Title
Catch More to Catch Less: Estimating Timing Choice as Dynamic Bycatch Avoidance Behavior

Journal
Environmental and Resource Economics, 82(4)

ISSN
0924-6460

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Publication Date
2022-08-01

DOI
10.1007/s10640-022-00699-6

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January 7, 2025

Abstract

We model harvesters' temporal participation behavior in a fishery with individual quotas for both a target and bycatch species. Harvesters make participation decisions given time-varying characteristics of the fishery (e.g., catch rates, price, and bycatch rates) and outside opportunities (e.g., other fisheries). A harvester's problem is seasonally dynamic under the individual quota scheme because quota acts as an intertemporal budget constraint. We construct a theoretical model to describe how the shadow value of individual quota plays a role in a harvester's decision and propose an empirical model that captures the dynamic effect of the seasonal quota usage. Our study finds support for the existence of dynamic bycatch avoidance: harvesters use the security provided by quota allocations to reduce harvesting around periods of high bycatch. Our policy simulation demonstrates that opening the season earlier could reduce bycatch while the main target catch is maintained due to temporal shift of quota usage.

Keywords Bycatch, Dynamic Avoidance, Policy Simulation, Prohibited Species Catch, Shadow Value of Individual Quota

JEL classifications C61, Q22, Q28

Introduction

The incidental catch of non-target species, so-called bycatch, is a key challenge for fisheries management: left unchecked, bycatch can create conflict with other user groups that claim the species as a valuable target or cause ecosystem issues through stock depletion. The fundamental cause of bycatch is imperfect selectivity of fishing gear to target specific species. While there are technical approaches that improve gears and enhance target-ability, behavioral approaches have been emphasized as an important margin along which fishers can adjust target-ability in a cost-effective manner (Branch & Hilborn, 2008; Reimer, Abbott, & Wilen, 2017). Bycatch avoidance is costly for harvesters because measures generally decrease the catch rates of target species. Economic analysis has informed bycatch reduction policies by demonstrating this trade-off between bycatch reduction and costly avoidance, using models to illustrate the margins that efficiently reduce bycatch. While the emphasis on spatial behavior has been made in bycatch management (Abbott, Haynie, & Reimer, 2015; Abbott & Wilen, 2011; Little, Needle, Hilborn, Holland, & Marshall, 2015; Miller & Deacon, 2017), this study focuses on relatively understudied temporal avoidance strategies by constructing a model of multi-fishery participation choice to analyze the effect of a season length policy on bycatch.

One of the challenges of empirically modeling participation choices for a fishery with individual quotas is to capture the forward-looking behavior of managing quota usage. Individual quotas introduce an opportunity cost of harvesting: harvesting today means that there is less quota available for harvesting in the future. The magnitude of this shadow cost depends on expected future catch rates, the amount of remaining quota, and the number of periods remaining in the season. The shadow cost associated with the use of quota is difficult to estimate because expectations regarding quota usage in future periods are unobserved. Previous work has approximated the shadow cost of binding fleet-wide quotas by interacting contemporaneous expected catch rates with the amount of remaining time periods and quota (e.g., Abbott & Wilen, 2011; Haynie, Hicks, & Schnier, 2009), but has not incorporated information regarding expected future catch rates or bycatch.

We address this gap by developing a theoretical framework to derive a harvester's optimal participation choice as a function of the shadow cost of target and bycatch quota, allowing for time-varying catch and bycatch rates. We use this decision mechanism to specify an empirical model of fishery participation with a composite variable, which we call Quota Speed, which serves as a proxy for the shadow cost of quota. We apply the model to the Bering Sea/Aleutian Islands (BSAI) pollock catcher-processor fleet, which targets pollock and other species while being subject to prohibited species catch (i.e., bycatch) of salmon species.

Our results show that harvesters have incentive to participate in the present period when bycatch rates are expected to be higher in the future, reflecting forward-looking bycatch avoidance behavior. With an emphasis on the harvesters' forward-looking behavior, we apply our model in the Alaska pollock fishery, where we simulate a counterfactual policy that sets a longer season length to give fishers more flexibility to avoid bycatch. The simulation results demonstrate that the new regulation reduces bycatch while maintaining target species catch, suggesting that the current season length policy, which was originally created for conserving the target species, is obsolete when considered jointly with quota and the newly emerged bycatch issue. Indeed, the bycatch restriction was layered on top of previous regulations without considering its potential interaction with the season length restriction. Updating the regulation by elongating the season may allow harvesters the flexibility to substitute the timing of target species catch to avoid bycatch.

There are two primary reasons why the timing of participation should be highlighted as an important margin of bycatch avoidance. First, previous work has suggested individual bycatch quota as a bycatch management instrument in addition to other policy tools such as financial instruments or spatial restriction (Boyce, 1996; Diamond, 2004; Edwards, 2003; Hannesson, 2010). The main idea of individual bycatch quota is to incentivize harvesters to avoid bycatch by creating a shadow value associated with use of the quota, which represents the marginal cost of bycatch today in terms of the foregone benefit of target species catch in the future. This shadow value incentivizes harvesters to allocate effort over a season to take advantage of low bycatch rates. Second, fishery choice is an important decision margin for fishers that can target multiple species (e.g., Bockstael & Opaluch, 1983). It is therefore natural to model the timing of quota use as a problem of sequential fishery participation choices over a season when harvesters have the opportunity to participate in more than one fishery and face the bycatch rate varies over a season. Arguing for the importance of considering outside options, Stafford (2018) models daily choices of participation in alternative fisheries using a nested logit model; we extend her approach by incorporating a dynamic term reflecting the shadow value of using a constraining bycatch quota.

Our study contributes to the literature by developing the first empirical model of individual's temporal choice of fishing under individual quota, and suggesting an approach to calibrating it without a full structural estimation. While seasonal allocation of fishing quota has been studied, as it is a key margin under individual quota management (e.g., Birkenbach et al., 2020), capturing individual harvester behavior based on microfoundations is challenging due to unobserved expectations and shadow values of quotas. The allocation of fishing effort through time has been studied to show how individual quotas can attenuate the race to fish. This has been modeled as an optimal control problem which maximizes the seasonal profit given individual quota (Boyce, 1992, 1996; Clark, 1980). Empirical models of optimal temporal fishing effort allocation, in contrast, are limited. Kellogg, Easley, & Johnson (1988) apply a dynamic seasonal model to a scallop fishery, but the main purpose is to find the optimal seasonal length for the management body rather than estimating a model of harvester behavior. Previous empirical studies have investigated the fishery choice problem for fisheries without individual quotas; however, these studies model harvesters' choice as static problem rather than dynamic because the management schemes under consideration created derby-style fisheries (Eggert & Tveteras, 2004; Pradhan & Leung, 2004). Curtis & McConnell (2004) model a forward-looking harvester's choice of fishery and location at the trip level, but no seasonal level study exists considering allocation of individual quota. Bisack & Sutinen (2006) study the effect of bycatch ITQs as a bycatch reduction measure; however, their approach is to simulate profits and efforts under policy alternatives given estimated revenue and costs rather than directly estimating harvesters' responses.

The empirical challenge of the dynamic participation choice problem in fisheries is to model harvesters' unobserved expectations of future quota usage. The most obvious way to tackle this issue is to solve a harvester's full dynamic programming (DP) problem; however the stochastic evolution of the state variables (remaining quotas) combined with the need to recursively solve for a harvester's optimal participation choice makes the model become intractable. Our approach does not fully solve the DP problem; instead, we include a composite variable derived from our theoretical model of optimal participation choice that approximates the forward-looking behavior of harvesters by specifically taking into account the future use of individual quota.

This paper is organized as follows. Section 2 presents our theoretical model to highlight the mechanism of harvesters' decision making for fishery participation under a quota managed fishery. Section 3 describes our case fishery, the Bering Sea and Aleutian Islands pollock catcher-processor fleet. Section 4 presents our empirical model and estimation strategy. Section 5 presents the estimation results. Section 6 shows the simulation results of an alternative policy based on the estimates of the empirical model. Section 7 concludes the article.

The Seasonal Participation Model

To investigate harvesters' temporal effort allocation under seasonal individual quota and bycatch avoidance, we construct a model of harvester's timing choice of fishery participation. We conceptualize harvesters as solving an annual (or seasonal) planning problem, given time-varying expected catches and prices and the constraints of individual quotas for target and bycatch species. The key implication of the model is the existence of a dynamic trade-off: a forward-looking harvester will balance current gains, the cost of bycatch, and future benefits from saved quotas when deciding on participation in a fishery. Our motivation for developing a theoretical model is to analyze how time-varying conditions and shadow costs affect the decisions of harvesters.

Our model builds on seasonally dynamic and single target fishery models (Boyce, 1992; Clark, 1980), but allows for multiple fishery choices. While these previous studies focus on the optimal management under stock externality from the perspective of a social planner, we present a model of individual private harvester's within-season decision on the extensive margin given an individual quota-based management scheme. Accordingly, we use a dynamic framework with remaining quota as the state variable of interest. We do not explicitly consider a stock externality. Instead, we assume that the catch of the fleet is only a small portion of the stock, which is managed to a steady state by a TAC, and individuals take the time-varying expected catch as given.

The model focuses on a harvester maximizing seasonal profit under individual target and bycatch quotas. The harvester allocates effort across two fisheries over a season. Fishery 1 is under individual quota management for both target and bycatch, and Fishery 2 is free access for the harvesters without quantitative restriction. The seasonal profit of harvester i is defined as

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

where q_{jt} is the time-varying catch of target species in Fishery j, b_t is the time-varying bycatch rate in Fishery 1, p_{1t} is the time-varying price of fish in Fishery 1, p_2 is the price of fish in Fishery 2. The choice variable $d_{it} \in [0, 1]$ denotes a harvester's fishery decision, and can be interpreted as the proportion of effort allocated to Fishery 1—e.g., the harvester chooses to fully commit to Fishery 1 if $d_{it} = 1$ and chooses to only harvest in Fishery 2 if $d_{it} = 0$. While the choice variable d_{it} is specified as continuous and can take on values between 0 and 1, the optimal fishery decision will be a corner solution (as we demonstrate below) since it enters the objective function linearly. The parameter c is the operating cost of fishing, and γ is the unit cost of bycatch, which represents a punishment of having bycatch even if the bycatch quota is not binding. This direct cost of bycatch is often seen in the bycatch management—for example, in the BSAI pollock fisheries, harvesters that catch a high number of salmon bycatch in a week are publicly listed on the "dirty 20 list".[1] In addition, harvesters with high bycatch may be restricted from accessing certain areas to fish. These measures work to provide harvesters with incentives to avoid bycatch in addition to the individual bycatch quota, and we take it into account as a form of direct cost of bycatch. We do not explicitly take into account discounting because the model presumes the within-season dynamics, and the effect of discounting is predictable while the main interest is the response to time-varying variables.[2]

The harvester is subject to individual quota constraints in Fishery 1: Q_{1i} is the amount of individual target species and Q_{bi} is the amount of individual bycatch quota. The sums of the catch and bycatch should not exceed these quotas:

$$\begin{aligned} Q_{i1} &\geq \int_0^T d_{it} q_{1t} dt \\ Q_{bi} &\geq \int_0^T d_{it} b_t q_{1t} dt. \end{aligned} \tag{2}$$

Including the constraints for the decision variable $0 \leq d_{it} \leq 1$, the Lagrangian formulation of the constrained maximization problem of harvester i is as follows:

$$\mathcal{L} = V + \lambda_{1i}[Q_{1i} - \int_0^T d_{it} q_{1t} dt] + \lambda_{bi}[Q_{bi} - \int_0^T d_{it} b_t q_{1t} dt] + \int_0^T \eta_{1it} d_{it} dt + \int_0^T \eta_{2it}(1 - d_{it}) dt, \tag{3}$$

where λ_{1i}, λ_{bi}, η_{1it} and η_{2it} are Lagrange multipliers which correspond to the target species quota, the bycatch species quota, and the upper and lower bounds of the decision variable,

[1] Number of appearance is reported on annual reports. e.g. Pollock Conservation Cooperative and High Sea Catchers' cooperative join annual report, https://www.npfmc.org/wp-content/PDFdocuments/catch_shares/CoopRpts2016/PCC_HSCC_AFA16.pdf

[2] For example, Birkenbach et al. (2020) includes discounting in their theoretical model for completeness, but not explicitly treat it in their empirical section. We exclude the discounting to keep the expression simple.

respectively. By rearranging the first-order condition of the Lagrangian in eq. 3 with respect to d_{it}, we obtain the following necessary condition:

$$Y_{it} = [p_{1t} - \lambda_{1i} - (\gamma + \lambda_{bi})b_t]q_{1t} - p_2 q_{2t}, \tag{4}$$

where $Y_{it} \equiv \eta_{2it} - \eta_{1it}$ is the difference between the Lagrange multipliers associated with the range conditions for d_{it}. The first term on the right-hand side is the net benefit from Fishery 1, and the second term is for Fishery 2. The operating cost, c, cancels out as we presume that the costs are same across fisheries. We refer to Y_{it} as a participation index. Intuitively, since the index is the difference in net revenues between the two fisheries, the harvester chooses Fishery 1 if the index is positive. In this case, $\eta_{2it} > 0$ and $\eta_{1it} = 0$, which implies the constraint $d_{it} = 1$ is binding. Conversely, if the index is negative, then $\eta_{1it} > 0$ and $\eta_{2it} = 0$, which implies the constraint $d_{it} = 0$ is binding. We can express this link between the index and the decision variable as $d_{it} = I\{Y_{it} \geq 0\}$, where $I\{\cdot\}$ is an indicator function.[3]

The interpretation of the index is straightforward: the harvester chooses the fishery with higher net benefit. Notice that the net benefit of Fishery 1 includes the shadow costs of both the target and bycatch quota. These shadow costs capture the cost of lost harvesting opportunities in the future due to less remaining quota; hence, the harvester's decision is dynamic. The participation index is the motivation for our empirical model specification, which we describe in detail below.

