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# Essays on labor supply and stock effect in fisheries

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**Essays on labor supply and stock effect in fisheries**

by

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The student author, whose presentation of the scholarship herein was approved by the program of study committee, is solely responsible for the content of this dissertation. The Graduate College will ensure this dissertation is globally accessible and will not permit alterations after a degree is conferred.

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# DEDICATION

To *Maa* and *Baba*.

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## ABSTRACT

This dissertation studies labor supply and stock effect in fisheries. Do people work more hours when paid a higher wage? The answer to this question has both micro (designing efficient workplaces) and macro (designing tax schedules) consequences. The occupation of fishermen provides a unique ground to test competing labor supply theories as fishermen have autonomy over the number of hours worked. Here the focus is on the commercial fishermen from the Alaskan halibut fishery. Chapter 2 summarizes the stylized facts of the fishery using detailed trip level data on catch, location, and target, among other things. The theoretical models of labor supply are introduced in chapter 3, and the wage elasticity of labor supply of commercial fishermen is estimated using the Poisson regression model. The results provide compelling evidence of nonlinear income targeting behavior among the fishermen. The policy implication is that financial motivation or providing higher wages will not always result in longer hours supplied from workers. Chapter 4 investigates the relationship between the cost of fishing and stock abundance, which is known as the stock effect. The estimation of the stock effect is essential for maximizing economic yield from fisheries. However, the estimation is complicated as the stock abundance is unobserved. The location and time-specific predicted values from the generalized linear model of catch per skate is used as the proxy variable for the unobserved stock in this chapter. Then the parameters of the cost function with optimal location and extraction condition are estimated using the generalized method of moments methodology. The estimation of the stock effect will allow fishery managers to implement the total allowable catch from maximum economic yield, which will result in higher stock abundance than the present regime. The last chapter concludes and notes future research topics.

# CHAPTER 1. GENERAL INTRODUCTION

Stock abundance of fish, particularly at the location of the gear set, is the single most critical factor for successful fishing activity. Due to variations in the marine environment, the stock abundance is heterogeneously distributed across location and time. Furthermore, for demersal species or bottom-dwelling species, the stock abundance at a location and time cannot be tracked with electronic equipment. Hence, the stock abundance of species is unknowable, but it is vital for harvest.

Fishermen resolve this uncertainty regarding stock abundance partially by setting gears and observing catch at a location and time. It is reasonable to assume that fishermen would respond optimally upon gaining this additional at sea information. Then, analyzing fishermen behavior without controlling for the stock abundance at the location and time, as the stock abundance is unobserved by the researcher, would introduce bias to the parameter estimates. Recommendations based on these biased estimates could result in mismanagement of the resource stock, leading to the collapse of the fishery.

This dissertation allows stock abundance to be spatially and temporally heterogeneous. Chapter 2 creates a proxy variable to control for the unobserved (by the researcher) stock abundance at the spatial and temporal scale of a fishing trip. The technique combines fishery-independent data from the annual Setline survey of the fishery management and fishery-dependent logbook data of commercial fishermen. This proxy variable could also be used to track the changes in the stock abundance both spatially and temporally across the fishery. The results show a gradual decline in stock abundance over the past 10 years as reported by the management's stock assessment models. Additionally, it provides background on the fishery and summarizes the stylized facts of commercial halibut fishing in the Alaskan halibut fishery. The constructed proxy variable is included in the rest of the analysis to control for the unobserved (by the researcher) stock abundance.

Chapter 3 utilizes the appropriate work environment of the fishery to test the theories of labor supply. Commercial halibut fishermen have autonomy over their working hours and it is reasonable to assume they respond to the remuneration or catch of the trip. The catch of the trip is the natural counterpart of wage in this setting. Assume catch depends on stock abundance and stock abundance varies from trip to trip. Then one can study fisherman's working hours within a trip when faced with transitory variations in the wage rate. In this setting, the neoclassical labor supply theory states a positive relationship between working hours and wages. However, the competing reference-dependent model of labor supply based on linear gain-loss utility formulation from the reference point predicts a negative relationship between hours and wages. Poisson regression framework estimates a negative relationship between hours and wage rate, but it significantly estimates negative wage elasticity of labor supply even before the target of the trip is reached. These results are inconsistent with both the neoclassical and linear reference-dependent models. Non-linear reference-dependent model based on diminishing sensitivity of gain-loss formulation is proposed which can explain these results, implying wage increase will not always motivate workers.

Chapter 4 focuses on the estimation of the stock effect in fisheries which has profound implications for economically optimal fishery management plans. The stock effect is defined as the increases in the productivity of the fishing effort or reductions in the cost per unit of catch due to higher fish stock abundance. The empirical measurement of the stock effect is rare in the literature. Empirical estimation is complicated by lacking data, unobserved or miss-measured stock abundance, endogenous and econometrically troublesome impacts on endogenous fishing behavior on data generating processes, among others. Using the generalized linear model of stock abundance developed in the chapter 2, expectation of productivity according to the fishermen and the realized productivity while at sea are controlled. Finally, these two stock conditions are mapped to the cost of fishing at the trip level to estimate the cost-stock elasticity or the stock effect consistently. The existence of stock effect implies switching to the maximum economic yield regime in the management of the resource stock. Finally, the Chapter 5 concludes and notes future research topics.

# CHAPTER 2. STYLIZED FACTS OF THE ALASKAN HALIBUT FISHERY

Modified from a manuscript to be submitted to *Marine Resource Economics*

Somenath Bera[1]

## 2.1 Abstract

This chapter summarizes the stylized facts of the Alaskan halibut fishery, which is the primary source of Pacific halibut in the US-Canada region. Using setline survey data from the fishery management and fishery-dependent data, I estimate a generalized linear model of catch per skate distribution for the fishery. This provides an alternate measurement of stock assessment, and I find the catch per skate model produces similar results as the predictions from the management. Additionally, the predictions from the catch per skate model are used as the proxy variable for the unobserved stock conditions to avoid the omitted variable bias in the estimates. Regression results show that better stock abundance allows fishermen to catch their target, and the weather does not play a significant role in fishing within a trip. Additionally, I find fishermen prefer to fish at locations with good prior experience and tip from a friend is least important in location choice.

## 2.2 Introduction

Alaskan halibut fishery is the primary source of the Pacific halibut in the US-Canada region and is one of the most economically important species. This chapter summarizes the stylized facts of the Alaskan halibut fishery by using fishery-independent and fishery-dependent data. The annual setline survey[2] conducted by the fishery management, International Pacific halibut Commission (IPHC) provides information on catch per skate across the fishery. The "Halibut Project" (Weninger, 2012) recorded responses of commercial halibut fishermen on various aspects of a fishing

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[2]The link to the IPHC annual setline survey data is here.

trip from the fishing seasons of 2006 and 2007. Using these two data sources, first, I estimate the catch per skate distribution, which proxies for the unobserved (by the researcher) stock abundance distribution. Second, I compare the trip level expectations and realizations of fishermen to summarize characteristics of halibut fishing trips. Finally, the regression analysis finds an association between the trip's catch and realized the stock abundance of a trip.

Stock abundance is the single most crucial factor behind harvest productivity, and invariably the researcher does not observe the stock abundance associated with a fishing trip. However, fishermen may have vital information about the stock abundance by observing catch and may respond to the productivity realizations. Then, omitting the stock abundance (as unobserved by the researcher) in the analysis of fisherman's decisions would introduce omitted variable bias in the estimated parameters. Using stock assessment literature, I propose to use catch per skate as a proxy for stock abundance and control for unobserved stock abundance in the analyses of fisherman's decisions. I estimate a generalized linear model of catch per skate distribution using 20 years of IPHC setline survey data and 2 years of fisherman's logbook data. It also provides an alternative way to estimate stock abundance of species.

To analyze the fishing behavior data of commercial fishermen of the fishery, I build the trip level data set by combining the pre-trip expectations and the post-trip realizations on various aspects of a trip like catch, weather, trip length. I study the relationship between the deviation of a trip's revenue from the target and productivity of the trip, among other covariates. I find the trips that experience higher productivity, achieves a higher percentage of pre-trip revenue target than others. I also find that halibut fishermen weight their experience and weather conditions heavily behind their location choice decisions but does not regard information from the setline survey data as relevant. When fishing trips get extended than planned, it is mostly due to the catching of less fish. On the other hand, if the trip is cut short, it is rarely due to a shortage of bait, ice, or mechanical problem, implying the planned nature of a commercial fishing trip.

The rest of the chapter is organized as follows. Section 2.3 provides a background of the fishery including location, management, fishing technique, costs of fishing, and revenues from fishing.

Section 2.4 introduces the generalized linear model of catch per skate, estimation methodology, and summarizes results. Section 2.5 discusses data sources of fishery-dependent data, the related cleaning procedures, and the construction of detailed trip level data. The next section summarizes the various data characteristics, presents expected and realized comparisons graphically, and analyzes Likert scale responses of essential factors influencing fishing decisions. Section 2.7 discusses the regression results of deviation of realized revenue from pre-trip target revenue of halibut fishing trip on various trip observables. The final section 2.8 concludes the chapter by summarizing the obtained stylized facts of the Alaskan Halibut fishery.

## 2.3 Fishery Description

**Location:** The Alaskan halibut fishery is located in the Gulf of Alaska[3]. It is the primary source of Pacific halibut (*Hippoglossus stenolepis*) in the United States-Canada region. Pacific halibut from this fishery accounted for less than 1% of the total landings by weight but 8% of total revenue generated by all species caught in the Gulf of Alaska for the year 2016. Pacific halibut is among the top 5 valuable species of the region, along with Pollock, Salmon, Pacific cod, and king crab. The Alaskan halibut fishery consists of commercial, recreational, and subsistence sectors. Among the 2017 total halibut landings, commercial fishermen were responsible for 60%, recreational fishermen caught 19%, subsistence removal by indigenous people were 3%, and rest were bycatch mortality and discards of sub-legal sizes. Here, the focus is on the commercial sector.

**Habitat:** The habitat of Pacific halibut is on the continental shelf through much of the northern Pacific Ocean, from California northward to the Chukchi Sea, and from the Gulf of Anadyr, Russia southward to Hokkaido, Japan. It is one of the largest flatfish that grows up to 8 feet, weighs up to 500 pounds, and lives up to 25 years. They are bottom dwellers, strong swimmers, and feed mainly on other fishes like cod, pollock, and salmon. The reproduction cycle is in winter months with a peak in activity occurring from December to February. Pacific halibut have a delicate sweet flavor and provides an excellent source of protein.

[3]Information about the fishery is compiled from the Alaska Department of Fish and Game, National Oceanic and Atmospheric Administration, and International Pacific Halibut Commission.

**Management:** International Pacific Halibut Commission (IPHC), which is a joint body between the United States and Canada, manages the Alaskan halibut fishery. For management purposes the entire fishery is divided into 10 regions as shown in figure 2.1. Every year, the commission recommends a total allowable catch of Pacific halibut for each management region that regulates the fishing operation. For example, in 2019 the IPHC allowed to catch 29.43 million pounds of halibut in total and the management area 3A had the highest amount of catch limit at 10.26 million pounds. Additionally, commercial fishermen can only retain halibut that are more than 32 inches in fork length[4]. The fishing season is closed during the winter months to encourage spawning. Typically, the fishery is open every year from mid-March 11 to mid-November.

Since 1995, the individual transferable quota system is used to manage the Alaskan halibut fishery. Before the quota system, management closed the fishery, once the harvest was equal to the total allowable catch of the year. This uncertainty regarding the fishery open season led to a race to fish, even in adverse weather conditions, leading to vessel sinking and fatalities among other problems. On the other hand, with the quota system, the quota owner reserves the right to fish the specified quantity of halibut at any time during the open season from the associated management area. They can also cover any additional (short) catch by buying (selling) quotas from (to) other owners.

**Fishing Technique:** Commercial fishermen use the longline fishing technique to catch the Pacific halibut. This technique uses strong nylon lines that are studded with equally spaced baited hooks to catch fish. Fishermen refer to the length of lines in the range of $350 - 1800$ feet as one skate. Hereafter following IPHC, I define 1800 feet length of the line as a standardized skate. After steaming from port to location, fishermen soak multiple baited skates tied together with the help of anchors and buoys are used to mark the lines. Fishermen refer to this simultaneous soaking of multiple skates as a set event. About 8 hours of gear soaking completes the set event, and a hydraulic winch pulls the skates. Then the harvest is separated from the hooks, and the fisherman realizes the catch of the set event. Captured fish is then gutted, cleaned, and placed on ice or

[4]Fork length is defined as the length of a fish measured as the distance between the tip of the snout and the point of the fork or V of the tail.

cooled with onboard refrigeration to maintain freshness. The fisherman sets another set event if desired; else, the vessel returns to a port and sells the catch to dealers at a spot price, typically known to the fisherman. During a regulatory cycle or open season, fishermen take multiple trips to the sea and back to fish their entire quota.

**Costs:** The fixed cost of fishing mainly originates from acquiring the vessel and fishing gears. The variable cost includes the expenses primarily incurred from using bait, fuel, and payment to crew members. Bait expenditures depend on the number of skates done, and it cannot be reused if fish are not trapped. Fuel is used for steam between port and location and to keep the vessel afloat while fishing. Hence steaming from port to the chosen location and setting gear is costly in terms of bait, fuel, and time spent. Also, the onboard refrigeration system should be kept running to keep the catch fresh.

**Revenues:** The revenue generated from fishing trips depends on the amount of halibut caught and the price of halibut. Weninger (2012) noted that the number of fishermen in the Alaskan halibut fishery during the 2006 and 2007 fishing season was likely to be more than $1,000$. Hence I assume that the prices should be reasonably exogenous to an individual fisherman. The amount of halibut caught mainly drives the trip's revenues. Additionally, some trips also capture another species, Black Cod (*Anoplopoma fimbria*), using the same technology which contributes to revenue.

## 2.4 Stock Abundance

Stock abundance of fish is the single most crucial factor behind harvest productivity on a fishing trip. Notably, the abundance of fish that is susceptible to gear set location or the *local* stock abundance. Fish species move across space and time in search of food, cover, and to breed. However, certain habitat qualities are preferred, and species tend to congregate in those areas (MacCall, 1990). These *niche* habitats are heterogeneously distributed across location and time. Also, the abundance of species at any location on a given time is subject to exogenous shocks like fluctuation in tides, water temperature, and competition. Hence, even if a fisherman knows the preferred habitat areas for the species, the natural variation in marine conditions implies that the fish present at the given location and time will be partially random. So the decision of where and when to set gear, is, therefore, made under uncertainty about the actual stock abundance.

Additionally, Pacific halibut are bottom-dwelling species, and it is difficult to *see* the location of species with sonar equipment. The only way to learn about the actual stock abundance of Pacific halibut at a location and time is to set gears and observe the productivity of gear sets. The harvest from the gear set provides fishermen a signal about the actual real-time abundance of the location and time that is susceptible to the gear set. It is reasonable to assume fishing decisions for the trip would be based on this signal on realized productivity, among other factors.

**Heterogeneity and Randomness in Stock:** Formally, let $X_{lt}$ denote the stock abundance at the location, $l$, and time, $t$. This implies the habitat quality, thus the stock abundance at a given $(l, t)$ is assumed to be fixed during the duration of a single fishing trip. Usually, fishing trips vary in the range of $1 - 15$ days, depending on the fishery under consideration. I assume stock abundance follows Log-normal distribution, $X_{lt} \sim LN(\mu'_{lt}, \sigma'^2)$. The parameter, $\mu'$, depends on $(l, t)$ but the parameter, $\sigma'$, does not vary across location and time. Hence, at port decisions of when and where to fish are taken under uncertainty of stock abundance.

The stock abundance is invariably unobserved to the researcher, particularly at the spatial-temporal scale of a single fishing trip. Fishermen, on the other hand, may have considerable information on the *local* $(l, t)$ stock abundance by fishing at $(l, t)$. Then, if stock abundance, $X_{lt}$, is not controlled for (as unobserved by the researcher) then it necessarily enters the error term and introduces omitted variable bias in the parameter estimates. The existence of the problem in fisheries studies are noted in the literature (Ekerhovd and Gordon, 2013).

**Stock Proxy:** Here, I propose to create a proxy variable to control for unobserved (by the researcher) stock abundance by following the stock assessment literature. Stock assessment in fisheries is based on the assumption that at a small spatial scale the catch of fish, measured as the number of fish or weight of fish harvested, will be proportional to the product of fishing effort and unobserved stock abundance (Campbell, 2015). It should be noted that when used for stock assessment, fishing effort is defined as the units of gear, such as nets, or baited hooks, that are deployed while fishing. Here, I measure fishing effort by using the number of 1800 feet skates used, by following the setline survey specification of IPHC.

Stock assessment proceeds by specifying catch per unit effort, or, in this case, catch per skate ($cps$) is proportional to stock ($X$), that is, $cps = qX$, where $q$ is the proportionality constant. The constant, $q$, measures the proportion of fish removed from the available stock by using a unit amount of gear. This proportion may vary across skipper depending on the quality of bait used by skippers, or how they are attached to hooks. Hence, I allow $q$ to change across skippers but omit the skipper subscript for simplicity in notation.

I started by assuming: $X_{lt} \sim LN(\mu'_{lt}, \sigma'^2)$, or, $\ln(X_{lt}) \sim N(\mu'_{lt}, \sigma'^2)$. Then, adding $\ln(q)$ to the stock distributional assumption implies $\ln(q) + \ln(X_{lt}) \sim N(\mu_{lt}, \sigma^2)$, where $\mu_{lt} = \ln(q) + \mu'_{lt}$. Taking logarithm of stock assessment equation: $\ln(cps_{lt}) = \ln(qX_{lt})$. Combining the above two relationships produce: $\ln(cps_{lt}) \sim N(\mu_{lt}, \sigma^2)$. That is, the distributional assumptions on the stock and proportionality of catch per skate to stock implies $cps_{lt} \sim LN(\mu_{lt}, \sigma^2)$. Hence, distributional assumption on stock has one-to-one mapping to catch per skate distribution and decisions of the fishermen based on stock abundance can be equivalently written as decisions based on catch per skate. This is advantageous as the unobserved stock abundance can be controlled in the analysis by using catch per skate, which is observed. Next, I introduce the available catch per skate data from this fishery and estimation methodology of the parameters $\mu_{lt}$ and $\sigma$, using generalized linear model of catch per skate.

### 2.4.1 Setline Survey Data

The IPHC conducts a fishery independent setline survey every year for management purposes. The setline survey records catch information on halibut using standardized longline gears on predefined locations across the fishery during summer months. Figure 2.2 shows the predefined locations in the major fishing areas of region 2C, 3A, and 3B. These predefined locations are known as stations and are located at the intersections of a $10 \times 10$ nautical miles square grid.

I build the data set by collecting setline survey information from IPHC webpage, covering years 1998 to 2018 in the management regions 2C, 3A, and 3B. Then the IPHC data is augmented by the logbook data of 43 commercial fishermen who participated in the "Halibut Project" and fished during 2006-07 season[5]. The combined data set has $20,374$ observations where $15,998$ or 78.5% are from the setline survey, and 4376 or 21.5% are from commercial fishermen. Each observation records the catch per skate (cps) of legal halibut caught in pounds, the exact location of the capture in terms of latitude and longitude, and the date of catch. Note that here 1800 foot longline gear with 16/0 circle hooks at $18'$ spacing is defined as skate, following IPHC protocol. The table 2.5 provides summary statistics of the full data, only setline survey data, and only logbook data.

### 2.4.2 Distribution of Catch per Skate

This subsection introduces the empirical model of catch per skate (cps) distribution of halibut at the Alaskan halibut fishery. Let $\{cps_{i,lt,lg,yr,wk}\}$ denote the catch per skate or cps observation for the skipper $i$, at location defined by north latitude $lt$ and west longitude $lg$, in the year $yr$ and week number $wk$. For notational simplicity, I use $CPS$ to denote $\{cps_{i,lt,lg,yr,wk}\}$. I model the distribution of $CPS$ as Generalized Linear Model (GLM) following McCullagh and Nelder (1989). This approach relaxes the unreasonable assumption imposed on the error term by the linear regression model to restrict $CPS$ as non-negative.

A GLM consists of three components. First, a random component specifying the conditional distribution of the response variable given the values of the explanatory variables in the model. Assume, the response variable, $CPS$ given the explanatory variables follows Log-normal distribution with parameters $\mu$ and $\sigma$. By construction, $CPS$ is a non-negative number, so a Log-normal distribution is a suitable choice. However, one disadvantage is that a Log-normal distribution does not support a zero value of $CPS$. The number of observations with $CPS$ value equal to 0 is less than 2% in the IPHC data, so by using a Log-normal distribution one would ignore a negligible amount of information. For estimation purposes, I drop the observations with $CPS$ equal to zero.

[5] Details on logbook data are provided in the Section 2.5.

Alternatives to a Log-normal distribution in this scenario would be Beta distribution or Truncated normal distribution.

The second component of GLM is a linear predictor which a linear function of explanatory variables. The explanatory variables in the objective $CPS$ distribution model are location, time variables, and skipper fixed effects. Combinations of latitude and longitude values describe location, so I use higher order polynomials of latitude and longitude values and their interactions as explanatory variables. Specifically, Chebyshev polynomials are used for their better state-space coverage and lesser collinearity as compared to the standard higher degrees of the variable (Miranda and Fackler, 2004). Similarly, Chebyshev polynomials are used for the week number of the year variable to capture any within season patterns. The IPHC management area and year specific fixed effects control annual stock recruitment at each area. The skipper fixed effect are used to control variability in skipper skill.

The third component of GLM is a link function that connects the parameters of the response variable's distribution to the linear predictor. The parameter $\mu$ of a Log-normal distribution has a complete real number line support. So the link function could be an identity function. The other parameter, $\sigma$, is strictly positive. Hence the suitable link function would be a logarithmic function.

The generalized linear model for $CPS$ distribution can be summarized as follows:

$$CPS \sim Lognormal(\mu, \sigma^2) \tag{2.1}$$

where,

$$\begin{aligned}\mu = \sum_{slt=0}^{S_{slt}} \sum_{slg=0}^{S_{slg}} \sum_{swk=\{0,2\}} \psi_{\{slt,slg,swk\}} \Phi_{slt}(lt) \Phi_{slg}(lg) \Phi_{swk}(wk) + \\ \sum_{y=1998}^{2018} \sum_{a=\{2C,3A,3B\}} (1 - \mathbb{1}[y = 1998, a = 2C]) \psi_{ya} D_{ya} + \sum_{skip=1}^{43} \psi_{skip} D_s\end{aligned} \tag{2.2}$$

$$\ln(\sigma) = \psi_\sigma \tag{2.3}$$

The Chebyshev polynomials are defined as follows:

$$\Phi_0(z) = 1$$

$$\Phi_1(z) = z$$

$$\Phi_2(z) = 2z^2 - 1$$

$$\vdots$$

$$\Phi_s(z) = 2z\Phi_{s-1}(z) - \Phi_{s-2}(z) \tag{2.4}$$

where $z$ takes the values $lt, lg, wk$ to create chebyshev polynomials for latitude, longitude, and the week of the year variable. For computational purposes, the domain of the variables is normalized to $[-1, 1]$.

The variables $DY_{ya}$ captures the year fixed effects for each management region and $D_s$ captures the skipper fixed effects. Dummy variable trap is avoided by not using fixed effect for the year 1998 and region 2C and by not including the fixed effect for IPHC setline survey data points. The logarithm of the other parameter, $\sigma$, is assumed to be a function of just an unknown parameter, $\psi_\sigma$. However, this would not restrict the variance to be constant across location and time as the Log-normal distribution's both mean and variance depends on $\mu$ and $\sigma$. That is,

$$E(CPS) = \exp\left(\mu + \frac{\sigma^2}{2}\right)$$

$$V(CPS) = \left(\exp(\sigma^2) - 1\right)\left(\exp(2\mu + \sigma^2)\right) \tag{2.5}$$

Finally, the vector of parameters to be estimated is given by:

$$\mathbf{\Psi} = \{\psi_0, \psi_{lt,s}, \psi_{lg,s}, \psi_{wk,s}, \psi_{int,s}, \psi_{yr}, \psi_{skip}, \psi_\sigma\} \tag{2.6}$$

Assuming the $CPS$ observations are independent, the parameters can be estimated by using maximum likelihood. The log-likelihood function is given by:

$$\ln L(\mathbf{\Psi}; CPS) = ln\left(\prod_{n=1}^{N} \frac{1}{CPS\sigma\sqrt{2\pi}} \exp^{-\frac{(\ln CPS - \mu)^2}{2\sigma^2}}\right) \tag{2.7}$$

The maximum likelihood estimator of $\mathbf{\Psi}$, $\widehat{\mathbf{\Psi}}$, is defined as the vector that maximizes $\ln L$.

### 2.4.3 Productivity Results

Various models are estimated using higher order Chebyshev polynomials of latitude, longitude, and week of the year variables. Akaike Information Criteria (AIC) is used to select the best model. The figure A.1 plots the AIC from the different models. Here, I discuss results from the model with Chebyshev polynomial of order 9 in latitude and longitude, order 2 in the week of the year, and all the interactions of these polynomial terms. Additionally, the year fixed effect for each IPHC region, and the skipper fixed effect of IPHC are used. The coefficients of the Chebyshev polynomials are difficult to interpret and are not reported. Rather the summary statistics of the parameter, $\mu$, and the associated expected catch per skate (cps) for the data is reported in table 2.6. The average of all fitted values of the IPHC setline survey data points is lesser than the logbook data points. This is a result of a directed search by fishermen as compared to the predetermined grid location of the IPHC survey data points.

The objective catch per skate Log-normal distributions for 12 (out of 22) IPHC management sub-regions are shown in the figure 2.3. The results are for representative IPHC stations within the sub-region with the standard IPHC gear configuration of 5 skates of 1800 feet in length used in mid-year 2007. The parameter, $\mu$, varies across location and time which makes the expected catch per skate vary across space and time.

The productivity contour maps or the expected catch per skate contour values for across the IPHC management region 3A and 3B are shown in figures 2.4 and 2.5. The darker contour is located away from the shoreline representing higher productivity. This gradient in productivity is stronger in the early 2000s but has changed to a more homogeneous distribution recently. However, during our study period of 2006-07, there exists a trade-off between steaming distance and productivity from major ports.

The within season trends for each management region is presented in figure 2.6. The seasonal effects vary across the regions. The within season productivity changes in all IPHC regions are similar but are more dramatic in the IPHC region 3A. Low productivity during summer months reflects enhanced fishing activity due to good weather.

The figure 2.7 shows the regional average values of cps, across all the IPHC stations from 1998-2018. The general trend is declining average cps for all the areas, except for region 2C, which has recovered to its 1998 abundance levels. The downward trend in the region 3B is alarming as it denotes the depletion of stocks and if this trend continues, the fishery could collapse. The generalized linear model of catch per skate provides an alternative measure of the stock assessment for the Alaskan halibut fishery. Also, the results obtained here are similar to 2017 IPHC stock assessment[6] report.

The expected catch per skate calculated based on an estimated $\mu$ and $\sigma$ parameters of the location and time specific catch per skate distribution would be used as a proxy variable for the unobserved expected stock abundance. Before that, in the next section, I discuss the fishery dependent data or the data collected from fishermen about the halibut fishing trips. This data contains behavioral information related to fishing, and it is used to summarize the stylized facts of the Alaskan halibut fishery.

### 2.5 Fishermen Response Data

The "Halibut Project" collected data from commercial halibut fishermen operating in the Alaskan halibut fishery during the 2006 and 2007 fishing seasons. The project invited all commercial halibut quota owners to participate in this research study and I observe the data from fishermen who agreed to participate. The project used pre-trip and a post-trip questionnaire administered through a handheld electronic device to gather information on fishing behavior.

Participating skippers in the study answered questions before the trip regarding their expectations on the length of the trip, location, catch, and weather. Upon trip completion, skippers reported whether the pre-trip plan was followed and the reasons for deviations, if any. They also recorded actual trip length and location, weather conditions, cost, and revenue for the trip. Both of the questionnaires also prompted skippers to rank the importance of pre-identified reasons on a Likert scale that determined their choice. It is important to note that fishing trips in this fishery

[6]The link to the IPHC report is here.

originate from various ports throughout the Gulf of Alaska at dates chosen by fishermen during the season.

Additionally, I observe the logbook records of the two seasons from the participating fishermen that provides information on precise fishing locations, amount of gear, and catch. All commercial fishermen maintain detailed logbook information from their trips to distinguish the productive locations. And halibut fishermen view the location as the most critical factor behind fishing success and their livelihoods. Hence, logbook records are sensitive, and participants agreed to share only after a formal confidentiality agreement. Supplementary information on the skipper's experience, vessel characteristics, and crew size were also obtained.

**Data Processing:** The trips in the data are uniquely identified by a combination of 3 variables, namely, skipper code, year of the trip, and the trip number of the year. To construct the complete data set, I merge the data from 3 different sources (survey, logbook, and supplementary information) by using the trip identifiers. The survey data is at the trip level and has 496 trip records. The logbook records information at the gear set level within a trip and I aggregate the information to the trip level, which resulted in 613 trips. Logbook data has records of all trips taken by participating skippers during the season, whereas, survey data had trip trips records when the survey questionnaire when was completed before and after a trip. Hence, the logbook has more trip records than the survey data.

The merging of the survey and the logbook data yields 492 trips. That is, 4 trips had survey information but were missing logbook information; hence, are dropped from further analysis. Supplementary data were collected from the participating skippers in the year 2007 only and added to the merged data.

The full data of 492 trips contains trip records that primarily targeted halibut, and few (less than 9% or 43) trips targeting black cod, has missing values, extreme observations, and also unreasonable values due to a recording error. I focus only on the 449 trips that targeted halibut during the data period. Dropping all the trips with missing or unreasonable values that cannot be imputed from other observations under reasonable assumptions leaves the complete halibut data with 405 trips.

The initial exploratory analysis, which follows next, is based on all of these trips. Appendix A notes the detailed data cleaning steps.

## 2.6 Data Characteristics

I begin by classifying the data set of 405 trips into years, skippers participated, and regulatory areas fished as shown in the table 2.1. The IPHC region 3 is the largest geographic region within the fishery and is close to big ports. The sample represents enhanced fishing activity in region 3. The percentage of trips taken by each skipper present in each year is shown in the bar chart of figure 2.8. Skippers can take any number of trips during the fishing season, quota permitting. So, there are variations in the number of trips taken by each skipper. Fishing trips mostly take place during the summer months when the weather is better as compared to late fall or early spring. The sample represents this phenomenon, as shown in figure 2.9.

**Trip Length**: The length of the fishing trips would depend on the steaming time to the fishing location and the number of set events performed. The variation in the set events conducted is presented in the top panel of figure 2.10. The median number of the set event is 4. Alternatively, the trip length can also be described by the number of days spent on the sea during a fishing trip. The bar graph for the duration of trip length is shown in the bottom panel of figure 2.10. As expected, both of the bar graphs look are similar to each other.

**Deviation Percentage:** This data set allows for comparing the expectation and realization of various variables and learn how well informed the fishermen are about halibut fishing activities. To measure their knowledge quality, I define the deviation percent as follows:

$$\text{deviation percent} = \left(\frac{\text{realized value - expected value}}{\text{expected value}}\right) * 100 \tag{2.8}$$

The deviation percent of any attribute around 0 would imply realized values closely matching expectations. On the other hand, a large magnitude of positive or negative values would imply realizations away from expectations. Deviation percentages can be graphically represented by violin plots which provide kernel density estimation with the inter-quartile range. So a thicker plot around 0 would imply a good match between expectation and realization.

**Trip Catch**: The variation in the amount of halibut captured in all the trips is shown in figure 2.11. The histogram represents the uncertainty of the fishing activity.

**Halibut Price**: The violin plot of price deviation percent for the 4 weight categories of halibut is presented in figure 2.12. The thick areas around 0 imply fisherman's expectation of the selling price of halibut closely matches with the actual prices for all weight categories. I observe only the total weight of species caught. Hence, to convert the pounds caught to dollar generated, I will use the realized price of the most abundant category of the halibut, $40 - 60$ pounds.

**Set events & Revenue**: The scatter plot of the number of set events done and revenue generated for each trip is presented in figure 2.13. The plot does not reveal any clear positive or negative relationship, but the correlation between the variables is 0.38.

**Revenue per Skate**: Halibut fishermen perceive revenue per skate as a noisy signal of the real-time abundance of halibut susceptible to the gear set at the given location and time. The histogram in figure 2.14 shows the variability of revenue per skate at the trip level during the data period. On the other hand, the violin plot for revenue per skate deviation percent is presented in figure 2.15. Most of the plot area is below the 0% line implying fishermen are generally over-optimistic about location's productivity. The same is observed for revenue deviation percentage from target revenue in the figure 2.16.

**Preferred Position**: The distance of first set event's position from the expected position is shown in the figure 2.17. The thick plot near 0 miles shows that trips can set gear at their preferred position at most times.

### 2.6.1 Likert Scale Responses

The pre and post trip survey elicited information on various aspects of fishing in the Alaskan Halibut fishery. Specifically, it collected data on the relative importance of factors that motivated location choice of fishing, deviation from the location choice, and deviation from the planned number of trip days. Skippers rated each factor on a Likert scale of 1 to 5, where 1 is for strongly disagree and 5 is for strongly agree. I analyze this data to understand the essential factors that drive the fishing decisions on a trip in Alaskan halibut fishery.

The first choice of location for setting gears is one of the major decisions on a trip. The top panel in figure 2.18 represents the summarized results from the Likert scale responses regarding the choice of the first location. The majority of the skippers believe the prior experience of the location and expectation of good weather at the location are the main drivers of choice. And a tip from a friend and annual survey results from the fishery management are least important. Lesser importance on a tip from a friend could be a result of incomplete information sharing about stock abundance in the fishery. Sometimes on a trip, the desired locations were not fished. In about 10% of the trips, the first choice location was not fished, and the summarized reasons are shown in the middle panel of figure 2.18. The primary reason for not fishing was the weather and in some cases tides. Issues like gear conflict, the presence of another boat, tip, whales are least important. When the primary location was unavailable, the alternative location choices were mainly driven by the realization of the good bottom (high stock) and better weather. Again tip from a friend and observing another boat catching are given least importance as shown in the bottom panel of figure 2.18.

Fishing trips do not go as planned. The essential factors that resulted in the trip extension are summarized in the top panel of a figure 2.19. I find getting lesser fish than expected is the main reason behind the delayed return. This could imply that skippers were targeting revenue and they continue fishing until the expected amount of fish is caught. There is no clear picture behind the importance of weather as some skippers say it is not essential (probably ones with bigger boats) and some say it is critical. But I find that mechanical problem and lost gear are never an issue for the trip delay. Important factors behind early return trips are summarized in the bottom panel of the figure 2.19. Like delayed returns, a mechanical problem and lost gear were unimportant. Even the shortage of bait and ice and injury were rarely an issue reflecting the well-planned nature of the activity. Instead, getting more fish than expected and bad weather were the leading reasons. Harvesting more fish than expected as a leading factor behind early return could imply revenue targeting and/or binding vessel hold constraint. However, I also find around 60% of the trips classified it to be unimportant, implying neo-classical labor supply response. Given this background, next, I investigate the quantitative relationship between target revenue deviation percent and other covariates at the trip level.

## 2.7 Deviation from Target Revenue

This section focuses on the relationship between the deviation of realized revenue from the target revenue of halibut and other observables. I create the variable, absolute target catch deviation percent, to measure the precision of the trips or how close they are to their pre-trip target level. I investigate the association of absolute target revenue deviation percentage with the significant factors behind fishing success like the realized abundance of stock, black cod catch share, weather shock percentage, regional trip number, and when the quota constraint binds or the last regional trip of the season. The motivation behind the selection of these variables lies in the previous discussion on Likert scale responses and qualitative analysis.

The primary factor of harvest productivity is the realized abundance of the halibut in the gear set location. The realized stock abundance during a fishing trip is unobserved by the researcher. So, I follow the stock assessment model and use catch per skate as a proxy for the realized local stock abundance. In the empirical application, I calculate catch per skate of the trip by taking the ratio of total pounds of halibut caught to the total number of 1800 feet skates used. The variation in the skill that allows one skipper to be more productive than others, given the same amount of stock abundance, is absorbed by the skipper fixed effect. To account for the impact of halibut price, I use revenue per skate which is obtained by multiplying catch per skate in pounds with halibut price per pound.

The wind speed measures the weather faced by the trips at the location during fishing. From the observed-expected wind speeds and realized wind speeds at the fishing locations on a trip, I create the variable, wind shock percent to measure the deviation between realized and expected wind speed. To distinguish between stronger than expected wind speed and weaker than expected wind speed, we create 2 more variables: positive wind shock percent[7] to measure magnitude of stronger winds and negative wind shock percent[8] to measure magnitude of weaker winds. For trips where the expected and realized wind speed matches exactly, these 2 variables take the value 0.

The quota constraint nature of fishery implies as the season progress, the number of available quota decreases. I use the previously constructed variable, region trip number, to track the trip number of the skipper to a particular IPHC region. Controlling for region-specific quota is essential as the quota restriction is IPHC regulatory area specific. I also use a dummy variable, last trip dummy, to identify the last trip of the season to an IPHC region by the skipper. The last regional trip of the season is the trip where quota becomes particularly binding, and they hit the hard constraint.

Halibut trips also capture another species, Black Cod, using the same technology which has market value. So I control for the amount of Black Cod captured during a trip by using the variable, black cod share percentage, which measures the weight percentage of black cod to the total weight of the catch. Finally, the participating skippers have heterogeneity in fishing experience, vessel length, and management skills. Hence, I use skipper specific fixed effects in the regression models.

In the complete data set, there are 405 trips, and it contains trips to IPHC region 4 and trips with extreme values. The IPHC region 4 by itself is an extreme location as it is far away from the ports and fishing is limited. Hence for the main results, trips fishing in IPHC region 4 is excluded, which are 31 trips or about 8%. Using boxplot of the various variables in figure 2.20, I find 34 trips as outliers that are beyond the whiskers. Again, these trips are excluded from the main results but are included for robustness checks.

[7]

$$\text{positive wind shock \%} = \begin{cases} \text{wind shock \%} & \text{if wind shock percent} > 0 \\ 0 & \text{else} \end{cases}$$

[8]

$$\text{negative wind shock \%} = \begin{cases} |\text{wind shock \%}| & \text{if wind shock \%} < 0 \\ 0 & \text{else} \end{cases}$$

Table 2.2 presents the summary statistics of the variables from the cleaned data set of 340 trips. On average, trips are off-target revenue by 36%, experiences 25% wind speed shock, takes about 3 trips to each IPHC region, and 17% of total trip catch by weight is Black Cod. Next, I discuss the association of revenue deviation percent and covariates by using regression analysis.

### 2.7.1 Regression Results

The cleaned data set contains 340 trips from 39 unique skippers. The associated regression results of OLS estimates for absolute target revenue deviation percent of halibut are presented in table 2.3. I observe a sample of skippers from the fishery who made trips during the 2 fishing seasons. And I would like to know the association between the target revenue deviation percent and the covariates across all the skippers in the fishery. Hence, we cluster standard errors at the skipper level as there are skippers in the fishery beyond those seen in the sample (Abadie et al., 2017). Liang and Zeger (1986) approach is used to cluster the standard errors at the skipper level.

The two specifications in the table 2.3 with skipper fixed effects explain about 54% of the variation in the absolute target deviation percent. The estimated coefficients are stable across the models, but some of them are not precisely estimated. The pairwise correlation between the major independent variables is presented in table 2.4 which shows a low correlation among them.

**Stock Proxy:** The local stock abundance of the location fished is the single most crucial factor behind a successful trip. Local stock abundance is unobserved, so we use a proxy variable, revenue per skate, to control for it. The coefficient of the stock proxy is significantly estimated to be $-0.013$ in both specifications. This implies \$100 increase in the revenue per skate is associated with a 1.3% decrease in the absolute target revenue deviation percent. That is, higher stock abundance is correlated with more precise trips where skippers end up closer to their revenue targets.

**Weather:** Unexpected weather changes could impact fishing and could be systematically related to target revenue deviation percent. The wind speed variable measures weather impacts. The variable, absolute wind shock percent, measures the magnitude of unexpected wind speed shock on a trip. I find that the effect of unexpected weather shock is not statistically different from 0.

