THREE ESSAYS ON FISHERIES ECONOMICS

BY

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DISSERTATION

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Abstract

This dissertation examines three themes of efficiency in fisheries economics and management. The first theme is intertemporal efficiency; by examining fishery management problems within a stochastic bioeconomic model, the tradeoffs between current and future consumption are clear. The second theme explored in this essay is the efficiency of tradable permits system in the presence of trade restrictions. The third theme explored in this dissertation is efficiency in the presence of ecosystem externalities.

Fisheries managers must often make decisions even while there is large amounts of uncertainty regarding stock level; furthermore, there are often fairly long periods of time in which they are unable to assess stock levels. The first essay examines a bioeconomic fishery model that includes rigidity in the policy-setting process, a management reality that has yet to be incorporated into these types of models. Although analytically intractable, the model is simulated across a range of biological and institutional parameters to learn how this rigidity affects the manager's optimization problem. While the effects of rigidity with deterministic stock growth are shown to be small; when growth is stochastic, the present value of fisheries revenue may drastically decline under rigid management. By solving for the present value of fisheries revenues across a wide range of parameter values, the economic tradeoffs between management and scientific activities can be clarified.

The second essay examines bilateral bargaining in a market for a unique synthetic input permits, Days-at-Sea, in the Northeast groundfish fishery. This research applies a quantile regression approach to the estimation of bargaining power and tests a key identification assumption of bargaining power equality made by previous researchers. One of the findings

of this research is that current regulations may have segmented this market, endowing some firms with bargaining power relative to others.

The final essay examines a small ecosystem-economy in which there are competing extractive and non-extractive uses for the fishery resource. In this ecosystem, herring are commerically harvested and are food for whales, which are an input in a non-extractive tourism industry, whale-watching. A finding of this research is that fishing negatively impacts the whale-watching industry; however, the magnitude of these effects are small. The results contained in this essay are useful inputs for managers seeking to implement Ecosystem Based Fishery Management.

To Diana.

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Chapter 1

Introduction

Economists have typically addressed three major issues in the field of fishery management: intertemporal efficiency, allocative efficiency of markets, and efficient production in the presence of externalities. This dissertation is composed of three essays that address these topics. The first essay examines the effects of stock-growth uncertainty and policy rigidity using a bioeconomic model. Policy rigidity is a management institution that utilizes a constant control variable (harvest or quota) for a relatively long period of time. During this time, the stock may experience multiple growth shocks. The second essay examines bilateral bargaining in the market for Northeast Multispecies Groundfish Days-at-Sea (DAS). This unique system was initially designed as a simple input control, but has since evolved into a tradable input control. The DAS market has few, if any characteristics of a market: prices are not publicly available, speculation is explicitly disallowed, there are legal limitations that govern potential trading partners, and finding a trading partner may be costly. The final essay examines a small economy containing extractive (fishing) and non-extractive uses (whale-watching) as an example of the Ecosystem Based Fisheries Management (EBFM) approach.

1.1 Fishery Management in the United States

Management of fisheries in the United States is a complex process with many involved parties. Under the Magnuson-Stevens Fishery Conservation and Management Act (MSFCA), regional Management Councils propose fishery management plans (MSFCA, 2007). The regional Councils are composed of stakeholders, typically fishing industry groups, and are advised by National Marine Fisheries Service (NMFS) and academics on scientific and technical issues. Proposed regulations are then adopted and enacted by the Department of Commerce. The regional Councils are guided by many pieces of legislation, including the MSFCA, the Marine Mammal Protection Act (MMPA), and the National Environmental Policy Act (NEPA).

The MSFCA and subsequent amendments establishes 10 “National Standards” or principles for fishery management.

1. Management plans should prevent overfishing and achieve Optimum Yield.
2. Managers should use the best available science.
3. Stocks of fish that are interrelated should be managed jointly and individual stocks should be managed as a single unit.
4. Management measures should not discriminate across states. Permits or priviledges should be assigned fairly and equitably; furthermore, no entities should acquire excessive share of those priviledges.
5. Management plans should consider efficiency, but not be solely based on economic efficiency.
6. Management plans should take variability of stocks and catches into account and include contingencies.
7. Management plans should minimize costs and duplication of compliance effort.
8. The economic and social impacts on fishing communities should be taken into account.
9. Management plans should minize bycatch and mortality of bycatch.
10. Management plans should promote safety at sea.

Many of the terms included in these standards are subject to interpretation; however, Optimum Yield has specifically been defined by Congress. Optimum Yield is defined as the harvest that produces the greatest net benefits to the United States and equal to the maximum sustained yield less any reduction for economic, social, or ecological factors. The last of these, “ecosystem considerations,” has served as motivation for the adoption of

Ecosystem Based Fisheries Management (Link, 2002; Pikitch et al., 2004). For stocks that are overfished, Optimum Yield is defined as the yield that allows for rebuilding stocks to levels that would produce the maximum sustained yield.

NMFS has produced guidance documents that interpret and operationalize the National Standards described in the MSFCA (NMFS, 2008). For example, the interpretation of National Standard 1 has produced many reference points for fish stocks. Maximum Sustained Yield (MSY) is defined as the largest long-run average yield of a stock, given ecological conditions and fishing technology in use. Acceptable Biological Catch (ABC) are catch levels which account for scientific uncertainty and must be less than Optimum Yield (OY). An Annual Catch Limit (ACL) is a threshold catch level that must be less than ABC; if catch rises above this level, Accountability Measures (AMs) are implemented. Together, ACLs and AMs are intended to act as a deterrent to overfishing. Finally, Annual Catch Targets (ACTs) are the target harvest rate of managers; these are less than ACLs and are set to account for management uncertainty.

As a part of the Executive Branch, Department of Commerce regulations are also guided by Executive Order 12866, which was signed by President Clinton in 1993. Under this Executive Order, regulatory agencies should assess costs and benefits of alternative regulations, including costs of enforcement and compliance that are borne by government agencies. Regulatory actions should maximize net benefits to the United States and use incentive based systems in place of command-and-control systems when possible. Furthermore, regulatory agencies should use “the best reasonably obtainable scientific, technical, economic, and other information.”

In 2008, the National Marine Fisheries Service reviewed the status of 531 fish stocks in the United States to determine whether these stocks were overfished or if overfishing was occurring (U.S. Department of Commerce, 2009). These determinations were made on a stock-by-stock basis and relied solely on biological indicators, estimated Maximum

Sustained Yield and current harvest levels[1]. An overfished stock of fish is characterized by stock levels that are "too low," while overfishing indicates that current harvest levels are "too high." Scientific uncertainty was so large that determination of overfished status could be made on only 199 of those 531 stocks. Of those 199 stocks of fish, 46 (23%) were classified as overfished. Determination of overfishing status could be made on only 251 of the 531 stocks reviewed. Of those 251 stocks, 41 (16%) were experiencing overfishing. Clearly, uncertainty is abundant in fisheries management.

1.2 Three Essays on Fisheries Economics

The first essay in this dissertation examines the impacts of policy rigidity and uncertainty on optimal fisheries policy and value. Intertemporal efficiency has been examined using bioeconomic models since the work of Clark (1976). By modeling the fishery as a capital asset, the tradeoff between present and future consumption is clear: increasing current consumption typically lowers the productivity of the resource and therefore future consumption. The analytical solutions of deterministic models typically lead to a natural resource "golden rule": optimal harvest of the resource precisely balances the marginal benefits of harvest against marginal opportunity costs of harvest that are derived from lower productivity. With this rule in hand, it is often possible to solve for the explicit harvest and stock levels that maximize net benefits. However, analytical solutions often become difficult to understand with the introduction of stochastic stock growth and/or measurement error (Clark and Kirkwood, 1986; Costello et al., 2001; Sethi et al., 2005). As noted by Thompson (1999), the analytical solutions produced by bioeconomic models are complex and infrequently implemented.

The classical bioeconomic models have assumed that the manager has information about the present stock size and is able to adjust the harvest or quota levels "quickly"

[1] These indicators are B_{MSY} - the stock that produces the Maximum Sustained Yield and F_{MSY} - the harvest rate associated with MSY, along with B and F, the actual stock and harvest rate.

(Reed, 1979; Clark and Kirkwood, 1986). However, this may not be a realistic assumption: the slow-moving political bodies may simply be unable to do so. These agencies may have chosen longer management intervals directly, perhaps to reduce the transactions costs of management. They may also have chosen them indirectly, through the allocations of labor and funds to scientific and management activities for various species and stocks of fish. Both time and money are required for accurate science and management; policy rigidity may a consequence of these allocation decisions. Examination of the effects of rigidity and uncertainty on the the present value of the fishery can clarify the embedded economic tradeoffs between gathering information and proceeding with management activities (Hansen and Jones, 2008; Mantyniemi et al., 2009).

The second essay in this dissertation examines the effects of institutional limitations on bargaining power in a synthetic market. This essay adapts Harding et al.'s (2003) hedonic bargaining power model to examine how characteristics of buyers and sellers determine prices for Days-at-Sea (DAS). This tradable effort control system is a synthetic permit market with many limitations on trade and a lack of an actual marketplace. Once buyers and sellers match, trades are likely to be negotiated through a bilateral bargaining process. The industrial-organization literature in this field typically assumes that trade generate economic surplus; the two parties bargain over the division of that surplus (Blair et al., 1989). Harding et al. (2003) make strong identification assumptions; the unique nature of DAS allows these assumptions to be critically examined.

When stock use is not rationed, either through price or quantity controls, the stock is typically overused in the production process, causing stock collapse. There are many possible solutions to the public goods problem: properly calibrated access fees, effort controls, landings taxes, and aggregate or individual quotas could all be used if the manager has full information about production technology. Transferable rights based systems, typically based on output, have become popular as a fisheries management tool to achieve allocative efficiency (Batstone and Sharp, 2003; Costello et al., 2008). However, input control systems continue to be popular with the fishing industry (Rossiter and Stead, 2003). National Standard 4 requires management plans and activities to prevent the entities from obtaining "excessive share" of fishing priviledges. While this term is never defined, a reasonable interpretation of this may include the ability to exert market or bargaining power. Examination of bargaining power in this market can provide insight into best practices for other synthetic markets.

The final essay in this dissertation is examines production in the presence of externalities. There are few commercial marine fisheries that are completely isolated. Many are linked to other commercial fisheries, either through biological (predator-prey) interactions or through joint production technology in harvest. Others are linked to recreational fisheries, non-extractive uses, or non-harvested (but desirable) species. Under the definition of Optimum Yield in the MSFCA these linkages must be accounted for in setting policy. Many economic methods have been used to examine and address the interconnections in the ecosystem, from bioeconomic predator-prey and ecosystem models (Ragozin and Brown, 1985; Brown et al., 2005; Finnoff and Tschirhart, 2003) to econometric characterization of the joint production technology (Squires, 1987; Squires and Kirkley, 1991). These economic methods can inform managers as they implement Ecosystem Based Fishery Management (EBFM), in which entire ecosystems, not just a single target species, are managed (Link, 2002; Pikitch et al., 2004).

Dynamic, long-run bioeconomic models are not always necessary for the implementation of the EBFM approach to management. This approach also requires knowledge of short-term ecosystem linkages, especially as they affect human activities. Using the ecosystem-externality model of Crocker and Tschirhart (1992), this research provides insight into the external effects of fishing activity on a non-extractive tourism industry.

The essays in this dissertation examine three general aspects of efficiency in fisheries economics and policy. Bioeconomic models can be used to examine intertemporal efficiency issues. Tradable permits are thought to be lead to efficient production; the second essay examines an existing market and provide insight into the effects of market institutions. The Ecosystem Based Management paradigm recognizes that the fishery is just one use of marine resources; the final essay examines the the short-term effects of fishing on a non-extractive (tourism) industry.

Chapter 2

The Effects of Policy Rigidity on Optimal Fisheries Management

2.1 Introduction

This essay examines the effects of policy rigidity in a bioeconomic model, with emphasis on the consequences for fishery value, the optimal policy function, and stock collapse. In this essay, policy rigidity is defined as a management institution in which the control variable (i.e. quota or Total Allowable Catch) is fixed for the duration of a "short-term planning period." During this time, the managed stock may experience multiple growth shocks. Two stylized facts about fisheries management motivate this research. First, frequent adjustment of policy has high direct and indirect transactions costs (Turner and Weninger, 2005; Singh et al., 2006). Policy rigidity may be a direct choice of fishery managers who are influenced by these high transactions costs (Table 2.1). Second, relative to terrestrial resources, marine fish stocks are difficult to measure and subject to large stochastic growth shocks; stocks are assessed using combinations of fishery-dependent and independent techniques that require large amounts of time and money to perform. The scientific assessment process may result in relatively long periods of time during which the manager lacks information about the stock size (Table 2.2). Infrequent assessments may be a management strategy that accounts for the allocation of scarce resources to scientific and management activities for many species of fish. Without current information about the stock the manager must condition policy on expectations about stock sizes. Indirectly, the limited amount of information possessed by managers may constrain them to adopt rigid policies. This management institution will reduce the present value of fishery revenues; however, the opportunity costs of rigidity are not well understood. This research generalizes the Clark and Kirkwood (1986) bioeconomic fishery model by introducing a short-term planning period and examining the tradeoffs between rigidity, information, and fishery value that fishery managers must consider in the decision-making process.

Under the Magnuson-Stevens Fishery Conservation Act (MSFCA), the National Marine Fisheries Service (NMFS) provides biological and economic advice to regional Fishery Management Councils that manage fish stocks in United States waters. The major component of that advice is related to the appropriate level of harvest and set-asides that account for scientific and management uncertainty. NMFS has produced guidance documents that interpret and operationalize the National Standards described in the MSFCA (NMFS, 2008). Maximum Sustained Yield (MSY) is defined as the largest long-run average yield of a stock, given ecological conditions and fishing technology in use. Optimum Yield (OY) is Congressionally defined as MSY less allowances for social, economic, and ecosystem considerations. Acceptable Biological Catch (ABC) are catch levels which account for scientific uncertainty and must be less than OY. An Annual Catch Limit (ACL) is a threshold catch level that must be less than ABC. Finally, Annual Catch Targets (ACTs) are the target harvest rate of managers; these are less than ACLs and must account for management uncertainty. The findings of this research, particularly the relationship between policy intervals and optimal harvest and extinction, can be used by managers to set some of these biological reference points.

Economists have typically constructed bioeconomic models to examine optimal harvest rates and value from a capital accumulation perspective (Clark, 1976; Reed, 1979; Clark and Kirkwood, 1986; Conrad and Clark, 1987). Three types of uncertainty were incorporated into a bioeconomic fishery model by Roughgarden and Smith (1996): growth, measurement, and harvest uncertainty. The first two types of uncertainty correspond to scientific uncertainty, while harvest uncertainty is closely related to the management uncertainty described in the MSFCA. Sethi et al. (2005) solve the model developed by Roughgarden and Smith (1996) and find that stock measurement uncertainty produces the largest qualitative changes in optimal policy. Costello et al. (2001) examine the ability of a manager to predict future growth stocks and find that prediction of a "good" growth shock leads to lower current harvests. A predicted good shock implies that the opportunity costs of harvest are larger than typical. While counterintuitive from a conservation standpoint, a prediction of a good shock indicates larger returns from allowing that stock to remain in the ecosystem to grow.

In general, the optimal policy prescribed by a bioeconomic model is a function that maps the state space to action space. After solving for the optimal policy function, economists (implicitly) assume that this policy function is simply adopted. The actual level of harvest, quota, or Total Allowable Catch is then set mechanistically when the uncertainty about the the stock level is resolved. However, this rarely occurs in fisheries management, especially when that policy is a complex harvest function (Thompson, 1999). Instead, quota levels are typically set through a bargaining and negotiation process; these quotas may be fixed for a period of multiple years. While rigid policy instruments have not been examined in bioeconomics models, capital rigidity has previously been incorporated in those models. Singh et al. (2006) construct a two-stock model (fishing capital and fish stock) to examine the impact of capital rigidity on policy. In that model, capital cannot be removed instantaneously and fishing capital is specific to the industry. The major finding is that the manager must balance the additional revenues of a very flexible harvest policy against the costs of constantly adjusting capital; Singh et al. (2006) describe this phenomenon as catch-smoothing.

Within the fisheries management literature there has been recent interest in the value of information about stock dynamics and the substitutability of management and scientific activities. Hansen and Jones (2008) examine the tradeoffs between gathering scientific information and management in a case study of the control of an aquatic pest. Mantyniemi et al. (2009) examine the benefits of correctly selecting the appropriate stock equation for herring from a set of possible choices using a Bayesian framework. These concepts have also been explored in the economics literature; Saphores and Shogren (2005) use a real-options framework to determine the optimal amount of information that should be gathered before costly actions should be undertaken to control an invasive species.

Many of the key findings of stochastic fishery models were developed by Reed (1979) and Clark and Kirkwood (1986). Both models implicitly assume that the manager's only source of information is an assessment that is conducted prior to the beginning of the fishing season. In Reed's (1979) model, this assessment occurs after the growth shock has occurred but before the policy is declared. This assessment perfectly measures the level of the harvestable stock; the manager can set policy conditional on the harvestable stock. Not surprisingly, the optimal policy is similar to the optimal policy when growth is deterministic and can be characterized as a constant target escapement policy[1] (Conrad and Clark, 1987). When stock levels are higher than the target, the entire "surplus" is harvested. When stock levels are lower, there is no harvest and the stock is allowed to recover to the target escapement level. The assumption of "real-time" knowledge of the stochastic shock drives this result and precludes the possibility of accidental extinction.

Clark and Kirkwood (1986) limit the information that the manager possesses by assuming that escapement, not harvestable stock, is assessed. A scientific assessment is performed at time t, which perfectly measures S_t, the escapement at time t. Based on S_t and knowledge of the stock dynamics, $G(S_t)$, the manager selects the harvest quota q_t for the current harvesting season. S_t grows according to the growth equation into the harvestable stock, X_t. Harvest occurs, producing the escapement in the next time period, S_{t+1}, and the process repeats infinitely. The manager's discrete-time optimization problem is to select

[1] Escapement is amount of fish that has not been harvested in the previous period.

the quota in order to maximize the present value of expected fisheries revenues:

$$\max_{q_t} \sum_{t=0}^{\infty} \delta^t p \mathrm{E}[h_t] \tag{2.1}$$

$$X_t = z_t G(S_t) \tag{2.2}$$

$$S_{t+1} = X_t - h_t \tag{2.3}$$

$$h_t = \min\{q_t, X_t\} \tag{2.4}$$

In this model, $\delta \in [0, 1)$ is the per-period discount factor, p is the output price, h_t is harvest, and z_t is a multiplicative shock with known distribution $\phi(z_t)$ that is centered at unity. Uncertainty enters the model through a stochastic growth function in Equation (2.2). In the terms of Regan et al. (2002), no distinction is made between natural variation, inherent randomness, and measurement error in the growth function[2]. Equation (2.4) can be interpreted as a feasibility restriction: because the manager does not know the level of harvestable stock when the quota is declared the harvest must be the lesser of the quota or the harvestable stock. If, due to a particularly bad growth shock, the declared quota is less than or equal to the harvestable stock, the stock is driven to extinction. Once the quota is set, the lesser of the quota or the entire stock is harvested[3].

Clark and Kirkwood's (1986) research advocates precaution when the level of uncertainty is high and finds that the constant-escapement policy is sub-optimal. Because the harvestable stock is not known when the quota is set, it is theoretically possible for the manager to set a quota that is higher than the actual stock size and accidentally drive the stock to extinction.

[2]While some of this uncertainty is irreducible, scientists and managers have some degree of control over the uncertainty in the system. For example, additional data could be gathered and incorporated into biological models, increasing the precision and accuracy of stock assessments.

[3]Clark and Kirkwood (1986) note that this may be an unrealistic assumption. Alternatively, they propose that harvesting within a season will stop once an arbitrary lower bound, $\overline{X}$, is achieved.

2.2 Policy Rigidity and Uncertainty

The planning horizon for natural resource problems is typically an infinite or arbitrarily large number of years, the short-term planning period is defined as a period of k years during which the policy instrument is held constant. However, the manager still optimizes the expected present value of the fishery over an infinitely long time horizon.

In this model, a scientific assessment is performed at time t, which perfectly measures escapement, S_t. $G^k(S_t, \mathbf{h}, \mathbf{z})$ is the growth function that returns the escapement, S_{t+k}, at the end of the short-term planning period[4]. The $(k \times 1)$ vectors **h** and **z** are the harvests and growth shocks that occur during the short-term planning period. The vector of growth shocks, **z**, has known probability distribution $\phi(\mathbf{z})$. The growth function $G^k(\cdot)$ is defined by k- applications of the $G(\cdot)$ as defined in equation (2.2) on S_t.

Based on measured escapement and knowledge of the stock dynamics, the regulator selects q_j, a harvest quota that is in effect for each year in the j^{th} short-term planning period. The other main assumptions of the Clark and Kirkwood model remain: harvest (h), quota (q), and stock size (S) are assumed to be non-negative and $E[\phi(z)] = 1$. The timing of the Reed, Clark & Kirkwood, and the current model are presented in Figure 2.1.

For short-term planning period of length k, the manager maximizes the expected present value of the fishery by setting a quota, q_j, which is held constant for the duration of the short-term planning period.

$$\max_{q_j} \sum_{j=0}^{\infty} \delta^{kj} \sum_{i=1}^{k} \delta^{k-1} pE[h_i] \tag{2.5}$$

[4]Since the planning period is $k-$years in length, S_{t+k} refers to the stock at the time k years or 1 planning period in the future. More generally, S_{t+mk} refers to the stock at the time mk years or m planning periods in the future.

subject to:

$$S_{t+k} = G^k(S_t, \mathbf{h}, \mathbf{z}) \tag{2.6}$$

$$X_{t+i} = z_{t+i} G^1(S_{t+i-1}) \quad \forall i \tag{2.7}$$

$$h_i = \min[q_j, X_i] \quad \forall i, j \tag{2.8}$$

The innovation of the model is contained in Equations (2.5) and (2.6). In equation (2.5), the "inner" summation produces the discounted expected revenues *within* each short-term planning period, while the "outer" summation adds these discounted revenues *across* planning periods. Equation (2.6) is the stochastic growth equation that maps the initial escapement level (S_t), harvests (**h**), and stochastic shocks (**z**) to escapement at the end of the short-term planning period (S_{t+k}).

Equations (2.7) and (2.8) function analogously to Equations (2.2) and (2.4) in the Clark and Kirkwood's (1986) model. Equation (2.7) describes the harvestable stock at any point within the short-term planning period. Accidental extinction is possible because the harvestable stock of fish (X), is never measured by the manager. Equation (2.8) links the policy instrument to the stock equation: either the entire quota or the entire harvestable stock is captured. Both the objective function (Equation 2.5) and the state-transition equation (2.6) are likely to be non-linear in q_j, suggesting that simple constant-escapement policies are likely to be non-optimal. [XXX quick transition] The Bellman equation can be written as:

$$J(t, S_t; k) = \max_{q_j} \{ \sum_{i=1}^{k} \delta^{(i-1)} p E[h_i] + \delta^k E[J(t+k, S_{t+k}; k)] \} \tag{2.9}$$

The value function is written as a function of parameter k, the length of the short-term planning period to make the dependence of J on this parameter more explicit. Solving the

Bellman equation provides the following condition for positive quotas:

$$\sum_{i=1}^{k}[\delta^{i-1}p\frac{\partial E[h_i]}{\partial q_j}] = \delta^k E[\frac{\partial J}{\partial S}(t+k, G^k(S_t, q_j); k)]E[\frac{\partial G^k}{\partial q_j}(S_t, q_j)] \tag{2.10}$$

Further algebraic manipulation of equation (2.10) is difficult due to the expectations operators and minimum function which defines h_i. However, Equation (2.10) retains the traditional "golden rule" interpretation of natural resource economics problems. When the efficient level of quota is positive, the marginal expected benefits of quota (*lhs*) must be equal to the (discounted) marginal expected costs (*rhs*). These expected costs are equal to the value of the stock, multiplied by the change in stock productivity.

There are two models of interest that are nested within this bioeconomic model. First, the Clark and Kirkwood model is a special case of this model in which $k = 1$. When $\phi(z)$ is degenerate, the model corresponds to policy rigidity with deterministic growth. Second, when stocks evolve deterministically, the manager's optimization problem becomes much simpler. Although the manager chooses q_j, quota is always equal to harvest and accidental extinction is ruled out. The deterministic optimization problem is:

$$\max_{q_j} \sum_{j=0}^{\infty}\delta^{kj}\sum_{i=1}^{k}\delta^{(i-1)}pq_j \tag{2.11}$$

$$\text{s.t. } S_{t+k} = G^k(S_t, q_j).$$

While the objective function is linear in the control variable, the state transition equation is linear in q_j only if $k = 1$. Defining a value function $J(t, S_t; k)$ that is dependent only on time and escapement provides:

$$J(t, S_t; k) = \max_{q_j}\{\sum_{i=1}^{k}[\delta^{(i-1)}pq_j] + \delta^k J(t+k, G^k(S_t, q_j); k)\} \tag{2.12}$$

Solving the associated Bellman equation when harvesting is positive yields:

$$\sum_{i=1}^{k}[\delta^{i-1}p] = \delta^k \frac{\partial J}{\partial S}(t+k, G^k(S_t, h_j); k)\frac{\partial G^k}{\partial q_j}(S_t, q_j) \tag{2.13}$$

The summation term on the left-hand side is the marginal benefit of increasing harvest levels within the short-term planning period. The right-hand side term captures the marginal cost of increasing harvest levels: $J_S(\cdot)$ is the marginal value of non-harvested fish and $G^k_h(\cdot)$ describes how escapement at the end of the planning period changes with harvest. Optimal policy requires that the marginal benefits of harvest are equal to marginal costs of harvest. Appendix A illustrates the model in some depth for logistic growth with a planning period of 2 years.

2.3 Methods

Numerical simulations are used to understand the effects of policy rigidity on fisheries management. The goal of these simulations are to understand the combined effects of rigidity and uncertainty on the value of fisheries revenues, optimal policy, and the possibility of extinction. In order to isolate the effect of policy rigidity, a deterministic model with rigidity is first simulated. Next, the stochastic growth model with rigidity is simulated to examine the combined effects of stochastic growth and rigidity. These simulations are repeated for a range of biological parameters to better understand the sensitivity of the results to these parameters.

The discrete-time, discrete-state dynamic programming problem is solved using Miranda and Fackler's (2002) `COMPECON` toolbox for MATLAB. Details about the numerical methods can be found in Appendix B. A discrete-time approximation to logistic growth is used; the single-year escapement equation is:

$$S_{t+1} = G(S_t, z_t, h_t) = z_t[rS_t(1 - \frac{S_t}{K}) + S_t] - h_t, \tag{2.14}$$

The annual discount factor (δ) is set to 0.95, and price is normalized to unity. For a short-term planning period greater than one year in length, repeated application of Equation (2.14) generates the appropriate state equation (See Appendix B for an illustration). Unless otherwise noted, the biological parameters, K and r are also set to unity. The K parameter is typically referred to as carrying capacity; without harvesting or stochastic growth, the population would evolve to a steady state at K. The r parameter is known as the intrinsic growth rate; for an arbitrarily-small, positive S, the stock grows at rate r. The speed at which the stock moves to K is related to both r and the distance of the stock from K. Under stochastic growth and no harvest, the stock will oscillate around K, with the size of the oscillations related to all 3 parameters (r, K, and ε). The state equation is symmetric with respect to K, which may be somewhat unrealistic. z_t is assumed to be independently and identically distributed from a uniform distribution with support $[1-\varepsilon, 1+\varepsilon]$, where ε is varied on the range $[0, 0.9]$.

