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Essays on Dynamic Behavior of Harvesters in Fisheries

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Abstract

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Dynamics is a key aspect of analyses on renewable natural resources, as it replenishes over time. While long-run dynamic aspect of harvester behavior has been traditionally explored, microeconomic short-run harvester behavior analyses have been attracting more attention recently. One of the main reasons of this attention is due to the demand on analyzing and predicting harvesters' reactions to regulations and management policies. A management policy could lead to an unwanted result because of undermined or mis-specified harvesters' incentives. Particularly, their forward-looking behavior in short-run, such as a trip or a season, is important to consider

because their behavior can be largely changed by a policy. In this dissertation, three different types of models are constructed to analyze harvesters' short-run dynamic behavior.

In the first chapter, harvesters' choice of trip duration is analyzed using dynamic discrete choice model. Production function, or harvest function in natural resource economics, is often estimated with temporally aggregated data. However, such estimations can be misleading if variable inputs are dynamically determined within a time period of the data, because the variation within a period is not taken into account. In this study, using a data from a longline fishery, I demonstrate a case that cruise-level production is determined not only by use of quasi-fixed inputs, but rather by dynamic consideration of the rate of daily harvest, balancing the quantity and quality of harvest to maximize their cruise level revenue. This response is modeled as a daily optimal stopping problem, with the state variables representing the decreasing freshness of fish caught on each previous day of the cruise. I estimate trip duration decisions based on unusually detailed daily logbook data on a Japanese longline fleet. The dynamic discrete choice problem is modeled with a conditional choice probability (CCP) estimator, which estimates the reduced form of CCP and transition probabilities in the first step to calculate the continuation value, and estimate the structural parameter using the calculated continuation value in the second step. The predictability is improved avoiding over-fitting in flexible logit to estimate CCP in the first step with elastic-net logit, a machine learning method. The results show harvesters are particularly sensitive to freshness deterioration of fish on board for more days, and are more likely to terminate their fishing cruise when more fish is caught around 15 or more days ago. This suggests that catching power defined by quasi-fixed inputs is not fully utilized due to a dynamic consideration of fish quality, and that a management strategy based solely on technical efficiency will systematically over-predict actual catches.

The second chapter discuss the harvesters' decision on weekly target choices in a horizon of a season. This study develops an empirical model of the harvesters' dynamic individual fishing quota (IFQ) use considering avoidance of bycatch, an incidental catch of non-targeted species, with the insight from a theoretical model. While theoretically shown, empirical analysis on allocation of IFQ over a season by harvesters have not been well-studied due to complexity of the seasonal dynamic problem. In this paper, we focus on participation and target species as harvester's margin, which are flexibly chosen under IFQ. To explore the incentive, we theoretically modeled the harvesters' behavior which purposes to maximize seasonal profit under constraints of the regulations. The solution motivates us to incorporate the dynamic quota use in a simple discrete choice model to estimate the harvesters' choice. To link the shadow cost of quota in our theoretical model and harvester behavior in the data, we construct a variable which captures harvesters forward-looking decision. The application of this empirical model is implemented with an offshore fleet in Alaskan groundfish fishery, which has appropriate feature to apply the model such as multiple target choices and individual quota. The result indicates that the dynamic variable adjusts the incentive to catch pollock for revenue, and the estimates of the coefficients on bycatch rate supports the dynamic avoidance behavior of bycatch.

The third chapter extends the model developed in the second chapter by incorporating spatial choice of harvesters. Because the main target and bycatch species are spatially heterogeneously distributed, the harvesters are possible to avoid bycatch while targeting the main species provided the participation decision in a given week. The harvesters decisions are modeled as two-stage process: target decision in the first stage, and location as the second. We adopt nested logit model to estimate this two-stage process. As a result, spatial choice is an important margin to avoid bycatch dynamically, but it is not in B season as the estimation result is not consistent

with utility maximization theory in B season. In A season, the timing of high bycatch rate and the timing of matured pollock roe that has high value overlap, hence the harvesters cannot flexibly change the timing. Instead, use the spatial margin to avoid bycatch while maximizing the revenue from pollock. In B season, there is more flexibility in timing choice. The harvesters rely on timing choice rather than spatial choice in the B season. Both avoidance behavior is driven by the forward-looking expectations since the interactions with dynamic variables are key factors to explain the harvesters' behavior.

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DEDICATION

To my parents and sister

Chapter 1. A DYNAMIC MODEL OF FISHING CRUISE DURATION

1.1 INTRODUCTION

Production function, or harvest function in natural resource analyses, characterizes a relationship between output and inputs. This function is empirically estimated using panel data to take into account time-invariant productivity. Any unobserved factors that affect productivity may be a source of bias in estimation if they are time-varying and correlated with the inputs. Olley and Pakes (1996) suggested an approach that incorporates time-varying productivity across the periods. However, it can be a problem if the unobserved factors vary within a data period because they could affect both variable inputs and output. Hence, temporal misspecification of production function may lead to the wrong characterization of output-inputs relationship if producers adjust variable inputs responding to factors that vary within a period. This study shows a case that producers in a fishery adjust their inputs in response to a variable that changes during a fishing cruise, suggesting that cruise-level production function estimation can be misleading.

Production function as output-inputs relationship is important for natural resource management, since the direct control of output may be difficult in some context, and input control are adopted instead. In fisheries for example, while it would be ideal to directly restrict mortality, output regulations including catch quotas and size limits are not very effective in practice. Merely imposing output control causes increased competition for limited supply of fish, known as race-for-fish [2] and over-investing in fishing power, called “capital stuffing” (Clark and Munro 2002). To control these issues, the management bodies need to implement regulation on inputs to control potential output of a fleet or a vessel. The management restricts fleet size based on the potential output (maximum attainable catch) of the fleet given fixed inputs (e.g. vessel size), the status of resource stock, the states of technology, and fully utilized variable inputs. Achieving potential

level of harvest is a result of a corner solution of harvester's profit- or utility-maximizing problem. Catching as much as one can by fully utilizing variable inputs may be optimal if harvest exhibits neither decreasing return to effort nor increasing marginal cost. However, revenue may exhibit decreasing return even if catch does not, because quality or value may become lower as a variable input increases. Specifically, days at sea of a trip is one of variable inputs of fishing production. As a harvester go on a longer fishing cruise, he can harvest more, but the freshness of fish may deteriorate as time goes by. Under this setting, attaining maximum catch may not be an optimal choice, because a longer trip may worsen the quality of fish already caught. To investigate this question, we model harvesters' strategies on fishing cruise duration in response to freshness deterioration.

This study employs daily data of a longline fishery and use a dynamic random utility model to analyze harvester choice of trip duration. We consider harvesters' decisions of duration choice as an optimal stopping problem. Harvesters face trade-offs between additional catch or revenue and the negative impact on quality from cruise continuation. While previous studies hypothesize that the negative impacts are disutility from days at sea or reduced marginal utility due to target revenue, we characterize the negative impact as freshness deterioration. Freshness is an important factor of the value of a fish, and is a particularly important determinant of price if the fish is to be consumed raw (Ishimura and Bailey 2013). Hence, we hypothesize that harvesters' trade-off between an additional day's catch and loss of freshness of fish already caught when they decide whether to cruise an additional day.¹

Results show that freshness matters in the harvester's decision on continuation of a trip. Holding 15 to 20 days old fish significantly reduce the probability of continuation while newly-

¹ Curtis and Hicks (2000) consider freshness deterioration as a cost associated with accessing a more distant fishing site, but the harvesters' evaluation of the deterioration itself is not estimated.

caught fish do not negatively affect the continuation decision. This implies that the cruise average catch approach used in previous literature may cause a problem, and the variation of event within a cruise matter.

The remainder of this paper is organized as follows. Section 2 introduces related literature and locates this study in the field. In Section 3, we introduce the swordfish and blue shark longline fisheries in Kesenuma, Japan and describe the data. We explain our conceptual model as an approach to the research question in Section 4. Section 5 provides the model-free evidence that supports our hypothesis. We then show the importance of freshness in this fishery from the market data in Section 6. Section 7 details our empirical model and describe the estimation method. In Section 8 we show and discuss the empirical results. Section 9 concludes.

1.2 RELATED LITERATURE

1.2.1 *Production Function in Fisheries*

Production function, or frontier, is estimated to reveal the relationship between output and inputs. The main interests in economics to estimate production functions include heterogeneous technology, technical progress, and production frontier given inputs. In this stand point, there is a series of production function studies in fisheries economics. Comitini and Huang (1967) revealed the heterogeneity in technology, interpreted as differences in managerial skill of the boat captains. Kirkley, Squires, and Strand (1995) estimate the production frontier, and consider the deviation from the frontier as technical inefficiency. Using technical efficiency approach, Kirkley, Squires, and Strand (1998) and Squires and Kirkley (1999) explicitly relates differences in the skills of boat captains to heterogeneous technical inefficiency.

Furthermore, in natural resource management, output-input relationship can be used to evaluate the effect of managements. Hannesson (1983) estimate the optimal vessel size and capital

intensity using the estimated production function. This idea is sophisticated with the technical efficiency approach, and leads to capacity utilization analyses. Capacity² is defined in terms of potential output, and capacity utilization is the actual output divided by the capacity [10]. Capacity utilization provides insights in terms of both biological and economic perspective, because large capacity is a potential threat on resource stock, and low capacity utilization represents inefficiency. To measure the capacity, production frontier is estimated using stochastic frontier and data envelope analysis (DEA) [11,12].

The question here is that how the inputs are determined to produce output. Capacity utilization approach estimates the potential output given the inputs, but the estimation may cause biases if the determination of the input is affected by unobserved factors that are correlated with output. Kirkley et al. [6] assume that the variable inputs are determined by expected profit maximization, and hence input choices are not correlated with the error term in the production function. Such assumption, however, may not be valid in the setting of fishing with multiple days trip. While daily-level production estimation with variable inputs, such as hours of tow (e.g. Eide et al. [13]), may support expected profit maximization hypothesis, it is unlikely in trips with multiple days since captains can observe the outcome and adjust the inputs. What we need is a model of harvesters' adjustment process during a trip.

Days at sea, or duration of a fishing cruise, has been analyzed to reveal the decision mechanism of cruise (fishing trip) duration choices. Choice of fishing time was first analyzed in terms of labor supply. McGaw [14] explains that the supply of each fishery responds to the ex-vessel price and catch in the previous period. Gamtam et al. [15] use an intertemporal labor supply

² The word "capacity" is a source of confusion in the discussion over management. While the definition of capacity varies by field and context and sometimes refer fixed inputs (e.g. vessel size), FAO defines the capacity as "...the maximum amount of fish over a period of time (year, season) that can be produced by a fishing fleet if fully utilised, given the biomass and age structure of the fish stock and the present state of the technology." [52].

model with rational expectations, and find that harvesters respond to profits per day from fishing and use that information to adjust the duration of their trip. These works assume that the harvesters are workers rather than producers, and maximize utility including disutility of labor. An interesting question raised by these studies is that harvesters negatively respond to temporal wage/revenue increases. In other words, harvesters shorten the duration of a fishing cruise if fishing performance is good. According to the traditional labor theory, they should positively respond to a temporal increase in revenue.

Some studies tackle this question with a target revenue or reference-dependent model³. Holland [16] shows anecdotal evidence of income target behavior in fisheries based on an ethnographic interview of harvesters in the groundfish fishery in New England. Given this evidence, Nguyen and Leung [17] estimate the effect of average daily revenue on length of trip with cruise-level data from the Hawaiian longline fishery, and find the negative response of cruise length to the average daily revenue. Ran et al. [18] empirically test the reference-dependent hypothesis with a proportional hazard model, and report that the harvesters are more likely to stop a cruise after the revenue achieves the target level which is assumed to be average revenue of previous trips.

A potential problem that these studies have is sourced from the cruise-level data. Estimating the duration choice behavior with cruise-level data has two issues. First, catch per cruise and duration of a cruise may be endogenous variables. If a harvester increases the duration, the total catch increases. On the other hand, the harvester would adjust the duration depending on catch performance. Next, the day-by-day behaviors of harvesters are averaged out with trip-level

³ Camerer et al. (1997) propose the target revenue hypothesis. Estimating the labor supply decisions of NYC taxi drivers, they find that the taxi drivers drive more on low-earning days. Since this result is inconsistent with the traditional theory, the authors hypothesize that taxi-drivers set a target revenue per day and marginal utility dramatically decreases after they achieve the target.

data. One accordingly needs to impose strong assumptions on the day-by-day behavior, and the estimation is not structural. The unique data available for our study resolve this issue by allowing us to specify the effect of daily catch on harvesters' decisions. With such data, we model the harvesters' choice as discrete choice rather than the number of days.

1.2.2 *Models of Harvester Behavior: Discrete Choice Models*

Discrete choice framework is commonly used to analyze harvesters' decisions in fisheries economics. Location and target fishery choices have been the focus in literature. The primary approach of these studies builds on the discrete choice random utility model (RUM). An advantage of RUM is the ability to estimate the structural parameters with appropriate modelling, and hence it can be used in policy simulations.⁴ The first work which applied RUM to the fisheries choice problem is [19]. Eales and Wilen [20] emphasize the location choice as an important margin, and point out that the short-run behavior may be a source of rent dissipation, and model the location choice problem as a discrete choice problem. Following these studies, there are series of works which analyze the harvester's location choice and fishery choice.^{5,6} Holland and Stinen [21] integrated these two choices. Namely, they build a model that estimates the joint choice of fishery and location.

Although these approaches illustrate the harvester's behavior, the model itself is static and hence it can only be applied to a limited subset of fisheries such as sedentary or coastal fisheries with short trips. Curtis and Hicks [22] extend the approach by modeling the forward-looking behavior and apply it to the Hawaiian longline fishery, where trip length is moderately long. With

⁴ It is structural in the sense that the parameters represent preferences and beliefs of harvesters who maximize utility by making choices. However, Smith (2000) argues that the structural approach explicitly models the biological process, and the approach that simply forms expectation about attributes of the choice from the past data is called reduced-form.

⁵ e.g. Dupont 1993; Haynie and Layton 2010; Mistiaen and Strand 2000; Smith 2005; Smith and Wilen 2003

⁶ e.g. Larson, Sutton, & Terry, 1999; Pradhan & Leung, 2004; Vermard, Marchal, Mahévas, & Thébaud, 2008

this model, the choice of location is not spot-maximizing behavior, but maximizes the sum of utility from multi-period trips. This dynamic approach was extended by Hicks and Schnier [23,24]. They modeled dynamic choice of location by explicitly modeling “trajectory” with the value function approach. While this approach explicitly illustrates the dynamics of location choice, it is computationally complicated. The main problem left unanswered in the literature is how to determine the length of a trip. Hicks and Schnier assume that the length of a trip is known before leaving the port. This assumption is critical for their value function approach which adopts backward recursion. Although ex-ante decisions are made given expectations, the realized outcome is the ex-post choice as harvesters adjust the margin in response to variables that changes during the cruise. Accordingly, the next step is to model harvester’s adjustment of cruise duration process within a trip.

1.3 KESENNUMA SWORDFISH/BLUE SHARK LONGLINE FISHERY AND DATA

This study draws on a data set of a fleet in a longline fishery based in Kesenuma, Japan. The data set tracks the daily decisions of harvesters at the vessel-operation level. The vessels in this fleet are relatively homogeneous due to the regulation. The longline fisheries in Japan are licensed commercial fisheries authorized by the Ministry of Agriculture, Forestry and Fisheries, and have two categories, 1) distant water (*enyou*) and 2) offshore (*kinkai*). Since these categories are defined by holding capacity rather than actual distances of operation from shore, almost all vessels in the offshore category have capacities of 119 MT, which is close to the maximum capacity (less than 120MT) of the offshore category. These vessels are equipped with 440 horsepower engines. The fleet consisted of 30 vessels in 2005 but shrunk to 17 in 2011. Vessels are also equipped with

mechanical refrigeration systems, but the refrigerated storage is filled with ice-water in order to uniformly expose fish to cold water.

The vessels operate in the north west Pacific Ocean after debarking from the Kesennuma port. The fishing area ranges from 140 degrees east to 180 degrees in longitude, and from 25 degrees to 43 degrees north in latitude. Each fishing operation takes about a day. The detail of an operation is as follows: Setting the line in the water for five hours, dragging the line for four hours, and landing the line for twelve hours. The number of cruise days was about 40 days on average before 2011. We limit the data to 2005 to 2010 due to the Great Earthquake and tsunami that happened in March 2011 and subsequent reconstruction policy.

Harvesters in this fishery primarily target swordfish and blue sharks. Swordfish (*Xiphias gladius*) has a high unit ex-vessel price (800-1000JPY/kg) and is often consumed raw, as is the case with sashimi, so freshness matters [4]. Although the fin of blue shark (*Prionace glauca*) is a luxury good and all parts of body (meat, bone and skin) are processed in the local industry, the ex-vessel price is relatively inexpensive (about 200JPY/kg). In the data, the average landing per cruise is 22.5 MT for blue shark and 15.8MT for swordfish. The aggregated value from swordfish catch is greater than blue shark on average (4.5 million JPY and 15.8 million JPY, respectively). Kesennuma area forms unique markets for swordfish and blue shark. There are many intermediary buyers of swordfish in Kesennuma since it has been traded historically. 72% of fresh landing of swordfish in Japan in 2014 was in Kesennuma. Kesennuma is also famous for shark processing, and there are processing factories in the area. The most valuable product is shark fin, but other body parts of sharks are also used to produce various goods. (e.g. skins for leather products, meat for surimi and bones for medicine and cosmetics). Due to these reasons, Kesennuma is a primary landing market for swordfish and blue shark.

The data consists of three data sources: vessel logbook data, cruise-level landing data collected at the port, and fuel price data. The summarized data are shown in Table 1 and Table 2 for daily and by trip, respectively. The logbook data and the cruise-level sales data of the offshore longline fleet in Kesennuma are supplied by Kesennuma Offshore Fishery Cooperative. The logbook data includes variables of catch (number and weight) by species, site of operation (longitude/latitude), and sea surface temperature. These variables are available on a daily and individual vessel basis from 2005 to 2010. We use the data from October to March only, because harvesters mainly target swordfish in this season.

The landing-per-cruise data complement the logbook data by providing the accumulated number of calendar days spent at sea and variables for previous cruise prices. All the vessels in the fleet belong to Kesennuma port, and basically, they land only at this port.⁷

Fuel price data is published on the website of Japanese Ministry of Agriculture, Forestry and Fisheries. The monthly average price of type-A heavy fuel oil for agriculture is used in this study. Although the market price of fuel at Kesennuma port is not available, the nationwide average price can be used as proxy because it captures the variation.

Table 1.1. Descriptive statistics (daily)

	N	Mean	S.D.	Median	Min	Max
Swordfish (n)	15127	10.81	7.35	10.00	0.00	75.00
Swordfish (kg)	15127	670.87	484.34	580.00	0.00	4500.00
Blue shark (n)	15127	74.29	94.40	45.00	0.00	1202.00
Blue shark (kg)	15127	942.90	1096.21	600.00	0.00	15000.00
Swordfish (kg/n)	14680	62.18	15.68	60.00	5.00	375.00
Blue shark (kg/n)	14576	14.89	6.39	13.85	1.50	173.62
Expected Swordfish Price (JPY/kg)	15127	846.68	105.68	842.18	612.23	1116.40

⁷ After the Great Earthquake, Kesennuma market was unable to accept any landing due to the destroyed port facilities and processing industries. The vessels were landing at Choshi port, Chiba, Japan instead temporarily in 2011-2012, but it is back to normal in 2013 and after.

	N	Mean	S.D.	Median	Min	Max
Expected Blue Shark Price (JPY/kg)	15127	213.27	36.35	208.10	32.76	331.74

Table 1.2. Descriptive statistics (Cruise)

	N	Mean	S.D.	Median	Min	Max
Swordfish (n)	609	268.51	109.28	260.00	0.00	726.00
Swordfish (kg)	609	16663.70	6970.08	16352.00	0.00	40306.00
Blue shark (n)	609	1845.21	1188.58	1665.00	0.00	7189.00
Blue shark (kg)	609	23420.66	13758.26	21861.00	0.00	81570.00
Swordfish (kg/n)	606	62.60	9.58	61.64	40.06	103.45
Blue shark (kg/n)	593	13.90	4.52	13.24	5.39	35.08
Trip Days	609	38.29	7.87	39.00	4.00	66.00
Operation Days	609	24.84	4.97	26.00	2.00	34.00
Move/Search days	609	13.45	5.92	13.00	1.00	37.00

1.4 CONCEPTUAL MODEL

Harvesters in offshore fisheries maximize their profits or utilities from a cruise rather than a day, because the aggregate landing values at the port matter. Accordingly, a longer cruise can be better since harvesters can catch more fish and gain more revenues and profits. If this is true, harvesters would lengthen a cruise as long as possible, and the primary reasons to stop a cruise are binding constraints such as fuel and storage capacity. In real-world fisheries, we observe many cases that the fishing capacities are not fully utilized. While it can be explained by random shocks or inefficiency of skippers, we hypothesize that harvesters respond to economic incentives and choose to stop the cruise to maximize their benefit. Specifically, the quality of fish that has already been caught deteriorates as a cruise gets longer due to loss of freshness. A harvester faces a trade-

off between the additional amount of catch and loss of freshness during a cruise. For this reason, the calendar days since the fish was caught is a state variable for the harvester's decision.

