relative to alternative employment in other sectors. Another aspect is that taxes and subsidies (e.g. R&D subsidies) are appropriately balanced with respect to government revenue needs, correction of market distortions and failures, and to provide sufficient incentives for required investments.

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Paper I

On the drivers of cost changes in the Norwegian salmon aquaculture sector: A decomposition of a flexible cost function from 2001 to 2014

ON THE DRIVERS OF COST CHANGES IN THE NORWEGIAN SALMON AQUACULTURE SECTOR: A DECOMPOSITION OF A FLEXIBLE COST FUNCTION FROM 2001 TO 2014.

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ABSTRACT

Since 2005, Norwegian salmon farmers have experienced increasing unit costs, contrasting pre-2005 trends characterized by innovations, rapid productivity growth and diminishing unit costs. This paper investigates these cost changes using a panel of salmon producers. The drivers behind cost changes in the industry are identified for the period 2001-2014 using a flexible cost function. In particular, it is explored how cost changes can be attributable to scale economies, negative productivity shocks, production expansion, and input prices. The results indicate that cost increases in the sector are affected by external factors out of the control of the individual firms such as input prices and environmental conditions like sea lice.

Keywords: flexible cost function, productivity shocks, input prices, salmon aquaculture, sea lice.

1 Introduction

The rapid growth of the salmon aquaculture sector in Norway can largely be attributed to productivity growth and accompanying cost reductions (Asche, Guttormsen, & Nielsen, 2013). High growth rates associated with productivity increases and industry concentration characterized the sector behavior for more than 30 years (Asche, Roll, Sandvold, Sørvig, & Zhang, 2013). Several factors have contributed to productivity growth, including the use of new technologies, improved inputs, better management practices and increased scale. However, the trend of productivity and efficiency growth started to be reversed in 2005 (Asche, Guttormsen, et al., 2013; Vassdal & Sørensen Holst, 2011). For the 12 following years production costs have exhibited an increasing trend. Little attention has been given to the drivers of these cost increases or why productivity growth has slowed down since 2005.

This paper provides an empirical analysis of cost changes in the Norwegian salmon aquaculture industry. Our purpose is twofold: First, we estimate a flexible cost function that allow us to analyze technical change and its components in a yearly basis; this will allow us to identify changes and patterns of Total Factor Productivity (TFP) in the sector. Second, by decomposing the cost function one can find the contribution of the three components technical change, economies of scale, and input prices. Hence, the relative importance of each component to costs changes is assessed and their impact on total costs evaluated.

The paper is organized as follows: Section 2 explains the background and evolution of the sector regarding productivity and costs. Section 3 discuss the estimation methodology. Then, section 4 describes the data within the main facts of the sector for the period under study. Section 5 presents the estimation results. In section 6, we discuss our results. Finally, section 7 concludes.

2 Background

The development of the Norwegian salmon aquaculture sector has been characterized by continuous productivity growth and output expansion. This downward trend in the unit cost curve tapered off in 2005 signaling the end to the period of strong productivity growth (Asche, 2008). Thereafter, both prices and unit costs have been trending upwards. To understand this shift, it is useful to first review developments in the salmon industry linked to productivity.

Salmon farming in Norway turned into an industrial food-producing industry with large productivity gains during the 1980s. The production process underwent several changes during this initial stage as a result of learning by doing, positive agglomeration externalities and the use of new technologies (Asche, Roll, & Tveteras, 2016; Roll, 2013; Tveterås, 2002; Tveterås & Heshmati, 2002). Examples of these improvements are the development of vaccines, better farming equipment, and feed types with higher protein content. These productivity improvements positioned Norway in the early 2000’s as the biggest producer of farmed salmon globally.

In this early period, there were also disease outbreaks and environmental problems that negatively affected productivity (Asche, Guttormsen, & Tveterås, 1999; Tveterås, 2002). Although the industry worked to resolve these challenges to the extent that know-how and innovations allowed it, Tveterås and Heshmati (2002) noticed that productivity growth measured as technical change was nonlinear with substantial year-to-year variations. For example, biophysical shocks such as extreme weather conditions and disease outbreaks could cause negative productivity shocks.

In addition to technological advances related to capital equipment and know-how accumulation, the fast growth during the 1980s and 1990s led to changes in the organizational structure of the industry (Asche, 2008; Nilsen, 2010). Changes towards higher flexibility on license ownership and capital allowed firms to increase horizontal and vertical integration marking the transition from a labor-intensive to a capital-intensive industry.

As this transition took place, it became increasingly important to have control over the different steps in the value chain. For example, Kvaløy and Tveterås (2008) showed that the cost penalty for processing suboptimal volume of fish was larger in the newer, larger, and more capital-intensive salmon processing facilities compared to the older more labor-intensive ones. Modern and larger processing facilities allowed increasing economies of scale, but those cost gains relied on a steady supply of raw material. The control with the supply chain extended beyond processing as an increasing share of salmon exports was sold on contracts (Asche & Larsen, 2011).

Since the early 2000s concentration in the sector increased both in number of firms and geographic location as a result of the maturing of the Norwegian salmon aquaculture sector (Asche, Roll, et al., 2013; Asche et al., 2016). This behavior was the result of the relaxing restrictions on production capacity, the presence of external scale economies, permanent regional differences, and agglomeration effects on the sector (Asche et al., 2016; Tveterås & Battese, 2006). In sum, a range of organizational and technological changes fueled the strong productivity growth in this period. The increased volume and output control helped the salmon industry to reach new markets and forge supply chains with retail food chains (Anderson, Asche, & Tveteras, 2010). However, agglomeration also produced negative externalities as farms in high-density regions faced a higher probability of fish disease spreads. These kinds of production risks are still very much part of the industry today.

As mentioned earlier, the long streak of productivity growth appears to end in 2005. Asche, Guttormsen, et al. (2013) noted that the lower growth rate in output *"means limited possibilities to increase productivity growth through technical development and more efficient production. The industry is then becoming more dependent upon external factors, such as demand and regulation, which they* *have less control over."* This led to two potential explanations on why costs have increased since 2005: First, that the productivity growth leveled off and no new major innovations took place to shift the production function. With a fixed technology, a main driver of cost changes could be external factors such as prices of input factors. The second explanation is that different sources of production risks could have driven up costs. Disease outbreaks and sea lice are negative externalities that the industry struggled with, which could have influenced mortality rates in fish farms and expenditure on disease prevention and treatment. Unless firms had knowledge and tools to manage those risks, they would represent real threat for output and cost efficiency.

While demand growth for salmon has been strong and positive for profitability in the industry (Asche, Dahl, Gordon, Trollvik, & Aandahl, 2011; Brækkan & Thyholdt, 2014; Brækkan, Thyholdt, Asche, & Myrland, 2018), the sector has encountered challenges such as rising input prices, stricter environmental regulations, disease outbreaks, and sea lice accumulation (Abolofia, Asche, & Wilen, 2017; Asche, Guttormsen, et al., 2013; Costello, 2009). This involves both the explanations above. However, it is unknown to what degree each of these factors have contributed to inflate unit costs in salmon farming. In the next section, we describe the empirical approach to decompose the different effects on productivity and how they relate to cost increases.

3 Methodology

To analyze cost changes we must specify a function that represents the production technology of the Norwegian salmon aquaculture sector. Asche, Kumbhakar, and Tveterås (2007) found evidence that the use of a cost function is appropriate to describe the sector behavior. Flexible cost functions have been generally used to analyze salmon farming in Norway as good approximations to an industry that has undergone accelerated technical change. Examples of flexible cost functions applied to Norwegian Salmon aquaculture can be found in (Guttormsen, 2002; Nilsen, 2010; Roll, 2013; Salvanes, 1993; Tveterås, 2002; Tveterås & Battese, 2006).

A translog restricted function is used to model costs in the Norwegian salmon aquaculture sector. The translog is a flexible function form that has the advantage of not imposing any assumptions on the underlying production technology neither on the behavior of technical change and input substitution patterns. Suppressing time and firm suffixes, this function is specified as follows:

$$
\begin{aligned}
\mathrm{lnVC} = {} & \alpha_0 + \sum_{\mathrm{i}} \lambda_i \mathrm{D_i} + \sum_{\mathrm{t}} \beta_t \mathrm{D_t} + \beta_{\mathrm{y}} \mathrm{lnY} + \beta_{\mathrm{k}} \mathrm{lnK} + \sum_{\alpha} \beta_\alpha lnw_\alpha \\
& + 0.5 \sum_{\alpha} \sum_{\mathrm{l}} \beta_{\alpha l} lnw_\alpha lnw_l + \sum_{\alpha} \beta_{\alpha k}\, lnK lnw_\alpha + \sum_{\alpha} \beta_{\alpha y}\, lnY lnw_\alpha \\
& + \sum_{\alpha} \sum_{t} \beta_{\alpha t} lnw_\alpha D_t + \beta_{yk} lny\, lnK + 0.5\, \beta_{yy} lnY^2 + 0.5\, \beta_{kk} lnK^2 \\
& + \sum_{t} \beta_{yt} lnY D_t + \sum_{t} \beta_{kt} lnK D_t + u_{it}
\end{aligned}
\qquad (1)
$$

Where $\mathrm{i} = 1, 2, \ldots, \mathrm{N}$ firms in the sample, D_i are dummies that capture firm-specific differences, VC is total variable costs of each firm, Y is the corresponding output, W_α is a vector of input prices, K is fixed capital costs, D_t are time dummies that capture technical change, and, finally, u_{it} are *i.i.d.* zero mean random error.

Equation 1 is a standard general form in linear estimations that does not impose any functional form on technical change (Baltagi, Griffin, & Rich, 1995; Kumbhakar, 2004). The specification allows both positive and negative technical change rates and, related to it, TFP growth. This flexibility is important for a maturing industry that at times experience negative supply shocks like disease outbreaks and varying input prices.

To estimate equation 1, it is necessary to impose the homogeneity and symmetry restrictions required by economic theory (Diewert, 1982). Equations 2 and 3 give the homogeneity and symmetry restrictions:

$$\sum_a \beta_a = 1 \; ; \; \beta_{al} = \beta_{la} \tag{2}$$

$$\sum_a \beta_{al} = \sum_a \beta_{ay} = \sum_a \beta_{ak} = \sum_a \beta_{at} = 0 \tag{3}$$

The translog cost function is estimated as a system of equations that includes n-1 input share equations, as one must be deleted to avoid a singular system. Shephard's lemma allows us to obtain input shares by taking the derivative of the cost function with respect to the input prices as follows:

$$S_\alpha = \frac{\delta lnVC}{\delta lnW_a} = \beta_a + \sum_l \beta_{\alpha l} lnW_l + \beta_{\alpha y} lnY + \beta_{\alpha k} lnK + \beta_{\alpha t} D_t \quad (4)$$

From the cost and share equation, conditional own and cross-price elasticities can be computed as (Diewert, 1974):

$$\epsilon_{ii} = \frac{\beta_{ii} + S_i^2 - S_i}{S_i} \quad (5)$$

$$\epsilon_{ij} = \frac{\beta_{ij} + S_i S_j}{S_i} \quad (6)$$

In addition, the effect of output, fixed factors, and technical change on variable costs can be obtained as follows (Kumbhakar, 2004):

$$\theta_t = \frac{\delta lnVC}{\delta lnY} = \beta_y + \beta_{yy} lnY + \sum_a \beta_{ay} lnW_a + \beta_{yk} lnK + \beta_{yt} D_t \quad (7)$$

$$\epsilon k_t = \frac{\delta lnVC}{\delta lnK} = \beta_k + \beta_{kk} lnK + \sum_a \beta_{ak} lnW_a + \beta_{yk} lnY + \beta_{kt} D_t \quad (8)$$

$$\begin{aligned} Tech.\text{change} = & -[(\beta_t - B_{t-1}) + (\beta_{yt} - \beta_{yt-1}) lnY + \sum_a (\beta_{at} - \beta_{at-1}) lnW_a \\ & + (\beta_{kt} - \beta_{kt-1}) lnK] \end{aligned} \quad (9)$$

Equation 7 measures the scale effects on the cost function and allow us to measure returns to scale (RTS) by calculating its inverse. Equation 8 describes capital effects or the elasticity of intensity with respect to capital while equation 9 is the rate of technical change that can be decomposed in four main components: Pure technical change $(\beta_t - \beta_{t-1})$; Scale augmentation $(\beta_{yt} - \beta_{yt-1})lnY$; non-neutral technical change $\sum_a(\beta_{at} - \beta_{at-1})lnW_a$; and capital augmentation $(\beta_{kt} - \beta_{kt-1})lnK$. Finally, we calculate total factor productivity growth $(T\dot{F}P)$ as follows (Kumbhakar, 2004):

$$T\dot{F}P = Tech.change + (1 - \theta_t)\dot{Y} \tag{10}$$

Where technical change is obtained from equation 9, θ_t from equation 7, and $\dot{Y}$ is the annual growth of input ($\dot{Y} = lnY_t - lnY_{t-1}$).

4 Data

We used an unbalanced panel data of salmon firms from the Norwegian Directorate of Fisheries that annually surveys production and profitability in the sector. For the empirical analysis, we used four variable inputs: Feed, labor, smolt, and other costs. Asche, Guttormsen, et al. (2013); Asche, Roll, and Tveterås (2009); Nilsen (2010) have shown that these factors are the main cost drivers in the Norwegian salmon aquaculture sector. Additionally, due to the short-run specification of the cost function, capital was treated as a fixed factor. The sample consists of 1550 observations from 251 firms for the period 2001-2014; table 1 provides a summary of the selected variables.

Table 1. Summary statistics

Variable	Mean	Standard Deviation	Minimum	Maximum
Production (ton)	5,481	9,350	197.5	91,600
Feed (1,000 NOK)	55,200	97,800	1,048.3	1,040,000
Labor (1,000 NOK)	8,539	17,100	9.6	169,000
Smolt (1,000 NOK)	11,800	18,200	289.0	170,000
Other Costs (1,000 NOK)	22,300	58,300	150.1	744,000
Capital (1,000 NOK)	61,300	144,000	165.4	1,540,000

Notes: We used the value of assets owned by firms as proxy for capital.

For the period 2001-2014, input prices showed an increasing tendency with the highest growth rates between 2005-2010 (Iversen et al., 2015). Feed and other costs had the highest price growth with an increase of 11.3% and 17.1% for the whole period respectively. Feed prices increased due to salmon feeds' dependency on fishmeal and fish oil. The strong demand from aquaculture have periodically inflated fishmeal and fish oil prices (Asche, Oglend, & Tveteras, 2013). While scarcity of fishmeal and fish oil reduced the inclusion of these marine resources in salmon feeds, prices of alternative protein and lipid sources also increased. The overall inflation of feed input prices have been linked to the increase of salmon price volatility. Oglend (2013) shows that the fish meal components and changes in the corresponding fish meal price accounts for most of the volatility behavior of salmon prices. This would also suggest that cost changes related to input prices are passed on to consumers (Landazuri-Tveteraas, Asche, Gordon, & Tveteraas, 2018). The development of input prices can explain the increasing trend of feed prices in figure 1.

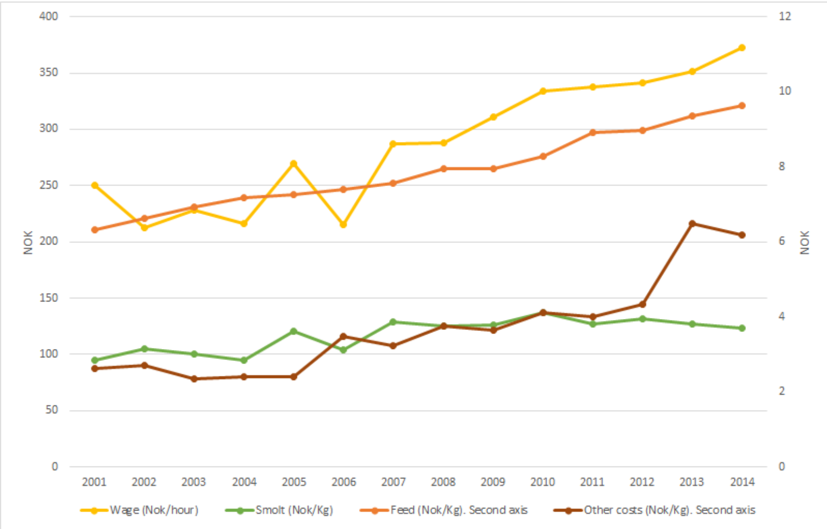

Figure 1. Unit input prices 2001-2014.

In addition to feed prices, the wage level also increased. Smolt prices increased more moderately, which is not surprising given that there has also been strong productivity growth in smolt production (Sandvold, 2016; Sandvold & Tveterås, 2014). The catch-all-remaining category "other costs" also grew over most of the period. This is not surprising given that this capture treatment costs associated with diseases and the increasing lice challenges (Abolofia et al, 2017).

A characteristic of the Norwegian salmon aquaculture sector is heterogeneity of firm size and output level. Despite the tendency of increasing concentration that has occurred during the last decade, there remains many small and medium size firms. This characteristic is a result of the regulations that aim to protect and maintain a "fair" distribution of producers along the Norwegian coastline (Liu, Olaussen, & Skonhoft, 2011). Our data set consisted of a range of companies with different sizes, output levels and constituted a large sample of the whole industry. The increasing divergence in output levels is depicted in figure 2.

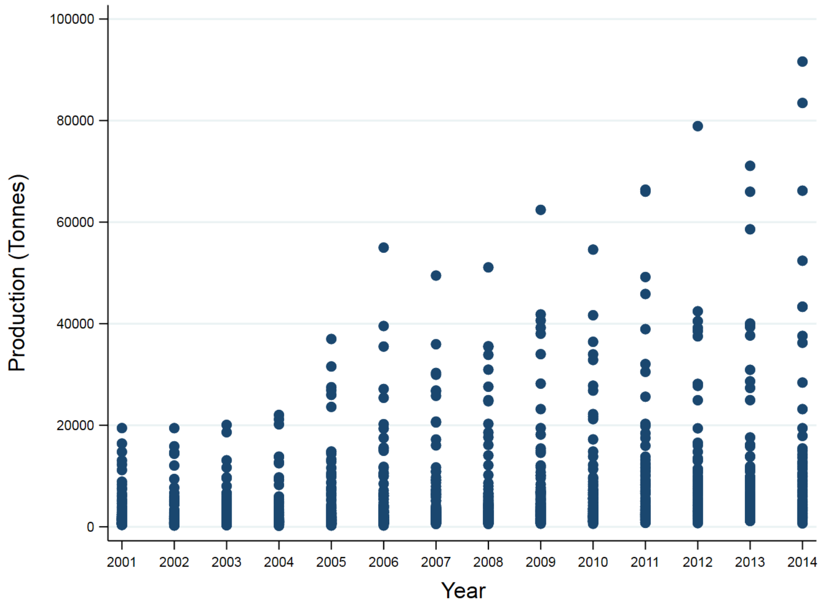

Figure 2. Production per firm 2001-2014.

5 Empirical results

The cost function was estimated jointly with the share equations using the seemingly unrelated regression (SUR) technique. To avoid singularity in estimation we dropped the share equation corresponding to the variable “other costs”. As there were no additional parameters to estimate in the equation system it is efficient to estimate equations simultaneously (Zellner & Huang, 1962). The data was normalized by transforming each independent variable as deviations from its mean before taking the logarithm.

To check the model specification, likelihood ratio tests were performed on the suitability of including fixed capital effects and firm effects. The tests result in table

2 reject the null that either fixed capital costs or firm dummies should be excluded from the cost function.

Table 2. LR tests of hypotheses for parameters of the Translog cost function

Test	Null Hypothesis (H_0)	LR χ^2	P-value
Fixed Capital effects	$H_0: \beta_k = \beta_{ky} = \beta_{k\alpha} = 0$	262.14 (7)	0.000
Firm effects	$H_0: \sum_i \lambda_i * D_i = 0$	564.21 (250)	0.000

Degrees of freedom in parentheses.

The main focus of the analysis is to identify the own and cross-price elasticities in addition to scale effects, fixed effects, technical change rates, and TFP growth as described in equations 5 to 10. These effects were calculated for the period 2001-2014 for the representative firm by using the mean values displayed on table 1.

The estimated system of equations and the calculation of elasticities are consistent with economic theory only if theoretical regularity conditions are satisfied (Diewert, 1982; Diewert & Wales, 1987). Linear homogeneity is already imposed by the symmetry restrictions described on equations 2 and 3. Monotonicity and positivity are satisfied if the estimated costs and shares are greater than zero[2]. Finally, curvature regularity is satisfied if the following matrix is negative semidefinite (Diewert & Wales, 1987):

$$\Phi = B - S + ss' \tag{11}$$

[2] The estimated shares and costs at mean values are:
$\widehat{\boldsymbol{lnVC}} = 17.59074$ $\widehat{S_{feed}} = 0.585$ $\widehat{S_{labor}} = 0.086$ $\widehat{S_{smolt}} = 0.148$ $\widehat{S_{other\ costs}} = 0.179$

Where B is a matrix with elements $\beta_{\alpha l}$, s is the share vector of size $(MX1)$ and S is a (MxM) matrix that has on the main diagonal the vector s. This matrix is negative semidefinite if its highest eigenvalue is equal to zero. We found that at mean values all the theoretical regularity conditions are met.