However, stronger than expected and weaker than expected could potentially have different impacts on fishing outcomes. Allowing for different has implications for stronger and weaker winds, I find the estimates are of the correct sign but imprecisely estimated. The results indicate that bad weather (stronger than expected winds) makes fishing difficult and the deviation percentage from target revenue increases, whereas, good weather (weaker than expected winds) makes fishing more manageable and the deviation percentage from target revenue decreases.

**Regional Trip Number:** The region trip number tracks the number of times the respective skipper within a season fishes a given IPHC region. As the season progresses, with repeated fishing trips, the remaining quota of any given skipper decreases and he would have more idea about the stock distribution for the season. These two forces acting together should result in lower absolute target deviation percent as the trip number increases. From the data, I find the estimated coefficient of the regional trip number to be negative for both specifications, but it is not precisely estimated. The higher standard deviation of the estimate could be due to the low variance of the region trip number variable. Similar results were obtained when region trip number was entered in quadratic form.

**Last Regional Trip:** The quota managed nature of the fishery creates a hard quota constraint on the amount that can be fished, particularly so in the last trip to any region. Fishermen would not leave any quota at sea, and so in the last regional trip of the season, the catch should closely match with the pre-trip target revenue. I used a dummy variable to differentiate the last trips to any region by a skipper. The coefficient of the last trip dummy variable is significantly estimated at $-11$ for both specifications. This implies, on average, the last regional trips have lower target revenue deviation percent, or realized revenue matching closely with pre-trip revenue target by 11% as compared to non-last trips.

**Black Cod Share %:** Fishermen capture another valuable species, Black Cod, with the same gears set for halibut. These are also cleaned and stored on board just like halibut. The coefficient of the Black Cod share percentage is significantly estimated to be at 0.4. This implies, 1% more black cod share in the total catch is associated with an increase in absolute target revenue deviation percent by 0.4%. Given the limited holding capacity of the vessel and gear availability, it is reasonable to assume that halibut catch decreases with Black Cod capture, which leads to higher absolute target revenue deviation percent.

### 2.7.2 Robustness Checks

I check the robustness of the regression results obtained above in various ways. First, the local stock abundance is not observed. Hence, I used average revenue per skate for the trip as the proxy variable. To check the sensitivity of the results for the choice of proxy variable, I use revenue per skate only from the first set event as a proxy for local stock abundance. The results are presented in the table A.1. I find that estimates are not sensitive. All of the variables that were significant before maintain their significance and are of the same sign. And the $R^2$ values drop a little bit, but they still explain the similar amount of total variation in the target deviation percent as before.

Second, I re-run the regressions by adding the extreme values but not the trips to IPHC region 4. The results from 367 trips are shown in table A.2. All estimates are consistent with the previously obtained values. However, with extreme values present, the coefficient of negative wind shock percent and its square is significantly estimated with a negative sign. This implies better weather helps trips reach their revenue targets more easily, but the effect gradually reduces.

Third, I re-run the regressions with the full data including extreme observations and the remote IPHC region four trips. The results are presented in table A.3. I find similar results with the complete data as found before with the clean data. The extra variation on the full data identifies the negative wind shock percent variable or the good weather impact on target revenue deviation percent.

## 2.8 Conclusion

This chapter analyzed both fishery independent and fishery dependent data to summarize the stylized facts of the Alaskan halibut fishery. The catch per skate model based on IPHC setline survey data from 1998 to 2018 produces the objective distribution of catch per skate across the fishery.

This allows controlling for heterogeneity and randomness in stock abundance as stock is invariably unobserved by the researcher. Additionally, this provides an alternative estimation technique of the changes in the stock abundance of species over time across the fishery. The differences between expectations and realizations of various trip characteristics are shown by analyzing the responses of professional halibut fishermen from the fishing seasons of 2006 and 2007. The summary of the stylized facts of the Alaskan halibut fishery are as follows:

- The expected catch per skate increases with distance from the port. That is, higher productivity areas or areas with higher expected stock abundance are located away from the land masses.
- The expected catch per skate shows a declining trend across the fishery. The effect is particularly prominent in area 3B, where the productivity is almost 50% of what it used to be 10 years ago. However, there have some stock rebuilding in area 2C, over the past few years.
- There is a cyclical trend in the catch per skate within a season, with minimum stock abundance around late summer and early fall. This is expected as the primary fishing activity ends around that time and the reproduction season starts in late fall around November to December.
- Fishing trips are mostly taken are taken during the summer months when the weather is favorable, the month of May is closely followed by June and July.
- In the data, I observe trips that decided to take a trip; hence, the minimum number of set events performed on a trip is 1. That is, the situation where skipper decided to take a trip but returned without any fishing activity did not happen. The maximum number of set events performed as seen in the data is 13. This closely matches with the number of days spent on the sea, which ranges from $1 - 15$ days.
- The distribution of pounds of halibut caught is right skewed, showing rarely trips catch large quantities of halibut.

- Commercial halibut fishermen are price takers in the output market of catch, and the realized halibut prices match closely with their expected halibut prices.

- Fishing trips rarely achieve high productivity as the average revenue per skate, or the average value to catch per skate in dollars is right skewed.

- Almost 75% of the trips overestimate the productivity of their locations, and the magnitude of overestimation is 40% on average.

- Trips rarely go beyond their revenue targets. Most trips quit their trip when the realized revenue is more than 60% of the revenue target.

- Fishermen closely follow the gear set position choices made in the pre-trip planning stage as the data shows that more than 75% of the trip's first set event position was less than 10 miles of their desired location.

- The Likert scale responses imply that the location choice of fishermen is primarily driven by experience to some extent by good weather. Interestingly, IPHC setline survey and tip from a friend are the least important factors.

- None of the options in the survey came out to be particularly crucial for not fishing a location. However, the weather is the leading reason for about half of the trips. At the same time, the weather is not essential for the other half of the trips. Mainly, unimportant ones are the presence of whales and the tip of no fish from fellow fishermen.

- And when alternate locations are fished, the realization of good productivity and weather are the leading factors.

- Trips are delayed, mainly due to lower catch. The weather turns out to be essential for some fishermen but not so much for the others.

- There is no particular reason for early return that is prominent. For about half of the trips getting more fish is an important reason but not for the other half. Shortage of inputs and lost gears are particularly unimportant reasons.

- The regression results show that the absolute target revenue deviation percentage and stock abundance is negatively related, implying better stock abundance helps to achieve the revenue target.

- Better weather than expected helps trips to get their revenue target, and worse weather increases the deviation from target revenue, but the effects are not precisely identified.

- Among all the trips, the last regional trips of the season are particularly precise. This is expected as the seasonal quota constraint binds for these trips and for that fishermen fish until the target for the trip is achieved.

- Higher amount of black cod caught on a trip is associated with higher halibut revenue deviation percent. Fishermen have a limited supply of fuel, bait, and storage facilities on board. If set events capture relatively more black cod, then trips would catch relatively fewer halibut, and hence, the revenue deviation percent of halibut increases.

I build on this background knowledge about the Alaskan halibut fishery to investigate the labor supply of commercial fishermen in the next chapter and the stock effect estimation in the chapter 4. The set up of the fishery where the fishermen can freely choose their working hours based on the remuneration or catch provides a fertile ground to test the labor supply theories. Understanding the labor supply of halibut fishermen would would shed light on the role of financial motivation of other autonomous workers like fishermen, taxi drivers, and stadium vendors. This will allow efficient designing of workplaces and country's tax schedules. The problem of stock effect estimation is addressed next. The generalized linear model of productivity constructed estimated in this chapter provides the proxy variable for unobserved stock abundance. The estimated stock effect allows to maximize economic yield from fisheries.

## 2.9 Tables and Figures

Table 2.1 Trips by Numbers

| | Year | |
|---|---|---|
| | 2006 | 2007 |
| Trips | 213 | 192 |
| Unique Skippers | 35 | 35 |
| Region 2C | 23 | 9 |
| Region 3A | 126 | 115 |
| Region 3B | 47 | 54 |
| Region 4 | 17 | 14 |

Note: 29 skippers present in both years.

Table 2.2 Summary Statistics

| Statistic | Mean | St. Dev. | Min | Max |
|---|---|---|---|---|
| \|Target Rev Deviation %\| | 35.770 | 30.510 | 0 | 120.125 |
| Stock Proxy ($) | 1,031.489 | 740.982 | 0 | 3,192 |
| \|Wind shock %\| | 25.374 | 23.904 | 0 | 100 |
| Positive Wind Shock % | 11.817 | 23.342 | 0 | 100 |
| Negative Wind Shock % | 13.557 | 18.652 | 0 | 67 |
| Region Trip Number | 3.276 | 2.055 | 1 | 9 |
| Dummy Last Trip (=1, Yes) | 0.224 | 0.417 | 0 | 1 |
| Black Cod Share % | 16.597 | 32.636 | 0 | 100 |

Note: Based on 340 trips from 2 fishing seasons.

Table 2.3 Revenue Deviation and Average rps

| | *Dependent variable:* \|Target Revenue Deviation %\| | |
|---|---|---|
| | (1) | (2) |
| Stock Proxy | $-0.013^{a}$ | $-0.013^{a}$ |
| | (0.003) | (0.003) |
| \|Wind Shock %\| | $-0.052$ | |
| | (0.055) | |
| Positive Wind Shock % | | 0.136 |
| | | (0.183) |
| Positive Wind Shock % Sq | | $-0.002$ |
| | | (0.002) |
| Negative Wind Shock % | | $-0.269$ |
| | | (0.224) |
| Negative Wind Shock % Sq | | 0.004 |
| | | (0.004) |
| Region Trip Number | $-0.368$ | $-0.263$ |
| | (0.701) | (0.696) |
| Last Trip Dummy | $-10.713^{b}$ | $-10.769^{b}$ |
| | (4.311) | (4.29) |
| Black Cod Share % | $0.4^{a}$ | $0.403^{a}$ |
| | (0.064) | (0.063) |
| Constant | $54.704^{a}$ | $54.022^{a}$ |
| | (8.974) | (6.083) |
| Observations | 340 | 340 |
| $R^2$ | 0.543 | 0.548 |
| Adjusted $R^2$ | 0.475 | 0.476 |
| F Statistic | $7.959^{a}$ | $7.542^{a}$ |

Note: OLS estimates of regression for absolute target revenue deviation percent on various controls. Skipper fixed effects used. Standard errors clustered at skipper level are presented in parenthesis. $a, b, c$ denotes significance at 1%, 5%, and 10% levels respectively.

Table 2.4 Pairwise Correlation Matrix

| | Stock Proxy | Pos Wind Shock % | Neg Wind Shock % | Region Trip Number |
|---|---|---|---|---|
| Stock Proxy | 1 | -0.043 | -0.008 | -0.011 |
| Pos Wind Shock % | -0.043 | 1 | -0.369 | -0.142 |
| Neg Wind Shock % | -0.008 | -0.369 | 1 | 0.030 |
| Region Trip Number | -0.011 | -0.142 | 0.030 | 1 |

Table 2.5 Summary Statistics of CPS Data

| Statistic | N | Mean | St. Dev. | Min | Max |
|---|---|---|---|---|---|
| IPHC Setline | 15,998 | 183.585 | 182.182 | 1.382 | 1,657.867 |
| cps, Area 2C | 3,108 | 168.021 | 139.486 | 1.879 | 1,200.255 |
| cps, Area 3A | 7,592 | 194.477 | 191.434 | 1.537 | 1,657.867 |
| cps, Area 3B | 5,298 | 177.109 | 189.606 | 1.382 | 1,631.275 |
| Latitude North | 15,998 | 57.034 | 1.903 | 50.836 | 60.843 |
| Longitude West | 15,998 | 148.71 | 9.742 | 129.192 | 167.47 |
| Week Number | 15,998 | 27.533 | 3.481 | 22 | 38 |
| Logbook | 4,376 | 290.646 | 265.745 | 1 | 1692 |
| cps, Area 2C | 482 | 211.551 | 219.162 | 2.5 | 1,650 |
| cps, Area 3A | 2,382 | 331.789 | 306.541 | 1 | 1,692 |
| cps, Area 3B | 1,512 | 251.043 | 186.765 | 1.35 | 1,364 |
| Latitude North | 4,376 | 57.291 | 1.715 | 53.9 | 60.553 |
| Longitude West | 4,376 | 150.079 | 8.006 | 131.818 | 163.395 |
| Week Number | 4,376 | 26.291 | 7.941 | 9 | 46 |
| Combined Data | 20,374 | 206.58 | 207.749 | 1 | 1692 |
| cps, Area 2C | 3,590 | 173.865 | 153.3 | 1.879 | 1650 |
| cps, Area 3A | 9,974 | 227.27 | 231.854 | 1 | 1692 |
| cps, Area 3B | 6,810 | 193.524 | 191.448 | 1.35 | 1,631.275 |
| Latitude North | 20,374 | 57.089 | 1.867 | 50.836 | 60.843 |
| Longitude West | 20,374 | 149.004 | 9.413 | 129.192 | 167.47 |
| Week Number | 20,374 | 27.267 | 4.829 | 9 | 46 |

Table 2.6 Summary Statistics of the Fitted Values

| Statistic | N | Mean | St. Dev. | Min | Max |
|---|---|---|---|---|---|
| IPHC Setline Survey | 15,998 | 213.622 | 148.113 | 7.342 | 1221.682 |
| Expected CPS, Area 2C | 3,108 | 209.302 | 124.454 | 8.093 | 1221.682 |
| Expected CPS, Area 3A | 7,592 | 210.708 | 130.622 | 14.573 | 1123.352 |
| Expected CPS, Area 3B | 5,298 | 220.332 | 180.683 | 7.342 | 849.616 |
| $\hat{\mu}$, IPHC Setline Survey | 15,998 | 4.697 | 0.733 | 1.572 | 6.686 |
| $\hat{\mu}$, Area 2C | 3,108 | 4.738 | 0.636 | 1.669 | 6.686 |
| $\hat{\mu}$, Area 3A | 7,592 | 4.73 | 0.66 | 2.257 | 6.602 |
| $\hat{\mu}$, Area 3B | 5,298 | 4.626 | 0.868 | 1.572 | 6.323 |
| Logbook Data | 4,376 | 318.041 | 180.929 | 1.304 | 1236.426 |
| Expected CPS, Area 2C | 482 | 235.707 | 140.447 | 27.709 | 632.955 |
| Expected CPS, Area 3A | 2,382 | 342.678 | 197.875 | 40.639 | 1236.426 |
| Expected CPS, Area 3B | 1,512 | 305.476 | 153.388 | 1.304 | 1054.218 |
| $\hat{\mu}$, Logbook Data | 4376 | 5.187 | 0.571 | -0.156 | 6.698 |
| $\hat{\mu}$, Area 2C | 482 | 4.863 | 0.617 | 2.9 | 6.029 |
| $\hat{\mu}$, Area 3A | 2,382 | 5.259 | 0.568 | 3.283 | 6.698 |
| $\hat{\mu}$, Area 3B | 1,512 | 5.175 | 0.523 | -0.156 | 6.539 |
| Combined Data | 20,374 | 236.049 | 161.537 | 1.304 | 1236.426 |
| Expected CPS, Area 2C | 3,590 | 212.847 | 127.017 | 8.093 | 1221.682 |
| Expected CPS, Area 3A | 9,974 | 242.225 | 159.691 | 14.573 | 1236.426 |
| Expected CPS, Area 3B | 6,810 | 239.236 | 178.523 | 1.304 | 1054.218 |
| $\hat{\mu}$, Combined Data | 20,374 | 4.802 | 0.73 | -0.156 | 6.698 |
| $\hat{\mu}$, Area 2C | 3,590 | 4.755 | 0.634 | 1.669 | 6.686 |
| $\hat{\mu}$, Area 3A | 9,974 | 4.857 | 0.678 | 2.257 | 6.698 |
| $\hat{\mu}$, Area 3B | 6,810 | 4.748 | 0.836 | -0.156 | 6.539 |

Note: Expected catch per skate is calculated with $\widehat{\sigma} = 0.918$.

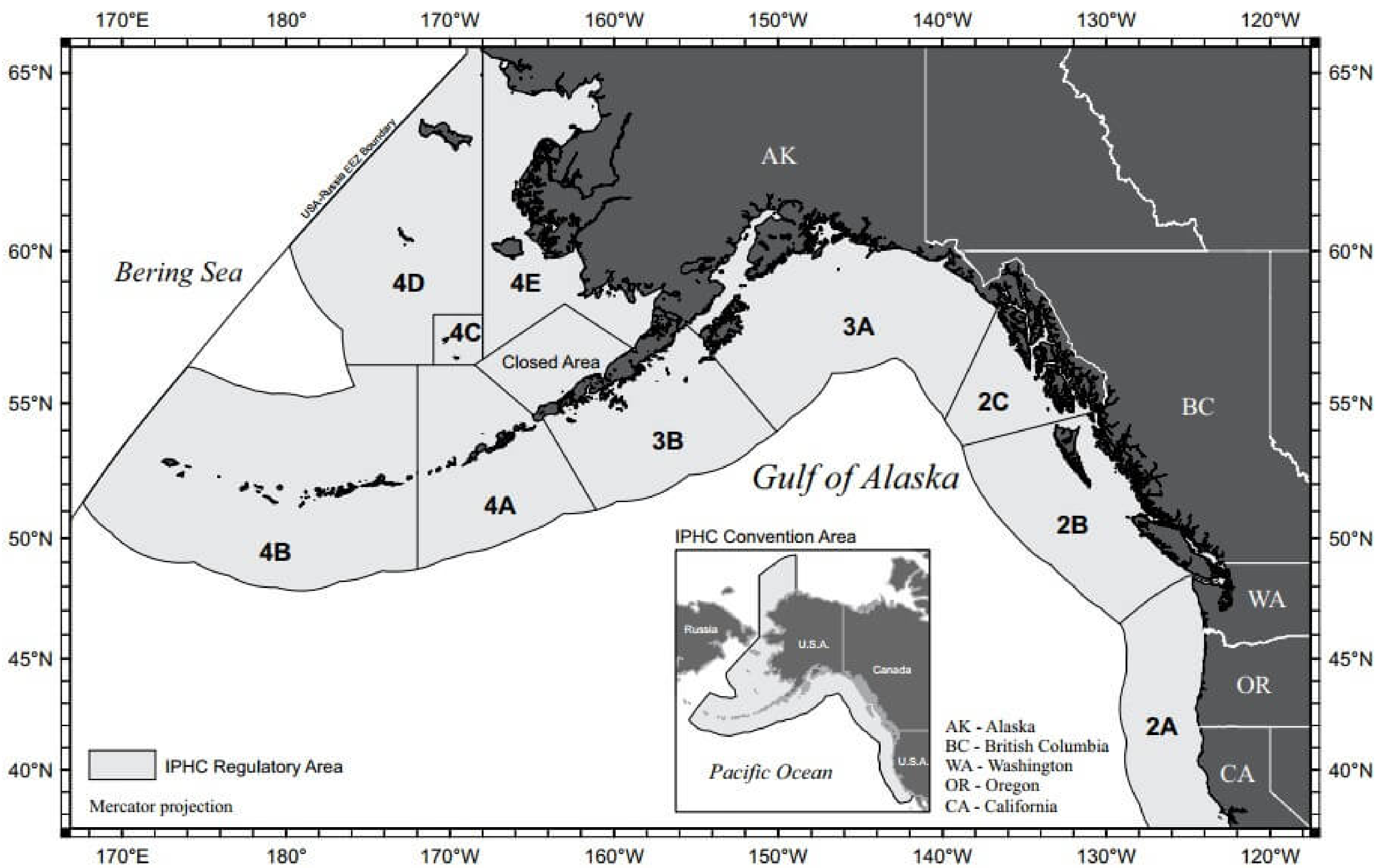


Figure 2.1 IPHC Regulatory Areas

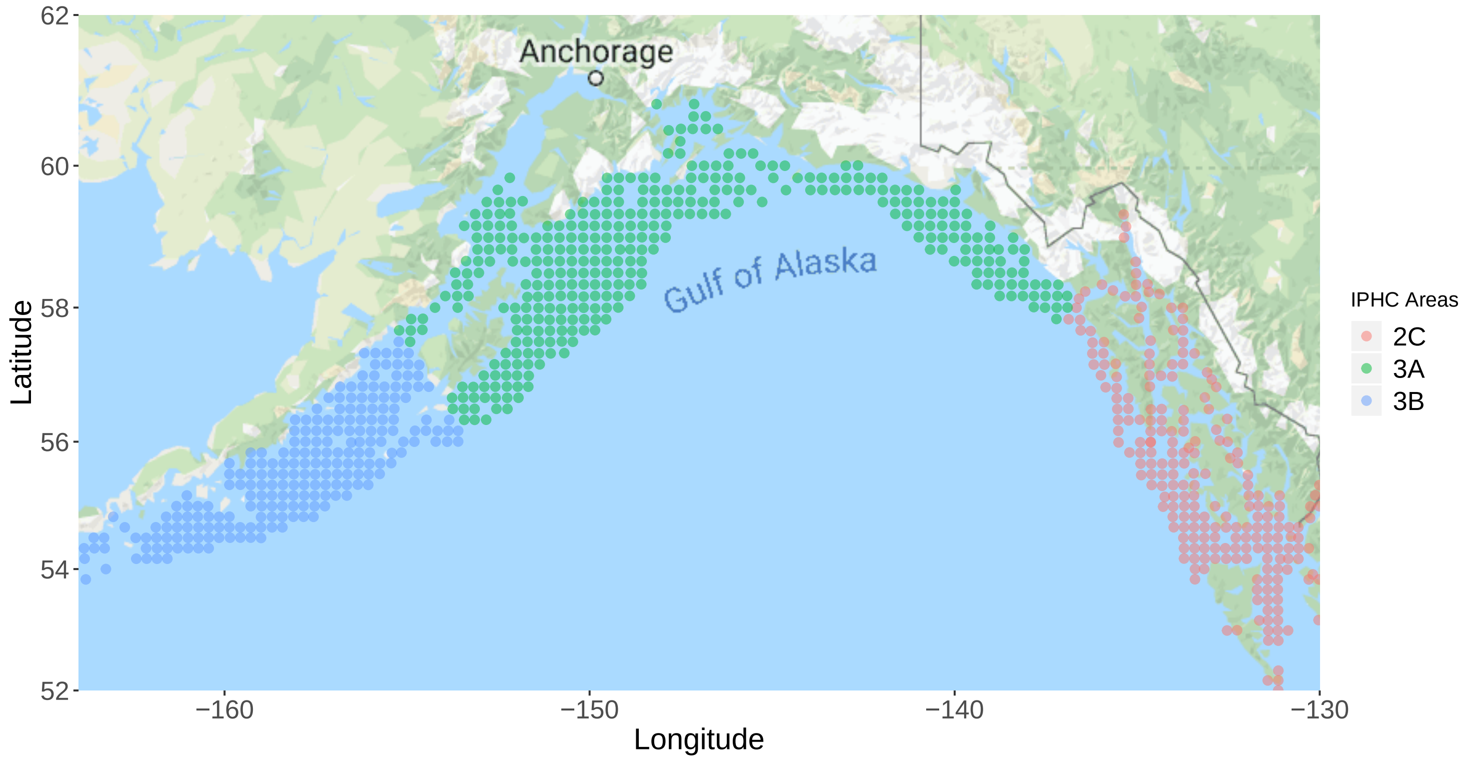


Figure 2.2 IPHC Setline Survey Station Locations for 3 areas

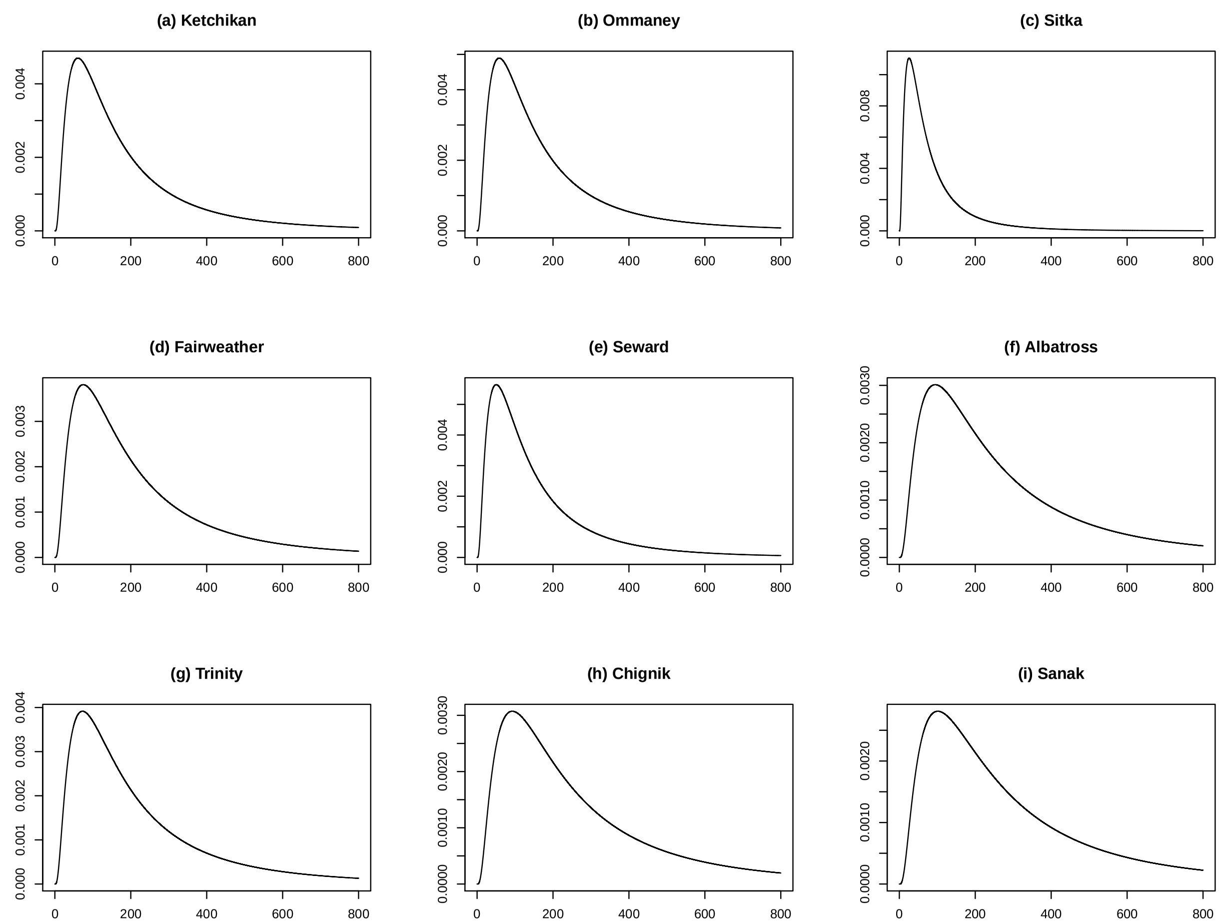


Figure 2.3 Objective CPS Distributions

Note: Figure shows objective (Log-normal) catch per skate distrbution by sub-region. Panels (a)-(c) are located in the IPHC region 2C; panels (d)-(f) are located in the IPHC region 3A; Panels (g)-(i) are located in the IPHC region 3B. Plots are for standard IPHC gear configuration of 5 skates of 1800 feet in length.

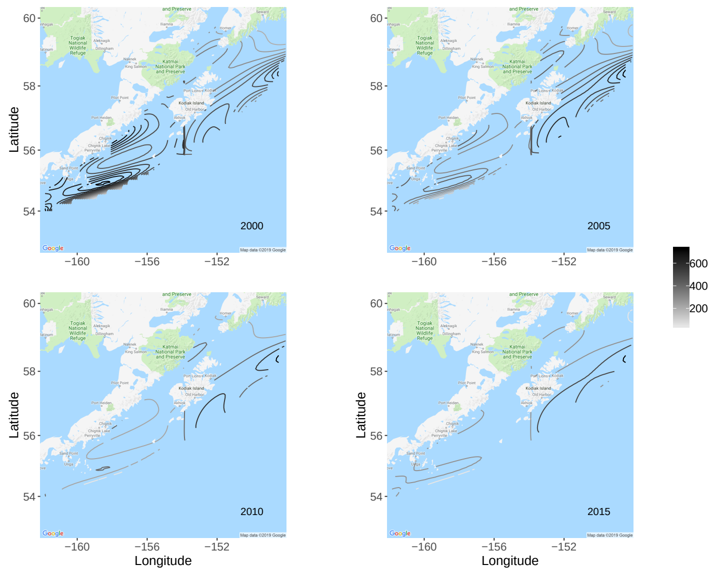


Figure 2.4 Contour Plots of Expected cps: First Week of July, 2007

Note: Darker contour line represents 50 pounds increase in expected cps of halibut during first week of July, 2007.

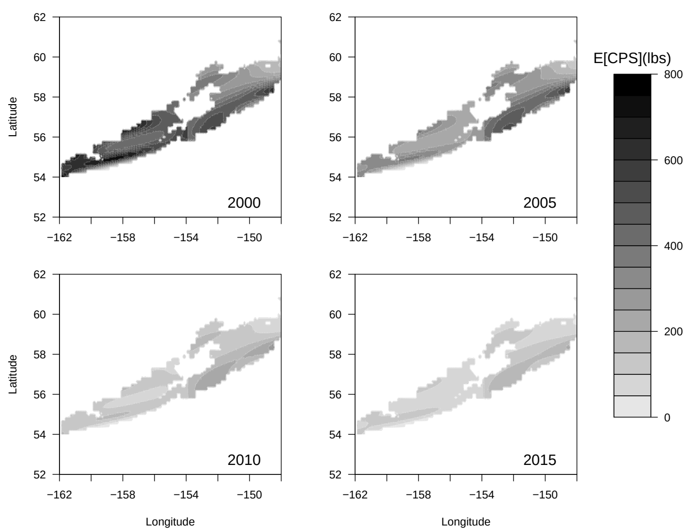


Figure 2.5 Filled Contour of Expected cps: First Week of July, 2007

Note: Darker contour shade fill represents 50 pounds higher expected cps of halibut during first week of July, 2007.

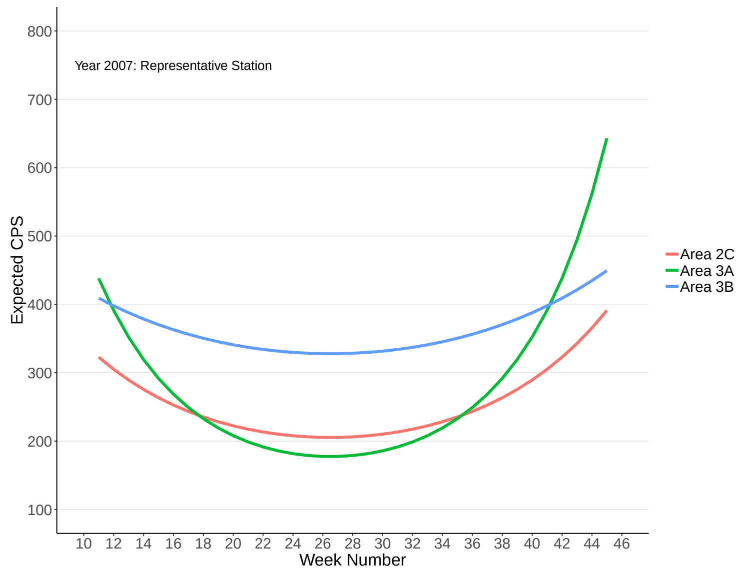


Figure 2.6 Seasonal Effects

Note: Figure shows within season variations in estimated mean cps for the representative station in the IPHC regions with standard IPHC gear configuration, mid-year 2007.

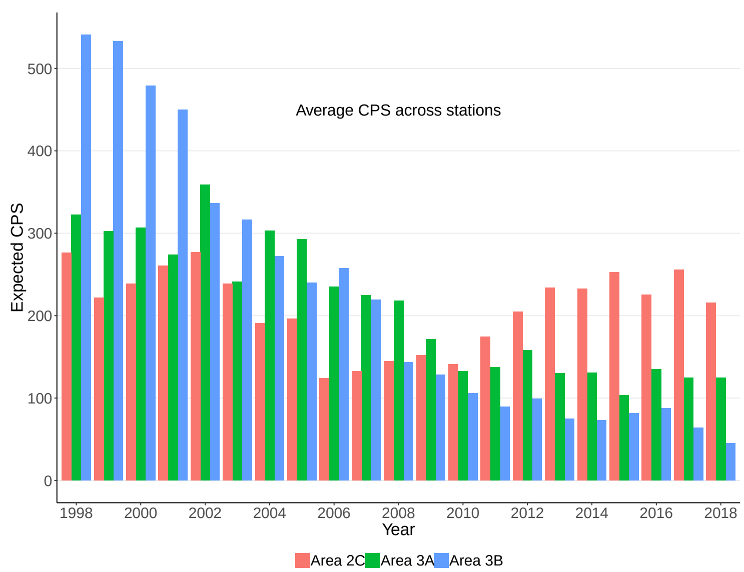


Figure 2.7 Mean CPS of Region: Years 1998-2018

Note: Figure shows estimated mean cps across all IPHC stations in the IPHC region with standard IPHC gear configuration, from 1998-2018.

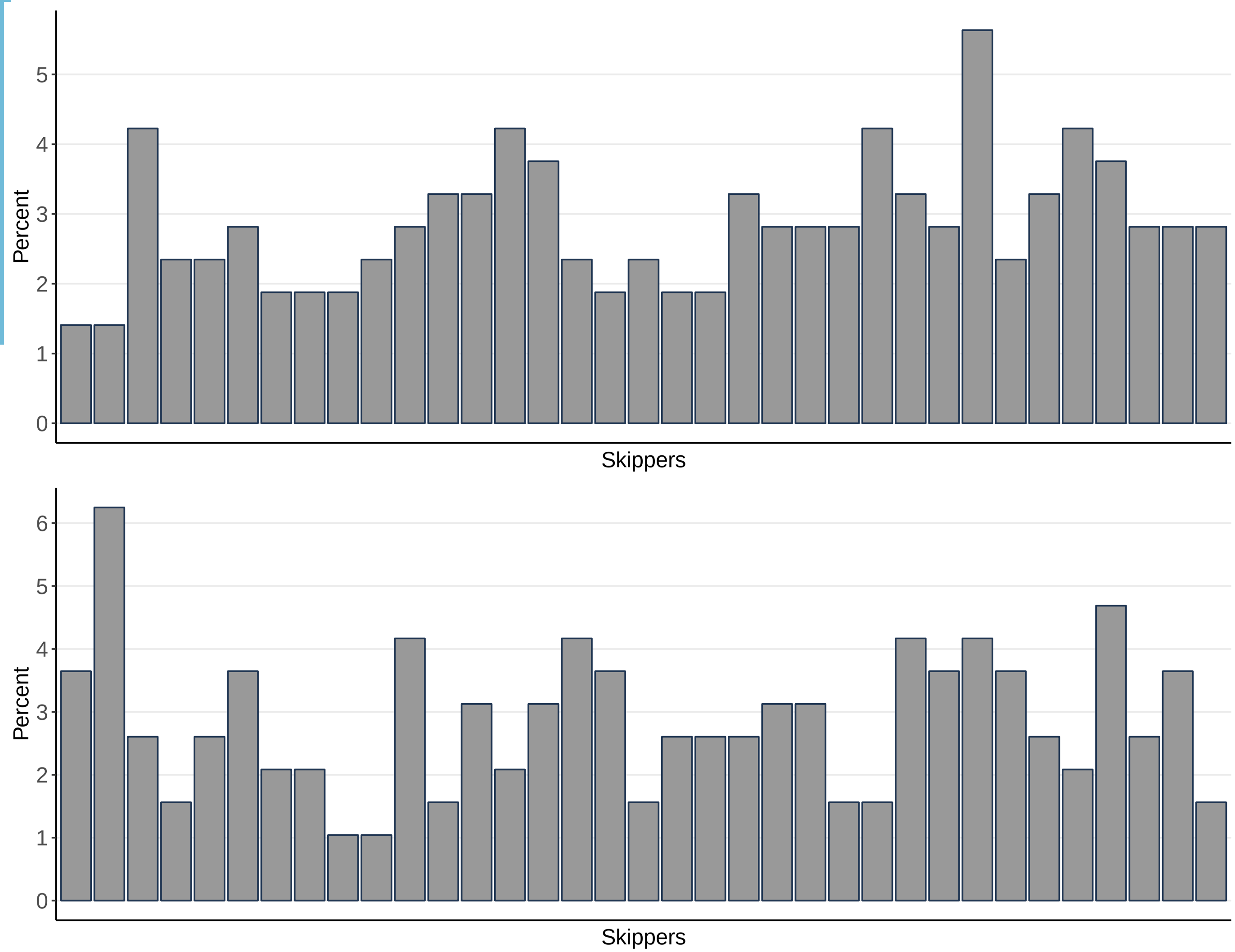


Figure 2.8 Percentage of Trips by Skippers

Note: Top panel is for Year 2006 and Bottom panel is for Year 2007. Each beam represents a skipper.

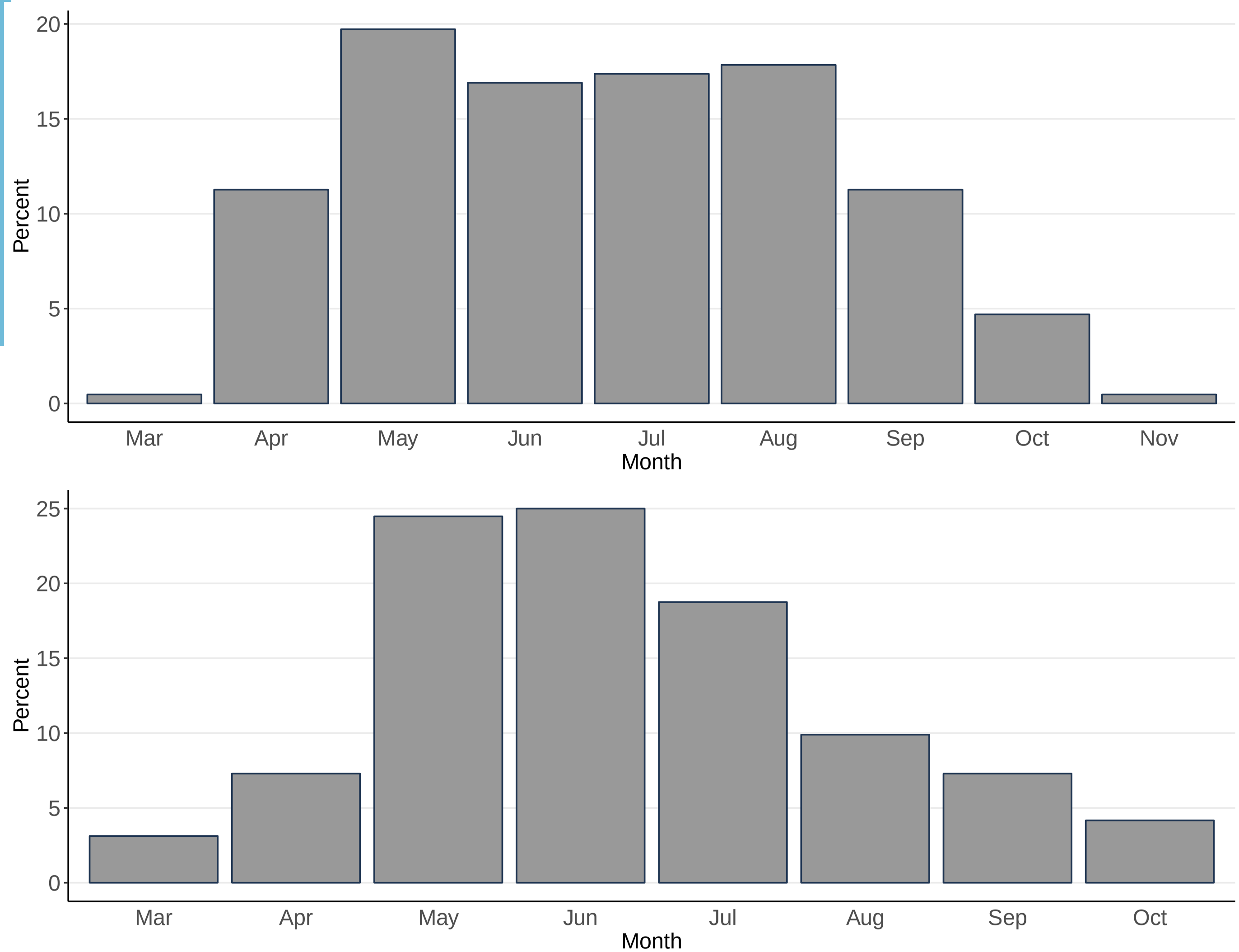


Figure 2.9 Percentage of Trips by Months

Note: Top panel is for Year 2006 and Bottom panel is for Year 2007.

