

# Three Essays on Analyses of Marine Resources

## Management with Micro-data

by

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Dissertation submitted in partial fulfillment of the requirements for the degree of  
Doctor of Philosophy in the Department of Environment  
in the Graduate School of Duke University  
2009

ABSTRACT  
(Environment)

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# Abstract

Chapter 1: There are widely accepted theoretical explanations for overexploitation of common-pool resources, however, empirically we have limited information about the micro-level mechanisms that cause individually efficient exploitation to result in macro inefficiency. This paper conducts the first empirical investigation of common-pool resource users' dynamic and strategic behavior at the micro level. With an application to the North Carolina shrimp fishery, we examine fishermen's strategies in a fully dynamic game that accounts for latent resource dynamics and other players' actions. Combining a simulation-based Conditional Choice Probability estimator and a Pseudo Maximum Likelihood estimator, we recover the profit structure of the fishery from fishermen's repeated choices. Using the estimated structural parameters, we compare the fishermen's actual exploitation path to the socially optimal one under a time-specific limited entry system with transferrable permits, and then quantify the dynamic efficiency costs of common-pool resource use. We find that individual fishermen respond to other users by exerting a higher level of exploitation effort than what is socially optimal. Based on our counterfactual experiments, we estimate the efficiency costs of this behavior to be 17.39% of the annual revenues from the fishery, which translates into 31.4% of the rent without deducting the cost of capital.

Chapter 2: Although hypoxia is a threat to coastal ecosystems, policy makers have limited information about the potential economic impacts on fisheries. Studies using spatially and temporally aggregated data generally fail to detect statistically

significant fishery effects of hypoxia. Limited recent work using disaggregated fishing data (microdata) reports modest effects of hypoxia on catches of recreationally harvested species. These prior studies have not accounted for important spatial and temporal aspects of the system, however. For example, the effects of hypoxia on catches may not materialize instantaneously but instead may involve a lagged process with catches reflecting cumulative past exposure to environmental conditions. This paper develops a differenced bioeconomic model to account for the lagged effects of hypoxia on the North Carolina brown shrimp fishery. It integrates high-resolution oxygen monitoring data with fishery-dependent microdata from North Carolina's trip ticket program to investigate the detailed spatial and temporal relationships of hypoxia to commercial fishery harvest. The main finding is that hypoxia potentially resulted in a 12.9% annual decrease in brown shrimp harvest from 1999-2005. The paper also develops two alternative models—a non-differenced model and a polynomial distributed lag model—and results are consistent with the main model.

Chapter 3: The emergence of ecosystem-based management suggests that traditional fisheries management and protection of environmental quality are increasingly interrelated. Fishery managers, however, have limited control over most sources of marine and estuarine pollution and at best can only adapt to environmental conditions. We develop a bioeconomic model of optimal harvest of an annual species that is subject to an environmental disturbance. We parameterize the model to analyze the effect of hypoxia (low dissolved oxygen) on the optimal harvest path of brown shrimp, a commercially important species that is fished in hypoxic waters in the Gulf of Mexico and in estuaries in the southeastern United States. We find that hypoxia alters the qualitative pattern of optimal harvest and shifts the season opening earlier in the year; more severe hypoxia leads to even earlier season openings. However, the quantitative effects of adapting fishery management to hypoxia in terms of fishery rents are small. This suggests that it is critical for other regulatory agencies to

control estuarine pollution, and fishery managers need to generate value from the fishery resources through other means such as rationalization.

To my parents

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The conservation of natural resources is the fundamental problem. Unless we solve that problem, it will avail us little to solve all others.

—Theodore Roosevelt, 1907

# Introduction

Ecosystem-based management augments traditional natural resource management by calling for the consideration of humans within the ecosystem, the spatial dimensions of the resource, and the dependence of extractive natural resources on the quality of the environment ([17], [21], [67]). Because the role of humans is central, meeting the challenges of ecosystem-based management requires integrating knowledge from different disciplines in the natural and social sciences.

Growing interest in ecosystem-based management has coincided with the emergence of detailed economic micro-data sets that track individual resource use and detailed monitoring of environmental conditions. Both of these data types increasingly are available with fine spatial and temporal resolution, and thus they present opportunities to harness new developments in microeconomic modeling. This thesis focuses on problems of managing one of the most crucial natural resources, marine resources. It employs empirical bioeconomic modeling as a means to integrate multidisciplinary themes of ecosystem-based management ([92]). In three chapters, the thesis addresses the following management related questions: 1) how to evaluate over-exploitation of natural resources at the micro level; 2) how to quantify the effects of water pollution on a fishery; 3) and how to design optimal harvest strategies that depend upon environmental conditions. Each question is investigated in a separate chapter. The first two chapters employ microeconomic modeling, while the third chapter uses numerical bioeconomic modeling based on some of the empirical

results in earlier chapters.

The first chapter <sup>1</sup>, titled “Measuring the Dynamic Efficiency Costs of Common-Pool Resource Exploitation”, deals with the traditional common-pool over-exploitation problem. The underlying economic intuition of this problem is that the individual exploiter does not internalize the stock externality, and the absence of well defined property rights has been widely held as the fundamental cause of the problem. Gordon ([33]) and Scott ([85]) first stated the commons theory and Hardin popularized the phenomenon with the phrase “the tragedy of the commons” [38]. From then on, considerable attention has been attracted to this topic, especially theoretically. Empirically, however, very little is known about the mechanisms of how efficient individual behavior leads to social inefficiency. This chapter seeks to fill this critical gap by proposing a game theoretical framework of how to isolate the micro-level causes of the problem and quantify dynamic efficiency costs of common-pool resource usage based on a dynamic structural model with strategic interactions.

The second chapter <sup>2</sup>, “Quantifying the Economic Effects of Hypoxia on a Shrimp Fishery”, corresponds to the second question mentioned above. Water pollution is one of the most important issues that environmental policies have to address. Hypoxia (low dissolved oxygen in water), for example, recently has attracted a lot of attention due to its increasing severity ([29], [22], [10]). To tackle the issue of hypoxia, we need good understandings of the ecological and economical consequences of hypoxia ([21]). Although considerable effort has examined the ecological influences of hypoxia, the economic effects have not been well investigated even though this

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is also particularly important in habitat or fishery management. Existing economic assessments based on fisheries data fail to detect economic effects attributable to hypoxia ([113], [27]). Most of these assessments have only used aggregated data but ignored micro-data analysis as well as detecting lagged hypoxia effects on catch. Aggregated fishery catch data cannot provide enough proof of existing hypoxia effects since the possible influences on catch could come from different causes with different timing. The central contribution of this chapter is to combine spatial and temporal effects of hypoxia on the fishery and use bioeconomic modeling to evaluate the ecosystem by linking water quality and the fishery.

The last chapter <sup>3</sup>, “Optimal Harvest Strategies with Water Pollution: A Bioeconomic Analysis of Shrimp Fisheries and Hypoxia”, represents an effort to address problems on setting optimal harvest strategy policies that are conditioned on fluctuating environmental factors in estuaries. Although previous bioeconomic studies have extensively examined how to set optimal harvest policies ([19], [76]), it is rarely known how water quality may influence harvest rates. In practice, natural resources use and water quality protection have always been interrelated with each other with both conflicts and accordance, and they are more related now with the current emphasis towards ecosystem-based management. In this chapter, I couple the analyses of optimal harvest policies and hypoxia control to add another dimension to optimize fishery harvest.

A common contribution of these three chapters is that I develop bioeconomic models to make use of micro-data, which allows us to utilize information to reveal micro-level mechanisms. The ability to utilize micro-level information in this thesis relies on both data availability and methodological developments in empirical industrial organization modeling. Hopefully, the understandings of the micro-level

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pathways can provide more accurate guidelines for the quantitative management of marine resources.

# Measuring the Dynamic Efficiency Costs of Common-Pool Resource Exploitation

## 1.1 Introduction

The inefficiency of common-pool resource exploitation has long interested economists. Common-pool resources are rival in consumption but exhibit some degree of non-excludability with the limiting cases being private goods (perfect excludability) and open access goods (perfect non-excludability). In his seminal article, H. Scott Gordon ([33]) observed that open access in a fishery leads to dissipation of economic rents and a resource stock that is below its economically optimal level. Subsequent work has applied common-pool resource theory to a wide range of natural resource uses including oil extraction ([56]), ground water withdrawals ([74]), hunting and large animal extinctions ([95]), deforestation ([62]), fuelwood collection and ([57]), and even depletion of the environmental basis for a whole society ([12]). In their classic reference on exhaustible resource theory, Dasgupta and Heal ([25]) observe, “A remarkable feature of the problem of common property resource is the variety of examples that one can rather readily construct in exemplifying it.” (p. 78) Indeed,

common-pool resource exploitation- known popularly as the “Tragedy of the Commons” due to Garrett Hardin’s 1968 article in *Science*-has attracted attention from numerous scholars representing a wide range of academic disciplines. In spite of considerable intellectual effort, very little is known empirically about the pathways through which the commons affects individual behavior and leads to inefficiency.

Open access to resources-or at least minimal levels of excludability-can generate multiple inefficiencies. Economists have focused much of their attention on the stock externality; the actions of one agent affect the stock of the resource, which in turn affects the well-being of another agent through decreased resource availability or increased costs. Gordon’s ([33]) original statement of the open access problem was one in which vessels ignore their impacts on the stock and myopically enter the fishery until profits are zero. This process eliminates all rents to the fixed resource input. The stock externality thus leads to a scale of fishing activity that is too high under open access. Smith ([94]) generalized the Gordon model to incorporate dynamics, and subsequent empirical work found support for the Gordon/Smith model ([110], [9])<sup>1 2</sup>. A key point in Smith’s dynamic model is that resource exploitation is sometimes too high and sometimes too low due to the stock externality, so open access can also lead to inefficient timing of exploitation<sup>3</sup>. Beyond dynamic inefficiencies that are mediated by the stock, Smith ([94]) also highlighted a separate congestion externality that is static in nature. Resource users can increase each other’s costs contemporaneously through crowding on harvest grounds.

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<sup>1</sup> A large literature on capacity utilization in fisheries emerged in part to quantify the excess capacity in fisheries due to open access, e.g. [86]. See [49] for a review. Moreover, excess fishing capacity can be exacerbated when the fishery is regulated with season closures but still subject to open access ([41]).

<sup>2</sup> If resource users are forward-looking rather than myopic, open access still leads to rent dissipation in the steady state but with a different dynamic adjustment path ([7]).

<sup>3</sup> Models that include growth and aging of biological resources reinforce the potential for timing effects ([20]). Open access can lead to harvest before animals are reproductively mature or before they have reached a size that maximizes economic yield.

The next wave of common-pool resource theory adopted a game-theoretic approach, but direct empirical testing has been elusive. Game-theoretic models posit that resource users directly affect the actions of other resource users, giving rise to the “tragedy of the commons.” Users are typically modeled as players in an N-person game ([26], [25], [39], [6], [69], [87]).<sup>4</sup> While an N-person game matches the story of the commons nicely, empirical work has focused on aggregate level and little progress has been made in empirically estimating the strategic interactions of resource users. We still have limited information about how micro behavior generates patterns of aggregate common-pool exploitation. Once individuals are considered, it is very important to incorporate behavioral heterogeneity in policy making. The aggregate response of a representative agent (an average person) might not represent responses from a heterogeneous population added up,<sup>5</sup> This phenomenon can lead to misleading policies([40]). Empirical developments using micro-data to study the commons ultimately have been hampered by the inability to observe repeated decisions of individual resource users and the methodological challenges of estimating dynamic games<sup>6</sup>.

A return to Gordon’s original application of the fishery provides a unique opportunity to estimate strategic interactions and quantify the inefficiencies of common-pool exploitation. In most U.S. fisheries, individual vessels are required to report daily landings as well as fishing location and gear use. These data, which are mostly used to assess the biological status of fish stocks, allow analysts to construct long pan-

<sup>4</sup> A complementary literature applies game theory to common-pool fishery exploitation ([54], [37], [101]). These studies focus on aggregate level modeling such that players are individual nations rather than fishing vessels.

<sup>5</sup> One simple example is that if the utility function of each individual is nonlinear, then the expected value of total benefit is not equal to total expected individual benefit.

<sup>6</sup> Many empirical studies examine whether Ostrom’s criteria for successful common property resource management ([68]) hold in particular cases. While these studies are important for understanding how different institutions succeed or fail in excluding common-pool users, they do not provide empirical estimates of strategic interactions, nor do they quantify the potential efficiency gains from rationalization.

els with repeated interactions of resource users. Ironically, the elaborate regulatory structures that generate such rich data sets often leave open access incentives in place ([41], [93]). Together, these factors make the fishery an ideal laboratory in which to study common-pool resource exploitation in a disaggregated way.

The specific application in this paper is the North Carolina shrimp fishery. Shrimp biology is well-suited to identifying separate inefficiencies due to scale, timing, and congestion. Shrimp renew annually and grow rapidly. As a result, the optimal exploitation path has meaningful temporal resolution at the scale of days or weeks. Strategic interactions can unfold over relatively short time scales, and the most disaggregated daily micro data can be used in the econometric analysis. We specifically model daily fishing decisions in a finite-horizon dynamic game. The choice-specific value function, which consists of the current payoff plus the discounted payoff for future periods, is defined for each fishing vessel in the fishery.

The ability to measure efficiency losses from common-pool resource exploitation hinges not only on data availability but also on recent methodological developments in dynamic discrete choice modeling. For estimating the choice model, we use a two-stage estimator developed by [43] and [2]. In the first stage, we estimate the evolution of the state variables, namely, factors influencing players' decisions. These factors are reflected in choice probabilities conditional on those state variables. In the second stage, since many of the state variables are continuous, we use a simulation-based conditional choice probability estimator ([43]) to evaluate a choice-specific value function for each individual. Then we apply the pseudo maximum likelihood (PML) estimator ([2]) to solve for the structural parameters. The intuition for applying a two-stage estimator is that there is a one-to-one mapping between the conditional choice probability and the choice-specific value function under certain conditions ([42]). With this mapping, the discounted part of the value function can be represented as a function by inverting the next period's conditional choice probabilities, which in turn

can be estimated non-parametrically or approximated parametrically in a separate first stage. This method avoids the curse of dimensionality in solving the dynamic programming problem for each parameter value in a likelihood approach.

The central contribution of this paper is to provide the empirical estimate of inefficiency from common-pool resource exploitation based on a dynamic structural model with strategic interactions accounting for heterogeneity. Figure 1.1 shows that 20% of the vessels account for 80% of the total harvest, which is an obvious indication of heterogeneity and is not unusual in fisheries data. Using estimates of the heterogeneous cost structure, we are able to compare the fishermen's actual exploitation path to the optimal one under a limited entry system with transferable permits, and measure the efficiency costs in terms of lost industry rents. We distinguish and evaluate two different efficiency costs in the annual fishing process: costs due to a stock externality, and those due to a congestion externality. The stock externality can be further decomposed into the traditional stock effects (more fishing reduces the stock and raises costs) and strategic interactions among players (fishermen go fishing earlier in the season because they anticipate lower stocks later due to the actions of others). These effects lead fishermen to exert more effort than is socially optimal. We find that the overall costs of inefficient exploitation of the North Carolina shrimp fishery are around \$2.31 million per year if we assume this fishery is rationalized by a limited entry system with transferable permits. This amount is 17.39% of the mean annual dockside revenue of the industry. Counter-intuitively, the congestion externality is positive and increases the fishery profits by \$0.239 million per year, which is 1.80% of the North Carolina annual shrimp revenue. The explanation turns out to be simple. Instantaneously, congestion reduces profits, but dynamically it reduces effort and mediates the stock externality, producing a net gain in profits.

The rest of the paper is organized as follows. Section 2 presents the main model, followed by an illustration of the estimation strategy in section 3. A description of

the shrimp fishery and data is in section 4. Section 5 discusses the estimation results. In the final section, we discuss future research directions.

## 1.2 Model

The shrimp fishery is an annual industry due to shrimp biology and migration. Shrimp reproduce annually and have a lifespan of roughly eighteen months. Juvenile shrimp migrate inshore in the spring and grow in estuaries during the summer and fall, and then swim back to the open ocean to spawn. This behavior results in a major harvest season from early summer to early winter that concentrates in the estuaries and nearshore in the open ocean.

The advantage of modeling an annual industry is that it simplifies the stock externality problem. There are two major types of stock externality problems in the fishing industry: 1) growth overfishing, which refers to harvesting a fish stock before it is economically mature (before the fish have grown enough), and 2) recruitment overfishing, which refers to overharvesting adult fish that compromises the size of the fish stock in the following year. While it is important to differentiate these two stock externalities while choosing specific policy tools, most empirical bioeconomic studies are not able to do so. Because shrimp are highly fecund and migrate offshore to spawn, the cross-year recruitment overfishing problem can be ignored, and we only need to consider growth overfishing within one year. This allows us to isolate the within-year stock growth externality and quantify the annual efficiency gains in the optimal scenario. Our empirical application resembles a repeated experiment in which each year of data is a replicate for examining the stock externality. Thus, we model individual fishing decisions in a finite-horizon framework in which one year is a complete decision period.

Another key feature of the shrimp industry is that, if a fisherman exits the industry, the cost of re-entering is low. After investing in a fishing vessel, a fisherman can

easily change the species target and enter a different fishery. Due to the low switching barrier, there is no clear boundary between entering and exiting the shrimp industry. For the purpose of this paper, therefore, we assume that there is a fixed and finite number of players (i.e., vessels) each year, indexed by  $i=1, \dots, N$ , in which,  $N$  is the maximum number of regular participants.

The timing of the game is as follows: on each day of a year, each fisherman receives a random productivity shock and then fishermen simultaneously decide whether or not to fish. The unobserved random shocks are independently and identically distributed across fishermen and across periods, they are assumed to be private information to the fishermen and are a source of heterogeneity. After each fisherman makes his decision, he receives a flow utility from his action. The game is repeated each day throughout the year.

Formally put, each player faces the same binary action set  $a_i \in \{0, 1\}$ , with 0 denoting not fishing and 1 denoting fishing. Let  $A \equiv \{0, 1\}^N$ , which is a comprehensive list of possible actions for all players, and let  $t$  denote the day of the year. All the factors other than the random productivity shocks that influence the fishermen's decisions, including shrimp price, vessel length (len), stock index, wind speed (WSPD), wave height (WVHT), diesel price, weekday or weekend, season closure ( $SC$ ), time  $t$ , and individual catchability, are encoded as state variables. Individual catchability is an unobserved characteristic associated with each player's fishing skill and provides another source of heterogeneity.

### 1.2.1 Payoff

In each period  $t$ , a fisherman  $i$  receives the time-specific profit,  $\Pi_{it}$ , which consists of a return to his individual characteristics and a random productivity shock. The profit function can be specified as a function of all the state variables. Let  $\mathbb{S}$  denote the combination of state variables, then fisherman  $i$ 's profit at time  $t$ , given his action,

is:

$$\Pi_{it}(a_i) = \begin{cases} \alpha Price_t * E(h_{it}) - \beta * \mathbb{S} + \xi_{it}, & \text{if } a_i = 1; \\ 0, & \text{if } a_i = 0; \end{cases} \quad (1.1)$$

In this equation, production revenues are estimated by prices ( $Price_t$ ) and expected harvest ( $E(h_{it})$ ). Harvest ( $h_{it}$ ) is a production function of the fish stock, to be discussed later. Vessel  $i$ 's private productivity shock,  $\xi_{it}$ , is assumed to be i.i.d. and drawn from an extreme value distribution. One explanation for  $\xi_{it}$  is that it reflects random personal fishing costs (for example, illness, fatigue, or mood). This is observed by the fishermen himself but not by the econometrician. And  $\beta * \mathbb{S}$  is the cost of fishing, which is a function of some state variables, vessel length and harvest:

$$\beta * \mathbb{S} = f(Len_i, WSPD_t, WVHT_t, Diesel_t, Weekend, h_{it}, X_t) \quad (1.2)$$

Generally, production costs consist of two parts: fixed costs and variable costs. The main component of fixed costs is the depreciation value of vessel and gear, labor costs (assuming a fixed wage), and associated food and safety equipment<sup>7</sup>. The number of workers required to operate a vessel is proportional to vessel length ( $Len_i$ ), thus it is reasonable to expect that the fixed costs of each trip are proportional to the vessel length. Fixed costs also include the costs caused by bad weather (wind speed ( $WSPD$ ) and wave height ( $WVHT$ )), diesel price ( $Diesel$ ), whether it is a weekend ( $Weekend$ ), and stock index ( $X$ ). The fixed cost from  $Weekend_t$  is due to industry regulations, which will be discussed later. Variable costs depend on how much shrimp are harvested. The coefficients  $\beta$  need to be estimated from the dynamic discrete choice model. In estimating the model, different specifications of the explanatory variables will be tested to find the best functional form.

With regards to harvest, my approach in this paper is similar to standard production competition models. Fishermen will compete to produce shrimp by fishing,

---

<sup>7</sup> Labor and storage costs (e.g. ice) are quasi-fixed in that they are incurred in a per trip.

and harvest is a function of fishermen’s input. Fishery economists usually measure fishermen’s input by “effort”, i.e. how many trip days they make, how many crew members they hire and how large the vessel is. In addition, harvest is also determined by the shrimp stock, which is not observed by econometricians. Fishermen, however, may have estimates of the quantity and location of the stock based on their experiences. Combining all these factors, we use the following standard Cobb-Douglas production function, to model the production.

$$h_{it} = e^{q_i} * X_t * e^{\epsilon_{it}^h} \quad (1.3)$$

In the above equation,  $e^{q_i}$  is an individual catchability rate which is associated with each fisherman’s equipment, fishing skill, and experience. This is estimated by fixed effects to capture the unobserved individual heterogeneity.  $e^{\epsilon_{it}^h}$  is a stochastic component and i.i.d. across both individuals and time with mean 1. To simplify my model, all the trips are assumed to occur in one day<sup>8</sup>. Although the number of trip days is usually a variable measuring fishing effort, it is not included in this model as the single-day trip is assumed.

In the fishing production function, the stock is common to every individual vessel while every individual has his own characteristics that influence the revenue. Besides stock and individual characteristics, there might exist agglomeration effects or congestion effects, which will also change each vessel’s revenue. Thus, Equation (1.3) itself is not entirely satisfactory. In order to incorporate the agglomeration or congestion effects, Equation (1.3) is modified to the following:

$$h_{it} = e^{q_i} * e^{\gamma * Tvessel_t} * X_t e^{\epsilon_{it}^h} \quad (1.4)$$

Here,  $Tvessel_t$  denotes the total number of vessels in day t and the coefficient  $\gamma$  is expected to capture the agglomeration or congestion effect. If an agglomeration

<sup>8</sup> The data shows that 73.7% of all the vessel trips are one day trip, and 25.9% of vessel trips are between 2 to 6 days trip. We adjust the data by allocating the average harvest of multiple trips to each day of this trip.

effect exists, we expect a positive  $\gamma$ . It means having more vessels will increase the productivity of fishing, most likely by reducing the search costs. On the contrary, a negative  $\gamma$  signals a congestion effect, i.e., the concentration of vessels reduces average harvest. If  $\gamma = 0$ , there is no agglomeration or congestion effect.

With  $e^{\epsilon_{it}^h}$  being stochastic with mean 1,  $E(h_{it})$  is equal to  $e^{q_i} * e^{\gamma * T_{vessel_t}} * X_t$ . Replacing  $E(h_{it})$  in Equation (1.1), we can obtain the period payoff function for vessel  $i$ .

$$\Pi_{it} = \alpha Price_t * e^{q_i} * e^{\gamma * T_{vessel_t}} * X_t - \beta * \mathbb{S} + \xi_{it} \quad (1.5)$$

In this equation, all the state variables except  $\xi_{it}$  can be either observed or estimated. The transitions of the state variables are explained in the next section.

### 1.2.2 Transitions Between States

Recall that the state variables include all individual characteristics and environmental information that affect a fisherman's utility. Except  $Len_i$  and  $Weekend_t$ , all other variables are stochastic. Wind speed and wave height are obviously not influenced by fishermen's decisions and modeled as exogenous variables with Markov chains. The product price is usually an endogenous variable and is influenced by supply and demand. However, the price of shrimp is determined by the global market and the North Carolina shrimp industry is only 0.63% of the world market<sup>9</sup>, therefore it is assumed exogenous and not affected by local harvest. Consequently, the shrimp price is also modeled as an exogenous variable.

Formally, the shrimp price, wind speed, and wave height will be modeled as

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<sup>9</sup> This number is roughly calculated using information from State of World Fisheries and Aquaculture (SOFIA), 2006.

follows:

$$\log(\text{Price}_{t+1}) = \rho_0 + \rho_1 \log(\text{Price}_t) + \epsilon_t^p \quad (1.6)$$

$$\log(\text{WSPD}_{t+1}) = \rho_2 + \rho_3 \log(\text{WSPD}_t) + \epsilon_t^w \quad (1.7)$$

$$\log(\text{WVHT}_{t+1}) = \rho_4 + \rho_5 \log(\text{WVHT}_t) + \epsilon_t^v \quad (1.8)$$

$$\begin{pmatrix} \epsilon_t^p \\ \epsilon_t^w \\ \epsilon_t^v \end{pmatrix} \sim i.i.d. \text{Normal} \left[ \begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_p^2 & 0 & 0 \\ 0 & \sigma_w^2 & \sigma_{w,v} \\ 0 & \sigma_{v,w} & \sigma_v^2 \end{pmatrix} \right] \quad (1.9)$$

The error term of shrimp price is assumed to be i.i.d. across time from normal distribution with mean 0. Note that the correlations between wave speed and wave height are not zero because they are not independent of each other, while the correlations between wind speed or wave height and shrimp price are assumed to be zero.

As for the diesel price, we parameterize it with a time trend:

$$\begin{aligned} \text{Diesel}_t &= \rho_6 \text{Year} + \rho_7 \text{Week} * \text{Year} + \rho_8 (\text{Week} * \text{Year})^2 + \rho_9 (\text{Week} * \text{Year})^3 + \epsilon_t^d, \\ \epsilon_t^d &\sim N(0, \sigma_d^2) \end{aligned} \quad (1.10)$$

The variable ‘‘Week’’ in the above equation is the week of a year and Year is the year dummy. The error term ( $\epsilon_t^d$ ) is also assumed to be i.i.d. across time and drawn from a normal distribution.

