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Behavioral Response to Stock Abundance in Exploiting Common-Pool Resources

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Behavioral Response to Stock Abundance in Exploiting Common-Pool Resources*

Junjie Zhang

Abstract

Successful regulation of common-pool resources calls for a better understanding of resource exploitation behavior. This paper introduces an approach that can measure fishermen's responsiveness to stock changes more accurately. In order to deal with the challenge of the latent fish stock, I adopt the method proposed by Zhang and Smith (2011) that derives a stock index from a heterogeneous production function. I use the imputed stock proxy in a count data model that describes fishing trip frequency. By these two steps, I can estimate the stock elasticity of fishing mortality. In the empirical study of the reef-fish fishery in the northeastern Gulf of Mexico, I find that the popular method that uses catch rate as a stock proxy significantly underestimates fishermen's responses to stock changes. This result suggests that policy predictions based on the traditional method are overly optimistic.

KEYWORDS: fishing behavior, latent variable, panel data

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1 Introduction

Governance of commons ignoring economic responses tend to be “costly, ineffective, or even counterproductive” (Stavins, 2011). For example, fishing licenses and permits grant limited entry to fishermen, but permit holders have incentives to catch fish before others can catch them, creating the fishing derby (Grafton, Squires, and Fox, 2000). Shortening the season length concentrates fishing pressure during the open season, exacerbating the fishing derby (Smith, Zhang, and Coleman, 2008). Spatial closures shift fishing pressure to surrounding areas (Holland, 2004). These examples demonstrate that fishermen’s behavioral adaptation can offset policy effects or even lead to unanticipated policy outcomes.

Economists argue that the failure of traditional fisheries management is due to ignorance about individuals’ responses to policies. This largely explains the puzzle raised by scientists why worldwide overfishing and stock depletion have not been stopped, although fisheries have been regulated for decades (Beddington, Agnew, and Clark, 2007). Because fisheries management must manage people in order to manage fish, understanding fishing behavior becomes the cornerstone of an effective fishery policy (Wilen, Smith, Lockwood, and Botsford, 2002). Successful regulation of fisheries calls for reliable knowledge about the interactions between the resource stock and its users. In particular, fishing behavior is driven by profit that is determined by fish stock. As such, this paper focuses on the relationship between fish stock and fishing pressure.

It is important to accurately measure fishermen’s responses to stock changes for both theoretical and practical reasons. In theory, Dietz, Ostrom, and Stern (2003) argue that it is easier to achieve effective commons management if the rate of change in resource use is moderate. Many fishery policies are designed to rebuild fish stock. If fishing behavior is constant and exogenous, harvest does not increase with stock rebuilding and the policy will be more likely to succeed. In addition, the cost of monitoring fishing pressure is low, because changes in fishing behavior are negligible. However, if fishermen are very responsive to fish abundance, the resource rent preserved by fisheries management will soon be dissipated. It also requires regulators to monitor fishing behavior more frequently.

In practice, the magnitude of fishermen’s responses to stock changes is directly related to fishing mortality. Fishing mortality is the share of the stock that is harvested, which is a key parameter used in the biological models for fisheries management (Hilborn and Walters, 1992). The Magnuson-Stevens Fishery Conservation and Management Act (MSA) explicitly requires fishing mortality to be maintained at a level that does not jeopardize the sustainability of a fishery. If fishermen’s responses to stocks are underestimated, the predicted fishing mortality will be too low. As a consequence, the prescribed policy will be overly optimistic.

Previous studies modeling fishing behavior have encountered two major empirical challenges. The first one is that the stock abundance is not always observable. The simplest solution is to use catch rate such as catch-per-unit-effort (CPUE) as a stock proxy. However, this approach has been questioned by both fishery scientists and economists (Taylor and Prochaska, 1985, Wallace, Lindner, and Dole, 1998, Harley, Myers, and Dunn, 2001, Zhang and Smith, 2011b). Sometimes using catch rate even produces counter-intuitive results. For example, Hausman, Leonard, and Mcfadden (1995) find that the "only puzzling result" is that a high catch rate reduces fishing trips. The second challenge is to model per-trip harvest and fishing participation choice jointly, which together determines fishing mortality. In the past, they are treated as separate issues: fish harvest is modeled by production functions (Wilen, 1976, Bjorndal and Conrad, 1987) and trip frequency is analyzed by discrete choice models (Morey, Rowe, and Watson, 1993, Murdock, 2006, Timmins and Murdock, 2007).

To address these challenges, I adopt a two-step approach to estimate a fishing behavior model with latent stock. In the first step, a stock index is estimated from a structural harvest-stock relationship. The estimate is then used in the second-step regression in which a count data model describes fishing trip frequency. The two-step estimator is consistent under regularity conditions (Newey and McFadden, 1994). However, the standard errors need to be corrected to account for the estimated regressor (Murphy and Topel, 1985). The estimation is implemented in two steps instead of full information maximum likelihood because of the cumbersome joint likelihood function that nests a fixed-effect linear model and a fixed-effect count data model. In addition, the two-step model is a natural extension of the traditional method that uses catch rate as a stock proxy.

The first step that derives the stock index from fisheries data is proposed by Zhang and Smith (2011b) (hereafter referred to as "ZS"). The major difference between this paper and the ZS paper lies on the second step. The ZS model focuses on estimating the biological parameters using the stock index. However, it does not proceed to estimate behavioral parameters. This paper completes the ZS analysis by studying how fishermen respond to the latent stock. The other differences between these two papers are mainly technical. In particular, this paper derives the correct asymptotic variance-covariance matrix for the second-step estimator instead of relying on a block bootstrap as is done in the ZS paper. Overall, except for the strategy of dealing with latent stocks, these two papers employ different models to answer different policy questions.

This approach is illustrated by the reef-fish fishery in the northeastern Gulf of Mexico. Besides the logbook data that are also used by ZS, I collected new data and information including landings tickets, permits, weather, fish price, fuel costs, unemployment, and a history of fisheries management. The empirical result shows that the traditional CPUE method significantly underestimates fishermen's responses to stock changes or even predicts the opposite effect. Using the stock inference approach proposed by ZS, estimates here predict that a one-percent increase in fish stock induces 0.79 percent more fishing trips, while the estimates by the conventional CPUE models are between -0.02 percent and 0.02 percent. These results suggest that the effect of the stock rebuilding policies such as season closures and spatial closures could be offset by increased fishing trips. Under the conventional model, the predicted policy effect might be exaggerated.

The remainder of this paper proceeds as follows: Section 2 describes the empirical background and data; Section 3 discusses the empirical strategy, including identification and estimation of the econometric model; Section 4 presents estimation results and discussion; Section 5 concludes.

2 Empirical Setting and Data

2.1 The Reef-Fish Fishery

The empirical study is based on the reef-fish fishery in the northeastern Gulf of Mexico. The reef-fish complex is a collection of 62 species including 10 snapper species and 11 grouper species. Reef-fish species are managed as a group by the Gulf of Mexico Fishery Management Council (Council). However, much of the management activities have focused on red snapper and gag grouper, which are two of the most economically important species. Overfishing has been a serious problem in this region. According to the stock assessment by the recent Southeast Data Assessment and Review (SEDAR), red snapper was classified as overfished and continued to experience overfishing. Gag grouper was classified as experiencing overfishing.[1]

To reduce fishing mortality, the Council implemented the reef-fish fishery management plan in 1984 and many regulatory amendments have since been added.[2] Three main groups of fisheries management policies attempt to limit fishing pressure. The first group is limited entry. The licensing policy only allows permit holders to catch and land reef fish, so it limits the total number of vessels. A separate permit is required for red snapper fishing. The class-1 license sets a trip limit of 2000 lbs/trip and the class-2 license's limit is 200 lbs/trip.

