A Dynamic Model of Fishing Cruise Duration

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Abstract

In many fisheries, particularly high seas fisheries, effort is controlled primarily by scaling estimated fleet capacity to available biomass. Capacity is traditionally estimated by relating inputs to outputs, with gaps between maximum harvest and actual harvest ascribed to technical inefficiency; precaution often dictates managing for maximum technical efficiency. I demonstrate that cruise-level production is determined not by use of quasi-fixed inputs, but rather by dynamic consideration of the rate at which fish is caught, balancing the quantity and quality of fish to maximize their cruise level revenue or profit. 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 cruise duration decisions based on unusually detailed daily logbook data on a Japanese longline fleet. The dynamic discrete choice problem is modeled with a two-step conditional choice probability (CCP) estimator. The large space of state variables is narrowed and overfitting is avoided in the first step with a machine learning method, elastic-net logit estimation. The results show that harvesters are more likely to terminate their fishing cruises when they have more of 20-days or older fish, reflecting that they respond to timing of catch during a cruise as well as cumulative catch itself. This suggests that catching power is constrained by a dynamic factor during a cruise, as well as quasi-fixed inputs, and that a management strategy based solely on technical efficiency will systematically overestimate actual catches.

1. Introduction

Fishing overcapacity is one of urgent issues that threaten the sustainability of marine fisheries resource stock. In order to address and resolve the issue, the FAO's Committee of Fisheries (COFI) raised the need of developing international guidelines in 1997. COFI adopted the International Plan of Action for the Management of Fishing Capacity (IPOA-Capacity) in 1999. In a response to IPOA, some states and reginal fishery management organizations (RFMOs) established management programs to counteract the issues related to excess fishing capacity. Over- or excess fishing capacity is often defined relative to biological or bio-economic reference point, which explains the sustainable and/or efficient use of the resource stock. One of the tasks for social scientists in this management scheme is to find the optimal fishing capacity given the information about biological aspects of the resource. While the definition of capacity varies by field and context, FAO defines the capacity as "the maximum amount of fish that can be produced by a fully utilized fleet or vessel during a time period, given the size of the stock being fished and the level of fishing technology being employed." (FAO 2000)

To manage the fishing pressure, managers need to find an optimal level of fishing capacity. Given the definition of capacity, the common approach to measure fishing capacity by economists is to use potential output, which allows managers to compute optimal inputs. The total fishing capacity of a fleet is a function of number of vessels and individual fishing capacity. Hence, the adjustment of fishing capacity regulates individual capacity and/or number of vessels. One way to find an optimal number of vessel is to estimate the vessel capacity and calculate the fleet capacity, then compare it with the reference points. Reid et al. (2005) assess the excess capacity in purse-seine fleets in different oceans using data envelopment analysis and estimate the technical efficiency. Their result show that there is excess capacity in purse-seine fleets and the capacity can be reduced without the cost of reduced catch. How do we reduce the fleet capacity? Decreasing number of vessels is one of ideas, since the least efficient vessel would exit first, and more efficient vessels tend to remain. As a result, the technical efficiency of the fleet improves and the capacity decreases. This result, however, holds only if fully utilizing capacity is optimal. We pose a question here: is utilizing full capacity optimal?

Catching as much as one can is intuitively optimal because neither harvest may not exhibit decreasing return to effort, nor increasing marginal cost. However, revenue may exhibit a concave function if the quality or value get lower as input increases. In fishery, such a phenomenon can be happened due to its nature: freshness of fish and time of fishing. As a harvester go on a longer fishing cruise, he can catch more fish. However, the freshness of fish may deteriorate as time goes by. Under this setting, utilizing full capacity or attaining maximum catch may not be an optimal choice, because longer trip to fill the storage may worsen the quality of fish already caught.

To investigate this question, we model harvesters' strategy on fishing cruise duration in a response to freshness deterioration. We adopt dynamic discrete choice model to analyze this problem, and treat harvesters' problem as an optimal stopping.