Let $q(S;k)$ be the quota function that solves equation (2.9) for a given policy interval k. Similarly, let $J(S, q(S;k);k) = J(S;k)$ be the optimized value of the equation (2.9). The model is solved for both the optimal policy, $q(S;k)$, and the corresponding expected value of fisheries revenues, $J(S;k)$, for short-term planning periods of one, two and three years in length ($k = 1, 2, 3$). The level of growth uncertainty and the length of the short-term planning period are treated as parameters in the model. By examining the sensitivity of the value function to changes in those parameters, it is possible to examine the costs and benefits of alternative management institutions. For example, holding all other parameters constant, changes in the length of the short-term planning period, k, give insight into the costs of different management institutions and the possible economic gains from flexible management. Similarly, changes in ε provide insight into the value of more accurate knowledge of stock dynamics.

2.4 Results and Discussion

When stock growth is deterministic, policy rigidity has only a minimal effect on the value of fishery revenues. The percentage difference in the present value of stock S under different planning periods can be written as:

$$\Delta J_{lm} = \frac{J(S;l) - J(S;m)}{J(S;l))}$$

Figure 2.2 plots ΔJ_{lm} for $l = 1$ and $m = 2, 3$. When growth is deterministic, rigidity produces only small decreases in the value of the fishery. Intuition for this result can be drawn from deterministic fishery models: when stocks evolve deterministically, the constant escapement target rule and Most Rapid Approach Path are optimal (Conrad and Clark, 1987). Once the target escapement level is achieved, rigidity cannot have an impact on either policy or the fishery value. The effects of rigidity are confined to the $k-$year transition to the target escapement level. The reductions in the value function are the consequence of moving "too slowly" to that escapement level. With policy rigidity, the deterministic fishery also takes the Most Rapid Approach Path to the target escapement. However, this is the length of the short-term planning period, k-years, instead of a single year. In contrast to a model with deterministic growth, stochastic growth can produce large economic losses under policy rigidity. The relative decrease in fishery revenues is robust to the initial stock size (S_0); for this set of biological and economic parameters evaluated, policy rigidity produces economic losses of twenty or thirty percent when two- or three-year planning periods are used and $\varepsilon = 0.5$.

The sensitivity of the fishery value to uncertainty is examined in Figure 2.3 by plotting the optimized value, $J(S_0 = 0.5; k)$, as a function of ε, the uncertainty parameter[5]. The vertical distance between curves in Figure 2.3 is the change in fishery value that can be

[5]When stock growth is deterministic, $S_0 = 0.5$ is the biomass that produces the Maximum Sustainable Yield (MSY) for this set of parameters. This stock level is commonly referred to as B_{MSY}. Using initial values of $S_0 = 0.2, 0.8$, and 1 does not produce qualitatively different results.

attributed to policy rigidity. Consider a fishery for which $\varepsilon = 0.5$ and policy is set every two years (point A). Adoption of flexible management institutions would move the fishery to point B, increasing the value of the fishery. Rigidity always reduces the value of the fishery; this effect is fairly small when stock growth uncertainty is either low or extremely high. However, at moderate and large levels of uncertainty, policy rigidity causes fairly large economic losses. This result suggests that rigid policies are best utilized when stock dynamics are well known and subject to little natural variation.

Movements along a curve in Figure 2.3 represent changes in fishery value due to changes in the amount of uncertainty in the stock growth equation. The uncertainty parameter (ε) may be partially under the control of fisheries managers (Regan et al., 2002). For example, additional scientific effort may increase the knowledge of the growth function, effectively reducing ε. Reductions in ε always lead to higher value of the fishery. If uncertainty in the growth function is reduced from $\varepsilon = 0.5$ to $\varepsilon = 0.4$, this would move the fishery from point A to point C, increasing the value of the fishery. Figures 2.4 and 2.5 are analogous figures for $r = 0.5$ and $r = 1.5$ respectively. The general shapes of the curves in Figures 2.3-2.5 are very similar, changes in r appear to scale the value of the fishery.

While the manager must fix the quota level for the duration of the short-term planning period, the causes that drive the use of a rigid policy lead to slightly different interpretations of these figures. When policy rigidity is a direct choice of managers, changes in fishery value directly reflect the opportunity costs of policy rigidity: Figures 2.3-2.5 make the opportunity costs of those decisions clear and highlight the biological parameters for which those institutions are particularly costly. Holding the level of uncertainty constant, these simulations suggest that stocks with a high intrinsic growth rates (r) relative to K will see the largest decline in fishery value when using rigid policy.

The model is consistent with an alternative interpretation: an informational constraint on decision-making due to infrequent stock assessments. If stock assessments are performed every k-years but policy adjusted more frequently, then managers are indirectly constrained to set policy infrequently as well. The manager only knows the probability distribution from which the shocks are drawn. During years when stock assessments are not performed, managers are unable to condition quota on the most recent escapement level. Instead, they must use expectations of stock levels to set policy; this is equivalent to declaring a multi-year policy at the time that the stock assessment is performed. Under this interpretation, Figures 2.3-2.5 can provide insight into the implied tradeoffs between speed and precision in the scientific and management activities. Suppose that there are two types of recurring scientific activities that can be used to learn about stock dynamics. The first type can be undertaken rapidly; however, it is associated with larger errors in the stock equation (ε is larger). The second type of activity takes longer amounts of time; however, it can explain more the stock dynamics. While assessment and management costs are not modeled directly in this research, the relative costs and benefits of either approach can be examined in Figures 2.3-2.5.

Figure 2.6 plots the elasticity of the value function with respect to the growth uncertainty for a stock with biological parameters $r = 1$ and $K = 1$.[6]. This elasticity peaks when uncertainty is fairly high. The location of this peak is slightly sensitive to the length of the planning period and occurs at lower levels of uncertainty when k is larger. This highlights the tradeoffs inherent in this bioeconomic model; for moderate and large amounts of uncertainty, there are increasing returns to increasing knowledge of the stock growth equation, the elasticity is much larger than unity. However, the elasticity of uncertainty drops below unity at fairly large levels of uncertainty. For values of ε less than this critical point, further reductions in uncertainty produce decreasing returns. At these lower levels of uncertainty, it may be optimal to adjust policy faster instead of focusing on reducing stock growth uncertainty. The exact location of the point at which this occurs depends on the opportunity costs of uncertainty in Figure 2.3 and the costs of scientific research, which are not explored in this essay.

[6]This is approximated as $\eta = \frac{\Delta V}{\Delta \varepsilon} \frac{\varepsilon}{V}$.

The optimal quota, conditional on a set of biological parameters and the amount of rigidity in the system, may be associated with a positive probability of extinction or collapse. As noted by Clark (1973), certain combinations of biological growth and economic parameters imply that immediate harvest of the entire stock is optimal; however, these sets of biological and economic parameters are not considered in these simulations. Surprisingly, extinction has received limited attention in the stochastic fishery models; many of the stochastic fishery models are based on Reed's (1979) fishery model, which precludes extinction.

Simulation of the state path is used to gain insight into the probability of extinction. Using an initial value of ($S_0 = 0.5$), the path of the fishery regulated by the optimal policy is simulated 1,000,000 times for a 100-year period at varying levels of policy rigidity and uncertainty. Tables 2.3 and 2.4 present the probabilities that a stock with given parameters will be extinct within a 100 year period under standard ($r = 1$) and low ($r = 0.5$) intrinsic growth rates. These simulations find that extinction does not occur when rigidity is not present unless uncertainty is extremely high. However, when the stock is managed with a rigid policy instrument, extinction may occur in the presence of moderate levels of uncertainty.

When the optimal policy is associated with a positive probability of extinction, it is difficult to classify extinction events as either accidental or purposeful. By definition, the optimal policy, q, maximizes the discounted expected revenues in Equation (2.5). These probabilities of extinction are a result of an optimization process in which the manager is risk neutral, discounts future fishery revenues at a positive rate, and faces no additional penalty from extinction beyond the inability to harvest the stocks. In this model, a positive probability of extinction is accepted in return for higher harvests; this is a byproduct of managing stocks under policy rigidity with limited information. These findings may partially explain historical fisheries collapse when stock growth is not well understood (ε is high) or if quota levels are infrequently adjusted (k is high). If stock levels are measured infrequently or quota levels cannot be updated quickly, the extinction occurs with fairly high probability, even if quota is chosen optimally. This highlights the need for timely, accurate assessment and management activities.

Two interesting features of the optimal quota function are illustrated in Figure 2.7. The optimal quota function is symmetric about the carrying capacity; this result is driven by the symmetry of the growth equation that is used. Healthy stock levels that are near carrying capacity indicate that future stock levels will also be fairly high. Unhealthy stock levels that are far from the carrying capacity indicate that future stock levels will be low. Because of the symmetry of the growth equation, both very low (S near 0) and very high (S near 2K) are unhealthy and will lead to low expected stock levels in the next time period. When stock levels are healthy, rigidity leads to precautionary quota levels; the optimal quota under under rigid management is less than the optimal quota for flexible management. However, this result is reversed for the relatively small interval that correspond to either extremely low or high stock levels. When constrained to use a rigid policy, the fishery manager prefers slightly higher quota levels over these intervals.

There is also a threshold stock level at which the fishery is closed. This level depends on the level of rigidity used to manage the fishery. Both findings can be partially explained by the way that rigidity is modeled; for computational purposes the quota levels are required to be constant during the entire short-term planning period. When rebuilding a stock from unhealthy levels under rigidity, a low level of harvesting is preferred to zero harvest. These results are also consistent with Singh et al.'s (2006) finding that capital rigidity in the fishery produces "catch-smoothing."

2.5 Conclusions

This chapter has examined the effect of a single modification, policy rigidity, to a bioeconomic fisheries model with uncertainty. A few stylized facts about management under policy rigidity emerge. Rigidity has limited impact when stock growth uncertainty is small and no practical impact when stock growth is deterministic. However, both optimal policy and the value of fisheries revenues are highly sensitive to management rigidity when growth is highly stochastic. These results suggest that rigid policies, if they must be used, should be confined to stocks where the dynamics are well understood and subject to little variation. The combination of rigidity and stochastic growth can have large consequences for fishery collapse or extinction, even when managed to maximize the net present value of the fishery. When managers are unable to respond quickly to growth shocks, either because they are unmeasured or because of rigidity in management, the present value of the fishery decreases and the probability of collapse increases, sometimes dramatically. These findings advocate for the explicit consideration for the speed at which policy itself can meaningfully be changed when setting fisheries policy.

The model as formulated requires the manager to select a harvest level that is *constant* within the short-term planning period. This strong assumption about the type of rigidity is made for computational simplicity to reduce the dimensionality of the dynamic programming problem. However, a weaker version policy rigidity is possible. Under this "weak rigidity," the quota level is not necessarily constant for the duration of short-term planning period; instead, it must only be declared at the beginning of the short-term planning period. For example, consider a stock that grows deterministically and is far below the desired level. Under the strict definition of policy rigidity employed in the paper, the optimal policy may be to harvest at a constant low level for the duration of the short-term planning period that produces a target escapement level at the end of that period. However, under a weaker version of rigidity, optimal policy may be to close the fishery for a portion of the short-term planning period and then allow a higher harvest level short-term planning period.

The model of rigidity in this essay is similar to the managment procedure for Atlantic Herring (U.S. National Archives and Records Administration, 2007). In the Northeast

United States, the major components of the Atlantic Herring Fishery Management Plan, including Total Allowable Catch, are specified every three years. Historically, these have been constant for those three years; however, this is not mandatory. During the three year planning period, adjustments are possible if warranted by new information. However, new information can only be obtained by the manager at infrequent intervals; stock assessments are performend infrequently (Table 2.2).

The bioeconomic model, as formulated, allows instantaneous biological extinction - if quota levels are mistakenly set above the actual stock size, the fishery collapses immediately. Immediate biological extinction is unlikely in practice; at a depleted stock level, fishing would become unprofitable and the directed fishery would shut down for economic reasons. Interpretation of biological extinction in this model as end of a viable *commercial* fishery is more realistic. With limited information or ability to control harvest, a stock may be quickly reduced to levels at which a large-scale, directed fishery is no longer profitable. This research suggests that stocks which grow slowly, are susceptible to large growth shocks, or are monitored infrequently may be particularly vulnerable to commercial extinction. The Atlantic Halibut fishery in the northeast United States is an historical example of this phenomenon (Col and Legault, 2009; Grasso, 2008). This species grows slowly and was subject to intense fishing in the mid 1800s, resulting in stock collapse by the 1870s. Both stock size and harvest rates are currently very low and rebuilding of the halibut stock is complicated because it is a bycatch species in the bottom trawl fishery.

The model used in this essay has abstracted away from costly harvesting in order to isolate the effect of policy rigidity. This assumption may be non-trivial; if harvest is costly and depends on the stock level, then observation of the costs of harvest in real-time could increase the manager's information about current stock levels. If the cost or production function is known, managers could use this relationship to determine stock sizes (Smith et al., 2009). However, this would require large amounts of information and it is unclear whether these data could be used in a timely manner. It is certainly possible that analysis of economic data requires as much, if not more, time as analysis of fisheries population data.

While this research shows that policy rigidity reduces the value of the fishery, there are benefits to rigidity that are not incorporated in the model. Firstly, both stock assessments and management activities are costly; there is likely to be an optimal mix of scientific and management activities that should be performed (Hansen and Jones, 2008). The precise point at which this occurs depends on the production of scientific knowledge about the stocks of fish, which is beyond the scope of this research. Secondly, the avoidance of the capital adjustment and other transactions costs studied by Singh et al. (2006) may be an important benefit of managing fish stock using a rigid policy instrument.

2.6 Tables and Figures

Species	Short-Term Planning Period	Landings (1,000s mt)	Value ($M)
Sea Scallop	2 years	27	$385
Atlantic Herring	2 years	73	$19
Skates	2 years	13	$7
Red Crab	2 years	1	$3
Ocean Quahog	3 years	15	$19
Tilefish	3 years	1	$4
Spiny Dogfish	3 years	3	$1

Table 2.1: Short-Term Planning Period length, landings, and value for selected stocks in the Northeast United States.

	Atlantic Herring	Cod (Georges Bank)	Sea Scallop
	2008	2008	2006
	2006	2005	2004
Year	2003	2002	2001
	1998	2001	1999
	1996	2000	1997

Table 2.2: Recent stock assessments dates for select fisheries in the Northeast United States.

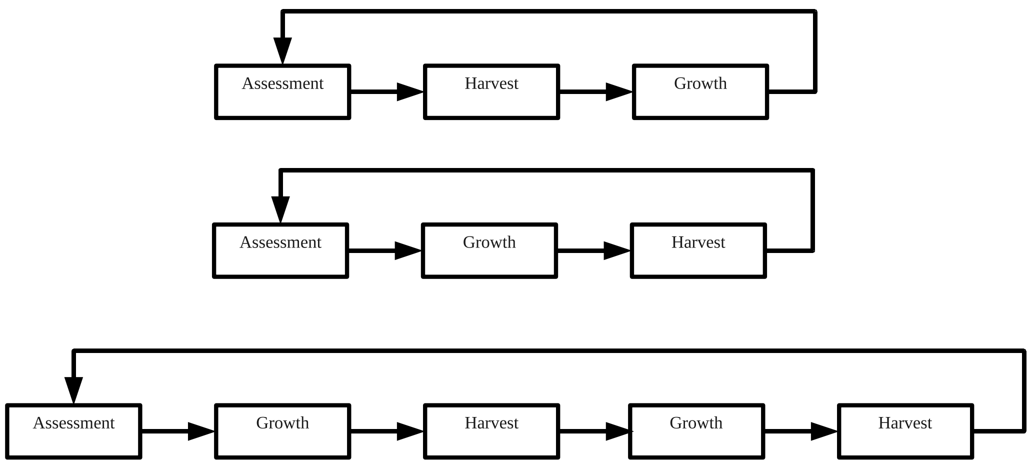


Figure 2.1: Timing of actions in the Reed (*top*), Clark and Kirkwood (*middle*), and Lee (*bottom*) bioeconomic models.

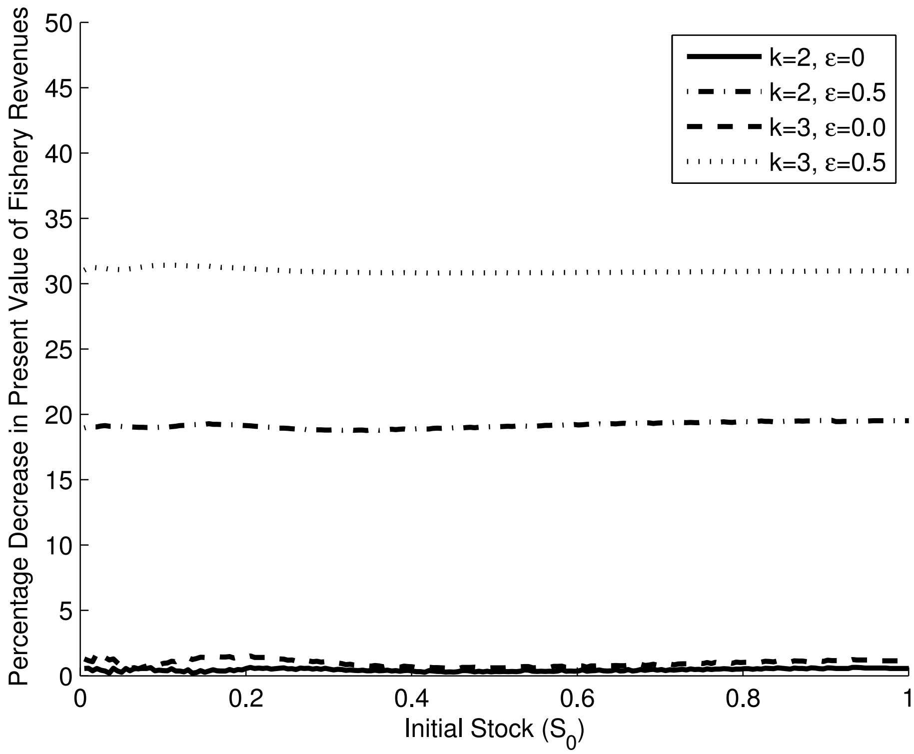


Figure 2.2: The impact of policy rigidity and stochastic growth on the present value of fishery revenues. Logistic stock growth with $r = 1, K = 1$,and $\delta = .95$.

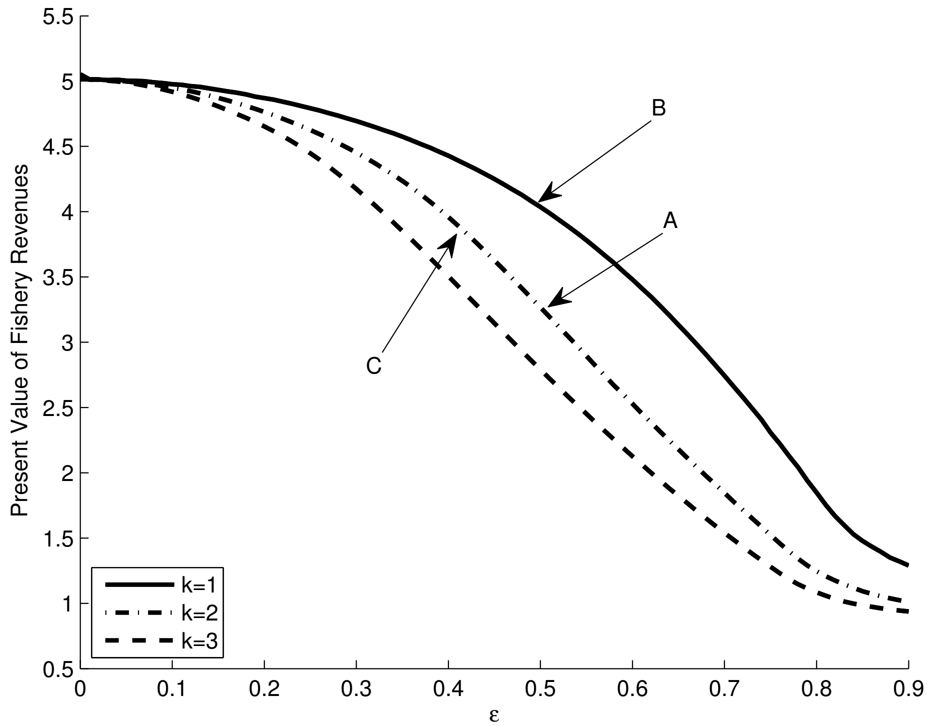


Figure 2.3: Present value of Fishery Revenues for one-, two-, and three-year planning periods. Point A corresponds to a fishery which is managed using a 2 year planning period and $\varepsilon = 0.5$. Point B is a fishery which is managed using a 1 year planning period with the same level of uncertainty. Point C is a fishery which is managed using a 2 year planning period with $\varepsilon = 0.4$. The vertical distance between A and B can be attributed to policy rigidity while the vertical distance between A and C can be attributed to scientific uncertainty. Stock growth is logistic with $r = 1$, $K = 1$, $\delta = .95$, and $S_0 = 0.5$.

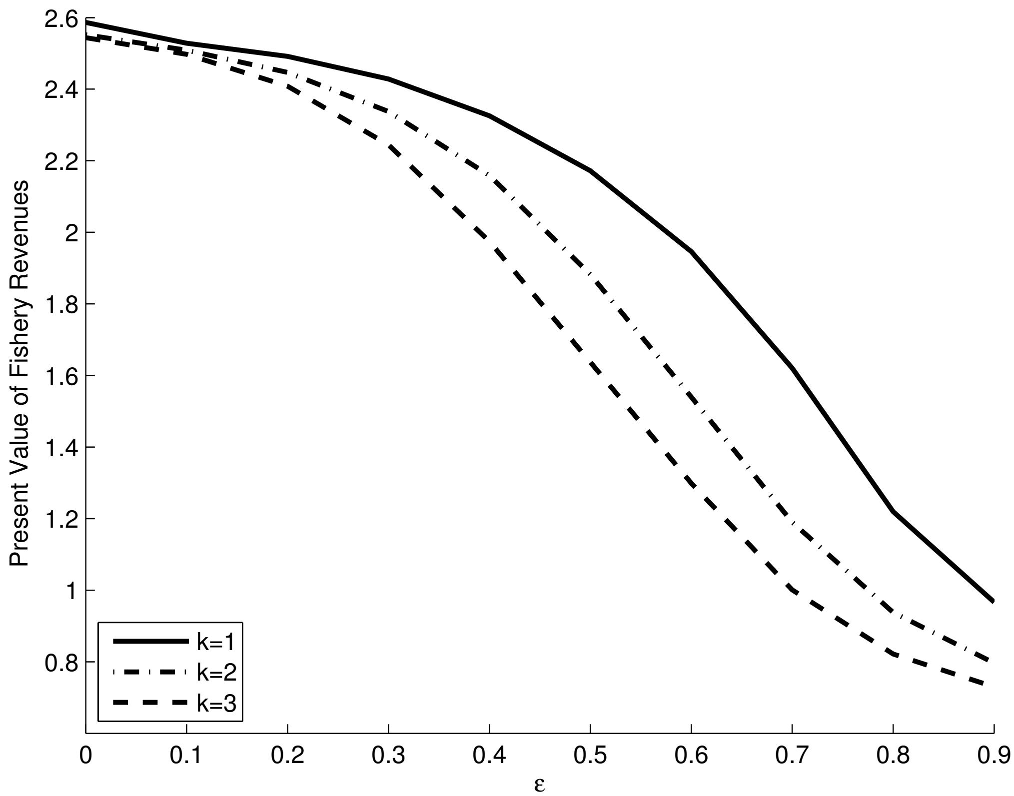


Figure 2.4: Present value of Fishery Revenues for one-, two-, and three-year planning periods. Stock growth is logistic with $r = .5, K = 1$, $\delta = .95$, and $S_0 = 0.5$. A reduction in r shifts the present value of fishery values downward.

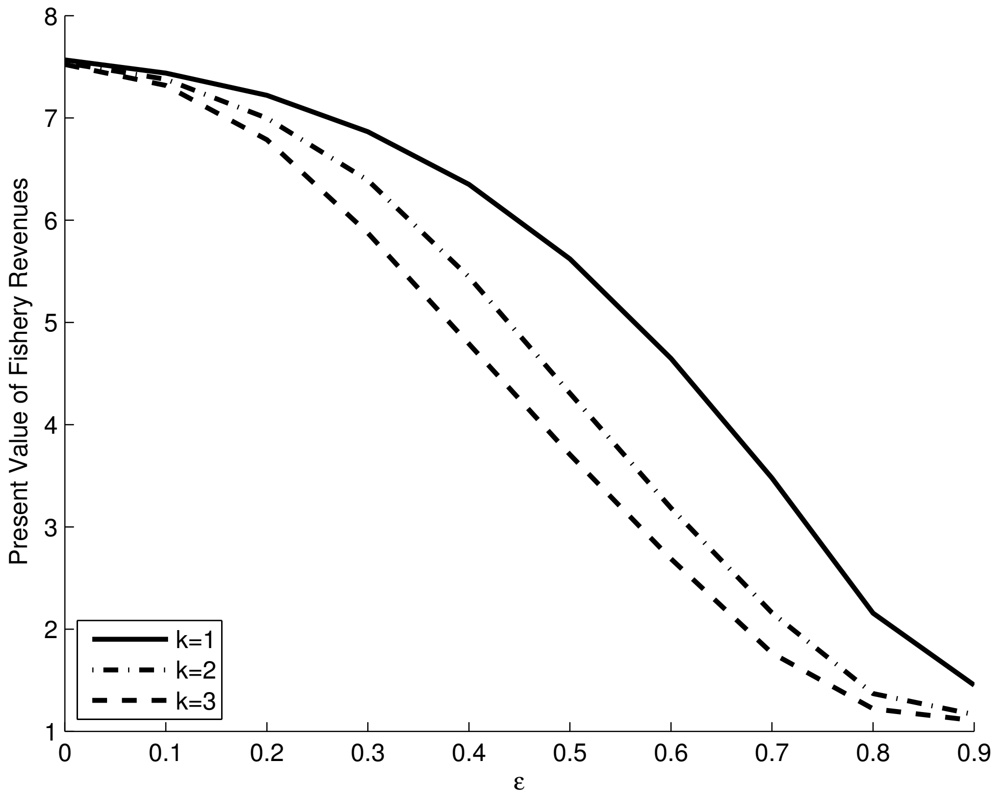


Figure 2.5: Present value of Fishery Revenues for one-, two-, and three-year planning periods. Stock growth is logistic with $r = 1.5$, $K = 1$, $\delta = .95$, and $S_0 = 0.5$. An increase in r shifts the present value of fishery values upwards.