Our interest is in empirically estimating the participation model in equation (4); however, this is made difficult by the existence of the shadow values λ_{1i} and λ_{bi}, for which analytical closed-form solutions are not easily attained. Moreover, the shadow values are functions of the target catch q_{1t}, bycatch rate b_t, and remaining quotas Q_{1i} and Q_{bi}. Thus, the participation index in equation (4) is potentially nonlinear with respect to the independent variables of interest.

[3]Note that a harvester is indifferent between the two fisheries when $Y_{it} = 0$. In this case, $\eta_{1it} = \eta_{2it} = 0$ and $0 \leq d_{it} \leq 1$. For simplicity, we assume that a harvester would allocate all effort to Fishery 1 if indifferent. In practice, this is rare. We provide a full derivation of the necessary condition in eq. 4 in Appendix A1.

We address this issue by forming a Taylor-series approximation of order one for the participation index Y in equation (4) around a point $x^0 = (b^0, q_1^0, Q_1^0, Q_b^0)$, such that

$$Y_{it}(x) \approx Y_{it}\left(x^0\right) + \frac{\mathrm{d}Y_{it}}{\mathrm{d}b_t}\left(x^0\right) b_t + \frac{\mathrm{d}Y_{it}}{\mathrm{d}q_{1t}}\left(x^0\right) q_{1t} + \frac{\mathrm{d}Y_{it}}{\mathrm{d}Q_{1i}}\left(x^0\right) Q_{1i} + \frac{\mathrm{d}Y_{it}}{\mathrm{d}Q_{bi}}\left(x^0\right) Q_{bi}, \tag{5}$$

where $x = (b_t, q_{1t}, Q_{1i}, Q_{bi})$ can be considered as deviations for the point x^0. We further decompose each of these partial effects below, with the goal of understanding the various components of the participation index so as to estimate it using a latent index model.

Change in bycatch rate: The second term of eq. 5 is the change in the index with respect to the bycatch rate. Using the implicit function theorem, the total derivative of the participation index Y_{it} with respect to the bycatch rate b_t can be shown to be:[4]

$$\begin{aligned}
\frac{\mathrm{d}Y_{it}}{\mathrm{d}b_t} &= \frac{\partial Y_{it}}{\partial b_t} + \frac{\partial Y_{it}}{\partial \lambda_{1i}}\frac{\partial \lambda_{1i}}{\partial b_t} I\{\lambda_{1i} > 0\} + \frac{\partial Y_{it}}{\partial \lambda_{bit}}\frac{\partial \lambda_{bi}}{\partial b_t} I\{\lambda_{bi} > 0\} \\
&= -(\gamma + \lambda_{bi}) q_{1t} + q_{1t}\frac{(\gamma + \lambda_{bi})\frac{\partial d_{it}}{\partial Y_{it}} q_{1t}^2}{\int_t^T \frac{\partial d_{is}}{\partial Y_{is}} q_{1s}^2 ds} I\{\lambda_{1i} > 0\} \\
&\quad - b_t q_{1t}\frac{(d_{it} - (\gamma + \lambda_{bi})\frac{\partial d_{it}}{\partial Y_{it}} b_t q_{1t}) q_{1t}}{\int_0^T \frac{\partial d_{is}}{\partial Y_{is}} b_s^2 q_{1s}^2 ds} I\{\lambda_{bi} > 0\}
\end{aligned} \tag{6}$$

The first term on the right-hand-side is the direct effect of the change in bycatch rate. The second term is the dynamic effect via the shadow value of the target species quota. This term is positive, and relevant only if the shadow value is positive (i.e., the target quota is binding). The third term is the dynamic effect via the shadow cost of the bycatch species quota, the sign of which is ambiguous and depends on the level of the participation index, as well as the magnitude of the catch rate, the direct cost of bycatch, the shadow cost of bycatch, and the bycatch rate. If $\lambda_{bi} = 0$, only the first and second terms are relevant.

Change in target catch: The total derivative of the participation index Y_{it} with respect to target catch q_{1t} can be shown to be:

[4] A full derivation of the derivative is provided in the Appendix A2.

$$
\begin{aligned}
\frac{\mathrm{d}Y_{it}}{\mathrm{d}q_{1t}} &= \frac{\partial Y_{it}}{\partial q_{1t}} + \frac{\partial Y_{it}}{\partial \lambda_{1i}}\frac{\partial \lambda_{1i}}{\partial q_{1t}} I\{\lambda_{1i} > 0\} + \frac{\partial Y_{it}}{\partial \lambda_{bi}}\frac{\partial \lambda_{bi}}{\partial q_{1t}} I\{\lambda_{bi} > 0\} \\
&= [p_{1t} - \lambda_{1i} - (\gamma + \lambda_{bi})b_t] + \frac{-q_{1t}\left\{\frac{\mathrm{d}d_{it}}{\mathrm{d}Y_{it}}[p_{1t} - \lambda_{1i} - (\gamma + \lambda_{bi})b_t] + d_t\right\}}{\int_0^T \frac{\mathrm{d}d_{is}}{\mathrm{d}Y_{is}} q_{1s}^2 ds} I\{\lambda_{1i} > 0\} \\
&+ \frac{-b_t q_{1t}\left\{\frac{\mathrm{d}d_{it}}{\mathrm{d}Y_{it}}[p_{1t} - \lambda_{1i} - (\gamma + \lambda_{bi})b_t] + d_t b_t\right\}}{\int_0^T \frac{\mathrm{d}d_{it}}{\mathrm{d}Y_{it}}^2 ds} I\{\lambda_{bi} > 0\}
\end{aligned} \tag{7}
$$

Note that $\frac{\partial Y_{it}}{\partial q_{1t}}$ is the direct effect of the catch rate in period t, whose sign depends on the price, bycatch cost, and shadow costs in period t. The second term is the indirect effect through the shadow cost of target species quota, where $\frac{\partial Y_{it}}{\partial \lambda_{1i}} < 0$, $\frac{\partial \lambda_{1i}}{\partial q_{1t}} \geq 0$, hence the whole term is negative or zero. The third term is the indirect effect through the shadow cost of bycatch species quota, where $\frac{\partial Y_{it}}{\partial \lambda_{bi}} < 0$, $\frac{\partial \lambda_{bi}}{\partial q_{1t}} \geq 0$, hence the whole term is negative or zero.

Change in target quota: The total derivative of the participation index Y_{it} with respect to target quota Q_{1it} can be shown to be:

$$
\begin{aligned}
\frac{\mathrm{d}Y_{it}}{\mathrm{d}Q_{1i}} &= \frac{\partial Y_{it}}{\partial \lambda_{1i}}\frac{\partial \lambda_{1i}}{\partial Q_{1i}} I\{\lambda_{1i} > 0\} + \frac{\partial Y_{it}}{\partial \lambda_{bi}}\frac{\partial \lambda_{bi}}{\partial Q_{1i}} I\{\lambda_{bi} > 0\} \\
&= \frac{q_{1t}}{\int_0^T \frac{\mathrm{d}d_{is}}{\mathrm{d}Y_{is}} q_{1s}^2 ds} I\{\lambda_{1i} > 0\}
\end{aligned} \tag{8}
$$

Note that the first term on the right-hand-side is unambiguously positive while the second term is zero, as main target species quota does not have any effect on shadow value of bycatch quota. Hence, the whole term is positive. This is also an intuitive result because the increase in the quota should means increases in the catch in each period, hence the opportunity cost is lowered.

Change in bycatch quota: The total derivative of the participation index Y_{it} with respect to target quota Q_{bi} can be shown to be:

$$
\begin{aligned}
\frac{\mathrm{d}Y_{it}}{\mathrm{d}Q_b} &= \frac{\partial Y_{it}}{\partial \lambda_{1i}} \frac{\partial \lambda_{1i}}{\partial Q_{bi}} I\{\lambda_{1i} > 0\} + \frac{\partial Y_{it}}{\partial \lambda_{bi}} \frac{\partial \lambda_{bi}}{\partial Q_{bi}} I\{\lambda_{bi} > 0\} \\
&= 0 + \frac{b_t q_{1t}}{\int_0^T {\frac{\mathrm{d}d_{is}}{\mathrm{d}Y_{is}}}^2 ds}
\end{aligned}
\tag{9}
$$

Note that the first term on the right-hand-side is zero while the second term is unambiguously positive. Hence, the overall effect is positive. This is also an intuitive result because the increase in the quota should means greater buffer of bycatch in each period.

Overall, we observe two important characteristics of the first order approximation. First, the total derivatives are decomposed into the direct (contemporaneous) effect and dynamic effects through the shadow costs of the quotas. Second, the magnitude of the dynamic effects depends on current fishing conditions relative to expected fishing conditions in the rest of the season. We utilize these characteristics to formulate an empirical specification of participation using a latent index model, which we discuss in more detail below.

The Bering Sea/Aleutian Islands Trawl Pollock Fishery

We apply our approach to the catcher-processor vessels which operate in the Bering Sea and Aleutian Islands (BSAI) pollock fishery in the North Pacific. A total of 17 vessels owned by seven companies are included in the data over the years 2005 to 2013. The fleet consists of similarly designed vessels with lengths from 270 to 376 feet. Employing pelagic (mid-water) trawl, vessels target walleye pollock in the BSAI and Pacific hake in West Coast of the United States. In addition, some vessels catch yellowfin sole (YFS) as a secondary fishery in the BSAI. The BSAI pollock fishery is the largest human food fishery in the world, and its harvest constitutes 40% of the competitive and highly substitutable global whitefish market (Fissel et al., 2015). There is a variety of products in this fishery including fillets, head and gutted, surimi and roe.

The fleet consists of the vessels listed in Section 208 (e) of the American Fisheries Act. The American Fisheries Act was enacted in 1998, and its purpose is facilitating the BSAI vessels to conduct their fishery in a more rational manner. The American Fisheries Act Pollock Cooperatives program was implemented by the U.S. congress and includes participation requirements, total allowable catch (TAC) allocations among sectors, the provision of an allocation to the Community Development Quota program, and authorization of the formation of cooperatives. 40% of the Bering Sea commercial pollock TAC is allocated to the catcher-processor sector. The catcher-processor fleet formed a cooperative to coordinate the pollock harvest under American Fisheries Act, called the Pollock Conservation Cooperative. The cooperative members allocate the sectoral quota among themselves, and this allocation is, by and large, treated as internally managed individual quotas.

Vessels in the BSAI pollock fleet stay at sea fishing and processing for several weeks due to their size and processing facilities. During each season, harvesters make decisions on which species to target depending on time-varying profit opportunities, constrained by economic (e.g., harvesting costs), biological (e.g., catch rate of species, maturity of roe), regulatory (e.g., time and area closures) and environmental (e.g., sea ice, oceanographic and climatic trends) conditions (Haynie & Pfeiffer, 2013; Pfeiffer & Haynie, 2012). The species provide differing opportunities during different periods, leading vessels to choose particular targets throughout the season.

The fishing year is divided into two regulatory seasons: the “A” season (January to June) is focused mainly on fishing pre-spawning pollock for the harvest of roe, which can consist over 4% of weight (Ianelli et al., 2013) but 20% to 40% of value (Fissel et al., 2015), and the “B” season (June to November) is aimed more to the production of fillets and surimi products. The main reason why the seasons are divided is that vessels intensively catch pollock in winter and spring due to the high value of matured roe. Too much fishing pressure on the spawning stock may result in low recruitment even though the annual fishing mortality satisfies the regulation. Accordingly, a portion of the annual quota is allocated to the B season after spawning is over. Given the nature of this difference in the seasons, we apply our model separately for the A and B seasons.

A recent major regulatory update to the pollock fishery changes the management of Chinook (king) salmon bycatch, which is designated as prohibited species catch (PSC) by the fishery management plan. Vessels in the BSAI pollock fishery are not allowed to retain or sell the species, even though it is valuable. While the pollock fishery achieves a high target species selectivity, bycatch numbers are still high in aggregate due to the large amount of pollock catch (Larson, House, & Terry, 1998). Initial regulations included time and area closures when bycatch limits were exceeded; however, Chinook salmon bycatch significantly increased between 2001 and 2007 (Gisclair, 2009; Stram & Ianelli, 2015). Changes in the migration pattern of Chinook salmon caused by environmental factors (e.g. temperature) are associated with the rise in bycatch in the pollock fishery, rather than other reasons such as common prey (Stram & Ianelli, 2015). To resolve the issue, the North Pacific Fishery Management Council implemented a new management measure under Amendment 91 to the BSAI Fishery Management Plan in 2011, which established a hard cap for Chinook bycatch (called the PSC limit) and required an industry-designed incentive program that would encourage harvesters to avoid bycatch even when cumulative bycatch is not close to the limit (NMFS, 2010). The PSC limit is set for the fleet and allocated by the cooperatives within the fleet proportional to the size of a vessel's pollock quota. The PSC limits for individual vessels are not binding over the sample period, largely because the allocation of the limit is set to address unexpected bycatch events (Madsen & Haflinger, 2015).