This study employs daily data of a longline fishery and use a dynamic RUM model to analyze harvester choice of trip duration. We consider harvesters' problem of duration choice as an optimal stopping. Harvesters face trade-off between additional catch or revenue and negative impact from continuation of the trip day by day. While the previous studies hypothesize that the negative impact are disutility from days at sea or reduced marginal utility due to target revenue, we adopt freshness deterioration as the negative impact. Freshness is an important factor of the value of a fish. In particular, freshness contributes its price formation if the fish are for eating raw (Ishimura and Bailey 2013). Hence, we hypothesize that harvesters have trade-off between additional catch from one more day and loss of freshness of fish already caught when they decide whether going one more day[1]. Provencher (1997) reviews optimal stopping problem in natural resource use and points out that the structural estimation with value function is better than reduced form, although it is difficult to get the expectation term of a value function. To overcome this point, we adopt the

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

conditional choice probability (CCP) estimation suggested in Hotz and Miller (1993) and extended in Arcidiacono and Miller (2011).

This study adopts daily logbook data. This setting solves the issue presents in the previous studies: the endogeneity between days spent at sea and catch or revenue. With trip-by-trip data, the average catch of a trip is a function of the number of days spent at sea, but the harvester's decision on how many days to spend at sea is affected by the catch rate. With day-by-day data and this approach, a decision on day $t + 1$ is based on the catch (and other variables) up to day t, but these variables are not affected by $t + 1$ decision because they are past values.

Results show that the freshness matters in harvesters' decision on continuation of a trip. Sufficiently old fish significantly reduce the probability of continuation while newly caught fish does not affect the continuation decision. This implies that the average catch approach used in previous literature may cause a problem. This result is obtained with the variables that are selected by the elastic-net logit regression which is used in the first step of the two step CCP estimation.

The remainder of this paper is organized as follows. Section 2 introduces related literature and locate this study in the field. In Section 3 we introduce the longline fisheries in 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 the 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.

2. Related Literature

In this study, we adopt a discrete choice model to analyze harvesters' problem. Harvesters are assumed to make daily binary decision: to continue the cruise or to return to the port. Discrete choice framework is commonly used to analyze harvesters' decision in fishery. Location and target fisheries choices have been mainly considered 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[2] with appropriate modelling, and hence it can be used to policy simulations. The first work which applied RUM to fisheries choice problem is Bockstael and Opaluch (1983). Eales and Wilen (1986) 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 harvesters' location choice[3] and fishery choice[4]. Holland and Sutinen (1999) integrated these two choices. Namely, they build a model that estimate joint choice behavior of fishery and location. Although these approaches illustrate the harvesters' behavior, the model itself is static and hence it could be applied to limited fisheries such as sedentary or coastal fisheries with short-trip. Curtis and Hicks (2000) extend the approach by modeling the forward-looking behavior and apply it to the Hawaiian longline fishery, where the trip length is moderately long. With this model, the choice of location is not spot maximizing behavior, but maximize sum of utility from multi-period trip. This dynamic approach was extended by Hicks and Schnier (2006, 2008). 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 trip. Hicks and Schnier assume that the length of trip is known before leaving the port. This assumption is critical for the value function approach. In reality, the harvesters adjust the length responding to the ocean condition, although they have some ex-ante decisions.

The duration of a fishing trip is analyzed in a different branch of literature. Choice of fishing time was first analyzed in terms of labor supply. McGaw (1981) explains that the supply of each fishery responds to the ex-vessel price and catches in the previous period. Gautam et al. (1996) use an intertemporal labor

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

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

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

supply 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 the utility rather than the profit or revenue. An interesting question raised by these studies is that the harvesters negatively respond to temporal wage/revenue increase. In other words, the harvesters shorten the trip/duration of fishing if the fishing performance is high. If the harvesters maximize profit, they should positively respond to temporal increase of revenue. Some studies tackle this question with target revenue model[5]. Holland (2008) shows anecdotal evidence of income target behavior in fisheries based on an ethnographic interview of harvesters in a ground fish fishery in New England. Given this evidence, Nguyen and Leung (2013) estimate the effect of average daily revenue on length of trip with a trip-level data in Hawaiian longline fishery. In addition, Ran et al. (2014) empirically test the revenue target model with a proportional hazard model. These studies use trip-level data. Estimating the duration choice behavior with trip-level data have two issues. First, catch per trip and duration of a trip 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 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 this study resolve this issue by allowing us to specify the effect of daily catch on harvesters decision.