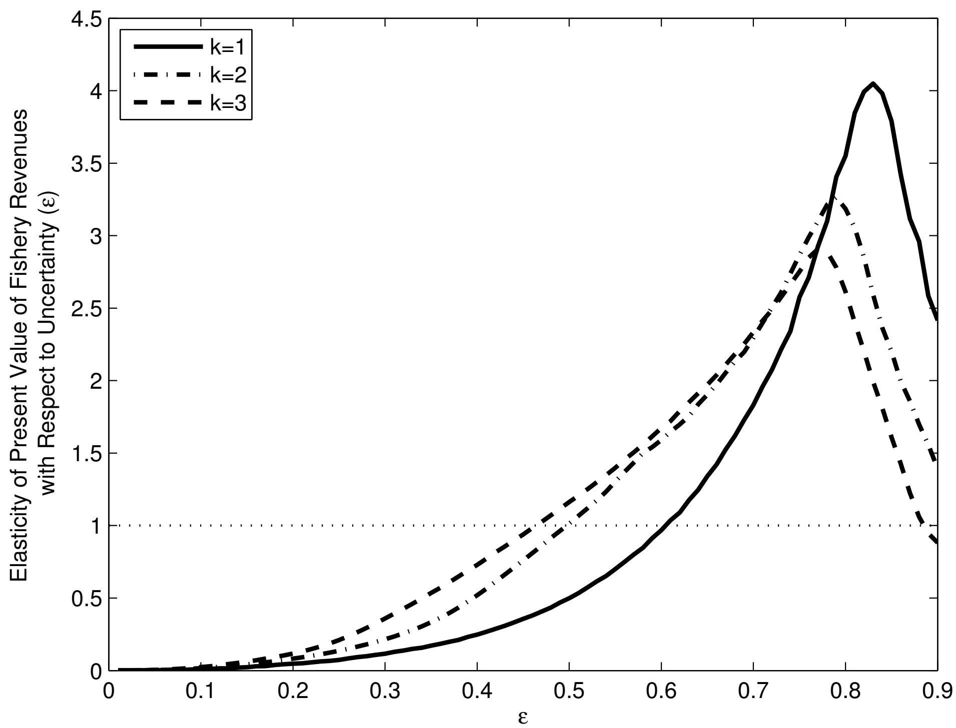


Figure 2.6: The elasticity of the Present Value of Fishery Revenues with respect to stock growth uncertainty (ε) calculated at $S_0 = 0.5$. Stock growth is logistic with $r = 1, K = 1$, $\delta = .95$.

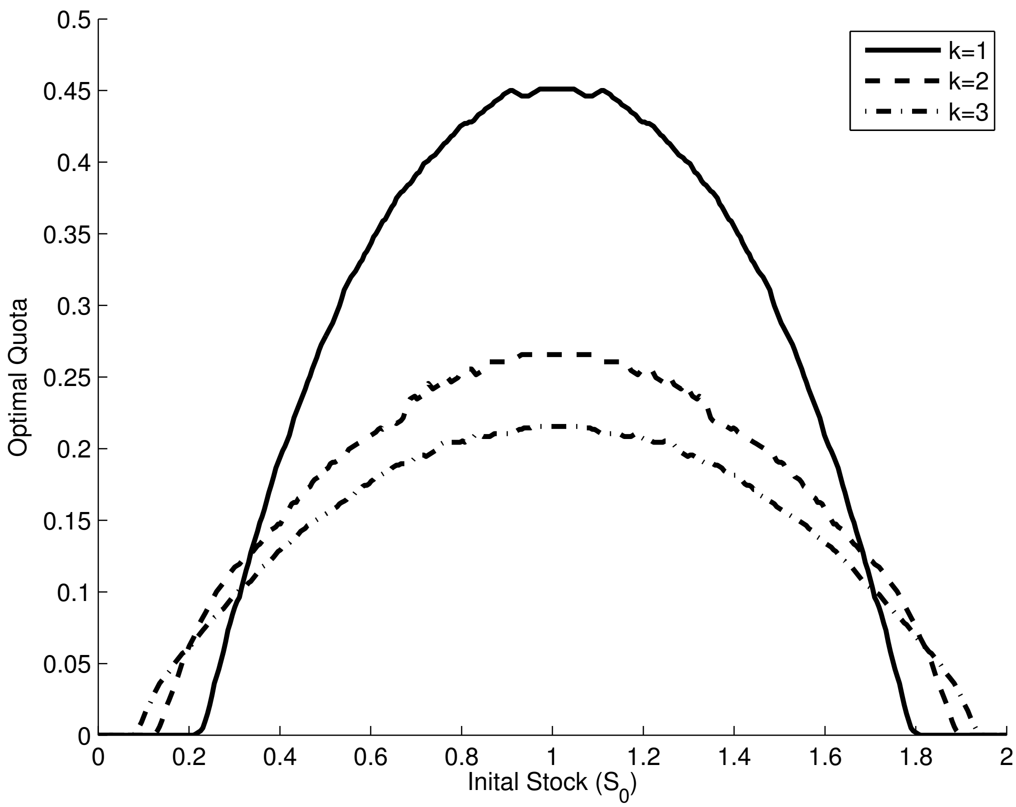


Figure 2.7: Optimal quota (q_j) for one-, two-, and three-year planning periods. Stock growth is Logistic with $r = 1, K = 1$ and $\delta = .95$.

ε	0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
$k = 1$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.041	0.999
$k = 2$	0.000	0.000	0.000	0.000	0.004	0.168	0.430	0.657	0.989	1.000
$k = 3$	0.000	0.000	1.2x10^{-4}	0.045	0.181	0.409	0.643	0.852	1.000	1.000

Table 2.3: Probability of Extinction within 100 years. Logistic stock growth with $r = 1, K = 1, \delta = 0.95$.

ε	0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
$k = 1$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.019	0.756	0.993
$k = 2$	0.000	0.000	0.000	0.000	0.004	0.100	0.362	0.728	0.989	1.000
$k = 3$	0.000	0.000	0.000	0.013	0.121	0.365	0.666	0.943	0.999	1.000

Table 2.4: Probability of Extinction within 100 years. Logistic stock growth with $r = 0.5, K = 1, \delta = 0.95$.

Chapter 3

Bargaining for Homogeneous Goods: The Days-at-Sea Market

3.1 Introduction

This chapter adapts Harding et al.'s (2003) hedonic pricing model to examine bargaining power in the Days-at-Sea (DAS) market. The DAS effort control system was implemented in 1994 as a means to end overfishing and allow depleted stocks of groundfish in the Northeast United States to recover. This fishery has historically been managed with an input control system and target or "soft" Total Allowable Catch (TAC). Fishing vessels were allocated a maximum number of fishing days per year based on historical patterns of use. In 2004, the DAS system was converted to a tradable input control system; however, regulations on trades may have limited the ability of the market to efficiently allocate DAS. The most restrictive trading regulations are likely to be the length and power limitations for trading pairs that were designed to limit increases in fishing power. Furthermore, there is no centralized market for DAS, trades are facilitated through brokers and prices are not publicly posted. Despite these limitations, there is robust activity in this market for DAS. From 2004 to 2008, there were 2,349 transactions in this market; approximately 53,400 Days-at-Sea worth \$17.9M have been exchanged (Table 3.1). During the 2008 fishing year, over one in four used DAS were leased. There has also been tremendous variation in prices of DAS and a lack of convergence to a single price (Figure 3.1). Furthermore, there has been excess allocation of DAS; the yearly aggregate allocation of DAS has never been approached. Economic theory claims that value of excess supply should be equivalent to zero; however, the market appears to be characterized by both large amounts of excess

DAS and positive prices.

The findings of this chapter suggest that this phenomenon can be explained by regulatory segmentation. The trading restrictions based on length and power have carved the DAS market into many smaller markets with few participants in each market. Some of these markets may clear at a positive price while others do not. Because a centralized market does not exist and there may be few participants in each market, trades are analyzed in a bilateral bargaining framework (Blair et al., 1989). In this model, the two firms first select the allocation of DAS that maximizes joint profits, then split the surplus using price. Price does not serve as a rationing mechanism; instead, it transfers trade surplus between parties.

This research is important and timely for multiple reasons. Firstly, National Standard 4 of the Magnuson-Stevens Fisheries Conservation Act (MSFCA) prohibits the acquisition of "excessive share" in limited access fisheries. This generally has been interpreted by economists as a prohibition on market power, in either the permit or output market (Anderson, 2008). The findings of this chapter suggest that exertion of market power by certain types of individuals has occured in this market. Secondly, fisheries managers were concerned with the effects of tradability on increases in total catch due to efficiency gains, the viability of small fishing vessels, and the preservation of fleet diversity. Small vessels are believed to be less efficient than large vessels; transfer of DAS to more efficient vessels would increase aggregate catch, an undesirable outcome. The continued operation of small vessels was viewed as a desirable social outcome. The findings of this research suggest that the trading regulations lowered the bargaining power of smaller vessels in the DAS market.

The applied research in bargaining and market power can be split into two general fields. The first type of analysis is primarily concerned with detecting the exertion of market power and often uses industry level time-series data. Fell and Haynie (In Press) examine the relationship between harvesters and processors in the Alaskan sablefish fishery. After an Individual Fishing Quota (IFQ) system was implemented, the bargaining power of harvesters increased relative to processors. Raper et al. (2000) examine bilateral bargaining in the US tobacco market. The authors apply an econometric model that allows for exertion of market power by either party to a time-series of input and output prices and find that buyers in this market are exerting market power relative to sellers. Gervais and Devadoss (2006) apply this general framework to chicken producers and processors. Mouchart and Vandresse (2007) recognize that the characteristics of each contract are endogenous to the bargaining processing for transportation contracts. Instead of an industry-level regression approach, the authors examine individual contracts using a frontier analysis approach to construct supply and demand bid functions and measures of bargaining power.

A second class of literature has attempted to identify attributes of individuals, firms, or contracts that are associated with high or low bargaining power. Ayres and Siegelman (1995) implement an audit study of bargaining for new cars and find that black and female buyers were quoted higher prices. Harless and Hoffer (2002) use transactions data to reinvestigate bargaining for new cars. The authors cannot replicate the finding that female buyers pay more, although they cannot control for race in the analysis. Examination of bargaining power has recently been popular in the hedonic housing literature, beginning with Harding et al.'s (2003) innovative bargaining model. The authors examine the causes of bargaining power by incorporating demographic characteristics that may confer bargaining power into the hedonic pricing model. The authors are particularly concerned with model misspecification due to omitted variable bias. The X matrix of characteristics of the heterogeneous good is partitioned as $[X_1 \mid X_2]$. X_1 are observed; however X_2 are not observed, but possibly correlated with with either buyer or seller demographics (D^s, D^b). The hedonic price equation is initially specified as:

$$p = X_1\beta_1 + X_2\beta_2 + b^b D^b + b^s D^s. \tag{3.1}$$

The b^i terms are intended to capture shifts in prices due to bargaining power differences that are derived from demographic characteristics of the buyer and seller. When X_2 is not observed, estimating a model based on Equation (3.1) results in biased estimates of the b^i parameters due to the correlation between X_2 and the D^i terms. To remove the omitted variable bias, Harding et al. (2003) instead formulate the price equation as:

$$p = X_1\beta + b^b D^b + d^b D^b + b^s D^s + d^s D^s + \varepsilon. \tag{3.2}$$

The d^i terms capture the correlations between X_2 and the D terms; however, direct estimation of Equation (3.2) cannot identify the parameters of interest. Harding et al. (2003) make two identifying assumptions:

$$b^b = -b^s = b \qquad \text{Bargaining Power Equality} \tag{3.3}$$

$$d^b = d^s = d \qquad \text{Preference Equality} \tag{3.4}$$

Equation (3.3) requires that identical buyers and sellers have identical bargaining power. Equation (3.4) requires that identical buyers have identical preferences for the unobservable characteristics. Equations (3.3) and (3.4) are then substituted into equation (3.2) to produce the estimating equation:

$$p = X\beta + b(D^b - D^s) + d(D^b + D^s) + \varepsilon \tag{3.5}$$

Equation (3.5) augments the traditional hedonic price equation with vectors of sums and differences of demographic characteristics. The coefficient vector associated with the demographic differences (b) captures bargaining power effects. The coefficient vector associated with the demographic sums (d) captures the effects of unobservable good characteristics that are correlated with buyers and seller demographic characteristics. There are three drawbacks with using this method. First, identification assumptions of bargaining power and preference equality must hold. For the housing market, these seem to be very reasonable identification assumptions. Second, the estimated coefficients can be slightly difficult to understand and interpret. Finally, the data must have sufficient variation between buyer and seller demographics in order to estimate the b coefficients with precision.

This model has been frequently used to analyze price formation in real estate. Colwell and Munneke (2006) apply the model to commercial property noting that the b terms may be capturing market imperfections while d may reflect different (unobservable) "classes" or market segments in which types prefer to be active. Ihlanfeldt and Mayock (2009) find that race is a determinant of sale price of Florida houses. Cotteleer et al. (2008) argue that the b terms are more properly characterized as "personal characteristics." They claim that the preference equality assumption in equation (3.4) is restrictive. Instead of using Equations (3.3) and (3.4) to identify b^i and d^i, the authors assume that there are no omitted characteristics in their estimating equation that are correlated with both price and demographic characteristics ($d^b = d^s = 0$). Therefore, buyer and seller demographics can enter the estimating equation directly. This identification assumption is not econometrically testable.

3.2 The Days-at-Sea Market

There are thirteen species and twenty-four separate stocks of groundfish which are managed jointly in the Northeast United States. These include both round (cod, haddock) and flat fish (flounders). Of these stocks, thirteen are classified as overfished and overfishing is currently occurring in five of the stocks (NMFS, 2008)[1]. These fish are caught by a diverse fishing fleet that uses a wide variety of fishing gear (otter trawls, gillnets, and hook-and-line) and fishing locations. The fishery is a a joint, multiproduct fishery (Squires, 1987; Kirkley and Strand, 1988). Labor is compensated using the lay or share system; employees receive a share of total revenue, after deducting variable operating costs (McConnell and

[1]When a stock of fish is "too small", it is overfished. When the flow of fish being harvested is "too high", overfishing is occurring. Neither an overfished stock nor the occurrence of overfishing necessarily implies the other.

Price, 2006). The exact share percentages and definitons of variable operating costs vary by vessel. The vessels that participate in the groundfish fishery typically participate in other fisheries in the Northeast United States, including the scallop, monkfish, lobster, and small pelagic fisheries. Some of these species are caught jointly with groundfish.

Days-at-Sea (DAS) has been the primary management tool used to reduce fishing effort directed at groundfish in the Northeast United States[2]. In 1996, there were approximately 1,700 vessels with an aggregate allocation of approximately 236,000 DAS (Code of Federal Regulations, title 50, Part 648, 2004). Substantial reductions in DAS were made so that by 2004, there were 1,400 vessels with a permit to fish 44,000 DAS, although not every permitted vessel had a DAS allocation. Leasing has become increasingly important; by 2008 over 40 percent of all used DAS were leased (Table 3.1). Although input controls have long been known to be an economically inefficient management tool (Wilen, 1979; Townsend, 1985), these management instruments have been popular in the fishing and fishery management communities (Rossiter and Stead, 2003).

At the beginning of the fishing year (May 1), vessels are allocated a stock of DAS which may be used at any time during the year. These DAS are similar to call options; a fishing vessel that owns a Northeast Multispecies DAS has the right to fish for groundfish in the Northeast United States federal waters for certain period of time during the fishing year. Up to 10 unused DAS may be carried forward to the subsequent fishing year. Surplus DAS, beyond ten, expire at the end of the fishing year on April 30 and are worthless. As options, the value can be decomposed into a time-value component and an intrinsic value component. The time-value component should decline to zero as the trade date approaches the end of the fishing year. DAS differ slightly from traditional options; the intrinsic value of the option varies across fishing vessels and is based on the fishing technology and other vessel characteristics. A vessel that chooses to sell DAS believes that the expected value from fishing is less than market price. A vessel that chooses to buy believes that the expected

[2]Other regulatory tools in use include daily trip limits for certain species, both permanent and rolling area closures, and minimum mesh sizes.

value from fishing is higher than market price.

Trades may occur at any time except the final month of the fishing year[3]. Prices and quantity traded must be reported to the National Marine Fisheries Service[4]. However, traded prices and quantities are not publicly available, limiting price discovery process and possibly affecting the market equilibration process (Anderson, 2004). The primary restriction on trade is related to fishing power:

> A lessor may not lease DAS to any vessel with a baseline horsepower rating that is 20 percent or more greater than that of the horsepower baseline of the lessee vessel. A lessor also may not lease DAS to any vessel with a baseline [length] that is 10 percent or more greater than that of the baseline of the lessee vessel's [length] (Code of Federal Regulations, title 50, Part 648).

Larger, more powerful vessels are believed to have higher catch rates, particularly for mobile gear relative to fixed or hook gear vessels. Furthermore, subleasing of DAS is prohibited. Combined with the size and power restrictions, the subleasing prohibition prevents "ratcheting," in which Days-at-Sea are successively transferred from small vessels to large vessels. However, this may also eliminate speculation and market-making activities, which are thought to be important for markets to efficiently allocate resources. These two limitations on trade are likely to prevent effort from shifting to larger, more efficient vessels by segmenting the DAS market in to many smaller sub-markets. Small vessels that desire to acquire DAS and large vessels that wish to divest DAS have the largest number of potential trading partners (Table 3.2). These types of firms may be able to exert market power in the Days-at-Sea market. Conversely, the largest buyers and the smallest sellers have the fewest number of potential trading partners and may have minimal bargaining power. There are two additional restrictions on trade which may reduce the ability of the market to efficiently

[3]These trades are technically leases - DAS are transferred for a single fishing year. While permanent transfer of DAS is allowed, these are infrequent and are not examined in this essay.

[4]A sample lease reporting form is available at `http://www.nero.noaa.gov/permits/forms.html`

allocate DAS. An upper limit on the number of DAS that a vessel can acquire was set at a vessel's 2001 DAS allocation, which may constrain the maximum number of days fished by some of the most efficient vessels. Because there is no centralized market, trading partners are found by word-of-mouth, advertisement in fishing-specific newspapers, or through brokers who match buyers to sellers.

A Day-at-Sea permit initially allowed fishing for a 24- hour period; however, there two major changes in fishery policy during the 2006 fishing year that changed the definition of a Day-at-Sea. The New England Fisheries Management Council (NEFMC) desired lower fishing mortality during the 2006 fishing year. However, the regulatory process could not be completed by the beginning of the fishing year. For approximately six months of the fishing year (May 1, 2006 to Nov 21, 2006), management of the the groundfish fishery proceeded under an Emergency Action. All vessels fishing for groundfish were charged 1.4 DAS for each day that was actually used. This Emergency Action was a temporary means to reduce fishing effort and harvest while the regulatory process was being finished. At the beginning of the 2006 fishing year, the exact specifications and effective date of the new regulations were not known with perfect certainty. However, fishermen probably had reasonably good predictions based on the extensive public notice given by the NEFMC. Georgianna *et. al* (2008) found that New Bedford based fishing vessels substituted non-DAS trips for DAS trips and delayed use of their DAS during the 2006 fishing year, waiting for a more favorable accounting rate. However, the timing of use at an aggregate level does not appear to have changed (Figures 3.3 and 3.4).

The permanent change to groundfish policy was titled Framework Adjustment 42 and published on October 23, 2006 with implementation date of Nov 22, 2006. This regulation created Differential DAS areas with heterogenous DAS costs (See Figure 3.2). Vessels that used the Differential DAS areas were charged at a rate of two DAS for each day fished. Fishing in other zones was charged at the normal rate (one-to-one). While fishing vessels are mobile and may be able to switch fishing locations, there are limits to that mobility.

Small vessels may not have be speed or size required to fish far off-shore, gear may be suitable to certain fishing areas, and crew many not have the knowledge required to use unfamiliar fishing areas. The differential DAS regulation contained in Framework Adjustment 42 can be thought of as a downward technological shock to the production function of fishing vessels that use differential Days-at-Sea areas. Fishing vessels that use the Differential Days-at-Sea areas will produce less revenue per DAS while those outside this area should be unaffected.

3.3 Empirical Model and Data Used

In the present application, the traded good confers the right to fish for a period of time. Harding et al. (2003) make the assumption that buyer and seller demographics confer bargaining power equally and that identical types (as measured by demographics) have identical preferences. These identification assumptions are made because the authors are concerned about omitted variable bias. A Northeast Multispecies Day-at-Sea has a well-specified legal definition that is consistent across fishing vessels. Prior to 2006, one DAS allowed vessels to fish for one day. During the Emergency Action period, 1.6 DAS were required for one fishing day. After the implementation of Framework 42, a DAS allowed vessels to fish at a a 1:1 ratio in the normal DAS areas or a 2:1 ratio in the differential DAS areas. While the legal definition of DAS has change over time and currently varies according to fishing area, there are no unobserved attributes of a DAS. the d^s and d^b terms in equation (3.1) must be zero and the assumption of bargaining power equality in equation (3.3) can be safely relaxed. The price equation can be estimated by OLS as:

$$p_i = b^b D_i^b + b^s D_i^s + \gamma Z + \epsilon_i \tag{3.6}$$

The demographic characteristics of buyers and sellers can enter the price equation directly and bargaining-power symmetry can be tested econometrically. For demographic

D_j, rejection of the hypothesis that $b_j^b = -b_j^s$ can be interpreted as evidence that characteristic D_j confers bargaining power asymmetrically to buyers and sellers. Z is a vector of controls that are not specific to either buyer or seller that may shift price.

The quantiles are modeled as linear. Let $Q_\tau(p|ZX)$ quantile of the distribution of Days-at-Sea price, conditional on X, the buyer and seller demographic characteristics and other price shifters. The conditional quantiles are modeled as:

$$Q_\tau(p|X) = X'\beta_\tau \tag{3.7}$$

For any $\tau \in (0,1)$, the coefficient vector $\beta(\tau)$ can be estimated by minimizing

$$\frac{1}{n}\sum_{i=1}^{n} \rho_\tau(p_i - X_i'\beta_\tau)$$

where

$$\rho_\tau(u) = u(\tau - I(u < 0))$$

For a given quantile, τ, the $\rho_\tau(u)$ function can be interpreted a function that incorporates asymmetric weights on the residuals that depend on the sign of those residuals.

OLS focuses on the conditional mean and imposes slope homogeneity - the partial effect of an independent variable on the dependent variable is assumed to be constant. In contrast, quantile regression allows the estimated coefficients to vary across the ranking of the dependent variable (Koenker and Bassett Jr., 1978; Koenker and Hallock, 2001). Using this method, it is possible to examine bargaining power across the distribution of DAS prices. The restrictions on trade may have segmented the large market for DAS into many small ones, each with few participants. Small changes in length or horsepower may have large effects on bargaining power. The bargaining power effects are likely to be most pronounced at both tails of the price distributions and quantile regression is able to uncover those effects.

The unit of observation in this analysis is a reported trade of a quantity of Days-at-Sea that occurred in fishing years 2004-2008. There are 1,788 observations for which DAS were exchanged at positive prices[5]. Demographic characteristics for buyers and sellers include length, horsepower, revenues from DAS and alternative fisheries, number of permits held, fishing gear used, and the amount of prior experience in this market. In general, vessels that purchased DAS had higher revenues, more experience in the market, and were more likely to fish using trawl gear and in the Differential DAS areas than the sellers (Table 3.3). Buyers were slightly shorter in length and had lower horsepower, a expected result of the trading regulations pertaining to those two characteristics. In general, prices had a downward intra-year trend with fairly large volatility (See Figure 3.1).

Revenues for DAS trips were aggregated at the yearly level and divided by the total Days-at-Sea used to construct a per-day measure of revenues for buyers and sellers from the groundfish fishery. The average revenue per-day, lagged one year, were used in the estimation as a measure of profitability. The decision to acquire or divest DAS is related to profitability, this is likely to be very closely related to revenue due to the share system of labor compensation. The DAS revenue variables captures the trade surplus over which the two parties bargain over. Because fishing vessels are often active in other fisheries, two other variables were constructed to account for the opportunity costs of buying and selling DAS. The first variable directly measures daily revenue from alternative fisheries; this variable is constructed analogously to the DAS Revenue variable. The second variable included is the number of other limited access permits held by each vessel. The Alternative Revenue and Permits variables control for the opportunity costs of fishing and are also related to the trade surplus. Vessels with high alternative revenues and many limited access permits have a relatively high opportunity cost using DAS; they have highly productive alternative fishing activities. All economic data (prices and revenues) was deflated using

[5]Of the 2,349 observed transactions, 561 transactions reported a price paid equal to zero. There were an additional 115 transactions for which the price was less than $100. There may represent intra-company trades, non-response, or indicate a catch-sharing agreement. Additionally, there are a few (n=7) outlying data points for which the price is far higher that the rest of the sample.

Bureau of Labor Statistics Producer Price Index for unprocessed finfish, with the base year set to 2008.

For each transaction, the buyer's and seller's experience is constructed as the number of times each party had previously participated in the DAS market. The expected effect of this variable is unclear: frequent participants are likely to have an informational advantage relative to infrequent participants which may translate to a bargaining power advantage. However, experience may reflect self-selection into the market; buyers with exceptionally high profitability may be more likely to purchase DAS at any price. Similarly, sellers with low productivity may be more likely to sell DAS at any price.

A dummy variable for the use of trawl gear is included in the model. Vessels that use trawl gear are typically larger, more powerful, and catch more fish than vessels that use long-line, hand-line, or gillnet gear. This variation is already captured in the variables used; however, trawl vessels also have higher operating expenses, mostly due to higher fuel usage. Although detailed variable cost information is not available at the vessel-level, inclusion of a dummy variable for trawlers may capture the higher variable operating costs associated with this type of gear.

Two variables are used to capture the possible the effects of the technological shock imposed by Framework 42's Differential Days-at-Sea regulations. The fraction of revenues derived from trips in the differential DAS areas was constructed using locational data from landings reports (Figure 3.2). This variable captures the relative importance of the Differential DAS areas for each fishing vessel. A dummy variable was included for trades that occur after Framework 42 was implemented; this variable is also interacted with the Differential DAS fraction. Yearly dummy variables were also included in the estimated model and based on the fishing year (May-April). The variable "Time Remaining" constructed from the reported trade date and is used to capture the time-value component of DAS. Ignoring carry-over to the next fishing year, the value of unused DAS is zero on the final day of the fishing year.

A linear model is estimated using OLS on the full sample (N=1,788) and two subsamples that drop prices over \$3,000 and \$1,500 respectively[6]. The model is then estimated using the full sample using quantile regression for the 10^{th} through 90^{th} quantiles, at intervals of 5%, using the `quantreg` package in `R`.

3.4 Results

The linear model fit by OLS fits moderately well; R^2 ranges from 0.21 to 0.51 (Tables 3.4 and 3.5). Results seem to be sensitive to outlying data points. Estimated coefficients and significance levels, particularly the Trawl_Buyer, Permits_Seller, Framework42, and Framework42$*$DDAS_ Buyer, are not stable across subsamples. Furthermore, inspection of the residuals reveals that the model has some difficulty fitting both the very high and very low prices (Figure 3.5). These findings partially motivate the use of quantile regression.

Because buyer and seller demographic characteristics enter the estimating equation separately, it is possible to examine the Bargaining Power equality assumption. Bargaining Power equality implies that coefficients for buyer and seller demographic characteristics sum to zero. Table 3.6 contains the linear combination $b^s + b^b$ and $t-$statistics for demographic characteristics. Rejection of the null hypothesis indicates that Bargaining Power equality does not hold. Postive values in Table 3.6 imply that increases in that characteristic are associated with increases in DAS price and may be interpreted as increasing the relative bargaining power of sellers. Negative values are associated with decreases in DAS price and may be interpreted as increasing the relative bargaining power of buyers.

A major finding is that segmentation induced by the trading restriction on length confers bargaining power unequally to buyers and sellers. The positive combination of coefficients for length implies that longer buyers have less bargaining power. Although there are also trading restrictions based on horsepower; neither buyer nor seller power affect DAS

[6]The specification presented standardize horsepower by dividing by vessel length. The appendix contains a slightly different analysis that uses raw horsepower and monthly dummy variables.

price. A somewhat surprising finding is that revenues-per-DAS have no effect on bargaining power; however, there is moderate evidence that alternative fishing revenue and limited access permits increase the bargaining power of sellers. Finally, there is weak evidence that use of the differential DAS areas either reduces the willingness-to-pay for DAS or decreases the bargaining power of sellers after the implementation of differential DAS.

