Revenue Targeting in Fisheries: The Case of Hawaii Longline Fishery

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ABSTRACT

I apply the target revenue model, a version of prospect theory, to investigate how fishermen adjust their trip length to changes in daily revenue. The key finding is that certain groups of fishermen seem more likely to behave according to the target revenue model rather than the standard model of labor supply. Asian American captains seem more likely to behave according to the target revenue model than Caucasian captains. I also find that vessel capacity has little effect on the captain's decision making behavior. The study strongly supports the integration of prospect theory into the framework of labor supply analysis.

Key Words: Behavioral economics; Fisheries; Hawaii Longline; Prospect Theory; Target revenue model.

I. INTRODUCTION

Fishing effort, as measured by the number of fishing days for a given trip is probably one of the most important decisions for any fisherman. Studies on fishing effort have been widely published. To the best of our knowledge, all of these studies use the standard assumptions of economic theory, namely that economic agents are rational and self-interested. In this paper, I explore the fishermen's decision-making behavior on the number of fishing days per trip by applying an alternative framework using the target revenue model. I will see how having a target revenue may influence the fisherman's decision regarding trip length and how this may result in a different prediction from the standard economic model regarding the relationship between daily fishing revenue and the number of fishing days. To investigate which model provides a more reasonable description of reality, I observe the empirical evidence from the Hawaii-based longline fisheries.

I credit a paper by Camerer et al. (1997) who apply the target revenue model on the taxi drivers in New York City as our primary inspiration for this research. Camerer et al. find strong evidence to show that cab drivers may behave according to the target revenue model as far as how many hours they work per day is concerned. As discussed later, fishermen and taxi drivers share a number of similar characteristics. These common characteristics make it worthwhile to study fishing behavior under the same framework as Camerer et al.

There are, however, factors that make fishery an interesting case study in and of itself. First, fishermen face capacity constraints for fuel and food supplies. These constraints may result in shortening the trip despite having not achieved the target revenue goal for a given trip as predicted by the target revenue model. Second, Hawaii longline fisheries consists of owners from different ethnic groups, each may behave differently in the decision-making process. Accordingly, certain groups of owners may be more likely to behave in accordance with the standard economic model; whereas the others are more likely to behave according to the target revenue model. Third, longline fishing experience is highly correlated with rational behavior defined in the standard model: the longer the fisherman has been longline fishing, the more likely he will behave according to the standard model (Camerer et al., 1997).

In this paper, I are going to investigate the following questions: (1) How well does the target revenue model describe the fishing behavior of Hawaii longline fishermen? (2) How do capacity constraints impact fishermen's behavior under the target revenue model framework? (3) How does ethnicity impact fishermen's behavior under the target revenue model framework? and (4) How significant does longline fishing experience have on fishermen behaving according to the target revenue model framework?

II. A LITERATURE REVIEW

An Inter-temporal Model of Labor Supply in Fishery

A great number of recent studies on labor supply have followed the inter-temporal formulation of the standard neoclassical model (Camerer et al., 1997; Chou, 2003; Farber, 2006). Applying this standard formulation to fishery, the number of fishing days for a trip can be determined by solving the lifetime utility function defined over lifetime consumption and fishing days. In particular, consider maximizing the lifetime utility of a fisherman with time separable utility function:

$$\underset{(c_t,d_t))}{\text{Max}} U(\text{Lifetime}) = \sum_{t=0}^{T} \beta^t [u(c_t) - v(d_t)] \tag{1}$$

Subject to a lifetime budget constraint

$$\sum_{t=0}^{T} p_t c_t (1+\rho)^{-t} = \sum_{t=0}^{T} w_t d_t (1+\rho)^{-t} \tag{2}$$

where $u(c_t)$ is the utility gained from consumption c_t in period t and $v(d_t)$ is the disutility from fishing effort, d_t, in the same period. By standard assumptions, $u(c_t)$ is concave whereas $v(d_t)$ is convex. w_t and p_t are the daily revenue and the price of consumption good in period t, respectively. β is the discount factor and ρ is the interest rate.

Setting up the Lagrangian, we have

$$L = \sum_{t=0}^{T} \beta^t [u(c_t) - v(d_t)] - \lambda [\sum_{t=0}^{T} p_t c_t (1+\rho)^{-t} - \sum_{t=0}^{T} w_t d_t (1+\rho)^{-t}] \tag{3}$$

Solving the first order condition with respect to c_t and d_t, results in

$$\frac{\partial L}{\partial c_t} = 0 \Leftrightarrow \beta^t u'(c_t) = \lambda p_t (1+\rho)^{-t} \tag{4}$$

$$\frac{\partial L}{\partial d_t} = 0 \Leftrightarrow \beta^t v'(d_t) = \lambda w_t (1+\rho)^{-t} \tag{5}$$

From (4) and (5), we can derive the following

$$\frac{v'(d_t)}{u'(c_t)} = \frac{w_t}{p_t} = r_t \tag{6}$$

where r_t is the real daily revenue.

Taking the expectation for t+1 at t, we have

$$\frac{v'(E(d_{t+1}))}{u'(E(c_{t+1}))} = \frac{E(w_{t+1})}{E(p_{t+1})} = E(r_{t+1}) \tag{7}$$

Dividing (7) by (6), we have

$$\frac{v'(E(d_{t+1})}{v'(d_t)} \bigg/ \frac{u'(E(c_{t+1}))}{u'(c_t)} = \frac{E(r_{t+1})}{r_t} \tag{8}$$

Now suppose the vessel operator expects an increase in the real daily fishing revenue in the next period, i.e., $E(r_{t+1}) > r_t$. From (8), by keeping the consumption level constant, it must be the case that $v'((E(d_{t+1})) > v'(d_t)$. By recalling the assumption of convexity of $v(d_t)$, we can then derive that $E(d_{t+1}) > d_t$. In other words, the model implies that under the standard framework that there is a positive correlation between the number of fishing days and the daily revenue.