3. Japanese Longline Fishery and Data

This study draws on a data set of a fleet in a longline fishery based in Kesennuma, Japan. The data set tracks the daily decisions of harvesters at vessel-operation day level. The vessels in this fleet are relatively

[5] 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 of revenue per day and the marginal utility dramatically decrease after they achieve the target.

homogeneous due to the regulation. The longline fisheries in Japan are licensed commercial fisheries authorized by the Ministry of Agriculture, Forestry and Fishery, and have two categories, 1) distant water (*enyou*) and 2) offshore (*kinkai*). Since these categories are defined by the holding capacity rather than actual distances of operation from shore, the almost all vessels in the second category, offshore, have capacities of 119 MT, which is close to its maximum capacity (less than 120MT) of the off-shore category. These vessels are equipped with 440 horsepower engines. The fleet consisted of 30 vessels in 2005 but shrunk to 17 in 2011. Vessels equip mechanical refrigeration system, but the refrigerated storage is filled with ice-water in order to uniformly expose fish to cold water.

The vessels operate fishing in the north west Pacific Ocean after debarking the Kesennuma port. The area of fishing 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 hour hours, and landing the line for twelve hours. Cruise days is about 40 days on average before 2011. We limit the data to 2005 to 2010 because the data after 2011 is under abnormal conditions due to the Great Earthquake and tsunami that happened in March 2011 and subsequent reconstruction policy.

This fishery primarily targets 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 (Ishimura and Baily 2013). 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 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. The share is 72% of fresh landing in Japan in 2014. 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, body 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: logbook data of vessels, cruise-level landing data collected at the port, and fuel price data. The logbook data and the cruise-level sales data of the offshore longline fleet in Kesennuma, Japan 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 of October to March only, because harvesters mainly target a single species, swordfish, in this season.

The cruise-level landing data complement the logbook data by providing the accumulated number of calendar days spent at sea and variables for past trip prices. All the vessels in the fleet belong to Kesennuma port, and basically, they land only at this port[6].

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 average price in nation wide can be used as proxy because it captures the variation.

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, the longer cruise can be better since harvesters can catch more fish and gain more revenues and profits. If this is true, harvesters lengthen a cruise as long as possible, and the primary reasons that stop a cruise is binding constraints such as fuel and storage capacity.

[6] After the Great Earthquake, Kesennuma market was unable to accept any landing due to the destroyed port facilities and processing industries. The vessel were landing at Choshi port, Chiba, Japan instead for a while.

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 incentive and choose to stop the cruise to maximize their benefit. Specifically, the quality of already caught fish deteriorates as a cruise gets longer due to loss of freshness. A harvester face trade-off between additional amount of catch and loss of freshness during a cruise. For this reason, the calendar days since fish caught is a state variable for harvester's decision.

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

$$\max_{\mathrm{T}} U = E_0[\textstyle\sum_{t=1}^{T} u(p, cost, \{d_s\}_{s=1}^{t}, \{h_s\}_{s=1}^{t})] \qquad (1)$$

$$s.t. f(T) \leq \bar{F} \qquad (2)$$

$$\textstyle\sum_{t=1}^{T} h_t \leq \bar{H} \qquad (3)$$

The total utility, U is aggregated profit from a cruise. The price of fish without deterioration is p. h_t is daily catch on an operation day t, $cost$ is daily operational cost. d_t is passed calendar days since h_t is 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 catch capacity (storage) constraint. The maximization problem seems to choose 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 the both constraints slacks, it implies that the marginal deterioration exceeds the gain from additional catch. This deterioration depends on the amount of fish already caught and 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 the revenue from the amount they caught. The choice rule at period t, δ_t, is specified as below.

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

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

$$\delta_t = \begin{cases} Continue & if\ u_t^{Cont} \geq u_t^{Ret} \\ Return & if\ u_t^{Cont} < u_t^{Ret}\ or\ f(t) \geq \bar{F}\ or\ \sum_{s=1}^t h_s \geq \bar{H} \end{cases} \quad (4)$$

Since u_t^{Fish} is gain from continuation, there is an expected continuation value. Hence, a harvester observes the new catch h_t and make decision considering the loss of freshness and 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.