Now the stock index is the only remaining state variable to be considered. Reed has developed a discrete time stochastic model for the management of a renewable resource whose stock growth can be described by a difference equation ([75]):

$$X_{t+1} = g(X_t - \phi(Q_t))e^{\zeta_t}, \quad \zeta_t \sim N(0, \sigma_x^2) \quad (1.11)$$

where

$$Q_t = \sum_{i=1}^M h_{it}$$

The error term  $\zeta_t$ , which incorporates the fluctuations in the population growth system, is assumed to be a sequence of i.i.d. random variables with mean 0. The term  $g$  denotes a biological growth function,  $Q$  is the total harvest on day  $t$ , and  $M$  is the number of vessels that go fishing. To transform real harvests to a compatible scale of a stock index,  $\phi$  is used to scale the harvest. As in Reed ([75]), we shall make the simplifying assumption that the stock population is not age-structured and can be described by a continuous variable. To capture seasonality of shrimp growth, we specify  $g$  as a function of time:

$$g(X_t - \phi(Q_t)) = (X_t - scale * Q_t)e^{\varphi(t)} \quad (1.12)$$

This function describes how the shrimp stock grows over time. Basically, the current period's stock after harvest, multiplied by growth rate ( $e^{\varphi(t)}$ ) and random shock from nature ( $e^{\zeta_t}$ ), yields the next period's stock. Parameter "scale" scales the real harvest to the stock index. Traditional ways of modeling growth use the Von-Bertalanffy growth function, which models changes in shrimp number and weight over time. However, since the stock consists of three different types of shrimp (brown shrimp, white shrimp, and pink shrimp) and biologists only collect parameters in the Von-Bertalanffy growth function for the three types of shrimp separately from the field experiments <sup>10</sup>, there is no good prior information to describe these species in the aggregate. Thus, here we specify the natural growth as  $e^{\varphi(t)}$  and estimate it directly from our data. The seasonal component of growth will proxy for age structure for an annual species like shrimp if growth and aging are linked to calendar days consistently across years. We discuss more about the estimation of the stock index later in the estimation strategy section.

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<sup>10</sup> See different species profile at [http://www.nbii.gov/portal/community/Communities/Plants\\_Animals\\_&\\_Other\\_Organisms/Fisheries\\_&\\_Aquatic\\_Resources/Aquatic\\_Organisms/Species\\_Profiles/](http://www.nbii.gov/portal/community/Communities/Plants_Animals_&_Other_Organisms/Fisheries_&_Aquatic_Resources/Aquatic_Organisms/Species_Profiles/)

### 1.2.3 Choice-specific utility and expected utility

To define the value function, it is useful to distinguish choice-specific utility from expected utility. Following common notation in the literature, let  $a = (a_1, \dots, a_N)$  denote the vector of actions for all players and  $a_{-i} = (a_1, \dots, a_{i-1}, a_{i+1}, \dots, a_N)$  denote the vector of strategies of all players excluding player  $i$ . Equation (1.5) has specified profit as a linear function of the state variables. Define  $s_i \in S_i$  as a vector of state variables  $\{Price_t, len_i, X_t, Weekend_t, WSPD_t, WVHT_t, Diesel_t, q_i, t\}$ , which are common knowledge to all the agents. Let  $\theta$  denote the set of all the parameters in the utility function. Dropping  $t$  subscripts, the choice-specific utility is represented as:

$$u_i(a_i, a_{-i}, s, \xi_i; \theta) = \begin{cases} \alpha Price * e^{q_i} * e^{\gamma * T vessel} * X - \beta * \mathbb{S} + \xi_i, & \text{if } a_i = 1; \\ 0, & \text{if } a_i = 0; \end{cases} \quad (1.13)$$

This equation is identical to the profit function (Equation 1.5) when  $a_i = 1$ . The choice-specific utility is the payoff corresponding to different choices. Note that the utility value only depends on player  $i$ 's private production shock and not on other agents' production shock. The density of  $\xi_i$  is denoted as  $f(\xi_i)$ .

In the choice-specific utility, "*T vessel*" is not a state variable at time  $t$ . It is an endogenous variable as it depends on players' actions. This makes the current period utility of a fisherman not only dependent on his own action, but also dependent on other fishermen's actions. Define  $\sigma_i(a_i = k | s)$  as the probability of player  $i$  choosing  $k$  conditional on known state information,  $k \in \{0, 1\}$ . Now we need to integrate out  $a_{-i}$  to obtain the expected utility  $u_i(a_i, s, \xi_i; \theta)$ .

$$u_i(a_i, s, \xi_i; \theta) = \sum_{a_{-i}} u_i(a_i, a_{-i}, s, \xi_i; \theta) * \sigma_{-i}(a_{-i} | s) \quad (1.14)$$

Note that  $u_i(a_i, a_{-i}, s, \xi_i; \theta)$  is a function of  $e^{\gamma * T vessel}$ . Integrating other players' actions in  $u_i(a_i, a_{-i}, s, \xi_i; \theta)$  with  $e^{\gamma * T vessel}$  directly does not yield an analytical ex-

pression for  $u_i(a_i, s, \xi_i; \theta)$ . Fortunately,  $e^{\gamma * T_{vessel}}$  can be approximated with a linear function of  $T_{vessel}_t$  and  $T_{vessel}^2$  using a Taylor expansion.

$$e^{\gamma * T_{vessel}} \approx 1 + \gamma * T_{vessel} + \frac{\gamma^2}{2} * T_{vessel}^2 \quad (1.15)$$

Then  $u_i(a_i = 1, a_{-i}, s, \xi_i; \theta)$  becomes:

$$u_i(a_i = 1, a_{-i}, s, \xi_i; \theta) = \alpha Price * e^{q_i} * (1 + \gamma * T_{vessel} + \frac{\gamma^2}{2} * T_{vessel}^2) * X - \beta * \mathbb{S} + \xi_i \quad (1.16)$$

in which

$$T_{vessel} = \sum_j 1\{a_j = 1\}$$

Integrating out all the other fishermen's actions for  $T_{vessel}$  (See appendix for the detailed information and [5] for a simple example)<sup>11</sup>, we obtain:

$$\begin{aligned} u_i(a_i = 1, s, \xi_i; \theta) &= \alpha Price * e^{q_i} * X \\ &* (1 + \gamma + \frac{\gamma^2}{2} + (\gamma + \frac{3\gamma^2}{2}) \sum_{j \neq i} \sigma_j(a_j = 1|s)) + \frac{\gamma^2}{2} \sum_{j \neq k, j \neq i} \sum_{k \neq i} \sigma_j(a_j = 1|s) \sigma_k(a_k = 1|s)) \\ &- \beta * \mathbb{S} + \xi_i \quad (1.17) \end{aligned}$$

#### 1.2.4 Equilibrium concept

Given the primitives of the model above, we shall be able to write down the choice-specific value functions. Let  $u_i(a_i, s; \theta)$  denote  $u_i(a_i, s, \xi_i; \theta)$  with no  $\xi_i$  term, the expected discounted present value for individual i can be represented as:

$$V_{it}(a_{it}, s_t) = u_{it}(a_{it}, s_t; \theta) + E_t \left( \sum_{\tau=t+1}^T \lambda^{\tau-t} u_{i\tau}(a_{i\tau}, s_\tau, \xi_{i\tau}; \theta) \right) \quad (1.18)$$

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<sup>11</sup> For a simpler expression, we just assume there is no  $h_i$  in  $\mathbb{S}$ . If there is  $h_i$ , the same logic of how to derive integration applies.

Here  $V_i(a_i, s)$  is the choice-specific value function, which consists of the deterministic current period utility plus expected discounted future utility values. This is a standard bellman algorithm on which our estimation will be based.  $\lambda$  is the daily discount rate.

In each time period, players will make fishing choices simultaneously. We only consider symmetric and Markovian strategies, and so the equilibrium concept we use is the Markov Perfect Nash Equilibrium (MPNE). Define the decision rule as  $a_i = \nu(s, \xi_i)$ , which maximizes the value function for each player  $i$  conditional on  $a_{-i}$  strategies. In this specific problem, it is straightforward to show that in any equilibrium, the optimal fishing decision must maximize the choice-specific value function. Let  $a_{it}^*$  denote the optimal strategy, the Markov Perfect Nash Equilibrium requires:

$$V_i(a_i^*, s) > V_i(a'_i, s) \tag{1.19}$$

for all  $a'_i \neq a_i^*$ .

This means that for all time periods and all alternative strategies  $a'_i$ , the optimal strategy achieves the maximum value for any player  $i$ ,  $i=1, \dots, N$ . Other players' actions enter into one player's value function by changing the expected harvest in current time (through total vessel number in a day) and by changing the next periods' stock. The equilibrium concept puts significant structure on the equilibrium noncooperative behavior of all players, and empirical two-stage estimators are based on this assumption.

### 1.3 Estimation Strategy

In general, two algorithms can be used to estimate the structural parameters: a nested fixed point algorithm (NFXP) and a conditional choice probability inversion (CCP) ([42]).

The NFXP is a gradient iterative method, which nests Dynamic Programming (DP) in obtaining the maximum likelihood. Thus it requires fully solving the DP problem in each step. This algorithm has been used in many applications. For instance, [82] applies this algorithm to optimal replacement of bus engines, [47] use it to model optimal retirement behavior, and [104] models the dynamic behavior of ground water administrators with this algorithm.

Since NFXP needs to fully solve the dynamic programming (DP) problem, the computational costs are often prohibitively high. In our model, several continuous state variables prevent solving the DP problem directly. Moreover, for a multiple-agent problem like our model, NFXP becomes computationally infeasible. Fortunately, Hotz and Miller propose the Conditional Choice Probability estimator, which does not require solving the dynamic programming problem even once. Subsequently in the literature, a number of computationally feasible estimators are proposed, e.g. recursive CCP, simulation-based CCP, two-step methods to improve or solve different problems. For instance, [88] applies this estimator to price adjustment in grocery stores and [1] applies it to inventories and markups in retailing firms. [3] reviews the estimators of dynamic discrete choice models.

For this particular model, we apply a two-stage estimation procedure developed by [43] and [2]. The first stage is to estimate the equations for stock growth, the evolutions of shrimp price, weather and diesel price independently, and then estimate conditional choice probabilities. The second stage recovers structural profit parameters by maximizing a Pseudo Log-Likelihood.

As mentioned above, the key assumption of this model is that the vessels' strategies depend only on the current state vector and form a Markov-Perfect Nash Equilibrium (MPNE). With MPNE, there is no need to solve the dynamic game in the estimation procedure. Once the choice probability is estimated from the state variables, utilities from dynamic actions can be evaluated through simulation. Since it

is a finite horizon dynamic problem, we will use backward induction to derive the value function.

In addition, the linear specification of the period utility function implies another important assumption of this model: Observed and unobserved components of utility are additive, where the unobserved error term is drawn from a known distribution (specifically, a Type I extreme value distribution), and are distributed i.i.d. across agents and time.

Separability of observed and unobserved components in utility implies that marginal utility of observed state variables does not depend on unobservables ([3]). This assumption is imposed to facilitate identification of the second-stage parameters. If the additive separability assumption is violated, then additional computational problems will occur in maximum likelihood estimation ([83]). The parametric known form of the error term is due to the fact that it is not possible to recover both parameters in observable components and the joint distribution of  $\xi_i$  simultaneously (see [4]). Therefore, the known distribution is also a necessary identification assumption imposed on the error term.

### *1.3.1 First-Stage Estimation*

The goal of the first stage is to estimate the state variable dynamics and choice probabilities flexibly without imposing the structure of the dynamic discrete choice model. We describe this first stage in the following subsection.

#### *Estimation of the state variables evolution*

We use a Generalized Least Square (GLS) estimator to estimate the evolution of shrimp price and diesel price and a Seemingly Unrelated Regression (SUR) model for WSPD and WVHT. To estimate the stock index, we first linearize Equation (1.4)

and use a two-way fixed effect model to estimate all the parameters.

$$\log(h_{it}) = \log(X_t) + Cons.Y_{ear} + \gamma * Tvessel_t + q_i + \epsilon_{it}^h \quad (1.20)$$

The regressors for  $X_t$  are dummy variables on each day. Because  $Tvessel_t$  is endogenous, we use *Weekend* as an instrumental variable. Given that vessel  $i$  is going fishing, *Weekend* is a valid instrument because it is correlated with fishing choices of everybody else but not correlated with  $h_{it}$ . Equation (1.12) is also linearized.

$$\log(\phi(X_{t+1})) = \log[\phi(X_t) - scale * Q_t] + \varphi(t) + \zeta_t \quad (1.21)$$

In which, the part  $\varphi(t)$  can be specified as linear function of time polinomials. This nonlinear equation can be estimated using the least squares method.

### *Choice probabilities*

We estimate the fishing decision policy conditional on the state vector with a probit model. In essence, we could use a non-parametric method to mimic the relationship between the state variables and the probabilities as closely as possible ([42]). But due to our large data set and long convergence rate of non-parametric methods, we use a Probit model. As a way to replace the non-parametric method, we include as many as possible state variables, squared terms, and the interactions among different state variables to best fit the model.

### *1.3.2 Second-Stage Estimation*

As discussed above, this model is a finite horizon repeated game with an end period denoted as T. Using backward induction, we derive the last period value function as

$$V_{iT}(a_{iT}, s_T; \theta) = u_{iT}(a_{iT}, s_T; \theta) \quad (1.22)$$

And the recursive function is:

$$\begin{aligned}
V_{it}(a_{it}, s_t; \theta) &= u_{it}(a_{it}, s_t; \theta) \\
&+ \sum_{\tau=t+1}^T \lambda^{\tau-t} \int \dots \int u_{i\tau}(a_{i\tau}, s_\tau, \xi_{i\tau}; \theta) \prod_{\tau=t+1}^T \Psi(s_\tau | a_{\tau-1}, s_{\tau-1}) \prod_{\tau=t+1}^T \nu(a_\tau | s_\tau) \prod_{\tau=t+1}^T d(s_\tau)
\end{aligned} \tag{1.23}$$

For the continuation part, we use simulations to approximate the recursive forward integration. At time  $t$ , based on the observations of current state variables and actions for each vessel, we simulate the next period state variables according to the state transitions ( $\Psi(s_{t+1} | a_t, s_t)$ ). At time  $t+1$ , the decision rule,  $\nu(a_{t+1} | s_{t+1})$ , is applied to determine the action of each vessel. Given state variables and actions at  $t+1$ , state variables can be simulated for  $t+2$ , and the procedure repeats until it reaches time  $T$ . The state variables from time  $t+1$  to  $T$  will be simulated a sufficient number of times to obtain the continuation part in Equation (1.23). Note that the error term in the utility function is also simulated over time  $t+1$  to  $T$  to obtain the present value at time  $t$ . The daily discount rate,  $\lambda$ , is equal to 0.05% in my estimation, which is identical to an annual discount rate of 18.25%.

The above equation enables us to simulate different paths of state evolution and evaluate the choice-specific value functions for different vessels at different times. Since  $\xi_{it}$  is generated from the Type I extreme value distribution, the equilibrium conditions in Equation (1.19) implies that:

$$\sigma(a_i = 1 | s) = \frac{\exp(V_i(a_i = 1, s; \theta))}{1 + \exp(V_i(a_i = 1, s; \theta))} \tag{1.24}$$

The above equation is a standard logit model except for the value function. We use the Pseudo Maximum Likelihood Estimator (PMLE) to estimate  $\theta$ . Auguirregabiria and Mira ([2]) show that PMLE is asymptotically equivalent to an estimator

obtained using Nested Fixed Point Algorithm. Define the log-likelihood function as:

$$L(\theta) = \sum_{i=1}^N \sum_{t=1}^T \sum_{k=0}^1 \log(\sigma(a_{it} = k|s)) * 1(a_{it} = k) \quad (1.25)$$

The entire model estimation is based on the assumption that fishermen's observed actions constitute a Markov Perfect Equilibrium. Given definitions 1.24 and 1.25, we shall be able to compute the estimator for  $\theta$ .

$$\hat{\theta} = \arg \max_{\theta \in \Theta} L(\theta) \quad (1.26)$$

With all the definitions and notation from above, the complete estimation procedure can be summarized in eight steps.

Step 1: Perform the first stage estimation;

Step 2: For state variable at time  $t=1$ , draw new state variables from  $\Psi(s'|a, s)$ ;

Step 3: Given the new state and new error term, redraw  $s$  and  $\xi_i$  for the next day. Decide actions according to the decision rule estimated in the first step. Repeat step three for  $t=2,3...T$ ;

Step 4: Repeat step 2 and 3 a sufficient number of times and compute the average;

Step 5: Repeat step 2 to 4 for each  $t= 2,3...T$ ;

Step 6: Repeat step 5 for 12 years;

Step 7: Compute Equation (1.23);

Step 8: Estimate  $\theta$  using Equation (1.26).

The simulation-based Conditional Choice Probability and Pseudo-Likelihood Maximization estimators save a lot of computational burden. Although this model is a finite horizon problem and we need to initiate simulation paths for every different

time period, the simulation procedure quickly converges. It is worth noting that since the period profit is a linear function of  $\theta$ , we can separate  $\theta$  from the variables. This implies that we do not need to repeat step 3 to step 7 as many times as we iterate over  $\theta$  to compute Equation (1.23). In other words, when we maximize log-likelihood function 1.25 to estimate  $\theta$ , we iterate over  $\theta$  spaces to find the maximum without simulating the model. If the utility function is nonlinear in  $\theta$ , it means that whenever there is a different  $\theta$  guess, we would need to redo the step 3 to step 7 to obtain a different value for Equation (1.23) for every different  $\theta$ .

#### 1.4 Empirical Setting and Data

The empirical study of common-pool resources is based on the shrimp fishery in the Albemarle-Pamlico Estuary of North Carolina. Many different types of shrimp are found in North Carolina, but white shrimp (*Penaeus setiferus*), brown shrimp (*Penaeus aztecus*) and pink shrimp (*Penaeus duorarum*) are the three major shrimp species harvested commercially. They are landed predominantly from the Pamlico Sound, the Core Sound and the Atlantic Ocean. The life history of these three species is similar to each other except that the spawning time of the species varies.

All three shrimp species have an annual life cycle that begins in the spring in deep offshore areas. After a few weeks of development, the postlarvae migrate inshore to estuarine nursery areas. These areas provide young shrimp with predation protection and feeding habitat, which are critical factors affecting growth and survival. As shrimp reach a certain length, they start to move from the shallow nursery areas into deeper water and become adult shrimp. The adult shrimp continue to emigrate to offshore areas, leaving the estuary and preparing to spawn. Most adults spawn a single time, thus completing an annual life cycle<sup>12</sup>.

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<sup>12</sup> Some shrimp can even survive as long as 18 months, but the annual life cycle is an accepted assumption in most shrimp biological modeling.

Ecologically and economically, the Albemarle-Pamlico Estuary is the critical nursery habitat for the juvenile stage of shrimp in North Carolina. The Albemarle-Pamlico Estuary is the second largest estuary system in terms of the surface area (30,000 square miles of watershed) in the United States, second only to the Chesapeake Bay. It is composed of seven sounds and five major river basins, as well as wetlands, beaches and bottomland forests. The economic value of the shrimp fishery has ranked first or second among all the fisheries in North Carolina over the last 30 years. The annual average landings between 1962 and 2003 are 7,011,236 lbs and the landings and shrimp abundance vary largely from year to year due to variation in environmental conditions ([65]).

There are two main regulations in North Carolina that affect the commercial shrimp industry besides rules about shrimp size, net size, and gear type. First, shrimping season and fishing areas are proclaimed almost every month to protect overfishing<sup>13</sup>. For a large fishing area of the Albemarle-Pamlico Estuary, the season usually closes in May and reopens in early June every year. Second, in order to protect recreational boating and fishing, shrimp trawling is banned in some of the inner estuaries on weekends ([65]).

Three datasets from different sources are used in this analysis: harvest data, weather data and diesel price data. Harvest data is the main dataset collected from the North Carolina Division of Marine Fisheries's (DMF) trip ticket program (2000-2005). The trip ticket is a form required by the dealers to report the commercial landings information. It collects data about the fishing vessel length, the number of crew, gear types, trip starting and landing dates, price, fishing location and quantity of each species landed for each trip. The dealers are required to submit the trip tickets to DMF every month. North Carolina is the first state to launch the trip ticket program. From 1978 to 1993, commercial landings information was collected

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<sup>13</sup> For the detailed proclamation, see <http://www.ncfisheries.net/procs/index2k8.html>

on a voluntary basis. Since 1994, the N.C. General Assembly has mandated trip-level reporting which has produced one of the most detailed fisheries data collection programs in the United States.

In the trip ticket data, each vessel has a unique vessel ID. According to the IDs, over two thousand vessels are identified. However, not all the vessels are “active” ones. Shrimp may be caught as bycatch, i.e. caught incidentally on fishing trips that predominantly target other species, or shrimp can be caught by some vessels that only go shrimping occasionally. These vessels have very few landings but would significantly increase the computing burden if included in the model. Thus, we define an active vessel as one that has more than 100 records of landing shrimp over twelve years. This elimination leaves only 442 individual vessels but the landings of these 442 vessels constitute 85% of the total landings. Thus, inactive vessels would likely have minor effects on the parameter estimation of our model.

The main harvest data with only active vessels still contain more than 63,000 observations of shrimp landings from 2000-2005. Figure 1.2 shows the total daily harvest over the 6 years and illustrates an annual season pattern. Actually the peak landing occurs from July to October, which comprises 80.83% of the annual harvest. This harvest distribution is consistent with a shrimp’s annual life cycle. Shrimp harvest also varies substantially from year to year. Between 2000 and 2005, 2000 has the highest landings, while 2005 has the least. For the percentage of the harvest due to gear type, shrimp trawl dominates with 90.8% of the total landings taken with shrimp trawl over the twelve years.

Weather data, including wind speed and wave height, are compiled from the National Data Buoy Center<sup>14</sup>. Since no buoy data directly represent the weather of the large Albemarle-Pamlico Estuary areas, we average weather data over three stations: Station DSLN7, Station CLKN7 and Station 44014. Vessels use #2 marine

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<sup>14</sup> The data source: [http://www.ndbc.noaa.gov/maps/southeast\\_hist.shtml](http://www.ndbc.noaa.gov/maps/southeast_hist.shtml).

diesel, but a detailed time series of its price is not available, As a substitute, we use weekly retail diesel price obtained from the Energy Information Administration (EIA).<sup>15</sup>

By merging the main data with weather and diesel price data, we construct a panel which includes daily decisions and harvest of 442 vessels in the Albemarle-Pamlico Estuary from 2000 to 2005, as well as vessels' characteristics, daily weather and weekly diesel price. Table 1.1 summarizes the statistics of some selected variables over the six years. The table shows that the total annual harvest varies over years and 2000 has the highest harvest in pounds. Both the daily total and trip harvest summary statistics demonstrate that the daily catches have high volatility. The daily total harvest ranges from about 0 pounds to about 175226.3 pounds per day at the most and the maximum trip harvest is 16326.1 pounds. The variations in catches are due in part to the variation in the shrimp stock. Another reason is that vessels are heterogeneous in catching power owing to different vessel sizes and fishermen's skill levels. As discussed in the model section, we account for this by modeling individual heterogeneity in the production function. The shrimp price in this table is a weighted average price obtained by dividing total value by total weight. The mean shrimp price shows that the price decreases over the six years. Erosion of shrimp prices is generally attributed to increased competition for imports, including farm-raised shrimp from Asia. The diesel price also has a large variance, and not surprisingly, a clear increasing trend over years. Incorporating the diesel prices into the cost structure allows the examination of the effect of energy price changes on shrimp supplies. Note that both the shrimp prices and diesel prices have been adjusted for inflation using the Consumer Price Index.

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<sup>15</sup> The data source: [http://tonto.eia.doe.gov/dnav/pet/pet\\_pri\\_gnd\\_a\\_epd2d\\_pte\\_cpgal\\_w.htm](http://tonto.eia.doe.gov/dnav/pet/pet_pri_gnd_a_epd2d_pte_cpgal_w.htm).

## 1.5 Empirical results

### 1.5.1 State transitions

As discussed in the empirical strategy section, we first estimate the dynamics of the state variables. Before estimating models of the time series state variables, we use Augmented Dickey-Fuller tests to see whether they are stationary processes. Table 1.2 shows the results of the tests. For each state variable, three different models are tested with one lag of the response variable. The “W/O Drift & Trend” refers to a random walk without drift and without trend. “Rho” is the coefficient of the lagged response variable, while “Tau” is the test statistic for whether the response series is non-stationary. The output indicates that the natural log of shrimp, wind speed and wave height are stationary processes, and the natural log of diesel price is in need of differencing in order to render it stationary.

Once shrimp price, wind speed and wave height have been shown to be stationary, we fit Autoregressive (AR) models to these variables. Table 1.3 reports the shrimp price dynamics. The output is a vector AR(1) model. Wind speed and wave height may be highly correlated with each other, so we use a Seemingly Unrelated Regressions (SUR) model to recover their data generating processes simultaneously. Indeed, Table 1.3 shows that the model correlation between logged wind speed and logged wave height is 0.57665. For diesel price evolution, we use *Week* as the regressor because the diesel prices are collected on a weekly base. In order to account for different levels of diesel price over the years, we incorporate year-specific fixed effects. The OLS results are also reported in Table 1.3. The output shows that the diesel price increase over time.

Part of the estimates of the production function and stock dynamics are presented in Table 1.4. The OLS column reports the result from regressing logged harvest on logged total vessel number ( $Tvessel$ ), season closure, and dummies for *year*, *vessel*

and  $t$ . The columns labeled “IV” use “Weekend” as an instrument for Total vessel number<sup>16</sup>. We omit reporting the stock index which has 365 time dummies and 442 vessel dummies. To deal with the incidental parameter problem, we use a within-groups model by using deviations from group means of each vessel and recover the fixed effect for vessels after obtaining other parameters. The coefficient for total vessel number is significantly positive in OLS, but is significantly negative in the two-stage least square estimation. It suggests that using an instrument changes the results. According to the IV coefficient, one percentage increase of vessel number will decrease each vessel’s harvest in one day by 0.33%. This captures a direct estimate of the congestion effect.