Studies on the supply of labor have empirically shown little support for the standard model's prediction (Falk: 2004, 2006). Most studies, rather, have found a positive correlation between labor wages and labor supply, though these results are not significant. This insignificant relationship found in the empirical studies is attributed to a number of factors. For instance, in many settings workers are required to work a fixed number of hours per day regardless of their hourly wage (Falk, 2004). Another question is whether changes in wages are temporary or permanent with respect to the time horizon of the decision-making framework. Under the standard model of labor supply, decisions are made under a long-run or lifelong horizon. Most empirical studies in fisheries, however, assume that decision making are short-term (i.e., a fishing trip). This short-run time horizon, for example, certainly impacts on the standard model's predictions of fishermen's behavior (Lokina, 2006).

In the search of a model to bridge the gap between theoretical prediction and empirical evidence, increasing attention has been paid to the target revenue model which offers an alternative description of labor supply. In what follows, I will briefly review the labor supply studies based on the target revenue model.

Revenue Target Model: A Prospect Theory Based Model

The seminal paper by Camerer et al. (1997) on the labor supply of taxi drivers in New York City is the first study on labor supply under the prospect theory framework. Camerer's basic estimation equation takes the following form:

$$\log(h_{i,t}) = \alpha + \beta \log(Y_{i,t} / h_{i,t}) + X_{i,t}\varphi + \varepsilon_{i,t}$$

where $h_{i,t}$ is the number of driving hours by driver i on day t; $Y_{i,t}$ is driver i's income on day t; $X_{i,t}$ is a vector of other variables that may have an effect on the number of driving hours. Camerer et al. find a negative elasticity for the taxi driver's working hours with respect to hourly wage in the range of [-0.61, -0.18]. According to the authors, the negative relationship between number of working hours and average wage rate results from the fact that each taxi driver has a daily target income level. On a given day, drivers continue driving until they achieve their target income levels. On a productive day with many customers, it takes only a few hours to meet that target goal. Conversely, on days with fewer customers, it takes more hours to reach that same target level.

Following the Camerer et al. paper, a number of labor supply studies based on target revenue model have been conducted. Using a similar approach, Chou (2002) finds that Singaporean cab drivers exhibit exactly the same decision making behavior on time allocation as those in New York City. Fehr and Gotte (2007) provide an innovative method of labor supply study. They use a randomized field experiment to explore how bike messengers in San Francisco respond to changes in hourly wages. They estimate the loss aversion parameters of the participants and find that messengers with strong loss aversion behaved in accordance with the target revenue model. Conversely, messengers with less loss aversion appear to follow the standard model of labor supply, i.e., they increase effort levels in response to an increase in the piece rate.

In support of the standard inter-temporal model, Farber (2004, 2008) conducts a study also on New York taxi drivers. Farber's approach focuses on the probability of continuing to drive at any given time by asserting that the greater the number of accumulated driving hours, the lower the probability a driver continues to drive. He argues that the key factor in determining the cab driver's daily driving hours is the number of hours driven. Farber's empirical model takes the following hazard model form:

$$\text{Stop}_{i,t} = \alpha + \beta Y_{i,t} + \delta h_{i,t} + X_{i,t}\Gamma + \varepsilon_{i,t}$$

The dependent variable is a binary variable $\text{Stop}_{i,t} = 1$, if driver i stops at time t. $Y_{i,t}$ is the cumulative income level for driver i given he stops at time t; $h_{i,t}$ is his cumulative driving hours, and X_{it} is other independent variables. To investigate how well the target revenue model explains the data, Farber aims at answering the question: Does a higher cumulative earning $Y_{i,t}$ lead to an increase in the probability of stopping ($\beta > 0$)? The estimated coefficient β would be positive and significant if cab drivers behaved according to the target revenue model. Farber finds a positive but not significant effect of cumulative earning $Y_{i,t}$ on the probability of stopping. This finding is qualitatively consistent with the target income model. Farber also finds a significant and positive impact of cumulative working hours on the probability of stopping which gives support for the standard model of labor supply.

Fisheries serve as an ideal application for the target revenue model because of the short time horizon of the decision making process and the uncertainties surrounding each trip. Decision on the length of a fishing trip is made one trip at a time. This short time horizon differs from the standard model's assumption of using a lifelong horizon. There is also a great deal of uncertainty surrounding each trip as it is possible that a vessel can have one very profitable trip followed by a very unprofitable trip, and the reasons may be due to uncontrollable factors such as bad weather or poor fishing grounds. Due to these reasons, it is not easy for a vessel operator to expect a certain return for each fishing trip and, thus, will also not know how long each trip will last. A possible strategy for the vessel operator is to establish a target revenue goal. This goal acts as a reference point to help decide whether to continue the fishing trip or not. From interviews with vessel operators in the Hawaii longline fisheries, I found that a majority of vessel operators do mentally have a target revenue goal for each fishing trip. The target revenue is typically the vessel's previous years' average trip revenue. For example, operators of average size longline vessels, mentioned aiming for a revenue of $20,000 for each trip. Once the operator has reached this goal he would very likely conclude the trip and return home. The probability of continuing the fishing trip after achieving $19,000 is much greater than continuing after receiving $21,000 of revenue. Psychologically, it is true that people will more likely work harder prior to reaching a goal than after exceeding that goal (Fehr and Falk, 2002). According to Goette et al. (2004), it is this type of decision-making behavior that makes the Kahneman–Tversky prospect theory a relevant framework in our study.

