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Essays on institutions and innovation in natural resource industries

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Essays on Institutions and Innovation in Natural Resource Industries

A dissertation submitted in partial satisfaction of the
requirements for the degree
Doctor of Philosophy

in

Economics

by

Benjamin Travis Gilbert

Committee in charge:

Professor Theodore Groves, Chair
Professor Richard Carson
Professor Josh Graff Zivin
Professor Mark Jacobsen
Professor Dale Squires
Professor Junjie Zhang

2011

The dissertation of Benjamin Travis Gilbert is approved, and it is acceptable in quality and form for publication on microfilm and electronically:

Chair

University of California, San Diego

2011

DEDICATION

To Mama.

EPIGRAPH

This is a valley of ashes–a fantastic farm where ashes grow like wheat into ridges and hills and grotesque gardens; where ashes take the forms of houses and chimneys and rising smoke and, finally, with a transcendent effort, of men who move dimly and already crumbling through the powdery air. Occasionally a line of gray cars crawls along an invisible track, gives out a ghastly creak, and comes to rest, and immediately the ash-gray men swarm up with leaden spades and stir up an impenetrable cloud, which screens their obscure operations from your sight.

—F. Scott Fitzgerald, The Great Gatsby

The evolution of the capitalist style of life could be easily – and perhaps most tellingly – described in terms of the genesis of the modern Lounge Suit.

—Joseph Schumpeter

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I would like to thank my wife Paige for believing in me, Ph.D. or not, and for reminding me that I'm a human.

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ABSTRACT OF THE DISSERTATION

Essays on Institutions and Innovation in Natural Resource Industries

by

Benjamin Travis Gilbert

Doctor of Philosophy in Economics

University of California, San Diego, 2011

Professor Theodore Groves, Chair

Technological progress is associated with both excessive depletion and improved conservation of environmental resources. This dissertation explores the role of technological progress under different regulatory and producing institutions.

The first chapter, "Firm Boundaries and Impure Public Goods", establishes a relationship between property rights, firm structure, and productivity. I adapt the theory of the firm to show that reducing common-pool externalities can lead to mergers (distinct from permit consolidation among low cost firms) and greater human capital investments. These predictions are supported by data from the New England groundfish industry where some groups called "sectors" were exempted from input controls and given a collective output quota. Sectors exhibited better managerial performance (i.e., higher productivity) relative to non-sector firms

following the change, but the species composition of their harvest shifted considerably.

The following two chapters investigate technology adoption and productivity in common-pool resource industries. The second chapter, "Technological Change and Managerial Ability: Evidence from a Malaysian Artisanal Fishery", uses stochastic frontier analysis to compare the productivity of technology adopters in the gillnet fishery on the east coast of Peninsular Malaysia. Technologies include cell phones, GPS, sonar, and mechanical winches for hauling nets. Electronics adopters were more productive than non-adopters on average but difficult to distinguish from efficient non-adopters, while adopters of mechanical net haulers had low technical efficiency, low labor productivity and high labor use. Our results suggest capital investments in new technology may tie the least successful participants to the fishery despite most respondents' self-reported desire to exit.

The dynamic implications of these findings are explored in the third chapter, "Exogenous Productivity Shocks and Capital Investment in Common-pool Resources". We develop a compound Poisson process to model rapid adoption of technologies in common-pool industries. Technology shocks lower the equilibrium resource stock while causing capital buildup based on transitory quasi-rents. The steady state changes from a stable node to a shifting focus with boom and bust cycles, even if only technology is uncertain.

Chapter 1

Firm Boundaries with Impure Public Goods

Abstract

This paper addresses how environmental regulations affect firms' organizational choices, such as the decision to merge or not with other firms, and how these choices further influence their environmental footprint. Market-based environmental regulations can represent large changes in the rights to use natural resources. I apply a model of firm boundaries to the case of a common pool resource and evaluate the effect of changes in property rights on firms' organization and performance. The model predicts that reducing common-pool externalities will influence ex ante performance investments, leading to mergers or collective ownership. The framework is extended to a "relational contract" setting where the size of the externality determines the informal agreements that can be sustained through repeated interactions. I provide supporting evidence from a quasi-experiment in the New England fishing industry where some groups called "sectors" were given collective rights to a quota share. I estimate time-varying, firm-specific productivity parameters to capture changes in firm performance. Sector participation lead to improved performance relative to similar independent fishing boats, even after controlling for selection and vessel fixed effects. Patterns of specialization and harvest composition also changed dramatically within sectors, suggesting potentially

large unintended ecological consequences associated with multi-product firms after a shift in property rights and firm structure.

1.1 Introduction

Market-based environmental regulations can represent large changes in the rights of firms to access and exploit natural resources. To a certain extent firms can make marginal adjustments to the new rules, but in response to large regulatory changes firms may choose to reorganize production processes or recombine with other firms with better complementarities. This observation raises two related issues. First, how do environmental regulations affect firms' organizational choices, such as the decision to merge or not with other firms? Second, how do organizational choices influence the environmental profile of the merged or reorganized firm relative to its status quo? This paper begins to unravel these questions for the case of a common pool resource industry. I use a model of firm boundaries (the Grossman-Hart-Moore "property rights theory" (Grossman and Hart (1986), Hart and Moore (1990))) to evaluate the effect of changes in resource rights on firms' organization and performance, and I provide supporting evidence for the theory using panel data from a quasi-experiment in the New England fishing industry.

A few examples may help illustrate why firm organization is an important factor in environmental regulation. Trading schemes for carbon emissions, wetland mitigation credits, and fishing catch shares are just a few examples of potentially transformative changes in the rules for natural resource industries. Carbon permit trading and renewable energy mandates may have different effects on a utility's decision between building its own wind or solar plants and buying clean power from merchant generators. The amount of renewable energy delivered to customers, however, depends on the match quality between technology (e.g., type of panel or turbine) and location (e.g., weather patterns and distribution networks). If ownership distorts the incentives for parties to collaborate to find the best match ex ante, then regulations that bias the make-or-buy decision will also bias the ex post fuel mix. In the wetland case, evidence suggests that in recent years land developers have been better able to mitigate wetland destruction by buying mitigation services from third-party "conservation bankers" (Robertson (2006)). This presents a puzzle as to why these services are more valuable when provided from outside the firm than from within.

In the fishing industry, independent vessels are rumored to provide each other services in informal networks despite fierce competition at the industry level (Wilen (2007)). Are these relationships more likely to become formalized or marginalized under individually tradable catch share systems? The most productive individuals could simply buy more shares and compete more independently, or fishers could retain the rights and invest in their collaborative partnerships. In many cases firms have not adhered to strictly competitive, cooperative, or corporate structures following the implementation of stronger rights, opting instead for hybrid structures. The production processes resulting under different organizational choices can have different impacts on the resource stocks and their habitats. Thus boundary issues could also affect how firms innovate based on complementarities with their potential partners, parents, or subsidiaries. The U.S. National Oceanic and Atmospheric Administration is promoting a draft policy to encourage catch share adoption in fisheries nationwide, the design of which is likely to influence these boundaries.

In this paper I explore how the property rights model of firm boundaries can inform policies that alter property rights in common-pool resource industries, e.g., where certain inputs are nonexcludable but rival in use. I show that closing off the commons can raise the incentives to invest in specific human capital that is more productive in integrated firms than in independent firms. Mergers are more likely, and collective ownership can dominate in some cases. The merger effect explored here is distinct from the simple consolidation or exit of redundant inputs and describes the optimal organizational form for a given production level and regulatory regime. I extend the framework to a repeated game setting where informal "relational contracts" over ex ante investments are supported by reputation through grim-trigger punishment strategies, following Baker et al. (2002). In this context, a wide variety of ownership structures exists and the equilibrium is highly dependent on case-specific parameters such as the variability of the resource, the long run value of human capital relative to deviation payoffs, and the relative rate at which externalities in the common-pool erode these values. This reflects empirical patterns in common-pool resources, particularly in the developing world, where observed ownership structures vary widely depending on local conditions and institutions (Ostrom (2007),Ostrom et al. (2007),Schlager and Ostrom (1992)).

I provide supporting empirical evidence using a quasi-experiment from the New England groundfish industry, where overfishing has been a persistent problem. Firms have typically been comprised of independent fishing vessels under command-and-control regulations. After 2004, federal regulators allowed two small groups of vessels called "sectors" to collectively manage a secure output quota for their primary fish species, Atlantic cod. They were allowed to choose any internal allocation rule for the cod catch as long as their harvest did not exceed their group quota. Thus the possible outcomes could have ranged from an internal "race to fish" among members, to a de facto trading system over portions of the quota, to an integrated corporate structure with coordinated harvest and marketing strategies. My theoretical model predicts that the stronger property right would lead to more centralized management and greater ex ante investments in performance.

The result was a hybrid of these possibilities. Sectors rewarded competitive fishing by making individual vessels residual claimants to their own harvest, but hired a central manager and held monthly meetings to coordinate the strategic timing of the harvests. One sector implemented a collective strategy to diversify its catch portfolio and pursue species with healthier stocks. This sector sponsored independent scientific research on new fishing techniques and shifted its pattern of specialization from being entirely specialized in cod to having different vessels specialized in different species. Still other vessels joined the sectors to sell or lease their groundfish rights to the rest of the group and stopped fishing for groundfish species entirely. This pattern of diversification and specialization suggests potentially large unintended ecological consequences associated with multi-product firms following a shift in property rights and firm structure. To measure performance, I exploit the near daily frequency of data from captains' logbooks to estimate time-varying, vessel-specific productivity parameters for both sector and independent vessels while addressing sources of bias from unobserved factors that may have influenced endogenous matching, sample and program selection, and input choice. Sector vessel performance, as measured by productivity gains, improved significantly relative to comparison vessels in most regression specifications[1]. These findings have implications for many other settings in which establishing environmental property rights may cause changes in institutional form and the composition of production.

The rest of the paper is organized as follows. Section 1.2 provides some background on the relationship between the environmental policy literature and the literature on institutional form and discusses important complementarities. Section 1.3 describes the model setup, and section 1.4 analyzes the equilibrium of the model and considers examples of collective ownership in addition to private integration and non-integration. Section 1.5 extends this analysis to settings with repeated interactions and reputational effects. Section 1.6 describes the experience with sector formation in the New England groundfish fishery and the data used in the empirical analysis. Section 1.7 describes the empirical approach. Section 1.8 discusses the results of the empirical investigation. Section 1.9 summarizes, discusses future research, and concludes.

1.2 Background

Much of the environmental economics literature on market-based regulation treats firms as fixed atomistic entities. But firm boundaries matter because they are determined by the same real-time managerial decisions and ex ante investments that influence the firm's external damages through technology choices, productivity, and abatement capabilities. These decisions and ex ante investments can be highly specific to the relationship between individual firms because of the

[1]Nonmarket social benefits such as intergenerational fishing opportunity, resource conservation, and community-based decision making were also primary motivations for forming the sectors, according to the participants (da Silva and Kitts (2006)). Thus productivity gains are only one possible measure of performance improvement, but they are the most tangible to measure given available data.

heterogeneity and variability of environmental assets across space and time. Thus the rights to make decisions about asset use - the residual control rights - can influence the size and character of external environmental costs. Residual control is important when agreements between firms don't specify responsibilities for every environmental contingency (i.e., when contracts are incomplete), because ex post decision-making falls to the asset owner. This insight is the essence of the Grossman-Hart-Moore property rights theory (PRT) of the firm, which I adapt in this paper for the case when firms use impure public goods as inputs. Residual control is important in many environmental contexts both in the short run when technology is fixed (e.g., oil spill cleanup, power plant fuel-switching, intraseason bycatch avoidance in fisheries, wetland mitigation for development projects, etc.), and in the long run when new innovations could reduce abatement costs, but the combination of ex ante human capital investments in breakthroughs and ex post managerial decisions about adoption and deployment, both matter for realized resource outcomes.

The PRT is analogous to the theory of induced innovation in the sense that both theories consider how to encourage ex ante investments that improve ex post value. Innovative activity responds to changes in relative prices in the induced innovation theory, and to changes in ownership in the PRT. Economists have increasingly emphasized the links between environmental policy and induced technological change, either through investments in knowledge or learning by doing (Grbler et al. (2002), Jaffe et al. (2003), Pizer and Popp (2008)). Smith (1972a) argues, for example, that incomplete property rights induce innovations that deplete the under priced resource, and pricing access alters the direction of innovation. Goulder and Mathai (2000) show that the optimal time paths of carbon taxes and pollution abatement are sensitive to the amount of innovation that can be induced through both learning by doing and investments in human capital or R&D. The induced innovation theory, however, assumes innovative efforts are contractible through expenditures on exogenous "innovation possibilities", whereas innovative efforts in the PRT are not contractible and ownership is required to induce agents to devote more resources to these investments.

A central theme of this paper is that changes in the firm's choice of organizational form are an important channel through which changes in property rights can influence a firm's ability to innovate and improve performance. The stylized facts that arise from case studies of fishing rights around the world support this claim. Rights-based fisheries have often taken the form of catch allocations managed by groups rather than individual boats, with vessels investing in the development of more effective and more coordinated harvest techniques, improved product quality, and scientific research to understand species and habitat conditions. Very few of these organizations narrowly behave like de facto internal trading organizations following the establishment of collective rights (Hannesson (1988), Huppert (2005), Townsend (2005), Matulich et al. (2001), da Silva and Kitts (2006), Townsend et al. (2008), Townsend (1995)). Furthermore, the actions and abilities of individual fishing firm managers, i.e., the boat captains, have been identified as a driving force behind firm performance (Barth (1966), Palsson and Durrenberger (1982), Squires and Kirkley (1999), Viswanathan et al. (2002), Thorlindsson (1998), Squires et al. (2003), Wilen (2007), Acheson (1981)).

There are very few formal treatments of the theory of the firm in response to market-based environmental regulation. Lueck (1995) uses the PRT to analyze wildlife regulatory institutions, but focuses more on the determinants of regulatory structure rather than the effect of regulatory change on firm structure and performance, which is the focus here. Similarly, Johnson and Libecap (1982), Libecap and Smith (1999), and Libecap and Wiggins (1984), take the property rights structure in resource extraction industries as given and examine either the development of regulatory systems, or directly examine the contracting potential (or failure therein) between firms or between industry and regulators. These studies highlight the difficulty of contracting rather than taking the incompleteness of contracts as the foundation for the analysis.

In the agricultural literature variants of the principal-agent approach have been used to analyze crop share contracts and the structure of the farming industry. Allen and Lueck (2004) argue for this approach because they observe that assets are not relationship-specific in farming, and the more relevant trade offs occur with task specialization, capital costs, and use of unpriced inputs or moral hazard. Deacon et al. (2008), Deacon et al. (2010), and Holzer-Bilbao (2009) have presented further variations of this approach in a fisheries context. In Holzer-Bilbao (2009) fishermen trade coordination gains from integration against missing information about how to coordinate. Deacon et al. (2008) and Deacon et al. (2010) trade off the provision of club goods (e.g., information about resource stock locations, shared capital inputs) inside a cooperative against forced sharing of skill rents and loss of outside opportunities. Deacon et al. (2008), Deacon et al. (2010), and Holzer-Bilbao (2009) all predict that the least productive agents gain the most by merging, which is substantiated by the data in Deacon et al. (2008) and Deacon et al. (2010). In this paper by contrast agents are assumed to have specific relationships so match quality is more important than ranking. I find that joiners came from a narrower but higher segment of the productivity distribution than the rest of the fleet, conditional on vessel and crew size.

These studies all include the important feature of an unpriced, impure public input that is common to the industry (in this case, the fish stock and its habitats), but have not explored potential relationship specificities that arise when dealing with the natural world. Relationship specificity arises when the spot market offers significantly inferior substitutes for partners or their assets. This is the driving force behind integration in most theories of the firm because it gives rise to opportunistic behavior (Williamson (1979), Klein et al. (1978), Grossman and Hart (1986), Hart and Moore (1990)). Williamson (1991) lists six potential sources of relationship specificity: (1) site specificity; (2) specialized physical capital; (3) specialized human capital; (4) brand name specificities; (5) dedicated asset requests from important customers; and (6) temporal specificity, a type of site-specificity when timely responses from partners are required.

Some variant of each of these features is often present in industries that rely on environmental inputs. Empirically, the question is how important they are in context relative to other forces. In fishing there is both temporal and spatial dependence in the relative distribution of different species and harvesting costs which makes both pre-season and pre-harvest preparation in tracking and monitoring ocean conditions valuable. Insofar as each individual captain can't track the entire ecosystem, but only specific pieces of it that are familiar to him, his ex ante preparations are specific to a set of other captains whose pieces of the ecosystem (or the market) are ecologically (or economically) adjacent. Captains may also adjust their fishing gear to the idiosyncrasies of the habitats they frequent. Williamson (1991) argues that insecure property rights will dampen ex ante investments when agents know that the value of these investments will be expropriated by other agents (e.g., through rivalry in the common pool). This paper formalizes and tests this effect on integration and firm performance outcomes using the property rights theory framework.

1.3 Model

This section lays out the basic Grossman-Hart-Moore framework (Grossman and Hart (1986), Hart and Moore (1990)) and incorporates key aspects of common-pool inputs. The model considers two managers, 1 and 2, who are a small part of a large industry with many firms. Each of the two managers $i = 1, 2$ has production decisions $\mathbf{q}_i \in \mathbb{R}^Q$. Managers 1 and 2 are considering a relationship in which they jointly choose $\mathbf{q} = (\mathbf{q}_1, \mathbf{q}_2) \in \mathbb{R}^{2Q}$. The rights to make these decisions are the assets in the relationship[2]. The assets are relationship-specific, meaning that the partners realize greater value by coordinating their use, and can't find alternative assets in the spot market that produce as great of value (e.g., by finding other similar partners with whom to coordinate similar decisions).

There are two stages in the game. At date 0, managers enter the game each holding the rights to her own set of decisions $\mathbf{q}_j$, for example, her own fishing vessel and permits which allow physical and legal access to the resource[3]. These decisions will not be made and executed until uncertainty is resolved at date 1. Managers

[2]Typically assets in this model are thought of as pieces of physical capital, but when there are incomplete property rights and externalities over physical inputs it is more convenient (and accurate) to define assets as decisions over things rather than the things themselves.

[3]This initial allocation is without loss of generality and is assumed in order to make the analogy concrete. Any initial allocation will result in the same equilibrium allocation and will matter only for the distribution of surplus (Grossman and Hart (1986), Hart and Moore (1990))

may reallocate the rights at date 0, which establishes the ownership or control structure. The aim of the model is to determine the optimal control structure given the contracting constraints. Before date 1 each manager then noncooperatively chooses a vector of ex ante actions $\mathbf{a}_i \in \mathbb{R}^M$ with $a_{im} \in [0, \bar{a}_{im}]$, where $\bar{a}_{im} \geq 0$. These actions are not contractible but will affect the value or productivity of the partnership at date 1. The actions are relationship-specific to managers 1 and 2 in that they're not as valuable when the managers work independently or work with any other manager they could hire from the spot market. The canonical model considers these actions as investments in human capital, but this need not be the only example; their essential features are that their value is inalienable from the individual manager but specific to the relationship, and they are observable by the partners but not verifiable by third parties (and are thus not contractible)[4]. In the fisheries case these actions could consist of time spent learning the unique features of specific fishing grounds, species behaviors, markets and regulations, studying recent oceanographic conditions and forecasts, search effort to find good crew members, investments in communicative capacity among partners, etc.

At date 1, the managers make the production decisions under their control and the gains are realized. The decisions $\mathbf{q}$ are not contractible until the start of date 1, when uncertainty about the production environment is revealed[5]. Because $\mathbf{q}_i$ is ex post contractible, however, firms may costlessly renegotiate these decisions at date 1 before executing them in production. This process always leads to ex post efficient production decisions, conditional on predetermined choices for the $\mathbf{a}$'s. For example, at date 1 managers 1 and 2 can calculate the Nash equilibrium $\tilde{\mathbf{q}}_1$ and $\tilde{\mathbf{q}}_2$ that they would choose independently and noncooperatively, but would see

[4]If these investments are alienable (e.g., an invention by manager 1 that can be operated without him) the model is still informative but results in different predictions (Hart (1995)).

[5]These assumptions are designed to capture situations in which it would be prohibitively costly to describe in advance every choice of $\mathbf{q}$ for every state of the world, but in which it is relatively easy to do so ex post, when the state is observed. As an example from fisheries, it is hard to imagine vessels writing out pre-season contracts that specify every effort level and gear type to be executed at every possible fishing location under all possible combinations of daily oceanographic and market variables. However, once the season begins and information about the relative spatial distribution of species and associated harvest costs begins to unfold, it would be relatively easier for vessels to communicate and coordinate their production plans. In this sense, $\mathbf{q}_i$ is a residual right of control and manager i has the right to choose it at date 1.

that they could both gain by renegotiating the $\mathbf{q}$'s to maximize their joint benefit and splitting the surplus. In other words, they Nash-bargain to a jointly optimal production profile, using their benefit at the Nash equilibrium $\tilde{\mathbf{q}}_j$ as the threat point. Realizing this at date 0, managers choose their ex ante non contractible actions $\mathbf{a}_j$ to maximize their Nash bargaining share of the expected joint surplus. For this reason, in equilibrium the decision rights are organized at date 0 to induce the choices of the $\mathbf{a}$'s that lead to the greatest date 1 surplus[6].

Unlike the previous literature on firm theory, I also model these two managers as small players in a large industry with many firms all exploiting a common resource. Thus each firm's production activities impose an externality on all other firms by lowering the availability or value of the remaining resource. Denote the aggregate level of this externality as E. These externalities expose the industry to potential regulations that could either reduce the externalities or reduce the value of coordinating production in partnerships. For the purposes of this paper, I assume that the size of the industry is large enough that each firm takes E as given and does not consider their individual impact on other vessels through E directly, or how their impact on others' decisions feeds back to their own payoffs through E indirectly. With a common-pool regime the aggregate harvest will reduce the availability for managers 1 and 2, but with hundreds of firms the strategic influence that managers 1 and 2 have on the actions of all other firms is plausibly negligible. I abstract from these industry-wide strategic decisions in order to focus on the relationship between the property rights regime and the motivations between individual partners. In the New England groundfish industry studied in the empirical section of this paper, there are approximately 1400 permitted fishing vessels, with approximately 500 vessels accounting for most of the annual catch. Any strategic influence an individual vessel has on the aggregate catch is very small, and likely to be absorbed by the 900 or so marginal vessels that can enter or exit as conditions

[6]I have assumed managers enter the game with an independent control structure determined by nature, but can costlessly reallocate control rights at date 0 if they anticipate generating a greater surplus under some other ownership structure. This increase in surplus from the superior control structure can be divvied up into a set of side payments for exchange of the assets at date 0; these trades are assumed to be made efficiently without additional transaction costs so that in equilibrium the best control structure is achieved (although the distribution of total payoffs may depend on the initial allocation).

change.

The benefit of the relationship to manager $i \in \{1,2\}$ at date 1 is $B_i(\mathbf{a}, \mathbf{q}, E)$, where $B : \mathbb{R}^{2Q+2M+1} \rightarrow \mathbb{R}$ is a mapping from the investment and production decisions of both managers in the relationship, and the production externalities of the industry as a whole, to manager-specific ex post benefits. I allow for the possibility that some or all of manager 2's investments may directly enter manager 1's benefit function and vice versa. Different subsets of all possible elements of $\mathbf{a}$, $\mathbf{q}$, and E may be more or less relevant for B_i depending on the setting and the industry being evaluated. The private costs of date 0 actions $\mathbf{a}_i$ are measured by their opportunity costs in dollar expenditures.

Except for some additional assumptions about the role E and some clarifying definitions for this setting, I adhere very closely to the canonical model of the property rights theory of the firm in making the following assumptions about $B_i(\cdot)$:

Assumption 1 *$B_i(\mathbf{a}, \mathbf{q}, E)$ is twice differentiable and concave in $\mathbf{a}$ and identical for $i \in \{1,2\}$. $\partial B_i / \partial a_{jm} \geq 0$ if $a_{jm} \in (0, \bar{a}_{jm})$, $\partial B_i / \partial a_{jm} = \partial B_j / \partial a_{im}$, $\forall i, j \in \{1,2\}, m = 1, ..., M$, and the Hessian of $B_i(\mathbf{a}, \mathbf{q}, E)$ with respect to $\mathbf{a}$ is negative definite.*

When one manager is dominant, it's obvious that she should control the decisions. I assume identical payoffs $B_i(\cdot)$ for managers 1 and 2 in order to highlight the importance of the different types of ex ante actions, rather than the relative characteristics of the managers, in determining optimal control structures under different common pool conditions. I will consider several ownership structures: *Nonintegration* (or *Non*), in which each manager controls the decisions over his capital units (e.g., each captain owns his own fishing vessel); *i-Integration* (or *i-Int*), in which manager i controls all the decisions for both vessels[7]; and *Collective Ownership* (or *CO*), in which the managers control the decisions collectively according to an established social choice mechanism[8]. I will discuss several familiar social choice mechanisms and their relative merits within the context of this model.

[7] In this case, the non-owner's disagreement point is whatever he or she could expect to gain in the spot market as a manager-for-hire.