Table 1.4 also shows the results of testing the validity of the instrument variable. The partial  $R^2$  and F denote the Partial R-squared and F statistics, respectively, of “Tvessel” for the first stage regression. Both tests suggest that “Weekend” is a valid instrument because it explains significant variation in  $Tvessel$ . Having estimated the stock index for different times from the production function, we recover the dynamic growth parameters through nonlinear estimation, which is also reported in Table 1.4.

In Figure 1.3 the first panel illustrates the stock index omitted from Table 1.4. Consistent with the harvest season, we estimate the stock index of a year. The figure shows that the stock has two local wave peaks, which is not surprising since there are three types of shrimp and their migration times vary. The estimated stock

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<sup>16</sup> “Weekend” will be an invalid instrument variable (IV) if it is correlated with harvest. This correlation could be sourced from the gear type, i.e. “Weekend” is correlated with gear type. Since the government forbids the use of trawl in some areas in weekends, this problem of invalid IV is possible. However, we find from the data that among 442 active vessels, 384 used only trawl during weekends, while 17 vessels (3.84% of total active vessel) used different gear other than trawl in the weekends, which account for only 5.4% of the total weekends trips. Another source for correlation between Weekend and harvest could be that in the weekends, fishermen change their fishing areas to avoid regulations, which decreases their harvest. To check whether this is true, we calculate the average harvest per day for weekdays and weekends and find out that weekends CPUE (catch per unit effort) is 244.28 pounds/day and weekends is 293.07 pounds/day, i.e. weekends even have higher CPUE than weekdays. Thus, the correlation between “Weekend” and harvest through gear type and area change can be eliminated.

in the early season has more volatility most likely because a few observations exist during those periods. The second panel of Figure 1.3 depicts the logged growth rate ( $\log(X_{t+1}) - \log(X_t - scale * h_t)$ ) and its predicted value.

### 1.5.2 Fishing policy

We use a flexible probit model to estimate the fishing decision policy. The results for different specifications are presented in Table 1.5, where “year2000” to “year2005” are dummies for year 2000 to 2005. The first specification is the full model and we find that two variables, *Shrimp price*<sup>2</sup> and an interaction of Wave height (*WVHT*) and individual vessel’s catchability(*q*), are not significant. We then rerun the Probit model after dropping these two variables. The result is reported in Specification 2, which we use to derive the following profit structure.

### 1.5.3 Profit structure

Recall that the error term of the profit structure is i.i.d. and drawn from a Type I Extreme Value distribution. Given the state transitions estimated above, we are able to simulate the state variables and compute the fishing probabilities conditional on current state variables. After obtaining the accumulated state variables in Equation (1.23), the Pseudo Maximum likelihood estimators are applied to derive the structural parameters.

The estimates are in Table 1.6 and comport with basic intuitions. The third column illustrates the scale of different independent variables. The coefficient column reports the parameters in the model. If we calculate the marginal effect of different variables on the profit based on these parameters, we find that if harvest increases, both the total revenue and the cost increase. In fact, the profit is a concave function of the harvest since the coefficient for harvest squared is negative. The profit is also a concave function of the stock index. Higher Wind speed and wave height induce

higher costs, which are expected. “Len\_wspd” and “Len\_wvht” are two interactions between vessel length and weather. It turns out that larger vessels reduce the costs of higher wave height, which is reasonable because larger vessels face lower risks in bad weather. However, considering the coefficients for  $len$  and  $len^2$ , the relationship between vessel and cost is concave. This is probably because larger vessels also face higher costs, in that they need a larger crew and use more energy, but the marginal cost decreases, suggesting that they can spread quasi-fixed costs over larger harvests.

## 1.6 Counterfactual experiments

In the above section, we have revealed the profit structure of the North Carolina shrimp fishery. With this structure recovered, we are able to compute the efficiency gains after the rationalization of this fishery. In the following, we first measure the economic gains if a daily limited entry system with transferable permits is enforced to improve the efficiency of this fishery, and then evaluate the currently adopted season closure policy. Finally we calculate the efficiency change if there is no congestion effect.

### *1.6.1 Efficiency gains under a limited entry system with transferable permits*

As individuals maximize their own profits taking other players’ actions as given, the system achieves micro-level efficiency. By contrast, at the macro-level the exploitation might not necessarily be efficient. Individuals pursuing their self-interests will not lead to the social optimum when there are externalities. The social planner should maximize the total benefits to fishermen from the common-pool resource in terms of all individuals and all periods. To achieve this goal, the social planner can enforce a limited entry system with daily transferable permits to improve the fishery.

Consider the social planner's problem:

$$V_t = \max_{\{I_\tau\}_{\tau=t}^T} E\left(\sum_{t=1}^T \lambda^{\tau-t} \Pi_\tau\right) \quad (1.27)$$

S.t.

$$\begin{aligned} \Pi_t &= \sum_i (\alpha Price_t * E(h_{it}) - Cost_{it}) * \sigma(a_{it} = 1|s) * I_{it} \\ X_{t+1} &= g(X_t - scale * \sum_{I_t} q_{it}) e^{\zeta t} \\ h_{it} &= e^{q_i} * X_t \\ & * (1 + \gamma + \frac{\gamma^2}{2} + (\gamma + \frac{3\gamma^2}{2}) \sum_{j \neq i} \sigma_j(a_j = 1|s)) \\ & + \frac{\gamma^2}{2} \sum_{j \neq k, j \neq i} \sum_{k \neq i} \sigma_j(a_j = 1|s) \sigma_k(a_k = 1|s)) \end{aligned}$$

In this equation,  $I_t$  is defined as a 442 by 1 vector determining whether vessel  $i$  has the fishing permit or not at time  $t$ .  $I_{it}$  is the  $i^{th}$  element of  $I_t$ . If the  $i^{th}$  element is equal to 1, it means that vessel  $i$  is permitted to fish, while 0 means vessel  $i$  is not permitted. The social planner seeks a path of vectors of permitted vessels ( $I_t$ ) to maximize the total profit for all vessels ( $\Pi_t$ ), given that he knows the stock dynamics and the profit structure. In addition,  $Cost_t$  denotes the total costs at time  $t$ .

If our goal is to maximize the total profits, we want the most profitable vessels to fish. For example, the social planner can auction the daily permits away in advance and allow the permits to be tradable among the fishermen. With this competitive permit market, the most profitable vessels are expected to obtain the limited daily permits and fish. This plan might also be achieved by forming a fishing cooperative that shares profits and dispatches vessels on each day. Mathematically, if we can rank the vessels by their profitability, we can determine which vessels should obtain the permits. Recall that because the profit structure (Table 1.6) is revealed for each individual vessel, we can use this information to sort their annual profitability. Then this maximization problem is simplified to finding the permitted vessel number  $sum(I_t)$  instead of  $I_t$ .

Using this limited entry system with tradable permits, the social planner influences the fishermen's decisions by changing the number of vessels in the system but

not the rule of the fishermen's decision making. In other words, the fishermen still make their decisions according to the same decision structure we have recovered in our model. Preserving the decision rule implies that the parameters revealed in our structural model remains the same, which can be used to compute the efficiency loss.

To solve this optimization problem, the social planner can use a backward induction procedure with discretized stock size. Before this procedure, the social planner first calculates the expected annual profit for every vessel and sorts them by their profits in equilibrium. Then starting from the last day of the year  $T$ , for each combination of discretized stock size and vessel permits number  $sum(I_t)$ , he computes the corresponding profits assuming that the most  $sum(I_t)$  profitable vessels are permitted to fish. Based on the profits, he can derive a mapping matrix between each discretized stock size and the optimal vessel permits number  $sum(I_T)^*$ . Then in the penultimate day  $T - 1$ , he continues to map each discretized stock size and  $sum(I_{T-1})^*$ . At this point, the profit is a summation of day  $T - 1$  and day  $T$  profits. The component of day  $T - 1$  profit is computed for each  $sum(I_{T-1})$ . Then he applies the stock dynamics and obtains the expected stock size at time  $T$  for each discretized stock size at time  $T - 1$ . With the known mapping matrix for time  $T$ , he can compute the day  $T$  profit component without difficulty. Then a new mapping matrix between each discretized stock size and the optimal vessel permits number  $sum(I_{T-1})^*$  can be derived according to the comparison of the profits. Repeating the procedure, he can derive the mapping matrices for all the time periods. If he knows the initial stock size, the social planner can derive the optimal vessel permit number  $sum(I_t)^*$  path using these mapping matrices.

Figure 1.4 depicts six years' optimal permitted vessel number using the method discussed above. The two panels in the same row show the results for weekdays and weekends separately. The solid lines in the graph illustrate the optimal permitted vessel number, while the dashed lines represents the actual permitted vessel number.

Since the actual fishery is a free entry industry, all the vessels are permitted to fish. Thus, the number of players, the dashed lines, is 442 throughout the six years. However, if we enforce the limited entry system with tradable permits, the optimal vessel number varies over time. For all the six years including weekdays and weekends, there should be fewer permitted vessels in the early and late seasons to minimize the fishing costs, as the stock size is lower in these seasons. In fact, in most of the early and late seasons, the optimal permits should be equal to zero. During the seasonal peak, we see that the optimal number of permits increases to the maximum (442) in the weekdays, while during the weekends, it depends on the time. This is because on the weekends, the vessels are not allowed to use shrimp trawls in the estuaries which significantly increases their travel cost.

This limited entry system changes the number of permitted vessel each day, and so will change the vessels' strategic behavior and rationalize their output. To see the efficiency gains of this system, we plot the number of fishing vessels and the harvest path under the limited entry system to the predicted data. Figure 1.5 illustrates the total number of fishing vessels in both the predicted and optimal scenarios. Again, the dashed lines refer to the predicted numbers of fishing vessels, which are derived from the simulation of the structural model. We use the observed data of weather and vessel characteristics, but assume that the stock size follows the growth dynamics with uncertainty. The fishermen make their fishing decisions according to the choice probabilities (Table 1.5). Averaging over thousands of stock paths, we obtain the predicted fishing vessel number. Correspondingly, the solid lines are fishing vessel number if we enforce the limited entry system with tradable permits. We also show the weekdays and weekends results separately. For the weekdays of these six years, we find that the optimal numbers of fishing vessels are lower than the predicted ones in the early and late seasons, while in the season peak, the optimal numbers are greater than the permitted ones except in 2005. In all the weekends, the optimal

numbers are lower than the predicted ones.

In addition to the fishing vessel numbers, we plot the harvest path and stock path in Figure 1.6. The third and sixth column panels depict the stock path. The dotted lines are stock dynamics after predicted harvest, the solid lines are the stock after optimal harvest, while the dotted lines are the stock without harvest. These graphs show that the stock is higher in the optimal scenario than that in the predicted one. In the panels, all columns except the third and sixth show the logged harvests, including the predicted and optimal ones. As usual, the dashed lines indicate the predicted logged harvests, which are derived along with the predicted fishing vessel number. The solid lines are optimal harvest paths. To clearly graph the results, we plot the logged harvest as zero if the harvest is zero. These logged harvest plots show that in the early and late seasons, the optimal harvest should be zero, lower than the predicted harvest. In the peak season, the harvest should be increased since at this time, the stock is high and the marginal fishing cost is reduced.

Figures 1.5 and 1.6 basically describe the sources of the efficiency loss in the common-pool resource exploitation problem under study. First, there are too many vessels fishing in the early and late seasons. During these periods, the stock is not high and the productivity of fishing vessels is fairly low. Thus the fishing effort exerted in these periods is excessive and should be reduced. Second, the excess fishing effort in the early season causes lower stock in the peak season. This lower stock reduces the harvest on the one hand, and increases the fishing cost on the other hand. Third, there is too much fishing effort on the weekends. If we combine all the sources of efficiency loss together, we find that 2.31 million dollars per year are lost due to the inefficient exploitation scale and timing ( $E1$ ). This result and yearly efficiency losses are reported in table 1.7. The table also reports the efficiency loss is about 17.39% of the observed annual revenue on average, since the annual revenue of the shrimp industry in the Albemarle-Pamlico Estuary is around \$13.28 million

on average from 2000 to 2005. We also estimate the status quo profit and find that the efficiency gain is about 31.4% of the rent without deducting the capital costs. Among the six years, 2002 has the highest efficiency loss in absolute value \$4.03 million dollars, while 2001 has the highest percentage loss relative to the observed revenue. In addition, the table indicates that 2005 has the lowest efficiency gains for both relative and absolute values. The reason is that since the average 2005 shrimp price is the lowest among all six years and the initial stock is also relatively low, the fishing probability is lower relative to other years. We could see that the observed revenue for 2005 is also much lower than in other years. Thus the problem of overfishing is relatively less significant as compared to the other years just as bioeconomic theory predicts ([33], [94]).

#### *1.6.2 Program evaluation of the current season closure policy*

Using our structural model, we could also evaluate the currently implemented season closure policy in North Carolina. The season closure policy closes part of fishing areas from April to May depending on the growing time of shrimp. We find that if the current season closure policy is cancelled, the efficiency loss will be about \$0.15 million per year. The related findings are summarized in Table 1.7. We denote the efficiency gain due to the season closure policy as  $E3$ . Among the six years, 2001 has the highest efficiency gain, which amounts to 0.26 million dollars. However, we find these efficiency gains ( $E3$ ) are relatively small as compared to the efficiency gains from the limited entry system ( $E1$ ). On average, the current season closure policy only corrects 1.12% of the observed revenue  $OR$ . Our interpretation for this relatively low efficiency correction is that this policy is not fully implemented. Only part of the fishing areas are closed and we can still observe a great deal of harvest during this closure period. To fully understand the season closure policy, we have done some experiments to measure the efficiency gain if this policy is strictly implemented. The

column denoted as  $E4$  in Table 1.7 reports this experiment result. We find that the efficiency gain would be \$0.56 million under the strict season closure policy ( $E4$ ), which would correct 19.52% of the total potential efficiency gains of  $E1 + E4$ . This result suggests that we should at least have a more stringent season closure policy for the North Carolina shrimp fishery. Nevertheless, the current season closure policy only corrects 26.49% of the efficiency loss if this policy would be fully implemented.

### 1.6.3 Congestion effects

The efficiency gains under both the limited entry system and the season closure policy consist of the gains from reducing players' strategic interactions and the impacts of the stock externality. Congestion is another externality involved in the harvest. In the process of estimating the stock index, we find a congestion effect in fishermen's harvest as the IV coefficient for  $Tvessel$  is negative (Table 1.4). To measure the congestion effect, we set the coefficient for  $Tvessel$  to zero and re-simulate the system. Table 1.7 reports our finding of the gains of congestion effects. Counter-intuitively, the congestion effect leads to a total gain of \$0.239 million, i.e., the congestion externality is positive. The reason is that congestion itself has two effects on profits. On the one hand, it increases the fishing cost by its negative sign; on the other, fishermen reduce their fishing effort due to this negative congestion effect, which increases the stock size. The higher stock reduces the fishing cost. Thus, whether congestion is a positive or negative externality is empirically determined by these two opposing effects. We find that, in the North Carolina shrimp fishery, the congestion has positive externality on the profits, which is about 1.80% of the mean annual revenue.

## 1.7 Conclusion

In this paper, we have estimated a dynamic discrete choice model of a shrimp fishery and measured the costs of open access. The fishermen are modeled as playing a dynamic game in which each fisherman's action is influenced by other fishermen's actions through the stock externality. Because the shrimp fishery is an annual industry, we model the dynamic programming problem with a finite horizon. The two-stage simulation-based Conditional Choice Probability estimation and Pseudo-Likelihood Maximum routine are employed to estimate the structural parameters. Our results have several important implications.

First and foremost, to promote the efficient use of the commons, policy instruments need to address the strategic and dynamic interactions of individuals. Our results strongly support the notion that the tragedy of the commons unfolds at the individual level. While this result alone may not be surprising in light of the voluminous theoretical literature on the commons, we are unaware of any previous empirical study demonstrating that individual strategic and dynamic behavior is the mechanism that drives inefficient use of the commons. In fisheries, the catch phrase to describe this strategic dynamic interaction is the race to fish, and the conventional wisdom amongst fisheries economists is that an individually transferable quota (ITQ) solves the commons problem. Under an ITQ, vessels are allocated a tradable share of a biologically sustainable cap each season, and the most efficient vessels fish by exploiting gains from trade. However, if the timing of exploitation within a season is an important source of inefficiency, it is unclear how an ITQ will solve the racing problem. In contrast, our daily limited entry policy does not change the rules of the game but steers individual strategic and dynamic interactions towards a more efficient outcome. As more fisheries around the world begin to rationalize, there will be many new empirical opportunities to analyze whether ITQs undo the race to fish

and to explore more spatially and temporally refined policy instruments to address inefficiencies in common-pool resource use.

A related point is the efficiency gains from rationalizing North Carolinas shrimp fishery, though sizable, may actually be smaller than one would find in a typical fishery. When rationalized by a daily limited entry system with tradable permits, the total efficiency gain is around \$2.31 million per year, which is 17.39% of the annual shrimp revenue in North Carolina. However, shrimp are atypical compared to most major commercial fisheries in that there is a weak stock-recruitment relationship; that is, what returns next season has little to do with how much is left this season because shrimp are highly fecund and recruitment depends largely on environmental conditions. This feature of shrimp biology obviates the need for a cap on total allowable catch and is the basis for economists promoting limited entry to manage shrimp ([46]). Most fisheries, in contrast, present the possibility of both recruitment overfishing (across seasons) and growth overfishing (within season). Rationalizing a typical fishery may thus generate larger efficiency gains by imposing a cap on total harvest for the season and by controlling the timing of exploitation within the season.

Less intuitively, we find that congestion has a net positive effect on resource rents, suggesting a cautionary tale about static models of congestion. As expected, the instantaneous effect is negative because congestion lowers productivity. This finding is sensible in our case, as shrimp trawlers require a wide berth, and there are many shallow areas of the Abermarle-Pamlico estuarine system that limit the areas in which trawling is possible. However, the resulting lower productivity leads to an instantaneous reduction in fishing effort and thus mitigates some of the dynamic stock externality. The net effect is a gain of \$0.239 million per year, which is about 1.80% of the observed annual revenue. A positive net effect may or may not arise in other settings. However, most empirical estimates of how congestion affects natural resource use is static. It may be important to consider the possibility that welfare

losses attributed to congestion actually would produce welfare gains dynamically if policy makers were unable to exclude resource users effectively.

An interesting extension of this present study would be to include entry and exit as endogenous decisions. Since in the present data, there is no information to identify whether a vessel is a new investment or has exited the industry permanently, we assume there is a fixed number of vessels every year. But if the investment or sale of the vessels is modeled, we might be able to explain whether overcapitalization persists in the fishery. Dixit ([30]) shows that since the potential exitors have paid a high entry fixed cost and sunk cost, there exists “hysteresis” in exiting. In other words, the entry-exit problem is asymmetric: it is easy to enter but harder to exit. With some extensions of my current work, it is possible to empirically test whether the asymmetric entry-exit problem causes overcapitalization.

Lastly, our application illustrates how new methodological developments in industrial organization and microeconometrics may find fishery data sets useful. There are notable complications relative to other applications in industrial organization, such as the importance of the fish stock, the inability to observe the stock directly, and the nonlinearity of its growth. And one naturally wants to exercise caution in generalizing from a single industry with some idiosyncratic features. Nevertheless, fisheries can be sources of high-quality data that document repeated choices of individual players over time. The heterogeneity of global seafood production also means that the number of players in a fishery can range widely from less than ten to more than 1,000. These extensions, along with other interesting applications about the dynamics of the common-pool resource exploitation, are left for future research.

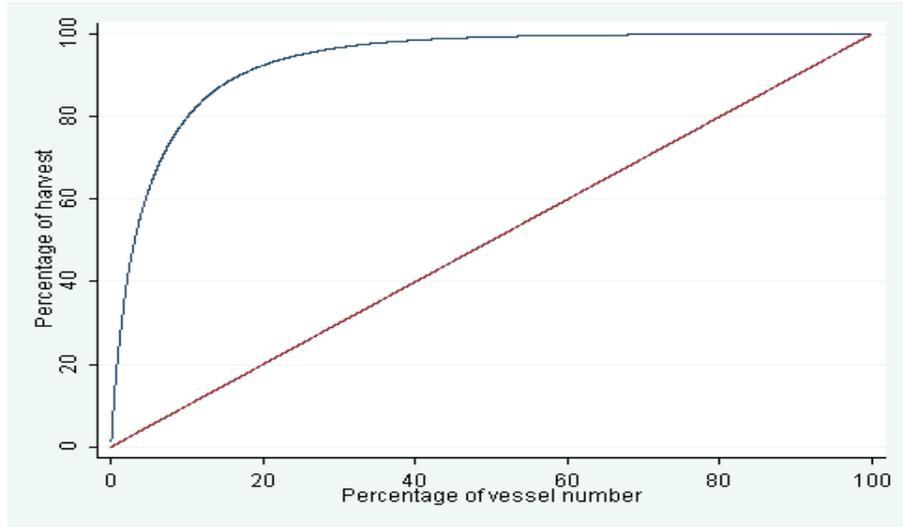


FIGURE 1.1: Quantile of harvest over vessels

Note: This figure shows that there is obvious heterogeneity among vessel harvest.

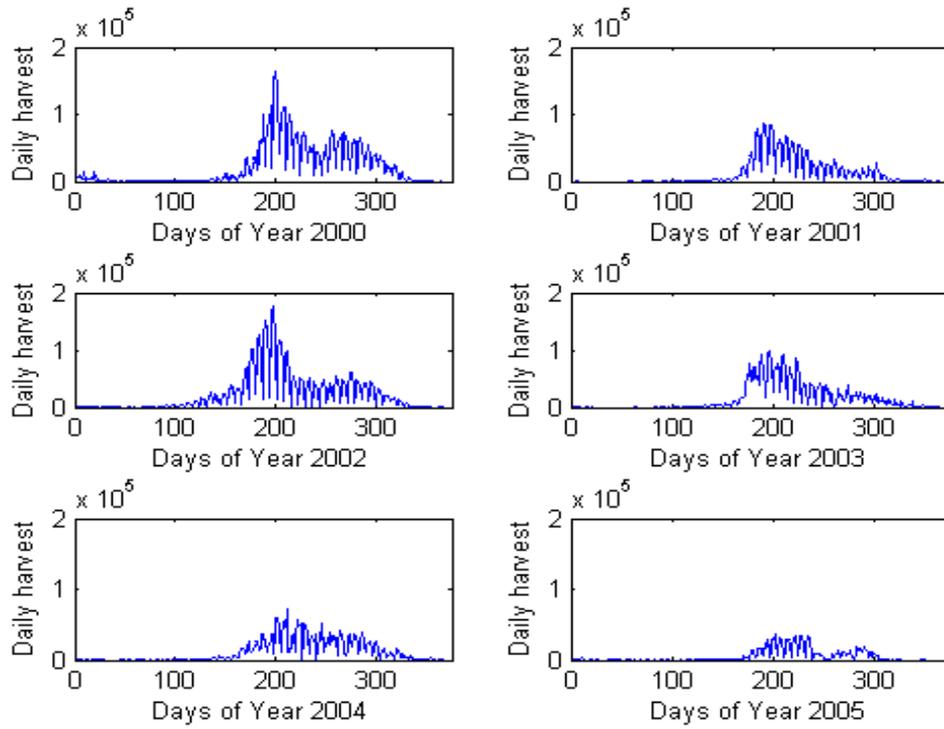


FIGURE 1.2: Total daily harvest (pounds) -2005

Note: Depicts the seasonality of shrimp industry.

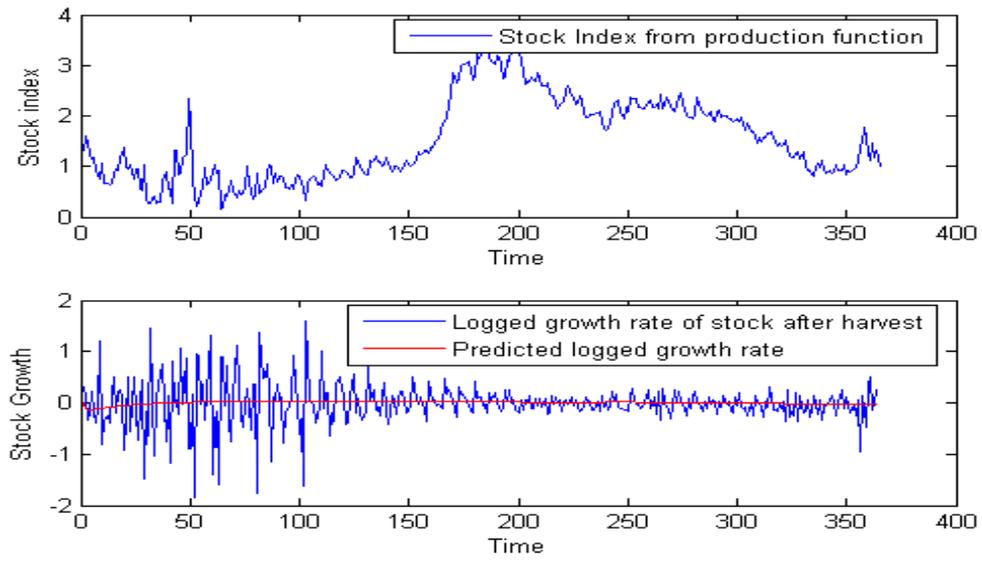


FIGURE 1.3: Stock Index Over One year

Note: Illustrates the stock index omitted from Table 1.4. Consistent with the harvest season, the stock indices of a year are estimated.