5. Model Free Evidence

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 relative amount of total catch per trip to the maximum value. Figure 1 panel (A) shows the 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 the fuel use is an increasing function of the total trip days. Although we do not have data of fuel use, we obtain the average fuel use per day through a personal communication with the vessel owners in this fishery. They are 1.64 kilo litter per day of operation, and 2.80 kilo litter per day of cruise (moving and searching). By multiplying to numbers to operation days and moving days respectively, we can obtain rough estimates of fuel use. If the primary reason of returning decision is the fuel constraint, the total fuel use of most of trip would be close to the maximum possible value. Figure 1 panel (B) shows the 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.

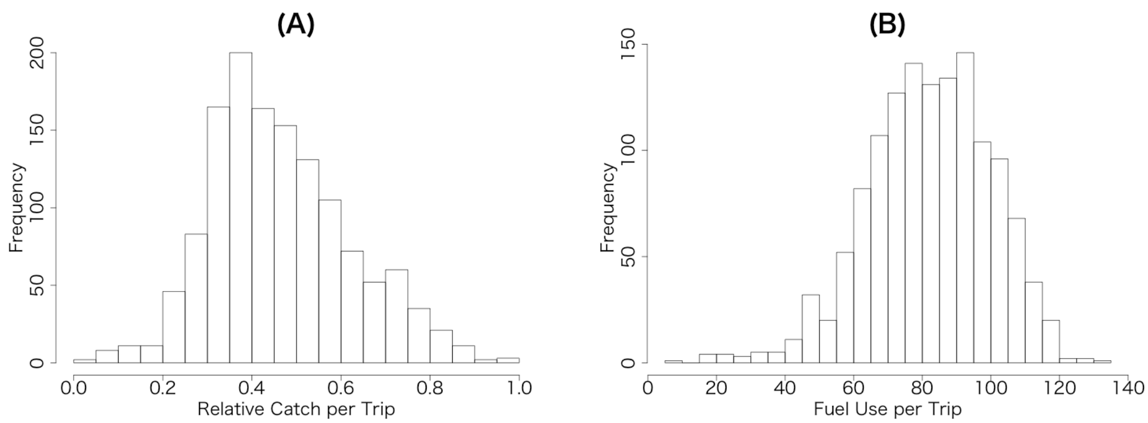

Figure 1. Histograms for checking constraints: (A) Relative Catch (B) Fuel Use

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 panel (A). While the daily catch shows a weak downward trend, there are large variance in daily catch within a trip. Figure 1 panel (B) shows the daily catch of an arbitrary trip from the data. We presume that the harvesters' decision on continuation of a trip depend on this stochastic event rather than a smoothed diminishing ex-ante catch.

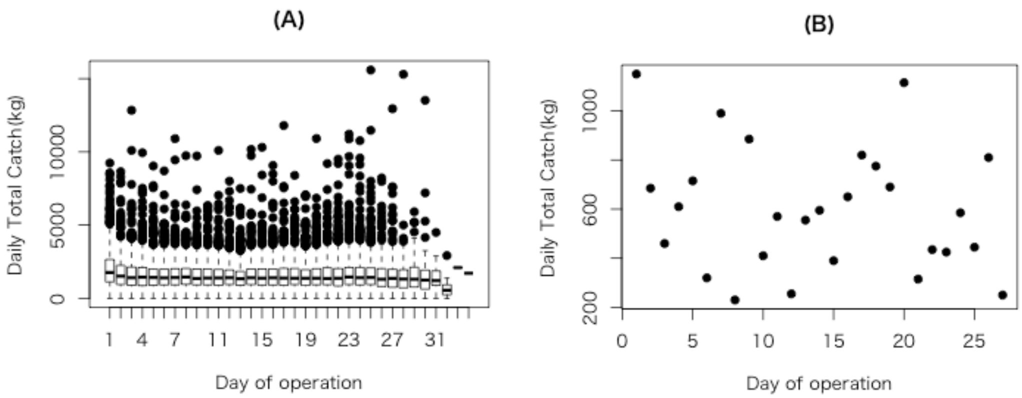

Figure 2. Daily Total Catch by Day of operation: (A) Whole Data and (B) A single arbitral trip

6. Freshness Evaluation in the market

Before we move on to the analysis of harvesters, we show how freshness is evaluated at the market. Ishimura and Bailey (2013) estimate the freshness premium in the swordfish price in Kesennuma, Japan, by constructing a freshness measure[7] from the daily logbook data. Their estimation uses the trip level landing data and panel data technique to show that a landing with long trip have lower price of swordfish. We use the augmented version of the data from the same source and add unit weight of swordfish and past prices to control for the potentially confounding factors. We include the five and ten days moving average of the market price of swordfish in order to control for the harvesters' response 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 responding the prices during a trip. The estimation equation is

$$\ln P_{ic} = \alpha_1 \ln Y_{ic} + \alpha_2 \ln F_{ic} + \alpha_3 UnitWght_{ic} + \alpha_4 \ln \bar{P}_{ic}^{MA5} + \alpha_5 \ln \bar{P}_{ic}^{MA10} + \theta_i + m_c + \varepsilon_{ic}^{P} \quad (5)$$

[7] 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.