The bycatch of the pollock fishery is carefully monitored. The vessels in our study have 100% on-board observer coverage (Gantz, 2018). It is often classified as 200% coverage, meaning that two observers are on board. Discarding is counted as a part of bycatch: The observers on board record the salmon catch regardless of whether it is retained or discarded. Hence we treat all the bycatch as fishing mortality which is tracked against the limit.

The American Fisheries Act generally does not allow the catcher-processor fleet to catch non-pollock species in the BSAI area, but it allocates a portion of other groundfish species as their "traditional catch", which are regulated by sideboard limits defined by pre-American

Fisheries Act catch history. The second fishery in the BSAI for the fleet, YFS, is categorized as non-pollock groundfish species along with pacific cod and Atka mackerel, which are caught by the catcher-processor fleet in small amounts. While a sideboard limit for YFS is determined on an annual basis, it is not binding for the fleet in any year between 2001 and 2015, and hence it is free to access without quota regulation.[5]

The fleet also participates in the Pacific Hake fishery on the US West Coast when it is not operating in the Bering Sea. Pacific Hake is managed under West Coast Groundfish Trawl Catch Share Program. This is a limited entry Fishery under the management of the Pacific Fishery Management Council. Any catcher-processor needs a permit to target hake. The council allocates 34% of the TAC to the cooperative of the catcher-processors. The member companies of the cooperative negotiate the apportionment of the allocation and sign contracts to enforce it. The season of Pacific Hake fishery for the catcher-processor vessels opens on May 15 every year. The catcher-processor vessels finish using their A season quota of pollock in early May although the season lasts until June 20, because they move to the West Coast to start targeting Pacific hake.

Empirical Strategy

Empirically estimable model

Our goal is to apply the theoretical model developed above to the BSAI pollock fishery. Our theoretical results demonstrate that fishery participation is driven by both contemporaneous and dynamic effects. A challenge in specifying an empirical version of the first-order approximated participation index (eq. 5) involves the dynamic effects of quota usage, the magnitude of which depends on the relative size of the catch (or bycatch) rate over the season. We adapt our theoretical model such that the first-order approximation of the latent

[5]This is not an open-access, because the fishery is not open to public. It is open in the sense that the catcher-processor fleet can access without quota regulation.

participation index in eq. 5 can be represented by an indirect utility specification within the random utility model framework.

The random utility model was initially applied to fishery choice by Bockstael & Opaluch (1983), and this approach established a sizable literature to analyze harvester behavior (e.g., Abbott & Wilen, 2011; Haynie & Layton, 2010; Holland & Sutinen, 2000; Smith & Wilen, 2003). Several studies adopt the random utility model framework to integrate dynamic aspects of fishers. There are primarily two approaches for dynamic empirical estimation of discrete choices. The full stochastic dynamic programming approach (e.g., Huang & Smith, 2014; Provencher & Bishop, 1997) is notoriously difficult: the stochastic evolution of the state space (remaining quota) combined with the need to recursively solve for a harvester's optimal participation choice makes the problem become quickly intractable. Moreover, the stochastic nature of catch makes it difficult to reduce the state space down to a manageable set of deterministic state variables under quota management, although some studies model in the empirical specifications for non-quota management fisheries (e.g., Hicks & Schnier, 2006, 2008; Abe & Anderson, 2022). For this reason, we do not follow the full stochastic dynamic programming approach. Instead, we follow the second approach that incorporates reduced-form approximations of dynamic trade-offs (Curtis & Hicks, 2000; Curtis & McConnell, 2004), which has been shown can be effective for evaluating marginal counterfactual policy changes, as we do here (Reimer, Abbott & Haynie, 2022).

To construct a seasonal-planning model without solving the full dynamic program, our empirical model includes an approximated key state variable that allows us to test for evidence of dynamic decision making and to simulate counterfactual bycatch-reduction policies. In addition to computational feasibility, the main advantage of our approach is the explicit linkage with the theoretical result that clarifies the mechanism of the dynamic decision. This theory-based estimation shares the idea of structural estimation, which estimates parameters in an explicitly specified economic model that is principally consistent with the data. We propose an approach to estimate the parameters that govern harvesters' decision making, yet tractable and applicable to the real-world data.

Just as a latent variable index is the difference between two alternative-specific utilities, the participation index from our theoretical model is the difference between the net benefits for two fisheries. Following from our Taylor-series approximation of the participation index (eq. 5), we specify a harvester's indirect utility as

$$\begin{aligned} Y_{it} =& \alpha_i + (\beta_{11} + \beta_{12} QSpeed_{it} + \beta_{13} BQSpeed_{it} A91_t) EREV_{it} + \\ & (\beta_{21} + \beta_{22} QSpeed_{it} + \beta_{23} BQSpeed_{it} A91_t) ECPR_{it} + \\ & (\beta_{31} + \beta_{32} QSpeed_{it} + \beta_{33} BQSpeed_{it} A91_t) Quota_i + \theta' Z_{it} + \xi_{it}, \end{aligned} \tag{10}$$

where the explanatory variables and their interactions are motivated by the total derivatives presented in eqs. 6-9. The variable $EREV$ denotes expected net revenue per unit effort, defined as the difference between pollock and YFS expected revenue: $EREV = E(\text{Revenue}^{\text{Poll}}) - E(\text{Revenue}^{\text{YFS}})$. Expected revenue is measured as expected catch (Metric Ton) divided by haul-duration multiplied by observed weekly price. The variable $ECPR_{it}$ denotes the expected Chinook-Pollock ratio (i.e. the bycatch rate). Expected revenue and bycatch rates are estimated using fleet-wide seasonal trends as common information and the previous week's realized catch as individual information.[6] $Quota_i$ is an individual quota for pollock, the main target species. We do not include the bycatch quota because it is defined as a fixed ratio of the main target species quota, and thus it causes perfect collinearity if included.

We use auxiliary variables, Quota Speed ($QSpeed$) and Bycatch Quota Speed ($BQSpeed$),

[6]Following the literature (e.g., Abbott & Wilen, 2011), we estimate harvesters' expectations outside of the fishery participation decision model. The formation and estimation of such expectations are discussed in detail in Appendix A4. We note that a potential problem with using estimates of expectations is that they likely contain measurement and prediction errors, which can lead to attenuation bias (assuming that these errors are not systematically related to the latent expectation). We also note that since we model expectations as a function of previous participation decisions, there is a possibility that our expectations are correlated with the unobserved component of indirect utility, resulting in endogeneity bias. However, we believe that such endogeneity bias is likely small since: i) an individual harvester contributes only a small portion to fleet-wide harvests; ii) the stochastic nature of bycatch rates means that there is considerable exogenous variation in bycatch, conditional on participation decisions; and iii) the inclusion of vessel fixed effects captures any endogeneity arising from unobserved factors that are vessel specific and constant over time. We thank an anonymous reviewer for pointing this out.

that capture the expectation of the quota uses in future periods, whose constructions are described below in detail. These variables are motivated by the dynamic shadow-cost effect of quota in the total derivatives in eqs. 6-9, which show that the participation index is a function of expected quota use over the entire season due to the intertemporal nature of the quota constraint.[7] We include a dummy variable A91 (equal to one if after 2011) to account for changes in bycatch avoidance behavior after the introduction of bycatch quota by Amendment 91. The covariates Z include the cost of switching fisheries as a dummy variable (equal to one if did not participate in the previous period), which captures the inertia to stay in one fishery, and monthly number of vessels in the Pacific Hake fishery, which reflects the net benefit of participating in that fishery.

Note that the model of eq. 10 is estimated for A and B season separately. As previously discussed, the underlying conditions between A and B are different due to the highly-valued pollock roe occurring during the A season. In addition, regulation on salmon bycatch is more lenient in A season (e.g., a relatively higher cap of bycatch quota in the A season). Thus, harvesting behavior can be different in A and B season, and we therefore estimate the model separately for each season.

Our theoretical model demonstrates that the dynamic effect of catch rates for target and bycatch species on fishery participation depends on current fishing conditions relative to expected fishing conditions in the rest of the season. Motivated by this result, we construct a variable called "Quota Speed" ($Qspeed$) that captures the dynamic component of quota usage. The constructed variable captures the pace of quota use relative to the time left in the season and consists of the remaining quota left, expected CPUE in future weeks, and the weeks remaining in the season:

$$Qspeed_t = \frac{\%QuotaLeft_t - \%WeightTimeLeft_t}{\%QuotaLeft_t + \%WeightTimeLeft_t}, \tag{11}$$

[7]Note that these dynamic effects only enter eq. 5 through the total derivatives in eqs. 6-9; thus, the Quota Speed variables only enter into the indirect utility function as interactions.

where $\%QuotaLeft_t$ is the percentage of remaining quota and $\%WeightTimeLeft_t$ is the percentage of the time left weighted by catch opportunities in the season. We describe the construction of these variables below.

In the beginning of the season, a harvester has a planned path of quota use: the harvester participates in Fishery 1 and uses quota when the profitability of target catch is high. During the season, the realized catch may be different from the expected catch, and thus the speed at which quota is being used may be too fast or slow relative to the remaining catch opportunities in the rest of the season. The variable ($Qspeed$) measures this fast-or-slow quota-use speed. The value of ($Qspeed$) ranges between -1 and 1. When it is too fast, implying that the realized catch is greater than the expectation, the variable is negative. This is interpreted that the shadow cost of the quota becomes higher, and hence the harvester is less likely to participate in a period. The variable $\%WeightTimeLeft$ is analogous to the denominators of the dynamic effects in equation 6-9, and captures the behavior of forward-looking harvesters. The integral of catch rates over the remaining season is approximated by the sum of the weighted remaining weeks, where a week with a high expected catch rate is weighted more heavily because it provides a more profitable opportunity for harvesters to spend their quota. The probability of participation in a future week is also taken into account to determine the weight. The participation probability is analogous to the change in participation relative to the change in the index $\frac{\partial d_{it}}{\partial Y_{it}}$ in the denominator of equation 6-9. The probability is simply calculated by the ratio of number of participating vessels in each week and the total number of vessels, assuming that the harvesters know the seasonal pattern of participation based on their experiences. Accordingly, the percent of weighted time left is specified as:

$$\%WeightTimeLeft_t = \frac{\sum_{w=t}^{T} Pr(DW_w)E(CPUE_w)^2}{\sum_{w=1}^{T} Pr(DW_w)E(CPUE_w)^2}, \tag{12}$$

where $Pr(DW_w)$ is a probability of participation in period w.

Estimation

To estimate the model, we employ a maximum likelihood estimator of the binary logit model. A limitation of a simple panel-data logit estimator is that individual fixed effects cannot be estimated consistently. So long as the number of periods observed for each individual is fixed, individual dummy variables will be incorrectly estimated, and this error contaminates the estimates of the other parameters of the model (this is known as the incidental parameter problem (Neyman & Scott, 1948)). Even if individual heterogeneity itself is not of interest, it is possible that the parameters of interest are biased if the homogeneity assumption is violated. Hence, we employ an unconditional logit estimator with bias correction (Hahn & Newey, 2004).

We adopt the bias correction method because it provides estimates of individual fixed effects, which can be used for post-estimation counterfactual policy simulations. A well-known estimation method used to combat the incidental parameter problem is the conditional logit approach proposed by Chamberlain (1980), which is an maximum likelihood estimator with a likelihood function that conditions out the individual fixed effects. While the conditional logit approach solves the incidental parameters problem, it does not recover estimates of the individual fixed effects. Hahn & Newey (2004) suggest an analytical bias correction approaches for nonlinear panel models based on asymptotics when the number of time periods T grows faster than the number of individual to the one-third, $n^{\frac{1}{3}}$. The bias-correction approach is computationally heavy; however, a recent algorithm has been proposed by Stammann et al. (2016) that is as fast as the conditional estimator. We adopt it in this study.

Data Description

We use multiple data sources for our analysis. Our primary data set is collected by the North Pacific Groundfish Observer Program (NPGOP) and provides a complete record of fishing effort and total catch for all vessels over 124 feet. The data available to us consists of vessel-week level observations for 17 vessels of the American Fisheries Act catcher-processor fleet 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 species catch, prohibited species catch, and the bycatch species harvested.