The maximization problem of a harvester in an offshore fishery is formulated as

$$\max_T U = \sum_{t=1}^T u(p, cost, \{d_{t-s}\}_{s=0}^{t-1}, \{h_{t-s}\}_{s=0}^{t-1}) \quad (1.1)$$

$$s. t. f(T) \leq \bar{F} \quad (1.2)$$

$$\sum_{t=1}^T h_t \leq \bar{H} \quad (1.3)$$

The total utility, U is the aggregated profit from a cruise. The price of fish is p . h_t is daily catch on operation day t , $cost$ is daily operational cost. d_t is passed calendar days since h_t was caught. The first constraint is a fuel constraint in which the fuel use is a function of total cruise days T , and the second is a catch capacity (storage) constraint. The harvester chooses total cruise days T to maximize the aggregated utility from a trip. If p is sufficiently high or the deterioration is not rapid, then the optimal choice would be at where either constraint binds. If both constraints are slack, it implies that the marginal deterioration exceeds the gain from additional catch. This deterioration depends on the amount of fish already caught and the timing of catch. In a deterministic framework, one can directly choose optimal total cruise days T , but the daily fishery catch is stochastic in reality. Accordingly, a harvester decides either to operate or to go back to the port on a day-by-day basis given the expectation conditional on state variables. A harvester chooses one of two options at the end of an operation day based on the amount of catch they have. In principle, a harvester will continue the cruise if the continuation value is higher than the revenue from the amount they caught. The choice rule at period t , δ_t , is specified as below.

$$u_t^{Cont} = u(p, cost, \{d_s\}_{s=1}^t, \{h_s\}_{s=1}^t; \delta_t = Continue) + E_t \left[\sum_{\tau=t+1}^{T(\delta)} u(p, cost, \{d_s\}_{s=1}^\tau, \{h_s\}_{s=1}^\tau) \right] \quad (1.4)$$

$$u_t^{Ret} = u(p, cost, \{d_s\}_{s=1}^t, \{h_s\}_{s=1}^t; \delta_t = Return) \quad (1.5)$$

$$\delta_t = \begin{cases} Continue & \text{if } u_t^{Cont} \geq u_t^{Ret} \\ Return & \text{if } u_t^{Cont} < u_t^{Ret} \text{ or } f(t) \geq \bar{F} \text{ or } \sum_{s=1}^t h_s \geq \bar{H} \end{cases} \quad (1.6)$$

Since u_t^{Cont} is the gain from continuation, there is an expected continuation value. Hence, a harvester observes the new catch h_t and makes a decision considering the loss of freshness and the future continuation value. The model tells us that the harvesters do not directly decide the days spent at sea, but it is a result of the day-by-day decision.

1.5 MODEL FREE EVIDENCE

1.5.1 Constraints

The conceptual model above shows that the possible reasons to stop a fishing cruise are binding constraints and greater choice-specific gain of return relative to one of continuation. A vessel would stop fishing when the storage is filled with fish (capacity constraint) or when the skipper realizes that the fuel is running out. If the choice-specific value of continuation exceeds the one of return, harvesters would not stop until either fuel or capacity constraint binds. What we need to check with the data is whether the constraints are binding or not.

Firstly, we examine whether the capacity constraint binds. We do not have specific values of maximum vessel capacity. Hence, we use the maximum value of trip landing in the data as the maximum capacity for all vessels, whose capacities are homogenous across the fleet. We calculate

the amount of total catch per trip relative to the maximum value. Figure 1.1 panel (A) shows a histogram of the relative catch by trip. High frequency occurs around 0.3 to 0.5, and the frequency near 1.0 is quite low. Accordingly, we can conclude that the capacity constraint is not a primary reason to stop a trip.

Next, we check the fuel constraint. We consider that fuel use is an increasing function of total trip days. Although we do not have data of fuel use, we obtain the average fuel use per day through personal communications with the vessel owners in this fishery. They are 1.64 kilo liter per day of operation, and 2.80 kilo liter per day of cruise (moving and searching). By multiplying the numbers of operation days and moving days respectively, we can obtain rough estimates of fuel use. If the primary reason of returning is the fuel constraint, the total fuel use for most trips would be close to the maximum possible value. Figure 1.1 panel (B) shows a histogram of the calculated fuel use. The maximum value is 132.92, but the observations are almost symmetrically distributed centered at around 80-90. According to this figure, we claim that the fuel constraint is not the primary reason to stop fishing and return to the port.

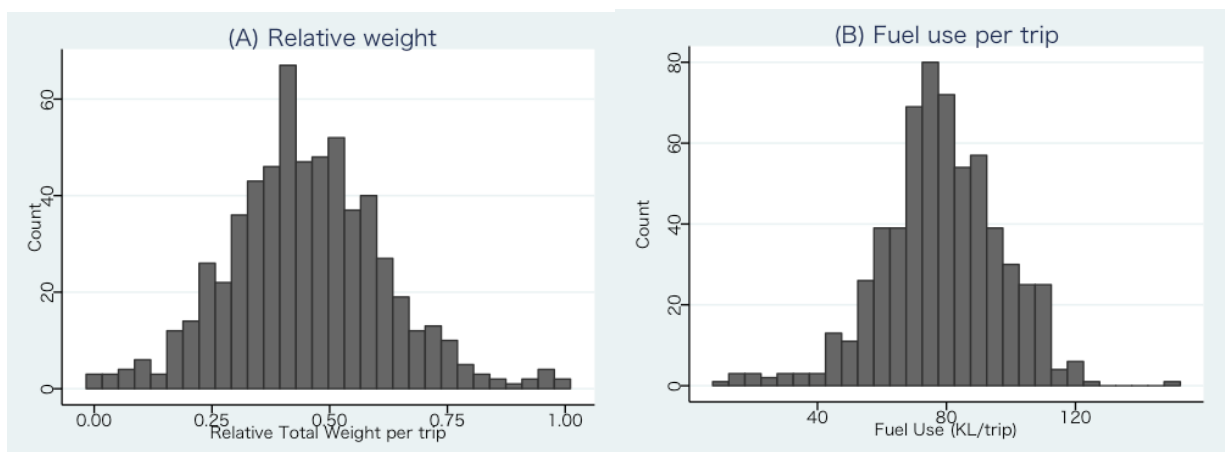


Figure 1.1. Histograms for checking constraints: (A) Relative Total Catch (B) Fuel Use.

1.5.2 Daily Catch Variance

If these constraints are not the primary factors to stop fishing, what would make harvesters return to the port? According to our conceptual model, the decision to stop fishing is made when the expected daily utility gets lower. What factor would decrease the daily utility? In the traditional production theory, the production function exhibits diminishing return to input. Indeed, although the trend is not obvious, the daily total catch seemingly decreases in days of operation in the whole data as shown in Figure 1.2 panel (A). While the daily catch shows a weak downward trend, there is large variance in daily catch within a trip. Figure 1.2 panel (B) shows the daily catch of an arbitrary trip from the data. We presume that the harvester's decision on continuation of a trip depends on this stochastic event rather than a smoothed diminishing ex-ante catch.

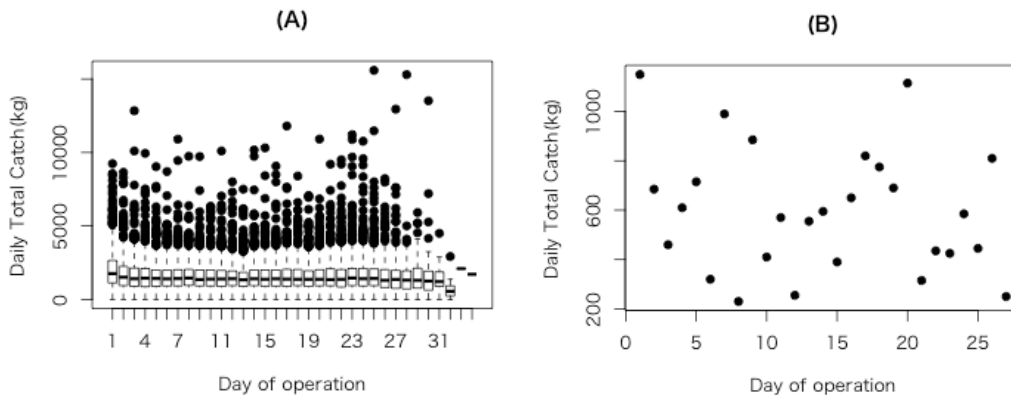


Figure 1.2. Daily Total Catch by Day of operation: (A) Whole Data and (B) A single arbitrary trip.

1.6 FRESHNESS EVALUATION AT THE MARKET

Before we move on to the analysis of harvesters, we show how freshness is evaluated at the market. Ishimura and Bailey [25] estimate the freshness premium in swordfish price in

Kesennuma, Japan, by constructing a freshness measure⁸ from the daily logbook data. Their estimation uses the cruise-level landing data and panel data technique to show that a landing with a long trip has a lower price of swordfish. We use an augmented version of the data from the same source and add unit weight of swordfish and past prices to control for potentially confounding factors. We include the five and ten day moving average of the market price of swordfish in order to control for the harvesters' responses to the market price. The trip length and hence the freshness measure may be correlated with the past price if the harvesters adjust the duration by responding to prices during a trip. The estimation equation is

$$\ln P_{ic} = \alpha_1 \ln Y_{ic} + \alpha_2 \ln F_{ic} + \alpha_3 \text{UnitWght}_{ic} + \alpha_4 \ln \bar{P}_{ic}^{MA5} + \alpha_5 \ln \bar{P}_{ic}^{MA10} + \theta_i + m_c + \varepsilon_{ic}^p \quad (1.7)$$

where Y_{it} is landing weight of swordfish measured as kilograms. F_{ic} is the freshness measure. \bar{P}_{ic}^{MA5} is the five-landing day moving average price, and \bar{P}_{ic}^{MA10} is the ten-landing day moving average price. The inclusion of vessel fixed effects, θ_i , and month fixed effects, m_c , controls for unobserved heterogeneity and seasonality. By definition, the coefficient α_2 represents the freshness premium, which is defined as the elasticity in price upon changes in freshness. α_1 defines the inverse price elasticity of demand.

The model is estimated with ordinary least squares. Table 1 shows the estimation results. Column 1 is the same specification as [25]. The parameter estimate has a smaller magnitude than in the original study, although the sign of the estimated coefficient is same. As we add other covariates, the magnitude of the estimate shrinks. However, the freshness measure is still negative and statistically significant elasticity in Column 4. Accordingly, we can see that freshness is positively evaluated in the market.

⁸ They defined the freshness measure as $F_{ic} = \frac{1}{H_{ic}} \sum_{t \in c} [h_{ict} \cdot (D_{ic} - d_{ict})]$. H_{ic} is the total harvest of vessel i on a cruise c . h_{ict} is catch on the t th day of the cruise. D_{ic} is total number of trip days. This can be interpreted as average catch per trip weighted by the days since caught.

Table 1.3. The Effect of Freshness on Swordfish Market Price

	<i>Dependent variable:</i>			
	Log SF Unit Price			
	(1)	(2)	(3)	(4)
Log Freshness Measure	-0.186*** (0.022)	-0.120*** (0.018)		-0.090*** (0.021)
Trip Days			-0.004*** (0.001)	-0.002*** (0.001)
Log SF Total Weight		-0.072*** (0.007)	-0.067*** (0.007)	-0.067*** (0.007)
Log SF Unit Weight		0.115*** (0.026)	0.111*** (0.027)	0.101*** (0.027)
Log Price MA5		1.064*** (0.146)	1.063*** (0.147)	1.059*** (0.145)
Log Price MA10		-0.349** (0.151)	-0.356** (0.152)	-0.339** (0.151)
Constant	7.243*** (0.082)	2.394*** (0.318)	2.226*** (0.319)	2.356*** (0.317)

Vessel FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Observations	902	819	819	819
R ²	0.438	0.717	0.713	0.720
Adjusted R ²	0.407	0.698	0.694	0.701
<i>Note:</i>		*p<0.1	**p<0.05	***p<0.01

1.7 EMPIRICAL MODEL OF HARVESTERS BEHAVIOR

1.7.1 *Dynamic Discrete Choice Model*

The empirical approach in this study is based on a discrete choice model. Our main interest is to identify the factors that affect a harvester's dynamic decision on duration of a cruise. Based on the conceptual model explained above, we construct an empirical discrete choice model which incorporates dynamic decision-making of harvesters. The decision variable for individual i on a cruise c at period t is now represented as $\delta_{ict} \in \{Continue, Return\}$. In addition, we translate the problem in (1) into a Bellman equation.

$$\begin{aligned}
 (H_{ict}, D_{ict}, \varepsilon_{ict}) = \max_{\delta} E_t [\sum_{s=t}^T u(H_{ics}, D_{ics}, \delta_{ics}; \theta) + \varepsilon_{ics} | H_{ict}, D_{ict}, \varepsilon_{ict}] = \\
 \max_{\delta} [u(H_{ict}, D_{ict}, \delta_{ict}; \theta) + \varepsilon_{ict} + E_t V(H_{ict+1}, D_{ict+1}, \varepsilon_{ict+1})]
 \end{aligned} \tag{1.8}$$

where ε_{ict} is an unobserved factor that affects harvester's daily benefit. We assume that the unobserved state additively enters the utility. The vector of past catches $H_{ict} = \{h_{icts}\}_{s=1}^t$ and the vector of passed calendar days $D_{ict} = \{d_{icts}\}_{s=1}^t$ are treated as state variables. It is important to

note that the passed calendar days d_{icts} and days of operations t are different. The passed calendar day d_{icts} on operation day t is a calendar day since fish h_{icts} is caught. This is not simply $t - s$, because it includes the days of travelling and searching the fishing grounds while t represents the operation day. $t + 1$ may not be the day after t , because there may be searching or moving days. Hence, d_{icts+1} can be $d_{icts} + 2$, $d_{icts} + 3$ or more. We treat this searching and moving as a stochastic process. There is some state transition function $f^D(D_{ict+1}|D_{ict}, H_{ict})$. Furthermore, we also need to note that H_{ict} is not just a cumulative catch, but we think of it as a vector. Because we distinguish between the fish caught on day t and day $t - 1$, the cumulative catch is expressed as $H_{ict} = \{h_{icts}\}_{s=1}^t$.

Because the discrete choice problem is binary, the value function can be rewritten as

$$V(H_{ict}, D_{ict}, \varepsilon_{ict}) = \max_{\delta^*} \{v(H_{ict}, D_{ict}, \delta_{ict} = Continue) + \varepsilon_{ict}, v(H_{ict}, D_{ict}, \delta_{ict} = Return) + \varepsilon_{ict}\} \quad (1.9)$$

where $v(\cdot)$ indicates the conditional choice-specific value function. Each conditional choice-specific value function is expressed as below.

$$v(H_{ict}, D_{ict}, \delta_{ict} = Continue) = u(H_{ict}, D_{ict}, \delta = Continue; \theta) + E_t V(H_{ict+1}, D_{ict+1}, \varepsilon_{ict+1}) \quad (1.10)$$

$$v(H_{ict}, D_{ict}, \delta_{ict} = Return) = u(H_{ict}, D_{ict}, \delta = Return; \theta) \quad (1.11)$$

For convenience, we write them v^{Cont} and v^{Ret} , respectively. Note that the choice ‘‘Return’’ is a terminal decision, and accordingly it does not have the expectation term. To compute the future value term, we need to obtain an ex-ante value function, denoted as \bar{V} . Since the state variable ε is not observed by researchers, we assume that ε has the independent and identical Type I extreme value distribution, the ex-ante value function is written as

$$\begin{aligned}
\bar{V}(H_{ict}, D_{ict}) &= \int \max_{\delta^*} \{v^{Cont} + \varepsilon_{ict}, v^{Ret} + \varepsilon_{ict}\} f(\varepsilon) d\varepsilon \\
&= \ln\{\exp(v^{Cont}) + \exp(v^{Ret})\} + \gamma
\end{aligned} \tag{1.12}$$

where γ is Euler constant.

Because the ex-ante value function is state-dependent, we need to obtain the expectation term by integrating over the transition probabilities.

$$E_t \bar{V}(H_{ict}, D_{ict}) = \int \int \bar{V}(H_{ict+1}, D_{ict+1}) f(H_{ict+1}, D_{ict+1} | H_{ict}, D_{ict}) dH dD \tag{1.13}$$

Using the expected ex-ante value function, we write the choice-specific value function of choice ‘‘Continue’’ as

$$v^{Cont} = u(H_{ict}, D_{ict}, \delta = Continue; \theta) + E_t \bar{V}(H_{ict}, D_{ict}) \tag{1.14}$$

Using the distributional assumption on the unobserved state and conditional choice-specific choice functions, we have a closed form for a choice probability.

$$\Pr(\delta = Return | H_{ict}, D_{ict}) = \frac{\exp(v^{Ret})}{\exp(v^{Cont}) + \exp(v^{Ret})} \tag{1.15}$$

By parameterizing the conditional choice-specific functions, we can estimate the model. However, there are two problems to estimating the model. The first problem is that the conditional choice-specific function of choice ‘‘Continue’’ is a function of the expected ex-ante value function $E_t \bar{V}$, hence we need to obtain the ex-ante value function \bar{V} to get v^{Cont} and estimate equation ((1.15)). However, the ex-ante value function \bar{V} relies on the conditional choice-specific functions of the both choices, v^{Cont} and v^{Ret} in the next period. The second problem is about the expectation term. We need transition probabilities of the observed states to obtain the expected ex-ante value function, because it depends on the observed states H' and D' in the next period.

To tackle these issues, we adopt Hotz and Miller's approach to the estimation [26]. First, we rewrite the ex-ante value function with respect to the conditional choice-specific value function associated with an arbitrarily selected choice. Suppose we use *Return* as the choice here.

$$\begin{aligned}
\bar{V}(H_t, D_t) &= \ln[\exp(v^{Cont}) + \exp(v^{Ret})] + \gamma \\
&= \ln \left\{ \exp(v^{Ret}) \frac{\exp(v^{Cont}) + \exp(v^{Ret})}{\exp(v^{Ret})} \right\} + \gamma \\
&= v^{Ret} - \ln \left\{ \frac{\exp(v^{Ret})}{\exp(v^{Cont}) + \exp(v^{Ret})} \right\} + \gamma
\end{aligned} \tag{1.16}$$

Notice that the inside of the logarithm is a logit formula of the choice probability. Hence, the ex-ante value function can be written as a function of the choice probability and the conditional choice-specific value function

$$\begin{aligned}
\bar{V}(H_t, D_t) &= v^{Ret} - \ln\{Pr(\delta = Return|D', H')\} + \gamma \\
&= -\ln\{Pr(\delta = Return|D', H')\} + \gamma
\end{aligned} \tag{1.17}$$

where the second equality holds when we normalize the terminal decision, *Return*, as zero. Here we have an expression of the ex-ante value function in terms of the conditional choice probability only.

For the second problem of the estimation, we need to obtain the transition probabilities of the observed states. Following Hotz and Miller's approach, we estimate the transition probabilities from the data, and we then calculate the expectation term using the transition probabilities.

$$E\bar{V}(H_t, D_t) = \int \int [-\ln\{\widehat{Pr}(\delta = Return|D', H')\} + \gamma] \hat{f}(H', D'|H_t, D_t) dH' dD' \tag{1.18}$$

where the hat notation indicates the estimated functions.

1.7.2 Flow Utility Specification

With the closed form of the ex-ante value function and the transition probability functions in hand, we can calculate the expectation term, and estimate the structural parameters. We now specify the flow utility of harvesters to answer our research question. Our main specification of the flow utility is shown below.

$$u_{ict}(H_{ict}^k, D_{ict}, \delta = \text{Continue}; \theta) = \sum_{k \in K} \sum_{s=0}^{t-1} \theta_2^k(d_{ict-s}) h_{ict-s}^k \quad (1.19)$$

$$u_{ict}(H_{ict}^k, D_{ict}, \delta = \text{Return}; \theta) = \theta_1 E(\text{Profit}_{ict}) \quad (1.20)$$

where D_{ict} is a vector of passed calendar days $\{d_{ict-s}\}_{s=0}^{t-1}$ back from the operation day t . The term in the flow utility for continuation represents the daily freshness deterioration. d_{ict-s} is calendar days passed since the $t - s$ th day of operation, and the h_{ict-s}^k is the species k catch on the $t - s$ th day of operation. In our analysis, two species are considered: $K = \{\text{Swordfish}, \text{Blue Shark}\}$. We assume that the marginal daily deterioration of freshness is a function of passed calendar days since caught. Accordingly, we expect that $\theta_2(\cdot)$ is a negative and decreasing function of passed calendar days. The parameter θ_1 represents the harvester's response to the profit expected to gain when the cruise stops. The expected profit at period t is calculated as below.

$$\text{profit}_{ict} = \sum_{k \in K} E(p_{ict}^k) \sum_{s=0}^{t-1} h_{ict-s}^k - \text{FuelPrice}_{ic} [m^{op} \cdot t - m^{mv}(\tilde{d}_{ict} - t)] \quad (1.21)$$

The first term represents the expected revenue at the period. $E(p_{ict}^k)$ is a market unit price of species k . The second term is the fuel cost of operations, and the third term is the fuel cost of moving and searching, which is the difference between total days of trip \tilde{d}_{ict} and the number of operation t . Because the cost data is not available, we proxy the fuel cost by fuel price, and fuel use per day. According to our interview with the vessel owners of the fleet, the average fuel use

day is $m^{op} = 1.64$ for operation, and $m^{mv} = 2.80$ for moving and searching. The unit is kilo litter (KL).

1.7.3 *Freshness Model*

There are some studies that incorporate freshness deterioration in fishers decision, but it presumes that the fishers rationally expect fish deteriorating at the rate in which the market determines, and calculate the future values based on the deterioration rate. [22], [27]. What we are looking at here is how fishers subjectively evaluate the freshness, and testing the hypothesis that the fishers take freshness into account.

There are various indicators of freshness used in food science, such as total viable counts (TVC) of bacteria, sensory score for flavor and K value [28]. The common characteristic of those indicators is simple: the freshness is a strictly monotonically decreasing function of time since the death of the fish. The functional form can vary depending on measures, all measures are strictly monotonic up to twenty days in [28]. For example, K-value (calculated from adenosine triphosphate, ATP) and sensory score of flavor seems to be linear, but TVC looks like a sigmoid curve. In addition, penetration force, which is used to measure the textual changes in the muscle, shapes as a quadratic function. Considering these functional forms, we specify the freshness deterioration as third degree polynomials.

$$\theta^k(d) = \theta_{21}^k d + \theta_{22}^k d^2 + \theta_{23}^k d^3 \quad (1.22)$$

Because the freshness deterioration in the flow utility is a marginal daily deterioration, we obtain the function $\theta_2(\cdot)$ by differentiating $\theta(\cdot)$ with respect to calendar days.

$$\theta_2^k(d) = \frac{d\theta^k}{dd} = \theta_{21}^k + 2\theta_{22}^k d + 3\theta_{23}^k d^2 \quad (1.23)$$

The main purpose here is not to estimate the actual freshness of swordfish, but the

harvester's response to the freshness deterioration. Accordingly, we adopt the interaction of time since caught and the amount of catch.