Given its unique feature of the decision-making process, fisheries also serve as an ideal application for the study of labor supply under the target revenue model. First, fishermen enjoy the flexibility to choose trip's fishing length which in turn allows for enough variation in the number of fishing days from trips to trips and vessels to vessels. Variation in the number of fishing days makes it possible to use fishing length as the dependent variable. Second, because there is little correlation between the trip revenue from different trips, it is reasonable to consider each fishing trip in isolation. If the vessel operator made decisions based on two trips as opposed to one, for instance, the additional revenue from one productive trip could offset the loss in the other unproductive trip. In order to reach the revenue target for the two trips, the vessel operator may fish longer during the productive trip and shorter during the unproductive trip. Despite having a revenue target (for the two trips together), the vessel operator's behavior follows in suit with the inter-temporal model of labor supply.

In general, fishing decisions regarding trip length is a very complex process due to a number of factors, like vessel capacity and auction fish prices. Vessel physical capacity determines the length of time that a vessel can fish for. The ability to produce ice during a trip is crucial in lengthening the amount of time a vessel is out at sea. Fish price, which is controlled by market supply and demand forces, can directly impact trip revenue and induce uncertainty regarding trip length. Fish prices are determined by high level of competition at the local United Fishing Agency fish auction and are also influenced by the number of fishing boats choosing to offload on a particular day. Depending on the number of boats offloading to the fish auction, vessel operators may gamble by shortening a trip and catching fewer pieces of fish, and offloading on a day with fewer boats at the auction with the hope of securing higher prices to compensate for the lower quantity in fish pieces.

This paper greatly simplifies this complex process by assuming that the vessel operator has a revenue target, as opposed to a target quantity of fish pieces caught. This assumption may cause one to ask how the vessel operator can estimate the accumulated revenue of the trip especially when the auction fish price fluctuates on a daily basis. This is possible thanks to the constant communication between the captain who is monitoring the boat in the ocean and the owner who follows closely what happens at the auction. Focusing solely on revenue rather than on fish prices will significantly simplify this complex price mechanism. Regarding the vessel's physical constraint to stay longer in the ocean, I use ice maker as a proxy for vessel capacity. Having ice maker enables larger and typically shallow-set vessels to fish longer. When fish are placed in an ice hole and are regularly repacked to maintain a desired level of freshness over the course of many weeks out at sea, ice will melt and will have to be replaced by fresh ice from an ice maker. Otherwise, there exists a trade-off between the fish quality and the trip length.

III. A REVENUE TARGET MODEL IN FISHERY

Our primary interest is seeing how having a target revenue goal impacts trip length. I first assume that this revenue goal is consistent for both the owner and the captain. Furthermore, I assume that the owner and the captain have the same objectives and jointly decide on the trip length. This second assumption is reasonable as net trip revenue is often shared between the owner and the captain. Moreover, joint decision making reflects how the information is transferred during the fishing trip. The captain is informed of their fishing productivity while the owner is cognizant of the market conditions at the auction. This cooperative effort is a common practice in fisheries and shows how each plays an equal role in deciding on the trip length.

Decisions on trip length are made one trip at a time rather than over an entire lifecycle. Hence, our model is based on a single trip. To incorporate revenue goal-setting, I assume that the captain's preference takes the following form:

$$U(Y,d) = \alpha(Y - T) - \frac{\theta}{1+\gamma} d^{1+\gamma} \qquad (Y<T) \qquad (9)$$

$$U(Y,d) = (Y - T) - \frac{\theta}{1+\gamma} d^{1+\gamma} \qquad (Y>T) \qquad (10)$$

where U(Y,d) is the utility function under prospect theory. d is the number of fishing days. Y is the fishing revenue for the trip; and Y=wd, where w is the average daily fish revenue. T is the reference (target) revenue level. α is a parameter representing how sensitive the captain is to deviation from the reference revenue. I assume that $\alpha>1$ reflects loss aversion. θ is a parameter for the disutility of fishing effort. γ is the inverse elasticity parameter of revenue with respect to fishing days.

There are two elements in the utility function. The first element represents utility, which varies depending on how much the actual fishing revenue exceeds the target (Y-T). The second element is the standard disutility function. The utility function is kinked at Y=T. When the captain exceeds the target revenue level (Y>T), the marginal utility is 1, which implies that a revenue increase of $1 results in a 1 unit increase in utility. When the captain has not exceeded the target revenue level (Y<T), the marginal utility is α, which is greater than 1, which implies that a revenue increase of $1 leads to more than a 1 unit increase in utility. In this case, the captain places more values on a $1 revenue increase because the captain has yet to reach the point where Y>T and, thus, is more willing to continue fishing. A productive fishing trip shortens the time before the captain can achieve the target goal (i.e. Y>T), whereas an unproductive trip lengthens the time the captain to achieve the target goal, as there is incentive to fish longer so long as Y<T Intuitively, this depicts the negative relationship between daily fishing revenue and trip length. I will formally show under what

circumstance this relationship will occur.