The second policy is season closures. The red snapper fishery is subject to periodic closures to allow the stock to rebuild. The average length of fishing seasons

[1] More detailed information is available at `http://www.sefsc.noaa.gov` (August 3, 2010).

[2] A complete history of the reef-fish fishery management plan is maintained by the Gulf Council. It is available at: `http://www.gulfcouncil.org/` (August 3, 2010).

during 1993-2004 was 80.8 days/year. The open days (often the first 10 days in each month) vary month by month.[3] In addition, the seasonal closure policy regulates shallow water groupers fishing. In each year since 2001, the harvest of gag grouper, black grouper, or red grouper from February 15 to March 15 has been prohibited.

Another important policy is spatial closures. Two marine reserves, Steamboat Lumps Marine Reserve and Madison-Swanson Marine Reserve, have been created in fishing statistical zones 6 and 8 since June 19, 2000. No harvest is allowed within the reserves. The rationale for a marine reserve is that it increases biomass in the reserve and may benefit surrounding areas in the long run through the spillover effect. Although the reserves are intended to conserve grouper species, particularly gags, other species are also protected.

2.2 The Data

The reef-fish fishery data in the northeastern Gulf of Mexico are well documented. The main dataset is the logbooks maintained by the Southeast Fisheries Science Center (SEFSC). The logbook data contain detailed fishing trip information including harvest, fishing effort, species, locations, and gear. The trip-specific data are used to estimate the production function and infer the stock size. In estimating count data models, the individual- and time-specific trip frequency is also generated from the logbook data. Only a subset of the logbook data are used, namely, the reef-fish fishing trips in fishing statistical zones 1 through 13 during 1994-2002. Since other species may also be caught in a fishing trip (referred to as by-catch in fisheries science), a reef-fish fishing trip is defined as a trip with more than 50 percent reef fish catch.

Vessel attributes and owners' information are included in the permit dataset, which includes vessel length, gear, date of birth, address, and permit types. The permit data relate to the logbook data by the unique vessel ID. Because only the active permit holders' information is available, the attributes of those vessels exiting reef-fish fishery are not observable. And, since this paper focuses on the short-run decision making process, the entry/exit behavior is not discussed. To simplify the problem, I only use these vessels that are active during 1994-2002.

The final dataset for stock inference contains 126,131 fishing trips from March 1994 to December 2003, or 234 periods. The dataset for the count data model has 396 fishing vessels in 234 periods. Note that the data used in the second-step regression are aggregated from the data used in the first step. Summary statistics for other variables are compiled in Tables 1 and 2.

[3]The historical information on snapper closures is provided by Jim Waters at the National Marine Fisheries Service.

Table 1: Summary statistics for categorical variables

Variable	Description	Frequency	Percentage
Permit 1	Snapper permit class 1 holder	27	11.02
Permit 2	Snapper permit class 2 holder	103	42.04
Gear 1	Traps	1600	5.43
Gear 2	Bottom longline	3527	11.97
Gear 3	Handline	20132	68.31
Gear 4	Electrical reel/bandit	2459	8.34
Gear 5	Trolling	1755	5.95

The holder of class-1 snapper permit can harvest up to 2000 lbs/trip, while the class-2 license's limit is 200 lbs/trip.

Table 2: Summary statistics for continuous variables

Variable	Description	Mean	SD	Min	Max
Individual attributes (n=396)					
Age	Age of owner	56.72	12.45	30	87
Vlength	Vessel length (feet)	37.64	7.77	21	65
Trip specific information (# of obs = 126131)					
Catch	Catch per trip (lbs)	1135	1704	1	6.2E+4
Effort 1	Traps	3.9E+4	1.9E+5	1	5.5E+6
Effort 2	Bottom longline	1.5E+6	3.5E+6	1	2.4E+8
Effort 3	Handline	1200	6.2E+4	0	9.5E+6
Effort 4	Electrical reel/bandit	955	2115	1	4.6E+4
Effort 5	Tolling	252	1.5E+4	0	1.3E+6
Temporal information (T=234)					
SnapperOpen	Snapper open days	3.27	5.36	0	16
PriceFish	Real reef-fish price ($/lbs)	2.06	0.21	1.51	2.53
PriceFuel	Real diesel price ($/gallon)	1.10	0.14	0.82	1.65
Weather	Days of bad weather	3.77	3.04	0	14

Definitions of gear-specific fishing effort: NUMGEAR is the amount of gear reported (e.g. how many lines); FISHED is the estimated time that gear is in the water; and PIECES is the number of pieces of gear per type of gear (e.g. number of hooks per line). For bottom longline, handline, trolling, gill net, and electric reel/bandit rigs, the effort is calculated by: NUMGEAR* PIECES *FISHED. For traps, divers with spears, divers with power heads, buoy lines, and cast nets, then the effort is calculated by: NUMGEAR*FISHED. The effort for all other gears equals FISHED.

3 Econometric Model

3.1 Latent Stock

Fish abundance information is essential to model fishermen's behavior. Although the stock is not directly observable to empirical researchers, it can be inferred from a structural harvest-stock relationship. The traditional method uses "catch-per-unit-effort"(CPUE) as a proxy for the stock, which is based on the Schaefer production function (Schaefer, 1954). Let t index time, H designate harvest, q designate a catchability coefficient, E designate effort, and N designate stock.[4] The classical Schaefer function is

$$H_t = qE_tN_t.$$

This functional form has become the *de facto* standard in natural resource economics since the seminal research by Gordon (1954) and Smith (1969). It is widely employed in theoretical and empirical literature such as in Squires (1992) and Brander and Taylor (1998). Under the classical Schaefer assumption, CPUE is a proxy for stock, since

$$\text{CPUE}_t \equiv H_t/E_t = qN_t. \tag{1}$$

The catch rate is straightforward to compute, and as a result is a popular stock proxy in fishery science and economics and recreational demand literature (Hilborn and Walters, 1992, Morey et al., 1993, Hausman et al., 1995, Murdock, 2006, Timmins and Murdock, 2007). However, this method has its shortcomings. First, it ignores individual heterogeneity, because it uses aggregated catch and effort. If q varies among fishermen, or over time, then H/E is not a good proxy for N. Second, it ignores the nonlinearity with respect to fishing effort in the production function. Finally, it ignores unobserved disturbances in the production process.

To address these challenges, I adopt the strategy proposed by Zhang and Smith (2011b) that use a generalized production function based on micro fishing data. The rationale for stock inference is that every vessel faces the same stock in the same period. Harvest is a process of "measuring" the stock by different scales (fishing effort), recognizing stochastic shocks to the measurement. A fishery production function provides a structural relationship between harvest, effort, stock, and the disturbance. I thus generalize the classical Schaefer model to accommodate disaggregated data, heterogeneity, nonlinearity, and unobserved disturbance:

$$H_{ikt} = q_{ikt}E_{ikt}^{\alpha_1}N_t^{\alpha_2}e^{\eta_{ikt}}. \tag{2}$$

[4] Catchability is an unknown constant which reflects the efficiency of a fishery. Fishing effort is defined in Table 1.