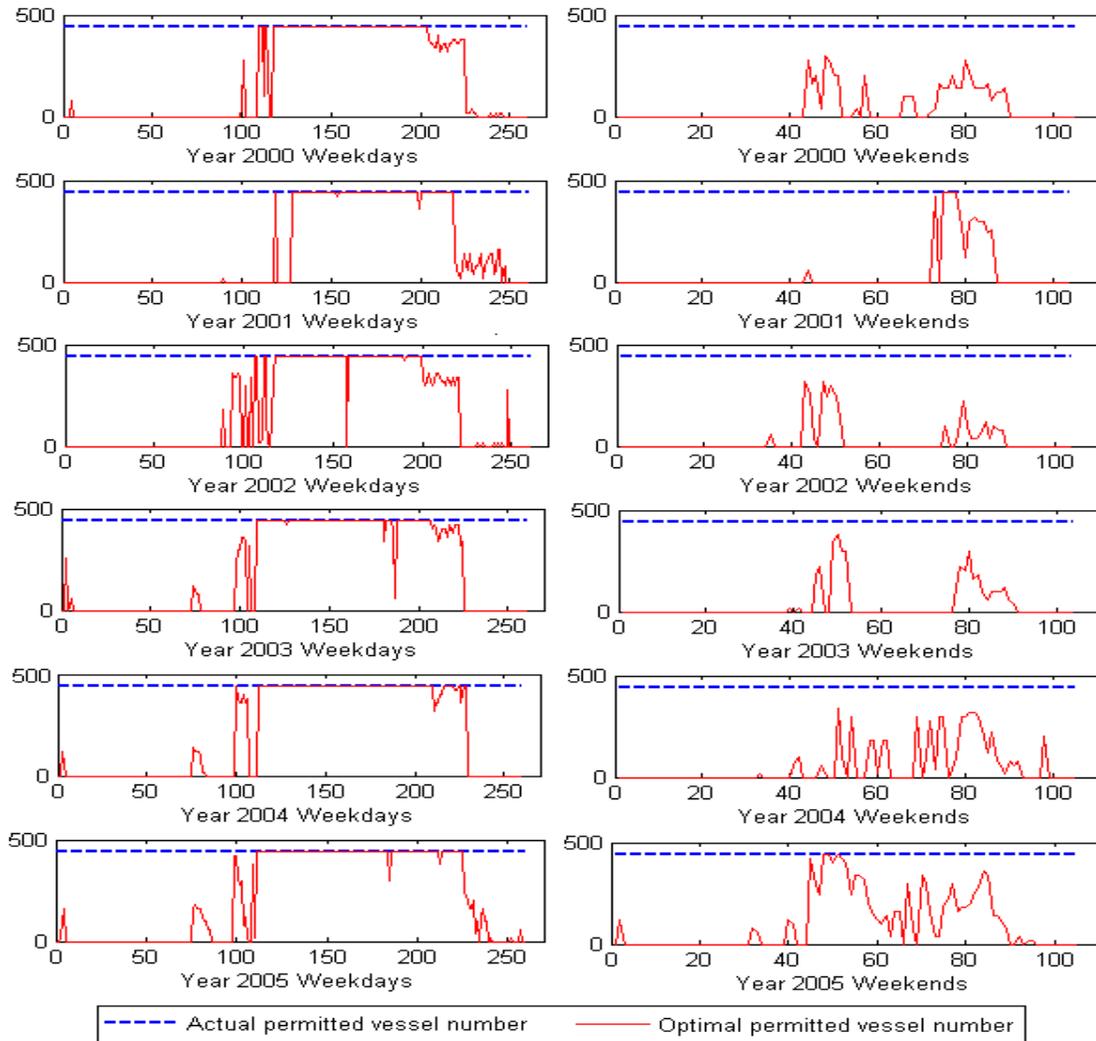


FIGURE 1.4: Comparison of actual permitted vessel number and optimal permitted vessel number

Note: Depicts the comparison of active vessel number and optimal active vessel number. The blue line is the active one which is constantly 442 while the red ones are the optimal active ones obtained from optimization in the counterfactual experiments.

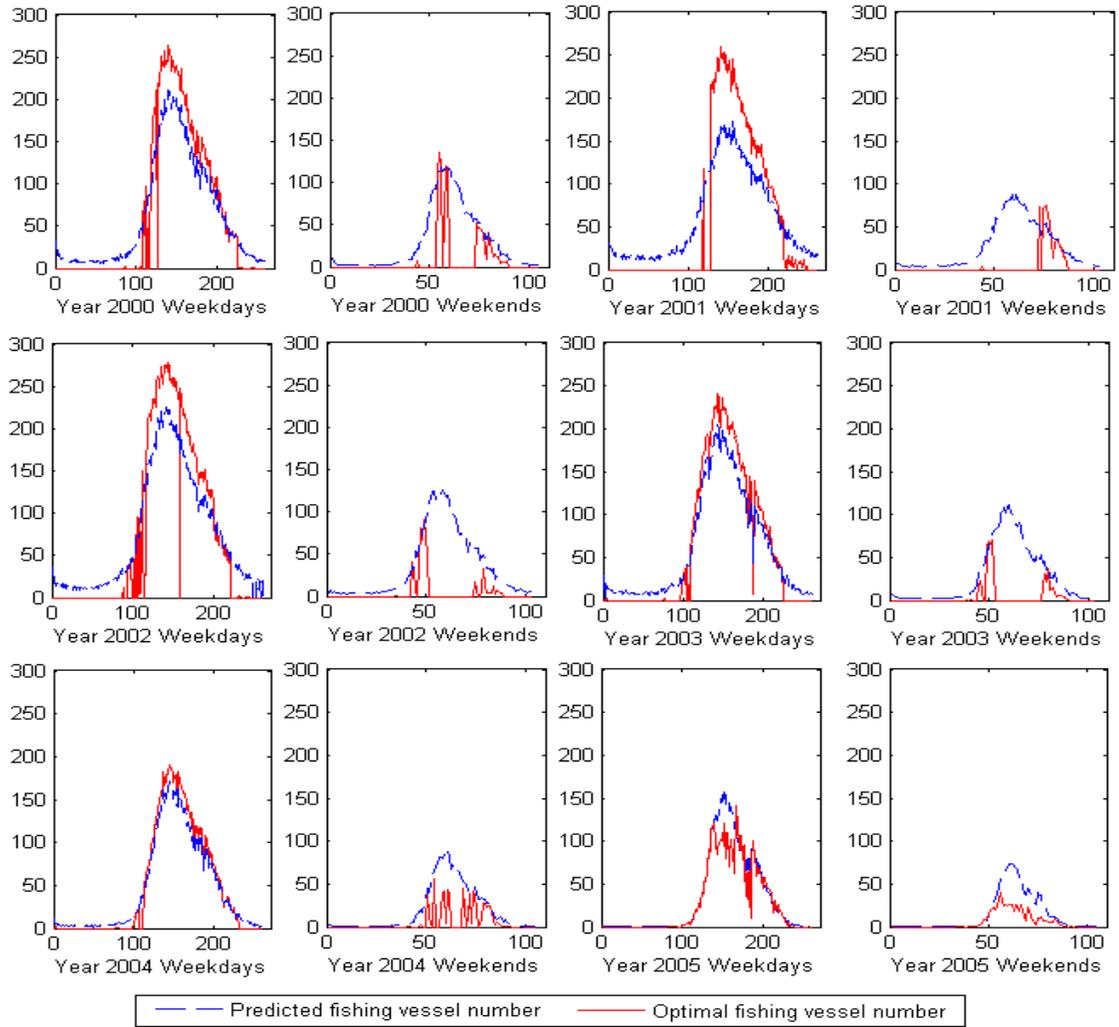


FIGURE 1.5: Comparison of simulated vessel number and optimal vessel number going fishing

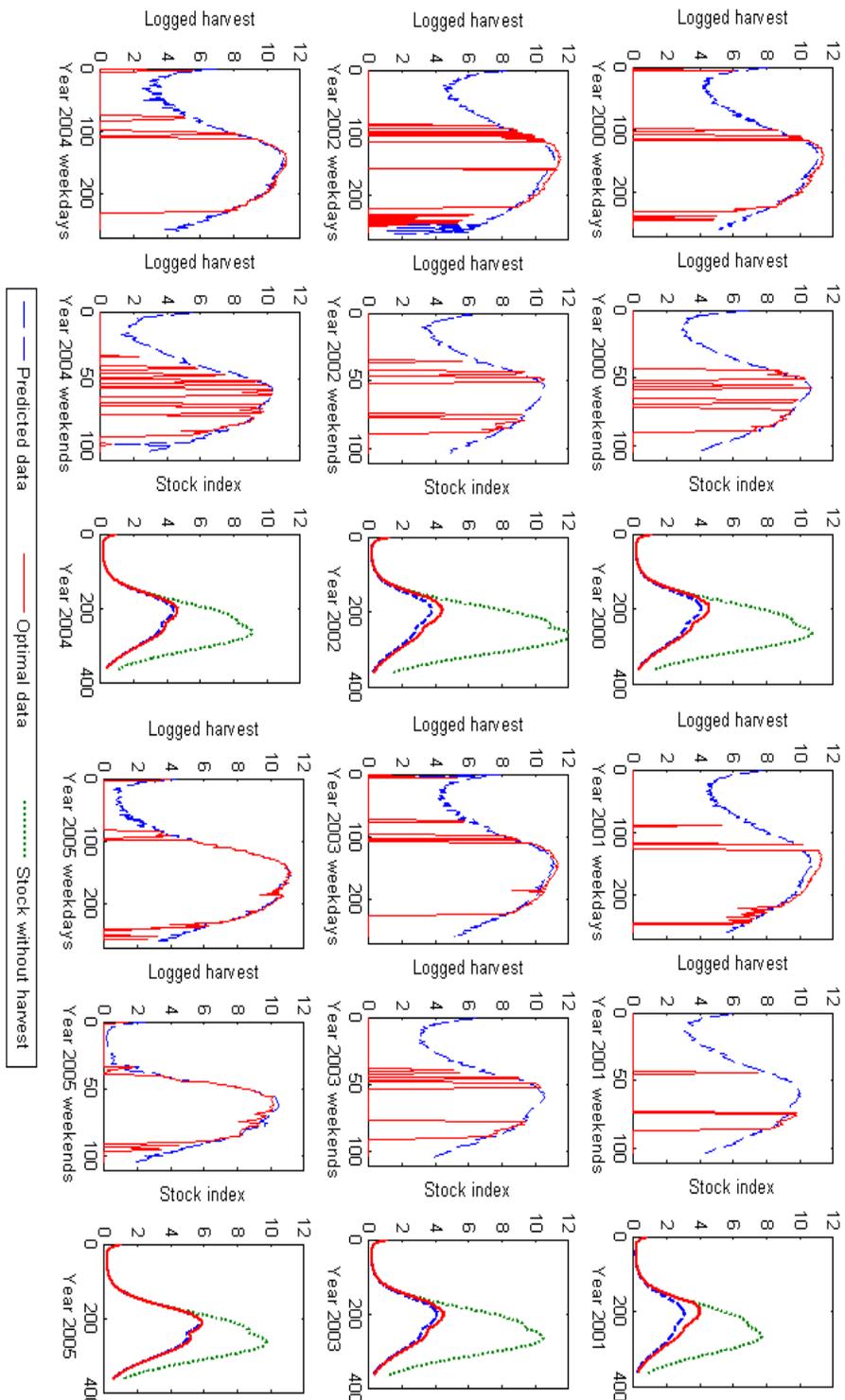


FIGURE 1.6: Predicted harvest and optimal harvest

Note: The blue lines is harvest path averaged over 10,000 simulated harvest path and the red one depicts the optimal harvest.

Table 1.1: Summary Statistics for Selected State Variables

Variable	Statistics	2000	2001	2002	2003	2004	2005
Annual harvest (Pound)	Sum	10334915.4	5254213.6	9969025.6	6167370.8	4880816.5	2123491.0
Daily total harvest(Pound)	Mean	28314.8	14395.1	27312.4	16896.9	13372.1	5817.8
	Std. Dev.	31163.6	20106.1	33949.6	23137.8	15176.6	8666.9
	Minimum	0	0	0	0	0	0
	Maximum	163003.2	87005.0	175226.3	99020.5	71091.7	36254.1
Trip harvest (Pound)	Mean	313.6	199.9	272.4	251.1	220.5	207.0
	Std. Dev.	473.8	255.3	333.3	371.4	309.3	228.0
	Minimum	0.3	1.0	0.9	1.0	0.2	0.5
	Maximum	16326.1	7067.0	10012.6	10281.5	6941.2	4051.9
Fishing vesel number	Mean	71.5	63.0	88.2	61.7	52.9	25.2
	Std. Dev.	75.5	76.5	87.1	75.6	58.4	37.0
	Minimum	0	0	0	0	0	0
	Maximum	277	273	303	292	230	145
Shrimp price (\$)	Mean	2.4	2.2	2.0	1.9	1.9	1.8
	Std. Dev.	0.6	0.5	1.6	0.9	0.9	0.7
	Minimum	1.0	1.0	0.6	0.9	0.7	0.7
	Maximum	7.1	6.4	16.1	15.7	15.1	7.1
Diesel price (\$)	Mean	150.3	135.8	126.1	144.0	164.0	212.9
	Std. Dev.	9.8	10.4	8.4	10.3	18.9	27.3
	Minimum	130.2	114.0	111.7	134.4	137.8	176.7
	Maximum	166.7	154.2	143.6	170.9	200.7	282.6
Wind speed (100m/s)	Mean	7.3	6.7	7.0	6.4	6.1	7.1
	Std. Dev.	2.7	2.6	2.3	2.5	2.7	2.9
	Minimum	2.0	2.1	2.5	1.8	1.8	1.2
	Maximum	17.0	14.5	14.2	19.3	14.9	21.6
Wave height (m)	Mean	1.2	1.3	1.4	1.5	1.4	1.5
	Std. Dev.	0.5	0.5	0.5	0.7	0.7	0.8
	Minimum	0.3	0.1	0.5	0.1	0.4	0.5
	Maximum	3.0	3.2	5.3	8.5	5.3	5.8

Table 1.2: Augmented Dickey–Fuller Unit Root Tests

Type	Rho	Pr<Rho	Tau	Pr<Tau	F	Pr>F
Shrimp price						
W/O Drift & Trend	-52.0167	<.0001	-4.59	<.0001		
Drift	-397.441	0.0001	-13.37	<.0001	89.60	0.0010
Trend	-710.034	0.0001	-17.66	<.0001	156.05	0.0010
WSPD						
W/O Drift & Trend	-67.7090	<.0001	-5.80	<.0001		
Drift	-2651.05	0.0001	-36.34	<.0001	660.33	0.0010
Trend	-2702.34	0.0001	-36.69	<.0001	672.98	0.0010
WVHT						
W/O Drift & Trend	-1013.70	0.0001	-22.75	<.0001		
Drift	-1138.93	0.0001	-24.05	<.0001	289.24	0.0010
Trend	-1153.03	0.0001	-24.21	<.0001	293.01	0.0010
Diesel Price						
W/O Drift & Trend	0.1063	0.7077	0.85	0.8930		
Drift	-2.2694	0.7460	-0.68	0.8498	0.61	0.9186
Trend	-7.4733	0.6245	-1.77	0.7183	2.26	0.7245

Note: Depicts the results of Augmented Dickey-Fuller tests. For each state variable, three different models are tested with one lag of the response variable. The first line “W/O Drift & Trend” is that of the random walk without drift and without trend. “Rho” is the coefficient of the lagged response variables, while “Tau” is the test statistic for whether the response series is non-stationary.

Table 1.3: Dynamics of Shrimp Price, Wind Speed, Wave Height and Diesel price

Parameter	Description	Coefficient	Standard Error
<b>Shrimp Price*</b>			
Intercept		0.16331	(0.00819)
Lag(log(price))	One day lagged of logged shrimp price	0.75188	(0.01148)
<b>Wave Speed*</b>			
Intercept		1.088944	(0.025376)
lag(log(WSPD))	One day lagged of logged wind speed	0.406951	(0.013396)
<b>Wave Height*</b>			
Intercept		0.039297	(0.006237)
lag(log(WVHT))	One day lagged of logged wave height	0.693213	(0.010822)
Cross Model Covariance	log(WSPD)	log(WVHT)	
log(WSPD)	0.129154	0.071702	
log(WVHT)	0.071702	0.119709	
Cross Model Correlation	log(WSPD)	log(WVHT)	
log(WSPD)	1.00000	0.57665	
log(WVHT)	0.57665	1.00000	
<b>Diesel Price**</b>			
year2000	Year dummy	142.90481	(1.662)
year2001		154.53229	(4.0718)
year2002		112.55758	(2.23462)
year2003		156.83482	(2.23536)
year2004		144.06513	(1.662)
year2005		190.50749	(4.74271)
year2001*week	Interaction of year and week	-1.74133	(0.68463)
year2002*week		0.51016	(0.07337)
year2005*week		-2.95243	(0.76761)
year2000*week <sup>2</sup>	Interaction of year and week <sup>2</sup>	0.00798	(0.00134)
year2001*week <sup>2</sup>		0.06639	(0.03076)
year2003*week <sup>2</sup>		-0.04423	(0.0081)
year2004*week <sup>2</sup>		0.0215	(0.00134)
year2005*week <sup>2</sup>		0.2387	(0.03348)
year2001*week <sup>3</sup>	Interaction of year and week <sup>3</sup>	-0.00094523	(0.00038867)
year2003*week <sup>3</sup>		0.00077337	(0.00016185)
year2005*week <sup>3</sup>		-0.00331	(0.0004155)

\*Note: Reports the results from the Autoregressive (AR) model fitted to shrimp price, wind speed and wave height. Wind speed and wave height may be highly correlated with each other, so a Seemingly Unrelated Regressions (SUR) model is used to recover their data generating processes simultaneously.

\*\*Note: Reports the result from a regression of diesel price with backward selection. Starting from the full model with year dummies, interactions of year and week, interactions of year and week<sup>2</sup> and interactions of year and week<sup>3</sup>, the backward selection procedure chooses the variables that are significant at 5% level.

Table 1.4: Stock Index and Stock Dynamics

Production Function and Stock Index*				
Parameter	<u>OLS</u>		<u>IV</u>	
	Coefficient	Standard Error	Coefficient	Standard Error
<i>Tvessel</i>	0.001211260	(0.00005325)	-0.000329923	(0.00010143)
year2000	-0.041630934	(0.01153881)	0.099353663	(0.01399737)
year2001	-0.359847465	(0.01141639)	-0.233082131	(0.01346024)
year2002	0.039895056	(0.01190190)	0.219668667	(0.01560284)
year2003	-0.051943208	(0.01123523)	0.076121050	(0.01334525)
year2004	-0.151071255	(0.01084388)	-0.062777980	(0.01193586)
year2005	0	-	0	-
day dummies	Yes	Yes	Yes	Yes
vessel dummies	Yes	Yes	Yes	Yes
Observations	132,456		132,456	
Stock Dynamics**				
Parameter			Coefficient	(Standard Error)
scale	--	(--)	9.82e-007	(1.7385e-011)
inital stock	--	(--)	1.01	(-6.5476e-005)
log(t)	--	(--)	-0.20891	(0.13661)
log(t <sup>2</sup> )(t<240)	--	(--)	0.094753	(0.058798)
log(t <sup>2</sup> )(t≥240)	--	(--)	0.094353	(0.05887)
log(t <sup>3</sup> )	--	(--)	-0.010271	(0.0062509)
N of Observations	--		364	
Tests for instrument validity				
	Partial R2	F( 1,191390)	P-value	
	0.1196	26011.43	0.0000	

\*Note: The OLS column reports the result from regressing logged harvest on logged total vessel number (*Tvessel*), dummies for *year*, *vess* and *t*. The columns labeled with “IV” use “Weekend” as an instrument for Total vessel number. I omit reporting the stock index which has 365 time dummies and 442 vess dummies.

\*\*Note: Reports nonlinear estimation of stock dynamics.

Table 1.5: Choice Probability

Variables	Specification1			Specification2		
	Coefficient	(Standard Error)	Pr > ChiSq	Coefficient	(Standard Error)	Pr > ChiSq
year2000	-4.4979	(0.1299)	<.0001	-4.522	(0.129)	<.0001
year2001	-4.2635	(0.1262)	<.0001	-4.2874	(0.1253)	<.0001
year2002	-4.2139	(0.1221)	<.0001	-4.2371	(0.1213)	<.0001
year2003	-4.4781	(0.126)	<.0001	-4.502	(0.1252)	<.0001
year2004	-4.6693	(0.1314)	<.0001	-4.6947	(0.1305)	<.0001
year2005	-5.4014	(0.1377)	<.0001	-5.4321	(0.1365)	<.0001
Shrimp price	0.181	(0.031)	<.0001	0.1826	(0.0307)	<.0001
Shrimp price <sup>2</sup>	-0.00258	(0.00187)	0.1673	--	(--)	--
stock	0.7772	(0.015)	<.0001	0.7698	(0.0141)	<.0001
stock <sup>2</sup>	-0.1083	(0.00236)	<.0001	-0.108	(0.00235)	<.0001
Shrimp price*stock	0.0316	(0.00464)	<.0001	0.0349	(0.0041)	<.0001
Shrimp price*diesel price	-0.001	(0.000199)	<.0001	-0.00113	(0.000178)	<.0001
stock*len	0.00184	(0.000111)	<.0001	0.00183	(0.000111)	<.0001
WSPD	-0.0332	(0.00591)	<.0001	-0.0355	(0.00488)	<.0001
WVHT	-0.089	(0.0222)	<.0001	-0.074	(0.00475)	<.0001
Weekend(1 if weekend)	-0.5279	(0.00551)	<.0001	-0.5282	(0.00551)	<.0001
Season closure(1 if open)	0.0428	(0.0092)	<.0001	0.0415	(0.00916)	<.0001
Diesel price	0.0114	(0.00103)	<.0001	0.0117	(0.001)	<.0001
Diesel price <sup>2</sup>	-0.00001	(2.17E-06)	<.0001	-0.00001	(2.17E-06)	<.0001
len	0.0104	(0.000854)	<.0001	0.0104	(0.000853)	<.0001
len <sup>2</sup>	-0.00011	(8.52E-06)	<.0001	-0.00011	(8.52E-06)	<.0001
q	0.5428	(0.0311)	<.0001	0.5438	(0.0311)	<.0001
WSPD*q	0.00539	(0.00141)	0.0001	0.00594	(0.00115)	<.0001
WVHT*q	0.00367	(0.00526)	0.4858	--	(--)	--
q <sup>2</sup>	-0.0744	(0.00375)	<.0001	-0.0744	(0.00375)	<.0001
N of Observations		575,737			575,737	

Note: Reports results from a flexible probit model with different specifications to estimate the fishing decision policy. “year2000” to “year2005” are dummies for year 2000 to 2005.

Table 1.6: Profit Structure

Parameter	Description	Scale	Coefficient	(Standard Error)
year 2000	Year dummy	1	-1.0343	(0.1020)
year 2001		1	-0.9205	(0.0994)
year 2002		1	-0.8343	(0.1038)
year 2003		1	-1.1223	(0.0999)
year 2004		1	-1.2041	(0.0933)
year 2005		1	-1.6456	(0.0961)
revenue	Shrimp price*Harvest	1000 dollars	0.9438	(0.0194)
wspd	Wind speed	100 m/s	-0.2405	(0.2355)
wvht	Wave height	1 meters	-0.0669	(0.00950)
diesel	Diesel price	100 dollars	-1.5414	(0.0919)
Weekend	Saturday or Sunday	1	-0.4536	(0.00466)
stock	stock size	10 stock index unit	10.3817	(0.0812)
Stock <sup>2</sup>	Stock index squared	100 stock index unit	-12.0062	(0.1889)
len	Vessel length	100 feet	0.2585	(0.1619)
len <sup>2</sup>	Vessel length squared	10,000	-2.4801	(0.0822)
len_wspd	Length*Wind speed	1000	-0.2874	(0.0488)
len_wvht	Length*Wave height	100	0.0690	(0.0197)
len_diesel	Length*diesel	10000	2.0161	(0.1402)
har	Harvest	1,000 pounds	-2.0815	(0.0861)
har_len	Harvest*length	100,000	2.6923	(0.1365)
har <sup>2</sup>	Harvest squared	1E+6	-1.8647	(0.0753)
N of Observations	967,980			

Note: In the table, the third column illustrates the scale of different independent variables. The coefficient column reports the parameters I use to derive the optimal policy. “Len\_wspd” and “Len\_wvht” are two interactions between vessel length and weather.

Table 1.7: Efficiency Gains of North Carolina Shrimp Fishery (in 2000 \$)

year	Observed revenue(OR)	Status Quo rent without deducting the cost of capital (SQR)	$\frac{SQR}{OR}$	Efficiency gains due to the limited entry system(E1)	$\frac{E1}{OR}$	Efficiency gains if removing congestion (E2)	$\frac{E2}{OR}$
2000	25,405,916	11,972,687	47.13%	2,543,759	10.01%	-249,099	-0.98%
2001	11,911,070	8,656,129	72.67%	3,864,802	32.45%	-333,863	-2.80%
2002	18,364,776	6,643,637	36.18%	4,032,846	21.96%	-402,204	-2.19%
2003	10,930,616	7,069,754	64.68%	2,548,315	23.31%	-249,629	-2.28%
2004	9,462,853	6,645,677	70.23%	819,030	8.66%	-108,710	-1.15%
2005	3,599,068	3,136,605	87.15%	45,349	1.26%	-91,015	-2.53%
Average	13,279,050	7,354,081	55.38%	2,309,017	17.39%	-239,087	-1.80%
year		Efficiency gains due to season closure policy (E3)	$\frac{E3}{OR}$	Efficiency gains due to strict season closure policy (E4)	$\frac{E4}{OR}$	$\frac{E3}{E4}$	
2000		186,798	0.74%	539,839	2.12%	34.60%	
2001		256,940	2.16%	1,250,053	10.49%	20.55%	
2002		182,984	1.00%	847,849	4.62%	21.58%	
2003		102,670	0.94%	416,614	3.81%	24.64%	
2004		158,932	1.68%	302,712	3.20%	52.50%	
2005		1,695	0.05%	3,285	6.75%	51.61%	
Average		148,337	1.12%	560,059	4.22%	26.49%	

Note: All the efficiency gains appeared in this table are compared relative to the “status quo rent without deducting the cost of capital”.

# Quantifying the Economic Effects of Hypoxia on a Shrimp Fishery

## 2.1 Introduction

Environmental policies to address nutrient pollution require understanding both the ecological and economic consequences of hypoxia ([21], [67]). While there is more to learn, the ecological dimensions of nutrient pollution have been well studied around the world ([80], [73], [66], [44], [106], [22], [28], [70], [48] and [14], [15]). The effects of hypoxia on individual growth ([98]), mortality ([63]), movement ([107]), reproduction ([103]), and food web interactions ([13]) have been documented for many species and ecosystems. Although hypoxia is becoming more frequent and widespread in coastal and estuarine systems ([28], [22], [10], [29]), the economic consequences for fisheries and the implications for fisheries management are largely unknown.