Case 1: Y<T

Substitute Y = wd into (6), we have:

$$U(d) = \alpha(wd - T) - \frac{\theta}{1+\nu} d^{1+\gamma} \tag{11}$$

Solving the first order condition (FOC) to optimize the captain's utility, we have:

$$\frac{\partial U(d{=}d^*)}{\partial d} = 0 \Leftrightarrow \alpha w = \theta (d^*)^{\gamma} \Leftrightarrow d^* = \left(\frac{\alpha w}{\theta}\right)^{1/\gamma} \tag{12}$$

The FOC then results in $d^* = \left(\frac{\alpha w}{\theta}\right)^{1/\gamma}$. To find the threshold values for w and d, we consider the case wd* =Y*=T*. Solving for d* and w* we have

$$d^* = \left(\frac{\alpha w}{\theta}\right)^{1/\gamma} \tag{13}$$

$$w^* = \left(\frac{\theta}{\alpha}\right)^{\left(\frac{1}{1+\gamma}\right)} T^{\left(\frac{\gamma}{1+\gamma}\right)} \tag{14}$$

Case 2: Y>T

In this case, α=1. Follow the same procedure as Case 1. By substituting α=1 into (13) and (14), we have

$$d^{**} = \left(\frac{w}{\theta}\right)^{1/\gamma} \tag{15}$$

$$w^{**} = \theta^{\frac{1}{1+\gamma}} T^{\frac{\gamma}{1+\gamma}} \tag{16}$$

Using equations (13) to (16), we can show that the optimal number of fishing days $d^{optimal}$ can be one of the following:

w<w* then $d^{optimal} = \left(\dfrac{\alpha w}{\theta}\right)^{1/\gamma}$ (17)

w>w** then $d^{optimal} = \left(\dfrac{w}{\theta}\right)^{1/\gamma}$ (18)

w*<w<w** then $d^{optimal} = \dfrac{T}{w}$ (19)

where $w^* = \left(\dfrac{\theta}{\alpha}\right)^{\left(\frac{1}{1+\gamma}\right)} T^{\left(\frac{\gamma}{1+\gamma}\right)}$ and $w^{**} = \theta^{\frac{1}{1+\gamma}} T^{\frac{\gamma}{1+\gamma}}$, respectively.

As such, there is a positive correlation between the optimal number of fishing days ($d^{optimal}$) and the average daily fishing revenue (w) when w<w* or w>w** (eq. 17 &18). This positive correlation is in accordance with predictions from the standard inter-temporal model of labor supply. In addition, there is a negative correlation between the number of fishing days and the daily fish revenue when w*<w<w** (eq. 19). Thus, the revenue target model can address a broader range of impacts that daily revenue may have on the fishing trip length. Under the revenue target model, it is plausible that an increase in daily fishing revenue results in shorter trips. The following section empirically explores revenue target model's ability to describe the behavior of Hawaii longline fishermen.

IV. EMPIRICAL EVIDENCE

Data Source and Model Specifications

Information on the number of fishing days by trip and trip revenue is obtained from 2004 logbook data and 2004 auction data, respectively. It is worth noting that the swordfish fishery was closed in Hawaii during 2004, thus, our data includes information on tuna fishery only. Hereafter, longline fishery refers to only the tuna fishery. The logbook is compiled by the National Oceanic and Atmospheric Administration (NOAA). The auction data is collected by the Hawaii Division of Aquatic Resources (HDAR). The logbook data contains information on the number of fishing days for every longline trip in 2004, and the auction data records the trip revenue for each longline vessel in that same year. These two datasets were combined for the estimation of the empirical model.

Table 1 presents the summary statistics of the main variables. The average length of a fishing trip in the Hawaii longline fisheries is about 19 days. Variation of the number of fishing days is relatively large. An average vessel earns about $32,000 per trip or $1,800 per fishing day.

The standard deviations in fish revenues are relatively large reflecting the diversity of vessel characteristics within the fisheries. The vessels are distributed almost equally across three ethnic groups of owners: Caucasian, Korean, and Vietnamese. About 50% of captains have 16 years of longline fishing. In terms of the vessel's capacity, about 35% of vessels have an ice maker.

Model Specifications

I first start with the basic empirical model, which takes the following form:

$$\ln D_{it} = \eta \ln W_{it} + X_{it}\beta + \varepsilon_{it} \qquad (20)$$ [1]

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[1]Given that number of fishing days is count data one can use a generalized linear model such as a Poisson model to investigate the relationship between the number of fishing days and daily revenue. In this study, we're more interested in the elasticity of fishing day with

where D_{it} represents the number of fishing days by vessel i on trip t, W_{it} is the average daily revenue of vessel i on trip t, X_{it} are the vessel's characteristics that may impact the trip's fishing length; ε_{it} is the standard error term. Camerer et al. (1997) points out that this method of estimating W_{it} is a very similar method used in the labor supply literature, where wage rate is estimated by dividing yearly (monthly) income by yearly (monthly) working hours. Thus, η is interpreted as the daily revenue elasticity.

I include a binary variable indicating the presence of an ice maker. To account for the high demand of fish during the holiday season, I use a dummy variable to represent the holiday seasons, i.e., Thanksgiving and Christmas.

In terms of model specification, ideally one can look at the daily revenue for each day in a given trip. This makes it possible to estimate the accumulated revenue at any given fishing day. The cumulative revenue is the deciding factor influencing whether the captain continues to fish or not. However, I don't have information on daily revenue for each individual fishing trip, thus I use the average daily revenue as the dependent variable.

