ABSTRACT

Title of Document: THE EFFECTS OF WATER QUALITY IMPROVEMENTS ON A COMMERCIAL FISHERY: EVIDENCE FROM THE MARYLAND BLUE CRAB FISHERY

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Developing and implementing total maximum daily loads (TMDLs) is a costly and controversial process. However, there are many potential benefits, such as improvements to commercial fisheries. A two-stage model is developed to estimate the benefits of the Chesapeake Bay TMDL on the Maryland blue crab fishery. In the first stage, a bio-economic model links water quality to stock and harvest and various hypotheses on this link are tested. In the second stage, a model of fisherman behavior links the effects of changes in water quality on stock and harvest to fisherman behavior, such as fishing, location, and effort decisions. A number of simulations are then run to predict the effects of the TMDL on the Maryland blue crab fishery. The simulations predict that the TMDL is likely to have a small, if not insignificant, effect on the fishery. This result is in part explained by the fact that the current level of water quality in the Chesapeake Bay is suitable for the blue crabs.

THE EFFECTS OF WATER QUALITY IMPROVEMENTS ON A COMMERCIAL FISHERY:
EVIDENCE FROM THE MARYLAND BLUE CRAB FISHERY

By

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Dedication

To Mom and Dad, for the preparation and encouragement to make it this far

To Andrew, for your patience and support

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Chapter 1

Introduction

Developing and implementing total maximum daily loads (TMDLs) is a controversial process. TMDLs are potentially costly and there is a disconnect between who pays and who benefits. For example, farmers are likely to bear a large portion of the costs whereas fishermen are likely to benefit the most. Furthermore, developing a TMDL is time-consuming as many parties with diverse interests must jointly develop their strategies to meet the TMDL standards. Finally, even establishing target water quality standards is challenging and sometimes controversial in and of itself. The target pollution limits to restore fisheries can be uncertain, as is the potential for a water body to support a fishery even in a pristine state. In some situations, such as in open access fisheries, improvements in water quality may even lead to negative social returns (McConnell and Strand, 1989). However, there are many potential benefits. For example, there may be benefits to commercial and recreational fisheries and recreation activities, increases to property values, avoided costs of future water treatments, and co-benefits of best management practices (BMPs) by farmers.

The goal of this paper is to value water quality changes using the Maryland commercial blue crab fishery as a component of social benefits. This fishery is chosen because it is one of the most productive fisheries in the Bay, accounting for over 65% of landings. The analysis is performed in two stages. First, a set of bio-economic models is developed and estimated using water quality data, stock data estimates, and harvest data from 2000-2010. Second, a model of fishermen behavior is developed and estimated using logbook data from 2000-2010. The models are then used to simulate the effects of a water quality policy, such as the Chesapeake Bay TMDL, on the Maryland blue crab fishery.

This analysis builds on an existing literature of habitat valuation (e.g., Anderson, 1989; Barbier et al., 2002; Huang et al., 2011, Kahn and Kemp, 1985; Mistiaen et al., 2003). These studies often use a bio-economic modelling approach to relate water quality to the stock and harvest of a species. As data are often difficult to obtain, only a few studies are able to capture spatial and seasonal variations (e.g., Barbier et al., 2002; Mistiaen et al., 2003; Smith, 2007; Smith and Crowder, 2011; Huang et al., 2011). Spatial variation is an important component as habitat quality, including water quality, varies across space and fish are able to adapt by migrating between areas. Seasonal variation is also important because changes in habitat and the effects of these changes can occur on a relatively fine time scale. For example, in some cases, fish can respond to instantaneous changes in water quality and fishermen can quickly adapt their effort level in response to changes in stock availability.

Most of the prior valuation studies assume that fishermen respond to changes in habitat in a limited way. For example, fishermen may be able to adjust the number of hours spent harvesting per trip, but not the number of trips. These studies typically follow an initial application by Bockstael and Opaluch (1983) of discrete choice modeling to study fishery choice behavior in New England's ports. This seminal study changed the focus of fisheries economics literature from bio-economic optimization to the prediction of fishermen's responses to changes in policy and management efforts.

Other studies apply a group of discrete choice models for studying fishermen behavior in terms of fishery choice (Holland and Sutinen, 1999; Larson et al., 1999; Curtis and Hicks, 2000; Curtis and McConnell, 2004; Pradhan and Leung, 2004; Vermard et al., 2008), fishing location (Eales and Wilen, 1986; Mistiaen and Strand, 2000; Smith, 2000; Smith and Wilen, 2003; Curtis and McConnell, 2004; Hutton et al., 2004; Strand, 2004; Smith, 2005), and fishing gear (Eggert and Tveteras, 2004).

The contributions of the present paper are to expand upon and unify the two bodies of literature - environmental valuation and fishermen behavior. This is achieved through the use of improved empirical techniques and the construction and use of a richer data set. The data set allows the analysis to include more refined temporal relationships and incorporate heterogeneity across fishermen. Furthermore, the trip-level and water quality data are spatially differentiated, allowing for spatial variations to be included. The present paper also extends the theoretical model by directly representing a fisherman's decision to switch to a new location. While many studies have recognized that inertia - the tendency for a fisherman to return to the same location - is an important factor, it has not been explicitly modeled. This study formally models this phenomenon as opposed to assuming it is an exogenous decision.

The results of this study indicate that water quality, measured as levels of dissolved oxygen, may affect stock mortality, harvest, stock distribution, or some combination of the three. These results also show that both stock and harvest respond inelastically to changes in water quality. With regards to fishermen behavior, the decision of whether to switch sites within the fishery is found to be a significant factor in a fisherman's decision making process. Finally, the benefits of increased water quality to the blue crab commercial fishery are found to be relatively small in the policy simulations.

The remainder of this paper is organized as follows. The first chapter below, Chapter 2, presents the model used for analyzing the effects of water quality on stock, harvest, and fishermen behavior. Then Chapter 3 describes the data set. The results are presented in Chapter 4. Chapter 5 applies these results in a policy setting. Finally, Chapter 6 discusses the implications of these findings.

Chapter 2

Model

The overall model used in this study combines an environmental valuation model with a fisherman choice model. The first part of the model tests the relationship between water quality, stock, and harvest using a traditional bio-economic model. The second part of the model estimates the determinants of a fisherman's daily decisions using a discrete-continuous choice model. These two models are linked through profit expectations: water quality affects the expected profitability of fishing, which in turn affects fisherman behavior.

2.1 Bio-Economic Model

This section examines multiple hypotheses for the effect of water quality on a given fish species. The first and most orthodox hypothesis, the Mortality Hypothesis, is that water quality affects the mortality of a species. Under this hypothesis, the stock level will rise as water quality improves. The second hypothesis is that water quality affects the availability of a species to fishermen. Under this hypothesis, as water quality improves, the species will become more mobile and more likely to interact with passive gear, thus becoming easier to harvest. The first hypothesis is purely biological. The second hypothesis, the Availability Hypothesis, is a fairly recent premise in the bio-economic literature (e.g., Mistiaen et al., 2003). There is a third potential mechanism for water quality and fish species to interact - that water quality affects the spatial distribution of a species. Under this hypothesis, the Distribution Hypothesis, the species will move towards areas with relatively higher levels of water quality. This hypothesis has the least empirical underpinning (e.g., Huang et al., 2011; Kociolek, 2011). Finally, there are four different combinations of these three base hypotheses: Mortality and Availability (Mortality/Availability), Distribution and Availability (Distribution/Availability), Mortality and Distribution (Mortality/Distribution), and Mortality, Availability, and Distribution (Mortality/Availability/Distribution). All seven hypotheses are tested to determine whether the assumed relationship between water quality and the fishery significantly affects the estimated benefits of water quality improvements.

In the context of the bio-economic model, dissolved oxygen is the policy-relevant water quality variable for two reasons. First, dissolved oxygen is one of the main measures of water quality that affect blue crabs, the others being water temperature and salinity. However, both water temperature and salinity are correlated with dissolved oxygen - when either increases, oxygen is less soluble in water. The second reason for using dissolved oxygen is because of its policy relevance. Dissolved oxygen is likely to be affected by a policy such as a TMDL whereas water temperature and salinity are not.