[8] Note that joint ownership would be one specific type of social choice mechanism in which

Assumption 2 *There is a unique Nash equilibrium* $\tilde{\mathbf{q}}_i^k$ *that maximizes each* $B_i(\cdot)$ *subject to* $\mathbf{q}_j^k$ *for each ownership structure* $k \in \{i\text{-}Int, Non, CO\}$ *and each state of the externality* E*.*

Assumption 3 *There is a unique optimum* $\mathbf{q}^*$ *that maximizes* $B_1(\cdot) + B_2(\cdot)$ *for each state of the externality* E*, independent of* $\mathbf{a}$.

The assumption of independence between $\mathbf{q}$ and $\mathbf{a}$ is made for consistency with the canonical model. Different kinds of human capital investments may also enter the payoff functions differently - for example, some investments my only enter the investors payoff, others may purely benefit the other manager in the relationship, and others may have a different value depending on the decision rights.

Definition 1 *Self investments are those that only enter the manager's own payoff function so that* $\frac{\partial B_i(\cdot)}{\partial a_{jm}} \equiv 0$*. Cross investments are those that only enter other managers' payoff functions so that* $\frac{\partial B_j(\cdot)}{\partial a_{jm}} \equiv 0$*.*

The cross investments can be thought of as investments in training partners to improve the fishing technique and ability to locate fish, developing effective systems of governance, group management capacity, organizational structure, communication mechanisms, understanding of market timing, or other cooperative benefits. Self investments can include better understanding of resource complexities, the ability to locate spatially and stochastically distributed resources, develop and deliver higher-value products, or the ability to produce or extract quickly at low cost under harsh conditions. While these self investments may also benefit the group through cooperative bargaining over the surplus, they do not require actions from other players and also help improve the firm's bargaining position relative to the rest of the group by improving it's disagreement payoff in negotiations. Managers can appropriate some of the value of others' self investments or recoup some of their own cross investments through Nash bargaining.

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each manager has a veto over any decision profile. This leads to an extreme emphasis on the group outcome because the managers have no outside value to negotiate with. As such, joint ownership will not be considered here.

Assumption 4 *For all $i, j \in \{1, 2\}$ and $m = 1, ..., M$,*

$$\frac{\partial B_i(\mathbf{a}, \mathbf{q}^*, E)}{\partial a_{jm}} > \frac{\partial B_i(\mathbf{a}, \mathbf{q}^{i-Int}, E)}{\partial a_{jm}} > \frac{\partial B_i(\mathbf{a}, \mathbf{q}^{Non}, E)}{\partial a_{jm}} > \frac{\partial B_i(\mathbf{a}, \mathbf{q}^{j-Int}, E)}{\partial a_{jm}}$$

Assumption 4 is a fairly common assumption that says that investments in manager i's performance (either self investments or manager j's cross investments) are more valuable the more decisions i controls. The magnitudes of these differences are rarely specified but, as will be shown, their relative values affect the outcome of the control structure when interacted with common-pool externalities.

Definition 2 *A particular investment a_{jm} is convex in control if the following inequalities hold, and concave in control if all the inequalities are reversed:*

$$\begin{aligned} \frac{\partial B_i(\mathbf{a}, \mathbf{q}^*, E)}{\partial a_{jm}} - \frac{\partial B_i(\mathbf{a}, \mathbf{q}^{i-Int}, E)}{\partial a_{jm}} &> \frac{\partial B_i(\mathbf{a}, \mathbf{q}^{i-Int}, E)}{\partial a_{jm}} - \frac{\partial B_i(\mathbf{a}, \mathbf{q}^{Non}, E)}{\partial a_{jm}} \\ &> \frac{\partial B_i(\mathbf{a}, \mathbf{q}^{Non}, E)}{\partial a_{jm}} - \frac{\partial B_i(\mathbf{a}, \mathbf{q}^{j-Int}, E)}{\partial a_{jm}} \end{aligned}$$

Convexity in control is similar to increasing returns, but it only allows increasing returns across control structures within a fixed set of relationship-specific production decisions. In practice a given investment could eventually exhaust convexities in control and exhibit concavity in control if there are many different decisions and many different firms over which to coordinate; in the analysis that follows investments are always one or the other. It's important to emphasize that the results here do not rely on increasing returns to scale assumptions in the neoclassical sense. In fact for a given control structure I assume concavity in investments as indicated in Assumption 2.

The question of this paper is how the intensity of inter firm externalities E affect the equilibrium control structure and consequent performance of firms. I include some assumptions on E that reflect many empirical examples of commons-type externalities, but its worth noting that depending on the case these externalities could influence relationship specificities in alternative ways and give rise to alternative predictions about institutions. For the purposes of this paper, I assume that E unambiguously erodes the value of relationship specificity:

Assumption 5

$$\frac{\partial}{\partial E}\left[B_i(\mathbf{a},\mathbf{q}^*,E)-B_i(\mathbf{a},\tilde{\mathbf{q}},E)\right]=\frac{\partial\Delta B_i(\mathbf{a},E)}{\partial E}<0$$

For example, a coordinated production plan could require additional time to execute, but could ultimately produce greater value. With a pure congestion externality (as in a fishing derby), competing firms outside the relationship would use up the resource capacity before the firms inside the relationship have a chance to execute their plan. This assumption reflects stylized empirical facts about common pool resources, and indeed many of the arguments for implementing rights-based management. In the competitive common-pool, firms do not often coordinate on the act of production (as described in Deacon et al. (2008), Deacon et al. (2010), and Hilborn et al. (2005), among others), or the timing of supply to improve product form, quality, or prices (e.g., Kitts et al. (2007), Townsend et al. (2008), among others). I recognize there may be other cases where the presence of intense inter firm externalities gives rise to opportunities for coordination as a way of maintaining value - and thus augment relationship specificity. These cases are not considered here but are simple extensions of this setup that can be derived by reversing Assumption 5.

When the value of relationship specificity is eroded because of E, either through physical resource constraints or policies regulating resource use and production decisions, this can in turn alter the equilibrium ownership allocations, ex ante investments, and joint decision profiles. For example, unregulated resource-extracting or pollution-emitting firms could choose to extract or pollute until the private benefits no longer exceed the private costs ($\mathbf{q}_i$ is unconstrained within the physical limits of the resource), representing a substantial loss in potential surplus outside the relationship resulting from resource depletion or pollution damages. If the entire industry (all N firms) are limited by common resource or regulatory constraints, such as a common pool quota or a resource of fixed size or limited regenerative capacity, then $\mathbf{q}_i$ may be privately unconstrained, but E can substantially alter the benefits and choices of $\mathbf{q}_i$. The purpose of the relationship between 1 and 2 is to gain benefits from coordinating the choices of $\mathbf{q}_1$ and $\mathbf{q}_2$, but the presence of E could alter this privately optimal coordinated production plan - representing a loss in potential surplus inside the relationship. While E represents an absolute loss in benefits for everyone in the relationship, it may affect the relative value of coordinating over $\mathbf{q}_i$ differently depending on the resource. In some cases, coordination may be the only way to maintain a surplus in the presence of intense externalities but as conditions improve independent production approaches the first best; in other cases coordination may have great potential value that is eroded by the externalities and restored when the externalities are removed, as in Assumption 5.

How do these externalities and regulations affect firm boundaries and environmental performance? Regulators could choose to mitigate the losses by targeting $\mathbf{q}_i$ directly, for example through firm-specific command and control quotas, tradeable property rights to $\mathbf{q}$, or any number of mechanisms that influence $\mathbf{q}_i$ and E. These regulations then determine the scope of the decisions under the firm's control. Additionally, there may be several types of ex ante investment, from those that affect the productivity of the private decisions $\mathbf{q}_i$, to those that only influence the value from the relationship at the coordinated outcome, to those that directly raise the value of production decisions made by other members of the relationship. For example, in the unregulated case with privately unconstrained $\mathbf{q}_i$, firms may be most interested in productivity investments that reduce production costs by effectively sourcing and using cheap, polluting inputs, or that reduce direct resource extraction costs. Under firm-specific regulations, firms may become more interested in productivity investments that improve the joint capacity to develop cleaner inputs or improve the quality of the resource rather than the pace of extraction. As observed by Wilen and Richardson (2008), "new rents are generated by maximizing the value of what is caught, reversing regulated open-access incentives to maximize the quantity of what is caught. Increasing net value has been accomplished by opening up new markets, by changing product mix, and by substituting capital and labor tasks in ways that preserve the quality of the harvest".

In what follows I consider formal partnerships, followed by relational contracts. Under a formal agreement, the $\mathbf{a}$'s are chosen independently and noncooperatively in order to maximize the firm's bargaining position over the date 1 returns, and this game is repeated one period at a time. Under a relational contract, the firms recognize that while an agreement over the $\mathbf{a}$'s can't be enforced by the courts it could be self-enforced through the threat of punishment in repeated interactions. Managers contract on the level of $\mathbf{a}_i$ that each firm will choose and a set of side payments; if a manager deviates from the agreement, a punishment phase is initiated in which the game reverts to a formal agreement in all future periods, taken one period at a time. In each period of the punishment phase, the managers will always find it in their interest to renegotiate back to the optimal one-shot formal agreement, in which they behave noncooperatively on all non contractible decisions.

1.4 A One-Shot Game: Formal Partnerships in the Commons

Each of the ownership structures is compared to the first-best outcome, where I denote by $\mathbf{a}^*$ and $\mathbf{q}^*$ the investment and production decisions that maximize the total ex ante net benefits of the managers for a given level of externalities:

$$V^{FB} = \max_{\mathbf{a}} B_1(\mathbf{a}, \mathbf{q}^*, E) + B_2(\mathbf{a}, \mathbf{q}^*, E) - \mathbf{1}'\mathbf{a}$$

Here the maximization is over $\mathbf{a}$ because the problem is taken ex ante assuming that the optimal $\mathbf{q}^*$ will be reached ex post in the first best. The first order conditions for optimum ex ante actions in the first-best case are:

$$\frac{\partial B_i(\mathbf{a}, \mathbf{q}^*, E)}{\partial a_{jm}} = 1, \quad \forall \;\; i, j \in \{1, 2\}, \;\; m = 1, ..., M. \tag{1.1}$$

I consider three types of ex ante investments: a self investment a_{i1} that is concave in control, a self investment a_{i2} that is convex in control, and a cross investment a_{i3} that is concave in control. The presence of alternative types of investments is intended to create a tension between control structures under different common-pool conditions. For ease of exposition I consider a_{i2} and a_{i3} separately in comparison to a_{i1}.

Many of the conclusions about the equilibrium ownership structure depend on the parameters and conditions in a particular problem. For this reason the following remark summarizes the general results of this section:

Result 1 ***General results***

1. *Integration of some form (complete control by one party, randomized allocation of control, or temporary dictatorship by an outside manager) is more likely to be observed when common-pool externalities are reduced (i.e., property rights are more complete).*

2. *The form of integration chosen depends on the the fixed organizational costs of each form and the relative value of different investment types. Stochastic control induces more cross investments than central management, but central management induces optimal self investments.*

3. *The optimal structure may change several times as the aggregate externality is reduced. For example, nonintegration may dominate at high E, with integration under one party or outside manager over an intermediate range of E, and stochastic control at low levels of E.*

1.4.1 Two types of self investments

For the time being I restrict attention to integration and nonintegration, and go into further depth on collective ownership in section 1.4.3. Depending on the control structure $k \in \{i\text{-}Int, Non\}$, each manager i can choose $\mathbf{q}_i^k$ at date 1 based on predetermined values of $\mathbf{a}$. If the managers choose these noncooperatively to maximize private benefits, they will reach a Nash equilibrium in $\mathbf{q}$ denoted by $\tilde{\mathbf{q}}^k = (\tilde{\mathbf{q}}_i^k, \tilde{\mathbf{q}}_j^k)$. The two firms can improve upon this outcome by renegotiating to the optimal $\mathbf{q}^*$ before executing the decisions, and splitting the additional surplus. The ex ante investment problem for the firms then becomes

$$\max_{a_{i1},a_{i2}} \pi_i = B_i(a_{i1}, a_{i2}, \tilde{\mathbf{q}}^k, E) + \frac{1}{2}[B_i(a_{i1}, a_{i2}, \mathbf{q}^*, E) + B_j(a_{j1}, a_{j2}, \mathbf{q}^*, E) - B_i(a_{i1}, a_{i2}, \tilde{\mathbf{q}}^k, E) - B_j(a_{j1}, a_{j2}, \tilde{\mathbf{q}}^k, E)] - a_{i1} - a_{i2}$$

The first order conditions for firm i are:

$$\begin{aligned} \frac{\partial}{\partial a_{i1}} B_i(\mathbf{a}, \tilde{\mathbf{q}}^k, E) + \frac{1}{2}\frac{\partial}{\partial a_{i1}} \Delta B_i(\mathbf{a}, E) = 1 \\ \frac{\partial}{\partial a_{i2}} B_i(\mathbf{a}, \tilde{\mathbf{q}}^k, E) + \frac{1}{2}\frac{\partial}{\partial a_{i2}} \Delta B_i(\mathbf{a}, E) = 1 \end{aligned} \tag{1.2}$$

Under the additional assumption that common-pool externalities erode the value of investments that are convex in control faster than those that are concave in control, it can be shown that firms with these types of human capital trade offs tend to integrate more often when there are no common-pool externalities (e.g., with well-defined and enforced property rights), and tend to remain independent under heavy common-pool externalities:

Assumption 6

$$\frac{\partial^2 B_i(\cdot)}{\partial a_{im} \partial E} = \zeta_m, \quad \textit{and} \quad \frac{\partial^2 B_i(\cdot)}{\partial a_{i2} \partial E} < \frac{\partial^2 B_i(\cdot)}{\partial a_{i1} \partial E} < 0,$$

where ζ_1 and ζ_2 are constants.

Under this assumption, greater externalities reduce the benefit of consolidating control by having a relatively greater impact on investments that favor control. This is stated in the following proposition:

Proposition 1 1. *Nonntegration will be weakly better than integration whenever the following condition holds:*

$$\frac{\partial B(\mathbf{a}^{Non}, \mathbf{q}^*, E)}{\partial a_2}\left(a_2^{i-Int} - a_2^{Non}\right) - \frac{\partial B(\mathbf{a}^{Non}, \mathbf{q}^*, E)}{\partial a_1}\left(a_1^{Non} - a_1^{i-Int}\right) \leq \mathbf{1}'\mathbf{a}^{i-Int} - \mathbf{1}'\mathbf{a}^{Non}$$

2. *Managers will be weakly better off under integration than nonintegration whenever the following condition holds:*

$$\mathbf{D}\left[B_i(\mathbf{a}^{i-Int}, \mathbf{q}^*, E) + B_j(\mathbf{a}^{i-Int}, \mathbf{q}^*, E)\right]\left(\mathbf{a}^{Non} - \mathbf{a}^{i-Int}\right) \leq \mathbf{1}'\mathbf{a}^{Non} - \mathbf{1}'\mathbf{a}^{i-Int}$$

Proposition 1 simply expresses the tradeoff between the emphasis on different investments under different ownership structures. Nonintegration will be chosen over integration if shifting away from investments that favor independence into investments that favor central control does not provide enough of a benefit to justify the increased investment cost. Under integration the owner invests relatively more in a_{i2} than the nonowner, but these investments are also relatively more valuable. Conversely, underinvesting in a_{i1} does relatively less to improve the manager's Nash bargaining position under nonintegration than integration, so larger investments in a_{i1} are maintained under nonintegration.

The second condition in the proposition can be expanded and rearranged to yield

$$\left\{\frac{\partial B_i(\mathbf{a}^{i-Int},\mathbf{q}^*,E)}{\partial a_{i2}}\left(a_{i2}^{i-Int}-a_{i2}^{Non}\right)-\frac{\partial B_j(\mathbf{a}^{i-Int},\mathbf{q}^*,E)}{\partial a_{j2}}\left(a_{j2}^{Non}-a_{j2}^{i-Int}\right)\right\}-$$
$$\left\{\frac{\partial B_j(\mathbf{a}^{i-Int},\mathbf{q}^*,E)}{\partial a_{j1}}\left(a_{j1}^{Non}-a_{j1}^{i-Int}\right)-\frac{\partial B_i(\mathbf{a}^{i-Int},\mathbf{q}^*,E)}{\partial a_{i1}}\left(a_{i1}^{i-Int}-a_{i1}^{Non}\right)\right\}$$
$$\geq\left\{a_{i2}^{i-Int}+a_{j2}^{i-Int}-a_{i2}^{Non}-a_{j2}^{Non}\right\}+\left\{a_{i1}^{i-Int}+a_{j1}^{i-Int}-a_{i1}^{Non}-a_{j1}^{Non}\right\} \tag{1.3}$$

The first set of brackets is the benefit from maintaining a higher level of a_{i2} under integration, after accounting for the imbalance in investment between the two managers when one is the owning partner. Likewise, the second set of brackets is the additional benefit that could be gained from investing more in a_{i1} under nonintegration, after accounting for the reduced investment from the owning partner when he no longer controls everything. The two terms on the right hand side are the net changes in costs for each of these investments between the two regimes.

Corollary 1 *Suppose that integration dominates at $E = 0$. Then the preferred control structure will eventually switch from integration to nonintegration as $E \to \infty$.*

Proof 1 (Proof of Proposition 1) *Consider the managers' first order conditions for each investment under each ownership structure. The first order conditions for the choice of a_{im} are given by*

$$\frac{1}{2}\frac{\partial}{\partial a_{im}}B_i(\mathbf{a},\mathbf{q}^*,E)+\frac{1}{2}\frac{\partial}{\partial a_{im}}B_i(\mathbf{a},\tilde{\mathbf{q}}^k,E)=1 \tag{1.4}$$

By Assumption 4, the second term is largest when $k = i$-Int and smallest when $k = j$-Int. But when $m = 1$ the gain for i of moving from $k = j$-Int to $k = Non$

is larger than the loss for i *if he moves from* $k = i\text{-}Int$ *to* $k = Non$ *because* a_{i1} *is concave in control. By the symmetry of the managers (Assumption 1) the total investment in* a_{i1} *is largest when* $k = Non$*. By the same argument, when* $m = 2$ *the gain for* i *of moving from* $k = j\text{-}Int$ *to* $k = Non$ *is not as great as the move from* $k = Non$ *to* $k = i\text{-}Int$ *because* a_{i2} *is convex in control. The total investment in* a_{i2} *is largest when* $k = i\text{-}Int$*. Because neither control structure is dominant in both investments, the relative value of the two investment types decides the optimal control structure. The conditions in Proposition 1 can be derived by comparing the value function of the partnership evaluated at the realized choices of* $\mathbf{a}^k$ *for each control structure.*

$$V(\mathbf{a}^k) = B_1(\mathbf{a}^k, \mathbf{q}^*, E) + B_2(\mathbf{a}^k, \mathbf{q}^*, E) - \mathbf{1}'\mathbf{a}^k$$

Because V *is a concave function, its value at* $\mathbf{a}^{i-Int}$ *can be compared to its value at* $\mathbf{a}^{Non}$ *using the rooftop theorem of concave functions. For the first condition,*

$$\mathbf{D}V(\mathbf{a}^{Non})(\mathbf{a}^{i-Int} - \mathbf{a}^{Non}) \leq 0 \Rightarrow V(\mathbf{a}^{i-Int}) \leq V(\mathbf{a}^{Non})$$

$$\begin{aligned} \Rightarrow \left[\frac{\partial B_i(\mathbf{a}^{Non}, \mathbf{q}^*, E)}{\partial a_{i1}} - 1\right](a_{i1}^{i-Int} - a_{i1}^{Non}) + \\ \left[\frac{\partial B_i(\mathbf{a}^{Non}, \mathbf{q}^*, E)}{\partial a_{i2}} - 1\right](a_{i2}^{i-Int} - a_{i2}^{Non}) + \\ \left[\frac{\partial B_j(\mathbf{a}^{Non}, \mathbf{q}^*, E)}{\partial a_{j1}} - 1\right](a_{j1}^{i-Int} - a_{j1}^{Non}) + \\ \left[\frac{\partial B_j(\mathbf{a}^{Non}, \mathbf{q}^*, E)}{\partial a_{j2}} - 1\right](a_{j2}^{i-Int} - a_{j2}^{Non}) \leq 0 \end{aligned}$$

Under nonintegration managers invest identically and have equal marginal values, so the marginal values for each investment type can be combined.

$$\begin{aligned} \left[\frac{\partial B_i(\mathbf{a}^{Non}, \mathbf{q}^*, E)}{\partial a_{i2}} - 1\right]\left(a_{i2}^{i-Int} + a_{j2}^{i-Int} - a_{i2}^{Non} - a_{j2}^{Non}\right) - \\ \left[\frac{\partial B_i(\mathbf{a}^{Non}, \mathbf{q}^*, E)}{\partial a_{i1}} - 1\right]\left(a_{i1}^{Non} + a_{j1}^{Non} - a_{i1}^{i-Int} - a_{j1}^{i-Int}\right) \leq 0 \end{aligned}$$

Rearranging this expression, combining a_i's measured in the same dollar units, and dropping redundant subscripts gives the first condition in Proposition 1.

For the second condition,

$$\mathbf{D}V(\mathbf{a}^{i-Int})(\mathbf{a}^{Non} - \mathbf{a}^{i-Int}) \leq 0 \Rightarrow V(\mathbf{a}^{Non}) \leq V(\mathbf{a}^{i-Int})$$

$$\begin{aligned}\Rightarrow \left[\frac{\partial B_i(\mathbf{a}^{i-Int}, \mathbf{q}^*, E)}{\partial a_{i1}} - 1\right](a_{i1}^{Non} - a_{i1}^{i-Int}) +\\ \left[\frac{\partial B_i(\mathbf{a}^{i-Int}, \mathbf{q}^*, E)}{\partial a_{i2}} - 1\right](a_{i2}^{Non} - a_{i2}^{i-Int}) +\\ \left[\frac{\partial B_j(\mathbf{a}^{i-Int}, \mathbf{q}^*, E)}{\partial a_{j1}} - 1\right](a_{j1}^{Non} - a_{j1}^{i-Int}) +\\ \left[\frac{\partial B_j(\mathbf{a}^{i-Int}, \mathbf{q}^*, E)}{\partial a_{j2}} - 1\right](a_{j2}^{Non} - a_{j2}^{i-Int}) \leq 0\end{aligned}$$

Under integration, the owner invests more in both investments than the employee, so $a_{im}^{i-Int} > a_{jm}^{i-Int}$ for $m = 1, 2$. Rearranging this expression provides the condition in equation 1.3.

Proof 2 (Proof of Corollary 1) *Consider the first condition in Proposition 1. Assumption 6 says the first term of the the condition in Proposition 1 is declining faster than the second term as E increases. The linearity of the declines in Assumption 6 assures that the left hand side will decline relative to the right hand side as E increases.*

1.4.2 A self investment and a cross investment

In this section I consider a self investment a_{i1} that is concave in control as before, and an additional cross investment a_{i3} that is also concave in control. The ability of managers to invest in their partners' productivity creates different incentives under Nash bargaining; the cross investments may be quite valuable to the coalition but will hurt the managers' ex post bargaining position by improving the disagreement payoff of their partner. The cross investments produce a slightly different expression for the first order conditions. The ex ante investment problem for the firms in this case is

$$\max_{a_{i1},a_{i3}} \pi_i = B_i(a_{i1}, a_{j3}, \tilde{\mathbf{q}}^k, E) + \frac{1}{2}[B_i(a_{i1}, a_{j3}, \mathbf{q}^*, E) + B_j(a_{j1}, a_{i3}, \mathbf{q}^*, E) - B_i(a_{i1}, a_{j3}, \tilde{\mathbf{q}}^k, E) - B_j(a_{j1}, a_{i3}, \tilde{\mathbf{q}}^k, E)] - a_{i1} - a_{i3}$$

The first order conditions for firm i are:

$$\begin{aligned} \frac{\partial}{\partial a_{i1}} B_i(\mathbf{a}, \tilde{\mathbf{q}}^k, \mathbf{Q}_{-1}) + \frac{1}{2}\frac{\partial}{\partial a_{i1}} \Delta B_i(\mathbf{a}, E) &= 1 \\ \frac{1}{2}\frac{\partial}{\partial a_{i3}} \Delta B_j(\mathbf{a}, E) &= 1 \end{aligned} \tag{1.5}$$

In this case, under an assumption similar to Assumption 6, the incentive to make cross investments may vanish completely as externalities increase, while the incentive to make selfish investments may remain positive:

Assumption 7

$$\frac{\partial^2 B_j(\cdot)}{\partial a_{i3} \partial E} = \psi_3, \quad \frac{\partial^2 B_i(\cdot)}{\partial a_{i1} \partial E} = \psi_1, \quad \textit{and} \quad \psi_3 < \psi_1 < 0,$$

where ψ_1 and ψ_3 are constants.