Despite the documented biological consequences of hypoxia, the severity of economic effects on fisheries is unclear. Some studies simply fail to detect economic effects ([113], [27]). Diaz and Solow ([27]) argue that a key difficulty is the lack of statistical power when analysts attempt to infer hypoxia effects from correlations

between spatially and temporally aggregated fishing data (e.g. landings) and coarse indicators of hypoxia severity. Most harvested species can respond behaviorally to hypoxia so that population-level effects are mostly indirect and mediated by avoidance behavior and associated shifts in spatial distribution that trophic and fishery interactions ([14], [79]). For example, by inducing habitat shifts and altering the spatial distribution of targeted species, hypoxia can affect the behavior of fishermen and the associated catch efficiency of the fishery ([112], [24], [23], [90], [94]). In addition, most harvested species occupy different habitats during the larval, juvenile, and adult stages. As a result, hypoxia effects are typically specific to particular life history stages and habitats that may be the same or different from those subject to the fishery. This creates the potential for spatio-temporal lags in the response of the fishery that may not be obvious in aggregate harvest data.

As an alternative to aggregate data, economists have used data on individual fisherman (microdata) to quantify the economic effects of hypoxia on fisheries. The degrees of freedom for detecting effects in a statistical model dramatically increase when using microdata, such as information on fishing effort and harvest at the level of individual trips, compared to data aggregated over time (e.g, annual) and space (e.g, the distribution of the stock). Microdata also allow for the control of spatio-temporal differences in fishing effort, which is often a confounding factor in analyses of environmental effects on fisheries. Lipton and Hicks ([58]) use microdata on recreational striped bass fishing and examine the effects of water temperature and dissolved oxygen. They report modest economic effects of low dissolved oxygen in the Patuxent River with the potential for large effects if environmental conditions were to deteriorate significantly. Massey et al. ([60]) also use microdata on recreational anglers to quantify the effects of low dissolved oxygen on the summer flounder fishery in a tributary to Chesapeake Bay. They are able to control for a larger set of environmental conditions (including dissolved oxygen, water temperature, salinity and turbidity)

than Lipton and Hicks ([58]) but also find modest economic effects of hypoxia.

Quantifying the economic effects of hypoxia on fisheries requires a statistical approach that can isolate the effects of hypoxia from other, potentially co-varying, environmental factors. Further, economic effects of hypoxia are not instantaneous but occur through a complex set of ecological and behavioral pathways. If low oxygen affects juvenile growth, mortality, or migration, fisheries data will not reveal these effects for some time, at least until the juveniles recruit into the fishery. As such, analyzing fishing microdata requires a dynamic approach that controls for correlated factors and allows for the possibility of lagged effects. Massey et al. ([60]) incorporate the dynamic effects of hypoxia in a population simulation model based on laboratory experiments, but their empirical analysis of catches only include contemporaneous effects of low dissolved oxygen. Not controlling for potential lagged effects of environmental conditions raises the possibility that inferences regarding the economic consequences to the fishery are influenced by a temporal mismatch between harvest and hypoxia.

In this paper, we develop a bioeconomic model to identify the lagged effects of hypoxia on commercial harvest in the North Carolina brown shrimp (*Farfantepenaeus aztecus*) fishery while also accounting for spatial aspects of shrimp life history and the fishery. Disentangling the effects of hypoxia from fishing pressure presents challenges because both are temporally dynamic and co-occur during summer and early fall in inshore estuarine water. Our approach to quantifying the lagged effects of hypoxia on the brown shrimp fishery proceeds in three steps. First, we develop a model to link the stock of brown shrimp, the commercial fishery, and multiple environmental factors. Second, shrimp stock dynamics and the associated effects of hypoxia are accumulated over time by determining how many days the system is below a dissolved oxygen threshold based on empirical data. We use detailed water quality data that provides a high resolution (15 minute sampling interval)

record of oxygen conditions in the estuary to characterize the temporal dynamics of hypoxia. Finally, we estimate model parameters empirically using available trip harvest and oxygen monitoring data. We account for the spatial dynamics of hypoxia and shrimp harvest by conducting parallel estimation of the model in two adjacent areas: the Neuse River and the Pamlico Sound. The Neuse River experiences severe hypoxia and low to moderate levels of shrimp harvest. The River is a nursery area that supplies shrimp to the larger Pamlico Sound which experiences little hypoxia but is where the majority of shrimp harvest occurs. We recover the parameters of both models using a backwards selection technique to identify the best fitting linear model. We then use a non-differenced model and a polynomial distributed lag model to check the robustness of our findings to alternative model structures. While our model application is to a medium-sized fishery with intermittent hypoxia, the approach we develop is general and can be applied to a number of other fisheries and environmental perturbations. Similar efforts to integrate water quality and fishery microdata in an econometric modeling framework could be a fruitful approach to explore many other ecosystem impacts on fisheries.

## 2.2 Materials and methods

### *2.2.1 Shrimp life history and fishery*

Brown shrimp spawn in offshore shelf waters during February to March and larvae recruit to estuarine nursery habitats, including riverine tributaries, during March-May ([52], [97]). As juveniles increase in size during the summer months, they gradually migrate to deeper areas of bays and sounds before returning to the shelf during the fall (September to November). The population dynamics of brown shrimp are thought to be strongly influenced by environmental factors, such as temperature, salinity, dissolved oxygen, and access to marsh habitat ([102], [36], [55], [81]) . Environmental effects on recruitment in conjunction with high fecundity and an annual life

history result in a weak stock-recruitment relationship. The weak stock-recruitment relationship simplifies our analysis because annual recruitment is not related, or only weakly related, to past recruitment and past environmental conditions. As a result, each year class can effectively be treated as independent of prior year classes.

The shrimp fishery has ranked first or second in terms of economic value among fisheries in North Carolina over the last 30 years<sup>1</sup>. The North Carolina shrimp trawl fishery is unique in the South Atlantic in that most of the harvest ( $\sim 76\%$  historically) occurs in inshore estuarine waters. The fishery harvests all three penaeid shrimp species (brown, white, pink shrimp), which are resident in estuaries for several months from May to October. Brown shrimp (*Farfantepenaeus aztecus*) have historically accounted for the majority (about two-thirds) of the catch. North Carolina currently accounts for about 61% of the total landings of brown shrimp from the South Atlantic. Most of the state landings (67%) come from Pamlico Sound, a large ( $\sim 6000 \text{ km}^2$ ) drowned river valley bounded seaward by an extensive network of barrier islands and fed landward by numerous riverine tributaries (Fig. 2.1). The fishery is also prosecuted in the tributaries, of which the Neuse River estuary is the largest, both in terms of areal extent and shrimp harvest ( $\sim 2\%$  of the total statewide landings). About 72% of the annual shrimp harvest in inshore North Carolina waters occurs during the summer and fall (July to October).

The Neuse River estuary is the major southern tributary to the larger Pamlico-Albemarle Estuary (Fig. 2.1). The Neuse experiences severe hypoxia during summer (May to August) due to excess nutrient loading from its 16,000  $\text{km}^2$  watershed ([71], [99]). Hypoxia has also been documented in other major tributaries ([96]) as well as in Albemarle Sound to the north ([105]). While the occurrence of hypoxia in these systems is largely driven by nutrient and freshwater inputs, it is typically

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<sup>1</sup> The following is summarized from the North Carolina Draft Shrimp Fishery Management Plan(NCDENR-DMFFMP, 2004).

highly dynamic spatially and temporally due to the shallow depths ( $\sim 3$  m) that promotes episodic, wind-induced mixing ([78]). Though not as well monitored as the river tributaries, hypoxia appears rare in Pamlico Sound, except under extreme climatological conditions ([72]).

### 2.2.2 A differenced model

Let  $C$  represent the average shrimp landings per trip (lbs/trip) made on a particular day  $t$  of a year  $y$ .  $C$  is a nonlinear function of fishing effort, which we measure as the average number of trips ( $K_{yt}$ ) and the average length of vessels that make those trips on each day of the year. Other terms in the model are month- and gear-specific catchability ( $q_{ym,g}$ , in which  $m$  indicates month and  $g$  indicates gear type), and shrimp biomass ( $X_{yt}$ ).  $\epsilon$  is an error term assumed to be independently and identically distributed (iid) with a normal distribution:

$$C_{yt} = q_{ym,g} K_{yt}^\alpha L e n_{yt}^\beta X_{yt} e^{\epsilon_{yt}} \quad (2.1)$$

This form of the production function allows  $\alpha$  and  $\beta$  to measure curvature in the relationship between catch and effort (see [91]). Shrimp biomass ( $X_{yt}$ ) can be decomposed into the total number of shrimp ( $Z_{yt}$ ) and individual shrimp weight ( $W_t$ ):

$$X_{yt} = Z_{yt} * W_t \quad (2.2)$$

$W_t$  reflects the baseline intra-annual growth before accounting for environmental factors, so it is only a function of  $t$  and not specific to a particular year  $y$ . We use the standard von-Bertalanffy growth function to model shrimp growth in length and an allometric function to relate length and weight. The von-Bertalanffy function is:

$$L(t) = L_\infty(1 - e^{-\delta t}) \quad (2.3)$$

where  $L$  denotes the total length of shrimp and  $L_\infty$  is the terminal length. The

parameter  $\delta$  captures the “decay” rate, or the rate at which shrimp approach asymptotic size. Shrimp weight is represented as an allometric function of shrimp length:

$$W(t) = \omega L(t)^\eta \quad (2.4)$$

The total baseline number of shrimp ( $Z_{yt}$ ) in Equation 2.2 is year-specific to account for recruitment variability and declines over the season due to natural mortality, emigration and fishing mortality:

$$Z_{yt} = Z_{y(t-1)} * e^{-\Delta m_0(t) - \Delta m_1(t)} * e^{m_f * \frac{H_{y(t-1)}}{W_{t-1}}} \quad (2.5)$$

In the above equation,  $\Delta m_0(t)$ ,  $\Delta m_1(t)$  and  $m_f$  are the loss rates of shrimp per day due to natural mortality, emigration from the system and fishing mortality, respectively. The first two factors,  $\Delta m_0(t)$  and  $\Delta m_1(t)$ , are also not year-specific. To simplify the model, the fishing mortality rate,  $m_f$ , is set constant over time.  $H_{y(t-1)}$  is the total catch (in pounds) on the previous day and  $\frac{H_{y(t-1)}}{W_{t-1}}$  converts pounds to the number of shrimp landed. Equations 2.1-3.3 describe the basic relationships among shrimp harvest, fishing effort, and stock dynamics. Substituting Equation 2.1 (catch) with Equations 2.2 (biomass) and 3.3 (abundance) gives the following:

$$C_{yt} = q_{ym,g} K_{yt}^\alpha L e n_{yt}^\beta Z_{y(t-1)} * e^{-\Delta m_0(t) - \Delta m_1(t)} * e^{m_f * \frac{H_{y(t-1)}}{W_{t-1}}} * W_t e^{\epsilon_{yt}} \quad (2.6)$$

In addition to the intrinsic growth variables above, external environmental factors, including dissolved oxygen, temperature, and salinity may affect shrimp harvest. The following equation captures the influence of various environmental factors:

$$C_{yt} = q_{ym,g} K_{yt}^\alpha L e n_{yt}^\beta Z_{y(t-1)} * e^{-\Delta m_0(t) - \Delta m_1(t)} * e^{m_f * \frac{H_{y(t-1)}}{W_{t-1}}} * W_t * e^{a_1 OI_{yt} + a_2 TI_{yt} + a_3 SI_{yt}} e^{\epsilon_{yt}} \quad (2.7)$$

In this equation,  $OI$ ,  $TI$ , and  $SI$  are binary indices of whether particular environmental factors (dissolved oxygen, temperature, and salinity, respectively) are within

a tolerable range based on information in the literature, a1-a3 are parameters, and other terms are as defined previously. For dissolved oxygen, laboratory experiments show that brown shrimp avoid areas with levels  $<2 \text{ } mgl^{-1}$  ([77]). Based on field data, Craig ([23]) reports a dissolved oxygen avoidance threshold of  $1.3 \text{ } mgl^{-1}$  for brown shrimp while Eby et al. ([31]) report an avoidance threshold of  $2.2 \text{ } mgl^{-1}$ . Based on laboratory experiments, Wannamaker and Rice ([107]) report that brown shrimp avoided  $1 \text{ } mgl^{-1}$  but not  $4 \text{ } mgl^{-1}$ . Furthermore, Renaud ([77]) reports that brown shrimp avoid  $1.5 \text{ } mgl^{-1}$  and  $2.0 \text{ } mgl^{-1}$ , but not  $3.0 \text{ } mgl^{-1}$ . Based on these empirical results we used 1.5, 2.0, and  $2.5 \text{ } mgl^{-1}$  as alternative thresholds for defining whether dissolved oxygen conditions were within a tolerable range.. Gunter et. al ([34]) find that temperatures of  $4.4^{\circ}C$  or less may cause “narcosis and mortality” of shrimp. Kutkuhn ([50]) reports that temperature over  $32.2^{\circ}C$  reduced shrimp growth and survival, which is also consistent with the findings of Zeineldin and Aldrich ([111]). In addition, the minimum tolerated salinity has been reported as 0.8 ppt (Gunter et al. 1964), while few shrimp are found in waters of less than 5 ppt ([59], [18]). Note that the effects of environmental factors captured by Equation 2.7 could be due to multiple, interdependent mechanisms that influence shrimp growth, mortality, migration, or catchability to the fishery. Our model does not distinguish the particular mechanism(s) by which environmental factors influence shrimp harvest.

In equation 2.7, a1-a3 measure the marginal daily effects of the environmental factors on shrimp catch (log-transformed). Ultimately, we are interested in the cumulative effects of each environmental factor over time and the direction and magnitude of their effect on harvest. If time ( $t$ ) is accumulated, then Equation 2.7 becomes:

$$C_{yt} = q_{ym,g} K_{yt}^{\alpha} L e n_{yt}^{\beta} Z_{y0} * e^{-m_0(t)-m_1(t)} * e^{m_f * \sum_{i=0}^{t-1} \frac{H_{yi}}{W_i}} * W(t) * e^A e^{\epsilon_{yt}} \quad (2.8)$$

in which

$$A = a_1 \sum_{i=\tau-t+1}^t OI_{yi} + a_2 \sum_{i=\tau-t+1}^t TI_{yi} + a_3 \sum_{i=\tau-t+1}^t SI_{yi}$$

where  $Z_{y0}$  is the initial number of shrimp in year  $y$  and  $\tau$  is the number of days over which the environmental effects are accumulated. For example, if  $\tau = 40$ , the marginal effects of environmental conditions are aggregated over 40 days before harvest (i.e., 40-day lagged effect). This means that the occurrence of one day of hypoxia (dissolved oxygen is less than some threshold) has marginal effects on shrimp harvest that can extend over the following 40 days, after which, there is no effect.

While the effects of low dissolved oxygen on shrimp production might reasonably be assumed to operate in a threshold manner (where there is no effect until conditions are below some critical level), dissolved oxygen as well as other environmental factors may also have continuous effects on shrimp harvest over the range of conditions experienced in the estuary. Therefore, we also developed the following equation to capture this broader range of potential environmental effects:

$$C_{yt} = q_{ym,g} K_{yt}^\alpha L e n_{yt}^\beta Z_{y0} * e^{-m_0(t)-m_1(t)} * e^{m_f * \sum_{i=0}^{t-1} \frac{H_{yi}}{W_i}} * W_t * e^A * (O_{yt}^{b_1} T_{yt}^{b_2} S_{yt}^{b_3}) e^{\epsilon_{yt}} \quad (2.9)$$

where  $O_t$  is the dissolved oxygen concentration ( $mg\ l^{-1}$ ),  $T_t$ , is the temperature ( $^{\circ}C$ ) and  $S_t$  is the salinity (ppt). Including both absolute values and binary indices to represent environmental effects in the model provides a flexible functional form that can capture the multiple levels over which environmental conditions may influence shrimp production and harvest.

In order to simplify the nonlinear estimation, we linearize Equation 2.9 by taking the log of both sides:

$$\begin{aligned}
\ln C_{yt} = & \ln q_{ym,g} + \alpha \ln K_{yt} + \beta \ln Len_{yt} + \ln Z_{y0} + (\ln W_t - m_0(t) - m_1(t)) + m_f * \sum_{i=0}^{t-1} \frac{H_{yi}}{W_i} \\
& + a_1 \sum_{i=\tau-t+1}^t OI_{yi} + a_2 \sum_{i=\tau-t+1}^t TI_{yi} + a_3 \sum_{i=\tau-t+1}^t SI_{yi} + b_1 \ln O_{yt} + b_2 \ln T_{yt} + b_3 \ln S_{yt} + \epsilon_{yt}
\end{aligned} \tag{2.10}$$

Note that in Equation 2.10, the parameters  $W_t$ ,  $m_0(t)$  and  $m_1(t)$  are not year-specific. Therefore, without a loss of generality, we can choose a basis year such that these non-year-specific terms cancel, obtaining the following:

$$\begin{aligned}
\ln C_{yt} - \ln C_{bt} = & (\ln q_{ym,g} - \ln q_{bm,g}) + \alpha (\ln K_{yt} - \ln K_{bt}) + \beta (\ln Len_{yt} - \ln Len_{bt}) \\
& + (\ln Z_{y0} - \ln Z_{b0}) + m_f * \left( \sum_{i=0}^{t-1} \frac{H_{yi}}{W_i} - \sum_{i=0}^{t-1} \frac{H_{bi}}{W_i} \right) + a_1 \sum_{i=\tau-t+1}^t (OI_{yi} - OI_{bi}) \\
& + a_2 \sum_{i=\tau-t+1}^t (TI_{yi} - TI_{bi}) + a_3 \sum_{i=\tau-t+1}^t (SI_{yi} - SI_{bi}) + b_1 (\ln O_{yt} - \ln O_{bt}) \\
& + b_2 (\ln T_{yt} - \ln T_{bt}) + b_3 (\ln S_{yt} - \ln S_{bt}) + (\epsilon_{yt} - \epsilon_{bt})
\end{aligned} \tag{2.11}$$

where  $b$  denotes the basis year. This equation provides a complete model structure describing how the environmental factors influence stock dynamics and harvest.

Estimates of the parameters in Equations 2.3-2.4 for brown shrimp are available in the literature though not necessarily specific to the North Carolina population (Table 2.1). With these two equations, we now can apply the model (Equation 2.11) to empirical data to test the hypothesis that environmental variables, and in particular low dissolved oxygen, affect shrimp harvest.

### 2.2.3 Data

We use harvest data from the North Carolina Division of Marine Fisheries (NCDMF) trip ticket program<sup>2</sup>. Each dealer reports commercial landings information for each individual fishing trip, including the gear type, trip starting and landing date, and price and quantity of landed fish and shrimp. From 1978 to 1993, North Carolina commercial landings information was collected on a voluntary basis. In 1994, the N.C. General Assembly mandated trip-level reporting of commercially harvested species. The data used in this paper contain complete shrimp landings in the Neuse River and Pamlico Sound from 1999-2005. This is the period over which water quality has been continuously monitored in the Neuse River estuary. Table 2.2 shows the summary statistics for the harvest of brown shrimp.

We use water quality monitoring data collected by the United States Geological Survey (USGS) from the Neuse River estuary<sup>3</sup>. Previous studies have documented that the Neuse River estuary experiences severe and recurring hypoxia during the summer months that leads to fish kills and other ecological effects ([71], [53], [32]). The data consist of surface and bottom measurements of dissolved oxygen, temperature, salinity and other water quality variables at a 15-minute sampling interval from 1999 to 2005 from three moorings in the Neuse river (Fig. 2.1). These data have been the basis for several water quality modeling efforts and other studies in the system ([11], [100]). We take the average of the 15-minute values each day over these three moorings as a daily measure of environmental conditions. Because shrimp are demersal and strongly associated with the bottom, we use bottom values for dissolved oxygen, temperature and salinity (Table 2.2). We quantify the severity of hypoxia by calculating the number of days during which average bottom dissolved oxygen

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<sup>2</sup> North Carolina Division of Marine Fisheries Trip Ticket Program, V. 7. Available at <http://www.ncfisheries.net/statistics/tripticket/index.htm>

<sup>3</sup> Available at: <http://nc.water.usgs.gov/infodata/waterquality.html>

concentrations are below some thresholds in each year from 1999 to 2005 (Range  $< 2 \text{ mgl}^{-1}$  is reported in the table. We also use ranges  $< 1.5 \text{ mgl}^{-1}$  and  $< 2.5 \text{ mgl}^{-1}$ ). The average number of hypoxic days over these seven years is 61 days per year for range  $< 2 \text{ mgl}^{-1}$ . For temperature and salinity conditions, the intolerable temperature threshold is defined as  $< 4.4^{\circ}\text{C}$  &  $> 32.2^{\circ}\text{C}$  and Intolerable salinity threshold is  $< 5$  ppt.

Similar water quality data are not available for Pamlico Sound. The Pamlico Sound may experience hypoxia, particularly near the mouths of major tributaries ([72]) but shrimp harvest in the Sound is more likely influenced indirectly by dissolved oxygen conditions in its tributaries. Therefore, hypoxia effects on growth, mortality or emigration of shrimp in the Neuse River and other tributaries may have important consequences for harvest in the Pamlico Sound. We use water quality data in the Neuse River estuary as a proxy for conditions in the major tributaries supplying the sound and then quantify the effects of hypoxia on shrimp harvest in both the Neuse River and the Pamlico Sound.

To test the hypothesis that environmental factors influence shrimp harvest using Equation 2.11, we need an estimate of the initial number of shrimp in each year. The NCDMF conducts annual monitoring surveys for shrimp and finfish in early May to June. The shrimp survey (program 510) samples multiple stations throughout the Albemarle-Pamlico Sound estuarine system and its tributaries during the last week of May or first week of June. The survey is designed to provide information on annual recruitment to set opening dates for the fishery. One minute tows are conducted during daytime with a 10.5 ft. bottom trawl with 1/4" mesh in the body and 1/8" mesh in the cod end. The estuarine trawl survey (program 120) samples about 100 fixed stations in shallow ( $< 2$  m) nursery habitats from Roanoke Island through Cape Fear River. One minute tows are conducted during daytime with a 3.2-m otter trawl with 6.4-mm mesh in the wings and body and 3.2-mm mesh in the cod end ([108]).

These surveys record shrimp species, catch-per-unit-effort (CPUE), and total length at each station. Additional details on the survey design can be found in West ([108]) and West and Wilson ([109]). We calculate the average CPUE of brown shrimp from each of these surveys and then average across the two surveys in each year to construct an annual index of initial brown shrimp abundance for each year from 1999 to 2005.

We specify the 80th day of the calendar year as the starting point for the model, which is about the time of larval ingress and subsequent settlement into juvenile nursery habitats ([52], [51]). In the estimation, we start with a full model including all variables and then use a backwards selection procedure to eliminate statistically insignificant variables based on F-tests. In addition to the environmental (oxygen, temperature, salinity) and fishing effort (trip days, vessel length) variables, we also consider the effects of month (July to November), gear, and their interaction. We only consider two types of gear in our model (“Shrimp Trawl” and “others”) because 91% of the brown shrimp harvested were taken by shrimp trawl. Month and Gear x Month interaction are used to capture the effect of catchability on shrimp harvest ( $q_{ym,g}$  in Equation 2.11). The variables in the model are each differenced between the current year and a basis year. We choose 2000 as the basis year. Choosing a different basis year would not affect the statistical results. We estimate the parameters of the differenced model with a 60-day lagged hypoxia effect separately for the Neuse River and the Pamlico Sound. We choose 60 days because this is probably the minimum period during which shrimp are resident in the estuary ([51]). We evaluate this assumption in a later section (see Robustness of Findings).

## 2.3 Results

### *2.3.1 Empirical results for the differenced model*

The fit of our regression model (Equation 2.11) indicates that the parameter estimates for the number of trip-days and vessel length are positive for both the Neuse River and Pamlico Sound, consistent with our expectation that increased fishing effort leads to increased harvest (Table 2.3). The parameter estimate for total harvest (“Accumulated harvest diff” in Table 2.3) which represents fishing mortality, is negative in both models. This is also consistent with our expectations that fishing reduces the abundance of the stock. Average daily temperature in the estuary is never outside of the tolerable range (4.4 to 32.2 °C (Table 2.2)) and so there is no associated parameter estimate for the binary effect of temperature. The effect of salinity is positive and significant for the Neuse River, indicating higher harvest when salinities are high, but not for the Pamlico Sound. For the variables representing the continuous effects of environmental factors on shrimp harvest, which describe contemporaneous conditions that are not cumulative over time, no variable is significant in either the Neuse River or the Pamlico Sound models.

The effect of dissolved oxygen on shrimp harvest (accumulated oxygen index, Table 2.3) is negative and significant for both the Neuse River and the Pamlico Sound models. For the Neuse River model, the coefficient is  $-0.01343$ , which means that one day of hypoxia leads to a decrease of 1.343% of the total shrimp harvest in the Neuse River for each of the 60 days after the hypoxic day. Similarly, for Pamlico Sound one day of hypoxia leads to a decrease in harvest of 1.01% for each of the following 60 days. Using these marginal effects, we then can measure the total annual hypoxia effects.

If we compare the observed pattern of hypoxia in the Neuse River to a pristine system with no hypoxia, then the total (1999-2005) decrease in harvest attributable

to hypoxia is 102 654 pounds or 12.87% of the total harvest over the seven year period (Table 2.3). We multiply the harvested weight of shrimp by the weighted average daily price over different shrimp sizes <sup>4</sup> to estimate the annual decrease in revenue to the shrimp fishery due to hypoxia. We estimate a decrease of about \$32 000 (converted to 1999 dollars using the Consumer Price Index<sup>5</sup>) per year in value, which is 13.08% of the total Neuse River catch revenue over the seven year period. Similarly, for the Pamlico Sound, there is a decrease of 12.9% of the total catch due to hypoxia, which translates into a value of \$1.24 million (in 1999 dollars), or 13.43% of total revenue from 1999-2005.

### *2.3.2 Robustness of Findings*

The results from our differenced bioeconomic model suggest that hypoxia can have substantial economic consequences for the North Carolina brown shrimp fishery. In this section, we address the robustness of our findings by varying the lag length in the differenced bioeconomic model, which determines the time over which hypoxia effects are accumulated. In order to check how sensitive of our 60-day differenced model results are to the hypoxia avoidance range ( $< 2 \text{ mgl}^{-1}$ ), we run models with different hypoxia thresholds. We then develop and analyze two different model types, a non-differenced model and a polynomial distributed lag model.