In addition to the NPGOP data, we use annual price data from the Economic Stock Assessment and Fishery Evaluation Report (Fissel et al., 2015), and monthly export data of fishery products that is collected by the U.S. Census Bureau and compiled by NOAA fisheries. While the unit export value is not exactly the price harvesters harvesters receive for their products, it captures the within-season variation in product values.[8] We assume that variation in the in-season price of pollock is exogenous for at least two reasons. First, pollock is not a fresh market fish, so week-to-week price variability based on week specific landings are negligible; companies hold frozen product until weeks of lower supply. While the total annual catch, and thus supply of the frozen primary product, might matter to price, the exogenous total allowable catch is always fully exploited. The threat of price endogeneity is further dampened by the fact that pollock is sold into the highly substitutable global whitefish market (Bronnmann et al, 2016), which is sensitive to other countries' total allowable catch for pollock (e.g. Russia, (Criddle and Strong, 2013)) and other high-volume whitefish species such as hoki, Pacific cod, Atlantic cod, and haddock.

The vessel-specific Pacific Hake harvest data is held by a separate regional agency and not available due to confidentiality concerns, so we use public data on the Pacific Hake fishery. The only available data is number of vessels targeting Pacific Hake, which we use as a proxy for the productivity of Pacific Hake.

Table 1 shows the summary statistics of the key variables for our analysis. "Expected" variables and "Quota Speed" variables are constructed based on the observed data. CPUE for each species and the bycatch rate (Chinook-pollock ratio) are constructed using only

[8] The actual in-season variations of ex-vessel or wholesale prices were not available.

target-species observations. The formation of the expectations is described in appendix A4.

[Table 1 inserted here]

Estimation Results

Table 2 and 3 show the estimation results for the A and B seasons, respectively. The first column of each table shows the estimates of the full model including all the relevant dynamic variables. The second and third column models reduce the interactions of $Qspeed$ and $BQspeed$ depending on the size of standard errors relative to the size of coefficient in the full model. To test whether the reduced variables have no effects, the likelihood ratio (LR) statistics provided at the bottom of the table (e.g., LR test for the Column 3 model against the Column 2 model is shown in the third column). The fourth column in each table show the model without any dynamic variables. According to the likelihood ratio tests, we reject the null hypothesis that dynamic variables are zero for both seasons. However, we are unable to reject the null hypothesis that the additional variables in the full model relative to the reduced models have effects. Accordingly, our preferred models are Column 3 models in both tables.

[Table 2 inserted here]

[Table 3 inserted here]

For the A season, the coefficient on the expected Chinook-pollock ratio shows a positive sign, which implies that high expected bycatch rates increase the likelihood of participation in the pollock fishery. This counter-intuitive result may arise because the effect of bycatch rates is not well-identified: the timing of mature pollock roe and high Chinook bycatch rates tend to coincide in the A season. Thus, it is possible that harvesters choose not to avoid high bycatch rates by adjusting their participation because mature roe is too valuable to give up. In terms of our theoretical model, this means that the index value, Y_{it}, remains above zero even though the bycatch rate is high because the price p_{1t} exceeds the cost of bycatch cost.[9] In other words, variation in the bycatch rate is not enough to induce fishery switching during periods of mature pollock roe, thereby creating an identification problem. The interaction of the pollock price and the bycatch rate is included to control for this effect, and indeed the coefficient on the $ECPR$ is not statistically significant while the interaction is.

The dynamic variable is important to explain the participation decision of the harvesters. This is in line with our theoretical model. Interestingly, the relevant dynamic variables in the A season are the interaction of $Qspeed$ and $EREV$, and $BQspeed$ and $ECPR$. The interpretation of the first interaction is straightforward: when the quota usage is too fast relative to the expected pace, the incentive to participate in the pollock is reduced, and vice versa. This is consistent with the sign of the second term in equation 7. The effect of the current expected revenue per unit through the shadow value is negative as it loses the opportunity cost to use the quota in the future. Similarly, the coefficient on the interaction of $BQspeed$ and $ECPR$ is positive, implying that the fast quota usage of bycatch quota weaken the incentive to participate in pollock fishery when the bycatch rate is high. The harvesters pay attention to the quota usage of the bycatch during the A season although it is less likely to bind. The high price due to mature roe is the main driver of the harvesters' behavior in the A season, but the newly created quota could enhance the incentive to avoid the bycatch in the dynamic allocation of quotas. Our theoretical framework predicts that the sign of this effect is ambiguous, depending on the participation. Because the A season is very attractive due to the high price of matured roe and the harvesters are already participating before the PSC limit is implemented, the result is consistent with the theory as it is the case $d_{it} = 1$ in the third term of equation 6.

The main variables that determine participation in the B season are persistence of participation (switching cost) and the relative benefit in the Pacific Hake fishery. The key dynamic variable in the B season is the individual quota and $Qspeed$. The coefficient is

[9] Anecdotal evidence suggests that while limits on salmon bycatch do influence harvesting behavior, harvesters tolerate a higher level of bycatch for the greater value of mature roe.

positive, suggesting that the harvesters will participate in pollock fishery if the quota use is slower and having larger quota. Given that the price is stable in the B season, the result is interpreted that the harvesters are simply willing to consume the pollock quota as early as possible. $ECPR$ has a negative coefficient, but statistically insignificant. The harvesters are already avoiding bycatch and hence attempt to consume the quota before the bycatch rate increases. Because many vessels are fishing using the quota before the large bycatch rate increase occurs, less variation may be observed.

Although the coefficients are statistically insignificant, the negative sign on the coefficient of expected revenue is not consistent with our expectations. The possible reason is that there are few vessels targeting YFS in B season, and there is not much variation in expected pollock revenue. The harvesters do not respond to these variables directly, but they participate in the pollock fishery to utilize the pollock quota according to the predetermined schedule.

Policy Simulation

The result of our empirical model highlights that there is a significant difference in the harvester's behavior between the A and B season: temporal avoidance behavior in the B season but not in the A season. Due to the specific background of the fishery in A season (overlapping timing of matured pollock roe and high salmon bycatch rate), a policy that affects the temporal margin may not be effective in the A season, but it could be helpful to reduce bycatch in the B season.

We use our estimated participation model to examine a policy counterfactual of interest to the pollock fleet: can current regulations be adjusted to provide opportunities for more profitable pollock quota usage without increasing salmon bycatch? We run a simulation of an alternative policy that has been raised for analysis in the North Pacific Fishery Management Council process—namely, opening the B season earlier, which aims to reduce bycatch of Chinook salmon. Because Chinook salmon is frequently caught later in the B season, the early opening of the B season may provide the harvesters opportunities to use their pollock quota while the bycatch rate is low. We simulate the harvesters' dynamic fishery choice in response to opening the B season two-weeks earlier, while 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 target-species quota, thereby avoid bycatch of Chinook salmon in future periods. 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. The other non-Chinook salmon bycatch is not currently limited, but monitored for a possible future restriction.

To understand the trade-off of the suggested policy, we simulate the harvesters' participation under current and the alternative policies using the parameter estimates from our empirical model. First, we evaluate prediction performance using out-of-sample predictions of our empirical model for the B season. The coefficients are estimated with the B season sample while removing a ”hold-out” year to compare our predictions against (e.g., to predict the participation pattern in 2005, use the data of 2006-2013 for estimation). The predicted number of participating vessels is a sum of predicted participation probability for individual vessels. As shown in Figure 1, the general trend of participation is well predicted with the model we estimated. Note that this prediction is performed using the observed catch and quota usage.

[Figure 1 inserted here]

The policy simulation we conduct here is different from the out-of-sample prediction above. While the out-of-sample prediction uses the observed catch and remaining quotas in the data, we allow remaining quota to evolve endogenously given the participation decisions and catches of previous periods in order to construct Quota Speed based on counterfactual decisions. The harvesters' decisions are predicted based on the estimated parameters for the first week of the B season. We then simulate each vessel's catch based on their predicted decision.[10] Simulated catch is determined by multiplying predicted catch by the probability of participation in the pollock fishery in the given vessel-year-week:

$$\widehat{PollockCatch}_{it} = \hat{P}r(d_{it} = 1)\exp(\hat{\rho}_t^w DW_t + \hat{\rho}_t^y DY_t + \hat{\rho}_i^v DV_i), \tag{13}$$

where $\hat{P}r$ represents the predicted probability of participation in the pollock fishery and $\hat{\rho}$ parameters are estimated using weekly catch from the data in the B season. The parameters are weekly-, yearly-, and individual-specific, respectively. DW_t, DY_t, DV_i are dummy variables of week, year and individual vessel, respectively. Because bycatch rates are seasonal and exogenous for harvesters, we use the observed weekly bycatch-pollock ratios and predicted catch to simulate the bycatch. This simulated catch is used to compute the quota use and QSpeed for the participation prediction of the next week. The simulations are performed for each year in the data (2005-2013) so that we can evaluate the policy against year-to-year variations in the bycatch rate.

The alternative policy simulation is performed by adding two weeks before the first week of the current B season. The current opening date is June 10th and the alternative policy will open the B season on May 27th. Practically, we add two weeks in the data and simulate the participation decisions. The observed bycatch-pollock ratio of the added weeks are interpolated using the LOESS estimations and observations in later A season and early B season used in the main estimation section. We are interested in the changes in the timing and total amount of bycatch species caused by changes in the target species.

The observed and predicted weekly number of vessels targeting pollock under the status quo policy are shown as the red and green lines, respectively, in Figure 2. The whiskers show the maximum and minimum value in a week among the simulated years (2005-2013)

[10] We note that performing such policy simulations does not require identification of deep primitive structural parameters; rather, only combinations of structural parameters need to be identified, so long as they remain the same under the different policies we consider—i.e., they are policy invariant (Heckman, 2010). Thus, an important assumption we make is that the parameters we identify in the indirect utility function (eq. 10) are policy invariant. The performance of our out-of-sample predictions provides evidence that our participation model is capturing mechanisms that are relevant for conducting counterfactual policy simulations. We thank an anonymous reviewer for raising this issue.

to express the year-to-year variations in participation. Although simulated participation under the status quo does not perfectly predict observed participation, it shares a common trend that the vessels participate in the early season and the number of vessels decreases over a season.[11] The blue line in Figure 2 shows the predicted number of vessels under the alternative policy. As expected, the vessels target pollock in the additional first two weeks under the new policy, and the number of vessels in the mid to later season is less than under the current policy. The difference between the blue and green lines indicate the effect of the policy on participation.

[Figure 2 inserted here]

As expected, the weekly total catch of pollock increases in the first two added weeks and decreases in the later weeks due to the shift of participation timing under the new management policy, as the bycatch rate (Chinook-pollock ratio) tends to be lower in the early periods in B season. As shown in Figure 3, Chinook salmon catch does not change in the early B season, but it gets lower than the current policy in the middle of B season as the number of vessels targeting pollock under the alternative policy decreases this time of the season. It is noteworthy that the maximum weekly catch of Chinook salmon is also reduced under the new policy, as the vessels are less likely to target pollock in the later season. This implies that the alternative policy may be effective at reducing salmon bycatch even in a year of the highest salmon bycatch among 2005-2013. Figure 4 shows the average, minimum and maximum weekly cumulative bycatch of non-Chinook salmon across the years simulated. Because of the early open of the B season, the non-Chinook salmon catch in early weeks increases.

[Figure 3 inserted here]

[Figure 4 inserted here]

[11] The slight overprediction of the simulated participation under status quo may be due to prediction error of pollock catch: predicted catch is not exactly the same as the actual catch, and hence Quota Speed and the participation in the next week may have prediction error. Our focus is the difference between the status quo and the policy alternative.

The differences of total seasonal catch of each species between status quo and the policy alternative are shown in Figure 5 in rate, and in Table 4 in value. Chinook salmon bycatch is reduced by about 24 percent on average, and is reduced even in the worst bycatch year, in which bycatch decreases by about 9.5 percent. Despite the reduction in Chinook bycatch, there is very little evidence of a decrease in pollock catch.[12] The possible drawback of the alternative policy is an increase in non-Chinook salmon bycatch; however, non-Chinook salmon bycatch is actually reduced by about 2.7 percent on average, and only increases by 2.6 percent in the worst year. The increased magnitude is not as large as the good years of Chinook bycatch reduction. As shown in Table 5, the total annual catch (in numbers) of non-Chinook salmon is reduced by 150, on average, and non-Chinook salmon bycatch increases in only one year under the policy alternative.[13] Thus, the simulation results indicate that the policy alternative would decrease non-Chinook salmon bycatch in most years, suggesting that the possible cost of the policy is low.

[Figure 5 inserted here]

[Table 4 inserted here]

In summary, the proposed policy alternative could reduce bycatch by giving the harvesters opportunity to catch pollock when Chinook salmon bycatch is less while not likely increasing non-Chinook salmon bycatch. Note that this result is based only on changes in participation timing and not due to any other bycatch avoidance measures. The dynamic bycatch avoidance behavior explains this outcome because the increase in the Chinook bycatch rate in the later B season induces harvesters to target pollock earlier and the additional first two weeks provide time to spend their pollock quota while Chinook bycatch rates are relatively low.

[12] The total seasonal catch of pollock seems to increase by a small amount. This is because catch predictions may exceed the quota in the last week of participation in the simulation process. In reality, there is no reason that the total pollock catch should increases since the individual quota is binding under the status quo.

[13] In 2006, many non-Chinook salmons were exceptionally caught in the early season, resulting in an increase of 647 non-Chinook salmon caught as bycatch under the alternative policy (a relative increment of only 2.6 percent).