1.7.4 *Conditional Choice Probability (CCP) two-step Estimator*

Following Hotz and Miller's approach, the estimation is performed in two steps. The first step is to estimate the conditional choice probability and the state transitions of cumulative catch and passed calendar days. Although a nonparametric approach is ideal for the conditional choice probability estimation, we encounter difficulties when the state space is large and there are small samples in each bin. We are obliged to adopt a flexible logit instead. The flexible logit is a logit estimation, but the functional form can be flexible to fit the model in the data. The conditional choice probabilities are

$$\widehat{Pr}(\delta = \textit{Continue}|D, H) = \frac{\exp(\psi(D_{ict}, H_{ict}))}{1 + \exp(\psi(D_{ict}, H_{ict}))} \quad (1.24)$$

where $\psi(\cdot)$ is a flexible function. The primary purpose of this step is to obtain the estimated CCP given the expected state variables. Accordingly, the predictability of the model is important. In addition, we have many explanatory variables because $H_{ct} = \{h_{c(t-s)}\}_{s=0}^{t-1}$ is a vector of past daily catch, and we include interactions with days since caught and past daily catch for each s . For these reasons, we use elastic-net logit regression to estimate the CCP. The elastic-net regression is a type of machine learning method for shrinking the regression coefficients toward zero so that a subset of predictors is used to fit a model. The objective function of the lasso estimator includes a term called a shrinking penalty in addition to the main objective function such as least squares. This is advantageous because it avoids overfitting and fits better when the number of predictors is large. The elastic-net logit regression is a version of the elastic-net regression for binomial models. The

objective function of the estimator includes a quadratic approximation to the log-likelihood and the shrinking penalty term.

Next, we estimate the transition probability functions of passed calendar days D and cumulative catch H . The probability of state realized in the next period is conditional on the state in the current period and the decision. The most general case is that the observed states and unobserved states have joint conditional distribution. To estimate the state transition from the data, we make an assumption about this probability in addition to the i.i.d. assumption of the unobserved state. We assume that observed and unobserved states are stationary controlled first-order Markov process, with transition

$$\begin{aligned}
 & \Pr(D_{t+1}, H_{t+1}, \varepsilon_{t+1} | D_t, H_t, \varepsilon_t, \delta_t) \\
 &= \Pr(\varepsilon_{t+1} | D_t, H_t, \varepsilon_t, \delta_t) \cdot \Pr(T_{t+1} | D_t, H_t, \varepsilon_t, \delta_t) \cdot \Pr(H_{t+1} | D_t, H_t, \varepsilon_t, \delta_t) c^2 \\
 &= \Pr(\varepsilon_{t+1}) \cdot \Pr(D_{t+1} | T_t, H_t, \delta_t) \cdot \Pr(H_{t+1} | D_t, H_t, \delta_t)
 \end{aligned} \tag{1.25}$$

Namely, the observed and unobserved state transitions are conditionally independent of each other. In our case, the transitions of cumulative catch and passed days are dependent, because the search behavior is incorporated in this stochastic process instead of an explicit decision-making process.

The passed calendar days D is a source of confusion in this model, because the decision period we assume is operation day t . That is, a harvester chooses “Continue” on an operation day t , then he conducts fishing on the next operation day $t + 1$. This does not necessarily mean that $t + 1$ is “tomorrow”, because the harvester may move and search fishing grounds between the operation day t and $t + 1$. We interpret this moving and searching behavior as a stochastic process that finding a good fishing ground may occur sooner or later, but harvesters are not certain about when it happens. Although it is a stochastic process, harvesters are more likely to stay on a good

fishing ground when they observe high catch rates. Hence, we estimate the transition of calendar days as a function of observed catch.

$$\log(d_{ict+1} - d_{ict}) = \rho_0 + \rho_1(d_{ic1} - d_{ict}) + \rho_2 h_{ict} + \eta_{ict}^d \quad (1.26)$$

Since $d_{ic1} - d_{ict}$ calendar days take positive and discrete values, we use Poisson regression to estimate the transition process.

For the cumulative catch, we only need to estimate the transition process of daily catch of the next period, because the transition of amount of fish already caught is deterministic. That is, h_{ict} becomes h_{ict-1} in the next period. Only h_{ict+1} is unknown in H_{ict+1} . We assume that the expectation of daily catch $E[h_{ict+1}]$ is formed based on the catch one day before. That is, the conditional expected daily catch is formulated as $E[h_{ict+1}|h_{ict}]$. As we saw in Section 4, the daily catch on average is stable while there's variation during a trip. From this, we adopt lag one autoregressive (AR) model.

$$h_{ict+1} = \phi_0 + \phi_1 h_{ict} + \eta_{ict+1}^h \quad (1.27)$$

In the second step, we estimate the CCPs, the transition probabilities and structural parameters in the utility function in eq. (1.19) and (1.20). We first estimate the CCPs and the transition probabilities, then construct the expectation term following eq. (1.18). With the expectation term in hand, we can construct the choice-specific value function of "Continue" expressed as eq. (1.14). The choice specific value function of "Return" is a static utility expressed in eq. (1.11). Hence, we have everything necessary to have the closed form probability eq. (1.15). The computed expected terms are included as an offset term in the estimating equation, and the parameters are estimated by maximum likelihood estimation. We show our estimation results in the next section.

1.8 ESTIMATION RESULTS

1.8.1 *Results of state transition functions*

Firstly, we highlight the estimation results of the first step. The transition of passed calendar days is intuitively deterministic, but it is treated as a stochastic process in our setting because of moving and searching between operations. The estimation results of the Poisson regression for this process are shown in Table 2. As we expect, the calendar days before next operation is shorter when the daily number of swordfish is high. This implies that harvesters conduct fishing ground searching when they observe low daily catch of swordfish. Days since leaving port (Passed Days) is seemingly not important for searching behavior. Hence, we adopt the Column 4 model to calculate the transition process of calendar days.

We next show the estimation results of the transition of daily catch. The results of the estimation are shown in Table 3. The estimated coefficient is consistent with the stationary assumption.

Table 1.4. Estimation Results of the Search/Move days before next operation

	<i>Dependent variable:</i>			
	Search/Move days before next operation			
	(1)	(2)	(3)	(4)
Passed Days	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	
Daily # of Swordfish	-0.009*** (0.001)		-0.009*** (0.001)	-0.009*** (0.001)
Daily weight of Blueshark		0.00000 (0.00001)	-0.00000 (0.00001)	
Constant	0.309*** (0.020)	0.196*** (0.017)	0.314*** (0.022)	0.328*** (0.013)
Observations	14,391	14,391	14,391	14,391
Log Likelihood	-17,342.300	-17,382.190	-17,342.080	-17,343.050

Akaike Inf. Crit. 34,690.600 34,770.390 34,692.150 34,690.110

Note: Standard Errors in Parentheses

* $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$

Table 1.5. Estimation Results of the AR1 model of daily catch

	<i>Dependent variable:</i>
	Daily SF Catch on d
SF Catch on d-1	0.521*** (0.007)
Constant	334.052*** (5.608)
Observations	14,501
Adjusted R ²	0.281

Note: Standard Errors in Parentheses *p<0.05 **p<0.01 ***p<0.001

1.8.2 Results of First Step CCP Estimation

The first step estimation of CCP is based on eq. (18). The flexible logit is estimated with an elastic-net logit estimator. We highlight the main effects instead of the parameter estimates because the number of parameters is large and the direct interpretation of this estimation is not of our interest. The primary effect that reduce the probability of continuation is passed calendar days since port. This is an advantage of using the CCP estimator in this model. The harvester's problem is optimal stopping, but it is not an infinite horizon problem. There must be the maximum operation day T^{max} or maximum possible calendar days since port due to fuel or capacity constraints. Harvesters expect less continuation value in the later periods of a cruise because they know T^{max} and that the rest of the cruise is not long. In terms of researchers, we can model the harvester's expectation of continuation value by having passed calendar days since port as a state variable in the first step estimation instead of having an explicit assumption about T^{max} .

The interactions of past catch and passed calendar days since caught also affects the choice probability. In this estimation, we do not specify the functional form and each interaction of past catch and passed calendar days since caught is additively separable with each coefficient,

$\sum_{s=0}^{t-1} \phi_{2t-s} d_{ict-s} h_{ict-s}$. The estimation result shows that 21 to 27 days ($s = 21$ to $s = 27$) since caught significantly decreases the probability of continuation while coefficients on 20 or less days since caught shrink toward zero.

1.8.3 *Result of Second Step Structural Parameters Estimation*

We have two specifications to see the fit of the model. Table 4 shows the estimation results of the models. For each specification, either the linear or quadratic form of freshness (Freshness) of each species (SF: swordfish, BS: blue shark) and expected profit are included. Comparing Column 1 and Column 2 models, the interaction of the second order of passed calendar days since caught and daily catch largely improve the model fit in terms of the log-likelihood and Akaike Information Criteria (AIC). Accordingly, the functional form of freshness deterioration can be approximated with a third-degree polynomial rather than lower degrees.

The estimated coefficients on the freshness deterioration function of blue shark are also statistically significant. This is an unexpected result because blue sharks are not consumed raw. According to a primary processor in Kesennuma, fresh sharks are relatively easier to process due to having the appropriate amount of water content. It may be additional value that harvesters recognize, but the magnitude of deterioration is smaller than swordfish. We expect the coefficient estimates on profit to be negative, since the flow utility of “Return” is normalized. The expected profit in the Column 2 model shows the negative signs.

Table 1.6. Estimates of structural parameters

	<i>Dependent variable:</i>	
	choice	
	(1)	(2)
Exp. Profit	0.00002* (0.00001)	-0.0001*** (0.00001)
$2\theta_{22}^{SF}$	-0.047*** (0.003)	0.056*** (0.012)
$3\theta_{23}^{SF}$		-0.004*** (0.0004)
$2\theta_{22}^{BS}$	-0.002*** (0.0003)	0.003** (0.001)
$3\theta_{23}^{BS}$		-0.0002*** (0.00004)
Constant	3.328*** (0.146)	2.839*** (0.153)
Observations	14,576	14,576
Log Likelihood	-1,715.500	-1,661.598
Akaike Inf. Crit.	3,439.000	3,335.197
<i>Note:</i>	*p<0.05, **p<0.01, ***p<0.001 Standard Errors in Parentheses	

1.8.4 Recovery of Freshness Deterioration Function

Given the coefficients estimated, we can recover the freshness deterioration function. To recover the function, we have two problems. First, we cannot identify θ_{21} in the estimation since it is constant and cannot be separately estimated from the constant of the second step dynamic logit. However, we assume that the deterioration function is monotonically decreasing. Hence, the

first order derivative of the function should be equal or less than zero. Using this condition, we calculate a possible value of θ_{21} .

$$\theta_{21} \leq \frac{\theta_{22}^2}{3\theta_{23}} \quad (1.28)$$

and we adopt the maximum possible value to recover the function here.

The second problem is that the function we recover is in the unit of utility. Hence, it is difficult to interpret the result. To aid this problem, we monetize the parameters in the utility by dividing them by the estimate of coefficient on the profit, because it is the marginal utility of gain in money value: $\tilde{\theta}_{22} = \frac{\theta_{22}}{\theta_1}$, and $\tilde{\theta}_{23} = \frac{\theta_{23}}{\theta_1}$ [29]. By integrating $\tilde{\theta}(d)$ over passed days since caught using the coefficient estimated, we obtain the function depicted in Figure 3. For swordfish, the freshness does not decrease in the first 10 to 15 days, but it decreases after the 20 days passed since its harvest. This result is consistent with the result of first step elastic-net logit estimation which showed that the coefficients on the passed days and daily catch interaction shrink toward zero for $s = 20$ or less, but the interactions with more than 20 days have the estimated coefficients.

The resulting functional form of the freshness deterioration indicates the increasing rate of reduction after 20 days. The shape of the function looks similar to the graph of penetration force as a measure of textural change [28]. At the landing market in Kesenuma, the intermediary buyers physically check the quality condition of each fish using hooks and light before they bid a price for the fish. They do not use any instruments to measure chemical or biochemical freshness quality, but depends only on physical methods based on their experiences. Knowing that the buyers rely on the physical methods, it is consistent that the harvester's response to freshness deterioration is similar to the form of textural change of fish as a physical freshness measure.

The monetary value shown in Figure 1.3 is per individual fish, because it is the unit used to estimate the freshness measure. The deterioration for swordfish is 464 JPY per fish in 20 days, and 2,310 JPY in 30 days. Using the average unit weight of swordfish, the loss per kilogram is 7.46 JPY (0.88% of the average unit price) in 20 days, and 37.15 JPY (4.38%) in 30 days. For blue shark, the loss of freshness is 1.63 JPY (0.76%) in 20 days and 1.93 JPY (0.90%) in 30 days. While the amount of blue shark does not largely affect the continuation decision, many swordfish catch in the early period of a cruise significantly decreases the duration of the cruise.

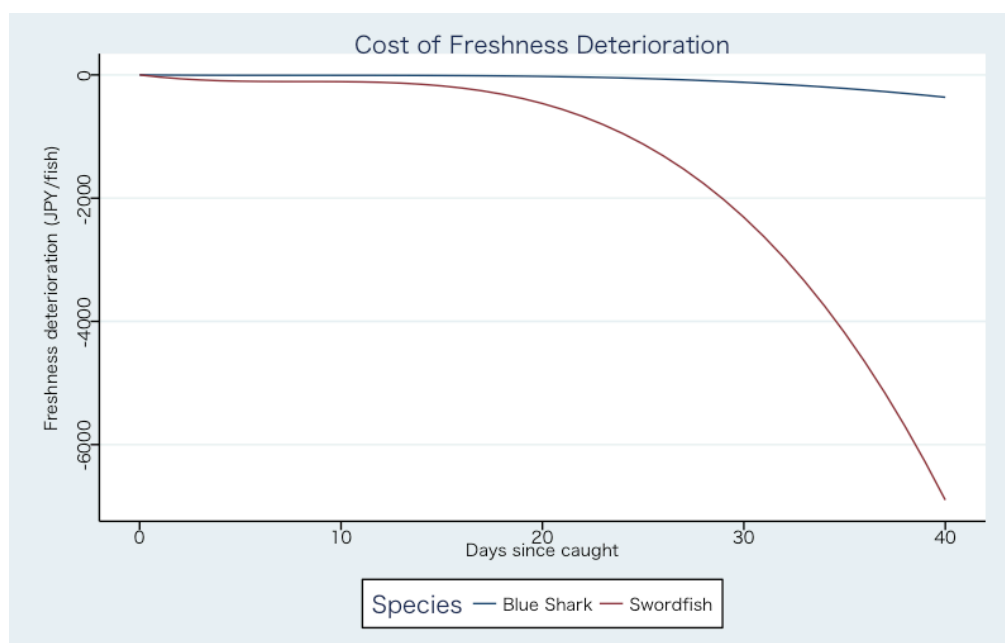


Figure 1.3. Recovered Freshness deterioration function.

1.9 DISCUSSION AND CONCLUSION

Harvesters in fisheries take fishing cruises that range from less than a day to several months in length. The harvester may not fully utilize capacity and stop a cruise at some point. This behavior can be explained due to technical efficiency or skipper skill, but we proposed alternative hypothesis: harvesters respond to freshness deterioration of fish already caught. This suggests that

the producers in fisheries adjust the days at sea observing the realized daily catch, and hence the cruise-level estimation of production function may cause a problem. Overall, our model estimates show that freshness measure is important for fish that was caught over 20 days since caught. This may suggest that the variation within a trip affects harvesters' decisions. Specifically, the large amount of catch in the early periods of a trip may lead harvesters to stop fishing early in order to avoid freshness deterioration. Given that freshness contributes to higher unit prices of swordfish, this behavior is consistent with profit maximization. The current approach of fishing capacity management, which is based on the relationship between potential output and quasi-fixed inputs, may not be economically efficient policy because vessels barely fully utilize their quasi-fixed inputs.

One may claim that this could be evidence of the target revenue hypothesis because they quit fishing when they catch more in the early period. It is, however, that the total amount of catch at the point of decision making is important for the target revenue rather than variation of catch within a trip. If the target revenue is the primary mechanism of harvester behavior, cumulative catch would be the key variable. Since the within-trip variation model fits better, this is not a strong evidence of target revenue hypothesis.

Another contribution of this study is related to the first step estimation with the elastic-net logit regression. Although the primary purpose of this estimation is to obtain a good prediction of conditional choice probability, the estimation results suggest the variable selection provides supportive evidence of the result of structural estimation. As a result, the harvester's response to the days since caught is nonlinear because harvester does not react to the passed calendar days since caught initially, then start reacting after 21 days. The random utility models (RUM) usually specify utility in a linear form because it ensures a unique maximum of the likelihood function.

Non-linear forms of utility make the estimation difficult. With the selected variables in the lasso logit regression, we implement the conceptually nonlinear specification while the actual estimation is with a linear form.

The model of duration choice can be applied to policy simulations. Limiting time of fishing is one of the major tools in fisheries management. For example, a days-at-sea regulation was implemented to the fleet in Kesenuma as a part of restoration policy from the Great Earthquake. The effect of the regulation is difficult to identify because it is bundled with other policies such as group operation and guaranteed minimum earnings supported with subsidies. By using a structural model to simulate the effect of fishing time regulation alone, we can separate the effect of the regulation and other policies.

This study can be integrated to harvester's choice of other decision variables. The choice of location may be important because the decisions on location and continuation may be mutually dependent through distance and catchability of location. Further, choice of target fish species should also be considered to combine with the duration model. As we discussed in the introduction, the multiple margin should be considered when one implements a policy on a quest to improve biological and economic outcomes in fishery. The joint decision is often formulated as a nested structure in multiple decision stages. For example Holland and Sutinen formulate the choice of target fishery as first stage and location choice as second stage, and adopt Nested Logit to estimate the model [21]. The two-step estimation of dynamic discrete choice adopted in this study can be extended to weaker distributional assumption such as GEV. Such a framework is developed in [30] and applied in other fields [31]. Hence, one of the directions of the future work could be a problem of joint choices with dynamic approach.

Chapter 2. CATCH MORE TO CATCH LESS: ESTIMATION OF FISHING TIMING CHOICE AS DYNAMIC BYCATCH AVOIDANCE BEHAVIOR IN THE CASE OF ALASKAN POLLOCK FISHERY

2.1 INTRODUCTION

Fisheries bycatch and discarding of non-targeted species has been common and urgent issues in fisheries management. Bycatch is an incidental catch of non-targeted species or size groups that would have little or no economic value. Harvesters tend to discard the catch, but it is often biologically and ecologically problematic. Since there are harmful biological and economic impacts on fisheries, resource managers have begun implementing regulations and policies to reduce bycatch. The policies include monitoring, spatial closure, enforcing specific gears and catch limits.

In economic approaches, the harvesters are incentivized to avoid bycatch. While regulations such as spatial closure or gear enforcement is limiting the harvesters fishing ability, catch limits leave room for harvesters to adjust their margins. The primary margins of bycatch avoidance for harvesters are gear choices and location choices. Location choice is one of the largest margins of bycatch avoidance. Harvesters may avoid a fishing ground where the bycatch rate is high, even though the primary target species is abundant in the ground. These margins are intensive and adjusted given the harvesters' participation in the fishery. Harvesters also can avoid bycatch by not participating in a fishery when the high bycatch rate is taking place in the fishery. While location choice as the margin of avoidance is well studied, studies on the extensive margin is limited.

The participation is not an important margin of avoidance under common property resource such as open access or regulated open access fisheries, because the opportunity to catch is too expensive to miss under such regime. Because it is a derby fishery, harvesters have no flexibility for participation timing. Under rights-based management scheme such as individual fishing quota (IFQ), however, harvesters are enabled to flexibly allocate their fishing effort over a season. That is, the timing shift of fishing efforts enables not only maximizing the seasonal profit, but also avoiding bycatch. Period by period, harvesters decide whether they participate in the fishery based on the expected bycatch rate in addition to the expected revenue from the main target species. Some theoretical works show that this flexibility of effort allocation improves welfare in fisheries [32]. Although the theoretical framework of IFQ is analyzed based on single fisheries, many harvesters in real world fisheries aim more than one species in a season (e.g. [33]). Accordingly, participation in a fishery may depend on biological and economic conditions of other fisheries as well.

Empirical analyses on harvester behavior under individual quota management is difficult because of its dynamic aspect. Harvesters problem is to maximize the seasonal profit by allocating individual quota over time, hence it is a seasonal dynamic problem. The state variable, remaining quota, changes depending on the harvester decision, but the state variable itself does not enter the flow utility function. The full dynamic programming approach is difficult to apply because it is a non-stationary problem. Instead of fully solving the dynamic problem, we propose a variable that takes into account the forward-looking use of individual quota.

To analyze the shift of harvest timing as a margin of bycatch avoidance, we first construct a theoretical model to get the relationship of variables, then utilize a random utility model that

specifies the benefits of participation in each fishery as a function of expected profit and bycatch. The theoretical approach is adopted to get the insight of how dynamic quota use plays a role in harvester decision. The result of the theoretical model motivates the specification of the random utility. Including bycatch expectation and forward-looking quota use, we estimate the harvesters repeated choice of participation to fisheries with the detailed weekly-level panel data. This approach extends the frontiers of analyses in dynamic behavior of natural resource harvesters.

Our result shows that harvesters adjust the timing of participation in Pollock fishery to avoid bycatch both contemporaneously and dynamically. The result varies by season, because the main driving factor of participations are different. When the seasonal trend of fish value and bycatch rate overlaps, then harvester's flexibility of timing choice is limited. In the season in which the seasonal trends are sufficiently different, harvesters adjust participation considering the dynamic quota use.

2.2 THEORETICAL MODEL

To understand harvester's timing choices of target fishery participation, we develop a seasonal temporal choice model of individual behavior. We conceptualize harvesters as solving an annual (seasonal) planning problem, given variations in expected catches and prices and the constraints of individual quotas of main target species and bycatch. The harvester chooses which fishery to target in each period so that they maximize the annual profit. Such behavior is modeled as an effort allocation problem across fisheries because the harvester selects a target fishery, not a quantity of fish or amount of effort. Moreover, it is dynamic because the choice is made based not only on

instantaneous gain (i.e. catch in a period), but also effect of choice on future catch via individual quota. The model needs to address the trade-off between today's catch and future opportunity of catch affected by the quota use.