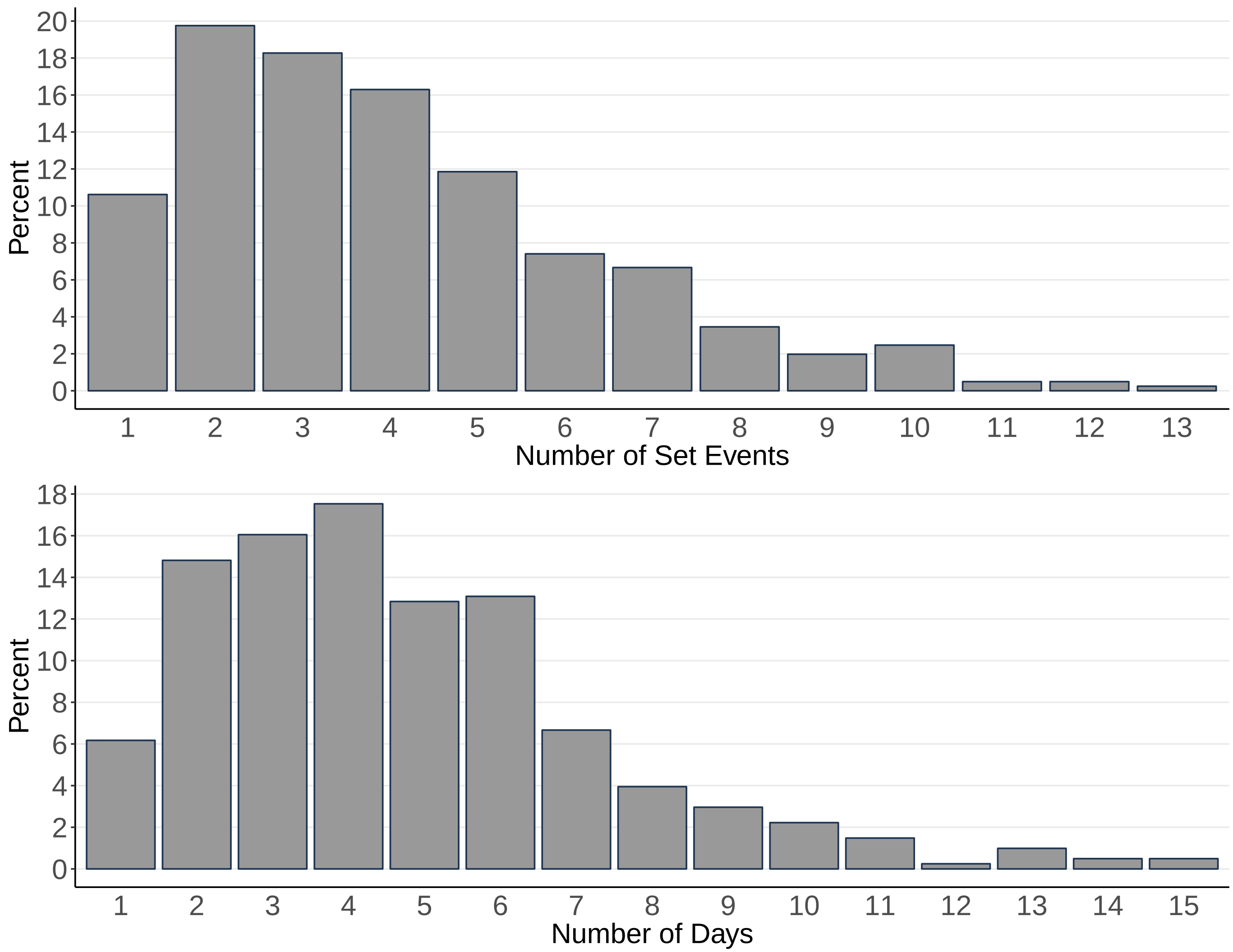


Figure 2.10 Working Hours on a Trip

Note: Top panel is number of set events and Bottom panel is for number of days on a trip respectively.

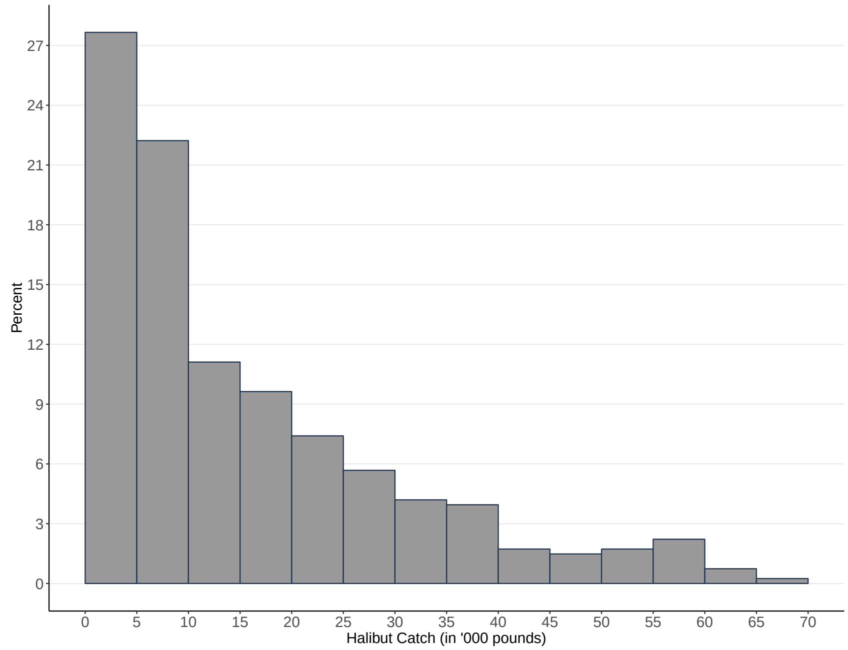


Figure 2.11 Halibut Catch Variation

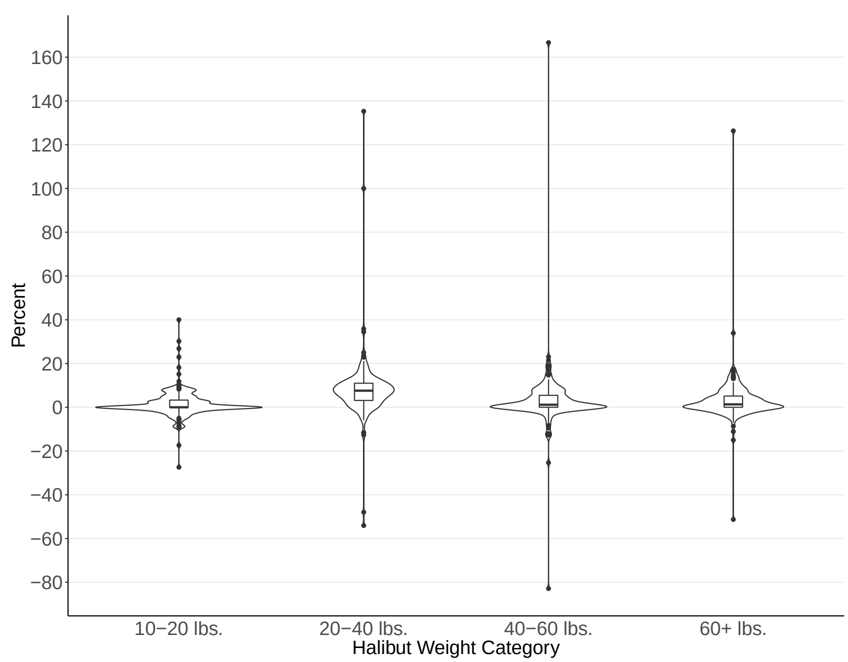


Figure 2.12 Price Deviation Percent

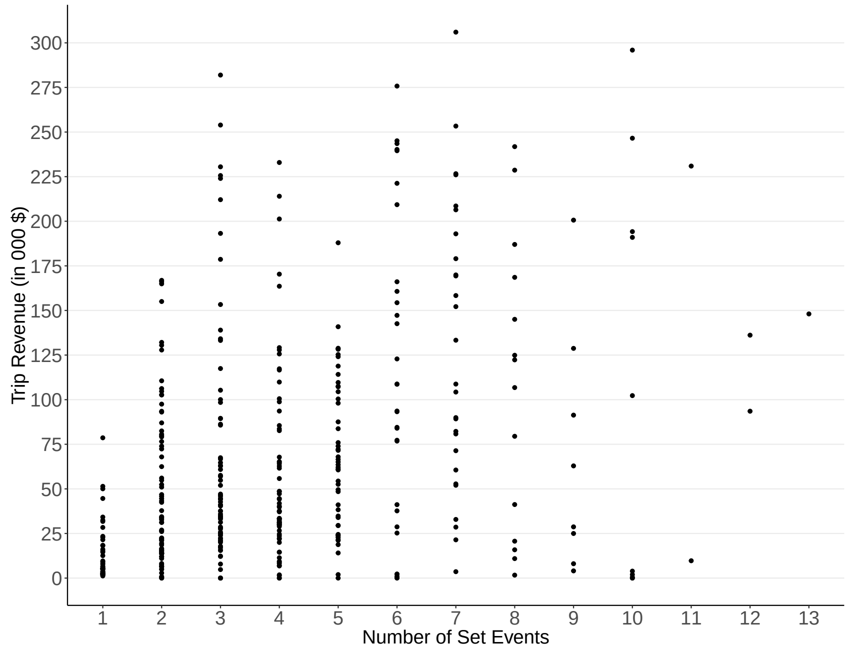


Figure 2.13 Set Events and Revenue

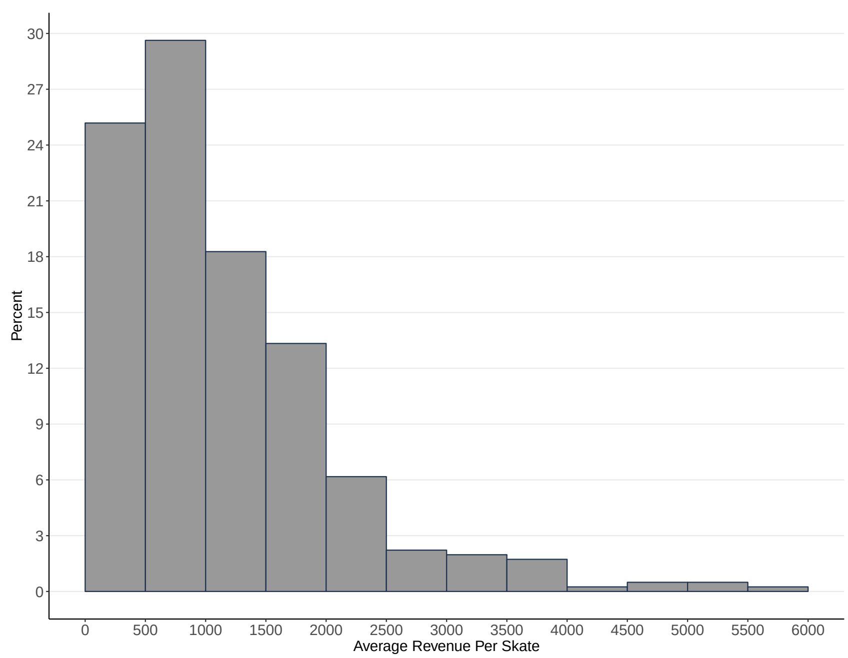


Figure 2.14 Revenue per Skate

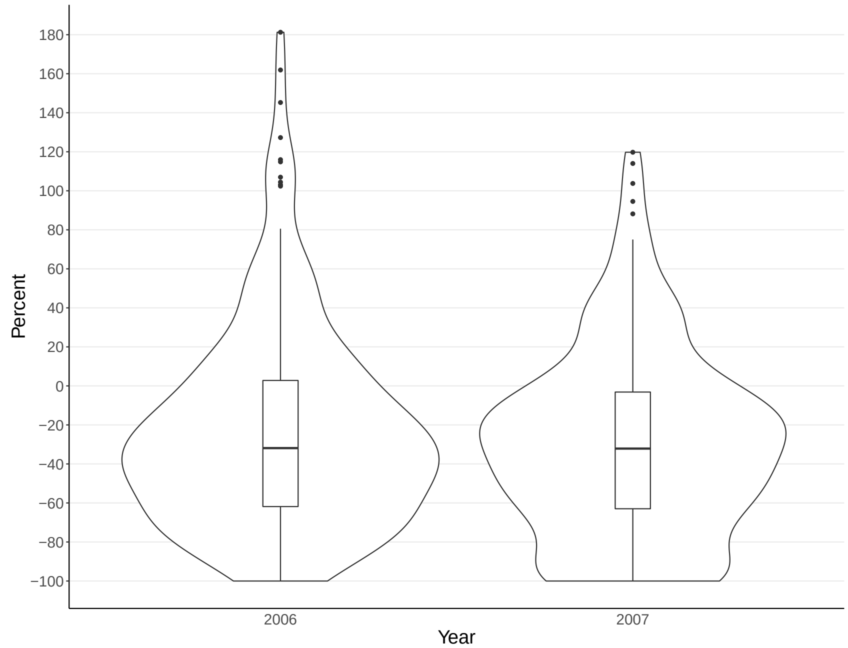


Figure 2.15 Revenue per Skate Deviation Percent

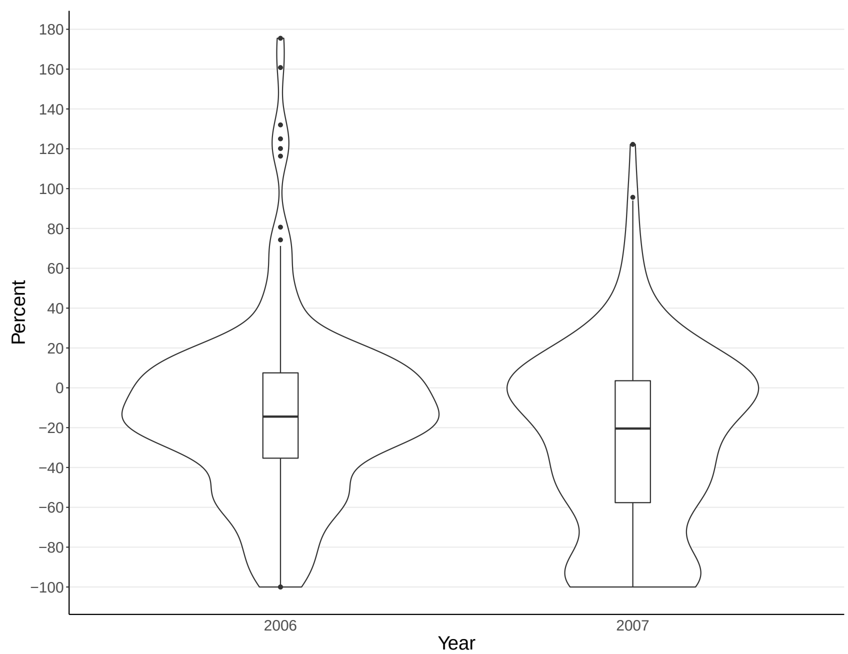


Figure 2.16 Revenue Deviation Percent

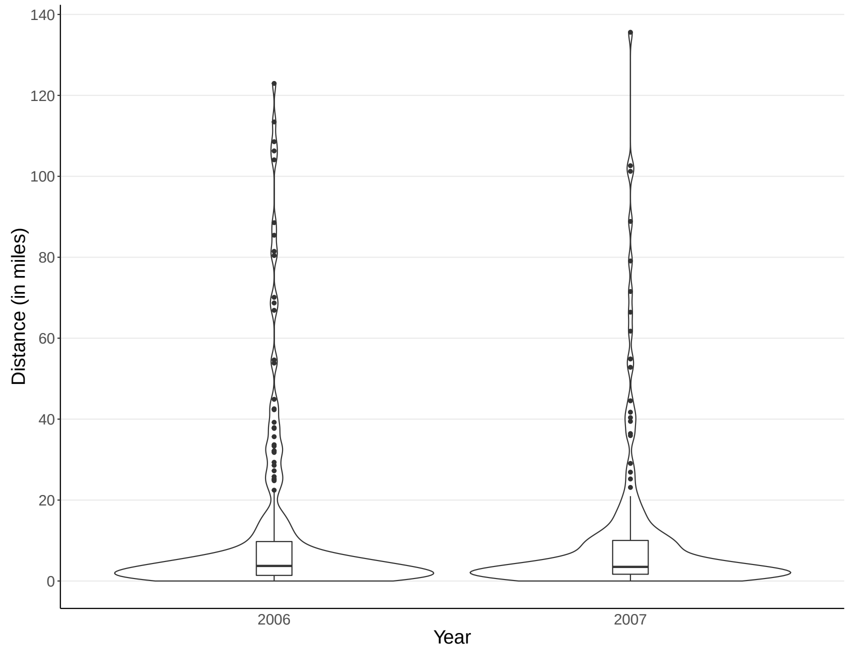


Figure 2.17 Distance from Desired Location

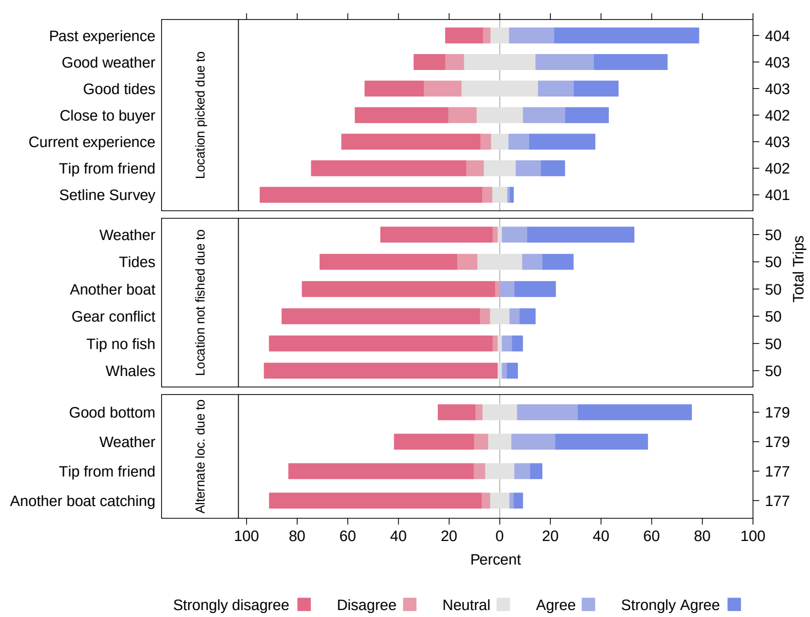


Figure 2.18 Likert Scale Responses for First Location Choice

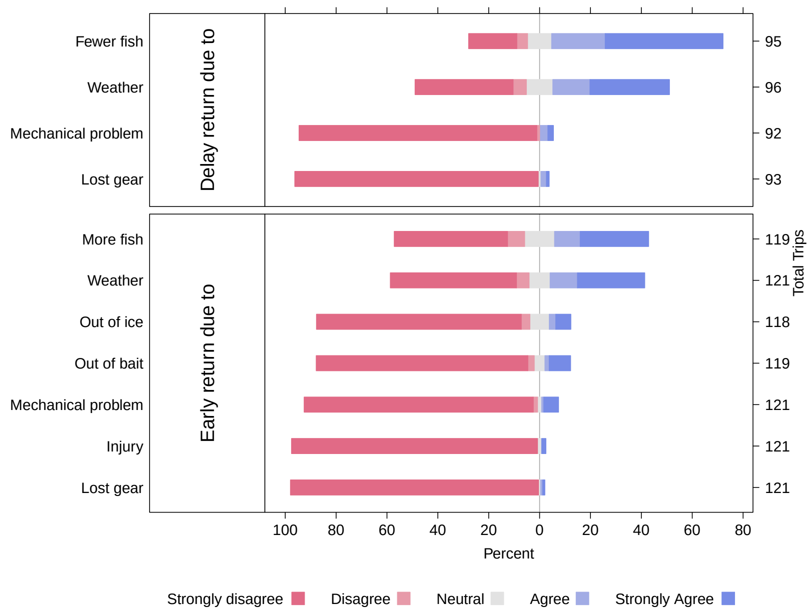


Figure 2.19 Likert Scale Responses for Trip Length

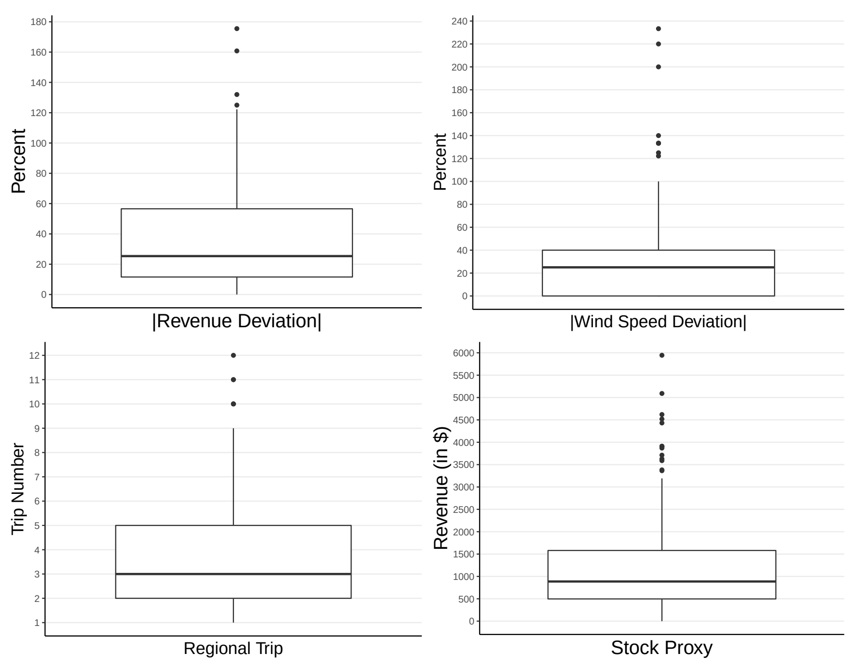


Figure 2.20 Outlier Detection

## 2.10 References

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# CHAPTER 3. ARE LABOR SUPPLY DECISIONS NEOCLASSICAL OR REFERENCE-DEPENDENT? EVIDENCE FROM THE ALASKAN HALIBUT FISHERY

Modified from a manuscript to be submitted to *Journal of Environmental Economics and Management*

Somenath Bera[1]

## 3.1 Abstract

Do people work more hours when paid a higher wage? In a setting in which the wage increase is transitory (implying, income effects are trivial), neoclassical theory suggests the answer is, yes. Yet, most classic studies reveal a statistically-weak (or even negative) relationship between wage and labor supply, suggesting the possibility of "backward bending" labor supply. A competing reference-dependence model of labor supply has also been proposed and tested. This theory relies on variation in gain or loss of utility based off deviations from a reference point – pre-set income targets – that incentivize shorter work hours when wages are high. Testing the latter theory is not without problems because these targets are seldom observed, and hence have to be approximated using measures of expected income which, in turn, introduce endogeneity concerns. In this paper, I directly test both theories using privately collected data from commercial fishing trips in the Alaskan halibut fishery. This is a setting where fishermen are able to freely adjust their labor supply in response to exogenous, natural variation in catch productivity, my proxy for the wage rate. Moreover, my data set contains explicit information on fishermen-specific, self-reported income targets, expected wage, catch, and revenue for each trip. My results, from a non-linear Poisson regression framework, reveal that fishermen respond negatively to transitory wage changes,

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a behavior inconsistent with neoclassical predictions. Additionally, the observed negative relationship between hours and wages when income is less than target cannot be explained by the linear gain-loss formulation of reference-dependent preferences. I find compelling evidence of non-linear income targeting which is more pronounced among experienced fishermen. My results suggest that traditional welfare analyses of wage-taxation policies which rely heavily on the wage elasticity of labor supply may need to be revised.

## 3.2 Introduction

What is the effectiveness of financial motivation in workplaces? Do people work more hours when paid a higher wage? In a setting in which the wage increase is transitory (implying, income effects are trivial), neoclassical labor supply theory suggests the answer is, yes. Workers substitute leisure for labor as they see the wage increase as raising marginal benefit from working an extra hour with no change in marginal cost in terms of lost leisure. Simultaneously, as the wage increase is transitory, there is a negligible change in the lifetime income; hence, the workers do not feel richer and demand more leisure, implying insignificant income effects. Recently, researchers have presented a contrarian view: workers may have an income target at the back of their minds, and any wage increase gets them to their target faster and hence may decrease work hours. This is the reference-dependent theory of labor supply.

So which is it, do people work more or fewer hours when the wage rate goes up? Is the elasticity of labor supply with respect to the wage – wage elasticity, for short – positive or negative? The question is not arcane: Understanding the determinants of labor supply is key to understanding every facet of the workplace, how to design it efficiently, how to motivate workers, and so on. At a macro level, it is the first step in the design of a country's tax and transfer programs. In this paper, I use a novel data set on the labor supply of fishermen from the Alaskan halibut fishery to test both the neoclassical and the reference-dependent theories.

There are three important econometric challenges that the literature has had to grapple with. First, most people have very little control over the hours they work – most work in 9-5 jobs. This is why the literature has had to focus their attention on the labor supply decisions of owner-operators such as cab drivers, bike messengers, stadium vendors and the like. Second, in many instances, the change in the wage rate is strictly speaking, not exogenous. For example, cab drivers may get more or less business depending on how many taxicabs are on the street. And third, the literature has trouble with mismeasurement of work hours or income targets. In the case of cabs, for example, the data cannot separate breaks or lulls in work. Similarly, the actual target is never observed; proxies are used, and many untested assumptions underlie their use. In this paper, I use a unique data set on the correctly-measured labor supply of autonomous workers responding to natural wage variations to empirically test both these theories.

The analysis of labor supply behavior for workers who can freely choose their hours has received much attention in the past two decades, starting with the seminal work of Camerer et al. (1997). Much of this research focused on taxi driver's data, where Camerer et al. (1997), Chou (2002), and Schmidt (2017) reported statistically significant negative wage elasticity but Farber (2015) found positive wage elasticity. Alternatively motivated by Farber (2005), papers have bypassed elasticity estimation and modeled driver's decision to continue or stop working for the day after ending a trip. Here too, the evidence is inconclusive: Farber (2005) and Farber (2015) supported neoclassical theory, Martin (2017) inclined to reference dependent labor supply, while Thakral and Tô (2017) found evidence against both of the theories. In another recent work, Stafford (2015) noted the endogeneity of wage and measurement error in hours for taxi data and reported a positive wage elasticity among fishermen. However, Hammarlund (2018) pointed out the non-constant wage during a fishing trip and used stopping the probability model to provide evidence for revenue targeting behavior among fishermen. However, direct testing of reference-dependent preferences is problematic as the target is seldom observed.

In this paper, I use privately collected data on the labor supply of commercial fishermen from Alaskan Halibut fishery to estimate the wage elasticity of labor supply. The distinguishing feature of the data set is that I observe fisherman's trip specific target which allows direct testing of reference-dependent preferences. From logbook records of fishing trips, I also observe the number of hours fishermen decided to work and the corresponding productivity during the trip, my proxy for wages. There is natural variation in the productivity conditions across trips, providing transitory wage changes. The results from a non-linear Poisson regression framework, reveal that fishermen respond negatively to transitory wage increases, behavior inconsistent with neoclassical predictions. Additionally, the observed negative relationship between hours and wages when income is away from the target cannot be explained by the linear gain-loss formulation of reference-dependent preferences. I find compelling evidence of non-linear income targeting behavior which is notably stronger for experienced fishermen.

The paper is organized as follows: Section 3.3 provides the background on the two competing theories of labor supply. After establishing neoclassical theory predictions, I generalize the Farber (2015) model of linear reference dependence. Section 3.4 summarizes findings of the literature from analyzing data from field experiments, taxi, and fisheries. The empirical model of labor supply for fishermen and the estimation strategy is discussed in section 3.5. The testable hypotheses arising from the theoretical models are noted in section 3.6. Section 3.7 describes the data set and section 3.8 presents estimates of wage elasticity of labor supply, and interpret the results. Finally, section 3.9 concludes and notes future research topics.

## 3.3 Competing Theories of Labor Supply

This section summarizes the individual labor supply models rooted in neoclassical theory and reference-dependent preferences. The theoretical predictions of the models from the two backgrounds have stark differences. The neoclassical theory states a positive relationship between transitory wage changes and labor supply due to the negligible income effect. On the other hand, a reference-dependent labor supply could decrease with an increase in wage rate due to targeting behavior. Numerous studies have estimated the labor supply responses to wage changes, providing evidence of which model better approximates the real world behavior. In order to interpret the estimates correctly, I discuss the theoretical models here. I begin with the one-period static neoclassical model and then extend it to a $T$ period intertemporal labor supply model. Next, I discuss different notions of wage elasticities of labor supply and their estimation depending on the assumptions and controls used in the econometric specification. Finally, the recently introduced competing model of labor supply based reference-dependent preferences are discussed.

### 3.3.1 Static Model

The starting point of the labor supply model[2] is the standard static within-period labor supply model which is grounded on consumer theory. The model assumes an individual has a quasi-concave utility function, $U(C,\ L)$, defined over $C$, consumption of goods and $L$, leisure. Given the total time at disposal, $L_0$ hours; then the length of time worked, $h$ hours, is given by $h = L_0 - L$. The utility function is increasing in both arguments and consumer desires to consume the highest quantity of goods and leisure.

An individual earns income from labor supplied in the market and from other non-labor sources like an investment and transfer income. Assume the real hourly wage be, $w$, and the non-labor income is $B$. Then the budget constraint of the agent can be expressed as $C \leq wh + B$. The constraint is also expressed as $C + wL \leq \overline{B} \equiv wL_0 + B$, resembling utility maximization problem of consumer theory. Hence in this set up the agent disposes of a potential income, $\overline{B}$, obtained by working $L_0$ hours, into buying two goods: consumption and leisure. The wage rate, $w$, serves as the price and the opportunity cost of leisure. The problem of the agent is then given as:

$$\max_{C,L} \quad U(C,L) \quad \text{subject to} \quad C + wL \leq \overline{B} \tag{3.1}$$

I focus on the interior solutions, where, $0 < L < L_0$ and $C > 0$.

The Lagrangian of the problem stated in (3.1) is :

$$\mathcal{L} = U(C,L) + \lambda(\overline{B} - C - wL) \tag{3.2}$$

The first order conditions are expressed as :

$$U_C(C,L) - \lambda = 0 \quad \text{and} \quad U_L(C,L) - \lambda w = 0 \tag{3.3}$$

[2] See Blundell and MaCurdy (1999); Cahuc et al. (2014) for more details.

where $U_C$ and $U_L$ denotes the partial derivatives of the function $U$ with respect to $C$ and $L$ respectively. Positive partial derivatives implies the budget constraint binds and $\lambda > 0$, which is the marginal utility of income. Hence from the first order conditions of (3.3), the optimal solution $(C^*, L^*)$ is given by:

$$\frac{U_L(C^*, L^*)}{U_C(C^*, L^*)} = w \quad \text{and} \quad C^* + wL^* = \overline{B} \tag{3.4}$$

That is, the Marshallian demand functions are:

$$C = C(w, \overline{B}) \quad \text{and} \quad L = L(w, \overline{B}) \tag{3.5}$$

The optimal labor supply hours can be obtained from $h^* = L_0 - L^*$. Replacing the full potential income, $\overline{B}$, in terms of $B$, I can express optimal labor hours or the Marshallian labor supply as,

$$h = h(w, B) \tag{3.6}$$

as function of wage and non-labor income.

The impact of a variation in wages on demand for leisure is obtained by differentiating $L(w, \overline{B})$ with respect to w to get:

$$\frac{dL^*}{dw} = \frac{\partial L^*}{\partial w} + \frac{\partial L^*}{\partial \overline{B}} L_0 \tag{3.7}$$

The term $\frac{\partial L^*}{\partial w}$ corresponds to the substitution effect (SE), and term $\frac{\partial L^*}{\partial \overline{B}} L_0$ corresponds to the income effect (IE) due to wage change. The sign of SE is always negative, and the sign of IE is always positive if leisure is normal good (calculations are shown in Appendix B). Hence, the total effect on leisure demand or hours supplied due to wage variation is ambiguous in the static one-period labor supply model. If the magnitude of SE is greater (smaller) than the magnitude of IE, then the wages and hours supplied are positively (negatively) related.

#### 3.3.1.1 CRRA utility: Static model

In order to understand under what conditions SE can dominate the IE in the static model, I use a constant relative risk aversion (CRRA) utility function of the following form:

$$U(C, L) = \frac{C^{1-\sigma}}{1-\sigma} + \frac{L^{1-\sigma}}{1-\sigma} \tag{3.8}$$

Maximizing equation (3.8) with the budget constraint $C+wL \leq \overline{B}$, yields the first order conditions as follows:

$$\left(\frac{L^*}{C^*}\right)^{-\sigma} = w \quad \text{and} \quad C^* + wL^* = \overline{B} \tag{3.9}$$

The Marshallian supply of hours are stated as:

$$h^* = L_0 - L^* = L_0 - \left(\frac{wL_0 + \overline{B}}{w^{\frac{1}{\sigma}} + w}\right) \tag{3.10}$$

I differentiate equation (3.10) by $h$ to get the variation in hours due to wage changes as:

$$\frac{dh^*}{dw} = -\left[\frac{(w^{\frac{1}{\sigma}} + w)L_0 - (wL_0 + \overline{B})(\frac{1}{\sigma}w^{\frac{1}{\sigma}-1} + 1)}{(w^{\frac{1}{\sigma}} + w)^2}\right] \tag{3.11}$$

If the value of $\sigma < 1$, which is the most prevalent value in the literature (Chetty, 2006), then the SE always dominates the IE irrespective of the non-labor income, $B$ (see Appendix B for details). The necessary condition for negative relationship between labor supply and wage rate or the backward-bending labor supply curve for CRRA type utility function is $\sigma > 1$. Even in that case, high enough wages are needed to generate backward bending part of labor supply. Hence, it is understood that under realistic parameter values the static one-period neoclassical model of labor supply predicts positive relationship between hours and wages.

The static model is a good approximation to reality if the agents are completely myopic or if the capital markets are completely constrained so that it is impossible to transfer capital across periods. To relax these stringent conditions, I discuss the intertemporal labor supply model where agents can save and substitute consumption of leisure over time when their flow of income undergoes transitory or permanent shocks.

### 3.3.2 Intertemporal Labor Supply

The intertemporal model of labor supply is based on the possibility of consumption of physical goods and leisure over time. Here a consumer must make his choices over the life cycle represented by a succession of periods that start with an initial date and end with an independent terminal date. Denote the time period by $t$, where $t = 0, 1, 2, \cdots, T$. The preferences of a consumer is represented by a time-separable utility function, $\sum_{t=0}^{T} U(C_t, L_t)$, where $C_t$ and $L_t$ are consumption of goods and leisure at $t$.

Next, I focus on how individual assets evolve over time. Let $A_t$ be consumer's asset at time $t$, $B_t$ be the non-labor income at time $t$, $r_t$ be the real interest rate between the periods $t-1$ and $t$. The total endowment of time for each period is an independent constant, so assume it to be 1 to simplify notation. Then labor supply at period $t$ is $h_t = 1 - L_t$. Further, let us assume $A_{-1} = 0$ and $B_0$ denote the initial wealth. The wage for time period $t$ is denoted by $w_t$. Then the evolution of assets of the consumer is given by:

$$A_t = (1 + r_t)A_{t-1} + B_t + w_t(1 - L_t) - C_t, \quad \forall t \geq 0 \tag{3.12}$$

which serves as the budget constraint. The objective of the consumer is to maximize the utility function $\sum_{t=0}^{T} U(C_t, L_t)$ subject to constraint (3.12).

The Lagrangian for the intertemporal problem can be stated as:

$$\mathfrak{L} = \sum_{t=0}^{T} U(C_t, L_t) + \sum_{t=0}^{T} \lambda_t \left[w_t(1 - L_t) + B_t + (1 + r_t)A_{t-1} - C_t - A_t\right] \tag{3.13}$$

Differentiate the Lagrangian with respect to $C_t$, $L_t$, and $A_t$; to get the first order conditions as

$$\begin{aligned} &U_C(C_t, L_t) = \lambda_t \quad \text{and} \quad U_L(C_t, L_t) = \lambda_t w_t \\ &\lambda_t = (1 + r_{t+1})\lambda_{t+1} \end{aligned} \tag{3.14}$$

Focusing only on the interior solutions, the optimal solutions for consumption of goods and leisure can be implicitly written as:

$$C_t^* = C(w_t, \lambda_t) \quad \text{and} \quad L_t^* = L(w_t, \lambda_t) \tag{3.15}$$

And the optimal supply of labor is $h_t = 1 - L(w_t, \lambda_t)$.

The implicit solutions in (3.15) implies that the labor supply in period $t$ depends on the current wage, $w_t$ and current Lagrangian multiplier, $\lambda_t$. Note that the Lagrangian multiplier, $\lambda_t$, is the marginal utility from the present value of income or wealth at period $t$. The first order condition in (3.14) with respect to $A_t$ can be rewritten to express the Lagrangian multiplier in period $t$ as a sum of individual effect and time effect common to all agents as (see Appendix B for derivation) :

$$\ln \lambda_t = \sum_{\tau=1}^{\tau=t} \ln(1 + r_\tau) + \ln \lambda_0 \tag{3.16}$$

This way of writing the current Lagrangian multiplier proves to be extremely useful in empirical estimation, which I discuss later.

Using equation (3.16), re-express the optimal leisure demand as:

$$L_t^* = L(w_t, \lambda_0, t) \tag{3.17}$$

The variation in labor supply due wage changes in the intertemporal model is given by:

$$\frac{dL_t^*}{dw_t} = \frac{\partial L^*}{\partial w_t} + \frac{\partial L^*}{\partial \lambda_0} \cdot \frac{\partial \lambda_0}{\partial w_t} \tag{3.18}$$

Assuming leisure is a normal good, $\left(\frac{\partial L^*}{\partial w}\right)$, the usual substitution effect to be negative[3]. However, the strength of income effect, $\left(\frac{\partial L^*}{\partial \lambda_0} \cdot \frac{\partial \lambda_0}{\partial w_t}\right)$ depends on the type of wage change whether transitory or permanent and anticipated or unanticipated. To see this, I first acknowledge that $\lambda_0$, the marginal utility of present value of income at the beginning of life cycle, $t = 0$, would depend on all wages received during the lifetime. I explicitly demonstrate this dependence using a 3 period CRRA utility function later.

A transitory wage change is defined as a wage change in period $t$ that is effective only for a period of $t$. A permanent wage change is defined as a wage change in period $t$ that is effective for the rest of the lifetime. Anticipated wage changes do not affect $\lambda_0$, whereas unanticipated wage changes have a negligible effect, if transitory, but substantial, if permanent. Hence, the intertemporal labor supply model states a positive relationship between transitory wage changes, either anticipated or unanticipated and labor supply. It also predicts a positive relationship between hours and anticipated permanent wage changes but the ambiguous relationship between hours and unanticipated permanent wage variations. These relationships are shown with an example of a 3 period CRRA utility function later. In this perspective, the intertemporal model is capable of distinguishing between the impacts of transitory and permanent wage changes, which the static model could not handle.

[3]See Heckman (1974) for exact derivation.