The elasticity estimates in table 3 show that all inputs are unresponsive to own price changes and that there are hardly any substitution possibilities between them, as noted by the low magnitude of the cross-price elasticicities in the off-diagonal elements. Of the four variable inputs, feed and other costs variables showed the highest rigidities to price changes with an own price elasticity estimates close to zero. Other costs, amongst other, includes expenditures associated with disease and sea lice treatment, where especially the parasitical issue has become an increasing concern the last decade. The near-perfect inelastic feed demand indicates that salmon aquaculture has reached a mature stage where feed is efficiently converted to proteins. This result is also in line with Guttormsen (2002), who argues that after the smolt has been released, feed is the only variable input factor. Also, the zero cross-price substitutability of other cost indicate that there are no means of addressing disease and parasitical issues by adjusting any of the other three inputs; it is all specialized treatments contained in the other cost group.

Table 3: Input price elasticity estimates evaluated at average prices

	Feed price	Labor price	Smolt Price	Other Costs
Feed Quantity	-0.151^{***}	0.041^{***}	0.111^{***}	-0.001
Labor Quantity	0.277^{***}	-0.424^{***}	0.087^{***}	0.059^{***}
Smolt Quantity	0.440^{***}	0.051^{***}	-0.557^{***}	0.066^{***}
Other Costs	-0.005	0.028^{***}	0.054^{***}	-0.078^{***}

*** Significant at the 1% level.

The effect of the fixed capital factor was calculated by taking the partial derivative of the cost function with respect to capital as formulated in equation 8. Our calculations show that capital had an increasing effect on the cost function for the representative firm of around 5%. However, the confidence interval is wide and includes zero, which can reflect heterogeneous capital effects that are not statistically significant when evaluated at average prices.

We computed returns to scale by calculating the inverse of cost elasticity with respect to output as defined in equation 7. We found increasing returns-to-scale in the short run with a value of 1.28. This indicates that producers, on average, could have obtained costs savings by increasing production levels. However, this is difficult to obtain in practice due to the regulation system with licenses and a Maximum Total Biomass (MTB) associated with each license and with each farm (Osmundsen, Almklov, & Tveterås, 2017).

The results suggest negative technical change rates that results from adverse productivity shocks showing that costs grew annually 1.58% by factors not directly attributable to variable input prices, fixed factor, or output expansion. To understand the factors influencing the negative productivity development we decomposed the technical change rate expression as explained in equation nine.

Table 4. Technical change rate decomposition

	Estimates (%)	
Pure tech. change	-0.940	(0.002)
Scale augmentation	-0.190	(0.002)
Non-neutral tech. change	0.010	(0.001)
Capital Augmentation	-0.040	(0.001)
Total Tech. Change	-1.580	(0.002)

Notes: standard deviations in parentheses

As shown in table 4, the main driver of the observed negative productivity shocks is the pure technical component. Pure technical change constitutes more than 80% of the productivity reduction while the effects of scale and capital augmentation play minor roles. The non-neutral component has not driven any cost increases in the period under analysis. The fact that the productivity shock is explained by the pure technical component sounds counterintuitive and suggests that factors external to the industry are the main culprits to inflate production costs.

By not imposing any functional form to technical change, we were able to identify annual variations of this component. Our estimations of the technical change rate do not show any recognizable trend with the high annual variations in costs, which is in line with Tveterås and Heshmati (2002). For most years, technical change rates are negative, or close to zero, indicating that annual costs are increasing in the sector.

Calculation of total factor productivity can shed further light on the consequences of the negative productivity shocks. Table five presents annual total factor productivity growth for the data period. On average, TFP grew annually 0.93% during the 2001-2014 period whereof five years contained negative growth values (2003, 2008, 2009, 2013, and 2014). In 2011, the sector experienced the highest rate of TFP growth (6.32%). However, the TFP rates obtained show that the negative productivity shocks – as captured by our technical change specification – have a strong effect on TFP growth as the years that present reductions in the technical component are those where TFP rates are negative.

Table 5. Average TFP growth

Year	Means	Standard Error
2002	N/A*	N/A*
2003	-4.31 %	0.01
2004	0.72 %	0.01
2005	3.65 %	0.01
2006	4.64 %	0.01
2007	2.25 %	0.01
2008	-1.21 %	0.01
2009	-0.98 %	0.01
2010	0.86 %	0.01
2011	6.32 %	0.02
2012	1.54 %	0.02
2013	-1.69 %	0.02
2014	-2.31 %	0.02
Overall sample mean	0.93 %	0.00

* N/A: Not Applicable

6 Discussion

The results identify two main drivers behind the cost increases in the Norwegian salmon aquaculture sector since the turn of the century: Input prices and negative productivity shocks, which likely are linked to disease and sea lice issues. Demand for the different inputs feed, smolt, labor and other factors are all unresponsive to own price and have low substitution possibilities; this result is a common characteristic for the salmon production technology found in other studies (Asche et al., 2009; Asche et al., 2016; Guttormsen, 2002; Tveterås, 2002). It is also a characteristic that aligns with a mature industry that have “exhausted” the opportunities for technological innovations due to constraints embedded by available know how, technology, and investment funds; with the technology more or less fixed, the main drivers of cost variations will be factors external to the industry.

More specifically, the results indicate that salmon firms have a low capacity to adjust the input mix in the short run when facing increasing input prices. Estimates of price elasticities show that feed is the main input for production; the basis of this technology is to convert feed into fish proteins. Limited or no substitution possibilities mean that if feed prices increase, costs will also increase. The data support this association since the average growth of feed prices was 11% and the growth of production costs was 15% for the period 2001-2014.

The other driver of cost increases, the negative productivity shocks, suggest that as the technology has matured the main sources of productivity changes have been factors of which salmon farmers have less control such as biophysical conditions, diseases and parasites. A mature technology means that the only way to increase output is by using more inputs in the production process (Asche, Guttormsen, et al., 2013; Asche et al., 2009; Vassdal & Sørensen Holst, 2011). This situation combined with higher input prices and external constraints like negative shocks to production can lead to the observed negative productivity growth.

The increase of sea lice along the Norwegian coastline is a source of cost growth in salmon farming that in our model is captured partially by the time dummies. Abolofia et al. (2017) estimate that on average an infestation of sea lice creates cost damages equivalent to 9% of farm revenues. This is because the sea lice infestation reduces output by increasing the mortality rate, ceteris paribus. In addition, sea lice infestations led to higher treatment costs negatively affecting cost-efficiency in the sector. The treatment element of sea lice is captured in the "other cost" category and as such it implies the sea lice issue is internalized in the cost function.

Nonetheless, sea lice treatment is unable to completely eliminate the negative effects of the parasites and, consequently, there will be external costs related to reduced output. In the cost function specification, these will be captured by the time dummies. The estimated negative productivity shocks captured by the time dummies share similarities to the pattern of sea lice increases (figure 3). In the years of the disease outbreak provoked by sea lice (2008-2010), productivity shocks showed higher negative values between -2.5% and -3.2%. This shows that sea lice likely have caused reduced productivity in certain years observed from the estimation.

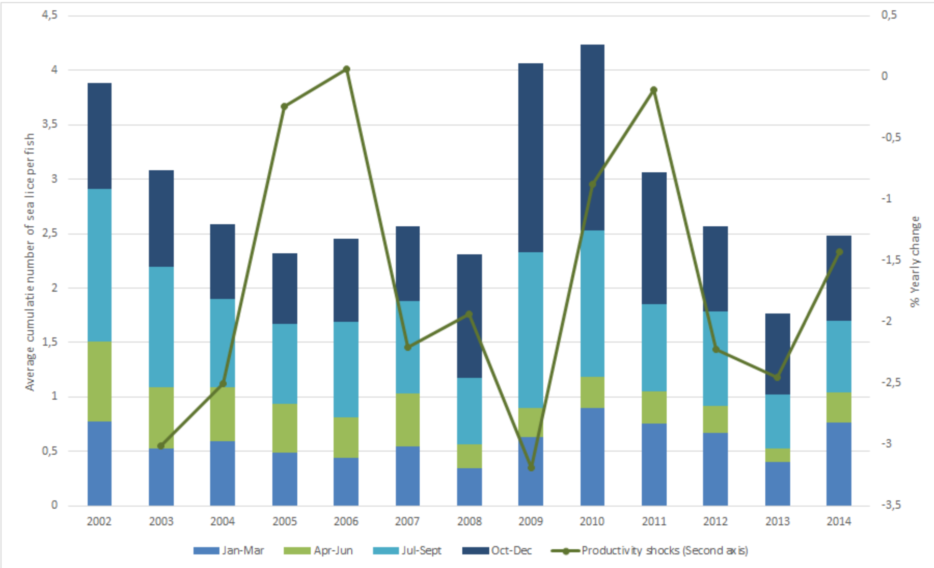

Figure 3. Quarterly average number of female sea lice per fish in Norway and annual technical change 2001-2014.

Even though our results are evaluated at the average firm, the comparison between the different effects associated with increasing input prices and disease outbreaks confirms the robustness of the cost function specification. Moreover, the flexible structure captures the influence of volatile external conditions – sea lice infestations, disease outbreaks – allowing us to retrieve individually the different components of costs changes.

We went further and analyzed total factor productivity growth (equation 10) by estimating separately its technical change component $\left(\frac{\delta lnVC}{\delta Dt}\right)$ and its scale component $\left[\left(1-\frac{\delta lnVC}{\delta lnY}\right)\dot{Y}\right]$. As figure 5 shows, a great part of TFP growth fluctuations correspond to fluctuations in technical change rates, which is negative for most of the years. This is in line with the findings of Asche, Guttormsen, et al. (2013) and Vassdal and Sørensen Holst (2011) who found negative contribution of technical change to TFP growth since 2002. The scale component has a strong influence on TFP growth between 2004 and 2007, the period in which production capacity increased the most with an average of 19.4%. These results indicate that irrespective of negative productivity shocks, TFP growth was on average positive due to the benefits of scale economies.

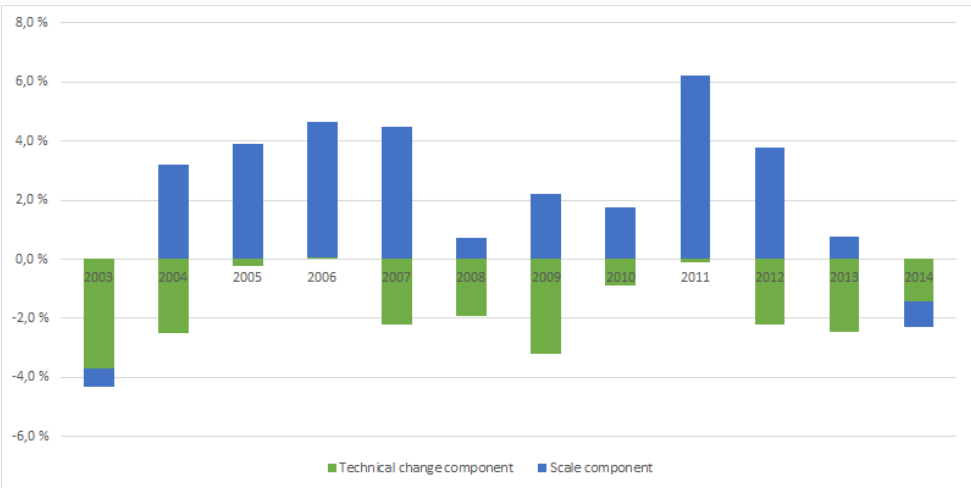

Figure 4. TFP growth and its components

Finally, our findings of scale economies should need to also account the sea lice problem. Scale economies predicted by an increase in average production levels can be undermined by environmental conditions associated with sea lice and diseases. In our analysis, we only capture the effect on “other costs”, which also contains costs other than disease and sea lice treatment, for example, like administrative costs. Otherwise, the model does not explicitly identify to what extent the magnitude of the time dummies is driven by these externalities and its exact impact goes beyond the scope of this paper.

However, our results suggest that environmental costs can limit production expansion via negative externalities and high abatement costs. Moreover, the productivity reductions show that despite the economic incentives to deal with the sea lice problem the technology does not appear to be in place to resolve it. This means that for government it should remain a high priority to design policies that stimulate innovations of new technologies for removing sea lice without sacrificing environment or fish health.

7 Concluding remarks

This paper has investigated cost changes in the Norwegian salmon aquaculture sector for the period 2001-2014. High salmon prices at a global scale have masked the increase in production costs since 2005, but also created extraordinary profits (Asche, Sikveland, & Zhang, 2018; Misund & Nygård, 2018). Increasing unit costs have made the profitability of the industry vulnerable to negative demand or supply shocks. We attempt to analyze the factors influencing cost changes by estimating a restricted translog cost function. Besides the increase in input prices like feed, we found that negative productivity shocks played an important role in explaining cost growth. The pure technical component is the main driver as it explains more than 80% of the negative productivity growth while the contribution of scale and capital augmentation effects were empirically unimportant. These results indicate that productivity growth has tapered off due to external factors such as biological conditions, input prices, and external market situations.

By decomposing the sources of cost changes, it was possible to approximate the contribution of each input to such changes. Our estimations identify two main inputs that influence costs changes: First, feed prices drive the increase in costs due to feed demand being highly inelastic. This implies near-zero substitutability options for feed leaving producers vulnerable to feed price shocks. Second, the increase of the variable “other costs”, which contains outlays for disease and sea lice treatments, suggests that external negative conditions are tormenting the industry and are a source of cost inefficiency.

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Paper II

Effects of regulations on quantity in natural resource industries: A Bayesian approach on the Norwegian salmon aquaculture

Effects of regulations on quantity in natural resource industries: A Bayesian approach on the Norwegian salmon aquaculture.

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ABSTRACT

In this paper, we estimate the effects of regulations and quantity restrictions on production costs in natural resource industries with high firm heterogeneity. To obtain such effects and to calculate their shadow price we use a Bayesian methodology to estimate a cost function that satisfies the theoretical regularity conditions. We apply this approach to the Norwegian salmon aquaculture sector as a suitable example of a regulated industry - by production quantities - with high firm dispersion. We found that the regulation system constrains salmon firms from benefiting from scale economies, as they cannot increase their production levels beyond the physical limits imposed. Therefore, such regulations have an increasing cost effect on small and medium-sized firms. Since regulations on the production capacity of firms are important in other industries, the methodology applied in this paper has broad application.

Keywords: Regulations, Bayesian, Production Costs, Firm Size, Shadow Price

1. Introduction

Quantity restrictions in production are widely used measures to control negative externalities in agriculture and natural resource industries. For instance, to avoid groundwater pollution and soil degradation, input restrictions on nitrates and herbicides are common. In other sectors, output quantities are regulated to avoid overexploitation or overproduction, with quotas and licenses being the most common policy instruments. It is well known that these policies can influence production practices as the interactions between production, input use, and quantity restrictions affect the firm's production and cost structure (Squires, 1987). A feature that has received less attention is that in industries with high dispersion in firm size and production levels, the effect of regulations can be heterogeneous, as some firms will benefit or be hindered more than others by the regulations. In such industries, an understanding of the impacts of quantity regulations requires an analysis of the effects on firm production and cost structure at multiple production levels.

In empirical studies, cost functions are the most common approach to analyze economic behavior at the firm and the industry level, including to investigate the effect of regulations.[1] In particular, flexible functional

[1] See for example Morrison Paul, Ball, Felthoven, Grube, and Nehring (2002) for the use of cost functions and pesticide regulations in U.S agriculture, Weninger (1998) for efficiency analysis of transferable quotas in fisheries, Ramos-Real (2005) for a review of cost functions and

forms are used due to their advantage of not imposing assumptions on factor substitution patterns and technical change. However, the use of flexible forms comes at a cost since econometric estimations of such functions often violate the positivity, curvature, and monotonicity conditions required by economic theory, making the estimated demand and supply equations invalid (Barnett, 2002). Researchers tend to overcome this problem by analyzing their results at only the point of approximation – commonly the mean values – of the estimated cost function where most (or all) of the regularity conditions are satisfied. The curvature conditions are of importance when evaluating the impact of quantity regulations because when evaluated only at the mean, the heterogeneity among producers is not taken into account which can mistakenly attribute the policy effect to other factors like economies of scale and/or technical change, masking different impacts for different types of firms. To avoid this challenge, empirical analysis of regulations and their implications must rely on estimation methodologies that satisfy theoretical regularity globally or at least in a reasonable region (Diewert & Wales, 1987).

This paper analyses the relationship between public regulation of input quantities and firms' cost structure by using a Bayesian approach to estimate a translog cost function. We will use the Bayesian approach of

regulations in electricity markets, Baltagi, Griffin, and Rich (1995) for deregulations in airline industry and Salvanes (1993) and Bjørndal and Salvanes (1995) for regulations in the aquaculture.

Griffiths (2003) and Serletis and Feng (2015) as this does not sacrifice the flexibility of functional form and it provides statistical inference on technical change, returns to scale, and input demand elasticities for large samples in an efficient way. Hence, it is well suited for a setting with the significant heterogeneity in firm size one can often observe in agricultural and natural resource industries. The flexibility given by the Bayesian framework allows analysis of regulatory effects for firms of different sizes by estimating the policy effect at different levels of the industry cost function. Moreover, as regularity conditions hold, the shadow value of the regulatory instrument (license, quotas) can be estimated by recurring to economic theory which is of interest when such instruments are transferable.

We apply this approach using a panel data of Norwegian salmon firms during the period 2005-2014. The Norwegian salmon sector is among the most successful and fastest-growing aquaculture industries, but due to a number of potential environmental externalities, it operates in a heavily regulated environment (Abolofia, Asche, & Wilen, 2017; Asche, Oglend, & Selland Kleppe, 2017; Hersoug, Mikkelsen, & Karlsen, 2019).[2] Norway is currently the world's largest producer of farmed salmon. Hence, this sector is a good case to understand how quantity regulations can affect production structure. Specifically, we aim to

[2] Similar challenges are present also in other salmon producing countries (Soto et al., 2019).

evaluate how cost changes can be attributable to input prices, scale economies, technical change, and – of key concern – the regulatory regime. We study how regulation effects vary with firm size and how it affects firm heterogeneity in the sector. Since regulations on the production capacity of firms are important in other industries, the methodology applied in this paper has broad application.

The article is organized as follows. Next, the cost function specification and regularity conditions are presented, the methodology and estimation approach are provided in section 3 before providing an overview of regulations in the Norwegian Salmon aquaculture sector in section 4. Then, in section 5 data is summarized; in section 6 our estimations results are presented and analyzed. Finally, we closed with our concluding remarks in section 7.

2. Cost functions with quantity restrictions

2.1 Cost function specification

Binding restrictions on input/output quantities affect firm behavior in two ways (Chambers, 1988): On the input side, restrictions alter the optimal input mix in production as other inputs will be used more intensively to “compensate” for the lack of the restricted input to the extent allowed by the substitution possibilities. As a result, the sub-optimal input mix will increase unit production costs. On the output side, higher costs are expected due to the unexploited economies of scale as the suboptimal input mix will lead firms to be moving up on the increasing portion of their short-run cost curve. Furthermore, in sectors with high firm size dispersion, restrictions will have effects that vary with firm size.

Regulations can be modeled by including the constrained input(s)/output(s) as a (quasi-) fixed factor in the cost function.[3] The translog cost function is the most popular functional form since it is a flexible functional form with the advantage of imposing fewer assumptions on the behavior of technical change and substitution patterns among inputs (Christensen, Jorgenson, & Lau, 1973). The function can be expressed as:

$$\begin{aligned} \mathrm{lnVC_{it}} = {} & \alpha_0 + \beta_Q \ln Q_{it} + \beta_z \ln Z_{it} + \sum_{\alpha} \beta_\alpha lnw_{\alpha,it} \\ & + 0.5 \sum_{\alpha} \sum_{j} \beta_{\alpha j} lnw_{\alpha,it} lnw_{j,it} + \sum_{\alpha} \beta_{\alpha z}\, lnZ_{it} lnw_{\alpha,it} \\ & + \sum_{\alpha} \beta_{\alpha Q}\, lnQ_{it} lnw_{\alpha,it} + \sum_{\alpha} \beta_{\alpha t} lnw_{\alpha,it}\, t \\ & + 0.5\, \beta_{QQ} lnQ_{it}^2 + 0.5\, \beta_{zz} lnZ_{it}^2 + \beta_{Qt} lnQ_{it} t \\ & + \beta_{ZQ} lnZ_{it} lnQ_{it} + \beta_{Zt} lnZ_{it} t + \beta_t t + 0.5\, \beta_{tt} t^2 + u_{it} \end{aligned} \tag{2}$$

where VC is total variable costs of unit $i = (1, \ldots., N)$ at time $t = (1, \ldots, T)$, Q_{it} is the corresponding output, $W_{\alpha,it}$ is a vector of input

[3] This is also possible for profit and revenue functions (Fulginiti & Perrin, 1993; Squires, 1987, 2016).

prices, Z_{it} is the quantity restriction expressed as a fixed factor, t is a time trend variable that captures technical change, and, finally, u_{it} are *i.i.d.* zero-mean random error.

Taking the derivative of the cost function with respect to input prices gives the input shares (Shephard's lemma):

$$S_\alpha = \frac{\delta lnVC}{\delta lnW_a} = \beta_a + \sum_j \beta_{\alpha j} lnW_l + \beta_{\alpha Q} lnQ + \beta_{\alpha Z} lnZ + \beta_{\alpha t} t \tag{2}$$

Together, input shares and the cost function contain all the necessary information about production technology, input demands, elasticities, scale economies, technical change, and regulation effects (Diewert, 1982). The system formed by equations 1 and 2 can be estimated by using Zellner's seemingly unrelated regression (SUR) technique.