The use the average daily revenue may cause potential measurement error. Camerer et al. (1997) and Chou (2002) in their studies on taxi drivers mention that there may have been measurement errors in the recorded number of driving hours. This problem is known as division bias in labor economics studies (Borjas, 1980). Likewise, one may suspect potential

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respect to daily revenue, thus we take the log of the number of fishing data in turn making the dependent variable continuous. We then use a standard linear model (OLS) accordingly. To check the robustness of the results, we also run the Poisson model. The finding indicates a more significant negative relationship between number of fishing days and daily revenue.

measurement errors in the number of fishing days compiled in the logbook. Since such is the case, inflated records may increase the number of fishing days and deflate average trip revenue, while deflated records may decrease the number of fishing days and inflate average trip revenue. Both cases of misreporting fishing days lead to spurious negative elasticity. On the other hand, the daily revenue elasticity may be biased towards zero due to an over reporting of total trip revenue. These two sources of bias will either reinforce or counteract each other, depending on whether the true daily revenue elasticity is positive or negative. Therefore, the net effect is uncertain; I show this result in the appendix.

In the fisheries context, the logbook contains the record of the number of fishing days made by each vessel, as it is required by law for fishermen to complete their logs. After every trip, NOAA collects the logbook directly from the captain and ensures that key information, such as fishing days, is recorded correctly. Thus, the data quality, particularly regarding fishing trip days, is quite accurate. Potential measurement errors are more likely to come from the trip revenue data.

Greene (2004) points out that measurement error in the dependent variable is less serious than in the independent variable. Accordingly, I will mainly focus on correcting potential measurement errors in the independent variable (i.e. the daily revenue). The corrections are made by finding an appropriate instrumental variable. Given the data available, I use the average daily fish revenue of other vessels landing on the same day as the instrument for daily revenue. In theory, a good instrument has the covariance of zero, or is unrelated to total fishing days, and has a strong correlation with the daily revenue of the concerned vessel. I believe that the chosen variable has minimal or no impact on the captain's decision to adjust the trip length (dependent variable) and is not highly correlated with the error terms in the trip length equation. I have also found that the greater (lower) the daily revenue of other vessels, the higher (lower) the daily revenue of the concerned vessel since they face the same market conditions at the auction. Understandably, this interpretation is made under the assumption that there is not much variation in the fishing conditions.

As a final note of this section, I realize that the above chosen instrumental variable is not perfect in any way. That being said, I believe that it is the best instrumental variable (IV) I can have given the data at hand. Another practical consideration is whether the chosen instrument is strong. Cameron and Trivedi (2006) point out that the weak IV estimator may be markedly biased in finite samples even though it is asymptotically consistent. To check whether or not the instrument variable is weak I use the Cragg-Donald Wald statistics, which is a F statistic in the first stage, and compare it with the Stock-Yoko (2005) critical values to check whether the instrumental variable is weak or not. The Cragg-Donald Wald statistics of 21.75 from our 2SLS model indicate a reasonably strong instrumental variable.

Main Empirical Findings

Table 2 presents the results of the estimation from OLS and 2SLS models. In addition to the OLS and 2SLS models, I also consider the fixed effects model given the heterogeneity of the vessels, such as the vessel's physical characteristics, the demographics of the vessel's owner and captain as well to check the robustness of the model. The key finding is that daily fishing revenue has a negative and significant impact on the number of fishing days in the OLS, 2SLS, and fixed effect models. That is, the higher the daily revenue is, the shorter the fishing trip. This finding is consistent with the taxi drivers studies by Camerer et al. (1997) and Chou (2002). From Heath, Larrick, and Wu's insights (1999), I can infer that fishermen seem more motivated to reach the revenue target rather than to surpass it.

The absolute value of the estimated revenue elasticity for the 2SLS model is marginally greater than the OLS implying that there may be marginal measurement error in the instrumental variable (Cameron and Trivedi, 2006). In comparison with Camerer et al. (1997) and Chou (2002) studies, the elasticity of labor supply with respect to daily revenue in the fisheries is smaller in magnitude. The smaller elasticity may reflect that fishermen have less flexibility in choosing the length of a fishing trip due to the vessel capacity constraints.

In addition to daily revenue, other variables also have significant and expected effects on the number of fishing days. The presence of an ice maker significantly increases the number of fishing days because it enables the vessel to preserve the fish quality longer. From the estimations, I can also infer that trip length is significantly shorter during the holiday seasons. One possible reason is that fishermen receive higher profits due to higher prices from the increased demand of fish during the holidays. Accordingly, there is an incentive to shorten the fishing trip, in exchange for increasing the number of fishing trips.

Following Chou (2002) and other traditional studies of labor supply, I also integrate non-budgetary variables into the fishing day's equation, such as captain's education and his longline fishing experience (Table 3). The effect of education on the number of fishing days is positive and is consistent with most other studies (e.g., Chou's). Regarding fishing experience, the more experienced the captain, the longer the fishing trip. Such finding, however, is not consistent with studies in other industries (e.g., Chou's)

V. ETHNICITY AND REVENUE TARGET MODEL

A distinguishing feature of the Hawaii longline fisheries is the ethnic diversity of its vessel owners. Chou (2002) argues that Chinese cab drivers are more business savvy and thus, are less likely to behave according to the revenue target model in comparison with other drivers. I find in the context of the Hawaii longline fisheries that ethnicity plays a key role in the decision-making process for labor supply. Vessels owners in the Hawaii fleet are one of three ethnicities: Caucasian, Korean, and Vietnamese. Due to some cultural similarities, I have combined Korean and Vietnamese under “Asian”. Ethnic backgrounds tell how vessel operators act in relation to the target revenue model. Asian owners, who are known for working hard, may continue fishing when the fishing conditions are good regardless of how long the trip has been going on. Hence, Asian owners may be less likely to follow the target revenue model. I expect that the integration of ethnicity into the empirical analysis of the target revenue model provides another perspective of decision-making behavior on labor supply.