The conceptual model comprises a stock growth function and a harvest production function as follows:

$$
\begin{aligned}
Stock_{j,t} &= f(Stock_{j,t-1}, Harvest_{j,t-1}, Predation_{j,t}[, WQ_{j,t}]) \\
Harvest_{i,j,t} &= f(Effort_{i,j,t}, Skill_{i,j,t}, Stock_{j,t}[, WQ_{j,t}])
\end{aligned}
$$

In this model, the stock at a given location j and time period t is a function of lagged stock in location j, the lagged harvest in location j, predation in location j and time period t, and potentially the level of water quality in location j and time period t. Lagged harvest ($Harvest_{j,t-1}$) is used instead of current harvest to satisfy the exclusion restriction for simultaneous equations. The harvest for individual i at a given location j and time period t is a function of his effort level in the given location j and time period t, skill in the given location j and time period t, the stock in the given location j and time period t, and, again, potentially level of water quality in location j and time period t.

Four assumptions are made when moving from the conceptual to the econometric model. First, that recruitment and juveniles are independent across seasons (Pearson, 1948). Therefore, it is not necessary to model growth between seasons. Second, that there are thresholds above or below which further changes in dissolved oxygen have no apparent effect. For example, Selberg (2001) finds that there are significantly fewer blue crabs in areas where dissolved oxygen is below 2.4 mg/l and that catch per unit effort increases from around 2.4 mg/l to somewhere between 4 mg/l and 6 mg/l. In order to account for these thresholds, splines with knots at two different thresholds will be used. Third, that the error terms may be correlated across the stock and harvest equations. Therefore, each system of equations is estimated using seemingly unrelated regressions (SUR). Fourth, that the annual stock index for striped bass (SBI) is a proxy for blue crab predation as striped bass are predators to the blue crab and the striped bass population is likely correlated with the populations of other blue crab predators.

One final note to make before developing the econometric models is that stock is measured in terms of combined male and female stock whereas harvest is measured in terms of male hard crabs (i.e., #1 and #2 Males). This is primarily due to data limitations as the stock is a combined measure of males and females. While a separate female harvest equation could be added, the restrictions on female harvests in Maryland are numerous and difficult to predict. Therefore, an additional term is added to the harvest production function in the econometric estimation to account for locations and months where female harvest is likely to be high.

Mortality Hypothesis

Under this hypothesis, water quality affects stock growth. Therefore, the stock growth equation is as follows:

$$\begin{aligned} X_{j,t} = \lambda_0 &+ \lambda_1 X_{j,t-1} + \lambda_2 H_{j,t-1} + \lambda_3 SBI_{j,t} \\ &+ \lambda_4 DO_{j,t} \cdot 1(DO_{4\to 8}) + \lambda_5 DO_{j,t} \cdot 1(DO_{8\to 12}) + \nu_{j,t} \end{aligned} \tag{2.1}$$

where $H_{j,t}$ is the sum of all harvests in location j during time period t, $X_{j,t}$ is the stock density in location j during time period t, $SBI_{j,t}$ is the striped bass stock index in location j during time period t, $DO_{j,t}$ is the milligrams of dissolved oxygen per liter of water in location j during time period t, $1(DO_{4\to 8})$ and $1(DO_{8\to 12})$ are indicator variables representing the thresholds at 4 mg/l and 8 mg/l, and $\nu_{j,t}$ is a normally distributed error term.

The motivation for this equation is that higher previous stocks are likely to lead to higher current stocks. On the other hand, higher previous harvests and higher predator population levels are likely to lead to lower current stocks. As stated previously, dissolved oxygen is assumed to affect stock growth, but only within certain ranges. The thresholds of 4 mg/l and 8 mg/l are chosen because 1) 4 mg/l has been shown to be a threshold for blue crabs (e.g., Selberg (2001)) and 2) those thresholds evenly divide the range of dissolved oxygen values.

The harvest production function is as follows:

$$H_{i,j,t} = \beta_0 + \beta_1 E_{i,j,t} + \beta_2 X_{j,t} + \beta_3 Age_{i,t} + \beta_4 Age_{i,t}^2 + \beta_5 FH_{j,t} + \eta_{i,j,t} \tag{2.2}$$

where $H_{i,j,t}$ is the harvest for fisherman i at location j and time period t, $E_{i,j,t}$ indicates the number of hours fished by fisherman i at location j and time period t, $X_{j,t}$ is the stock density in location j during time period t, $Age_{i,t}$ is the age of fisherman i during time period t, $FH_{j,t}$ is a dummy variable equal to one if female harvest is expected to be high and zero otherwise, and $\eta_{i,j,t}$ is a normally distributed error term. For the female harvest dummy variable, female harvest is expected to be high in the southern portion of the Bay and in the eastern tributaries during October and November.

The motivation for this equation is that as effort and stock increase, the fisherman's harvest is expected to increase as well. Individual specific characteristics are often included in harvest production functions to account for heterogeneous fishermen. Age and home state are the only individual specific characteristics available, so age was chosen as it is a better proxy for skill and it has more variation than home state. Finally, the female harvest dummy is incorporated to account for female harvests.

Availability Hypothesis

Under this hypothesis, water quality affects the harvest production function:

$$\begin{aligned} H_{i,j,t} = {} & \beta_0 + \beta_1 E_{i,j,t} + \beta_2 X_{j,t} + \beta_3 Age_{i,t} + \beta_4 Age_{i,t}^2 + \beta_5 FH_{j,t} \\ & + \beta_6 DO_{j,t} \cdot 1(DO_{4\to 8}) + \beta_7 DO_{j,t} \cdot 1(DO_{8\to 12}) + \eta_{i,j,t} \end{aligned} \tag{2.3}$$

Therefore, the stock growth function is as follows:

$$X_{j,t} = \lambda_0 + \lambda_1 X_{j,t-1} + \lambda_2 H_{j,t-1} + \lambda_3 SBI_{j,t} + \nu_{j,t} \tag{2.4}$$

It should be observed that the water quality terms move from the stock equation to the harvest equation under this hypothesis.

Distribution Hypothesis

Under this hypothesis, "relative water quality" enters the stock growth equation in the following form:

$$\Delta DO_{j,t}$$

where $\Delta DO_{j,t}$ is the difference between the level of dissolved oxygen in location j and the average level of dissolved oxygen in the adjacent locations.

Therefore, the system of equations is:

$$\begin{aligned} X_{j,t} &= \lambda_0 + \lambda_1 X_{j,t-1} + \lambda_2 H_{j,t-1} + \lambda_3 SBI_{j,t} \\ &\quad \lambda_4 \Delta DO_{j,t} \cdot 1(\Delta DO_{-3\to 0}) + \lambda_5 \Delta DO_{j,t} \cdot 1(\Delta DO_{0\to 3}) + \nu_{j,t} \\ H_{i,j,t} &= \beta_0 + \beta_1 E_{i,j,t} + \beta_2 X_{j,t} + \beta_3 Age_{i,t} + \beta_4 Age^2_{i,t} + \beta_5 FH_{j,t} + \eta_{i,j,t} \end{aligned} \tag{2.5}$$

where $1(\Delta_j DO_{-3\to 0})$ and $1(\Delta_j DO_{0\to 3})$ are indicator variables representing the thresholds at -3 and 0.

The motivation for this representation is that, as with the mortality and availability hypotheses, relative dissolved oxygen is assumed to affect stock growth, but only within certain ranges. The thresholds of -3 and 0 are chosen in order to evenly divide the range of relative dissolved oxygen values.