Conclusion

This paper empirically investigates the temporal bycatch avoidance pattern of harvesters based on a theoretical dynamic optimization framework. We contribute to the literature by establishing the timing of participation as an important margin of behavior for avoiding bycatch. Our theoretical model clarifies the relationship between a harvester's participation decision and the shadow cost of quota. Further, the Taylor-series approximation of the participation index from the model motivates the development of a composite variable, Quota Speed, which approximates the dynamic effect of instantaneous variables through quota shadow values. This variable allows us to incorporate harvesters' forward-looking behavior into a tractable and parsimonious empirical model of seasonal fishery participation. We applied the model to Bering Sea/Aleutian Island pollock catcher-processor fishery and investigated a counterfactual policy aimed at reducing bycatch without foregoing target species harvests. Our results confirm the hypothesis that harvesters are seasonally dynamic and that temporal substitution of target species catch opportunities is present under the bycatch regulation. The implication is that a season length policy change leads to a significant reduction in Chinook salmon bycatch as a result of harvesters shifting the timing of their participation timing and using individual quota before bycatch rates are high. Our results suggest that the current season length policy should be redesigned to consider recently added bycatch limits to minimize the adverse effect on target species harvesting.

In this study, we demonstrate the importance of the temporal margin of harvesting behavior in a resource sector. While the spatial margin of harvester behavior has been investigated extensively in the literature, the temporal margin is also important with the assignment of individual property rights. Ultimately, the extent to which spatial versus temporal margins should be represented in a model of harvesting behavior depends on the question at hand and the characteristics of the fishery. In our case, temporal modelling of harvesting behavior provides important information for policy design under individual quota management due to seasonal variations in key variables, such as the catch rates of target and bycatch species.

The application in the current paper considers a participation choice between a single individual quota fishery and a single free-to-access fishery, but the model could be extended to include multiple fisheries managed by individual quotas. With multiple fisheries, the choice of target fishery during a season may be affected by the dynamic use of quota in other fisheries. In particular, a quota may not be fully used if selectivity is not perfect among target species. This problem of inter-related shadow values of multiple fisheries with individual quotas is an important consideration for future research.

Table 1: Summary Statistics of the data

	season	Mean	SD	Min	P25	P75	Max
Pollock Price (USD/lb)	A	1.667	0.194	1.370	1.370	1.815	1.815
	B	1.248	0.036	1.206	1.221	1.258	1.430
Pollock CPUE (kg/haul min.)	A	10367.247	7671.061	2.705	6750.431	13016.753	114821.720
	B	9464.034	4538.566	55.499	6282.908	11822.008	34370.692
YFS CPUE (kg/haul min.)	A	1097.789	3503.577	0.000	0.008	26.913	38434.042
	B	7.469	152.975	0.000	0.000	0.000	4249.027
Chinook Pollock ratio	A	0.038	0.062	0.000	0.003	0.046	0.748
	B	0.008	0.032	0.000	0.000	0.004	0.880
Hake vessels	A	0.000	0.000	0.000	0.000	0.000	0.000
	B	3.709	3.661	0.000	1.500	5.000	14.000
Expected Pollock CPUE	A	11556.441	2883.116	5549.666	9876.611	12848.871	48317.908
	B	10427.116	3110.148	0.000	8413.705	12933.014	19130.586
Expected YFS CPUE	A	5300.339	1299.166	4158.190	4638.287	5038.616	16771.791
	B	3137.268	844.811	1836.699	2557.107	3277.516	5170.523
Expected Chin. Poll. ratio	A	0.042	0.010	0.015	0.035	0.049	0.068
	B	0.009	0.015	0.000	0.000	0.011	0.092
Quota Speed Pollock	A	-0.001	0.279	-1.000	-0.056	0.061	1.000
	B	0.156	0.287	-0.942	0.000	0.253	1.000
Quota Speed Chinook	A	0.305	1.399	-35.148	0.046	0.669	8.455
	B	-0.024	1.273	-22.451	-0.016	0.001	39.911

Note: Pollock Price is the average monthly price of all product type of pollock obtained from Fissel et al (2015). *Pollock CPUE* and *YFS CPUE*, and *Chinook Pollock ratio* are observed data and computed from the catch and effort duration (haul minutes). *Hake Vessels* is the monthly number of vessels participating in the Pacific Hake fishery off the west coast of the mainland U.S. *Expected Pollock CPUE*, *Expected YFS CPUE* and *Expected Chin. Pollock ratio* are formulated expectation of the variables. The formulation process is described in the appendix A4.*Quota Speed Pollock* and *Quota Speed Chinook* are the variables that capture the expectations of the quota uses in the future period. The construction of the variables is described in the empirical model section.

Table 2: Binary Logit Result, A season

	Dependent variable:			
	Pollock Target Dummy			
	(1)	(2)	(3)	(4)
EREV	0.181***	0.184***	0.186***	0.047
	(0.043)	(0.042)	(0.041)	(0.028)
Expected Chin-Poll Ratio	70.402	70.544	84.628	74.830*
	(52.518)	(51.770)	(48.403)	(36.653)
Switch Cost	−3.686***	−3.654***	−3.779***	−3.803***
	(0.669)	(0.663)	(0.631)	(0.430)
Quota	0.107*	0.107*	0.117*	0.150**
	(0.052)	(0.052)	(0.050)	(0.046)
EREV x Q Speed	0.296**	0.296**	0.233***	
	(0.099)	(0.099)	(0.030)	
ECPR x Q Speed	7.124	10.422		
	(42.568)	(42.015)		
Quota x Q Speed	−0.106	−0.113		
	(0.105)	(0.105)		
ECPR x Price (Poll)	145.674***	141.802***	136.264***	70.453**
	(39.436)	(38.682)	(37.082)	(24.473)
EREV x BQ Speed x A91	0.040			
	(0.234)			
ECPR x BQ Speed x A91	75.059	174.789***	177.091***	
	(111.833)	(41.828)	(41.448)	
Quota x BQ Speed x A91	0.126			
	(0.256)			
AIC	410.13	407.15	404.41	532.41
LR test		1.016	1.262	132.005***
Observations	1,356	1,356	1,356	1,356
Log Likelihood	−178.065	−178.573	−179.204	−245.207

Note: *p<0.05; **p<0.01; ***p<0.001. *EREV* is the difference in the expected revenues between pollock and YFS. *ECPR* stands for *Expected Chinook-pollock ratio.Quota* is the size of individual quota. *Q Speed* is the Quota Speed of pollock, and *BQ Speed* is the Quota Speed of Chinook salmon. *A91* is the policy indicator of the amendment 91 of American Fisheries Act, which implements the bycatch individual quota.*Switch cost* is an indicator whether the vessel was out of the pollock fishery in the previous period. Likelihood Ratio (LR) test shows the statistics of the test comparing the model of the column and one column left.

Table 3: Binary Logit Result, B season

	Dependent variable:			
	Pollock Target Dummy			
	(1)	(2)	(3)	(4)
EREV	−0.175	−0.164	−0.148	−0.100
	(0.112)	(0.111)	(0.109)	(0.103)
Expected Chin-Poll Ratio	−64.580	−50.424	−41.469	−19.665
	(35.055)	(29.037)	(25.751)	(22.498)
Switch Cost	−4.630***	−4.588***	−4.732***	−4.715***
	(0.459)	(0.449)	(0.437)	(0.429)
No. of Hake Vessels	−0.118***	−0.114***	−0.101***	−0.114***
	(0.031)	(0.030)	(0.029)	(0.029)
Quota	0.058*	0.059*	0.062**	0.063**
	(0.024)	(0.024)	(0.023)	(0.023)
EREV x Q Speed	−0.172	−0.169		
	(0.140)	(0.142)		
ECPR x Q Speed	66.387	43.698		
	(53.985)	(50.541)		
Quota x Q Speed	0.147	0.158	0.112***	
	(0.081)	(0.083)	(0.034)	
EREV (Poll) x BQ Speed x A91	1.027			
	(1.659)			
ECPR x BQ Speed x A91	−235.384			
	(357.320)			
Quota x BQ Speed x A91	0.299			
	(1.102)			
AIC	549.7	545.99	544.76	552.26
LR test		2.285	2.776	9.501**
Observations	1,983	1,983	1,983	1,983
Log Likelihood	−247.850	−248.993	−250.381	−255.132

Note: *p<0.05; **p<0.01; ***p<0.001. *EREV* is the difference in the expected revenues between pollock and YFS. *ECPR* stands for *Expected Chinook-pollock ratio.Quota* is the size of individual quota. *Q Speed* is the Quota Speed of pollock, and *BQ Speed* is the Quota Speed of Chinook salmon. *A91* is the policy indicator of the amendment 91 of American Fisheries Act, which implements the bycatch individual quota.*Switch cost* is an indicator whether the vessel was out of the pollock fishery in the previous period. *No. of Hake Vessels* is the monthly number of vessels participating in the Pacific Hake fishery off the west coast of the mainland U.S. Likelihood Ratio (LR) test shows the statistics of the test comparing the model of the column and one column left.

Table 4: Change in catches of each species by policy simulation

	Mean	Min	Max
Chinook (num)	-272.175	-423.917	-85.417
Non-Chinook (num)	-183.726	-335.730	119.992
Pollock (MT)	4016.642	-2592.760	12024.450