In this form, i indexes individual vessels ($i \in I$) and k indexes trips. Let α_1 designate the catch-effort elasticity and α_2 designate the catch-stock elasticity. Diminishing returns to effort in fisheries then implies that $\alpha_1 < 1$. Catchability q is a gear- and area-specific constant that allows for technical and spatial heterogeneity. The catch-effort elasticity is also assumed be gear-specific in the empirical study. Accounting for unobserved individual attributes that may affect fishing effort, I use fixed effects to control for individual heterogeneity. The error term is then decomposed into $\eta_{ikt} = a_i + \varepsilon_{ikt}$, in which a_i is an individual fixed effect and ε_{ikt} is an idiosyncratic term. With these assumptions, I take logs of equation (2) and it is simplified as

$$h_{ikt} = x'_{ikt}\beta + a_i + \varepsilon_{ikt}, \tag{3}$$

where

$$x'_{ikt}\beta = \sum_{g=1}^{5} \beta_g \ln(\text{Effort}_{ikt}) \times \text{Gear}_{ikt} + \beta_6 \text{Gear}_{ikt} + \beta_7 \text{Area}_{ikt} + S_t.$$

In this form, h_{ikt} is log harvest, x_{ikt} contains explanatory variables, β is a conformable vector of parameters, and S_t is latent stock (discussed below).

In the empirical model, fishing effort is determined by the amount of gear, estimated time that the gear is in the water, and the number of pieces of gear. The definition of gear-specific effort is explained in detail in Table 1. Gear includes dummy variables for different types of fishing gear. Different types of gear have varying associated fishing efficiencies, so that the catch-effort elasticity is assumed to be gear-specific. Area is also a dummy variable indicating the location of fishing across 13 statistical zones. I use gear- and area-dummies to control for heterogeneous catchability.

I run two alternative regressions to infer the latent fish stock. The preferred model is the generalized Schaefer model that imposes no restrictions on β_g. For comparison purpose, I also estimate the classical Schaefer model that assumes $\beta_g = 1$. The latent stock, S_t, is treated as unknown parameters and estimated as time-specific constants. Note that the stock index is only identified up to scale.[5] The exact identification needs further assumptions of stock dynamics. This topic is beyond the scope of this paper, but it is discussed in detail by Zhang and Smith

[5] The estimated stock proxy is a lumped parameter. Econometrically any variables that do not change across individuals will be captured by the time effect. Just for this reason, my paper does not focus on the absolute stock. To partly address this problem, I include temporal variables in the second-step regression. Other temporal variations being controlled, the effect of the measured stock proxy is mainly determined by the underlying fish stock.

(2011b). I define S_t as a stock index, because it is a log linear function of the real stock such that

$$S_t = \alpha_2 \ln N_t. \tag{4}$$

In order to avoid multicollinearity, I normalize the stock in the first period to be one such that $\ln N_1 = 0$. It is worth noting that the stock index degenerates to log of catch-per-unit-effort if I assume no heterogeneity, constant returns, and no unobservables. For this reason, I also use $\ln(\text{CPUE})$ as an alternative stock proxy in the second-step regression.

3.2 Trip Frequency

The second-step analysis is concerned with fishermen's responses to stock changes. Discrete choice models are widely used to describe participation choice in commercial fishing. These models assume that individual fishermen maximize their profit by deciding whether or not to go fishing. However, this paper adopts a count data model instead of a logit/probit model for two reasons. First, since the inferred stock is aggregated to the semimonthly level, the binary discrete model cannot predict multiple trips in one period. Second, the fixed-effect logit/probit model may suffer from the incidental parameters problem. Even if the number of periods approaches infinity, asymptotic bias is still a risk (Arellano and Hahn, 2007).

In addition, low fishing trip frequency is another problem when using binary discrete choice models based on daily activities. The probability of taking a fishing trip is very low in the data. The average trip frequency in ten years is about 4.83 trips per year per vessel in the Gulf of Mexico reef-fish fishery. Therefore, the data are dominated by non-fishing records, which makes the identification difficult. I deal with this problem by means of aggregating the time scale from day to half month. The aggregation is consistent with stock recruitment periods, seasonality, and periodic fishery management policies such as season closures.

To illustrate the discreteness of fishing trips, trip frequency is depicted in Figure 1. The histogram shows that the distribution of trip numbers follows the pattern of a count data model. The frequency of trip days is plotted for comparison, which has a flat distribution conditional on going fishing. This is because most trips are one-day trips. The trip length is mainly explained by vessel size. With the length of vessel controlled, I focus on the number of trips in a two-week period. A multi-day trip is counted as one trip in the analysis.

The count data model is also consistent with utility/profit maximization (Hausman et al., 1995). It can be derived from binary discrete choice models according to the "law of rare events" (Cameron and Trivedi, 1998). If a fisherman

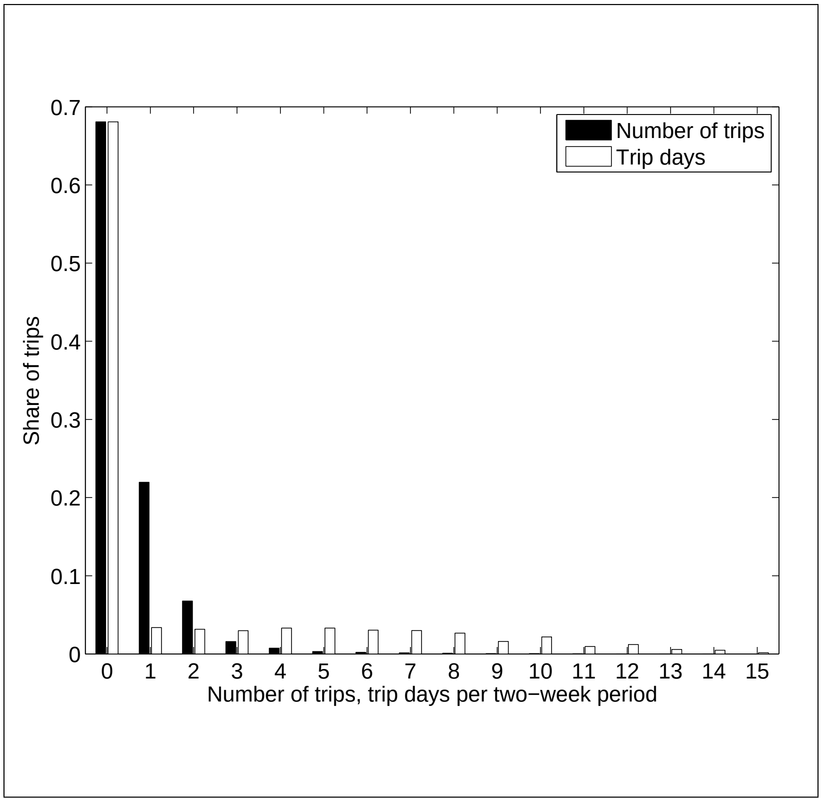

Figure 1: The number of trips and the length of trip days per two-week periods follows a distribution of count data.

makes repeated choices in period t with a low choice probability, the total number of fishing trips y_{jt} in this period has the Poisson distribution

$$f\left(y_{jt}|z_{jt},\delta_j\right) = \frac{e^{-\mu_{jt}}\mu_{jt}^{y_{jt}}}{y_{jt}!}. \tag{5}$$

In this form, the expected number of trips can be approximated by an exponential mean function

$$\mu_{jt} \equiv E\left(y_{jt}|z_{jt},\delta_j\right) = \exp\left(z'_{jt}\theta + \delta_j\right), \tag{6}$$

where z_{jt} contains explanatory variables (including the stock index estimated from the first step) and θ is a conformable vector of parameters to be estimated. The fixed effect δ_j controls for unobserved individual attributes in determining trip frequency. With no distributional assumption on δ_j, (5) is a fixed-effect Poisson model. This model allows arbitrary correlations between z_{jt} and δ_j. Note that the fixed effect δ_j is not necessarily the same as a_i in the first step.