Mortality/Availability Hypothesis

Under this combined hypothesis, water quality affects both stock growth and the harvest production function:

$$
\begin{aligned}
X_{j,t} &= \lambda_0 + \lambda_1 X_{j,t-1} + \lambda_2 H_{j,t-1} + \lambda_3 SBI_{j,t} \\
&\quad + \lambda_4 DO_{j,t} \cdot 1(DO_{4\to 8}) + \lambda_5 DO_{j,t} \cdot 1(DO_{8\to 12}) + \nu_{j,t} \\
H_{i,j,t} &= \beta_0 + \beta_1 E_{i,j,t} + \beta_2 X_{j,t} + \beta_3 Age_{i,t} + \beta_4 Age^2_{i,t} + \beta_5 FH_{j,t} \\
&\quad + \beta_6 DO_{j,t} \cdot 1(DO_{4\to 8}) + \beta_7 DO_{j,t} \cdot 1(DO_{8\to 12}) + \eta_{i,j,t}
\end{aligned}
$$

Distribution/Availability Hypothesis

Under this combined hypothesis, water quality affects both stock distribution and the harvest production function:

$$
\begin{aligned}
X_{j,t} &= \lambda_0 + \lambda_1 X_{j,t-1} + \lambda_2 H_{j,t-1} + \lambda_3 SBI_{j,t} \\
&\quad + \lambda_4 \Delta DO_{j,t} \cdot 1(\Delta DO_{-3\to 0}) + \lambda_5 \Delta DO_{j,t} \cdot 1(\Delta DO_{0\to 3}) + \nu_{j,t} \\
H_{i,j,t} &= \beta_0 + \beta_1 E_{i,j,t} + \beta_2 X_{j,t} + \beta_3 Age_{i,t} + \beta_4 Age^2_{i,t} + \beta_5 FH_{j,t} \\
&\quad + \beta_6 DO_{j,t} \cdot 1(DO_{4\to 8}) + \beta_7 DO_{j,t} \cdot 1(DO_{8\to 12}) + \eta_{i,j,t}
\end{aligned}
$$

Mortality/Distribution Hypothesis

Under this combined hypothesis, water quality affects both stock growth and distribution:

$$
\begin{aligned}
X_{j,t} &= \lambda_0 + \lambda_1 X_{j,t-1} + \lambda_2 H_{j,t-1} + \lambda_3 SBI_{j,t} \\
&\quad + \lambda_4 DO_{j,t} \cdot 1(DO_{4\to 8}) + \lambda_5 DO_{j,t} \cdot 1(DO_{8\to 12}) \\
&\quad + \lambda_6 \Delta DO_{j,t} \cdot 1(\Delta_j DO_{-3\to 0}) + \lambda_7 \Delta DO_{j,t} \cdot 1(\Delta DO_{0\to 3}) + \nu_{j,t} \qquad (2.6) \\
H_{i,j,t} &= \beta_0 + \beta_1 E_{i,j,t} + \beta_2 X_{j,t} + \beta_3 Age_{i,t} + \beta_4 Age^2_{i,t} + \beta_5 FH_{j,t} + \eta_{i,j,t}
\end{aligned}
$$

Mortality/Availability/Distribution Hypothesis

Under this combined hypothesis, water quality affects stock growth and distribution as well as the harvest production function:

$$
\begin{aligned}
X_{j,t} &= \lambda_0 + \lambda_1 X_{j,t-1} + \lambda_2 H_{j,t-1} + \lambda_3 SBI_{j,t} \\
&\quad + \lambda_4 DO_{j,t} \cdot 1(DO_{4\to 8}) + \lambda_5 DO_{j,t} \cdot 1(DO_{8\to 12}) \\
&\quad + \lambda_6 \Delta DO_{j,t} 1 \cdot (\Delta_j DO_{-3\to 0}) + \lambda_7 \Delta DO_{j,t} \cdot 1(\Delta DO_{0\to 3}) + \nu_{j,t} \\
H_{i,j,t} &= \beta_0 + \beta_1 E_{i,j,t} + \beta_2 X_{j,t} + \beta_3 Age_{i,t} + \beta_4 Age_{i,t}^2 + \beta_5 FH_{j,t} \\
&\quad + \beta_6 DO_{j,t} \cdot 1(DO_{4\to 8}) + \beta_7 DO_{j,t} \cdot 1(DO_{8\to 12}) + \eta_{i,j,t}
\end{aligned}
$$

2.2 Fisherman Choice Model

A discrete-continuous choice model is developed in this section to model daily fisherman decisions. The discrete portion models a fisherman's fishing and location choice decisions using a repeated nested logit. The continuous portion models fishermen's daily effort in hours spent harvesting using a linear regression. As it is a discrete-continuous choice model, the discrete choices made by a fisherman are incorporated into his effort decision.

2.2.1 Discrete Choice Model

Each day, a fisherman makes a series of discrete choices. The first is whether to fish on that day. If he chooses to fish, then he must decide whether to fish in his prior location or switch locations. If he chooses to switch locations, then he needs to decide which location to choose from the remaining locations available.

A repeated nested logit (McFadden, 1973) is used to model this set of decisions. Using this type of model, individual fishermen assign different utilities to each alternative (i.e., fish/no fish, switch/no switch, and location) based on the characteristics of the fisherman and each alternative. The fisherman then chooses the alternative which maximizes his utility for each decision.

The decision tree each fishermen faces is shown in the Figure 2.1.

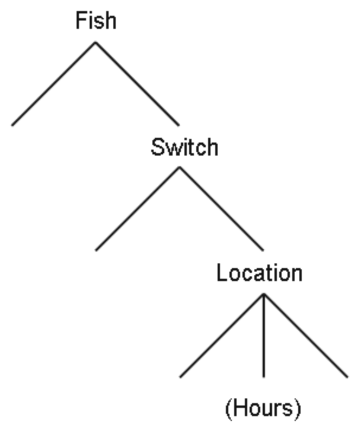

Figure 2.1: Decision Tree

The first three decisions are discrete: fish/no fish, switch/no switch, location. Each time a fisherman makes these decisions, he solves them bottom-up. First, assuming he had chosen to fish and switch to a new location, he determines which location would generate the maximum utility. Then, assuming he had chosen to fish, he compares the expected utility from returning to the same location with the utility from the chosen alternative location. Finally, he compares the utility from fishing (i.e., maximum utility from deciding whether to switch) with the utility from not fishing. When making decisions sequentially, the fisherman incorporates the expected utilities of subsequent decisions in the sequence to his evaluation of the current choice.

The final decision is continuous: hours. Based on his location choice, fishermen who choose to fish must then decide how many hours to spend harvesting.

Three main variables are typically used in fishermen decision models: 1) a measure of risk aversion, 2) a measure of "inertia," and 3) a measure of information sharing or congestion.

In this study, fishermen are assumed to be risk neutral. Since Bockstael and Opaluch (1983), it has been customary to assume that fishermen are expected utility maximizers; that is, they care about profits as well as the variability of profits. Thus, variables representing risk are commonly included in preference models. However, there are several reasons to doubt that risk aversion is an important determinant in the decision making process. Arrow (1971) shows that expected utility maximizers are almost everywhere arbitrarily close to risk neutral when the stakes are arbitrarily small. Furthermore, Rabin (2000) presents a theorem that shows that, "within the expected utility model, anything but virtual risk neutrality over modest stakes implies manifestly unrealistic risk aversion over large stakes." Additionally, a few survey-based studies have targeted this question. For example, Eggert and Martinsson (2003) present stated preference data indicating that risk aversion is not an important influence for choice among locations.

In the formulation of this nested logit model, "inertia," a reluctance to switch fishing locations, enters as a decision nest (i.e., switch/no switch) as opposed to a dummy variable in the location decision (i.e., inertia is equal to 1 if the given location was chosen in the previous period and 0 otherwise). Inertia is a commonly used variable in fishermen decision studies; however, it appears to be a "catch all" and masks the effects of other variables. In the studies by Bockstael and Opaluch (1983) and Opaluch and Bockstael (1984), the coefficient on inertia is four times as large as their other variables. Holland and Sutinen (1999) include seven inertia variables in their model. When these variables are removed, the model's predictive power falls from 0.5 to 0.35. Other studies which incorporate some measure of inertia include Curtis and Hicks (2000), Eggert and Tveteras (2004), Curtis and McConnell (2004), Pradhan and Leung (2004), Vermard et al. (2008), and Andersen et al. (2010).

Finally, information sharing or congestion is represented by the number of other fishermen in a given location. If there are many fishermen in a given location, then that might be a sign of "hot spot" fishing (Larson et al., 1999). However, too many fishermen may indicate congestion. A few studies include this type of information sharing. Larson et al. (1999) and Curtis and McConnell (2004) both find positive information sharing effects, suggesting that information sharing dominates congestion. Alternatively, Curtis and Hicks (2000) find evidence of congestion effects.

The utility derived from choosing to fish on a given day, V^F, is modeled as follows:

$$V_{i,t}^F = \alpha_1^F Sun \mid Mon_t + \alpha_2^F Age_{i,t} + \alpha_3^F Age_{i,t}^2 + \alpha_4^F Weather_t \tag{2.7}$$

where $Sun \mid Mon_t$ represent whether the day of the week is a Sunday or Monday during time period t, $Age_{i,t}$ is the age of fisherman i during time period t, and $Weather_t$ are the weather conditions during time period t.