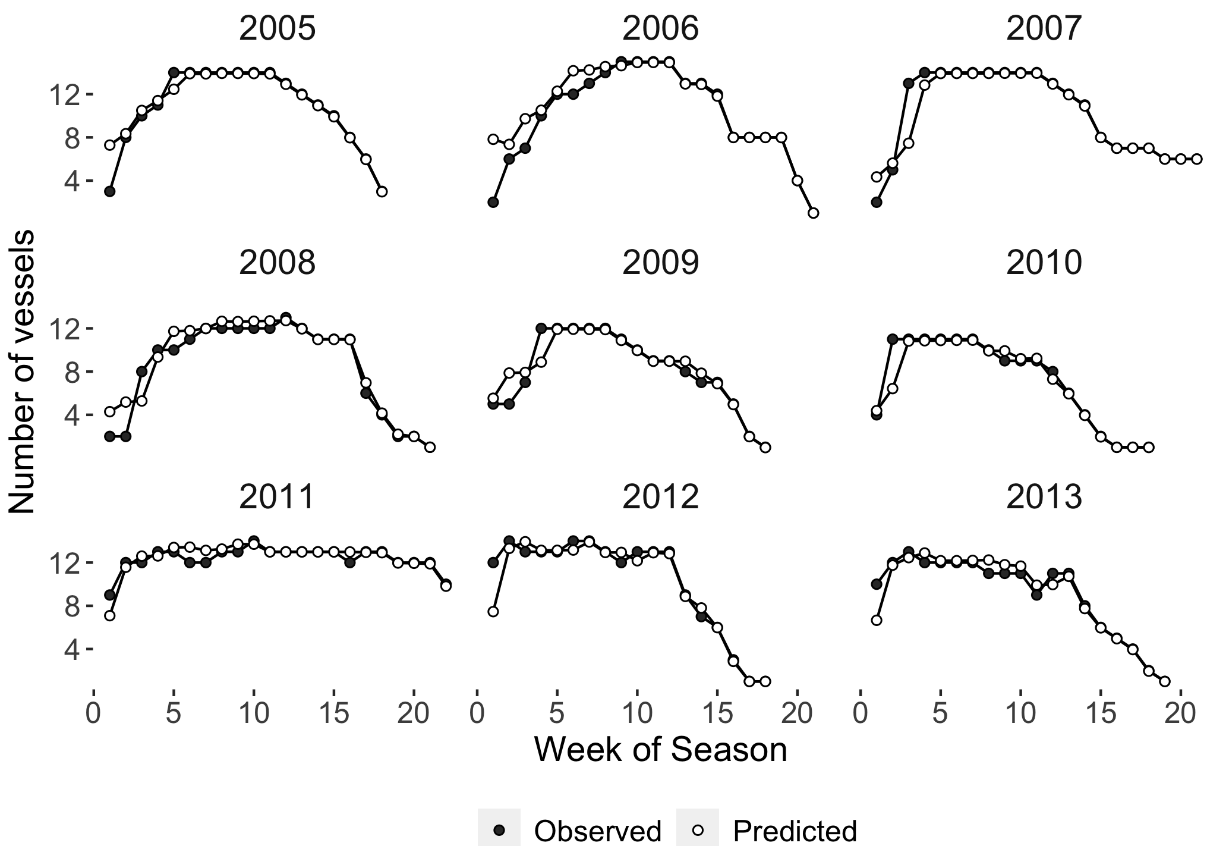

Figure 1: Out-of-sample Predicted Participation in pollock, B season

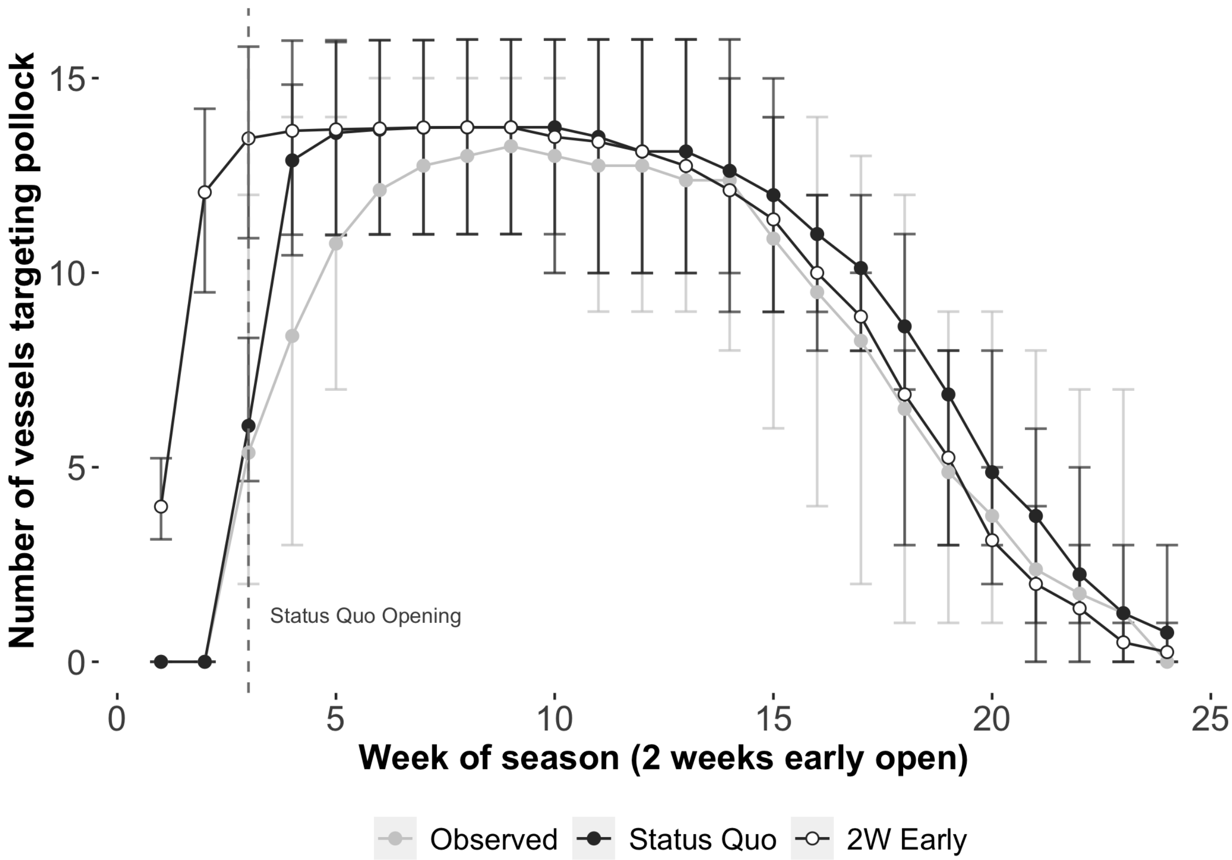

Figure 2: Simulated weekly number of vessels targeting pollock, B season

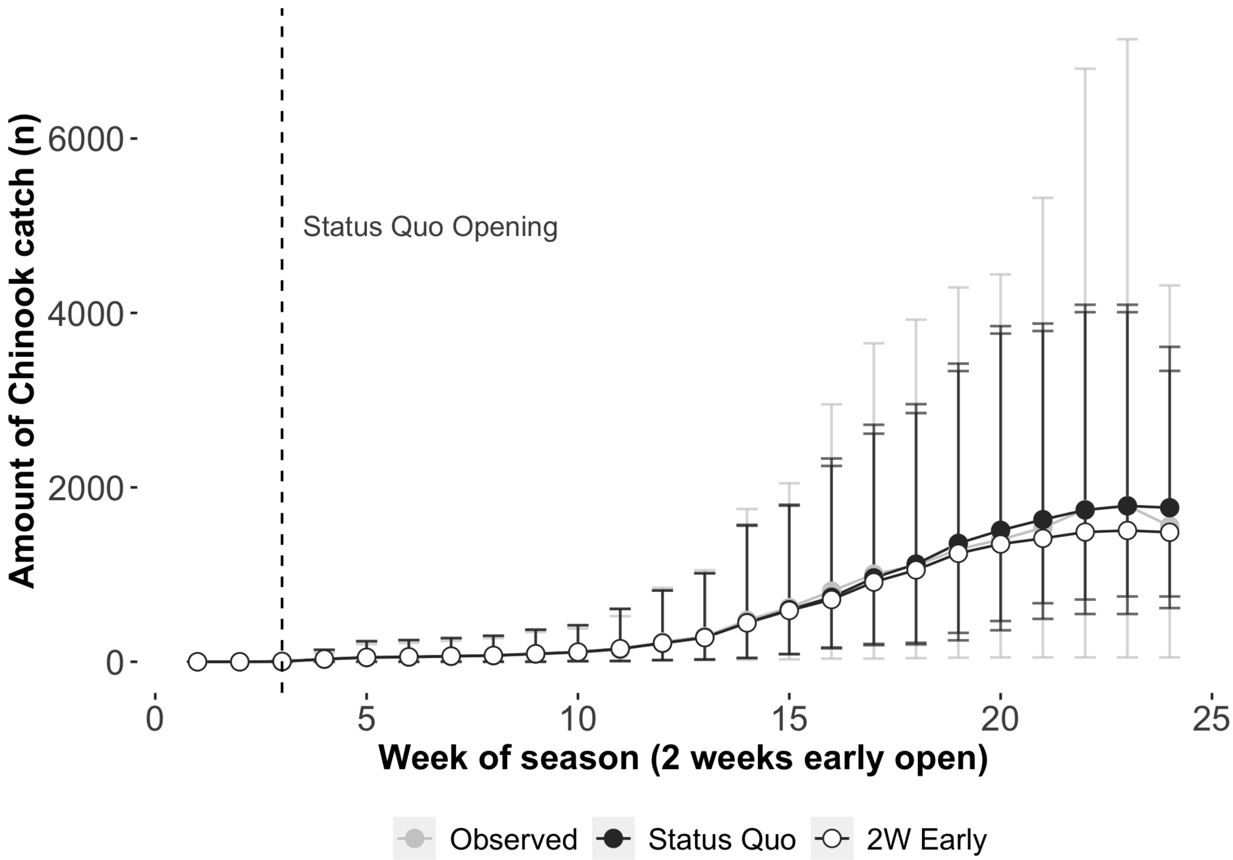

Figure 3: Simulated weekly Chinook catch, B season

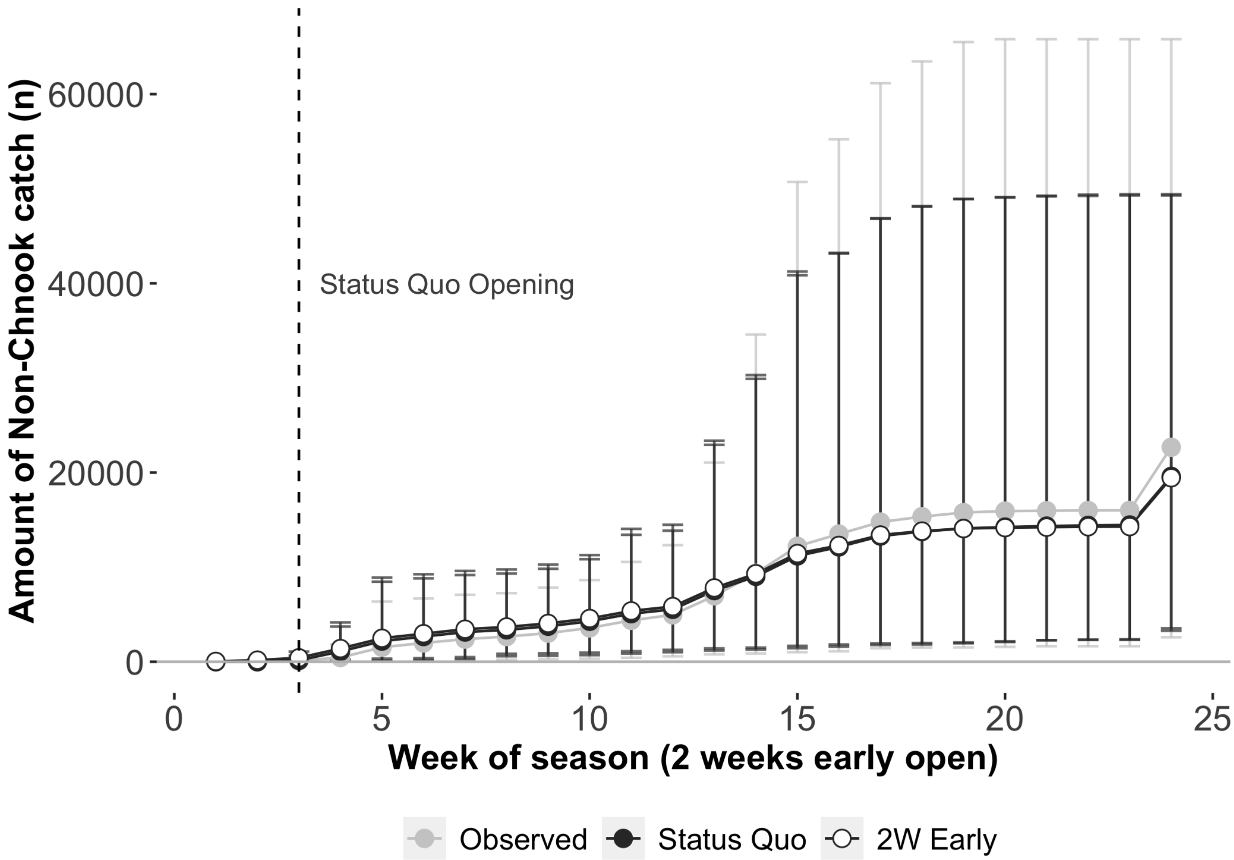

Figure 4: Simulated weekly non-Chinook catch, B season

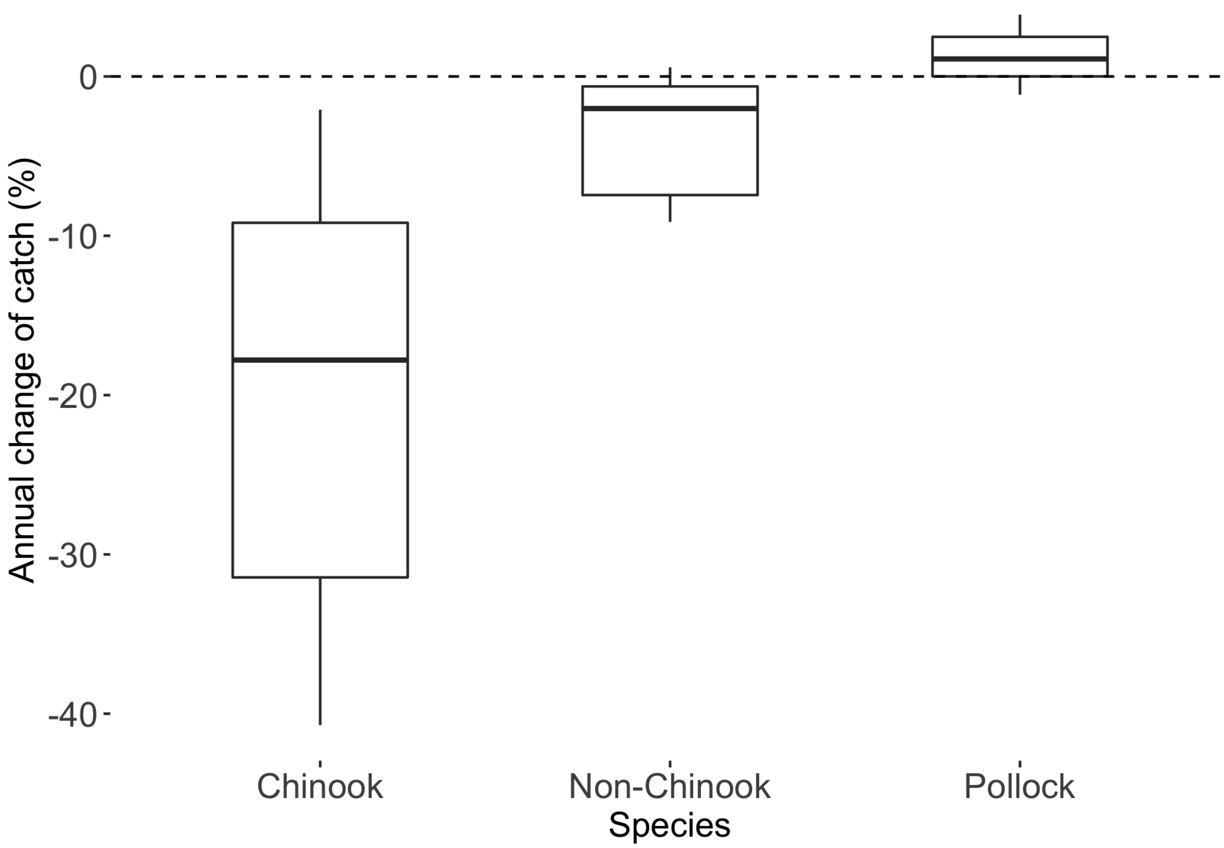

Figure 5: Percentage changes of catch by species under alternative policy in B season