Our model highlights the trade-offs of gains on-the-spot, cost of bycatch, and future benefit from saved quotas when harvesters make decisions on participations in fisheries. The contemporaneous gain is modeled as expected values in the week, but the cost of bycatch and the future gain from quota are modeled as shadow costs in a dynamic optimization problem to maximize the seasonal profit from the fisheries. The key motivation to develop a theoretical model is to analyze how these time-varying conditions and shadow costs affect decisions of harvesters.

Clark established the first intra-season dynamic model of fisheries decision to theoretically describe the stock externality [34], and Boyce corrects and extends the model to address potential issues with ITQ management [32]. While these models attempt to explain the theoretical relationship of externality and harvester behavior at the equilibrium, our model simply focus on the prediction of harvester behavior given the management scheme. For this reason, we assume that the catch of the fleet is only small portion of the biomass, and do not consider resource dynamics within a season, although the models in literature have a resource stock as a state variable. In terms of the social planners or resource managers, resource dynamics within a season may be important to take into account. Each individual harvester, however, would consider it as an exogenous variable and it is treated as expected catch rate (CPUE).

The model settings are as follows. A harvester i chooses one of two fisheries in every period t in a season length T . Fishery 1 is managed with individual quota system, and Fishery 2 adopts total allowable catch (TAC) system. TAC is denoted as \bar{Q}_2 . In addition, bycatch in Fishery 1 is limited by individual bycatch quota. We can think of that Fishery 1 is an IQ-managed fishery

targeting high value species, and Fishery 2 is targeting low value species with derby induced by the nature of the management scheme. Each harvester i has individual quota for target species for Fishery 1, Q_{1i} , and individual bycatch quota, Q_{bi} . In each period, a harvester chooses a fishery to participate in. This binary choice is expressed as, $d_{it} \in [0,1]$. If $d_{it} = 1$, the harvester chooses to fully commit Fishery 1 in the period t . We assume that fishing effort in each period is constant, and normalized to one. To operate fishing, the harvesters incur a constant cost c in each period.

There are time-varying biological and economic variables that affect the benefit of harvesters from participating in each fishery. The catch rates of main target species in both fisheries are time-varying, q_{1t} and q_{2t} , respectively. Bycatch rate, b_t , is assumed to change over time as well. The price of main target species in Fishery 1 changes over a season, p_{1t} . On the other hand, the price in Fishery 2 is constant, p_2 . In this theory model, we assume that the harvesters completely know the variation of these time-varying variables over a season.

In addition to the operation cost, we include an instantaneous cost of bycatch, denoted by γ . Harvesters may dislike the bycatch not only because of the shadow cost of bycatch quota, but also other reasons. The reason why we include this variable is observations that harvesters in real world fisheries avoid bycatch even without bycatch quota. This may be due to preference of harvesters on environmental or ecological value, or fear of additional regulatory changes if there is excessive bycatch, or pressures from environmental-friendly parties⁹.

⁹ For example, “Dirty twenty list”, which is the list of 20 boats with the highest weekly bycatch rates, is published in Bering Sea Pollock fisheries.

We consider the individual problem of developing an optimal plan for allocating effort across fisheries within a season. An individual harvester i maximize the profit through allocating efforts in two fisheries. The individual's seasonal profit is defined as

$$V = \int_0^T [d_{it}(p_{1t}q_{1t} - \gamma b_t q_{it}) + (1 - \delta_{it})p_2 q_{2t} - c] dt \quad (2.1)$$

The individual problem is

$$\max_{\{d_{it}\}} V$$

subject to

$$\int_0^T d_{it} q_{1t} dt \leq Q_{1i} \quad (2.2)$$

$$\int_0^T d_{it} b_t q_{1t} dt \leq Q_{bi} \quad (2.3)$$

$$\int_0^T \sum_{j=1}^N (1 - d_{jt}) q_{2t} dt \leq \bar{Q}_2 \quad (2.4)$$

$$0 \leq d_{it} \leq 1 \quad (2.5)$$

The objective function expresses that a harvester decides which fisheries to participate in by choosing d_{it} . The individual quota of target species and bycatch species are used only when participating in Fishery 1, that is $d_{it} > 0$. Total allowable catch in Fishery 2 is used by the harvester when is $d_{it} = 0$, but it is also affected by other harvesters. Unless indifferent, the optimal values of the choice variables will be either zero or one because these choice variables enter the function linearly.

We set up Lagrangian function to solve this problem.

$$L = V + \lambda_{1i} \left[Q_{1i} - \int_0^T d_{it} q_{1t} dt \right] + \lambda_{bi} \left[Q_{bi} - \int_0^T d_{it} b_t q_{1t} dt \right] + \lambda_{2i} \left[\bar{Q}_2 - \int_0^T \sum_{j=1}^N (1 - d_{jt}) q_{2t} dt \right] + \eta_{1t} d_{it} + \eta_{2t} (1 - d_{it}) \quad (2.6)$$

The first term is the objective function. Second to fourth terms are the individual quotas and TAC constraints. λ_{1i} , λ_{bi} and λ_{2i} are Lagrange multipliers for individual quota of main target species in Fishery 1, bycatch quota, and TAC in Fishery 2, respectively. Fifth and sixth terms are constraints for the range of the choice variable with Lagrange multipliers η_{1t} and η_{2t} .

By taking first order conditions with respect to d_{it} , we obtain the equations below.

$$H_{it} = [p_{1t} - \lambda_{1i} - (\gamma + \lambda_{bi})b_t]q_{1t} - (p_2 - \lambda_{2i})q_{2t} \quad (2.7)$$

The first and second terms on the left-hand side are the net revenue from Fishery 1 and Fishery 2, respectively. On the right-hand side, $H_{it} \equiv \eta_{2it} - \eta_{1it}$ is the difference of the Lagrange multipliers of conditions for d_{it} . The difference is positive if $d_{it} = 1$ and negative if $d_{it} = 0$, because either condition holds and the other slacks. We call this H_{it} a participation index. Because the participation index is the difference between the net revenues from Fishery 1 and Fishery 2, the harvester chooses Fishery 1 if the index is positive. Hence, the relationship between the decision d_{it} and the participation index is expressed as an indicator function.

$$d_{it} = I\{H_{it} \geq 0\} \quad (2.8)$$

The net revenue from Fishery 1 consists of four factors: output price, p_{1t} , shadow cost of individual main-target quota, λ_{1i} , instantaneous cost of bycatch, γ , and shadow cost of bycatch

quota, λ_{bi} . Output price and shadow cost of TAC are the only factors for the net profit of Fishery 2. The shadow cost of the main target quota or bycatch quota is positive, but the other one can be zero because of the transversarity condition. Either quota constraint could slack if the other one binds, hence the shadow cost is zero. Amount of operation cost matters when the harvester decides whether participating in fisheries or not, but it does not matter in the choice of fisheries since they are identical between fisheries. These shadow values are functions of integration of variables over the season, because the quota constraints are the integration of decisions, $d_{it} \forall t \in T$, and these decisions are functions of economic variable such as price, catch rate, and bycatch rate. The perfect foresight harvester calculates the shadow value of quota using the information about future periods, and determines the contemporaneous choice. In this sense, the harvester's choice is dynamic.

Our interest lies in the dynamic behavior of harvesters in response to the change in exogenous variables, such as price and bycatch rate. Intuitively, an increase in price of Fishery one raises the incentive to participate in Fishery one, and an increase in bycatch discourages a harvester to target Fishery one. These effects are instantaneous, or merely myopic, but the dynamic effects could induce inverse behavior. These total effects are expressed in the following propositions.

Proposition 1: Change in the price of Fishery One

Suppose that the harvester maximizes the ex-ante seasonal profit by choosing one from two fisheries in each period given the constraints:

(1) Assuming that the main target species individual quota is binding (i.e. $\lambda_{1i} > 0$), an increase in the price of Fishery One in a given period raises the participation index to participate in Fishery One in the period as a direct effect but decreases the index as the shadow cost of the main target

species individual quota rises.

(2) *Assuming that the bycatch individual quota is binding (i.e. $\lambda_{bi} > 0$), an increase in the price of Fishery One in a given period raises the participation index to participate in Fishery One in the period as a direct effect, but decreases the index as the shadow cost of the bycatch individual quota rises.*

Proof. The total derivative of the decision with respect to the price of Fishery One is expressed as below.

$$\begin{aligned} \frac{\partial d_{it}}{\partial H_{it}} \frac{dH_{it}}{dp_{1t}} &= \frac{\partial d_{it}}{\partial H_{it}} \left(\frac{\partial H_{it}}{\partial p_{1t}} + \frac{\partial H_{it}}{\partial \lambda_{1i}} \frac{\partial \lambda_{1i}}{\partial p_{1t}} I\{\lambda_{1i} > 0\} + \frac{\partial H_{it}}{\partial \lambda_{bi}} \frac{\partial \lambda_{bi}}{\partial p_{1t}} I\{\lambda_{bi} > 0\} \right) \\ &= \frac{\partial d_{it}}{\partial H_{it}} \left(q_{1t} - q_{1t} \cdot \frac{\left(\frac{\partial d_{it}}{\partial H_{it}} \right) q_{1t}^2}{\int_0^T \left(\frac{\partial d_{is}}{\partial H_{is}} \right) q_{1s}^2 ds} I\{\lambda_{1i} > 0\} - b_t q_{1t} \cdot \frac{\left(\frac{\partial d_{it}}{\partial H_{it}} \right) b_t q_{1t}^2}{\int_0^T \left(\frac{\partial d_{is}}{\partial H_{is}} \right) b_s^2 q_{1s}^2 ds} I\{\lambda_{bi} > 0\} \right) \end{aligned}$$

The first term in the bracket is the partial effect, which is the myopic effect of price change. The second term is the effect via the shadow cost of main target species quota. This term is negative, and relevant only if the shadow cost is positive. The third term is the effect via the shadow cost of bycatch species quota. This term is negative as well, and relevant only if the shadow cost of bycatch quota is positive. The participation index may or may not change the decision. The derivative of the decision with respect to the index, $\frac{\partial d_{it}}{\partial H_{it}}$, is defined as a Direc Delta function (see appendix) and takes one only if the index is zero. It takes zero otherwise. Q.E.D.

The terms of the effect of shadow costs are a multiplication of the partial derivative of the participation index with respect to the shadow cost, and the change in the shadow cost with respect

to the change in the price of Fishery One, respectively. The shadow costs increase as the price increases, because the direct price effect may lead a harvester to participate in Fishery One, then the harvester uses either quota. It decreases the future opportunity to use the quota, and thus the shadow cost increases. The magnitude of the change in the shadow cost depends on the catch quantity in the period relative to the whole season.

A similar discussion is applied to a change in bycatch rate.

Proposition 2: change in bycatch rate

Suppose that the harvester maximizes the ex-ante seasonal profit by choosing one from two fisheries in each period given the constraints:

(1) Assuming that the main target species individual quota is binding ($\lambda_{1i} > 0$), an increase in the bycatch rate in a given period may hinder participation in Fishery One in the period as a direct effect, but may facilitate the participation as the shadow cost of the main target species individual quota drops.

(2) Assuming that the bycatch individual quota is binding ($\lambda_{bi} > 0$), an increase in the bycatch rate in a given period may hinder in Fishery One in the period as a direct effect, but the dynamic effect on the chance is indeterminate since the shadow cost may increase or decrease depending on the magnitude of catch rate, bycatch rate and bycatch costs.

Proof. The total derivative of the decision with respect to the price of Fishery One is expressed as below.

$$\frac{\partial d_{it}}{\partial H_{it}} \frac{dH_{it}}{db_t} = \frac{\partial d_{it}}{\partial H_{it}} \left(\frac{\partial H_{it}}{\partial b_t} + \frac{\partial H_{it}}{\partial \lambda_1} \frac{\partial \lambda_1}{\partial b_t} I\{\lambda_{1i} > 0\} + \frac{\partial H_{it}}{\partial \lambda_{bi}} \frac{\partial \lambda_{bi}}{\partial b_t} I\{\lambda_{bi} > 0\} \right)$$

$$\begin{aligned}
&= \frac{\partial d_{it}}{\partial H_{it}} \left(-(\gamma + \lambda_{bi})q_{1t} + q_{1t}(\gamma + \lambda_{bi}) \frac{\left(\frac{\partial d_{it}}{\partial H_{it}}\right) q_{1t}^2}{\int_0^T \left(\frac{\partial d_{is}}{\partial H_{it}}\right) q_{1s}^2 ds} I\{\lambda_{1i} > 0\} \right. \\
&\quad \left. - b_t q_{1t} \frac{\left(d_{it} q_{1t} - \frac{\partial d_{it}}{\partial H_{it}} (\gamma + \lambda_{bi}) b_t q_{1t}^2\right)}{\int_0^T \left(\frac{\partial d_{is}}{\partial H_{is}}\right) b_s^2 q_{1s}^2 ds} I\{\lambda_{bi} > 0\} \right)
\end{aligned}$$

The first term in the bracket is the myopic effect of the change in bycatch rate. The second term is the effect via the shadow cost of main target species quota. This term is negative, and relevant only if the shadow cost is positive. The third term is the effect via the shadow cost of bycatch species quota. The sign of the term depends on the magnitude of the catch rate, direct cost of bycatch, and the shadow cost of bycatch, and bycatch rate, as the sign in the bracket in the numerator is ambiguous. This term is relevant only if the shadow cost of bycatch quota is positive. The participation index may or may not change the decision as the derivative of the decision with respect to the index, $\frac{\partial d_{it}}{\partial H_{it}}$, is defined as a Direc Delta function. Q.E.D.

The direct effect is negative on the participation index because it increases the cost of bycatch. The dynamic effect through the main target species quota raises the participation index as the shadow cost of the main target quota may decrease due to decreased participation index. The effect of the bycatch quota has two components. The rise in bycatch rate simply increases the shadow cost of bycatch quota due to more bycatch given the participation decision. However, it also may reduce the shadow cost of bycatch quota because of the saved bycatch quota if the decision is switched to Fishery Two.

These dynamic effects are more illustrative if we look into the effect of the change in bycatch rate on the different period. To highlight the important point, we consider the case in which

only main target species quota binds. The total derivative of the decision in period t with respect to the bycatch rate in period $r \neq t$ is

$$\begin{aligned} \frac{\partial d_{it}}{\partial H_{it}} \frac{dH_{it}}{db_r} &= \frac{\partial d_{it}}{\partial H_{it}} \left(\frac{\partial H_{it}}{\partial \lambda_1} \frac{\partial \lambda_1}{\partial b_r} I\{\lambda_{1i} > 0\} \right) \\ &= \frac{\partial d_{it}}{\partial H_{it}} \left(q_{1r} \gamma \frac{\left(\frac{\partial d_{it}}{\partial H_{it}} \right) q_{1r}^2}{\int_0^T \left(\frac{\partial d_{is}}{\partial H_{it}} \right) q_{1s}^2 ds} \right) \end{aligned}$$

The harvester may switch to Fishery One in period t if the bycatch rate in period $r \neq t$ increases. This is because the harvester would want to use the quota when the bycatch rate is low all else equal, and hence intertemporally substitutes the quota use. We call it a dynamic bycatch avoidance. It is important that the dynamic avoidance occurs even if the shadow cost of bycatch quota, λ_{bi} , is zero. That is, the harvester dynamically avoid bycatch even if the bycatch quota is not binding. The direct bycatch cost, γ , is the key to observe this result because it turns off the harvester to participate in Fishery One and cause the substitution under individual quota.

Finally, we investigate the change of decision in response to the policy variables, which are amount of individual quotas and direct bycatch cost.

Proposition 3

Assuming that the main target species individual quota is binding ($\lambda_{1i} > 0$), an increase in the main target species quota may facilitate the participation in Fishery One in any periods as the shadow cost of the main target species individual quota drops.

Proof.

$$\frac{dd_t}{dQ_{1i}} = \frac{\partial d_t}{\partial H_{it}} \frac{\partial H_{it}}{\partial \lambda_{1i}} \frac{\partial \lambda_{1i}}{\partial Q_{1i}} = \frac{\partial d_{it}}{\partial H_{it}} \left(\frac{q_{1t}}{\int_0^T \left(\frac{\partial d_{is}}{\partial H_{is}} \right) q_{1s}^2 ds} \right) \geq 0$$

Proposition 4

Assuming that the bycatch individual quota is binding ($\lambda_{bi} > 0$), an increase in the bycatch individual quota may facilitate the participation in Fishery One in any periods as the shadow cost of the bycatch individual quota drops.

Proof.

$$\frac{dd_{it}}{dQ_{bi}} = \frac{\partial d_t}{\partial H_{it}} \frac{\partial H_{it}}{\partial \lambda_{bi}} \frac{\partial \lambda_{bi}}{\partial Q_{bi}} = \frac{\partial d_{it}}{\partial H_{it}} \left(\frac{b_t q_{1t}}{\int_0^T \left(\frac{\partial d_{is}}{\partial H_{is}} \right) b_s^2 q_{1s}^2 ds} \right) \geq 0$$

Proposition 5

(1) Assuming that the main target species individual quota is binding ($\lambda_{1i} > 0$), an increase in the bycatch cost may hinder participation in Fishery One in any periods as a direct effect, but may facilitate the participation as the shadow cost of the main target species individual quota drops.

(2) Assuming that the bycatch individual quota is binding ($\lambda_{bi} > 0$), an increase in the bycatch cost may hinder the participation in Fishery One in any period as a direct effect, but the dynamic effect facilitates the participation as the shadow cost of the bycatch quota decreases, and the total effect is zero as the direct effect and the dynamic effect offset.

Proof.

$$\begin{aligned} \frac{dd_{it}}{d\gamma} &= \frac{\partial d_{it}}{\partial H_{it}} \frac{dH_{it}}{d\gamma} = \frac{\partial d_{it}}{\partial H_{it}} \left(\frac{\partial H_{it}}{\partial \gamma} + \frac{\partial H_{it}}{\partial \lambda_1} \frac{\partial \lambda_1}{\partial \gamma} I\{\lambda_{1i} > 0\} + \frac{\partial H_{it}}{\partial \lambda_{bi}} \frac{\partial \lambda_{bi}}{\partial \gamma} I\{\lambda_{bi} > 0\} \right) \\ &= \frac{\partial d_{it}}{\partial H_{it}} \left(-b_t q_{1t} + q_{1t} \frac{\int_0^T \left(\frac{\partial d_{is}}{\partial H_{it}} \right) b_s q_{1s}^2 ds}{\int_0^T \left(\frac{\partial d_{is}}{\partial H_{it}} \right) q_{1s}^2 ds} I\{\lambda_{1i} > 0\} + b_t q_{1t} I\{\lambda_{bi} > 0\} \right) \end{aligned}$$

The net effect of the increase in bycatch cost on the decision in each period differ due to the bycatch rate in each period. The rise in the bycatch cost cause the reallocation of the timing of targeting, and from the period with high bycatch rate to one with low rate, because the second term in the bracket may be higher than the first one if the bycatch rate is low. In addition, this may facilitate the participation in Fishery Two because it decreases the net revenue of Fishery One in any periods.

To summarize, the theoretical model shows that a seasonal profit-maximizing harvester dynamically substitute the timing of catch in response to the exogenous change in economic variables such as price and bycatch cost and biological variables including bycatch rate. An empirical question here is whether the dynamic effects play important roles in the decision-making of harvesters in real-world fisheries which is managed by individual quotas. To answer the question, we build an empirical model motivated by the results of the theoretical model and apply it to a fleet in Bering Sea Pollock Fishery.

2.3 FISHERIES PROFILE

This study uses a panel dataset of Catcher Processor (CP) vessels (17 vessels owned by seven companies) which operate in Bering Sea/Aleutian Islands (BSAI) region of the North Pacific. They utilize pelagic and bottom trawls as fishing gears. The fleet participates in the offshore fisheries and process fish onboard. The fleet consists of similar design vessels with lengths from 270 to 376

feet. The primary targets are Walleye Pollock in the BSAI and Pacific Hake in East Pacific (West Coast of the U.S.). In addition, some vessels catch yellowfin sole (YFS) as a sub-target in the BSAI. BSAI pollock fishery is one of the largest commercial fisheries in the world. BSAI pollock harvests occupies 40% of global whitefish production (Fissel et al. 2013), and it makes the fishery the largest in the U.S. There is a variety of products in this fishery including fillets, whole head and gutted (H&G), surimi, and roe.

The vessels stay at seas to operate fishing and processing for several weeks due to their size and processing facilities. During a trip, harvesters would make decisions on which species to target depending on the time-varying profit opportunities constrained by economic and biological (e.g. catch rate of species, maturity of roe) conditions driven by oceanographic and climatic trends. The species exhibit differing opportunities on varying time scales, leading to choose particular targets through the season. The fishing season is divided into two parts: “A” season (January to May) focused mainly on fishing pre-spawning pollock for the harvest of roe, which can consist over 4% of weight [35] and “B” season (June to November) aims more to the production of fillets and surimi products.

The regulation plays a large role in this fishery. The CP fleet consists of the vessels listed in Section 208 (e) of the American Fisheries Act (AFA). The AFA was enacted in 1998, and its purpose is to provide the BSAI vessels to conduct their fishery in a more rational manner and strengthen the U.S. ownership standards. The AFA Pollock Cooperatives program was implemented by the U.S. congress under AFA. The program includes participation requirements, defined the list of eligible vessels, finalized the TAC allocation among sectors, provided an allocation to the Community Development Quota (CDQ) program, and authorizing the formation of cooperatives. 40% of the Bering Sea commercial pollock TAC is allocated to the CP sector. The

CP fleet formed a cooperative to coordinate the pollock harvest under AFA, called The Pollock Conservation Cooperative. The cooperative members allocate the sectoral quota among themselves, and this allocation is treated as individual transferable quota (ITQ).

AFA does not allow the CP fleet to catch non-pollock species in the BSAI more than their “traditional catch” levels which is defined by the NPFMC based on pre-AFA level. This additional target is subject to “sideboard limits”¹⁰. The second target fishery in BSAI, YFS, is categorized as non-pollock groundfish species along with pacific cod and Atka mackerel, which are caught by C/P vessels at small amount. During the data period, a part of AFA C/P fleet targets YFS. The number of vessels ranged from 5 to 12, and the catch amount ranged from 7,900 MT to 23,900 MT [36] YFS is subject to the management of total allowable catch (TAC) scheme since this traditional catch is not individually allocated within the cooperative, but the TAC does not bind in any year between 2001 and 2015, and hence it is simply treated as an open access.