As in section 1.4.1, greater externalities reduce the benefit of consolidating control by having a relatively greater impact on investments that favor control, although in this case the cross investment must be much more valuable than the self investment in order to drive integration because of the penalty it imposes on the investor in the bargaining phase. This is stated in the following proposition:

Proposition 2 *1. Nonintegration will be weakly better than integration whenever the following condition holds:*

$$\frac{\partial B(\mathbf{a}^{Non}, \mathbf{q}^*, E)}{\partial a_3} \left(a_3^{i-Int} - a_3^{Non}\right) - \frac{\partial B(\mathbf{a}^{Non}, \mathbf{q}^*, E)}{\partial a_1} \left(a_1^{Non} - a_1^{i-Int}\right) \leq \mathbf{1}'\mathbf{a}^{i-Int} - \mathbf{1}'\mathbf{a}^{Non}$$

2. Managers will be weakly better off under integration than nonintegration whenever the following condition holds:

$$\mathbf{D}\left[B_i(\mathbf{a}^{i-Int}, \mathbf{q}^*, E) + B_j(\mathbf{a}^{i-Int}, \mathbf{q}^*, E)\right] \left(\mathbf{a}^{Non} - \mathbf{a}^{i-Int}\right) \leq \mathbf{1}'\mathbf{a}^{Non} - \mathbf{1}'\mathbf{a}^{i-Int}$$

Corollary 2 *Suppose that integration dominates at $E = 0$. Then the preferred control structure will eventually switch from integration to nonintegration as $E \to \infty$.*

Proposition 2 is very similar to Proposition 1 except that in this case it is much more difficult to support integration. The partnership will invest more in $\mathbf{a}_3$ under integration than nonintegration, but by a potentially smaller margin than with $\mathbf{a}_2$ because of the damage to the managers' bargaining position. Therefore the marginal value of the cross investment at the joint decision profile must exceed the marginal self investment value by a greater margin - enough to make up for a smaller net change in the investment level. Managers can only benefit from their cross investment at the joint production profile, as opposed to the previous case where managers still benefit from a_2 outside the relationship. The proofs of Proposition 2 and Corollary 2 are almost identical to those for Proposition 1 and Corollary 1 and are available from the author upon request.

1.4.3 Collective Ownership

Now consider the case where the managers have collective control over production decisions. Managers could adopt a social choice mechanism to aggregate their preferences and determine a production plan $\grave{\mathbf{q}}$ at date 1. Each mechanism may do a good or bad job depending on its properties, but upon learning the outcome of the mechanism, managers can bargain to the optimal decision $\mathbf{q}^*$ using their benefits from the social choice outcome as a disagreement point. In other words, the mechanism would determine the disagreement point that managers are stuck with if they fail to bargain to a better solution, in the same way that under i ownership, j was stuck with $\tilde{\mathbf{q}}$ if he could not convince i that $\mathbf{q}^*$ would be an improvement. I continue to assume they equally split the surplus from any gain over the social choice outcome.

The ex ante investment problem for firm i then becomes

$$\max_{\mathbf{a}} B_i(\mathbf{a}, \grave{\mathbf{q}}^{CO}, E) + \frac{1}{2}[B_i(\mathbf{a}, \mathbf{q}^*, E) + B_j(\mathbf{a}, \mathbf{q}^*, E) - B_i(\mathbf{a}, \grave{\mathbf{q}}^{CO}, E) - B_j(\mathbf{a}, \grave{\mathbf{q}}^{CO}, E)] - \mathbf{1}'\mathbf{a}$$

ΔB_i will be smaller or larger depending on how well $\grave{\mathbf{q}}$ reflects his preferences. The first order conditions for firm i, for each investment type m, are:

$$\frac{\partial}{\partial a_{im}} B_i(\mathbf{a}, \grave{\mathbf{q}}^{CO}, E) + \frac{1}{2}\frac{\partial}{\partial a_{im}} \Delta B_i(\mathbf{a}, E) = 1 \tag{1.6}$$

The first term will equal zero if a_{im} is a cross investment. The best ownership structure not only depends on the importance of selfish and cooperative investments and the intensity of the externalities, but on how close $\grave{\mathbf{q}}_i$ comes to the optimal choice for i and whether or not the social choice outcome is influenced by the ex ante investments[9].

I consider two simple decision mechanisms for comparison, each of which reflects practices implemented empirically in common-pool settings[10]:

1. Hiring an outside manager as a temporary dictator or central manager. This central manager makes all the production decisions but is not directly involved in production and has no investments to make.

2. Stochastic control. Each manager faces some general probability p_i of being assigned sole ownership at date 1, and using his $\tilde{\mathbf{q}}^{i-Int}$ as the disagreement point in negotiations.

The central manager has no relationship-specific decisions to make; his role is to coordinate the relationship-specific decisions of other parties and his only incentive is to choose $\mathbf{q}^*$ at the beginning of date 1. If he doesn't, he can be fired. There are no distortionary investments to improve bargaining position. There are

[9] With three or more managers considering integrating it might seem appropriate to investigate a voting mechanism, such as electing a manager to make decisions or electing a decision profile directly at date 1. Yet elections are problematic in the context of this model for several reasons. First, electing a manager to make decisions is akin to assigning him control rights, which could be done at date 0 if it were efficient. Second, because $\mathbf{q}$ is multidimensional, the median voter theorem can't guarantee a unique median policy if the election is held on a choice of $\mathbf{q}$. In the absence of a unique voting outcome, a winner from the resulting tied outcomes must be chosen at random. Consider, for example, if the managers could offer successive proposals for $\mathbf{q}$ which could be rejected by any other manager. If the identity of the first proposer matters for which non-rejected proposal is ultimately selected, then the group would have to randomize over non-rejected proposals or randomize over first-proposers. Probabilistic voting models have been developed to deal with these issues, but this approach isn't consistent with the Grossman-Hart-Moore model because all actions and payoffs are common knowledge.

[10] See for example: da Silva and Kitts (2006), Townsend et al. (2008), Johnston and Sutinen (2009), Huppert (2005), Deacon et al. (2008), Deacon et al. (2010), Holland (2007)

also no incentives to make cross investments, however, and there are additional costs in the form of a fixed salary w_{center} for the central manager. A similar type of control is often observed in practice in more temporary settings, hence the existence of the profession of "project manager". Project managers are often hired within large firms to coordinate projects between multiple divisions of the firm. The project manager may have a low rank in the corporate hierarchy, but still be responsible for coordinating important production decisions. Project managers are also often hired as independent contractors for joint projects involving multiple firms or institutions, nonprofits, or governmental organizations. Once the disparate divisions or organizations have committed to a joint project in a legally binding contract (or through the directive of a higher executive), the amount of residual control they have depends on how much direct control has been allocated to the project manager. If the individual units are bound to the directives of the project manager they may have very little residual control during the project, even though the assets may revert to their control after the project ends. Likewise, the project manager has no residual control in the sense that he can't walk away from the parties with all of their assets and deploy them as he pleases [11].

In the second case, the incentives to invest in cross and selfish investments are distorted by the possibility of eventual complete control[12], however, this distortion acts as a weighted average of all the possible sole owners. Although blatantly randomized absolute control is rarely observed in practice, this weighted-dictatorship setup is in the spirit of collective management in the sense that each participant has a voice in management decisions and a chance that their ideas will be implemented. In that sense it may also capture part of what a voting model can't in this context because each agent has a chance at control.

[11] Alternatively, I could consider hiring an outside party who does have an interest in production, such as a major customer of the output (e.g., a fish processor). Then this outside party would have a self-interested initial $\mathbf{q}'$ from which to bargain. Cases where the outside manager also has cross investments to make could also be considered

[12] One could also examine which dimensions of $\mathbf{q}$ should be turned over to collective management and which should remain in the residual control of the managers. For example, if there are group allocations of species-specific catch limits, it may be best to have fishing locations decided centrally, but gear choices, fishing time, etc., decided individually.

Stochastic control The combination of central management and randomized control resemble cooperative structures that are observed in practice, where groups hire a coop manager to execute some decisions, while other decisions are decided through debates between members, committees, or elected representatives. In the case of symmetric managers randomized control simply reproduces the same total investment for the coalition as a whole as with integration under one manager, but the investments are more evenly distributed between the managers (as opposed to the lopsided incentives with one manager in complete control from date 0). Under stochastic control, each manager has some probability of being chosen to decide on a production profile at the start of date 1.

$$\max_{\mathbf{a}} p_i \left\{ B_i(\mathbf{a}, \tilde{\mathbf{q}}^{i-Int}, E) + \frac{1}{2} \left[\Delta B_i(\mathbf{a}, \mathbf{q}^{i-Int}, E) + \Delta B_j(\mathbf{a}, \mathbf{q}^{i-Int}, E) \right] \right\} +$$
$$(1-p_i) \left\{ B_i(\mathbf{a}, \tilde{\mathbf{q}}^{j-Int}, E) + \frac{1}{2} \left[\Delta B_i(\mathbf{a}, \mathbf{q}^{j-Int}, E) + \Delta B_j(\mathbf{a}, \mathbf{q}^{j-Int}, E) \right] \right\} - \mathbf{1}'\mathbf{a}$$

The first order conditions for firm i are:

$$p_i \left[\frac{\partial}{\partial a_{im}} B_i(\mathbf{a}, \tilde{\mathbf{q}}^{i-Int}, E) + \frac{1}{2} \frac{\partial}{\partial a_{im}} \Delta B_i(\mathbf{a}, \mathbf{q}^{i-Int}, E) \right] +$$
$$(1-p_i) \left[\frac{\partial}{\partial a_{im}} B_i(\mathbf{a}, \tilde{\mathbf{q}}^{j-Int}, E) + \frac{1}{2} \frac{\partial}{\partial a_{im}} \Delta B_i(\mathbf{a}, \mathbf{q}^{j-Int}, E) \right] = 1$$

This case is very similar to integration, only the sole owner is not revealed until after investments are made, so the incentives to make cross investments are a weighted average of being the owner and being the employee, and similarly for self-investments. Because managers are symmetric in this case, however, the reduced investment by one manager caused by the weighting is exactly balanced by increased investment by the other manager. This reallocation of investments between the managers makes them better off than under integration because of the concavity of the benefit functions, as stated in Proposition 3.

Proposition 3 ***Stochastic Control***

Suppose that (i) the randomization process incurs a fixed cost Γ, and (ii) at $E = 0$ managers prefer stochastic control over integration.

1. *If $\Gamma = 0$, managers are strictly better off under stochastic control than under integration.*

2. *For low, nonzero Γ, the preferred control structure is more likely to switch from stochastic control to nonintegration as $E \to \infty$.*

3. *For high enough Γ, integration under one party will dominate over an intermediate range of E. The preferred control structure will switch from stochastic control to integration as E increases from 0, then switch again from integration to nonintegration as E continues to increase.*

Proof 3 (Proof of Proposition 3) *This is again shown by comparing the value functions evaluated at the stochastic control investment level $\mathbf{a}^{SC}$ and the integrated investment level.*

$$\mathbf{D}V(\mathbf{a}^{i-Int})(\mathbf{a}^{SC} - \mathbf{a}^{i-Int}) \leq 0 \Rightarrow V(\mathbf{a}^{SC}) \leq V(\mathbf{a}^{i-Int})$$

$$\begin{aligned}
\Rightarrow \left[\frac{\partial B_i(\mathbf{a}^{i-Int}, \mathbf{q}^*, E)}{\partial a_{i1}} - 1\right](a_{i1}^{SC} - a_{i1}^{i-Int}) + \\
\left[\frac{\partial B_i(\mathbf{a}^{i-Int}, \mathbf{q}^*, E)}{\partial a_{i2}} - 1\right](a_{i2}^{SC} - a_{i2}^{i-Int}) + \\
\left[\frac{\partial B_j(\mathbf{a}^{i-Int}, \mathbf{q}^*, E)}{\partial a_{j1}} - 1\right](a_{j1}^{SC} - a_{j1}^{i-Int}) + \\
\left[\frac{\partial B_j(\mathbf{a}^{i-Int}, \mathbf{q}^*, E)}{\partial a_{j2}} - 1\right](a_{j2}^{SC} - a_{j2}^{i-Int}) \leq 0
\end{aligned}$$

The aggregate investments are the same under the two regimes so all of the terms accounting for additional investment costs cancel. In addition, the changes in a given investment $a_{jm}^{SC} - a_{jm}^{i-Int}$ are symmetric for a given m between managers and can be written Δa_m. Combining terms and rearranging yields

$$\Delta a_1 \left[\frac{\partial B_j(\mathbf{a}^{i-Int}, \cdot)}{\partial a_{j1}} - \frac{\partial B_i(\mathbf{a}^{i-Int}, \cdot)}{\partial a_{i1}}\right] \leq \Delta a_2 \left[\frac{\partial B_i(\mathbf{a}^{i-Int}, \cdot)}{\partial a_{i1}} - \frac{\partial B_j(\mathbf{a}^{i-Int}, \cdot)}{\partial a_{j2}}\right]$$

The left hand side is positive and the right hand side is negative, so this condition never holds (i.e., integration is never better than stochastic control when *randomization is costless). However, both terms approach zero as E grows. With a fixed cost of randomization, stochastic control is only preferable if*

$$V(\mathbf{a}^{SC}) - \Gamma \geq V(\mathbf{a}^{i-Int})$$

As the difference between the two value functions shrinks as common-pool externalities grow, a switching point will be crossed.

Keeping in mind that the aggregate investment is the same between integration and stochastic control, the following condition holds at $E = 0$:

$$\mathbf{D}V(\mathbf{a}^{Non})(\mathbf{a}^{i-Int} - \mathbf{a}^{Non}) \geq V(\mathbf{a}^{SC}) - V(\mathbf{a}^{Non}) > V(\mathbf{a}^{i-Int}) - V(\mathbf{a}^{Non})$$

The first inequality provides the condition for either stochastic control or integration to dominate nonintegration for a given E. Subtracting a large enough fixed cost Γ from the middle term in the inequality will make the rankings of the last two terms more likely to switch as E increases.

The Central Manager The central manager is paid a fixed salary w_{center} that is negotiated at date 0 before the investments are made. The salary must be less than the difference between the expected surplus under central management and the next best ownership structure, but greater than the central manager could earn elsewhere. Once the salary is agreed upon, however, it does not influence any further investment or production decisions[13].

In this case, the central manager has no direct hand in production, and simply chooses the decisions for the other managers to implement; date 1 bargaining is not required because the central manager has no private incentives that are in conflict with the group-optimal production plan, and all of the residual control of the individual managers has been allocated to the central manager as direct

[13] In Hart and Moore (1990), an outside party should be granted ownership if they are an indispensable trading partner, but should not be granted control if it's possible to randomize the assignment of control among the inside parties just after investments are made, and if the outsider is completely dispensable. The case considered here is a middle case; the inside parties can still create value without the outside manager, so he is neither completely indispensable nor completely dispensable. Randomization over control in this case prioritizes the investment types differently. A more complete political economy model where managers expend some resources influencing their control probability is an interesting topic for future research

control. In this sense, no party has residual control. Each manager simply receives his own firm's value from the optimal production plan:

$$\max_{\mathbf{a}_i} \pi_i^{CO} = B_i(\mathbf{a}, \mathbf{q}^*, E) - \frac{1}{2} w_{center} - \mathbf{1}'\mathbf{a}_i$$

The first order condition for firm i is

$$\frac{\partial}{\partial a_{im}} B_i(\mathbf{a}, \mathbf{q}^*, E) = 1 \tag{1.7}$$

In a one-shot game, central management provides optimal incentives for self-investments, but no incentives for cross investments (the derivative of B_i with respect to a_{i3} is zero). Clearly, in the case in section 1.4.1 with only self-investments, central management will be optimal if the gains from improved investments exceed the fixed cost of hiring the coordinating employee, i.e.,

$$V(\mathbf{a}^*, \mathbf{q}^*, E) - V(\mathbf{a}^k, \mathbf{q}^*, E) \geq w_{center} \tag{1.8}$$

This condition is less likely to hold for any alternative k as E increases (Assumption 6). For high enough management costs it may not even be met at $E = 0$.

Proposition 4 ***Self Investments***
Suppose that (i) both investments are self investments as in Section 1.4.1, (ii) the central manager has a fixed salary w_{center}, and (iii) managers 1 and 2 to prefer central management over any other control structure at $E = 0$.

1. *If $w_{center} = 0$, then the partnership is strictly better off under central management than any other control structure for all E.*

2. *At low nonzero levels of w_{center}, the preferred control structure is more likely to switch from central management to nonintegration as $E \to \infty$.*

3. *For high enough w_{center} integration under one party will dominate over an intermediate range of E. The preferred control structure will switch from*

central management to integration as E increases. As E continues to increase, the preferred control structure will switch again from integration to nonintegration as described in Proposition 1.

Proof 4 (Proof of Proposition 4) *Part 1 holds because with self investments only, central management induces the first best investments.*

Because the investments are always greater for central management than any other structure k, $V(\mathbf{a}^*, \mathbf{q}^*, E)$ declines more steeply than $V(\mathbf{a}^k, \mathbf{q}^*, E)$ as E increases (Assumption 6).

By Proposition 1, nonintegration dominates integration at high E. Therefore at low w_{center}, $V(\mathbf{a}^*, \mathbf{q}^*, E) - w_{center}$ is more likely to intersect $V(\mathbf{a}^{Non}, \mathbf{q}^*, E)$ than $V(\mathbf{a}^{i-Int}, \mathbf{q}^*, E)$. As w_{center} goes up and $V(\mathbf{a}^*, \mathbf{q}^*, E) - w_{center}$ shifts down in V-E space, this curve is more likely to intersect $V(\mathbf{a}^{i-Int}, \mathbf{q}^*, E)$, leaving central management dominant only at the very lowest externality levels.

Proposition 5 ***Cross Investments***
Suppose that (i) there is only one self investment and one cross investment as in Section 1.4.2, (ii) the central manager has a fixed salary w_{center}, and (iii) managers 1 and 2 to prefer integration over any other control structure at $E = 0$.

Even at $w_{center} = 0$, central management will only dominate when

$$\frac{\partial B_i(\mathbf{a}^{CO}, \mathbf{q}^*, E)}{\partial a_{i3}} < 1.$$

This condition is more likely to hold at very high levels of E. Nonintegration will be preferred over an intermediate range of E and will switch to integration under one party as $E \to 0$.

In the case of section 1.4.2, gains from central management will only be achieved if the marginal benefit of the first unit of cross investment is not worth its marginal cost. The equilibrium cross investment in central management is $a_3 = 0$, although the optimal level of a_1 is chosen. Nonintegration can only improve on this when a_3 is worth some nonzero investment, and likewise for integration.

Proof 5 (Proof of Proposition 5) *Nonintegration will be preferred over central management when*

$$\mathbf{D}V(\mathbf{a}^{CO})(\mathbf{a}^{Non} - \mathbf{a}^{CO}) \geq 0$$

$$\Rightarrow \left[\frac{\partial B_i(\mathbf{a}^{CO}, \mathbf{q}^*, E)}{\partial a_{i1}} - 1\right](a_{i1}^{Non} - a_{i1}^{CO}) + \left[\frac{\partial B_i(\mathbf{a}^{CO}, \mathbf{q}^*, E)}{\partial a_{j3}} - 1\right](a_{j3}^{Non} - a_{j3}^{CO}) +$$
$$\left[\frac{\partial B_j(\mathbf{a}^{CO}, \mathbf{q}^*, E)}{\partial a_{j1}} - 1\right](a_{j1}^{Non} - a_{j1}^{CO}) + \left[\frac{\partial B_j(\mathbf{a}^{CO}, \mathbf{q}^*, E)}{\partial a_{i3}} - 1\right](a_{i3}^{Non} - a_{i3}^{CO}) \geq 0$$

Recall that $a_{i1}^{CO} = a_{i1}^* \Rightarrow \partial B_i(\mathbf{a}^{CO}, \mathbf{q}^*, E)/\partial a_{i1} = 1$*. These terms cancel in the above expression. Furthermore,* $a_{i3}^{CO} = 0$*.*

$$\Rightarrow \frac{\partial B_i(\mathbf{a}^{CO}, \mathbf{q}^*, E)}{\partial a_{j3}} \cdot a_{j3}^{Non} + \frac{\partial B_j(\mathbf{a}^{CO}, \mathbf{q}^*, E)}{\partial a_{i3}} \cdot a_{i3}^{Non} \geq a_{j3}^{Non} + a_{i3}^{Non}$$

The marginal value terms can be combined because they are evaluated at the same level of $\mathbf{a}^{CO}$ *and managers are symmetric.*

$$\Rightarrow \frac{\partial B_i(\mathbf{a}^{CO}, \mathbf{q}^*, E)}{\partial a_{j3}} \cdot (a_{j3}^{Non} + a_{i3}^{Non}) \geq a_{j3}^{Non} + a_{i3}^{Non}$$

Rearranging terms provides the condition.

1.5 Relational contracts

This section extends the model of sections 1.3 and 1.4 to a repeated game setting by modifying the relational contracting model developed by Baker et al. (2002) to accommodate changes in intra-industry externalities. Under relational contracts, at date 0 firms not only agree on the allocation of decision rights, but they contract on a set of side payments $\beta(\mathbf{a})$ to be paid at date 1 after the outcomes are realized. The reason $\mathbf{a}$ and $\mathbf{q}$ are not contractible in this model is that they cannot be verified by neutral third parties (e.g., courts and regulators) even though they are observable to the agents. In a repeated game, however, the players can make self-enforcing agreements enforced through trigger-type punishments in the event of a deviation. They can agree to make the jointly optimal coordinated production decisions $\mathbf{q}$ at the start of date 1, rather than come to the table brandishing threat points, in exchange for a given set of ex ante choices $\mathbf{a}$ and a set of side payments β. Because the side payments are based on the outcomes, they depend on the ex ante investments, and the investments are made in anticipation of how they will affect the realized side payments. At date 1, after any production uncertainty is resolved but before actually engaging in production, firms decide whether or not to renege on the agreement. If they don't renege, they produce at $\mathbf{q}^*$ and pay $\beta(\mathbf{a})$. If they renege, they refuse to pay (or receive) $\beta(\mathbf{a})$, they threaten to produce at $\tilde{\mathbf{q}}$, and Nash-bargain to the coordinated outcome of $\mathbf{q}^*$, before executing the production decisions. If a player reneges, he is punished by being excluded from all future relational contracts. The benefits of reneging are the foregone side payments and the share of surplus gained in bargaining. The costs of reneging are the loss of all future gains from the agreement. The stages of the game are infinitely repeated by managers who live forever and share a common interest rate r.

Let $\beta_i = \sum_j b_{ij} + b_{ji}$, or the net payments from i to all other players, and from all other players to i. In general, i will keep his word if the net present value of enhanced ex ante investments net of the side payments in every period is greater than this period's deviation payoff earned at the current ownership structure (by refusing to pay the side payments and Nash bargaining over $\mathbf{q}$), plus the punishment value for all future periods. [14]:

$$\begin{aligned} &B_i(\mathbf{a}^R, \mathbf{q}^*, E) + \beta_i + \frac{\pi^R}{r} \geq B_i(\mathbf{a}^R, \tilde{\mathbf{q}}^k, E) + \\ &\frac{1}{2}\left[\sum_{j=1}^{2} B_j(\mathbf{a}^R, \mathbf{q}^*, E) - \sum_{j=1}^{2} B_j(\mathbf{a}^R, \tilde{\mathbf{q}}^k, E)\right] + \frac{\pi^F}{r} \end{aligned} \tag{1.9}$$

where R stands for the outcome of the relational contract, and F stands for the outcome of the next best formal, or one-shot, relationship described in section 1.4.

[14]With multiple players, if one defects the others could revert to the next best relational contract without the defector, but still deal with the defector in a formal relationship. This might weaken the punishments. Allowable punishments may also be constrained by regulations; if the defector is protected under formal legal agreements, the non-defectors may have limited ability to wrest control from the defector

When one manager reneges, the other manager may still find it optimal to work with him in a formal setting, but won't engage in future relational contracts that rely on trust. So the punishment payoff is a reversion to the ownership structure that provides the best one-shot coalition profits, earned every period in the future. During the deviation stage, however, the reneging firm gets his Nash bargaining share based on the current ownership structure - so some ownership structures may provide greater reneging temptations than others. The results of this analysis rely on the parameter values and functional forms specific to a given context and thus don't lend themselves to formal propositions. Before discussing several ownership structures I summarize these results below:

Result 2 ***Relational Contracts***

- *Relational contracts are more likely to be supported under any ownership structure as $E \to 0$*
- *Greater variability in the production environment makes cooperation in relational contracts more difficult to support at any level of E.*
- *Integrated ownership under one party creates the greatest temptation to renege. This temptation is declining as E increases; with less overall value, there is less value in the deviation payoff. However, the value of the contract could decline at an even faster rate in E so the range where cooperation is supported is ambiguous.*
- *Nonintegrated ownership provides the lowest temptation to renege on relational contracts. This temptation is stable over E. Central management differs from this only by the size of the fixed salary.*

1.5.1 Relational Integration

Under relational integration, the owner has a relational contract with the other manager (now his employee) to choose the optimal decisions from the beginning of date 1, and will choose the actions $\mathbf{a}_i^{RI}$ to solve

$$\pi^{RI} = \max_{\mathbf{a}_i} \beta_i(\mathbf{a}) + B_i(\mathbf{a}, \mathbf{q}^*, E) - \mathbf{1}'\mathbf{a}_i$$

Notice no bargaining over $\mathbf{q}$ is required, so B_i isn't shared directly, except through the side payments. While the relational contract is in place, the non-owner can choose $\mathbf{a}_j^{RI}$ to solve

$$\max_{\mathbf{a}_j} \beta_i(\mathbf{a}) + B_j(\mathbf{a}, \mathbf{q}^*, E) - \mathbf{1}'\mathbf{a}_j$$

where the total surplus under relational integration is equal to

$$V^{RI} = B_i(\mathbf{a}^{RI}, \mathbf{q}^*, E) + B_j(\mathbf{a}^{RI}, \mathbf{q}^*, E) - \mathbf{1}'\mathbf{a}_i^{RI} - \mathbf{1}'\mathbf{a}_j^{RI} \tag{1.10}$$

The owner will honor this contract as long as

$$\begin{gathered} B_i(\mathbf{a}^{RI}, \mathbf{q}^*, E) + \beta_i + \frac{\pi_i^{RI}}{r} \geq B_i(\mathbf{a}^{RI}, \tilde{\mathbf{q}}^{i-Int}, E) + \\ \frac{1}{2}\left[\Delta B_i(\mathbf{a}^{RI}, E) + \Delta B_j(\mathbf{a}^{RI}, E)\right] + \frac{1}{r}\max\left[\pi_i^{FN}, \pi_i^{FI}, \pi_i^{FC}\right] \end{gathered} \tag{1.11}$$

Where FN, FI, and FC stand for formal nonintegration, formal integration, and formal central management, respectively. Likewise, the non owner will honor the contract as long as

$$\begin{gathered} B_j(\mathbf{a}^{RI}, \mathbf{q}^*, E) + \beta_j + \frac{\pi_j^{RI}}{r} \geq B_j(\mathbf{a}^{RI}, \tilde{\mathbf{q}}^{i-Int}, E) + \\ \frac{1}{2}\left[\Delta B_i(\mathbf{a}^{RI}, E) + \Delta B_j(\mathbf{a}^{RI}, E)\right] + \frac{1}{r}\max\left[\pi_j^{FN}, \pi_j^{FI}, \pi_j^{FC}\right] \end{gathered} \tag{1.12}$$

Combining these conditions yields a necessary condition for relational employment to be self-enforcing:

$$\begin{gathered} \frac{1}{r}\left\{V^{RI} - \max\left[V^{FN}, V^{FI}, V^{FC}\right]\right\} \geq \\ \max\left\{\beta_i - \frac{1}{2}\left[\Delta B_i(\mathbf{a}^{RI}, E) - \Delta B_j(\mathbf{a}^{RI}, E)\right]\right\} - \\ \min\left\{-\beta_j - \frac{1}{2}\left[\Delta B_i(\mathbf{a}^{RI}, E) - \Delta B_j(\mathbf{a}^{RI}, E)\right]\right\} \end{gathered} \tag{1.13}$$

The left hand side of this condition is the expected surplus from improved investments - the value of moving from the distorted investments in spot ownership structures to optimal investments supported by relational contracts, evaluated at the expected value of any random variables not realized until date 1. How E affects the value of these investments will determine the size of this surplus.