Table 4 presents related statistics of the vessel by ethnicity. I can see that Asian vessels fish longer (day per trip) than Caucasian boats, though the difference is negligible. Caucasian boats, however, appear more profitable than their Asian counterparts.

As far as the regression analysis is concerned (Table 5), the only significant result is a negative impact of daily revenue on fishing length among Asian-owned vessels. One possible reason for the insignificant result among Caucasian boats is due to reduced efficiency in the 2SLS model (increase in the standard errors). In the pooled OLS model which I do not report here, the revenue elasticity is negative and significant among both groups of vessels. In both econometric models, the absolute value of elasticity is greater for Asian-owned vessels, and thus, I can infer that Asian-owned boats are more likely to behave according to the target revenue model.

This finding describes how ethnicity impacts the modeling of preferences. Caucasian owners seems quicker to make optimal decisions regarding trip length as suggested by the standard model. They will find it advantageous to fish longer on a productive trip or to fish shorter on an unproductive trip.

VI. LONGLINE FISHING EXPERIENCE AND THE TARGET REVENUE MODEL

The relevance of working experience in the target revenue model has been investigated in Camerer et al. (1997) and Chou (2002). Camerer et al. find that more experienced cab drivers have smaller revenue elasticities than less experienced divers. Chou, on the other hand, finds that this difference is not statistically significant. I expect that, over time, more experienced vessel operators will learn that it is efficient to behave according to the standard economic model. I also expect to see that more experienced vessel operators exhibit lower daily revenue elasticities in magnitude than vessels with less experienced captains.

Summary statistics of the Hawaii longline fisheries from Table 6 reveal that vessels with more experienced captains have longer trip length as well as higher total trip revenues. On the other hand, vessels with less experienced captains have higher daily revenues.

Table 7 presents the major regression estimation results. As expected, less experienced captains are more likely to behave according to the target revenue model. More experienced captains also shorten their trips as their daily revenue increases; however, the effect is not significant. The Wu-Hausman test (Davidson and MacKinnon, 1993) indicates that the difference in revenue elasticity is insignificant.

VII. CAPACITY CONSTRAINTS AND THE REVENUE TARGET MODEL

Unlike taxi drivers who in principle, can drive for an indefinite period of time, vessel captains face capacity constraints that prevent them from fishing past a certain amount of time, such as fuel and the preservation of fish quality. Therefore, the prediction of a positive revenue elasticity by the standard model of labor supply may not apply to fishing vessels due to the existing constraints. For instance, the captain might decide to go home even in a good trip to preserve the fish freshness. To proxy for the dependence of vessels on capacity constraint, I use a binary variable representing whether or not the vessel has an ice-maker. Because of their less dependence on capacity constraints, vessels with ice makers are more likely to behave according to the standard model of labor supply provided the standard model correctly describes the captain's fishing behavior.

Table 8 summarizes statistics of vessels with and without an ice maker. As expected, vessels with ice makers fish longer than vessels without ice makers though the difference is insignificant. Vessels with ice makers are also more profitable on a per trip and per day basis. To investigate the effect of capacity constraints on fishing behavior under the target revenue framework, I run the 2SLS model for vessels with and without ice makers separately. The key result is presented in Table 9.

Our results suggest that only vessels with ice makers seem likely to follow the target revenue model: an increase in revenue would decrease the trip length. This result enhances support for the target revenue model since vessels with ice makers are more able to follow the standard model if the captains behaved according to the standard model. The difference in daily revenue elasticity among these two groups of vessels; however, is not statistically significant. The Wu-Hausman's t-value is well below the 5% significant level.

VIII. CONCLUSIONS

This study attempts to provide another perspective within the existing labor supply literature. I developed a simple target revenue model to show, under certain conditions, that increases in daily fishing revenue lead to decreases in trip length. Using OLS, 2SLS, and fixed effects models, I found a significantly negative correlation between daily revenue and the trip length. The more productive their fishing trip is, the shorter the captain will choose to make their fishing trip. This finding implies that Hawaii fishermen tend to have a revenue target for their fishing trips. In terms of policy implication, the finding that Hawaii fishermen seem to behave in accordance with the target revenue model prove very relevant as Lynham et al., (2007) using simulation point out that standard policies can achieve biological goals under such circumstance.

I also investigated how unique features of the fisheries impact fishermen behavior under the target revenue framework. I separated the vessels into groups with and without ice makers to see if capacity constraint impact trip length. I found that vessels with ice makers are more likely to follow the target revenue model. I also found that Asian American vessel owners exhibit negative daily revenue elasticities, but Caucasian vessels owners appear more optimal in that there is a less significant negative response to increases in daily revenue. Regarding the longline fishing experience of the vessel operator, I found that only vessels with less experienced captains behave in accordance with the target revenue model.

This study, like Camerer et al. (1997), Chou (2002), and Fehr and Goette (2004, 2006), highlights the relevance of integrating prospect theory into the framework of labor economics. The fact that certain clusters of fishermen are more likely to behave according to the target revenue model suggests the necessity of classifying agents into certain groups before modeling their decision-making behavior.