Appendix

A1.Derivation of the participation index

The participation index for harvester i (equation 4) follows from the necessary first-order condition for the following constrained maximization problem:

$$\begin{aligned} \max_{d_{it}} \quad & V = \textstyle\int_0^T [d_{it}(p_{1t}q_{1t} - \gamma b_t q_{1t}) + (1-d_{it})p_2 q_{2t} - c]dt \\ \text{subject to} \quad & \textstyle\int_0^T d_{it}q_{1t}dt \leq Q_{1i} \\ & \textstyle\int_0^T d_{it}b_t q_{1t}dt \leq Q_{bi} \\ & 0 \leq d_{it} \leq 1 \ \forall t. \end{aligned}$$

The corresponding Lagrange function for the constrained maximization problem above is (including all inequality constraints):

$$\mathcal{L} = V + \lambda_{1i}[Q_{1i} - \int_0^T d_{it}q_{1t}dt] + \lambda_{bi}[Q_{bi} - \int_0^T d_{it}b_t q_{1t}dt] + \int_0^T \eta_{1it}d_{it}dt + \int_0^T \eta_{2it}(1-d_{it})dt,$$

where λ_{1i}, λ_{bi}, η_{1it} and η_{2it} are Lagrange multipliers corresponding to the target species quota constraint, the bycatch species quota constraint, the lower-bound constraint on d_{it}, and the upper-bound constraint on d_{it}, respectively. The solution to the constrained maximization problem can be characterized by the following necessary first-order conditions:

$$\frac{\partial \mathcal{L}}{\partial d_{it}} = (p_{1t}q_{1t} - \gamma b_t q_{1t}) - p_2 q_{2t} - \lambda_{1i}q_{1t} - \lambda_{bi}b_t q_{1t} + \eta_{1it} - \eta_{2it} = 0 \ \forall t \qquad \text{(A1)}$$

$$\begin{aligned}
\lambda_{1i}[Q_{1i} - \int_0^T d_{it} q_{1t} dt] &= 0 \\
\lambda_{bi}[Q_{bi} - \int_0^T d_{it} b_t q_{1t} dt] &= 0 \\
\eta_{1it} d_{it} &= 0 \ \forall t \\
\eta_{2it}(1 - d_{it}) &= 0 \ \forall t \\
\lambda_{1i}, \lambda_{bi}, \eta_{1it}, \eta_{2it} &\geq 0 \ \forall t
\end{aligned} \tag{A2}$$

The participation index is derived by defining $Y_{it} \equiv \eta_{2it} - \eta_{1it}$ in eq. A1 and solving for Y_{it}:

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

Intuitively, if the participation index is positive (i.e., the net benefits of fishing are higher in Fishery 1 than Fishery 2), then all effort is allocated to Fishery 1. Conversely, if the participation index is negative (i.e., the net benefits of fishing are higher in Fishery 2 than Fishery 1), then all effort is allocated to Fishery 2.

To see this formally, note that it is not possible for both the upper-bound and lower-bound constraints on d_{it} to be binding simultaneously. Thus, it must be that:

(1) $\eta_{1it} > 0$ and $\eta_{2it} = 0 \implies d_{it} = 0$,

(2) $\eta_{1it} = 0$ and $\eta_{2it} > 0 \implies d_{it} = 1$, or

(3) $\eta_{1it} = \eta_{2it} = 0 \implies 0 \leq d_{it} \leq 1$.

Case 1 simply says that if $Y_{it} \equiv \eta_{2it} - \eta_{1it} < 0$, then all fishing effort is allocated to Fishery 2 ($d_{it} = 0$). Conversely, Case 2 says that if $Y_{it} \equiv \eta_{2it} - \eta_{1it} > 0$, then all fishing effort is allocated to Fishery 1 ($d_{it} = 1$). Finally, Case 3 says that if $Y_{it} \equiv \eta_{2it} - \eta_{1it} = 0$, then a harvester is indifferent between the two fisheries and can allocate any proportion of effort between the two fisheries ($0 \leq d_{it} \leq 1$). For simplicity, we rule out this ambiguous case by assuming $d_{it} = I\{Y_{it} \geq 0\}$, meaning that the harvester would allocate all effort to Fishery 1 if they are indifferent between the two fisheries. In practice, this occurrence is rare and has no bearing on our empirical application.

A2.Derivations of total derivatives

In this section, we provide the full derivations of the total derivatives described in the model section.

As shown in the equation 5, the total derivative of the participation index with respect to bycatch rate is decomposed into two parts.

$$\frac{\mathrm{d}Y_{it}}{\mathrm{d}b_t} = \frac{\partial Y_{it}}{\partial b_t} + \frac{\partial Y_{it}}{\partial \lambda_{1i}}\frac{\partial \lambda_{1i}}{\partial b_t} I\{\lambda_{1i} > 0\} + \frac{\partial Y_{it}}{\partial \lambda_{bi}}\frac{\partial \lambda_{bi}}{\partial b_t} I\{\lambda_{bi} > 0\}. \tag{A3}$$

The first term is the direct effect of the bycatch rate on participation, and is derived simply by taking the partial derivative of Y_{it} in equation (4) with respect to b_t. The second and third terms are the indirect (or dynamic) effects of the bycatch rate on participation through its influence on the shadow values of quota. To derive these effects, we invoke the implicit function theorem to obtain the partial derivative of the shadow values with respect to the bycatch rate. Recall that shadow values are determined by the participation index (equation 4) in combination with the quota constraint conditions:

$$\begin{aligned} G_1(b_t, \lambda_{1i}) &= Q_{1i} - \int_0^T d_{it} q_{1t} dt \geq 0 \\ G_b(b_t, \lambda_{bi}) &= Q_{bi} - \int_0^T d_{it} b_t q_{1t} dt \geq 0. \end{aligned} \tag{A4}$$

and the equality holds when the constraints are binding, implying that $\lambda_{1i} > 0$ and $\lambda_{bi} > 0$, respectively. Suppose the constraint of main target species quota is binding. The derivative of the shadow value for target species quota with respect to the bycatch rate is

$$
\begin{aligned}
\frac{\partial \lambda_{1i}}{\partial b_t} &= -\frac{\frac{\partial G_1}{\partial b_t}}{\frac{\partial G_1}{\partial \lambda_{1i}}} \\
&= -\frac{-\frac{\partial d_{it}}{\partial Y_{it}} \frac{\partial Y_{it}}{\partial b_t} q_{1t}}{-\int_0^T \frac{\partial d_{is}}{\partial Y_{is}} \frac{\partial Y_{is}}{\partial \lambda_{1i}} q_{1s} ds} \\
&= -\frac{(\gamma + \lambda_{bi}) \frac{\partial d_{it}}{\partial Y_{it}} q_{1t}^2}{\int_0^T \frac{\partial d_{is}}{\partial Y_{is}} q_{1s}^2 ds} \leq 0.
\end{aligned}
\tag{A5}
$$

where the function G_1 is the binding constraint of the target species quota, which is defined when $\lambda_{1i} > 0$ (i.e., when the quota constraint is binding). Recall that d_{it} is a function of Y_{it}, which in turn is a function of b_t and λ_{1i}. Hence, the derivative $\frac{\partial \lambda_{1i}}{\partial b_t}$ is defined. Notice that changes in the bycatch rate in period t only influence the contemporaneous participation index but changes in the shadow value of the quota constraint change the participation index in all periods. Combined with the effect of the shadow value on contemporaneous participation, $\frac{\partial Y_{it}}{\partial \lambda_{1i}} = -q_{1t}$, we have the following expression for the second term in equation (A3),

$$
\frac{\partial Y_{it}}{\partial \lambda_{1i}} \frac{\partial \lambda_{1i}}{\partial b_t} = q_{1t} \frac{(\gamma + \lambda_{bi}) \frac{\partial d_{it}}{\partial Y_{it}} q_{1t}^2}{\int_0^T \frac{\partial d_{is}}{\partial Y_{is}} q_{1s}^2 ds} \geq 0, \tag{A6}
$$

which is unambiguously positive. Thus, the dynamic effect of the bycatch rate through the shadow value of the target species quota counters, but does not completely offset, the direct effect of the bycatch rate on participation.

We can follow a similar procedure for deriving the third term in equation (A3). The derivative of the shadow value for bycatch species quota with respect to the bycatch rate is

$$
\begin{aligned}
\frac{\partial \lambda_{bi}}{\partial b_t} &= -\frac{\frac{\partial G_b}{\partial b_t}}{\frac{\partial G_b}{\partial \lambda_{bi}}} \\
&= -\frac{-(d_{it} + \frac{\partial d_{it}}{\partial Y_{it}} \frac{\partial Y_{it}}{\partial b_t} b_t) q_{1t}}{-\int_0^T \frac{\partial d_{is}}{\partial Y_{is}} \frac{\partial Y_{is}}{\partial \lambda_{bi}} b_s q_{1s} ds} \\
&= -\frac{-(d_{it} + \frac{\partial d_{it}}{\partial Y_{it}} [-(\gamma + \lambda_{bi}) q_{1t}] b_t) q_{1t}}{-\int_0^T \frac{\partial d_{is}}{\partial Y_{is}} b_s q_{1s} ds} \\
&= \frac{(d_{it} - (\gamma + \lambda_{bi}) \frac{\partial d_{it}}{\partial Y_{it}} b_t q_{1t}) q_{1t}}{\int_0^T \frac{\partial d_{is}}{\partial Y_{is}} b_s^2 q_{1s}^2 ds},
\end{aligned}
\tag{A7}
$$

the sign of which is ambiguous and depends on the value of the participation index Y_{it}. For example, if $Y_{it} > 0$ so that a vessel is already participating in Fishery 1, then $d_{it} = 1$ and $\frac{\partial d_{it}}{\partial Y_{it}} = 0$, which implies that $\frac{\partial \lambda_{bi}}{\partial b_t} > 0$. Intuitively, the shadow value of bycatch quota will increase with the bycatch rate so long as a vessel derives a benefit from having more bycatch quota in terms of increased target species catch in Fishery 1. Conversely, if $Y_{it} < 0$ so that a vessel is participating in Fishery 2, then $d_{it} = 0$ and $\frac{\partial d_{it}}{\partial Y_{it}} = 0$, which implies no impact on the shadow value because $\frac{\partial \lambda_{bi}}{\partial b_t} = 0$. In this case, a vessel derives no value from additional bycatch quota since no bycatch is encountered in Fishery 2. The only case in which the shadow value of bycatch quota will decrease with the bycatch rate is if the increased cost of bycatch is large enough to push a vessel from Fishery 1 into Fishery 2. In this case, $Y_{it} = 0$, $d_{it} = 1$, and $\frac{\partial d_{it}}{\partial Y_{it}} = 1$, which implies that $\frac{\partial \lambda_{bi}}{\partial b_t} < 0$ if and only if $1 > (\gamma + \lambda_{bi}) b_t q_{1t}$. Combined with the effect of the shadow value on contemporaneous participation, $\frac{\partial Y_{it}}{\partial \lambda_{bi}} = -b_t q_{1t}$, we have the following expression for the third term in equation (A3):

$$
\frac{\partial Y_{it}}{\partial \lambda_{bi}} \frac{\partial \lambda_{bi}}{\partial b_t} = -b_t q_{1t} \frac{(d_{it} - (\gamma + \lambda_{bi}) \frac{\partial d_{it}}{\partial Y_{it}} b_t q_{1t}) q_{1t}}{\int_0^T \frac{\partial d_{is}}{\partial Y_{is}} b_s^2 q_{1s}^2 ds}. \tag{A8}
$$

Hence, the total derivative of the participation index with respect to the bycatch rate is expressed as the equation (6).

The total derivatives of the participation index with respect to other variables $(\frac{\partial Y_{it}}{\partial q_{1t}}, \frac{\partial Y_{it}}{\partial Q_{1i}}, \frac{\partial Y_{it}}{\partial Q_{bi}})$ can be derived in a similar manner. We provide the partial derivatives that are necessary for the derivations in the next appendix section.