I use j to index the individual in the second step, where $j \in J$ and $J \subseteq I$. I use I to denote the sample of fishermen in the first step, while J is the sample of fishermen in the second step. Because individual characteristics are not available for all fishermen, the sample used in the second step is a subset of that of the first step. With the explanatory variables summarized in Tables 1 and 2, I adopt the following specification in the empirical analysis:

$$\begin{aligned} z'_{jt}\theta = {} & \theta_1 \ln(\widehat{\text{Stock}_t}) + \theta_2 \text{Age}_{jt} + \theta_3 \text{Age}^2_{jt} + \theta_4 \ln(\text{FishPrice}_t) \\ & + \theta_5 \ln(\text{FuelPrice}_t) + \theta_6 \ln(\text{Weather}_t) + \theta_7 \frac{\ln(\text{Weather}_t)}{\ln(\text{Vlength}_j)} \\ & + \theta_8 \text{Reserve}_{jt} + \theta_9 \text{GrouperOpen}_t + \theta_{10} \text{Spawning}_t \\ & + \sum_{k \in \{0,1,2\}} \theta_{11+k} (\ln(1 + \text{SnapperOpen}_t) \times \text{Permit}_{jk}). \end{aligned} \tag{7}$$

In the above model, stock is the major variable of concern. I use six alternative stock proxies derived from the first-step regression. The preferred stock index is estimated using the model in equation (3), that is, I use $\widehat{S}_t$ to replace $\ln(\widehat{\text{Stock}_t})$ according to equation (4). The second one is based on the classical Schaefer model which ignores the curvature in the production function. The remaining four specifications use the log catch-per-unit-effort, that is, $\ln(\widehat{\text{CPUE}_t})$ is used to replace $\ln(\widehat{\text{Stock}_t})$. Because different gear types imply different catch rate, I compute CPUEs for four dominant gears: traps, bottom longline, handline, and trolling.

Age is included to capture the evolution of trip frequency over the fishermen's life cycle. When a fisherman ages, he accumulates more experience, but his physical skill deteriorates. The quadratic specification posits an inverted-U relationship between trip frequency and age: fishermen may increase their trip frequency before some certain age and then fish less frequently after that point. FishPrice designates real fish price, a semimonthly average price of reef-fish species weighted by landings. In the northeastern Gulf of Mexico reef-fish market, I observe 3182 vessels and 829 dealers. It is reasonable to assume fish price is competitive and each individual fisherman is a price taker. FuelPrice designates semimonthly national No.2 diesel price in real values. It is time varying but common to all vessels.

Weather conditions are correlated with physical risks in fisheries. Wave height is used as an indicator for bad weather. The original dataset is hourly, but the time scale in the analysis is half month. To avoid aggregate weather information, I define a bad weather day if its wave height is worse than the 75th percentile (1.67 meter). The number of bad weather days is used in the regression. Fishermen's responses to weather hinge on the vessel size: I expect that large boats are less likely to be affected by adverse weather conditions. Therefore, an interaction term between weather and vessel length (Vlength) is included.

Reserve is a dummy for the vessel whose home port is located within zones 5-10 and after June 19, 2000, where and when two marine reserves are present. These vessels are close to the reserves so that they are expected to be affected by the policy. GrouperOpen designates whether the grouper fishery is open or not. Fishermen are expected to fish less frequently if the profitable grouper fishery is closed. Spawning is a dummy for months 3-7, when gag groupers aggregate to spawn, which facilitates their capture in this period. SnapperOpen is the number of days that the red snapper fishery is open. I use $\ln(1+\text{SnapperOpen}_t)$, because some periods are completely closed. It is interacted with three types of vessels: non-permit holders, class-1 permit holders, and class-2 permit holders. The holder of class-1 snapper permit can harvest up to 2000 lbs/trip, while the class-2 license's limit is 200 lbs/trip. I expect that vessels with class-1 permits fish more frequently when the red snapper fishery is open.

3.3 Estimation

The first-step regression estimates a standard fixed-effect panel data model. If $E(\varepsilon_{ikt}|x_{ikt},a_i)=0$, model (3) can be consistently estimated by a within-estimator, which is briefly discussed in Appendix A.1. The stock index can be consistently estimated given a large sample of cross-sectional units. If fishing activities are not sufficiently large in a period, the stock index might contain significant noise. This is a major reason why the stock index is semimonthly, which is the most disaggregated level with a reasonable number of vessels going fishing.

I focus on the second-step regression and especially the derivation of correct standard errors. According to the model specification (5) and (6), the number of trips y_{jt} is assumed to be $i.i.d.$ generated by the Poisson model conditional on μ_{jt}. The likelihood contribution for individual j conditional on total number of trips is

$$\Pr\left(y_{j1},\cdots,y_{jT}\middle|\sum_t y_{jt}\right)=\frac{(\sum_t y_{jt})!}{\prod_t y_{jt}}\prod_t\left(\frac{\mu_{jt}}{\sum_\tau \mu_{j\tau}}\right)^{y_{jt}}. \tag{8}$$

Because $\sum_t y_{jt}$ is a sufficient statistic for δ_j, the conditional maximum likelihood estimator (CMLE) is used (Hausman, Hall, and Griliches, 1984). It is worth noting that the Poisson ML estimator does not suffer from the incidental parameter problem either (Lancaster, 2002). The concentrated log likelihood function is

$$\mathscr{L}(\theta)\propto\sum_j\sum_t y_{jt}\left(z'_{jt}\theta-\ln\left(\sum_t\exp\left(z'_{jt}\theta\right)\right)\right). \tag{9}$$

The concentrated log likelihood function shows no incidental parameters problem, because the individual fixed effects δ's cancel.

In the above likelihood function, the latent stock is estimated from the first-step regression. Deriving unobserved regressors from an auxiliary regression is widely implemented in empirical studies. A two-step method is often used when the full information maximum likelihood is inappropriate. Under regularity conditions, the second-step estimator is consistent if the unobservables can be consistently estimated (Newey and McFadden, 1994). However, since the estimate instead of the true value is used, the standard error of the second-step estimator is incorrect. Following the approach proposed by Murphy and Topel (1985), the correct asymptotic covariance matrix for the second-step estimator is (see Appendix A.1 for the derivation)

$$\widehat{\text{Avar}(\hat{\theta})} = \hat{V}_2 + \sqrt{\hat{\rho}}\hat{V}_2\big(\sqrt{\hat{\rho}}\hat{C}'\hat{V}_1\hat{C} - \hat{R}'\hat{Q}_1^{-1}\hat{C} - \hat{C}'\hat{Q}_1^{-1}\hat{R}\big)\hat{V}_2, \tag{10}$$

where

$$\hat{Q} = \frac{1}{n_1 T}\sum_{i,k,t}\ddot{x}_{ikt}\ddot{x}'_{ikt},$$

$$\hat{V}_1 = \hat{Q}^{-1}\left(\frac{1}{n_1 T}\sum_{i,k,t}\ddot{x}_{ikt}\tilde{\varepsilon}_{ikt}\tilde{\varepsilon}'_{ikt}\ddot{x}'_{ikt}\right)\hat{Q}^{-1},$$

$$\hat{V}_2 = \left(\frac{1}{n_2 T}\sum_{j,t}z_{jt}\hat{\eta}_{jt}\hat{\eta}'_{jt}z'_{jt}\right)^{-1},$$

$$\hat{C} = \frac{1}{n_2 T}\sum_{j,t}\hat{\gamma}l_{jt}\hat{\eta}'_{jt}z'_{jt}, \text{ and}$$

$$\hat{R} = \frac{1}{n_2 T}\sum_{j,k,t}\ddot{x}_{jkt}\tilde{\varepsilon}_{jkt}\hat{\eta}'_{jt}z'_{jt}.$$