The right hand side is the temptation to renege, evaluated at the maximum and minimum of any random variables realized at date 1 (thus giving the maximum and minimum possible bargaining values and side payments). As I discussed in Section 1.3, the difference in value between the noncoordinated and coordinated decisions (ΔB) is greater for the non owner than for the owner. This means that the values in square brackets on the right hand side (the difference in the ΔB's) are negative. Furthermore, this disparity is likely to be greater when a good state of the world is realized at date 1 than in a bad state (in the worst state they would get nothing for either decision profile) - so these differences augment the potential difference in maximum and minimum side payments, making relational employment potentially difficult to sustain. This is similar to one of the main findings in Baker et al. (2002). The owner has a strong incentive to simply make his decisions independently, refuse to pay the side payment, and benefit from his superior bargaining position.

But how does this change as inter firm externalities intensify? The reneging temptation declines with an increase in these externalities, but whether this makes relational employment more palatable depends on how fast the relational surplus (the left hand side) is also declining. And as will become clear in the next section, the reneging temptation for relational integration declines until it reaches the temptation in relational non-integration, where it remains for greater externalities, while the relational surplus continues to decline. Depending on these relative rates of decline, there may be different intervals of externalities over which each ownership form is supported.

1.5.2 Relational Nonintegration

The same reasoning can be used to derive an analogous expression when each manager controls a separate set of decisions. The nonintegrated managers agree to choose jointly optimal decisions from the beginning of date 1, an agreement which is supported by side payments and trust that the other will abide by the agreement. Managers will choose the actions $\mathbf{a}_i^{RN}$ to solve

$$\pi^{RN} = \max_{\mathbf{a}_i} \beta_i(\mathbf{a}) + B_i(\mathbf{a}_i, \mathbf{q}^*, E) - \mathbf{1}'\mathbf{a}_i$$

and similarly for j. The total surplus under relational nonintegration is equal to

$$V^{RN} = B_i(\mathbf{a}^{RN}, \mathbf{q}^*, E) + B_j(\mathbf{a}^{RN}, \mathbf{q}^*, E) - \mathbf{1}'\mathbf{a}_i^{RN} - \mathbf{1}'\mathbf{a}_j^{RN} \tag{1.14}$$

Notice the optimization problem is the same as in relational integration, however, the reneging temptations will be different. A manager will honor this contract as long as

$$B_i(\mathbf{a}^{RN}, \mathbf{q}^*, E) + \beta_i + \frac{\pi_i^{RN}}{r} \geq B_i(\mathbf{a}^{RN}, \tilde{\mathbf{q}}^{Non}, E) +$$
$$\frac{1}{2}\left[\Delta B_i(\mathbf{a}^{RN}, E) + \Delta B_j(\mathbf{a}^{RN}, E)\right] + \frac{1}{r}\max\left[\pi_i^{FN}, \pi_i^{FI}, \pi_i^{FC}\right] \tag{1.15}$$

Although this condition looks similar to 1.11, the current period reneging payoff is the Nash bargaining solution from a position of Nonintegration, rather than from a position of sole ownership. So the first term on the right hand side has a different value than in the previous case.

Combining these conditions yields a necessary condition for relational Nonintegration to be self-enforcing:

$$\frac{1}{r}\left\{V^{RN} - \max\left[V^{FN}, V^{FI}, V^{FC}\right]\right\} \geq \tag{1.16}$$
$$\max\left\{\beta_i - \frac{1}{2}\left[\Delta B_i(\mathbf{a}^{RN}, E) - \Delta B_j(\mathbf{a}^{RN}, E)\right]\right\} -$$
$$\min\left\{-\beta_j - \frac{1}{2}\left[\Delta B_i(\mathbf{a}^{RN}, E) - \Delta B_j(\mathbf{a}^{RN}, E)\right]\right\} \tag{1.17}$$

The more homogeneous the managers are, the more similar are their gains from coordinating (ΔB). In the perfectly symmetric case, the right hand side collapses to just the maximum difference between side payments. This difference is less sensitive to inter firm externalities than the augmented reneging temptation under Relational Integration, which eventually converges to the reneging temptation here as externalities increase. In general, the difference in value between independent choices of q and coordinated choices of q drives the temptation to renege. For high externalities, relational integration and relational nonintegration offer the same benefits. If there are any organizational costs to integrating, relational non-integration will be preferred over a greater range of externalities than relational integration. At very intense inter firm externalities, no relational contract can be supported.

Furthermore, the uncertainty in the random variable realized at date 1 matters. The left hand side is the expected gain from better investments, while the right hand side is the difference in production values at extreme states of nature. For wide extremes, the relational contract is less likely to be supported (and this will affect the relative value of relational integration and nonintegration over different values of E). The left hand side has a greater value at low E but may decline faster depending on the variability in the state of nature.

1.5.3 Relational Central Management

In this case, the central manager chooses optimal decisions from the beginning of date 1, and firms agree to make optimal investments which are supported by side payments and trust that the other will abide by the agreement. Managers will choose the actions $\mathbf{a}_i^{RC}$ to solve

$$\pi^{RC} = \max_{\mathbf{a}_i} \beta_i(\mathbf{a}) + \beta_{iC}(\mathbf{a}) + B_i(\mathbf{a}_i, \mathbf{q}^*, E) - \mathbf{1}'\mathbf{a}_i$$

and similarly for j, where β_{iC} is i's share of the relational contracting payment to the central manager. Because the realized benefits are contractible in the repeated game, the central manager can demand a share of the surplus or threaten to quit. The total surplus under relational central management is equal to

$$V^{RC} = B_i(\mathbf{a}^{RC}, \mathbf{q}^*, E) + B_j(\mathbf{a}^{RC}, \mathbf{q}^*, E) - \mathbf{1}'\mathbf{a}_i^{RC} - \mathbf{1}'\mathbf{a}_j^{RC} - \beta_C \tag{1.18}$$

Notice in this case some of the surplus goes to the central manager. Otherwise the optimization problem is the same as in the other two cases, however, the reneging temptations will again be different. A manager will honor this contract as long as

$$B_i(\mathbf{a}^{RC}, \mathbf{q}^*, E) + \beta_i + \beta_{iC} + \frac{\pi_i^{RC}}{r} \geq \\ B_i(\mathbf{a^{RC}}, \mathbf{q}^*, E) - \frac{1}{2}w_{center} + \max\left[\pi_i^{FN}, \pi_i^{FS}, \pi_i^{FC}\right] \tag{1.19}$$

In this case, if i reneges, he's still bound by the central manager's decision profile and still has to pay his portion of the central manager's formal salary. The central manager will honor the contract if today's realized side payment plus the present value of expected future side payments exceed the formal salary he could demand this period and the present value of his outside wage in future periods:

$$\beta_C + \frac{\beta_C^e}{r} \geq w_{center} + \frac{w_{out}}{r} \tag{1.20}$$

Combining these conditions yields a necessary condition for a relational central management contract to be self-enforcing:

$$\frac{1}{r}\left\{V^{RC} - \max\left[V^{FN}, V^{FS}, V^{FC}\right]\right\} \geq \max\left[\beta + \beta_C + \frac{w_{out}}{r}\right] - \min\left[\beta + \beta_C\right] \tag{1.21}$$

The right hand side of this condition is slightly greater than the reneging temptation under relational Nonintegration with symmetric firms, but if firms are sufficiently asymmetric, then relational central management offers the lowest reneging temptations. If I assume that E only affects the probability of getting a good or bad state of nature, but not the value once that state is realized, then the difference in max and min side payments is constant over any values of E while the expected surplus from better investments is still declining.

The institutional form ultimately chosen depends on comparative derivatives with respect to E, initial values at $E = 0$, and the variability in states of nature.

1.6 New England Groundfish Sector Allocations

This section describes a quasi-experiment with property rights in the New England fishing industry that exhibits several important features from the theory of the firm. In the remainder of the paper I will use this setting to empirically estimate performance changes under different property and regulatory regimes. The New England Groundfish Fishery consists of hundreds of vessels with access permits to harvest over a dozen bottom-dwelling species that are regulated under one umbrella (including cod, halibut, haddock, pollock, hake, and flounder). Many vessels are not active, or also fish for additional species regulated under different sets of rules, but there are several hundred vessels that are consistently active and rely on groundfish for a substantial portion of their income. Prior to 2004, all vessels in this fishery were regulated through a combination of limited access command-and-control policies such as individual limits on days-at-sea (DAS) and other catch limits and spatial restrictions. In 2004 vessels were given an opportunity to form groups to manage output quotas, and to participate in trading and leasing markets for their DAS allocations.

Large aggregate externalities generated by individuals through the common-pool have persisted in the groundfish fishery for decades. Common-pool externalities in this setting have taken two main forms: dynamic impacts on the fish stocks because of overfishing, and reduced fishing opportunity for individuals within each season because of regulatory responses to aggregate catches. Most of the groundfish stocks were classified by federal scientists as either overfished (in a depleted state), or experiencing overfishing (heading towards or remaining in a depleted state) as of 2007. Within-season regulations included industry-wide soft annual caps on individual species (called "target total allowable catches", or target TACs). When the industry reached the TAC for a given species there were no shutdown provisions, but an individual's remaining DAS were devalued and regulators would implement area closures and uniform harvest limits for individual trips ("trip limits"). In other words, an individual vessel could face reductions in fishing opportunity and catch based on the catches of all the other vessels in the industry. When trip limits were exceeded vessels could legally discard the excess but were not allowed to sell it; furthermore, overages at the trip and season level were not deducted from the following years' limits to allow the stock to rebound, creating more long-run externalities. Vessels could also be restricted to specific times of year and areas depending on the type of gear they used and the status of the TAC each year. These soft limits on catch at the season and trip level did little to reduce the impact of overfishing, while significantly raising the costs to fishermen of complying with the regulations.

In 2004 new regulations allowed trading of DAS allocations, but tightened the species-specific trip limits and issued fewer DAS[15]. As an experimental program, the new regulations also allowed groups of vessels to apply for their own share of the TAC of individual species to manage themselves, according to their own rules. Groups could voluntarily form "sectors", design a plan for managing their collective allocation, and submit the plan to federal regulators for approval. Vessels that didn't form sectors could participate in the DAS market and were subject to the same complicated system of regulations[16]. Sectors, by contrast, were allowed to determine their own distribution of fishing activity among their members as long as they stayed below their allocated catch limits, did not enter prohibited areas, or otherwise violate the terms of their federally-approved operations plan. Sector vessels were, however, prohibited from transferring their DAS outside the sector.

Sectors resemble the theoretical model in this paper in several important ways:

1. *Reduction in common-pool externalities*
   Sector vessels were shielded from intraseason common-pool resource externalities from the rest of the industry. According to the new regulations, "A primary motivation for the formation of a sector is the assurance that members of the sector will not face reductions of catch or effort as a result of the

[15] Amendment 13 to the Northeast Multispecies Fishery Management Plan.

[16] The DAS market had many frictions designed to prevent excessive consolidation while reducing fishing capacity. Trades required application to and approval from federal regulators following a 45-day waiting period. Permanent transfers of DAS were subject to automatic 40 percent reductions in the remaining DAS for the buyer. In addition, there was no central clearinghouse for trades, which relied on bilateral bargaining and brokers.

actions of vessels outside of the sector (i.e., if the other vessels exceed their target TACs)" (of Commerce (2004)).

2. *Timing*

   There was a distinct "ex ante" period during which sector participants chose the internal allocation mechanism and had the opportunity to take actions that would improve the value of the sectors ex post. Sectors were required to submit their operations plan at least one year before they were to begin fishing operations as a sector, each year. After the initial formation, members were required to commit to membership several months in advance of the following fishing year, but could only change their minds before the season began. These decisions were made with some uncertainty about the production environment in the forthcoming seasons. Once in the sector, vessels were required to stay in the sector for a full year, and could not fish until the following year if they quit mid-season. Rounds of ex ante investment and ex post negotiation may also have taken place within the season as members held periodic meetings to adjust their strategy in between trips.

3. *Organizational form*

   Sectors hired a salaried manager to monitor and enforce operations plans who was not involved in production, and they elected a board to determine sector rules and make strategic decisions. There were additional fixed costs of organizing including ensuring compliance with federal rules, and paying for third-party monitoring requirements imposed by federal regulators. Individual sector vessels sacrificed some of the residual control over their own fishing operations attached to their fishing permits by relinquishing control to the hired, salaried manager, the rules determined by and with other participants, and the elected board members of the sector. For example, unlike the common-pool vessels who each individually owned their DAS, the sector entity officially owns the DAS allocations of its members and intrasector transfers must be approved by the sector manager. The sector manager can also order vessels to stop fishing when limits are approaching, unlike regulators in the common pool. The board can prohibit any fishing activities it deems in conflict with sector goals, and violators can be punished with heavy fines or expulsion, which would prevent them from fishing in the common pool for a year.

Two such sectors formed following the regulatory change. The Georges Bank Cod Hook Sector formed in 2004 to manage a cod allocation but remained under common pool regulations for the catch of all other species. In 2006 the Georges Bank Fixed Gear Sector formed to harvest an allocation of cod as well. These sectors were bound by their operations plans to use specific technologies (gear) in the harvest of their targeted species. Although these sectors only received a share allocation of one species, the individual vessels' DAS for all species were controlled by the sector entity.

Although the sectors were allocated quota only for cod, as figure 1.1 indicates, the actual species composition of the catch changed substantially within one of the sectors following its formation, particularly with the Hook Sector. Within the groundfish fishery, Hook Sector vessels had been cod specialists but shifted away from targeting cod and focused more on haddock, which had begun to show strong signs of stock recovery (figure 1.11). These sectors were advocating that they be managed by species quota allocations only, rather than the hybrid of effort controls and cod quota they faced (da Silva and Kitts (2006)). But the Hook Sector had very little history catching other groundfish species, and thus very little basis to make a claim to catch rights of other species. Thus in order to make the case for expanded quota allocations they needed to pursue a joint strategy to expand their species portfolio. Fixed Gear Sector vessels, on the other hand, had always harvested a diverse portfolio of groundfish but had shifted out of cod (and groundfish in general) in the years leading up to the passage Amendment 13. Following their formation as a sector in 2006, they shifted back into a greater focus on cod harvesting. It's less clear whether this was a concerted strategy or a reflection of industry trends (figures 1.11 and 1.11). Sector vessels also shifted effort toward other fisheries outside the groundfish complex, most notably into the shellfish fishery as well as monkfish, dogfish, and other inshore predator fishes.

The data used in this study includes logbook and landings data between the fishing years 1999 and 2008. Fishing years run from May 01 to April 30. For each fishing trip, captains record the catch, landings, discards, and prices by species as well as the general location of harvest, the gear used, the crew size, and the amount of time on the water. When vessels land their catch in port, the buyers fill out a "dealer report" that also includes many of the same variables, including when the vessel left, how long it was gone, the size of the crew, and catches and prices by species. Although both of these datasets are self reported, they are reported by different sources and matched by National Marine Fisheries Service data auditors to ensure consistency. Capital stock variables including the length, tonnage, horsepower, age and owner, are recorded in a federal vessel registry. The federal observer program also provides occasional trip data from independent observers who ride along on fishing trips and record data independently, including species composition, locations, inputs, and records of capital equipment including electronics and processing technologies in use on board the vessel. However, the sample size of independently observered trips is very small and this data is not used in this version of the paper but will be incorporated in later versions. Biomass indices for individual species were taken from the Northeast Fisheries Science Center's annual spring research bottom trawl survey cruises on Georges Bank and represent abundance estimates independent of commercial fishing data. Daily weather and oceanographic data on sea surface temperature and wave height is downloaded from NOAA data buoys on Georges Bank to control for fishing participation and environmental variability. Weekly diesel prices were gathered from the U.S. Energy Information Administration web site. Combined, these sources result in a dataset that has almost daily frequency on inputs, outputs, and environmental and market shocks. For econometric analysis, I aggregate the data to the weekly level to reduce some of the noise and time series gaps caused by irregular length and frequency of individual fishing trips.

1.7 Empirical Approach

This section estimates changes in performance for sector vessels following the policy change, relative to similar independent vessels. To measure performance changes, I estimate vessel-specific time-varying productivity parameters in a difference-in-differences framework. I address selectivity bias that arises from the decisions to enter or exit the fishery in a given week and to join sectors in a given year. I also address the potential endogeneity of variable inputs caused by unobserved ex ante managerial choices, and correct for problems with difference-in-difference estimators themselves (Donald and Lang (2007), Bertrand et al. (2004)).

These productivity estimates are intended to capture managerial performance. The availability of frequent and abundant data on inputs and outputs for individual fishing trips makes production estimation an obvious first choice for capturing firm performance. Many authors have argued that the decisions of the captain have a major impact on realized productivity (Squires et al. (2003), Viswanathan et al. (2002)). In a recent study of multiple industries, Bloom and Reenen (2007) found that managerial practices are strongly correlated with firm productivity in medium-sized firms throughout Europe and the U.S. This precedent provides a natural analogy to my theoretical model, wherein individual managers are modeled as having some ex ante influence over the value of their ex post production decisions. I recognize that there are alternative measures of performance and later versions of this paper will examine additional metrics, such as changes in the market category (and consequently, value) of fish sales, investments in alternative fishing technologies, and fishing location choices.

As a crude illustration of the difference-in-differences approach, figure 1.11 plots the annual revenue per fishing hour (total revenues and groundfish only revenues) for all three vessel groups: Hook Sector vessels, Fixed Gear Sector vessels, and the rest of the fleet. Both measures indicate large gains for the Hook Sector following its formation between 2003 and 2004, although it is less clear from this depiction alone that the Fixed Gear Sector enjoyed similar gains. The econometric approach described below provides a less crude measure of productivity differences by adjusting for more factors than just time on the water.

Once firm-year-specific productivity estimates are reached, I use contract choice (sector membership) as a right hand side variable to examine whether performance changes are consistent with the predictions of the property rights theory, and I exploit the timing of the contract choice to control for endogeneity[17]. The groundfish fishing season begins May 1 of each year, and sector members were required to commit by the beginning of the season for a full year of either fishing within a sector or fishing in the common pool. So preparations to form, organize, and join sectors take place in the months leading up to the start of the season, and choices are fixed for a year once the season starts. I then observe the firms' subsequent production decisions and performance each year, when the contract choice is a predetermined variable.

According to the theoretical model, an individual's expected returns to his and his partners' ex ante managerial actions $\mathbf{a}_{iy}$ and $\mathbf{a}_{jy}$ determine the individual's ex ante choice of organization through the partners' individual and joint characteristics, i.e., the parameters of their payoff functions. I treat these as vessel fixed-effects, but allow for annual shocks as described below. Investments themselves are made after the organizational decision is locked in, and contribute to realized productivity in each period. Because organizational decisions are made at the annual level, I also model ex ante managerial decisions on an annual basis. I use weekly variation in the dataset to estimate these annual parameters as boat-by-year fixed effects. I address concerns about possibly more frequent managerial choices below.

The benefit function B_{iyd} described in section 1.3 can be written as the fishing trip-level profits of vessel i for fish landed on date d in year y.

$$B_{iyd} = p \cdot f(\mathbf{X}_{iyd}, \mathbf{Z}_{iyd}, \omega_{iy}(\mathbf{a}_{iy}(G_{iy}), y)) - \mathbf{w}' \cdot \mathbf{X}_{iyd}$$

$\mathbf{X}_{iyd}$ is a vector of production inputs, including the crew size, vessel length, and time spent on the water. $\mathbf{Z}_{iyd}$ is a vector of controls that capture environmental and market conditions. $\mathbf{Z}_{iyd}$ captures daily variation in the productivity of the fishery, including Inverse Mills terms to address sample and sector selectivity as

[17] Much of the empirical contracting literature is concerned with explaining the determinants of observed contracts, with contractual form on the left hand side.

described below, ocean conditions including the sea surface temperature and wave height, a within season trend, a daily measure of the catch per fishing hour of the entire industry, and the individual's cumulative catch in each season in order to capture any learning-by-doing effects or expectations about productivity. These variables enter the manager's daily decisions about how to prepare for fishing trips and whether or not to go fishing. The $\omega_{iy}(\mathbf{a}_{iy}(G_{iy}), y)$ are time-varying productivity parameters that evolve according to the managerial abilities of the vessel captain. If managerial inputs are Hicks-neutral in their augmentation of physical inputs, this can be expressed as

$$B_{iyd} = p \cdot h\left[\omega_{iy}(\mathbf{a}_{iy}(G_{iy}), y)\right] \cdot f(\mathbf{X}_{iyd}, \mathbf{Z}_{iyd}) - \mathbf{w}' \cdot \mathbf{X}_{iyd}$$

The organizational structure G_{iy} is chosen first to induce the best choice of $\mathbf{a}_{iy}$, as described in Section 1.3. After $\mathbf{a}_{iy}$ is chosen and ω_{iy} is determined, productive inputs $\mathbf{X}$ are chosen and production can be expressed in the estimating equation

$$\ln Y_{iyd} = \alpha + \mathbf{X}_{iyd}'\beta_x + \mathbf{Z}_{iyd}'\beta_z + \omega_{iy} + \eta_{iyd} \tag{1.22}$$

where η_{iyd} captures idiosyncratic variability in the vessel's output because of stochastic environmental factors, luck, etc. In the results shown in the next section these daily observations are aggregated to the weekly level. Productivity in a given year ω_{iy} is composed of ex ante productivity investments by a given manager and his partners in a given year; vessel fixed effects θ_i that capture time-invariant characteristics of the vessel and it's relationship with other vessels; and factors that are idiosyncratic to the vessel for a given year, such as mechanical problems or other non-fishing issues that impact the manager's performance, or other exogenous vessel-specific forces.

$$\omega_{iy} = g(a_{iy}, a_{jy}) + \rho y + \tilde{\mathbf{X}}_{iy}'\tilde{\beta} + \theta_i + \nu_{iy} \tag{1.23}$$

$\tilde{\mathbf{X}}_{iy}$ accounts for production inputs that are fixed at the year level and thus removed from equation 1.22 when vessel- or year-fixed effects are used (e.g., capital and resource stock levels). Equation 1.24 describes a fixed effects, differences-in-differences regression with the indicator variable G_{iy} as a proxy for $g(a_{iy}, a_{jy})$.

If firms select a newly available governance structure because it induces greater investment in human capital, then firms in the sector should see an increase in ω_{iy} relative to nonsector firms after the option was introduced.

$$\omega_{iy} = \gamma G_{iy} + \rho y + \delta G_{iy} * y + \tilde{\mathbf{X}}'_{iy}\tilde{\beta} + \theta_i + \nu_{iy} \tag{1.24}$$

This framework is similar to the multilevel model described in Donald and Lang (2007); with only two sectors, the number of treated groups may seem too small to gain any power from a difference-in-difference approach. With multiple observations per vessel for each year, however, I treat each vessel as a group and each vessel's fishing day (or week) as an individual within that group. Donald and Lang (2007) present a two-step estimation method to correct for unknown within-group correlation in the errors, which in this case may be present at the boat level across days or weeks. Some of these groups select into the treatment category, e.g., join a sector. This approach suggests a particular form of potential dependence across "individuals" (days), namely a possible autoregressive error structure. As Donald and Lang (2007) point out, if the within group correlation is known, equations 1.22 and 1.24 can be estimated directly in one step using feasible GLS. Tables 1.2 and 1.3 present estimates of this one-step approach using fixed effects, feasible GLS, and clustered standard errors from the full sample for comparison, while tables 1.4 and 1.5 present these results for the comparison groups derived from a matching estimator described below. Tables 1.6 and 1.7 present results from Donald and Lang (2007)'s two-step estimator using the full sample and matched comparison groups. All results of the difference-in-difference approach are reported with time periods collapsed into pre- and post- sector periods to account for over-rejection of the null that is a common problem in difference-in-difference estimates across multiple time periods (Bertrand et al. (2004)).