The elasticity of output, quantity regulations, and rate of technical change on production costs can be obtained by taking the derivative of the translog cost function with respect to the variable of interest as follows:

$$\theta = \frac{\delta lnVC}{\delta lnQ} = \beta_Q + \beta_{QQ} lnQ + \sum_a \beta_{aQ} lnW_a + \beta_{Qt} t + \beta_{zQ} lnZ \tag{3}$$

$$\epsilon_Z = \frac{\delta lnVC}{\delta lnZ} = \beta_Z + \beta_{ZZ} lnZ + \sum_a \beta_{aZ} lnW_a + \beta_{zQ} lnQ + \beta_{Zt} t \tag{4}$$

$$Tech.\text{change} = -\frac{\delta lnVC}{\delta t}$$
$$= -\left[\beta_t + \beta_{tt}t + \beta_{Qt}\, lnQ \ + \sum_a \beta_{at} lnW_a + \beta_{Zt} lnZ\right] \quad (5)$$

Equation 3 measures the output elasticity allowing a measure of the returns to scale (RTS) by calculating its inverse. Equation 4 can be interpreted as the quantity regulation elasticity, that is the effect of the regulation on production costs that can be decomposed in direct $[\beta_Z + \beta_{ZZ} lnZ \ + \beta_{zQ} lnQ + \beta_{Zt} t]$ and indirect $[\sum_a \beta_{aZ} lnW_a]$ components. The former shows the regulation effect on costs due to deviations from the long-run cost curve while the latter shows the regulation effect on input misallocation. Finally, equation 5 is the technical change measure.

From the estimated cost function it is also possible to retrieve the shadow value of the restricted input(s)/output (Hauver, Yee, & Ball, 1991; McLaren & Zhao, 2009) :

$$SV(Y, W, Z) = \frac{\delta C}{\delta Z} = \frac{C}{Z}\frac{\delta lnC}{\delta lnZ} \quad (6)$$

The shadow price should be evaluated at optimal quantities which can be found by assuming that the market rental price equals the shadow price. Any deviation will represent deviations in the long-run equilibrium. When there are no market prices, optimal quantities can be either estimated or assumed, by using the parameters of the estimated cost function and an expansion ray of the output elasticity (equation 3) to find the optimal production level. In a cost function, the output elasticity reflects the ratio of marginal costs to average costs and thus, the optimum level can be found when this ratio is equal to 1.

Theoretical regularity in the cost function is needed to ensure that the estimated parameters have an economic interpretation. Even though both regularity and flexibility are desirable properties for a cost function, there is a tradeoff between them as functions that easily satisfy regularity (Cobb Douglas or CES) are inflexible while flexible functions (Quadratic, Fourier and Translog) often violate regularity (Gallant & Golub, 1984; Wales & Diewert, 1987). To analyze the effects of quantity regulations is necessary to satisfy regularity at more than one point of the estimated function while maintaining flexibility so regulation-input interactions can be obtained. In the following sections, we describe the restrictions needed to satisfy regularity in the translog cost function and how to empirically impose those restrictions.

2.2 *Theoretical Regularity*

Four conditions are needed for the cost function to satisfy theoretical regularity. These are: linear homogeneity, positivity, curvature, and monotonicity (Diewert, 1982). Linear homogeneity implies that costs will increase proportionately to an increase in all input prices;

homogeneity requires the following restrictions in the translog cost function:

$$\sum_a \beta_a = 1 \; ; \; \beta_{aj} = \beta_{ja} \tag{7}$$

$$\sum_a \beta_{aj} = \sum_a \beta_{aQ} = \sum_a \beta_{aZ} = \sum_a \beta_{at} = 0 \tag{8}$$

Positivity means that the estimated costs are always positive for any production level. Formally:

$$\widehat{VC}(w, Q, t, Z) > 0; \tag{9}$$

Monotonicity implies that if there is any increase in input prices, then the minimum cost of producing any output level will increase accordingly. Monotonicity is satisfied if the estimated input shares (equation 2) are positive:

$$\widehat{S_\alpha} > 0, \qquad \forall\, \alpha = 1, \ldots, M \tag{10}$$

Finally, curvature requires the cost function to be a concave function of input prices, which means that the Hessian matrix of the cost function is negative semidefinite. Instead of constructing the Hessian matrix for each data point, is more efficient to check the curvature constraint by evaluating if the following matrix is negative semidefinite (Diewert & Wales, 1987):

$$\Phi = B - S + ss' \tag{11}$$

Where B is a matrix with elements $\beta_{\alpha j}$, S is the share vector of size $(MX1)$, and S is a MxM diagonal matrix with the share vector s on the diagonal. Unfortunately, econometric estimation of flexible functional forms generally violates at least one of such conditions when not imposed directly (Barnett, 2002).

The first method suggested in the literature to impose regularity upon flexible functions is the Cholesky factorization. Popularized by Diewert and Wales (1987) this method is mainly used to impose curvature by using transformations of the bordered Hessian as an expression of the parameters of interest. However, when applied to a translog system this method imposes so strong restrictions that the functional form is no longer flexible. Hence, this method is unsatisfactory for evaluating input/output restrictions as flexibility and regularity are needed in more than one point when using a translog. The second approach is the non-linear constrained optimization introduced by Gallant and Golub (1984) which maximizes the value of the likelihood function subject to regularity constraints. Although this approach can incorporate all the regularity constraints over a region of data points, it does not provide exact statistical inference on input elasticities, technical change, and scale economies and it does require computationally intensive/time consuming re-sampling techniques to obtain them (Feng & Serletis, 2010). The third approach is Bayesian estimation, an approach that has been applied in different contexts to flexible functional forms by Terrell (1996), Koop, Osiewalski, and Steel (1997), Griffiths, O'Donnell, and Cruz (2000), and O'Donnell and Coelli (2005). By using Gibbs sampling and Metropolis-Hastings algorithms, the Bayesian approach provides a convenient way to estimate flexible functions, satisfy regularity conditions, and obtain direct statistical inference of desired effects. Thus, due to its advantages, we consider the Bayesian approach as the most suitable methodology for investigating quantity regulation effects on cost functions. To impose regularity in the SUR system we follow Griffiths (2001) and Serletis and Feng (2015) as described in the following sections.

3. Methodology

3.1 Bayesian Seemingly Unrelated Regression

Zellner (1971) was the first to use the Bayesian framework to a SUR system of equations. As in the frequentist approach of SUR, one of the share equations must be dropped to avoid singularity. To proceed with the estimation, first stack the M-1 equations as follows:

$$Y = X\beta + e \tag{12}$$

where Y is a $(TM\ x\ 1)$ vector of dependent variables, X is a matrix of explanatory variables of dimension $(TM\ x\ K)$, with $K = \sum_{i=1}^{M} K_i$, β is a $(K\ x\ 1)$ vector of parameters to be estimated, and e is a vector of classical errors of size $(TMx1)$. The errors follow the stochastic assumption $e \sim N(0, \sum \otimes I_t)$ where $\sum$ is the variance-covariance matrix.

Regularity conditions need to be imposed directly as constraints on the Bayesian SUR, by using these restrictions the parameters of the model can be separated into a "free" vector γ to be estimated and a "non-free" vector η which can be obtained from γ (Griffiths, 2003; Serletis & Feng, 2015). To do so, lets' express the restrictions of equations nine and ten in a matrix form:

$$R\beta = (R_1\ R_2)(\eta\ \gamma)' = r \qquad (13)$$

Where R is of size $(J\ x\ K)$ with J equal to the number of restrictions of equations nine and ten, R_1 is a $(J\ x\ J)$ matrix of constraints related to η, and R_2 is a $(J\ x\ K - J)$ matrix of constraints related to γ. This partition of parameters requires to rearrange the elements in β and X so the SUR model can be written as

$$Y = X\beta + e = (X_1\ X_2)(\eta\ \gamma)' + e \qquad (14)$$

Moreover, we can reduce the number of parameters to be directly estimated by transforming the previous model as functions of only the γ vector. From equation 13 solve for η

$$\eta = R_1^{-1}(r - R_2\gamma) \tag{15}$$

And substitute in 14

$$Y - X_1 R_1^{-1} r = (X_2 - X_1 R_1^{-1} R_2)\gamma + e \tag{16}$$

That we express compactly as

$$\phi = \Phi\gamma + e \tag{17}$$

After rearranging the terms, a SUR model can be estimated with fewer parameters, as translog systems are of high dimensionality, reducing the number of parameters save computational time. Even though the new vector of observations Φ and γ can no longer be separated into M equations, the stochastic properties of the classical error e remain the same (Griffiths, 2003).

A Bayesian model requires to specify our knowledge and assumptions about the data via the prior and the likelihood function (Koop, Poirier, & Tobias, 2007). The Bayes theorem can be stated as

$$f(\gamma, \Sigma | \phi) \propto L(\phi | \gamma, \Sigma)\, p(\gamma, \Sigma) \tag{18}$$

Where $f(\gamma, \Sigma|\phi)$ is the joint posterior density function, $L(\phi|\gamma, \Sigma)$ is the likelihood function, and $p(\gamma, \Sigma)$ is the joint prior density function.

We assume a non-informative (Jeffreys) prior distribution of the form

$$p(\gamma, \Sigma) \propto |\Sigma|^{-\frac{(M+1)}{2}} I_F(\gamma) \tag{19}$$

Where $I_F(\gamma)$ is an indicator function that evaluates the satisfaction of the inequality constraints of equations 9 and 10 (Positivity and monotonicity) plus the curvature constraints. Let the feasible region defined by these constraints to be denoted by F as follows:

$$I_F(\gamma) = \begin{cases} 1 \; if \; \gamma \in F \\ 0 \; otherwise \end{cases}$$

Under the assumptions of e as a classical error, the likelihood function can be shown to be of the normal family (Koop et al., 2007):

$$L(\phi|\gamma, \Sigma) \propto |\Sigma|^{-\frac{T}{2}} exp[-0.5 \; tr(A\Sigma^{-1})] \tag{20}$$

Where A is a $(M \; x \; M)$ symmetric matrix with $a_{ij} = (\phi_i - \Phi_i\gamma)' \left(\phi_j - \Phi_j\gamma\right) \quad i = 1,2, \dots, M.$

The posterior joint density function is:

$$f(\gamma, \Sigma|\phi) \propto |\Sigma|^{-\frac{(M+T+1)}{2}} I_F(\gamma)\, exp[-0.5\, tr(A\Sigma^{-1})] \tag{21}$$

This posterior joint density function is not analytically tractable. Thus, to obtain our estimations is necessary to use simulation methods that use the conditional posteriors for γ and Σ. If we treat Σ as a constant in equation 21 we obtain the full conditional posterior of γ

$$p(\gamma|\phi, \Sigma) \propto I_F(\gamma)\, exp[-0.5(\gamma - \hat{\gamma})'\Omega\,(\gamma - \hat{\gamma})] \tag{22}$$

Where $\Omega = \Phi'(\Sigma^{-1} \otimes I_t)\Phi$, and $\hat{\gamma}$ is the GLS estimator for γ

$$\hat{\gamma} = \Omega^{-1}\, \Phi'(\Sigma^{-1} \otimes I_t)\phi \tag{23}$$

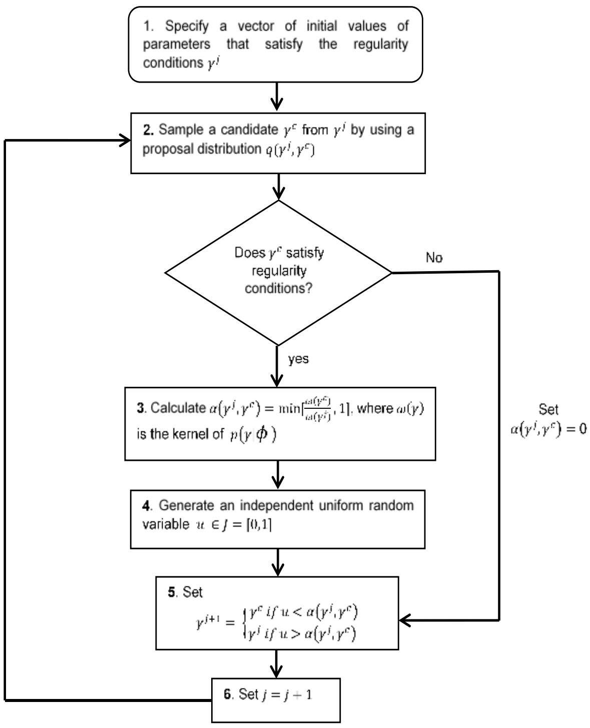
The full conditional posterior for Σ can be obtained by treating γ as a constant in 21

$$p(\Sigma|\phi, \gamma) \propto |\Sigma|^{-\frac{(M+T+1)}{2}} exp[-0.5\, tr(A\Sigma^{-1})] \tag{24}$$

Which is the form of an inverted Wishart distribution (Koop et al., 2007)

3.2 Estimation Methodology

Following Griffiths et al. (2000), Griffiths (2003) and Serletis and Feng (2015), we apply a random-walk Metropolis-Hastings (M-H) algorithm to impose the regularity conditions in our equation system. The M-H algorithm is a sampling technique based upon Markov Chain Monte Carlo (MCMC) methods that use the full conditional posteriors to sample parameter estimates that will approach the full posterior joint density when the samples go to infinity (Chen, Shao, & Ibrahim, 2012; Chib & Greenberg, 1995; Hastings, 1970). The following flow chart summarizes the applied M-H algorithm:



To allow for optimal sampling the initial candidates for parameter values need first to satisfy regularity conditions and second, they need to be not too far away from their "true" value. The larger the distance of the initial vector of parameter is from its "true" value the longer the sampling needs to be to approach the full posterior (Chib & Greenberg, 1995). Therefore, we choose our initial values as follows: We set the interaction terms related to variable inputs equal to zero ($\beta_{\alpha j} = \beta_{\alpha Q} = \beta_{\alpha Z} = 0$) the remaining parameters of γ to the values obtained by the GLS estimation technique of the SUR equation system. For better performance of the M-H algorithm, the proposal distribution is chosen to match with the target distribution by being multivariate normal with mean equal to γ^j and covariance matrix equal to $\Omega * \mathrm{h} = [\Phi'(\Sigma^{-1} \otimes I_t)\Phi]^{-1} * \mathrm{h}$ where h is a tuning parameter that adjusts the acceptance rate. The optimal acceptance rate for models with high dimension space has been shown to lie between 0.45 and 0.23 (Gelman, Roberts, & Gilks, 1996). We choose h to make the acceptance rate fall on this interval.

4. The industry: Norwegian salmon aquaculture

Salmon farming is divided into two main production phases: The first one starts with the production of eggs and juveniles in freshwater with a duration of about 10-18 months and is carried out in land-based tanks where there are few concerns with environmental externalities (Sandvold & Tveterås, 2014). In the second phase, the juveniles (smolt) are transferred to open cages in offshore waters where they grow for 14-22 months until harvest (Abolofia et al., 2017). Salmon aquaculture commenced in the 1970s with the introduction of the sea pen. In Norway, the government sought to facilitate an owner-operated industry, and no company could have a majority interest in more than one license. This restriction was lifted in 1992, leading to a rapid growth in the size of some companies by purchasing licenses, while others remained as one-license operators (Asche, Sikveland, & Zhang, 2018; Hersoug et al., 2019). Production expanded at a rapid rate, increasing from 1,431 tonnes in 1976 to 29,473 tonnes in 1985. This increase necessitated the introduction of regulations in the sector to avoid negative environmental externalities including a licensing system (Färe, Grosskopf, Roland, & Weber, 2009). The license became the basic unit of the management system, and different restrictions were linked to the license at various times. These restrictions always specified a measure of how large the pens could be and the density of fish within a pen, and for a period, there was also a limit on how much feed could be used.

Growing concerns about the efficiency of Norwegian salmon farmers in a globalized market led to a search for better regulatory mechanisms. In 2005 a biomass-based license system was introduced where the Maximum Total Biomass (MTB) limits the amount of fish (in weight) that a producer can have in the pens at any time. A standard license is allowed to have 780 tonnes MTB, while licenses located in the northern regions of Troms and Finnmark were given a higher limit of 900 tonnes due to less favorable conditions for farming as lower temperatures reduce growth rates.[4] The MTB system marked a shift in the Norwegian salmon aquaculture sector since it is a regulation that allows farmers to choose "freely" the mix of the traditional input factors.

The Norwegian government issues new licenses in auction rounds where salmon producers need to satisfy several criteria[5] to place a bid. By using this mechanism, the government controls the total aggregate biomass in the sector and influences the geographical distribution of production. Additionally, firms can trade their license(s) in the market; similar to ITQs in a fishery, to achieve allocative efficiency by transferring production from low productivity producers to high productive ones (Arnason, 2012; Newell, Papps, & Sanchirico, 2007). Fees for licenses have been increasing both in the auction system and the private market. For instance, in the 2013 auction, the Government set a base price of 10 million NOK per license and bids were up to 60 million NOK (Hersoug et al., 2019).

The MTB system should – at least in theory – lead to an increase in efficiency. However, the industry has experienced a continuous increase in production costs since the introduction of the MTB regulation in 2005. It is not clear how the regulation has contributed to this cost increase

[4] In 2011, this limit was increased again for Troms and Finnmark to 945 tonnes

[5] These criteria have not been consistent in the different rounds with more emphasis lately on environmental issues (Hersoug et al., 2019).

since some complexities in the industry structure make difficult to evaluate the effect on production costs. For example, as discussed by Asche et al. (2017) the standing biomass can be considered at the same time as an output (the results of the expended inputs) and an input (as a basis for how much fish can grow). Given this duality of the regulation and the biological conditions of fish growth, it is hard to elucidate if producers' decisions are optimal. Additionally, to increase production, firms with several licenses tend to move biomass from one site to another. This can create the illusion that production on one site is suboptimal while the total production of the firm's licenses is being maximized. In many regions, several licenses are "merged" in the same production site – where biological conditions allow this –leading to agglomeration effects (positive and negative). Finally, salmon prices have been high as the production constraints have been binding, leading to high prices on the output as well as on licenses (Asche et al., 2017; Hersoug et al., 2019)

5. Data

The Norwegian Directorate of Fisheries annually surveys production and profitability of the fish farming sector, fish farmers must report their earnings and costs accounts. Our sample consists of an unbalanced panel with a total of 996 observations for the period 2005-2014. Based on

Asche, Guttormsen, and Nielsen (2013); Asche, Roll, and Tveteras (2009); Nilsen (2010) we include feed, labor, and smolt as inputs into our model. We will also include the category other costs as input due to its participation increase in total costs in recent years; table 1 provides a summary of the selected variables.

Table 2 – Summary Statistics

Variable	Mean	Standard deviation	Minimum	Maximum
Production (Tonnes)	7,122.60	10,996.21	256	91,600
Licenses	6.37	8.67	1	57
MTB (Tonnes)	5,235.52	7216.52	780	44,460
Feed (NOK/Kg)	8.09	1.19	2.86	12.05
Labor (NOK/hour)	309.23	91.19	65.18	675.92
Smolt (NOK/Kg)	123.51	69.12	2.01	1076.62
Other Costs (NOK/kg)	3.60	2.31	0.13	18.50
Variable Costs (NOK/kg)	14.48	3.45	5.75	42.43

During the period 2005-2014 nominal production costs in the sector have increased by 90%. The category other costs have increased its share going from 18% in 2005 to 27.41% in 2014. Feed still constitutes the main input for salmon farming as it represents, on average, 56% of total production costs; smolt costs present a moderate increase in prices that are related to the increase of the size of the average smolt bought by producers. Finally, wages present an average increase of 5% during the period but its participation in total costs fell from 10.58% in 2005 to 8.59% in 2014.

Production of salmon had an average yearly increase of 7% for the period 2005-2014 while the number of total licenses remained almost constant.

This increase in production with a relatively static production capacity can be an indicator of higher efficiency per license since the introduction of the MTB.

The total number of firms in the sector has a decreasing tendency since 2005. An interesting trend is that smaller firms tend to disappear mainly by being merged with or bought by larger companies. Although the number of large firms remains almost the same, one can observe that they become bigger as the number of licenses they own has increased.

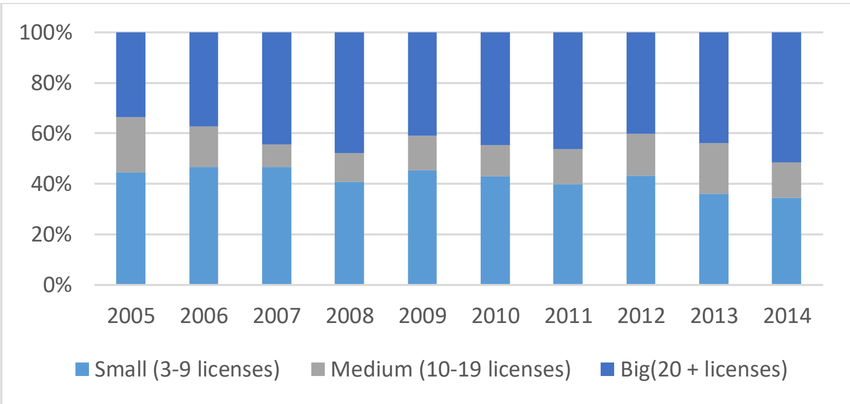


Figure 6 - Percentage of licenses owned by group size 2005-2014

6. Results

Our primary focus in this study is to estimate the effects of quantity regulation on production costs. As our interest lies in these effects along with the main characteristics of the sector (input price elasticities, scale economies, and technical change) and not in the estimated cost function, we present the estimation results in the Appendix.

6.1 Imposition of Restrictions

For the estimation, the right-hand side variables were normalized at the mean and the share equation corresponding to the variable "other costs" dropped. Given our constraints in computational time and sample size, we decided to impose the curvature conditions regionally over a sub-sample of our dataset. We choose to eliminate around the highest 20% of the input price values and production levels and to evaluate regularity conditions to the remaining 80% of the sample (803 data points). Linear homogeneity is imposed by our model as explained above. Positivity and monotonicity are checked by evaluating if the estimated costs and shares are greater than 0 over our 803 data points. Curvature is checked by evaluating the eigenvalues of equation 13. Finally, due to the high dimensionality of our function, we perform 5,000,000 simulations and apply thinning to the MCMC chain to reduce autocorrelation.