The motivation for this equation is as follows. Fishermen are less likely to fish on a Sunday or Monday due to Maryland state regulations requiring blue crab fishermen to take at least one of those days off each week. Age is included to link a given fisherman's decisions across choice occasions and to act as a proxy for outside opportunities. For example, age may be correlated with wealth or the availability of part-time employment, both of which may affect a fisherman's decision to fish on a given day. Finally, fishermen are less likely to fish during inclement weather. Weather is defined as a vector of weather conditions, including temperature, precipitation, and wind speed.

The utility derived from switching locations from the last location fished, $V^{S|F}$, is modeled as follows:

$$V_{i,j,t}^{S|F} = \sum_{n=1}^{N} Location_{i,t-1} \cdot Month_t \tag{2.8}$$

$$\tag{2.9}$$

where $Location_{i,t-1}$ is the location choice made by fisherman i in time period $t-1$, $Month_t$ is month during time period t, and N is equal to $(J-1) \cdot (T-1)$.

The motivation for this equation is that fishermen are likely to exhibit seasonal and regional patterns based on expected stock migration when deciding whether or not to switch locations. Generally speaking, juveniles migrate north during the spring and females migrate south during the fall.

The utility derived from selecting a given location after a decision to switch, $V^{L|S}$, is modeled as follows:

$$V_{i,j,t}^{L|S} = \alpha_1^L E(\Pi_{i,j,t}) + \alpha_2^L E(N_{j,t}) \tag{2.10}$$

where $E(\Pi_{i,j,t})$ is the expected profit for individual i in location j during time period t and $E(N_{j,t})$ is the expected number of vessels in location$j$ at time period t.

Expected profits are calculated as expected location-specific revenue less expected individual-specific costs, where revenue is the value of the catch and costs are a function of time spent fishing and distance traveled to the fishing location.

The motivation for this equation is that fishermen are expected profit maximizers. Additionally, they may either view other fishermen as information about which locations are hot spots or as sources of congestion.

An autoregressive model of order seven (AR(7)) with month and location fixed effects is used to forecast expected harvests, number of trips, and hours spent fishing. The model is of order seven to capture the trends of the previous week. The general specification of the model is:

$$Y_{i,j,t} = \sum_{d=1}^{7} \beta_d Y_{i,j,t-d} + \sum_{m=1}^{M} \beta_{m+7} Month_{m,t} + \sum_{n=1}^{N} \beta_{n+M+7} Location_{n,t} + \varepsilon_{i,j,t}$$

where $Y_{i,j,t}$ represents the variable being forecast, $Month_{m,t}$ and $Location_{n,t}$ are indicator variables equal to 1 if t occurs during month m or location n, respectively, and 0 otherwise.

The four equations are estimated simultaneously using three-stage least squares (3SLS) regression: #1 Male harvest, #2 Male harvest, number of trips, and hours. The equations are estimated simultaneously in order to account for cross-equation error correlations. For example, factors that increase the expected harvest of #1 Males are likely to also increase the expected harvest of #2 Males. Moreover, if expected harvest is greater, then expected effort (trips and hours) is likely to be higher, as well.

From the results of the discrete choice model, the probability that each fishermen chooses a given location can be estimated (Small and Brownstone, 1989) (individual and time subscripts have been omitted to simplify the notation):

$$P_j^* = P_{j|s} \cdot P_{s|f} \cdot P_f \tag{2.11}$$

where

$$P_f = \frac{e^{V_f + \rho_s IV_s}}{1 + e^{V_f + \rho_s IV_s}} \tag{2.12}$$

$$P_{s|f} = \frac{e^{\frac{V_{s|f} + \rho_j IV_j}{\rho_s}}}{e^{\frac{V_{j'}}{\rho_s}} + e^{\frac{V_{s|f} + \rho_j IV_j}{\rho_s}}} \tag{2.13}$$

$$P_{j|s} = \frac{e^{\frac{V_{j|s}}{\rho_j}}}{\sum_j^J e^{\frac{V_{j|s}}{\rho_j}}} \quad \text{where } j \neq j' \tag{2.14}$$

where the subscript j is an index for the given location, subscript j' is an index for the previously chosen location, subscript s is an index for switch, and subscript f is an index for fish. The dissimilarity parameters for the switch and location nests are ρ_s and ρ_j. IV_s and IV_j are the inclusive values for the switch and location nests.

Sequential estimation, rather than simultaneous estimation, will be used to derive these parameters since the alternatives in the location nests are different for each person and time period. The coefficients for the location model will be estimated first. Using these estimated coefficients, the inclusive value is calculated for the location decision. Then, the coefficients for the switch model will be estimated with the inclusive value for the location decision entering as an explanatory variable. Finally, using the estimated coefficients, the inclusive value for the switch decision is calculated and enters as an explanatory variable in the fish model.

When using simultaneous estimation, the regression outputs include "base" coefficients and scaling factors (dissimilarity parameters) for each nest. In order to obtain the nest-specific coefficients, the base coefficients must be divided by the dissimilarity parameters for that nest. When using sequential estimation, nest-specific data are used to obtain nest-specific coefficients. In order to obtain the base coefficients that correspond to simultaneous estimation, these nest-specific coefficients need to be scaled (multiplied) by their nest-specific dissimilarity parameters.

Additionally, when using simultaneous estimation, the error terms within a nest are positively correlated. That is, for two alternatives j and i in a given nest:

$$Var(\epsilon_j - \epsilon_i) = Var(\epsilon_j) + Var(\epsilon_i) - 2Cov(\epsilon_j \epsilon_i)$$

It is assumed that $Var(\epsilon_j) = Var(\epsilon_i) = \sigma^2$ and $Cov(\epsilon_j\epsilon_i) = \rho\sigma_j\sigma_i = \rho\sigma^2$ where ρ is the measure of correlation between ϵ_j and ϵ_i. Thus:

$$\begin{aligned}
Var(\epsilon_j - \epsilon_i) &= 2\sigma^2 - 2\rho\sigma^2 \\
&= 2\sigma^2(1-\rho) \\
&= 2\sigma^2\tau^2 \quad (\tau = \sqrt{1-\rho}) \quad \text{(Heiss, 2002)}
\end{aligned}$$

Therefore, the variance is deflated by τ^2 to reflect correlations within a nest. However, when using sequential estimation, the error terms are assumed to be independent. Therefore, the variances from the sequentially estimated models must be corrected using the τ^2 deflation factor.

Table 2.1 summarizes the relations between simultaneous and sequential estimations of coefficients and standard errors and the nest-specific estimates:

Table 2.1: Recovering Nest-Specific Parameters

	Sequential	Simultaneous	Nest
Coefficients	$\frac{\beta}{\tau}$	β	$\frac{\beta}{\tau}$
Standard Errors	σ	σ	$\sigma\tau$

Finally, as noted by Cameron and Trivedi (2005), there is one further complication which must be addressed when using this approach:

> This sequential estimator is less efficient than the FIML [Full Information Maximum Likelihood] estimator, and at the second stage the usual CL [conditional logit] standard errors understate the true standard errors of the sequential estimator since they do not allow for the estimation error in computing the inclusive value. McFadden (1981) gives the formula for correct standard errors, or the bootstrap can be used.

In this study, the models of the fishing and location switch decisions will be bootstrapped in order to obtain correct estimates of standard errors.

2.2.2 Continuous Choice Model

The next step in the fisherman's decision process is to decide how many hours to spend harvesting. As this is estimated within a discrete-continuous choice framework, the fisherman's predicted probabilities of choosing each location are used as opposed to using a set of dummy variables to indicate location choice.

The choice of hours is modeled as an input demand function. The number of hours spent harvesting depends on the location choice as well as potential costs (fixed costs) and benefits (prices). These trade-offs may vary by age. Additionally, if an individual's license allows him to drop more crab pots, then he may allot more time towards harvesting. Season-location fixed effects are also included.

The choice of hours is modeled as follows:

$$\begin{aligned} E_{i,j,t} = \gamma_0 + \sum_{l=1}^{J-1} \gamma_l Pr^*_{i,j,t} + \gamma_J FC_{i,j,t} + \gamma_{J+1} P_t + \gamma_{J+2} Age_{i,t} \\ + \gamma_{J+3} Age^2_{i,t} + \gamma_{J+4} Pot\ Limit_{i,t} + \gamma_{J+5} P(\#1)_t + \gamma_{J+6} P(\#2)_t + \mu_{i,j,t} \end{aligned} \tag{2.15}$$

where $Pr^*_{i,j,t}$ are the predicted probabilities for individual i to choose location j in time period t, $FC_{i,j,t}$ is the fixed costs for individual i, location j, and time period t, $Age_{i,t}$ is the age for individual i at time period t, $Pot\ Limit_{i,t}$ is the maximum amount of pots individual i is allowed to drop at time period t, $P(\#1)_t$ and $P(\#2)_t$ are the prices for #1 and #2 male crabs, respectively, at time period t, and $\mu_{i,j,t}$ is a normally distributed error term.