In addition to the allocation of pollock quota among sectors, another problem in this fishery is bycatch. The primary bycatch problem is incidental catch of Chinook salmon. The fishery management plans designate Chinook salmon bycatch as prohibited species catch (PSC), and harvesters in BSAI pollock fishery were not allowed to retain or sell it although Chinook salmon is valuable. The restriction includes time and area closure when bycatch limits were exceeded. Chinook salmon bycatch, however, significantly increased in this fishery in 2001 to 2007 [37,38]. To resolve the issue, the North Pacific Fishery Management Council (NPFMC) decided to implement a new management measure under Amendment 91 to the Bering Sea Aleutian Islands

¹⁰ Section 211 (b) of the AFA establishes sideboards (limits for AFA catcher processors), stating that the AFA CPs are prohibited from “*exceeding the percentage of the harvest available in the offshore component of any Bering Sea and Aleutian Islands groundfish fishery (other than the pollock fishery) that is equivalent to the total harvest by such catcher/processors and the catcher/processors listed in section 209 in the fishery in 1995, 1996, and 1997 relative to the total amount available to be harvested by the offshore component in the fishery in 1995, 1996, and 1997*”.

Fishery Management Plan in 2011. The program under Amendment 91 establishes a hard cap of Chinook salmon bycatch (called Prohibited Species Catch (PSC) limit), and employ an industry-designed incentive program to reduce Chinook salmon bycatch below the regulatory cap (NMFS, 2010). The PSC limit is set for the fleet, and allocated by the cooperatives within the fleet proportional to the individuals' pollock quota [39].

The harvesters avoid bycatch not only because of the hard cap, but also the costs and incentives. The program under Amendment 91 aims not only to meet the cap, but decrease bycatch Chinook salmon as much as possible below the cap level. Hence, the incentive program includes fishing area prohibition for vessels with poor bycatch performance. Accordingly, the harvesters would avoid bycatch even if the cumulative catch of salmon is not close to the limit.

The fleet also join Pacific Hake fishery in the West Coast when they are not operating in Bering Sea. Pacific Hake is managed under West Coast Groundfish Trawl Catch Share Program. This is a limited entry fishery, and any Catcher Processor needs a permit to target hake. The regulation allows vessels to form a cooperative, and require the coop to allocate the catch among members. The season of Pacific Hake fishery for the CP vessels opens on May 15 every year. The CP vessels finish using their quota of pollock in early May although the A season is until June 20, because they move to the West Coast to start targeting Pacific Hake in the middle of May.

In summary, the CP fleet of the Alaskan pollock fishery is characterized by individual quota management that is generated as a result of resolution of the allocation issue, bycatch problem of Chinook salmon, and yet diverse target species. These characteristics allow us to analyze the important aspects of fishery choice problem. First, targeting more than one species allow us to estimate the discrete choice behavior in multi-fisheries. In addition, individual quota

management setting is the key of dynamic problem in the fishery, and bycatch problem highlights the trade-off with catch or revenue opportunities.

2.4 DATA DESCRIPTION

This study uses a few data sources. The main data is collected by the North Pacific Groundfish Observer Program (NPGOP). The observers collect a complete record of fishing effort and total catch for all vessels over 124 feet. The data available to us consists of week-vessel level observations of the fleet of 17 vessels from 2005 to 2013, when they are targeting pollock and YFS in Alaskan waters. Weekly variables for each vessel include number of hauls, tow duration, gear setting, and amounts of target catch, prohibited species catch, and bycatch species harvested.

In addition to the NPGOP data, we use annual price data from Economic Stock Assessment and Fishery Evaluation Report [40], and monthly export data of fishery products that is collected by the U.S. Census Bureau and compiled by NOAA fisheries. The export value is not exactly the price the harvesters face, but it captures the in-season trend of values. The actual in-season variations of ex-vessel or wholesale prices are not available.

The vessel-specific Pacific Hake harvest data is held by a separate regional agency, so we use public data on the Pacific Hake. The only available data is number of vessels targeting Pacific Hake for a confidential reason. We use this variable as a proxy for the productivity of Pacific Hake, and treat it as an attribute of “outside of Alaska” alternative.

2.5 EMPIRICAL MODEL

2.5.1 *Overview*

The largest gap between our theoretical model and an empirical analysis is that the harvesters are subject to uncertainty, and hence their decision-making is based on expectations. To empirically analyze the harvester's decision-making, one needs to form weekly expected values of catch rates of target species, bycatch rate, and prices. An issue is that the weekly data aggregates the harvesters' behavior within a week. In this study, we do not take into account the behavior of the harvesters within a period (e.g. spatial deployment of effort), hence we assume that the catch rates are the result of optimal behavior within a period, and we form the expectation assuming that harvesters expect to behave optimally within a period.

To form weekly-level expectations, we assume that the harvesters know the seasonal pattern of catch and bycatch rates. Given the available data, the expectation is formed based on the past catch of own and other vessels.

The empirical investigation of participation and target fisheries choice has been treated as discrete choice framework. The analysis of harvesters' behavior as discrete choice initially started by Backstael and Opaluch [19]. They find that the harvesters choose fishing gear reacting to the expected rent positively, and to the variance negatively showing risk-averse behavior. Target choices are estimated in some studies, some focuses on risk preference [41,42] information sharing [27]. The target choice estimation in the context of dynamic quota use, however, has not been done to the extent of our knowledge. Although only minimal attention has focused on the dynamic choice of the target, dynamic factors has been integrated within single-fishery location choice models. While some of the studies solve a full dynamic programming [23,24], others include computed expectation term to incorporate forward-looking behavior of harvesters [22],

[27]. Approach of this study is similar to the latter. We do not solve a full dynamic programming, but the estimating equation contains a variable that captures the aspect of the dynamic planning problem which harvesters face in fisheries with quota management. The usage of total quota (not individual) has been incorporated in empirical choice studies by including the amounts of quota remaining [43] or the percent utilization of total quota [29], but our approach improves it by including a measurement of future quota use.

What we test here is whether individual's timing decision to participate in which fisheries are driven by the dynamic decisions: they may not participate in the myopically best fishery, because they want to save quota for participating later when it is even more valuable. The emphasis here is that the seasonal plan in the beginning of a season drives the fishery choice behavior of harvesters. In particular, the shadow values of quota use in the beginning of a season play important roles in harvesters' decision as our theoretical model highlights. To empirically estimate such behavior, we need a dynamic model.

As noted above, there are two approaches of dynamic empirical estimation of discrete choice; The full dynamic programming and the estimation with approximated key state variables. The full dynamic programming approach may not be appropriate for our study which is quota managed fisheries problems. In a dynamic problem of quota-managed fisheries, the remaining quota left is the key dynamic variable for harvesters' decision. However, it is not the state variable that directly influences the benefit flow in a period. Rather, it affects future benefits, which are in the expectation term in the Bellman equation. Since the remaining quota differently affects the decision period by period, the problem is not conventionally recursive. In this study, we construct a seasonal-planning model of the dynamic program of controlling the harvest quota by choosing target fisheries without solving the full dynamic program. Our empirical model includes an

approximated key state variable to track the usage of individual quota over the season by relating the data and the theoretical model.

2.5.2 Model Specification

Our empirical model builds on a random utility maximization model (RUM). The participation decision made at a margin affects vessels' instantaneous profitability, and also the future profit through the usage of fishery quota, as illustrated in our theoretical model. In addition, the choice is affected by expected bycatch associated with the target species. The RUM approach specifies the fisheries choice based on the alternative-specific expected utility. In our estimation, a binary discrete choice estimator is adopted. The latent variable approach is often used to analyze binary responses. This latent variable can be interpreted as a participation index, H_{it} , in eq (2.7) of our theoretical model. The participation index is essentially a difference between net revenues from Fishery 1 and 2. In the empirical model, this index is modeled as a difference between utility from Pollock fishery and others including YFS and Hake. The latent variable for harvester i in week w of year y and is specified as follows.

$$U_{iyw} = \beta^{poll}(QSpeed_{iyw})EREV_{iyw}^{poll} + \beta^{yfs}EREV_{iyw}^{yfs} + \gamma (QSpeed_{iyw}, A91)ECPR_{iyw} + \theta'Z_{iyw} + \xi_i + \varepsilon_{iyw} \quad (2.9)$$

where EREV is expected revenue per unit effort, measured as species catch (MT) divided by number of haul-duration multiplied by price. In the theoretical model, the shadow cost of quota is an important variable that affects harvester's decision. While the actual shadow cost is not observed, we capture the role of the shadow cost by constructing a variable, $QSpeed$, which is explained later. To take into account the perceived change in bycatch cost induced by Amendment

91 of FMP, the dummy variable A91 (1 if after 2011) is included. The covariates Z include the switching cost and monthly number of vessels in pacific hake fishery.

2.5.3 *Modelling the Expectations*

The modelling of expectations in empirical fisheries analyses is critical since the harvester choice largely depends on their expectations. The expected return from an alternative such as catch or revenue has been modeled as simple measure of the past data across the fleet such as rolling average [44, 45] and auto-regressive moving averages [27,46]. With the fine resolution of location data, Abbott and Wilen formed individual-level expectation rather than assuming the common fleet-wide knowledge about information to estimate individual choices based on transitory and specific information [29].

In the temporal choice of fisheries participation, such idiosyncratic information may not play a large role, but the prior knowledge about seasonality and the updated current season information would matter. While Abbott and Wilen focus on the individual choice of fine resolution of location given the decision of participation, such fine-grained information is aggregated for participation timing choice [29]. Hence, we assume that the information about seasonality is commonly shared, and only individual realized outcome of catch matters to individual's expectation. To capture the seasonal trend from the data, we estimate standardized catch per unit effort (haul-hour) and bycatch rate (chinook-pollock ratio) of each week by using log-normal and Poisson regression, respectively.

$$PollCPUE_{iyw} = e^{\sum_w \delta_w DW_w + \sum_y \delta_y DY_w + \sum_i \delta_i DV_i} \quad (2.10)$$

$$Chin_{iyw} = e^{\sum_w \eta_w DW_w + \sum_y \eta_y DY_w + \sum_i \eta_i DV_i} + \log(Poll_{iyw}) \quad (2.11)$$

where DW is a week dummy variable, DY is a year dummy, and DV is an individual vessel dummy. The weekly standardized CPUEs and bycatch rates are estimated as the coefficients δ_w and η_w .

Because these coefficients are estimated by dummy variables, the estimates may not be smooth in week. To obtain seasonal trend of these variables, we apply loess regression to these estimates. The loess, or local regression method, is a nonparametric method to fit a smooth curve to the data. At each point of the data, a polynomial is fitted to the subset of data, where the range of subset is arbitrary determined. We apply this method to estimated weekly CPUEs and bycatch rates so that the smooth seasonal trends are obtained. The standardized CPUEs and bycatch rates, and their smoothed trend are estimated using the whole data. We assume that the seasonal trend is known by the harvesters. The estimated standardized CPUE and bycatch rates, and their smoothed trends are shown in Figure 2.1.

The individual expectation of a week is formed using the observed seasonality from the same week and from the previous week in the current year. We simply regress the trend and lagged CPUE on the current CPUE, and use the fitted values as the individual expectations.

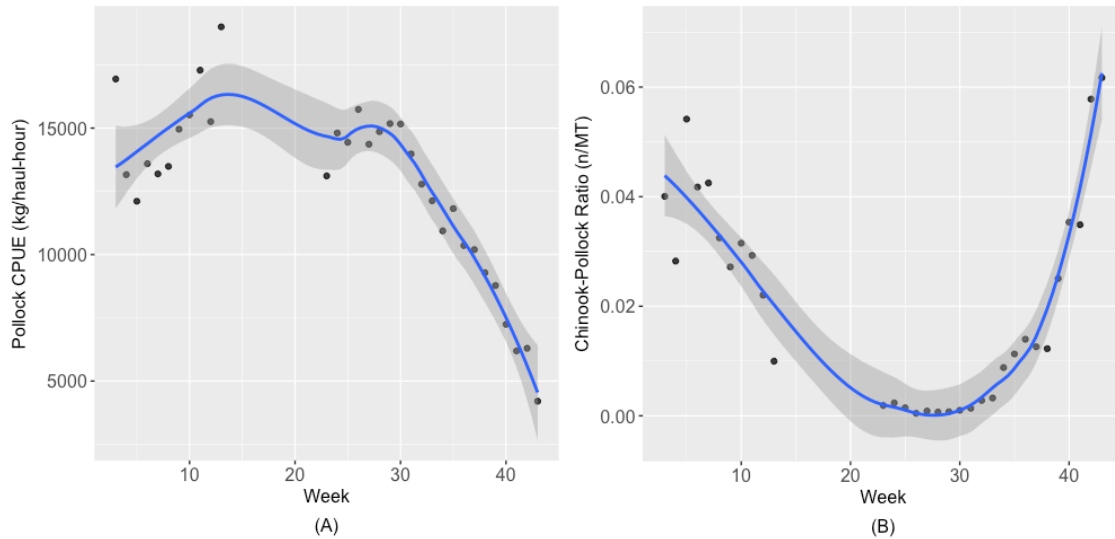


Figure 2.1. Estimated Seasonal Trend of Pollock CPUE (A) and Chinook-Pollock ratio (B).

2.5.4 *The Quota Speed Variable*

We construct variables that capture the individual quota usage in a season. In the dynamic problem, the harvester's solution is a path of choice and usage of quota. In our theoretical model, the perfect foresight agents solve the dynamic optimization problem and obtain λ_{1i} and λ_{bi} which are time-invariant shadow value of quotas. However, the realization of individual quota usage deviates from the planned path, due to uncertainty of catch. Hence, we assume that the harvesters recalculate the shadow values at each period based on the remaining quotas. Proposition 3 shows that the participation decision may be changed by the change in remaining quota through the change in the shadow value, and the magnitude of change in the participation index depends on the catch rate of the week and interaction of participation decisions and the catch rates in the rest of the season. This term is interpreted as the opportunity of catch (catch rate) relative to the rest of the season. This theoretical result is translated into the empirical setting.

We construct a variable that consists of the remaining quota left, expected CPUE in future weeks, and the weeks remaining in the season. This variable is called Speed of Quota Use (Qspeed). The idea is that the variable captures the pace of quota use relative to the time left in the season. In the beginning of the season, the harvester has a planned path of the quota use, which is that the quota is used when the profitability of main target catch is high, and used less when it's low. During the season, the realized catch may be different from the expected one, and thus the quota use speed may be too fast or slow relative to the remained profit opportunities in the rest of season. To measure this fast-or-slow quota use, we formulate the variable below.

$$Qspeed_{iyw} = \frac{\%QuotaLeft_{iyw} - \%WeightTimeLeft_{iyw}}{\%QuotaLeft_{iyw} + \%WeightTimeLeft_{iyw}} \quad (2.12)$$

where $\%QuotaLeft_{it}$ is the percentage of remaining quota, and $\%WeightTimeLeft_t$ is the percentage of the time left weighted by revenue opportunities in the season. The value of this variable ranges -1 to 1. If the value is negative, quota is being used too fast relative to the benchmark pace, and it is too slow if the value is positive. We expect the coefficient on this variable is positive, because harvesters will slow their quota use down if the quota usage is too fast.

The construction of the variable tracks the quantity of quota remaining relative to the future opportunity to use the quota and catch the main target. Suppose the catch opportunity is constant throughout the season. Then harvesters might target using quota at a constant rate: using it more slowly is somehow falling behind their fishing opportunity, and using it more quickly is getting ahead and using quota too fast. It is, however, not realistic that the revenue opportunity is constant, but varies over a season. How can we capture this variation? The revenue opportunity can be approximated by expected CPUE and price of fish. Again, Proposition 3 states that the increase in the quota may increase the participation index by the opportunity of catch relative to the rest of

the season. Using this term as an analogy, we weight the time left by the interaction of expected probability of participation and the expected revenue in each period of the rest of the season. Intuitively, a period with high revenue is “more time” or more opportunity to catch fish and spend quota compared to a period with low revenue, because it is worth more to spend their quota in the same time length. However, the harvesters know the probability of participation in each week of the rest of the season based on their experience. This probability is simply calculated by the ratio of number of participated vessels in each week and the total number of vessels. The percentage of the weighted time left, $\%WeightTimeLeft_t$, is calculated as the ratio of an integration of expected revenue opportunity (interaction of participation probability and expected revenue) over the rest of the season and an integration over the whole season.

$$\%WeightTimeLeft_{iyw} = \frac{\sum_{w=1}^T \Pr(DW_w)E(CPUE_{iyw})^2 - \sum_{w=1}^t \Pr(DW_w)E(CPUE_{iyw})^2}{\sum_{w=1}^T \Pr(DW_w)E(CPUE_{iyw})^2} \quad (2.13)$$

Where $\Pr(DW_w)$ is a probability of participation in week w .

2.5.5 Estimation

Because our interest is the participation in pollock fishery, which is under individual fishing quota management, given the outside opportunities including yellowfin sole and pacific hake fisheries, we adopt binary logit estimator. This models the problem as entry problem to the pollock fishery by placing a dummy variable that takes one if the harvester target pollock in the week as a left-hand side variable.

Limitations of a simple logit estimator is that heterogeneous characteristics over individuals are not taken into account, and the unobserved part of the random utility is assumed to be uncorrelated across time. While the heterogeneity itself is not of our interest, there is a possible source of bias if the homogeneous assumption is violated. To combat with these possible problems, we adopt conditional logit estimator.

Including individual fixed effects in a nonlinear model causes a bias, known as the incidental parameters problem [47]. The estimates of the parameters of interest are inconsistent if the number of individuals is large while the number of time period is small. To overcome this problem, there are two approaches: conditional logit and bias correction. Chamberlain suggested a maximum likelihood estimator with a likelihood function which conditions out the individual effects [48]. Although this approach does not allow to estimate the individual effects per se, the estimates are free from the bias caused by the correlation with persistent individual effects. The other approach is bias correction [49]. suggests analytical bias correction approaches for nonlinear panel models.

2.6 ESTIMATION RESULTS

2.6.1 *Main Results*

The estimation results of binary conditional logits for A season and B season are shown in Table 2.1 and **Error! Reference source not found.**, respectively. Column 1 shows a myopic model, which does not include any dynamic variable interactions. Column 2 model adds Q speed interactions. Column 3 includes Amendment 91 interactions in addition to Column 2 model, and Column 4 augments Column 3 by adding Bycatch Qspeed (BQspeed) interactions. Column 5

model includes dynamic variables that generates the best AICs. In terms of model fit, likelihood ratio test rejects the null hypothesis that additional parameters in Column 2 model are zero for A season and B season, suggesting that the dynamics play in a role in harvester's decision. While likelihood ratio test rejects that BQ speed is in effect for A season, it does not reject the null hypotheses that any additional parameters to Column 2 model are zero for B season. In summary, harvesters consider possibility of binding bycatch quota (prohibited species catch limit) and incentive structure has changed in A season, but they merely take into account main target species quota as a dynamic variable in B season.

Table 2.1. Binary Conditional Logit Result, A season

	<i>Dependent variable:</i>				
	Pollock Target Dummy				
	(1)	(2)	(3)	(4)	(5)
EREV (Poll)	0.023 (0.032)	0.137** (0.042)	0.148*** (0.043)	0.130** (0.045)	0.155*** (0.044)
EREV (YFS)	-0.808*** (0.232)	-0.621** (0.237)	-0.489* (0.239)	-0.523* (0.246)	-0.498* (0.241)
Expected Chin-Poll Ratio	186.550*** (21.806)	227.954*** (27.200)	243.141*** (28.046)	263.979*** (32.707)	
Switch Cost	-3.554*** (0.479)	-5.060*** (0.650)	-5.645*** (0.708)	-4.738*** (0.696)	-2.683*** (0.565)
EREV (Poll) x Q Speed		0.121* (0.059)	0.274*** (0.077)	0.210** (0.080)	0.208*** (0.028)
ECPR x Q Speed		58.039 (38.543)	-5.334 (46.882)	-1.085 (49.699)	
ECPR x A91	3.855 (5.871)	3.111 (6.235)	-3.064 (6.512)	-13.622 (7.071)	
ECPR x Price (Poll)					205.772*** (24.091)
EREV (Poll) x Q Speed x A91			-0.386* (0.184)	-0.975 (0.550)	-0.476** (0.155)
EREV (Poll) x BQ Speed x A91				0.537 (0.479)	0.323* (0.127)
ECPR x Q Speed x A91			76.976 (147.617)	374.089 (333.766)	
ECPR x BQ Speed x A91				-136.094 (231.361)	
AIC	459.03	373.23	349.9	330.57	320.01
LR test		89.806***	27.328***	23.324***	
Observations	1,356	1,356	1,356	1,356	1,356
R ²	0.274	0.320	0.334	0.345	0.347
Log Likelihood	-224.517	-179.614	-165.950	-154.287	-153.004

Note:

* p ** p *** p<0.001

Table 2.2. Binary Conditional Logit Result, B season

	<i>Dependent variable:</i>				
	Pollock Target Dummy				
	(1)	(2)	(3)	(4)	(5)
EREV (Poll)	-0.096 (0.101)	-0.134 (0.106)	-0.134 (0.106)	-0.146 (0.108)	
EREV (YFS)	0.533 (0.516)	0.494 (0.526)	0.535 (0.529)	0.521 (0.531)	
Expected Chin-Poll Ratio	-19.497 (26.293)	-54.890 (35.371)	-56.319 (35.178)	-68.702 (36.127)	-10.572 (23.594)
Switch Cost	-5.188*** (0.611)	-5.103*** (0.645)	-5.112*** (0.643)	-5.107*** (0.650)	-5.190*** (0.390)
Number of Hake Vessels	-0.100** (0.031)	-0.092** (0.032)	-0.097** (0.032)	-0.101** (0.033)	-0.087** (0.027)
EREV (Poll) x Q Speed		0.011 (0.079)	0.056 (0.103)	0.045 (0.102)	
ECPR x Q Speed		99.885 (57.794)	103.884 (89.455)	104.914 (81.991)	97.030* (41.402)
ECPR x A91	17.008 (26.460)	22.659 (33.156)	26.081 (33.810)	4.150 (46.529)	
EREV (Poll) x Q Speed x A91			-0.120 (0.148)	-0.118 (0.151)	
EREV (Poll) x BQ Speed x A91				-0.960 (1.520)	
ECPR x Q Speed x A91			2.285 (117.855)	26.014 (125.193)	
ECPR x BQ Speed x A91				699.942 (1,194.110)	
AIC	475.1	471.25	474.17	476.96	466.75
LR test		7.846*	1.085	1.203	
Observations	1,983	1,983	1,983	1,983	1,983
R ²	0.299	0.302	0.302	0.303	0.345
Log Likelihood	-231.548	-227.625	-227.083	-226.481	-229.376

Note:

*p<0.05 **p<0.01 ***p<0.001

In A season, the signs on the parameter estimates are consistent with the predictions of the theoretical model, except for the expected chinook-pollock ratio. The expected revenue of pollock promotes the participation in pollock fishery, and the expected revenue of yellowfin sole disincentivizes the participation. However, the coefficient on the expected chinook-pollock ratio shows the positive sign, which implies high bycatch facilitates the participation in pollock fishery. As seen in the data, the timing of the matured pollock roe and high chinook salmon bycatch rates in the A season overlap. Because the variation of these two variables are largely explained in timing, it is difficult to identify the effect separately. Although the bycatch species, Chinook salmon, is a high valued fish, vessels in the fleet are not allowed to sell these species, hence the harvesters do not have incentive to catch salmon. We therefore estimate Column 5 model excluding the Chinook-pollock ratio.