6.2 Input demand elasticities and technical change

Own and cross-price elasticities show how producers react to changes in input prices and can be derived from the estimated cost function. As our model assumes that firms are price takers in the input market, we estimate elasticities for average input values without loss of generality. Our elasticity estimates are generally higher when compared with earlier studies as the imposition of regularity conditions tend to inflate elasticity estimates (Serletis & Feng, 2015), but with a similar ranking with feed as the least elastic.

Table 2 shows the posterior means for the elasticity estimates; own elasticities show low responsiveness to own price changes, feed, and other costs present the smallest elasticities, while labor has an elasticity close to unity. These results corroborate the maturing of the salmon aquaculture sector as it presents similar patterns to mature industries: Shrinking labor share as part of total costs, more elastic demand for labor, and transition from a labor-intensive to a capital-intensive production process (Dorn, Katz, Patterson, & Van Reenen, 2017). The cross-price elasticities estimates are all less than unity meaning limited substitutability among inputs. Given the inelastic demands for the main input (feed), any distortion created by regulations that led to input misallocations will increase producer's vulnerability to input price changes, this volatility is generally transmitted to consumers via salmon prices (Landazuri-Tveteraas, Asche, Gordon, & Tveteraas, 2018).

Table 3 - Price elasticities at average prices

	Feed price	Labor price	Smolt Price	Other Costs
Feed Quantity	-0.417 (0.002)	0.101(0.000)	0.149 (0.000)	0.167 (0.000)
Labor Quantity	0.657 (0.001)	-0.958 (0.002)	0.125 (0.000)	0.176 (0.000)
Smolt Quantity	0.568 (0.002)	0.073(0.001)	-0.810 (0.001)	0.169 (0.001)
Other Costs	0.458 (0.000)	0.074 (0.001)	0.122 (0.001)	-0.657 (0.001)

Notes: Numerical standard errors in parentheses.

Shifts in the cost function over time are measured by the rate of technical change as defined in equation 7 for the average firm in the industry. As in any cost function specification, this measure reflects not only technical change but also other factors that shift the cost function over time including internal and external factors (Morrison & Siegel, 1997). We estimate the 95% highest posterior density interval (HDPI) for our distribution of technical change estimates and found negative shifts as costs are increasing every year between 0.76% and 0.79% by factors not directly included in the cost function; this can be the result of negative productivity shocks or external factors outside the control of producers. Inelastic input demands and negative technical change diminishes the adjustment options that producers have when facing volatility and shocks, also these results imply that if regulation affects input use, the effect on costs will be of higher magnitude due to the inelastic demand for variable factors.

6.3 Regulation effects of production capacity

Any restriction on production capacity can influence costs via two mechanisms: Input misallocation and insufficient use of scale economies (Salvanes, 1993). When capacity is restricted, producers will expand output along their short-run cost curves as they will try to overcome restrictions by increasing factor intensities and/or changing the input mix. The second effect comes from the fact that producers cannot freely adjust their production level to fully benefit from the presence of scale economies. It is expected that the effect of the MTB on costs will vary within-firm size as bigger firms will face fewer constraints to adapt their biomass levels with very large firms not experiencing any effect at all.

6.3.1 Production levels and economies of scale

Regulations of production can affect the scale of production by altering the input mix and the level of resource availability (Squires, 1987). By computing scale economies as the inverse of output elasticity (equation 3) it is possible to compare the current state of the industry with the long-run equilibrium. We compute the 95% HPDI at average industry values and found increasing economies of scale with values between 1.11 and 1.13 meaning that, on average, a lower unit production cost would have been achieved by increasing production levels. However, given the high dispersion of production, this average estimate cannot be taken as a generalization for the whole industry. Thus, we proceed to compute the expansion ray of the output elasticity to locate in which region most firms are and how far they are from the optimal production point. By computing the expansion ray of the output elasticity for different production levels and keeping input prices constant – at average prices – is possible to determine the theoretical long-run equilibrium where firms are at optimal production levels and at optimal sizes. The optimal size is the level of production at which average costs are minimum, this level can be found where output elasticity has a value of 1 (Frisch, 1965).

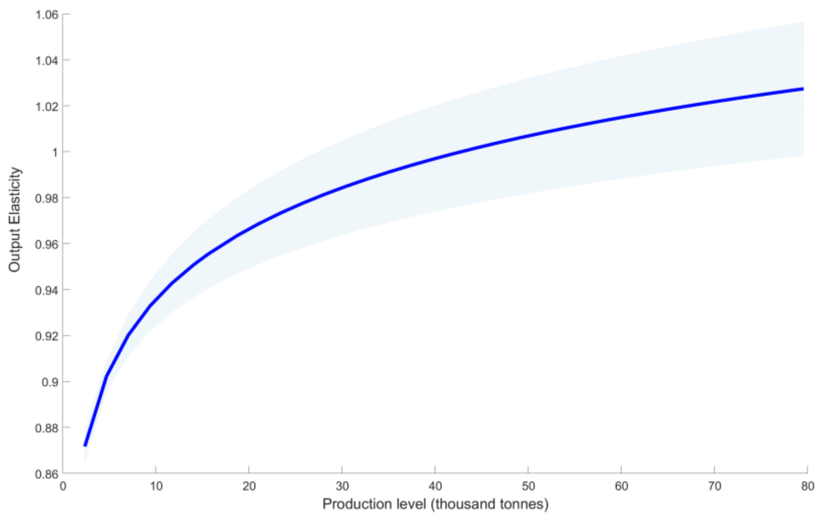


Figure 7 - Output elasticity expansion ray
Notes: The shadow region represent the 95% credible interval centered at mean values

Figure 2 shows the expansion ray for the output elasticity, we found that the optimal long-run point at which costs are minimized correspond to a production level of 25,000 tonnes per year, the output elasticity has a 95% probability of having a value of 1 at this point which is the equivalent of having from 21 to 23 licenses. In our data sample, 89% of the firms are smaller than this while only 11% are above optimum in the diseconomies of scale region. Hence, most firms in the sector would have benefited from increasing their production levels, indicating that there are incentives to expand and at least partly explaining the consolidation process that has been observed. From these calculations, we infer that regulations of production - in the form of the license system - constrain firms from benefiting from scale economies as companies cannot increase their production levels beyond the physical limits imposed by the MTB.

6.3.2 The shadow price of a license

Since shadow values should be evaluated at the optimal quantities, we calculated these by using the optimal long-run firm size and production levels found above with a firm size between 21 and 23 licenses. Table 3 shows the estimated values with their respective numerical standard errors. From these estimates, we found a value range from 4.1 to 6.1 million NOK per license. However, since licenses are a scarce input that is “rationed” by Norwegian authorities, the price for actual licenses is higher than the values calculated, in extreme cases the price of a license will equal the highest willingness to pay of the firms’ group. Thus, we proceed to estimate the shadow value for the 803 points that satisfy regularity conditions to identify the whole range of the willingness to pay for the production license. We graph the kernel densities of these shadow values for a single license in Figure 3 including kernels with values one standard deviation above and below-average prices.

Table 4 – Shadow value of a single license at long run optimal sizes

Size (Licenses)	Shadow Values (NOK)	NSE
21	4,130,601.9	2,463,594.7
22	5,091,906.6	2,827,631.1
23	6,142,719.6	3,266,985.3

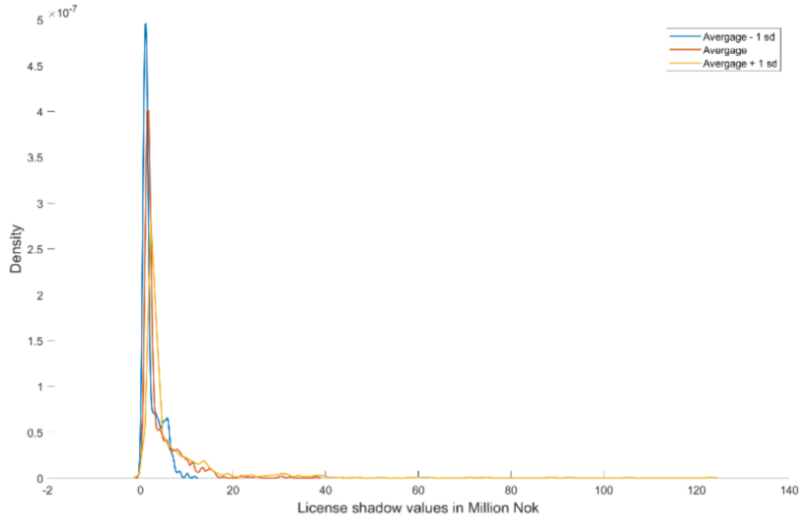


Figure 8 - Kernel distributions of shadow values for a license

The distributions are skewed to the right with mean values of 2.8, 4.7, and 10 million NOK. Maximum values range between 20 and 125 million NOK. Finally, we calculate the 95% HDPI for the shadow values distribution and found that the price for a license lies between 6.3 and 9.6 million NOK. For the licensing rounds that occurred between 2005 and 2014, Norwegian authorities have issued licenses via two mechanisms: a flat rate per license and an auction system. For the first one, licenses were sold with a fixed price between 8 to 10 million NOK; for those licenses that were auctioned, prices between 55 to 65 million NOK were reached (Hersoug et al., 2019). These prices fall inside our shadow value distribution estimates and as expected show that when auctioned, regulatory authorities can extract the maximum willingness to pay for a license. A tradeoff remains thus between the desire of the government to capture the willingness to pay for a license and the desire to promote efficiency and competitiveness - lower production costs - by allowing firms to grow towards the industry equilibrium.

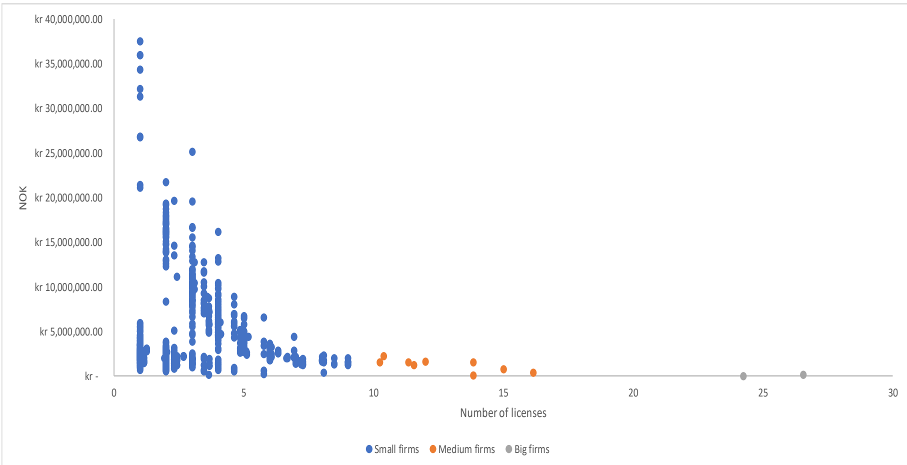


Figure 9 – Estimated shadow values per firm size

Figure 4 shows our results for the shadow values of a single MTB license organized by firm size. From a cost point of view, smaller companies will have a higher willingness to pay for a license as the marginal contribution of an additional license is higher for small producers than for bigger ones. The observed dispersion in the small group is due to each firm cost efficiency, inefficient firms will have a very low or no willingness to pay for an additional license while the efficient ones will be willing to expand production by acquiring new licenses.

6.3.3 Direct and indirect effects of capacity regulation

Our model assumes that firms are price takers in input markets, and this assumption is confirmed by the relatively low dispersion of input prices in our sample as can be seen in table 1. Thus, the effect of MTB regulation at average input prices constitutes an appropriate description for the industry. We estimated the elasticity of the MTB regulation as described by equation 4; the 95% HPDI for this elasticity is positive with values between 0.09 and 0.096 indicating that capacity regulation increases variable costs for the mean firm. Furthermore, we decompose the regulation elasticity on its direct (production capacity) and indirect (input misallocation) effects. Our calculation for the indirect effect has a mean value of -0.004 with a 95% HPDI of [-0.0039, -0.0041] which provides evidence of input misallocation. However, a closer look at the interaction effect input-regulation individually, we found a small but positive effect regarding feed use (0.0005) while the effects for labor, smolt, and other costs are negative with mean values of -0.0006, -0.0001, and -0.0002 respectively. These results suggest that there are input misallocation for all inputs except feed as they are more intensively used by farms with sizes below average.

On the other side, the direct effect explains most of the costs increases due to the MTB regulation with a mean value of 0.095. The coefficients of the regulation measure β_Z and β_{ZZ} have mean values of 0.101 and -0.042 respectively; the negative sign of the second order term β_{ZZ} shows that regulation effects on costs diminish as firm size increases and corroborates our previous assumption on large firms being able to adjust their input use and production levels better than the small ones. The interaction term with technical change β_{Zt} has a mean value of -0,003 which shows that the regulation effect on costs has diminished within the years and can be a result of better management of each producer MTB. Due to the high dispersion on firm size we calculate the expansion ray for the MTB effect in the same way as we did with the output elasticity.

Figure 5 shows the expansion ray for the MTB elasticity; as expected, the effect diminishes as production levels increase. The curve of the expansion ray shows that cost increases generated by the MTB system are mainly due to unexploited economies of scale as the effect drastically falls as it approaches the optimal production point, with the effect wearing off completely at a production level between 30 and 40 thousand tonnes. From the expansion ray, we can infer that, compared to the long-run optimal level, small firms face between 9% and 5% higher production costs; medium firms face between 5% and 2% higher costs and big firms face up to 2% higher costs.

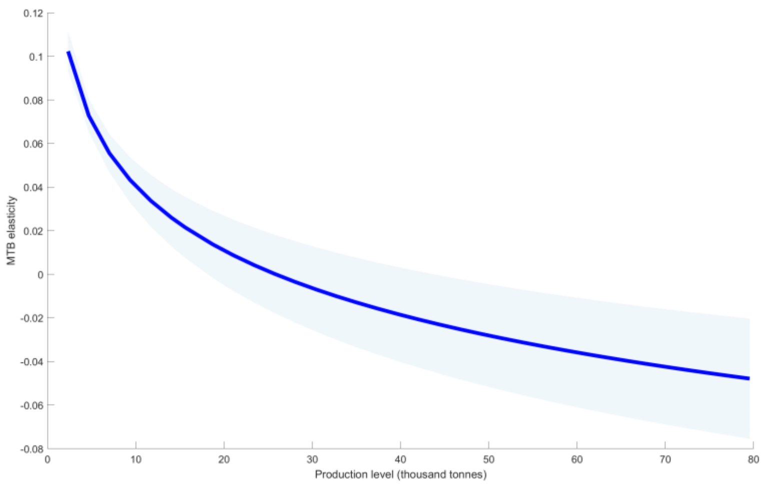


Figure 10 - MTB elasticity expansion ray
Notes: The shadow region represent the 95% credible interval centered at mean values

Furthermore, we estimate the MTB elasticity for each data point and see their evolution for the 2005-2014 period. As figure 6 shows, there is a decreasing tendency on the MTB elasticity values which implies that the effect of quantity regulation on production costs increases has diminished within the years. The decline of MTB elasticity is most likely due to the fact that production per license has increased which is a strong indicator that producers have become more efficient over time at managing their maximum biomass.

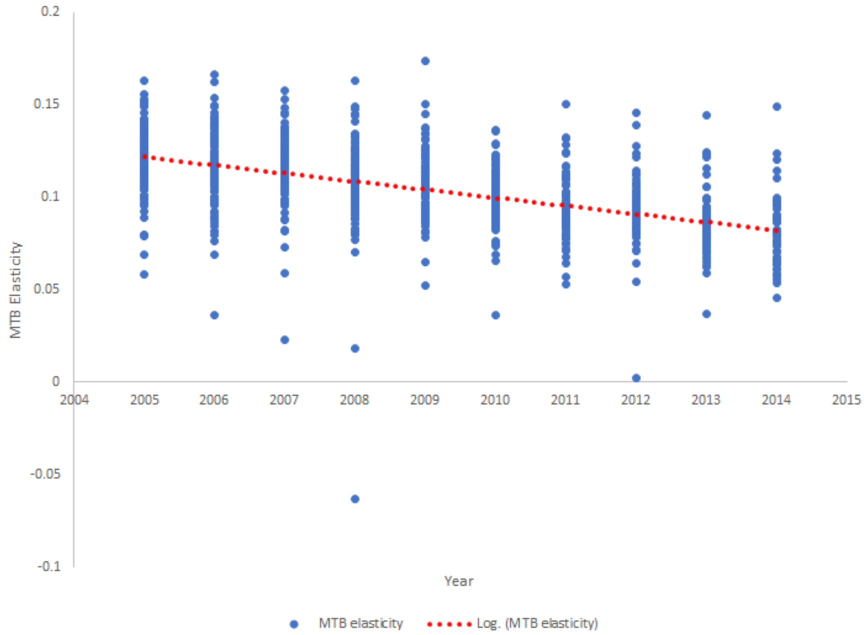


Figure 11 - MTB elasticity estimates by year (2005-2014)

7. Concluding Remarks

Curvature and regularity conditions are essential to analyze the effect of input/output regulations in a classical cost/production function. Without such conditions, any inference along the estimated cost/production function becomes invalid as duality theory fails. In particular, when evaluating the effects of public regulations in a sector with high heterogeneity in firm size, curvature conditions are crucial as the policy effect needs to be evaluated for different groups of firms. In this paper, we implemented a Bayesian methodology to impose theoretical regularity so the effects and shadow prices of regulations can be obtained at different points of the estimated cost function. We use the methodology to estimate a restricted cost function to assess the effects of public regulation on production and input quantities in the Norwegian salmon aquaculture sector.

The results show that the Maximum Total Biomass (MTB) regulation causes cost inefficiencies in the industry but its effect varies within-firm size; small firms faced on average 6% higher costs while medium-size firms faced 2.8% higher costs compared to a hypothetical firm in long-rung optimal production levels. The regulation shows no average effect for big companies. When we decompose the regulation effect by direct and indirect components, we found evidence of input misallocation in labor and smolt use as these inputs are less intensively used by larger firms, we found the opposite behavior for feed and other costs. The direct component of the regulation elasticity seems to be the main driver for cost inefficiencies and is related to unused scale economies. We corroborate this assumption by estimating the optimal production level for the industry where we found that 89% of the firms in our sample are below such optimum. Even though this increase in costs has been masked by high salmon prices, the consolidation of the market globally, and the increasing demand for salmon make competitive costs to become an important issue in the industry.

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Paper III

Firm dispersion and total factor productivity: Are Norwegian salmon producers less efficient over time?

Firm dispersion and total factor productivity: Are Norwegian salmon producers less efficient over time?

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Firm dispersion and total factor productivity: Are Norwegian salmon producers less efficient over time?

Abstract

The Norwegian salmon farming sector has experienced an increase on industry concentration for the last 20 years attributed to agglomeration externalities and scale economies; big firms increase their size and market share while small firms remain operating at the minimum level. However, small firms have higher profitability ratios than their big counterparts, a fact that contradicts economic theory as less efficient firms (and less profitable) will not grow and eventually will disappear. This paper quantifies the role of idiosyncratic demand and distortions on observed productivity differences across Norwegian salmon producers from 2001 to 2016. By using a data set that measures directly firm-level quantities, prices and sales, it is possible to break down the sources of total factor productivity dispersion on technical inefficiency and firm fundamentals. The understanding of TFP dispersion is useful as micro-productivity changes can point out aggregate productivity movements that matter on industrial and macroeconomic policies.

Keywords

Total Factor productivity, Firm dispersion, salmon aquaculture, profitability, technical efficiency, idiosyncratic demand.

1. Introduction

The growth of the Norwegian salmon aquaculture sector has been driven mainly by productivity growth and technological change (Asche, 2008). However, salmon farming shows a decline on productivity growth rates and higher production costs since 2005. This observed productivity slow-down can be attributable to a maturing of the industry and the exhaustion of suitable production sites (Asche, Guttormsen, & Nielsen, 2013). At the same time, industry concentration and firm dispersion have increased with a small number of big firms controlling more than 50% of total production; positive returns to scale in the sector and positive agglomeration externalities seems to explain the concentration dynamics as firms size acts in favor of innovation and lower production costs (Asche, Roll, Sandvold, Sørvig, & Zhang, 2013; Asche, Roll, & Tveteras, 2016; Tveterås & Battese, 2006). It is not clear if the concentration and dispersion of firms in the sector is a sign of higher inefficiency or just result of the global salmon market dynamics. Identifying the sources of total factor productivity dispersion is of importance as market fundamentals can be confounded with inefficiency distortions, which can lead to misguided industrial policies. Therefore, the study of productivity dispersion can serve as input for regulatory authorities regarding competitiveness, innovation, and resource allocation in the industry.

In most sectors, dispersion and dynamics are driven more by demand differences than by technical efficiency differences (Haltiwanger, 2016). There is evidence that even for very homogeneous products, price heterogeneity exists at the firm/plant level related to idiosyncratic characteristics of the firm (Haltiwanger, 2016; Syverson, 2007). Particularly, demand side factors like firm capacity to build a customer base, spatial location respect to clients, and other supplier-customer relationship characteristics seem to play an important role on firm growth and productivity dispersion (Syverson, 2014). Hence, most sectors present enormous differences in firm production levels with the observed dispersion reflecting not only misallocation but also idiosyncratic differences across producers that can be confounded with inefficiency (Decker, Haltiwanger, Jarmin, & Miranda, 2018; Foster, Haltiwanger, & Syverson, 2016; Haltiwanger, Kulick, & Syverson, 2018).