#### 3.3.2.1 Wage elasticities of labor supply

In the intertemporal model, three types of wage elasticities are well defined: Frischian, Marshallian, and Hicksian. Frischian elasticity measures the impact in a variation of wage at period $t$ on the labor supply at period $t$, assuming the present value of lifetime wealth remains constant or in other words, the marginal utility from wealth at period $t$, $\lambda_t$ remains constant. That is, Frischian wage elasticity measures the phenomenon of intertemporal substitution: it indicates the amount by which agents are willing to modify today's labor as a response to changes in today's wage, knowing the present value of lifetime wealth remains unchanged. This notion of elasticity is essential for measuring the impact of transitory variation in wages, either anticipated or unanticipated. For transitory anticipated changes in wage, there is no income effect as this wage change was expected and was already taken into account while calculating the present value of lifetime wealth. On the other hand for unanticipated transitory changes in wage, there is an income effect as the wage change was not known at the beginning of the optimization problem at $t = 0$ and realizing the modified wage at period $t$ changes the marginal utility of wealth at period $t$, $\lambda_t$ and also changes $\lambda_0$ using the equation (3.16). However, for a sufficiently large terminal period, $T$, the change in $\lambda_t$ due to one period's transitory unanticipated wage change is small and hence negligible.

Marshallian wage elasticity measures the total impact of wage variations on labor supply taking into account the changes in lifetime wealth. This type of elasticity is essential for measuring the impact on labor supply due to permanent unanticipated wage changes where the associated income effects are substantial, hence not negligible. Lastly, the Hicksian wage elasticity measures the variation in labor supply, assuming the intertemporal utility remains constant.

I will focus here on studying the Frischian wage elasticity. Under the neoclassical framework, for transitory changes (anticipated or unanticipated) in wage, the income effect is absent or negligible, leaving only the substitution effect to influence labor supply. Hence, for a transitory (anticipated or unanticipated) increase in wage, by substitution effect, the demand for leisure falls, and labor supply increases. That is, the neoclassical intertemporal labor supply model predicts a positive estimate of Frischian elasticity or intertemporal substitution.

#### 3.3.2.2 CRRA utility: Dynamic model

In order to demonstrate the impact of labor supply due to transitory anticipated and unanticipated wage change, I use a three period, $t = 0, 1, 2$ CRRA utility function. For simpler notation, assume total endowment of time in each period to be 1, constant real interest rate for all periods, that is $r_t = r \; \forall \; t$, and $A_{-1} = 0$. Since the terminal date of the problem is $t = 2$, so the agent has no savings for $t = 3$.

The Lagrangian of the associated problem is as follows:

$$\begin{aligned} \mathscr{L} = \frac{C_0^{1-\sigma}}{1-\sigma} + \frac{L_0^{1-\sigma}}{1-\sigma} + \beta\frac{C_1^{1-\sigma}}{1-\sigma} + \beta\frac{L_1^{1-\sigma}}{1-\sigma} + \beta^2\frac{C_2^{1-\sigma}}{1-\sigma} + \beta^2\frac{L_2^{1-\sigma}}{1-\sigma} \\ + \lambda_0[B_0 + w_0(1 - L_0) - C_0 - A_1] + \lambda_1[(1 + r)A_1 + B_1 + w_1(1 - L_1) - C_1 - A_2] \\ + \lambda_2[(1 + r)A_2 + B_2 + w_2(1 - L_2) - C_2] \end{aligned} \tag{3.19}$$

First order conditions with respect to $C_0$, $C_1$, and $C_2$ are as follows:

$$C_0^{-\sigma} = \lambda_0 \quad \text{and} \quad \beta C_1^{-\sigma} = \lambda_1 \quad \text{and} \quad \beta^2 C_2^{-\sigma} = \lambda_2 \tag{3.20}$$

First order conditions with respect to $L_0$, $L_1$, and $L_2$ are as follows:

$$L_0^{-\sigma} = \lambda_0 w_0 \quad \text{and} \quad \beta L_1^{-\sigma} = \lambda_1 w_1 \quad \text{and} \quad \beta^2 L_2^{-\sigma} = \lambda_2 w_2 \tag{3.21}$$

First order conditions with respect to $A_1$ and $A_2$ are as follows:

$$\lambda_0 = (1 + r)\lambda_1 \quad \text{and} \quad \lambda_1 = (1 + r)\lambda_2 \tag{3.22}$$

From the equations in (3.20):

$$C_t = \left(\frac{\beta^t}{\lambda_t}\right)^{\left(\frac{1}{\sigma}\right)} \quad , \; t = 0, 1, 2 \tag{3.23}$$

From the equations in (3.21):

$$L_t = \left(\frac{\beta^t}{\lambda_t w_t}\right)^{\left(\frac{1}{\sigma}\right)} \quad , \; t = 0, 1, 2 \tag{3.24}$$

And the associated labor supply function is:

$$h_t = 1 - L_t = 1 - \left(\frac{\beta^t}{\lambda_t w_t}\right)^{\left(\frac{1}{\sigma}\right)} \quad , \; t = 0, 1, 2 \tag{3.25}$$

From the equations in (3.22), express the Lagrangian multiplier at period $t$ as function of period $t = 0$ multiplier and common time effect as follows:

$$\lambda_t = \frac{\lambda_0}{(1+r)^t} \tag{3.26}$$

Hence, the Marshallian demands for consumption of goods and leisure are a function of current wage and Lagrangian multiplier. The Lagrangian multiplier serves as the sufficient statistic which summarized relevant information from all other periods. Using the relationship in (3.26) in (3.23) and (3.24), express the optimal demands as a function of current wage and period $t = 0$ Lagrangian multiplier:

$$C_t = \left[\tfrac{\beta^t(1+r)^t}{\lambda_0}\right]^{\frac{1}{\sigma}} \quad \text{and} \quad L_t = \left[\tfrac{(\beta(1+r))^t}{w_t\lambda_0}\right] \quad \text{where } t = 0,1,2 \tag{3.27}$$

The expression of $C_t$ and $L_t$ as a function of $w_t$ and $\lambda_0$ helps to see how $\lambda_0$ depends on all wages of the agent's lifetime. The budget constraints for the above problem are related through savings $A_1$ and $A_2$. So rewrite the 3 budget constraints in present value form by substituting $A_2$ and $A_1$ in the budget constraint of $t = 2$, to get:

$$C_0 + \frac{C_1}{1+r} + \frac{C_2}{(1+r)^2} = w_0h_0 + \frac{w_1h_1}{(1+r)} + \frac{w_2h_2}{(1+r)^2} + B_0 + \frac{B_1}{1+r} + \frac{B_2}{(1+r)^2} \tag{3.28}$$

Substituting the values of $C_t$ and $L_t$ from (3.27) in to the present value budget constraint:

$$\begin{aligned}\left(\frac{1}{\lambda_0}\right)^{\frac{1}{\sigma}} + \left(\frac{1}{1+r}\right)\left(\frac{\beta(1+r)}{\lambda_0}\right)^{\frac{1}{\sigma}} + \left(\frac{1}{(1+r)^2}\right)\left(\frac{\beta^2(1+r)^2}{\lambda_0}\right)^{\frac{1}{\sigma}} = \\ w_0\left(1 - \left(\frac{1}{w_0\lambda_0}\right)^{\frac{1}{\sigma}}\right) + w_1\left(1 - \left(\frac{\beta(1+r)}{w_1\lambda_0}\right)^{\frac{1}{\sigma}}\right) + w_2\left(1 - \left(\frac{\beta^2(1+r)^2}{w_2\lambda_0}\right)^{\frac{1}{\sigma}}\right) + \\ B_0 + \frac{B_1}{1+r} + \frac{B_2}{1+r}\end{aligned} \tag{3.29}$$

The Lagrangian multiplier at $t = 0$, $\lambda_0$ is implicitly defined by the equation (3.29) and it depends on all wages received by the agent during his lifetime and other model parameters.

**Anticipated transitory wage change:** Let us assume, there is anticipated wage increase in $t = 1$. This increase in wage was anticipated so was already accounted in calculation of total wealth at the beginning of the problem and the value of $\lambda_0$ can be considered as a constant. Then to find the impact in hours in $t = 1$ due to anticipated transitory wage change in $t = 1$, differentiate the optimal labor supply function in (3.27) with respect to $w_1$ to get:

$$\frac{dL_1}{dw_1} = \left(\frac{\beta(1+r)}{\lambda_0}\right)^{\frac{1}{\sigma}} \left(-\frac{1}{\sigma}\right) w_1^{-\frac{1}{\sigma}-1} < 0 \tag{3.30}$$

Hence anticipated transitory wage increase (decrease) results in decrease (increase) in leisure demand or increase (decrease) in labor supply.

**Unanticipated transitory wage change:** Assume that there is unanticipated transitory increase in wage in $t = 1$. As this change was unknown at $t = 0$, so it was not included in calculation of $\lambda_0$. Once the time period $t = 1$ arrives, the news of wage increase arrives and agent updates $\lambda_1$ which in turn updates $\lambda_0$ through the euler equation (3.26). As unanticipated transitory wage increase impacts $\lambda_1$ directly so start with the leisure demand in equation (3.24) for $t = 1$ and differentiate with respect to $w_1$:

$$\frac{dL_1}{dw_1} = -\frac{\beta^{\frac{1}{\sigma}}}{\sigma} w_1^{-\frac{1}{\sigma}-1} \lambda_1^{-\frac{1}{\sigma}} - \frac{\beta^{\frac{1}{\sigma}}}{\sigma} w_1^{-\frac{1}{\sigma}} \lambda_1^{-\frac{1}{\sigma}-1} \frac{\partial \lambda_1}{\partial w_1} \tag{3.31}$$

Intuitively as $w_1$ increases, then the present value of lifetime income at $t = 1$ increases. This implies marginal utility of wealth at $t = 1$, measured by $\lambda_1$ decreases which implies $\frac{\partial \lambda_1}{\partial w_1} < 0$. This leaves the sign of $\frac{dL_1}{dw_1}$ as ambiguous. However, for sufficiently large $T$, the magnitude of income effect becomes small and can be neglected.

In order to see how the income effect becomes non-existent for unanticipated transitory wage changes for large $T$, one need to total differentiate the implicit equation defining $\lambda_1$ and determine $\frac{\partial \lambda_1}{\partial w_1}$. The implicit equation describing $\lambda_1$ is derived in the same way as it done for $\lambda_0$ and it is given by:

$$\begin{aligned}\left(\frac{1}{\lambda_1(1+r)}\right)^{\frac{1}{\sigma}} + \left(\frac{1}{1+r}\right)\left(\frac{\beta}{\lambda_1}\right)^{\frac{1}{\sigma}} + \frac{1}{(1+r)^2}\left(\frac{\beta^2(1+r)}{\lambda_1}\right)^{\frac{1}{\sigma}} = \\ w_0\left(1 - \left(\frac{1}{\lambda_1(1+r)w_0}\right)^{\frac{1}{\sigma}}\right) + \left(\frac{w_1}{1+r}\right)\left(1 - \left(\frac{\beta}{\lambda_1 w_1}\right)^{\frac{1}{\sigma}}\right) + \\ \left(\frac{w_2}{(1+r)^2}\right)\left(1 - \left(\frac{\beta^2(1+r)}{\lambda_1 w_2}\right)^{\frac{1}{\sigma}}\right) + B_0 + \frac{B_1}{1+r} + \frac{B_2}{(1+r)^2}\end{aligned} \tag{3.32}$$

Rewrite equation (3.32) in the following way:

$$\lambda_1^{-\frac{1}{\sigma}}(A+B) = C \tag{3.33}$$

$$\text{where, } A = \frac{1}{(1+r)^{\frac{1}{\sigma}}} + \frac{\beta^{\frac{1}{\sigma}}}{1+r} + \frac{\beta^{\frac{2}{\sigma}}}{(1+r)^{2-\frac{1}{\sigma}}}$$

$$B = \frac{w_0^{\frac{\sigma-1}{\sigma}}}{(1+r)^{\frac{1}{\sigma}}} + \left(\frac{\beta^{\frac{1}{\sigma}}}{1+r}w_1\right)^{\frac{\sigma-1}{\sigma}} + \frac{\beta^{\frac{2}{\sigma}}w_2^{\frac{\sigma-1}{\sigma}}}{(1+r)^{\frac{2\sigma-1}{\sigma}}}$$

$$C = w_0 + \frac{w_1}{(1+r)} + \frac{w_2}{(1+r)^2} + B_0 + \frac{B_1}{1+r} + \frac{B_2}{(1+r)^2}$$

Then total differentiating equation (3.33) (details in Appendix B):

$$\frac{\partial\lambda_1}{\partial w_1} = -\lambda_1\left(\frac{\sigma\lambda_1^{\frac{1}{\sigma}}w_1^{\frac{1}{\sigma}} - \beta^{\frac{1}{\sigma}}(\sigma-1)}{(1+r)w_1^{\frac{1}{\sigma}}(A+B)}\right) \tag{3.34}$$

Note that for every time period there are 2 terms in the expression $(A+B)$ which is function of that period's wage and model parameters. Now as the terminal date, $T$, increases, the term $(A+B)$ in the denominator becomes larger and larger with numerator remaining constant which makes $\frac{\partial\lambda_1}{\partial w_1}$ closer to 0. This leaves $\frac{dL_1}{dw_1} < 0$ in equation (3.31). Hence, the intertemporal model states there is negligible income effect in labor supply hours due to unanticipated transitory wage changes for sufficiently large $T$.

In conclusion, the neoclassical intertemporal model of labor supply predicts a positive relationship between labor supply and transitory wage variation, for both anticipated and unanticipated wage changes.

#### 3.3.2.3 Estimation of frischian elasticity

The equation (3.25) states the labor supply as a function of wage and Lagrangian multiplier. Estimation of the equation in (3.25) allows for computation of Frisch elasticity as it can measure the effect of changes in hours holding the marginal utility of wealth constant. A prototype of empirical specification of labor supply models takes the following form:

$$\ln h_t = \alpha_1 \ln w_t + \alpha_2 Q_t + \epsilon_t \tag{3.35}$$

where $\alpha_1$ and $\alpha_2$ are parameters, $Q_t$ is a vector of controls and $\epsilon_t$ captures unobservable to the researcher. Using relationship in equation (3.16), for Frisch labor supply, $\alpha_2 Q_t$ takes the following form:

$$\alpha_2 Q_t = F_0 + \alpha_3 t + \alpha_4 X_t \tag{3.36}$$

where $F_0$ is the individual specific fixed effect, $t$ captures the common across all agents age effect, other exogenous controls are included in $X$, and $\alpha_3$ and $\alpha_4$ are the associated parameters.

One can fit panel data to the specification in (3.35) to yield an estimate of $\alpha_1$, which captures Frischian wage elasticity or the intertemporal substitution elasticity. This elasticity holds the marginal utility of wealth constant. Hence, it is a suitable measure of changes in labor supply due to transitory wage changes which are either anticipated or unanticipated.

However using real-world data on labor supply, the evidence for intertemporal substitution elasticity is mixed which implies neoclassical theory could be a weak approximation of actual labor supply behavior. There are known issues with these estimates, which I discuss later. Nevertheless, I highlight the emergence of the alternative labor supply theory from the seminal work of Camerer et al. (1997) based on reference-dependent preferences.

### 3.3.3 Reference Dependent Labor Supply

The central idea behind the theory of reference-dependent preferences[4] is that outcomes are experienced relative to some point of reference and there exists loss aversion that is, losses relative to reference point are felt more severely than commensurate gains. Kahneman and Tversky (1979) formally introduced the idea of reference dependence as a model for decision making under uncertainty but its' applicability in various risk-free choices was quickly recognized. One such area of riskless choice is how people trade off consumption of good and leisure which I discuss next.

Consider the following model of labor supply with reference dependent preferences in a static set up. Agents face wage rate $w$ and when provide hours of labor, $h$, they receive utility from income, $wh$, and disutility from from hours, $g(h)$. Assume $g(h)$ is increasing and (weakly) convex.

[4] See ODonoghue and Sprenger (2018) for more details.

Also assume there is an exogenous reference income level, $I$. Then decision maker evaluates the payoff as follows:

$$\mathcal{U}(h) = u(wh) + v(wh - I) - g(h) \tag{3.37}$$

where $u(wh)$ represents the intrinsic utility and $v(wh-I)$ represents reference-dependent sensations from gain and loss. Assume $u(wh)$ increasing and (weakly) concave. Kahneman and Tversky (1979) argued that the function $v(wh - I)$ is an increasing function with the following three features:

1. Zero value at reference point: $v(wh - I) = 0$ if $wh - I = 0$. This is just normalization.

2. Diminishing sensitivity: $v''(wh-I) < 0$ if $wh > I$, but $v''(wh-I) > 0$ if $wh < I$. This feature states that the people have diminishing sensitivity to the magnitude of gain and losses. For gains or $wh > I$, this property is analogous to diminishing marginal benefit from income. But for losses or $wh < I$, this property implies $v(\cdot)$ to be convex.

3. Loss aversion: For $wh > I$, $v(wh-I) < -v(-(wh-I))$ and $v'(wh-I) < v'(-(wh-I))$. This feature implies a loss has larger magnitude utility consequences and larger marginal utility consequences than equally sized gain.

Combining the three above features, Tversky and Kahneman (1991) suggested the following functional form for $v(wh - I)$:

$$v(wh - I) = \begin{cases} \eta(wh - I)^{\alpha} & \text{if } wh \geq I \\ -\eta\mu(-(wh - I))^{\beta} & \text{if } wh \leq I \end{cases} \tag{3.38}$$

where $\eta \geq 0$ captures the importance of gain-loss utility relative to intrinsic utility, and $\mu \geq 1$ captures the degree of loss aversion. The parameter $\alpha$ captures the degree of diminishing sensitivity in the gain domain where $\alpha = 1$ implies no diminishing sensitivity. Similarly $\beta$ captures the diminishing sensitivity in the loss domain, where $\beta = 1$ implies no diminishing sensitivity. This model reduces to standard neoclassical model for $\eta = 0$.

In a general way, the problem of the reference dependent agent can be stated as follows:

$$\max_h \mathcal{U}(h) = \begin{cases} u(wh) + \eta(wh - I)^{\alpha} - g(h) & \text{if } wh \geq I \\ u(wh) - \eta\mu(-(wh - I))^{\beta} - g(h) & \text{if } wh \leq I \end{cases} \tag{3.39}$$

The marginal benefits, $MB_a(h)$, for above the reference point or when $wh > I$ and marginal benefits, $MB_b(h)$, for below the reference point or when $wh < I$ are given as follows:

$$MB_a(h) = wu'(wh) + \eta w\alpha(wh - I)^{\alpha-1} \quad \text{if } wh > I \tag{3.40}$$

$$MB_b(h) = wu'(wh) + \eta\mu w\beta(-(wh - I))^{\beta-1} \quad \text{if } wh < I \tag{3.41}$$

Marginal cost, $MC(h) = h^{\gamma}$, do not depend on the reference point. The parameter restrictions $0 < \alpha \leq 1$ and $\beta \geq 1$ ensure benefits are concave and costs are convex: $MB_a(h) > 0$, $MB_b(h) > 0$; $MB_a'(h) < 0$, $MB_b'(h) < 0$; $MC(h) > 0$, $MC'(h) > 0$.

The optimal labor supply hours would be given either below or above the reference income point. Hence the optimal hours would come from one of the following first order conditions which equates the relevant marginal benefit and the marginal cost:

$$wu'(wh) + \eta w\alpha(wh - I)^{\alpha-1} = g'(h) \quad \text{if } wh > I \tag{3.42}$$

$$wu'(wh) + \eta\mu w\beta(-(wh - I))^{\beta-1} = g'(h) \quad \text{if } wh < I \tag{3.43}$$

In the special case of $wh = I$, optimal hours is $\frac{I}{w}$. Differentiate both above and below first order conditions in (3.42) to find the sign of $(\frac{dh}{dw})$ as ambiguous (proofs in Appendix B). Only in the special case of $h = \frac{I}{w}$, $\frac{dh}{dw} < 0$ always. This implies reference dependent preferences can produce negative wage elasticity estimates of labor supply unlike neoclassical theory under transitory wage variations.

Now use a CRRA type reference dependent utility function to investigate the sign of $\left(\frac{dh}{dw}\right)$ with respect to CRRA coefficient, $\sigma$. Note that the common value of $\sigma$ is less than 1, so particularly interesting is to see whether $\sigma < 1$ is able to produce negatively sloped labor supply under reference dependent preferences. Assume the following functional forms:

$$u(wh) = \frac{(wh)^{1-\sigma}}{1-\sigma} \quad \text{and} \quad g(h) = \frac{h^{1+\gamma}}{1+\gamma} \tag{3.44}$$

Then the problem is as follows:

$$\max_{h} \mathcal{U}(h) = \begin{cases} \frac{(wh)^{1-\sigma}}{1-\sigma} + \eta(wh - I)^{\alpha} - \frac{h^{1+\gamma}}{1+\gamma} & \text{if } wh \geq I \\ \frac{(wh)^{1-\sigma}}{1-\sigma} - \eta\mu(-(wh - I))^{\beta} - \frac{h^{1+\gamma}}{1+\gamma} & \text{if } wh \leq I \end{cases} \tag{3.45}$$

Equating the marginal benefits when income is above or below the reference level to marginal cost, the potential first order conditions given as follows:

$$w(wh)^{-\sigma} + \eta w\alpha(wh - I)^{\alpha-1} = h^{\gamma} \quad \text{if } wh > I \tag{3.46}$$

$$w(wh)^{-\sigma} + \eta\mu w\beta(-(wh - I))^{\beta-1} = h^{\gamma} \quad \text{if } wh < I \tag{3.47}$$

Parameter restrictions implies benefits are concave and costs are convex. Differentiate each potential first order condition to get the sign of $\left(\frac{dh}{dw}\right)$ as ambiguous (see Appendix B for proofs) for both below or above target even with $\sigma < 1$. This implies reference dependent utility function could potentially produce negatively sloped labor supply curves with realistic parameter values, unlike neoclassical model. Given this theoretical background, focus next on how the literature has estimated the labor supply response to transitory wage variations.

### 3.4 A Brief Review of Literature

The data set required to estimate labor supply responses to transitory wage variations should ideally come from a set up where workers are free to adjust their hours upon facing an exogenous transitory wage change either anticipated or unanticipated, across periods. However, there is strong evidence that workers are not free to flexibly adjust their working hours in most working environments (Dickens and Lundberg, 1985; Kahn and Lang, 1991). As a solution, the literature has used a randomized field experiment to examine workers' labor supply responses, who have control over their hours, to temporary anticipated and unanticipated wage increase. Also, the literature has studied a few specific industries where workers can freely adjust their hours supplied such as taxi drivers, fishermen, and stadium vendors. The knowledge gained from these studies is summarized here.

### 3.4.1 Evidence from Field Experiments

Fehr and Goette (2007) analyzed the labor supply behavior of bicycle messengers in Zurich, Switzerland when messengers were provided with an exogenous anticipated transitory (four week period) increase of 25% in the commission rate. The study found that messengers increased the number of shifts (5 hour period) worked but decreased the revenue generated (messages delivered or effort). The authors preferred the reference-dependent model as a plausible explanation to the observed negative relationship between anticipated transitory wage and effort given working on a shift, after measuring loss-aversion among the messengers. In more recent work, Andersen et al. (2014) induced both anticipated and unanticipated experimental wage variations for vendors in Shillong, India to study the labor supply response. To mimic the anticipated transitory wage increase, vendors were informed on date $t$ about increased wage rate at dates $t+1$ and $t+2$. The authors found that vendors decreased their labor supply on the first day but increased the labor supply on the second day. On the other hand, with unanticipated transitory shock in the form of a large tip on period $t$, vendors opted for additional leisure but returned to work later on period $t$. The study concluded that initially, vendors follow income targeting models until they learn from their experience and behave as neoclassical optimizers.

### 3.4.2 Evidence from Taxi Industry

The labor supply of taxi drivers from New York City (NYC) is the most intensely studied area of this literature. A typical NYC taxi driver would rent their cab from a fleet, by paying a fixed fee, for 12 hour shift and he is free to drive as long as he wants within that period. Although the regulatory agency determines the fare rate per mile, drivers face variations in earnings across days due to various demand and supply shocks. The realized earnings of the day serve as the natural counterpart of wages in this setting. Additionally, drivers are required to fill up trip sheets which are a sequential list of trips taken on the day with information on pick-up and drop-off time and the amount of fare, excluding tip.[5] The number of hours supplied by the cab driver for the day is

[5]From 2008, electronic meters are used which tracks tip payment by card and Global Positioning Coordinates for pick-up, and drop-off locations in addition to the previous information recorded by hand filled trip sheets.

defined as the time difference between the first fare is picked up, and the last fare is dropped off. So total fare earnings are divided the number of hours to get the average hourly wage rate. Now, the logarithm of hours is regressed on the logarithm of wage with other time and weather controls to estimate the wage elasticity of labor supply for taxi drivers.

#### 3.4.2.1 Wage elasticity of labor supply

Camerer et al. (1997) was the first study to report negative wage elasticity estimates for a sample of NYC taxi drivers, using trip sheet data from Spring 1994. The estimates remained negative after controlling for division bias,[6] using instruments of the wage for other workers, implying the importance of targeting behavior among workers having flexible hours. Also, the magnitude of the negative response was stronger among inexperienced drivers. The same results were replicated by Chou (2002), following the same methodology, among Singaporean taxi drivers using survey data from a selected sample of drivers' labor supply for 5 days. Farber (2005) pointed out, using a sample of trip sheet data from 1999-2001 for NYC, that hourly wage rate is neither constant nor highly auto-correlated within a day and hence, using average hourly wage as the determinant of labor supply would yield unreliable estimates. Upon estimating negative wage elasticities following Camerer et al. (1997) methodology, Farber (2005) proposed an alternate way to analyze labor supply, discrete choice stopping model, which I discuss later. However in Farber (2015), he reversed his stance and used average wage in estimating positive wage elasticity for the first time in the literature, using the most substantial data set till date of all taxi fares[7] between 2009-13. Using the same data set, Schmidt (2017) estimated negative wage elasticity of labor supply with respect to abnormally large tips (unanticipated variation) but positive wage elasticity concerning market-wide earnings opportunity (anticipated variation).

The validity of these negative wage elasticity estimates has been questioned in the literature. Oettinger (1999) and Farber (2005) noted how the wage elasticity estimates could be biased in

[6] Wage rate is defined as the ratio of total earnings to total hours supplied. From the trip sheets, the total hour supplied includes break times in between the working day which implies hours are overstated. This leads to low wage-high hours observations resulting in spurious negative estimates.

[7] However, he only used randomly sampled $\frac{2}{15}$ of the drivers present in the full data for estimation purposes.

the absence of exogenous variation in the wage rate for taxi drivers' set up. Particularly not controlling for supply shifters would induce a correlation between the error term and wage rate. Using instruments to control for measurement error in hours could also lead to biased estimates if there are calendar date effects on the wage and also on the labor supply conditional on a wage like major US holiday.[8] Finally, these estimates are only at the intensive margin, that is, labor supply response conditional on working on a day. However, a complete labor supply response should also take into account the extensive margin, that is, whether to work today or not.

#### 3.4.2.2 Modeling of stopping probability

The alternate approach, introduced by Farber (2005), avoids elasticities and focuses on modeling driver's decision to continue or stop after the end of a passenger trip for each day. Given wages throughout the day are neither constant nor monotonic increasing or decreasing, the solution to this optimal stopping problem should consider the option value of continuing to drive. Instead of providing a complete solution to the stochastic dynamic optimization problem, which is not readily amenable to empirical implementation, the literature has used an approximate solution by estimating a discrete choice problem of whether to drive or stop for the day after a fare is completed. In this regard, a latent variable known as continuation value is defined as the function of cumulative income, cumulative hours, income level relative to the target, an hour of the day and other controls. Then the driver will continue to drive if this latent variable is positive and with a distributional assumption on the error term, one can estimate the probability of continuing for the driver at a particular time during the day. For reference-dependent preferences, the probability of continuing should fall once the reference point or target of the day is reached; else, for neoclassical preferences, the probability of continuing should not depend on cumulative income.

The major obstacle in the estimation of this alternate approach comes from the fact that reference income or target is rarely observed. Farber (2008) attempted to estimate the target jointly with other parameters. The results were contradicting to each other as he estimated higher

[8] For example, on the 4th of July, there would be an increased demand for cabs, and there could low preference to drive a taxi as drivers also would like to spend time with family.

marginal utility before the target is reached (implying targeting is important), but the continuation probability was smooth in cumulative income (implying targeting is not important). Ignoring target, Farber (2005) and Farber (2015) reported probability of stopping for the day is strongly positively related to hours worked and at best weakly related to income earned, supporting the neoclassical model. However, using data from NYC (same as Farber (2015)) and San Francisco taxi drivers (from 2010-13), Martin (2017) presented evidence of reference-dependent labor supply. More recently, Thakral and Tô (2017) found evidence of reductions in labor supply due to higher accumulated earnings (inconsistent with neoclassical model) and stronger effects for more recent earnings (inconsistent with targeting as fungibility of income is violated) among NYC taxi drivers.

In the absence of an observed target, motivated by Kőszegi and Rabin (2006) theory of reference dependence, the literature has also assumed the target as rational expectations. Crawford and Meng (2011) estimated a model with both income and hours target, using Farber (2005) data set. They proxied the targets as drivers' past earnings and hours for the particular day of the week. They found if the wages are lesser than average during the beginning of the shift such that drivers will get to their hours' target first and hence drivers' will have a positive relationship between the probability of stopping and cumulative income. On the other hand, if wages are higher than average then drivers will get to their income target first and hence stopping probabilities would be correlated with hours but not income. This work proposed reconciliation of the previous conflicting conclusions of the literature. Farber (2015) proposed a reference-dependent model of labor supply, which is a special case of the reference dependent labor supply introduced in subsection 3.3.3. The prediction Farber (2015) model is that labor supply is positively related to wage when income is either more or less than target and negatively related to wage when income is equal to target. However, this model could not be tested empirically as the target for the day of drivers are rarely observed.

### 3.4.3 Evidence from Fisheries

Stafford (2015) estimated positive wage elasticity of labor supply of commercial fishermen from Florida spiny lobster fishery, both at the extensive and intensive margin, using data from 1996-2007. She corrects for the endogeneity of wage problem (present in taxi data) with an imputed wage that is correlated with the moon cycle for this particular fishery. However, the number of traps used to capture lobster is fixed by regulation, and they can be pulled from water only during daylight. This constraint the hours supplied on each day, as seen in the data with mean hours of 8.14 hours with a standard deviation of 0.32. This implies even on high earning days, and fishermen cannot pull more traps due to binding trap quota or daylight restriction. Higher earnings or traps filled with lobster needs more hours to empty, clean, re-bait traps and set them back again, which is possibly captured by the positive wage-hours elasticity estimate and not intertemporal substitution.

In another study, Giné et al. (2017) studied extensive margin only using the same strategy of imputed wages to estimate positive wage elasticity, from labor supply data on South Indian boat owners from 2001-2007. They also found the influence of fatigue and recent earnings on daily participation but concluded that the neoclassical model is a good approximation. However, Nguyen and Leung (2013) used Camerer et al. (1997) approach on 2004 logbook data from Hawaii-based longline fishery and found evidence of revenue targeting behavior.

There is also evidence of reference-dependent preferences from the estimation of discrete choice stopping model with fisheries data. Hammarlund (2018) indicated higher revenue on a fishing trip leading to lesser days at sea among Swedish Baltic cod fishermen, using logbook data (equivalent to trip sheets of taxi drivers) from 2011-13. This study controls for vessel hold capacity and catch of secondary species but cannot control the target as it is unobserved. Ran et al. (2014) reported reference dependent behavior among shrimpers in the Gulf of Mexico using sampled data by port agents from 1995-2004.

#### 3.4.3.1 Gaps

The literature is yet to reach a consensus on which model describes the labor supply behavior of workers. The main barriers to wage elasticity estimation were endogeneity of wage and measurement error in hours. The unique data set from Alaskan Halibut fishery allows us to bypass these problems. This study uses a natural variation of fishing productivity that generated exogenous variation in wage rate to estimate the wage elasticity of labor supply. Unlike the taxi data, the working hours of our data set are free from searching time and leisure or break time. Also, as a response to higher earnings or better productivity fishermen can fish as long as they want given the supply of inputs they have on board. Moreover, there are seasonal quota restrictions for the fishery, but that would only affect the last trips of the season, and I explicitly control for the last trips of the season. I acknowledge that wages are not constant throughout the trip; hence, taking an average wage for the trip is not sensible. I use the wage where the decision to quit is taken as an alternative. However, I can only estimate the wage elasticity at the intensive margin due to data restrictions.

Until now, the estimation of negative wage elasticity or increased probability of stopping after a certain income level implied reference-dependent preferences. However, with this data, I observe the exogenous target before each trip. Hence, I can directly test reference-dependent preferences for the first time. Particularly, I can take the theoretical reference-dependent model of Farber (2015) to data as I observe both target and expected wages. I also observe the experience of fishermen and can test whether with the experience their behavior changes. Overall this paper contributes to the growing literature on empirical evidence of labor supply behavior.

## 3.5 Empirical Model of Labor Supply

### 3.5.1 Labor Supply of Skipper

The labor supply decisions of how long to fish and when to fish may be taken jointly by the skipper of the vessel and the hired crew members in commercial fishing trips. In this chapter, I focus on the labor supply of the crew members as their payoff can be delineated clearly from the total catch as compared to payoff to the vessel skipper. Specifically, I focus on the labor supply decision of the most skilled crew member, hereafter, referred to as first mate skipper; and the labor supply decision of the least important crew member, hereafter, referred to as greenhorn. It is essential to differentiate among the crew members as they receive an unequal share of the total catch as the payoff. I study the labor supply of crew members within a trip or the number of hours worked within a trip, that is, at the intensive margin[9].

### 3.5.2 Working Hours

The labor supply decisions within a trip are taken in blocks of a time period, which is the time required to soak and pull the longline gears, around 12 hours. I define these 12 hours, where long lines of gears are simultaneously soaked and pulled as a set event. Hence, the number of set events on a trip measures the total amount of labor supplied by a fishermen within a trip. Note here that the fishermen are free to do as many set events as they want. However, the number of set events has an upper limit due to the finite amount of space on board, finite inputs while at sea, and annual quota limits (only binds at the last trips of the season). The number of set events performed on a trip as a measure of working hours is free from searching and steaming time from port to locations, thereby making it free from measurement error.

### 3.5.3 Wage Rate

The amount of catch and prices determine the pay off from a fishing trip. Assuming skippers are price takers, the pay off is determined by the productivity experienced during a fishing trip. It is important to note here that halibut are bottom-dwelling species; hence, their location cannot be tracked by electronic equipment like sonar. The only way to experience the current productivity of a location is to soak and pull gears. Even set events performed at the same location subsequently within a trip results in fluctuating productivity due to factors like mining,[10] movement of fish,

[9]I acknowledge that the complete labor supply decision should also include the extensive margin, that is, whether to start a trip or not. Due to data limitations, I cannot address this part of the labor supply decision.

[10]Mining is referred to depletion of available stock biomass at any location due to continued fishing which decreases productivity. Typically, fishermen would like to rest a location that would allow natural factors to repopulate the location.

and other biological factors. Also, there are no known physical conditions like moon cycles or weather conditions that are particularly favorable for the catch. Hence, I assume that nature drives productivity or catch of each set event and skipper has limited control over it, making productivity genuinely exogenous.

The total length of long lines used in a set event could vary across both set events and trips. So to compare productivity or the amount of catch across set events, I define $1,800$ feet length of the long line as a standard skate. Then a set event consisting of $18,000$ feet of a long line is equal to 10 standard skates. Now, define catch per standard skate as the ratio of the total catch from set event to the number of standard skates used. Then the standardized catch per skate (*cps*) is a comparable real productivity measure across set events. The variable, *cps*, serves as the natural counterpart of the wage rate in this setting, measuring the real payoff per skate. Since the catch from a trip is shared among the vessel skippers and crew members in a known pre-determined rate, so I will make necessary adjustments while calculating the wage elasticities of crew members.

### 3.5.4 Decision Problem

The labor supply problem of fishermen at the intensive margin only begins after the trip has started. Specifically, after the first set event is done. Formally, the problem can be stated as follows. After the catch from the first set event is retrieved, the skipper arrives at the first decision node, $n = 1$, where he has additional information on the current productivity among other variables which guides him to decide whether to fish or quit. Suppose, the decision to fish is taken at $n = 1$, which implies the second set event is performed, the catch is retrieved, and the skipper arrives at the second decision node, $n = 2$. At $n = 2$, suppose skipper decides to quit, given the set of state variables at that decision node. Hence, at this example trip, the skipper did 2 set events given the productivity and other factors during the trip.

Essentially, the labor supply of the fishermen at the intensive margin is an optimal stopping problem, given the decision to quit is irreversible. The complete solution to this problem would involve solving the stochastic dynamic optimization problem where one can learn about all the infra-marginal decisions. Rather than taking this approach, I study the optimal stopping problem in an alternate way that can be quickly taken to data. Mainly, I study the association between the state variables when the decision to quit was taken on a trip and the number of set events done on a trip. The dependent variable, number of set events on a trip, is a measure of labor hours supplied during a trip. The set of independent variables would include all the variables of the state space at the point of quitting. Among the independent variables, the applicable wage rate of the trip or the wage rate for the set event not done is the single most crucial variable as it captures the remuneration to labor supply. Estimation of this empirical relationship between hours and wage rate allows for the testing of the predictions from theoretical labor supply models. Next, I discuss the methodology used for estimating the parameters of the empirical model, followed by the discussion of testable hypotheses.

### 3.5.5 Count Dependent Variable

The empirical model of labor supply associates number of hours worked or the number of set events performed by skipper on a trip to the state space when the skipper decided to quit on that trip. Let, $h_{it}$, be the number of set events performed by skipper $i$ on trip $t$. By construction, $h_{it}$ is a count variable that is a strictly positive integer. The natural starting point of count variables is the Poisson regression model. One can also think of standard linear regression models but are not preferred as it allows negative outcomes and the probability of a particular outcome is zero. Here I follow the recent approach of Honoré and Kesina (2017), which allows estimating effects of both time-varying and time-invariant explanatory variables, and applies it to the Poisson regression model. Assume the number of set events on a trip, $h_{it}$, where, $i = 1, ..., I$ and $t = 1, ..., T_i$ is Poisson distributed with conditional mean as follows:

$$E[h_{it}|x_{it}, z_i, c_i] = \exp\left(x'_{it}\beta + z'_i\gamma + c_i\right) \tag{3.48}$$

The time-varying explanatory variables are denoted by $x_{it}$, the time-invariant explanatory variables are denoted by $z_i$, and $c_i$ captures the skipper specific fixed effect.

### 3.5.6 Parameter Estimation

The estimation of the above model proceeds in two steps. In the first step, effects of time-varying variables, $\beta$ are estimated. And in the second step, the effects of the time-invariant variables, $\gamma$ are estimated. Assume the trips for a given skipper are independent, that is, $h_{it}$ and $h_{ir}$ are independent conditional on $x_{it}$ and $c_i$, when $t \neq r$. Hausman et al. (1984) showed that the conditional distribution of $\{y_{it}\}_{t=1}^{T_i}$ given $\left(\{x_{it}\}_{t=1}^{T_i}, z_i, c_i, \sum_{t=1}^{T_i} y_{it}\right)$ depends on $\beta$ but not on $(z_i, c_i)$. This implies estimates of $\beta$ can achieved by using conditional likelihood approach and it is known as fixed effects Poisson (FEP) estimator (Wooldridge, 2010). One can get identical estimates of $\beta$ by treating all the $(z_i'\gamma + c_i)$'s as parameters to be estimated (Lancaster, 2002). Following this result, I use a dummy variable for each skipper present in the data to obtain maximum likelihood estimates of $\beta$ in step 1.

Wooldridge (1999) notes FEP estimator is consistent for $\beta$ under the conditional mean assumption (3.48) only. Except for the conditional mean, the distribution of $h_{it}$ is entirely unrestricted, that is, it is robust to over-dispersion or under-dispersion and does not require that the dependent variable is truly Poisson distributed. Also, there is no incidental parameters problem in the Poisson fixed effects model with multiplicative fixed effects. That is, the parameters $\beta$ of the conditional mean function can be estimated consistently for a fixed number of trips $T$, as long as the number of clusters or skippers, $I \to \infty$.