A3. Partial Derivatives

The partial derivative of shadow values with respect to the catch rate of main target species.

$$\begin{aligned}
\frac{\partial \lambda_{1i}}{\partial q_{1t}} &= -\frac{\frac{\partial G_1}{\partial q_{1t}}}{\frac{\partial G_1}{\partial \lambda_{1i}}} \\
&= -\frac{-\left(\frac{\partial d_{it}}{\partial Y_{it}} \cdot \frac{\partial Y_{it}}{\partial q_{1t}} + d_{it}\right)}{-\int_0^T \frac{\partial d_{is}}{\partial Y_{is}} \frac{\partial Y_{is}}{\partial \lambda_{1i}} q_{1s} ds} \\
&= \frac{\left\{\frac{\mathrm{d}d_{it}}{\mathrm{d}Y_{it}} \left[p_{1t} - \lambda_{1i} - (\gamma + \lambda_{bi}) b_t\right] + d_t\right\}}{\int_0^T \frac{\mathrm{d}d_{is}}{\mathrm{d}Y_{is}} q_{1s}^2 ds}
\end{aligned} \tag{A9}$$

The sign of the effect depends on the sign of the net benefit per unit catch of the main target.

$$\begin{aligned}
\frac{\partial \lambda_{bi}}{\partial q_{1t}} &= -\frac{\frac{\partial G_b}{\partial q_{1t}}}{\frac{\partial G_b}{\partial \lambda_{bi}}} \\
&= -\frac{-\left(\frac{\partial d_{it}}{\partial Y_{it}} \cdot \frac{\partial Y_{it}}{\partial q_{1t}} + d_{it} b_t\right)}{-\int_0^T \frac{\partial d_{is}}{\partial Y_{is}} \frac{\partial Y_{is}}{\partial \lambda_{bi}} b_s q_{1s} ds} \\
&= \frac{\left\{\frac{\mathrm{d}d_{it}}{\mathrm{d}Y_{it}} \left[p_{1t} - \lambda_{1i} - (\gamma + \lambda_{bi}) b_t\right] + d_t b_t\right\}}{\int_0^T \frac{\mathrm{d}d_{is}}{\mathrm{d}Y_{is}} b_s^2 q_{1s}^2 ds}
\end{aligned} \tag{A10}$$

The sign of the effect depends on the sign of the net benefit per unit catch of the main target.

The partial derivative of shadow values with respect to the main target quota.

$$
\begin{aligned}
\frac{\partial \lambda_{1i}}{\partial Q_{1i}} &= -\frac{\frac{\partial G_1}{\partial Q_{1i}}}{\frac{\partial G_1}{\partial \lambda_{1i}}} \\
&= -\frac{1}{-\int_0^T \frac{\partial d_{is}}{\partial Y_{is}} \frac{\partial Y_{is}}{\partial \lambda_{1i}} q_{1s} ds} \\
&= -\frac{1}{-\int_0^T \frac{\mathrm{d}d_{is}}{\mathrm{d}Y_{is}} q_{1s} ds} \\
&= -\frac{1}{\int_0^T \frac{\mathrm{d}d_{is}}{\mathrm{d}Y_{is}} q_{1s}^2 ds} < 0
\end{aligned}
\tag{A11}
$$

$$
\begin{aligned}
\frac{\partial \lambda_{bi}}{\partial Q_{1i}} &= -\frac{\frac{\partial G_b}{\partial Q_{1i}}}{\frac{\partial G_b}{\partial \lambda_{bi}}} \\
&= -\frac{0}{-\int_0^T \frac{\partial d_{is}}{\partial Y_{is}} \frac{\partial Y_{is}}{\partial \lambda_{1i}} q_{1s} ds} \\
&= -\frac{0}{-\int_0^T \frac{\mathrm{d}d_{is}}{\mathrm{d}Y_{is}} q_{1s} ds} \\
&= -\frac{0}{\int_0^T \frac{\mathrm{d}d_{is}}{\mathrm{d}Y_{is}} q_{1s}^2 ds} = 0
\end{aligned}
\tag{A12}
$$

The partial derivative of shadow values with respect to the bycatch target quota.

$$
\begin{aligned}
\frac{\partial \lambda_{1i}}{\partial Q_{bi}} &= -\frac{\frac{\partial G_1}{\partial Q_{bi}}}{\frac{\partial G_1}{\partial \lambda_{1i}}} \\
&= -\frac{0}{-\int_0^T \frac{\partial d_{is}}{\partial Y_{is}} \frac{\partial Y_{is}}{\partial \lambda_{1i}} q_{1s} ds} \\
&= -\frac{0}{-\int_0^T \frac{\mathrm{d}d_{is}}{\mathrm{d}Y_{is}} q_{1s} ds} \\
&= -\frac{0}{\int_0^T \frac{\mathrm{d}d_{is}}{\mathrm{d}Y_{is}}^2 ds} = 0
\end{aligned}
\tag{A13}
$$

$$
\begin{aligned}
\frac{\partial \lambda_{bi}}{\partial Q_{bi}} &= -\frac{\frac{\partial G_b}{\partial Q_{bi}}}{\frac{\partial G_b}{\partial \lambda_{bi}}} \\
&= -\frac{1}{-\int_0^T \frac{\partial d_{is}}{\partial Y_{is}} \frac{\partial Y_{is}}{\partial \lambda_{1i}} q_{1s} ds} \\
&= -\frac{1}{-\int_0^T \frac{\mathrm{d}d_{is}}{\mathrm{d}Y_{is}} q_{1s} ds} \\
&= -\frac{1}{\int_0^T \frac{\mathrm{d}d_{is}}{\mathrm{d}Y_{is}}^2 ds} < 0
\end{aligned}
\tag{A14}
$$

A4. Modeling Expectations

In our estimation of Eq. 10, we employ proxies of expected revenues $EREV$ and bycatch rates $ECPR$. To form proxies of weekly-level expectations of catch, we assume that harvesters know the distribution of seasonal catch and bycatch rates. There are two key aspects for formulating catch expectations in the fisheries literature: 1) common and private information, and 2) temporal and spatial resolution of information. While some studies assume that harvesters use only common information and utilize a rolling average or autoregressive moving average as a common expectation associated with fishing alternatives (e.g., Curtis & Hicks, 2000; Curtis & McConnell, 2004; Smith & Wilen, 2003), recent work considers the role of private information to form individual expectations with fine resolution of data (Abbott & Wilen, 2011). At the week level, however, idiosyncratic information may not play a large role in the participation choice; instead, prior knowledge about seasonality and the updated current season information would matter most. In addition, we aggregate fine-grained information to model weekly level decisions. Thus, we model catch expectations using weekly and annual trends, in addition to time invariant vessel effects.

We first estimate weekly standardized catch per unit effort (CPUE) and bycatch rates. To capture seasonal trends in the data, we estimate standardized catch per unit effort (haul-hour) and bycatch rate (Chinook-pollock ratio) for each week, assuming a log-normal and Poisson distribution, respectively, and the following specifications for the mean:

$$\ln(PollCPUE_{it}) = \sum_t \delta_t DW_t + \sum_t \delta_t DY_t + \sum_i \delta_i DV_i \tag{A15}$$

$$\ln(Chin_{it}) = \sum_t \eta_t DW_t + \sum_t \eta_t DY_t + \sum_i \eta_i DV_i + \ln Poll_{it}, \tag{A16}$$

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 vectors δ

and η. We assume that harvesters base their beliefs on within-season trends of catch and bycatch rates that are smooth over a season. Hence, we apply a local regression method (LOESS) to the estimated weekly CPUEs and bycatch rates to obtain smooth seasonal trends. Given the assumption that vessels know the true distribution of catch, we use all periods and vessels in the sample to estimate the standardized CPUEs and bycatch rates. Harvesters' expectations are assumed to be based on the seasonality which is formed at the fleet level and taken as exogenous for each vessel.

The weekly expected CPUEs of individual harvesters are formed using the estimated seasonal trend (common information) and the observed standard CPUE of the previous week (individual information). We assume that individuals form rational expectations based on those variables, regress the trend and one-week lagged CPUE on the current CPUE, and use the fitted values as individual expectations. Table A.1 shows the result of the estimated model of rational expectations. As expected, both of the common and individual information are important for the formation of the expectation.

Note that our measure of expected bycatch rates are the product of both intra-annual mixing of salmon and pollock and underlying bycatch avoidance decisions of the entire fleet (e.g., spatial avoidance). Hence, the expected bycatch rate in each period reflects the best practice of bycatch avoidance under existing measures. The expected bycatch uses information from the whole fleet; an individual harvester's participation decisions are only a small contribution to this measure, so we believe the degree to which this measure is endogenous is small. We acknowledge that our measure of expected bycatch is not completely exogenous (i.e., natural mix of Chinook salmon and pollock), but the impact of endogeneity in terms of estimation bias is negligible.

Figure A.1 shows the observed and expected pollock CPUE and Chinook-pollock ratio. As Panels A and B show, there are some large outliers in the observed data, but the weekly mean exhibits trends across a season. The pollock CPUE is relatively stable over the A season but decreases midway through the B season.The Chinook-pollock ratio starts high in the beginning of A season, reduces toward the end of the A season and beginning of the B season, and then increases again towards the end of the B season. These trends are largely captured by the predicted expectations, depicted by the solid lines in Panels C and D. Each individual harvester forms their expectation based on this common trend, as well as individual information based on the result of Table A.1.

Table A.1: Estimation results of the expected pollock CPUE and Chinook-pollock ratio

	Pollock CPUE	Chinook-Pollock ratio
Pollock CPUE Trend	0.544***	
	(0.036)	
Pollock CPUE Lag (1)	0.363***	
	(0.015)	
Pollock CPUE Trend x Lag (1)	0.437***	
	(0.023)	
Chinook-Pollock Ratio Trend		1.258***
		(0.043)
Chinook-Pollock Ratio lag (1)		0.009***
		(0.002)
Chinook-Pollock Ratio Trend x Lag (1)		-0.130
		(0.084)
Num.Obs.	4204	4204
R2	0.271	0.197
R2 Adj.	0.268	0.193

Note: + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Standard errors in parentheses

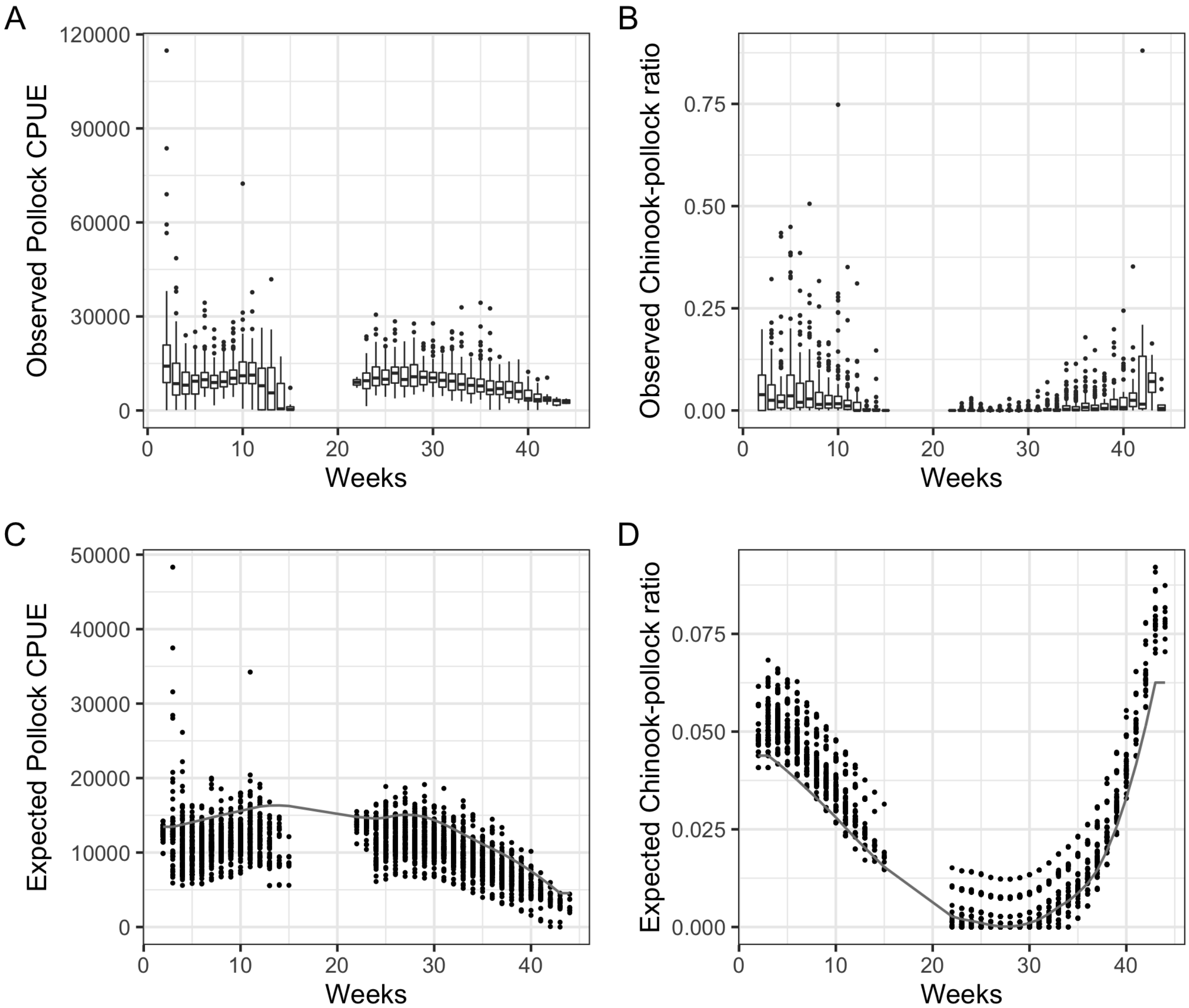

Figure A.1: Seasonal variation of Pollock CPUE and Chinook-pollock ratio, (A) observed pollock CPUE ,(B) observed Chinook-pollock ratio, (C) expected pollock CPUE and (D) expected Chinook-pollock ratio. The grey lines in panel (C) and (D) indicate the in-season trends.

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