This paper quantifies the role of idiosyncratic demand and distortions on observed productivity differences across Norwegian salmon producers in from 2001 to 2016. By using a data set that measures directly firm-level quantities, prices and sales, it is possible to break down the sources of total factor productivity dispersion on technical inefficiency and firm fundamentals. The understanding of TFP dispersion is useful as micro-productivity changes can point out aggregate productivity movements that matter on industrial and macroeconomic policies. Moreover, policy impacts may be misunderstood if the sources of firm-level idiosyncrasies are not fully understood (Syverson, 2014). An analysis of TFP dispersion factors can shed light on the role of TFP growth on firm growth, profitability, and size distribution which can serve as inputs for wage, investment, and sectoral policies. This paper add to the existing literature on productivity in salmon aquaculture by explicitly linking productivity differences with market fundamentals. In particular, the methodology employed allows to separate the effects of firm-specific demand and technical inefficiency on productivity dispersion.

The rest of the paper is organized as follows: Section 2 describes the Norwegian salmon aquaculture sector. In section 3, the methodology is presented. Section 4 summarizes the data and section 5 provides results and discussion. I present concluding remarks on the last section of the paper, section 6.

2. Productivity in the Norwegian Salmon Aquaculture sector

Norway is probably the most successful case of salmon aquaculture production and the country is currently the global supplier with more than 1,200,000 tonnes produced in 2016 (Directorate of Fisheries Norway, 2018). Salmon farming has evolved in Norway from a single owner production system to an intensive one with a diverse firm structure, ranging from single-owners to vertically integrated multinationals; high rates of productivity and technological change have been possible due to the fact that many aspects in the production process can be monitored and controlled leading to improvements across all the supply chain, from inputs innovations to better distribution channels (Asche, Roll, & Tveterås, 2008).

In the sector early years, productivity improvements came mainly from learning by doing and scale economies as volume produced increased steadily (Bjørndal & Salvanes, 1995; Salvanes, 1993). Further studies showed how in the 90's the sector profited from increased volume, new regulations, and better management techniques; these positive effects of technical change reduced production costs by more than one third which turned into lower prices and allowed an increasing demand for salmon (Asche, Guttormsen, & Tveterås, 1999; Tveterås & Heshmati, 1999). Productivity improvements came also from the input side with more efficient feed types and higher specialization from suppliers (Guttormsen, 2002). Furthermore, agglomeration and specialization in specific locations created positive productivity effects as innovations and new practices spread fast in clustered spaces (Asche et al., 2016; Tveterås, 2002; Tveterås & Battese, 2006).

However, since the early 2000's salmon farming in Norway has experienced an increase on industry concentration and firm dispersion. Vassdal and Sørensen Holst (2011) and Asche, Guttormsen, et al. (2013) found a decreasing tendency on productivity growth since 2005 with both studies arguing that improvements on the best production technology - shifts of the production frontier - are slowing down, a fact that could reflect the maturing of the industry and that gives more weight on allocative efficiency across firms. Although larger companies can be seen as a consequence of agglomeration externalities and scale economies (Asche, Roll, et al., 2013), small firms have lower production costs than their big counterparts, a fact that contradicts economic theory as less efficient (and less profitable) firms will not grow and will eventually exit markets. While most empirical studies in the Norwegian salmon aquaculture sector have focused on physical productivity estimations at the firm level, to the knowledge of the author there are no studies that explicitly link productivity differences with demand side factors, even though there is the recognition of other influencing factors like agglomeration externalities, biological conditions, and regulations.

3. Data

I use an unbalanced data panel with a total of 1674 observations for the period 2001-2016. The data is provided by the Norwegian Directorate of Fisheries that annually surveys profitability and costs of the sector. However, the sample has great variation as the Directorate exclude firms that fail to fully report their accounts. Thus, is not possible to know if some firms have exited the market or have just failed to report in a given year. To make the sample more homogeneous, I decided to include in our analysis those firms that report a minimum of two consecutive years and that do not have more than 3 years gap in their reporting. After cleaning the data according to these rules, the panel was reduced to 1585 observations. Table 1 provides a summary of the selected variables.

Table 1 – Summary Statistics

Variable	Mean	Standard Deviation	Min	Max
Production (Tonnes)	6,095	10,500	197.50	94,100
Feed (Nok/kg)	6.05	0.90	2.46	12.44
Labor (Nok/Hour)	409.57	257.44	4.78	3,899.54
Smolt(Nok/Kg)	55.42	41.04	0.96	704.51
Other Costs (Nok/Kg)	3.59	2.81	0.18	37.33
Capital (1000 Nok)	50,000	112,000	150.17	1,450,000
Prices (Nok/kg)	24.74	8.66	10.37	66.11

Production costs show two different tendencies during the period 2001-2016, during 2001-2005 there is a decreasing pattern while 2005 onwards production costs start increasing steadily. This behavior is present in all firms regardless their size and production levels and can be the result of increases on input prices or external shocks that have a negative effect on production. I classified firms according to their size - small firms are those who own 1 to 9 licenses, medium firms own 10 to 19 licenses, and big firms own 20 licenses or more - to analyze if there are significant differences in production costs and salmon prices.

Feed prices, the main input for production, remain stable with an average growth for the whole period of 1%, there is not significant differences between feed prices faced by different group sizes of producers. Labor costs present an increasing tendency of 10% for the whole period, which goes accordingly with the growth of the Norwegian economy and the labor market. Smolt costs had an average yearly increase of 0.6% between 2001 and 2016 and have the highest dispersion in all groups as producers tend to buy different sizes of smolt which make prices to vary greatly. The variable other costs show an increasing tendency and for 2016 this cost was in average 8.5 Nok per kilogram of salmon produced, which is four times higher than the costs incurred in 2001 for this category. Significant differences are found on the other costs variable by group size, small firms had the lowest value for this category with 3.4 Nok/Kg, while medium firms had an average of 4.2 Nok/Kg and big firms show the highest value with 6.4 Nok/kg.

While the total number of firms in the industry has diminished, total production has increased going from 260,000 tonnes in 2001 to 1,230,000 tonnes in 2016 as a result of the increase of Total Biomass in the sector and better production systems. Salmon prices have been increasing as a result of higher global demand with an increase also in price volatility.

Figure 1 - Number of firms by year and size group 2001-2016

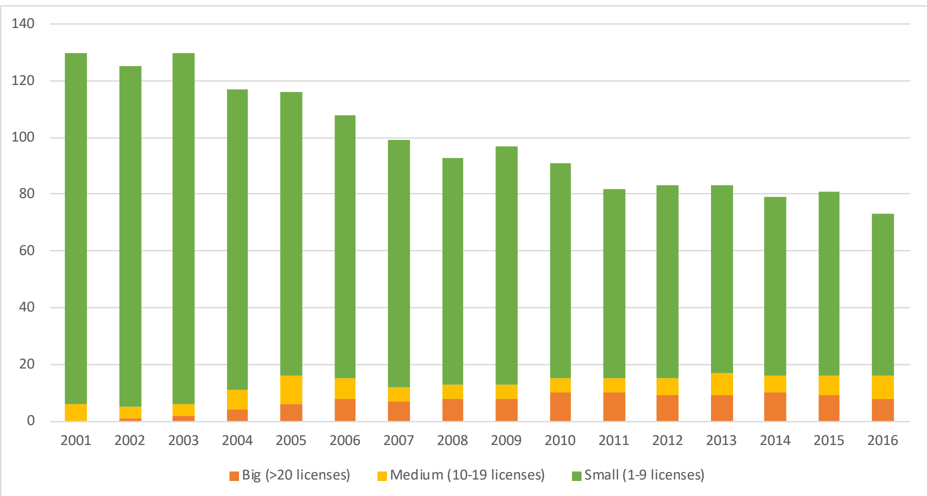


Figure 2 - Salmon Prices by firm size 2001-2016

4. Methodology

Generally speaking, productivity is an output(s) to input(s) ratio. One firm is more productive than another (or than itself in a different point in time) if it can produce more outputs with the same quantity of inputs. Thus, differences on productivity reflect shifts on the isoquants of a production function (Syverson, 2011). Several methodologies are available to estimate total factor productivity (TFP) and can be labeled in two big groups: Non-parametric and parametric methods. From the non-parametric approach, the most popular techniques are data envelopment analysis (DEA) and index numbers. DEA uses linear programming to estimate productivity as a ratio of output to a linear combination of inputs; DEA is very flexible as it does not impose any particular functional form to the underlying production function but as it estimates productivity from the data directly make the results very sensitive to the presence of outliers and data measurement errors (Van Biesebroeck, 2007). The second technique, index numbers, use economic theory to aggregate inputs and outputs; if the assumptions that first-order conditions with cost minimization hold (in average) and firm-level prices/quantities are observed, then productivity can be estimated as the difference between log output/revenue and log inputs times their cost shares. Index numbers provide an easy computation for productivity without imposing production technology assumptions on firms (Haltiwanger, 2016; Van Biesebroeck, 2007).

On the other side, parametric methodologies are generally related with econometric estimations of a production, cost, or frontier function. While the stochastic formulation in parametric estimates reduces the effects of measurement error in the data, the fact that they generally measure productivity as a residual make their estimates very dependent on modelling assumptions and to confound productivity with demand and supply shocks (Syverson, 2011). As such, the error term in production function regressions used for TFP estimations combines both demand and technology shocks and can wrongly attribute high productivity estimates to units that are only facing high demand shocks (Gorodnichenko, 2007). Since the very purpose of this paper is to identify and disentangle demand factors on productivity, a cost-share index number TFP measure is used. An additional benefit of using cost-share TFP indexes is that they are generally robust measures (Syverson, 2014).

The productivity measures follow the index form:

$$tfp_{it} = y_{it} - \alpha_f f_{it} - \alpha_l l_{it} - \alpha_s s_{it} - \alpha_k k_{it} - \alpha_{oc} oc_{it} \tag{1}$$

where tfp is the total factor productivity, y is salmon quantity produced, f is feed quantity, l is labor hours, s is smolt quantity, k is capital stocks, and oc are other costs. i is a firm index for $i = 1, \dots, n$ and t is a time index for $t = 1, \dots, T$. Lower case letters indicate logarithms of variables. Finally, $\alpha's$ are the factor elasticities for the variable inputs that are obtained using each firm average cost share.

Equation 1 reproduces the supply and technological side aspects of total factor productivity and as such, it constitutes a non-parametric measure for technical efficiency. This measure is called the physical total factor productivity (TFPQ). The second index I use is a revenue one (TFPR) which uses instead of production quantity (the y variable in equation 1) the deflated nominal revenue from product sales[1]. Theoretically, TFPR satisfies the following identity (Syverson, 2011):

$$TFPR = TFPQ \cdot Price \tag{2}$$

TFPR can be decomposed as technical efficiency and prices that proves useful to further explore demand influences – via prices – on productivity development and dispersion in the sector. If differences on prices and demand between firms prove to be significant, then dispersion in TFPR will reflect more than inefficiency, including demand shocks and firm movements along its marginal cost curve. To measure the demand components an isoelastic demand is estimated in the following form:

$$lnq_{it} = \beta_0 + \beta_1 lnp_{it} + \beta_2 Income_t + \sum_t \beta_t D_t + \epsilon_{it} \tag{3}$$

[1] As in Foster, Haltiwanger, and Syverson (2008) I use as deflator a revenue-weighted geometric mean price across all plants.

where q_{it} is quantity of salmon sold, p_{it} is the firms' selling price, D_t are time year dummies that control for year effects, ϵ_{it} is a firm-year disturbance term. Finally, $Income_t$ is a weighted index variable constructed as the GDP per capita (as proxy for average income) in the main four markets for Norwegian salmon for the period 2001-2016.[2] Simple OLS estimation of the demand equation would lead to biased estimates due to the positive correlation of the disturbance term and prices (a positive demand shock captured in ϵ_{it} would make producers to increase prices). Instead, equation 3 is estimated using an IV technique controlling for prices with supply side instruments. Following Foster et al. (2008) each firm idiosyncratic demand is obtained as the sum of the residual ϵ_{it} and the contribution of income β_2. This measure will capture output variations due to shifts on each producer idiosyncratic demand and if significant would have explanatory power over productivity dispersion.

The revenue-based productivity measure is used to disentangle the sources of dispersion in the sector as it contains both demand and supply side factors. Following the model proposed by Haltiwanger et al. (2018) a variance decomposition of TFPR is estimated to quantify the influence of demand, technical efficiency, and distortions on the observed productivity dispersion. Here I briefly described how to get the components of TFPR variance, for greater details on the model please refer to the aforementioned paper.

From equation 2 TFPR equals technical efficiency (as expressed by TFPQ) times the price. If firm-specific demand matters, then producers have room for a mark-up which can be obtained by doing the following manipulation to equation 2:

$$TFPR = TFPQ \cdot \frac{Price}{MC} \cdot MC = \Lambda \cdot \Gamma \tag{4}$$

where MC = marginal costs, $\Lambda = \frac{Price}{MC}$ is the markup, and $\Gamma = TFPQ \cdot MC$.

Thus, the variance of TFPR in logged form can be written as:

$$var(tfpr) = var(\lambda) + var(\gamma) + 2cov(\lambda, \gamma) \tag{5}$$

The first term on the right of the equality in equation 5 is the influence of revenue and demand side on productivity variation, the second term contains the influence of supply side factors (marginal costs and technical efficiency), and the last term is the covariance between supply

[2] The four main markets are the European Union, Japan, Russia, and the US as reported by the Statistical central department of Norway SSB. GDP per capita data are obtained from the Penn World table (Feenstra, Inklaar, & Timmer, 2015). Weights are constructed by aggregating Norwegian salmon exports for the group of countries by year and taking the percentages of each country.

and demand factors. To obtain the expression for each component, start by assuming a variable elasticity demand, which is basically the demand equation in 3 plus a quadratic term as follows:

$$lnq_{it} = \beta_0 + \beta_1 lnp_{it} + \beta_2(lnp - ln\bar{p})^2 + \sum_t \beta_t D_t + \epsilon_{it} \tag{6}$$

Where $\bar{p}$ is the average price. This flexible demand allows to accommodate for mark-up pricing and for incomplete pass-through of productivity improvements to price. The demand elasticity is then:

$$\eta = \beta_1 + 2\beta_2(lnp - ln\bar{p}) \tag{7}$$

The model assumes that firms have some market power due to the importance of idiosyncratic demand. Hence, firms charge prices following the markup rule as follows (Tirole, 1988):

$$P = \frac{1}{1+\frac{1}{\eta}} \cdot MC \Rightarrow \frac{P}{MC} = \frac{1}{1+\frac{1}{\eta}} = \frac{\beta_1 + 2\beta_2(lnp - ln\bar{p})}{1 + \ \beta_1 + 2\beta_2(lnp - ln\bar{p})} \tag{8}$$

Taking the log of equation 8 gives us λ. By using a first-order Taylor expansion around β_1 and $1 + \beta_1$ the variance of the logged markup is:

$$var(\lambda) \approx \left[\frac{2\beta_2}{\beta_1(1+\beta_1)}\right]^2 var(p) \tag{9}$$

Note that a non-linear demand is needed as under the linear demand model (equation 2) this variance is equal to zero as $\beta_2 = 0$; thus, there would be no effect of demand on productivity dispersion.

To find the variance expression of gamma in equation 5 consider the following generalized cost function:

$$C(TFPQ, Y) = \frac{1}{\theta}\left[\frac{Y}{TFPQ}\right]^{\frac{1}{\theta}} \phi(W) \tag{10}$$

where θ is a scale parameter measuring increasing, constant, or decreasing returns to scale. $\phi(W)$ is a function of input prices W. From 10, marginal costs can be obtained as:

$$MC(TFPQ, Y) = \frac{1}{\theta}[Y]^{\frac{1}{\theta}-1}\, TFPQ^{-\frac{1}{\theta}}\phi(W) \tag{11}$$

And thus, gamma is equal to:

$$\Gamma = \frac{1}{\theta}\left[\frac{Y}{TFPQ}\right]^{\frac{1}{\theta}-1} \phi(W) \tag{12}$$

Distortions are then included in equation 10 as shifters of the cost function, distortions can be regarded as the technical inefficiency and misallocation component that originates in the supply side. Multiplying equation 12 by those distortions (T) and taking logarithms the expression for gamma can be found as follows:

$$\gamma = ln\frac{1}{\theta} + \ln\phi(W) + \left(\frac{1}{\theta} - 1\right)(y - tfpq) + \tau \tag{13}$$

And its variance:

$$\begin{gathered} var(\gamma) = (\psi)^2[var(y) + var(tfpq) - 2cov(y, tfpq)] + var(\tau) \\ + 2(\psi)cov(y,\tau) - 2(\psi)cov(tfpq,\tau) \end{gathered} \tag{14}$$

Where $\psi = \left(\frac{1}{\theta} - 1\right)$.

Finally, putting equations 9 and 14 into equation 5, the following expression of productivity dispersion is obtained:

$$\begin{aligned} var(tfpr) = {} & \left[\frac{2\beta_2}{\beta_1(1+\beta_1)}\right]^2 var(p) + (\psi)^2[var(y) + var(tfpq) - 2cov(y, tfpq)] + \\ & var(\tau) + 2(\psi)cov(y,\tau) - 2(\psi)cov(tfpq,\tau) + \\ & 2\left[\frac{2\beta_2}{\beta_1(1+\beta_1)}\right]\psi[cov(p,y) - cov(p,tfpq)] + 2\left[\frac{2\beta_2}{\beta_1(1+\beta_1)}\right]cov(p,\tau) \end{aligned} \tag{15}$$

Equation 15 allows to separate the influence of demand, prices, physical productivity, and distortions (inefficiency and misallocation) in the following manner:

Table 2 - TFPR variance decomposition

Fundamentals	$\left[\frac{2\beta_2}{\beta_1(1+\beta_1)}\right]^2 var(p) + (\psi)^2[var(y) + var(tfpq) - 2cov(y, tfpq)]$
Supply-Demand interactions	$2\left[\frac{2\beta_2}{\beta_1(1+\beta_1)}\right]\psi[cov(p,y) - cov(p,tfpq)]$
Distortions	$var(\tau)$
Covariance distortions fundamentals	$2(\psi)cov(y,\tau) - 2(\psi)cov(tfpq,\tau) + 2\left[\frac{2\beta_2}{\beta_1(1+\beta_1)}\right]cov(p,\tau)$

The only element remaining in the variance decomposition is a measure of distortions, they can be obtained econometrically by estimating a production function or measured directly. Since productivity is measured in a non-parametric way on this paper, I decided to use a direct measure that uses the observable data and the parameters from the demand function as follows[3]:

$$\mathrm{T} = \frac{\theta\pi}{C}\left[\frac{\beta_1 + \beta_2(lnp - 2ln\bar{p}) + 1}{\beta_1 + \beta_2(lnp - 2ln\bar{p})}\right] \tag{16}$$

Where π are revenues and C are total costs.

5. Results

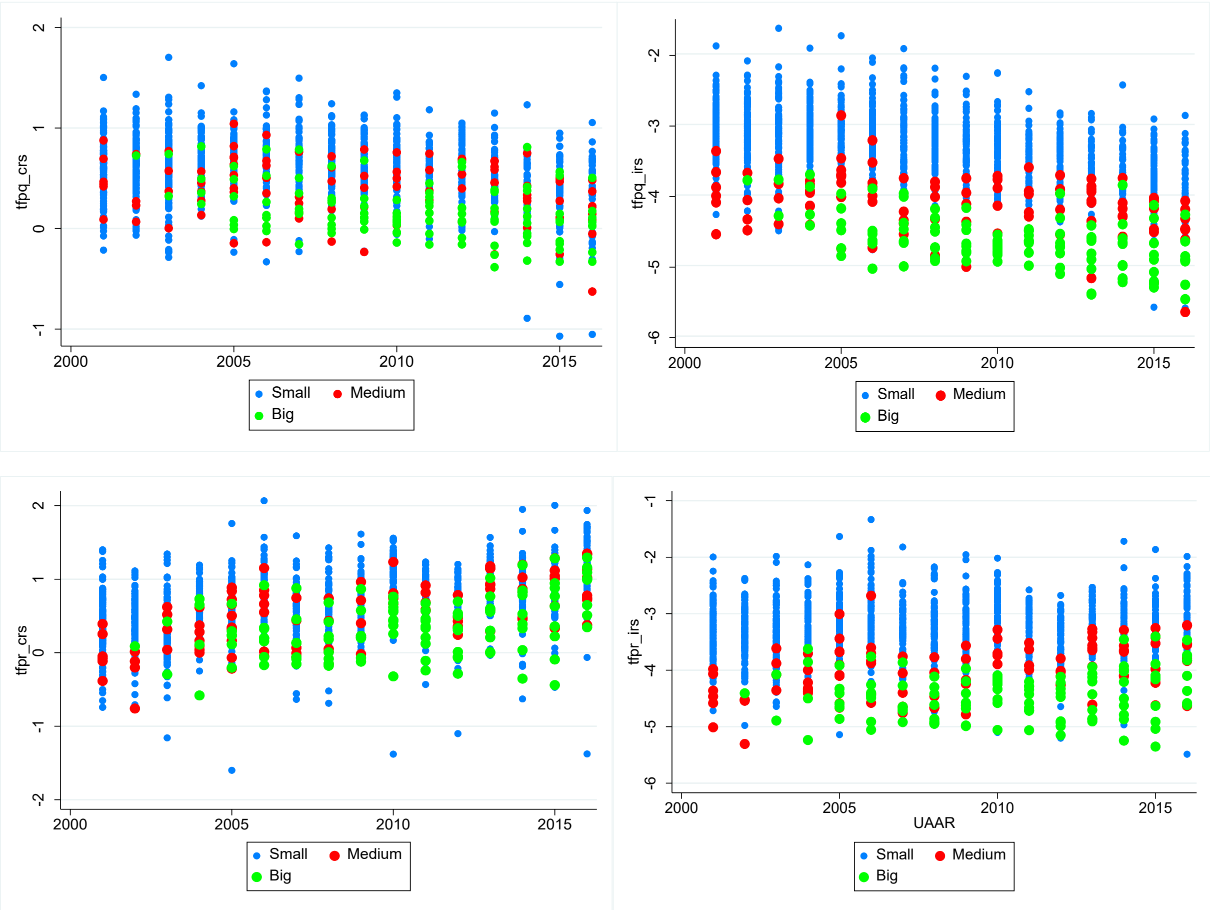
To identify how demand factors affects productivity dispersion first I analyze the evolution of TFP indexes, including also TFP differences between groups' sizes and its dynamics. Then, a linear demand model is estimated to retrieve the idiosyncratic demand. I test also the influence of idiosyncratic demand on TFP variation and finally, the variance of TFPR is calculated and decomposed on fundamentals, distortions, and covariance elements.