In step 2, the focus is on the time-invariant parameters. Rewrite conditional mean (3.48) as follows:

$$E[\exp(-x_{it}'\beta)h_{it}|(z_i, c_i)] = \exp(z_i'\gamma + c_i) \tag{3.49}$$

Assuming $E[\exp(c_i)|z_i]$, a constant, one can estimate $\gamma$ using Poisson regression model as in step 1, where the mean function is specified by

$$E[\exp(-x_{it}'\hat{\beta})h_{it}|(z_i, c_i)] = \exp(z_i'\gamma + \gamma_0) \tag{3.50}$$

In the second stage regression, the dependent variable is $\exp(-x'_{it}\hat{\beta})h_{it}$ where $\hat{\beta}$ is the estimate of $\beta$ as obtained in step 1. Thus, the estimates of both time-variant and time-invariant explanatory variables are obtained.

### 3.5.7 Variance of Parameter Estimates

The estimated variance for parameter estimates, $\widehat{V}(\hat{\theta})$, where $\hat{\theta} = (\hat{\beta}, \hat{\gamma})$, is obtained using bootstrap procedure, following Cameron and Miller (2015). To implement the bootstrap, proceed as follows:

1. Sample skippers or clusters with replacement $I$ times from the original sample of skippers or clusters present.

2. For the sampled $I$ skippers or clusters, retain all the trips taken by $I$ skippers to form the first bootstrap sample.

3. Obtain estimates from the first sample, $\hat{\theta}_1 = (\hat{\beta}_1, \hat{\gamma}_1)$.

4. Repeat steps 1, 2, and 3 up to $B$ times to obtain $B$ bootstrap estimates $(\hat{\theta_1}, \hat{\theta_2}, \cdots, \hat{\theta_B})$.

Finally, calculate the variance of the $B$ bootstrap estimates, to obtain the estimated variance:

$$\widehat{V}(\hat{\theta}) = \frac{1}{B-1}\sum_{b=1}^{B}(\hat{\theta}_b - \bar{\hat{\theta}})(\hat{\theta}_b - \bar{\hat{\theta}})' \tag{3.51}$$

where $\bar{\hat{\theta}} = \frac{1}{B}\sum_{b=1}^{B}\hat{\theta}$. In most cases, $B = 400$ is sufficient.

It is important to note that the re-sampling is done over entire clusters or skippers, rather than over trips. In this way, in bootstrap samples, some original clusters may not appear at all while other clusters will appear multiple times. Since all the trips of the selected clusters are used in the re-sampled data set, the size of the data set varies in bootstrapped samples. Next, I state the hypotheses that are tested with this estimation technique.

## 3.6 Hypotheses

### 3.6.1 Neoclassical Model

The neoclassical theory of labor supply suggests that labor supply should increase whenever there is a transitory wage increase. The wage changes in this fishery are transitory in the sense that the amount of fish caught and the stock abundance experienced varies from trip to trip, and the skipper has limited control over catch amount. In this setup, estimates of the Frischian elasticity following estimating equation (3.35) should be positive if the Neoclassical labor supply model is valid.

The standard neoclassical model assumes that the wage rate is fixed within the period. However, in this fishery, the wage rate within a period (trip) varies as the total amount of fish caught in every set event within a trip varies. This situation is similar to taxi literature where the amount of fare collected in every hour varies. It is well recognized that using the average wage of the fishing trip or equivalently average wage of the day in a taxi set up would lead to misleading results. Hence the applicable wage rate in this set up would be the wage rate when the decision to quit was taken during the trip.

The prevailing wage rate under which the quitting decision was taken is seldom observed in the real world. Specifically, in taxi literature, it is never observed. However, in longline fishing, the applicable wage rate can be approximated by using prior wage rates realized on a particular trip. In longline fishing, repeated gear sets on a particular location fish from the given local stock condition. Hence the wage rate from repeated set events are related and can be estimated using prior catches. I propose 4 different form of estimates for the relevant wage rate at the point of quitting: (i) *naive wage*: The naive wage is defined as the wage rate or the *cps* of the last set event of the trip; (ii) *naive wage adjusted*: The naive wage adjusted is defined as the wage rate or *cps* of the last set event of the trip, adjusted for mining effect of the stock; (iii) *location wage*: The location wage is the average of wage rate or *cps* from the set events done in the location[11] of the

[11] I use cluster analysis to find out whether set events done on a trip are done in the same location of each other.

last set event; and (iv) *location wage adjusted*: The location wage adjusted is defined as the wage rate of the last set event of the trip, adjusted for the mining effect of the stock.

Using, $w_{it}$, as the relevant wage rate of skipper $i$ in trip $t$ as one of the explanatory variables in the Poisson regression model, I estimate the following conditional mean function:

$$E[h_{it}|w_{it}, x_{it}, z_i, c_i] = \exp\left(\alpha w_{it} + x'_{it}\beta + z'_i\gamma + c_i\right) \tag{3.52}$$

Then with the estimate of the impact of wage rate on the number of set events, $\alpha$, I can test the neoclassical prediction which is stated as follows:

**Hypothesis 1** *Increase in transitory wages causes labor supply to increase.*

If the neoclassical model is a good approximation to labor supply of fishermen, then the estimate of $\alpha$ should be significantly different from 0 and positive.

### 3.6.2 Reference Dependent Preferences

Under general reference-dependent preferences, the labor supply response to wage changes are ambiguous as shown in the subsection (3.3.3). However, imposing some restrictions on the parameters provides labor supply predictions under these preferences. Specifically, one need to assume risk aversion coefficient, $\sigma = 0$, and linear utility from the gain-loss part, $\alpha = 1$, and $\beta = 1$, as shown in Farber (2015). Then this linear reference-dependent preferences predict that (a) there is a positive relationship between wages and hours when income is either less than target or more than target; and (b) there is a negative relationship between wages and hours when income is equal to target. The range of wages where it is optimal to earn exactly equal to target would depend on model parameters such as loss aversion, the relative importance of gain-loss utility part as compared to consumption utility, disutility from hours; and target.

While on a fishing trip, it is difficult to stop precisely when income is equal to target as fishermen do have limited control on catch and, the hours supplied here is in chunks of 12 hour period–the time required to complete the one set event. Hence, the prediction of the negative relationship between wage and hours is approximately valid when the income of the trip is in the neighborhood of the target of the trip if the labor supply of skippers is based on reference-dependent preferences. Similarly, if the income of the trip is away from the target of the trip, the theory predicts a positive relationship between hours and wages.

The hypotheses related to restricted reference dependent preferences are as follows:

**Hypothesis 2a** *Increase in wages causes labor supply to decrease, if income is in the neighborhood of target.*

**Hypothesis 2b** *Increase in wages causes labor supply to increase, if income is not in the neighborhood of target.*

There is no straight forward definition of the neighborhood in this case. Hence, I test the relationship between wages and hours in various neighborhoods around the target in the estimation of equation (3.52).

### 3.6.3 Experience and Vessel Effects

The literature notes that the wage elasticity of high experience taxi drivers differs from the low experience drivers. The high experience drivers respond positively to wage changes, but the low experience drivers respond negatively to wage changes. I test whether high experience fishermen behave differently from low experience fishermen. Also, I test whether this behavior changes when the catch is more or less than the target. In fisheries, the size of the vessel plays an important factor in fishing activities. The size of the vessel determines the distance traveled on a trip, storage capacity, number of onboard crew members, among other things. So, I test whether the wage elasticity varies across large and small vessels; and does the behavior change when the catch is more or less than the target. Next, I summarize descriptive statistics of the data before presenting the main results from the estimation of the Poisson regression model.

## 3.7 Data

The data source for this study is compiled from the "Halibut Project", logbook data, and setline survey of IPHC. The clean data set[12] has 329 trip level records on the number of set events done, and catch per skate or wage rate information, among other variables for 40 skippers from the 2006 and 2007 fishing season. The table 3.1 presents the summary statistics of all relevant variables, and the table summarizes the variable definitions.

There are two important things to note in this data set. First, the skippers are free to take trips whenever they want within a season. That is, the first trip for a skipper is not necessarily at the same calendar date as another skipper. Hence, the data set is not a standard panel data set. Second, skippers voluntarily participated in the "Halibut Project" study which allows me to observe their trip level information. Assuming the participation in the study was random from the pool of active commercial halibut fishermen in the 2006-07 fishing season, the data set I observe is a cluster sample of skippers, containing multiple trip level observations for each skipper. The skipper index, $i$, indexes the cluster where $i = 1, 2, 3, ..., I$ and the trip index, $t$, indexes the observation number within cluster where $t = 1, 2, 3, ..., T_i$. That is, clusters are allowed to have different sizes, implying a different number of trips for each skipper. Following Wooldridge (2010), panel data methods can be extended to cluster data set up which allows me to use Honoré and Kesina (2017) methodology to estimate the empirical model.

### 3.7.1 Relevant Wage Rate

Previously, I proposed 4 different ways to measure the applicable wage rate or the wage rate on the basis of which the decision to quit is taken. The first choice, naive wage, is just the wage rate or catch per skate measured in dollars from the last set event. The other two definitions of relevant wage, namely, neighborhood wage and mining wage require to specify if the set events are close to each other. I use cluster analysis, to find if the set events are in the neighborhood of each other.

[12] Details about the data is in Chapter 2.

The objective of cluster analysis with longitude-latitude of fishing points is to identify the set event locations, which are relatively closer to each other. These relatively closer locations would be identified as one cluster. It is assumed that the set events fishing on the same cluster would be exploiting the given amount of stock abundance for the trip. Hence, identifying clusters would help in defining whether consecutive set events are exploiting the stock abundance from the same cluster and the exploitation rate of each set event at the same cluster.

I proceed by pooling the longitude-latitude points of all the set events performed by a given skipper to do a k-means clustering. The first step in the clustering process requires to specify the optimal number of clusters for each skipper. I find the optimal skipper specific number of clusters by using the elbow plot criteria. The plots for all the skippers are presented in figures B.2, B.3, B.4, and B.5. The chosen number of clusters for each skipper is shown with dotted lines in the elbow plot graphs. The results from the k-means clustering algorithm on the data set show a maximum of 3 different clusters visited on a single fishing trip. The location wage is defined as the average of the catch per skate obtained from the set events at the same cluster as the cluster fished at the last set event of the trip.

I also hypothesize that repeated gear set at the same cluster would be exploiting the given amount of stock abundance. Hence, there will be a gradual decay in the catch per skate obtained, as if the stock is *mined*. Anecdotal evidence from the commercial halibut fishermen states that initially, the fishermen find the optimal depth of gear set in the first couple of set events and then exploit the given stock abundance. They also allow a location to *rest* before it is fished again so that the stock abundance is replenished. To find the rate of exploitation of the consecutive set events in the same cluster, I proceed as follows.

I assume the mining effect not to be skipper specific; hence I pool all the trips from all skippers together. Let at trip, $t$, fishing happened in $c$ longitude-latitude clusters, where, $t = 1, 2, 3, \cdots, T$ and $c = 1, 2, 3 \cdots, C$. Now in any cluster, multiple set events may be performed during a trip. Then, the catch per skate at the set event, $s$, in cluster, $c$, and trip $t$ is given $cps_{s,c,t}$. Let the average of catch per skate across the set events be $\overline{cps_{c,t}}$. Then the ratio, $\frac{cps_{s,c,t}}{\overline{cps_{c,t}}}$, for each set event for a given trip $t$ and cluster $c$, would go increase initially (due to optimal depth search) and then decrease, if there is a mining effect. I observe the ratio, $\frac{cps_{s,c,t}}{\overline{cps}_{c,t}}$, for all set events done at the clusters on all the trips. The average of the exploitation ratio for any set event, $s$, is then given by averaging the exploitation ratios across all $c$ and $t$. This averaged exploitation ratio times the cluster- and trip-specific catch per skate average would give the mining adjusted catch per skate for the set event at the cluster, $c$, and trip, $t$, when the trip ended.

The averaged exploitation ratio across the set events and associated number of observations are presented in the table B.2. The averaged exploitation ratio initially increases and then decreases, as expected. The pattern is missing for higher set events as the number of observations decreases since it is rare to see a high number of set events performed in the same cluster. Hence, if the trip ended at $s$ set events, then, I estimate the mining adjusted relevant wage rate of the set event $(s+1)$, mining wage, for each trip by multiplying the obtained cluster- and trip- specific averaged catch par skate with the associated exploitation ratio. However, for set event number equal to or more than 5, I use the constant ratio of 0.936, which is the associated exploitation ratio for the fifth set event.

### 3.7.2 Objective Productivity

The longitude-latitude position for the gear set on a fishing trip is a skipper's choice. There exist objective productivity differences in these longitude-latitude positions as the stock abundance is heterogeneously distributed across space and time. I propose to control for these differences in objective productivity by using the estimated generalized linear model of catch per skate distribution, which was introduced in chapter 2 . I represent a trip's objective productivity by averaging across the estimated $\mu$ parameter of the clusters fished on a trip. The variation in the objective $\mu$ parameter associated with each trip is in figure B.1. The expected value of the catch per skate, assuming a Log-normal distribution is obtained with averaged estimated $\mu$ across the cluster centres and cluster-independent $\sigma$. This expected value at the trip level is used to control for heterogeneity in objective productivity across trips.

## 3.8 Results and Discussions

### 3.8.1 Preliminary Analysis

I estimated the empirical model of labor supply stated in equation (3.52) using the data on fishing trips from the Alaskan halibut fishery. The dependent variable is the number of set events performed on a fishing trip. The primary independent variable is the associated wage rate when the decision to quit was taken during the trip. Since wages or catch per skate varies across the set events during a trip, it is sensible to avoid the average catch per skate or average wage to guide the decision to quit fishing for the trip. Further, I found the mining effect phenomenon (the gradual decline of catch per skate or mining of stock, if fished at the same location on a trip), and hence adjusted the relevant wage accordingly to produce mining adjusted wages. As noted before, there are 4 different forms of relevant wage rate that can be used to study this problem.

To identify the causal effect of wage on the number of set events, I consider many other explanatory variables as controls. Black cod is another species that is caught in a few trips while fishing for halibut. This species is also valuable and uses the same fishing technique and requires the same storage facilities. Hence, to make everything else equal, I control for the amount of black cod captured. Also, the locations fished in our sample are heterogeneous in their objective productivity. There could be some areas which are always better (or worse) than others. I use the previously introduced GLM of catch per skate[13] to control for the differences in the objective productivity. In trips where fishermen set gear in multiple locations, I use the average across the locations as the representative productivity of the trip.

Additionally, I use skipper fixed effects to make the trips by a given skipper independent to each other. There are 3 different geographical regions, namely, IPHC region 2C, 3A, and 3B where the fishing takes place. I controlled for the region of fishing by using dummies for region 3A and 3B. Similarly, I used a dummy for the year 2007 as there were two years in the data. Due to quota regulation, the last regional trips of the season could face some fishing constraints which are controlled by using a dummy variable.

[13] See chapter 2 for details.

In other trips, the fishing activity could be restricted due to onboard storage constraints in the event of receiving a high wage rate. I do not observe the storage capacity of the vessels. Hence, I approximated the storage capacity of the vessel with the maximum recorded catch or target of the vessel from the two years. Moreover, on average, catch from a set event occupies about 18% of the storage space on the vessel. So, I used a dummy variable for the trips to control for storage constraint whenever the catch from the trip was more than 85% of the vessel storage capacity. I also controlled for the by-catch of black cod species.

Among the trip-invariant variables, I considered the length of the vessel and the number of crew members present on board which controls for the fatigue during the trip. Note that the length of the vessel and number of crew are correlated as the number of berths on the vessel is fixed. After controlling all these variables, I did not find any explanatory power of other time-invariant variables like the interaction between the length of the vessel and crew members, the experience of the vessel's skipper. However, I find vessel skippers who share productivity information performs more set event, on average, as the compared skipper who does not share information.

In halibut fishing trips, weather as measured by wind speed shock or unexpected deviation of wind speed during the trips did not play any role on trip's working hours, after controlling for other factors. The halibut fishing trips are planned after obtaining information on the weather forecasts; hence, I do not find these results surprising. The independence of working hours from the weather is robust to different weather specifications too. For example, even after allowing stronger wind speed than expected to have a different effect than milder wind speed than expected did not change the results. The same holds for the stronger impact of more significant deviations than weaker deviations or the squared wind shock variable. In other alternate specifications, I considered a seasonal linear and quadratic trend, and a dummy variable to denote the late spring and early fall trips. I found both of them to be insignificant, hence dropped them from my analysis. Next, I present the results regarding Hypothesis (1) or the testing of the neoclassical prediction of the impact of wages on working hours.

### 3.8.2 Neoclassical Prediction Testing

The Poisson regression results used for testing the neoclassical prediction between set events and wage is presented in Table (3.3). The coefficient of wage rate, which is adjusted for mining effects, is estimated to be $-0.033$ and is statistically different from 0, after using associated controls. The wage coefficient of $-0.033$ means, 1 pound in the catch per skate causes the expected number of set events to decrease by 0.033%. This implies at sample averages, a 1 pound increase in catch per skate decreases the expected number of set events by 0.0013.

The slope coefficient of the wage from the Poisson regression model do not represent wage elasticity. The wage elasticity of labor supply from the above estimates is derived as follows. Here I focus on the wage elasticity of labor supply of the most important crew member or the first-mate as the remuneration is known from the data. The wage elasticity of labor supply is defined as the ratio of the percentage change in working hours to the percentage change in remuneration. When the catch per skate increases by 1 pound, then the number of set events performed changes, which changes the total working hours. Also, the change in the catch per skate influences the remuneration from the trip. These two effects jointly determine the wage elasticity.

The impact of 1 pound increase in catch per skate is a decrease of 0.0013 set events in absolute terms. The soaking time of a single set event, on average, is 12.2889 hrs; this means 1 pound increase in catch per skate would reduce the soaking time by 0.0160 hours. Assuming the fishermen fish at the same location, the steaming time remains constant; so the total working hours change by $-0.0160$ hours in absolute terms. On average, the trip length in days is 4.3982. Assuming the fishermen work for 16 hours per day, the average time spent working on a trip is 70.3712 hours. Hence, the percentage change in working hours due to 1 pounds increase in catch per skate is $-0.0227$%.

The total revenue from the trip is calculated by taking the product of price ($4.2014), number skates used per set event (15.8327), catch per skate (252.9769), number of set events (3.9818) at data average values. First, quota lease rent is paid from the trip revenue, which is 60%

on average[14] during the sample time period. Then the first mate receives a given percentage of the leftover revenue (or, 40% of the total revenue) as remuneration to labor hours, which in the data period is 11.1290% on average. That is, the base remuneration of the first mate is 11.1290% of (0.40)(4.2014)(15.8327)(252.9769)(3.9818), which is \$2982.8091. When the catch per skate increases by 1 pound then the new number of set events is 3.9805. The new remuneration of the first mate due to 1 pound catch per skate increase then becomes 11.1290% of (0.40)(4.2014)(15.8327)(253.9769)(3.9805), which is \$2993.6222. The absolute change in remuneration is \$10.8131 and the percentage change is 0.3625%. Then the wage elasticity of labor supply is given by the ratio of $-0.0227$ and 0.3625, which is $-0.063$. The standard error is computed by delta method, which is 0.031. So, I fail to reject the null hypothesis of wage elasticity of labor supply $= 0$, against the alternative hypothesis of wage elasticity of labor supply $> 0$. One sided test is done as the neoclassical prediction is positive wage elasticity. Hence, the hypothesis (1) is inconsistent with the data.

The signs of the other control variables came out to be as expected. I found a positive association between the expected number of set events and the amount of black cod caught but not statistically significant. Trips fishing in locations with better objective productivity performs lesser set events on average as they might get to their target easier (implying income targeting behavior). Interestingly, when the vessel is nearing its full hold capacity, fishermen are more motivated to work more. This extra motivation could be a result of pride in getting a big catch, and it is precisely estimated.

On the other hand, when faced with binding seasonal quota constraint, even if the fishing is good, fisherman cannot fish. The coefficient of the quota constraint is significantly estimated, and it implies on the last trips, fishermen, on average, do 10% lesser set events as compared to non-last trips. The time and area fixed effects imply a higher number of set events done area 3B, and there is no difference in the working hours between the two years present in the data.

Among the trip invariant variables, vessel length and the dummy indicating information sharing is significant and positively estimated. As expected, larger vessels perform a higher number of

[14] Quota lease rent collected from Pinkerton and Edwards (2009).

expected set events, and it is the same among information sharing skippers. These results are robust to various weather specifications implying after controlling for other factors weather does not play a role. Hence, I drop the weather effects from further analysis. Next, I discuss results related to testing of reference-dependent preferences.

### 3.8.3 Reference-Dependent Prediction Testing

The linear reference-dependent model predicts wage elasticity of labor supply to be $-1$, when the catch is equal to target catch and wage elasticity to be positive, otherwise. I allow the wage variable to have different slopes depending on the relative position of catch and target catch of the trip. It is difficult to stop precisely when the catch is equal to the target catch. So I define a neighborhood around target catch to find the trips when the catch is equal to target and catch away from the target. The results based on the catch to target ratio between 0.85 to 1.10 is presented in table 3.4. The definition of wage used is location wage adjusted for mining effects. Robustness checks with various definitions of the neighborhood and other wage definitions are also done.

The wage slope coefficient when the catch is below the target catch is significantly estimated at $-0.061$. This implies a 1 pound increase in catch per skate decreases the expected set events done by 0.061% when the catch is less than 85% of the target catch. The slope coefficient of the wage is not significantly different from 0, for both the segments: the catch equal to the target or more than the target.

The wage elasticity of labor supply when the catch is below the target is estimated at $-0.127$ and is significantly different from 0. This also implies the null hypothesis of elasticity equal to 0 cannot be rejected when the alternative hypothesis of positive wage elasticity when the catch is less than the target. The wage elasticity of labor supply when the catch is more than the target is estimated to be $-0.063$. The null hypothesis of the wage elasticity equal to 0 cannot be rejected when the alternative hypothesis of positive wage elasticity. On the other hand, when the catch is equal to the target, the wage elasticity is estimated at $-0.039$ and is significantly different from $-1$. Hence, the behavior of the fishermen is inconsistent with the linear reference-dependent model's predictions, and both the hypotheses (2a) and (2b) cannot be supported with the data. The tables 3.5, 3.6, 3.7, and 3.8 summaries the wage elasticities of labor supply based on various definitions of the neighborhood, stating when the catch is equal to the target or not. The results are also robust different definitions of the neighborhood.

The negative relationship between wages and hours, even before the target is achieved can be explained by the non-linear reference-dependent model. Under non-linear sensations from gain and loss, there is decreasing sensitivity to loss or the catch less than the target. Then, as a response to the wage increase, the skipper may respond by working more hours so that the catch gets closer to the target, and the fisherman gets more utility. However, due to diminishing sensitivity, when the catch is less than the target, this channel fails to increase the utility efficiently. On the other hand, as a response to the increased wage rate, the skipper can reduce working hours, thereby decreasing the disutility from work and finally increasing utility. Also note that the estimated wage elasticity is inelastic, so reducing hours would also lead to an increase in remuneration.

### 3.8.4 Experience Effects

Do experienced fishermen behave differently from inexperienced fishermen? I allowed different wage coefficients for low and high experienced fishermen to test for experience effects. I define low experience as experience less than or equal to median data years of skipper experience (20 years) and high experience, otherwise. The column (1) of table 3.9 presents the estimates associated with experience effects specification. I find for low experience fishermen: the wage coefficient is not significantly different from 0. This implies low experience fishermen do not respond to wages in determining working hours. However, among high experience fishermen, a 1 pound increase in catch per skate decreases the expected number of set events by 0.061%, and this effect is statistically significant.

The wage elasticity of labor supply for high experience fishermen is $-0.127$, but for low experienced fishermen, it is not statistically different from 0. This is just the opposite of the behavior of taxi drivers as highly experienced taxi drivers have positive wage elasticity. Next, I present results from the likelihood ratio test to check whether the slopes are the same across low and high experience. The log-likelihood of the restricted model with the same slope for either low or high experience is $-575.977$ and for the unrestricted model is $-575.092$. The test statistic is 1.769, with a p-value of 0.183. Hence, I fail to reject the null hypothesis of the same slope for low and high experience.

Do fishermen behave differently given the relative position of the catch to the target catch, given low or high experience? I allow for 4 different slopes of the wage for this testing, and the results are presented in the column (2) of the table 3.9. I define the catch is less than the target if the catch is 85% or less than the target. When the catch is more than 85% of the target, then it is defined as the catch is more than the target. Again the wage elasticity of high experience fishermen is significantly different from 0 and the magnitude is stronger when the catch is less than the target catch. The log-likelihood of this unrestricted model is $-572.982$ and the log-likelihood of the restricted model allowing for the same slope irrespective of the relative position of the catch and the target is $-575.092$. The likelihood ratio statistic is 4.315, with a p-value of 0.115. Hence, I fail to reject the null hypothesis of equal slopes.

### 3.8.5 Vessel Length Effects

The length of the vessel is an essential part of the fishing operations as it determines how far the vessel can steam, the capacity of fish that can be stored, number of crew members on board, among other things. So, I investigate whether fishermen with large vessels behave differently from fishermen with small vessels? I allowed different wage coefficients for small and large vessels to test for vessel length effects. I define small vessels as the vessels with length less than or equal to data median vessel length (54 foot) and large vessel, otherwise. The column (1) of table 3.10 presents the estimates associated with vessel length effects specification. I find both small and large fishermen have the wage coefficient not significantly different from 0.

The wage elasticity of labor supply for both small and large vessel fishermen is not statistically different from 0. Next, I present results from the likelihood ratio test to check whether the slopes are same across small and large vessels. The log-likelihood of the restricted model with the same slope for either small or large vessel is $-575.977$ and for the unrestricted model is $-575.759$. The test statistic is 0.436, with a p-value of 0.509. Hence, I fail to reject the null hypothesis of the same slope for small and large vessels.

Do fishermen behave differently given the relative position of the catch to the target catch, given small or large vessel? I allow for 4 different slopes of the wage for this testing, and the results are presented in the column (2) of table 3.10. I define the catch is less than the target if the catch is 85% or less than the target. When catch is more than 85% of the target then it is defined as the catch is more than the target. The wage elasticity of large vessel fishermen when the catch is below the target is significantly different from 0. The log-likelihood of this unrestricted model is $-575.462$, and the log-likelihood of the restricted model allowing for the same slope irrespective of the relative position of the catch and the target is $-575.759$. The likelihood ratio statistic is 0.595, with a p-value of 0.743. Hence, I fail to reject the null hypothesis of equal slopes.

### 3.8.6 Robustness Checks

The results discussed above are based on the location wage adjusted for the mining effect. I redo the above analyses with 3 other different definitions of the wage rates: location wage, naive wage adjusted, and the naive wage. The neoclassical results, as seen in table 3.11, table 3.12, and table 3.13 are robust to different wage definitions, and the wage elasticity of labor supply is negative but not significantly different from 0. The other explanatory variables maintain their signs and significance levels. For completeness, I also included squared wage effects in table B.1. The squared wage coefficient is negative and significantly estimated, but the linear wage coefficient is not different from 0. Adding the quadratic effect does not significantly improve the model fit; hence, the quadratic wage effects are not used.

The reference-dependent testing with the other definitions of wage shows similar results to location wage adjusted for mining effects as shown in tables 3.14, 3.19, and 3.24. The wage elasticity of labor supply estimates for various neighborhood definitions are also presented: location wage (tables 3.15, 3.16, 3.17, 3.18), naive wage adjusted (tables 3.20, 3.21, 3.22, 3.23), and naive wage (tables 3.25, 3.26, 3.27, 3.28). The finding of statistically significant negative wage coefficient when the catch is less than the target is robust. Also when the catch is equal to the target, the wage elasticity of labor supply is significantly different from $-1$ is robust.

Finally, the tables 3.29, 3.30, and 3.31 presents the wage elasticities for experience effects under other wage definitions. The tables 3.32, 3.33, and 3.34 presents the wage elasticities for vessel length effects under other wage definitions. I find results are similar to what was obtained under location wage adjusted for mining effects.

### 3.9 Conclusion

This chapter investigated the effectiveness of financial motivation in workplaces. Do workers always work more hours when paid higher wages? Analyzing labor supply decisions of autonomous workers, I find workers work lesser hours when faced with higher wages–income targeting behavior. I estimated negative wage elasticity, particularly among highly experienced commercial halibut fishermen at the intensive margin. Specifically, I estimated wage elasticity of $-0.063$, and the magnitude of wage elasticity becomes stronger ($-0.127$) when the catch of the trip is less than the target catch of the trip. These results are inconsistent with the neoclassical theory of labor supply. Moreover, the negative relationship between hours and wages even when the catch is below the target cannot be explained by the linear gain-loss utility of reference-dependent preferences. I find strong evidence of non-linear income targeting behavior among commercial halibut fishermen. The policy implication is that increasing wages does not always increase the labor supply.

The obtained negative wage elasticities should be interpreted with caution. The nature of longline fishing activity requires planning by the vessel skipper on the location of the trip, buying fishing supplies, and scheduling the crew. After steaming to the fishing location and investing time, if the vessel returns to port almost empty-handed due to low productivity, this could reflect poorly on the management skills of the skipper, and it would be difficult to find crew members in future as their pay also depends on the catch. Instead, vessel skippers could set a trip specific target to motivate the crew members and some catch target to work to, even if the productivity is low. In this way, the crew members have some idea about the trip-specific payoff under fishing uncertainty, and the skipper will find motivated crew members working towards a target. The downside is that it would be challenging to make crew members work more hours when the target is achieved, even when the productivity is high. Future research should investigate the role of group dynamics and the importance of bargaining between the vessel skipper and crew members in labor supply decisions. Moreover, this chapter analyzed the marginal decision to quit by studying the relationship between working hours and wage rate at the point of quitting the trip. One can potentially learn more about the labor supply decisions of the skipper by accounting for all the infra-marginal decisions by solving the complete dynamic optimal stopping problem.

## 3.10 Tables and Figures

Table 3.1 Summary Statistics for labor supply results

| Statistic ($N = 329$) | Mean | St. Dev. | Min | Max |
|---|---|---|---|---|
| Set events | 3.982 | 2.314 | 1 | 13 |
| Location wage adjusted ( '00 lbs.) | 2.446 | 1.608 | 0.139 | 6.021 |
| Location wage ( '00 lbs.) | 2.527 | 1.638 | 0.148 | 6.047 |
| Naive wage adjusted ( '00 lbs.) | 2.416 | 1.754 | 0.01 | 6.259 |
| Naive wage ( '00 lbs.) | 2.494 | 1.791 | 0.011 | 6.31 |
| Black cod ('000 lbs.) | 4.04 | 10.415 | 0 | 60.357 |
| Objective prod ('00 lbs) | 3.268 | 1.593 | 1.036 | 6.563 |
| Dummy vessel hold (= 1, if bind) | 0.158 | 0.365 | 0 | 1 |
| Dummy quota constraint (= 1, if bind) | 0.231 | 0.422 | 0 | 1 |
| Dummy year 2007 (= 1, if bind) | 0.459 | 0.499 | 0 | 1 |
| Dummy area 3A (= 1, if bind) | 0.62 | 0.486 | 0 | 1 |
| Dummy area 3B (= 1, if bind) | 0.292 | 0.455 | 0 | 1 |
| Vessel Length (feet) | 53.243 | 13.665 | 30 | 100 |
| Average crew size | 3.988 | 1.304 | 1.667 | 6.8 |
| Dummy share info (= 1, if share) | 0.708 | 0.455 | 0 | 1 |

Table 3.2 Variable Description for labor supply results

| Variable | Description |
|---|---|
| | *Dependent Variable* |
| Set Events | Number of set events performed on a trip which is a positive integer. |
| | *Independent Variables: Time-Variant* |
| Location wage adjusted | Average catch per skate at the last location of the trip, adjusted for mining effect. |
| Location wage | Average catch per skate at the last location of the trip. |
| Naive wage adjusted | Catch per skate from the last set event of the trip, adjusted for mining effect. |
| Naive wage | Catch per skate from the last set event of the trip |
| Black Cod | Weight of Black Cod caught on each trip (in '000 pounds). |
| Objective productivity | Expected catch per skate of the skipper at the trip's location (in '00 pounds). If multiple locations fished, then the measure reflects average productivity. Location is determined by using cluster analysis. |
| Vessel hold | Dummy variable = 1, if the ratio of vessel's catch to the maximum capapcity of the vessel is $\geq 0.85$; else 0. |
| Quota constraint | Dummy variable = 1, if seasonal quota binds on a trip; else 0. Assuming quota binds on the last regional trip of the skipper. |
| Year 2007 | Dummy variable = 1, if trip is in year 2007; else 0. |
| Region 3A | Dummy variable = 1, if trip is in IPHC region 3A; else 0. |
| Region 3B | Dummy variable = 1, if trip is in IPHC region 3A; else 0. |
| | *Independent Variables: Time-Invariant* |
| Vessel Length | Length (in feet) of the vessel used for the trip. |
| Average crew | Average number of crew members present on board during all the trips of the vessel. |
| Share information | Dummy variable = 1, if productivity information is shared; else 0. |

Table 3.3 Neoclassical testing (location wage adjusted)

| | *Dependent variable:* Set Events | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| | Panel A: Estimates and Standard Errors | | |
| *Trip variant variables:* | | | |
| Wage ($\times 10^{-2}$ lbs.) | $-0.033^{**}$ | $-0.032^{**}$ | $-0.032^{*}$ |
| | (0.015) | (0.015) | (0.017) |
| Black cod | 0.004 | 0.004 | 0.004 |
| | (0.004) | (0.004) | (0.004) |
| Objective productivity | $-0.028$ | $-0.027$ | $-0.027$ |
| | (0.031) | (0.030) | (0.032) |
| Vessel hold | $0.205^{***}$ | $0.206^{***}$ | $0.202^{***}$ |
| | (0.050) | (0.051) | (0.054) |
| Quota constraint | $-0.101$ | $-0.106^{*}$ | $-0.107^{*}$ |
| | (0.065) | (0.061) | (0.064) |
| Region 3A | $-0.074$ | $-0.075$ | 0.074 |
| | (0.133) | (0.133) | (0.132) |
| Region 3B | $0.262^{*}$ | $0.261^{*}$ | $0.259^{*}$ |
| | (0.146) | (0.146) | (0.148) |
| *Trip invariant variables:* | | | |
| Vessel length | $0.019^{***}$ | $0.018^{***}$ | $0.019^{***}$ |
| | (0.006) | (0.005) | (0.006) |
| Average crew | 0.011 | 0.009 | 0.009 |
| | (0.046) | (0.043) | (0.045) |
| Share information | $0.213^{*}$ | $0.217^{*}$ | $0.218^{*}$ |
| | (0.126) | (0.120) | (0.131) |
| | Panel B: Wage Elasticity | | |
| Wage elasticity | $-0.063$ | $-0.061$ | $-0.061$ |
| | (0.031) | (0.031) | (0.031) |
| Wind effects | No | Yes | Yes |
| Linear wind effects | No | Yes | Yes |
| Sq wind effects | No | No | Yes |
| Observations | 329 | 329 | 329 |
| Log-likelihood | $-575.977$ | $-575.749$ | $-575.525$ |

Note: Skipper and year fixed effects are included. Bootstrapped standard error from 400 replications are in parenthesis. Log-likelihood value is from the first stage regression. Elasticity calculated at sample average values. Null hypothesis of elasticity = 0 is tested against elasticity > 0. Significant at $^{*}$10%, $^{**}$5%,$^{***}$1%.

Table 3.4 Reference-Dependent testing (location wage adjusted)

| | *Dependent variable:* Set Events |
|---|---|
| | (1) |
| | Panel A: Estimates and Standard Errors |
| *Trip variant variables:* | |
| Wage $\left(\frac{\text{catch}}{\text{target}} \leq 0.85\right)$ | $-0.061^{***}$ |
| | (0.023) |
| Wage $\left(0.85 < \frac{\text{catch}}{\text{target}} \leq 1.10\right)$ | $-0.021$ |
| | (0.018) |
| Wage $\left(\frac{\text{catch}}{\text{target}} \geq 1.10\right)$ | $-0.033$ |
| | (0.021) |
| Objective productivity | $-0.027$ |
| | (0.029) |
| Vessel hold | $0.172^{***}$ |
| | (0.053) |
| Quota constraint | $-0.121^{*}$ |
| | (0.069) |
| *Trip invariant variables:* | |
| Vessel length | $0.019^{***}$ |
| | (0.006) |
| Average crew | 0.011 |
| | (0.045) |
| Share information | $0.210^{*}$ |
| | (0.121) |
| | Panel B: Wage Elasticity |
| Wage elasticity $\left(\frac{\text{catch}}{\text{target}} \leq 0.85\right)$ | $-0.127$ |
| | (0.057) |
| Wage elasticity $\left(0.85 < \frac{\text{catch}}{\text{target}} \leq 1.10\right)$ | $-0.039^{***}$ |
| | (0.035) |
| Wage elasticity $\left(\frac{\text{catch}}{\text{target}} \geq 1.10\right)$ | $-0.063$ |
| | (0.044) |
| Observations | 329 |
| Log-likelihood | $-575.001$ |

Note: Skipper, region, and year fixed effects are included and Black cod pounds controlled. Bootstrapped standard error from 400 replications are in parenthesis. Log-likelihood value is from the first stage regression. Elasticity calculated at sample average values. For revenue below and above target, elasticity = 0 is tested against elasticity > 0; for revenue equal to target, elasticity = −1 is tested against elasticity ≠ −1. Significant at $^{*}$10%, $^{**}$5%,$^{***}$1%.

Table 3.5 Elasticity: Reference-Dependent model 1 (location wage adjusted)

| | Wage elasticity |
|---|---|
| Revenue less than target $\left(\frac{\text{catch}}{\text{target}} \leq 0.90\right)$ | $-0.110$ |
| | (0.050) |
| Revenue equal to target $\left(0.90 < \frac{\text{catch}}{\text{target}} \leq 1.05\right)$ | $-0.045^{***}$ |
| | (0.036) |
| Revenue more than target $\left(\frac{\text{catch}}{\text{target}} \geq 1.05\right)$ | $-0.053$ |
| | (0.041) |

Note: Elasticity calculated at sample average values. The null hypothesis for Revenue less than target and Revenue more than target rows are wage elasticity is equal to 0 against the alternative hypothesis of wage elasticity is positive. The null hypothesis for Revenue equal to target row is wage elasticity is equal to $-1$ against the alternative hypothesis of wage elasticity not equal to $-1$. Significant at $^{*}10\%$, $^{**}5\%$, $^{***}1\%$.

Table 3.6 Elasticity: Reference-Dependent model 2 (location wage adjusted)

| | Wage elasticity |
|---|---|
| Revenue less than target $\left(\frac{\text{catch}}{\text{target}} \leq 0.90\right)$ | $-0.108$ |
| | (0.049) |
| Revenue equal to target $\left(0.90 < \frac{\text{catch}}{\text{target}} \leq 1.10\right)$ | $-0.039^{***}$ |
| | (0.033) |
| Revenue more than target $\left(\frac{\text{catch}}{\text{target}} \geq 1.10\right)$ | $-0.061$ |
| | (0.044) |

Note: Elasticity calculated at sample average values. The null hypothesis for Revenue less than target and Revenue more than target rows are wage elasticity is equal to 0 against the alternative hypothesis of wage elasticity is positive. The null hypothesis for Revenue equal to target row is wage elasticity is equal to $-1$ against the alternative hypothesis of wage elasticity not equal to $-1$. Significant at $^{*}10\%$, $^{**}5\%$, $^{***}1\%$.

Table 3.7 Elasticity: Reference-Dependent model 3 (location wage adjusted)

| | Wage elasticity |
|---|---|
| Revenue less than target $\left(\frac{\text{catch}}{\text{target}} \leq 0.85\right)$ | $-0.129$ |
| | (0.057) |
| Revenue equal to target $\left(0.85 < \frac{\text{catch}}{\text{target}} \leq 1.15\right)$ | $-0.045^{***}$ |
| | (0.034) |
| Revenue more than target $\left(\frac{\text{catch}}{\text{target}} \geq 1.15\right)$ | $-0.059$ |
| | (0.044) |

Note: Elasticity calculated at sample average values. The null hypothesis for Revenue less than target and Revenue more than target rows are wage elasticity is equal to 0 against the alternative hypothesis of wage elasticity is positive. The null hypothesis for Revenue equal to target row is wage elasticity is equal to $-1$ against the alternative hypothesis of wage elasticity not equal to $-1$. Significant at $^{*}$10%, $^{**}$5%, $^{***}$1%.