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 $\bar{P}_{it}^{MA10}$ 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, what the coefficient α_2 represents is 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 square. Table 1 shows the estimation result. Column 1 is the same specification as Ishimura and Bailey (2013). The parameter estimate has a smaller magnitude than one 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 shows still negative and statistically significant elasticity in Column 4. Accordingly, we can see that the freshness is positively evaluated in the market.

Table 1. The Effect of Freshness on Swordfish Market Price

	Dependent variable:			
	Log SF Unit Price			
	(1)	(2)	(3)	(4)
Log Freshness Measure	-0.186***	-0.120***		-0.090***
	(0.022)	(0.018)		(0.021)
Trip Days			-0.004***	-0.002***
			(0.001)	(0.001)
Log SF Total Weight		-0.072***	-0.067***	-0.067***
		(0.007)	(0.007)	(0.007)
Log SF Unit Weight		0.115***	0.111***	0.101***
		(0.026)	(0.027)	(0.027)
Log Price MA5		1.064***	1.063***	1.059***
		(0.146)	(0.147)	(0.145)
Log Price MA10		-0.349**	-0.356**	-0.339**
		(0.151)	(0.152)	(0.151)
Constant	7.243***	2.394***	2.226***	2.356***
	(0.082)	(0.318)	(0.319)	(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
Note:				$^{*}p<0.1$ $^{**}p<0.05$ $^{***}p<0.01$

7. Empirical Model of Harvesters' Behavior

7.1 Dynamic Discrete Choice Model

The empirical approach in this study is based on discrete choice model. Our main interest is to identify the factors that affect harvesters' 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.

$$V(H_{ict}, T_{ict}, \varepsilon_{ict}) = \max_{\delta^*} E_t[\textstyle\sum_{s=t}^{T} u(H_{ics}, D_{ics}, \delta_{ict}; \theta) + \varepsilon_{ics} | H_{ict}, D_{ict}, \varepsilon_{ict}] \quad (6)$$

$$= \max_{\delta^*}[u(H_{ict}, D_{ict}, \delta_{ict}; \theta) + \varepsilon_{ict} + E_t V(H_{ict+1}, D_{ict+1}, \varepsilon_{ict+1})]$$

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 catch 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 days 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 "tomorrow" of 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 days as 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 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

$$V(H_{ict}, D_{ict}, \varepsilon_{ict}) = \max_{\delta^*}\{v(H_{ict}, D_{ict}, \delta_{ict} = Continue) + \varepsilon_{ict}, v(H_{ict}, D_{ict}, \delta_{ict} = Return) + \varepsilon_{ict}\} \quad (7)$$

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

$$v(H_{ict}, D_{ict}, \delta_{ict} = Continue) = u(H_{ict}, D_{ict}, \delta = Continue; \theta) + E_t V(H_{ict+1}, D_{ict+1}, \varepsilon_{ict+1}) \quad (8)$$

$$v(H_{ict}, D_{ict}, \delta_{ict} = Return) = u(H_{ict}, D_{ict}, \delta = Return; \theta) \tag{9}$$

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

$$\bar{V}(H_{ict}, D_{ict}) = \int \max_{\delta^*}\{v^{Cont} + \varepsilon_{ict}, v^{Ret} + \varepsilon_{ict}\} f(\varepsilon) d\varepsilon$$

$$= \ln\{\exp(v^{Cont}) + \exp(v^{Ret})\} + \gamma \tag{10}$$

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.

$$E_t\bar{V}(H_{ict}, D_{ict}) = \int\int \bar{V}(H_{ict+1}, D_{ict+1}) f(H_{ict+1}, D_{ict+1} | H_{ict}, D_{ict}) dHdD \tag{11}$$