5.1 Total Factor Productivity in Norwegian salmon aquaculture: Facts and Dynamics

I compute the cost-share based tfp indexes as explained in equations 1 and 2 for physical and revenue total factor productivity. Figure 4 shows the evolution for the yearly TFPQ and TFPR - in logs - for the whole sector under two scenarios: Constant returns to scale (CRS) and increasing returns to scale (IRS). There is a general agreement that the sector operates under scale economies that facilitates firm growth and generates positive agglomeration externalities (Asche et al., 2016; Guttormsen, 2002; Rocha Aponte & Tveterås, 2018; Tveterås, 2002; Tveterås & Battese, 2006). Through this paper I use the CRS scenario as a baseline comparison useful for decomposing the productivity variance and estimating the demand models.

[3] For the derivation of this expression please refer to Haltiwanger et al. (2018).

Figure 3 - tfpq and tfpr dispersion by group size and year



Notes: Each dot represent a firms' tfp, constant returns to scale measures are on the left while increasing returns to scale are on the right. Regardless of the returns to scale assumption, dispersion is high and same patterns are found.

Physical TFP presents an average decreasing tendency with a compound annual growth rate (CAGR) of -2% and -6% under the CRS and IRS scenarios respectively. Revenue TFP shows the opposite behavior with a CAGR of 3% and 1% for CRS and IRS. It is observed that TFPQ and TFPR dispersion increases within the years with a variance 2.2 times bigger in 2016 when compared with 2001. For the different groups of firms, small firms tend to be in average more efficient than medium and big ones in both TFP measures. However, bigger dispersion is found in the small group, which contains at the same time firms with the highest and lowest productivity indexes for most years.

TFPQ can be regarded as a technical efficiency measure and could indicate the presence of misallocation. However, due to the nature of the production process which involves external biological and economic factors, tfpq alone is not a sufficient indicator of firms' optimal behavior. For example, in their study of agglomeration externalities, Asche et al. (2016) found that profitable clusters are found in very high costs areas suggesting that costs and supply side factors are not the only aspects driving profitability in salmon aquaculture, revenues also play a very important role on firms decisions. If bigger firms tend to locate in agglomerated areas – which is reasonable as they are also vertical integrated – then their lower productivity indexes could be a signal of trade-offs between technical efficiency and higher revenues while the indexes of small firms may only reflect technical efficiency. This hypothesis is consistent with the findings that firms in the medium and big group grow more when compared with small firms.

Table 3 - Correlations Output, Price, Sales, and Productivity

	Output	Sales	Price	tfpq	tfpr	Capital
Output	1					
Sales	0.943	1				
Price	0.157	0.320	1			
tfpq	-0.369 [-0.722]	-0.441 [-0.798]	-0.295 [-0.289]	1		
tfpr	-0.022 [-0.483]	0.238 [0.380]	0.335 [0.122]	0.343 [0.719]	1	
Capital	0.871	0.841	0.173	-0.532 [-0.821]	-0.110 [-0.620]	1

Notes: all measures are in logs. Values in parentheses are correlation for measures under the assumption of increasing returns to scale

Table 3 show correlations for the total factor productivity measures, output, sales revenue, price, and capital. Output and sales revenue have very high correlation and reflects the high dispersion of firm size within the industry. Notice that physical productivity and prices are inversely correlated meaning that, despite the price differences, the negative correlation will make tfpr to show less dispersion than physical productivity as observed in figure 3.

An interesting fact rises from the inverse correlation between tfpq and prices; theoretically, firms with higher productivity will grow and will charge lower prices as their marginal costs are lower. However, the empirical data shows the opposite behavior, small companies in addition of having higher tfp tend to charge higher prices (in average) than their big counterparts. This result may be due to specific firm-client relationships as in general, big firms tend to sign long term contracts, so prices are more stable in time (Asche & Larsen, 2011). On the contrary, small firms operate following the spot market which allows them to profit from short term price volatility shocks. Both correlations and tfp measures are signaling that firm-specific demand factors play a role in productivity; given that salmon is a very homogeneous product (commodity), price differences cannot be attributed to product differentiation and may be the result of firm-specific demand shifts.

5.2 Idiosyncratic demand

I seek to separate the influence of demand side factors from inefficiency distortions on total factor productivity dispersion in the Norwegian salmon sector. To do so, the TFPR measure is used as it incorporates the role of price on TFP evolution. As explained before, the revenue-based measure of TFP is equal to the physical measure – that shows supply side factors – times price. As salmon is a very homogeneous product, the tfpq measure reflects technical efficiency while price variations show factors not related with product quality differences. Such factors can include transportation costs, non-spatial horizontal differentiation, customer-supplier relationships, and long-run buyer-supplier ties (Foster et al., 2008, 2016).

The influence of such differentials is obtained by estimating an inverse demand as the one described by equation 3. As in Foster et al. (2008) and Haltiwanger et al. (2018) I estimate the demand controlling for the correlation of prices and the error term by using cost influences on prices. I use as instruments the firm's physical productivity measure (TFPQ) and the firm maximum allowed biomass (MTB); since firms have biomass restrictions, this instrument controls for the fact that producers cannot satisfy demand (expand production) beyond the physical limits of their MTB. The instruments reflect technical efficiency and are unlikely to be correlated with any short-term demand shocks.

Table 4 - Estimates of Price Elasticity

	OLS Estimation	IV Estimation	
		CRS	IRS
Price Coefficient	-0.297	-4.409	-2.648
	(0.078)	(0.632)	(0.468)
Income Coefficient	0.028	0.088	0.063
	(0.001)	(0.009)	(0.006)
First-stage R2		0.773	0.772

Notes: clustered standard errors in parentheses.
All estimations included firm-year fixed effects

Table 4 shows the demand estimates. For reference purposes, I report in the first column the OLS estimates while the second column uses tfpq and MTB as instrumental variables. In all regressions price elasticity is negative but shows to be elastic (greater than one in absolute value) only in the IV results. As the IV estimates are of higher magnitude that the OLS this reassures the instrumental variable strategy as is consistent with the simultaneity bias present in the OLS. Therefore, the IV estimates are consistent while the OLS are biased. Results also show that the market is competitive as demand is highly elastic with respect to price. Finally, the firm-specific demand is obtained by using the residuals of the demand equation plus the contribution of the income variable that – given the assumptions and the conditions of the market – should measure output variation due to shifts in the demand curve for each firm.

The idiosyncratic demand estimations differ on both scenarios: In the constant returns to scale calculations, the small group has the largest variance. However, in average, the big group of firms presents the highest measure of idiosyncratic demand, which means that firm-specific demand factors have a greater influence as firm size increase. On the other side, in the increasing returns to scale scenario, the estimations of firm-specific demand are less dispersed, but the small group remains the more dynamic with a variance almost three times bigger than the other two groups. These estimations indicate that even though there is market competition on salmon aquaculture production, individual demand factors seem to affect firm productivity levels.

I continue by testing the persistence of productivity, prices, and demand. Tables 5 and 6 display the results of regressing each variable on its own lag and also include a column with weighted regression[4] results. There is high persistence on both productivity measures indicating that productive firms remain productive while there is low expectation that inefficient firms improve. Idiosyncratic demand shows also high persistence while price although persistent has the lowest coefficients of all variables. All coefficients are of higher magnitude under the increasing returns to scale scenario and under the weighted regressions, which implies big firms have more persistent individual characteristics.

Table 5 - Persistence of Productivity

	CRS		IRS	
	Weighted	Unweighted	Weighted	Unweighted
tfpq	0.850	0.711	0.958	0.941
	(0.033)	(0.044)	(0.012)	(0.014)
tfpr	0.711	0.464	0.834	0.655
	(0.044)	(0.059)	(0.033)	(0.056)

Notes: Standard error clustered by firms in parentheses.

Table 6 - Persistence of Demand and Prices

	CRS		IRS	
	Weighted	Unweighted	Weighted	Unweighted
Idiosyncratic demand	0.913	0.833	0.963	0.918
	(0.020)	(0.024)	(0.013)	(0.015)
Prices	0.465	0.438	0.465	0.438
	(0.063)	(0.032)	(0.063)	(0.032)

Notes: Standard error clustered by firms in parentheses.

[4] Weighted regressions are weighted by revenue.

5.3 Total Factor Productivity Dispersion: The influence of firm-level demand and distortions

As mentioned before, firm-specific demand is persistent and significant overtime. If firms face different individual demands, then some of the observed dispersion present in the productivity measure (tfpr) may be due to demand shifts and not entirely by inefficiency. Furthermore, the observed dispersion can be reflecting movements in the firm's marginal cost curve towards a more profitable position (given certain demand shock) and as such can be optimal decisions (Haltiwanger et al., 2018). To test this hypothesis, I start by regressing TFPR on the idiosyncratic demand measure to see if they have some explanatory power over productivity behavior, results are provided on table 7.

Table 7 - Elasticity of Revenue Productivity to Idiosyncratic Demand

	CRS	IRS
Idiosyncratic Demand	0.142	0.150
Std. Error	(0.002)	(0.027)

Notes: This table shows the results of regressing tfpr on demand. Regressions include year and firm fixed effects.

Results show that demand is positively correlated with revenue productivity levels, both regressions reject the null hypothesis of zero covariance between demand and TFPR with a t-statistic of 6.26 and 5.43 for the CRS and IRS scenarios respectively. The estimated coefficients imply that a unit percent increase in firm-specific demand will increase revenue productivity by 14%-15%; it seems that demand side factors have a significant influence on tfpr. Further, I test the relationship between physical productivity and prices to evaluate how supply side factors are transmitted to prices. Theoretically, higher physical productivity should reflect lower prices (lower marginal costs). In perfect competition prices are unit elastic with respect to productivity (price equals marginal cost), I empirically test this as follows:

$$lnp_{it} = \alpha_0 + \alpha_1 tfpq_{it} + \sum_t \alpha_t D_t + \varepsilon_{it} \tag{15}$$

where D_t are dummies that control for year effects; a complete pass-through will mean $\alpha_1 = -1$. If this is not the case, then the assumption of firms being complete price takers on the market does not hold. As shown on table 8, coefficients differ from 1 meaning that producers do not fully pass their costs savings to consumers. These findings also mean that TFPR is positive correlated with TFPQ (as shown in table 3) and provide support that even in a sector with a very homogeneous production, demand at the firm level drive variations on observed productivity levels.

Table 8 - Elasticity of firm price to TFPQ

Dep. Variable: Price	CRS	IRS
tfpq coefficient	-0.139	-0.123
Std. Error	(0.016)	(0.014)
95% Conf. Interval	[-0.170, -0.108]	[-0.152, -0.094]

Notes: Estimates are performed on log variables

Given that there is not complete pass through of costs reductions to price and that demand factors affect productivity, I proceed to use the Haltiwanger et al. (2018) theoretical framework that allows for mark-up pricing and variant elasticity demand as explained in the methodology section. This framework adapts better the empirical findings and allows to decompose tfpr variance in fundamentals (supply-demand), distortions, and covariances. To do so, first I estimated the quadratic demand of equation 6, the results are displayed on table 9.

Table 9 - Quadratic Demand Estimates

Coefficient	CRS	IRS
Price	-3.280	-2.059
	(0.840)	(0.538)
Price^2	-7.593	-3.648
	(2.884)	(1.547)

Notes: Regressions include fixed year-firm effects. Standard errors in parentheses.

All coefficients are significant at a 90% confidence level. The fact that the quadratic term is big in magnitude and significant implies that there is big variation in markups. Then, I calculate price elasticities and got values of -5.42 and -3.08 for the CRS and IRS scenarios respectively; Both elasticities are higher than the elasticity obtained with the linear demand model (-1.41) and capture better the within firm demand variation to own price changes. As explained in the methodology section, TFPR variance is a function of physical productivity (tfpq), prices, demand, and distortions. Distortions contain the portion of dispersion that can be attributable to misallocation and inefficiencies; I calculate distortions as stated on equation 14 and found that they are of higher magnitude in the IRS scenario but present the same patterns as the CRS calculations. Distortion magnitude and variance tends to diminish with firm size reflecting that most allocative inefficiencies are present in the small group. To see the relationship between distortions and fundamentals their correlations are computed for the pooled set and by group size. From table 10 it is evident that all fundamentals are correlated with distortions, there is no significant difference across size groups and both CRS and IRS scenarios produce similar results. Of particular interest is the negative correlation between distortions and physical productivity, this is an indication that distortions are capturing inefficiencies in a correct way.

Table 10 - Correlations between distortions and fundamentals

CRS	Pooled	Small	Medium	Big
$Corr(lnp_i, \tau_i)$	0.446	0.453	0.301	0.531
$Corr(tfpr_i, \tau_i)$	0.800	0.813	0.890	0.873
$Corr(tfpq_i, \tau_i)$	-0.076	-0.088	-0.063	-0.097
$Corr(demandshock_i, \tau_i)$	-0.078	-0.112	-0.497	0.232
IRS	Pooled	Small	Medium	Big
$Corr(lnp_i, \tau_i)$	0.446	0.452	0.301	0.531
$Corr(tfpr_i, \tau_i)$	0.547	0.630	0.791	0.759
$Corr(tfpq_i, \tau_i)$	-0.171	-0.209	-0.018	-0.042
$Corr(demandshock_i, \tau_i)$	-0.066	-0.105	-0.495	0.216

Notes: The first part of the table shows correlations under the constant returns to scale (CRS) while the second part show results for increasing returns to scale

I estimate tfpr variance using equation 15, for both scenarios productivity dispersion diminishes with size as medium and big groups' present lower average variance than the small one. These results point that most allocative dynamics occur in the small group; unfortunately, intragroup dynamics cannot be quantified given our data limitations as is not possible to accurate identify which firms exit the market, which ones are merged, and which ones just stop reporting to Norwegian authorities. The decomposition of the variance, displayed in table 11, shows that supply and demand factors make up to 97% and 130% of tfpr dispersion for CRS and IRS respectively. Each component is a variance measure of either fundamentals, prices, or distortions and the covariance between them. Both interactions and distortions have a heavier influence on dispersion under constant returns to scale accounting for 109% of variation while under increasing returns they only account for 60%. The interactions between distortions and fundamentals contribute negatively to productivity variance with similar magnitudes for both scenarios, this is a result of factors not explicitly accounted by the model that contribute negatively on TFPR dispersion.

Table 41 - Productivity Variance Decomposition

	CRS	IRS
Fundamentals	0.979	1.305
Interaction Supply-Demand	0.132	0.074
Distortions	0.963	0.527
Covariance Fundamentals and Distortions	-1.066	-0.906

Finally, the variance decomposition has showed that fundamentals matter for productivity dispersion. It was possible to separate firm-specific demand factors from the observed distortions where there is evidence that idiosyncratic characteristics play an important role in productivity measures. Specifically, demand seems to affect not only revenues but also physical productivity levels; the mechanism of how this process work remains an open question for future research. The comparison between constant and increasing returns to scale was an interesting exercise as it points out that for the increasing returns scenario demand characteristics have a greater influence in productivity levels and dispersion.

6. Concluding Remarks

In this study a flexible demand and non-constant marginal cost framework has been used to assess the effects of idiosyncratic demand factors on total factor productivity dispersion for the Norwegian salmon aquaculture sector from 2001 to 2016. It was possible to quantify the effects of fundamentals on TFP dispersion; for all firms – regardless their size – fundamentals have more weight on productivity variance than distortions generated from inefficiency and misallocation.

The results indicate that idiosyncratic characteristics have a greater influence on revenue productivity for big firms. Distortions magnitude and variance tend to diminish with firm size reflecting that most allocative inefficiencies are present in the small group of firms. Small firms profit from prices in the spot market which explains in part why they present higher revenue productivity than their big counterparts. This study make progress on better isolating distortions and their influence on firm dispersion in the sector; the observed dispersion in productivity is not necessarily a sign of higher inefficiency and may reflect shifts on firm-specific demand and the consequently adaptation of production decisions in directions of higher profitability.

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Paper IV

Price Forecasting with a Market in Flux: A TVP-VAR Approach for Salmon Prices

Price Forecasting with a Market in Flux: A TVP-VAR Approach for Salmon Prices

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Abstract

The salmon market is in transition due to rapid changes in regulations, production technology, and environmental conditions. This paper models and forecasts salmon prices via a time-varying parameter VAR model (TVP-VAR) that deals with structural changes as it allows for both smooth and structural changes on the estimated coefficients and the volatility structure. Using monthly data that span 2000-2019, the model considers supply-side fundamentals such as input prices, exchange rates, and available supply. The results showed that the TVP-VAR models predict the direction of price changes accurately 8 out of 12 months. The TVP-VAR model better captures the changes in market conditions, such as structural changes in regulation, the volatility of input prices (soybean and fishmeal), and models the seasonality present in salmon prices.

Keywords: Forecasting, Salmon Prices, Stochastic Volatility, Time Varying Parameters

1. Introduction

Salmon prices have received a lot of attention in recent years, in particular, because of the surge leading to record high price levels (Asche, Misund, & Oglend, 2019; Bloznelis, 2016a, 2018a). The high level of investments in the industry, not only in the traditional producing countries like Norway and Chile, but also in new markets like the USA and China, makes it highly relevant to forecast salmon prices. However, a challenge with forecasting salmon prices is how to deal with the structural changes that have taken place and that keep taking place in the industry. For example, the latest large-scale investments in new salmon production capacity is based on onshore and offshore technologies, as opposed to the traditional coastal production systems that dominate the industry (Hagspiel, Hannevik, Lavrutich, Naustdal, & Struksnæs, 2018; Liu et al., 2016). This latest shift in technology is recent and not really affecting the market yet. Nonetheless, this latest technological development exemplifies, during its relatively short history, how the salmon industry has adapted and keeps adapting to changing market conditions and production constraints.

For price forecasting, these structural changes pose a challenge. It is harder to predict a future that differs radically from the past. In this sense, the salmon market represents a special case for price forecasting. Salmon production has faced serious obstacles not least due to the outbreak of diseases and parasitic problems that have led to large production shocks and long-term supply constraints. These issues have spurred regulatory changes and resulted in a reorganization of parts of the industry (Abolofia, Asche, & Wilen, 2017; Iversen, Asche, Hermansen, & Nystøyl, 2020). On the market side, changes have also taken place including more gradual supply chain developments, the introduction of new product varieties and more abrupt ones like the imposition of international trade barriers (Chen & Garcia, 2016; Poblete, Drakeford, Ferreira, Barraza, & Failler, 2019). In sum, these changes imply that the salmon market today is not the same as 10 or 20 years ago. To account for changes in the underlying data generating-process of salmon prices, we propose to use a forecasting model that builds on time-varying parameter estimates. Specifically, we propose a TVP-VAR approach. To test if a TVP-VAR approach is appropriate we compare with model specifications based on traditional VAR and the naïve model.

Studies for the salmon price have been mainly focused on volatility modeling, an early exception is Guttormsen (1999) that forecasts weekly salmon prices finding that VAR models show the best accuracy measures for different weight classes of salmon in the spot market. Volatility has increased since 2006 due to the inelastic supply of salmon as a consequence of stagnating production either by regulations or disease problems (Asche et al., 2019). Oglend and Sikveland (2008) show how volatility modeling can provide useful information for the price formation process in the short-run (3-4 weeks). Additionally, aquaculture products tend to be less volatile than wild products due to better control of the production process that aquaculture implies, except for salmon farming where there is no evidence of lower volatility (Asche, Dahl, & Steen, 2015; Roy Dahl & Oglend, 2014). Thus, salmon prices face high volatility and require dynamic modeling; Bloznelis (2016b) found that a dynamic modeling of the correlation structure between different weight classes of salmon provides better information for understanding volatility patterns in salmon spot prices. Moreover, Roy Dahl and Jonsson (2018) and Roy Dahl and Yahya (2019) found time-varying volatility structure in seafood markets and low connectedness between fish markets and financial markets. The most recent paper on salmon price forecasting is Bloznelis (2018b) where he evaluates sixteen alternatives for predicting 4-5 week ahead prices; the author found that forecasting can be used in a simple trading strategy which can lead to a 7% increase on producers' profit.

Given this gap in forecasting studies, we will focus on the monthly forecast of spot prices with medium and long term accuracy (4, 8, and 12 months ahead). The reason for these intervals lies in the biological processes and timing involved in salmon prices; medium and long term forecasts can serve as a useful tool for production planning which can improve producers' profit. The rest of the paper is organized as follows: Next section introduces the salmon aquaculture market and their supply and demand developments. Then, we explain the empirical methodology. Section 4 describes the data while section 5 presents the results of our modeling and forecasting strategies. Finally, section 6 discusses the results and provides the concluding remarks of the paper.