This framework is analogous to difference-in-difference studies of the effect of a given policy adopted by multiple counties or states, with potential correlation across individuals within the state or county; in this case there could be correlation across weeks for a given vessel. There could still be correlation at the sector level across vessels, however, which I address in several ways. First, the National Marine

Fisheries Service subdivides the fishing grounds into "statistical areas" to facilitate spatial regulation and measure spatial differences in abundance, as in figure 1.11. I cluster the standard errors by these areas, as well as by port. The standard errors are larger when clustered by vessel or by year, so only year and vessel clusters are reported. In addition, I include in $\mathbf{Z}_{iyd}$ the weekly aggregate catch per hour fished for all vessels in each area and port to account for common shocks across vessels.

If productivity variation within the year is driven by managerial decisions $\mathbf{a}_{iy}$ in equation 1.22, instead of being idiosyncratic at the daily or weekly level as assumed, the year-by-vessel fixed effect will only capture the average impact of these effects over the year. For example if the investments take some time during the year to take effect, or if the managerial choices are made on a trip-by-trip or week-to-week basis, then the error should be written

$$\eta_{iyd} = \alpha_{iyd} + \epsilon_{iyd},$$

where α_{iyd} depends on $\mathbf{a}_{iyd}$ and ϵ_{iyd} is truly idiosyncratic. Then ω_{iy} and η_{iyd} will be correlated through the choice of $\mathbf{a}_{iyd}$ (notice the additional d index in this case). If the theory in Sections 1.3 and 1.4 is wrong, there will be no correlation and thus no bias because ex ante investments won't vary across organizational forms. If the theory is correct, *and* if the $\mathbf{a}_{iyd}$ accrue at the daily level and not just the annual level, α_{iyd} will be positively correlated with the individual in a given year and organizational structure.

The standard interpretation of this omitted variable problem would suggest a positive bias and an exaggerated difference in ω_{iy} across organizations and time periods. In the present case, however, this is not bias per se, but rather an average of an effect that I would like to directly observe. Taking an average of firm productivity within each year (i.e., naively calculating the firm-year fixed effects ω_{iy}) actually understates the ongoing evolution of productivity within the year if it exists. If the evolution is driven by the non-contractible actions of the managers, then this actually captures the effect I wish to capture at a lower level of precision. The procedure of estimating ω_{iy} ignoring these unobserved within-year effects from productivity investments will be the same as the result if data on the evolution of within year productivity were available, but averaged over the year (this follows from a straightforward derivation of the expression for the bias in this case).

Variable inputs chosen within a year may still be correlated with α_{iyd}. If I assume α_{iyd} is a managerial input, then it has an equilibrium demand based on ownership structure and current conditions. The ownership structure is fixed at the beginning of the year, and the remaining variation in α_{iyd} is captured by variables likely to enter its demand function, such as daily temperature and ocean conditions, fuel and output prices, daily aggregate catch per hour fished for the industry, port, or statistical area, and the individual vessel's cumulative catch for the year. These are already included in the regression. In the next section I describe another potential solution for this issue that I will pursue in future versions of this paper.

The possibility of selectivity bias is addressed in several ways. Sample selectivity is likely to be present because on any given day, vessels can choose to go fishing or stay in port and pursue leisure or other income opportunities. I include factors in the regression that attempt to capture an individual vessel's decision to stay home or go fishing. First, I include measures of aggregate catch per fishing hour at the industry, port, or statistical fishing area level. This proxy for industry productivity is intended to capture what an individual boat might know about its prospects on a given day based on what the captain hears from other captains. Second, I include an Inverse Mills ratio from a first stage probit regression to predict daily participation as described below.

Group selectivity bias may also be present. While the sector option was available to all vessels, many vessels that may have benefited from forming a sector chose to remain independent because of their skepticism about the program. There is strong inertia in negative attitudes towards property rights systems among fishing communities, which is likely to have accounted for significant foregone participation. This was one of the first programs of its kind in the region and one of very few in the United States, so many vessels may have been viewing the program as a test case. Therefore many nonparticipants could differ from participants more in their attitudes than in their potential for cooperative gains. If this is not the case for all vessels, selectivity bias could still be an issue in estimation. Selection into a sector based on firm-specific characteristics is a fundamental assumption in the theory derived earlier; firms that integrate are assumed to have a pre-existing "specific relationship" or partnership potential that may not be observable in the data.

I deal with this potential issue in several ways. First, the difference-in-differences estimator with vessel-level fixed effects using data from several years before and after the policy change should remove much of the unobserved heterogeneity in vessels and captains. Second, comparison vessels are chosen to most closely resemble sector vessels as described below. Lastly, I include an Inverse Mills Ratio term to correct for selection into a given sector in a given year after 2004. Each of these terms is significant in most specifications.

Inverse Mills Ratios I calculated the Inverse Mills Ratios using the following procedures:

- For the fishing participation choice on a given day, I expanded the panel to a fully balanced panel. An indicator for whether the vessel was out fishing on a given day is regressed (using a probit regression) on current and multiple lagged prices of all available fish species (including non groundfish species); current and lagged temperature, wave height and diesel prices; the total number of other vessels fishing each day; capital stock size; dummies for whether the vessel is in a sector; a dummy for being owner-operated; yearly, monthly, and day-of-week dummies; and the lagged proxy for industry aggregate productivity.

- For selection into sectors, I assume that vessels join sectors based on their expectations about their own future productivity and that of their potential partners in the next year (since sector participation is decided one year at a time), and that those expectations are formed based on productivity during the current year. To capture this I regressed participation in a given year on the average value of inputs and outputs for the preceding year from all vessels in the same home port as each vessel, again using a probit.

Comparison vessels Regression results from the full sample include comparison vessels that used similar fishing gear to sector vessels. Sector vessels almost never reported using any gear other than hook and line gear, sink gillnets, scallop dredges, traps or pots, so the sample was limited to vessels using these gears. This eliminates various types of trawlers and drift gillnets, which are very different technologies.

From this set of vessels, I constructed several additional comparison groups. First, I chose vessels who landed fish in ports of similar size or regional proximity to the sectors' home ports of Chatham and Harwichport[18]. Second, I chose vessels that formed sectors in 2009 when the sector program expanded. The rules for non-sector vessels were changed in 2009 from input controls to hard common-pool annual harvest caps on individual species. The spectre of a fishing derby lead many vessels to form new sectors. From these vessels I formed three comparison groups: one with vessels from any 2009 sector with more than 5 percent of its participants using hook-and-line or sink gillnets[19], one with the same vessels but using only the hook-and-line or sink gillnet trips (excluding trips using pots, traps, and dredges) and one with vessels only from sectors that had stated goals of sustainability and community-based management which resembled the Hook and Fixed Gear sectors[20].

My emphasis on similar communities or cooperative entities, rather than simply matching from the entire fleet on vessel observables, is intended to capture groups of comparison vessels that might exhibit similar relationship specificity as the Hook and Fixed Gear Sectors, absent the formal quota allocation and contract structure during the study period. The difference-in-difference estimates from these comparisons are summarized in Table 1.9.

The size and statistical significance of the results are sensitive to the comparison group, indicating significant heterogeneity in the response of different vessels to the post-2004 regulatory changes. Difference-in-difference estimators

[18]These ports included Barnstable, Bass River, Chilmark, Cotuit, Dartmouth, Eastham, Edgartown, Fairhaven, Falmouth, Mattapoisett, Nantucket, Nauset, Onset, Orleans, Seabrook, Tisbury, Truro, Wellfleet, Woods Hole, Yarmouth, New Bedford, Hyannis, Provincetown, Menemsha, Oak Bluffs, Vineyard Haven, and Dennis.

[19]The Sustainable Harvest Sector, Northeast Seafood Coalition Sectors III and XI, Northeast Coastal Communities Sector, and the Port Clyde Community Sector.

[20]The Port Clyde Community Sector and the Northeast Coastal Communities Sector

only remove pre-treatment mean differences but do not control for heterogeneous changes in response to post treatment conditions; if the comparison groups do not respond to the new regulations in the same way as the sector vessels would have, absent their sector status, then they are not a good control group. To deal with this, I also implemented a matching estimator.

Matching estimator To implement the matching estimator, I first estimated the production function described in equation 1.22 using only pre-sector data and individual time-invariant fixed effects. I then captured these fixed effects as a variable representing time-invariant ability levels to help explain the propensity to join sectors. I identified 8 nearest-neighbor vessel matches for each sector vessel's weekly observation by combining a Mahalanobis distance and propensity score procedure. I selected matches by minimizing the Mahalanobis distance between the date the sector vessel was observed and the date its matches were observed, combined with a propensity score estimated from a probit regression of future sector membership on the ability variable (fixed effect estimates), the production inputs, and weekly production conditions. The propensity score was only estimated when sector vessels and their matches used the primary gear type (hook and line or sink gillnets). This procedure produced a comparison group that was likely to fish at the same time of year, using the same gear and similar inputs, with similar ability levels. The results of this probability model for both sectors are reported in Table 1.1. As figures 1.11 and 1.11 indicate, the propensity scores for sector and nonsector vessels share common support. For any vessel that had been identified as a match in at least one week, I averaged the propensity scores over all the times it had been chosen as match to get a single propensity score for each matched vessel.

I used the boat-year fixed effects ω_{iy} from equation 1.22 as an outcome variable for the matching estimator. I estimated the mean difference in these boat-year effects between sector vessels and matches, before and after sector formation, using propensity score matching with four equally-weighted nearest neighbors based on the averaged propensity score for each matched vessel described above. I also re-estimated equations 1.22 and 1.24 using all of the data in the two-step procedure, but using only the vessels identified as matches for the comparison group. These results are reported in Table 1.8.

1.7.1 Empirical Limitations and Extensions

The use of productivity as the sole measure of performance has its limitations. Investments in the value of a coalition may also include potential non-market or social benefits that I do not attempt to measure here, such as increased job satisfaction, improved community ties, intergenerational access to the resource, and on-the-job safety. Although an observed increase in productivity for sector vessels is consistent with the proposed theoretical model, there may be a number of explanations for productivity increases. It is important to interpret the empirical results as consistent with the theory, but not an exact test of the theory[21]. Sectors might reallocate fishing activity to only the most productive vessels, who can produce the same overall quantity with fewer inputs. This is an econometric issue; if I have adequately captured sample selection at the vessel, trip level then observing the more productive vessels more frequently should not bias my results. Sectors were also exempt from trip limits for cod harvests (but subject to limits for other species); sectors might automatically appear more productive by not having to discard catches on each trip that exceeded the limits. This problem is reduced if independent vessels adjusted inputs to hit the trip targets, but mistakes in these adjustments would be truncated. However, sector vessels were subject to more stringent monitoring, leaving less leeway to throw back smaller fish for larger, more valuable fish. So while trip limits for cod could create a bias in the productivity estimates across groups, it's not obvious which direction the bias might go.

To address both the sample selection and endogeneity issues, a later version of this paper will apply corrections similar to those developed by Levinsohn and

[21]Whinston (2003) highlights the difficulty in devising an exact test of the property rights theory of the firm. Yet this difficulty does not imply that the theory provides no insight into organizational decisions or performance, or regulatory changes in this case. As discussed in section 1.6, the theory closely resembles the case studied here and the stylized facts of many cases with common property regimes.

Petrin (2003) and Olley and Pakes (1996). Rather than rely on within transformations to estimate productivity, these methods assume that managers have better information and more accurate expectations about future productivity realizations than the researcher, and that the manager choose ex ante observables based on these expectations. In this case, the size of the crew for a given trip may be based on expectations about the productivity of that trip, as well as vessel size and governance structure. I then use higher-order polynomial interactions of labor, vessel size, and governance structure in equation 1.22 to nonparametrically proxy for α_{iyd}.

This issue could persist at the annual level. An unobserved annual productivity process may also cause sample selection and omitted variable biases in equation 1.24 if ν_{iy} contains a process component that is correlated with $\mathbf{a}_{iy}$ or G_{iy}, and/or if it drives the vessel owner's liquidation decision (Olley and Pakes (1996)). The coefficient on governance structure will be biased if a manager has a good forecast about how he will fair in a given year, and this influences his decisions about whether or not to exit the fishery, which governance structure to choose if he does not exit, and how much to invest in ex ante productivity enhancements under a given governance structure.

The size of this bias is likely to be small if it exists at all. Much of what is typically unobserved in the production process, e.g., a manager's individual characteristics and the market and production conditions in a given year, are captured by the vessel fixed effects and resource stock measure in equation 1.24, and by the daily and weekly covariates in equation 1.22. However, if there are additional unobserved annual factors influencing productivity and governance choices, the method described below should capture those effects.

The direction of this bias is not immediately clear. If high-productivity vessels are more likely to integrate because of the greater returns that they get from improved productivity investments of their managers, then the bias will be positive. If low-productivity vessels are more likely to integrate as a way to survive against high-productivity vessels, as is maintained by several other studies on fishing cooperatives, then the bias will be negative. Again, following Olley and

Pakes (1996), I will account for this by assuming that the manager has better expectations about the random component of their annual productivity than the researcher, and makes investments in physical capital based on these expectations. Thus a kernel estimator or higher-order polynomial series estimator using annual capital investment activity interacted with vessel age, vessel characteristics, resource stock size, and governance structure is a suitable proxy for the unobserved, exogenous productivity process. Data on annual physical investment activity is only available for a subset of the vessels from semi-annual investment surveys conducted through the federal observer program. I will use vessel characteristics and past revenues to project investment activity from vessels that were surveyed onto vessels that were not surveyed but similar along observable dimensions.

1.8 Results

What were the impacts of sectokr participation on performance? Taken together, the regression tables suggest consistently positive gains to sector participation, although the size of the gains are sensitive to specification and comparison group. The results from the one-step approach in Tables 1.2, 1.3, 1.4, and 1.5 all suggest consistently large positive productivity gains for the Hook Sector in the 40% range, but perhaps negligible gains for the Fixed Gear Sector. The fixed effects results in Table 1.2 indicate that variables that control for sample selection are significant in most cases, but that their inclusion or exclusion does not alter the coefficients of other explanatory variables. It is likely that the selection decision is already captured by one of these variables; as Figures 1.11 and 1.11 indicate, there was some reallocation of effort within the sectors, but no dramatic retirements of capacity or fishing activity. Even the point mass at zero hours for the Hook Sector is not vastly different from the distribution of activity in the rest of the fleet. The Inverse Mills Sample selection term is consistently positive and significant in most other specifications, suggesting that sample selection is on unobserved productivity. For these reasons I will interpret estimated productivity gains as actualy increases in vessel-specific ability, not an artefact of deploying better units more often (which would also cause a mean increase at the group level).

The single stage results rely on assumed perfect knowledge of the structure of within-vessel error correlation, which imposes unnecessary structure on the estimation. Tables 1.6 and 1.7 present results using the Donald and Lang (2007) two-step approach, with the data at the second step collapsed to the year-vessel level and estimated using several approaches. Donald and Lang (2007) suggest feasible GLS at the second stage. In addition, I have included results using Fixed Effects, and clustered standard errors at the boat and year level. Table 1.7, which includes suggestions by both Donald and Lang (2007) and Bertrand et al. (2004) for obtaining consistent difference-in-difference estimates, indicates average productivity improvements of 16% for the Hook Sector vessels and 44% for the Fixed Gear Sector vessels.

Table 1.9 suggests that sector vessels performed well relative to vessels from similar communities, but not necessarily better than vessel groups that may have been similarly organized. When compared with vessels from similar ports or vessels that would eventually form community-based sectors, the Hook Sector showed between 30% and 40% gains, while the Fixed Gear Sector showed between 40% and 140% improvements. Compared to any future sector, however the gains were negligible. This is not necessarily surprising considering the composition of this group. The “Any Future Sector” comparison group contains vessels that belong to the Northeast Seafood Coalition, which is large, very well-organized fishermen’s advocacy group.

Lastly, Table 1.8 gives results from the comparison group constructed with matching methods. Hook Sector productivity appears to have improved between 16% and 28% relative to its control group. Using the midpoint of this range and an average annual groundfish revenue of $23,500 for Hook Sector vessels, this amounts to an annual gain of about $5000. Annual sector fees totalled $10,000 which may explain why the Hook Sector shrank from 58 vessels to 19 vessels between 2004 and 2008. Most of the exiting vessels had low aggregate earnings, despite having high production efficiency. The Fixed Gear Sector appears to have faired better, with gains between 44% and 71%. Using the midpoint of this range and an average annual groundfish revenue of \$56,100, this amounts to an annual gain of about \$32,000 in groundfish revenues for the average Fixed Gear Sector vessel. This may explain why the sector nearly doubled its membership between its first and second years of operation.

1.9 Conclusion

This paper proposes a model that explains some of the heterogeneity in observed ownership structures under various common property regimes. When complementarities are potentially valuable, integration or other centralized control structures are more likely at lower levels of externalities while nonintegration is more likely at higher levels. However, it should be noted that implementing a policy to close off the commons will not necessarily immediately lead to the efficient outcome, particularly if the policy is implemented at a point when agents have already prepared and invested for the status quo regime, e.g., between date 0 and date 1. If managers are operating in a nonintegrated structure before the policy, i.e., when the externality is at some high level E^h, coalitions invest expecting an outcome of $V(\mathbf{a}^{Non}, \mathbf{q}^*, E^h)$. If a policy is implemented, such as a cap and trade policy, which allocates to each of the N managers in the industry a full property right over their historical use of the resource, eliminating the symmetric externalities, then the value of those decisions will rise ex post to $V(\mathbf{a}^{Non}, \mathbf{q}^*, 0) > V(\mathbf{a}^{Non}, \mathbf{q}^*, E^h)$. However, if the policy would also have lead to a different management structure, then there is a different investment profile that the coalition would have chosen had the policy been implemented at date 0; the potential value of their decisions is then greater than the realized value: $V(\mathbf{a}^k, \mathbf{q}^*, 0) > V(\mathbf{a}^{Non}, \mathbf{q}^*, 0)$. Firms may only value those rights at the predetermined investment profile $\mathbf{a}^{Non}$, so there may be systematic undervaluing by some firms. Firms that may have integrated and survived, or even dominated, may inefficiently liquidate their rights[22]. As Wilen

[22]If a choice is given to firms of whether or not to participate in the system, the commons problem may intensify for non joiners, but joining may involve fixed costs. If $\mathbf{a}$ are durable investments firms could be left with persistently unproductive skills in either system if the system is introduced at date 1.

(2007) has observed, "many rationalization programs have witnessed changes in incentives so different than those under regulated open/restricted access, that often the technology in place before rationalization is not evident afterwards." If the best potential users of the new technology, or even its inventors, exit before they have a chance to adapt to new conditions, there may be a long and costly adjustment path to the efficient equilibrium.

In the case of the two initial New England groundfish sectors, the allocation rules required vessels to consider their strategic integration and production options, providing an opportunity to invest in new capabilities to create value. Later versions of this paper will examine in more detail the exact mechanisms through which each sector was able to make use of the collective allocation of cod. For example, the abilities of hook sector and fixed gear sector vessels appear to have taken very different trajectories following their formation because of the unique skills associated with each gear type.

Despite the relative gains to forming the sectors, the fixed costs of organizing (in the form of sector fees) and the size of the gains in real terms appear to have determined the size of these cooperatives. At $5000 per year, the gains for the average Hook Sector vessel would not have covered the membership fees, although higher performers in the group may have enjoyed substantially larger benefits, and been willing to compensate other vessels to join in order to expand the DAS and species quota holdings of the group. The Hook Sector did experience large attrition rates, however. At about $32,000, the gains for the average Fixed Gear Sector vessel were substantially larger, which may have drawn in additional participants.

Although in this case collective ownership appears to provide tangible benefits to participants, it also allows for spillovers onto alternative resources. In this case, the expanded impact on haddock was sanctioned by regulators, but this need not be the case in general. These ecological spillovers are not unique to fisheries regulation and are well known in the literature on multi-pollutant problems. This paper provides a unique perspective by examining how these problems are affected by a shift in firm boundaries and ownership following regulations of one dimension within multi-product firms.

1.10 Acknowledgements

I am indebted to Ted Groves, Dale Squires, and Drew Kitts for invaluable assistance. I am also grateful to Richard Carson, Eric Thunberg, Mark Jacobsen, Junjie Zhang, Eric Janofsky, Jacob LaRiviere, and seminar participants at IIFET 2010, CU Boulder's Environmental Economics Workshop, UCSD's Center for Environmental Economics workshop series, UCSD's Applied Economics seminar, and all of the participants in my job market seminars. Generous support was provided by NOAA Sea Grant and NSF-IGERT through the Center for Marine Biodiversity and Conservation.