This paper can be improved in a number of aspects. The use of an imperfect instrumental variable may lead to less biased estimations at the expense of an efficiency loss. In some estimations, the results from the 2SLS model became less significant than the OLS by increasing the standard errors. An approach based on a system of structural equations and natural experiments may help solve this problem (Cameron and Trivedi, 2006).

As a potential extension of the paper, I can conduct further field experiments with Hawaii longline fishermen to measure the loss aversion parameter for each participant and identify a model that best describes the agent's risk behavior. Fehr and Goette (2006) suggest either a reference dependence model or neoclassical model with non-separable preferences. They also find that loss-averse participants are more likely to behave in accordance with the target model. Integrating the risk behavior of fishermen under prospect theory of which loss aversion is an important aspect, into the framework of fisheries decision making is a promising area in fisheries research.

Another potential extension of this study is to investigate how well the target model performs relative to the hazard model by Farber. In his study of taxi cab drivers, Farber

(2005, 2008) finds the standard model more favorable than the target revenue model. Our study of the Hawaii longline fisheries reveals that the target revenue model gives robust findings under different model specifications. As a result, I believe that our results will probably hold under Farber's approach. That being said, the current study would be more complete if I could also use Farber's approach to check the robustness of the results. However, I presently do not have information on the daily vessel revenue for a given fishing trip. Improvement on logbook data collection will allow us to investigate the relative performance of the target revenue model against the standard model of labor supply.

APPENDIX

PROOF OF AMBIGUOUS DIVISION BIAS IN OLS

Consider an econometric model for fishing trip length:

$$\ln D_i^* = \alpha + \beta * \ln W_i^* + \varepsilon_i \qquad \text{A1}$$

where D_i is the true number of fishing days for vessel i; W_i is the corresponding true daily revenue. By definition, $W_i = Y_i / D_i$ where W_i is the trip revenue.

Suppose, there is some measurement error in the number of fishing days and trip revenue, such that, $\ln D_i = \ln D_i^* + \eta_i$ and $\ln W_i = \ln W_i^* + \gamma_i$. I are assuming that:

$Cov(\eta_i, \varepsilon_i)= Cov(\gamma_i, \varepsilon_i)=0$

Due to measurement errors, model (1) becomes:

$$\ln D_i - \eta_i = \alpha + \beta * (\ln Y_i - \ln D_i + \gamma_i - \eta_i) + \varepsilon_i \qquad \text{A2}$$

or equivalently,

$$\ln D_i = \alpha + \beta * (\ln Y_i - \ln D_i + \gamma_i - \eta_i) + \eta_i + \varepsilon_i \qquad \text{A3}$$

Therefore, we end up estimating the following equation:

$$\ln D_i = \alpha + \beta * (\ln W_i + \gamma_i - \eta_i) + \eta_i + \varepsilon_i \qquad \text{A4}$$

Using OLS to estimate, we have:

$$\text{plim}\,\hat{\beta}_{ols} = \frac{\text{cov}(\ln W_i + \gamma_i - \eta_i, \ln D_i)}{\text{var}(\ln W_i + \gamma_i - \eta_i)} = \frac{\text{cov}\{\ln W_i + \gamma_i - \eta_i, \alpha + \beta * (\ln W_i) + \eta_i + \varepsilon_i\}}{\text{var}(\ln W_i) + \text{var}(\gamma_i) + \text{var}(\eta_i)}$$

$$\text{plim}\,\hat{\beta}_{ols} = \frac{\beta\,\text{var}(\ln W_i) - \text{var}(\eta_i) + \text{cov}(\eta_i, \gamma_i)}{\text{var}(\ln W_i + \gamma_i - \eta_i)}$$

$$\text{plim}\,\hat{\beta}_{ols} = \beta \frac{\text{var}(\ln W_i)}{\text{var}(\ln W_i) + \text{var}(\gamma_i) + \text{var}(\eta_i)} + \frac{\text{cov}(\eta_i, \gamma_i) - \text{var}(\eta_i)}{\text{var}(\ln W_i) + \text{var}(\gamma_i) + \text{var}(\eta_i)} \qquad \text{A5}$$

From A5, I can infer that:

i. If $\text{cov}(\eta_i, \gamma_i) < \text{var}(\eta_i)$ then $\text{plim}\,\hat{\beta}_{ols} < \beta$, thus OLS gives negative bias.

ii. If $\text{cov}(\eta_i, \gamma_i) > \text{var}(\eta_i)$, the effect of measurement errors on β_{OLS} is ambiguous.

As discussed, in the case of Hawaii thanks to good quality on the number of fishing days I can assume $\eta_i \approx 0$, therefore:

$$\text{plim}\,\hat{\beta}_{ols} = \beta \frac{\text{var}(\ln W_i)}{\text{var}(\ln W_i) + \text{var}(\gamma_i)} < \beta \qquad \text{A6}$$

This is a classical case of measurement error where OLS's estimate is attenuationly (decreasingly) bias toward zero. Accordingly, 2SLS with valid instrumental variable will give $\left|\hat{\beta}_{2SLS}\right| > \left|\hat{\beta}_{OLS}\right|$.