Utilization of the Differential DAS area by either buyer or seller prior to implementation of Framework 42 has no statistically significant impact on bargaining power. The implementation of Framework 42 may have increased price; however this results is not robust across models[7]. For the smallest subsample (Model 3), buyers that use the differential Days-at-Sea will pay less after the implementation of Framework42. Vessels that heavily utilize the differential DAS areas find those areas less profitable and therefore are willing to pay less in order to fish there. It is plausible that the trade surplus decreased under Framework 42, driving down prices.

The Time Remaining coefficient is positive and significant, providing support for the time-value component of Days-at-Sea valuation. The estimated coefficient is relatively stable across the three estimated models, ranging from \$0.36-0.52 per day. The coefficients for yearly dummies are presented in Table 3.5. There were substantial price increases in 2006-2008, relative to 2004. Real DAS prices were up to \$200 higher in 2006-2008; although the estimated coefficients vary by specification and year.

The quantile regression method can provide further insight into the bargaining process beyond analysis of the conditional mean price. Tables 3.6 and 3.7 contain coefficient estimates and standard errors for 5 selected quantiles along with Koenker and Machado's (1999) R^1 statistic[8]. The model has little explanatory power at the lower tail of the price

[7] Based on Model 2, the sum of the F42xDifferential_seller and Framework42 coefficients is \$77; however, the standard error of that estimate is 52, indicating that it cannot be statistically distinguished from zero. Similarly, the sum of F42xDifferential_buyer \$40, with a standard error of 45, also not distinguishable from zero.

[8] The R^1 is an analog of the R^2 statistic and is calculated as $R^1 = 1 - \frac{V_u}{V_c}$, where V_u is the value of the objective function produced by a "full regression" and V_c is the value of the objective function produced by regression of price against only a constant.

distribution; there is little variation in the dependent variable and prices are clustered just above zero. Fit improves markedly at higher quantiles. Visualization is the easiest way to interpret results of quantile regression; each of the estimated coefficients, β_τ, are plotted as a function of τ, along with shaded 90% confidence bands and a dotted line that represents the OLS coefficient estimate. The graphs and associated coefficients can be interpreted as the marginal effect of an independent variable on price at a given quantile. A line with zero slope would be consistent with the slope-homogeneity restriction imposed by least squares. Departures from zero slope imply that the marginal effects are different across different price quantiles. Many, but not all of the coefficient lines appear to have non-zero slope.

These results are consistent with regulatory segmentation hypothesis based on length. Length reduces the bargaining power of buyers; however, this effect is strongest at the upper tail of the price distribution and non-existent at the lower tail. An extra foot of buyer's length increases the price of DAS by \$5.20 at the 25^{th} percentile and by \$10 at the 90^{th} percentile (Figure 3.7). In addition, seller length has a similar, though smaller in magnitude, effect on prices at the higher price quantiles (Figure 3.8). Power, as measured by the horsepower/length ratio does not seem to impact the bargaining power of buyers or sellers (Figures 3.9 and 3.10). Length, and not power, seems to be more restrictive in determining feasible trades in this market.

Groundfish revenues for both buyer and seller are related to the trade surplus over which each party bargains. Buyer's groundfish revenue appears to have no effect on prices while seller's groundfish revenues have a small effect, increasing price by approximately \$7 per \$1,000 of daily revenues at all but the lowest price quantiles (Figures 3.11 and 3.12). The effects of the alternative revenue and limited access permits are similar: conferring small amounts of bargaining power to sellers at the low and moderate price quantiles (Figures 3.13 and 3.14) and having no effect on the bargaining power of buyers (Figures 3.15 and 3.16). These findings could indicate a gradient of market classes. There may be one market class for the large vessels; in this segment, size is an important determinant of price and bargaining power. There is another market class for the smaller vessels; within this class, the profits and opportunity costs of the seller, as measured by Permits, DAS Revenue, and Alternative Revenue become more important in the bargaining process.

Implementation of Framework 42's Differential DAS system had an interesting effect on prices and bargaining power. As expected, prior to the implementation of Framework 42, the bargaining power of vessels that used the Differential DAS areas did not systematically vary from vessels that did not use these areas (Figures 3.17 and 3.18). The signs and significance of the Framework42, Differential DAS, and interaction variables were not robust in the OLS model. The quantile regression results suggests that is due to fairly substantial heterogeneity in the effect of these variables. After implementation of Framework 42, the prices in the lower quantiles were unchanged or slightly lower; however, prices at the middle and higher quantiles increased substantially, by $80-150 (Figure 3.19). However, there is an additional effect due the interaction of the Framework 42 and Differential DAS variables. Table 3.8 further examines the effects of Framework 42 when the buyer, seller, both, or neither use the Differential DAS areas. In general, prices after Framework 42 remained constant if the buyer exclusively used the Differential DAS areas. If the buyer did not use those areas, prices were sustantially higher.

The yearly price effects estimated by quantile regression are similar to the effects estimated by OLS. Relative to 2004, all prices were higher in 2006. However, prices in 2007 and 2008 were only higher in the middle quantiles of the price distribution (Figure 3.23). Higher prices in 2006 could reflect some of the regulatory uncertainty regarding the Emergency Action and the timing of the adoption of Framework 42. The large coefficient on the 2006 dummy variable reflects higher prices during the time in the fishery operated under the 1.4-to-1 DAS counting mandated by the Emergency Action. Also consistent with the OLS results, trades that occur later in the year occur at lower prices (Figure 3.22). Consistent with the interpretation of DAS as options; the value of a DAS decays at the rate of approximately \$0.50 per day across most of the price quantiles.

It is also possible to examine bargaining power at individual quantiles. Table 3.9 contains the sums of buyer and seller demographic coefficients ($b^s + b^b$) and $t-$statistics for demographic characteristics at 5 selected quantiles. A positive combination indicates that increases in the independent variable lead to higher price. This may be evidence that the independant variable confers bargaining power to sellers. Conversely, a negative combination indicates that increases in the dependent variable leads to lower prices. This may be evidence that the independent variable confers bargaining power to buyers.

In general, there is substantial heterogeneity in the net effect of buyer and seller characteristics across quantiles. Sums of coefficients are generally insignificant at the $\tau = 0.10$ quantile. These results strongly reject the hypothesis that length confers bargaining power equally to buyers and sellers at the 50^{th} percentile and higher; length lowers the bargaining power of buyers relative to sellers. This effect seems to be slightly larger at the higher price quantiles. The bargaining effects of power are not robust across quantiles. There is also very weak evidence that higher groundfish revenues confer bargaining power to sellers in the middle price quantiles. The two measures of opportunity costs of using DAS are also non-robust across quantiles. Permits have a fairly large positive effect on seller's bargaining power, but this only occurs at the 25^{th} percentile of price. At this price level, alternative revenue have a small negative effect on seller bargaining power; while at the 50^{th} percentile alternative revenue has a small positive effect on seller bargaining power.

Trawl usage may confer bargaining power to buyers at the middle quantiles of price. However, this finding is also consistent with higher costs and therefore lower willingness-to-pay for buyers that use trawl gear. Usage of the Differential DAS areas has a fairly large negative effect on seller bargaining power at the higher price quantiles, although this effect reverses itself and disappears at the lower price levels. Again, these findings are consistent with lower productivity of DAS under the Differential DAS managment regime and may not be directly indicative of changes in bargaining power.

3.5 Conclusions

This chapter expands on the Harding et al.'s (2003) model in two ways. First, by examining a good without unobserved characteristics, the assumption of bargaining power equality used for identification can be econometrically tested. Based on analysis using least squares, the hypothesis of bargaining power equality can be rejected for some demographic characteristics, most notably vessel length. Secondly, this research applies an alternative econometric technique, quantile regression, to examine the effects of bargaining power. This method allows for the effects of demographic characteristics on price to vary across the price distribution.

The major finding of this research is the trading restrictions based on size and power led to unequal bargaining power for buyers and sellers. This finding can resolve an apparent inconsistency in this market; DAS trade at positive prices even though, in aggregate, there is excess supply of DAS (as measured by unused DAS). The size and power trading restrictions appear to have segmented the DAS market so that there is only excess supply for smaller, less powerful vessels. A well-designed market for an input permit can efficiently allocate those permits to the most efficient firms. In this market, limitations on trade have conferred market power to certain types of individuals.

The productivity of DAS (revenues) do not affect the bargaining power to either buyers or sellers. This surprising finding may occur because the restrictive size and power regulations dominate bargaining power changes of revenues. Alternatively, the revenue variable used may be a poor measure of firm-level profitability. The share (or lay) system of labor compensation is used in this fishery; crew are typically paid a fraction of total revenues minus variable costs and the owner of the fishing vessel receives a share of total revenues. Therefore, the returns to the owner from using a DAS should be reasonably correlated to revenues although heterogeneity in the shares system may limit the ability of revenue to control for firm-level profitability.

The negative relationship between price and Time Remaining is likely related to decay in the time-value of the option. However, alternative interpretations are possible, although less likely. Sellers could lose bargaining power relative to buyers during the year. However, a reason for decreases in bargaining power is not clear. Furthermore, the timing of purchases matters because a vessel cannot hold a negative amount of DAS. If a vessel runs out of DAS, it must stop fishing unless it can acquire DAS. This may explain higher willingness-to-pay for DAS early in the fishing year.

These results have implications for fisheries management and general design of markets. Fishery managers were likely concerned with an increase in total catch associated with transferring DAS from small vessels to larger, more-efficient vessels. The trading restrictions based on size and power designed to limit expansion of effort appear to have segmented the market, inflating the prices paid by largest buyers relative to vessels of other sizes and depressing the prices received by smaller vessels. Ensuring the continued operation of a diverse fishing fleet was a goal of managers; while the strict regulations on trade may have accomplished that goal, the cost of this regulation is lower bargaining power for the smaller fishing vessels.

3.6 Tables and Figures

Year	Allocated DAS[a]	Used DAS	Aggregate Leased DAS	Aggregate Value of Leased DAS
2004	44,030	30,060	6,192	$ 2,590,182
2005	51,112	32,194	8,068	$ 2,709,263
2006	48,175	32,399	11,245	$ 3,279,149
2007	47,802	33,264	13,900	$ 4,815,603
2008	47,021	31,701	13,996	$ 4,494,270

[a]:Includes DAS carried over from previous fishing year.

Table 3.1: Historical Days-at-Sea Allocations, Usage, and Leases. Extracted from NMFS DAS and DAS2 databases.

Length	Potential Buyers	Potential Sellers
30 feet	924	132
40 feet	810	540
53 feet	517	816
70 feet	318	1,069
80 feet	209	1,204
100 feet	33	1,263

Table 3.2: Number of feasible trading partners by length.

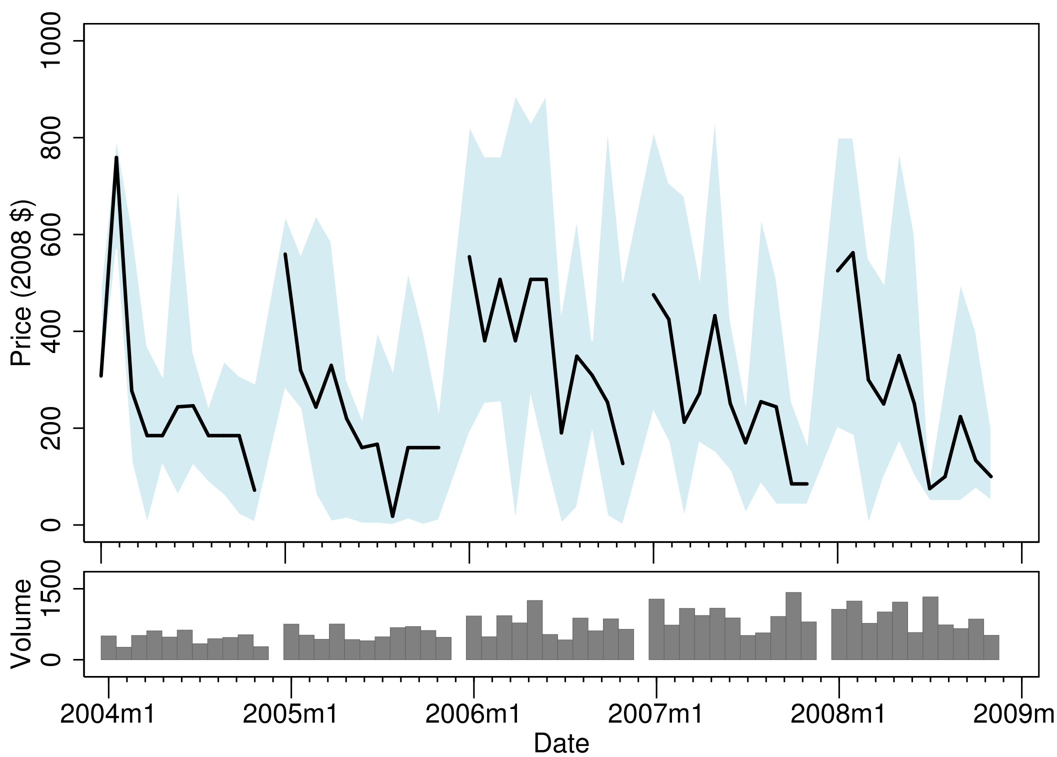


Figure 3.1: Median and Interquartile range of real DAS prices, Monthly DAS volume

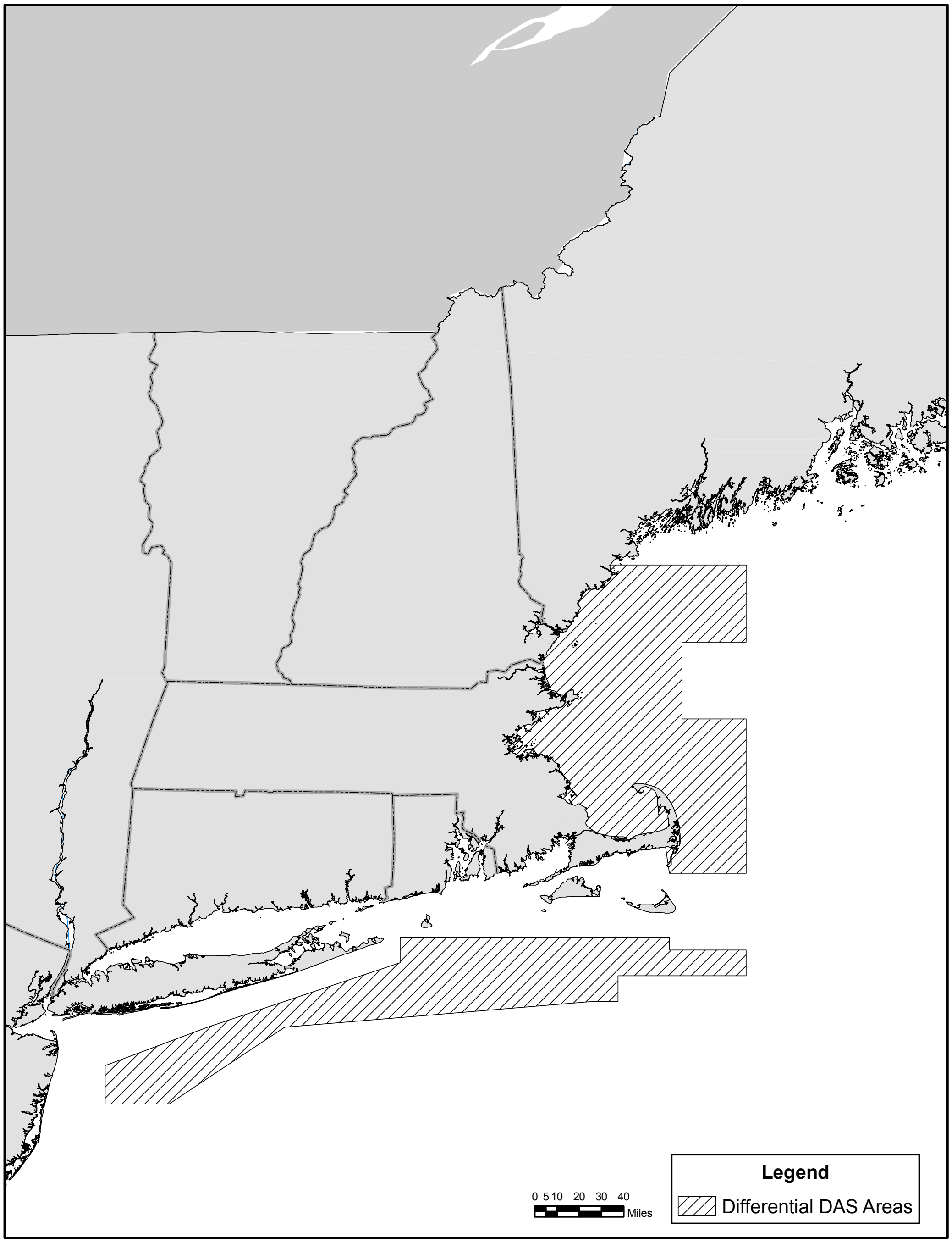


Figure 3.2: The Differential DAS areas were implemented with Framework Adjustment 42 on Nov 22, 2006.

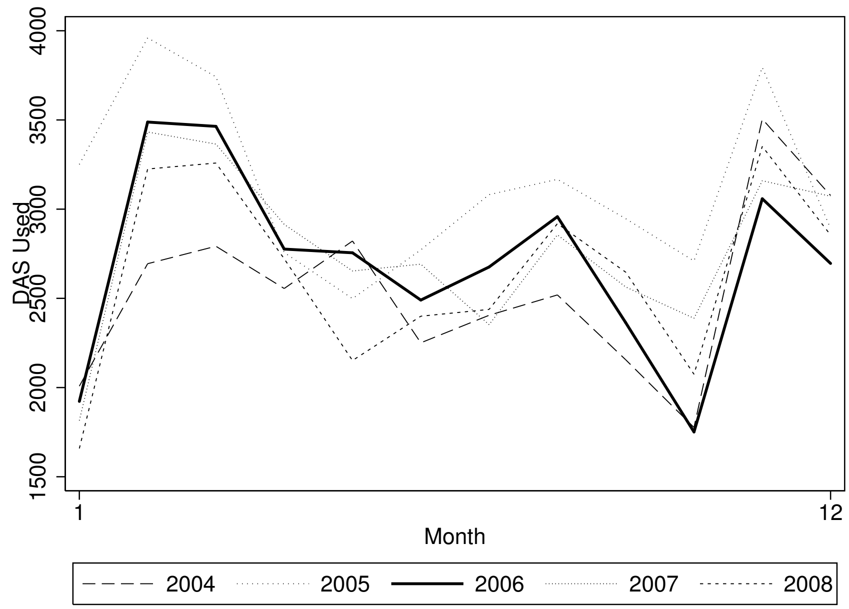


Figure 3.3: Monthly DAS Usage.

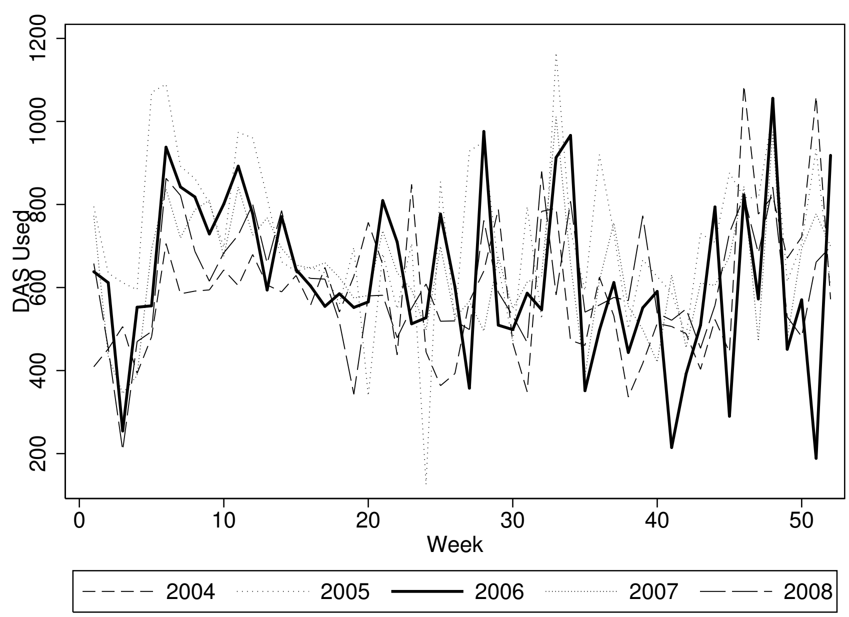


Figure 3.4: Weekly DAS Usage.

		Buyer		Seller	
Variable	Definition	Mean	Std. Dev	Mean	Std. Dev
Price	Price per DAS in 2008 Dollars	$360	521		
Quantity	Days traded	22.3	15.3		
Length	Vessel length in feet	60.2	19.1	62.3	18.9
Horsepower	Vessel Horsepower Rating	437	190	504	241
Power	Horsepower/Length	7.20	1.78	8.04	2.56
DAS	Revenue per DAS, 000s of dollars per day	$3.92	3.13	$1.03	2.39
Alternative	Revenue per Day Fished, no DAS used, 000s of dollars per day	$1.93	3.20	$1.82	4.21
Permits	Number of limited access permits	2.35	1.59	1.46	1.99
Experience	Number of times a vessel has traded in the DAS market	4.5	4.5	2.5	2.5
Trawl	Dummy variable=1 if vessel uses trawl gear, =0 otherwise	0.69	0.46	0.80	0.40
Differential	Fraction of revenues from differential DAS areas	0.458	0.439	0.149	0.332
Time Remaining	Number of Days remaining in Fishing Year	171	95.6		

Table 3.3: Summary Statistics (N=1,788): Economic variables normalized to 2008 real values using Producer Price Index for Unprocessed Finfish. Buyer and seller means, except Alternative Revenue, are statistically different at the 1% level.

Coefficient	Model 1	Model 2	Model 3
Length_Buyer	9.219***	8.723***	7.610***
	(1.25)	(1.08)	(0.93)
Length_Seller	0.444	1.363	1.420
	(1.36)	(1.02)	(0.89)
Power_Buyer	-9.500	-1.511	3.417
	(5.84)	(4.78)	(3.70)
Power_Seller	5.539	-0.0972	0.509
	(4.67)	(2.78)	(2.50)
DAS_Buyer	1.017	-2.880	-0.0648
	(5.07)	(3.70)	(3.06)
DAS_Seller	6.733	8.866	5.269
	(6.23)	(6.43)	(5.49)
Alternative_Buyer	2.880	1.786	1.866
	(3.21)	(2.59)	(2.01)
Alternative_Seller	8.039***	7.437***	7.934***
	(1.96)	(1.92)	(1.68)
Permits_Buyer	25.41*	0.536	-4.091
	(14.0)	(7.06)	(4.41)
Permits_Seller	7.077	14.79***	26.94***
	(6.97)	(4.83)	(4.06)
Experience_Buyer	0.619	-3.545*	-3.059*
	(3.58)	(2.05)	(1.67)
Experience_Seller	-4.417	-4.598	-3.275
	(5.66)	(2.92)	(2.53)
Trawl_Buyer	13.41	-53.25***	-68.06***
	(33.6)	(14.4)	(10.5)
Trawl_Seller	-87.11*	-3.723	-18.06*
	(44.6)	(14.2)	(10.7)

Robust standard errors in parentheses

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

Table 3.4: Coefficients estimated by Ordinary Least Squares. Model 1 uses the full sample, Model 2 omits observations for which price is higher than \$3,000, and Model 3 omits observations for which price is higher than \$1,500. Trimming of the sample leads to moderate changes in estimated coefficients. Dummy variables for Year are based on the fishing year for groundfish, which runs from May-April. Part 1 of 2.

Coefficient	Model 1	Model 2	Model 3
Time Remaining	0.360**	0.592***	0.528***
	(0.15)	(0.086)	(0.065)
Framework42	12.79	102.4**	84.64**
	(61.9)	(46.2)	(37.4)
Differential_Buyer	84.15	7.735	17.88
	(54.0)	(27.2)	(23.9)
Differential_Seller	-8.835	3.540	1.376
	(37.2)	(27.3)	(24.4)
F42 x Differential_Buyer	-92.97	-60.41*	-85.12***
	(67.7)	(34.5)	(26.8)
F42 x Differential_Seller	70.71	-18.72	-25.91
	(73.6)	(30.6)	(25.1)
D2005	-17.82	2.351	-34.15
	(30.2)	(27.2)	(20.9)
D2006	206.7***	156.5***	140.8***
	(47.0)	(30.7)	(26.5)
D2007	128.7*	33.01	39.24
	(66.8)	(45.7)	(37.5)
D2008	182.0***	74.25	72.60*
	(68.8)	(49.1)	(39.7)
Constant	-436.1***	-439.6***	-405.9***
	(61.2)	(53.5)	(48.5)
Observations	1788	1781	1756
R^2	0.21	0.38	0.51

Robust standard errors in parentheses

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

Table 3.5: Coefficients estimated by Ordinary Least Squares. Model 1 uses the full sample, Model 2 omits observations for which price is higher than $3,000, and Model 3 omits observations for which price is higher than $1,500. Part 2 of 2.

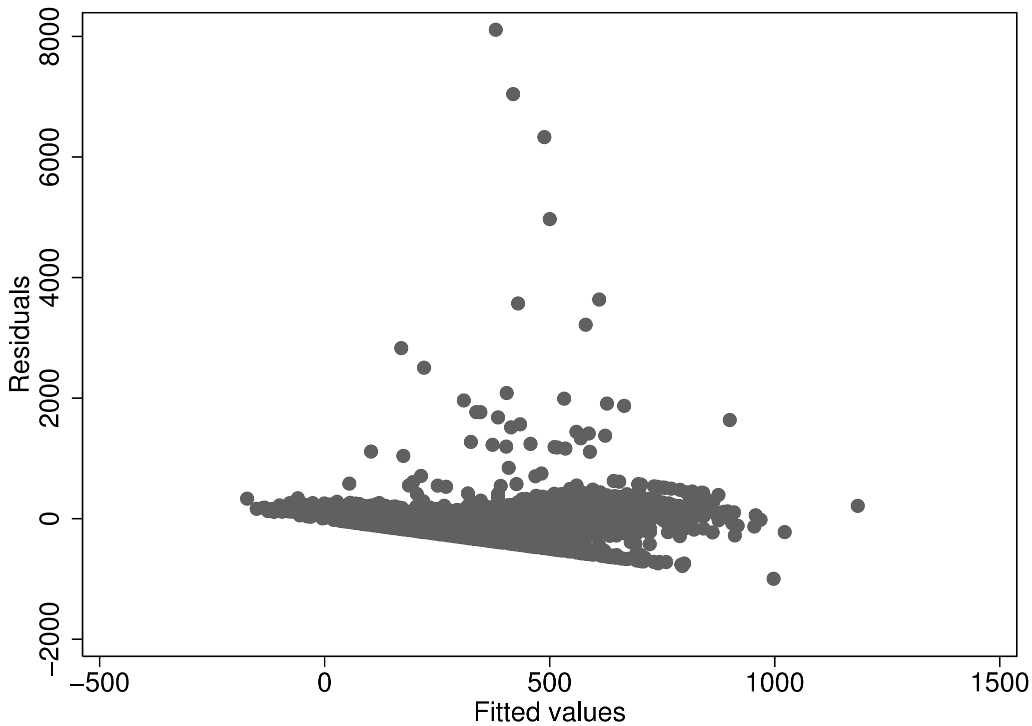


Figure 3.5: Residuals vs. Fitted values, Model 1. While most residuals are fairly small, there are a good number observations for which predicted prices were low but actual prices were high.