Fixed costs are calculated as the costs an individual incurs for traveling from his home location to his fishing location.

Chapter 3

Data

Several data sets were combined in this study. The primary data set is derived from daily logbooks submitted by fishermen from 2000-2010 (MDNR). These logbooks contain information about when and where fishermen harvested, as well as information about harvest, effort, and fishermen age. Monthly crab abundances were taken from a study by Drs. Lipton and Holzer (manuscript in progress). Monthly crab prices were derived from dealer reports. Daily weather data was obtained from the Chesapeake Bay Program (CBP). Finally, monthly water quality data was derived from the 2002 Chesapeake Bay Eutrophication Model (EPA, 2004) and a separate study which analyzes the spatial effort of Maryland commercial crab pot fishermen (Versar, 2012). The 2002 Chesapeake Bay Eutrophication Model divides the Chesapeake Bay into grids and interpolates the water quality data for each grid at approximately 1 meter intervals through the water column based on water quality measurements taken from monitoring stations. The spatial effort data records the GPS locations and depths of a sample of crab pots in the Maryland portion of the Chesapeake Bay.

The following procedure was used to derive the water quality estimates:

1. From the spatial effort data set, the average depths at which crab pots are

dropped is determined.

- March to May: 0.5 to 6 meters deep
- June to September: 0.5 to 5 meters deep
- October to December: 0.5 to 8 meters deep

2. All grid points in the Eutrophication Model which are considered to be "too deep" are removed.
3. The bottom level estimates of water quality for the remaining grides are averaged for each area as crab pots rest at the bottom of the Bay.

This procedure derives a more accurate measurement of the water quality encountered by the blue crabs than other potential measurements, such as bottom level measurements (Mistiaen et al., 2003, Huang et al., 2011) or averages across depths.

The geographical region considered is divided into 26 fishing sites as defined by the National Oceanic and Atmospheric Administration (NOAA). Of those sites, six sites have both harvest and stock data (see Figure 3.1).

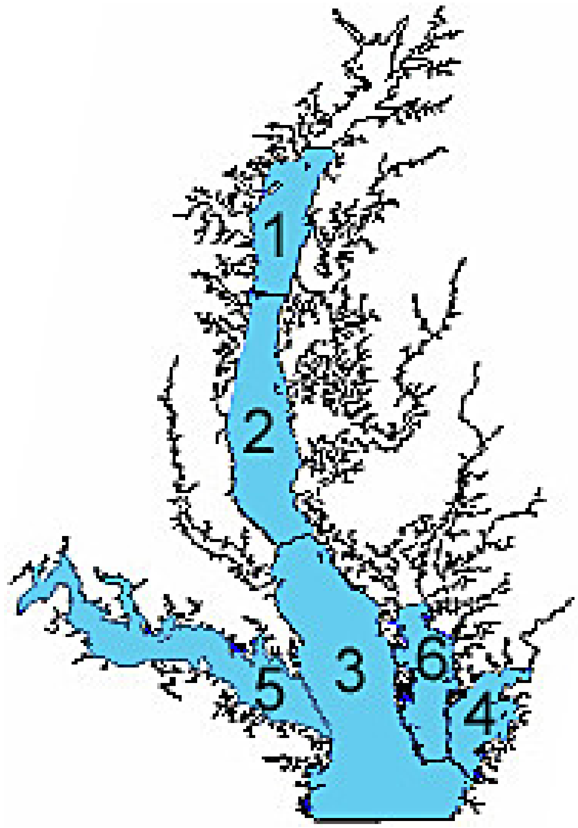

Figure 3.1: Selected Fishing Sites

The specific subset of fishermen analyzed in this study are those using crab pots. Only one gear type was chosen because there are variations in catch rate per unit of gear, targeted crab market category, and so on, among gear types. A model with too many variations would, most likely, lead to indeterminacy. Crab pots in particular were chosen because they are one of the most common gear types used in the Bay and the value of their catch comprises roughly 80% of the total value of crabs caught in the Bay.

Crab pots are large square traps made out of galvanized chicken wire or PVC mesh. The trap has two internal chambers: a bottom chamber which consists of two or four entrance tunnels which allow the crabs to enter and a top chamber which is the holding area. Inside the bottom chamber is a mesh bait box constructed to attract the crabs without allowing them to reach the bait. Once trapped, the crabs instinctively swim towards the surface and become trapped in the holding area. Most crab pots have two small exit holes in the holding area to allow smaller crabs to escape. An important regulation regarding crab pots is that there are restrictions on where they can be set. For example, they cannot be set in water less than four feet deep at mean low tide except for certain areas in the Pocomoke and Tangier Sounds. Therefore, many crabbers place their crab pots at the mouths of tributaries.

The specific crab market categories analyzed are #1 and #2 Male crabs. This is for three main reasons. First, due to the migration patterns of the blue crab, male crabs are more likely to be found in the Maryland side of the Bay and females in the Virginia side. Second, there are harvest restrictions against harvesting female crabs in Maryland which are provided by public notice. These regulations make it more difficult to model female harvests. Third, the value of male catches is roughly 70% of the total value of crabs caught by crab pots in Maryland.

Travel costs and fuel costs are used as the costs to harvesting and data are unavailable for labor costs. Travel costs are based on an estimated cost per meter for the distances to the site. ESRI ArcGIS is used to approximate the distances to the centroid of the fishing sites based on the ZIP codes of the fishermen. Total distance is then doubled to account for a two-way trip and multiplied by the Internal Revenue Service (IRS) national reimbursement rate per meter (converted from per mile), yielding an estimated cost of fuel and maintenance for a vehicle.

Following Weninger (1998), vessel fuel consumption can be estimated as the product of engine horsepower, hours spent fishing, and a constant 0.04 to account for gallons used per unit horsepower. Fuel costs are then calculated as the product of hourly fuel consumption and fuel prices for #2 diesel (U.S. Department of Energy). Therefore, trips costs are calculated in the following way:

$$\text{trip costs} = \text{two-way distance} \cdot \text{reimbursement rate} + \text{hours} \cdot \text{hp} \cdot 0.04 \cdot \text{diesel price}$$

As the travel cost distance is measured as the shortest distance between two points and labor costs are not considered, the profit results of this study can be considered as an upper bound.

The data sets contain missing values for some observations. Single-imputation techniques were used to estimate the missing variables and allow the remainder of the data in the observations to be used.

The data set is missing 9% of age observations and 49% of horsepower observations. These missing age observations were imputed using the number of hours, trips, and harvest per time period. As there are no apparent trends to the missing observations, the average motor horsepower across the data set was used to estimate these missing values.

Table 3.1 summarizes the total number of trips, the total number of trips per season, and the total number of switches per location in the logbook data set.

Table 3.1: Fishing Trips and Location Switches Using Fisherman Logbook Data

Location	Trips	Spring	Summer	Fall	Switch (to)	Switch (from)
1	88,007	7,590	49,712	30,705	583	557
2	100,394	13,404	51,204	35,786	500	501
3	80,349	14,289	39,054	27,026	496	499
4	27,876	6,415	15,608	5,853	126	131
5	39,771	7,425	21,073	11,326	78	84
6	56,361	10,448	31,645	14,336	330	346
Total	408,391	59,822	217,285	131,284	2,411	2,411

Table 3.2 summarizes the trip level means for the significant variables in this study.

Age is measured in years, profit in dollars, harvests in pounds, stock in crabs per 1,000 square meters, and dissolved oxygen (DO) in milligrams per liter.

Table 3.2: Mean Values of Significant Variables

Location	Age	Profit	#1 Harvest	#2 Harvest	Stock	DO	Hours
1	49.52	328.61	137.58	45.69	95.70	7.74	6.06
2	49.78	332.78	146.62	38.18	64.06	8.39	6.47
3	48.32	361.31	164.00	39.89	47.24	8.60	6.89
4	48.01	249.50	63.62	50.15	29.89	8.43	6.99
5	49.42	182.89	76.26	20.82	69.01	7.86	4.41
6	48.88	237.00	86.75	34.05	76.59	8.22	6.80
Mean	49.17	306.09	127.83	40.43	67.60	8.20	6.32

Chapter 4

Results

The results of the bio-economic and fisherman choice models defined in Section 2 are presented in this chapter.