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

$$v^{Cont} = u(H_{ict}, D_{ict}, \delta = Continue; \theta) + E_t\bar{V}(H_{ict}, D_{ict}) \tag{12}$$

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

$$\Pr(\delta = Return | H_{ict}, D_{ict}) = \frac{\exp(v^{Ret})}{\exp(v^{Cont}) + \exp(v^{Ret})} \tag{13}$$

By parameterizing the conditional choice-specific functions, we can estimate the model. However, there are two problems to estimate 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 (13). 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 (1993) approach of the estimation. 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.

$$\begin{aligned}\bar{V}(H_t, D_t) &= \ln\left[\exp\left(v^{Fish}\right) + \exp\left(v^{Return}\right)\right] + \gamma \\ &= \ln\left\{\exp(v^{Return})\frac{\exp\left(v^{Fish}\right) + \exp(v^{Return})}{\exp(v^{Return})}\right\} + \gamma \\ &= v^{Return} - \ln\left\{\frac{\exp(v^{Return})}{\exp(v^{Fish}) + \exp(v^{Return})}\right\} + \gamma\end{aligned} \tag{14}$$

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

$$\begin{aligned}\bar{V}(H_t, D) &= v^{Return} - \ln\{Pr(\delta = Return|D', H')\} + \gamma \\ &= -\ln\{Pr(\delta = Return|D', H')\} + \gamma\end{aligned} \tag{15}$$

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 approach, we estimate the transition probabilities from the data, and we then calculate the expectation term using the transition probabilities.

$$E\bar{V}(H_t, D_t) = \int\int\left[-\ln\left\{\widehat{Pr}(\delta = Return|D', H')\right\} + \gamma\right]\hat{f}(H', D'|H_t, D_t)dH'dD' \tag{16}$$

where the hat notation indicates the estimated functions.

7.2 Flow Utility Specification

The closed form of the ex-ante value function and the transition probabilities 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.

$$u_{ict}(H_{ict}, D_{ict}, \delta = Continue; \theta) = -\theta_1 cost + \sum_{s=0}^{t-1} \theta_2 \left(d_{ict-s}\right) h_{ict-s} \tag{17}$$

$$u_{ict}(H_{ct}, D_{ct}, \delta = Return; \theta) = \theta_3 p_{ic} \sum_{s=1}^{t} h_s$$

where p_{ic} is a market price of fish. $cost$ is a constant that represents the daily operation cost. D_{ict} is a vector of passed calendar days $\{d_{ict-s}\}_{s=0}^{t-1}$ since catch on the operation day t. The second term in the flow utility for continuation represents the freshness deterioration. d_{ict-s} is calendar days passed since $t-s$ th day of operation, and the h_{ict-s} is the fish catch on $t-s$ th day of operation. 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 negative and decreasing function of passed calendar days. The parameter θ_3 represents the harvesters' response to the revenue expected to gain when the cruise stops.

7.3 Freshness Model

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 (Lougovois and Kyrana 2005). The common characteristic of those indicators is simple: the freshness is a strictly monotonically decreasing function of time since death of fish. The functional form can vary depending on measures, all measures are strictly monotonic up to twenty days in Lougovois and Kyeana. For example, K-value (calculated from ATP) and sensory score of flavor seems to be linear, but TVC looks a sigmoid curve. In addition, penetration force, which is used to measure the textual changes in the muscle, shapes a quadratic function. Considering these functional forms, we specify the freshness deterioration as third degree polynomials.

$$\Theta(d) = \theta_{21}d + \theta_{22}d^2 + \theta_{23}d^3$$

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.

$$\theta_2(d) = \frac{\mathrm{d}\Theta}{\mathrm{d}d} = \theta_{21} + 2\theta_{22}d + 3\theta_{23}d^2$$

The main purpose here is not to estimate the actual freshness of swordfish, but the harvesters' response to the freshness deterioration. Accordingly, we adopt the interaction of time since caught and the amount of catch.

7.4 CCP two-step estimator

7.4.1. First step: CCP estimation

Following Hotz and Miller 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 sample in each bin. We are obliged to adopt 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

$$\widehat{Pr}(\delta = Fish|D, H) = \frac{\exp\left(\psi(D_{ict}, H_{ict},)\right)}{1 + \exp(\psi(D_{ict}, H_{ict}))} \tag{18}$$

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 $H_{ct} = \left\{h_{c(t-s)}\right\}_{s=0}^{t-1}$ 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 methods for shrinking the regression coefficients toward zero so that the subset of predictor 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 square. 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.