	(1)	(2)	(3)
Length	9.66	10.10	9.03
	(9.09)	(11.58)	(14.53)
Power	-3.96	-1.61	3.93
	(-0.72)	(-0.37)	(1.21)
DAS	7.75	5.99	5.20
	(0.94)	(0.80)	(0.83)
Alternative	10.90	9.22	9.80
	(2.66)	(2.62)	(3.89)
Permits	32.50	15.30	22.90
	(2.43)	(2.03)	(4.29)
Experience	-3.80	-8.14	-6.33
	(-0.66)	(-2.39)	(-2.13)
Trawl	-73.70	-57.00	-86.10
	(-2.75)	(-3.00)	(-6.00)
Differential	75.30	11.30	19.26
	(1.65)	(0.33)	(0.69)
F42xDifferential	-22.30	-79.10	-111.00
	(-0.25)	(-1.96)	(-3.47)

Figure 3.6: Sums of buyer and seller demographic coefficients with $t-$ ratios for H_0: $b^b + b^s = 0$ in parentheses.

Coefficient	0.10	0.25	0.50	0.75	0.90
Length_Buyer	0.667	5.199	7.922	9.649	10.050
	(0.674)	(0.941)	(0.799)	(0.923)	(1.400)
Length_Seller	− 0.186	− 2.150	2.103	2.815	4.390
	(0.421)	(0.700)	(0.863)	(0.870)	(1.366)
Power_Buyer	0.130	− 0.777	4.867	5.728	0.585
	(1.315)	(2.608)	(2.978)	(2.912)	(4.104)
Power_Seller	− 0.417	− 1.109	0.181	2.067	4.779
	(1.075)	(1.637)	(2.273)	(2.425)	(3.999)
DAS_Buyer	− 1.592	− 4.240	6.007	1.657	− 1.052
	(2.275)	(2.987)	(2.902)	(2.927)	(4.248)
DAS_Seller	− 1.528	8.208	7.314	12.151	10.087
	(4.461)	(6.085)	(2.598)	(4.154)	(4.884)
Alternative_Buyer	0.367	0.172	1.584	1.323	− 0.869
	(1.040)	(2.284)	(1.987)	(2.173)	(2.451)
Alternative_Seller	5.245	15.179	8.551	4.545	1.050
	(5.438)	(2.641)	(1.865)	(1.315)	(2.071)
Permits_Buyer	− 0.125	− 2.373	− 13.068	− 2.528	9.833
	(1.557)	(3.662)	(4.180)	(5.004)	(8.198)
Permits_Seller	9.263	41.311	15.096	3.518	− 9.053
	(7.579)	(4.647)	(3.710)	(3.791)	(5.919)
Experience_Buyer	− 0.556	− 2.065	− 3.002	− 1.014	− 3.123
	(0.736)	(1.277)	(1.372)	(1.535)	(1.684)
Experience_Seller	− 0.752	− 3.645	− 0.311	− 1.630	0.375
	(1.013)	(1.861)	(1.899)	(2.325)	(3.025)
Trawl_Buyer	− 8.604	− 52.179	− 52.038	− 43.986	− 1.131
	(9.579)	(11.213)	(11.086)	(12.307)	(18.000)
Trawl_Seller	3.249	9.677	− 32.638	− 7.800	6.117
	(5.789)	(13.039)	(12.176)	(10.301)	(14.074)

Table 3.6: Quantile Regression coefficients for selected quantiles. Standard errors in parentheses, generated using 20,000 bootstrap replications. Part 1 of 2.

Covariates	0.10	0.25	0.50	0.75	0.90
Differential_Buyer	0.397	1.594	17.511	− 3.032	39.947
	(9.725)	(25.413)	(22.884)	(22.834)	(32.264)
Differential_Seller	− 17.131	14.084	5.103	24.513	16.597
	(33.098)	(32.045)	(21.190)	(21.992)	(29.168)
F42xDifferential_Buyer	12.593	− 8.434	−126.417	−112.816	−135.419
	(13.019)	(28.892)	(26.750)	(27.407)	(40.827)
F42xDifferential_Seller	5.948	− 37.435	13.272	− 27.688	− 25.748
	(33.090)	(31.792)	(26.175)	(24.822)	(36.810)
Framework42	− 7.724	− 14.435	80.510	155.838	156.209
	(11.626)	(48.910)	(37.454)	(39.940)	(46.290)
Time Remaining	− 0.001	0.265	0.460	0.421	0.485
	(0.024)	(0.077)	(0.062)	(0.056)	(0.083)
D2005	− 4.280	− 28.047	− 15.203	− 15.065	− 5.681
	(9.205)	(18.378)	(21.566)	(18.928)	(26.049)
D2006	0.989	73.089	162.121	190.622	235.257
	(8.075)	(43.789)	(24.739)	(25.992)	(41.658)
D2007	4.093	92.762	102.670	10.803	13.752
	(12.236)	(46.744)	(38.664)	(40.789)	(51.254)
D2008	10.460	102.200	117.070	30.039	35.930
	(15.353)	(47.997)	(39.598)	(41.915)	(53.385)
Constant	− 12.181	−129.895	−451.113	−511.274	−567.143
	(19.915)	(54.597)	(48.248)	(38.782)	(50.622)
R^1	0.02	0.17	0.41	0.51	0.47

Table 3.7: Quantile Regression coefficients for selected quantiles. Standard errors in parentheses, generated using 20,000 bootstrap replications. Part 2 of 2.

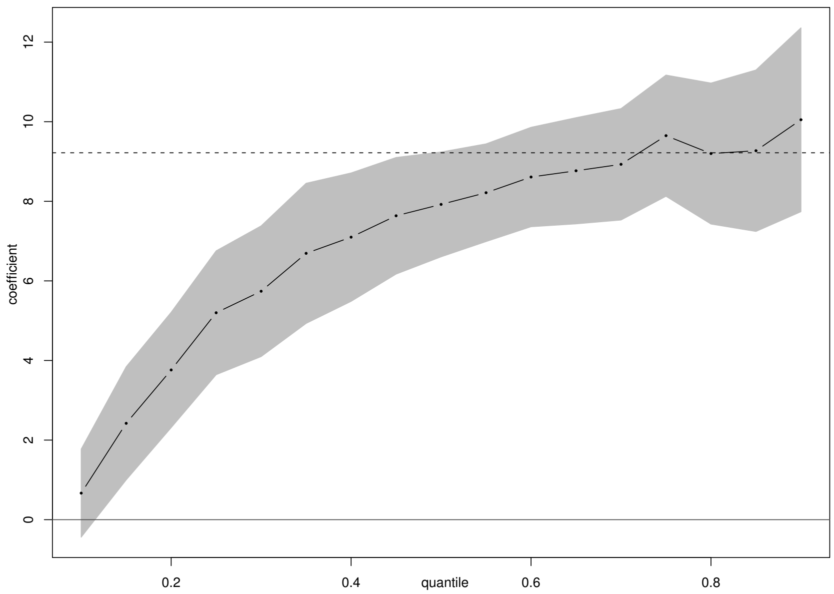


Figure 3.7: Quantile Regression Coefficients - Buyer Length.

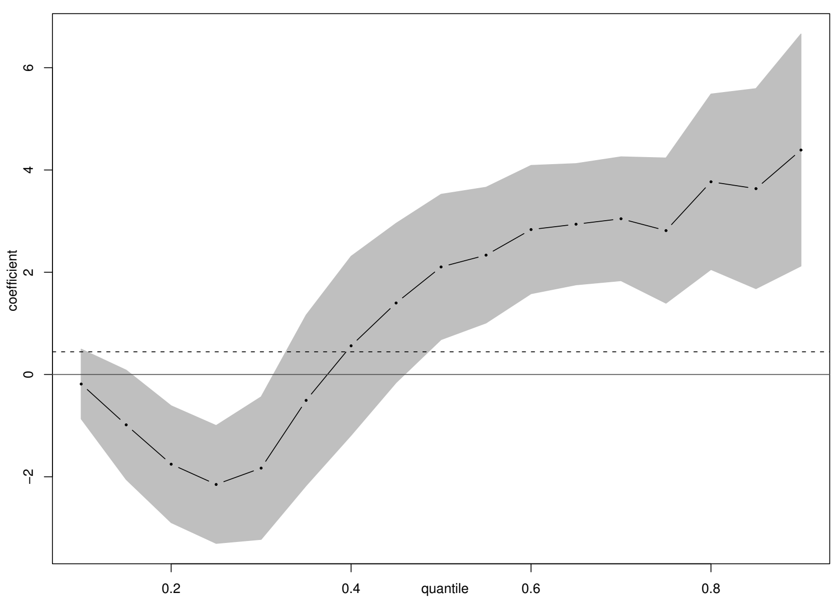


Figure 3.8: Quantile Regression Coefficients - Seller Length.

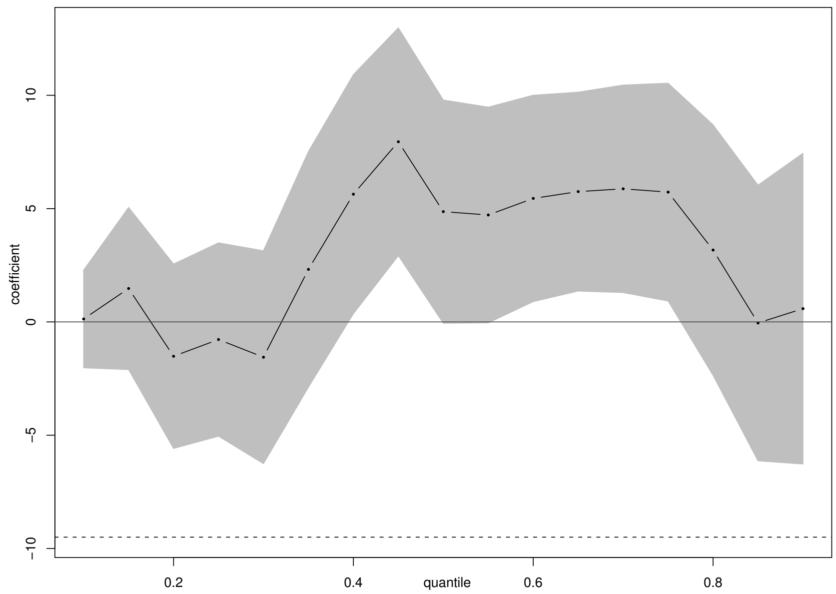


Figure 3.9: Quantile Regression Coefficients - Buyer Power.

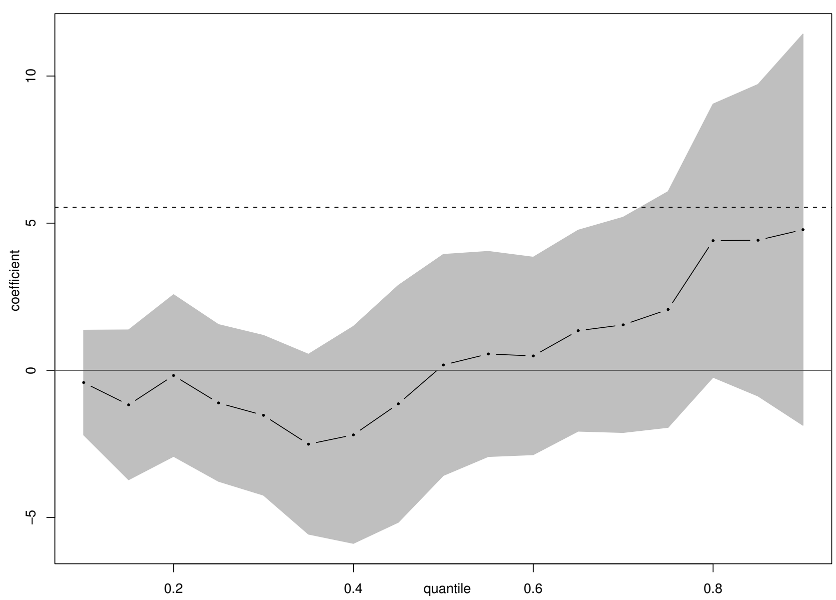


Figure 3.10: Quantile Regression Coefficients - Seller Power.

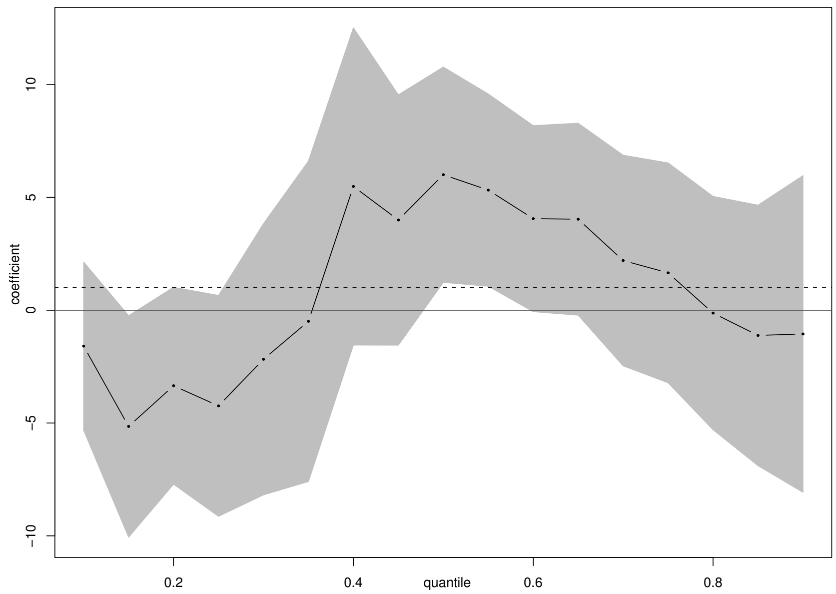


Figure 3.11: Quantile Regression Coefficients - Buyer DAS Revenue.

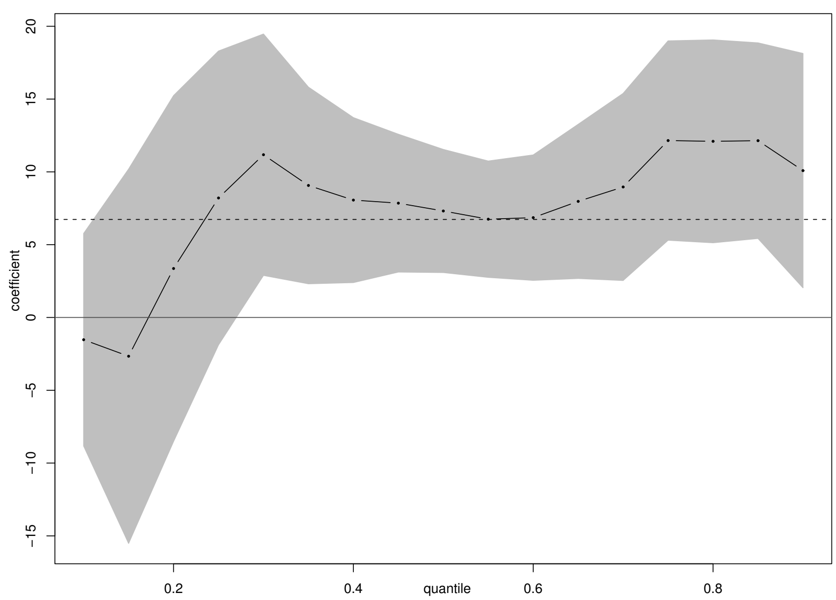


Figure 3.12: Quantile Regression Coefficients - Seller DAS Revenue.

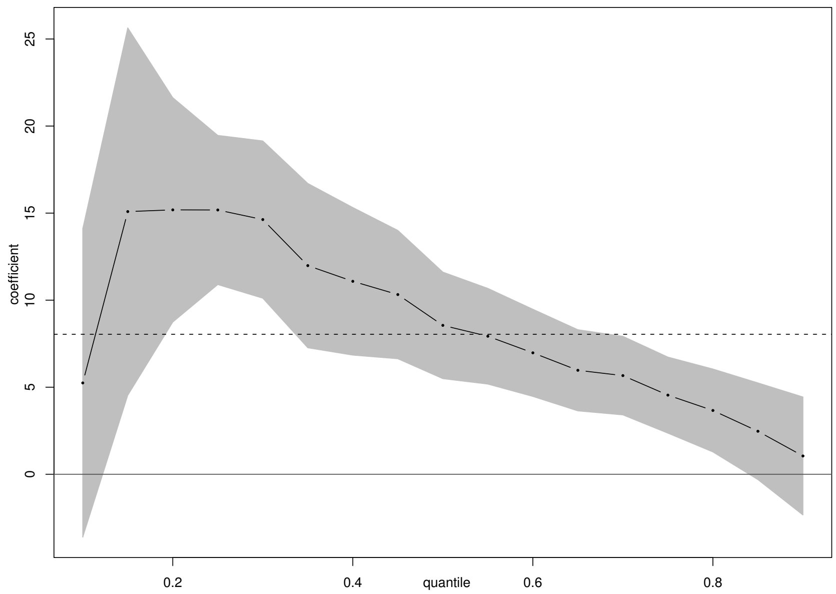


Figure 3.13: Quantile Regression Coefficients - Seller Alternative Revenue.

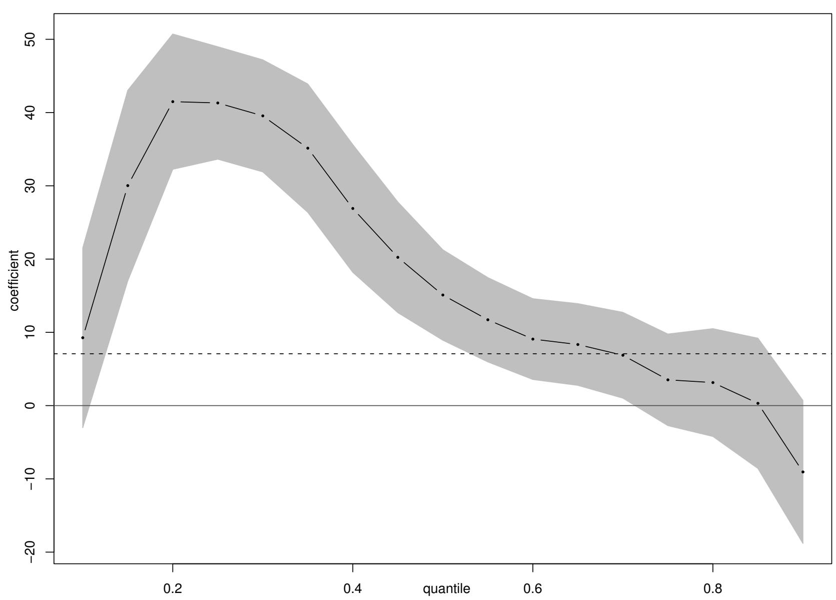


Figure 3.14: Quantile Regression Coefficients - Seller Permits.

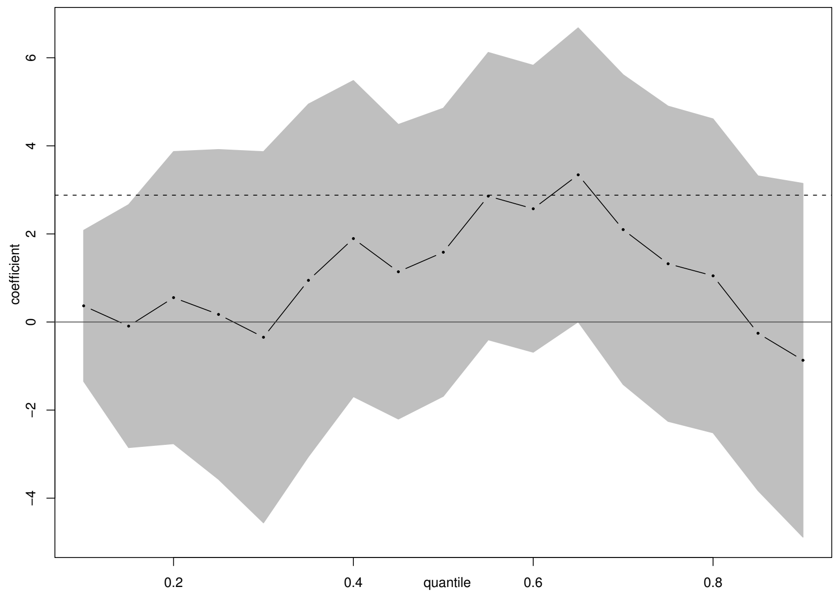


Figure 3.15: Quantile Regression Coefficients - Buyer Alternative Revenue.

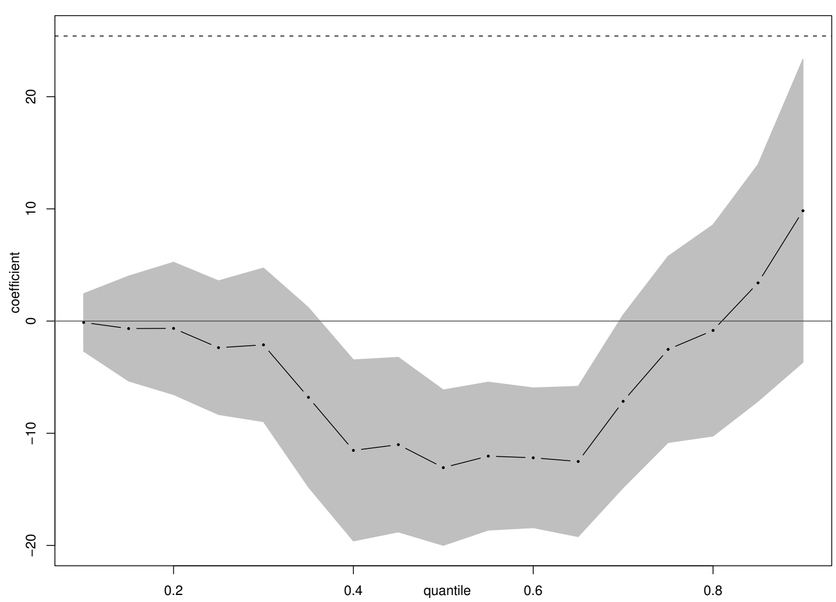


Figure 3.16: Quantile Regression Coefficients - Buyer Permits.

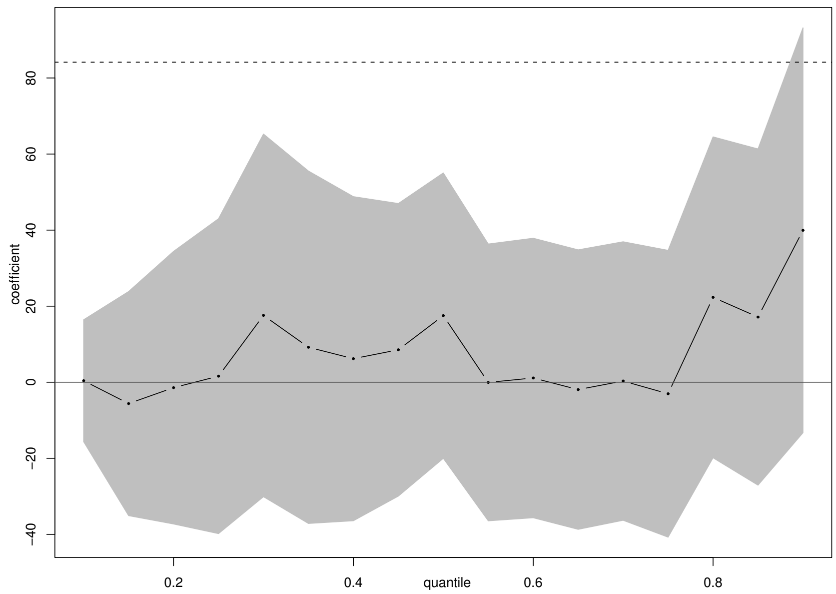


Figure 3.17: Quantile Regression Coefficients - Buyer Differential DAS.

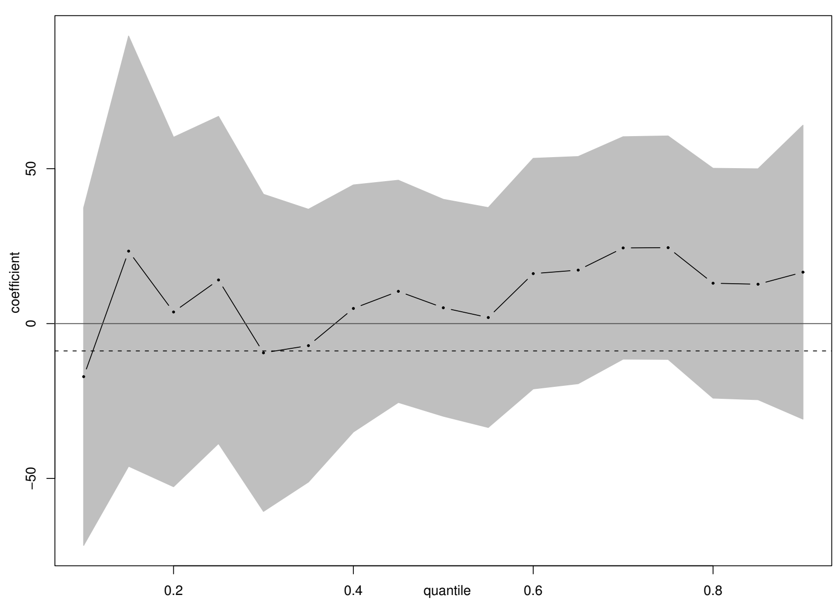


Figure 3.18: Quantile Regression Coefficients - Seller Differential DAS.

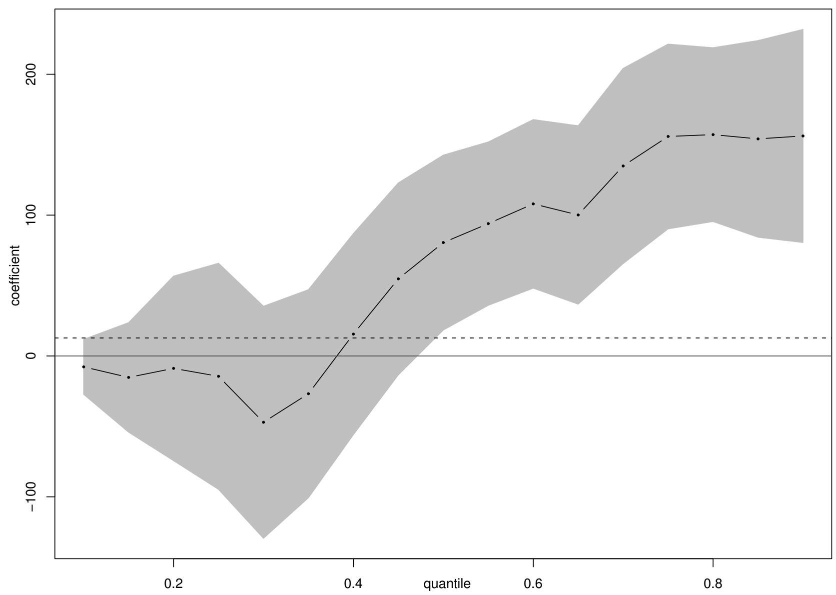


Figure 3.19: Quantile Regression Coefficients -Framework 42.