#### *The differenced model with different day lags*

The previous results show that there is a significant effect of hypoxia on shrimp harvest in the Neuse River and the Pamlico Sound when environmental effects are accumulated over 60 days (Table 2.3). Figure 2.2 reports the results from the same

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<sup>4</sup> The weighted average daily price of shrimp is calculated by dividing the total shrimp value(\$ on day t by the total shrimp catch(lbs) on the same day.

<sup>5</sup> All the economic values in this paper are converted to 1999 dollars using the US Consumer Price Index for all urban consumers.

model but with the number of lagged days set from 30 to 100 days. There are statistically significant effects of hypoxia on shrimp harvest in the Neuse River for almost all of the different lags (except 50-day lag). The coefficients for the hypoxia effect on shrimp harvest are all negative, suggesting a trend toward decreased shrimp harvest in the Neuse with increasing severity of hypoxia. Similarly, there are significant negative effects of hypoxia on shrimp harvest in Pamlico Sound at almost all lags except for 80 days. The reduction in harvest in the Neuse River based on parameter estimates from models with different lags varies from 9.23% to 14.92%, which is of similar magnitude to that at 60-day lag (12.87%). For the Pamlico Sound model, the reduction in harvest ranges from 9.21% to 13.41%, which again is similar to that at 60-day lag (12.90%). Therefore, hypoxia effects on shrimp harvest are robust to variation in the duration over which these effects are accumulated in the model.

*The differenced model with different hypoxia thresholds*

In order to check the robustness of the differenced model to the hypoxia threshold, we run models for the Neuse River and Pamlico Sound using  $<1.5 \text{ mgl}^{-1}$  and  $< 2.5 \text{ mgl}^{-1}$  as two alternative intolerable oxygen ranges, while keeping other assumptions the same as in the 60-day differenced model. We find that for the Neuse River model, the hypoxia effect is significant with the  $1.5 \text{ mgl}^{-1}$  threshold, but not significant with  $2.5 \text{ mgl}^{-1}$  threshold. While for the Pamlico Sound model, the hypoxia effects are significant for both ranges. The coefficients are similar in magnitude to those from the 60-day differenced model. The reduction in harvest is also similar. We estimate a 11.43% decrease in harvest in the Neuse River with the  $1.5 \text{ mgl}^{-1}$  threshold, and a 11.41% and 13.26% decrease in harvest in the Pamlico Sound with the  $1.5 \text{ mgl}^{-1}$  and  $2.5 \text{ mgl}^{-1}$  thresholds, respectively.

### A Non-differenced model

The differenced model (Equation 2.11) allows us to simplify the original model (Equation 2.10) by omitting terms describing the growth and loss rate (mortality and emigration) of shrimp, which are not well-known. If these biological parameters were known, then the non-differenced version of the model (Equation 2.10) could be fit. The advantage of the non-differenced model is that we can use more detailed information on shrimp harvest that is specific to each trip  $j$  on day  $t$  instead of the average catch on each day. We develop a non-differenced form of the model by using a natural mortality rate to represent shrimp loss. Thus, Equation 2.10 can be rewritten as:

$$\begin{aligned} \ln C_{ytj} = & \ln q_{ym,g} + \alpha \ln K_{ytj} + \beta \ln Len_{ytj} + \ln Z_{y0} + (\ln W_t - m_0(t) - m_1(t)) + m_f * \sum_{i=0}^{t-1} \frac{H_{yi}}{W_i} \\ & + a_1 \sum_{i=y\tau-yt+1}^{yt} OI_{yi} + a_2 \sum_{i=y\tau-yt+1}^{yt} TI_{yi} + a_3 \sum_{i=y\tau-yt+1}^{yt} SI_{yi} + b_1 \ln O_{yt} + b_2 \ln T_{yt} + b_3 \ln S_{yt} + \epsilon_{ytj} \end{aligned} \quad (2.12)$$

Equation 2.12 is identical to Equation 2.10 except that the catch ( $C$ ), number of trip days ( $K$ ) and vessel length ( $Len$ ) are specific to each shrimping trip. Natural mortality can then be modeled as a function of shrimp length:

$$m_0(t) = \int_0^t \phi L(s)^\rho ds \quad (2.13)$$

where  $L(t)$  is shrimp length (modeled by Equation 2.3) at time  $t$ , and  $\phi$  and  $\rho$  are parameters. The daily instantaneous natural mortality rate of shrimp ( $\Delta m_0(t)$ ) decreases as shrimp increase in body size ( $\phi > 0$  and  $\rho < 0$ ). Estimates of  $\phi$  and  $\rho$  in Equation 3.4 were taken from Minello et al. ([64]) (Table 2.1). Figure 2.3 shows the temporal dynamics of shrimp biomass with no hypoxia, no harvest, and

the dynamics driven by the natural mortality rate from Equation 3.4 and weight dynamics (Equation 2.4).

The only remaining unknown parameter in the non-differenced model (equation 12) is the migration rate  $m_1(t)$ <sup>6</sup>. Emigration rates of shrimp from estuarine systems are not well-documented and are probably highly variable across species and ecosystems. Therefore, we fit the non-differenced model assuming the migration rate is zero. Although this assumption will induce some unknown bias in the parameter estimates, the results are still useful for making qualitative comparisons of the magnitude of hypoxia effects on shrimp harvest between the non-differenced and differenced models.

Based on the non-differenced model, hypoxia effects on shrimp harvest in the Neuse River and the Pamlico Sound are both negative and significant (Table 2.4). Compared to the differenced model, the magnitude of the hypoxia effect is larger in both models (-0.01682 versus -0.01343 for the Neuse River and -0.02164 versus -0.01014 for the Pamlico Sound), indicating that our initial results from the differenced model may be conservative. This difference in the magnitude of the hypoxia effect between the two models may be due to the omission of the migration parameter in the non-differenced model so that any effect of hypoxia on shrimp emigration is absorbed in part by the accumulated effect of hypoxia. Alternatively, the differenced model may underestimate the magnitude of the hypoxia effect if hypoxia induces emigration from the system over that in the absence of hypoxia. Both models have potential sources of bias but yield qualitatively similar results.

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<sup>6</sup> For the Neuse model, migration rate is the rate of emigration from the Neuse to the Pamlico and for the Pamlico model, from the Pamlico to the ocean

*Polynomial Distributed Lag model*

The differenced model assumes that the marginal effect of hypoxia on shrimp harvest is the same over each day of the chosen number of lagged days. To relax this assumption, we use a polynomial distributed lag (hereafter, PDL) to model the lagged effect of hypoxia allowing different marginal effects for each day. Equation 11 becomes:

$$\begin{aligned}
 \ln C_{yt} - \ln C_{bt} &= (\ln q_{ym,g} - \ln q_{bm,g}) + \alpha(\ln K_{yt} - \ln K_{bt}) + \beta(\ln Len_{yt} - \ln Len_{bt}) \\
 &+ (\ln Z_{y0} - \ln Z_{b0}) + m_f * \left( \sum_{i=0}^{t-1} \frac{H_{yi}}{W_i} - \sum_{i=0}^{t-1} \frac{H_{bi}}{W_i} \right) + \sum_{i=\tau-t+1}^t a_{1i}(OI_{yi} - OI_{bi}) \\
 &+ \sum_{i=\tau-t+1}^t a_{2i}(TI_{yi} - TI_{bi}) + \sum_{i=\tau-t+1}^t a_{3i}(SI_{yi} - SI_{bi}) + b_1(\ln O_{yt} - \ln O_{bt}) \\
 &+ b_2(\ln T_{yt} - \ln T_{bt}) + b_3(\ln S_{yt} - \ln S_{bt}) + (\epsilon_{yt} - \epsilon_{bt}) \tag{2.14}
 \end{aligned}$$

Note that now the marginal effects of each environmental factor on shrimp harvest can vary on each day ( $a_i$  in the above equation). The  $a_i$  can then be modeled with orthogonal polynomials as:

$$a_i = \rho_0 + \sum_{k=1}^d \rho_k f_k(i) \tag{2.15}$$

where  $\rho_1-\rho_d$  are the coefficients to be estimated,  $d(\leq \tau)$  is the degree of the polynomial, and  $f_k(i)$  is a polynomial of degree  $k$  in the lag day  $i$  (see Judge et al. (1988) for a detailed discussion of the PDL).

To compare results from the PDL model to our earlier results we set  $\tau = 60$ , the number of lagged days in the differenced and non-differenced models above. We fit the differenced PDL model with different degrees for the polynomials ( $d = 1$  to 16) and use the Akaike Information Criterion (AIC) to choose the best model. The values of AIC for each of these models are shown in Table 2.5. The best models for both the Neuse River and the Pamlico Sound had a polynomial of degree one ( $d=1$ )

(reported in Table 2.6). As expected, the coefficients for trip days and vessel length are positive and significant. The marginal daily effects of hypoxia on shrimp harvest are below zero (not shown), which is consistent with our earlier result of negative effects of hypoxia on harvest in the Neuse River and the Pamlico Sound. Based on the PDL model, the average potential loss of shrimp harvest for the Neuse River that is attributable to hypoxia is 15.47% (range: 6.94% to 35.18% over the seven years). For the Pamlico Sound, the average loss is 20.56% (range: 12.75% to 29.54% over the seven years) (Fig. 2.4). The predicted effect of hypoxia from the PDL model is larger than that of the differenced model, but the estimates are of similar magnitude. The PDL model likely overestimates the hypoxia effect somewhat because some of the marginal daily effects in the PDL model are negative but not significant.

## 2.4 Conclusion

In this paper, we develop a bioeconomic model to assess the economic effect of hypoxia on the North Carolina brown shrimp fishery. In the Neuse River, a major tributary to the larger estuarine system, model estimates indicate about a 12.87% decrease in shrimp harvest relative to a pristine system with no hypoxia. Model estimates for the Pamlico Sound, which does not experience severe hypoxia but is the primary fishing ground for shrimp that use riverine tributaries as nursery habitat, also indicate about a 12.90% decrease in harvest attributable to hypoxia. In terms of lost revenue, the decline in harvest due to hypoxia equates to a loss of \$32 000 (in 1999 dollars) per year in the Neuse River fishery and about \$1.24 million (in 1999 dollars) per year in the Pamlico Sound fishery. This difference in magnitude of lost revenue is due to the much larger size of the Pamlico Sound fishery, which accounted for about 50.9% of the statewide harvest over the 1999-2005 period. Our results are robust to different assumptions about the duration of temporal lags between when hypoxia effects occur and when they are expressed in the fishery, as well as

several alternative model structures (differenced, non-differenced, and polynomial distributed lags) with different underlying assumptions. In fact, permutations of the model indicate that harvest losses attributable to hypoxia range from 8 to 35% suggesting our primary results (12.9%) are conservative.

A major contribution of this paper is the integration of trip-level catch and effort data (microdata) from a commercial fishery with high-resolution (daily), continuous water quality monitoring data to capture the complex relationships between environmental factors and fishery harvests with lagged effects. Compared to previous approaches, our model makes use of detailed temporal and spatial information, which we argue is important for evaluating the economic effects of hypoxia, particularly in dynamic systems where environmental conditions, fishing effort, and harvest are changing through time. Because hypoxia influences shrimp harvest both through effects on processes underlying production (e.g., growth, mortality), including effects on juveniles before they are subject to fishing mortality, and on processes influencing catchability (e.g., emigration, avoidance behavior), it is necessary to model these bioeconomic pathways throughout the life history. Our model is able to take these complexities into account and, thus, able to evaluate the economic effects of hypoxia on the fishery using a highly disaggregated fishery dataset.

An important caveat is that our model is only able to measure the net effect of hypoxia on the fishery but is unable to distinguish among various underlying causal mechanisms. For example, hypoxia can lead to reduced growth and survival due to direct exposure to low oxygen ([63], [98]). Organisms that avoid hypoxia may also experience reduced growth and survival via a number of indirect mechanisms ([13], [32]). In either case, decreases in abundance and biomass due to hypoxia may influence subsequent harvest by the fishery. Hypoxia may also alter spatial distributions or emigration rates of shrimp, thus altering catchability to the fishery. For example, Craig ([23]) and Craig and Crowder ([24]) have showed that brown

shrimp aggregate at high density near the edges of hypoxic zones and suggested that catchability to the commercial shrimp trawl fishery may be locally enhanced in these regions. Alternatively, hypoxia may enhance dispersion leading to decreases in catchability. While our results indicate a significant economic effect of hypoxia on the North Carolina shrimp fishery, additional research is necessary to identify the particularly ecological and fishery interactions that contribute to this effect.

In this paper, we provide the first empirical bioeconomic assessment of hypoxia-induced declines in harvest and revenues in a commercial fishery using microdata. Studies that use aggregated data typically fail to detect statistically significant economic impacts of hypoxia on fisheries ([27]). Of the papers that use microdata, Massey et al. ([60]) is the most similar case to ours. They analyze the economic consequences of hypoxia for the summer flounder recreational fishery in a tributary of Chesapeake Bay using a bioeconomic simulation model that considers the dynamic effects of low dissolved oxygen. They report that recreational catches could potentially increase by approximately 2% if the number of hypoxic days was reduced by 50% in the study region (a modest amount). If the number of hypoxic days were reduced by 50% in all of Maryland's coastal bays, however, they find a potential 20% increase in harvest. Our finding of a potential 12.9% increase in shrimp harvest in the North Carolina commercial fishery as a result of eliminating hypoxia in the Neuse is seemingly large, as the Neuse is just one of several major tributaries that contribute to the shrimp fishery. However, it is the largest tributary to the system, suggesting it may be an important source of recruits to the fishery, and it is morphologically similar to the other major tributary to the north (the Pamlico River) that is also known to experience hypoxia ([96]). To the extent that year class strength of shrimp and the severity of hypoxia are spatially correlated across riverine tributaries, perhaps due to regional patterns in climatic conditions and freshwater and nutrient loading, then environmental conditions in the Neuse may reflect broader patterns influencing

the fishery. From this perspective, our results appear to be of comparable magnitude to those of Massey et al. ([60]).

It is important to note that our analysis compares the actual shrimp harvest to a scenario with no hypoxia for one whole year (the dissolved oxygen level is at least  $2 \text{ mg l}^{-1}$ ). To conduct a complete cost-benefit analysis, it would be necessary to calculate the non-fishery benefits of reduced hypoxia, benefits to other fisheries, and to quantify the costs of reducing nutrient pollution in order to achieve improved oxygen conditions. Our result of \$1.24 million (in 1999 dollars) in lost annual revenues to the Pamlico Sound fishery would amount to \$27.56 million total lost revenues over time (in perpetuity) using a 4.5% real discount rate. If we assume no behavioral changes in the fishery (a strong assumption), we can equate this revenue loss to lost fishery rents. In a simulation model, Smith ([94]) found that a 30% reduction in nutrient loading to the Neuse would lead to \$0.7-6.4 million (1999 dollars) present value rent increases for the blue crab fishery depending on model parameters. Our results for the North Carolina brown shrimp fishery are not directly comparable to those for the blue crab fishery because the biology of blue crab is very different from that of brown shrimp, the industry structures are different, a 30% reduction in nutrients would not necessarily eliminate hypoxia, and the blue crab simulation model allows for entry to the fishery in response to increased fishery productivity. With these caveats in mind, the economic gains from reducing nutrient pollution include the gains that accrue to both of these important commercial fisheries, which have historically been the most valuable in the state. By way of comparison to the potential lost fishery revenues due to hypoxia, the perpetuity cost of reducing nutrient pollution would range from \$155-266 million, a range based on converting annual 1994 dollars from Schwabe ([84]) to a perpetuity value in 1999 dollars. Therefore, gains in fishery rents appear to pay for a small fraction of the costs of reducing nutrient pollution. Benefits from other sources, such as consumer gains from lower seafood prices, gains to other

fisheries, and non-market benefits, would need to be substantial in order to justify dramatic policy actions to reduce nutrient pollution based on cost-benefit analysis applied to individual fisheries alone.

Our model provides a road map for resolving spatio-temporal lagged effects of habitat degradation on fisheries. We calculate the economic effects of hypoxia by analyzing the dynamics of catch data in both the nursery and in the adjacent primary fishing ground, noting that many of the economic consequences result from how juvenile shrimp are affected in the nursery grounds before the fishing season. Linking the nursery habitat and fishing grounds requires making some assumptions, but establishing causality via other approaches is likely to present similar challenges. Many fished species spend critical life stages in habitat that differs from where they are fished, and tracking larvae and juveniles from nursery areas to fishing grounds is notoriously difficult. Because fishing effort, fleet composition, and other environmental factors are in flux, the effects of habitat degradation will be difficult to detect given the noise inherent in aggregate fisheries data. We demonstrate that controlling for dynamic factors in finely resolved fishery microdata provides a structure for extracting this noisy signal.

On a broader level, our analysis illustrates a useful approach for providing input into ecosystem-based fishery management. Though we focus on a specific case of intermittent hypoxia in a moderate sized fishery, our model could be adapted to study potentially more economically consequential cases such as the effects of the Gulf of Mexico dead zone on Gulf shrimp fisheries. Perhaps more importantly, econometric modeling that links water quality data and fishing microdata can be used to study a wide range of ecosystem impacts on fisheries and their economic consequences. A similar model to the one in our paper could analyze the economic consequences of toxic algal blooms, changes in fresh water supply to estuaries (e.g., due to drought or upstream diversions), sedimentation, or other habitat disturbances. The key in-

redients in all of these cases would be: 1) water quality data with sufficient temporal resolution to address lags in responses of fishery productivity to environmental changes, 2) fishing microdata that allows the analyst to control for changing fleet composition over time such as the number of fishing trips by gear type and vessel size, and 3) a bioeconomic link that connects the two spatially. These ingredients are likely to be present for many managed fisheries in the U.S. and elsewhere, which increasingly require spatially-detailed logbooks and vessel monitoring systems, trip landings tickets, and observer coverage. Econometric modeling of fishery-dependent data is not a panacea, but it offers a useful empirical approach for translating the effects of environmental degradation into economic terms that can be used to help inform policy decisions.

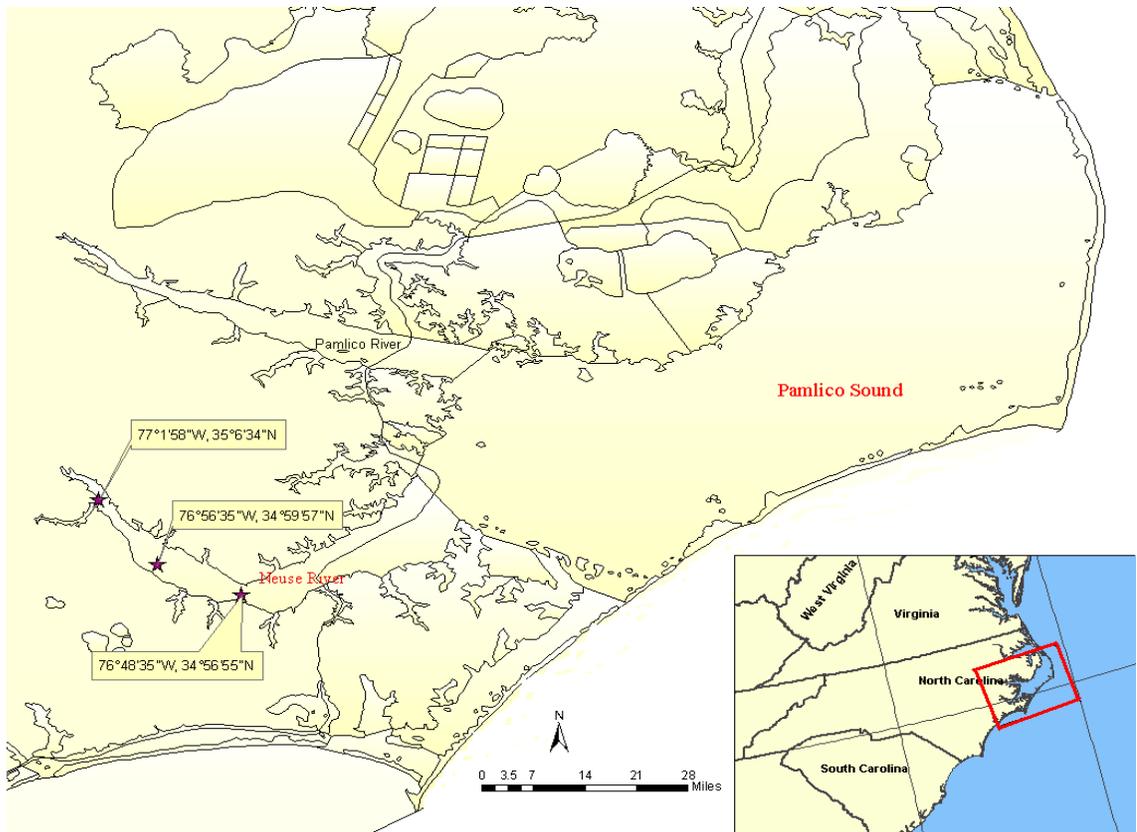


FIGURE 2.1: Waterbodies and water quality monitoring sites

Note: Most of the North Carolina shrimp fishery is conducted in the Pamlico Sound, major tributaries feeding the Sound such as the Neuse River and Pamlico River, and in nearby estuaries such as the Core Sound. Three water quality monitoring sites are located in the Neuse River.

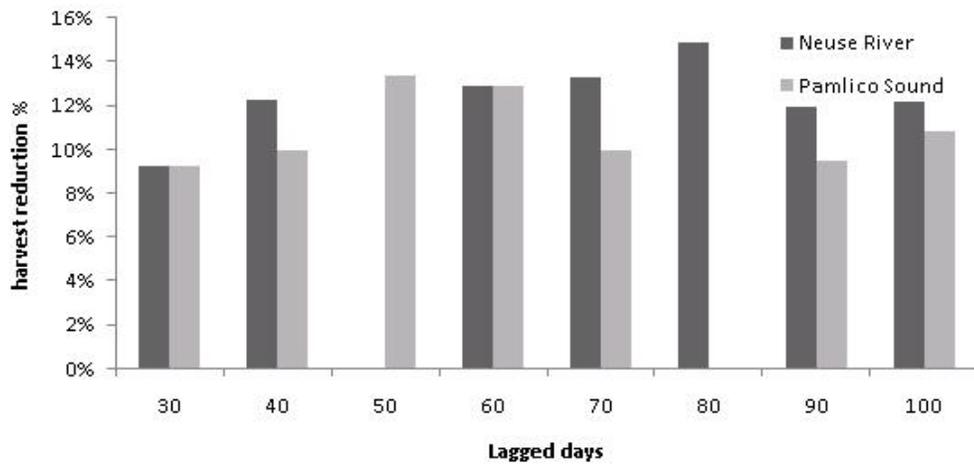


FIGURE 2.2: Harvest reduction due to hypoxia with different lagged days

Note: Depicts the results of the differenced model with different lagged days. In almost all cases, the hypoxia variable is negative and statistically significant.

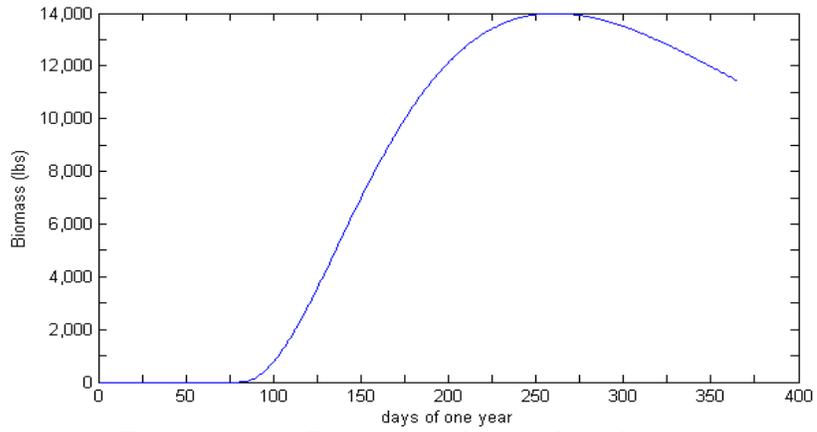


FIGURE 2.3: Biomass index within the season

Note: Depicts the time path of a shrimp biomass index when there is no harvest and no hypoxic effects. The path is based on the population parameters in Table 2.1 and the initial shrimp number is set to  $10^6$ .

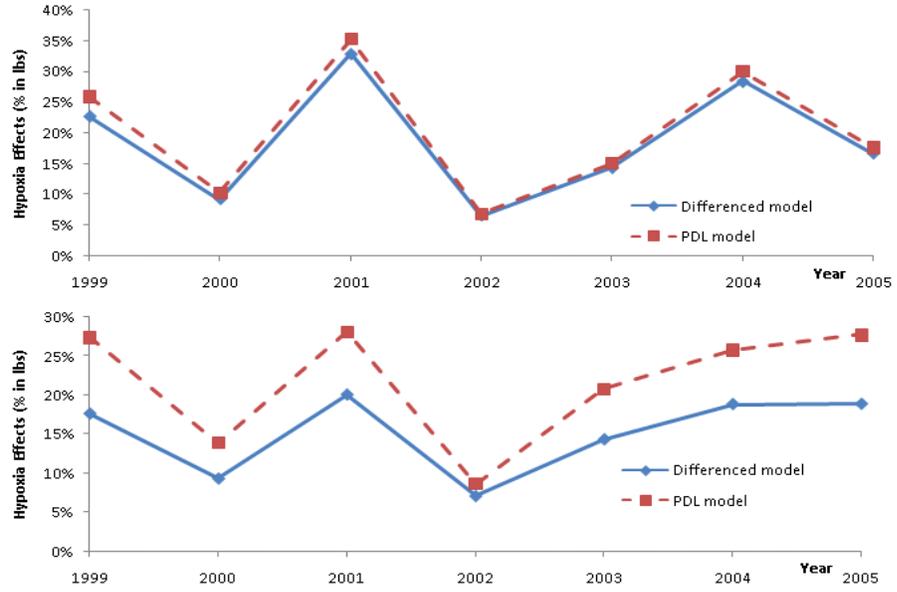


FIGURE 2.4: Yearly hypoxia effect

Note: Depicts the percent losses in revenue due to hypoxia (compared to the baseline case of no hypoxic days) for each year of the study period. The differenced model (solid line) is our main result, while the PDL (dashed line) serves as a robustness check.