1.11 Figures and Tables

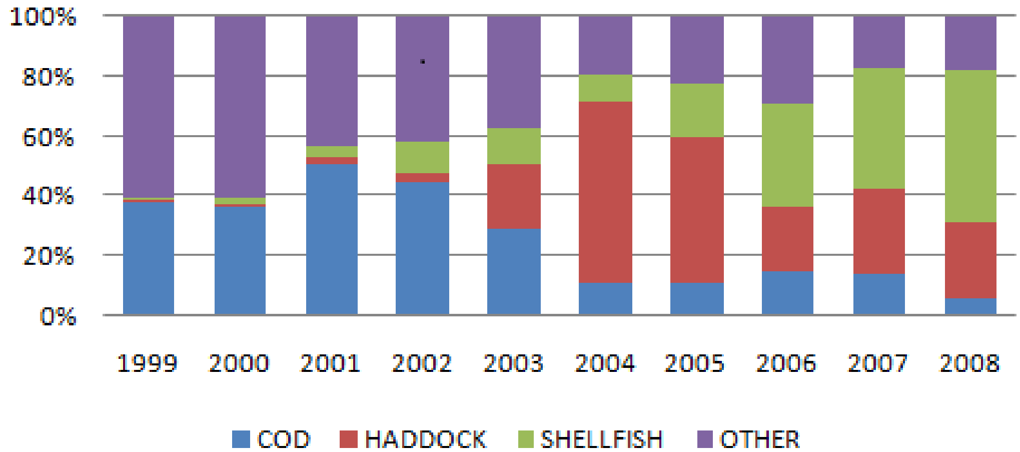

Figure 1.1: Hook Sector Harvest Composition

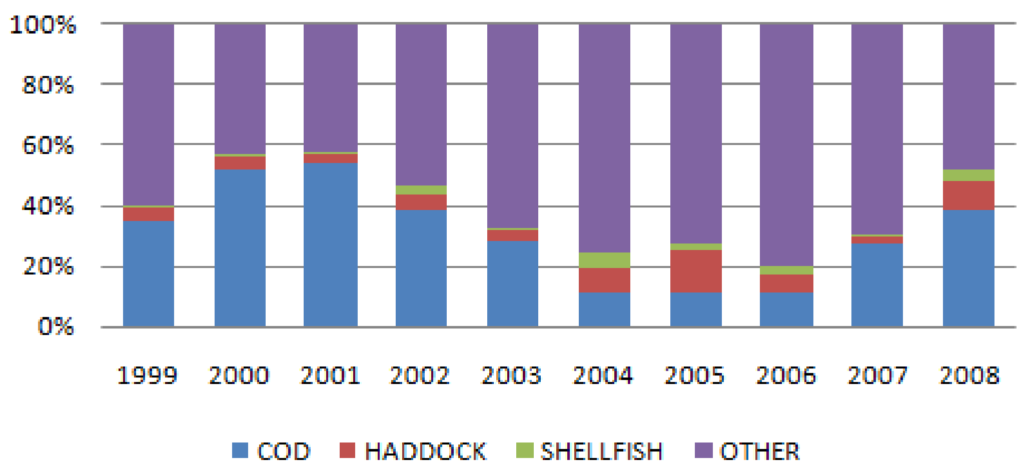

Figure 1.2: Fixed Gear Sector Harvest Composition

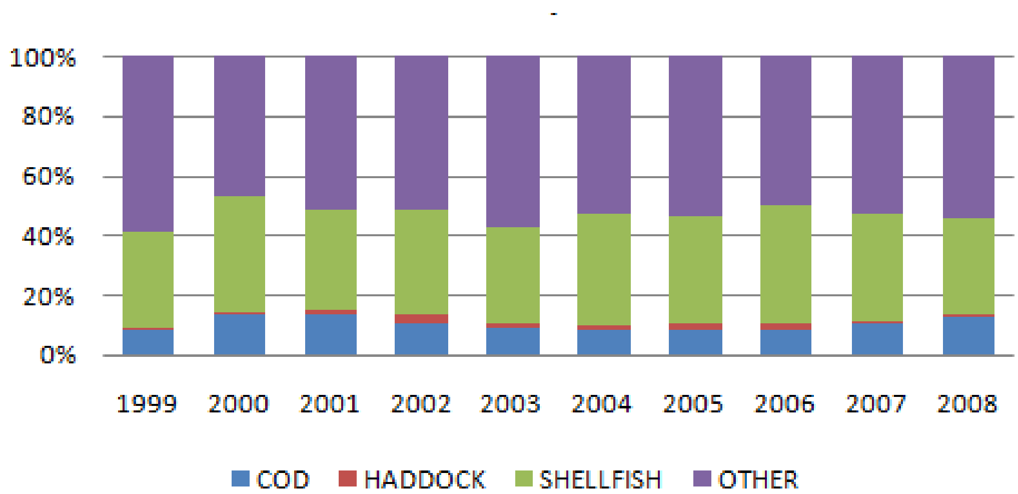

Figure 1.3: Rest of Fleet Harvest Composition

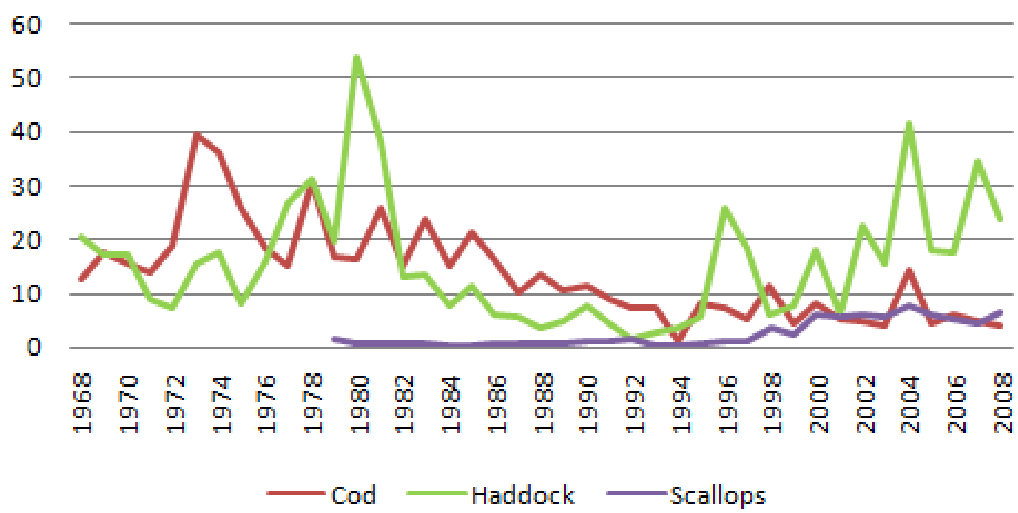

Figure 1.4: Biomass Indices

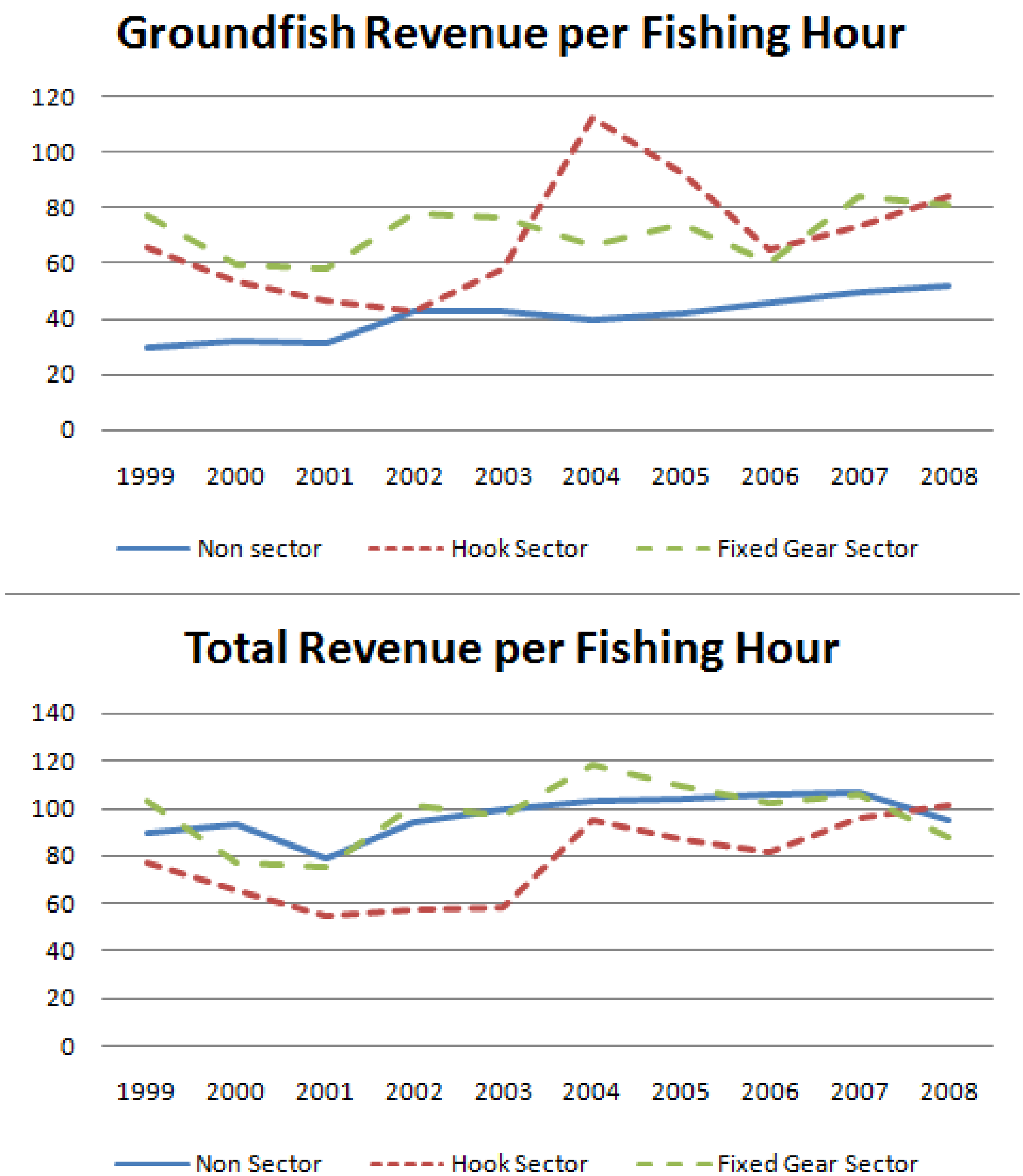

Figure 1.5: Revenue per Hour

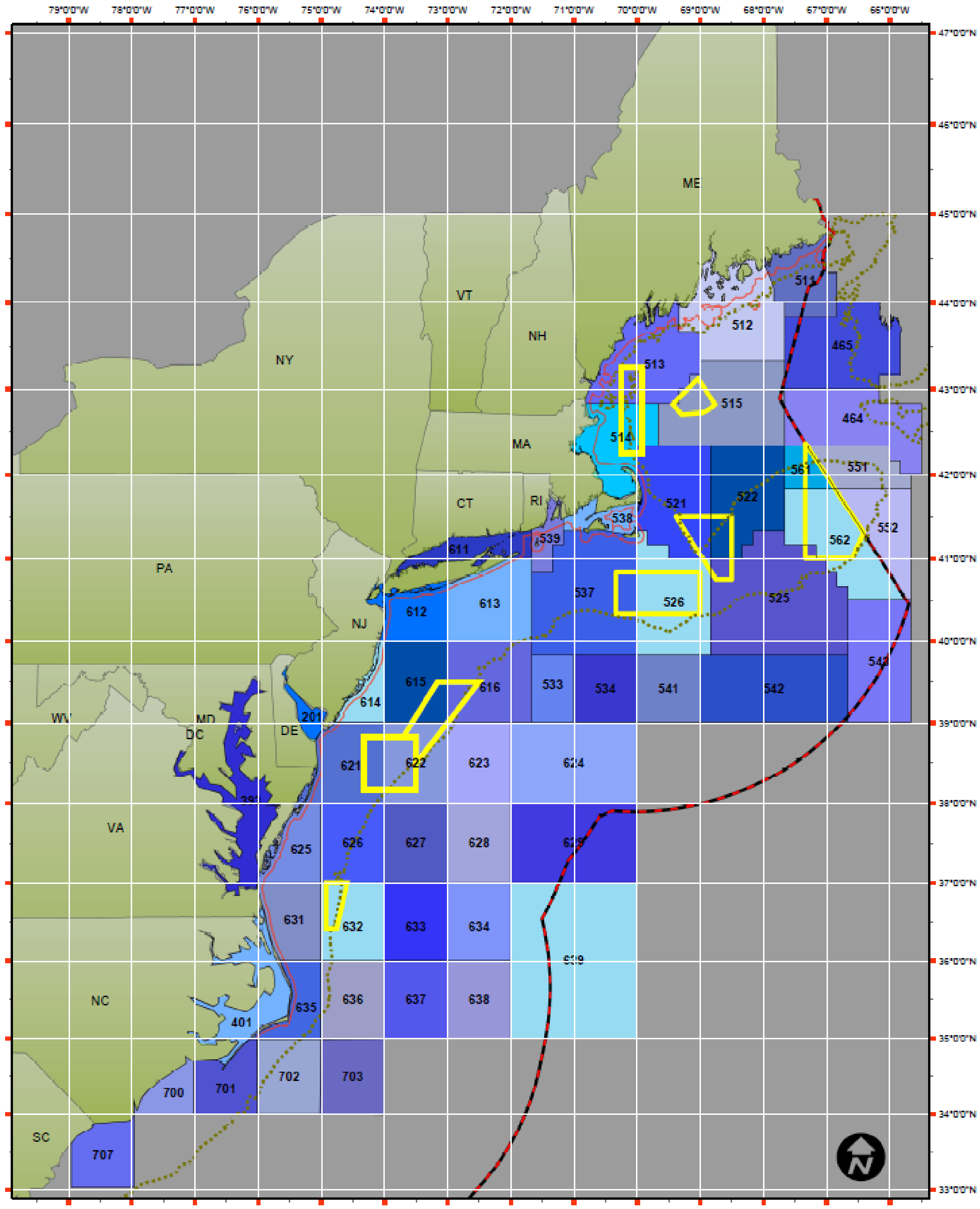

Figure 1.6: Northeast Statistical Areas

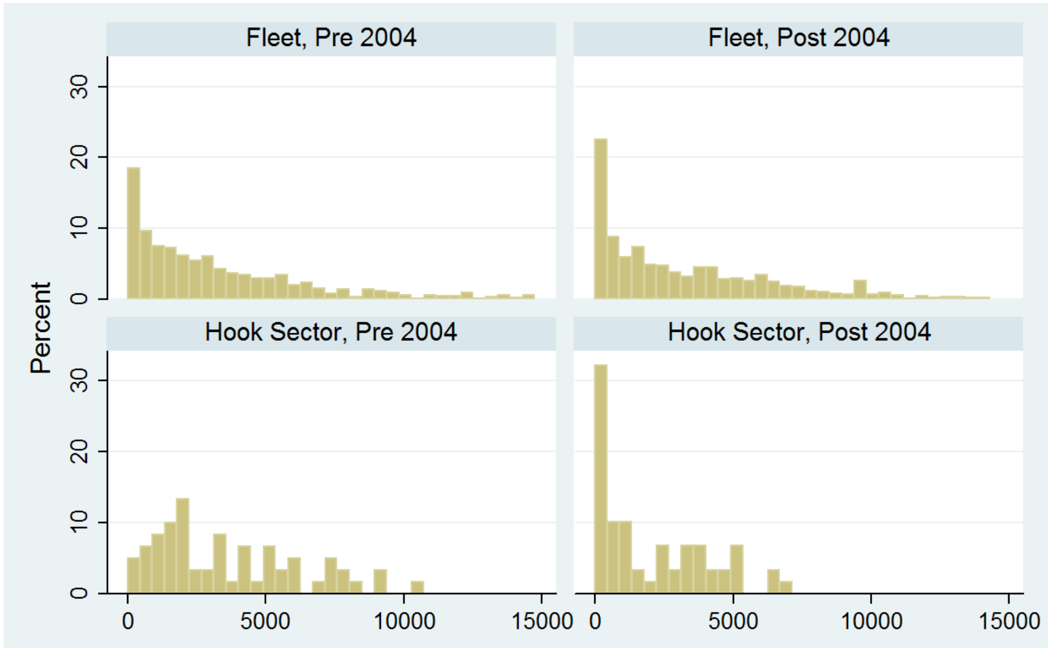

Figure 1.7: Fishing Hours per Vessel: Hook Sector vs. Fleet

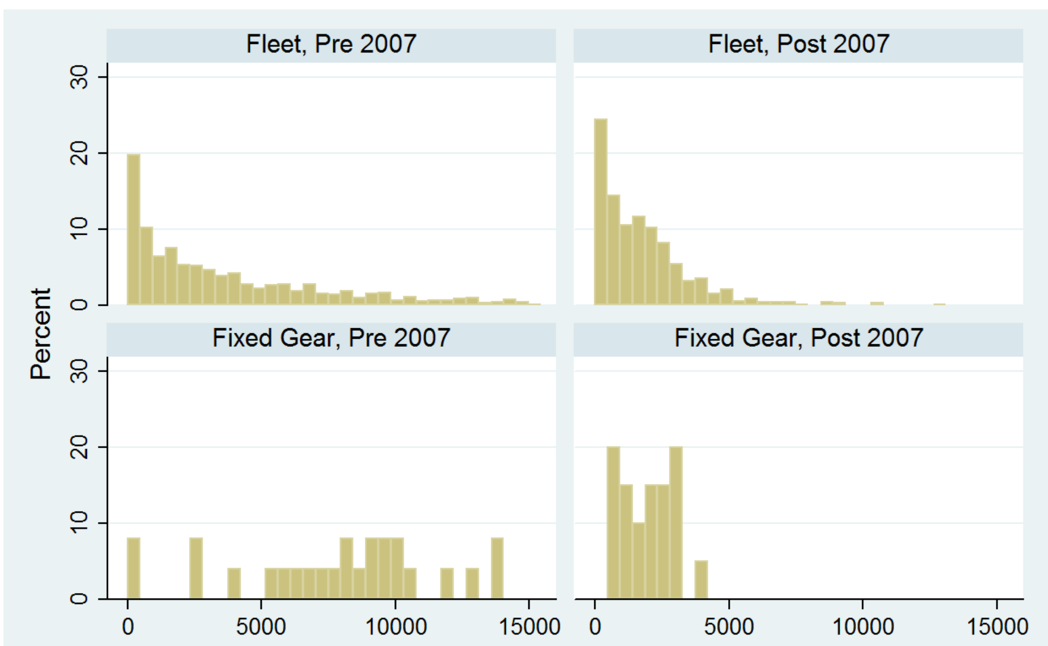

Figure 1.8: Fishing Hours per Vessel: Fixed Gear Sector vs. Fleet

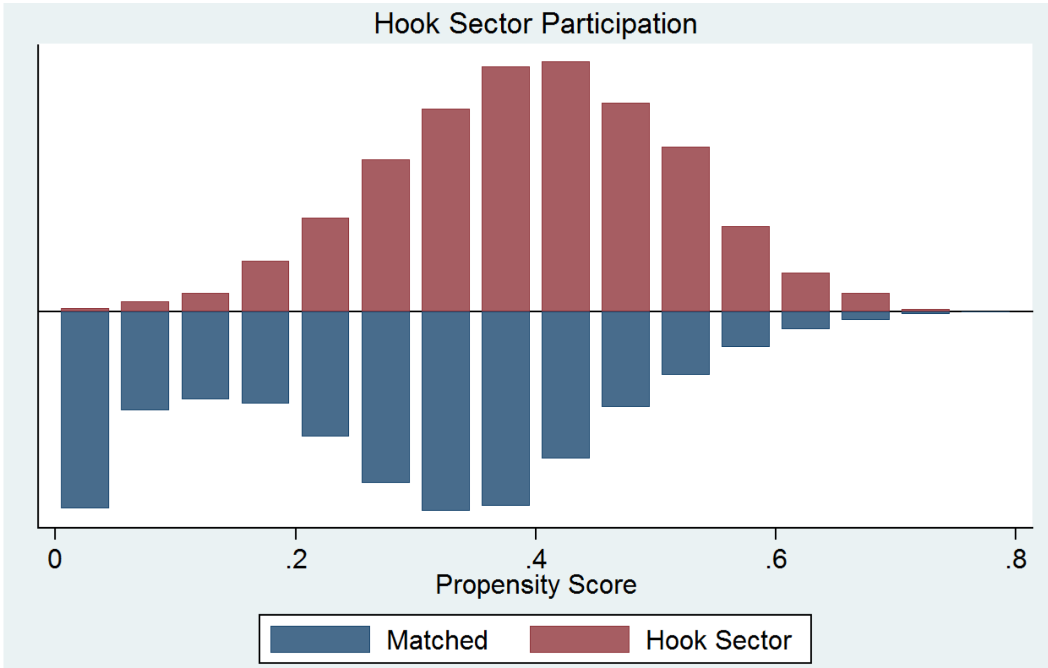

Figure 1.9: Hook Sector Propensity Score Common Support

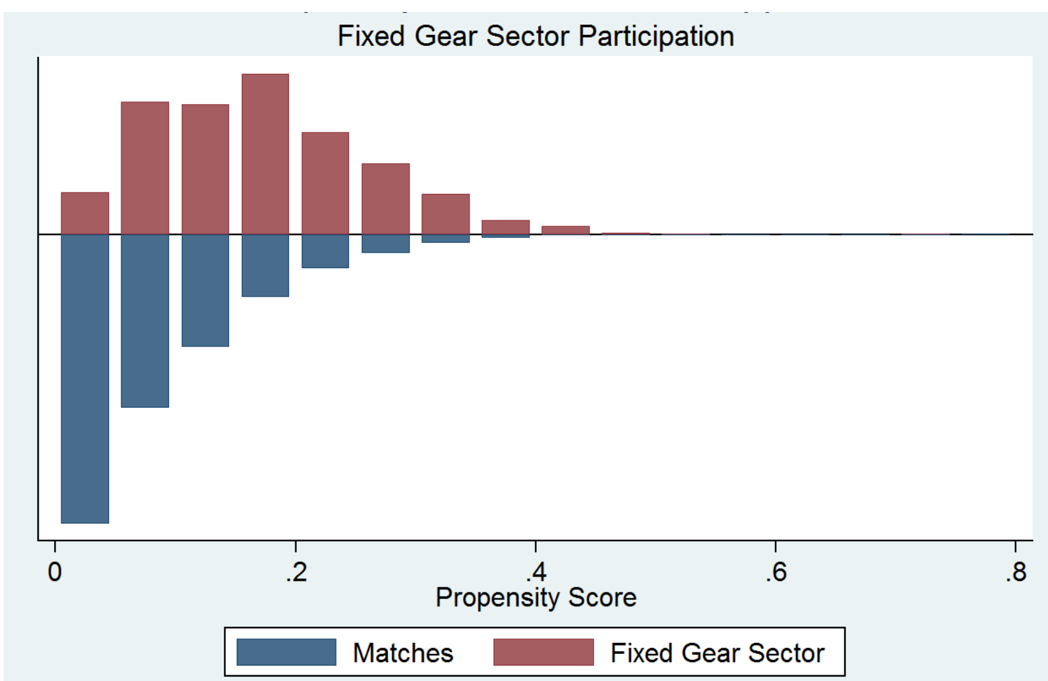

Figure 1.10: Fixed Gear Sector Propensity Score Common Support

Table 1.1: Propensity Score Model

	(1) Hook Sector	(2) Fixed Gear Sector
ability	-0.048***	0.37***
	(0.00336)	(0.0198)
crew	0.074*	0.91***
	(0.0393)	(0.0547)
hours	0.18***	-0.18***
	(0.0204)	(0.0189)
length	-4.34***	-2.99***
	(0.179)	(0.151)
tonnage	0.37***	0.41***
	(0.0324)	(0.0296)
horsepower	0.21***	0.60***
	(0.0433)	(0.0358)
trend	0.0019***	0.0019***
	(0.000352)	(0.000292)
industry CPUE	-0.0016**	0.00042
(all fish)	(0.000684)	(0.000729)
industry CPUE	0.0071***	0.0015
(groundfish)	(0.00121)	(0.00124)
owner	0.25***	-0.034
	(0.0799)	(0.0315)
SST	-0.076**	0.22***
	(0.0344)	(0.0339)
wave height	-0.047	-0.32***
	(0.0352)	(0.0337)
constant	-1.21***	-1.70***
	(0.105)	(0.0758)
N	10992	20674
R^2	0.11	0.13
ll	-6105.5	-5828.7

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.2: Cobb Douglas Fixed Effects Estimation

Dependent Variable: Groundfish Sales

	(1)	(2)	(3)	(4)	(5)	(6)
Hook	0.42***	0.43***	0.42***	0.41***	0.41***	0.42***
	(0.0494)	(0.0494)	(0.0495)	(0.0494)	(0.0491)	(0.0492)
Fixed Gear	0.041	0.039	0.052	0.026	0.030	0.024
	(0.0621)	(0.0621)	(0.0623)	(0.0620)	(0.0616)	(0.0618)
Length	1.10*	1.10*	1.12*	1.29**	1.28**	1.26**
	(0.584)	(0.584)	(0.584)	(0.581)	(0.580)	(0.579)
Crew	0.23***	0.23***	0.23***	0.22***	0.22***	0.21***
	(0.0244)	(0.0244)	(0.0245)	(0.0244)	(0.0242)	(0.0243)
Hours	0.77***	0.77***	0.77***	0.76***	0.75***	0.76***
	(0.00941)	(0.00941)	(0.00945)	(0.00950)	(0.00936)	(0.00939)
Trend	0.0059***	0.0059***	0.0059***	0.0064***	0.0059***	0.0059***
	(0.000156)	(0.000157)	(0.000157)	(0.000161)	(0.000155)	(0.000156)
N	49808	49808	49500	49500	49808	49500
R^2	0.229	0.230	0.230	0.240	0.240	0.242
ll	-77256.2	-77230.1	-76738.5	-76425.1	-76893.1	-76353.0
N_g	896	896	894	894	896	894
g_min	1	1	1	1	1	1
g_avg	55.6	55.6	55.4	55.4	55.6	55.4
g_max	336	336	335	335	336	335

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Biomass indices and monthly dummies included in all regressions

Table 1.2, Cont.: Cobb Douglas Fixed Effects Estimation
Dependent Variable: Groundfish Sales

	(1)	(2)	(3)	(4)	(5)	(6)
TEMP		-0.22***				-0.26***
		(0.0373)				(0.0375)
WAVE		0.056***				0.058***
		(0.0149)				(0.0157)
fishing			-0.10	0.32***		0.17
			(0.0997)	(0.102)		(0.105)
Daily Industry Productivity						
-All Fish					-0.0018***	-0.0016***
					(0.000309)	(0.000311)
-Groundfish					0.012***	0.012***
					(0.000463)	(0.000467)
PRICES	NO	NO	NO	YES***	NO	NO
_cons	0.12**	-0.049	0.16***	-0.64***	-0.089	-0.35***
	(0.0507)	(0.0570)	(0.0592)	(0.108)	(0.0574)	(0.0741)
N	49808	49808	49500	49500	49808	49500
R^2	0.229	0.230	0.230	0.240	0.240	0.242
ll	-77256.2	-77230.1	-76738.5	-76425.1	-76893.1	-76353.0
N_g	896	896	894	894	896	894
g_min	1	1	1	1	1	1
g_avg	55.6	55.6	55.4	55.4	55.6	55.4
g_max	336	336	335	335	336	335

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Biomass indices and monthly dummies included in all regressions

Table 1.3: Sector Effect, Full Sample
Dependent Variable: Groundfish Sales

	(1) FE	(2) boat cluster	(3) FGLS (iid)	(4) FGLS
Hook	0.42***	0.51**	0.27***	0.098
	(0.0492)	(0.241)	(0.0575)	(0.0653)
Post 2004	-0.48***	-0.81***	-0.51***	-0.52***
	(0.0599)	(0.164)	(0.0712)	(0.0625)
Fixed Gear	0.024	0.33**	-0.045	-0.045
	(0.0618)	(0.165)	(0.0755)	(0.102)
Post 2007	0.89***	1.14***	0.69***	0.89***
	(0.0607)	(0.181)	(0.0707)	(0.0604)
fishing	0.17	2.97***	1.38***	0.32***
	(0.105)	(0.572)	(0.112)	(0.0663)
N	49500	49500	49500	49427
R^2	0.242	0.315		
ll	-76353.0	-96368.2	-87522.9	
N_g	894		894	821

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.4: Hook Sector Effect, Matched Comparisons
Dependent Variable: Groundfish Sales

	(1) FE	(2) boat cluster	(3) FGLS (iid)	(4) FGLS
Hook	0.36***	0.46*	0.17***	0.11
	(0.0542)	(0.252)	(0.0632)	(0.0694)
Post 2004	0.38***	0.32**	0.29***	0.18***
	(0.0443)	(0.143)	(0.0524)	(0.0536)
fishing	0.42***	4.93***	1.54***	0.54***
	(0.137)	(0.566)	(0.144)	(0.0954)
cons	0.24	-2.16***	-0.28***	-0.13***
	(0.672)	(0.353)	(0.0621)	(0.0404)
N	20369	20369	20369	20365
R^2	0.270	0.374		
ll	-30193.2	-37035.2	-34617.7	

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.5: Fixed Gear Sector Effect, Matched Comparisons
Dependent Variable: Groundfish Sales