For simplification, I use the hat to denote an estimate, the bar to denote a mean, the double dot to denote a demeaned variable, and the tilde to denote the estimate of a demeaned variable. In the above equations, $\ddot{h}_{ikt} = h_{ikt} - \bar{h}_i$, $\bar{h}_i = \frac{1}{m_i}\sum_{k,t}h_{ikt}$, $\ddot{x}_{ikt} = x_{ikt} - \bar{x}_i$, and $\bar{x}_i = \frac{1}{m_i}\sum_{k,t}x_{ikt}$, where m_i is the total number of trips for individual i; $\hat{\rho} = n_2/n_1$, $\tilde{\varepsilon}_{ikt} = \ddot{h}_{ikt} - \ddot{x}'_{ikt}\hat{\beta}$, $l_{jt} = \partial z_{jt}/\partial\beta$, and $\hat{\eta}_{jt} = y_{jt} - \lambda_{jt}\bar{y}_j/\bar{\lambda}_j$, where $\bar{y}_j = \frac{1}{T}\sum_t y_{jt}$, $\bar{\lambda}_j = \frac{1}{T}\sum_t\lambda_{jt}$, and $\lambda_{jt} = \exp(z'_{jt}\hat{\theta})$. The fishery dataset is a long panel in the sense that n is comparable to T, so that the $\sqrt{nT}$-asymptotics are adopted. Note that the dataset used in the second step is an aggregated sub-sample of the first-step regression, as a result $\hat{R} \neq 0$. In addition, because of the $i.i.d.$ assumption, observations for different individuals and in different periods are independent, therefore $E\ddot{x}_{ikt}\ddot{\varepsilon}_{ikt}\partial L_{js}/\partial\theta' = 0$ for $i \neq j$ or $t \neq s$.[6]

[6] The $i.i.d.$ assumption is not essential, but it greatly simplifies the computation. Equation (10) can also be applied to the case with serial correlation or clustered standard errors.

4 Results and Discussion

4.1 Estimation Results

The empirical models are estimated sequentially. The first-step regression estimates a heterogeneous production function (Table 3). Model 1.1 is the generalized Schaefer model (3), while model 1.2 restricts the coefficient for effort to 1. All estimates are highly significant. Statistical tests show that the coefficient for fishing effort is less than one at the one-percent confidence level. This implies a diminishing return to fishing effort. As a result, the classical Schaefer model might be misspecified and should be rejected. The coefficients for gear- and area-dummies are suppressed for conciseness, but they are jointly significant. This result shows significant heterogeneity in the reef-fish fishery.

Table 3: Step 1 - stock inference

	Model 1.1		Model 1.2	
Variable	Estimate	S.E.	Estimate	S.E.
ln(Effort)-traps	0.0161***	0.0048		
ln(Effort)-bottom longline	0.1534***	0.0034		
ln(Effort)-handline	0.3720***	0.0027		
ln(Effort)-electrical reel/bandit	0.3328***	0.0061		
ln(Effort)-trolling	0.3068***	0.0104		
Gear Dummies (4)	Yes		Yes	
Area Dummies (12)	Yes		Yes	
S (Stock Index, 233)	Yes		Yes	
Individual Fixed Effects	Yes		Yes	

The dependent variable is log harvest for each vessel in each trip. The total number of trips is 126,131 and the number of periods is 234. Model 1.1 is the generalized Schaefer model. Model 1.2 is the classical Schaefer model, in which the coefficient for effort is restricted to 1 (the blank area). The stock index (233 time dummies) is also estimated but not reported here for conciseness. Significance level: * 10 percent, ** 5 percent, and *** 1 percent.

I derive two stock indices from the first-step regressions. One is based on the generalized Schaefer function and the other one is the classical Schaefer. The regression results reject the null hypothesis that catch is linearly related to effort ($\alpha_1 = 1$), so the generalized Schaefer specification is the preferred model. I also compute the gear-specific catch-per-unit-effort based on the aggregate data. Since stock proxies can only be identified up to scale, I focus on the variations instead of stock proxies can only be identified up to scale, I focus on the variations instead of the magnitudes.[7]

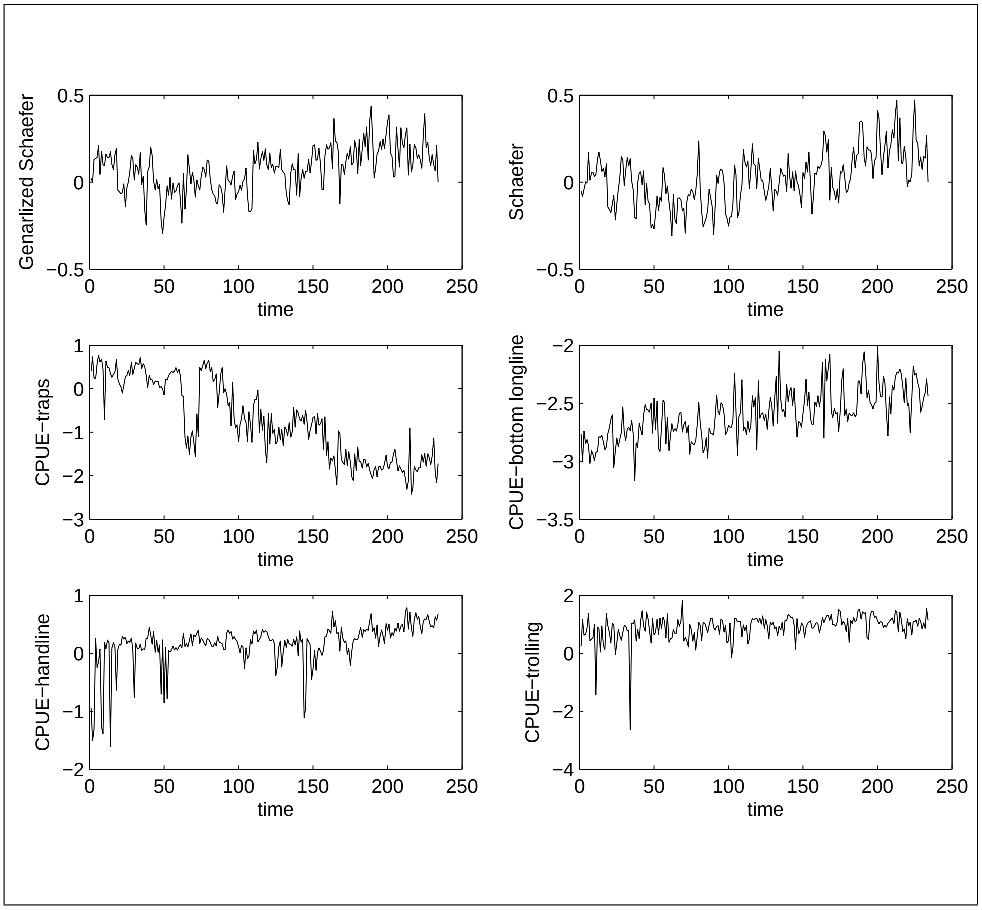

Figure 2: Estimated stock proxies

Six stock proxies are depicted in Figure 2. The top two panels are results from regression, in which two stock indices have similar patterns. However, gear-specific CPUEs report significantly different patterns based on visual observations. The CPUE is not a proper stock proxy, because the variations in the stock proxy may be attributed to heterogeneity instead of true stock changes.