Table 3.8 Elasticity: Reference-Dependent model 4 (location wage adjusted)

| | Wage elasticity |
|---|---|
| Revenue less than target $\left(\frac{\text{catch}}{\text{target}} \leq 0.80\right)$ | $-0.160$ |
| | (0.075) |
| Revenue equal to target $\left(0.80 < \frac{\text{catch}}{\text{target}} \leq 1.15\right)$ | $-0.049^{***}$ |
| | (0.032) |
| Revenue more than target $\left(\frac{\text{catch}}{\text{target}} \geq 1.15\right)$ | $-0.061$ |
| | (0.044) |

Note: Elasticity calculated at sample average values. The null hypothesis for Revenue less than target and Revenue more than target rows are wage elasticity is equal to 0 against the alternative hypothesis of wage elasticity is positive. The null hypothesis for Revenue equal to target row is wage elasticity is equal to $-1$ against the alternative hypothesis of wage elasticity not equal to $-1$. Significant at $^{*}$10%, $^{**}$5%, $^{***}$1%.

Table 3.9 Experience effects (location wage adjusted)

| | *Dependent variable:* Set Events | |
|---|---|---|
| | (1) | (2) |
| | Panel A: Estimates and Standard Errors | |
| *Trip variant variables:* | | |
| Wage (low experience) | $-0.004$ | |
| | (0.020) | |
| Wage (high experience) | $-0.061^{**}$ | |
| | (0.026) | |
| Wage (catch $<$ target & low experience) | | $-0.014$ |
| | | (0.026) |
| Wage (catch $\geq$ target & low experience) | | 0.007 |
| | | (0.021) |
| Wage (catch $<$ target & high experience) | | $-0.144^{***}$ |
| | | (0.052) |
| Wage (catch $\geq$ target & high experience) | | $-0.059^{**}$ |
| | | (0.029) |
| Black cod | 0.004 | 0.004 |
| | (0.004) | (0.004) |
| Objective productivity | $-0.020$ | $-0.018$ |
| | (0.030) | (0.031) |
| *Trip invariant variables:* | | |
| Vessel length | $0.017^{***}$ | $0.017^{***}$ |
| | (0.006) | (0.006) |
| Average crew | 0.023 | 0.026 |
| | (0.050) | (0.050) |
| Share information | 0.198 | 0.167 |
| | (0.134) | (0.119) |
| | Panel B: Wage Elasticity | |
| Elasticity (low experience) | $-0.007$ | |
| | (0.036) | |
| Elasticity (high experience) | $-0.127^{**}$ | |
| | (0.064) | |
| Elasticity (catch $<$ target & low experience) | | $-0.026$ |
| | | (0.049) |
| Elasticity (catch $\geq$ target & low experience) | | 0.012 |
| | | (0.036) |
| Elasticity (catch $<$ target & high experience) | | $-0.399^{*}$ |
| | | (0.227) |
| Elasticity (catch $\geq$ target & high experience) | | $-0.122^{*}$ |
| | | (0.071) |
| Observations | 329 | 329 |
| Log-likelihood | $-575.092$ | $-572.982$ |

Note: Skipper, year, and region fixed effects are included. Dummies for vessel hold and quota constraint used. Bootstrapped standard error from 400 replications are in parenthesis. Log-likelihood value is from the first stage regression. Significant at $^{*}$10%, $^{**}$5%,$^{***}$1%.

Table 3.10 Vessel length effects (location wage adjusted)

| | *Dependent variable:* Set Events | |
|---|---|---|
| | (1) | (2) |
| | Panel A: Estimates and Standard Errors | |
| *Trip variant variables:* | | |
| Wage (small vessel) | −0.059 | |
| | (0.043) | |
| Wage (large vessel) | −0.025 | |
| | (0.017) | |
| Wage (catch $<$ target & small vessel) | | −0.101* |
| | | (0.052) |
| Wage (catch $\geq$ target & small vessel) | | −0.037 |
| | | (0.036) |
| Wage (catch $<$ target & large vessel) | | −0.041 |
| | | (0.027) |
| Wage (catch $\geq$ target & large vessel) | | −0.017 |
| | | (0.018) |
| Black cod | 0.004 | 0.004 |
| | (0.004) | (0.004) |
| Objective prod. | −0.029 | −0.030 |
| | (0.033) | (0.033) |
| *Trip invariant variables:* | | |
| Vessel length | 0.017*** | 0.017*** |
| | (0.006) | (0.006) |
| Average crew | −0.005 | 0.003 |
| | (0.054) | (0.047) |
| Share information | 0.234* | 0.218* |
| | (0.136) | (0.121) |
| | Panel B: Wage Elasticity | |
| Elasticity (low exp) | −0.122 | |
| | (0.105) | |
| Elasticity (high exp) | −0.047 | |
| | (0.034) | |
| Elasticity (catch $<$ target & small vessel) | | −0.018 |
| | | (0.015) |
| Elasticity (catch $\geq$ target & small vessel) | | 0.007 |
| | | (0.017) |
| Elasticity (catch $<$ target & large vessel) | | −0.098** |
| | | (0.048) |
| Elasticity (catch $\geq$ target & large vessel) | | −0.072 |
| | | (0.047) |
| Observations | 329 | 329 |
| Log-likelihood | −575.759 | −575.462 |

Note: Skipper, year, and region fixed effects are included. Dummies for vessel hold and quota constraint used. Bootstrapped standard error from 400 replications are in parenthesis. Log-likelihood value is from the first stage regression. Significant at *10%, **5%,***1%.

Table 3.11 Neoclassical testing (location wage)

| | *Dependent variable:* Set Events | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| | Panel A: Estimates and Standard Errors | | |
| *Trip variant variables:* | | | |
| Wage ($\times 10^{-2}$ lbs.) | −0.025 | −0.024 | −0.024 |
| | (0.017) | (0.016) | (0.016) |
| Black cod | 0.004 | 0.004 | 0.004 |
| | (0.004) | (0.004) | (0.004) |
| Objective productivity | −0.028 | −0.028 | −0.028 |
| | (0.031) | (0.031) | (0.030) |
| Vessel hold | 0.194*** | 0.195*** | 0.191*** |
| | (0.055) | (0.053) | (0.056) |
| Quota constraint | −0.101 | −0.106* | −0.107 |
| | (0.062) | (0.062) | (0.065) |
| Region 3A | −0.085 | −0.085 | −0.085 |
| | (0.130) | (0.129) | (0.129) |
| Region 3B | 0.257* | 0.257* | 0.254* |
| | (0.152) | (0.146) | (0.143) |
| *Trip invariant variables:* | | | |
| Vessel length | 0.019*** | 0.019*** | 0.018*** |
| | (0.005) | (0.005) | (0.005) |
| Average crew | 0.009 | 0.007 | 0.007 |
| | (0.045) | (0.043) | (0.042) |
| Share information | 0.213 | 0.217** | 0.217 |
| | (0.137) | (0.126) | (0.136) |
| | Panel B: Wage Elasticity | | |
| Wage elasticity | −0.047 | −0.045 | −0.045 |
| | (0.034) | (0.032) | (0.032) |
| Wind effects | No | Yes | Yes |
| Linear wind effects | No | Yes | Yes |
| Sq wind effects | No | No | Yes |
| Observations | 329 | 329 | 329 |
| Log-likelihood | −576.341 | −576.102 | −575.877 |

Note: Skipper and year fixed effects are included. Bootstrapped standard error from 400 replications are in parenthesis. Log-likelihood value is from the first stage regression. Elasticity calculated at sample average values. Null hypothesis of elasticity = 0 is tested against elasticity > 0. Significant at *10%, **5%,***1%.

Table 3.12 Neoclassical testing (naive wage adjusted)

| | *Dependent variable:* Set Events | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| | Panel A: Estimates and Standard Errors | | |
| *Trip variant variables:* | | | |
| Wage ($\times 10^{-2}$ lbs.) | $-0.024^{**}$ | $-0.023^{*}$ | $-0.024^{*}$ |
| | (0.012) | (0.013) | (0.014) |
| Black cod | 0.004 | 0.004 | 0.005 |
| | (0.004) | (0.004) | (0.004) |
| Objective productivity | −0.026 | −0.026 | −0.026 |
| | (0.031) | (0.0301 | (0.032) |
| Vessel hold | $0.186^{***}$ | $0.187^{***}$ | $0.184^{***}$ |
| | (0.052) | (0.050) | (0.051) |
| Quota constraint | −0.099 | $-0.105^{*}$ | $-0.106^{*}$ |
| | (0.064) | (0.063) | (0.064) |
| Region 3A | −0.086 | −0.087 | −0.085 |
| | (0.125) | (0.133) | (0.125) |
| Region 3B | $0.256^{*}$ | $0.255^{*}$ | $0.254^{*}$ |
| | (0.143) | (0.151) | (0.143) |
| *Trip invariant variables:* | | | |
| Vessel length | $0.018^{***}$ | $0.018^{***}$ | $0.018^{***}$ |
| | (0.005) | (0.006) | (0.005) |
| Average crew | 0.006 | 0.005 | 0.005 |
| | (0.046) | (0.042) | (0.044) |
| Share information | 0.211 | $0.214^{**}$ | 0.214 |
| | (0.130) | (0.134) | (0.137) |
| | Panel B: Wage Elasticity | | |
| Wage elasticity | −0.045 | −0.043 | −0.045 |
| | (0.024) | (0.026) | (0.028) |
| Wind effects | No | Yes | Yes |
| Linear wind effects | No | Yes | Yes |
| Sq wind effects | No | No | Yes |
| Observations | 329 | 329 | 329 |
| Log-likelihood | −576.136 | −575.950 | −575.680 |

Note: Skipper and year fixed effects are included. Bootstrapped standard error from 400 replications are in parenthesis. Log-likelihood value is from the first stage regression. Elasticity calculated at sample average values. Null hypothesis of elasticity = 0 is tested against elasticity > 0. Significant at $^{*}$10%, $^{**}$5%, $^{***}$1%.

Table 3.13 Neoclassical testing (naive wage)

| | *Dependent variable:* Set Events | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| | Panel A: Estimates and Standard Errors | | |
| *Trip variant variables:* | | | |
| Wage ($\times 10^{-2}$ lbs.) | −0.019 | −0.018 | −0.018 |
| | (0.013) | (0.013) | (0.013) |
| Black cod | 0.004 | 0.005 | 0.004 |
| | (0.004) | (0.004) | (0.004) |
| Objective productivity | −0.027 | −0.027 | −0.027 |
| | (0.032) | (0.030) | (0.031) |
| Vessel hold | 0.181*** | 0.181*** | 0.178*** |
| | (0.052) | (0.053) | (0.054) |
| Quota constraint | −0.101 | −0.105 | −0.106* |
| | (0.063) | (0.066) | (0.061) |
| Region 3A | −0.093 | −0.094 | −0.092 |
| | (0.127) | (0.126) | (0.131) |
| Region 3B | 0.253* | 0.252* | 0.251* |
| | (0.143) | (0.142) | (0.146) |
| *Trip invariant variables:* | | | |
| Vessel length | 0.018*** | 0.018*** | 0.018*** |
| | (0.006) | (0.005) | (0.005) |
| Average crew | 0.006 | 0.004 | 0.004 |
| | (0.045) | (0.042) | (0.044) |
| Share information | 0.210 | 0.214** | 0.214 |
| | (0.138) | (0.134) | (0.134) |
| | Panel B: Wage Elasticity | | |
| Wage elasticity | −0.035 | −0.033 | −0.033 |
| | (0.025) | (0.025) | (0.025) |
| Wind effects | No | Yes | Yes |
| Linear wind effects | No | Yes | Yes |
| Sq wind effects | No | No | Yes |
| Observations | 329 | 329 | 329 |
| Log-likelihood | −576.381 | −576.178 | −575.921 |

Note: Skipper and year fixed effects are included. Bootstrapped standard error from 400 replications are in parenthesis. Log-likelihood value is from the first stage regression. Elasticity calculated at sample average values. Null hypothesis of elasticity = 0 is tested against elasticity > 0. Significant at *10%, **5%,***1%.

Table 3.14 Reference-Dependent testing (location wage)

| | *Dependent variable:* Set Events |
|---|---|
| | (1) |
| | Panel A: Estimates and Standard Errors |
| *Trip variant variables:* | |
| Wage $\left(\frac{\text{catch}}{\text{target}} \leq 0.85\right)$ | $-0.051^{**}$ |
| | (0.022) |
| Wage $\left(0.85 < \frac{\text{catch}}{\text{target}} \leq 1.10\right)$ | $-0.013$ |
| | (0.017) |
| Wage $\left(\frac{\text{catch}}{\text{target}} \geq 1.10\right)$ | $-0.025$ |
| | (0.020) |
| Objective productivity | $-0.027$ |
| | (0.031) |
| Vessel hold | $0.163^{***}$ |
| | (0.055) |
| Quota constraint | $-0.122^{**}$ |
| | (0.066) |
| *Trip invariant variables:* | |
| Vessel length | $0.018^{***}$ |
| | (0.005) |
| Average crew | 0.010 |
| | (0.045) |
| Share information | $0.209^{*}$ |
| | (0.125) |
| | Panel B: Wage Elasticity |
| Wage elasticity $\left(\frac{\text{catch}}{\text{target}} \leq 0.85\right)$ | $-0.103$ |
| | (0.051) |
| Wage elasticity $\left(0.85 < \frac{\text{catch}}{\text{target}} \leq 1.10\right)$ | $-0.024^{***}$ |
| | (0.032) |
| Wage elasticity $\left(\frac{\text{catch}}{\text{target}} \geq 1.10\right)$ | $-0.047$ |
| | (0.040) |
| Observations | 329 |
| Log-likelihood | $-575.001$ |

Note: Skipper, region, and year fixed effects are included and Black cod pounds controlled. Bootstrapped standard error from 400 replications are in parenthesis. Log-likelihood value is from the first stage regression. Elasticity calculated at sample average values. For revenue below and above target, elasticity = 0 is tested against elasticity > 0; for revenue equal to target, elasticity = $-1$ is tested against elasticity $\neq -1$. Significant at $^{*}$10%, $^{**}$5%, $^{***}$1%.

Table 3.15 Elasticity: Reference-Dependent model 1 (location wage)

| | Wage elasticity |
|---|---|
| Revenue less than target $\left(\frac{\text{catch}}{\text{target}} \leq 0.90\right)$ | $-0.187$ |
| | (0.047) |
| Revenue equal to target $\left(0.90 < \frac{\text{catch}}{\text{target}} \leq 1.05\right)$ | $-0.031^{***}$ |
| | (0.035) |
| Revenue more than target $\left(\frac{\text{catch}}{\text{target}} \geq 1.05\right)$ | $-0.037$ |
| | (0.041) |

Note: Elasticity calculated at sample average values. The null hypothesis for Revenue less than target and Revenue more than target rows are wage elasticity is equal to 0 against the alternative hypothesis of wage elasticity is positive. The null hypothesis for Revenue equal to target row is wage elasticity is equal to $-1$ against the alternative hypothesis of wage elasticity not equal to $-1$. Significant at $^{*}$10%, $^{**}$5%, $^{***}$1%.

Table 3.16 Elasticity: Reference-Dependent model 2 (location wage)

| | Wage elasticity |
|---|---|
| Revenue less than target $\left(\frac{\text{catch}}{\text{target}} \leq 0.90\right)$ | $-0.085$ |
| | (0.044) |
| Revenue equal to target $\left(0.90 < \frac{\text{catch}}{\text{target}} \leq 1.10\right)$ | $-0.024^{***}$ |
| | (0.032) |
| Revenue more than target $\left(\frac{\text{catch}}{\text{target}} \geq 1.10\right)$ | $-0.045$ |
| | (0.042) |

Note: Elasticity calculated at sample average values. The null hypothesis for Revenue less than target and Revenue more than target rows are wage elasticity is equal to 0 against the alternative hypothesis of wage elasticity is positive. The null hypothesis for Revenue equal to target row is wage elasticity is equal to $-1$ against the alternative hypothesis of wage elasticity not equal to $-1$. Significant at $^{*}$10%, $^{**}$5%, $^{***}$1%.

Table 3.17 Elasticity: Reference-Dependent model 3 (location wage)

| | Wage elasticity |
|---|---|
| Revenue less than target $\left(\frac{\text{catch}}{\text{target}} \leq 0.85\right)$ | $-0.105$ |
| | (0.056) |
| Revenue equal to target $\left(0.85 < \frac{\text{catch}}{\text{target}} \leq 1.15\right)$ | $-0.029^{***}$ |
| | (0.034) |
| Revenue more than target $\left(\frac{\text{catch}}{\text{target}} \geq 1.15\right)$ | $-0.043$ |
| | (0.042) |

Note: Elasticity calculated at sample average values. The null hypothesis for Revenue less than target and Revenue more than target rows are wage elasticity is equal to 0 against the alternative hypothesis of wage elasticity is positive. The null hypothesis for Revenue equal to target row is wage elasticity is equal to $-1$ against the alternative hypothesis of wage elasticity not equal to $-1$. Significant at $^{*}$10%, $^{**}$5%, $^{***}$1%.

Table 3.18 Elasticity: Reference-Dependent model 4 (location wage)

| | Wage elasticity |
|---|---|
| Revenue less than target $\left(\frac{\text{catch}}{\text{target}} \leq 0.80\right)$ | $-0.132$ |
| | (0.070) |
| Revenue equal to target $\left(0.80 < \frac{\text{catch}}{\text{target}} \leq 1.15\right)$ | $-0.033^{***}$ |
| | (0.031) |
| Revenue more than target $\left(\frac{\text{catch}}{\text{target}} \geq 1.15\right)$ | $-0.047$ |
| | (0.044) |

Note: Elasticity calculated at sample average values. The null hypothesis for Revenue less than target and Revenue more than target rows are wage elasticity is equal to 0 against the alternative hypothesis of wage elasticity is positive. The null hypothesis for Revenue equal to target row is wage elasticity is equal to $-1$ against the alternative hypothesis of wage elasticity not equal to $-1$. Significant at $^{*}$10%, $^{**}$5%, $^{***}$1%.

Table 3.19 Reference-Dependent testing (naive wage adjusted)

| | *Dependent variable:* Set Events |
|---|---|
| | (1) |
| | Panel A: Estimates and Standard Errors |
| *Trip variant variables:* | |
| Wage $\left(\frac{\text{catch}}{\text{target}} \leq 0.85\right)$ | $-0.052^{**}$ |
| | (0.022) |
| Wage $\left(0.85 < \frac{\text{catch}}{\text{target}} \leq 1.10\right)$ | $-0.009^{***}$ |
| | (0.017) |
| Wage $\left(\frac{\text{catch}}{\text{target}} \geq 1.10\right)$ | $-0.019$ |
| | (0.017) |
| Objective productivity | $-0.027$ |
| | (0.032) |
| Vessel hold | $0.142^{***}$ |
| | (0.047) |
| Quota constraint | $-0.121^{**}$ |
| | (0.061) |
| *Trip invariant variables:* | |
| Vessel length | $0.018^{***}$ |
| | (0.006) |
| Average crew | 0.006 |
| | (0.042) |
| Share information | 0.209 |
| | (0.128) |
| | Panel B: Wage Elasticity |
| Wage elasticity $\left(\frac{\text{catch}}{\text{target}} \leq 0.85\right)$ | $-0.108$ |
| | (0.052) |
| Wage elasticity $\left(0.85 < \frac{\text{catch}}{\text{target}} \leq 1.10\right)$ | $-0.016^{***}$ |
| | (0.031) |
| Wage elasticity $\left(\frac{\text{catch}}{\text{target}} \geq 1.10\right)$ | $-0.035$ |
| | (0.033) |
| Observations | 329 |
| Log-likelihood | $-574.952$ |

Note: Skipper, region, and year fixed effects are included and Black cod pounds controlled. Bootstrapped standard error from 400 replications are in parenthesis. Log-likelihood value is from the first stage regression. Elasticity calculated at sample average values. For revenue below and above target, elasticity $= 0$ is tested against elasticity $> 0$; for revenue equal to target, elasticity $= -1$ is tested against elasticity $\neq -1$. Significant at $^{*}$10%, $^{**}$5%,$^{***}$1%.

Table 3.20 Elasticity: Reference-Dependent model 1 (naive wage adjusted)

| | Wage elasticity |
|---|---|
| Revenue less than target $\left(\frac{\text{catch}}{\text{target}} \leq 0.90\right)$ | $-0.098$ |
| | (0.211) |
| Revenue equal to target $\left(0.90 < \frac{\text{catch}}{\text{target}} \leq 1.05\right)$ | $-0.029^{***}$ |
| | (0.034) |
| Revenue more than target $\left(\frac{\text{catch}}{\text{target}} \geq 1.05\right)$ | $-0.026$ |
| | (0.030) |

Note: Elasticity calculated at sample average values. The null hypothesis for Revenue less than target and Revenue more than target rows are wage elasticity is equal to 0 against the alternative hypothesis of wage elasticity is positive. The null hypothesis for Revenue equal to target row is wage elasticity is equal to $-1$ against the alternative hypothesis of wage elasticity not equal to $-1$. Significant at $^{*}$10%, $^{**}$5%, $^{***}$1%.

Table 3.21 Elasticity: Reference-Dependent model 2 (naive wage adjusted)

| | Wage elasticity |
|---|---|
| Revenue less than target $\left(\frac{\text{catch}}{\text{target}} \leq 0.90\right)$ | $-0.098$ |
| | (0.046) |
| Revenue equal to target $\left(0.90 < \frac{\text{catch}}{\text{target}} \leq 1.10\right)$ | $-0.018^{***}$ |
| | (0.031) |
| Revenue more than target $\left(\frac{\text{catch}}{\text{target}} \geq 1.10\right)$ | $-0.037$ |
| | (0.035) |

Note: Elasticity calculated at sample average values. The null hypothesis for Revenue less than target and Revenue more than target rows are wage elasticity is equal to 0 against the alternative hypothesis of wage elasticity is positive. The null hypothesis for Revenue equal to target row is wage elasticity is equal to $-1$ against the alternative hypothesis of wage elasticity not equal to $-1$. Significant at $^{*}$10%, $^{**}$5%, $^{***}$1%.

Table 3.22 Elasticity: Reference-Dependent model 3 (naive wage adjusted)

| | Wage elasticity |
|---|---|
| Revenue less than target $\left(\frac{\text{catch}}{\text{target}} \leq 0.85\right)$ | $-0.105$ |
| | (0.049) |
| Revenue equal to target $\left(0.85 < \frac{\text{catch}}{\text{target}} \leq 1.15\right)$ | $-0.020^{***}$ |
| | (0.032) |
| Revenue more than target $\left(\frac{\text{catch}}{\text{target}} \geq 1.15\right)$ | $-0.031$ |
| | (0.033) |

Note: Elasticity calculated at sample average values. The null hypothesis for Revenue less than target and Revenue more than target rows are wage elasticity is equal to 0 against the alternative hypothesis of wage elasticity is positive. The null hypothesis for Revenue equal to target row is wage elasticity is equal to $-1$ against the alternative hypothesis of wage elasticity not equal to $-1$. Significant at $^{*}$10%, $^{**}$5%, $^{***}$1%.

Table 3.23 Elasticity: Reference-Dependent model 4 (naive wage adjusted)

| | Wage elasticity |
|---|---|
| Revenue less than target $\left(\frac{\text{catch}}{\text{target}} \leq 0.80\right)$ | $-0.122$ |
| | (0.058) |
| Revenue equal to target $\left(0.80 < \frac{\text{catch}}{\text{target}} \leq 1.15\right)$ | $-0.024^{***}$ |
| | (0.030) |
| Revenue more than target $\left(\frac{\text{catch}}{\text{target}} \geq 1.15\right)$ | $-0.033$ |
| | (0.033) |

Note: Elasticity calculated at sample average values. The null hypothesis for Revenue less than target and Revenue more than target rows are wage elasticity is equal to 0 against the alternative hypothesis of wage elasticity is positive. The null hypothesis for Revenue equal to target row is wage elasticity is equal to $-1$ against the alternative hypothesis of wage elasticity not equal to $-1$. Significant at $^{*}$10%, $^{**}$5%, $^{***}$1%.

Table 3.24 Reference-Dependent testing (naive wage)

| | *Dependent variable:* Set Events |
|---|---|
| | (1) |
| | Panel A: Estimates and Standard Errors |
| *Trip variant variables:* | |
| Wage $\left(\frac{\text{catch}}{\text{target}} \leq 0.85\right)$ | $-0.044^{**}$ |
| | (0.021) |
| Wage $\left(0.85 < \frac{\text{catch}}{\text{target}} \leq 1.10\right)$ | $-0.004^{***}$ |
| | (0.017) |
| Wage $\left(\frac{\text{catch}}{\text{target}} \geq 1.10\right)$ | $-0.014$ |
| | (0.017) |
| Objective productivity | $-0.027$ |
| | (0.033) |
| Vessel hold | $0.139^{***}$ |
| | (0.047) |
| Quota constraint | $-0.121^{*}$ |
| | (0.067) |
| *Trip invariant variables:* | |
| Vessel length | $0.018^{***}$ |
| | (0.005) |
| Average crew | 0.006 |
| | (0.045) |
| Share information | 0.209 |
| | (0.129) |
| | Panel B: Wage Elasticity |
| Wage elasticity $\left(\frac{\text{catch}}{\text{target}} \leq 0.85\right)$ | $-0.087$ |
| | (0.047) |
| Wage elasticity $\left(0.85 < \frac{\text{catch}}{\text{target}} \leq 1.10\right)$ | $-0.007^{***}$ |
| | (0.031) |
| Wage elasticity $\left(\frac{\text{catch}}{\text{target}} \geq 1.10\right)$ | $-0.026$ |
| | (0.032) |
| Observations | 329 |
| Log-likelihood | $-575.264$ |

Note: Skipper, region, and year fixed effects are included and Black cod pounds controlled. Bootstrapped standard error from 400 replications are in parenthesis. Log-likelihood value is from the first stage regression. Elasticity calculated at sample average values. For revenue below and above target, elasticity = 0 is tested against elasticity > 0; for revenue equal to target, elasticity = −1 is tested against elasticity ≠ −1. Significant at $^{*}$10%, $^{**}$5%,$^{***}$1%.

Table 3.25 Elasticity: Reference-Dependent model 1 (naive wage)

| | Wage elasticity |
|---|---|
| Revenue less than target $\left(\frac{\text{catch}}{\text{target}} \leq 0.90\right)$ | $-0.081$ |
| | (0.042) |
| Revenue equal to target $\left(0.90 < \frac{\text{catch}}{\text{target}} \leq 1.05\right)$ | $-0.022^{***}$ |
| | (0.034) |
| Revenue more than target $\left(\frac{\text{catch}}{\text{target}} \geq 1.05\right)$ | $-0.016$ |
| | (0.035) |

Note: Elasticity calculated at sample average values. The null hypothesis for Revenue less than target and Revenue more than target rows are wage elasticity is equal to 0 against the alternative hypothesis of wage elasticity is positive. The null hypothesis for Revenue equal to target row is wage elasticity is equal to $-1$ against the alternative hypothesis of wage elasticity not equal to $-1$. Significant at $^{*}$10%, $^{**}$5%, $^{***}$1%.

Table 3.26 Elasticity: Reference-Dependent model 2 (naive wage)

| | Wage elasticity |
|---|---|
| Revenue less than target $\left(\frac{\text{catch}}{\text{target}} \leq 0.90\right)$ | $-0.081$ |
| | (0.039) |
| Revenue equal to target $\left(0.90 < \frac{\text{catch}}{\text{target}} \leq 1.10\right)$ | $-0.009^{***}$ |
| | (0.031) |
| Revenue more than target $\left(\frac{\text{catch}}{\text{target}} \geq 1.10\right)$ | $-0.027$ |
| | (0.032) |

Note: Elasticity calculated at sample average values. The null hypothesis for Revenue less than target and Revenue more than target rows are wage elasticity is equal to 0 against the alternative hypothesis of wage elasticity is positive. The null hypothesis for Revenue equal to target row is wage elasticity is equal to $-1$ against the alternative hypothesis of wage elasticity not equal to $-1$. Significant at $^{*}$10%, $^{**}$5%, $^{***}$1%.

Table 3.27 Elasticity: Reference-Dependent model 3 (naive wage)

| | Wage elasticity |
|---|---|
| Revenue less than target $\left(\frac{\text{catch}}{\text{target}} \leq 0.85\right)$ | $-0.087$ |
| | (0.047) |
| Revenue equal to target $\left(0.85 < \frac{\text{catch}}{\text{target}} \leq 1.15\right)$ | $-0.011^{***}$ |
| | (0.029) |
| Revenue more than target $\left(\frac{\text{catch}}{\text{target}} \geq 1.15\right)$ | $-0.022$ |
| | (0.030) |

Note: Elasticity calculated at sample average values. The null hypothesis for Revenue less than target and Revenue more than target rows are wage elasticity is equal to 0 against the alternative hypothesis of wage elasticity is positive. The null hypothesis for Revenue equal to target row is wage elasticity is equal to $-1$ against the alternative hypothesis of wage elasticity not equal to $-1$. Significant at $^{*}$10%, $^{**}$5%, $^{***}$1%.

Table 3.28 Elasticity: Reference-Dependent model 4 (naive wage)

| | Wage elasticity |
|---|---|
| Revenue less than target $\left(\frac{\text{catch}}{\text{target}} \leq 0.80\right)$ | $-0.103$ |
| | (0.053) |
| Revenue equal to target $\left(0.80 < \frac{\text{catch}}{\text{target}} \leq 1.15\right)$ | $-0.013^{***}$ |
| | (0.027) |
| Revenue more than target $\left(\frac{\text{catch}}{\text{target}} \geq 1.15\right)$ | $-0.024$ |
| | (0.030) |

Note: Elasticity calculated at sample average values. The null hypothesis for Revenue less than target and Revenue more than target rows are wage elasticity is equal to 0 against the alternative hypothesis of wage elasticity is positive. The null hypothesis for Revenue equal to target row is wage elasticity is equal to $-1$ against the alternative hypothesis of wage elasticity not equal to $-1$. Significant at $^{*}$10%, $^{**}$5%, $^{***}$1%.

Table 3.29 Experience effects (location wage)

| | *Dependent variable:* Set Events | |
|---|---|---|
| | (1) | (2) |
| | Panel A: Estimates and Standard Errors | |
| *Trip variant variables:* | | |
| Wage (low experience) | 0.005 | |
| | (0.021) | |
| Wage (high experience) | $-0.053^{**}$ | |
| | (0.026) | |
| Wage (catch < target & low experience) | | $-0.004$ |
| | | (0.025) |
| Wage (catch $\geq$ target & low experience) | | 0.016 |
| | | (0.022) |
| Wage (catch < target & high experience) | | $-0.133^{**}$ |
| | | (0.052) |
| Wage (catch $\geq$ target & high experience) | | $-0.052^{*}$ |
| | | (0.029) |
| Black cod | 0.004 | 0.004 |
| | (0.004) | (0.004) |
| Objective productivity | $-0.020$ | $-0.018$ |
| | (0.031) | (0.032) |
| *Trip invariant variables:* | | |
| Vessel length | $0.017^{***}$ | $0.016^{***}$ |
| | (0.006) | (0.006) |
| Average crew | 0.022 | 0.026 |
| | (0.049) | (0.056) |
| Share information | 0.196 | 0.167 |
| | (0.128) | (0.122) |
| | Panel B: Wage Elasticity | |
| Elasticity (low experience) | 0.009 | |
| | (0.036) | |
| Elasticity (high experience) | $-0.108^{*}$ | |
| | (0.061) | |
| Elasticity (catch < target & low experience) | | $-0.007$ |
| | | (0.045) |
| Elasticity (catch $\geq$ target & low experience) | | 0.027 |
| | | (0.036) |
| Elasticity (catch < target & high experience) | | $-0.353^{*}$ |
| | | (0.209) |
| Elasticity (catch $\geq$ target & high experience) | | $-0.105$ |
| | | (0.068) |
| Observations | 329 | 329 |
| Log-likelihood | $-575.366$ | $-573.285$ |

Note: Skipper, year, and region fixed effects are included. Dummies for vessel hold and quota constraint used. Bootstrapped standard error from 400 replications are in parenthesis. Log-likelihood value is from the first stage regression. Significant at $^{*}$10%, $^{**}$5%,$^{***}$1%.

Table 3.30 Experience effects (naive wage adjusted)

| | *Dependent variable:* Set Events | |
|---|---|---|
| | (1) | (2) |
| | Panel A: Estimates and Standard Errors | |
| *Trip variant variables:* | | |
| Wage (low experience) | −0.007 | |
| | (0.015) | |
| Wage (high experience) | $-0.051^{**}$ | |
| | (0.023) | |
| Wage (catch $<$ target & low experience) | | −0.016 |
| | | (0.028) |
| Wage (catch $\geq$ target & low experience) | | 0.003 |
| | | (0.019) |
| Wage (catch $<$ target & high experience) | | $-0.125^{***}$ |
| | | (0.037) |
| Wage (catch $\geq$ target & high experience) | | $-0.041^{*}$ |
| | | (0.024) |
| Black cod | 0.004 | 0.005 |
| | (0.004) | (0.004) |
| Objective productivity | −0.018 | −0.016 |
| | (0.031) | (0.034) |
| *Trip invariant variables:* | | |
| Vessel length | $0.017^{***}$ | $0.018^{***}$ |
| | (0.005) | (0.006) |
| Average crew | 0.013 | 0.012 |
| | (0.048) | (0.052) |
| Share information | 0.202 | 0.180 |
| | (0.132) | (0.130) |
| | Panel B: Wage Elasticity | |
| Elasticity (low experience) | −0.012 | |
| | (0.025) | |
| Elasticity (high experience) | $-0.103^{**}$ | |
| | (0.053) | |
| Elasticity (catch $<$ target & low experience) | | −0.029 |
| | | (0.054) |
| Elasticity (catch $\geq$ target & low experience) | | 0.005 |
| | | (0.033) |
| Elasticity (catch $<$ target & high experience) | | $-0.322^{**}$ |
| | | (0.140) |
| Elasticity (catch $\geq$ target & high experience) | | −0.081 |
| | | (0.053) |
| Observations | 329 | 329 |
| Log-likelihood | −575.499 | −573.269 |

Note: Skipper, year, and region fixed effects are included. Dummies for vessel hold and quota constraint used. Bootstrapped standard error from 400 replications are in parenthesis. Log-likelihood value is from the first stage regression. Significant at $^{*}$10%, $^{**}$5%,$^{***}$1%.

Table 3.31 Experience effects (naive wage)

| | *Dependent variable:* Set Events | |
|---|---|---|
| | (1) | (2) |
| | Panel A: Estimates and Standard Errors | |
| *Trip variant variables:* | | |
| Wage (low experience) | $-0.002$ | |
| | (0.013) | |
| Wage (high experience) | $-0.045^{**}$ | |
| | (0.022) | |
| Wage (catch < target & low experience) | | $-0.010$ |
| | | (0.023) |
| Wage (catch $\geq$ target & low experience) | | 0.007 |
| | | (0.018) |
| Wage (catch < target & high experience) | | $-0.116^{***}$ |
| | | (0.037) |
| Wage (catch $\geq$ target & high experience) | | $-0.036$ |
| | | (0.023) |
| Black cod | 0.005 | 0.005 |
| | (0.004) | (0.003) |
| Objective productivity | $-0.018$ | $-0.017$ |
| | (0.030) | (0.031) |
| *Trip invariant variables:* | | |
| Vessel length | $0.017^{***}$ | $0.017^{***}$ |
| | (0.005) | (0.005) |
| Average crew | 0.013 | 0.012 |
| | (0.047) | (0.056) |
| Share information | $0.202^{*}$ | 0.181 |
| | (0.121) | (0.119) |
| | Panel B: Wage Elasticity | |
| Elasticity (low experience) | 0.004 | |
| | (0.023) | |
| Elasticity (high experience) | $-0.089^{*}$ | |
| | (0.049) | |
| Elasticity (catch < target & low experience) | | $-0.018$ |
| | | (0.043) |
| Elasticity (catch $\geq$ target & low experience) | | 0.012 |
| | | (0.031) |
| Elasticity (catch < target & high experience) | | $-0.289^{**}$ |
| | | (0.131) |
| Elasticity (catch $\geq$ target & high experience) | | $-0.070$ |
| | | (0.049) |
| Observations | 329 | 329 |
| Log-likelihood | $-575.734$ | $-573.537$ |

Note: Skipper, year, and region fixed effects are included. Dummies for vessel hold and quota constraint used. Bootstrapped standard error from 400 replications are in parenthesis. Log-likelihood value is from the first stage regression. Significant at $^{*}$10%, $^{**}$5%,$^{***}$1%.

Table 3.32 Vessel length effects (location wage)

| | *Dependent variable:* Set Events | |
|---|---|---|
| | (1) | (2) |
| | Panel A: Estimates and Standard Errors | |
| *Trip variant variables:* | | |
| Wage (small vessel) | −0.045 | |
| | (0.042) | |
| Wage (large vessel) | −0.018 | |
| | (0.016) | |
| Wage (catch < target & small vessel) | | −0.077 |
| | | (0.054) |
| Wage (catch ≥ target & small vessel) | | −0.022 |
| | | (0.038) |
| Wage (catch < target & large vessel) | | −0.033 |
| | | (0.024) |
| Wage (catch ≥ target & large vessel) | | −0.011 |
| | | (0.017) |
| Black cod | 0.004 | 0.005 |
| | (0.004) | (0.004) |
| Objective prod. | −0.029 | −0.030 |
| | (0.030) | (0.032) |
| *Trip invariant variables:* | | |
| Vessel length | 0.018*** | 0.018*** |
| | (0.006) | (0.006) |
| Average crew | −0.004 | 0.003 |
| | (0.052) | (0.047) |
| Share information | 0.230* | 0.214* |
| | (0.130) | (0.128) |
| | Panel B: Wage Elasticity | |
| Elasticity (small vessel) | −0.089 | |
| | (0.094) | |
| Elasticity (small vessel) | −0.033 | |
| | (0.031) | |
| Elasticity (catch < target & small vessel) | | −0.168 |
| | | (0.147) |
| Elasticity (catch ≥ target & small vessel) | | −0.041 |
| | | (0.075) |
| Elasticity (catch < target & large vessel) | | −0.063 |
| | | (0.050) |
| Elasticity (catch ≥ target & large vessel) | | −0.020 |
| | | (0.032) |
| Observations | 329 | 329 |
| Log-likelihood | −576.200 | −575.859 |

Note: Skipper, year, and region fixed effects are included. Dummies for vessel hold and quota constraint used. Bootstrapped standard error from 400 replications are in parenthesis. Log-likelihood value is from the first stage regression. Significant at *10%, **5%,***1%.

Table 3.33 Vessel length effects (naive wage adjusted)

| | *Dependent variable:* Set Events | |
|---|---|---|
| | (1) | (2) |
| | Panel A: Estimates and Standard Errors | |
| *Trip variant variables:* | | |
| Wage (small vessel) | −0.046 | |
| | (0.034) | |
| Wage (large vessel) | −0.017 | |
| | (0.014) | |
| Wage (catch $<$ target & small vessel) | | −0.099 |
| | | (0.068) |
| Wage (catch $\geq$ target & small vessel) | | −0.027 |
| | | (0.038) |
| Wage (catch $<$ target & large vessel) | | −0.031* |
| | | (0.018) |
| Wage (catch $\geq$ target & large vessel) | | −0.007 |
| | | (0.018) |
| Black cod | 0.005 | 0.005 |
| | (0.004) | (0.004) |
| Objective prod. | −0.028 | −0.031 |
| | (0.031) | (0.032) |
| *Trip invariant variables:* | | |
| Vessel length | 0.018*** | 0.017*** |
| | (0.008) | (0.006) |
| Average crew | −0.007 | −0.002 |
| | (0.052) | (0.045) |
| Share information | 0.226* | 0.220* |
| | (0.132) | (0.128) |
| | Panel B: Wage Elasticity | |
| Elasticity (small vessel) | −0.092 | |
| | (0.077) | |
| Elasticity (large vessel) | −0.031 | |
| | (0.027) | |
| Elasticity (catch $<$ target & small vessel) | | −0.233 |
| | | (0.213) |
| Elasticity (catch $\geq$ target & small vessel) | | −0.051 |
| | | (0.077) |
| Elasticity (catch $<$ target & large vessel) | | −0.059 |
| | | (0.037) |
| Elasticity (catch $\geq$ target & large vessel) | | −0.013 |
| | | (0.033) |
| Observations | 329 | 329 |
| Log-likelihood | −575.927 | −575.251 |

Note: Skipper, year, and region fixed effects are included. Dummies for vessel hold and quota constraint used. Bootstrapped standard error from 400 replications are in parenthesis. Log-likelihood value is from the first stage regression. Significant at *10%, **5%,***1%.