	(1) FE	(2) boat cluster	(3) FGLS (iid)	(4) FGLS
Fixed Gear	-0.11*	0.43***	-0.12	-0.18*
	(0.0661)	(0.139)	(0.0740)	(0.1000)
Post 2007	0.60***	0.68***	0.47***	0.66***
	(0.0388)	(0.114)	(0.0422)	(0.0383)
fishing	-0.49***	-0.82	0.23	-0.043
	(0.150)	(0.572)	(0.156)	(0.101)
_cons	0.23**	0.17	-0.19***	-0.20***
	(0.0967)	(0.274)	(0.0499)	(0.0346)
N	27787	27787	27787	27784
R^2	0.286	0.299		
ll	-42916.1	-49939.3	-46610.0	

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.6: Second Stage, Full Sample

Dependent Variable: ω_{iy}

	(1) FE	(2) boat cluster	(3) FGLS (iid)	(4) FGLS
Post 2004	0.044	0.026	0.019	0.026
	(0.171)	(0.142)	(0.0143)	(0.146)
Hook	0.20	0.12	0.11**	0.12*
	(0.125)	(0.0834)	(0.0429)	(0.0664)
Post 2007	0.41**	0.37***	0.39***	0.37**
	(0.170)	(0.141)	(0.0162)	(0.144)
Fixed Gear	0.58***	0.50***	0.43***	0.50***
	(0.218)	(0.174)	(0.141)	(0.174)
_cons	-0.48***	-0.100**	-0.100***	-0.100***
	(0.157)	(0.0392)	(0.00424)	(0.0379)
N	4019	4019	3845	4019
R^2	0.019			0.017
ll	-5044.1	-5049.1		-5049.1

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.7: Second Stage, Matched Comparisons
Dependent Variable: ω_{iy}

	(1) FE	(2) boat cluster	(3) FGLS (iid)	(4) FGLS
Hook Sector Matches				
Post 2004	0.42***	0.40***	0.40***	0.40***
	(0.117)	(0.101)	(0.0355)	(0.121)
Hook	0.25**	0.16*	0.085*	0.16*
	(0.124)	(0.0870)	(0.0478)	(0.0796)
N	1661	1661	1643	1661
R^2	0.024			0.021
ll	-2015.8	-2018.7		-2018.7
Fixed Gear Sector Matches				
Post 2007	0.59***	0.54***	0.54***	0.54***
	(0.108)	(0.0947)	(0.0145)	(0.0990)
Fixed Gear	0.51**	0.44**	0.36**	0.44***
	(0.221)	(0.183)	(0.164)	(0.169)
N	1672	1672	1664	1672
R^2	0.046			0.042
ll	-2040.2	-2043.8		-2043.8

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.8: Matching Estimation for Differences in ω_{iy}

	(1) Pre-Sector	(2) Post-Sector	(3) Difference	(4) FGLS (Matched)
Hook Sector				
Matched				
Sector	0.6	0.73	0.13	
Matches	-0.7	-0.85	-0.15	
Difference	1.3***	1.58***	0.28	0.16**
	(0.16)	(0.27)	(0.32)	(0.08)
Unmatched				
Sector	0.6	0.73	0.13	
Matches	-0.68	-0.73	-0.05	
Difference	1.28***	1.46	0.18	
	(0.12)	(0.20)	(0.23)	
Fixed Gear Sector				
Matched				
Sector	0.31	1.76	1.45	
Matches	0.097	0.84	0.743	
Difference	0.21	0.92**	0.71*	0.44***
	(0.14)	(0.38)	(0.41)	(0.17)
Unmatched				
Sector	0.31	1.76	1.45	
Matches	-0.6	-0.15	0.45	
Difference	0.91	1.91***	1.0**	
	(0.15)	(0.44)	(0.46)	

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.9: 2nd Stage, Port and Sector Comparison Groups

	(1) OLS	(2) FE	(3) boat cluster	(4) FGLS
Similar Landing Ports				
Hook Sector	0.11	0.32*	0.26	0.28**
	(0.22)	(0.17)	(0.17)	(0.12)
Fixed Gear	1.48***	1.37***	1.36***	1.24***
	(0.39)	(0.29)	(0.26)	(0.23)
N	1332	1332	1332	1240
R2	0.139	0.182	0.167	
LL	-2521.8	-1833.2	-1844.8	
Ng		348	348	256
Any Future Sector				
Hook Sector	-0.00061	-0.015	-0.02	0.047
	(0.12)	(0.10)	(0.13)	(0.09)
Fixed Gear	-0.037	-0.031	-0.022	0.16
	(0.21)	(0.17)	(0.21)	(0.15)
N	1265	1265	1265	1260
R2	0.062	0.074	0.07	
LL	-1657.3	-1266.5	-1268.4	
Ng		180	180	175

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.9, Cont.:
2nd Stage, Port and Sector Comparison Groups

	(1) OLS	(2) FE	(3) boat cluster	(4) FGLS
Any Future Sector, Longline Trips Only				
Hook Sector	0.079	0.26*	0.25	0.31***
	(0.16)	(0.15)	(0.15)	(0.12)
N	588	588	588	570
R2	0.115	0.075	0.073	
LL	-763.6	-548.8	-549.6	
Ng		123	123	105
Any Future Sector, Gillnet Trips Only				
Fixed Gear	0.16	-0.018	-0.02	0.095
	(0.20)	(0.17)	(0.22)	(0.15)
N	769	769	769	760
R2	0.051	0.087	0.087	
LL	-927.8	-686	-686	
Ng		109	109	100
Future Sectors with Community Goals				
Hook	0.30*	0.42***	0.38*	0.42***
	(0.17)	(0.16)	(0.22)	(0.14)
Fixed Gear	0.29	0.37	0.32	0.40**
	(0.27)	(0.24)	(0.26)	(0.20)
N	638	638	638	633
R2	0.073	0.055	0.05	
LL	-915.6	-738.9	-741.3	
Ng		98	98	93

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Chapter 2

Technological Change and Managerial Ability: Evidence From a Malaysian Artisanal Fishery

Abstract

We compare the productivity of technology adopters to non-adopters using a cross-sectional survey of artisanal gillnet vessels on the east coast of Peninsular Malaysia. Technologies include cell phones, GPS, sonar, and mechanical winches for hauling nets. Stochastic frontier analysis is used to measure differences in production frontiers and technical efficiency scores. Adopters of mechanical net haulers had low technical efficiency, low labor productivity and high labor use. Electronics adopters were more productive than non-adopters on average, but difficult to distinguish from efficient non-adopters. This is the first paper that we know of to examine the role of new technologies in the production process of artisanal fishers. Our results suggest capital investments in new technology may tie the least successful participants to the fishery despite most respondents' self-reported desire to exit. Impacts may be fishery-specific and ambiguous, so the consequences of technology subsidies should be carefully considered in development policy.

2.1 Introduction

"Perhaps one of the main reasons for studying economic development is to understand better how individuals are able to make the transition out of poverty. Technology may be viewed as a means to this end." (Besley and Case (1993))

Technological change in less developed economies has received continued attention because of its potential to improve welfare by raising output and reducing inefficiencies[1]. But what is the role of new technology in the production process for users of a common resource? Are technological improvements unambiguously welfare-enhancing among small scale common resource users? Are the most skilled agents better able to adopt and benefit from these technologies, or do the technologies substitute for skill? This paper is the first that we know of to study the role of new technology in the production process of artisanal fishers.

Output-augmenting technological change has become a subject of concern for common resources like fisheries. Unlike agricultural improvements that raise yields and lower costs, short run fishing productivity improvements can lead to lower long-run resource stocks, yields and welfare, particularly when rights of exclusion are weak or nonexistent (Squires and Vestergaard (2009)). This "technology trap" makes it even more difficult to raise standards of living in artisanal fishing communities[2]. As in many industrialized nations, developing country institutions and resources remain limited in their ability to offset increases in fishing productivity by reducing effort or managing fish stocks (Viswanathan et al. (2002)). Managers are particularly limited in their ability to adjust for unobservable inputs like fishing or managerial skill, which may be augmented by the use of new technologies. Russell and Alexander (1998) observe that in some developing country fisheries, innovations in electronic fish finding and navigational equipment, as well

[1]Jensen (2007) shows that cell phone use gives artisanal fishermen in India the information to choose between coastal fish markets with different prices, bringing these markets in line with the law of one price and reducing price risk, travel time and wasted catch.

[2]In the sample studied in this paper, 92% of survey respondents said they don't want their children to fish, and 50% said they would like to change jobs themselves. Among those who said they don't want to change jobs, 72% said it was because they were too old, can't learn new skills, or don't have enough education or alternative opportunities.

as boat design, can substitute for traditional fishing skill, but that this has not been the case in all developing country fleets.

This paper examines the intersection of skill and technology adoption using cross sectional data from a survey of artisanal gill net vessels on the east coast of Peninsular Malaysia. We consider whether technology adopters and non-adopters differ with respect to their production efficiency, and the shape and location of their production frontiers. We introduce a distinction between innovation that is complementary to the skill endowment (and is thus "skill-augmenting") versus technical change that substitutes for skill (and is thus "skill-diluting"). We employ stochastic frontier analysis to characterize technical efficiency, combined with information about the adoption of new technologies like cell phones, global positioning systems (GPS), echo locaters, sonar, and a mechanical winch used to haul in fishing nets.

The rest of the paper is organized as follows: section 2.2 reviews the literature on fishing skill. Because each of these technology types may play a different role in the production process, section 2.3 describes the hypotheses we will explore and provides a summary of results. Section 2.4 discusses issues with the data. Section 2.5 specifies the empirical approach, section 2.6 presents the results of the analysis, and section 2.7 concludes.

2.2 Fishing Skill

A number of studies have attempted to identify and measure metrics of skill and their determinants for artisanal fisheries in less developed countries. Individual skipper and vessel observables often do not show a strong statistical relationship with technical efficiency estimates or other measures of skill, and when they do, the findings have been only moderately consistent. Skill in this context is defined as the ability to consistently catch the most fish, given observable input levels (Barth (1966); Palsson and Durrenberger (1982); Thorlindsson (1998), Viswanathan et al. (2002)), or in other words, to produce on the production possibilities frontier. Thus, technical efficiency scores that measure firm-specific distances from an estimated frontier are often considered good proxies for skill (Viswanathan et al. (2002), Squires et al. (2003)), while technological change is defined by shifts in the frontier.

As noted by Thorlindsson (1998), some authors have argued that estimated skipper effects are driven by a handful of star performers, with performance among the rest of the fleet distributed randomly, while other authors hold that skipper skill is a classic fixed effect – and fleet-wide performance rankings should be consistent over time (Barth (1966); Palsson and Durrenberger (1982), Squires and Kirkley (1999)). Palsson and Durrenberger (1982) found no clear relationship between experience and catch. Acheson (1975) found that age and education were not strong proxies for skill. Using a stochastic production frontier, Squires et al. (1998) found that skipper-specific variables were generally insignificant as predictors of technical efficiency. Using panel data, Squires and Kirkley (1999) found that differences in technical efficiency were better explained by inter-vessel fixed effects than by production inputs.

Viswanathan et al. (2002) and Squires et al. (2003) identify several significant explanatory variables for technical efficiency, but they are not all consistently significant in different fisheries. Viswanathan et al. (2002) find that Malaysian trawlers fishing in the peak season with smaller boats and Chinese captains were significantly more efficient, all else equal. Squires et al. (2003) find that in the gill net artisanal fishery on the east coast of peninsular Malaysia, more efficient vessels had newer engines, more experienced or Chinese captains, smaller vessels, larger families, and at least a primary school education. On the west coast, more efficient boats had older hulls and engines but newer nets, Chinese captains, less formal training, and larger boats with a particular brand of engine. A common theme in these findings is that proxies for fishery-specific knowledge, such as ethnicity, family size, and capital vintage, tend to be significant even if direct measures of experience are not.

Fishing skill has been broken down into a number of individual components, all of which depend on specific types of experience. Foremost of these is the ability to find the best fishing location, as emphasized by Barth (1966), Acheson (1981), and Marcoul and Weninger (2008). One important question is whether electronic fish finding equipment substitutes for this dimension of skill or augments it. Echo locaters, sonar, and GPS are obvious examples, but in the presence of informal networks even cell phones could be used at sea to share information about good locations among cooperating captains. Acheson (1981) also listed knowledge of the oceanographic environment and knowledge of the species as two additional components of skill, both of which could also be augmented by electronics. To these aspects of skill, Thorlindsson (1998) added the ability to read the ecological environment, the willingness to search independently and take risks, and leadership or management qualities, although it's less clear how the technologies under discussion here would influence these components of skill.

2.3 Technology Hypotheses

In this section we list and briefly discuss several hypotheses that we will test about the use of technology. Tables 2.1 – 2.4 provide a brief summary of the evidence for each hypothesis.

Net Hauler

Hypothesis N1: *Net hauler adopters will have higher labor productivity.*

The use of a mechanical winch makes it possible for only one crew member to haul in a net after each fishing set, potentially reducing the crew size required for a given catch size.

Hypothesis N2: *Net hauler adopters will exhibit higher total factor productivity.*

If this equipment reduces the amount of time it takes to haul in and empty the gear, it may allow the vessel to fish more sets in any given trip for a given level of inputs.

Electronics

Hypothesis E1: *Electronics users will exhibit higher total factor productivity.*

If electronics allow vessels to find more fish faster, then the productivity of all production inputs should increase. Cell phones can play this role if different vessels communicate in informal networks to find the best fishing locations.

Hypothesis E2: *Cell phone users fetch higher prices.*

If fishermen have a choice between markets, cell phones should allow them to always pick the highest price market.

Adoption

Hypothesis A1: *Newer, more modern vessels will have adopted newer technologies.*

It may be more convenient to install new equipment when the vessel is built. The characteristics of a fisher who would reinvest in the fishery with a more modern boat may also be the same as someone who would purchase advanced equipment.

Hypothesis A2: *Adopters will be found in clusters according to location.*

This is a form of the well-known "S-curve" diffusion hypothesis – that adoption follows an S-curve over time; as information about the technology spreads, adoption rates increase until the market becomes saturated. We may be able to see this pattern in our cross-sectional data; if information is locally obtained then adoption should take place near locations with other adopters, where skippers can observe the benefits of particular technologies.

Skill

Hypothesis S1: *Technology is skill-augmenting, i.e., technology adopters should exhibit greater technical efficiency than non-adopters.*

We define technical change to be skill-augmenting if the distribution of technical efficiency scores is wider with a new technology than without, e.g., if firms producing at or near the frontier are innovators who shift the frontier out, while non-adopters don't move relative to the new frontier without further diffusion. This is the canonical view proposed by Fare et al. (1994). This could occur if the new technology is complementary with managerial skill, so that new technology augments the performance of high-ability managers more than that of low-ability managers. This could also be the case if more capable managers have better information about useful technological developments. In either case we would observe adopters clustered near the frontier with non-adopters lower down in the technical efficiency rankings, regardless of the causal direction of adoption and skill.

Conversely, we define technical change to be skill-diluting if the distribution of technical efficiency scores is narrower with a new technology than without, e.g., if inefficient firms adopt and move closer to an existing frontier. This would be the case if the new technology is a substitute for managerial skill, so that managers will only adopt if the cost is very low relative to the improvement over their skill endowment. In this case we would observe adopters towards the bottom or middle of the technical efficiency distribution. These terms refer to the ability to distinguish between pre-adoption high and low skilled boats when technology is adopted, rather than the effect of the technology on individual boats. Naturally the technical efficiency of a low-skilled firm is "augmented" if it moves closer to the frontier because of a technological adoption, but we will call this change "skill-diluting" because it's now more difficult to distinguish the skill of this firm from other efficient firms. It's possible that skill-diluting and skill-augmenting effects will offset each other, leading to no observed difference in the technical efficiency of adopters and non-adopters, but rather a shifting out of the entire technical efficiency distribution. Our cross-sectional snapshot will not allow us to distinguish the two effects. Another – albeit unlikely – explanation is that these technologies are actually ineffectual. Adopters are a small portion of our sample – and may be the gullible few who took a risk on new technologies whose benefits may be nullified by natural resource constraints and excess industry-wide effort.

Finally, we examine two hypotheses that have been of interest throughout the literature on skipper skill:

Hypothesis S2: *Observable skipper characteristics are not good predictors of technical efficiency.*

Hypothesis S3: *Skill rankings are stable and consistent.*

2.4 Data

The data comes from a survey of 354 fishers on the east coast of peninsular Malaysia, and was collected in an effort to explore linkages between sea turtle interactions and local perceptions through a detailed inquiry into fishing activity – including technologies (Yeo et al. (2007)). This paper focuses on a sub-sample of 120 small-scale gasoline-powered drift net vessels and their use of new technologies. The data was collected as part of a collaboration between the Malaysian Department of Fisheries (DOF), the Turtle and Marine Ecosystem Centre (TUMEC), World Wildlife Fund-Malaysia, National Oceanic and Atmospheric Administration (NOAA)-Fisheries, the Department of Economics at UC San Diego, and The WorldFish Center.

The data is based on recall from the most recent trip, as well as recall estimates of the long run average of a few variables, including monthly fishing income, and catch and revenue on a typical trip in a given season. Production inputs surveyed include crew size, fuel quantity, time spent fishing, and capital measures such as boat length and width, net length and width, horsepower, gross tonnage, and the age and expected life of boats and nets. A number of socioeconomic characteristics are also present, including marital status, family size, education, income sources, and attitudes towards fishing.

The fishermen in the sample come from 18 villages spaced roughly 5 to 10 miles apart, spanning 5 districts (or states). We are interested in the relationship between adoption of new innovations and the vessel's production possibilities, so we employ dummy variables for adopters of specific technologies. Table 2.5 provides summary statistics for the variables in the study. The self-reported peak fishing season varies by respondent because we are studying a multi-species fishery and respondents are heterogeneous in their outside opportunities and reliance on the fishery. "Peak Season" describes whether or not the most recent trip occurred during this self-reported peak season, or during the self-reported "lean" fishing season. "Region" lists the districts from south to north, along with a dummy variable for the southernmost three districts. Respondents were asked to report their total revenue in Malaysian Ringgits and total catch in kilograms for their most recent fishing trip, as well as the typical values for the season in which they were interviewed. “Typical Catch” and “Typical Revenue” are the respondent’s guess at average outcomes in the same season as the most recent trip. These values are approximately double those reported for the most recent trip, suggesting either the fishing year during this survey was a bad one, or respondents exaggerate their general performance.

Table 2.6 compares group summary statistics of outcome variables between adopters and non-adopters of process innovations. These groups are defined in three ways: as adopters of any innovation, adopters of electronic innovations, and adopters of mechanical innovations – in this case, net haulers. About 60 percent of respondents reported typical catch and earnings to be quite a bit higher than in their most recent trip, leading to greater variation in these figures. Mean outcomes were higher for adopters in all categories, which is consistent with the productivity and skill hypotheses discussed in Section 2.3. However, the differences in maximum outcomes between adopters and non-adopters are often negative, consistent with a hypothesis that adopters may have come from the middle or lower tail of the output distribution. While this is always the case with catch, maximum revenue among electronics adopters is higher than for non-adopters, indicating electronics may allow vessels to find higher prices, or catch higher value species in lower quantities. Table 2.7 suggests that this pattern persists at the local level by comparing outcomes in each district. While mean differences are usually positive, the minimum outcome tends to be higher among adopters in any given area and the maximum output tends to be somewhat lower. This is consistent with the “skill-diluting” hypothesis for new technology, as well as a pattern of selection into adoption groups based on skill or other vessel heterogeneity. Adopters are concentrated in the southernmost region, with 11 adopters out of 43 vessels in the southernmost district and 8 out of 15 in the southernmost village. These represent a large portion of the 23 adopters in the entire sample – consistent with the information hypothesis of technology diffusion.

Respondents were asked the age of their boats, as well as how long they expected their boats to last. Figure 2.9 plots the frequency distribution of these values for adopters and non-adopters of each technology type. While the distribution of boat age does not appear to be noticeably different among adopters and non-adopters of net haulers (the thicker tail for non-adopters could be attributed to the small sample of adopters), it is worth noting that all of the adopting boats are less than 10 years old and half of them are less than five years old. A stronger difference appears when we consider the amount of usable life remaining in the boat. Among net hauler adopters, mass is concentrated towards boats that are younger relative to their expected life – that have used only 20 percent to 40 percent of their boat's life (bottom left panel of Figure 2.9). Non-adopters, meanwhile, are approximately normally distributed over the range of boat usage. Electronics adopters, on the other hand, more closely mirror the distributions of electronics non-adopters.

There may be two interrelated explanations for the difference in age distribution by technology type. Net haulers have been adopted more recently than electronics, and represent more of a capital investment; they are more expensive and less likely to be quickly superseded by a rapidly changing and cheaper electronics-based production process. While most net haulers were adopted in 2003 and 2005, electronics – mostly cell phones – began to be adopted in 2000. The average net hauler cost among respondents was RM3000, while the mean boat and gear costs were RM5750 and RM1200, respectively, so net haulers fall in the cost range of other major capital investments. If urban economic growth in Malaysia has put upward pressure on labor demand and wages in recent years, then adopting an expensive labor-saving innovation would have become more attractive in the years directly preceding the survey. We would therefore expect the effect of net hauler adoption on productivity to be labor biased. Net haulers may replace or augment labor inputs which have become more expensive, without necessarily increasing output. However, because firms with existing lower labor productivity also have an incentive to adopt, we may not see the expected signs for coefficients; boats may improve labor productivity because of adoption but still have lower labor productivity than non-adopters. In a cross section, adopters could appear less productive.

This discussion paints a dual portrait of a net hauler adopter: someone who has relatively recently invested or re-invested in the fishery, with higher fixed costs and a potentially longer time horizon than the average non-adopter. This profile could be consistent with two types of fishermen: "high types" who remain in the industry by choice because their skill at fishing is relatively better than their next best option, and "low types", who have low skill but must remain in the industry because their outside options are even worse. When selection into adopter and non-adopter groups is confounded with unobserved attributes in this way, it's not immediately clear what the adoption effect on outcomes will be, as is partially illustrated in Figures 2.9 and 2.9.

2.5 Empirical Approach

We are interested in how technology adopters and non-adopters differ with respect to their ability to produce on the fleet's best practice frontier, as well as whether adopters and non-adopters face different frontiers (Aigner et al. (1977); Kumbhakar and Lovell (2000)). Technical inefficiency in this methodology is measured as the distance of each firm's output from the estimated frontier. The stochastic frontier methodology was originated by Aigner et al. (1977), and Meeusen and van den Broeck (1977). Kirkley et al. (1995) justified using a stochastic approach in fisheries because of the inherent variability in weather, resource availability, and environmental influences. We combine this approach with a modified application of Baltagi and Griffin (1988) use of dummy variables to capture discrete technological changes. Instead of using dummy variables to represent discrete changes in individual time periods, we use them to represent technological differences across firms within a single time period. Figures 2.9 and 2.9 plot total revenue against each input with adopters marked in white.

We estimate a stochastic translog production frontier of the form:

$$\log y_i = \beta_0 + \sum_{j=1}^{3} \beta_j \log x_{ij} + \frac{1}{2} \sum_{l=1}^{3} \sum_{j=1}^{3} \beta_{jl} \log x_{ij} \log x_{il} + \phi' D_i + \\ \alpha_0 I_i + \sum_{j=1}^{3} \alpha_j I_i \log x_{ij} + \frac{1}{2} \sum_{l=1}^{3} \sum_{j=1}^{3} \alpha_{jl} I_i \log x_{ij} \log x_{il} + \varepsilon_i$$

where D is a vector of location and time of year dummies, I is a dummy variable which takes a value of 1 when the boat has adopted the innovation of interest (electronic equipment or a net hauler), and $\mathbf{x}_i$ = (labor, fuel, capital) for each boat's most recent trip. The data set contains several measures of capital stock, but because the small sample size limits the number of parameters we can estimate, each model is estimated three times using a different variable to capture capital stock, including net length, horsepower, and the shape of the boat, measured as the ratio of vessel width to length (as a measure of the capacity of the boat relative to its maneuverability in the water as well as the maneuverability of the crew within the vessel). In addition, these vessels exploit a multispecies fishery, but the data does not provide disaggregated catch by species. We estimate each model with total catch in kilograms as the dependent variable, and again with revenue as the dependent variable as a way of weighting the various species by their value.

In the stochastic frontier specification above, the error term is defined as

$$\varepsilon_i = v_i - u_i$$

where v and u are assumed to be distributed independently of each other and of the regressors $\mathbf{x}$, I, and D. The first component of the error term, v, is an idiosyncratic, two-sided error term capturing exogenous shocks and is assumed to be distributed as $\nu_i \sim iidN(0, \sigma_\nu^2)$.

The second component of the error term, u, is a non-negative stochastic inefficiency component drawn from a normal distribution truncated at zero (Kumbhakar et al. (1991)). This term captures differences in technical inefficiency and gives a firm-specific measure of the distance of the firm from the best practice frontier. We assume u_i is distributed $N^+(\mu_i, \sigma_u^2)$, where $\mu_i = Z_i\delta$, and Z is a vector of firm-specific explanatory variables that account for differences in efficiency.

This approach assumes technical inefficiency u_i to be uncorrelated with technology adoption, while in reality u_i and I are likely to be correlated. Skill may cause adoption if skill includes the ability to find and deploy new methods first, or if low skill fishers adopt technologies to improve outcomes. Adoption may cause changes in skill if fishers differ in their ability to effectively use the technology or if the fisher was not producing on the frontier before adopting. If skill drives adoption, so that u_i causes I, random assignment of technology is required to consistently estimate causal parameters for I[3]. Lacking random assignment, we attempt to control for this source of correlation by including variables in Z that capture the propensity to adopt and explain variation in u_i.