In the second step, I estimate the trip frequency model using different stock proxies. Model 2.1 is the preferred model with the stock index estimated from

[7] Although the true stock is not the focus of this paper, it might be interesting to compare the prediction of different methods. Zhang and Smith (2011b) shows that the maximum sustainable yield derived from the generalized Schaefer model is significantly higher than the classical Schaefer model. Actually the prediction of the classical Schaefer model is pretty close to the number specified in the Gulf reef-fish fisheries management plan.

model 1.1 while model 2.2 uses the result from model 1.2. Models 2.3-2.6 use log catch-per-unit-effort as the stock proxy, in which each CPUE is calculated based on four different types of gear. Because the electrical reel/bandit is not available until January 2001, its CPUE is excluded. Tables 4 and 5 report the result of the second-step estimation.

The central question for policy makers is how the fishermen respond to stock changes. According to equations (6) and (7), the coefficient for $\ln\widehat{(\text{Stock})}$ is the elasticity of the expected trip frequency with respect to fish stock, since

$$\frac{\partial \mu_{jt}/\mu_{jt}}{\partial \text{Stock}_t/\text{Stock}_t} = \theta_1.$$

Note that the ln(Stock) is replaced by various stock proxies. According to (4), the stock index is defined as: $S_t = \alpha_2 \ln(\text{Stock})$. According to (1), log catch-per-unit-effort is: $\ln(\text{CPUE}) = \ln(\text{Stock}) + \ln q$. In order to simplify the comparison, I assume that the catch-stock elasticity α_2 is 1, which is the assumption adopted by the CPUE approach. In this case, I focus on the nonlinearity in fishing effort.

Table 4: Step 1 - Trip frequency model using regression-based stock indices

	Model 2.1		Model 2.2	
Variable	Estimate	S.E.	Estimate	S.E.
S (generalized Schaefer)	0.7882***	0.0807		
S (classical Schaefer)			0.4500***	0.0486
Age	0.1680*	0.0952	0.1725*	0.0957
Age^2	−0.0593	0.0797	−0.0599	0.0808
ln(FishPrice)	0.2953***	0.0663	0.2672***	0.068
ln(FuelPrice)	0.0593	4.5592	−2.7092	3.0582
ln(Weather)	0.4145***	0.1020	0.3987***	0.0995
ln(Weather)/ln(Vlength)	−1.9764***	0.3601	−2.0184***	0.3519
Reserve	−0.2384*	0.1259	−0.2157*	0.1277
GrouperOpen	0.1367	0.1057	0.2063**	0.1021
Spawning	0.0291**	0.0133	0.0270*	0.0143
SnapperOpen	0.0011	0.0018	0.0000	0.0018
SnapperOpen × Permit1	0.0675***	0.0038	0.0673***	0.0037
SnapperOpen × Permit2	0.0318***	0.0021	0.0318***	0.002
Individual Fixed Effects	Yes		Yes	

Dependent variable: semimonthly number of trips. Number of vessels: 396; time periods: 234. The stock for model 2.1 is estimated by the generalized Schaefer model 1.1. Model 2.2 uses the stock index estimated by the Schaefer model 1.2. Significance level: * 10 percent, ** 5 percent, and *** 1 percent.

Table 5: Step 2 - trip frequency model using catch-per-unit effort as the stock proxy

	Model 2.3		Model 2.4		Model 2.5		Model 2.6	
Variable	Estimate	S.E	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.
ln(CPUE-traps)	-0.0047	0.0054						
ln(CPUE-longline)			0.0012	0.0143				
ln(CPUE-handline)					-0.0152^{**}	0.0078		
ln(CPUE-trolling)							0.0229^{***}	0.0063
Age	0.1784^{***}	0.0087	0.1822^{***}	0.0082	0.1834^{***}	0.0081	0.1783^{***}	0.0081
Age^2	-0.0553^{***}	0.0076	-0.0565^{***}	0.0076	-0.0549^{***}	0.0076	-0.055^{***}	0.0076
ln(FishPrice)	0.2082^{***}	0.0562	0.2143^{***}	0.0560	0.2166^{***}	0.0561	0.2228^{***}	0.0560
ln(FuelPrice)	0.0593	0.7293	-2.8370^{***}	0.7127	0.0383	0.7800	0.0722	0.6820
ln(Weather)	0.3867^{***}	0.0982	0.4031^{***}	0.0981	0.3870^{***}	0.0981	0.3843^{***}	0.0978
ln(Weather)/ln(Vlength)	-1.9497^{***}	0.3460	-2.0082^{***}	0.3456	-1.9481^{***}	0.3457	-1.9468^{***}	0.3447
Reserve	-0.1934^{***}	0.0176	-0.1887^{***}	0.0175	-0.1894^{***}	0.0175	-0.1920^{***}	0.0175
GrouperOpen	0.1952^{***}	0.0303	0.1977^{***}	0.0313	0.1961^{***}	0.0302	0.2088^{***}	0.0304
Spawning	0.0196^{*}	0.0108	0.0190^{*}	0.0108	0.0125	0.0113	0.0223^{**}	0.0108
SnapperOpen	-0.0016	0.0016	-0.0016	0.0016	-0.0016	0.0016	-0.0015	0.0016
SnapperOpen $\times$ Permit1	0.0674^{***}	0.0035	0.0674^{***}	0.0035	0.0674^{***}	0.0035	0.0674^{***}	0.0035
SnapperOpen $\times$ Permit2	0.0318^{***}	0.0020	0.0318^{***}	0.0020	0.0318^{***}	0.002	0.0318^{***}	0.0020
Individual Fixed Effects	Yes		Yes		Yes		Yes	

Dependent variable: semimonthly number of trips. Number of vessels: 396; time periods: 234. Log catch-per-unit-effort is used to replace ln(Stock). Significance level: * 10 percent, ** 5 percent, and *** 1 percent.

Examining the first rows of Tables 4 and 5, six model specifications yield significantly different elasticities. The preferred model predicts that a one-percent increase in stock results in 0.79 percent more fishing trips. The model that ignores curvature has a significant but smaller estimate of 0.45. More interestingly, the models that use $\ln(\text{CPUE})$ as the stock proxy yield contradicting results. The models based on traps (not significant) and handline (significant) produce negative elasticities. The models based on bottom longline (not significant) and trolling have the expected signs, but they are much smaller than the preferred estimate in magnitude.

The above result suggests that ignoring nonlinearity, heterogeneity, and unobserved disturbances will significantly underestimate fishermen's responsiveness to the fish stock. For the classical Schaefer model, the bias comes from the fact that it restricts harvest-effort elasticity to one. When the first-step model is misspecified, the second step yields an inconsistent estimator. For the CPUE model, its stock proxy contains significant noise due to the underlying homogeneity assumption. The measurement error has an attenuation effect and biases the estimates towards zero.

The effect of age on trip frequency turns out to be mixed. It suggests that older fishermen make more trips than younger ones. The quadratic term has the expected sign, but it is statistically insignificant. This outcome may be due to a data constraint: I do not have observations on senior fishermen who exited the fishery, which prohibits the precise estimation of the quadratic term. I should not over-interpret the age effect, because I use a single cross-section of data to construct a "synthetic cohort." The behavior of a senior fisherman when he was young is proxied by the behavior of another fisherman at the same young age. This approach becomes problematic if their behaviors do not evolve with age in the same manner.

The sign for fuel price is puzzling. It is positive, although it is insignificantly different from zero. One reasonable explanation is that I used the same fuel price for every fisherman. The spatial heterogeneity in fuel price could lead to an imprecise estimate.