Table 3.34 Vessel length effects (naive wage)

| | *Dependent variable:* Set Events | |
|---|---|---|
| | (1) | (2) |
| | Panel A: Estimates and Standard Errors | |
| *Trip variant variables:* | | |
| Wage (small vessel) | −0.038 | |
| | (0.031) | |
| Wage (large vessel) | −0.013 | |
| | (0.013) | |
| Wage (catch $<$ target & small vessel) | | −0.084 |
| | | (0.064) |
| Wage (catch $\geq$ target & small vessel) | | −0.018 |
| | | (0.032) |
| Wage (catch $<$ target & large vessel) | | −0.026 |
| | | (0.017) |
| Wage (catch $\geq$ target & large vessel) | | −0.003 |
| | | (0.019) |
| Black cod | 0.005 | 0.006 |
| | (0.004) | (0.004) |
| Objective prod. | −0.028 | −0.031 |
| | (0.031) | (0.033) |
| *Trip invariant variables:* | | |
| Vessel length | 0.018$^{***}$ | 0.017$^{***}$ |
| | (0.006) | (0.006) |
| Average crew | −0.006 | 0.001 |
| | (0.047) | (0.044) |
| Share information | 0.224 | 0.219$^{*}$ |
| | (0.142) | (0.128) |
| | Panel B: Wage Elasticity | |
| Elasticity (small vessel) | −0.074 | |
| | (0.067) | |
| Elasticity (large vessel) | −0.024 | |
| | (0.024) | |
| Elasticity (catch $<$ target & small vessel) | | −0.188 |
| | | (0.182) |
| Elasticity (catch $\geq$ target & small vessel) | | −0.033 |
| | | (0.062) |
| Elasticity (catch $<$ target & large vessel) | | −0.049 |
| | | (0.034) |
| Elasticity (catch $\geq$ target & large vessel) | | −0.005 |
| | | (0.034) |
| Observations | 329 | 329 |
| Log-likelihood | −576.220 | −575.560 |

Note: Skipper, year, and region fixed effects are included. Dummies for vessel hold and quota constraint used. Bootstrapped standard error from 400 replications are in parenthesis. Log-likelihood value is from the first stage regression. Significant at $^{*}$10%, $^{**}$5%,$^{***}$1%.

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# CHAPTER 4. STOCK EFFECT ESTIMATION: AN APPLICATION TO THE ALASKAN HALIBUT FISHERY

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## 4.1 Abstract

Maximizing the economic value of fisheries resources requires knowledge of the growth potential of the fish stock and the benefits and costs of harvesting fish. The influence of stock abundance on costs of fishing or the stock-cost elasticity (stock effect, in short) is a crucial element of this rent maximization problem, which has not been previously estimated. The main challenge in stock effect estimation comes from the fact that the stock abundance is observable. Even when stock abundance estimates generated by assessment models are available, they are rarely spatially delineated and contain unmeasurable noise. This paper consistently estimates the stock-cost elasticity in the Alaskan halibut fishery. This paper combines recent advances in estimating harvest technologies when abundance is unobserved (Weninger et al., 2018) with industry-independent stock abundance survey data collected by the International Pacific Halibut Commission (IPHC) to estimate the stock effect. A generalized linear model is fit to the IPHC data to construct a space-time-varying map of relative halibut stock abundance. Then the abundance index is embedded into a structural model of halibut fishing costs, which is then estimated using the generalized method of moments. Consistent estimation of the stock-cost elasticity is obtained under the reasonable assumptions for fisheries data generating processes. The stock-cost elasticity of $-0.794$ with a 90% confidence interval of $[-0.896,\ -0.508]$ is obtained under the assumption that the spatial distribution of fishing

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is stock invariant. These results have profound implications for setting harvest policies in fisheries: the estimated stock-cost elasticity from the model favors maintaining abundance at levels well above the maximum sustainable yield benchmark. Doing so will substantially lower halibut fishing costs and increase fishery rent.

## 4.2 Introduction

The stock effect in fisheries is defined as the increases in the productivity of fishing effort or reductions in the cost per unit of catch due to higher fish stock abundance. The importance of the stock effect in maximizing the economic value of fisheries is well-recognized (Clark, 2010). Despite its crucial role in resource management, there are only a few attempts to estimate the stock effect, and it remains elusive. The main empirical obstacle comes from the unobservability of the stock abundance. Even in cases, when the abundance estimates from stock assessment models are available, they pertain to larger spatial scale (for example the entire fishing ground) or the larger temporal scale (for example entire year), leading to measurement error in stock abundance. This chapter consistently estimates the stock-cost elasticity by combining recent advances in estimating harvest technologies when the abundance is unobserved (Weninger et al., 2018) and fishery-independent stock data. The method is demonstrated using trip level data from Alaskan halibut fishery, and the stock-cost elasticity is estimated to be $-0.794$, with a 90% confidence interval $[-0.896, -0.508]$. The negative stock-cost elasticity has profound implications for setting harvest policies in fisheries. It implies building stock abundance higher than the maximum sustainable yield benchmark, and doing so would also lower the cost of harvesting halibut and increase fishery rent.

Stock assessment models proceed by assuming catch per unit of gear is proportional to the unobserved stock. Following that, I estimate a generalized linear model of catch per skate (unit of longline gear in halibut fishery) with the fishery-independent data and fishery-dependent data (discussed in chapter 2). This allows creating a proxy variable for the unobserved stock abundance at the spatial-temporal scale of a trip. Next, this proxy variable is embedded in the structural model of halibut fishing costs. A consistent estimate of stock-cost elasticity is obtained by using a generalized method of moments approach, under reasonable assumptions for fisheries data generating processes.

The application to the sample of commercial halibut trips from the Alaskan halibut fishery yielded a stock-cost elasticity of $-0.794$, given the fishermen fished at the same fishing locations. That is, these cost savings comes only from extracting the resources from a higher abundance when the steaming cost of accessing the location remained the same. Under higher abundance, fishermen would re-optimize their fishing locations, and there could be potentially more cost savings than the estimated stock effect. Additionally, input-price and harvest-cost elasticities are also reported.

The rest of the chapter is arranged as follows. The next section discusses the production technologies in fisheries, the impact of the unobserved stock abundance in the estimation, and some of the stock effects estimates from the literature. Section 4.4 details the production environment regarding a fishing trip. The production decisions of the fishermen and information available at each stage, which is essential for identification of the stock-cost elasticity, is discussed. Based on this, section 4.5 outlines the structural model of halibut fishing costs at the trip level. Parametric functional forms and the estimation strategy is discussed in section 4.6. The data and variables are summarized in section 4.7. Results are in section 4.8 and the section 4.9 concludes.

## 4.3 Related literature

In fisheries economics, the Gordon-Schaefer model (Gordon, 1954) is the starting point for stating the harvest technology. The model states harvest, $h = qEX$, where $q$ is the catchability coefficient, $E$ denotes fishing effort, and $X$ is the fish stock abundance. The fishing effort is a composite index[2] of various factors of production such as labor, capital, fuel, bait, fishing gears, etc. The catchability coefficient measures the proportion of the fish stock that is harvested using a unit amount of effort. Dual models of harvest technology are also common, where the cost function is specified as $C = C(w, h, X)$, with $w$ denoting the input prices (Smith, 1968).

[2]Squires et al. (1987) shows a consistent aggregate input index can be formed only if the technology exhibits the property of homothetic separability of inputs.

The distinguishing feature of resource extracting technologies, either in the primal or dual form, is the presence of resource stock, $X$. The literature maintains the existence of the stock effect, that is, an increase in the productivity of factor inputs or decrease in the harvesting cost as the resource stock increases. This stock effect hypothesis is practically untested in the literature, mainly due to unobserved stock abundance. Additionally, the estimation of the primal approach suffers from high correlation among inputs (labor, capital) and endogeneity of input quantities (Jensen, 2002). The dual approach relies on the input price data, but estimates would be biased if stock is not controlled. Using a generalized Gordon-Schaefer model, next, I demonstrate the omitted variable bias in cost function estimation. I also review the methods that have been proposed to control for the stock abundance in estimation.

### 4.3.1 Omitted stock abundance and bias in estimation

The stock abundance in fisheries is spatially and temporally heterogeneous due to different habitat quality, food availability, and competition, among other factors. I maintain the assumption of heterogeneity in stock abundance across location $l$ and date $t$, denoted by $X_{lt}$. The harvest at $(l, t)$ is assumed to be given by: $h = qE^{\alpha}X_{lt}^{\beta}$. In quota regulated fisheries, fishermen typically harvest seasonal quota through multiple trips with trip-level harvest target, $\tilde{h}$. Then the problem of the fisherman is to minimize the cost of fishing by choosing the input amount, $E$, such that $\tilde{h}$ is produced. Here I assume the decision maker is the vessel skipper, who has complete knowledge of abundance $X_{lt}$. Then the skipper's problem is as follows:

$$\min_{E} \ wE \text{ such that } \ qE^{\alpha}X_{lt}^{\beta} \geq \tilde{h} \tag{4.1}$$

where, $w$ is the unit price of effort. An interior solution to the problem (4.1) satisfies $E^* = \left(\frac{\tilde{h}}{qX^{\beta}}\right)^{\left(\frac{1}{\alpha}\right)}$. That is, the cost of harvesting is a function of exogenous variables ($w$, $\tilde{h}$, $X_{lt}$, $q$) and model parameters ($\alpha$, $\beta$).

The identification of the cost function parameters requires data on input prices, harvest target, and spatial-temporal stock abundance. The stock abundance is unobservable to both researcher and fishermen at the spatial-temporal scale of a fishing trip. However, fishermen may have considerable information about the local ($l$, $t$) stock abundance by observing the productivity of the gear sets. Then if $X_{lt}$ is not included in the error term, it necessarily enters the error term. In this case, ordinary least squares regression obtains consistent estimates of the parameters ($\alpha$, $\beta$) if the trip-harvest target $\tilde{h}$ is independent of the $X_{lt}$. Alternatively for the primal model, for consistent estimates, one needs $E^*$ to be independent of $X_{lt}$. The problem of omitted variable bias due to ignoring stock abundance is noted in the fisheries literature (Ekerhovd and Gordon, 2013). Additionally, it is reasonable to assume that upon receiving information on the local stock abundance, a fisherman may update trip-harvest plans to $h^*$. In this scenario, one needs to control for this additional information to obtain consistent estimates of model parameters.

### 4.3.2 Attempts to control for bias

The few studies that attempted to estimate the stock effect relied on *estimate* of stock abundance as a control in the primal or dual regression model. The fishery management uses fishery-dependent and independent data to produce abundance estimates for the entire fishery. These abundances are rarely available at the spatial-temporal scale of a trip. Hence, if the true stock abundance is spatially-temporally heterogeneous, then using a seasonal or regional average value of abundance will not address the problem. There will be measurement error in the stock over which the fishing takes place as the average would be either above or below the actual stock. This may reduce omitted variable bias but under particular conditions.

Sandberg (2006) estimated cost-stock elasticity in the range of $-0.21$ to $-0.59$ for the Norwegian herring and Arctic cod fishery using annual cost and catch data from 1999-2000. This paper uses stock abundance estimates from the International Council for the Exploration of the Sea (ICES) which may be valid for the entire fishing zone but only partially relevant in the spatial-temporal scale of the fishing trips. Hence, estimates could be biased. Weninger (1998) estimated cost-stock elasticity for the Mid-Atlantic surf clam and ocean quahog fishery by using stock estimates from National Marine Fisheries Service, but the stock effect was not statistically different from 0. Moving away from yearly stock estimates, Eide et al. (2003) interpolated daily stock levels from yearly stock estimates of ICES. This study estimated the harvest-stock elasticity at 0.4, using the primal model for Norwegian bottom trawlers from 1971-1985. In another study, Ekerhovd and Gordon (2013) estimated the stock effect among Northeast Arctic cod and saithe, using stock estimates of ICES from 1977-2011. Both of these approaches assumed stock to be spatially homogeneous, which does not characterize the data generating process in commercial fisheries.

In this chapter, I follow Weninger et al. (2018) to address the omitted variable bias problem in stock effect estimation by exploiting the natural and economic processes that underlie most commercial fisheries data generating processes. The next section reviews the production environment and their role in the specification and estimation of the cost function in fisheries.

## 4.4 The production environment

**Heterogeneity and randomness in stock abundance**: The stock abundance of halibut is spatially and temporally heterogeneous due to varying bottom substrate, water depth, rock structure, food availability, predator and prey movements among other factors. The true abundance of halibut is unobservable both by the stock assessment scientists and fishermen. I assume the true abundance at location $l$ and date $t$, $X$, follows probability density function $f(X|l,t)$, where the conditioning arises from the stable and predictable features on the marine habitat. I assume that $f$ and its moments vary smoothly across $(l,t)$. It should be emphasized that both $X$ and $f$ are unobservable.

**cps proportional to stock**: A long-standing tenet in the fisheries science and stock assessment literature is that the observed catch per unit of gear deployed will be proportional to the unobserved abundance. The units of halibut longline gear are referred to as skates. Letting $s$ denote skates, then the stock-catch per skate relationship is,

$$\frac{h}{s} = cps = qX, \tag{4.2}$$

where $h$ denotes catch or harvest and $q$ is a constant of proportionality that determines the proportion of $X$ harvested per skate. That is, catch per skate or $cps$ is proportional to stock abundance at $(l, t)$. Fishermen and researchers observe *cps* observations or productivity information from repeated spatial-temporal fishing activity. This provides information to fishermen and researchers about spatial and temporal patterns in stock abundance. This knowledge is used to direct the location and timing of fishing operations to improve the production efficiency in fisheries.

Formally, under the assumption that catch per skate is proportional to the stock abundance, the spatial-temporal distribution of catch per skate or *cps* can be written as $f\left(\frac{cps}{q}\middle| l, t\right)\left(\frac{1}{q}\right)$. I use $g(cps|l, t)$, to denote the known spatial-temporal probability distribution of the catch per skate. I assume both $f$ and $q$ is unknown to fishermen and researcher, but $g$ is known to both fishermen and researcher. Also, fishermen use knowledge of *cps* as a proxy for stock abundance (as unobserved) in their production decisions.

**Regulations**: The fishery managers regulate commercial and recreational fishing during a specified calendar period in one of the two ways: either indirectly through input controls, or, directly through harvest or landings controls. For example, the fishery management decided to allow for 29.43 million pounds of halibut for the 2019 fishing season, which is from mid-march to mid-November. Regulations generally do not dictate the spatial location or the within-calendar-period date that fish can or must be extracted. The fishing sector decides where, when, and how much to fish, given the regulations.

**Fishery-induced stock gradient**: Commercial and recreational fishing extracts between 15%-20% of the estimated spawning stock biomass in each year in Pacific halibut fishery. Fishing is the primary cause of halibut mortality, and as I hypothesize a significant determinant of spatial-temporal stock abundance. Commercial and recreational fishing originates from land-based ports. Steaming from port to at-sea fishing locations and back is costly, e.g., fuel expenditures account for 44% of commercial halibut fishing expenses, on average.

I hypothesize that a fishery-induced stock abundance *gradient* will exist in which abundance at locations closer to ports will be lower than at more distant locations. Put simply, fishing closer to port is preferred due to the relatively lower cost of access. If close-to-port locations held equal or higher abundance than more distant locations, all harvesting would take place within earshot of port. A spatial-temporal abundance equilibrium, therefore, must be characterized as increasing (non-decreasing) stock abundance with additional steaming costs from port locations. This is also based on the graphical evidence in Chapter 1, where I show that the higher expected *cps* locations are away from land masses.

Additionally, table 4.1 provides quantitative evidence of fishery-induced gradient. The table shows the correlation between the distance traveled on a trip and the expected catch per skate, which is the proxy for expected abundance. I measure expected catch per skate in 2 ways: first, I use the fitted generalized linear model of *cps* (from chapter 1) to calculate the expected catch per skate. The first row in the table 4.1 shows a statistically significant and positive correlation between distance and expected productivity in each management region. Second, I use the revealed catch per skate beliefs of fishermen and present in the correlations in the second row. The correlations are weaker but still positive.

**Fishing trips**: Commercial longline fishing is conducted from a vessel that transports the captain and crew, gear, bait, and supplies from port to an at-sea location at which gear is deployed and fish are captured. Harvesting is organized as fishing trips: a vessel is supplied with fuel, gear, bait, food for the captain and crew, and other miscellaneous supplies at the port. The vessel steams from port to a chosen location to deploy gear. At-sea operations (gear deployment) are conducted for 4-5 days typically; trip lengths ranging between 1 and 13 days are observed in our data. The trip ends with a decision to return to port to offload the harvest, replenish supplies, and rest the captain and crew in preparation for a subsequent trip.

**Longline fishing process**: Halibut are a bottom-dwelling demersal species that cannot be easily detectable from the surface using sonar equipment. A halibut longline gear set involves anchoring the main longline, with smaller gangion lines attached at $10-25$ feet intervals, to the sea floor. A baited hook is attached to each gangion line. The typical soak time for a gear set is $6-8$ hours. When the gear is retrieved, the harvest is observed. The harvested catch is eviscerated and refrigerated onboard the vessel.

The total length of the main longline varies across each gear set. In commercial halibut fishing, length of 1800 feet of longline is referred to as skate. We will count the amount of gear used on a trip with the number of skates soaked. Also, the gears are soaked sequentially, and each sequential soaking is referred to as a set event, which lasts for about $6-8$ hours. The average trip in our data used 64 skates of gear in 4 subsequent set events.

**Production decisions**: Key production decisions include: (i) the starting date of the trip; (ii) pre-trip planning including organization of factors inputs (crew labor, fuel, gear, bait) and the target quantity of halibut that will harvested on the trip; (iii) selection of the location at which the first gear set will be made, hereafter referred to as the *primary* location choice; (iv) the decision to end at-sea harvesting operations and return to port.

Assume the vessel skipper makes all production decisions. I do not model the decision of the trip starting date, $t$. The date of the trip is assumed to be pre-determined and uncorrelated with the trip-level decisions that are the focus of this analysis. These include factor input allocations and corresponding harvest, and choice or primary fishing location and the decision to end the trip.

**Information and timing**: I separate trip production decision making into a pre-trip-departure *planning* stage and an at-sea *operations* stage. The distinction between stages arises due to the information that is available to the skipper at each stage. Planning occurs at port under an information set that includes prices for factor inputs and landed fish, denoted $w$ and $p$, respectively, the total pounds of halibut targeted for the trip, denoted $\tilde{h}$, regulations $R$, for example, skippers on some trips may face a binding quota constraint where the trip must end when the harvest matches the available quota, the quasi-fixed vessel capital, $k$, and the skippers knowledge of spatial-temporal abundance in terms of *cps* distribution. The planning stage information set is denoted by $\Omega = (p, w, \tilde{h}, R, k, g(cps|l, t))$.

The actual stock at any location and date, $X$ can be expressed as, $X = \mathbb{E}(X)\exp(\chi)$, where, the anticipated part of the stock is $\mathbb{E}(X)$ and $\chi$ is the unanticipated part. Using stock assessment assumptions of $cps \propto X$, one can express,

$$\chi = \ln cps - \ln \mathbb{E}(cps) \tag{4.3}$$

where $cps$ is the realized catch of the trip and $\mathbb{E}(cps)$ is the related expectation. This difference between the realized and expected catch per skate is the real-time productivity signal of actual stock abundance obtained upon retrieval of a soaked longline gear, while at the operations stage.

Hence the information at the operations stage will include $\Omega$ plus a productivity signal, $\chi$. Conditional on signal $\chi$, I hypothesize that the skipper may make adjustments to the pre-trip plans and update harvest decisions. For example, if $\chi$ is low, then less gear may be set than planned at the location of fishing. A high productivity signal may result in additional gear being set relative to what was planned.

Feasible at-sea adjustments to the location at which gear is set are constrained by choice of the primary fishing location. Put another way, the cost of moving the vessel in response to observed $\chi$ will depend on the vessel's location. The primary location choice effectively constrains the stock abundance that can be accessed on a trip given the limits on the fuel capacity and thus the range of the vessel. Additionally, there is an upper bound on the gear set adjustments given the onboard supplies like bait, and refrigeration capacity.

**Behavioral assumptions**: The planning stage objective is to minimize the expected cost of harvesting the targeted catch of the trip. The objective of the skipper is assumed to change to one of constrained profit maximization if the productivity signal $\chi$ deviates from pre-trip expectations. In this case, it is also likely that the actual trip harvest deviates from the planned harvest. I use $h$ to denote the realized halibut harvest for the trip. Assuming the vessel skipper to be risk neutral, the next section models the skipper's decision of the primary location choice for fishing based on expected catch per skate, $\overline{cps}$, and the harvest quantity of the trip depending on at-sea information $\chi$, with other information in $\Omega$.

## 4.5 Model

The cost on a representative fishing trip is assumed to originate from two cost sources as follows. First, $\phi(w, \tilde{h}, \overline{cps})$ is the component of costs that derive from transporting the vessel from port to the chosen primary fishing location, hereafter, $\phi$ is the steaming cost component of fishing cost.

Assume $\phi$ is increasing and concave in $w$, and increasing and concave in $\tilde{h}$. Second, $\psi(w, h, \overline{cps}, \chi)$, denotes the costs incurred while setting and retrieving gears on the trip. These costs are comprised of expenditures on fuel, crew labor, bait, and any other factors used to produce *skates*, hereafter, $\psi$ is the trip extraction cost component of the fishing cost. $\psi$ is assumed to be increasing and concave in $w$, and increasing and convex in $h$. The general cost function is expressed as follows:

$$C(w, h, \overline{cps}, \chi) = C\left(A, \phi(w, \tilde{h}, \overline{cps}),\ \psi(w, h, \overline{cps}, \chi)\right). \tag{4.4}$$

where, $A$ is a constant term.

The location choice is effectively a choice of the expected stock abundance or expected catch per skate on which gear will be set during the trip. Following our hypothesis of the existence of fishery-induced stock abundance gradient in any exploited fisheries, we assume that the steaming costs are non-decreasing in $\overline{cps}$. It should be emphasized that the arguments of $\phi$ are elements of $\Omega$ only; the operations stage productivity signal, $\chi$, does affect the steaming cost component. This is consistent with our assumptions on the timing of decisions wherein the primary location choice is made at the planning stage. However, the extraction costs depend on both $\overline{cps}$ and at-sea signal $\chi$.

**Stock effect**: The fisheries economics literature assumes, without empirical evidence, that harvesting costs decline with increased *in situ* stock abundance. It is worth emphasizing the mechanism by which changes in stock abundance affect (reduce) costs in this model. I have assumed that the primary location is chosen to minimize the expected costs of harvesting $\tilde{h}$. Suppose stock abundance increases uniformly across all $l$, for example, suppose at every location abundance were higher by 100 pounds of halibut. An optimizing skipper may choose to fish at the same primary location under the higher abundance, in which case costs savings enter solely through the extraction component $\psi$, that is, fewer skates will be required to extract $\tilde{h}$. An increase in abundance may, however, lead to a new primary location, in which case $\phi$ is affected. In general, the optimal primary location decision will balance the cost increase from accessing higher abundance with the cost savings arising from fishing on higher stock abundance. This necessary condition is derived next.

**Optimal location condition**: The condition for the optimal primary fishing location choice is,

$$\left\{ \left( C_\phi \frac{\partial \phi(w, \tilde{h}, \overline{cps})}{\partial \overline{cps}} + C_\psi \frac{\partial \psi(w, \tilde{h}, \overline{cps})}{\partial \overline{cps}} \right) \middle| \Omega \right\} = 0. \tag{4.5}$$

where, $C_\phi$ denotes the marginal contribution of steaming costs, and $C_\psi$ denotes the marginal contribution of extraction costs to total trip costs. The primary location condition is based on the planning stage information, $\Omega$, alone. Hence, the harvested amount in the above condition is the targeted amount, $\tilde{h}$, and there is no role of at-sea information (as it is unobserved at the planning stage).

**At-sea adjustment**: It is reasonable to expect that halibut skippers revise the harvest plans if the operations stage productivity signal is sufficiently informative, that is, if $exp(\chi)$ is sufficiently different from unity. The skipper, based on the realized $\chi$, choose to set fewer or more skates on the trip than initially planned. Two possibilities arise (1) conditional on $\chi$ the number of skates is adjusted from planning stage levels to maintain $h = \tilde{h}$; (2) based on $\chi$ the skipper re-optimizes and chooses a new harvest quantity, which we denote $h^*$ for the trip. Given that our regressions control for $\chi$, the case (1) does not cause additional estimation concerns. Case (2), however, describes a scenario where the realized trip catch is chosen endogenously. We require an optimization rule to control for the endogenous variable, $h^*$.

**Optimal extraction condition**: Recall that steaming costs are sunk at the operations stage, that is, when $\chi$ is observed. Assume that the skipper who choose to deviate from planning stage plans do so with the goal of maximizing operations stage profit:

$$\left\{ \gamma(p - r) - \frac{\partial \psi(w, h, \overline{cps}, \chi)}{\partial h} \middle| \Omega \cup \chi \right\} = 0. \tag{4.6}$$

The first term in (4.6) is residual marginal revenue that flows to the skipper. As in most commercial fisheries, halibut longline crew are paid a share of the trip revenue; the parameter $\gamma \in [0, 1]$ denotes the residual share to the skipper and $r$ is the halibut quota lease price. The second term in (4.6) is the marginal extraction cost, given $\chi$. Then the skipper chooses $h^*$, such that condition (4.6) is satisfied. Next, I specify functional forms to facilitate estimation of model parameters.

## 4.6 Empirical Model

This section specifies the parametric forms for the trip level cost $C(\cdot)$, steaming cost component $\phi(\cdot)$, and the extraction cost component $\phi(\cdot)$. The associated error terms and assumptions are also presented; and the estimation strategy is outlined.

### 4.6.1 Parametric functional forms

The functional form for trip level harvest cost function is as assumed as follows:

$$C = A\phi\psi \exp(\epsilon_C) \tag{4.7}$$

where, $\epsilon_C$ is the regression error term. The error term $\epsilon_C$ captures all unobserved by researcher variables that influences cost. The steaming cost function is:

$$\ln \phi = \alpha_w \ln w + \alpha_k \ln k + \alpha_{\tilde{h}} \ln \tilde{h} + \alpha_X \ln \overline{cps} + 0.5\alpha_{XX}(\ln \overline{cps})^2 \tag{4.8}$$

Inclusion of the quasi-fixed capital variable in (4.8) effectively transforms the behavioral objective to one of short-run cost minimization. The quadratic term for $\overline{cps}$ allows for potential non-linearity in the mapping from stock abundance and steaming cost. The extraction cost term is specified as follows:

$$\ln \psi = \beta_w \ln w + \beta_k \ln k + \beta_h \ln h + \beta_X \overline{cps} + \beta_X \chi \tag{4.9}$$

Substituting equations (4.8) and (4.9) in equation (4.8) and collecting of terms obtains the trip-level cost function:

$$\begin{aligned} \ln C = \ln A &+ (\alpha_w + \beta_w) \ln w + (\alpha_k + \beta_k) \ln k + \alpha_{\tilde{h}} \ln \tilde{h} + \beta_h \ln h + (\alpha_X + \beta_X) \ln \overline{cps} \\ &+ 0.5\alpha_{XX}(\ln \overline{cps})^2 + \beta_X \chi + \epsilon_C \end{aligned} \tag{4.10}$$

The optimal location condition of (4.5) with the assumed specification becomes:

$$\alpha_X + \beta_X + \alpha_{XX} \ln \overline{cps} + \epsilon_L = 0 \tag{4.11}$$

where $\epsilon_L$ denotes optimization error of fishermen.

The condition for optimal at-sea adjustments, in equation (4.6) becomes:

$$\gamma(p - r) - \psi(\cdot)\left(\frac{\beta_h}{h}\right) + \epsilon_E = 0 \tag{4.12}$$

where $\epsilon_E$ denotes optimization error of fishermen.

Further, assume the model error terms each have zero mean and finite variance. The error terms $\epsilon_C$, $\epsilon_L$, and $\epsilon_E$ are uncorrelated with $\{\Omega \cup \chi\}$.

The stock effect parameters in equation (4.10) are denoted as $\alpha_X$ and $\beta_X$. While it is true that halibut abundance is unobserved, their effects on harvest costs are identified as *cps* is proportional to the unobserved stock.

### 4.6.2 Estimation Strategy

I use generalized method of moments (GMM) to estimate the parameters in the cost function and the two optimal conditions. The parametric cost function in equation (4.10) has 10 parameters to be estimated. The parameters in the equations (4.11) and (4.12) are already present in the estimable equation (4.10). Hence, at least 10 moment conditions are required to identify the parameters. Note, I am assuming the skipper's share of revenue, $\gamma$, is not estimated, rather it is observed from the data.

The equation (4.10) provides 8 moment conditions in total. Assuming that the unobserved factors by the researcher do not systematically affect the cost of fishing, the first moment condition is $\mathbb{E}(\epsilon_{\mathbb{C}}) = 0$. The second to eight moment condition is given by $\mathbb{E}(Z\epsilon_C) = 0$; where $Z$ represents the 8 explanatory variables in the equation (4.10). This moment condition is based on the assumption that the covariance between the explanatory variables and the error term is 0.

The optimal location condition provide 2 more moment conditions: $\mathbb{E}(\epsilon_L) = 0$ and $\mathbb{E}(\ln \overline{cps}\epsilon_L) = 0$. This is based on the assumption that the fisherman's optimization error in choosing the optimal gear set location is not biased.

The 6 moment conditions from the optimal extraction condition are:
$\mathbb{E}(\epsilon_E) = 0$, $\mathbb{E}(\ln w\epsilon_E) = 0$, $\mathbb{E}(\ln k\epsilon_E) = 0$, $\mathbb{E}(\ln h\epsilon_E) = 0$, $\mathbb{E}(\ln \overline{cps}\epsilon_E) = 0$, $\mathbb{E}(\ln \chi\epsilon_E) = 0$. This is based on the assumption that the fisherman's optimization error in choosing the optimal harvest

amount is not biased and there is no correlation between the optimization error and the information set of the fishermen.

Compactly, all these 16 moment conditions are written as $\mathbf{E[g(Y_t, \theta_0)] = 0}$, where $Y_t$ is the observed data from trip $t$, and $\theta_0$ is the parameter vector. The sample analog to the theoretical moment conditions are given by: $\mathbf{\frac{1}{T}\sum_{t=1}^{T} g(Y_t, \theta)]}$

Then the GMM estimator, $\hat{\theta}$, is obtained by minimizing

$$\left(\mathbf{\frac{1}{T}\sum_{t=1}^{T} g(Y_t, \theta)]}\right)' \widehat{W} \left(\mathbf{\frac{1}{T}\sum_{t=1}^{T} g(Y_t, \theta)]}\right) \tag{4.13}$$

where $\hat{W}$ is the appropriately chosen weighting matrix.

The implementation of the estimation proceeds in two steps. In the first step, identity matrix is used as a weighting matrix to compute preliminary GMM estimate, $\hat{\theta_1}$. This estimator is consistent for $\theta_0$ but not efficient. In the second step, the weighting matrix, $\hat{W}$, is constructed using $\hat{\theta_1}$ construct as follows:

$$\mathbf{\widehat{W}(\hat{\theta_1}) = \left(\frac{1}{T}\sum_{t=1}^{T} g(Y_t, \hat{\theta_1}) g(Y_t, \hat{\theta_1})'\right)^{-1}} \tag{4.14}$$

Then the $\hat{\theta}$ obtained by using this weighting matrix will be asymptotically efficient. Finally, bootstrapping across the skippers with replacement is used to find the standard error of the GMM estimates.

## 4.7 Data

The empirical application studies the Alaskan halibut fishery of the Gulf of Alaska from 2006-07, which was introduced in chapter 1. The logbook data of trips that records detailed catch and location of gear sets are also observed. The cleaned data set consisted of 327 commercial long-line fishing trips from 40 unique fishermen to three management regions of the fishery. I dropped 2 trips from the data set used in the chapter 3 as they recorded very low halibut catch causing extremely high average halibut cost for these two trips. Such costs are not common within the data period, hence, I assumed those are recording errors and the trips are not considered further.

The cost of fishing arises from fuel, bait, and labor expenditures. Skippers typically fuel their vessels before each trip and the participating skippers recorded trip expenses after each trip. Similarly, they also recorded the bait expenditure after each trip. In few trips, they use other species caught during halibut fishing as bait, so there were no bait expenses. The major part of the fishing cost arises from the labor cost. In this fishery, there is catch share system present between the skipper and the crew members. I calculated the labor cost from the data as follows. For each skipper present in the year 2007, I observe the percentage of the catch that was paid to the major crew member (first mate) and the least important crew member (greenhorn). I also observed the total crew members present in each trip. Using these two information, I calculated the total percentage of catch that was paid to all crew members; then the leftover share goes to the vessel skipper. However, before skipper-crew catch sharing, the quota owner receives the rent in terms of the catch. During the data period, fuel expenditure on average was 8%, bait expenditure on average was 12%, and the rest is labor expenditure.

The generalized linear model of catch per skate as introduced in chapter 2 controls for the unobserved stock abundance at the spatial-temporal scale of a single fishing trip. Recall, the stock is unobservable but catch per skate, *cps*, which is proportional to stock is observed. The generalized linear model of *cps* estimated the parameters of catch per skate distribution at the location and time of fishing activity, based on fishery-independent (from 1998-2018) and fishery-dependent data (2006-07). The productivity information to the skipper at the pre-trip planning stage is measured by the expected catch per skate from the estimated generalized linear model. On the other hand, the at-sea information, that is available at the extraction stage, is measured as the deviation of the realized catch per skate from the expected catch per skate for each trip.

I observe input prices for fuel for the trips and use it as one of the controls. I assume the bait prices which end up in the regression error term are not correlated with the fuel prices. In 23% of the trips, the fishermen also harvest another species, black cod, using the same technology, and it also has market value. So, I control for the black cod catch in the regression both linearly and quadratically. In about 8% of the trips, extreme fuel prices, either low or high, are reported. I use an extreme fuel price dummy for these trips. Finally, I use dummies for management region 3A and 3B with 2C as the baseline, a dummy for the fishing trips in the year 2007, and a dummy variable indicating trips that targetted both halibut and black cod.

Table 4.2 reports descriptive statistics of the data from 327 trips from 2006-07 season. The average trip incurred a fishing cost of $\$11,269$, with a fuel price of \$2.8 per gallon, and used 53 feet vessel. The trips harvested about $15,125$ pounds of halibut, on average. The expected productivity or the catch per skate was 268 pounds of halibut. The trips faced, on average, at-sea negative productivity shock of 63% (as $e^{-0.469} = 0.626$) of the expected abundance. Less than 10% of the trips face extreme fuel price; the majority of the trips fish in 3A; and the sample has close to an equal number of trips in both the years.

## 4.8 Results

The cost function specified in the equation (4.9) and the two optimal conditions (4.10) and (4.11) are estimated using 2-step GMM with the data. The specification has 16 parameters, and there are 22 moment conditions in total from the three estimating equations. The estimates and the bootstrapped 90% confidence interval are reported in the table (4.3). All the explanatory variables are entered in log-form, so the coefficient estimates represent the elasticity.

The main parameter of interest is the coefficient of the unanticipated productivity shock, $\beta_X$, or the at-sea shock. This coefficient measures cost-stock elasticity, given the fishermen fished at the same location. That is, in the counter-factual world if the expected productivity was the same but a fisherman got a better draw, or, a better $\chi$, then what would be the cost savings. This cost-savings completely comes from extracting the same harvest from a higher abundance but at the same location. The cost-stock elasticity parameter is estimated at $-0.794$. That is, a 10% increase in stock abundance would lead to a 7.9% decline in the extraction cost of the resource.

The rest of the parameters have the expected sign and are significantly identified except fuel price effect at the extraction stage. The input price-cost elasticity, or, the fuel price elasticity is given by $(\alpha_w + \beta_w)$ and is estimated to be at 3.334. That is, as fuel price increases, the cost of fishing increases as expected. The vessel length-cost elasticity, given by $(\alpha_k + \beta_k)$ is estimated to be 1.129, implying larger vessels incur more fishing cost. The harvest-cost elasticity, $\beta_h$ (1.395) is also of the expected sign. The positive coefficient of expected productivity, or, an estimate of $\alpha_X$ at 1.086 supports the stock-gradient hypothesis, implying to access more stock; one has to steam further distances. The negative coefficient estimate of the squared productivity term, $\alpha_{XX}$, means that the stock abundance increases at a decreasing rate away from the port.

## 4.9 Conclusion

Maximizing the economic value of fisheries resources requires the knowledge of stock-cost elasticity or how the cost of fishing changes with changes in stock abundance. However, the empirical estimation of the stock effect is rare. The main challenge comes from the fact that the stock abundance is unobservable. This chapter combines recent advances in estimating harvest technologies and fishery-independent stock survey data to estimate the stock effect consistently. The methodology allows for heterogeneous stock abundance across space and time, unlike previous approaches. An application to the Alaskan halibut fishery produced an estimate of $-0.794$ as the stock effect. The negative stock effect supports maintaining stock abundance levels more than the current standard of maximum sustainable yield. This will simultaneously reduce the cost of fishing and preserve the stock abundance.

Catch per unit of effort or skate in the halibut fishery is proportional to unobserved stock, as per stock assessment literature. The data on catch per skate is available, and the generalized linear model of catch per skate produces the proxy variable of stock abundance at the spatial-temporal scale of a single fishing trip. Then the estimated catch per skate is embedded in the structural cost function to estimate the stock effect. The results from the generalized method of moments estimated stock-cost elasticity of $-0.794$, given the same locations, are fished under higher abundance. Hence, this effect provides a lower bound on the magnitude of cost savings under higher abundance. The fishermen could potentially re-optimize their fishing locations and could generate even more cost savings. The generalized linear model of catch per skate could be used to simulate the re-optimized fishing locations under new abundance and can produce the full stock effect. Then the estimated stock can used in determining harvest plans to maximize the economic yield. This is the next step along this line of research. Further, this model could be extended to accommodate multiple species of fisheries.

## 4.10 Tables

Table 4.1 Correlation between distance and productivity

| | Distance steamed | | |
|---|---|---|---|
| | 2C | 3A | 3B |
| $cps_{GLM}$ | 0.828*** | 0.466*** | −0.018 |
| | [0.454, 0.954] | [0.281, 0.618] | [−0.269, 0.235] |
| $cps_{Belief}$ | 0.201 | 0.233** | 0.088 |
| | [−0.453, 0.715] | [0.021, 0.425] | [−0.167, 0.333] |

Note: 95% confidence intervals are in square brackets. *** and ** denotes significance at 1% and 5% respectively.