The dynamic effect seems to play a role in the A season as the coefficients on Qspeed interactions are statistically significant, but the effects are small. The interaction term of the quota speed and expected revenue of pollock has a positive coefficient. This implies that the harvesters are more likely to participate in pollock if the actual pollock quota usage is slower than the “planned” usage. If the quota usage is slower than planned, the shadow cost of the quota gets lower, and hence the participation is promoted. This result is consistent with Proposition 3, and indicates that the harvesters consider dynamic planning in a season under individual quota management. However, the elasticities of the Qspeed interactions, shown in **Error! Reference source not found.**, show that they are very small relative to other contemporaneous effects. While the bycatch individual quota (PSC limit) does not usually bind, the effect of BQspeed is relatively large. The harvesters may accept some degree of bycatch because they would like to catch pollock with mature roes, but resulting high bycatch may threaten them to bind their PSC limit. In this

case, their perceived cost of bycatch (expressed as γ in the theoretical model) is small, but shadow cost of bycatch quota can be positive.

Table 2.3. Elasticities of variables in A season

	Elasticities
EREV (Pollock)	0.267
EREV (YFS)	-0.139
Switch Cost	-0.048
EREV x Q Speed	0.019
ECPR x Price	1.287
EREV x Q Speed x A91	0.000
EREV x BQ Speed x A91	0.083

The B season result of logit estimation is shown in **Error! Reference source not found.** Unlike the A season, the harvesters are avoiding bycatch and not sensitive to revenue opportunities. However, these coefficients are statistically insignificant. The key variables that determines the participation in B season are persistence of participation (switching cost) and the relative benefit in pacific hake fishery. The likelihood ratio tests suggest that the additional variables in Column 2 model do not have zero coefficients, but the test does not reject that further additions of state variables play a role, suggesting that only main target species quota matters. Although the coefficients are statistically insignificant, the negative sign on the coefficient of expected pollock revenue and the positive sign on the one of expected YFS revenue do not make sense. The possible reason is that there are only few vessels target YFS in B season, and there are not much variation in expected pollock revenue. We exclude EREV of YFS and included EREV of pollock as an offset term to estimate Column 5 model for B season. While the coefficients are robust across the models, the AIC for Column 5 model is the best among estimated models. The likelihood ratio test does not reject the null hypothesis that the coefficients on the variables that are in Column 2 but not in Column 5 are zero ($X^2 = 3.501, DF = 4, p\text{-value} = 0.477$).

The participation elasticities of explanatory variables in Season B are shown in **Error! Reference source not found.** We interpret this result that the harvesters need to consume their quota as quick as they can because they know that the bycatch rate increases in the later season. If they have remained quota, they are forced to use their quota when the bycatch rate is very high. Hence, the slower usage of quota leads the harvesters to participate in the pollock fishery despite of the high bycatch rate in the period. This result supports the existence of dynamic avoidance of bycatch. Specifically, the harvesters attempt to catch less salmon in the later season by catching more earlier and consuming their quota. The shadow cost of the quota is influenced by the bycatch in the later season, and hence the decreased shadow cost promotes the participation regardless of the current bycatch rate.

Table 2.4. Elasticities of variables in B season

	Elasticities
ECPR	-0.02
Switch Cost	-0.14
# of Hake vessels	-0.05
ECPR x Q Speed	0.02

2.6.2 Robustness Check: Random Parameter on YFS Revenue

As highlighted in the theoretical model, the opportunity cost of participating a fishery should be taken into account to analyze the participation. While the outside options of pollock include yellowfin sole fishery, some vessels do not target YFS at all. Between 2005 and 2013, 5 to 12 vessels targeted YFS (Northern Economics, 2017). This implies that some vessels do not prefer targeting YFS while others do. To take into account this aspect, we estimate a random parameter logit model.

Random parameter logit, which is a type of mixed logit, is a model that allow coefficients

to have distributions over individuals. While fixed effect model consider heterogeneity by a different constant, the random parameter takes it into account by heterogenous response to variables. This model is appropriate to look into the difference in response to YFS revenue opportunities. We adopt two specifications to estimate the model. One assumes that the distribution of the parameter on YFS revenue is normal distribution, and the other assumes uniform distribution.

The result of the random parameter logit estimations is shown in **Error! Reference source not found.** For A season, the mean of the estimate is close to the one estimated in the main estimation. However, the standard errors in both model of normal and uniform distributions are statistically significant, implying that the heterogenous response to YFS revenue is present. This result does not hold for B season. The standard errors of the estimates of standard deviation of the distributions are large for both specifications. Harvesters barely participate in YFS fishery in B season (5 out of 1983 observations). In summary, the preferences on YFS fishery can be heterogenous based on the A season result, and that is not really observed in B season. Hence, it is justified that Column 6 model of B season excludes the YFS revenue as an explanatory variable.

Table 2.5. Random Parameter logit: Coefficient Estimates on YFS Revenue

Model	Parameter	Estimates	Std..Error
Normal, A season	Mean	-0.465	0.239
	S.D.	0.221	0.079
Uniform, A season	Mean	-0.493	0.252
	S.D.	0.36	0.111
Normal, B season	Mean	0.461	0.466
	S.D.	0.117	0.261
Uniform, B season	Mean	0.439	0.464
	S.D.	0.163	0.467

2.6.3 *Robustness check 2: Adjustment of Effort by Internal Margin*

While we show the supporting evidence of dynamic decision in fisheries participation of harvesters, the harvesters may exhibit bycatch avoidance behavior in different margins. The usage of quota can be adjusted by the amount of effort to catch fish given the participation in the fishery.

The internal margin (fishing effort) is estimated by OLS using the sample that limits those which participate in the pollock fishery. We estimate the effect of explanatory variables (revenue per effort and bycatch rate which are used in the participation model) and their interactions with the dynamic variables including Qspeed on effort variables, which are duration per week and the number of hauls per week. We include observed revenue per effort and chinook-pollock ratio instead of expected one as explanatory variables, because their decisions during a week can be determined based on their observation in the week. CPUE, which is a part of expected revenue per effort, is calculated by catch per week divided by duration per week. Hence, duration appears on the left-hand side and in denominators of right-hand side variables. If duration includes measurement error, it may cause a bias on estimated coefficient, known as division bias. In addition, duration per week can be shorter if fish is locally abundant, because it is landed on board when the trawl net is filled quickly. However, the total duration per week can be longer if harvesters increase the number of hauls. Number of hauls captures only this behavior, so it is worth to estimate both and compare them.

The overall result of effort estimation is as expected, as shown in **Error! Reference source not found.** The effort is reduced when the bycatch rate is high, and positively reacts to revenue when the quota usage is slow. Bycatch avoidance behavior is weakened when the quota speed is slow, and this result is reinforced after Amendment 91 is implemented. This implies that the result

in the participation decision still holds; the harvesters avoid less current bycatch to avert future bycatch. In addition, the bycatch quota speed and revenue per effort reduces the effort, suggesting that the shadow quota of bycatch quota affects the effort decision, and the possible bycatch quota binding threatens the harvesters. Interestingly, the signs of current revenue per effort (duration) are opposite in the two models. One possible reason may be the division bias, but the other could be simply the capacity of trawl nets. When the catch per duration is high, the net is quickly filled up and the harvesters are forced to land on board faster. As a result, total duration per week can be shorter. On the other hand, the harvesters would increase the number of hauls when the catch per duration is high as their decisions.

Overall, the fishing effort variables, which are the internal margins, are influenced by the dynamic variables. In our theoretical model, the internal margin within a period is omitted for the simplicity. Although the empirical result of participation (external margin) is consistent with our theoretical model, the internal margin model may additionally explain the dynamic behavior of the harvesters.

Table 2.6. Effort Estimation Result, B season

	<i>Dependent variable:</i>	
	Duration (1)	Haul (2)
REV (Poll)	-0.006*** (0.0003)	0.00005*** (0.00001)
Chin-Poll Ratio	-543,338.400** (171,604.000)	-47,913.950** (17,078.800)
REV (Poll) x Q Speed	0.005*** (0.001)	0.00004*** (0.00001)
CPR x Q Speed	596,827.300** (224,884.700)	35,409.990 (22,603.740)
CPR x A91	-254,907.300 (746,081.500)	-219,017.900** (74,723.060)
REV (Poll) x Q Speed x A91	-0.001 (0.001)	0.00001 (0.00001)
ECPR x Q Speed x A91	-1,355,206.000 (1,087,329.000)	378,667.700*** (112,467.800)
REV (Poll) x BQ Speed x A91	-0.009* (0.004)	-0.0002*** (0.00004)
ECPR x BQ Speed x A91	1,288,352.000 (796,530.900)	116,290.700 (79,053.670)
Observations	1,776	1,776
R ²	0.271	0.112
Adjusted R ²	0.261	0.100
Residual Std. Error (df = 1751)	69.931	6.964
F Statistic (df = 24; 1751)	27.109***	9.182***
<i>Note:</i>	* p<0.05 ** p<0.01 *** p<0.001	

2.7 POLICY SIMULATION

One of the important objectives of constructing economic models for harvesters in resource use industry is to conduct policy simulation that explore the economic and biological impact of alternative regulation scenarios. We run a simulation of an alternative policy that has been raised for analysis in the Council Process—namely, opening the B season earlier, which aims to reduce bycatch of Chinook salmon which frequently caught in the later B season. Specifically, we simulate the harvesters' dynamic fishery target choice in a response to opening the B season two weeks earlier. The end date of the season remains at the status quo. We expect that the harvesters will participate earlier so that they can catch enough pollock using their main target species quota, while they avoid bycatch of Chinook salmon. One concern of this alternative is that the other Non-Chinook bycatch species, mainly Chum salmon, may be caught more than the amount under the current policy. We predict the harvesters' participation under current and the alternative policies using the parameter estimates from our empirical model.

We conduct the simulation as follows. The harvesters' decisions are predicted based on the estimated model, then we calculate the catch of a week based on the decision. This calculated catch is used to compute the quota use and Qspeed for the prediction of the next week. We use the observed CPUE of each species and bycatch-pollock ratios from the data. B seasons of each year from 2005 to 2013 are simulated.

The alternative policy simulation is done by adding two weeks before the first week of the current B season. The CPUEs and bycatch-pollock ratio of the added weeks are interpolated using the loess estimations used in the main estimation section. our interest in this policy change is the

changes in the timing and total amount of bycatch species caused by changes in the target species choice of the harvesters.

The simulated weekly number of vessels targeting pollock is shown as the green line in Figure 2.2. The error bars show the maximum and minimum value in a week among the simulated years (2005-2013). The simulated number under status quo are underpredicted relative to the observed number, which is shown as the red line. This may be due to two reasons. First, the predicted number of the vessels is simply a sum of the predicted probabilities of the participation in pollock in a given week. Because the probability may not be one for every vessel, the sum can be lower than the actual number of the vessels. In addition, the conditional logit model estimates the parameters of the model controlling for the vessel fixed effects, but it does not estimate the fixed effects *per se*. Although some vessels persistently target pollock, and it is captured by the model to estimate the parameter, such effects are not taken into account to predict here. Although the prediction of the model does not perfectly predict the number of participation, it shows the common feature that the vessels participate in the early season and the number of vessels decreases over a season. The blue line shows the simulated number of vessels under the alternative policy. As expected, the vessels target pollock in the first two weeks which is added under the new policy, and the number of the vessels in the mid to later season is less than the current policy.

The change in the vessels behavior is expected to affect the catch performance of a season. The weekly catch of pollock increases in the first two added weeks, and decreases in the later as expected, shown in Figure 2.3. This is primarily explained by the shift of participation timing under the new management policy, as the catch rate tends to be higher in the early periods in B season. As shown in Figure 2.4, Chinook salmon catch does not change in the early B season by the alternative policy, but it gets lower than the current policy in the middle of B season as the number

of vessels targeting pollock reduces in this time of a season. Figure 2.5 shows the average, minimum and maximum weekly catch of non-Chinook salmon. Because of the early open of B season, the non-Chinook salmon catch in those weeks increases some amount. It is noteworthy that the maximum weekly catch of both Chinook and non-Chinook salmon catch also decrease under the new policy, as the vessels are less likely to target them in the middle of the season. This implies that the policy may be effective even in a “bad” year of salmon bycatch.

The differences of total seasonal catch of each species between status quo and the policy alternative are shown in Figure 2.6. Chinook salmon bycatch is reduced by about 25 percent on average. As the policy aimed, Chinook salmon bycatch is effectively reduced even in the worst outcome year, in which the bycatch is decreased by about 14 percent, while the total pollock catch does not change much. The undesired outcome is that non-Chinook salmon bycatch. Non-Chinook bycatch is cut by about 7 percent on average, but it increases by 18 percent in the worst year. It is large in a relative term (percentage of total seasonal catch), but the magnitude is not as large as the good years of bycatch reduction. As shown in **Error! Reference source not found.**, the maximum number of the total annual catch of non-Chinook salmon is 273, which is the worst, but it is reduced by about 2,000 on average.

In summary, the proposed policy alternative could cut bycatch by giving the harvesters opportunity to catch pollock while avoiding Chinook salmon bycatch, and it is less likely to increase the non-Chinook salmon bycatch. The dynamic bycatch avoidance behavior explains this outcome because the increase in Chinook bycatch rate in the later B season pushes the harvesters to target pollock earlier as the empirical result shows, and additional first two weeks provide time to spend their pollock quota before Chinook catch arrives.

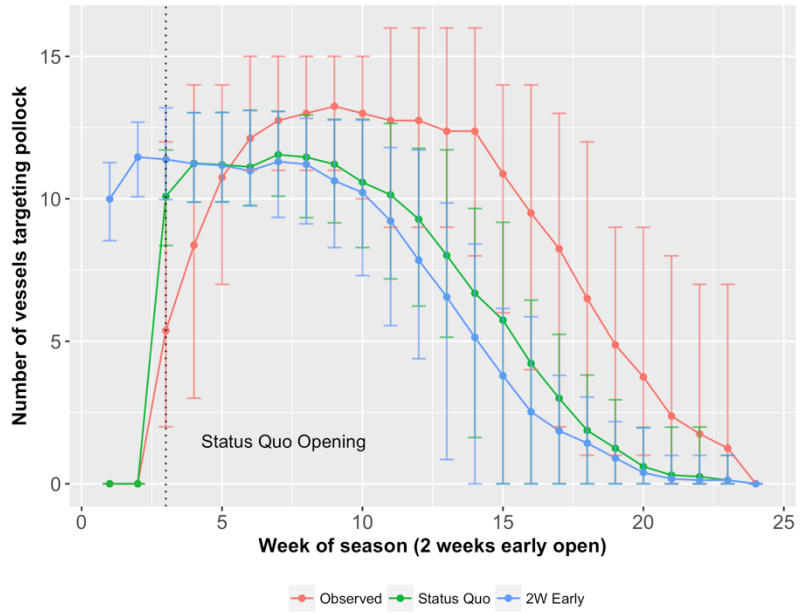


Figure 2.2. Simulated numbers of vessels targeting pollock under status quo and alternative policy.

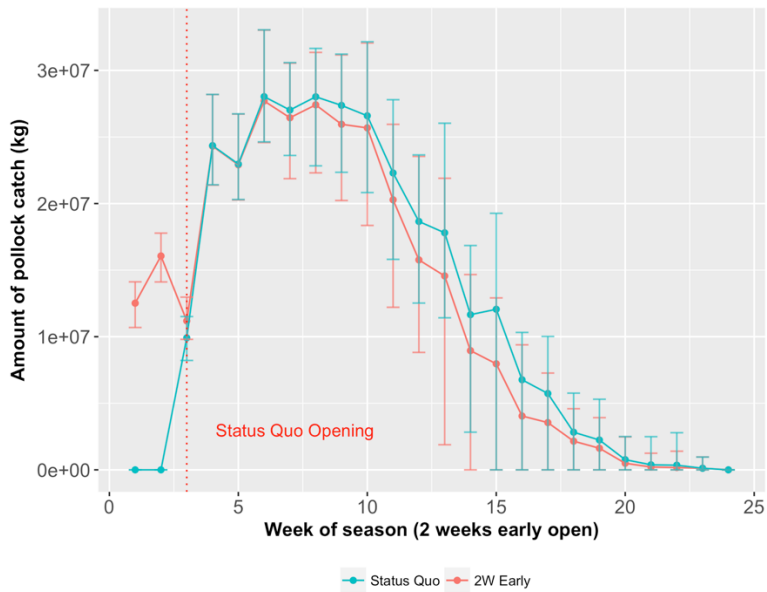


Figure 2.3. Simulated weekly amount of pollock caught under status quo and alternative policy.

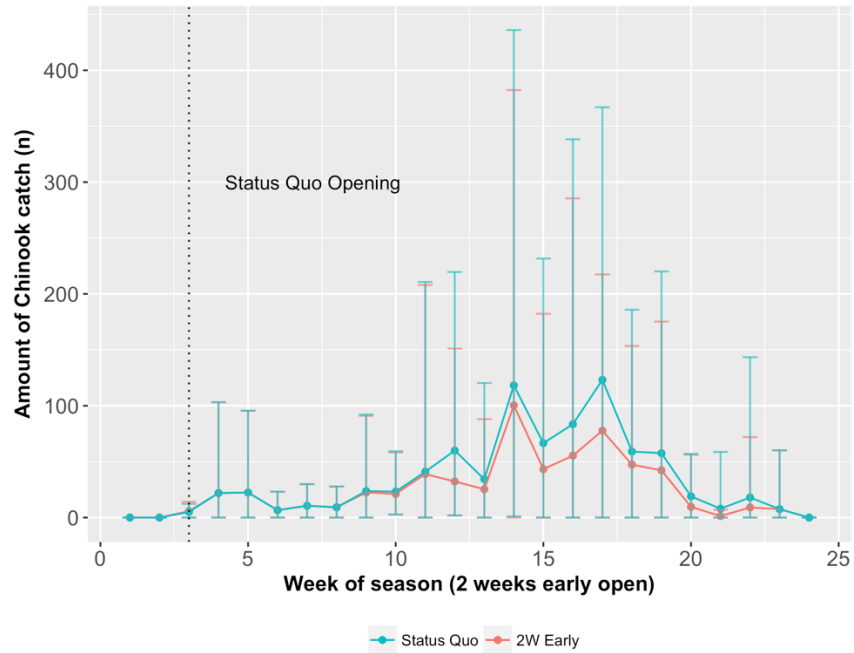


Figure 2.4. Simulated weekly number of chinook salmon catch under status quo and alternative policy.

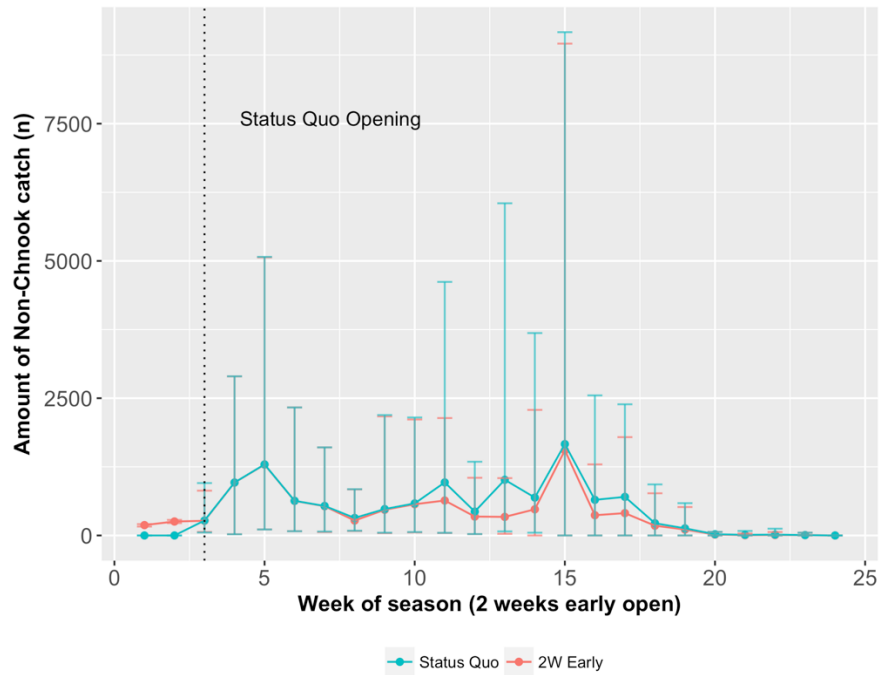


Figure 2.5. Simulated weekly number of Non-chinook salmon catch under status quo and alternative policy.