2. Salmon Aquaculture Market

Short-run salmon price movements are largely independent of other fish prices such as cod, tuna or mackerel due to salmon's highly distinct sensory characteristics and because salmon is available fresh all year long due to the farming technology. This has allowed salmon to penetrate markets such as the sushi market, and more importantly, become a staple in supermarkets' counters as one of a handful of seafood products. Thus, to forecast salmon prices it is normally more important to understand what particularly happens in the salmon market, rather than on the continuing events in seafood markets more generally. This is why we give a run-down of the development of the salmon industry in this section based on previous research.

The salmon industry is relatively young and it was during the 1990s its output growth made it into the industry we know today. Several changes of the industry structure, government regulations, and demand growth have shaped the industry to what it is today: A heavy industrialized production system with high specialization, R&D, and a high-value product (Asche & Roll, 2013; Nilsen, 2010; Vassdal & Sørensen Holst, 2011). However, during its young age, the salmon industry has gone through many turbulent periods leading to structural changes in the industry. Particularly, there have been periods of environmental issues, productivity growth, trade issues, disease outbreaks leading to low and high price periods (Asche, Oglend, & Selland Kleppe, 2017) . The turbulent periods in the industry have also influenced regulatory changes linked to the salmon licenses and practices associated with salmon farming. It has also led to changes in the cost structure. For example, Chile which used to be the lowest-cost producer has become the highest-cost producer (Iversen et al., 2020). This cost development must be linked to the disease outbreak of the ISA virus in 2007 (Asche, Hansen, Tveterås, & Tveterås, 2009) and the subsequent restructuring of the industry in Chile (Asche, Cojocaru, & Sikveland, 2018).

Of particular importance for salmon production are the improvements of feed inputs as feed constitutes more than half of producer costs (Asche & Oglend, 2016) and the amount of protein on feed can influence salmon grow rates and harvest patterns. Initially, feed inputs were heavily reliant on fishmeal, but technological improvements and R&D on feed have led to a reduction of the total amount of fishmeal present on feed for salmon, going from 50% of feed protein in the 1990s to less than 15% on the 2010s (Asche, Oglend, & Tveteras, 2013). The issue of what influences feed cost is key to understand the development of salmon production costs and thus influences pricing.

Salmon prices started to show an increasing trend since 2005 mostly linked with increases in production costs. Three main factors have been attributed to this tendency: lower productivity, biological/environmental factors, and regulatory changes in the sector. Since 2005, productivity growth has slowed down because of the disease and parasitic challenges and because shifts on the production frontier are less common and productivity improvements rely solely on allocative efficiency (Asche, Guttormsen, & Nielsen, 2013; Vassdal & Sørensen Holst, 2011). This slowdown could reflect a maturing of the industry that combined with negative biological shocks has produced negative productivity growth for the last 10 years (Asche, Roll, & Tveteras, 2009; Rocha Aponte & Tveterås, 2019). This means that salmon is becoming more like poultry production where feed is the main variable cost input.

Disease outbreaks like ISA and pancreas also have affected production volumes in the largest salmon producer: Norway. However, the biggest challenge during the last decade has been the parasitic issues associated with sea lice. As several studies have shown, the lice issue has caused large cost increases in salmon farming (Abolofia et al., 2017; Rocha Aponte & Tveterås, 2019). Disease problems have also influenced the observed costs and price increases. Sea lice contagion generates cost increases via treatment costs, reduced fish growth, and food conversion efficiency (Costello, 2009). Additionally, these costs are not completely individualized as lice spread patterns share a connectivity structure in areas with a high density of salmon farms (Samsing, Johnsen, Dempster, Oppedal, & Treml, 2017), which provides evidence of negative agglomeration externalities in the sector. The effect of lice diseases on salmon aquaculture can be captured on other production costs (related to disease treatments) that went from accounting 19% of total costs in 2001 to 28% in 2014 (Aponte, 2019). Lice disease problems in Norway have been estimated to sum up to US $436 million or approximately 9% of farm revenues (Abolofia et al., 2017).

Regarding regulatory changes, in 2005 the Norwegian government introduced a Maximum Total Biomass (MTB) restriction on salmon farming producers in Norway. This system restricts the maximum amount of standing biomass that a producer can have at any time via a licensing system[1]. The effects of the MTB system on production costs are not clear due to the intricacies of the production process, the MTB works at the same time as an input and an output and to some extent may increase production costs by binding the quantity produced (Asche et al., 2019; Asche, Roll, & Tveteras, 2016). However, the MTB may also have helped in reducing costs by constraining the number of production sites and therefore limiting negative agglomeration externalities (Asche, Roll, et al., 2009; Asche et al., 2016).

From the demand side, strong growth in the 2000's had a positive effect on profitability but the growth has not been smooth with a potential effect on price volatility (Asche, Dahl, Gordon, Trollvik, & Aandahl, 2011; Brækkan & Thyholdt, 2014; Brækkan, Thyholdt, Asche, & Myrland, 2018). The consolidation of a global aquaculture market, global population, and income growth had an increasing effect on salmon prices. For instance, Roy Dahl and Yahya (2019) found volatility co-movements between prices of salmon and other aquaculture species (tilapia, catfish, and trout) which indicates market integration in the long run. However, there is no evidence of volatility spillovers from other markets (commodities and financial) into salmon prices (Asche et al.,

[1] A single license have a standing biomass of 780 tonnes of salmon except for the northern regions that have a higher MTB of 945 tonnes.

2019; Roy Dahl & Jonsson, 2018). The salmon market has expanded geographically via higher number of product forms in the early 2000s (Asche & Bjorndal, 2011) although this growth greatly varies within regions and overtime having an influence on salmon price volatility (Brækkan & Thyholdt, 2014).

The interactions of all the factors mentioned above make salmon prices face discontinuous shifts and higher volatility which makes their modeling an intricate job; thus, models for salmon price must be flexible enough to capture such shifts in market fundamentals and varying volatility in a simple and parsimonious manner. In the next section, we elucidate the modeling strategy for the salmon prices.

3. Methodology

To model and forecast monthly salmon prices we focus on time series models for two main reasons: First, time series models are simple and intuitive; this is convenient for practitioners and producers on the sector. Second, the frequency and span of our data allows time series models to be parsimonious when compared with different techniques such as neural networks and machine learning algorithms. Among time series models, we choose the following:

VAR

Vector autoregressive (VAR) models are the generalization of ARIMA models for multiple time series. VAR models allows for estimation of multiple time series without the strong assumptions of multiple equations regression models (Sims, 1980). After choosing the appropriate backshift operator, a VAR model has the following general form:

$$Ay_t = F_0 + F_1 y_{t-1} + \cdots + F_p y_{t-p} + u_t \tag{1}$$

Where y_t is a $kx1$ vector of observed variables, u_t is a $kx1$ structural shock that is assumed to be $u_t \sim N(0, \Sigma\Sigma)$. A and F are kxk matrices of coefficients with A being the simultaneous relationship across variables. Furthermore:

$$\Sigma = \; diag(\sigma_1, \dots, \sigma_k) \tag{2}$$

$$\mathrm{A} = \begin{pmatrix} 1 & 0 & \cdots & 0 \\ a_{21} & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ a_{k1} & \cdots & a_{k,k-1} & 1 \end{pmatrix} \tag{3}$$

Equation 2 can be written in reduced form as follows:

$$y_t = \beta_1 y_{t-1} + \cdots + \beta_p y_{t-p} + A^{-1}\Sigma\mathrm{\varepsilon_t} \tag{4}$$

Where $\beta_i = A^{-1}F_i, \quad i = 1, \dots, p$ and $\varepsilon_t \sim N(0, I_k)$ with I_k as an identity matrix of order k.

VAR models allow for multiple relationships across variables, which is convenient when modeling series where the causality is unknown and/or series affect each other. We estimate VAR models including different lag specifications and combinations of the selected supply and demand-side variables. Additionally, we also estimate the same models assuming some of the variables as exogenous ones (VARX models).

TVP-VAR

A time varying parameter VAR model is an extension of VAR models that allows time variation of the coefficients, this lets *"to capture possible non linearities or time variation in the lag structure of the model. The stochastic volatility is meant to capture possible heteroscedasticity of the shocks and nonlinearities in the simultaneous relations among the variables of the model"* (Primiceri, 2005). The TVP-VAR can be obtained from equation 4 as follows (Nakajima, 2011):

$$y_t = c_t + \beta_{1t} y_{t-1} + \cdots + \beta_{pt} y_{t-p} + e_t, \quad e_t \sim N(0, \Omega_t) \tag{5}$$

For $t = p+1, \dots, T$, $\Omega_t = A_t^{-1} \Sigma_t \Sigma_t A_t'^{-1}$. All the time varying parameters are assumed to follow a random walk process

$$\beta_{t+1} = \beta_t + v_t, \quad \beta_{t+1} \sim N(\mu_{\beta_0}, \Sigma_{\beta_0}) \tag{6}$$

$$a_{t+1} = a_t + \varsigma_t, \quad a_{t+1} \sim N(\mu_{a_0}, \Sigma_{a_0}) \tag{7}$$

$$h_{t+1} = h_t + \eta_t, \quad h_{t+1} \sim N(\mu_{h_0}, \Sigma_{h_0}) \tag{8}$$

Where $h_{it} = log\sigma_{it}^2$. The assumption of random walk is useful as it allows the model to focus on permanent shifts while reducing the total number of parameters to be estimated (Primiceri, 2005). The innovations of equations 5 to 8 are jointly normally distributed as follows:

$$\begin{pmatrix} e_t \\ v_t \\ \varsigma_t \\ \eta_t \end{pmatrix} \sim N \left(0, \begin{pmatrix} I_k & 0 & 0 & 0 \\ 0 & \Sigma_\beta & 0 & 0 \\ 0 & 0 & \Sigma_a & 0 \\ 0 & 0 & 0 & \Sigma_h \end{pmatrix} \right) \tag{9}$$

The TVP-VAR model can be understood as a non-linear state-space model due to the time variation of the underlying volatility structure where the standard Kalman filter estimation is computationally time-consuming (Koop, 2017). Therefore, we estimate the TVP-VAR through Bayesian inference using MCMC methods.[2] However, MCMC methods became highly computationally demanding when forecasting because the posterior simulation algorithm has to be run recursively on an expanding window of data (Koop, 2013). To avoid such a burden, we estimate the forecast by using shrinkage priors and forgetting factors following the methodology developed by Koop and Korobilis (2013). Their estimation methodology allows not only to produce forecast in a computationally simple manner but also to perform model selection and dynamic model averaging for models with different number of variables, which proves useful in our case.

[2] For a detailed treatment of MCMC methods for TVP-VARS see (Koop & Korobilis, 2013; Nakajima, 2011; Primiceri, 2005)

Forecast performance measures

Four main performance measures are considered for evaluating the forecasting performance of the models: Root mean squared error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE), and Theil's U –statistic. These set of statistic measures can be presented as below:

$$RMSE = \sqrt{\frac{1}{T}\sum_{t=1}^{T} e_t^2}$$

$$MAE = \frac{1}{T}\sum_{t=1}^{T} |e_t|$$

$$MAPE = \frac{1}{T}\sum_{t=1}^{T} 100 \cdot |\frac{e_t}{y_t}|$$

$$U = \frac{\sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(\frac{f_{t+1} - y_{t+1}}{y_t}\right)^2}}{\sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(\frac{y_{t+1} - y_t}{y_t}\right)^2}}$$

Where y_t is the value of the variable at time t and f_t is its forecast, $e_t = y_t - f_t$ is the forecast error. Several remarsk should be taken when choosing the right accuracy measure to compare forecast models: RMSE has the disadvantage of being dependent on the scale of the variable to be forecasted, and can provide very loose accuracy because the forecast error variance varies over time, particularly when predicting variables with increasing volatility over time (Fair, 1986). MAE is also dependent on the scale but less sensitive to large variance on forecast errors. MAPE has the advantage of not being sensitive to the scale of the variable but can lead to large errors when outliers are present or when the value of the original series is close to zero. Finally, Theil's U statistic presented above refers more to a measure of forecast quality than accuracy; Theil's U measures compares the forecast model with the naïve model forecast[3], if its value is above 1 then the naïve model is more accurate than the proposed one.

4. Data

To model salmon spot price is necessary to take into account possible drivers, we choose to use the following variables: salmon spot price, salmon export volume (as a proxy for quantity supply), EUR/NOK exchange rate, soybean for feed price index, and fishmeal price index. Our sample consists of monthly data for all of the variables from March 2001 until April 2018 (219 observations). We evaluate the forecast accuracy for each model 1, 4, 8, and 12 months ahead going from May 2018 until May 2019. Table 1 presents the summary statistics for the selected variables:

[3] Naïve forecast is the forecast technique when all the future values are set to be the value of the last observation $f_{t+1} = y_t$. This forecast is also called random walk forecast and tend to perform better than more sophisticated forecast models when the frequency of the data is high (references).

Table 5 - Descriptive statistics

Variable	Mean	Median	Min	Max	SD	Skewness	Kurtosis
EUR/NOK rate	8.3418	8.1575	7.2953	9.8412	0.6759	0.6533	2.3559
Soybean Index	92.1477	96.4202	47.2476	167.2781	29.1553	0.1654	2.2516
Fishmeal Index	87.2841	89.3172	33.7910	168.3923	30.9099	0.0737	2.1531
Export volume	53712.77	52975	15093	104621	21541	0.2765	2.2008
Spot price	34.91781	28.8240	15.6060	74.5150	14.5236	0.9587	2.9578

Salmon spot price series are publicly available on the fishpool website. As in (Bloznelis, 2016a, 2018b), we adjust the prices by substracting $0.75kg^{-1}$ to the price after 2013. As observed in figure 1, salmon prices present an increasing time trend, seasonality, and growing monthly price variation that becomes evident from 2011 and onwards. Salmon price is influenced by demand factors as variations in supply from competing countries, this can be seen in the period 2009 -2012 when Chilean supply went down because of mass disease infections(Asche, Hansen, et al., 2009). On the other side, supply-side factors as input prices, regulatory changes, and biological conditions can force variations in the salmon price via variations on the volume produced.

We use the export volume of salmon as a proxy for the total supply. In Norway, more than 90% of total production is exported while only 4% of the total production is kept for local consumption. Data on volume exported is obtained from the Norwegian statistical central bureau (SSB). The volume of salmon exported presented an average growth of 8% from the period 2001-2018 going from 254 thousand tonnes in 2001 to 902 thousand tonnes in 2018. This steady growth reflects the increasing demand for salmon products worldwide and the consolidation of the market (Iversen et al., 2020). As depicted in figure 2, salmon exports are highly seasonal with peaks around Christmas and Easter periods. In the same way as with the spot price, the difference between peaks and downs increases since 2011.

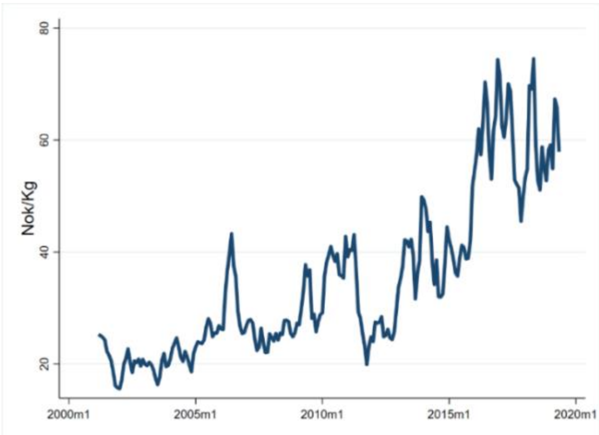

Figure 12 - Salmon spot price 2001-2019

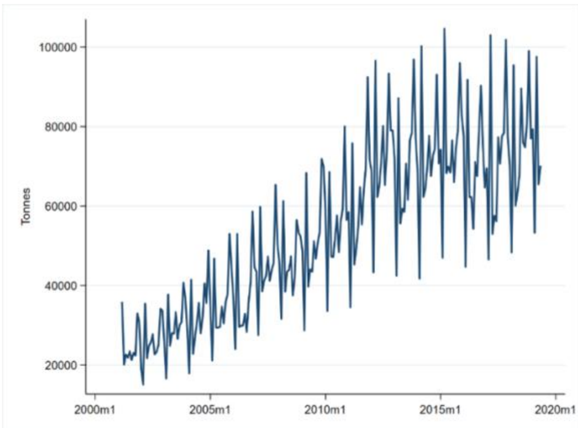

Figure 2 - Volume of salmon exported (fresh and frozen) 2001-2018

The exchange rate data is obtained from Norges Bank, exchange rates do not present any particular trend except with high variations during the economic crisis in Europe of 2008 and 2012 (figure 5). Exchange rates can affect the relative competitive advantage of the Norwegian salmon sector by affecting the relative production cost. Finally, soybean for feed and fishmeal indexes data are available on the FAO website. Both indexes exhibit similar behavior with a notorious increase in volatility after 2005 as represented in figures 3 and 4.

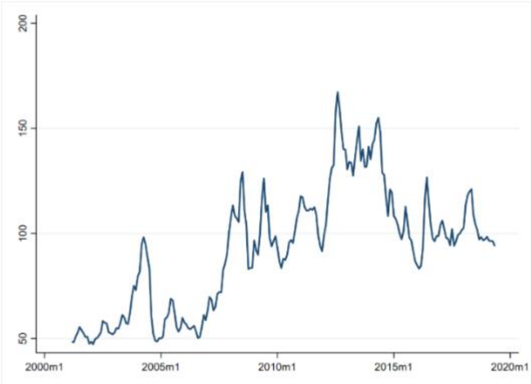

Figure 13 - Soybean for meal Index 2001-2019

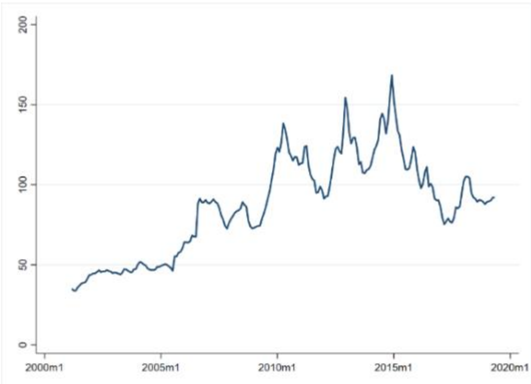

Figure 14 - Fishmeal index 2001-2019

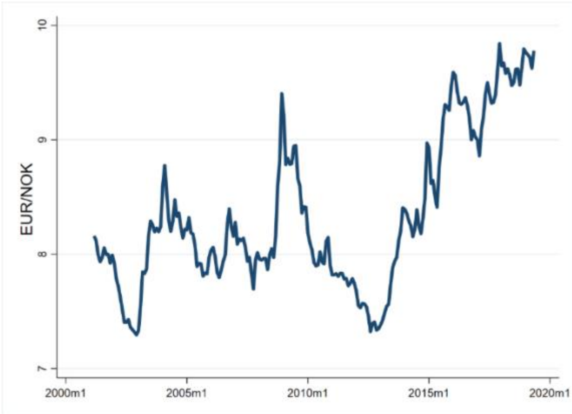

Figure 15 - Exchange rate EUR/NOK 2001-2019

5. Empirical Results

Modeling of the salmon price via VAR models requires stationarity, so we need to deal with the seasonality and trend in the selected variables. Exchange rates, soybean, and fishmeal indexes are transformed to stationarity by taking first order log differences. Given the strong seasonality in both volume exported and spot price we apply two different transformations: 1) Seasonal differences -12 month- of the log volume and log spot price, and 2) Baxter-King (BK) filter to remove both seasonality and trend of the levels of volume and spot price.

We estimate VAR models with 2, 3, and 4 lags. Due to the structural changes and increasing volatility of the salmon market as described in section 2, we use the time-varying parameter VAR model with stochastic volatility (TVP-VAR)[4]. The TVP-VAR allows specification and estimation of the relationships of the VAR system and present their interactions with the spot price via the impulse response functions (IRF). Second, we forecast the monthly price of salmon (or monthly variation of price) over a 12 month period and we evaluate the forecast accuracy of the models 1, 4, 8, and 12 months ahead.

VAR models and Impulse response functions

As stated before, VAR models of different lags are estimated. The lags are selected among possible candidates as indicated by the ACF and PACF functions of the 5 variables. We estimated the marginal likelihood to find the best model as in Chan and Eisenstat (2018) for the TVP-VAR. The model with the lowest marginal likelihood is the TVP-VAR with 4 lags (TVP-VAR4) with a value of 765.8, while the TVP-VAR3 and the TVP-VAR2 got values of 858.5 and 945.0 respectively.

Volatility estimation for each of the variables is depicted in figure 6. It can be seen that none of the series present constant volatility, which provides support for the TVP-VAR methodology; soybean and export volume exhibit a declining trend, spot price shows an increasing one and fish and exchange rates show no clear trend. The decreasing volatility estimates of exported volume can be attributed to the licensing system in Norway because each license constrained volume growth on the

[4] Estimation results of the Bayesian procedure for TVP-VAR can be found in the appendix.

extensive margin; thus, production growth is dependent on productivity improvements (Aponte, 2019; Asheim, Dahl, Kumbhakar, Oglend, & Tveteras, 2011).