7.4.2. First step: State transitions estimation

Next, we estimate the transition probabilities 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 i.i.d. assumption of the unobserved state. We assume that observed and unobserved states are stationary controlled first-order Markov process, with transition

$$\begin{aligned}
&\Pr(D_{t+1}, H_{t+1}, \varepsilon_{t+1} | D_t, H_t, \varepsilon_t, \delta_t) \\
&\qquad = \Pr(\varepsilon_{t+1} | D_t, H_t, \varepsilon_t, \delta_t) \cdot \Pr(T_{t+1} | D_t, H_t, \varepsilon_t, \delta_t) \cdot \Pr(H_{t+1} | D_t, H_t, \varepsilon_t, \delta_t) \\
&\qquad = \Pr(\varepsilon_{t+1}) \cdot \Pr(D_{t+1} | T_t, H_t, \delta_t) \cdot \Pr(H_{t+1} | D_t, H_t, \delta_t) \qquad (19)
\end{aligned}$$

Namely, the observed and unobserved state transitions are conditionally independent 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 passed D is a source of confusion in this model, because the decision periods 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 the 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 in a good fishing ground when they observe high catch rate. Hence, we estimate the transition of calendar days as a function of observed catch.

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

The 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 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.

$$h_{ict+1} = \phi_0 + \phi_1 h_{ict} + \eta_{ict+1}^{h} \tag{21}$$

7.4.3. Second step: Structural Parameter estimation

In the second step, we estimate the CCPs, the transition probabilities and structural parameters in the utility function in eq. (17). We first estimate the CCPs and the transition probabilities, then construct the expectation term following eq. (16). With the expectation term in hand, we can construct the choice-specific value function of "Continue" expressed as eq. (12). The choice specific value function of "Return" is a static utility expressed in eq. (9). Hence, we have everything necessary to have the closed form probability eq. (13). 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.

8. Estimation Result

8.1 Result 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 result of the Poisson regression for this process is 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 (Days past) is seemingly not important for searching behavior. Hence, we adopt Column 4 model to calculate the transition process of calendar days.

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

Table 2. Estimation Result of the AR1 model of daily catch

	Dependent variable:			
	Search/Move days before next operation			
	(1)	(2)	(3)	(4)
Days Past	0.001	0.001	0.001	
	(0.001)	(0.001)	(0.001)	
daily # of Swordfish	-0.009***		-0.009***	-0.009***
	(0.001)		(0.001)	(0.001)
daily weight of blueshark		0.00000	-0.00000	
		(0.00001)	(0.00001)	
Constant	0.309***	0.196***	0.314***	0.328***
	(0.020)	(0.017)	(0.022)	(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:				*p **p ***p<0.001
				Standard Errors in Parentheses

Table 3. Estimation Result of the AR1 model of daily catch

	Dependent variable:
	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:	*p**p***p<0.001
	Standard Errors in Parentheses

8.2 Result of first step CCP estimation

The first step estimation of CCP is based on eq. (18). The flexible logit is estimated with elastic-net logit estimator. We highlight the main effects instead of the parameter estimates because the number of parameters are 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 left the shore. This is an advantage of using the CCP estimator in this model. The harvesters' 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 left the 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 harvesters' expectation of continuation value by having passed calendar days since left the port as a state variable in the first step estimation instead of having 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 decrease the probability of continuation while coefficients on 20 or less days since caught shrunk toward zero.

<u>8.3 Result of second step structural parameters estimation</u>

We have several specifications to see the fit of the model. Table 3 shows the estimation result of the models. For each specification, either the linear or quadratic form of freshness (Freshness) of each species (SF: swordfish, BS: blue shark) and revenue from each species are included. Comparing Column 1 and Column 2 models, the interaction of the second order of passed 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 third degree polynomial rather than lower degree.

The estimated coefficients on freshness deterioration function of blue shark are also statistically significant. This is an unexpected result because blue sharks are not consumed as raw dish but processed. According to a primary processer in Kesennuma, fresh sharks are relatively easier to process due to its 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 revenues are negative, since the flow utility of "Return" is normalized. The revenue in Column 2 model shows the negative signs for both species, but it is not statistically significant for swordfish.