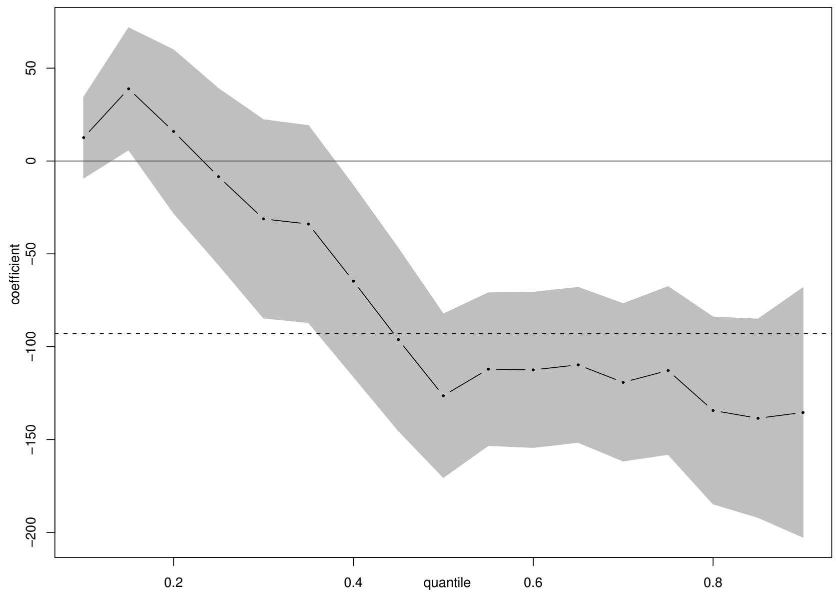


Figure 3.20: Quantile Regression Coefficients - Buyer F42xDifferential DAS.

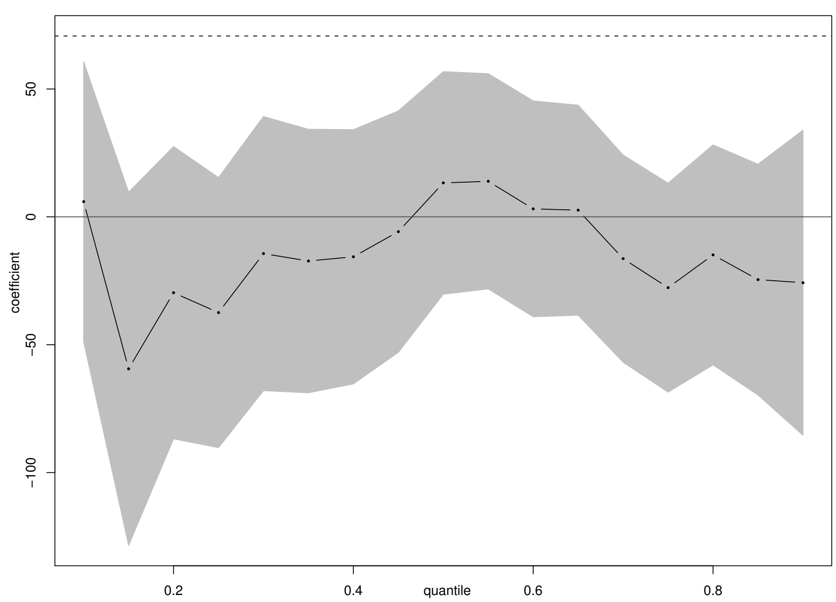


Figure 3.21: Quantile Regression Coefficients - Seller F42xDifferential DAS.

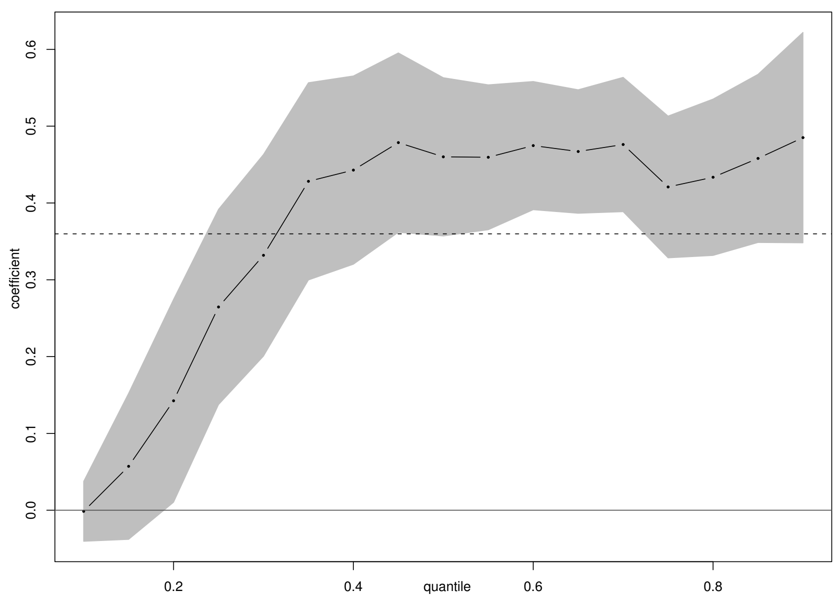
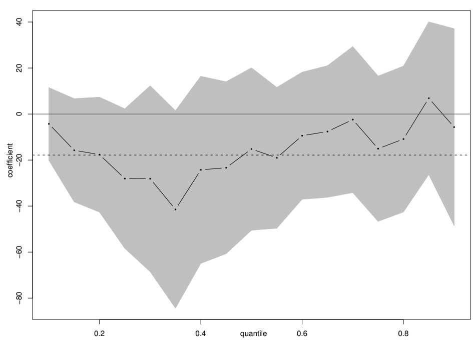
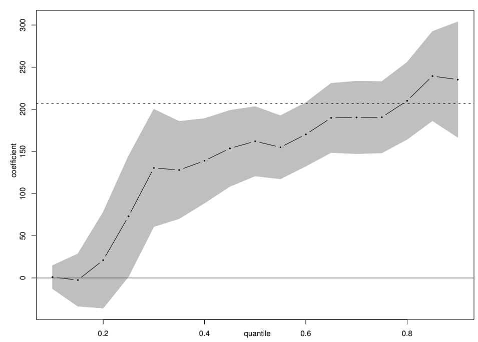


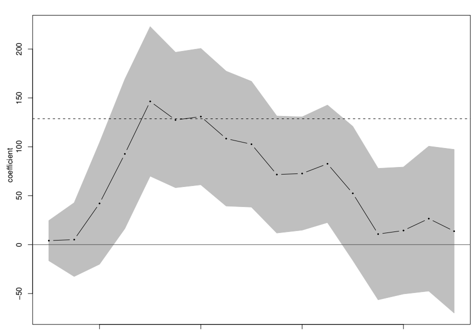
Figure 3.22: Quantile Regression Coefficients - Time Remaining in Fishing Year.



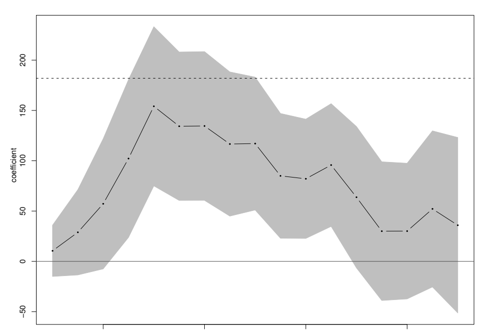
(a) D2005



(b) D2006



(c) D2007



(d) D2008

Figure 3.23: Dummy Variables for 2005-2008 Fishing Years.

	Differential_Seller=1	Differential_Seller=0
Differential_Buyer=1	-60.3	-22.87
	(-1.40)	(-0.49)
Differential_Buyer=0	-51.87	-14.43
	(-1.04)	(-0.30)

(a) 25^{th} Quantile

	Differential_Seller=1	Differential_Seller=0
Differential_Buyer=1	-32.64	-45.91
	(-0.88)	(-1.26)
Differential_Buyer=0	93.78	80.51
	(2.21)	(2.15)

(b) 50^{th} Quantile

	Differential_Seller=1	Differential_Seller=0
Differential_Buyer=1	15.33	43.02
	(0.38)	(1.06)
Differential_Buyer=0	128.15	155.84
	(2.87)	(3.91)

(c) 75^{th} Quantile

	Differential_Seller=1	Differential_Seller=0
Differential_Buyer=1	-4.96	20.79
	(-0.09)	(0.37)
Differential_Buyer=0	130.46	156.21
	(2.31)	(3.39)

(d) 90^{th} Quantile

Table 3.8: Partial Effect of Framework 42's Differential Days-at-Sea, for combinations of Differential Days-at-Sea users (t-statistics in parentheses).

	0.1	0.25	0.5	0.75	0.9
Length	0.48	3.05	10.03	12.46	14.44
	(1.12)	(3.85)	(13.05)	(19.31)	(14.14)
Power	-0.29	-1.89	5.05	7.80	5.36
	(-0.22)	(-0.74)	(1.89)	(3.22)	(1.68)
DAS	-3.12	3.97	13.32	13.81	9.04
	(-0.62)	(0.66)	(3.57)	(2.69)	(1.40)
Alternative	5.61	15.35	10.14	5.87	0.18
	(1.08)	(4.33)	(3.73)	(2.35)	(0.06)
Differential	-16.73	15.68	22.61	21.48	56.54
	(0.53)	(0.44)	(0.86)	(0.78)	(1.46)
Experience	-1.31	-5.71	-3.31	-2.64	-2.75
	(-1.08)	(-2.43)	(-1.50)	(-0.98)	(-0.91)
Trawl	-5.35	-42.50	-84.68	-51.79	4.99
	(-0.59)	(-2.60)	(-5.45)	(-3.64)	(0.24)
Permits	9.14	38.94	2.03	0.99	0.78
	(1.22)	(6.73)	(0.38)	(0.18)	(0.08)
F42xDifferential	18.54	45.87	-113.15	-140.50	-161.17
	(0.60)	(-1.20)	(-3.41)	(-4.60)	(-3.46)

Table 3.9: Sums of buyer and seller demographic coefficients with $t-$ ratios for H_0: $b^b + b^s = 0$ in parentheses.

Chapter 4

Economic Tradeoffs in the Gulf of Maine Ecosystem: Herring and Watching

4.1 Introduction

In contrast to traditional fisheries management which has historically focused on the extractive fishing industry, Ecosystem Based Fisheries Management (EBFM) prioritizes overall ecosystem health and attempts to consider all users of ecosystem resources in the decision-making calculus (Link, 2002; Pikitch et al., 2004). This research examines the effect of a recent change in fisheries policy, a seasonal ban on trawling for herring in the inshore Gulf of Maine, on the commercial whale-watching industry. Drawing upon Crocker and Tschirhart's (1992) ecosystem-externality model and Sanchirico and Wilen's (1999) spatially-explicit fishery model, this research examines the theory of localized depletion as it affects the commercial whale-watching industry.

This theory claims that intense trawling for herring causes temporary reductions the their abundance, depressing the abundances of whales and other highly mobile predators of herring (Schreiber, 2005; Moser, 2007; Herring Alliance, 2008). If true, this is likely to lead to increased search times by whale-watching vessels. Extensive search by whale-watching vessels is costly for firms and is also likely to reduce consumer welfare. Time spent viewing whales is a "good" while time spent searching is likely to be a "bad." While an extensive consumer valuation literature exists for whales (Hoagland and Meeks, 2000; Loomis et al., 2000; Shaikh and Larson, 2003), this research examines the value of leaving a stock of fish in the ecosystem.

This research is the inverse of Flaaten and Stollery's (1996) model, which examined the costs imposed by predatory whales on a fishery. It also related to a large bioeconomic literature which seeks to understand economically efficient harvest levels in a predator-prey system (Hannesson, 1983; Ströbele and Wacker, 1995; Brown et al., 2005; Hoekstra and van den Bergh, 2005). In this ecosystem, the spatial location of predators and prey is of vital importance: whale-watching firms depend on a high abundance of whales that are close to shore.

4.2 Background

4.2.1 The Whale-watching Industry

Whale-watching is a \$30M industry (revenue/year) in New England with approximately one million commercial passengers and is growing at roughly 10% per year (Hoyt, 2001). In addition, consumer surplus from commercial trips has been estimated at roughly \$29 per trip in the Stellwagen Bank National Marine Sanctuary (Hoagland and Meeks, 2000). However, no research exists that examines the cost (or value) of the search process from a consumer point of view. While consumers may view search as a "good", a "bad", or both, firms undoubtedly view increases in search time as an additional cost. The whale-watching season runs from late spring through early fall, overlapping with a large portion of the herring fishing season.

Fin, humpback, and minke whales are most commonly sighted on whale-watching trips. These animals are thought to have fairly strong site fidelity at both large and small scales; they consistently use the Gulf of Maine to feed on herring, sand lance, and other small fish (Overholtz et al., 2000; Read and Brownstein, 2003; Robbins, 2007). Despite this site fidelity, whales are known to be responsive to changes in prey availability (Weinrich et al., 1997, 2005).

The commercial whale-watching vessels are based in many ports in the Gulf of Maine, ranging from Provincetown, Massachusetts to Bar Harbor, Maine (Figure 4.1). Fixed costs (physical capital, insurance, wharfage, and crew labor) are high relative to variable costs (fuel). Higher fuel costs due to increased search time are likely to be the largest short-run impact of localized depletion. Most whale-watching companies have a home searching area that is limited by the speed of their vessel and their proximity to oceanographic features with which whales are commonly associated. A whale-watching trip is advertised to last between 3 to 4 hours; however, a large portion that time is spent in search and travel. Vessels depart from port and travel towards a whale-watching area. While whales can be seen at any time, they are typically found close to the large oceanographic features, where prey aggregate in large numbers. Because the whale-watching industry is limited to a relatively small part of the Gulf of Maine, decreased abundance of whales in this area could impact this industry even if whale populations remain stable across the entire Gulf of Maine.

In this chapter, the determinants of search time of five of the seven whale-watching companies located between Gloucester, MA and Rye, NH are examined. The whale-watching companies analyzed in this study overlap spatially with the southernmost portion of the herring fishing grounds. These vessels typically travel to the two large oceanographic features located in this area: the shallow, sandy-bottomed Stellwagen Bank and the somewhat deeper, rocky-bottomed Jeffrey's Ledge. In this region, herring fishing occurs fairly often on Jeffrey's Ledge and very infrequently on Stellwagen Bank.

4.2.2 The Herring Fishery

In the Gulf of Maine, herring are prey for many species of marine life (Overholtz et al., 2000; Read and Brownstein, 2003; Chase, 2002) and are also target of a $9-20M fishery (NMFS, pers. comm.) The fishery is primarily pursued with purse seine and mid-water trawl gear. The herring fishery is a limited-access fishery that is divided into four zones and managed with a zonal Total Allowable Catch (TAC). The aggregate TAC for herring are based on a set of reference points that are designed to ensure that fishing occurs at Optimal Yield (OY), which is set at Maximum Sustainable Yield (MSY) less an allowance for uncertainty and socioeconomic considerations. The herring stock is currently classified as underutilized; the industry does not catch the entire aggregate TAC. However, this classification is based on traditional single-species management, which does not consider use by non-human consumers such as whales or predatory fish, or the impacts of herring fishing on whale-watching. Fishing in the inshore Gulf of Maine (Zone 1A) is most active during the summer months, spatially and temporally overlapping the whale-watching industry (Figure 4.2).

In addition to a zonal TAC, the inshore fishery is subject to seasonal closures to protect spawning herring. This closure is designed to ensure reproductive success of spawning fish. When spawning, herring aggregate into large numbers in the shallow, nearshore areas. In the southern Gulf of Maine, this closure occurs from mid-September to mid-October.

4.3 Modeling Approach

Localized depletion is thought to be a fundamentally short-term and spatially dependent; the effects of this phenomenonon are modeled as an ecosystem externality in the spirit of Crocker and Tschirhart (1992). In this model, there is a (known) relationship between predator and prey in the ecosystem. The actions of one group of users (fishers) will affect the welfare of the other group of users (whale-watchers) through the ecosystem processes that govern the two species. The localized depletion hypothesis requires two processes to occur: a biological depletion effect on herring and a migration response by whales. As Crocker and Tschirhart (1992) note, the exact relationships between the predator and prey are often unknown; however, the impact on human activities is of primary concern, not the exact workings of the biological system.

Furthermore, the localized depletion hypothesis is concerned with the fine-scale spatial characteristics of the system. Because whale-watching vessels are confined to the nearshore area by speed and time constraints, whales located in the offshore areas cannot be utilized by whale-watching firms. Sanchirico and Wilen's (1999) spatial bioeconomic model provides a useful framework in which to understand the spatial considerations of the herring-, whale-, and whale-watching interactions.

The search behavior of whale-watching vessels is assumed to be simple. Whale-watching vessels leave port in search of whales, traveling at high speeds towards the areas where whales are likely to be seen. Vessels stop traveling when a whale is sighted and view the whale(s) for an extended period of time. When this occurs, a trip is considered to be completed and successful. Not all whale-watching trips are successful; after an extended period of unsuccessful search, whale-watching vessels may return to port without sighting a whale.

We assume that whale-watching firms minimize expected search time conditional on the availability of whales in the searchable area of the ecosystem.

$$\begin{aligned} \min \ & SearchTime_{it}(Whales_{Nt}) \\ \text{s.t.} & Whales_{Nt} = f(Herring_{Nt}) \end{aligned} \tag{4.1}$$

Subscripts i, t, and N refer to individuals, time periods, and nearshore whale-watching zones respectively. While the actual search time is observable; the choice variables, such as search direction, speed, or labor devoted to searching, are unobservable. However, the $SearchTime$ function is decreasing in whale availability; the existence of large numbers of whales in the nearshore area leads to low search times for whale-watching vessels. The localized depletion hypothesis maintains that the availability of whales in the nearshore area is an increasing function of herring in the search area. Whales may move from areas of low prey availability to areas of high prey availability.

The actions of the fishing industry are not modeled in this research; however, it is useful to consider the industry's objectives. We assume that vessels in this industry are profit-maximizing entities, choosing both when and where to fish based on profitability. The assumptions that fishers prefer times and areas that have high expected revenues and low expected costs are at the common to the recent economic efforts to model the spatial behavior of fishing vessels (Bockstael and Opaluch, 1983; Holland and Sutinen, 2000; Hicks and Schnier, 2008). The catch data generally supports these ideas; catch in the inshore zone is high relative to catch in the offshore regions [1]. All things being equal, fishing in the inshore area is preferable due to both lower costs of access and faster round trip steaming times. Indirectly, location and amounts of fishing can provide some insight into the availability of herring: fishing activity may be an indicator of high herring availability. When unregulated, fishing vessels prefer to fish in the inshore area and will not take into account the depletive effects of their fishing on the whale-watching industry. This is the (potential) source of the ecosystem externality; and the quantifying this effect is necessary to successfully implement Ecosystem Based Fisheries Management.

4.4 Data and Econometric Model

In this analysis, three sources of data are used: five whale-watching organizations in the southern part of the Gulf of Maine provided trip-level data, fishing effort and catch data were extracted from the NMFS Vessel Monitoring System (VMS) and Vessel Trip Report (VTR) datasets, and oceanographic data were obtained from the Gulf of Maine Oceanographic Observation System (GoMOOS).

The dependent variable in this study is amount of time, in minutes, that a whale-watching vessel spends searching for a whale (*Search Time*). It is constructed from whale-watching trip reports that are maintained by whale-watching companies and their affiliated research groups[2]. These data span the 2002-2006 whale-watching seasons for Gloucester

[1] `http://www.nefmc.org/herring/safe_reports/herringsafe.html`

[2] While whale-watching companies typically undertake multiple trips per day, only the first trip of the day is used in this analysis. The reliability of the dependent variable for subsequent trips is poor.

based vessels and the 2003-2006 seasons for New Hampshire and northern Massachusetts based vessels. During this period, none of the vessels made capital improvements that would substantially affect their speed or ability to find whales.

The localized depletion theory claims that fishing will be detrimental to subsequent whale-watching outcomes, but is vague about the appropriate spatial and temporal scales. A two-step process is used to categorize fishing that occurs in the nearshore whale-watching areas. First, the whale-watching areas are defined by using depth contours of the oceanographic features in the region: Stellwagen Bank and Jeffrey's Ledge. The edge that is farthest from the coast is assumed to be the boundary beyond which whale-watching vessels do not search. Areas of the ocean closer to whale-watching ports are defined as the whale-watching areas.

The second step in this process is to isolate fishing catch and effort that is located within these the areas that whale-watching vessels use. The variables *Catch* and *Effort* are constructed using the Vessel Trip Report (VTR) and Vessel Monitoring System (VMS) datasets. The VTR dataset is composed of self-reported logbooks that include trip dates, locations, and catch amounts. The VTR data are used directly to construct a measure of herring catch. The reported locations of herring catch are plotted and observations that lie within the two defined whale-watching areas are extracted. The total catch is then aggregated at the daily level to form one version of the *Catch* variable [3].

An alternate measure of fishing activity is constructed using the Vessel Monitoring System (VMS). This system reports detailed positions of fishing vessels at frequent intervals (30 minutes to 1 hour) and is required for all major vessels in the herring fishery. Palmer and Wigley (2007) developed an algorithm to use the VMS system to locate fishing effort at a fine spatial-scale;this technique relies on correlating vessel speeds with activities. Very slow speeds correspond to fishing and related activities while high speeds correspond to traveling. The points corresponding to fishing activity are plotted and observations lying

[3] 100 metric tons of herring corresponds to a large catch of fish by a single vessel.

within the two whale-watching areas are extracted. The number of the unique vessels is used to construct an alternative measure of the *Effort* variable. While VMS can be used for very fine scale location and time observations of fishing effort, the actual catch is not recorded along with the locations.

The variables *Depletion_Catch* and *Depletion_Effort* are constructed using a 7-day moving sum of the *Catch* and *Effort* respectively [4]. In this dataset, purse seine fishing makes up only a small fraction of the overall fishing activity; no distinction is made between the two in this analysis. In addition to the *Catch*, *Effort*, and the *Depletion* variables, a final indicator of herring availability is used. Because the inshore Gulf of Maine herring fishery is subject to a seasonal spawning closure, a dummy variable, *Spawning*, is included in the model to account for high abundances of herring during these periods.

Weather and oceanographic conditions are likely to affect the ability of vessels to find whales. In order to control for this, two oceanographic measures, *Visibility* and *Wind Speed*, were extracted from GoMOOS. Poor visibility may be caused by haze, rain or fog and directly affects the ability of a whale-watching boat to find whales. Low visibility is expected to increase search time. Additionally, high winds can cause whitecaps to form on the surface of the ocean, introducing visual clutter and decreasing the ability of vessels to find whales. Therefore, high wind speeds might be expected to increase search times. Unfortunately, data that would control directly for changes in herring or whale abundances is not available at the fine scale and precision necessary for this analysis. Estimates are unavailable for herring stock levels for 2006 (Transboundary Resource Assessment Committee, 2006). Similarly, stock assessments for whales are not performed yearly and estimates are fairly imprecise (Waring *et al.*, 1997). Figure 4.3 maps the locations of home ports of whale-watching vessels studied, the locations of GoMOOS data buoys, and a representation of the Stellwagen Bank and Jeffrey's Ledge whale-watching areas. Table 4.1 contains summary statistics for the variables used.

[4] The bandwidth used to construct the moving sum is varied in order to verify robustness of the results. Results are robust to moderate changes in the construction of this variable.

The two fixed-effects model estimated are:

$$
\begin{aligned}
SearchTime_{it} =& \beta_1 Depletion\_Catch_{it} + \beta_2 Catch_{it} + \beta_3 WindSpeed_{it} \\
& + \beta_4 Visibility_{it} + \beta_5 Spawning_{it} + \alpha Z u_i + e_{it},
\end{aligned} \tag{4.2}
$$

and

$$
\begin{aligned}
SearchTime_{it} =& \beta_1 Depletion\_Effort_{it} + \beta_2 Effort_{it} + \beta_3 WindSpeed_{it} \\
& + \beta_4 Visibility_{it} + \beta_5 Spawning_{it} + \alpha Z + u_i + e_{it},
\end{aligned} \tag{4.3}
$$

where i indexes vessels, t indexes days, Z is a vector of yearly dummy variables, and u_i and e_{it} are individual specific and idiosyncratic errors respectively. Standard errors are calculated that are robust to arbitrary heteroskedasticity and first-order autocorrelation (Schaffer, 2007).

Although whale-watching firms guarantee that at least one whale will be sighted, approximately 7.2% of trips in this dataset did not successfully find a whale. When estimating the fixed-effects model, the trips that did not encounter whales were dropped from estimation. This potentially creates a sample-selection problem, the coefficients estimated in equation (4.2) and (4.3) are the effects of the independent variables on search time, conditional on a trip being successful. However, the same factors that affect search time may also cause a trip to be unsuccessful. The linear model in equation (4.2) and (4.3) cannot account for this sample censoring effect. Therefore, two right-censored Tobit model is estimated:

$$
\begin{aligned}
SearchTime^*_{it} =& \gamma_1 Depletion\_Catch_{it} + \gamma_2 Catch_{it} + \gamma_3 WindSpeed_{it} \\
& + \gamma_4 Visibility_{it} + \gamma_5 Spawning_{it} + \alpha Z + u_i + e_{it}, \qquad (4.4) \\
SearchTime_{it} =& \min\{SearchTime^*_{it}, \overline{SearchTime}\},
\end{aligned}
$$

and

$$\begin{aligned}SearchTime_{it}^{*} =& \gamma_1 Depletion\_Effort_{it} + \gamma_2 Effort_{it} + \gamma_3 WindSpeed_{it}\\ &+ \gamma_4 Visibility_{it} + \gamma_5 Spawning_{it} + \alpha Z + u_i + e_{it}, \qquad (4.5)\\ SearchTime_{it} =& \min\{SearchTime_{it}^{*}, \overline{SearchTime}\},\end{aligned}$$

where $\overline{SearchTime}$ is the upper limit of the search time and is set at the highest observed search time. While the coefficients estimated with a fixed-effects Tobit model are known to be biased, the magnitude of this bias is small and decreases quickly as T increases (Greene, 2004).

For both sets of models, a positive coefficient for the *Depletion* variable is consistent with the model of localized depletion. The localized depletion model does not generate any hypotheses about *Fishing*. However, economic intuition suggests it may be a proxy for high abundances of herring since profit maximizing fishermen are likely to fish only in areas of high abundances of fish. A negative coefficient for the *Spawning* dummy variable would also be consistent with "localized aggregation" and provide indirect supporting evidence that whales are sensitive to prey abundances.

4.5 Results and Discussion

The search times of whale watching firms are highly variable and there are only a small number of explanatory variables in this analysis. Therefore, it is not surprising that the overall fit of the estimated models is fairly low, the pseudo-R^2 is approximately 0.13 for the Tobit model and the R^2 is 0.085 for the linear model (Table 2). The two R^2 statistics are not directly comparable; the datasets used to estimate the two classes of models are slightly different. In general, the signs of the estimated coefficients are consistent across the two general models (linear fixed-effects and Tobit). The coefficients in the Tobit model are larger in magnitude, and in some cases they are much larger. Because the fixed-effects model ignores trips in which no whales are sighted, the interpretation of these results is limited to successful trips. To be precise, they are the effects that an independent variable has on the search time, *conditional* on that trip finding a whale to view. For this reason, discussion of results is focused on the Tobit model; those coefficients can be interpreted as the effect of an independent variable on the search time of all trips.

In general, the results provide moderate support for the theory of localized depletion; this effect is largest in the Tobit models. Using the catch based measure of depletion, an increase of 100 mt of catch will lead to search time increases of approximately 1.6 minutes. Using the effort based measure, a fishing trip is found toincrease search times by approximately 0.6 minutes.

The fishing coefficients ($Catch$ and $Effort$) are negative; however, they are statistically significant in only one of the two Tobit model (and neither of the linear models). This is slightly surprising, although fishing may simply be a poor proxy for local herring abundances in the nearshore Gulf of Maine. The herring fishing fleet consists of relatively few vessels and it is possible that the "good" fishing locations simply do not get visited. In contrast, the spawning coefficient is large in magnitude, negative, and highly significant. During the spawning period in which the herring fishery is closed, whale-watching search times decrease by approximately 19 minutes, or nearly 25%. It is important to note that the spawning closure should not be interpreted as the effect of zero fishing effort. During this time, the availability of herring is likely to be much higher than normal. While the exact increase in the nearshore herring biomass are not known during this time, the increase in availability of prey fish seems to be beneficial for the whale-watching industry. Wind speeds are not informative about search time; however, low visibility is,unsurprisingly, bad for whale-watchers.