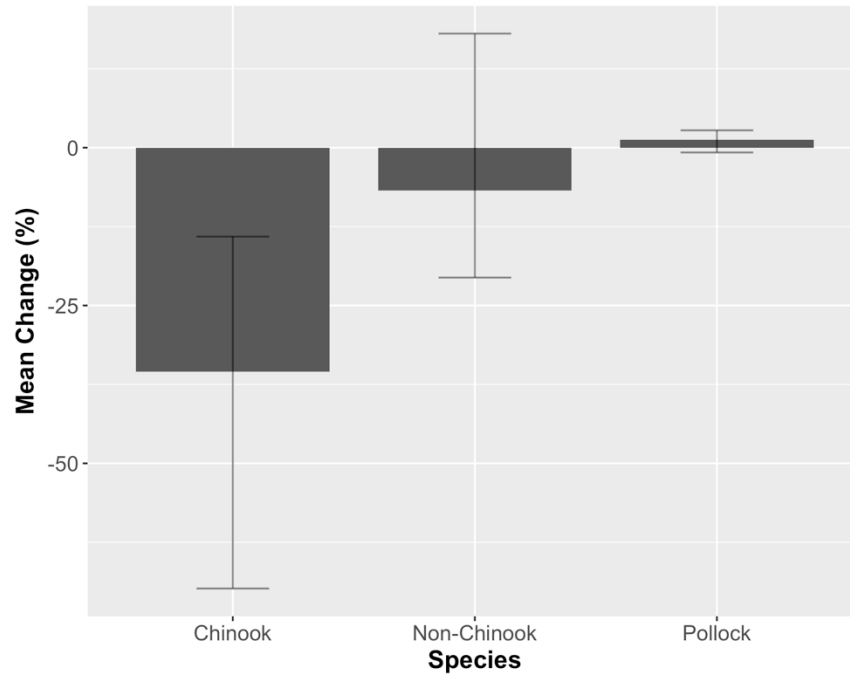


Figure 2.6. Seasonal percentage differences of Pollock, Chinook salmon, and Non-chinook salmon catch under status quo and alternative policy.

Table 2.7. Change in catches of each species by policy simulation (Amount)

	Mean	Min	Max
Chinook (n)	-203.071	-507.851	-41.848
Non-Chinook (n)	-2050.332	-7795.592	273.602
Pollock (MT)	3903.272	-1735.942	9655.766

2.8 CONCLUSION

This paper investigates the temporal choice of harvesters as a margin of bycatch avoidance in the context of seasonal dynamic problem. We construct a simple theoretical model to explicitly illustrate harvester's individual quota allocation problem over a season, then we formulate the empirical model based on the theoretical result. To empirically incorporate the dynamic aspect of

harvester's problem, we develop a variable named Quota Speed which captures the deviation of actual quota use from the possible planned path. Our result shows that the bycatch avoidance by timing choice of participation matters, but the responses vary by seasons and individuals. When the timing of the high value and the timing the high bycatch rate overlaps, harvesters are not very flexible to change timing to avoid bycatch. When these timings are different, harvesters adjust participation considering the dynamic quota use and bycatch that occurs later in a season.

Our findings provide a new insight to ongoing discussion on reducing bycatch in fisheries. While bycatch reduction policies focus on spatial margins and gear selection, our result indicates that timing flexibility in a season also matters. Specifically, in the Alaskan Pollock fishery, a possible policy recommendation is to open the B season earlier which currently opens in June. Since bycatch rate is low in summer, early opening of the B season provides harvesters flexibility to use their quota with less total bycatch yet unchanged total Pollock catch. For fisheries in general, the managers should consider the seasonality of bycatch rates in addition to other biological conditions when deciding fishing seasons.

It is important to note that our specification to capture the shadow value of quota use may still be limited. As discussed in the result section, the estimates of expected bycatch rate (ECPR) may not separately identify the instantaneous effect, which is possibly negative according to Proposition 2 of our theoretical model, and future expectation effect, which is possibly positive. The difficulty of the identification is caused by that the quota of pollock is always binding. As stated in Proposition 2, the effect of change in bycatch rate is decomposed into contemporaneous and dynamic part, but dynamic part is in effect only when the quota binds. In multispecies fisheries with multiple individual quota, such effects can be decomposed because the binding quota may vary season by season and hence the variation of shadow cost may be exploited.

A natural question is how the result changes if we incorporate the internal margin of bycatch avoidance. In this study, the internal margin of fisheries is aggregated, and the weekly expected variables are common across fleet and exogenously given. For example, specifically, the catch rate of Pollock in B season seems decreasing, while the Chinook salmon bycatch rate increases. These seasonal trends are taken as given for harvesters and treated as exogenous change in our empirical model. However, it is possible that the harvesters choose their fishing location to avoid high bycatch area, while accepting lower Pollock CPUE. The more realistic decision process could be a nested structure; The harvesters would decide whether participating in a fishery, then decide where to fish. This lower decision level may affect the upper one, and vice versa. This extension is left for future research.

Chapter 3. TIMING VERSUS LOCATION: DIFFERENT MARGINS OF DYNAMIC BYCATCH AVOIDANCE

3.1 INTRODUCTION

Fisheries bycatch, is an incidental catch of non-targeted species or size groups, negatively affects the fish stock and eco-system, while it may not generate positive economic return to the harvesters. The reasons of the no economic value may be due to the economic value of species itself, but also due to the regulatory schemes. When the bycatch is regulated or causes negative impacts on the harvesters, they have incentives to avoid bycatch while targeting main species.

Bycatch avoidance takes place in a variety of forms. Primary margins for harvesters to avoid bycatch is selections of fishing gears (e.g. mesh size). In addition, we discussed that the harvesters choose the timing to target specific species to avoid bycatch that is likely to occur in a certain time of a season. Abbott, Reimer and Haynie claim that the both large and fine scales of location choice are important margins to avoid bycatch in addition to timing of fishing in a day [50]. Relative importance of margins for bycatch avoidance can be different depending on the context of fisheries, but such structure of the harvesters' margins is important information for policy design.

In this study, we extend the model in Chapter two, which focused on the targeting timing choice of the catcher-processor vessels in Alaskan Pollock fisheries. In the previous model, the harvesters choose a target species or not fishing in a given week considering the revenue opportunity, bycatch rate, and dynamic quota usage in the week. The spatial information was aggregated in the model, and we assumed that the harvesters make weekly decision given the weekly expectations. This assumption may have missed out an important aspect of the harvester's decision, which is a spatial choice. That is, the harvesters could avoid bycatch within a period

given the choice of target in a week. Hence, this structure naturally leads us to a model of two-stage decision-making process. First stage, as shown in Chapter two, the harvesters decide which fishery to target (or not fishing), then choose where to fish in the second stage.

3.2 DATA DESCRIPTION

The main data set for this study is provided by the North Pacific Groundfish Observer Program (NPGOP). This data set is collected by observers and includes complete record of fishing effort and total catch for catcher-processor vessels operating pollock fishery in Bering Sea. The data available to us consists of week-vessel level observations of the fleet of 17 vessels from 2005 to 2013, when they are targeting pollock and yellowfin sole in Bering Sea. The locations of operations is based on National Marine Fisheries Service (NMFS) management area. The original data (which is not available to us) records operation location of each haul, and it is aggregated over a week by counting the number of hauls in an area, and the area with highest number of hauls is assigned as the location in a week. In addition to location, variables for each vessel include number of hauls, tow duration, gear setting, and amounts of target catch, prohibited species catch, and bycatch species harvested.

NMFS management area splits the Exclusive Economic Zone in Bering Sea into 17 areas (Figure 3.1). We set these areas as a unit of location choice for our study. Many of fishing operations by the fleet are held in the middle of Bering sea, such as 509, 517, 513, 521, 523, and 524. The average monthly number of hauls by the fleet in each area is shown in Figure 3.2. In A season, from January to May, many hauls occur in area 521, 517, and 509. In B season, from June to October, most of hauls are held in area 521, but it shifts to the north, 524 as it approaches to Autumn. For both season, the popular areas seem to have high abundance of Pollock (Figure 3.3).

However, the bycatch rate is relative low for the popular areas both in A and B season as shown in Figure 3.4. Particularly for the B season, the area 521 and other area have low bycatch rate in July, but it rises in August and September, and the area 524 has lower bycatch in those months.

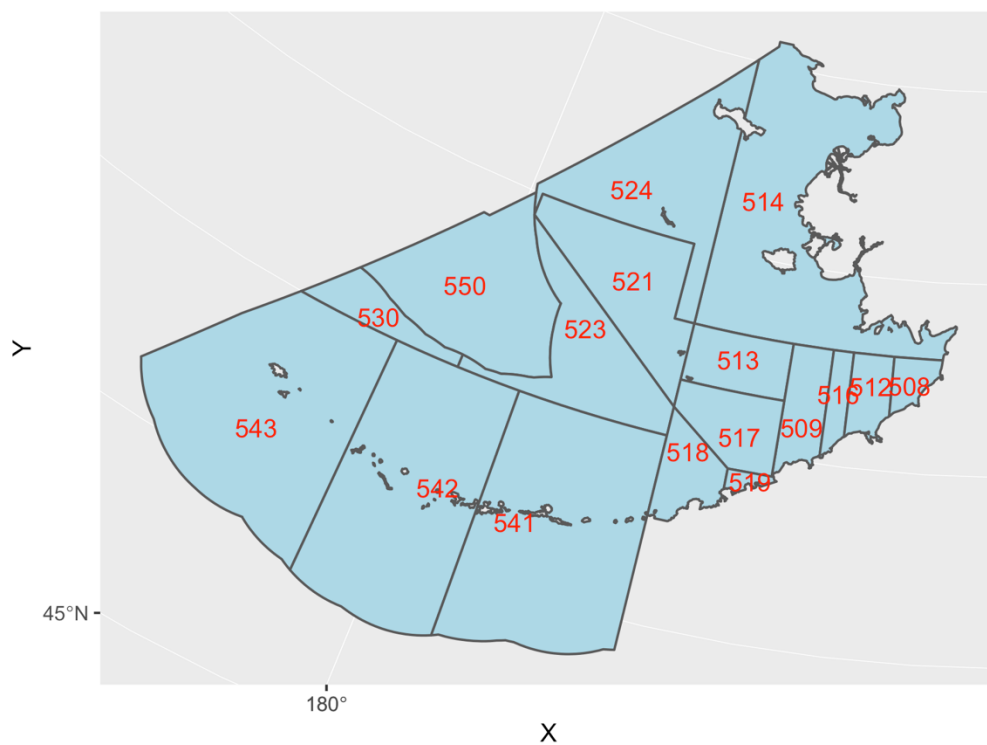


Figure 3.1. NMFS management area in Bering Sea.

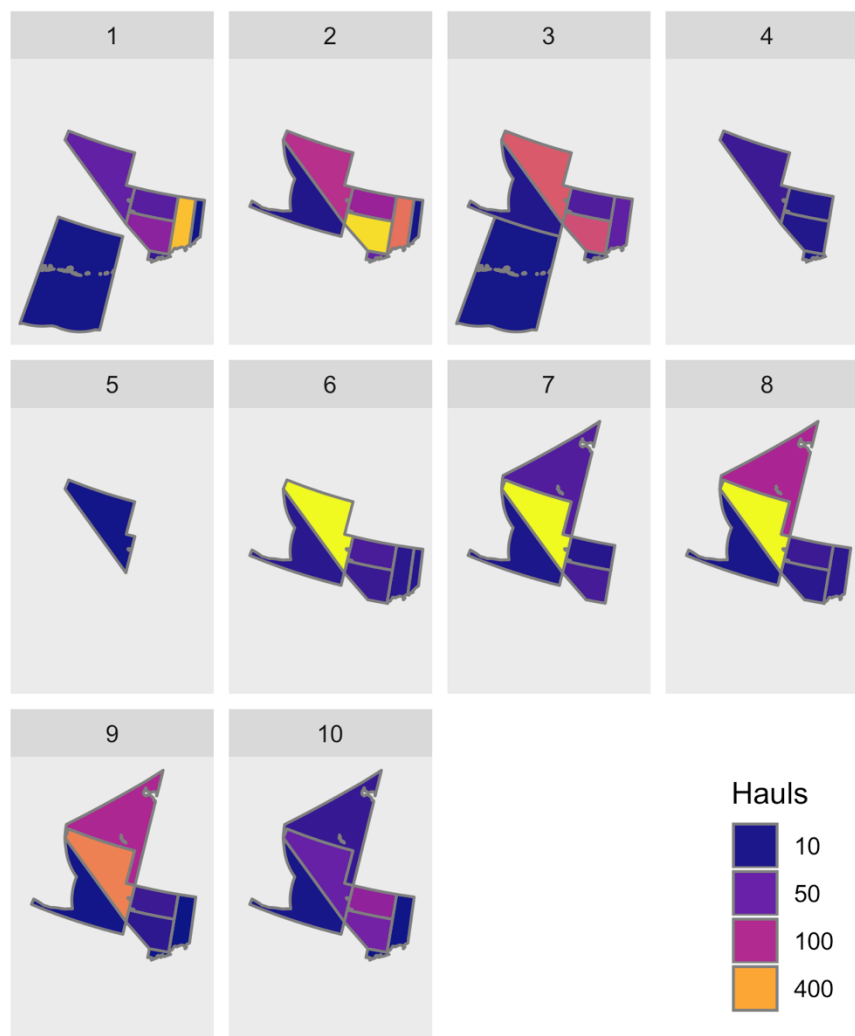


Figure 3.2. Average monthly number of hauls by the fleet.



Figure 3.3. Average monthly Pollock CPUE.

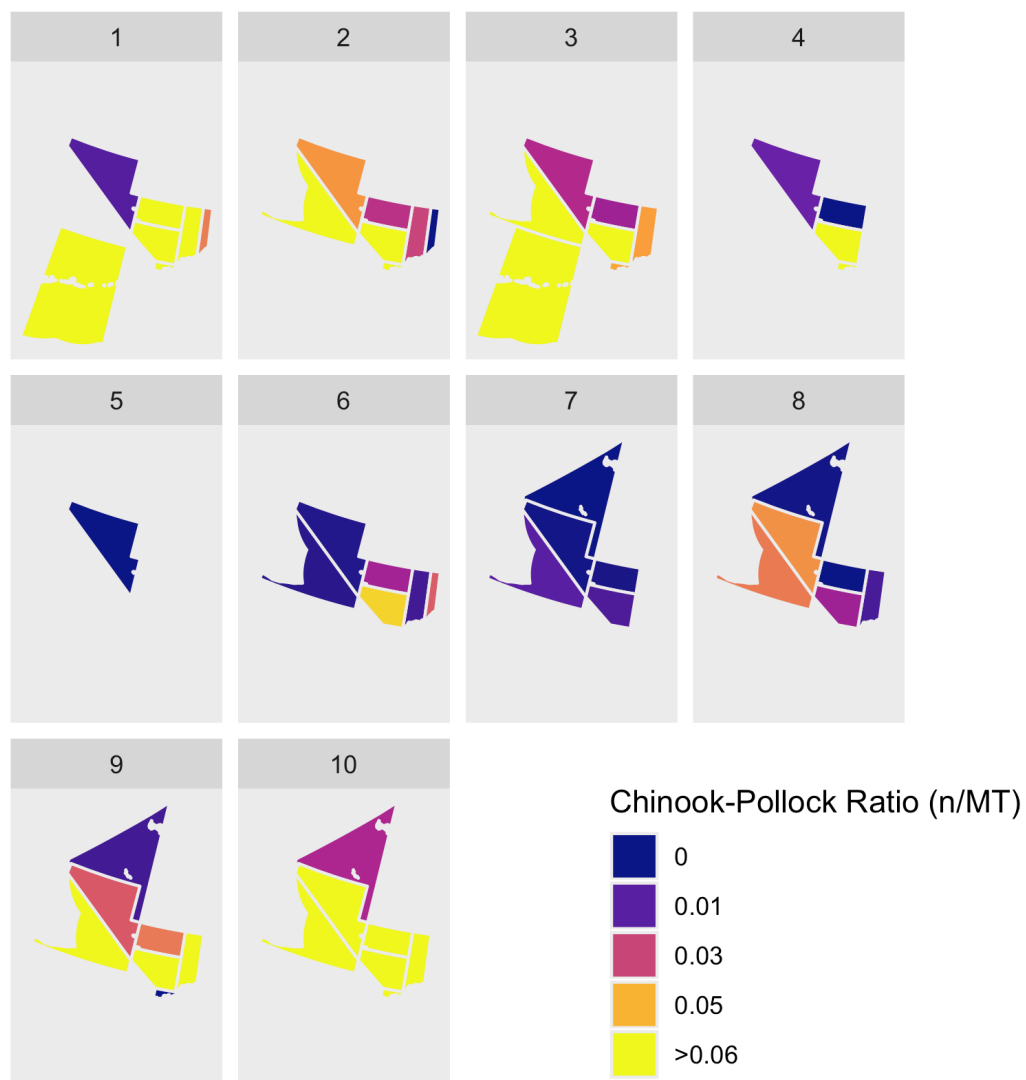


Figure 3.4. Average monthly Chinook-Pollock ratio (Bycatch rate).

We complement the NPGOP data with annual wholesale price data from Economic Stock Assessment and Fishery Evaluation Report (NMFS, 2014), and monthly export data of fishery products that is collected by the U.S. Census Bureau and compiled by NOAA fisheries. While seasonal variation of price in a year is important particularly for pollock, the in-season variation of wholesale price is not available. Hence, we get the monthly variation of export value, and

convert it into wholesale level by estimating the relationship between annual average export value and annual wholesale price. Furthermore, we include the number of vessels targeting Pacific Hake in the west coast of the mainland U.S. The detailed data for Pacific hake is not publicly available, but it is an important outside option for the catcher-processor fleet. We use the monthly number of the vessels as a proxy for the attractiveness of Pacific Hake, and treat it as an attribute of “outside of Alaska” alternative.

3.3 EMPIRICAL MODEL

Our model illustrates a two-stage decision process of harvesters, whereby a vessel selects a species to target or not fishing in Alaska in the first period, and subsequently choose an area to conduct fishing given the species chosen. In the second chapter, the model depicts the choice behavior of target over a season, while the internal margin within a period was aggregated and taken as given. We extend the model by allowing harvesters to choose fishing location within a period.

The decision-making individual is a vessel in this model. The captains’ decisions or collective decisions of crews are modeled. Given the data set available, we model weekly decision of harvesters. The fishing locations are based on NMFS management areas. The targeting behavior is defined based on the choice of gear (midwater or bottom trawl) which is recorded in the data.

A harvester maximizes seasonal profit by catching pollock and yellowfin sole given individual quota of pollock and prohibited species catch of Chinook salmon (after Amendment 91 is implemented in 2011). While the harvester is a profit-maximizer, it takes into account implicit costs of fishing operations and bycatch avoidance. To illustrate these aspects, we adopt a random utility model. The indirect utility is specified as follows.

$$U_{jkt} = \delta_{jk} + \beta_{1j}(Qspeed_{jt}, BQspeed_{jt})EREV_{jkt} + \beta_{2j}(Qspeed_{jt}, BQspeed_{jt})ECPR_{jkt} + \beta_3 Dist_{jkt} + \gamma' X_{jkt} + \varepsilon_{jkt} \quad (3.1)$$

The harvesters' primary incentive to choose a target is expected revenue per unit effort (duration of haul), $EREV$. This is formed by the previous year and week's data and price information. The bycatch avoidance behavior is captured by the expected Chinook-Pollock ratio ($ECPR$) of each location. $Dist$ is a distance from the location in a previous period to the alternative location k . X_{jkt} includes other controls such as a dummy variable for missing information and the number of hake vessels. δ_{jk} is an alternative-specific constant term. This captures time-invariant fishery- and location-specific effects. These effects include underlying ecological features based on geographic characteristics and economic variables such as distance from home ports.

3.3.1 Expectation formation

The expectation formation of each location-time is a key step of location choice studies. We model expected catch per unit effort (duration of haul) and bycatch-pollock ratio for a given week using information of previous year and week. We follow the idea of Abbott and Wilen by weighing previous year's and week's information differently depending on the available information for a given week [29]. Specifically, we form CPUE or bycatch-pollock ratio as follows

$$E(Y_{jkt}) = \exp\{\psi_0(d_{1jkt}, d_{2jkt}) + \psi_1(d_{1jkt}, d_{2jkt})y_{1jkt} + \psi_2(d_{1jkt}, d_{2jkt})y_{2jkt}\} \quad (3.2)$$

Where y_{1jkt} is previous week's info of CPUE or bycatch-pollock ratio of target j , location k and week t , and y_{2jkt} is previous year's information. $\psi_1 = 0$ if $d_{1jkt} = 0$ because there is no information of the previous week. Similarly, $\psi_2 = 0$ if $d_{2jkt} = 0$ for the previous year's information. The coefficients are differently weighed depending on the availability of the other data. For example, $\psi_1(d_{1jkt} = 1, d_{2jkt} = 1)$ and $\psi_1(d_{1jkt} = 1, d_{2jkt} = 0)$ can be different because the expectation depends more on previous week's information when previous year's information is not available. In case that $d_{1jkt} = 0$ and $d_{2jkt} = 0$, the expected value is set as zero, and we include a dummy variable $Missing_{jkt} = 1$ in the indirect utility function. (Hicks and Schnier, 2010). The expected CPUE is converted into revenue per unit effort by multiplying monthly export price of pollock and annual wholesale price of yellowfin sole.

3.4 ESTIMATION RESULTS

We estimate three different models for A and B season separately. Model 1 specification is a full model, but the estimation is by multinomial logit, which holds the independence of irrelevant alternative assumption. Model 2 to Model 5 are estimated with nested logit model. Model 2 includes the Expected RPUE of Pollock and YFS, and Expected Chinook-Pollock ratio, and distance from the previous location, but the interactions with quota speed are not included. Model 3 adds the interactions of $Qspeed$ with Expected Revenue and $ECPR$ as we estimate in the Chapter two. In addition, Model 4 adds $BQspeed$ only for after-2011 observation as amendment 91, which

implement the individual limits management of prohibited species catch. Model 5 re-estimate Model 4 with some coefficients are zero as they are statistically insignificant.

The result of A season is shown in **Error! Reference source not found.** The variables without quota speed interactions are consistent across the models, but they are not statistically significant except for distance. This result implies that the harvesters responds to the cost of changing location when putting aside the dynamic planning of quota usages. The interactions with the dynamic variables show interesting results. Expected revenue per unit effort and distance have statistically significant coefficient when interacted with the bycatch quota speed, while the expected bycatch rate (*ECPR*) is significant with the *Qspeed* of main target species. Positive coefficient on *ECPR-Qspeed* interaction suggests that the harvesters' implicit cost of bycatch decreases when the main target quota usage is behind the schedule. The shadow price of quota becomes lower in such case, hence the harvesters tend to select a good location for pollock regardless of expected bycatch rate. *BQ speed* interactions with *EREV* and *Dist* show that lower shadow cost, or lower risk of binding bycatch quota reinforce the incentive to choose high pollock revenue area and lower the perceived cost of relocation. This tendency is consistent across the models in A season.