Table 3. Estimates of structural parameters

	Dependent variable:	
	Choice: Continue = 1	
	(1)	(2)
$2\theta_{22}^{SF}$	-0.046***	0.055***
	(0.003)	(0.011)
$3\theta_{23}^{SF}$		-0.004***
		(0.0004)
$2\theta_{22}^{BS}$	-0.001***	0.006***
	(0.0003)	(0.001)
$3\theta_{23}^{BS}$		-0.0003***
		(0.00004)
θ_3^{SF} (Revenue)	0.00004***	-0.00001
	(0.00001)	(0.00001)
θ_3^{BS} (Revenue)	-0.00003	-0.0001*
	(0.00002)	(0.00002)
Constant	2.984***	2.356***
	(0.111)	(0.121)
Observations	15,127	15,127
Log Likelihood	-2,528.685	-2,425.444
Akaike Inf. Crit.	5,067.369	4,864.887
Note:	$p^{*}<0.05$ $p^{**}<0.01$ $p^{***}<0.001$	
	Standard Errors in Parentheses	

8.4 Recovery of freshness deterioration function

Given the coefficients estimated, we can recover the freshness deterioration function. We cannot identify θ_{21} since it is constant and cannot separately estimated from the constant of second step dynamic logit, we set it as zero and recover the function only using θ_{22} and θ_{23}. By integrating $\theta_2(d)$ over passed days since caught using the coefficient estimated, we obtain the function depicted in Figure 3. The freshness does not decrease in the first 20 days, but it decreases after the 20 days passed since caught. 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 resulted functional form of the freshness deterioration indicates the increasing rate of reduction after 20 days. Such shape of function looks similar to the graph of penetration force as a measure of textural change (Lougovois and Kyrana 2005). At the landing market in Kesennuma, 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 method based on their experiences. Knowing that the buyers rely on the physical methods, it is consistent that the harvesters' response to freshness deterioration is similar to the form of textural change of fish as a physical freshness measure.

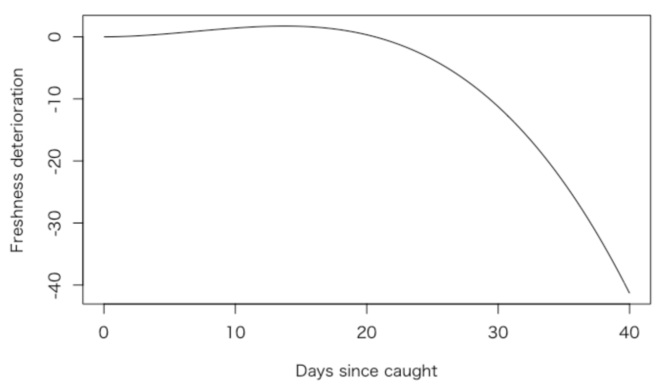

Figure 3. Recovered Freshness deterioration function.

9. Discussion and Conclusion

Harvesters in fisheries takes fishing cruises from within a day to months. The harvester may not fully utilize the harvester 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. Overall, the model estimates show that freshness measure with after 20 days old fish matters. This may suggest that the variation within a trip affects harvesters' decision. Specifically, the large amount of catch in the early periods of a trip may lead harvesters to stop fishing early in order to avoid the freshness deterioration. Given that the freshness contributes to raise the unit price of swordfish, this behavior is consistent with profit maximization. One may claim that this could be an 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 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 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 result suggests the variable selection which provides us a supportive evidence of the result of structural estimation. As a result, the harvesters' 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 with 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 major tools in fisheries management. For example, a days-at-sea regulation was implemented to the fleet in Kesennuma 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 harvesters' 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 catch-ability 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 outcome in fishery. The joint decision is often formulated as a nested structure in multiple decision stages. For example, Holland and Sutinen (1999) formulate the choice of target fishery as first stage and location choice as second stage, and adopt Nested Logit to estimate the model. The two-step estimation of dynamic discrete choice adopted in this study can be extended to weaker distributional assumption such as GEV. Such framework is developed in Arcidiacono and Miller (2011) and applied in other field (e.g. Yoganarasimhan 2013). Hence, one of the directions of the future work could be a problem of joint choices with dynamic approach.

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