The differences between the Tobit and fixed effects models are most striking for two of the explanatory variables: Visibility, which is over 3 times larger in the Tobit specification and the 2004 dummy variable, which is 8 times larger. The statistical mechanism by which poor visibility works is straightforward: more unsuccessful trips occur during periods of poor visibility. These trips are not modeled in the fixed-effects estimation, but are included in the Tobit model. Poor visibility probably impacts whale-watching vessels in two ways: increasing search times and increasing tor probability of an unsuccessful trip. The large difference in the 2004 coefficient is due to the the same statistical reasons; 16% of all trips failed to see whales in 2004, compared to 5% of trips in all other years. However, it is difficult to explain the exact reason why 2004 was a comparatively unsuccessful season.

The yearly dummy variables are included to control for large scale oceanographic processes and are highly significant and similar in magnitude across specifications. The 2002 dummy variable was dropped from the estimation; the coefficients may be interpreted as an average change in search time relative to search time in 2002. Between 2002-2005, the spawning stock biomass of herring has been roughly constant[5], fluctuating between 1.04-1.12 million metric tons (Transboundary Resource Assessment Committee, 2006). While historical population growth rates for humpback whales were estimated at 6.5% (Barlow and Clapham, 1997), estimates of whale populations are subject to large amounts of uncertainty. Recent stock assessments for the two most commonly sighted species show fluctuations within the range of uncertainty (Waring *et al.*, 1997).

The estimation results from this model can be used to evaluate the effect of the recently enacted trawling-ban. After lobbying by whale-watching, recreational, and hook-and-line fishing interests, NEFMC closed the inshore region (Zone 1A) to trawling during the summer months (June-September). These groups claimed that trawling leads to localized depletion of herring, reducing the abundance of whales and larger fish. The summer Zone 1A fishery remains open to purse seine gear. Fishing effort and catch were aggregated into a single localized depletion variable due to the extremely low occurrence of purse seining in the dataset. Of the 2,480 observed whale-watching trips, 670 trips experienced increased

[5]2006 stock assessments are not yet available

search times due to localized depletion. Elimination of fishing would reduce search of those 670 trips by an average of 6 minutes. Whale-watching vessels use between 60-100 gallons of fuel per hour (McInnis, pers. comm.), which translates to an additional $13 in costs per-affected-trip [6].

This inshore fishery closure is costly for fishermen. If they wish to continue fishing for herring, they may convert from trawl to purse seine gear or they may fish exclusively in the offshore regions during the closure. Conversion is believed to cost approximately $300,000 while fishing in offshore zones is increase variable costs (primarily fuel) by $3,000-6,000 per trip (U.S. National Archives and Records Administration, 2007). The effects of this closure may also propagate through the regional economy. Lobster fishermen in Maine use herring as bait in their traps; it is unclear whether a partial closure will disrupt that market (U.S. National Archives and Records Administration, 2007).

It is important to note the limitations of this data and therefore the limitations of this study. Fine-scale spatial data on the availabilities of whales and their prey is unavailable. Additional, it is not possible to model the information sets of the whale-watching vessels. Anecdotally, whale-watching captains share information, particularly during times of low whale availability. This mechanism is likely to mitigate the effect of localized depletion. This is a specific example of “averting behavior”: the ability of rational optimizing agents to change their actions to avoid economic losses. Because this is not modeled, the effects of reduced prey availability on the search times of whale-watching firms are underestimated in the statistical model. In addition to sharing information, whale-watching firms may alter their search locations and patters or simply cancel trips when searching is expected to be difficult. Only a sub-sample of the whale-watching industry in the Gulf of Maine was examined in this research. Other firms may be affected more or less by fishing activity.

In addition, the assumption that firms are minimizing search times is likely to be slightly

[6] Mean diesel price from April 1, 2002 to October 30, 2006, as calculated from the US Department of Energy’s Energy Information Administration’s website. `http://tonto.eia.doe.gov/dnav/pet/pet_pri_spt_s1_d.htm`

inaccurate; while search time minimization would be consistent with short-run profit maximization, whale-watching firms are maximizing long-run profits. This would include accounting for the ability of current whale-watching outcomes to affect future demand through updating of consumer expectations. Whale-watching trips are likely to be an hedonic good in which demand is a function of prices and attributes (Rosen, 1974). These attributes probably include not just search time, but perhaps the number of whales that are seen on a trip. Firms may have some ability to substitute between these attributes; it is reasonable to believe that firms will favor other quality attributes during times of high whale-availability, but favor low search times during periods of poor availability. If true, the statistical model again underestimates the localized depletion effect.

4.6 Conclusions and Future Research

Resource economists have a long history of modeling predator-prey interactions in bioeconomic models (Flaaten and Stollery, 1996; Hannesson, 1983; Brown et al., 2005; Ragozin and Brown, 1985). Recently, non-extractive ("ecosystem") uses of resources have been incorporated in these models (Hoekstra and van den Bergh, 2005; Boncoeur et al., 2002). This research examines the short-run interactions between prey, predators, and users of both of those resources. In the southern Gulf of Maine, herring fishermen are direct and depletive users of herring while whale-watchers are indirect and non-depletive users of the resource.

This study examines a small portion of the localized depletion theory: search times of whale-watching vessels. There are certainly other ways that fishing could affect whale-watching, including reducing the number of whales sighted by vessels or altering the activities of whales seen. In the long-run, this may affect the consumer's demand for whale-watching trips. This research finds moderate evidence that the herring fishing has an impact on whale-watching search times through a localized depletion mechanism. However, at current stock levels of both herring and whales, the estimated economic impacts are small.

The statistical model finds strong evidence for a "localized aggregation" effect; when herring are spawning, search times drastically decrease. During the spawning period, much of the herring biomass is concentrated in the nearshore area. Relative to periods in which herring are not spawning, abundances are extremely high during this period, and the decrease in search times is most likely attributable to the increase in prey that are available to whales.

Recent policy decisions to close the nearshore herring fishery were enacted with the aim of preserving forage levels for predators of herring, such as whales, tunas, and groundfish. This research finds a small effect on whale-watching firms; closure of the nearshore fishery results in slightly shorter search times and small economic gains for whale-watching firms relative to the costs imposed on the fishing industry.

It is important to note that the results in the paper are fundamentally short-term in nature and do not take into account the long-run dynamics of either the biological or economic systems. The impacts of herring fishing at different stock levels are difficult to quantify and may be very different from the effects found in this research. However, because search times decline so dramatically during the time that herring are spawning in the southern Gulf of Maine, it seems reasonable to believe that increases of herring stock levels would be beneficial for the whale-watching industry. Long-run changes to demand for whale-watching trips may also be important. If "quality" declines due to increased search times, this may change the demand for whale-watching, leading to either lower prices, fewer participants, or both. This research has examined only the short-term interactions of herring fishing and whale-watching; the much more difficult long-run analysis of the consumer side must be left to future research.

4.7 Tables and Figures

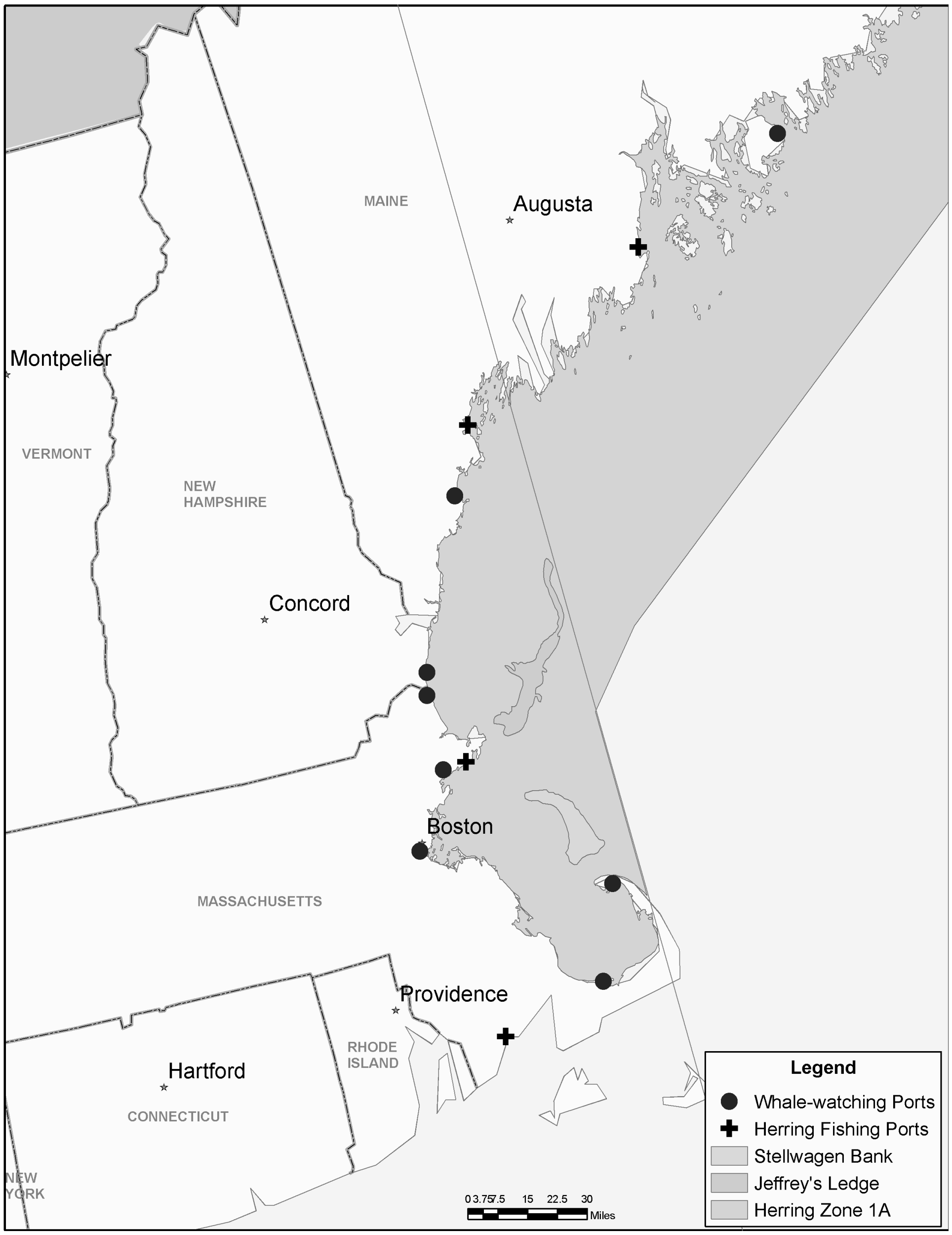


Figure 4.1: Location of whale-watching ports,fishing ports, and oceanographic features in the Gulf of Maine.

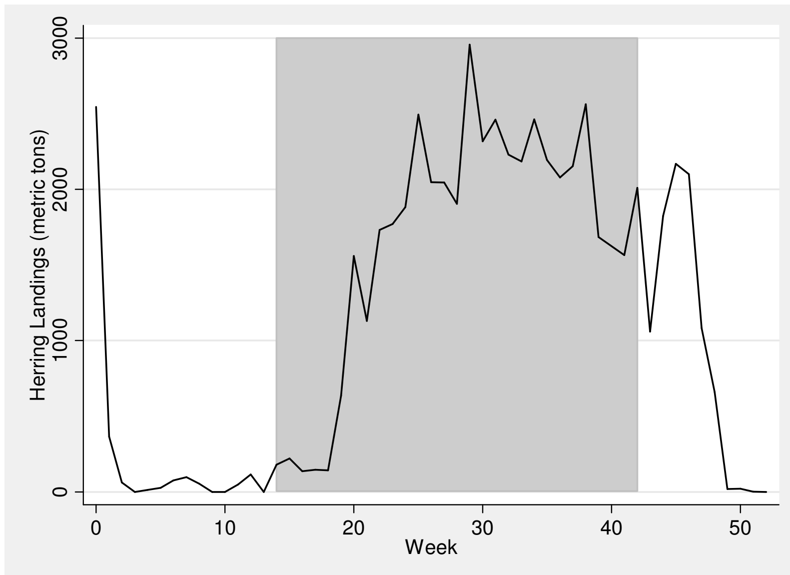


Figure 4.2: Average Weekly landings for inshore Gulf of Maine herring. Shaded portion indicates whale-watching season.

Variable	Units	Mean	Std. Dev.	Min	Max
Dependent Variable, n=2301					
Search Time	Minutes	91.2	37.1	12	379
Censored Observations		7.2%			
Fishing Measures					
Fishing	Trips/Day	0.608	1.61	0	12
	100s of metric tons/Day	.282	1.06	0	11.9
Spawning	=1 if fishery closed due to spawning	9.31%			
Oceanographic Variables					
Wind Speed	Meters/second	3.74	1.88	0	11.2
Visibility	Kilometers	2.62	0.656	0.091	2.96

Table 4.1: Summary Statistics for Search Time, Fishing, and Oceanographic variables.

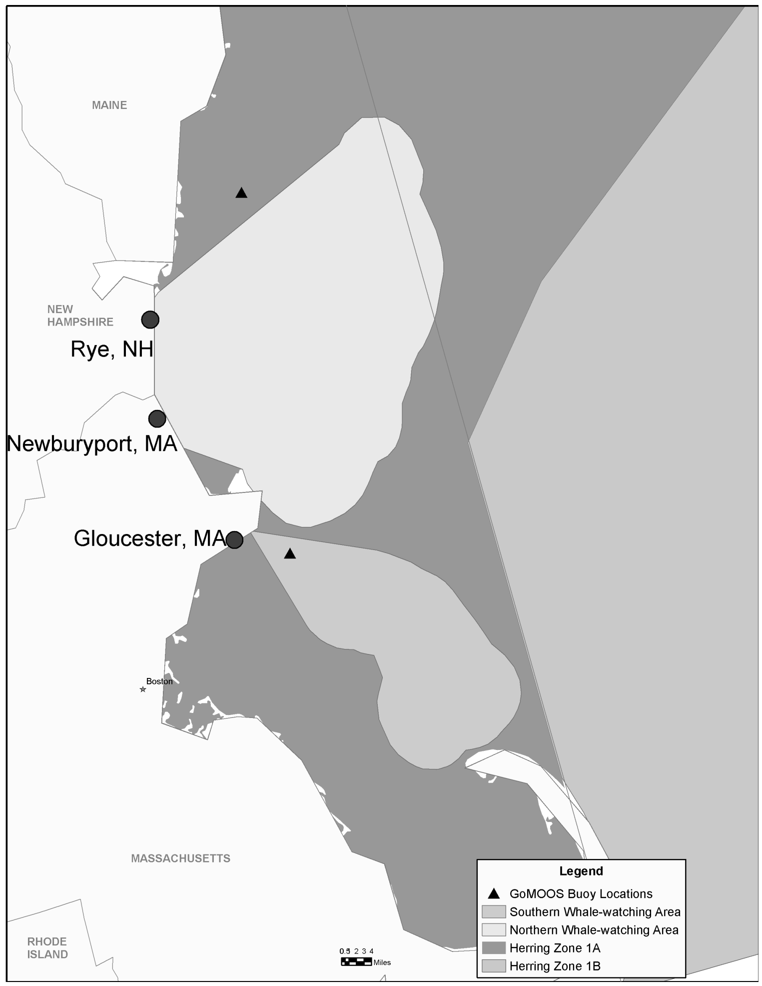


Figure 4.3: Study area including data buoys, whale-watching area, and home ports vessels analyzed.

	Tobit Model		Linear Model	
	(1)	(2)	(3)	(4)
Depletion - Catch	1.640***		.556***	
	(.548)		(.214)	
Depletion - Effort		.626**		.210*
		(.279)		(.107)
Catch	-3.330		.015	
	(2.200)		(.743)	
Effort		-2.792**		.113
		(1.290)		(.518)
Wind Speed	1.696*	1.724*	-.116	-.119
	(.923)	(.924)	(.387)	(.387)
Visibility	-20.555***	-20.398***	-6.598***	-6.637***
	(2.558)	(2.563)	(1.217)	(1.221)
Spawning	-32.937***	-33.549***	-18.948***	-19.121***
	(6.079)	(6.079)	(2.134)	(2.128)
D2003	19.886***	19.248***	8.778***	8.836***
	(5.269)	(5.300)	(2.398)	(2.413)
D2004	41.066***	40.539***	5.630**	5.689**
	(5.345)	(5.371)	(2.402)	(2.410)
D2005	-18.287***	-18.065***	-10.882***	-10.808***
	(5.284)	(5.282)	(2.245)	(2.246)
D2006	-9.006*	-8.218	-10.164***	-10.049***
	(5.468)	(5.466)	(2.237)	(2.239)
N	2480	2480	2301	2301
R^2	0.130	0.130	.084	.083
F			25.288	25.096

Table 4.2: Estimation Results for Linear and Tobit Models.

Chapter 5

Conclusions

The first essay, "The Effects of Policy Rigidity on Optimal Fisheries Management," examines the consequences of policy rigidity for fisheries management. Use of rigid policies is a frequent management strategy in fisheries management. Firstly, rigidity without stochastic growth causes only minor changes in the value of the stock. Negative impacts to the fishery are confined to the adjustment phase, during which the fishery moves towards a steady-state stock level. Secondly, rigidity combined with stochastic growth can produce large effects on both the value of the fishery and the probability of collapse. By examining changes in the value function, the tradeoffs between management speed and scientific accuracy and the threshold at which the returns to scientific information diminish can be determined. Finally, the effect of policy rigidity on the optimal policy is not uniformly "conservative." Rigidity implies precaution (lower harvest levels) when the stock of fish is healthy. However, when anticipated future growth is low (current stocks either very low or very large), management with a rigid policy advocates *higher* harvest levels compared with flexible policy.

In the simulations presented, the biological and economic parameters were chosen so that immediate extinction was non-optimal. When growth is stochastic, extinction is a byproduct of the optimizing manager; higher current period payoffs are preferred to a lower probability of collapse. For any level of uncertainty, management with rigidity implies (weakly) higher probabilities of fishery collapse. This finding may partially explains some historical collapse of fisheries; if low stock growth is difficult to detect, continued high levels of harvest will rapidly deplete a resource. However, rigid policies may have advantages relative to flexible policies; these avoid transactions costs associated with negotiation of policy as well as frequent changes in capital mix or output disruptions, neither of which are considered in this analysis.

The second essay in this dissertation, "Bargaining for Homogeneous Goods: The Days-at-Sea Market, " examines a tradable input permit market. Economists believe that markets can achieve allocative efficiency; however, the *ad-hoc* market that was created for Days-at-Sea in the groundfish fishery suffers from many trading restrictions that may impede efficiency. Using linear and quantile regression, the Harding et al. (2003) model of bargaining is applied to price formation in this market. By examining a homogeneous good, it is possible to econometrically test the bargaining power homogeneity assumption that Harding et al. (2003) use for identification. Using OLS and quantile regression, this analysis rejects the bargaining power homogeneity restrictions for many demographic characteristics. The major trading restriction is related to fishing power (length); this restriction has endowed certain parties (large sellers) with bargaining power that enables them to appropriate a larger share of the gains from trade. While this restriction may have desirable conservation outcomes (limited harvests by the fishing fleet), it appears to have created market power in certain market segments.

The final essay in this dissertation, "Economic Tradeoffs in the Gulf of Maine Ecosystem: Herring and Whales" examines a small ecosystem-economy. Resource economists modeled long-run predator-prey interactions in bioeconomic models (Hannesson, 1983; Brown et al., 2005; Boncoeur et al., 2002; Hoekstra and van den Bergh, 2005). This research examines the short-run interactions between prey, predators, and users of both of those resources. This study examines a small portion of the localized depletion theory: search times of whale-watching vessels and finds moderate evidence that the herring fishing has an negative impact on whale-watching search times. However, at current stock levels of both herring and whales, the estimated economic impacts are small. A simulated closure of the nearshore fishery results in slightly shorter search times and small economic gains for whale-watching firms relative to the costs imposed on the fishing industry.

Appendix A

Logistic Growth and a 2 Year Planning Period

To ilustrate the mathematics of the model and the role of the logistic equation, we present a brief exposition of the deterministic model of logistic growth with a two-year planning period.

The Bellman equation (Equation 2.12) is:

$$J(t, S_t; k) = \max_{q_j}\{\sum_{i=1}^{k}[\delta^{i-1}pq_j] + \delta^k J(t+k, k, G^k(S_t, q_j))\}$$

The logistic growth function is often used in fisheries models because of it's relative simplicity, flexibility, and non-convexity. With logistic stock growth, the discrete-time, single-year state equation is:

$$S_{t+1} = G(S_t) = rS_t(1 - \frac{S_t}{K}) + S_t - h_j.$$

For a two-year planning period, the G^2 function can be written by recursion as:

$$\begin{aligned} G^2(S_t) &= G(S_{T+1}) = G(G(S_t)) = \\ &= r[rS_t(1 - \frac{S_t}{K}) + S_t - h_j]\{1 - \frac{rS_t(1 - \frac{S_t}{K}) + S_t - h_j}{K}\} \\ &+ rS_t(1 - \frac{S_t}{K}) + S_t - h_j) - h_j \end{aligned} \tag{A.1}$$

Differentiating equation (A.1) with respect to h_j produces:

$$G_h^2 = -r\{1 - \frac{rS_t(1-\frac{S_t}{K}) + S_t - h_j}{K}\} + \frac{1}{K}\{rS_t[rS_t(1-\frac{S_t}{K}) + S_t - h_j]\} - 2$$
$$= -r\{1 - \frac{2rS_t(1-\frac{S_t}{K}) + S_t - h_j}{K}\} - 2 \tag{A.2}$$

Substitution into equation (2.12) produces the conditions for optimality that implicitly define h_j^*, the optimal harvest level:

$$p + \delta p = \delta^2 J_S[rS_t\{1 - \frac{2rS_t(1-\frac{S_t}{K}) + S_t - h_j}{K}\} - 2] \tag{A.3}$$

The terms on the left-hand side are the marginal benefits of harvest. A marginal increase in the harvest level leads to p additional revenues in the first and second years, the second of which is discounted at rate δ. The right-hand side is the discounted change in value of escapement due to changes in harvest level. As before, J_S retains its interpretation as the marginal value of escapement at the end of the planning period. The term in the square brackets is the marginal effect of increasing h_j on the escapement.

While the objective function is linear in the control variable, $G^2(S_t)$ is not. Therefore, Equation (A.3) implicitly defines h_j^*, the optimal harvest policy. When J_S is known, it is possible to characterize the path of h_j^*.

Appendix B

Numerical Methods for Dynamic Programming

A numerical simulation approach is used to learn about optimal harvest, escapement, and fishery value. For an infinite time horizon, the problem is autonomous and Equation (2.9) can be written as a non-linear rootfinding problem in J:

$$J(s) - \max_q \{f(q) + \delta^k P(s,q) J(s')\} = 0, \tag{B.1}$$

where $P(s,q)$ is a function that returns the probability of moving to state s' conditional on being located in state s for any action q. The value of any state is equal to the largest sum of the current payoffs plus the discounted expected value of the the state variable in the next decision-making period.

The expected harvest is $f(q)$ and is calculated as:

$$f(q) = Pr[q_j \leq X_i] * q_j + Pr[q_j \geq X_i] * E[X_i | q_j \geq X_i] \tag{B.2}$$

An iterative optimization method, often referred to as policy iteration, is used to find J (Judd, 1998). The policy iteration process is:

1. Specify an initial value J_0.
2. Given J_0, choose q_0 that maximizes the term in curly braces in equation (B.1).
3. Calculate J_1, the value function that results from q_0.
4. If equation B.1 holds, then stop. Otherwise, update J_0 and repeat steps 2 and 3.

The results of this iterative method are $q^*(s)$, the optimal control, and $J^*(s)$, the resulting value function. As noted by Miranda and Fackler, “the curse of dimensionality has

has represented the most severe practical problem encountered in solving discrete Markov decision models" (p167). While the state and action space are fairly small, introducing uncertainty and rigidity exponentially increases both the state space and computation time.

Appendix C

Days-at-Sea Leasing

This Appendix contains estimation results for an alternative specification of the linear and quantile regression models. These specifications use untransformed horsepower as a independent variable instead of the version of power (horsepower divided by length) that is presented in the main text. These figures include OLS estimates and the corresponding Wald tests for bargaining power equality, quantile regression results for 5 selected quantiles, graphical representations of quantile regression results for selected independent variables, and corresponding bargaining power equality tests.

Coefficient	(1)	(2)	(3)
Length_buyer	10.28***	8.768***	7.039***
	(1.47)	(1.21)	(0.96)
Length_seller	0.0161	1.818*	1.517*
	(1.61)	(1.04)	(0.85)
Horsepower_buyer	-0.156	-0.0465	0.0663
	(0.11)	(0.095)	(0.079)
Horsepower_seller	0.0676	-0.0131	-0.00891
	(0.073)	(0.055)	(0.049)
DAS_buyer	1.546	-2.879	-0.395
	(4.87)	(3.63)	(3.08)
DAS_seller	7.213	8.983	5.225
	(6.34)	(6.57)	(5.38)
Alternative_buyer	2.642	1.059	1.610
	(3.28)	(2.56)	(1.95)
Alternative_seller	7.790***	7.637***	8.028***
	(2.00)	(1.88)	(1.67)
Differential_buyer	93.56	4.653	20.14
	(57.4)	(27.8)	(24.2)
Differential_seller	-4.347	7.095	0.535
	(38.9)	(27.7)	(24.3)
Experience_buyer	0.448	-3.796*	-3.477**
	(3.65)	(2.04)	(1.65)
Experience_seller	-4.348	-3.905	-2.940
	(5.65)	(2.92)	(2.53)
Trawl_buyer	12.55	-55.82***	-70.76***
	(34.5)	(14.8)	(10.5)
Trawl_seller	-85.60*	-0.512	-14.76
	(45.5)	(14.4)	(11.0)
Permits_buyer	23.88*	0.0186	-3.882
	(13.9)	(7.11)	(4.46)
Permits_seller	7.952	14.52***	26.88***
	(6.93)	(4.84)	(4.04)
F42xDifferential_buyer	-97.83	-57.80	-88.53***
	(69.3)	(35.5)	(27.1)
F42xDifferential_seller	67.39	-19.13	-19.60
	(73.1)	(30.7)	(25.4)
Framework42	10.38	98.61**	75.21**
	(62.4)	(45.3)	(37.1)
N	1,788	1,781	1,756
R^2	0.21	0.38	0.51

Robust standard errors in parentheses

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

Table C.1: Alternative OLS Specification Results, Part 1 of 2.