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TABLE 1: SUMMARY STATISTICS

	Mean	Median	SD
Total (1309 obs)			
# Fishing days	18.77	19.00	5.03
Daily revenue ($)	1794	1648	871
Trip revenue ($)	32225	31033	14239
Having Ice Maker (1: Yes, 2:No)	0.35	0	0.47
Ethnicity (1: Caucasian, 2: Korean, 3: Vietnamese)	1.86	2	0.82
Longline Fishing Experience (years)	17.13	16	10.22

TABLE 2: ESTIMATED DAILY FISHING REVENUE ELASTICITY FROM OLS, 2SLS AND FIXED EFFECT MODELS

	OLS		2SLS		Fixed Effect	
	Coef	t value	Coef	t value	Coef	t value
Log of daily revenue	-0.13	-7.27(***)	-0.19	-2.45(***)	-0.17	-9.88(***)
Ice maker	0.04	2.38(***)	0.05	2.48(***)	0.07	1.41
Holiday seasons	-0.15	-7.01(***)	-0.14	-6.08(***)	-0.15	-8.09(***)
Adjusted R^2	0.12		0.10		0.12	
Number of observations	864		864		864	

Note: (***) indicates significance at 1% level

TABLE 3: ESTIMATED DAILY FISHING REVENUE ELASTICITY FROM OLS, 2 SLS AND FE MODELS INCLUDING NON-BUDGET CONSTRAINT VARIABLES

	Pooled OLS		2SLS		Fixed Effect	
	Coef	T value	Coef	t value	Coef	t value
Log of daily revenue	-0.12	-7.10	-0.15	-2.07(**)	-0.17	-9.88(***)
Ice maker	0.04	1.93	0.04	1.95(**)		
Holiday seasons	-0.15	-7.10	-0.15	-6.33(***)	-0.16	-8.09(***)
Fishing experience	0.01	5.03	0.01	5.00(***)		
Fishing experience squared	-0.0003	-4.90	-0.0003	-4.89(***)		
Education level	0.04	3.16	0.04	3.11 (**)		
Adjusted R^2	0.15		0.14		0.12	
Number of observations	840		840		840	

Note: (**) indicates 1% significance level, (***) indicates 5% significance level

TABLE 4: SUMMARY STATISTICS OF VESSELS BY OWNER ETHNICITY

	Mean	Median	SD
Caucasian Owner (533 obs)			
# Fishing days	18.40	18	4.43
Daily revenue ($)	1910	1798	909
Trip revenue ($)	33828	32502	15292
Caucasian Owner (776 obs)			
# Fishing days	19	19	5.39
Daily revenue ($)	1715	1590	835
Trip revenue ($)	31124	30136	13108

TABLE 5: ESTIMATED DAILY FISHING REVENUE ELASTICITY BY VESSEL OWNER'S ETHNICITY ESTIMATED BY 2SLS

	Caucasian		Asian	
	Coef	t value	Coef	t value
Log of daily revenue	-0.10	-1.02	-0.17	-1.64 (*)
Ice maker	0.01	0.43	0.04	1.09
Holiday season	-0.10	-2.38 (***)	-0.19	-6.24 (***)
Fishing experience	0.01	2.87 (***)	0.01	2.70 (***)
Fishing experience square	-0.0001	-1.67 (*)	-0.0004	-3.47 (***)
Education	0.10	4.05 (***)	0.04	2.36 (**)
Number of observations	351			489
Adjusted R^2	0.15			0.15

Note: (*) indicates 10% significance level; (**) indicates 5% significance level (***) indicates 1% significance level.

TABLE 6: SUMMARY STATISTICS OF VESSELS BY CAPTAIN'S FISHING EXPERIENCE

	Mean	Median	SD
Less Experienced (405 obs)			
# Fishing days	18.38	18	5.34
Daily revenue ($)	1836	1695	908
Trip revenue ($)	31971	31160	14142
More Experienced (461 obs)			
# Fishing days	19.1	19	4.71
Daily revenue ($)	1763	1603	849
Trip revenue ($)	32568	31222	14693

TABLE 7: ESTIMATED DAILY FISHING REVENUE ELASTICITY BY CAPTAIN'S LONGLINE FISHING EXPERIENCE

	Less Experienced		More Experienced	
	Coef	T value	Coef	t value
Log of daily revenue	-0.31	-2.43$^{(***)}$	-0.05	-0.5
Ice maker	0.07	2.48$^{(***)}$	0.03	0.88
Holiday season	-0.07	-1.60	-0.21	-7.14$^{(***)}$
Education	0.03	1.45	0.04	2.15$^{(**)}$
Number of observations	397		443	

Note: (**) indicates 5% significance level, (***) indicates 1% significance level

TABLE 8: SUMMARY STATISTICS OF VESSELS BY WHETHER HAVING ICE MAKER

	Mean	Median	SD
Vessels without ice maker (577 obs)			
# Fishing days	18.61	19	4.91
Daily revenue ($)	1732	1612	859
Trip revenue ($)	30886	30289	13918
Vessels with ice maker (304 obs)			
# Fishing days	19.10	19	5.27
Daily revenue ($)	1927	1760	900
Trip revenue ($)	35124	33595	15262

TABLE 9: ESTIMATED DAILY FISHING REVENUE ELASTICITY BY VESSEL'S CAPACITY BY 2SLS

	Without Ice Makers		With Ice Makers	
	Coef	t value	Coef	t value
Log of daily revenue	-0.15	-1.31	-0.16	-1.71 (*)
Holiday season	-0.13	-4.29(***)	-0.18	-4.85 (***)
Fishing experience	0.01	3.66(***)	0.02	2.33 (**)
Fishing experience square	-0.0003	-3.91(***)	-0.0005	-2.15 (**)
Education	-0.05	-3.26(***)	-0.02	-1.05
Number of observations	546		294	
Adjusted R^2	0.12		0.18	

Note: (*) indicates 10% significance level, (**) indicates 5% significance level

(***) indicates 1% significance level.