4.1 Bio-Economic Results

The results for the bio-economic model are summarized in Tables 4.1, 4.2, and 4.3. Each column represents a different hypothesis about the interactions between density, harvest, and dissolved oxygen. In Table 4.1, the Mortality Hypothesis assumes that dissolved oxygen affects the stock level, the Availability Hypothesis assumes that dissolved oxygen affects the harvest level, and the Distribution Hypothesis assumes that dissolved oxygen affects the spatial distribution of the stock. In Tables 4.2 and 4.3, the Mortality/Availability Hypothesis combines the Mortality and Availability Hypotheses, the Distribution/Availability Hypothesis combines the Distribution and Availability Hypotheses, the Mortality/Distribution Hypothesis combines the Mortality and Distribution Hypotheses, and the Mortality/Availability/Distribution Hypothesis combines the Mortality, Availability, and Distribution Hypotheses. For notational simplicity, $DO_{4\to 8}$ represents $DO \cdot 1(DO_{4\to 8})$, $DO_{8\to 12}$ represents $DO \cdot 1(DO_{8\to 12})$, $\Delta DO_{-3\to 0}$ represents $\Delta DO \cdot 1(\Delta DO_{-3\to 0})$, and $\Delta DO_{0\to 3}$ represents $\Delta DO \cdot 1(\Delta DO_{0\to 3})$. Additionally, Season·Location fixed effects are included in both the density and harvest equations and Year fixed effects are included in the density equation.

Table 4.1: Bio-Economic Results

	Mortality	Availability	Distribution
Density			
Lag Density	0.06***	0.06***	0.06***
	(1.57E-3)	(1.55E-3)	(1.55E-3)
Lag Total Harvest	-3.45E-5***	-3.36E-5***	-2.98E-5***
	(1.27E-6)	(1.26E-6)	(1.28E-6)
$DO_{4\to8}$	0.30***	–	–
	(0.09)		
$DO_{8\to12}$	-0.84***	–	–
	(0.08)		
$\Delta DO_{-3\to0}$	–	–	8.58***
			(0.27)
$\Delta DO_{0\to3}$	–	–	-3.25***
			(0.23)
SBI	-2.74***	-2.68***	-2.52***
	(0.07)	(0.07)	(0.07)
Constant	56.84***	56.34***	58.08***
	(0.95)	(0.66)	(0.68)
Fixed Effects	Season·Location	Season·Location	Season·Location
	Year	Year	Year
Male Harvest			
Density	0.07***	0.07***	0.07***
	(4.47E-3)	(4.47E-3)	(4.47E-3)
Female Harvest	85.72***	70.20***	85.52***
	(1.94)	(2.03)	(1.94)
Age	5.59***	5.58***	5.59***
	(0.22)	(0.22)	(0.22)
Age^2	-0.07***	-0.07***	-0.07***
	(2.20E-3)	(2.20E-3)	(2.20E-3)
Hours	35.74***	35.66***	35.73***
	(0.16)	(0.16)	(0.16)
$DO_{4\to8}$	–	-0.47*	–
		(0.24)	
$DO_{8\to12}$	–	3.34***	–
		(0.23)	
Constant	-221.83***	-224.88***	-221.86***
	(5.51)	(5.70)	(5.51)
Fixed Effects	Season·Location	Season·Location	Season·Location
Observations	367,478	367,478	367,478
BIC	9,085,175	9,084,983	9,084,614

***p<0.01, **p<0.05, *p<0.1

All coefficients are of the expected sign and significant and are similar across models. If the units for density (crabs/1,000 square meters) and lag total harvest (pounds) are both converted to crabs, then the interpretation becomes: for every crab that is harvested, there are approximately 8 fewer crabs in the population. One reason that this ratio is not 1:1 could be that there are other crab market types (e.g., female), gear types (e.g., trot lines), and recreational fishermen which are not included in the analysis. For the Mortality Model, dissolved oxygen increases density from 4 to 8 mg/l and decreases density from 8 to 12 mg/l. For the Distribution Model, relative dissolved oxygen increases density from -3 to 0 and decreases density from 0 to 3. Dissolved oxygen has the opposite effect in the Availability Model: male harvest decreases from 4 to 8 mg/l and increases from 8 to 12 mg/l.

Table 4.2: Bio-Economic Results - Density

	Mort/Avail	Mort/Dist	Dist/Avail	Mort/Avail/Dist
Density				
Lag Density	0.06***	0.06***	0.06***	0.06***
	(1.57E-3)	(1.57E-3)	(1.55E-3)	(1.57E-3)
Lag Total Harvest	-3.45E-5***	-3.05E-5***	-2.99E-5***	-3.04E-5***
	(1.27E-6)	(1.28E-6)	(1.28E-6)	(1.28E-6)
$DO_{4\to 8}$	0.30***	-1.16***	–	-1.15***
	(0.09)	(0.11)		(0.11)
$DO_{8\to 12}$	-0.86***	-1.97***	–	-1.99***
	(0.08)	(0.10)		(0.10)
$\Delta DO_{-3\to 0}$	–	10.14***	8.59***	10.13***
		(0.30)	(0.27)	(0.30)
$\Delta DO_{0\to 3}$	–	-2.46***	-3.26***	-2.46***
		(0.24)	(0.23)	(0.24)
SBI	-2.74***	-2.67***	-2.52***	-2.68***
	(0.07)	(0.07)	(0.07)	(0.07)
Constant	56.89***	68.96***	58.06***	68.99***
	(0.95)	(1.02)	(0.68)	(1.02)
Fixed Effects	Season·Location	Season·Location	Season·Location	Season·Location
	Year	Year	Year	Year
Observations	367,478	367,478	367,478	367,478
BIC	9,084,532	9,084,098	9,084,031	9,083,458

***p<0.01, **p<0.05, *p<0.1

Table 4.3: Bio-Economic Results - Male Harvest

	Mort/Avail	Mort/Dist	Dist/Avail	Mort/Avail/Dist
Male Harvest				
Density	0.07***	0.07***	0.07***	0.07***
	(4.47E-3)	(4.47E-3)	(4.47E-3)	(4.47E-3)
Female Harvest	70.20***	85.78***	70.25***	70.26***
	(2.03)	(1.94)	(2.03)	(2.03)
Age	5.58***	5.59***	5.58***	5.58***
	(0.22)	(0.22)	(0.22)	(0.22)
Age^2	-0.07***	-0.07***	-0.07***	-0.07***
	(2.20E-3)	(2.20E-3)	(2.20E-3)	(2.20E-3)
Hours	35.66***	35.74***	35.66***	35.66***
	(0.16)	(0.16)	(0.16)	(0.16)
$DO_{4\rightarrow 8}$	-0.48**	–	-0.52**	-0.48**
	(0.24)		(0.24)	(0.24)
$DO_{8\rightarrow 12}$	3.39***	–	3.29***	3.38***
	(0.23)		(0.23)	(0.23)
Constant	-224.91***	-221.83***	-224.51***	-224.89***
	(5.70)	(5.51)	(5.70)	(5.70)
Fixed Effects	Season·Location	Season·Location	Season·Location	Season·Location
Observations	367,478	367,478	367,478	367,478
BIC	9,084,532	9,084,098	9,084,031	9,083,458

***p<0.01, **p<0.05, *p<0.1

All coefficients are of the expected sign and significant and are similar across models. As with the three base models, for every crab that is harvested, there are approximately 8 fewer crabs in the population. In all four models, dissolved oxygen decreases harvest from 4 to 8 mg/l and increases harvest from 8 to 12 mg/l. Additionally, relative dissolved oxygen always increases harvest from 0 to 3 and decreases harvest from 3 to 5. However, the effect of dissolved oxygen on stock becomes negative whenever relative dissolved is also included. Therefore, it is unlikely that a model containing both the Mortality and Distribution hypotheses is realistic. Of the remaining five models, Mortality/Availability and Distribution/Availability have the lowest Bayesian Information Criterion (BIC) values, so they will be used in the rest of the analysis.