Table 2.1: Parameter sources

Parameter	Value	Function	Parameter source
$L_{\infty}$	177.7	Von-Bertalanffy growth function	McCoy 1968
$\delta$	-0.0104	Von-Bertalanffy growth function	McCoy 1968
$\phi$	1.4866	Natural mortality rate	Minello et. al. 1989
$\rho$	-1.1163	Natural mortality rate	Minello et. al. 1989
$\omega$	10.52*E-06	Allometric function(weight)	Fontaine and Neal 1971
$\eta$	2.94	Allometric function(weight)	Fontaine and Neal 1971

Table 2.2: Summary statistics

Harvest Data: Neuse River									
Variable	Obs.	Mean	Std. Dev	Minimum	Maximum				
Catch/trip(lbs)	2245	308.4	579.1	4.0	7985.6				
Trip days(days)	2245	1.9	1.3	1.0	10.0				
Vessel Length(feet)	2211	37.0	13.6	15.0	80.0				
Harvest Data: Pamlico Sound									
Variable	Obs.	Mean	Std. Dev	Minimum	Maximum				
Catch/trip(lbs)	11690	1524.7	1808.7	1.0	22097.0				
Trip days(days)	11690	3.5	3.9	1.0	366.0				
Vessel Length(feet)	11651	51.9	18.1	12.0	91.0				
Annual Data									
year		1999	2000	2001	2002	2003	2004	2005	Mean
<b>Neuse River</b>	Annual Catch(lbs)	17 915	193 960	18 063	162 860	99 077	73 550	108 228	96 236
<b>Pamlico Sound</b>	Annual Catch(lbs)	1 208 294	5 096 432	2 495 106	4 618 086	1 991 780	1 602 778	547 580	2 508 579
<b>Water</b>	Mean of Bottom DO ( $mg\ l^{-1}$ )	5.28	6.03	5.46	5.89	5.96	5.52	6.52	5.81
	Mean of Bottom Temp( $^{\circ}C$ )	17.39	19.49	18.43	18.94	17.64	18.01	17.63	18.22
<b>Quantity</b>	Mean of Bottom Salinity(ppt)	8.38	8.35	12.21	15.29	5.25	7.94	7.70	9.30
<b>Annual intolerable days</b>	days of Bottom DO < 2 $mg\ l^{-1}$	50	38	80	43	69	87	57	61
	days Bottom Temp < 4.4 $^{\circ}C$ or > 32.2 $^{\circ}C$	0	0	0	0	0	0	0	0
	days of Bottom Salinity < 5 ppt	78	51	26	2	224	100	80	80

Note: DO represents dissolved oxygen concentration ( $mg\ l^{-1}$ ).

Table 2.3: 60 days lagged hypoxia effect with the differenced model

	Neuse River			Pamlico Sound		
Variable	Year specific			Parameter Estimate	(Std. Error)	Pr > F
Intercept	-0.22601	(0.09228)	0.0149	-0.38668	(0.05173)	<.0001
Gear*Month7 diff	-	-	-	-	-	-
Gear*Month8 diff	-	-	-	-	-	-
Gear*Month9 diff	-0.63218	(0.23135)	0.0067	-	-	-
Gear*Month10 diff	-	-	-	-	-	-
Gear*Month11 diff	-	-	-	1.22423	(0.29705)	<.0001
Initial shrimp abundance diff	-	-	-	-	-	-
Log of trip days diff	1.11913	(0.09397)	<.0001	0.16995	(0.04304)	<.0001
Log of vessel length diff	0.94943	(0.17746)	<.0001	2.61114	(0.10939)	<.0001
Accumulated oxygen index diff	-0.01343	(0.00535)	0.0126	-0.01014	(0.0029)	0.0005
Accumulated salinity index diff	0.00804	(0.00282)	0.0047	-	-	-
Accumulated harvest diff	-8.50E-08	(3.05E-08)	0.0056	-2.06E-09	(7.69E-10)	0.0077
Log of oxygen diff	-	-	-	-	-	-
Log of temperature diff	-	-	-	-	-	-
Log of salinity diff	-	-	-	-	-	-
Obs.	297			549		
R-square	0.3869			0.6062		
	Weight(lbs)	Value(\$)		Weight(lbs)	Value(\$)	
Actual harvest (7 years total)	695 061	1 467 358		17 823 727	55 867 879	
Predicted harvest reduction due to hypoxia (7 years total)	102 654	220 887		2 631 971	8 645 167	
Reduced harvest due to hypoxia(%) <sup>7</sup>	12.87%	13.08%		12.90%	13.43%	

Note: Reports our main findings using daily data for the fishery. “Month” is a dummy variable, while “Gear\*Month” is an interaction of a gear type dummy and month dummy. There are two types of gear in the model: shrimp trawl and others. Estimation uses backwards selection to eliminate statistically insignificant variables based on F tests. All variables left are significant at the 2% level. Variables are differenced between the current year and the basis year (2000). The “log of trip days diff” and the “log of vess length diff” are the differenced average trip days and average vessel length. “Accumulated oxygen index diff” is the variable that measures the dynamic effect of hypoxia. “Accumulated harvest diff” captures fishing mortality. The variables starting with “Log of” control for contemporaneous environmental conditions.

Table 2.4: 60 days lagged hypoxia effects with the non-differenced model

	Neuse River			Pamlico Sound		
	Year specific					
Variable	Parameter Estimate	(Std. Error)	Pr > F	Parameter Estimate	(Std. Error)	Pr > F
Intercept	-6.77884	(2.20338)	0.0021	-3.02186	(0.5775)	<.0001
Month5	1.99866	(0.65568)	0.0023	1.59276	(0.14744)	<.0001
Month6	2.78769	(0.53748)	<.0001	2.11061	(0.10331)	<.0001
Month7	2.18377	(0.54421)	<.0001	1.45981	(0.26284)	<.0001
Month8	2.06308	(0.55043)	0.0002	1.66689	(0.09791)	<.0001
Month9	1.33622	(0.54405)	0.0141	1.43574	(0.10027)	<.0001
Month10	-	-	-	0.89198	(0.10414)	<.0001
Gear*Month7	0.33852	(0.10104)	0.0008	0.75958	(0.24524)	0.0018
Gear*Month8	-0.41178	(0.13199)	0.0018	-	-	-
Initial shrimp abundance	0.46926	(0.12262)	0.0001	0.19393	(0.03343)	<.0001
Log of trip days	0.98428	(0.03638)	<.0001	0.62187	(0.01484)	<.0001
Log of vessel length	1.22298	(0.05503)	<.0001	2.00255	(0.02629)	<.0001
Accumulated oxygen index	-0.01682	(0.0019)	<.0001	-0.02164	(0.00091242)	<.0001
Accumulated salinity index	0.01223	(0.0025)	<.0001	-	-	-
Accumulated harvest	-8.32E-08	(1.49E-08)	<.0001	-4.31E-09	(2.93E-10)	<.0001
Log of oxygen	0.21609	(0.05739)	0.0002	-	-	-
Log of temperature	-	-	-	-	-	-
Log of salinity	-	-	-	-	-	-
Obs.	2 186			11 503		
R-square	0.5235			0.6286		

Note: Reports a robustness check of Table 3 using a non-differenced model with individual trip-level data. The model assumes deterministic population dynamics based on the parameters in Table 1 and no emigration.

Table 2.5: PDL model selection

Degrees	1	2	3	4	5	6	7	8
Neuse River	823.49*	825.52	828.14	831.17	833.19	830.20	832.28	835.00
Pamlico Sound	1286.57*	1288.99	1290.07	1292.87	1289.43	1293.15	1295.94	1297.68
Degrees	9	10	11	12	13	14	15	16
Neuse River	838.77	841.49	845.28	848.83	847.91	849.87	849.17	850.87
Pamlico Sound	1296.35	1299.24	1299.36	1301.12	1304.22	1303.86	1306.5	1300.14

Note: Reports the Akaike Information Criterion (AIC) for models with different polynomial degrees. The best model for each water body has the lowest AIC (indicated with a ‘\*’) and is used for comparisons to the differenced model.

Table 2.6: PDL models

	PDL for the Neuse river with 60 lags			PDL for the Pamlico Sound with 60 lags		
Year specific						
Variable	Parameter Estimate	(Std. Error)	Pr >  t	Parameter Estimate	Std. Error	Pr >  t
Intercept	-	-	-	-1.0133	(1.3998)	0.4694
$do_{ind} diff ** 0$	-0.1335	(0.045)	0.0033	-0.1464	(0.0326)	<.0001
$do_{ind} diff ** 1$	-0.0249	(0.0557)	0.6552	0.0389	(0.032)	0.2239
$sal_{ind} diff ** 0$	0.0172	(0.0684)	0.802	-0.027	(0.0271)	0.3204
$sal_{ind} diff ** 1$	0.2586	(0.0655)	<.0001	0.1137	(0.0378)	0.0028
gear_month6 diff	0.118	(0.2134)	0.5806	1.0273	(1.417)	0.4688
gear_month7 diff	-0.004601	(0.1801)	0.9796	0.8304	(1.4132)	0.557
gear_month8 diff	0.0259	(0.1697)	0.8787	0.6922	(1.4118)	0.6241
gear_month9 diff	-0.7698	(0.2426)	0.0017	0.5427	(1.4091)	0.7003
gear_month10 diff	-	-	-	0.3983	(1.409)	0.7775
gear_month11 diff	-	-	-	1.9129	(1.4388)	0.1842
Initial shrimp abundance diff	0.1252	(0.3219)	0.6977	-0.0425	(0.1522)	0.7801
Log of trip days diff	1.078	(0.0938)	<.0001	0.1645	(0.0428)	0.0001
Log of vessel length diff	0.8748	(0.1784)	<.0001	2.6055	(0.1108)	<.0001
Accumulated harvest diff	-6.17E-08	(3.76E-08)	0.0997	-3.89E-09	(1.20E-09)	0.0013
Log of oxygen diff	-0.0645	(0.0238)	0.0072	-0.008917	(0.0159)	0.5745
Log of temperature diff	-2.7802	(1.51)	0.0666	-0.3519	(0.6393)	0.5823
Log of salinity diff	-0.1717	(0.1565)	0.2738	-0.035	(0.0503)	0.4871
Obs.	297			549		
R-Square	0.4416			0.6232		
	Weight(lbs)	Value(\$)		Weight(lbs)	Value(\$)	
Reduced harvest due to hypoxia(%)	15.47%	15.79%		20.56%	21.31%	

Note: Reports parameter estimates for the Neuse River and the Pamlico Sound using 1<sup>st</sup> degree polynomial models.

# Optimal Harvest Strategies with Water Pollution: A Bioeconomic Analysis of Shrimp Fisheries and Hypoxia

## 3.1 Introduction

With the current shift towards ecosystem-based management, traditional natural resource management and protection of environmental quality are increasingly inter-related. Environmental quality affects the productivity of the natural resource base, and resource extraction can influence environmental quality. In spite of these feedbacks, natural resource extraction and environmental quality are typically managed by different agencies.

For fisheries resources, managers often have little or no control over environmental quality. Of particular importance for many fisheries is the degradation of estuarine habitat in which many fish spend critical life stages. Estuaries often experience hypoxia (low dissolved oxygen) and other environmental disturbances due to nutrient pollution from agricultural runoff and atmospheric deposition from fossil fuel combustion ([22]). Hypoxia, in turn, can lead to juvenile mortality and a range

of sub-lethal effects that have growth consequences. Several recent studies document the deleterious effects of hypoxia on fishery productivity by analyzing micro-level data from fishermen ([45], [60], [58]). These studies quantify the increased value to the fishery from improved environmental quality, but they presume that a regulator would be able to influence pollution. Unfortunately, fishery managers cannot control the flows of nutrients into estuaries and can only react to pollution levels. In this paper, we explore how fishery managers can set optimal harvest policies that condition on fluctuating environmental conditions in estuaries.

Previous bioeconomic studies have examined related issues but have not considered how environmental conditions may influence harvest rates within a season. In a theoretical study, McConnell and Strand ([61]) demonstrate that optimal management of the fishery is necessary to capture gains from water quality improvements. They compare only steady states under open access and optimal management. In a similar vein, Smith ([89]) develops a bioeconomic model calibrated to the North Carolina blue crab fishery. He analyzes the full dynamic path of fishery rents and shows that gains from reduced hypoxia are higher when the fishery is rationalized. However, these gains are dwarfed by the gains from rationalization even with no water quality improvements. In this paper, we examine specifically how the path of optimal management changes in the presence of hypoxia. Most recently, Carson et al. ([16]) theoretically model optimal harvest under cyclical population dynamics. They show that when ENSO cycles induce periodically fluctuating growth rates, optimal harvest is asynchronous with the ENSO cycle.

We analyze the brown shrimp fishery. Brown shrimp is one of the largest fisheries in the U.S. with nominal ex vessel landings over the past decade ranging from over \$156 million to nearly \$377 million.<sup>1</sup> Moreover, brown shrimp are fished in areas that experience seasonal hypoxia, most notably in the Gulf of Mexico. Like other

<sup>1</sup> See <http://www.st.nmfs.noaa.gov/st1/commercial/index.html>.

shrimp species, brown shrimp have an annual life cycle and a weak stock recruitment relationship, i.e. recruitment is virtually uncorrelated with the previous years' stock. As a result of these reproductive features, shrimp are managed with seasonal closures rather than total allowable catches. Nonetheless, our results indicate that there are opportunities to design more efficient harvest policies by adjusting season closures to take environmental disturbances into consideration.

We develop an age-structured bioeconomic model that accounts for growth and aging of brown shrimp based on Clark ([20]). We incorporate the effect of hypoxia directly into shrimp growth. In a numerical illustration, we calibrate the level of hypoxia to recent empirically-based growth effects from hypoxia in the Neuse River in North Carolina ([45]). Our results show that fishery managers should open the shrimp season earlier in years with more severe hypoxia. In a pristine year, there is a larger payoff from waiting to open the season and allowing shrimps to grow larger. However, greater environmental stress increases the opportunity cost of waiting.

### 3.2 The model

In this section, we develop a stylized bioeconomic model to consider the optimal harvest strategy of an annual species in the presence of an environmental disturbance. Our motivating example and numerical results are based on brown shrimp subjected to hypoxia, but our model could apply more broadly to other annual species like squid and other seasonally varying pollution problems. Shrimps have annual life cycles, usually spawning in spring and completing their life cycles in winter in deep offshore areas. Brown shrimp spend most of their lives growing in estuarine and inshore areas. In addition, shrimp have high fecundity rates. The features of an annual life cycle and high fecundity rates imply that the following year's shrimp stock does not depend on this year's stock and harvest. As such, it is reasonable to assume exogenous recruitment. We derive the optimal policy from the perspective

of a social planner in which the planner's objective is to choose the harvest path to maximize the total present value profits from harvesting.

### 3.2.1 The problem of optimal Harvest

Let  $p_t$  indicate the price of fish per unit at time  $t$  and  $q_t$  be the harvest in weight at time  $t$ . Let  $C(q_t, X_t)$  denote the cost function depending on harvest  $q_t$  and stock biomass  $X$  at time  $t$ . Then the social planner's problem can be formally described as:

$$\begin{aligned} \max_{\{q, T_0, T_1\}} \int_{T_0}^{T_1} (p_t * q_t - C(q_t, X_t)) e^{-rt} dt \\ \text{s.t. } \dot{X}_t = f(X(t), t) - q_t \end{aligned} \quad (3.1)$$

The first equation illustrates that the planner is to maximize the total present value profits by choosing the optimal harvest path between starting time  $T_0$  to end  $T_1$ , where  $r$  is the instantaneous discount rate. For the cost function, we assume that  $C_q(\cdot) > 0$ ,  $C_{qq}(\cdot) < 0$  and  $C_X(\cdot) < 0$ . The first two properties imply that the cost function is concave in fish harvest, while the third assumption indicates that higher total fish stock reduce harvest cost (the traditional stock effect). The constraint describes the stock dynamics consisting of a growth component ( $f(X(t), t)$ ) and harvest intervention ( $q_t$ ). We can decompose the growth component ( $f(X(t), t)$ ) into biological growth rates that are available in the biology literature. In general, the stock at time  $t$  can be represented as the following:

$$X_t = N_t * W_t \quad (3.2)$$

In this function,  $N_t$  is the number of individuals at time  $t$  and  $W_t$  is the weight of individual, so the total biomass ( $X_t$ ) is the product of number and weight. Furthermore, the number of fish can be modeled as a function of initial number and the mortality rate:

$$N_t = N_0 e^{\int_0^t -m(t) dt} \quad (3.3)$$

in which,  $N_0$  is the initial number of each season, which is independent of last season's stock and determined by nature. That is, we assume exogenous recruitment. In addition,  $m_t$  is the instantaneous mortality rate, thus the mortality rate at time  $t$  is an integration of  $m(t)$  over time. Because larger fish are typically subject to less predation,  $m(t)$  can be further modeled as:

$$m(t) = \beta(L(t))^\rho \quad (3.4)$$

In Equation 3.4,  $L(t)$  is the fish length and  $\beta$  and  $\rho$  are two parameters. We know that the number of fish decreases over time, so  $\beta > 0$  and  $\rho < 0$ . Correspondingly, the marginal mortality rate decreases over time while  $L(t)$  is always positive.  $L(t)$  itself can be modeled with a Von-Bertalanffy function:

$$L(t) = L_\infty(1 - e^{\delta t}) \quad (3.5)$$

In this von-Bertalanffy equation,  $L_\infty$  is the maximum length of an individual fish. The parameter  $\delta$  is less than zero to ensure that  $L(t)$  increases over time. Now we finally decompose the number of fish ( $N_t$ ) to a function of  $t$ . Recall that Equation 3.2 has two components, number of fish and weight  $W_t$ , which can also be modeled with an allometric function of shrimp length:

$$W_t = \omega L(t)^\eta \quad (3.6)$$

Here, weight is a function of length with parameters  $\omega$  and  $\eta$ . We require  $\omega > 0$  and  $\eta > 0$  to ensure that shrimp weight increases over time with an upper limit. Until now, the stock dynamics are due to natural growth without pollution stress. However, there might exist water pollution that influences their growth.

$$X_t = N_t * W_t * e^{\int_0^t -\phi A(t) dt} \quad (3.7)$$

In this equation,  $A(t)$  is an indicator of whether there is water pollution, specifically, hypoxia in our case. The coefficient,  $\phi$ , is the marginal effect of water pollution

on the fish growth. Note that we measure the effect at time  $t$  by integrating the effects over time since water quality problems like hypoxia can have cumulative effects ([45]).

With all the above equations, we are able to take the derivative of  $X_t$  with respect to  $t$  (see the Appendix for the details):

$$\dot{X}_t = X_t[-m(t) - \phi A(t) + \frac{\dot{W}_t}{W_t}] \quad (3.8)$$

At this point, the stock is expressed in a differential equation of mortality rate, weight and the hypoxia effect without the harvest intervention. If we include harvest, this equation becomes:

$$\dot{X}_t = X_t[-m(t) - \phi A(t) + \frac{\dot{W}_t}{W_t}] - q_t \quad (3.9)$$

To complete the specification of the social planner's problem, we further assume that the costs associated with harvest and stock are linearly separable which require that  $C_{hX}(\cdot) = 0$ . More specifically,

$$C(q_t, X_t) = \begin{cases} c_0 + cq_t^2 - kX_t & \text{if } q_t > 0; \\ 0 & \text{if } q_t = 0; \end{cases} \quad (3.10)$$

In this expression,  $c_0$ ,  $c$  and  $k$  are all positive parameters, in which  $c_0$  is the fixed cost and  $c$  is the variable cost coefficient. These parameters also satisfy the assumption that  $C(q_t, X_t) > 0$  if  $q_t > 0$ . With all the expressions of profit structure and stock dynamics, we can fully write down the social planner's problem in the

following:

$$\max_{\{q, T_0, T_1\}} \int_{T_0}^{T_1} (p_t * q_t - c_0 - cq_t^2 + kX_t)e^{-rt} dt \quad (3.11)$$

$$s.t. \dot{X}_t = X_t * (-m(t) - \phi A(t) + \frac{\dot{W}_t}{W_t}) - q_t$$

$$m(t) = \beta(L(t))^\rho$$

$$W_t = \omega L(t)^\eta$$

$$L(t) = L_\infty(1 - e^{\delta t})$$

$$N_0 \text{ known}$$

### 3.2.2 The Interior solution for the social planner's problem

In this section, we derive the optimal harvest strategy for the annual fishery in the presence of pollution. With the model specifications in the social planner's problem (Equation 3.11), we can write down the current value Hamiltonian. The solution is the admissible path  $\{q_t, X_t, T_0, T_1\}$  that maximizes the Hamiltonian, in which  $q_t$  is the control variable and  $X_t$  is the state variable. In addition,  $T_0, T_1$  are the season starting and ending points, respectively. To simplify the model, we only consider the interior solution. Thus the profit is always positive if  $q_t > 0$ . Let  $g(t)$  denote the expression  $-m(t) - \phi A(t) + \frac{\dot{W}_t}{W_t}$ . Then the current Hamiltonian value is:

$$\tilde{H} = p_t * q_t - cq_t^2 + kX_t - c_R R_t^2 + \lambda_t(X_t * g(t) - q_t) \quad (3.12)$$

The necessary conditions for the interior solution in the optimization of Hamiltonian are two equations of derivatives with respect to the control variable  $q_t$  and state variable  $X_t$ . The first necessary condition is:

$$\frac{\partial \tilde{H}}{\partial q} = p_t - 2cq_t - \lambda_t = 0 \quad (3.13)$$

The above condition is in addition to the original state equation 3.9. We need the co-state equation as the second necessary condition, which is about the stock path:

$$-\frac{\partial \tilde{H}}{\partial X} = -(k + \lambda_t g(t)) = \dot{\lambda}_t - r\lambda_t \quad (3.14)$$

Equations 3.9, 3.13 and 3.14 is a system equations and solving this system produces a locally optimal harvest path. In fact, these equations are not only necessary conditions for optimizing the Hamiltonian, but also sufficient conditions. This is because  $\tilde{H}$  is a strictly concave function of harvest and stock biomass. Thus, the solution yields a global maximum. Starting from Equation 3.14, we can obtain  $\lambda_t$ :

$$\lambda_t = \frac{cons_\lambda - \int_0^t k e^{-rt} * W_t * e^{\int_0^t (-m(t) - \phi A(t)) dt} dt}{e^{-rt} * W_t * e^{\int_0^t (-m(t) - \phi A(t)) dt}} \quad (3.15)$$

In this  $\lambda_t$  expression,  $cons_\lambda$  is an unknown constant. We need more conditions to determine it later. Combining Equation 3.15 and Equation 3.13, we can obtain the optimal harvest path:

$$q_t^* = \begin{cases} \frac{p_t}{2c} - \frac{cons_\lambda - \int_0^t k e^{-rt} * W_t * e^{\int_0^t (-m(t) - \phi A(t)) dt} dt}{2c e^{-rt} * W_t * e^{\int_0^t (-m(t) - \phi A(t)) dt}} & \text{if } t \in [T_0^*, T_1^*]; \\ 0 & \text{if } else; \end{cases} \quad (3.16)$$

In the above expression for  $q_t^*$ ,  $q_t^*$  is  $\geq 0$  when  $t$  is in the range of  $[T_0^*, T_1^*]$ , where  $T_0^*$  and  $T_1^*$  are optimal starting and ending time. Otherwise,  $q_t^*$  is equal to zero. Besides the optimal harvest path, we also want to derive the optimal stock path. According to Equation 3.9, we can obtain the stock path with harvest by solving the first order differential equation:

$$X_t^* = \frac{(cons_X - \int_{T_0}^t \frac{q_t^* e^{\int_0^t (m(t) + \phi A(t)) dt}}{W_t} dt) * W_t}{e^{\int_0^t (m(t) + \phi A(t)) dt}} \quad (3.17)$$

In this expression, we have another unknown constant value  $cons_X$ . However, this constant can be determined using the known initial condition of  $N_0$ . According

to  $X_0 = N_0 * W(0)$ , we can solve for  $cons_X$ :

$$X_t^* = \frac{(N_0 - \int_{T_0}^t \frac{q_t^* e^{\int_0^t (m(t)+\phi A(t))dt}}{W_t} dt) * W_t}{e^{\int_0^t (m(t)+\phi A(t))dt}} \quad (3.18)$$

As we can see from the above expression, optimal stock path  $X_t^*$  is a function of  $q_t^*$ . As long as we can obtain  $q_t^*$ ,  $X_t^*$  can be derived. In the expression for  $q_t^*$  (Equation 3.16), there are altogether three unknown parameters:  $cons_\lambda$ ,  $T_0$  and  $T_1$ . In order to have more conditions to determine these parameters, we prove this following proposition.

**Proposition 1:** In the interior solution, stock and harvest go to zero at the optimal terminal time. That is,  $X^*(T_1^*) = 0, q^*(T_1^*)$ .<sup>2</sup>

*Proof.* With  $T_0^*$  and  $T_1^*$ , we can write down the maximized profit:

$$\Pi^* = \int_{T_0^*}^{T_1^*} (p_t * q_t^* - c_0 - c(q_t^*)^2 + kX_t^*)e^{-rt} dt$$

Now if  $X^*(T_1^*) > 0$ , there exist another  $T_1' > T_1^*$  to satisfy  $X'(T_1') = 0$  and a path of harvest  $q_t'$

$$q_t' = \begin{cases} q_t^* & \text{if } t \in [T_0^*, T_1^*]; \\ q_t'' & \text{if } t \in (T_1^*, T_1']; \end{cases}$$

which yield a new profit:

$$\Pi' = \Pi^* + \int_{T_1^*}^{T_1'} (p_t * q_t' - c_0 - c(q_t')^2 + kX_t')e^{-rt} dt$$

---

<sup>2</sup> Setting up the model to have a terminal stock of 0 is an analytical convenience. We could alternatively introduce a constraint that the terminal stock must be at least  $\tilde{X}$ , which would be the minimum stock required for successful recruitment. Without introducing this complication, our model can be viewed as driving the stock to zero on the fishing ground, while part of our natural mortality parameter reflects migration from the fishing ground to an un-fished spawning area.