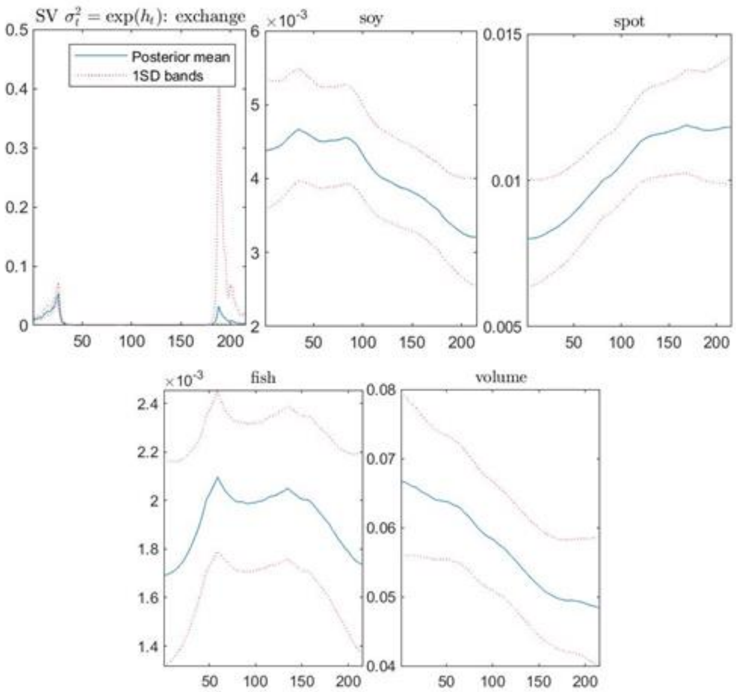

Figure 16 - Stochastic volatility of structural shock

Impulse response functions (IRF) for mapping the shocks in each of the five variables to salmon spot price are presented in figure 7. The IRF's are estimated by fixing a shock equal to the average size of the stochastic volatility for the varying parameters at each point in time, then every step is averaged over all the time periods and 95% credible intervals are constructed around them. We plot the IRF's up to 12 steps ahead, as expected, a positive shock on the EUR/NOK exchange rate will make the salmon price relatively more expensive internationally. A shock in the soybean index has a positive effect on spot price but the effect disappears quickly. On the contrary, the effect of fishmeal has an initial negative shock on spot price; even though feed inputs constitute around of 50-60% production costs, fishmeal has become relatively less important as a component of salmon feed given productivity improvements in the feed process while soybean constitutes the price leader in the protein market. Finally, a positive shock in exported volume has a negative effect on spot price which goes accordingly with economic theory.

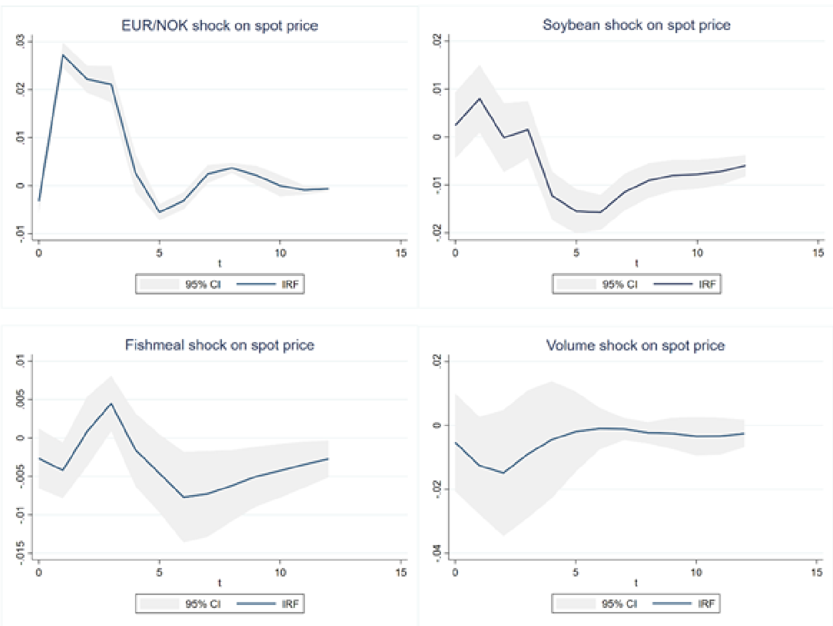

Figure 17 - Impulse response functions on salmon spot price

Additionally, the TVP-VAR models allow us to identify the simultaneous relationship between the variables as expressed by the non-zero elements of the A_t^{-1} matrix as shown in equation 3. Figure 8 shows the simultaneous relations, we found that most of them are constant over time except for the relation between soybean and fishmeal that increases over time, which demonstrates that soybean is the price leader regarding protein feed options. Of particular interest is the instant relation between fishmeal and spot price, with a negative slope, reflecting the diminishing relative importance of this variable on feed composition and feed input costs for salmon farming.

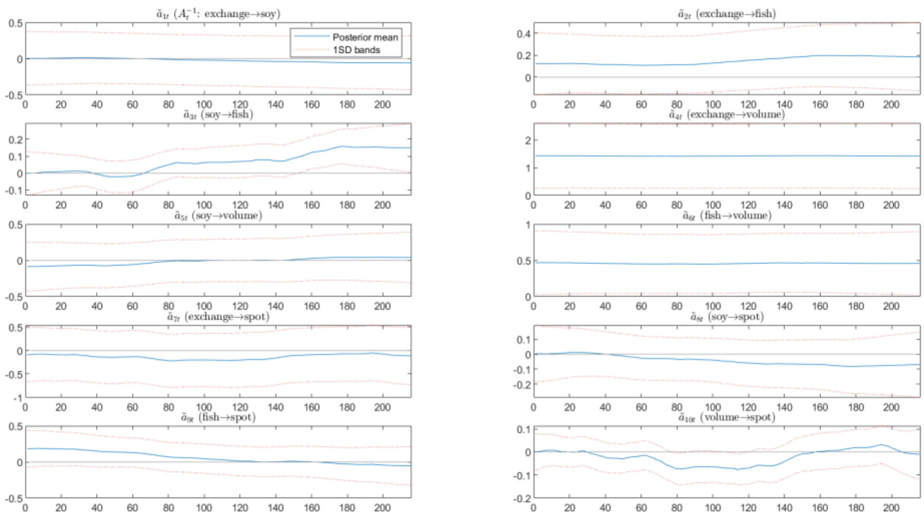

Figure 18 - Simultaneous relationship among variables

Forecasting models

In this section we test the forecast accuracy of the TVP-VAR model against traditional VAR models, to do so we forecast the monthly salmon spot price for horizons up to 1 year ($h = 1, 4, 8, 12$) and we choose the evaluation period to be May 2018 – May 2019. As forecast performance measures we focus on absolute values (MAE), and Theil's U statistic, but we also present absolute percentage values (MAPE) and root mean squared errors (RMSE) for completeness. Tables 2 and 3 display the forecast measures for the fixed VAR and VARX[5] models with the BK filter and the seasonal transformation respectively. For models with BK filter, most of them predict the monthly price relatively well for all forecast horizons with VARX4 and VAR4 presenting the lowest MAE calculations and the lowest Theil's U statistic for all horizons, meaning that these models outperform the naïve model in the 1-year horizon. Similar results are found with the seasonal transformation models regarding MAE measures with 4 lags VAR models having the lowest error measures; however, when looking at Theil's U all models fail to outperform the naïve model at horizon 12.

[5] VARX models are VAR models with one or more exogenous variables. In our system, we decide to model the exchange rate as exogenous as this variable is the only one to be not directly affected for any of the other variables.

Table 6 - Forecast accuracy VAR models 1

Baxter King Filter							
	Horizon	**VARX2**	**VAR2**	**VARX3**	**VAR3**	**VARX4**	**VAR4**
RMSE	1	0.0047	0.0047	0.0046	0.0047	0.0039	0.0041
	4	0.0064	0.0064	0.0068	0.0067	0.0054	0.0055
	8	0.0081	0.0079	0.0080	0.0077	0.0070	0.0068
	12	0.0104	0.0098	0.0095	0.0089	0.0084	0.0078
MAE	1	0.0033	0.0033	0.0033	0.0033	0.0028	0.0029
	4	0.0055	0.0054	0.0057	0.0056	0.0045	0.0046
	8	0.0069	0.0067	0.0068	0.0065	0.0059	0.0058
	12	0.0091	0.0086	0.0084	0.0079	0.0074	0.0070
MAPE	1	0.2014	0.2014	0.1978	0.2031	0.1676	0.1767
	4	0.5147	0.5039	0.5455	0.5709	0.4745	0.4870
	8	0.0334	0.3076	0.2450	0.2177	0.2906	0.0880
	12	0.0585	0.0533	0.0807	0.0757	0.0260	0.0177
Theil's U	1	0.5256	0.5257	0.5163	0.5301	0.4376	0.4613
	4	0.6315	0.6277	0.6491	0.6276	0.4859	0.4845
	8	0.6833	0.6807	0.6836	0.6608	0.5649	0.5537
	12	1.0657	0.9955	0.9498	0.8803	0.8650	0.7983

Table 7 - Forecast accuracy VAR models 2

Seasonal Filter							
	Horizon	**VARX2**	**VAR2**	**VARX3**	**VAR3**	**VARX4**	**VAR4**
RMSE	1	0.1483	0.1456	0.1441	0.1345	0.1301	0.1224
	4	0.1535	0.1514	0.1450	0.1357	0.1281	0.1214
	8	0.1275	0.1261	0.1274	0.1259	0.1248	0.1232
	12	0.1097	0.1084	0.1094	0.1082	0.1076	0.1061
MAE	1	0.1049	0.1029	0.1019	0.0951	0.0920	0.0865
	4	0.1257	0.1244	0.1171	0.1088	0.1019	0.0960
	8	0.1058	0.1052	0.1082	0.1092	0.1088	0.1081
	12	0.0887	0.0884	0.0887	0.0891	0.0882	0.0883
MAPE	1	0.6889	0.6762	0.6697	0.6246	0.6043	0.5683
	4	1.3280	1.3241	1.1824	1.0716	0.9814	0.9076
	8	0.3382	0.3326	0.2028	0.0956	0.0233	0.0376
	12	0.9421	1.2174	0.2595	0.3098	0.1079	0.3919
Theil's U	1	0.9770	0.9590	0.9493	0.8858	0.8571	0.8060
	4	1.0408	1.0232	1.0027	0.9365	0.8999	0.8480
	8	0.7994	0.7900	0.8336	0.8512	0.8743	0.8850
	12	1.4233	1.4887	1.1572	1.1332	1.0628	1.1046

As observed in tables 2 and 3, none of the forecast consistently outperform the others. This is why we proceed to apply the Diebold-Mariano (DM) test. The DM test evaluates the null hypothesis that the competing models are equally accurate on average; this is done by evaluating the loss function associated with each model. For the DM test, we use absolute loss because farmer revenues depend linearly on the salmon price (Bloznelis, 2016a, 2018b). Results for the DM tests are summarized in tables 4 and 5. The results for the BK filter models show that for all lags full VAR models outperform the forecast of VARX models. The VAR4 model has the highest forecast accuracy at a 5% significance level. In contrast, for the seasonal transformation models, we fail to reject the null hypothesis of equal forecast accuracy for all lags and all horizons.

Table 8 - DM tests for models with BK filter

Models	**Lag**	**Test Statistic**	**p-value**
VAR2 vs VARX2	1	2.125	0.0335**
	4	1.769	0.0769*
	8	1.938	0.0526*
	12	2.318	0.0205**
VAR3 vs VARX3	1	2.518	0.0118**
	4	2.239	0.0251**
	8	2.288	0.0222**
	12	2.729	0.0064**
VAR4 vs VARX4	1	1.690	0.0910*
	4	1.613	0.1068
	8	1.662	0.0966*
	12	1.984	0.0472**
VAR3 vs VAR2	1	1.858	0.0632*
	4	1.500	0.1337
	8	1.606	0.1083
	12	1.920	0.0548*
VAR4 vs VAR3	1	2.597	0.0094**
	4	3.720	0.0002**

Models	Lag	Test Statistic	p-value
	8	5.861	0.0000**
	12	6.777	0.0000**

Notes: *** denotes 99% significance, ** 95% significance, and * 90% significance levels

Table 9 - DM tests for models with seasonal transformation

Models	Lag	Test Statistic	P-Value
VAR2 vs VARX2	1	0.1438	0.8856
	4	0.1954	0.8451
	8	0.2027	0.8393
	12	0.2345	0.8140
VAR3 vs VARX3	1	-0.1245	0.9000
	4	-0.1289	0.8974
	8	-0.1289	0.8974
	12	-0-2239	0.8229
VAR4 vs VARX4	1	0.2604	0.7946
	4	0.2907	0.7713
	8	0.3545	0.7229
	12	0.4262	0.6700

Table 6 shows the forecast performance measures for the TVP-VAR models, these results are the average measures over the forecast simulations of the Bayesian algorithm employed. All models perform well and the four performance measures present similar numbers. It should be noted that all models in all horizons clearly outperform the naïve model as given by the Theil's U results. On the other hand, when applying the DM-tests there is a clear winner, the TVP-VAR4 has higher forecast accuracy for all horizons when tested against the TVP-VAR3 and TVP-VAR2 models as seen in table 7.

Table 10 - Forecast accuracy TVP-VAR models

		TVP-VAR		
	Horizon	**VAR2**	**VAR3**	**VAR4**
RMSE	1	0.1118	0.1133	0.1134
	4	0.1127	0.1099	0.1122
	8	0.1149	0.1162	0.1182

	TVP-VAR			
	Horizon	**VAR2**	**VAR3**	**VAR4**
	12	0.1116	0.1145	0.1169
MAE	1	0.0937	0.0960	0.0970
	4	0.0926	0.0901	0.0931
	8	0.0948	0.0955	0.0970
	12	0.0935	0.0981	0.1001
MAPE	1	1.3258	1.3470	1.3168
	4	1.0519	1.0160	1.0379
	8	1.0046	1.0085	1.0196
	12	1.0291	1.0104	1.0162
Theil's U	1	0.8345	0.8193	0.8144
	4	0.9707	0.9336	0.9324
	8	0.9713	0.9758	0.9808
	12	0.9807	0.9788	0.9869

Table 11 - DM tests TVP-VAR model

Models	**Lag**	**Test Statistic**	**P-Value**
VAR4 vs VAR3	1	6.10	0.0000***
	4	11.63	0.0000***
	8	13.76	0.0000***
	12	17.96	0.0000***
VAR4 vs VAR2	1	-2.463	0.0138**
	4	-2.351	0.0187**
	8	-2.635	0.0084**
	12	-3.76	0.0021**

Notes: *** denotes 99% significance, ** 95% significance, and * 90% significance levels

To make the different estimated models comparable, we transform the forecast calculations of the winner models back to their original levels and apply the DM test on them. Given the change of scale when applying the forecast in levels, the loss function used this time is the absolute percentage loss as this measured normalize the errors by the true observations. As displayed in table 8, the TVP-VAR4 model has a forecast accuracy that is statistically significant better than all the other models for all horizons. Next in rank according to forecasting accuracy is the VAR4 model for the BK filter and the VAR4 model for the seasonal transformations. One of the main reasons the TVP-VAR model better forecasts salmon spot prices is that the fixed VAR models very quickly converge towards the long-term mean price while the TVP-VAR models captures better short term changes via both the varying parameters and more the stochastic volatility as it can be seen in figure 9.

Table 12 - DM tests for models in levels

Models	**Lag**	**Test Statistic**	**P-Value**
TVP-VAR4 vs VAR4bk	1	-2.373	0.0177**
	4	-4.757	0.0000***
	8	-5.975	0.0000***
	12	-7.066	0.0000***
TVP-VAR4 vs VAR4	1	-2.130	0.0332**
	4	-3.940	0.0001***
	8	-5.140	0.0000***
	12	-6.117	0.0000***
TVP-VAR4 vs VARX4	1	-2.062	0.0392**
	4	-3.837	0.0001***
	8	-4.994	0.0000***
	12	-5.970	0.0000***
TVP-VAR4 vs VARX3	1	-1.849	0.0644*
	4	-3.272	0.0011***
	8	-4.314	0.0000***
	12	-5.135	0.0000***
TVP-VAR4 vs VARX2	1	-1.681	0.0927*
	4	-2.800	0.0051***
	8	-3.729	0.0002***
	12	-4.434	0.0000***
TVP-VAR4 vs VAR2	1	-1.699	0.0892*
	4	-2.809	0.0050***
	8	-3.736	0.0002***
	12	-4.442	0.0000***
TVP-VAR4 vs VAR3	1	-1.990	0.0466**
	4	-3.556	0.0004***
	8	-4.688	0.0000***
	12	-5.578	0.0000***

Notes: *** denotes 99% significance, ** 95% significance, and * 90% significance levels

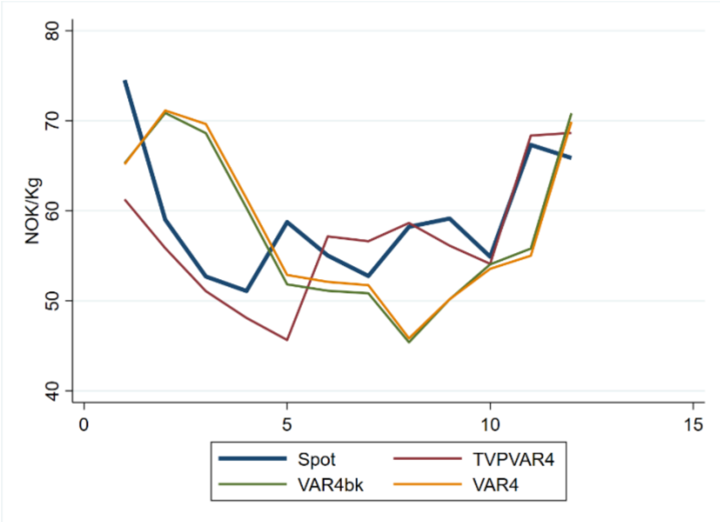

Figure 13 - Forecast of monthly salmon spot prices

6. Discussion

The results support the proposition that when past data represents a period of structural changes the accuracy of price forecasts can be improved by applying a time-varying parameter approach. In such cases, one would presume that forecast models built on constant parameters will be misspecified. In fact, the DM test results indicate that the TVP-VAR model outperforms all the alternative models for all included forecasting horizons. As discussed earlier, the salmon market is an exemplar of a market that has undergone large structural changes. These include both supply and demand induced changes driven by factors like disease issues, environmental externalities, changes in factor prices, international trade restrictions and technological innovations among the most important ones (Rocha Aponte & Tveterås, 2019).

The application of a TVP-VAR model allow us to capture the effect of the structural changes of the global salmon market on salmon prices in a parsimonious way. The impulse response functions allow us to identify a declining effect of fishmeal shocks on salmon prices, this situation reflects the introduction of other protein sources on feed. However, as soybean meal is the price leader of protein meal markets, a permanent increase in the soybean price implies an increase in the fishmeal price and a double effect on salmon prices. Exported volume has a negative instant effect on salmon spot price. Salmon supply is price inelastic in the short run, due to a biological production cycle that takes around 18 months (Andersen, Roll, & Tveterås, 2008; Asheim et al., 2011). Therefore it is reasonable to believe that volume shocks affect price rather than vice versa as observed from the impulse response functions.

None of the series analyzed have a constant volatility. On the contrary, the salmon price exhibits an increasing volatility trend. The increasing price volatility can be explained by supply fundamentals that have made the price-elasticity of supply more inelastic in the short run (Asche et al., 2019). Several factors come into play, as production volume is restricted by the number of salmon production licenses emitted by the authorities, the only way to increase total production is by reducing salmonid growth duration and harvesting more frequently – a race to raise – (Asche et al., 2019). In order to raise salmon faster, all inputs must be used more intensively (specially feed) which makes the production costs (and prices) more dependent on input prices (Andersen et al., 2008; Asche et al., 2019; Oglend & Sikveland, 2008; Rocha Aponte & Tveterås, 2019).

For producers and distributors short and medium term forecasts are of importance since price risk together with production risks generates uncertainty and higher volatility in revenues. Therefore, a more accurate forecasting model can improve production planning and increase profits. This is why it is important to evaluate how accurate is each model to capture positive and negative changes in salmon prices. All the models compared in table 8 predict price direction in at least 6 of the 12 months of the evaluated forecast period with TVP-VAR models predicting price changes correctly 8 out of 12 months. The TVP-VAR model is more accurate at predicting prices for the 4, 8, and 12 months horizons than the fixed VAR models. As expected, the TVP-VAR model better captures the changes on market conditions, such as structural changes in regulation, volatility of input prices (soybean and fishmeal), and models the seasonality present in salmon prices. The naïve random walk model outperforms all of our forecasting models for the 1 month horizon, this can be due to market efficiency and unpredictable shocks in the short term (Bloznelis, 2018b).

7. Concluding Remarks

Many studies have addressed the stochastic volatility present in salmon prices, but few have addressed the effects of such behavior on salmon price forecasting. Access to accurate forecasts is important in the short and medium-term since it gives better opportunities for more informed hedging decisions to producers. In this article, we estimated a time varying parameter VAR model with stochastic volatility for monthly salmon spot prices for the period 2001-2019. We include a set of variables that affect spot price behavior including exchange rates, soybean for meal price, fishmeal price, and export volume. Based on the TVP-VAR model, we calculated impulse response functions and forecast the spot price every month for a 12 month window.

The results support the rationale of using a TVP-VAR model, since the model lead to more accurate forecasts than competing models. In our case, the rationale for using the TVP-VAR approach was clear cut as we were dealing with past data that contained large shocks and structural shifts as documented in several studies (e.g., Asche, Cojocaru, & Sikveland, 2018; Asche, Misund, & Oglend, 2019; Rocha-Aponte & Tveterås, 2019). The salmon industry is at the verge of new large technological shift towards onshore and offshore production, which also can lead to structural changes in which regions of the World where salmon is produced. This sends a clear signal to anyone interested in forecasting salmon prices that the time-varying parameter approach will remain a relevant choice.

Whether TVP-VAR will perform similarly well for price forecasts in other market contexts where one suspect structural changes is an empirical question. Hopefully, this research will spur more interest in investigating the usefulness of this approach in cases where a rationale for applying it is present.

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