Weather is an important determinant for fishing trips. A fisherman's response to weather is dependent on the size of the vessel. Large boats are more capable of dealing with adverse weather conditions than smaller ones. The trip-weather elasticity is:

$$\frac{\partial \mu_{jt}/\mu_{jt}}{\partial \text{Weather}_t/\text{Weather}_t} = 0.4145 - \frac{1.9764}{\ln(\text{Vlength})}.$$

Since the vessel length varies between 21 and 65 feet, the elasticity falls in the domain of [-1.08,-0.68]. All vessels fish less frequently in a period with more bad weather days. However, their responses are heterogeneous. If the number of days with inclement weather increases by 1 percent, the smallest boat reduces fishing trips by 1.08 percent while the largest boat reduces by 0.68 percent.

Marine reserves have a negative effect on fisheries in areas between 5 and 10. The spatial closures reduce the fishable biomass and discourage surrounding fisheries in the first couple of years after creation (2.5 years in this case). This result is within expectations, because it takes such a long time for reserves to benefit outside fisheries (Smith, Zhang, and Coleman, 2006, 2007). The grouper-fishery opening has a positive sign, but it is insignificant. The spawning season has a positive and significant sign. Seasonal openings of red snapper have a heterogeneous impact on different vessels. When the snapper fishery is open, permit holders tend to make more trips, but the access to this fishery has no effect on non-permit holders. More important, class-1 holders go fishing more frequently than class-2 holders. The coefficient for the former fishermen is 0.0675 and for the latter is 0.0318. This result makes sense, since the regulation sets a much higher quota for the class-1 permit holders.

4.2 Caveats and Robustness Checks

Fishermen's rational expectation is a maintained assumption in this paper as I am using contemporaneous fish stocks, prices, and fuel costs. I conducted a robustness check using one-period lagged values of the three mentioned variables. The estimates are slightly different, but the the qualitative conclusion still holds: the CPUE models significantly underestimate fishermen's responsiveness. Note that these temporal variables evolve slowly, which may explain why these results are not very different.

The data used to infer the latent stock do not include recreational fishing, which has become significant in the Gulf of Mexico reef-fish fisheries. If recreational fishing interferes with commercial fishing, the measured stock index may be not consistent. However, because the quality of recreational data cannot match that of commercial fishing, they are not included in the analysis. I suggest fisheries managers to collect recreational fishing data at the same caliber as commercial fishing data. With the better data and information, my model can be adapted to incorporate recreational fishing explicitly. This will be left for future studies.

The corrected standard error in equation (10) uses the $i.i.d.$ assumption, which is made to simplify the empirical estimation. This assumption can be relaxed to accommodate more flexible specifications of error terms. I conducted robustness checks that use block bootstrapping to test the impact of the $i.i.d.$ assumption, which is robust to clustering and serial correlation. Bootstrapping produces slightly different results, but it does not change the statistical inference. Note that bootstrapping has a very high computational burden in this analysis due to large data and nonlinearity. For this reason, I prefer the analytically corrected standard errors.

The paper does not explicitly model the spatial dimension in the fishing behavior, because a model with unobservable spatial-temporal varying stocks can not be identified. We can only focus either on the spatial resolution or the temporal resolution (Zhang and Smith, 2011a). In addition, the stock inference approach relies on large samples in each period. With a fine spatial resolution, the number of active vessels will be so small that the estimated stock index becomes very noisy. My model incorporates area dummies into the production function, which helps to ameliorate the single stock assumption. Although fishermen are facing the same stock, catchability differs in different locations. A single stock with spatially heterogeneous catchability is somewhat equivalent to a spatially heterogeneous stock.[8]

4.3 Policy Implications

The econometric results have important implications in determining fishing mortality, which is frequently used as a policy target in fisheries management. Fishing mortality F is defined as the ratio of total catch C and stock N such that $F = C/N$, which is widely used in population dynamics and stock assessment. Conventional fisheries management assumes no behavioral responses, that is, total catch is independent of stock and other economic parameters. With this assumption, the stock elasticity of fishing mortality $\mathscr{E}_{F,N}$ is -1.

The assumption of exogenous fishing behavior is oversimplified. I have shown that fishermen respond to economic conditions such as stock changes by increasing both catch per trip H and trip frequency y. Thus, total catch is a function of stock such that $C = y(N)H(N)$. With this relationship, the stock elasticity of fishing mortality is:

$$\mathscr{E}_{F,N} = \mathscr{E}_{y,N} + \mathscr{E}_{H,N} - 1. \tag{11}$$

In this form, $\mathscr{E}_{y,N}$ is the stock elasticity of trip frequency, which is θ_1 estimated in equation (7). The stock elasticity of per-trip harvest $\mathscr{E}_{H,N}$ is equal to α_2 in equation (2). It is restricted to be 1 for both classical and generalized Schaefer models. The conventional fisheries models assume that both $\mathscr{E}_{y,N}$ and $\mathscr{E}_{H,N}$ are zeros.

Different model assumptions yield very different elasticity estimates. As the stock rebuilds by 1 percent, the model that ignores behavioral adaptation predicts that fishing mortality decreases by 1 percent. The CPUE model predicts the percentage change in fishing mortality is between -0.0047 and 0.0229, depending on the type

[8] One referee points out that population dynamics are not relatively constant across space. In this case, area dummies cannot fully control for spatial heterogeneity.

of gears. The classical Schafer model predicts that fishing mortality increases 0.45 and the generalized Schaefer's prediction is 0.7882. In a scenario that the stock is rebuilding, the predicted fishing mortality based on the traditional CPUE approach is too low. If a significantly underestimated fishing mortality is used a fisheries management model, the prescribed policy will be overly optimistic.

My empirical finding sheds light on current fisheries management problems. Limited entry, season closures, and spatial closures are embedded in the model. They work in the expected direction as predicted by fisheries scientists. However, their impacts on reducing fishing mortality should not be exaggerated. Consider the case for season closures. When a fishery is closed, the fish stock is rebuilt because of reduced fishing trips. Subsequently, the fishery is opened, and a higher abundance of fish will induce more fishing trips, which might offset the policy effect. This is similar to the "rebound effect" that is discussed in the energy efficiency literature.

The maintained assumption of the traditional fisheries management is no rebound effect at all.[9] The standard practice of fisheries policy is to treat fishing effort as constant and exogenous without accounting for behavioral adaptations. This assumption is somewhat supported by the catch-per-unit-effort models which estimate small elasticities and thus predict that fishermen may be unresponsive. However, the two-step method predicts that fishermen's responses are nontrivial. Ignoring this rebound effect might lead to policy failures. It also shows that the treatment of stock latency is important in quantifying the rebound effect.

However, my model is not able to evaluate the net effect of the policy on fish stocks because of the biological process is not modeled. In this paper, fishermen's behavior is modeled in a decoupled system. The natural system is unknown and summarized by the latent stock. The rationale is that each individual is subject to the same natural process. The decoupled model is easy to estimate and useful in retrospective analysis. But when it comes to the prediction, it is necessary to know the stock dynamics. Estimating a dynamic bioeconomic model fully coupling human behavior with the natural system remains a challenging topic that is left for future research.

5 Concluding Remarks

This paper presents a new approach to model fishing behavior with latent abundance information. The estimation is implemented in two steps. In the first step, I estimate a generalized Schaefer production function in which the stock index is estimated as an unknown parameter. The identification relies on heterogeneous individuals

[9] Some fisheries are controlled by an aggregate cap such as total allowable catch. If the cap is bounding, the rebound effect is not policy relevant.

exploiting a common-pool resource. Although empirical researchers do not observe the stock, fishermen are supposed to know this information and reveal it through their own behavior. I find that heterogeneity, nonlinearity, and unobservables are important in the empirical model. The classical Schaefer function is misspecified, and its stock inference may be biased.