Based on the results from these models, Figure 4.1 shows the stock and harvest elasticities with respect to changes in dissolved oxygen for both the Mortality/Availability and Distribution/Availability Models.

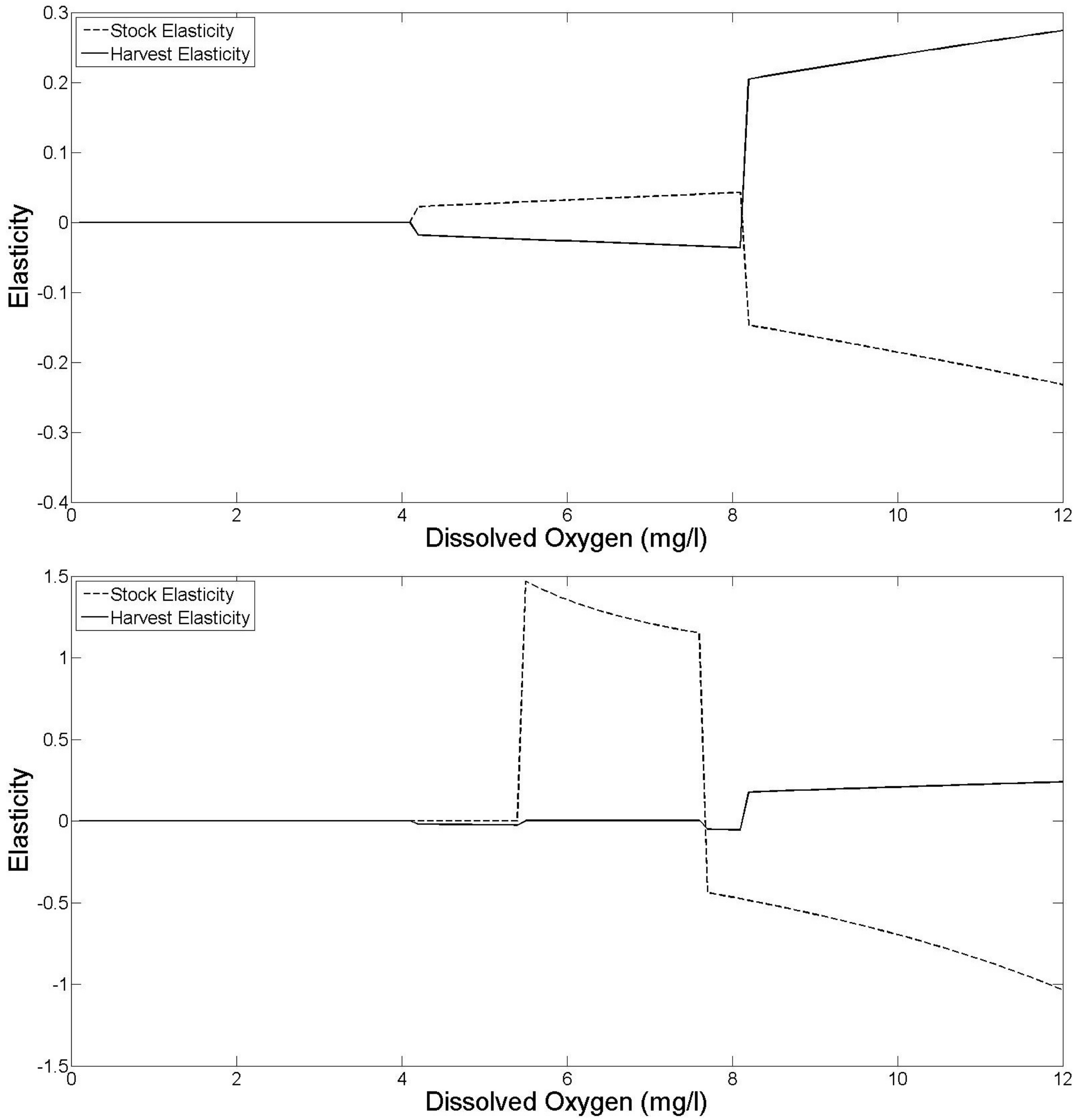

Figure 4.1: Harvest and Stock Elasticity With Respect to Dissolved Oxygen; Top: Mortality/Availability Model, Bottom: Distribution/Availability Model

As these elasticities show, the assumptions on how water quality affects stock and harvest appear to have a significant affect on stock and harvest predictions. While both models predict similar trends, only stock responds elastically to changes in dissolved oxygen in the Distribution/Availability Model from 5.4 to 7.5 mg/l and 11.8 to 12 mg/l.

4.2 Fisherman Choice Results

4.2.1 Discrete Choice Results

Table 4.4 summarizes the coefficient estimates derived from the nested logit model. The Fish and Switch equations are estimated using 500 bootstrap replications. This number of replications was chosen because at this size the standard errors did not change significantly when the random seeds were changed. None of the variables became insignificant with the use of bootstrapping. The Fish and Switch models are also clustered at the individual level. The Location model is not clustered as it is estimated using a conditional/fixed effects logit. The coefficients and standard errors for the Switch and Location models are nest-specific. This is because there is only one non-degenerate nest in each level of the model. Finally, month fixed effects are included in the fish choice model and year fixed effects in the Fish and Switch models.

Table 4.4: Discrete Choice Results

Fish		**Switch**		**Location**	
Sun|Mon	-0.35***	IV_L	0.03	E(Profit)	0.16***
	(0.05)		(0.15)		(4.80E-4)
Age	0.01	Constant	-3.71	E(N)	0.03***
	(0.02)		(0.48)		(4.37E-5)
Age^2	-1.43E-4				
	(1.88E-4)				
Air Temperature	-1.01***				
	(3.28E-3)				
Air $Temperature^2$	3.33E-4***				
	(8.86E-5)				
Wind Speed	-0.05***				
	(0.01)				
Cloud Cover	-0.05***				
	(4.84E-3)				
Precipitation	0.10***				
	(0.02)				
IV_S	5.04				
	(4.27)				
Constant	0.36***				
	(0.47)				
Fixed Effects	Month		Month·Location		
	Year				
Observations	133,844		391,813		15,830
LL	-88,210.23		-16,802.16		-4511.69
Clusters	1,331		1,372		
Bootstrap Replications	500		500		

***p<0.01, **p<0.05, *p<0.1

All coefficients are of an expected or reasonable sign and magnitude, except for the coefficient on IV_S. In order for the model to be consistent with utility-maximizing behavior, this coefficient must be between 0 and 1. If this coefficient is equal to zero, then there is no nesting of the decisions. That is, the decision to switch is not made separately from the location choice. One possible explanation for this result is that there may be misreporting of location choice by fishermen. If fishermen are inaccurately reporting their locations, then they are not correctly being assigned as "switchers" or "non-switchers." If this is the case, then it makes sense that the switching decision would not appear to be significant when estimated.

A separate study has looked into the spatial effort of Maryland commercial crab pot fishermen (Versar, 2012). The GPS coordinates of crab pots were recorded for the years 2002-2004 and 2007-2010. Their data show that fishermen switch locations much more frequently than previously thought. Of the roughly 10,000 recorded trips, about half of them are considered "switches." Unfortunately, this data set does not contain much additional information, so a complete analysis is not possible. However, a more accurate representation of location choice can be estimated for the logbook data set. In order to correct for potential misreporting, fishermen were "assigned" locations based on the proportion of trips and switches taken to and from each location. For example, according to the GPS data set, fishermen switch out of Location 1 roughly 40% of the time in May. Those that switch choose Location 2 61% of the time, Location 3 30% of the time, and Location 5 9% of the time. This information was estimated for each month using the GPS data set and applied to the fishermen in the logbook data set.

The fisherman choice model was then re-estimated using the estimated location choices (Table 4.5).

Table 4.5: Discrete Choice Results

Fish		**Switch**		**Location**	
Sun|Mon	-0.36***	IV_L	0.04***	E(Profit)	0.04***
	(0.05)		(0.01)		(4.58E-5)
Age	0.01	Constant	0.19***	E(N)	0.04***
	(0.02)		(0.04)		(5.33E-6)
Age^2	-1.20E-04				
	(1.93E-04)				
Air Temperature	-0.01***				
	(3.32E-03)				
Air $Temperature^2$	3.10E-4***				
	(8.96E-05)				
Wind Speed	-0.05***				
	(0.01)				
Cloud Cover	-0.05***				
	(4.88E-3)				
Precipitation	0.10***				
	(0.02)				
IV_S	0.69***				
	(0.07)				
Constant	-0.22***				
	(0.49)				
Fixed Effects	Month		Month·Location		
	Year				
Observations	134,467		392,186		1,012,492
LL	-90,533.87		-244,125		-258,956.55
Clusters	1,325		1,375		
Bootstrap Replications	500		500		

***p<0.01, **p<0.05, *p<0.1

All coefficients are of the same sign (except for the constants) and similar magnitudes as with the logbook data. However, now the coefficient on IV_S is within the unit interval. Furthermore, the coefficients in the switching equation are now significant (see Table 2.1). These results suggest that misreporting may be the reason for the insignificant coefficient on IV_S.