We should note that the inclusive value parameter estimates of the nested logit models are greater than one. If this parameter is greater than one, it is not consistent with the utility maximization for all possible values of explanatory variables. Particularly in this case, the positive and statistically significant estimate of coefficient on bycatch rate (*ECPR*) does not make sense, because the harvesters do not prefer Chinook salmon as they are not allowed to sell or keep prohibited species catch. Hence, we exclude the chinook-pollock ratio from the model and estimate it as Model 4. The estimated coefficients of explanatory variables are not largely changed, but the

estimates for the inclusive value parameter lies in the range between zero and one, which is consistent with the utility maximization.

A problem in B season is that the inclusive value parameters for the pollock nest are negative across all nested logit models. This is totally inconsistent with the random utility theory, because the negative coefficients suggest that any improvement in attributes of pollock nest would decrease the probability that the alternative in the nest is chosen. This can be due to misspecification of the model: systematic component, structure of nesting, or both. The structure could lead to erroneous result because the YFS is a choice in the upper level, while it is only chosen for five observations out of 1,973 observations in B season in the data.

Although Model 1 imposes IIA assumption, the result seems to be convincing. Putting aside the effect of quota usage, the expected revenue of pollock and distance from the previous location influence the decision of harvesters. The positive and statistically significant coefficient on ECPR and BQspeed interaction implies that lower risk of binding bycatch quota means lower shadow cost of the quota, hence the cost of bycatch becomes smaller and accepts the area with relatively higher bycatch rate. While these coefficients are consistent with the theory we suggested in Chapter two, the coefficient estimate on the interaction of expected revenue and Qspeed casts a puzzle. The negative sign shows that less likely to choose high catch rate of pollock when the quota usage is slow. It may cause the remainder of the quota in the end of the season, which does not support the profit maximization behavior of the harvesters. This result requires further considerations of the analysis.

Overall, the estimation for A seasons supports the two-stage fishery-location choice structure, but we do not gain the significant result for B season. For A season, the main driver of the harvesters fishing behavior is matured pollock roe. From January to March, female pollocks

carry roes that are traded at high values. Harvesters have some incentive to rush to catch pollock otherwise they miss the opportunity to high unit value of pollock due to matured roe. Hence, the harvesters choose to catch pollock although Chinook salmon bycatch rate is also high. Because these timing overlaps, the margin that the harvesters can use is spatial rather than temporal. This is consistent with our result in Chapter two, where bycatch avoidance behavior by timing margin was not observed in A season, while in this analysis high bycatch areas are avoided.

In B season, the harvesters want to consume all of pollock quota over a season while they avoid Chinook salmon catch. That is, they are not picky about participation timing as long as they can use up their quota over the season. In other words, the harvesters can be more flexible to choose timing to target pollock. Because the timing largely explains the behavior in B season, imposing a complicated structure about the location on harvesters' behavior may have mislead the result. In summary, it is likely that the harvesters cautiously select locations due to short "season" constrained by the opportunity to catch pollock with mature roe, while they are flexible about timing to target pollock in B season.

Although the discussion above is a plausible story behind the result we obtained, we should note that some potential technical issue about the estimation. First of all, the location choice set may be largely different from the actual decision-making process. In location choice studies of fisheries, we model harvesters' decision as a discrete choice, where a choice is one of partitioned areas in fishing ground. However, the actual decision-making is not clearly discretized. The modeling may cause an issue if their scale of decision making and model's scale greatly differ. Specifically, we use NMFS management area as a choice set, but each area may be too large as an alternative. The harvesters' decision may be modeled with finer resolutions. In that case, the

harvesters' spatial choices are aggregated at a coarse scale, and the result may obscure the actual process.

Second, the decision-making structure may be different from our specification. We modeled the harvesters' decision as a two-stage process: target species in the first stage, then fishing area in the second stage. However, the harvesters may actually have different structure, such as location first and species second. Furthermore, the choice of location may be more dynamic. In our model, the harvesters are assumed to select an area to operate fishing week by week. However, the harvesters may choose a trajectory of cruise instead of myopic location [23,24]. As some studies modeled [51], we may add another stage to their choice structure. For example, the harvesters choose location at finer scale after chose species and large area. These potential extensions of the model should be considered when we address the result.

Table 3.1. Fishery-Location Choice Estimation, A season

	(1)	(2)	(3)	(4)	(5)
	Choice: Fishery-location				
EREV (Poll)	0.00109 (1.91)	0.000853* (2.10)	0.00167 (1.95)	0.00190 (1.95)	0.00102 (1.90)
EREV (YFS)	-7.682 (-0.85)	-10.32 (-0.96)	-1.939 (-0.70)	-1.858 (-0.78)	
ECPR	0.793 (1.51)	1.060 (1.67)	1.292 (1.52)	2.054* (2.11)	1.785 (1.90)
Dist	-0.00345*** (-20.03)	-0.00330*** (-7.49)	-0.00458*** (-8.50)	-0.00571*** (-10.03)	-0.00576*** (-10.39)
EREV (Poll) x Qspeed	-0.0176 (-0.93)		-0.0314 (-1.07)	-0.0385 (-1.17)	
ECPR x Qspeed	9.559*** (4.44)		17.75*** (4.89)	19.60*** (5.21)	19.95*** (5.37)
Dist x Qspeed	-0.000474 (-0.98)		-0.00127 (-1.62)	-0.00141 (-1.68)	-0.00146 (-1.73)
EREV (Poll) x BQspeed	2.842*** (6.78)			5.697*** (5.96)	5.372*** (6.13)
ECPR x BQspeed	-3.523 (-1.60)			-4.510 (-1.17)	
Dist x BQspeed	0.00381*** (8.42)			0.00602*** (6.50)	0.00607*** (6.57)
Missing	-1.166*** (-5.75)	-1.333*** (-4.86)	-1.874*** (-5.03)	-2.000*** (-5.43)	-2.017*** (-5.50)
IV Poll		1.249*** (7.07)	1.781*** (7.80)	1.961*** (8.85)	1.966*** (9.15)
IV YFS		0.935*** (6.37)	1.369*** (6.73)	1.491*** (8.38)	1.526*** (8.91)
<i>N</i>	21696	21696	21696	21696	21696
<i>AIC</i>	4655.7	4760.9	4736.1	4632.2	4629.8

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.2. Fishery-Location Choice Estimation, B season

	(1)	(2)	(3)	(4)	(5)
	Choice: Fishery-location				
EREV (Poll)	2.496*** (7.52)	-0.910 (-1.20)	-0.921 (-1.13)	-1.251 (-1.55)	-0.974 (-1.24)
EREV (YFS)	2497.1 (0.45)	3050.3 (0.02)	2504.2 (0.03)	2497.2 (0.01)	
ECPR	-1.398 (-1.23)	-5.467* (-2.52)	-6.751* (-2.45)	-5.065 (-1.53)	-6.832** (-2.96)
Dist	-0.00287*** (-11.52)	0.0390*** (15.77)	0.0402*** (14.54)	0.0397*** (14.86)	0.0396*** (15.08)
EREV (Poll) x Qspeed	-3.038** (-3.07)		-0.411 (-0.12)	-0.904 (-0.24)	-0.0805 (-0.03)
ECPR x Qspeed	-0.391 (-0.21)		0.745 (0.11)	-2.982 (-0.40)	
Dist x Qspeed	0.00108 (1.87)		0.0202 (1.72)	0.0176 (1.55)	0.0187 (1.76)
EREV (Poll) x BQspeed	-1.857 (-0.38)			37.40 (1.04)	
ECPR x BQspeed	12.99*** (3.54)			22.37 (0.35)	11.70 (0.30)
Dist x BQspeed	-0.000720 (-0.27)			-0.0611** (-2.78)	
Missing	-0.674** (-3.20)	-0.164 (-0.34)	-0.184 (-0.37)	-0.161 (-0.32)	-0.192 (-0.39)
Hake Vessels	0.244*** (15.20)	0.0534* (2.45)	0.0518* (2.33)	0.0554* (2.46)	0.0519* (2.33)
IV Poll		-9.478*** (-13.59)	-11.55*** (-7.16)	-11.38*** (-6.86)	-11.01*** (-8.07)
IV YFS		13.72 (1.12)	11.01** (2.60)	33.18*** (4.23)	13.32* (2.10)
<i>N</i>	19730	19730	19730	19730	19730
<i>AIC</i>	3629.3	2999.1	3002.1	3002.6	2999.4

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

BIBLIOGRAPHY

- [1] G. S. Olley and A. Pakes, “The Dynamics of Productivity in the Telecommunications Equipment Industry,” *Econometrica*, vol. 64, no. 6, pp. 1263–1297, 1996.
- [2] F. R. Homans and J. E. Wilen, “A model of regulated open access resource use,” *J. Environ. Econ. Manage.*, vol. 32, pp. 1–21, 1997.
- [3] C. W. Clark and G. R. Munro, “The Problem of Overcapacity,” *Bull. Mar. Sci.*, vol. 70, no. 2, pp. 473–483, 2002.
- [4] G. Ishimura and M. Bailey, “The market value of freshness: observations from the swordfish and blue shark longline fishery,” *Fish. Sci.*, vol. 79, no. 3, pp. 547–553, Mar. 2013.
- [5] S. Comitini and D. S. Huang, “A Study of Production and Factor Shares in the Halibut Fishing Industry,” *J. Polit. Econ.*, vol. 75, no. 4, pp. 366–372, 1967.
- [6] J. Kirkley, D. Squires, and I. Strand, “Assessing Technical Efficiency in Commercial Fisheries: The Mid-Atlantic Sea Scallop Fishery,” *Am. J. Agric. Econ.*, vol. 77, pp. 686–697, 1995.
- [7] J. Kirkley, D. Squires, and I. Strand, “Characterizing managerial skill and technical efficiency in a fishery,” *J. Product. Anal.*, vol. 160, pp. 145–160, 1998.
- [8] D. Squires and J. Kirkley, “Skipper skill and panel data in fishing industries,” *Can. J. Fish. Aquat. Sci.*, vol. 56, pp. 2011–2018, 1999.
- [9] R. Hannesson, “Bioeconomic Production Function in Fisheries : Theoretical and Empirical Analysis,” *Can. J. Fish. Aquat. Sci.*, vol. 40, pp. 968–982, 1983.
- [10] C. J. Morrison, “Primal and dual capacity utilization: An application to productivity measurement in the u.s. automobile industry,” *J. Bus. Econ. Stat.*, vol. 3, no. 4, pp. 312–324, 1985.
- [11] J. E. Kirkley and D. E. Squires, “Measuring capacity and capacity utilization in fisheries,” Rome, 386, 1999.
- [12] C. Reid, J. E. Kirkley, D. Squires, and J. Ye, “An analysis of the fishing capacity of the global tuna purse-seine fleet,” Rome, Italy, 2005.
- [13] A. Eide, F. Skjold, F. Olsen, and O. Flaaten, “Harvest Functions : The Norwegian Bottom

- Trawl Cod Fisheries,” *Mar. Resour. Econ.*, vol. 18, pp. 81–93, 2003.
- [14] R. L. McGaw, “The supply of effort in a fishery,” *Appl. Econ.*, vol. 13, no. 2, pp. 245–253, Jun. 1981.
- [15] A. Gautam, I. Strand, and J. Kirkley, “Leisure/labor tradeoffs: the backward-bending labor supply in fisheries,” *J. Environ. Econ. ...*, vol. 31, pp. 352–367, 1996.
- [16] D. Holland, “Are fishermen rational? A fishing expedition,” *Mar. Resour. Econ.*, vol. 23, pp. 325–344, 2008.
- [17] Q. Nguyen and P. Leung, “Revenue targeting in fisheries,” *Environ. Dev. Econ.*, vol. 18, no. 05, pp. 559–575, Apr. 2013.
- [18] T. Ran, W. Keithly, and C. Yue, “Reference-Dependent Preferences in Gulf of Mexico Shrimpers’ Fishing Effort Decision,” *J. Agric. Resour. Econ.*, vol. 39, no. 1, pp. 19–33, 2014.
- [19] N. Bockstael and J. Opaluch, “Discrete Modelling of Supply Response under Uncertainty : The Case of the Fishery,” *J. Environ. Econ. Manage.*, vol. 10, pp. 125–137, 1983.
- [20] J. Eales and J. Wilen, “An examination of fishing location choice in the pink shrimp fishery,” *Mar. Resour. Econ.*, vol. 2, no. 4, pp. 331–351, 1986.
- [21] D. S. Holland and J. G. Sutinen, “An empirical model of fleet dynamics in New England trawl fisheries,” *Can. J. Fish. Aquat. Sci.*, vol. 56, pp. 253–264, 1999.
- [22] R. E. Curtis and R. L. Hicks, “The Cost of Sea Turtle Preservation: The Case of Hawaii’s Pelagic Longliners,” *Am. J. Agric. Econ.*, vol. 82, no. 5, pp. 1191–1197, Dec. 2000.
- [23] R. L. Hicks and K. E. Schnier, “Dynamic random utility modeling: A Monte Carlo analysis,” *Am. J. Agric. ...*, vol. 88, no. November, pp. 816–835, 2006.
- [24] R. L. Hicks and K. E. Schnier, “Eco-labeling and dolphin avoidance: A dynamic model of tuna fishing in the Eastern Tropical Pacific,” *J. Environ. Econ. Manage.*, vol. 56, no. 2, pp. 103–116, Sep. 2008.
- [25] G. Ishimura and M. Bailey, “The market value of freshness: observations from the swordfish and blue shark longline fishery,” *Fish. Sci.*, vol. 79, no. 3, pp. 547–553, 2013.
- [26] V. J. Hotz and R. A. Miller, “Conditional Choice Probabilities and the Estimation of Dynamic Models,” *Rev. Econ. Stud.*, vol. 60, no. 3, pp. 497–529, 1993.
- [27] R. E. Curtis and K. E. McConnell, “Incorporating information and expectations in fishermen’s spatial decisions,” *Mar. Resour. Econ.*, vol. 19, pp. 131–143, 2004.

- [28] V. P. Lougovois and V. R. Kyrana, *Freshness Quality and Spoilage of Chill- Stored Fish*, no. March. 2005.
- [29] J. K. Abbott and J. E. Wilen, “Dissecting the tragedy: A spatial model of behavior in the commons,” *J. Environ. Econ. Manage.*, vol. 62, no. 3, pp. 386–401, 2011.
- [30] P. Arcidiacono and R. A. Miller, “Conditional Choice Probability Estimation of Dynamic Discrete Choice Models With Unobserved Heterogeneity,” *Econometrica*, vol. 79, no. 6, pp. 1823–1867, 2011.
- [31] H. Yoganarasimhan, “The Value of Reputation in an Online Freelance Marketplace,” *Mark. Sci.*, vol. 32, no. 6, pp. 860–891, 2013.
- [32] J. R. Boyce, “Individual Transferable quotas and production externalities in a fishery,” *Nat. Resour. Model.*, vol. 6, no. 4, pp. 385–408, 1992.
- [33] N. C. Pradhan and P. Leung, “Modeling trip choice behavior of the longline fishers in Hawaii,” *Fish. Res.*, vol. 68, no. 1–3, pp. 209–224, Jul. 2004.
- [34] C. W. Clark, “Towards a Predictive Model for the Economic Regulation of Commercial Fisheries,” *Can. J. Fish. Aquat. Sci.*, vol. 37, no. 7, pp. 1111–1129, 1980.
- [35] J. N. Ianelli, T. Honkalehto, S. Barbeaux, S. Kotwicki, K. Aydin, and N. Williamson, “Assessment of the walleye pollock stock in the Eastern Bering Sea. Stock Assessment and Fishery Evaluation Report for the Groundfish Resources of the Bering Sea/Aleutian Islands Regions for 2014,” Anchorage, AK, USA, 2013.
- [36] Northern Economics Inc., “American Fisheries Act Program Review,” 2017.
- [37] B. R. Gisclair, “Salmon Bycatch Management in the Bering Sea Walleye Pollock Fishery : Threats and Opportunities for Western Alaska,” in *American Fisheries Society Symposium 70*, 2009, pp. 799–816.
- [38] D. L. Stram and J. N. Ianelli, “Evaluating the efficacy of salmon bycatch measures using fishery-dependent data,” *ICES J. Mar. Sci.*, vol. 72, no. 4, pp. 1173–1180, 2015.
- [39] S. Madsen and K. Haflinger, “Chinook Salmon Bycatch Reduction Incentive Plan Annual Report 2014,” 2015.
- [40] B. Fissel, M. Dalton, R. Felthoven, B. Garber-Yonts, A. Haynie, A. Himes-Cornell, S. Kasperski, J. Lee, D. Lew, L. Pfeiffer, and C. Seung, “Stock Assessment and Fishery Evaluation Report for the Groundfish Fisheries of the Gulf of Alaska and Bering Sea/Aleutian Islands Area: Economic Status of the Groundfish Fisheries off Alaska,”

- 2014.
- [41] D. M. Larson, W. R. Sutton, and J. M. Terry, "Toward behavioral modeling of Alaska groundfish fisheries: A discrete choice approach to Bering Sea Aleutian Islands trawl fisheries," *Contemp. Econ. Policy*, vol. 17, no. 2, pp. 267–277, 1999.
- [42] H. Eggert and R. Tveteras, "Stochastic Production and Heterogeneous Risk Preferences: Commercial Fishers' Gear Choices," *Am. J. Agric. Econ.*, vol. 86, no. 1, pp. 199–212, 2004.
- [43] A. C. Haynie, R. L. Hicks, and K. E. Schnier, "Common property, information, and cooperation: Commercial fishing in the Bering Sea," *Ecol. Econ.*, vol. 69, no. 2, pp. 406–413, 2009.
- [44] J. Mistiaen and I. Strand, "Location Choice of Commercial Fishermen with Heterogeneous Risk Preferences," *Am. J. Agric. Econ.*, vol. 82, no. 5, pp. 1184–1190, 2000.
- [45] M. D. Smith, "State dependence and heterogeneity in fishing location choice," *J. Environ. Econ. Manage.*, vol. 50, no. 2, pp. 319–340, Sep. 2005.
- [46] D. Dupont, "Price Uncertainty, Expectations Formation and Fishers' Allocation Choice," *Mar. Resour. Econ.*, vol. 8, pp. 219–247, 1993.
- [47] J. Neyman and E. L. Scott, "Consistent Estimates Based on Partially Consistent Observations," *Econometrica*, vol. 16, pp. 1–32, 1948.
- [48] G. Chamberlain, "Analysis of Covariance with Qualitative Data.," *Rev. Econ. Stud.*, vol. 47, no. 146, p. 225, 1980.
- [49] J. Hahn and W. Newey, "Jackknife and Analytical Bias Reduction for Nonlinear Panel Models," *Econometrica*, vol. 72, no. 4, pp. 1295–1319, 2004.
- [50] J. K. Abbott, A. C. Haynie, and M. N. Reimer, "Hidden Flexibility: Institutions, Incentives, and the Margins of Selectivity in Fishing," *Land Econ.*, vol. 91, no. 1, pp. 169–195, 2015.
- [51] D. Holland and J. Sutinen, "Location choice in New England trawl fisheries: old habits die hard," *Land Econ.*, vol. 76, no. 1, pp. 133–149, 2000.
- [52] FAO, "Report of the Technical Consultation on the Measurement of Fishing Capacity," Rome, 2000.
- [53] C. Camerer, L. Babcock, G. Lowenstein, and R. Thaler, "LABOR SUPPLY OF NEW

- YORK CITY CABDRIVERS : ONE DAY AT A TIME,” *Q. J. Econ.*, vol. 112, no. 2, pp. 407–441, 1997.
- [54] M. Smith, “Spatial search and fishing location choice: methodological challenges of empirical modeling,” *Am. J. Agric. Econ.*, vol. 82, no. 5, pp. 1198–1206, 2000.
- [55] M. D. Smith and J. E. Wilen, “Economic impacts of marine reserves: the importance of spatial behavior,” *J. Environ. Econ. Manage.*, vol. 46, no. 2, pp. 183–206, Sep. 2003.
- [56] A. C. Haynie and D. F. Layton, “An expected profit model for monetizing fishing location choices,” *J. Environ. Econ. Manage.*, vol. 59, no. 2, pp. 165–176, Mar. 2010.
- [57] Y. Vermard, P. Marchal, S. Mahévas, and O. Thébaud, “A dynamic model of the Bay of Biscay pelagic fleet simulating fishing trip choice: the response to the closure of the European anchovy (*Engraulis encrasicolus*) fishery in 2005,” *Can. J. Fish. Aquat. Sci.*, vol. 65, no. 11, pp. 2444–2453, 2008.

APPENDIX A

Dirac Delta Function

In the theoretical model, the decision d is a function of H , which is a continuous index of relevant variables. The decision d is equal to 1 if H is greater than 0, and it is 0 otherwise. In the comparative statics, we take a derivative of d with respect to H . However, the derivative of this indicator function at $H = 0$ does not exist in the usual sense, because it is not continuous at $H = 0$. Hence, we define a function using the concept of Dirac's Delta function.

Delta is a symmetric function. Delta function can be thought of as the derivative of the Heaviside function (unit step function).

$$h(x) = \begin{cases} 1 & \text{for } x > 0 \\ 0 & \text{for } x < 0 \end{cases}$$

If the function $d_{it}(H_{it}) = I\{H_{it} > 0\}$ is smooth except for a jump discontinuity at $H_{it} = 0$ with $\lim_{x \rightarrow 0^+} d_{it}(H_{it}) - \lim_{x \rightarrow 0^-} d_{it}(H_{it}) = 1$,

$$\frac{\partial d_{it}}{\partial H_{it}} = \delta(H_{it}) + (\text{derivative of continuous part of } d_{it}) = \delta(H_{it})$$

The second equality holds because the derivative is 0 elsewhere. We define the Delta function $\delta(H_{it})$ as follows.

$$\delta(H) = \begin{cases} 1 & \text{for } H = 0 \\ 0 & \text{for } H \neq 0 \end{cases}$$

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