Table 4.2 Summary statistics: fishing cost

| Statistic (N= 327) | Mean | St. Dev. | Min | Max |
|---|---|---|---|---|
| trip cost ($) | 11268.929 | 12209.443 | 205.321 | 80327.125 |
| fuel price ($/gallon) | 2.799 | 0.203 | 1.95 | 3.92 |
| vessel length (foot) | 53.055 | 13.434 | 30 | 100 |
| halibut harvest (lbs) | 15124.639 | 14463.884 | 60 | 62675 |
| exp productivity (lbs) | 267.762 | 97.211 | 96.485 | 463.692 |
| at-sea shock | −0.469 | 1.044 | −5.966 | 1.737 |
| black cod (lbs) | 3823.344 | 9998.988 | 0 | 60357 |
| dummy ext fuel price | 0.083 | 0.276 | 0 | 1 |
| dummy area 3A | 0.621 | 0.486 | 0 | 1 |
| dummy area 3B | 0.291 | 0.455 | 0 | 1 |
| dummy year 2007 | 0.456 | 0.499 | 0 | 1 |

Table 4.3 GMM estimates

| | Estimates | 90% CI |
|---|---|---|
| | *Panel A: steaming cost* | |
| fuel price ($\alpha_w$) | 2.610 | $[0.315, 5.091]$ |
| vessel length ($\alpha_k$) | 2.262 | $[1.029, 2.194]$ |
| stock ($\alpha_X$) | 1.086 | $[0.773, 1.311]$ |
| stock sq ($\alpha_{XX}$) | −0.053 | $[-0.101, -0.029]$ |
| | *Panel B: extraction cost* | |
| fuel price ($\beta_w$) | 0.724 | $[-0.040, 1.482]$ |
| vessel length ($\beta_k$) | −1.133 | $[-1.270, -0.675]$ |
| harvest ($\beta_h$) | 1.395 | $[1.206, 1.438]$ |
| stock ($\beta_X$) | −0.794 | $[-0.896, -0.508]$ |
| black cod | 0.142 | $[-0.033, 1.253]$ |
| black cod sq | −0.038 | $[-0.290, 0.007]$ |
| dummy ext fuel p | 0.393 | $[-0.213, 1.268]$ |
| region 3A | 0.272 | $[-0.255, 1.696]$ |
| region 3B | −0.048 | $[-0.498, 1.576]$ |
| year 2007 | 0.026 | $[-0.694, 0.360]$ |

Note: 90% confidence interval for parameters from 400 bootstrap samples. Bootstrap sample is created by sampling across skippers with replacement and then keeping all the trips from the sampled skippers.

## 4.11 References

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# CHAPTER 5. GENERAL CONCLUSION

This dissertation investigated the labor supply and stock effect using data from the Alaskan halibut fishery. In fisheries, the stock abundance, at the spatial location of the gear set is crucial for fishing success. It is reasonable to believe the fishing decisions are based on the current stock conditions. However, in demersal species fisheries like the Alaskan halibut fishery, the absolute stock abundance cannot be observed by the researcher. As a result, the stock abundance ends up in the error term and biases behavioral estimates of fishermen, which could mismanage the resource stock and collapse the fishery. The chapter 2 of this dissertation estimated a generalized linear model of catch per skate, creating a productivity map at the spatial-temporal scale of the gear set. This productivity map serves as the index of absolute abundance and later used as the proxy variable for stock in the remainder of the dissertation. This chapter also summarized the stylized facts of the Alaskan halibut fishery using the trip level from commercial halibut fishermen. The chapter found that expected stock abundance increases with distance from the ports, and there exists a declining trend in abundance, with some recovery in area 2C. Most of the fishing trips happen in May and June, where they typically do 4 set events on a trip. Skippers prefer to fish previously fished locations, but they regularly overestimate the productivity of the locations by 40% on average. Interestingly, skippers do not pay much attention to the IPHC survey data and advice from fellow fishermen. Fishermen can catch the amount they planned if they encounter better stock conditions or if it is the last trip of the season where the quota constraint binds.

Chapter 3 utilizes the working environment of the fishery to investigate the effectiveness of financial motivation in workplaces. In the Alaskan halibut fishery, fishermen decide working hours on a trip that provides a fertile ground to test labor supply theories, particularly when the trip specific target catch is observed. I found evidence of income targeting behavior among commercial fishermen as they worked lesser hours when faced with higher remuneration or better catch. I estimated negative wage elasticity of labor supply, particularly among highly experienced fishermen at the intensive margin. Specifically, I estimated wage elasticity of $-0.063$, and the magnitude of wage elasticity becomes stronger ($-0.127$) when the catch of the trip is less than the target catch of the trip. These results are inconsistent with the neoclassical theory of labor supply. Moreover, the negative relationship between hours and wages even when the catch is below the target cannot be explained by the linear gain-loss utility of reference-dependent preferences. I find strong evidence of non-linear income targeting behavior among commercial halibut fishermen. The policy implication is that increasing wages does not always increase the labor supply. Future research should investigate the role of group dynamics and the importance of bargaining between the vessel skipper and crew members in labor supply decisions. Moreover, this chapter analyzed the marginal decision to quit by studying the relationship between working hours and wage rate at the point of quitting the trip. One can potentially learn more about the labor supply decisions of the skipper by accounting for all the infra-marginal decisions by solving the complete dynamic optimal stopping problem.

The stock effect plays a vital role in determining the economically optimal harvest plans in fisheries. Chapter 4 introduced a methodology to estimate the stock-cost elasticity or the stock effect when the stock abundance is unobservable. The methodology allowed for heterogeneous stock abundance across space and time, unlike previous approaches, by combining recent advances in estimating harvest technologies and fishery-independent stock survey data. The estimated model of catch per skate, which acts as a proxy variable to unobserved stock abundance, is embedded in the structural cost function to estimate the stock effect. The main cost function is supported by two additional optimal conditions based on fisheries data generating processes. An application to the Alaskan halibut fishery produced an estimate of $-0.794$ as the stock effect. The negative stock effect supports maintaining stock abundance levels more than the current standard of maximum sustainable yield. This will simultaneously reduce the cost of fishing and preserve the halibut stock abundance, which is showing a declining trend. This result assumes the fishing locations remain the same when higher stock abundance, which implies this is a lower bound on the cost savings.

Further research should be done on simulating re-optimized fishing locations under improved abundance, which can then be used to estimate the full stock effect. This can then be incorporated in determining harvest plans to implement the maximum economic yield regime.

# APPENDIX A. STYLIZED FACTS APPENDIX

This appendix details the data cleaning procedures, and contains supplementary tables and figures for the stylized facts chapter.

## Data Cleaning Procedures

1. The pre and post trip information about expected and realized fishing outcomes at the trip level is in the *survey* data set. Each trip is uniquely identified by three things: skip code, year, trip number of the year. There is a trip record in the *survey* data whenever a survey respondent completed the pre and post trip questionnaire administered by the "Halibut Project". The *survey* data has record of 496 trips.

2. All the participating skippers also shared their logbook from the fishing seasons of 2006-07. Logbook records all the trips taken by the skipper during the two seasons, even when they did not complete the survey questionnaire. The data set *logbook* contains the logbook information and each trip is also identified by the same identifiers as the *survey* data. *Logbook* data has 6092 rows recording all the gear set information for each trip by the skipper.

3. The catch record for every gear set is recorded as the pounds of the species caught. There were 459 trip records with NA entries in weight. However, 422 records out of them had number of fish caught. I converted the number to weight following the average weight of the species, obtained from the IPHC setline survey data. Also, I separated the species caught in to halibut and black cod caught by weight.

4. Using the gear set location, I associated every gear set with a IPHC region. Also, created the week number of the year for the gear set's day and month information.

5. Then converted the set event level *logbook* data to trip level which yielded 613 trips. Using trip date and gear set location, I assigned regional trip number to each trip, denoting the number of time the skipper fished in a given IPHC region during the season. I also denoted the last regional trips to any region with a dummy as seasonal catch quota is binding in these trips.

6. Finally, the *survey* and *logbook* data are joined which yields 492 trips. The supplementary data from skippers was also attached to this data set. This is the full data set containing information from all the trips including trips that targeted either halibut or black cod, has unreasonable values, extreme values, and fishing trips from the extreme IPHC region 4. I focus on all the trips that targeted halibut, which are 449 trips.

7. Cleaning the data errors in location, target pounds of halibut, unavailable skipper experience for two skippers, unavailable halibut price for the $40 - 60$ pounds category, and one unreasonably high expected cps, leaves the data with 416 trips.

8. There are 10 trips with no information on realized wind speed of the trip and there is one trip with unreasonably high realized wind speed. Dropping these trips, leaves the data set with 405 trips. This is the complete data with no missing and unreasonable values but has extreme observations and trips to extreme region 4.

9. I use the complete data of 405 for visualization and I use 340 trips, which are free from outliers and region 4, for the main regression results. Finally the full data is used for robustness checks.

10. Among the 340 fishing trips that targeted halibut, there are 11 trips which reported 0 pounds of halibut catch. I assume the incidence of 0 pounds of halibut catch in all set events of the trips as data recording error as this is a rare occurrence.

11. The amount of halibut caught is the payoff from the fishing trip and critical fishing decision like whether to do another set event or not depends on the halibut catch. Hence, in the next

chapter where the labor supply of fishermen is investigated, I drop these 11 halibut where the halibut catch might be recorded incorrectly.

12. For the stock abundance model, the raw data was collected from the IPHC webpage which covers setline survey from 1998 to 2018. There were 26, 587 observations in total covering all the management areas.

13. The major fishing areas of the Alaskan Halibut fishery are 2C, 3A, and 3B. So I use only the IPHC stations located in these regulatory areas. However, some of the neighboring stations from area 2B and 4A are also included which shares border with the major fishing areas. In total, there were 16, 287 observations from these 3 major fishing areas.

14. The longitude and latitude data quality were checked and were expressed in degrees. The weight of legal halibut caught recorded 0 pounds in 289 or 1.7% of total observations. These observations are dropped from further considerations, leaving the IPHC data at 15, 998 observations.

15. Catch per skate (cps) were calculated from each gear set by taking the ratio of legal halibut weight size caught and the number of 1800 feet skates used. Note that 1800 foot longline gear with 16/0 circle hooks at $18'$ spacing is defined as skate, following IPHC protocol.

16. The cleaned logbook data from (*Step 4*) had 6092 observations. Among them 584 observations were located in the remote IPHC region 4 which are not considered. Due to recording error, 135 observations are on land masses which is impossible. Cleaning both of these type of records from the *logbook* data returned 5373 observations.

17. There were 973 records, or about 18% records of 0 catch per skate of halibut and 24 observations with extreme catch per skate of more than 1700 pounds. I dropped these extreme observations to yield 4376 *logbook* data observations.

18. Finally, these two data sets, *IPHC* and *logbook*, were joined together yielding a total of 20, 374 observations on which the generalized linear model of stock abundance is based.

## Supplementary Tables and Figures

Table A.1 Revenue Deviation and First Set Event rps

| | *Dependent variable:* \|Target Revenue Deviation %\| | |
|---|---|---|
| | (1) | (2) |
| Stock Proxy | $-0.01^{a}$ | $-0.01^{a}$ |
| | (0.002) | (0.002) |
| \|Wind Shock%\| | −0.062 | |
| | (0.058) | |
| Positive Wind Shock % | | 0.119 |
| | | (0.193) |
| Positive Wind Shock % Sq | | −0.002 |
| | | (0.002) |
| Negative Wind Shock % | | −0.323 |
| | | (0.238) |
| Negative Wind Shock % Sq | | 0.005 |
| | | (0.004) |
| Region Trip Number | −0.38 | −0.265 |
| | (0.703) | (0.696) |
| Last Trip Dummy | $-10.478^{b}$ | $-10.631^{b}$ |
| | (4.365) | (4.337) |
| Black Cod Share % | $0.474^{a}$ | $0.475^{a}$ |
| | (0.067) | (0.066) |
| Constant | $45.784^{a}$ | $46.234^{a}$ |
| | (4.965) | (5.916) |
| Observations | 340 | 340 |
| $R^2$ | 0.528 | 0.535 |
| Adjusted $R^2$ | 0.458 | 0.46 |
| F Statistic | $7.516^{a}$ | $7.154^{a}$ |

Note: Skipper fixed effects used. Standard errors clustered at skipper level are presented in parenthesis. $a, b, c$ denotes significance at 1%, 5%, and 10% levels respectively.

Table A.2 Revenue Deviation and Average rps with Outliers

| | *Dependent variable:* \|Target Revenue Deviation %\| | |
|---|---|---|
| | (1) | (2) |
| Stock Proxy | $-0.007^{a}$ | $-0.006^{b}$ |
| | (0.002) | (0.003) |
| \|Wind Shock%\| | 0.078 | |
| | (0.050) | |
| Positive Wind Shock % | | 0.096 |
| | | (0.133) |
| Positive Wind Shock % Sq | | 0.001 |
| | | (0.001) |
| Negative Wind Shock % | | $-0.433^{c}$ |
| | | (0.222) |
| Negative Wind Shock % Sq | | $0.008^{c}$ |
| | | (0.005) |
| Region Trip Number | −0.407 | −0.43 |
| | (0.803) | (0.794) |
| Last Trip Dummy | $-8.74^{c}$ | $9.114^{c}$ |
| | (4.789) | (3.992) |
| Black Cod Share % | $0.468^{a}$ | $0.467^{a}$ |
| | (0.068) | (0.074) |
| Constant | $40.784^{a}$ | $44.852^{a}$ |
| | (4.916) | (5.817) |
| Observations | 374 | 374 |
| $R^2$ | 0.449 | 0.46 |
| Adjusted $R^2$ | 0.375 | 0.381 |
| F Statistic | $5.942^{a}$ | $5.778^{a}$ |

Note: OLS estimates of regression for absolute target revenue deviation percent on various controls. Skipper fixed effects used. Standard errors clustered at skipper level are presented in parenthesis. $a, b, c$ denotes significance at 1%, 5%, and 10% levels respectively.

Table A.3 Revenue Deviation and Average rps with Outliers & IPHC Region 4

| | *Dependent variable:* \|Target Revenue Deviation %\| | |
|---|---|---|
| | (1) | (2) |
| Stock Proxy | $-0.007^{a}$ | $-0.007^{a}$ |
| | (0.002) | (0.002) |
| \|Wind Shock%\| | 0.072 | |
| | (0.048) | |
| Positive Wind Shock % | | $-0.112$ |
| | | (0.125) |
| Positive Wind Shock % Sq | | 0.001 |
| | | (0.001) |
| Negative Wind Shock % | | $-0.513^{b}$ |
| | | (0.220) |
| Negative Wind Shock % Sq | | $0.01^{b}$ |
| | | (0.005) |
| Region Trip Number | $-0.204$ | $-0.268$ |
| | (0.751) | (0.734) |
| Last Trip Dummy | $-12.473^{a}$ | $-12.514^{a}$ |
| | (4.225) | (3.999) |
| Black Cod Share % | $0.434^{a}$ | $0.43^{a}$ |
| | (0.077) | (0.075) |
| Constant | $41.045^{a}$ | $45.979^{a}$ |
| | (5.429) | (6.218) |
| Observations | 405 | 405 |
| $R^2$ | 0.442 | 0.456 |
| Adjusted $R^2$ | 0.372 | 0.383 |
| F Statistic | $6.316^{a}$ | $6.217^{a}$ |

Note: OLS estimates of regression for absolute target revenue deviation percent on various controls. Skipper fixed effects used. Standard errors clustered at skipper level are presented in parenthesis. $a, b, c$ denotes significance at 1%, 5%, and 10% levels respectively.

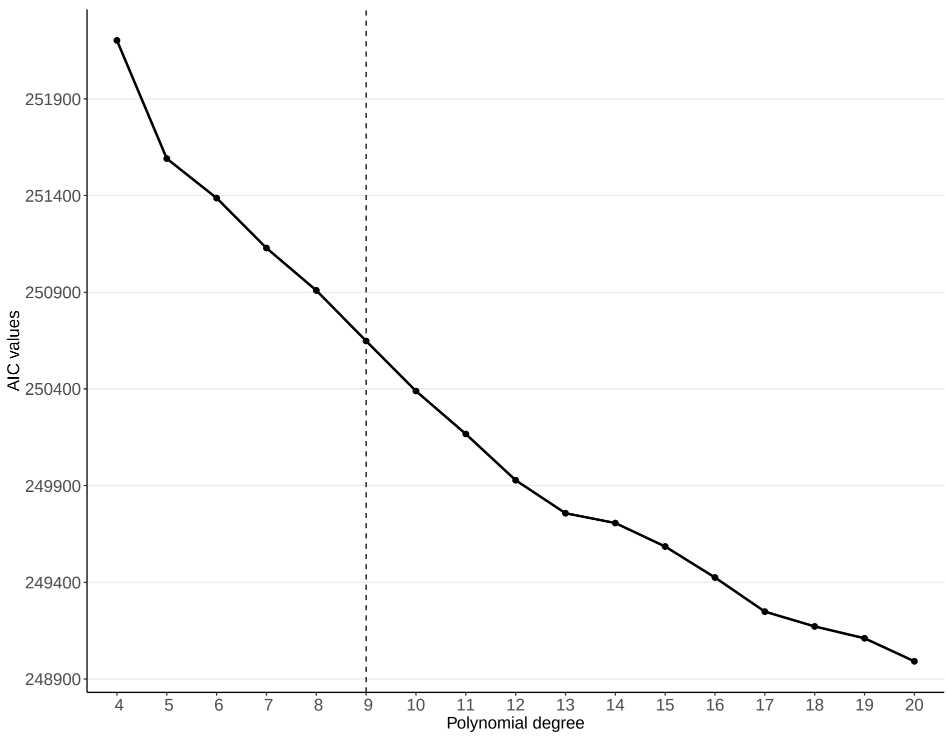


Figure A.1 AIC from Different Models

Note: The polynomial degrees are for longitude and latitude, with the polynomial of week held constant at second degree. Initially, there is substantial drop in AIC when higher polynomials are added. But later on the AIC decline is low, around $< 0.001\%$. So, the polynomial degree of 9 is chosen, by balancing model complexity and model fit.

# APPENDIX B. LABOR SUPPLY APPENDIX

## Theory Proofs

This section of the appendix contains the proof of the results discussed in section 3.3.

### SE and IE for the Static Model

We rewrite the first order condition (3.4) as:

$$U_L(\overline{B} - wL^*, L^*) - wU_C(\overline{B} - wL^*, L^*) = 0 \tag{B.1}$$

Then total differentiate equation (B.1) to get:

$$dL^*[w^2U_{CC} - 2wU_{LC} + U_{LL}] + dw[-L^*U_{LC} - U_C + wL^*U_{CC}] + d\overline{B}[U_{LC} - wU_{CC}] = 0 \tag{B.2}$$

We replace the optimal condition $w = \frac{U_L}{U_C}$ in equation (B.2) to get:

$$\frac{\partial L^*}{\partial w} = \frac{\left[-L^*(U_CU_{LC} - U_LU_{CC}) - U_C^2\right]U_C}{(-U_L^2U_{CC} + 2U_LU_CU_{LC} - U_C^2U_{LL})} \tag{B.3}$$

and

$$\frac{\partial L^*}{\partial \overline{B}} = \frac{(U_CU_{LC} - U_LU_{CC})U_C}{(-U_L^2U_{CC} + 2U_LU_CU_{LC} - U_C^2U_{LL})} \tag{B.4}$$

The second order condition of maximum ensures the denominator in equation (B.3) and equation (B.4) is positive. We have assumed that leisure is normal good which implies $\frac{\partial L^*}{\partial \overline{B}} > 0$. This implies, $(U_CU_{LC} - U_LU_{CC}) > 0$. This in turn implies, $\frac{\partial L^*}{\partial w} < 0$. Hence we have shown that substitution effect is negative and income effect is positive for wage variations on leisure demand, if leisure is normal good.

### SE and IE for the Static Model: CRRA

We can rewrite equation (3.11) as:

$$\frac{dh^*}{dw} = -\frac{L_0}{(w^{\frac{1}{\sigma}} + w)} + \frac{(wL_0 + B)(\frac{1}{\sigma}w^{\frac{1-\sigma}{\sigma}} + 1)}{(w^{\frac{1}{\sigma}} + w)^2} \tag{B.5}$$

Then $\frac{dh^*}{dw} < 0$ if and only if

$$\frac{L_0}{(w^{\frac{1}{\sigma}} + w)} > \frac{(wL_0 + B)(\frac{1}{\sigma}w^{\frac{1-\sigma}{\sigma}} + 1)}{(w^{\frac{1}{\sigma}} + w)^2}$$

$$(w^{\frac{1}{\sigma}} + w)L_0 > (wL_0 + B)(\frac{1}{\sigma}w^{\frac{1-\sigma}{\sigma}} + 1)$$

$$w^{\frac{1}{\sigma}}L_0 > \frac{1}{\sigma}w^{\frac{1}{\sigma}}L_0 + \frac{Y}{\sigma}w^{\frac{1-\sigma}{\sigma}} + B \tag{B.6}$$

All the terms on the right side is positive. So if $\sigma < 1$, then for all values of $B$ and $w$, the inequality will not hold and labor supply will be always positively related to wages. But if $\sigma > 1$, there is a possibility of IE dominating SE producing negative relationship between wages and labor supply. Even in that case, we will have negatively sloped labor supply only for high enough wages. This provides the background behind existence of backward-bending labor supply curve in static neoclassical model. Also note that $\sigma > 1$ is uncommon in the literature.

### MU of Wealth Expressed as Fixed and Time Effect

To rewrite $\lambda_t$, the marginal utility of wealth at period $t$ as the sum of $\lambda_0$ and common time effect as shown in equation (3.16), we take natural log and lag equation (3.14) the first order condition with respect to $A_t$ by one period to get:

The marginal utility of wealth at period $t$, $\lambda_t$ is expressed as the sum of $\lambda_0$ and common time effect as shown in equation (3.16) using the following steps. First lag the first order condition with respect to $A_t$ in equation (3.14) by one period and take natural logarithm to get:

$$\ln \lambda_{t-1} = \ln(1 + r_t) + \ln \lambda_t \tag{B.7}$$

Lag the above equation one more period to get:

$$\ln \lambda_{t-2} = \ln(1 + r_{t-1}) + \ln \lambda_{t-1} \tag{B.8}$$

Then use the substitute $\ln \lambda_{t-1}$ into $\ln \lambda_{t-2}$ to get:

$$\ln \lambda_{t-2} = \ln(1 + r_{t-1}) + \ln(1 + r_t) + \ln \lambda_t \tag{B.9}$$

Continuing in this way till the last period $t = 0$, we get the desired result:

$$
\begin{aligned}
\ln \lambda_0 &= \sum_{\tau=1}^{\tau=t} (1 + r_\tau) + \ln \lambda_t \\
\ln \lambda_t &= -\sum_{\tau=1}^{\tau=t} (1 + r_\tau) + \ln \lambda_0
\end{aligned}
\tag{B.10}
$$

**Sign of Income Effect: CRRA Example**

We total differentiate (3.33) to derive the expression for $\frac{\partial \lambda_1}{\partial w_1}$:

$$
\begin{aligned}
-\frac{1}{\sigma}\lambda_1^{-\frac{1}{\sigma}-1}\frac{\partial \lambda_1}{\partial w_1}(A+B) + \lambda_1^{\frac{-1}{\sigma}}\left(\frac{\beta^{\frac{1}{\sigma}}}{1+r}\frac{\sigma-1}{\sigma}w_1^{\frac{-1}{\sigma}}\right) &= \frac{1}{1+r} \\
-\left(\frac{1}{\sigma\lambda_1^{-\frac{1+\sigma}{\sigma}}}\right)(A+B)\frac{\partial \lambda_1}{\partial w_1} &= \frac{1}{1+r} - \left(\frac{\beta^{\frac{1}{\sigma}}}{1+r}\frac{\sigma-1}{\sigma}w_1^{\frac{-1}{\sigma}}\lambda_1^{\frac{-1}{\sigma}}\right) \\
\frac{\partial \lambda_1}{\partial w_1} &= -\left(\frac{\sigma\lambda_1^{\frac{1}{\sigma}}w_1^{\frac{1}{\sigma}} - \beta^{\frac{1}{\sigma}}(\sigma-1)}{(1+r)\sigma\lambda_1^{\frac{1}{\sigma}}w_1^{\frac{1}{\sigma}}}\right) * \left(\frac{\sigma\lambda_1^{\frac{1+\sigma}{\sigma}}}{A+B}\right) \\
\frac{\partial \lambda_1}{\partial w_1} &= -\lambda_1\left(\frac{\sigma\lambda_1^{\frac{1}{\sigma}}w_1^{\frac{1}{\sigma}} - \beta^{\frac{1}{\sigma}}(\sigma-1)}{(1+r)w_1^{\frac{1}{\sigma}}(A+B)}\right)
\end{aligned}
$$

**Labor Supply: General Case for Reference-Dependent**

For $wh > I$ case, we differentiate $u'(wh)w + \eta\alpha(wh - I)^{\alpha-1}w = c'(h)$ with respect to $w$:

$$
\begin{aligned}
&wu''(wh)(w\frac{dh}{dw} + h) + u'(wh) + \\
&\qquad \eta\alpha(w(\alpha-1)(wh-I)^{\alpha-1}(w\frac{dh}{dw} + h) + (wh-I)^{\alpha-1}) = c''(h)\frac{dh}{dw}
\end{aligned}
\tag{B.11}
$$

$$
\left.\frac{dh}{dw}\right|_a = \frac{-whu''(wh) - u'(wh) - \eta\alpha wh(\alpha-1)(wh-I)^{\alpha-2} - \eta\alpha(wh-I)^{\alpha-1}}{w^2u''(wh) + \eta\alpha w^2(\alpha-1)(wh-I)^{\alpha-2} - c''(h)}
\tag{B.12}
$$

The sign of numerator is ambiguous and the sign of denominator is negative producing ambiguous result.

For $wh < I$ case, we differentiate $u'(wh)w + \eta\mu w\beta(-(wh-I))^{\beta-1}w = c'(h)$ with respect to $w$:

$$wu''(wh)\left(w\frac{dh}{dw}+h\right)+u'(wh)+ \\ \eta\mu\beta\left(-w(\beta-1)(-(wh-I))^{\beta-1}\left(w\frac{dh}{dw}+h\right)+(-(wh-I))^{\beta-1}\right)=c''(h)\frac{dh}{dw} \quad \text{(B.13)}$$

$$\left.\frac{dh}{dw}\right|_b = \frac{-whu''(wh)-u'(wh)-\eta\mu\beta wh(\beta-1)(-(wh-I))^{\beta-2}-\eta\mu\beta(-(wh-I))^{\beta-1}}{w^2u''(wh)-\eta\mu w^2\beta(\beta-1)(-(wh-I))^{\beta-2}-c''(h)} \quad \text{(B.14)}$$

The sign of both numerator and denominator is ambiguous, resulting in ambiguous sign.

**Labor Supply: CRRA case for Reference-Dependent**

For $wh > I$ case, with CRRA reference dependent preferences, we differentiate $w^{1-\sigma}h^{-\sigma} + \eta w\alpha(wh-I)^{\alpha-1} = h^{\gamma}$ with respect to $w$:

$$(1-\sigma)w^{-\sigma}h^{-\sigma}-\sigma w^{1-\sigma}h^{-\sigma-1}\frac{dh}{dw}+ \\ \eta\alpha\{(wh-I)^{\alpha-1}+w(\alpha-1)(wh-I)^{\alpha-2}(w\frac{dh}{dw}+h)\}-\gamma h^{\gamma-1}\frac{dh}{dw}=0 \quad \text{(B.15)}$$

$$\left.\frac{dh}{dw}\right|_a = \frac{-(1-\sigma)w^{-\sigma}h^{-\sigma}-\eta\alpha(wh-I)^{\alpha-1}-\eta\alpha w(\alpha-1)(wh-I)^{\alpha-1}h}{-\sigma w^{1-\sigma}h^{-\sigma-1}+\eta\alpha(\alpha-1)w^2(wh-I)^{\alpha-2}-\gamma h^{\gamma-1}} \quad \text{(B.16)}$$

The sign of numerator and denominator is both ambiguous and hence the sign of $\left.\frac{dh}{dw}\right|_a$ is ambiguous, even with $\sigma < 1$.

For $wh < I$ case, with CRRA reference dependent preferences, we differentiate $w^{1-\sigma}h^{-\sigma} + \eta\mu w\beta(-(wh-I))^{\beta-1} = h^{\gamma}$ with respect to $w$:

$$(1-\sigma)w^{-\sigma}h^{-\sigma}-\sigma w^{1-\sigma}h^{-\sigma-1}\frac{dh}{dw}+ \\ \eta\mu\beta\{(-(wh-I))^{\beta-1}-w(\beta-1)(-(wh-I))^{\beta-2}(w\frac{dh}{dw}+h)\}-\gamma h^{\gamma-1}\frac{dh}{dw}=0 \quad \text{(B.17)}$$

$$\left.\frac{dh}{dw}\right|_b = \frac{-(1-\sigma)w^{-\sigma}h^{-\sigma}-\eta\mu\beta(-(wh-I))^{\beta-1}-\eta\mu\beta wh(\beta-1)(-(wh-I))^{\beta-2}}{-\sigma w^{1-\sigma}h^{-\sigma-1}-\eta\mu\beta(\beta-1)w^2(-(wh-I))^{\beta-2}-\gamma h^{\gamma-1}} \quad \text{(B.18)}$$

The sign of numerator and denominator is both ambiguous and hence the sign of $\left.\frac{dh}{dw}\right|_b$ is ambiguous, even with $\sigma < 1$.

## Supplementary Tables and Figures

Table B.1 Neoclassical testing (additional results)

| | *Dependent variable:* Set Events | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| | Panel A: Estimates and Standard Errors | | |
| *Trip variant variables:* | | | |
| Wage ($\times 10^{-2}$ lbs.) | $-0.070$ | $-0.068$ | $-0.072$ |
| | (0.061) | (0.059) | (0.062) |
| Wage sq ($\times 10^{-5}$ lbs.) | $-0.173^{*}$ | $-0.169^{**}$ | $-0.176^{*}$ |
| | (0.088) | (0.083) | (0.087) |
| Objective productivity | $-0.023$ | $-0.022$ | $-0.022$ |
| | (0.032) | (0.031) | (0.033) |
| Vessel hold | $0.200^{***}$ | $0.202^{***}$ | $0.197^{***}$ |
| | (0.050) | (0.056) | (0.053) |
| Quota constraint | $-0.102^{*}$ | $-0.107^{*}$ | $-0.108^{*}$ |
| | (0.062) | (0.065) | (0.063) |
| *Trip invariant variables:* | | | |
| Vessel length | $0.019^{***}$ | $0.019^{***}$ | $0.019^{***}$ |
| | (0.006) | (0.006) | (0.005) |
| Average crew | 0.008 | 0.007 | 0.007 |
| | (0.043) | (0.041) | (0.044) |
| Share information | $0.203^{*}$ | $0.206^{*}$ | 0.206 |
| | (0.122) | (0.128) | (0.137) |
| Wind effects | No | Yes | Yes |
| Linear wind effects | No | Yes | Yes |
| Sq wind effects | No | No | Yes |
| Observations | 329 | 329 | 329 |
| Log-likelihood | $-574.940$ | $-574.765$ | $-574.463$ |

Note: Skipper, year, region fixed effects, black cod lbs. are included. Bootstrapped standard error from 400 replications are in parenthesis. Significant at $^{*}$10%, $^{**}$5%,$^{***}$1%.

Table B.2 Exploitation Ratio

| Set Event | Obs | Ratio |
|---|---|---|
| 1 | 394 | 0.991 |
| 2 | 307 | 0.962 |
| 3 | 218 | 1.000 |
| 4 | 145 | 0.989 |
| 5 | 96 | 0.936 |
| 6 | 60 | 0.963 |
| 7 | 39 | 0.910 |
| 8 | 16 | 1.391 |
| 9 | 12 | 2.569 |
| 10 | 7 | 1.555 |
| 11 | 3 | 0.955 |
| 12 | 1 | 1.022 |

Note: Exploitation ratio for set events done at a given cluster on a trip. The adjustment factor for set events equal to or more than 5 is assumed to 0.936 as the there is lack of sufficient observations for higher set events.

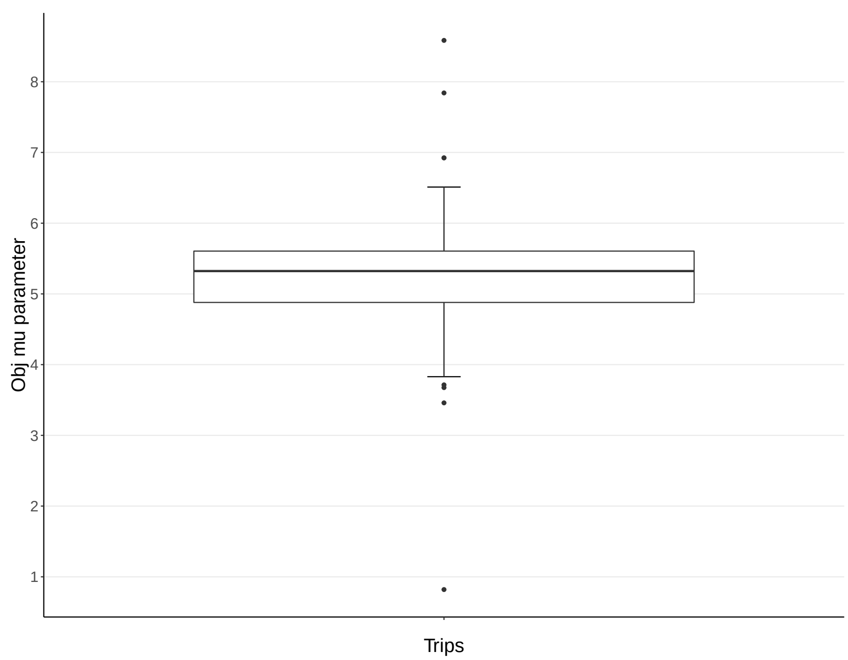


Figure B.1 Objective productivity

Note: Boxplot for the $\mu$ parameter associated with each trip, from the estimated objective catch per skate distribution.

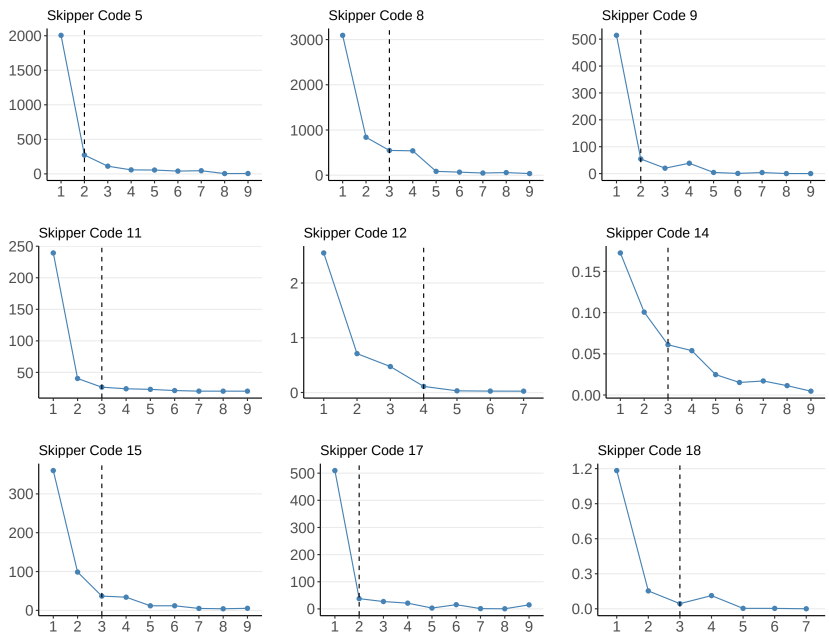


Figure B.2 Elbow Plot 1

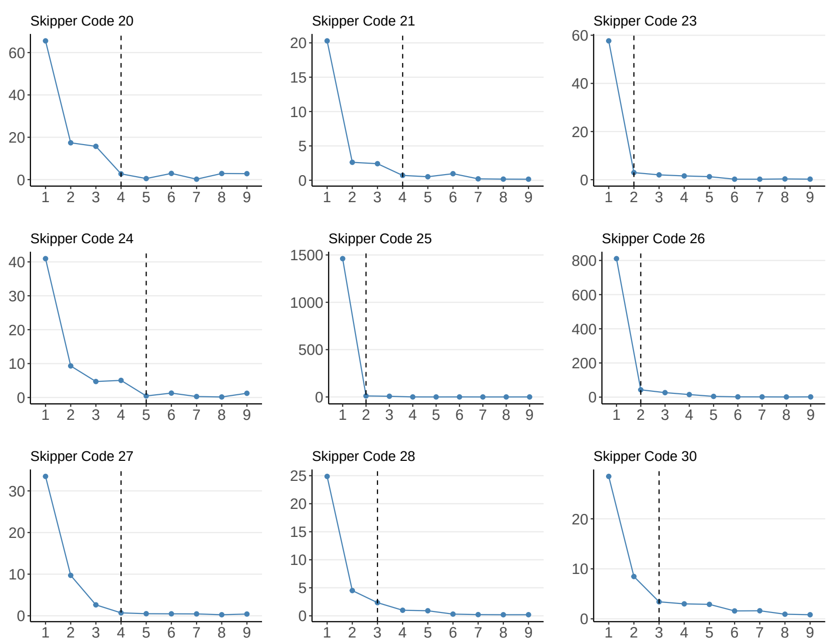


Figure B.3 Elbow Plot 2

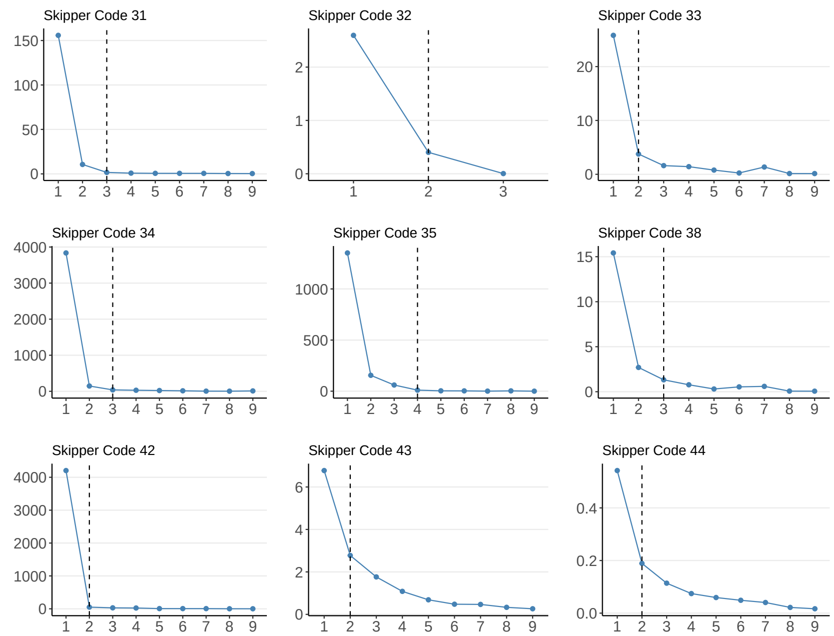


Figure B.4 Elbow Plot 3

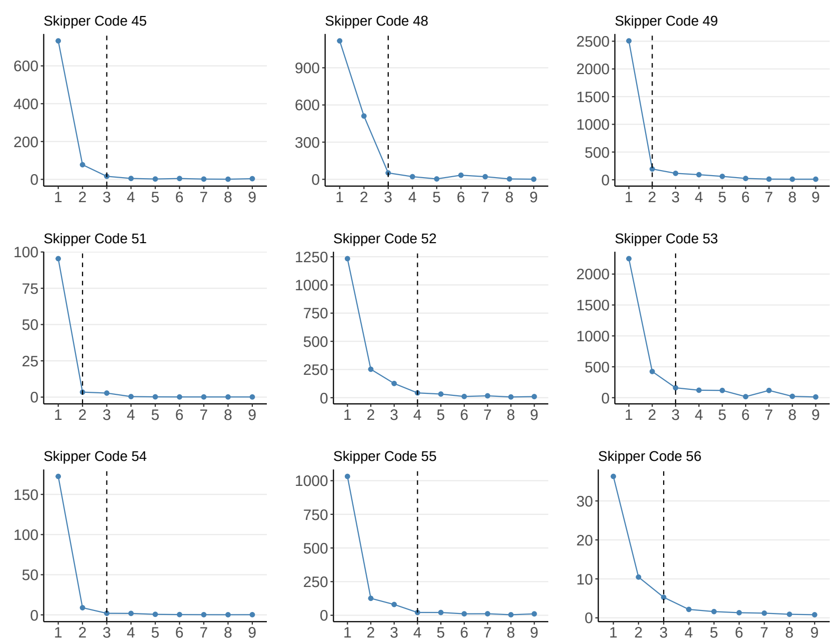


Figure B.5 Elbow Plot 4