In the second step, I use a fixed-effect count data model to describe the fishing participation choice. The stock proxy is estimated from the first-step regression as well as the conventional catch-per-unit-effort. The standard error of the second-step estimator is corrected, because the estimated stock is used rather than the real stock. I find that the trip-stock elasticity predicted by the preferred model is significantly greater than the estimate of the conventional method. This suggests that a successful fisheries policy should not ignore fishermen's adaptation to stock changes.

Because effective fisheries management depends on the degree to which fishing behavior is understood *ex ante*, demand for compelling micro behavioral modeling has been on the rise. My approach could become a routine method for analyzing fishing pressure based on vessel-level logbook data. While my application is the fishery, econometric modeling of latent state variables is applicable to a broad range of environmental and natural resource settings. This method could be applied to management of soil fertility, ground water extraction, pest management, and the spread of invasive species. Resource managers are plagued by not observing state variables. However, economic agents such as farmers and foresters are responding to these latent variables. Researchers can learn from their behavioral responses and make inference for a better management. For example, if groundwater is exploited by many farmers, the latent abundance of groundwater can be inferred from farmers' extraction effort and output. The inferred resource abundance can then be used to model farmers' extraction behavior. This approach could also be applied to the recreational demand studies, which often use catch rate as a stock proxy. A better proxy for the stock abundance will improve the estimate of the non-market value for other environmental attributes.

A Appendix

A.1 Asymptotic covariance matrix for the second-step estimator

The derivation in this section follows the same procedure proposed by Murphy and Topel (1985). However, the method is adapted to accommodate the unique needs of this study: 1) the first step is a linear fixed-effect model and the second step is a fixed-effect count data model, and 2) the data used in the second step (n_2 individuals and T periods) are the aggregated information from a sub-sample of the first step

(n_1 individuals and T periods). I assume both sample sizes approach infinity with $\lim_{n_1,n_2\to\infty} n_2/n_1 = \rho < 1$. It is a long panel dataset such that both n and T approach infinity. Therefore, the two-step estimator is $\sqrt{nT}$-consistent.

The first step is implemented by a within-estimator. Let $\ddot{h}_{ikt} = h_{ikt} - \bar{h}_i$, $\bar{h}_i = \frac{1}{m_i}\sum_{k,t} h_{ikt}$, $\ddot{x}_{ikt} = x_{ikt} - \bar{x}_i$, and $\bar{x}_i = \frac{1}{m_i}\sum_{k,t} x_{ikt}$, where m_i is the total number of trips for individual i. The sampling error can be expressed as

$$\sqrt{n_1T}(\hat{\beta}-\beta^*) = \Big(\frac{1}{n_1T}\sum_{i,k,t}\ddot{x}_{ikt}\ddot{x}'_{ikt}\Big)^{-1}\frac{1}{\sqrt{n_1T}}\sum_{i,k,t}\ddot{x}_{ikt}\ddot{\varepsilon}_{ikt}, \tag{12}$$

where $\ddot{\varepsilon}_{ikt} = \ddot{h}_{ikt} - \ddot{x}_{ikt}\beta^*$. By the central limit theorem, $\sqrt{n_1T}(\hat{\beta}-\beta^*) \xrightarrow{d} N(0, \text{Avar}(\hat{\beta}))$, where $\text{Avar}(\hat{\beta}) = (E\ddot{x}_{ikt}\ddot{x}'_{ikt})^{-1}E\ddot{x}_{ikt}\ddot{\varepsilon}_{ikt}\ddot{\varepsilon}'_{ikt}\ddot{x}'_{ikt}(E\ddot{x}_{ikt}\ddot{x}'_{ikt})^{-1}$.

The second-step regression employs a maximum likelihood estimator, which regards β as a known parameter. Let $L_{jt}(\theta,\beta) = \log\Pr(y_{j1},\cdots,y_{jT}|\sum_t y_{jt})$ designate the likelihood contribution. By the mean value expansion, I have

$$\begin{aligned}\frac{1}{\sqrt{n_2T}}\sum_{j,t}\frac{\partial L_{jt}(\hat{\theta},\hat{\beta})}{\partial\theta} =& \frac{1}{\sqrt{n_2T}}\sum_{j,t}\frac{\partial L_{jt}(\theta^*,\beta^*)}{\partial\theta} + \frac{1}{n_2T}\sum_{j,t}\frac{\partial^2 L_{jt}(\bar{\theta})}{\partial\theta\theta'}\sqrt{n_2T}(\hat{\theta}-\theta^*)+\\ & \sqrt{\frac{n_2}{n_1}}\frac{1}{n_2T}\sum_{j,t}\frac{\partial^2 L_{jt}(\bar{\theta})}{\partial\theta\beta'}\sqrt{n_1T}(\hat{\beta}-\beta^*).\end{aligned} \tag{13}$$

In this form, the LHS of the equation is zero and $\bar{\theta} = [\bar{\beta},\bar{\theta}]$ is a mean value lying between θ^* and $\hat{\theta}$. Substituting equation (12) into equation (13) and using the asymptotic equivalence, I obtain

$$\sqrt{n_2T}(\hat{\theta}-\theta^*) \overset{A}{=} \Sigma_2^{-1}\frac{1}{\sqrt{n_2T}}\sum_{j,t}\frac{\partial L_{jt}}{\partial\theta} - \sqrt{\rho}\Sigma_2^{-1}C'Q^{-1}\frac{1}{\sqrt{n_1T}}\sum_{i,k,t}\ddot{x}_{ikt}\ddot{\varepsilon}_{ikt}. \tag{14}$$

In this form, I define:

$$\begin{aligned}&Q = E\ddot{x}_{ikt}\ddot{x}'_{ikt},\\ &\Sigma_1 = E\ddot{x}_{ikt}\ddot{\varepsilon}_{ikt}\ddot{\varepsilon}'_{ikt}\ddot{x}'_{ikt},\\ &\Sigma_2 = E\frac{\partial L_{jt}}{\partial\theta}\frac{\partial L_{jt}}{\partial\theta'} = -E\frac{\partial^2 L_{jt}}{\partial\theta\theta'},\\ &C = E\frac{\partial L_{jt}}{\partial\beta}\frac{\partial L_{jt}}{\partial\theta'} = -E\frac{\partial^2 L_{jt}}{\partial\beta\theta'}, \text{ and}\\ &R = E\ddot{x}_{ikt}\ddot{\varepsilon}_{ikt}\frac{\partial L_{jt}}{\partial\theta'}.\end{aligned}$$

I have the following joint normal distribution for the first-step moment condition and the second-step score function:

$$\begin{pmatrix} \frac{1}{\sqrt{n_1 T}} \sum_{i,k,t} \ddot{x}_{ikt} \ddot{\varepsilon}_{ikt} \\ \frac{1}{\sqrt{n_2 T}} \sum_{j,t} \frac{\partial L_{jt}(\theta^*,\beta^*)}{\partial \theta} \end{pmatrix} \xrightarrow{d} N\left[0, \begin{pmatrix} \Sigma_1 & R \\ R' & \Sigma_2 \end{pmatrix}\right]. \tag{15}$$

According to (14) and (15), I know $\sqrt{n_2 T}(\hat{\theta} - \theta^*) \xrightarrow{d} N(0, \text{Avar}(\hat{\theta}))$. The asymptotic covariance matrix for the second-step estimator is

$$\text{Avar}(\hat{\theta}) = V_2 + \sqrt{\rho} V_2 \big(\sqrt{\rho} C' V_1 C - R' Q^{-1} C - C' Q^{-1} R\big) V_2, \tag{16}$$

where $V_1 = Q^{-1} \Sigma_1 Q^{-1}$ is the asymptotic covariance matrix for $\hat{\beta}$ and $V_2 = \Sigma_2^{-1}$ is the asymptotic covariance matrix for $\hat{\theta}|\beta^*$.

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