4.2.2 Continuous Choice Results

Using Equations 2.11 and 2.12 and the results from Table 4.5, the predicted probabilities are estimated. The results for the hours estimation are shown in Table 4.6 and the standard errors are clustered at the individual fisherman level.

Table 4.6: Hours Choice Results

Hours	Coefficient (SE)
Pr(1)	8.71E-5
	(1.16E-4)
Pr(2)	3.40E-4***
	(5.65E-5)
Pr(3)	1.31E-3***
	(2.28E-4)
Pr(4)	2.90E-3
	(3.54E-3)
Pr(5)	-0.01***
	(1.83E-3)
Pr(6)	-0.01
	(1.49E-3)
LN(Fixed Costs)	0.27***
	(0.06)
Age	-0.07***
	(0.04)
Age^2	4.49E-4
	(3.55E-4)
Pot Limit	3.45E-03***
	(1.78E-4)
#1 Male Price	0.06***
	(0.02)
#2 Male Price	0.21***
	(0.07)
Constant	6.11***
	(0.85)
Fixed Effects	Location·Season
Observations	394,081
R^2	0.31
Clusters	1,373

***p<0.01, **p<0.05, *p<0.1

The results indicate that, except for the two locations, fishermen do take into account their location choice when deciding the number of hours to spend harvesting. Fixed costs, measured in terms of the travel cost to get from the home location to the fishing site, have a positive effect on effort, as expected. The linear term on age is negative and significant. The effect of the maximum number of allowable pots (pot limit) is positive and significant. As the maximum number of allowable pots is 900, this effect could be as high as 3 hours. Finally, the effect of both #1 and #2 male prices are positive and significant.

Chapter 5

Policy Application

The results of the bio-economics and fisherman choice models are used to simulate the effects of a policy geared toward water quality improvement. In 2010, the U.S. Environmental Protection Agency (EPA) established the Chesapeake Bay Total Maximum Daily Load (TMDL) to restore clean water in the Chesapeake Bay and its tributaries by 2025. Implementing the TMDL will be costly to states and local jurisdictions. For example, the projected costs to Maryland are approximately \$14.5 billion, whereas the value of the commercial blue crab fishery has averaged \$52.9 million annually from 2008 to 2012, an increase of 49% since 2005 to 2007 (MDNR). As previously noted, there are concerns that improvements to water quality may not yield long-term benefits to fisheries.

The simulation runs from 2010-2019 and uses baseline and TMDL dissolved oxygen data derived from the 2002 Chesapeake Bay Eutrophication Model (EPA, 2004). Initial values, as well as striped bass population indices and juvenile recruitment, are estimated using Monte Carlo simulations.

Four scenarios are tested: the two chosen bio-economic models (Mortality/Availability and Distribution/Availability) with and without the fisherman behavior model incorporated. The scenarios using only the bio-economic models are run to test the value of incorporating fisherman behavior into the analysis.

Table 5.1 shows the percentage change in profit, revenue, cost, and stock from the TMDL for each of the fourteen scenarios.

Table 5.1: Simulation Results - Percent Changes under TMDL

Model	Profit (SE)	Revenue (SE)	Cost (SE)	Stock (SE)
Mort/Avail				
Full	4.01*	2.63*	0.48	36.64
	(2.40)	(1.51)	(1.15)	(93.61)
Bio-Economic	0.90	0.77	0.22	-18.39
	(1.06)	(0.90)	(0.57)	(32.32)
Dist/Avail				
Full	3.04	1.98	-0.04	11.94
	(4.38)	(3.23)	(1.40)	(48.85)
Bio-Economic	0.70	0.61	0.22	-16.45
	(1.12)	(0.94)	(0.57)	(29.89)

***p<0.01, **p<0.05, *p<0.1

There are a few general observations that can be made about these results. The first is that the mean percent changes in the variables of interest tend to be greater under the full specification than the bio-economic only model. Furthermore, the mean percent changes (standard errors) tend to be greater (smaller) under the Mortality/Availability Model than the Distribution/Availability Model. Finally, while most of the results are positive, only profit and revenue increase significantly under the Mortality/Availability Model. Therefore, it appears as if the TMDL may have a small, positive effect on both profits and revenues if any effect at all. This result is likely due to the fact that, under the TMDL, dissolved oxygen is roughly 8.4 mg/l on average - outside of the range where significant effects were expected.

Chapter 6

Conclusion

The goal of this paper was to develop and estimate a model of water quality improvement on a commercial fishery. The first step was to develop a set of bio-economic models linking the effects of water quality to stock and harvest. Seven hypotheses on the effect of water quality were examined using data on the Maryland commercial blue crab fishery. The statistical analysis demonstrated that the Mortality/Availability and Distribution/Availability models are the most plausible. That is, water quality is likely to affect both stock and harvest simultaneously. One-period elasticity results highlighted the effect that these assumptions have on stock and harvest predictions. Stock and harvest were found to respond inelastically to changes in dissolved oxygen under the Mortality/Availability Model, but elastically for certain ranges of dissolved oxygen under the Distribution/Availability Model.

The increase in fishermen productivity due to an increase in water quality has interesting implications for the dynamics of the stock. For example, in areas with relatively high levels of dissolved oxygen, the harvests are likely to be higher and, therefore, the stocks are likely to be lower than in areas with relatively low levels of dissolved oxygen. If this is the case, then low water quality areas may act as a refuge (Mistiaen et al., 2003). This hypothesis is supported by the results of the models incorporating the Mortality Hypothesis.

The second step was to model fishermen behavior. Four decisions - fish, switch, location, and effort - were modeled and estimated. The decision to switch was found to be significant as its inclusive value was both positive and significant. However, when using the logbook data, this value was insignificant. This is most likely caused by misreporting of fishing locations. This hypothesis is supported by an examination of a spatial effort data set, which confirms that switching occurs more frequently than previously believed. When fishermen were assigned locations based on the spatial effort data set, the inclusive value became significant and within the unit interval, supporting the misreporting hypothesis. This is an important result as the majority of studies assume that the decision to switch is exogenous.

Modeling the decision to switch locations has important policy implications, as well, as it provides more insight into the location choices made by fishermen. As fishery policies are becoming more spatially-oriented (e.g., area closures, restrictions on gear placement), understanding how commercial fishermen choose their fishing grounds is crucial in effective fishery management.

The results of the bio-econometric and fisherman behavior models were incorporated into a simulation of the Chesapeake Bay TMDL on the Maryland commercial blue crab fishery. Four scenarios were run. The first two combined the fisherman behavior model with the two chosen bio-economic models. The next two only used the bio-economic models. The results show that the predicted effects of the TMDL are greater and more significant under the full model than under the bio-economic model. However, only profit and revenue under the Mortality/Availability Model increased significantly. This is likely due to the fact that the current levels of dissolved oxygen are suitable for the blue crabs.

These results do not imply that the benefits from improved water quality are insignificant. There are a number of other benefit categories not considered in this paper. For example, there may be improvements to other commercial fisheries, recreational fishing, other recreational activities, and property values. The avoided costs of future water treatment and co-benefits of BMPs by farmers should be considered, as well.

Finally, the overall modeling structure used in this study has policy implications of its own. First, this type of model may be able to determine the potential benefits from different areas of a body of water. This information can be used to determine which spatial land use policies will be the most cost-effective at improving water quality. Second, this type of model is useful when estimating the effects of climate change on a fishery. Climate change is likely to have spatially differentiated effects on marine organisms, such as changes in stock productivity, species distribution, and ecosystem productivity. The current literature on this subject is growing, but is mainly focused on biologic models as opposed to ones which incorporate fishermen behavior. Knowing how fishermen will react to these changes, as well as how they may directly react to changes in climate, is key when determining the effects of climate change on a fishery.

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