Because the stock biomass between  $T_1^*$  to  $T_1'$  is positive,  $q_t''$  can be positive. Recall that we assume that the profit is always positive if harvest is positive. Then  $\Pi' > \Pi^*$ . This means that we can find another  $T_1'$  that is different from  $T_1^*$  to improve the profits, which contradicts that  $T_1^*$  is optimal. Therefore,  $X^*(T_1^*) = 0$ . Consequently,  $q^*(T_1^*) = 0$ .  $\square$

According to Proposition 1, we have two conditions to determine the unknown parameters in the optimal harvest path:

$$\begin{cases} p(T_1)e^{-rT_1} * W(T_1) * e^{\int_0^{T_1} (-m(t)-\phi A(t))dt} = cons_{\lambda} - \int_0^{T_1} ke^{-rt} * W_t * e^{\int_0^t (-m(t)-\phi A(t))dt} dt \\ \int_{T_0}^{T_1} \frac{q_t e^{\int_0^t (m(t)+\phi A(t))dt}}{W_t} dt = N_0 \end{cases} \quad (3.19)$$

These two conditions describe two implicit functions defining the implicit relationship between  $T_0$ ,  $T_1$  and  $cons_{\lambda}$ . At this point, we have only two equilibrium conditions but three unknown parameters. Therefore, these three parameters are still unidentifiable and there are multiple solutions to this system equations. So the final step we take is to calculate the profits associated with these multiple solutions and choose the optimal set of  $T_0^*$ ,  $T_1^*$  and  $cons_{\lambda}^*$  that maximize the total profits.

### 3.3 Materials and numerical simulation results

In this section, we first use the known parameters for shrimp growth and real hypoxia data in the Neuse River of North Carolina to illustrate the optimal harvest path for brown shrimp. Then using the simulation methods, we calculate the efficiency loss for the case when the optimal policy hasn't taken hypoxia into account. The parameters in Equations 3.3 to 3.5 for brown shrimp are available in the scientific literature. Table 3.1 lists the parameter values and sources we use for the simulations.

The hypoxia data we use is collected by the USGS (The United States Geological

Survey) for the Neuse River estuary. This area has been reported to undergo severe and recurring hypoxia, mostly in the summer months, which causes fish kills and other negative ecological damage ([71], [53], [32]). The USGS data records measurements of bottom and top dissolved oxygen and other water quality variables every 15 minutes from three moorings in the Neuse River. Since shrimps live near the bottom, we create the daily bottom dissolved oxygen values by taking an average of each day's 15-minute bottom dissolved oxygen measurements from three moorings. However, these continuous dissolved oxygen values cannot be directly used since laboratory experiments show that a tolerable lower bound is a threshold for shrimp's normal growth. Specifically, Renaud ([77]) shows that brown shrimp avoid areas with levels  $< 2 \text{ mgl}^{-1}$ . Therefore, we use  $2 \text{ mgl}^{-1}$  as a threshold to indicate whether it is a hypoxic day. Mathematically, if the daily dissolved oxygen measurement is  $< 2 \text{ mgl}^{-1}$ , the hypoxia indicator ( $A(t)$ ) is 1, otherwise 0. The average number of hypoxic days from 1999 to 2005 is 61 days per year. We use 2005 hypoxia data since the number of hypoxia days is 57, which represents the average hypoxia days between 1999 and 2005.

Before we analyze the hypoxia effect on the optimal harvest strategy, we first derive the optimal strategy when there is no hypoxia. Figure 3.1 illustrates the optimal harvest path with different parameter values. The three rows in this figure describe three different scenarios with alternative shrimp price ( $p$ ), marginal cost coefficient ( $c$ ) and marginal stock effect ( $k$ ), respectively. The solid lines in all the panels depict the baseline case with  $p = 3$ ,  $c = 0.0015$ ,  $k = 0$  and hypoxia effect ( $hyp$ ) equal to 0. Hereafter, we use "hyp" as the specific hypoxia effect coefficient to replace the general pollution effect coefficient,  $\phi$ , used in the model description.

The dashed lines in the first panel row of Figure 3.1 depict the case when the shrimp price is reduced to \$2 per pound. In contrast, the dotted lines represent the shrimp price of \$4 per pound. The left column of the first row describes the optimal

harvest paths when the shrimp prices are different. We find that the baseline optimal harvest has an inverse U-shape with a peak in the summer time. This is consistent with the actual seasonal shrimp fishery. If shrimp prices increase, the optimal harvest path becomes more steep and the optimal fishing interval shrinks to a shorter period. The right column of the same row depicts the corresponding stock path.

As mentioned before, the second row of Figure 3.1 depicts the scenarios when  $c$  is different. Specifically, the dashed lines describe the case when  $c$  is only half of the baseline's marginal cost coefficient, while dotted line illustrates the case when  $c$  doubles the baseline coefficient. From the relative positions, we find that a higher marginal cost coefficient makes the optimal harvest path more flat. It suggests that the managers should decrease the harvest in the peak time while increasing the fishing period.

Similarly, the last row of Figure 3.1 illustrates the cases when stock effect is increased. Among these three cases, the starting point is the earliest when  $k = 0.001$  (the dashed line) while the ending time is the earliest when  $k = 0$  (the solid line). The graph suggests a lower stock effect leads to a higher peak harvest and an earlier start date for the season. The stock dynamics in the right column shows that the higher stock effect makes us wait longer in order to maximize profits.

With different hypoxia coefficients, we can derive different optimal harvest and stock paths. These paths are illustrated in Figure 3.2. The first panel describes the harvest path while the second panel depicts the corresponding stock path. As usual, the solid lines are the baseline scenario with  $p = 3$ ,  $k = 0$ ,  $c = 0.0015$  and  $hyp = 0$ . The dashed lines and the dotted lines depict increasing hypoxia effects. Recall that the hypoxia indicators  $A(t)$  vary over days, so the optimal harvest lines are not smooth, since the optimal harvest strategy needs to respond to daily hypoxia status. Although these lines are not as smooth as the baseline case, the trends of these lines are clear. We find that a higher hypoxia effect makes the optimal harvest

starting and peak point earlier. The stock dynamics depicted in the second panel suggest these trends even more clearly. Where there is low water quality, we need to start fishing earlier. Correspondingly, the peak time of the optimal stock is also earlier than in the case with the lower hypoxia effect.

Figure 3.2 reveals that the optimal harvest strategies for the case when there is no hypoxia and for two hypoxic scenarios. Ignoring hypoxia might lead to a suboptimal policy, which again will lead to efficiency loss. In the shrimp fishery of North Carolina, one of the current adopted policies is to set the season opening date. The optimal harvest path suggests that we should wait until the stock size has grown to a relatively high level also set the opening date according to the optimal harvest path derived above. However, if we neglect the hypoxia effect, we would set the wrong initial opening date.

Figures 3.3 depicts the situations when we follow different harvest strategies. The difference between the first panel and the second panel is that they illustrate the cases of  $hyp = 0.003$  and  $hyp = 0.006$ , respectively. The parameters other than  $hyp$  are all the same as the baseline scenario. The dashed vertical lines in these two panels are the opening dates if the social planner neglects the hypoxia effect. The solid lines depict the baseline case while the dashed lines are the correct optimal harvest paths. If the social planner set the opening date according to the optimal harvest path without considering the hypoxia effect, we can set two strategies. The first one is that we might neglect the hypoxia influences and naively follow the baseline optimal harvest, which is depicted by the dash-dotted line. We call this the “non-adaptive strategy”. The graph shows that since we overfish relative to the correct optimal strategy (dashed line), the stock quickly runs out and the harvest becomes zero too early in the season. The other strategy we might set is that we realize the hypoxia effect and adapt to the hypoxia effect even if the opening date is set wrong. This result is depicted by the dotted line, which shows that the new adaptive strategy

under the suboptimal season opening policy is higher than the optimal one when there is no restriction of season opening (dashed line).

In order to clearly show how much the social planner might lose due to the suboptimal season opening policy, we calculate the rents for different harvest strategies, which are reported in Table 3.2. This table describes fourteen combinations of parameters. While the line with “*Optimal(hyp = 0)*” describes the baseline case where there is no hypoxia, the line with “*Optimal(hyp > 0)*” reports the rent when there is hypoxia and if the planner take the water quality into account and derives the correct optimal strategy. The following line denoted with “*Adaptive strategy*” describes the situation that although the season opening date is set without considering the hypoxia, we choose an adaptive policy to respond to the suboptimal policy. It is depicted as the dotted line in Figure 3.3. The last line of Table 3.2 is the one denoted “*Non – adaptive strategy*”, which corresponds to the dash-dotted line in Figure 3.3. In this case, we ignore the hypoxia influences and follow the baseline harvest strategy. We calculate the hypoxia effect by dividing the rent under each cases by the baseline optimal rent with  $hyp = 0$ . Policy loss is the difference between the adaptive strategy (or “Non-adaptive strategy”) and the optimal rent with  $hyp > 0$ . In additon, the daily policy loss percentage is derived by dividing the policy loss by the rent of “*Optimal(hyp > 0)*”.

Table 3.2 shows that the rent loss from the hypoxia effect is big in both absolute and relative magnitude. For example, when  $hyp = 0.003, p = 3, c = 0.0015$  and  $k = 0$ , the loss due to hypoxia effect is about 14% of the baseline optimal rent. If the hypoxic coefficient,  $hyp$ , increases, the loss increases. However, the policy loss is low relative to the economic loss of hypoxia. With the same parameter combinations, if we use the adaptive harvest strategy, the loss would reduce to only 0.2% of the potential maximum rent. Even if we use the non-adaptive strategy, we lose only 0.8% of the maximum rent. This is also true for other parameter values. In all the fourteen

cases in Table 3.2, the biggest policy loss, 3.53% of the maximum rent, occurs when hypoxia and marginal cost coefficients double ( $\text{hyp}=0.006$ ,  $c=0.003$ ) and the stock effect is relatively high ( $k = 3$ ). These numbers suggest that the fishery management gains from adapting to hypoxia are small in spite of what appear to be substantial qualitative differences in the harvest paths shown in Figure 3.3.

### 3.4 Conclusion

We develop a stylized bioeconomic model for optimal harvest of an annual species (shrimp) in the presence of environmental degradation (hypoxia) that has growth consequences. In the absence of hypoxia, the optimal harvest path becomes more peaked as price increases, marginal cost of harvest decreases, and the stock effect decreases. This is a direct consequence of the assumption of exogenous recruitment and is analogous to more controlled systems like rotationally managed forests or aquaculture ponds ([8]; [35]). If one eliminates convexity of harvest costs and stock effects altogether, the optimal strategy for wild shrimp harvest would be to wait for the shrimp to grow and harvest all at once, balancing shrimp and price growth over time with the cumulative effects of natural mortality and discounting.

When hypoxia is introduced, we find that the optimal harvest path changes qualitatively. In particular, as hypoxia worsens, the optimal season opening shifts earlier. The intuition follows from a standard capital-theoretic view of natural resources. Hypoxia slows the internal rate of return of the fish stock and thus shifts more harvest towards the present due to discounting. Conversely, in a pristine year managers are better off waiting longer to open the season. Under hypoxia, the path of optimal harvest also becomes adaptive. However, quantitatively the consequences are rather small. Previous empirical work finds that hypoxia in North Carolina's Neuse River has sizable effects on shrimp harvest— in the range of 11% ([45])— and our bioeconomic model finds comparable rent losses from hypoxia under the optimal policy.

Yet, when managers fail to adapt to hypoxia and instead implement what would be optimal under no hypoxia, the rent losses are small. That is, the difference between following the optimal policy under hypoxia and following a naive policy is small. An important caveat is that our hypoxia scenarios are based on North Carolina's Neuse river and not the more sizable and notorious dead zone in the Gulf of Mexico. The benefits of adaptation to hypoxia could be more substantial in this much larger fishery that is subject to more severe hypoxia.

Our quantitative findings constitute a negative result of sorts; we set out to find how fishery managers can adapt to water pollution that they are unable to control and generate more value from fishery resources, but we found only small potential changes in aggregate outcomes. Nonetheless, our results suggest important policy implications. First, because fishery managers are extremely limited in their ability to adapt to water pollution, reducing pollution takes on greater importance for other regulatory agencies. Second, fishery managers must find ways to generate value through some other means. One possibility is generating value through rationalization. For instance, Smith ([89]) finds that the benefits from rationalization for North Carolina blue crabs are more than an order of magnitude larger than the benefits from reducing nutrient pollution and the resulting hypoxia. Similarly, the gains from some form of rationalization of the shrimp fishery will likely outweigh gains from reduced nutrient pollution and almost certainly would be larger than gains from optimal adaptation to hypoxia.

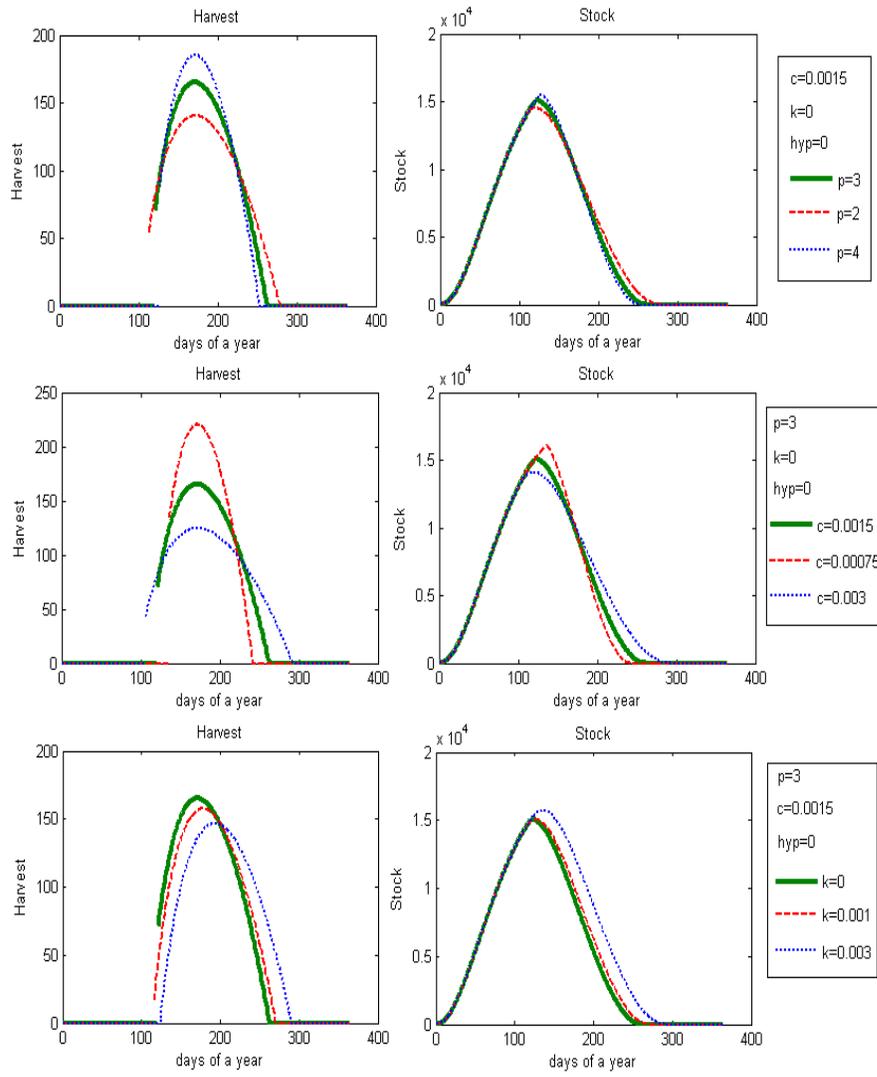


FIGURE 3.1: Optimal harvest without hypoxia

Note: Depicts the optimal harvest and corresponding stock paths when shrimp price ( $p$ ), marginal harvest cost ( $c$ ) and the stock effect ( $k$ ) vary.

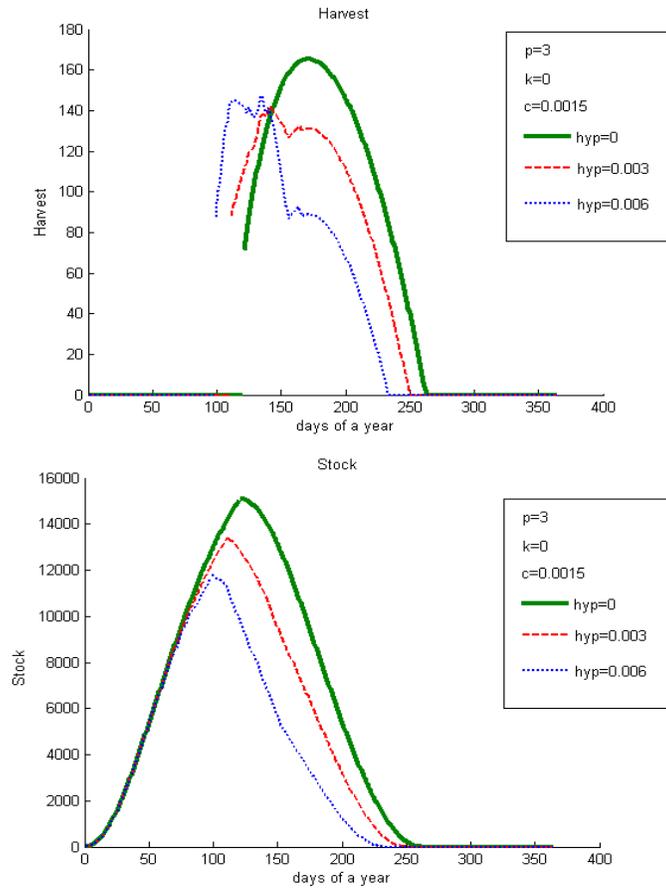


FIGURE 3.2: Hypoxia effects

Note: Depicts optimal harvest paths (top panel) and stock paths (bottom panel) at different levels of hypoxia (*hyp*).

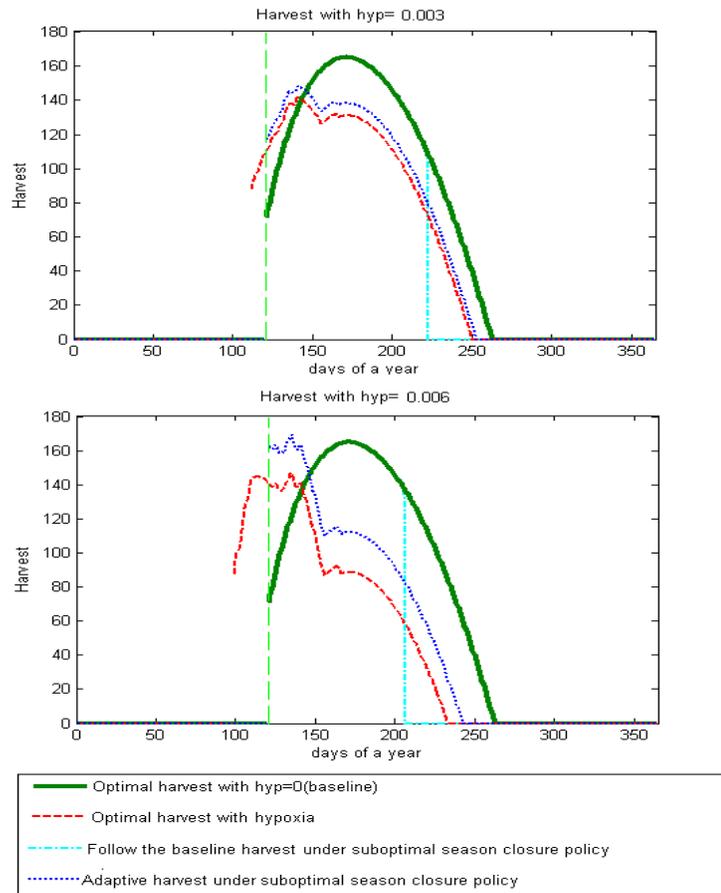


FIGURE 3.3: Harvest strategies under the policy of season opening

Note: Depicts four different harvest strategies for moderate impacts of hypoxia (top panel) and severe impacts of hypoxia (bottom panel).

Table 3.1: Parameter sources

Parameter	Value	Note	Parameter source
$L_\infty$	177.7	Von-Bertalanffy growth function	McCoy 1968
$\delta$	-0.0104	Von-Bertalanffy growth function	McCoy 1968
$\beta$	1.4866	Natural mortality rate	Minello et. al. 1989
$\rho$	-1.1163	Natural mortality rate	Minello et. al. 1989
$\omega$	10.52*E-06	Allometric function(weight)	Fontaine and Neal 1971
$\eta$	2.94	Allometric function(weight)	Fontaine and Neal 1971
$N_0$	10 000 000	Initial number of shrimp	
$r$	0.0005	daily discount rate	
$c_0$	0	fixed cost of fishing	
$p$	3	price of per pound shrimp	

Table 3.2: Efficiency loss due to hypoxia and a suboptimal season opening policy(\$)

	hyp=0.003				hyp=0.006			
	Rent	Hypoxia effect	Policy loss	Policy loss percentage	Rent	Hypoxia effect	Policy loss	Policy loss percentage
p=3, c=0.0015,k=0								
Optimal(hyp=0)	467550				467550			
Optimal(hyp>0)	403110	86.22%			351600	75.20%		
Adaptive strategy	402300	86.04%	810	0.20%	347380	74.30%	4220	1.20%
Non-adaptive strategy	399880	85.53%	3230	0.80%	342390	73.23%	9210	2.63%
p=2, c=0.0015,k=0								
Optimal(hyp=0)	302110				302110			
Optimal(hyp>0)	261870	86.68%			229000	75.80%		
Adaptive strategy	261610	86.59%	260	0.10%	227010	75.14%	1990	0.87%
Non-adaptive strategy	259530	85.91%	2340	0.89%	223330	73.92%	5670	2.48%
p=4, c=0.0015,k=0								
Optimal(hyp=0)	634450				634450			
Optimal(hyp>0)	545150	85.92%			474850	74.84%		
Adaptive strategy	544300	85.79%	850	0.16%	468030	73.77%	6820	1.44%
Non-adaptive strategy	541230	85.31%	3920	0.72%	462100	72.83%	12750	2.69%
p=3, c=0.0015/2,k=0								
Optimal(hyp=0)	485380				485380			
Optimal(hyp>0)	415380	85.58%			361300	74.44%		
Adaptive strategy	413430	85.18%	1950	0.47%	354130	72.96%	7170	1.98%
Non-adaptive strategy	411900	84.86%	3480	0.84%	350330	72.18%	10970	3.04%
p=3, c=0.0015*2,k=0								
Optimal(hyp=0)	440790				440790			
Optimal(hyp>0)	383690	87.05%			336350	76.31%		
Adaptive strategy	383450	86.99%	240	0.06%	334570	75.90%	1780	0.53%
Non-adaptive strategy	380340	86.29%	3350	0.87%	328200	74.46%	8150	2.42%
p=3, c=0.0015*2,k=0.001								
Optimal(hyp=0)	456280				456280			
Optimal(hyp>0)	396470	86.89%			346810	76.01%		
Adaptive strategy	395430	86.66%	1040	0.26%	344460	75.49%	2350	0.68%
Non-adaptive strategy	392830	86.09%	3640	0.92%	337980	74.07%	8830	2.55%
p=3, c=0.0015*2,k=0.003								
Optimal(hyp=0)	487990				487990			
Optimal(hyp>0)	423670	86.82%			369280	75.67%		
Adaptive strategy	420190	86.11%	3480	0.82%	362230	74.23%	7050	1.91%
Non-adaptive strategy	417310	85.52%	6360	1.50%	356240	73.00%	13040	3.53%

Note: Reports efficiency losses for different harvest strategies and parameter combinations, including low and high impacts of hypoxia (*hyp*), three levels each of shrimp price (*p*), marginal harvest cost (*c*), and the stock effect (*k*).

# Appendix A

## Chapter 1

A1. Compute  $u_i(a_i = 1, s, \xi_i; \theta)$

In  $u_i(a_i = 1, a_{-i}, s, \xi_i; \theta)$ , except  $Tvessel$ , other part of utility does not depend on other fishermen's actions.

$$\begin{aligned}\sum_{a_{-i}} Tvessel * \sigma_{-i}(a_{-i}|s) &= 1 + \sum_{j \neq i} a_j * \sigma_j(a_j|s) \\ &= 1 + \sum_{j \neq i} 1\{a_j = 1\} * \sigma_j(a_j|s) \\ &= 1 + \sum_{j \neq i} \sigma_j(a_j = 1|s)\end{aligned}$$

$$\begin{aligned}\sum_{a_{-i}} Tvessel^2 * \sigma_{-i}(a_{-i}|s) &= \sum_{a_{-i}} (\sum a_j)^2 * \sigma_{-i}(a_{-i}|s) \\ &= \sum_{a_{-i}} (1 + 2 \sum_{j \neq i} a_j + \sum_{j \neq i} a_j^2 + \sum_{j \neq k, j, k \neq i} a_j * a_k) \sigma_{-i}(a_{-i}|s) \\ &= 1 + 3 \sum_{j \neq i} \sigma_j(a_j = 1|s) + \sum_{j \neq k, j, k \neq i} \sigma_j(a_j = 1|s) \sigma_k(a_k = 1|s)\end{aligned}$$

Then

$$\begin{aligned}
u_i(a_i = 1, s, \xi_i; \theta) &= \alpha Price_t * e^{q_i} * X \\
&* \left( 1 + \gamma + \frac{\gamma^2}{2} + \left( \gamma + \frac{3\gamma^2}{2} \right) \sum_{j \neq i} \sigma_j(a_j = 1|s) + \frac{\gamma^2}{2} \sum_{j \neq k, j, k \neq i} \sigma_j(a_j = 1|s) \sigma_k(a_k = 1|s) \right) \\
&- \beta * \mathbb{S} + \xi_i
\end{aligned}$$

# Appendix B

## Chapter 3

B1:

$$\begin{aligned}\dot{X}_t &= \frac{d(N_t * W_t)}{dt} \\ &= \frac{d(N_0 e^{\int_0^t (-m(t) - \phi A(t)) dt} * W_t)}{dt} \\ &= N_0 e^{\int_0^t (-m(t) - \phi A(t)) dt} (-m(t) - \phi A(t)) * W_t * + N_0 e^{\int_0^t (-m(t) - \phi A(t)) dt} * \dot{W}_t \\ &= N_t W_t [-m(t) - \phi A(t) + \frac{\dot{W}_t}{W_t}] \\ &= X_t [-m(t) - \phi A(t) + \frac{\dot{W}_t}{W_t}]\end{aligned}$$

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# Biography

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