Coefficient	Model 1	Model 2	Model 3
D2005	-15.85	7.439	-31.05
	(30.8)	(27.3)	(21.2)
D2006	207.8***	152.8***	143.0***
	(51.4)	(33.8)	(28.1)
D2007	132.7*	36.13	46.80
	(68.1)	(46.7)	(38.0)
D2008	192.2***	80.14	85.87**
	(70.3)	(49.6)	(39.4)
Month2	-22.73	-4.073	11.53
	(36.5)	(33.2)	(29.8)
Month3	-88.99**	-61.76*	-49.25
	(40.1)	(37.0)	(33.7)
Month4	-24.50	-4.285	-71.78**
	(50.9)	(48.4)	(30.8)
Month5	38.16	16.13	-16.79
	(51.5)	(38.3)	(28.4)
Month6	-36.61	-40.55	-64.41**
	(47.3)	(39.7)	(30.9)
Month7	-136.2***	-138.2***	-137.3***
	(38.1)	(35.7)	(28.2)
Month8	-97.72**	-95.88**	-125.0***
	(42.5)	(40.0)	(28.7)
Month9	-128.4***	-128.6***	-117.4***
	(37.6)	(35.1)	(28.6)
Month10	-104.5***	-116.3***	-115.7***
	(38.1)	(34.3)	(26.3)
Month11	-90.52	-189.4***	-170.9***
	(66.6)	(33.2)	(26.6)
Intercept	-336.3***	-270.9***	-192.4***
	(60.0)	(49.9)	(39.5)

Robust standard errors in parentheses

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

Table C.2: Alternative OLS Specification Results, Part 2 of 2.

	(1)	(2)	(3)
Length	56.61	87.39	136
Horsepower	0.80	0.52	0.74
DAS	1.16	0.66	0.61
Alternative	6.43	6.32	15.08
Permits	5.42	3.54	18.38
Trawl	7.29	8.50	34.78
Experience	0.49	5.26	4.75
Differential	3.42	0.12	0.55
F42xDifferential	0.12	3.63	11.21

Table C.3: F-statistics for the Hypothesis that Buyer and Seller Characteristics have equal effects on bargaining power. Critical values corresponding to 10%, 5%, and 1% level of significance are 2.71, 3.85, and 6.65 respectively.

Coefficient	0.10	0.25	0.50	0.75	0.90
Length_buyer	0.854 (0.821)	4.909 (0.891)	7.212 (0.918)	7.883 (1.021)	10.073 (1.545)
Length_seller	−0.149 (0.505)	−1.604 (0.701)	1.981 (0.775)	3.056 (0.899)	2.614 (1.365)
Horsepower_buyer	0.003 (0.032)	−0.035 (0.063)	0.131 (0.072)	0.116 (0.071)	−0.066 (0.097)
Horsepower_seller	−0.008 (0.021)	−0.039 (0.036)	0.001 (0.050)	0.069 (0.053)	0.186 (0.072)
DAS_buyer	−2.210 (2.715)	−1.137 (3.040)	3.814 (2.937)	0.000 (3.026)	−1.004 (4.462)
DAS_seller	−1.784 (5.203)	9.957 (5.795)	6.862 (2.618)	11.799 (4.197)	11.992 (5.346)
Alternative_buyer	0.220 (1.350)	−0.112 (2.027)	1.363 (1.952)	1.640 (2.071)	−1.802 (2.686)
Alternative_seller	6.759 (5.344)	14.561 (2.690)	7.731 (1.995)	3.454 (1.318)	−1.824 (2.100)
Permits_buyer	−0.353 (1.975)	−0.657 (3.776)	−10.279 (4.285)	−3.929 (5.279)	12.380 (8.516)
Permits_seller	12.447 (8.124)	40.371 (4.445)	14.460 (4.224)	5.371 (3.925)	−8.442 (5.965)
Experience_buyer	−0.622 (0.816)	−1.762 (1.303)	−2.695 (1.486)	−1.009 (1.441)	−2.337 (1.742)
Experience_seller	−0.872 (1.188)	−2.855 (1.859)	−0.361 (2.030)	−0.038 (2.252)	−1.926 (2.738)
Trawl_buyer	−14.255 (10.699)	−52.475 (12.334)	−54.349 (11.994)	−45.843 (12.905)	13.507 (19.233)
Trawl_seller	6.858 (6.874)	11.573 (12.697)	−27.599 (13.207)	−2.853 (11.097)	−0.972 (13.965)
Differential_buyer	−1.465 (14.596)	17.585 (24.974)	18.322 (23.413)	−0.759 (23.540)	−2.644 (37.113)
Differential_seller	−15.996 (34.778)	−8.472 (29.986)	9.087 (22.962)	8.037 (21.823)	23.900 (28.101)
F42xDifferential_buyer	20.378 (16.590)	−16.411 (28.298)	−116.923 (26.762)	−110.910 (26.839)	−124.477 (43.324)
F42xDifferential_seller	−1.930 (34.518)	−21.644 (30.647)	4.972 (27.866)	−14.022 (24.589)	−23.115 (35.038)
Framework42	−14.906 (16.291)	−76.149 (43.438)	64.810 (36.412)	112.486 (39.673)	153.177 (44.661)
R^1	0.020	0.153	0.311	0.401	0.331

Table C.4: Quantile Regression coefficients for selected quantiles. Standard errors in parentheses, generated using 20,000 bootstrap replications.

Coefficient	0.10	0.25	0.50	0.75	0.90
D2005	-11.096	-32.719	-16.189	5.769	15.747
	(13.311)	(18.664)	(21.782)	(19.119)	(28.295)
D2006	0.029	119.485	165.352	196.953	237.286
	(13.620)	(38.532)	(26.231)	(27.168)	(44.000)
D2007	4.217	141.415	113.362	51.977	21.836
	(17.412)	(41.228)	(37.866)	(42.161)	(53.087)
D2008	12.949	160.261	129.515	74.537	53.866
	(19.628)	(41.974)	(37.661)	(43.237)	(56.494)
Month2	3.442	3.332	-8.616	-37.677	-33.908
	(62.256)	(39.837)	(30.966)	(24.977)	(36.690)
Month3	-15.771	-101.273	-25.851	-36.630	-44.334
	(35.817)	(40.199)	(38.079)	(23.700)	(36.504)
Month4	-21.662	-83.689	-38.963	-15.668	-10.572
	(36.529)	(39.651)	(35.462)	(27.310)	(75.752)
Month5	-13.954	-29.094	-20.906	-12.802	7.270
	(36.524)	(37.407)	(30.759)	(27.578)	(41.083)
Month6	-15.445	-88.896	-49.437	-31.453	-22.141
	(35.479)	(37.472)	(33.565)	(25.045)	(47.770)
Month7	-13.047	-96.516	-105.533	-90.975	-60.769
	(35.953)	(35.559)	(32.629)	(28.390)	(36.030)
Month8	-19.656	-97.027	-87.510	-48.499	-59.583
	(36.538)	(36.896)	(34.680)	(25.785)	(35.036)
Month9	-17.040	-83.806	-93.458	-86.511	-92.707
	(35.535)	(37.695)	(32.815)	(23.230)	(38.463)
Month10	-10.705	-97.825	-106.522	-106.064	-112.975
	(35.417)	(34.204)	(30.298)	(22.890)	(32.652)
Month11	-7.036	-103.497	-152.206	-144.816	-149.638
	(35.276)	(34.900)	(31.734)	(24.205)	(31.943)
Constant	-4.370	-19.664	-267.883	-313.626	-334.546
	(40.554)	(51.999)	(54.406)	(41.414)	(49.018)

Table C.5: Quantile Regression Results, continued.

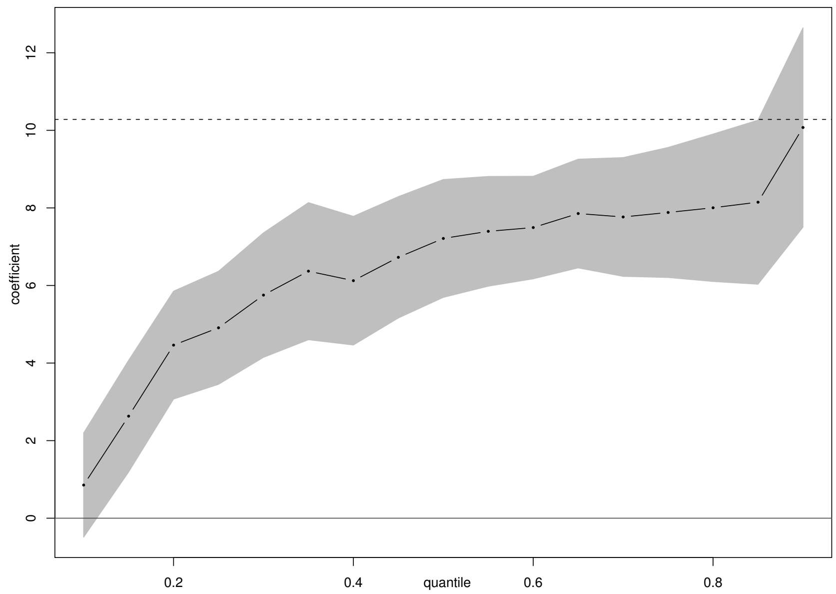


Figure C.1: Quantile Regression Coefficients - Buyer Length.

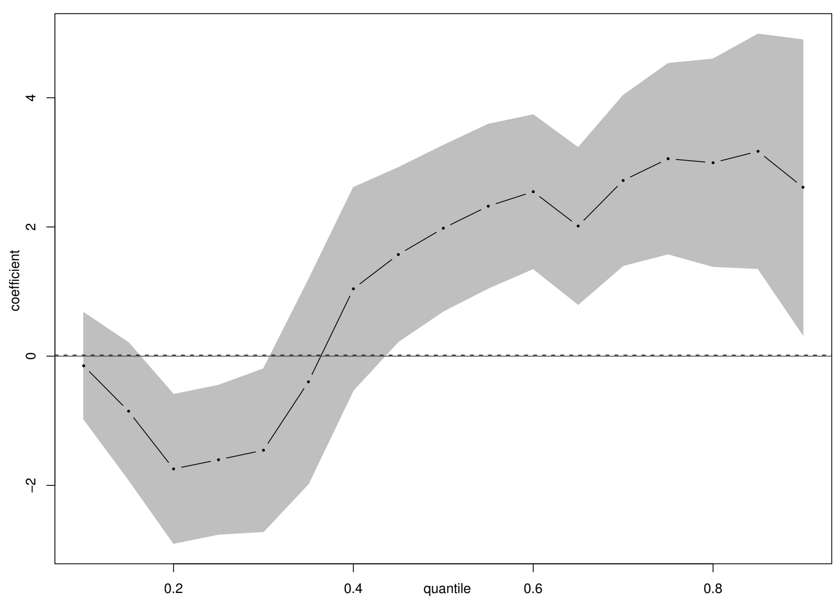


Figure C.2: Quantile Regression Coefficients - Seller Length.

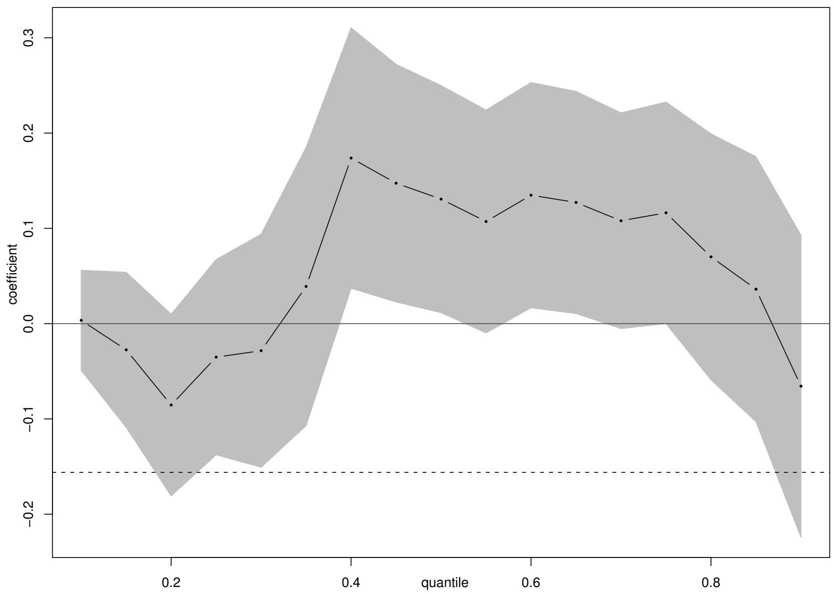


Figure C.3: Quantile Regression Coefficients - Buyer Horsepower.

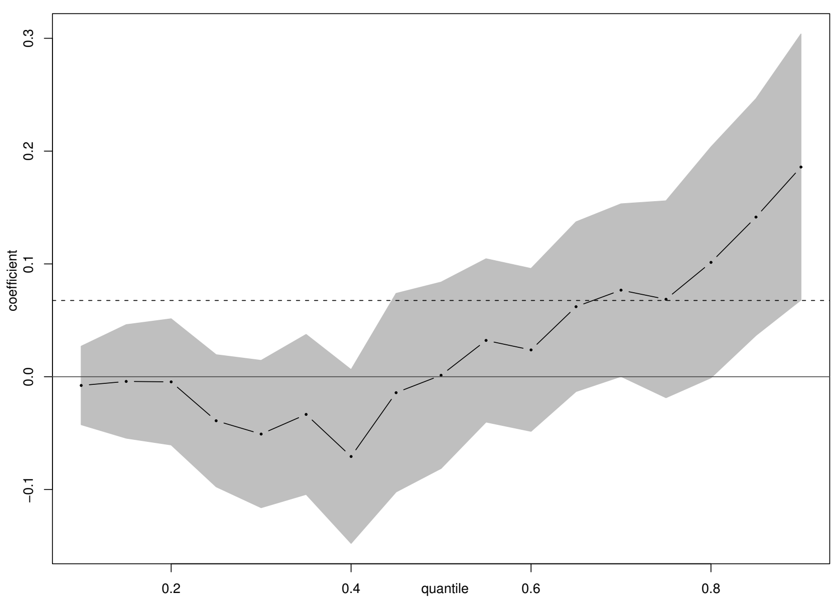


Figure C.4: Quantile Regression Coefficients - Seller Horsepower.

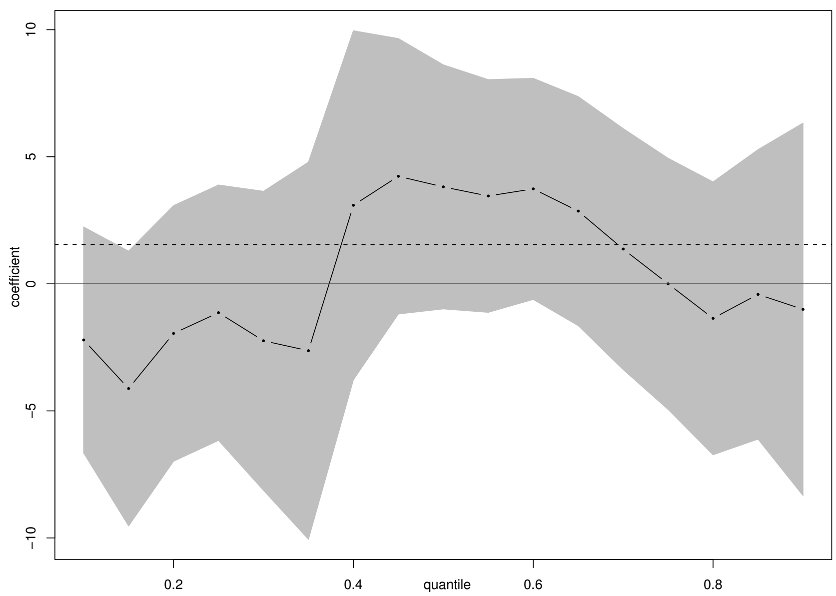


Figure C.5: Quantile Regression Coefficients - Buyer DAS Revenue.

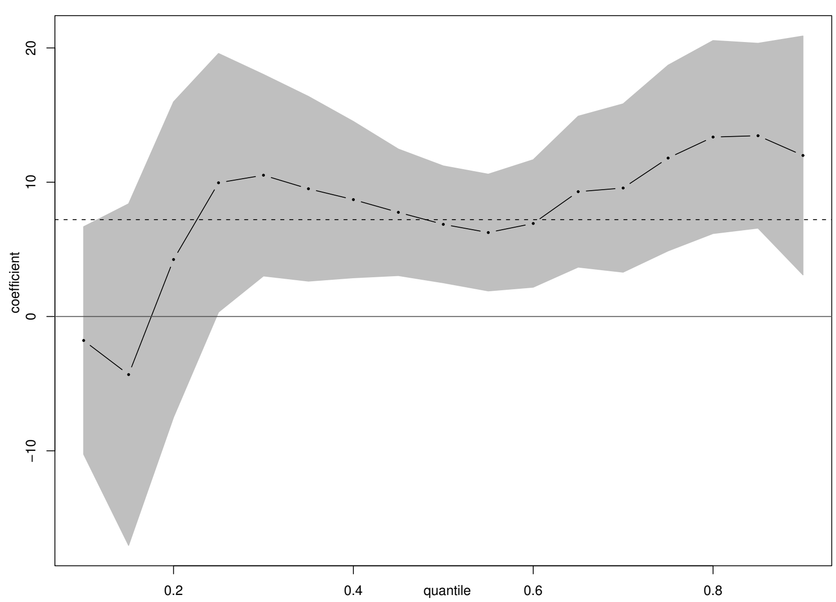


Figure C.6: Quantile Regression Coefficients - Seller DAS Revenue.

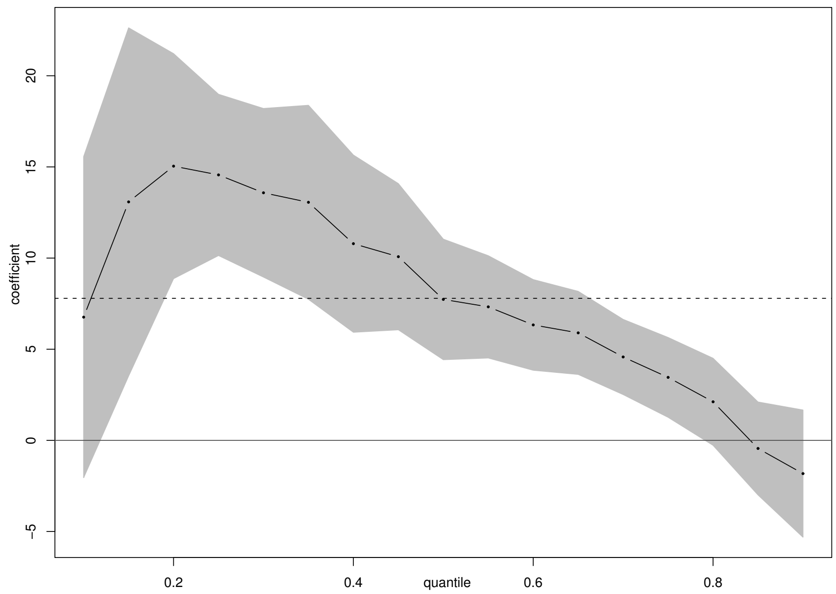


Figure C.7: Quantile Regression Coefficients - Seller Alternative Revenue.

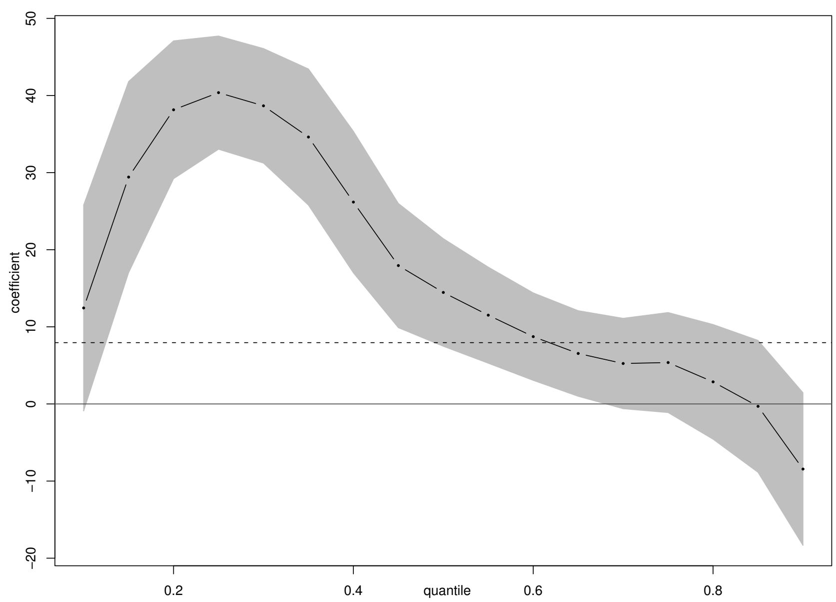


Figure C.8: Quantile Regression Coefficients - Seller Permits.

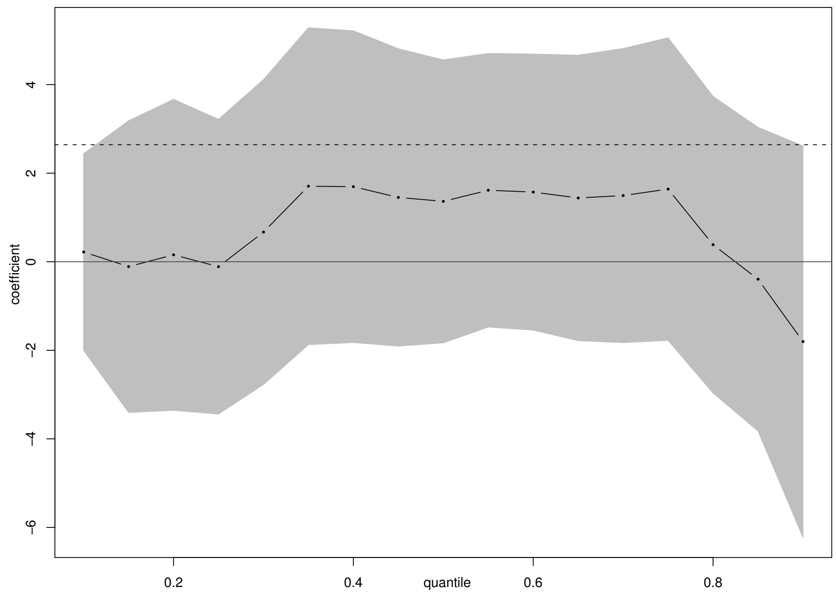


Figure C.9: Quantile Regression Coefficients - Buyer Alternative Revenue.

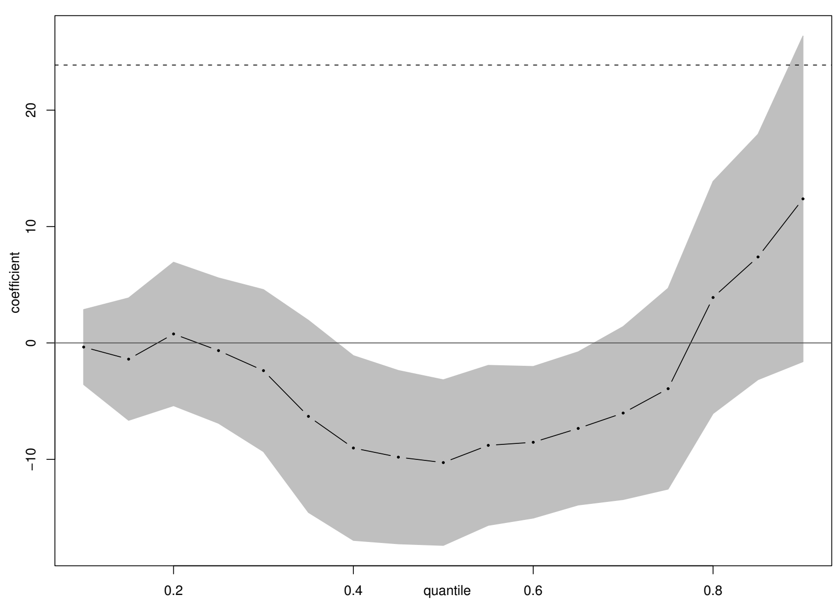


Figure C.10: Quantile Regression Coefficients - Buyer Permits.

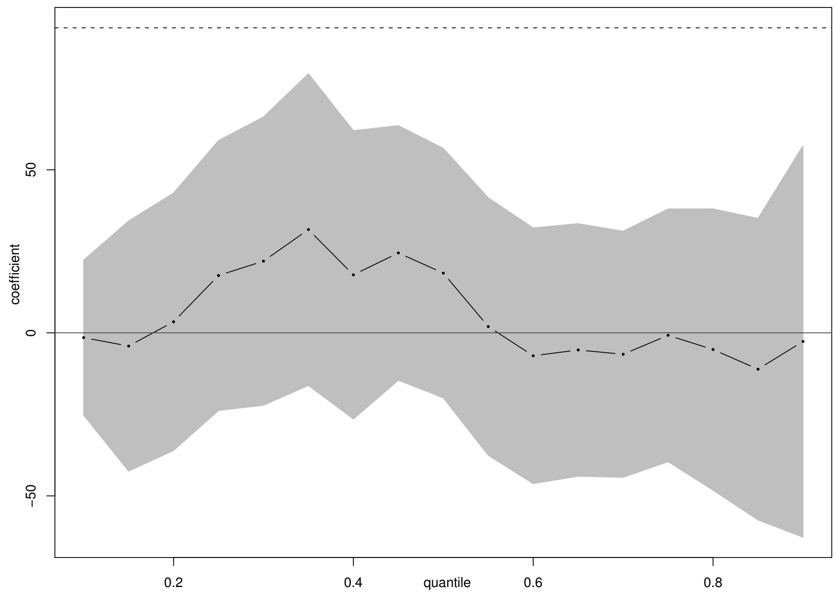


Figure C.11: Quantile Regression Coefficients - Buyer Differential DAS.

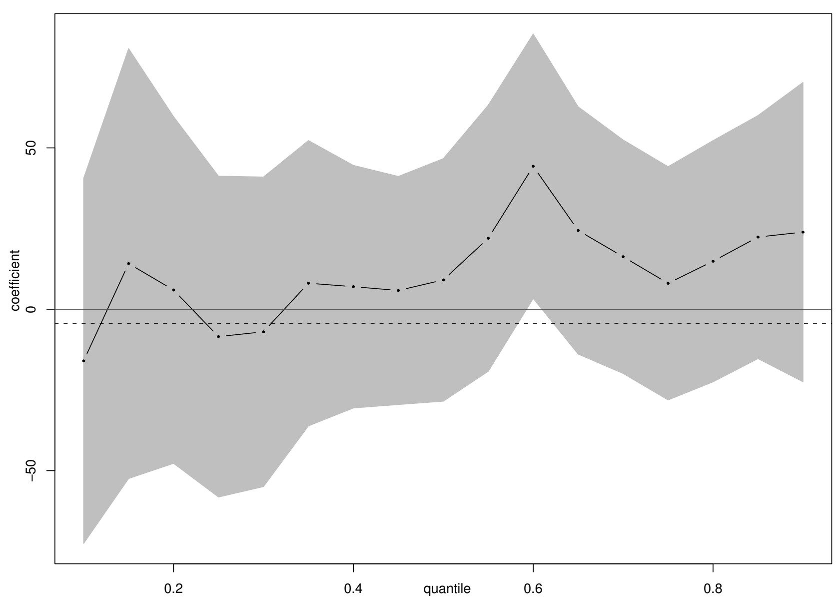


Figure C.12: Quantile Regression Coefficients - Seller Differential DAS.

	0.10	0.25	0.50	0.75	0.90
Length	1.473	16.667	101.905	186.280	103.971
Horsepower	0.082	5.466	7.391	12.240	3.375
DAS	0.023	1.900	4.504	9.571	2.502
Alternative	0.678	0.150	1.724	0.001	0.034
Permits	0.102	1.660	1.234	0.013	0.015
Experience	0.079	2.751	6.809	8.042	2.555
Trawl	1.812	17.187	10.767	4.438	1.186
Differential	0.490	2.395	7.474	4.944	2.521
F42xDifferential	0.286	0.076	1.041	0.057	0.270

Table C.6: Wald Test statistics for Bargaining Power Homogeneity at select quantiles.

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