On the other hand, if adoption and use of technology determines technical efficiency, even random assignment of technology will induce correlation between u_i and I. We attempt to control for this source of correlation by including variables in Z that capture the propensity to make productive use of technology and explain variation in u_i (e.g., the number of technologies used and the education level). Causality is likely to run in both directions as adoption and skill are jointly determined, and there is some overlap in the Z that will control for both the propensity to adopt technology and the propensity to effectively use technology. Therefore, a number of models with different variables included in Z are tested. The likelihood function and efficiency measures in this application are generalizations of the conventional case (Battese et al. (1993)). For the bulk of the analysis, the Z variables include whether the respondent attended primary or secondary school, the number of times the net was hauled in on the most recent trip, the respondent's share of earnings on the most recent trip, the number of innovations adopted by the respondent's vessel, and in one model, squared values of the logged input variables. We also estimate several specifications that mirror as closely as possible the inefficiency hypotheses tested by Viswanathan et al. (2002) and Squires et al. (2003), who found that inefficiency is influenced by vessel characteristics, fishing season, crew incentives and human capital, although only a few of these were individually statistically significant.

[3]Another argument put forth by Zellner et al. (1966) holds that predetermined, fixed production inputs may be thought of as exogenous when examining the most recent period of outputs. A capital investment decision (e.g., boat size, engine size, etc.) made several years ago also determines the choice of crew size and fuel use in every subsequent trip. At the point of the most recent fishing trip, these input decisions are predetermined. Thus, this argument holds that output cannot simultaneously influence input decisions. One drawback to this argument, however, is that if fixed vessel- or skipper-specific attributes are constant in the long run, such as innate skill, motivation, or ability, the same attributes that influenced the capital decision years ago may also influence this period's output.

2.6 Results

2.6.1 Establishing functional form and the presence of a stochastic frontier

We explore three functional form models to account for the production environment. Model 1 is a translog production function as described above. Likelihood ratio tests of the significance of the second-order terms overwhelmingly reject the translog form in favor of a Cobb-Douglas production function (Table 2.8).

Based on these results, Model 2 is a modified Cobb Douglas with input interactions only included where they are interacted with technology dummies:

$$\log y_i = \beta_0 + \sum_{j=1}^{3} \beta_j \log x_{ij} + \phi' D_i + \alpha_0 I_i + \sum_{j=1}^{3} \alpha_j I_i \log x_{ij} + \frac{1}{2} \sum_{l=1}^{3} \sum_{j=1}^{3} \alpha_{jl} I_i \log x_{ij} \log x_{il} + \varepsilon_i$$

We also estimated a third modified translog model with cross-input interactions included in the production function but with squared input terms included in Z. Likelihood ratio tests of the technology effects (the α's) across all three models indicate a significant difference in the frontier between adopters and non-adopters of net haulers, particularly when revenue is the dependent variable. This difference is not significant for electronics adoption, however (Table 2.9).

Lastly, we conducted generalized likelihood ratio tests to establish the existence of a frontier and the significance of the Z vector in explaining inefficiency. As indicated in Table 2.10, the existence of a stochastic frontier is confirmed in almost all specifications. The likelihood function for these specifications is not well-behaved and did not converge in many cases, so we chose several sets of explanatory variables for the inefficiency function and compare results where convergence was achieved. Several specifications significantly explained variation in technical efficiency, particularly those that include experience, location, boat width class, season, and number of technologies adopted (Tables 2.11 and 2.12). These findings are more robust when net haulers are the adoption of interest than when electronics are considered. In other words, it is more difficult to explain deviations from the frontier when we account for electronics adoption.

2.6.2 Explaining technical efficiency

The individual coefficients in the inefficiency function are presented in Tables 2.13 and 2.14. Although these sets of variables are often significant as a group, few of them are individually significant. Positive signs are associated with lower efficiency. Coefficients on primary school education and catch share paid to the respondent are positive and often significant. Catch shares paid to the respondent were included to capture fishing incentives, but greater shares are highly correlated with fewer crew members. Rather than capturing incentive effects, this result likely indicates that, *ceteris paribus*, vessels with smaller crew sizes were less efficient. The positive sign on primary school completion may be hinting at the selection issue with fishing; skippers who completed school but could find no other job may have found fishing as a last resort, not because they are particularly skilled at it. Vessels in the southern districts (D3-D5) tend to be more efficient, as well as vessels in the smaller width classes, although wider boats are associated with more modern designs. This is consistent with the finding among boats with net haulers: these are relatively younger boats with less efficient captains attempting to substitute technology for skill. It is also worth noting that the number of new technologies adopted and the number of times the net was hauled during the most recent trip had negative signs in the revenue regressions (i.e., are associated with more efficient vessels), although these are not significant at conventional levels.

2.6.3 Stability of skill rankings

As discussed in Section 2.3, hypothesis S3 concerns whether skill is concentrated in a handful of star performers with efficiency more or less driven by luck in the rest of the fishery, or whether skill is a fixed attribute leading to efficiency rankings that are stable over time. We attempt to answer this question through the following exercise: we ranked vessels by their efficiency score and by their performance in different seasons, and then provide a simple correlation matrix of these rankings (Table 2.15). Respondents in this data set were asked to estimate their catch and revenue during a typical fishing trip in their peak season and in their lean season, as well as during the most recent trip. Inputs are only available for the most recent trip. Assuming that input levels used in the most recent trip are similar to inputs used in a typical trip, we re-estimated a series of frontiers with typical peak and lean revenues as the dependent variable. We compared the technical efficiency rankings from these estimates to those from the most recent trip, as well as rankings of the size of catch and revenue, and found that rankings are not stable. Correlations are very low for the most part and are only high where one would expect them to be, for example, comparing the peak earnings rank to the peak catch rank. Technical efficiency rankings, which should be a better measure of skill, are not correlated. This is in contradiction to Squires and Kirkley (1999) who estimate vessel fixed effects using panel data. Our analysis requires stronger assumptions than Squires and Kirkley (1999) because our data set is less rich. However, their paper looks at an industrial, developed country fishery with larger, more advanced vessel technology. It may be that this artisanal fishery is more prone to random forces.

2.6.4 Parameters of the production frontier

The output elasticities with respect to particular inputs can be expressed as:

$$\xi_j = \frac{\partial \log y_i}{\partial \log x_{ij}} = \beta_j + \frac{1}{2}\sum_{l=1}^{3} \beta_{jl} \log x_{il} + \alpha_j I_i + \frac{1}{2}\sum_{l=1}^{3} \alpha_{jl} I_i \log x_{il}$$

Scaling the variables by their respective means allows us to summarize the output elasticity at the mean by $\xi_j = \beta_j + \alpha_j I_i$, with the elasticity differing by adoption status. The α_j term captures the input bias from technical change – a value we will be particularly interested in. Without scaling variables to have unit means, the firm-specific input bias would be expressed as:

$$IB_{ij} = E(\xi_j | \, I = 1) - E(\xi_j | \, I = 0) = \alpha_j + \frac{1}{2}\sum_{l=1}^{3} \alpha_{jl} \log x_{il}$$

Technical change from innovation can be expressed as:

$$\begin{aligned} TC_i &= E(\log y_i | \, I = 1) - E(\log y_i | \, I = 0) \\ &= \alpha_0 + \textstyle\sum_{j=1}^{3} \alpha_j \log x_{ij} + \sum_{l=1}^{3} \sum_{j=1}^{3} \alpha_{jl} \log x_{ij} \log x_{il} \end{aligned}$$

where once again technical change at the mean is captured by α_0. We will also be interested in measuring the scale bias from technical change, or $SB_i = \sum_{j=1}^{3} IB_{ij}$.

Tables 2.16 and 2.17 report estimates of these quantities for Model 2. Consistently negative and significant coefficients of technological change for net hauler adoption suggest that less productive vessels are adopting the net haulers. Particularly, less productive labor seem to be associated with adopting net haulers; the sign of labor bias is negative in most cases and significant when the length of the net is used to measure the capital stock. The result is indeterminate for fuel and capital biases, however, because the signs flip depending on the specification. Unfortunately, we cannot measure the degree to which adoption has improved labor or total productivity for these vessels.

To examine this further, we compared technical efficiency scores between adopters and non-adopters of both technologies (Table 2.18) and found that the mean technical efficiency score for net hauler adopters was about 28 percentage points higher than for non-adopters. In other words, the frontier for this group of vessels is distinct and interior to the frontier for non-adopters, but adopters operate more efficiently with respect to this interior, "skill-challenged" frontier. Technology in this sense may be a way of compensating for a lack of skill. It is possible that these technologies are cost reducing, or skill diluting, or some combination of these effects which allow adopting firms to appear more efficient relative to different frontiers – adopters may be the inefficient, low-skill firms in which case pure technical change effects would appear to be negative. Another explanation is that adopters are simply inefficient users of the new technologies. It is likely we have a confounding of these effects going on.

It is worth noting, also, that net haulers adopters were asked about their crew size before and after adoption. In the sample of gasoline-powered vessels examined here, 3 out of the 10 net hauler adopters reduced their crew size by one person; if we include diesel-powered vessels in this count the proportion is 5 of 15, and one vessel reduced crew size by two. In other words, about one third of artisanal drift net vessels using net haulers reduced their crew size after adopting the technology, and none of the vessels increased crew size after adoption. Furthermore, four of the vessels stated as their reason for using a net hauler that it was "difficult to find labor," six said it was "to save energy," four said it was "to make work easier," and one said "to save cost." Even after adoption, net hauler adopters had larger average labor usage; the mean crew size among adopters was 2.1 in the overall sample and 2.2 in the largest width class, vs. 1.4 and 1.8, respectively, among non-adopters in those groups.

The technical change coefficient for electronic equipment, on the other hand, is positive and usually significant, indicating that either more productive vessels are adopting this equipment or the equipment is improving productivity. Although the coefficients on input biases are insignificant, they seem to tell a sensible story: adopters generally had lower fuel productivity and higher capital and labor productivity. This would suggest that adopters are vessels that burn a lot of fuel searching for fish with limited crew and capital endowment – more evidence of the skill-diluting theory of technical change in fisheries. This result is stronger when revenue is the dependent variable, so it is worth asking whether the electronics are a fish-finding tool or whether cell phones, which comprise most of the electronics use in this sample, are being used to find markets with higher prices (Jensen (2007)). Table 2.19 provides a simple regression of fish prices on cell phone use and other variables, and the coefficient on cell phone use is small and not significant. Cell phone users in this sample are concentrated in the south; rather than contradict recent findings that cell phones help artisanal fishermen find higher priced markets, our result may be idiosyncratic and simply reflect geographic or social factors preventing access to alternate markets in this particular fishery and in this particular season. One interpretation is that cell phones in this fishery are used more for fish finding than price finding – and in particular, for finding higher-value species – suggesting the presence of informal networks and cooperation in fishing activities.

Notably, fuel and capital stock are often significant explanatory variables for catch and revenue, while crew size is never significant. There is minimal variation in crew size in this sample – the minimum is one crew member and the maximum is three. It seems that fuel use, which can be interpreted as time spent searching for good fishing spots or willingness to travel to good spots, along with luck, skill, and vessel characteristics drive productivity in this fishery.

2.6.5 Vessel design characteristics

One consistent result has been that the shape of the boat – its width relative to its length, has a significant relationship with output. Older, more traditional boats in this fishery tend to be longer and narrower, which provides less room for the crew to maneuver. More modern designs use wider hulls, so that boats in this sample range from less than 1 meter to over 3 meters wide. As indicated by our discussion of the profile of technology adopters, and of the relationship between boat age and net-hauler adoption pictured in Figure 2.9, it is worth examining whether these more modern designs include more technology adopters.

Based on the CDF of boat width (Figure 2.9) we split the sample into four "width classes." Figures 2.9 – 2.9 compare the frequency distributions of outcomes for adopters and non-adopters by width class. From these figures we can see that the vast majority of adopters (of any technology) are in the largest, more modern width class. This width class breakdown may remove some of the unobserved heterogeneity, if choice of boat width is a good proxy for that heterogeneity. Table 2.20 provides summary statistics by technology, width class, and location, with the left column corresponding to the southernmost district. It is easy to see from the lower left quadrant of this table that vessels in the southernmost district and the largest width class were both the most frequent adopters and the most successful fishermen in the most recent trip. Adopters outside this group performed markedly less well. It is difficult to disentangle technology and boat width effects, but this pattern of improvement by width class holds among adopters and non-adopters (of any technology). Also, adopters in the smallest two width classes perform worse than non-adopters, but adopters in the largest two width classes perform better. Both of these patterns hold up across innovation type. Boat width is positively correlated with typical peak season earnings (0.40) and catch (0.43). Respondents who said they were only fishermen because they had no other source of income also had narrower boats; a "yes" answer to this question was negatively correlated with boat width (-0.24).

We estimated simple Cobb-Douglas production functions and frontiers for the 27 vessels in the largest width class. Tables 2.21 and 2.22 break down the signs of technology interaction coefficients for the different models, and presents estimates of mean technical efficiency for this group. When a technology adoption dummy is included without interactions terms with inputs, it appears that the mean is shifting out in the OLS regressions. When interactions are included and in frontier estimations, however, it appears that although adopters may have a higher intercept, and may be more productive at low input levels, adopters have lower output elasticities for most inputs. Vessels in this width class are also noticeably more efficient at producing value than volume.

2.7 Concluding Remarks

The direction and magnitude of the effects of new fishing technologies on technical efficiency is as yet unclear; we do not have information about exogenous variation in the provision of technology, so we do not identify a causal effect of technology on technological change or technical efficiency. However, we can measure observed relationships between technology use and these values. This cross-section of individual vessels in the artisanal Malaysian gill net fishery suggests that new technologies can be skill-diluting. Adopters tend to be less technically efficient vessels, with low labor productivity and higher reliance on labor inputs. Skill, search, and embodied vessel characteristics seem to drive productivity in this fishery. Fishermen who claim to have fewer outside options and use fishing as an occupation of last resort tend to be less efficient and have less modern vessel designs.

There are several implications for policy and development assistance programs. This study highlights the need to take a comprehensive look at technology impacts in artisanal fisheries before promoting technology assistance programs. Our study raises important questions about the role of technology assistance in any development policy aimed at artisanal fishing communities. Although our limited data restricts the inferences we can make, our study does not confirm Jensen's (2007) results that cell phone users find higher prices. Geographical or social barriers unique to this fishery may limit access to alternate markets. Technology impacts, and by extension, the desirability of technology assistance, may thus be fishery-specific. Technical efficiency and technology adoption effects vary by locality even within our sample.

Our findings suggest that in this fishery cell phones may be used in informal networks for fish-finding, rather than price finding. More generally, our analysis of advanced equipment supports a theory of skill-diluting technical change, improving the technical efficiency of less-efficient vessels. Yet most fishery participants – adopters and non-adopters alike – remain dissatisfied with fishing as an occupation and only remain because of their inability to find suitable outside options. The anecdotal effect of using a mechanical net hauler, if any, is to reduce reliance on labor, yet adopters still continued to use more labor with less marginal productivity than non-adopters. Furthermore, net haulers are a more expensive technology, requiring specific investment, and are typically adopted by younger boats with longer expected usable lives – and may thus tie these participants to the fishery in the long run.

These concerns are irrespective of the impact of advanced technology on resource abundance, which is also a subject of concern but is not measured here. Technology assistance may not unambiguously improve fishery outcomes, even without considering impacts on the fish stock. Even improved short-run outcomes must be weighed against long run considerations as well as alternative policies to technology assistance. Rather than invest in technologies which further tie the less successful fishery participants (i.e., the best candidates for exit) to a declining resource, programs may be better targeted at providing occupational alternatives or other means to exit the fishery.

2.8 Acknowledgements

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2.9 Figures and Tables

Table 2.1: Overview: Net Hauler

Hypothesis	Evidence	Interpretation
Net Hauler Hypotheses		
N1: Net Hauler adopters have higher labor productivity	*one third of adopters reduced crew size after adoption, none increased crew size, but nethauler adopters had larger average crew size on most recent trip	*except for the reduction in crew size for a third of adopters, the evidence does not support this hypothesis
	*coefficients on labor-bias are always negative and occasionally significant in full sample	*however, the evidence does not support or reject the idea that net haulers are labor-augmenting,
	*even in largest boat width class, labor bias is usually negative, but not in all specifications	e.g., if vessels with low labor productivity/high labor reliance were adopters.
N2: Net Hauler adopers have higher total factor productivity	*mean output larger for adopters, but max output lower for adopters, even when disaggregated by region	*"skill-diluting" technical change:
	*coefficient on net hauler always negative and often significant	adopters may be less efficient boats moving towards the frontier, rather than most efficient boats shifting the frontier itself
	*for largest boats, adoption coefficient positive for OLS, but not for frontier	

Table 2.2: Overview: Electronics

Hypothesis	Evidence	Interpretation
Electronics Hypotheses		
E1: Electronics users have higher total factor productivity	*mean output larger for adopters, but max output lower for adopters, even when disaggregated by region *electronics coefficient is positive and significant, frontiers are not significantly different *for largest boats, electronics coefficient is positive but marginal productivity is lower	*"skill-diluting" technical change: no significant frontier difference but higher technical efficiency among adopters.
E2: Cell phone users fetch higher prices	*OLS regressions of fish price on cell phone adoption show no significant relationship	*ambiguous result. electronics may improve fish-finding, rather than price-finding *geographic or social factors may block alternate markets, or markets may have already equilibrated across regions

Table 2.3: Overview: Adoption

Hypothesis	Evidence	Interpretation
Adoption Hypotheses		
A1: More modern vessels are more likely to be adopters	*net haulers used on younger boats (3.5 yrs vs 5.2 yrs) with longer expected lives (16 yrs vs 10 yrs *adoption of both technologies mainly among wider boats (more modern design)	*results consistent with hypothesis
A2: Adopters will be found in clusters by location	*11 adopters out of 43 vessels (26%) in southernmost district, comprising 48% of all adopters in the sample *8 adopters out of 15 vessels (53%) in southernmost village, comprising 35% of all adopters in the sample	*consistent with information hypothesis of technology diffusion

Table 2.4: Overview: Skill

Hypothesis	Evidence	Interpretation
Skill Hypotheses		
S1: Technology is skill-augmenting	*adopters have significantly higher average technical efficiency scores	*adopters are more efficient, their fishing skill is harder to distinguish from the best non-adopters
	*vessels adopting more technologies were more efficient, although this is only marginally significant in a one-sided test	*evidence exists for both skill-diluting and skill-augmenting, better data needed
S2: Observable skipper/vessel characteristics are not good predictors of technical efficiency	*individual coefficients on education, season, location, and share of catch paid to respondent are significant in some specifications, although some signs are unexpected	*observable attributes can explain some variation in technical efficiency
	*set of inefficiency variables is significant as a group in most specifications	*because skill rankings are not stable (S3), it is difficult to conclude these will always be good predictors of skill
S3: Skill rankings are stable and consistent	*skill rankings are stable across different frontier specifications of the most recent trip, but are not correlated across season	*in this fishery, luck may be as important as skill in determining technical efficiency

Table 2.5: Summary Statistics

Variable	N	Mean	Std. Dev.	Min	Max
Catch	115	30	46	1	270
Typical Catch	115	54	86	0	500
Revenue	115	116	156	1	1000
Typical Revenue	115	252	426	1	3000
Peak Season	114	0.54	0.5	0	1
Fish Price	114	5.03	2.39	1	13
Hauls/Trip	114	4.16	2.68	1	20
Share	115	0.75	0.31	0	1
Years Fishing	113	27	15	3	66
Household Size	111	2.61	2	0	8
Boat Ownership	115	0.89	0.32	0	1
Region:					
Kuantan	115	0.37	0.49	0	1
Kemaman	115	0.1	0.3	0	1
Dungun	115	0.1	0.31	0	1
Marang	115	0.17	0.37	0	1
Setiu	115	0.26	0.44	0	1
South	115	0.57	0.5	0	1
Inputs:					
Crew Size	115	1.42	0.61	1	3
Fuel	115	20	11	4	62
Gear Size	114	731	586	40	3200
Horse Power	114	22	14	6	120
Boat Length	115	6.21	1.71	4.15	18
Boat Width	115	1.65	0.59	0.83	6
Boat Shape	115	0.27	0.04	0.15	0.4
Width Class	115	2.36	1.16	1	4
Technology:					
Any	115	0.2	0.4	0	1
Net Hauler	115	0.09	0.28	0	1
Electronics	115	0.15	0.36	0	1
No. Adoptions	115	0.42	0.94	0	5
Education:					
Primary	114	0.82	0.39	0	1
Secondary	114	0.15	0.36	0	1

Table 2.6: Summary statistics: outcome variables by adoption status

	N	Mean	Min	Max	N	Mean	Min	Max	Mean Diff	Min Diff	Max Diff
Outcome	Innovate = 1				Innovate = 0				Difference		
catch	23	57	1	200	92	23	1	270	34	0	-70
typical catch	23	107	0	400	92	42	0	500	65	0	-100
revenue	23	228	1	1000	92	88	1	600	139	0	400
typical revenue	23	538	1	3000	92	181	1	1500	357	0	1500
	Electronics = 1				Electronics = 0				Difference		
catch	17	65	5	200	98	23	1	270	42	4	-70
typical catch	17	104	0	300	98	45	0	500	58	0	-200
revenue	17	263	18	1000	98	91	1	600	173	17	400
typical revenue	17	588	1	3000	98	194	1	1500	394	0	1500
	Net Hauler = 1				Net Hauler = 0				Difference		
catch	10	46	1	120	105	28	1	270	18	0	-150
typical catch	10	113	0	400	105	48	0	500	65	0	-100
revenue	10	198	1	650	105	108	1	1000	90	0	-350
typical revenue	10	415	1	1200	105	237	1	3000	178	0	-1800

Table 2.7: Summary statistics: outcome variables by district and technology

District	N	Mean	Min	Max	N	Mean	Min	Max	Mean	Min	Max
	Electronics = 1				Electronics = 0				Difference		
Catch											
Kuantan	7	75	5	200	36	18	1	120	57	4	80
Kemaman	3	17	5	40	8	41	4	120	-23	1	-80
Dungun	3	143	30	200	9	78	4	270	66	26	-70
Marang	2	40	30	50	17	15	2	50	25	28	0
Setiu	2	13	5	20	28	12	1	30	0	4	-10
Revenue											
Kuantan	7	342	18	800	36	98	1	480	244	17	320
Kemaman	3	121	24	310	8	170	15	600	-49	9	-290
Dungun	3	450	150	1000	9	148	20	320	302	130	680
Marang	2	105	100	110	17	59	10	120	46	90	-10
Setiu	2	80	60	100	28	60	1	135	20	59	-35
	Net Hauler = 1				Net Hauler = 0				Difference		
Catch											
Kuantan	6	53	1	120	37	23	1	200	29	0	-80
Marang	4	35	10	50	15	13	2	40	22	8	10
Revenue											
Kuantan	6	274	1	650	37	115	1	800	158	0	-150
Marang	4	84	18	110	15	58	10	120	27	8	-10

(only districts with adopters included)

Table 2.8: Generalized Likelihood Ratio Tests of Translog Coefficients

Null Hypothesis: all second-order coefficients = 0

Capital Measure	Likelihood Ratio (I = Net Haul)	Likelihood Ratio (I = Electronics)	df	Critical Value (5%)
Model 1: Full translog with technology interactions				
Dependent Variable: Log of Revenue				
Net Length	9.06	11.71	6	12.59
Horsepower	5.27	4.71	6	12.59
Boat Shape	4.37	4.48	6	12.59
Dependent variable: Log of Catch				
Net Length	2.77	2.36	6	12.59
Horsepower	1.80	1.39	6	12.59
Boat Shape	6.68	5.58	6	12.59
Model 3: Modified translog with technology interactions				
Dependent Variable: Log of Revenue				
Net Length	6.94	*31.47**	3	7.815
Horsepower	0.82	1.98	3	7.815
Boat Shape	4.69	3.06	3	7.815
Dependent variable: Log of Catch				
Net Length	1.71	2.04	3	7.815
Horsepower	0.47	0.40	3	7.815
Boat Shape	7.60	5.43	3	7.815

*This is more likely due to a failed grid search while running Stata 10's frontier routine than significant coefficients. This specification produced many other unlikely values, including individual t-values well above 10,000.

Table 2.9: LR Test of Technology Effects

Null Hypothesis: all technology coefficients = 0

Capital Measure	Net Haul (df=9*) Log Revenue	Net Haul (df=9*) Log Catch	Electronics (df=10) Log Revenue	Electronics (df=10) Log Catch
Model 1: full translog with tech interactions				
Net Length	30.14	14.87	22.54	11.58
Horsepower	30.67	14.29	7.38	10.77
Boat Shape	27.57	15.79	14.89	12.03
Model 2: Cobb-Douglas with tech interactions				
Net Length	29.37	15.03	18.05	12.15
Horsepower	28.93	14.17	13.89	11.06
Boat Shape	28.66	15.62	15.86	12.96
Model 3: modified translog with tech interactions				
Net Length	28.59	15.04	*44.06***	13.06
Horsepower	23.73	14.04	15.66	11.14
Boat Shape	30.57	17.19	16.85	12.59

Degrees of Freedom:	Critical Value 10%	Critical Value 5%	Critical Value 1%
9	14.68	16.92	21.67
10	15.99	18.31	23.21

*STATA drops one regressor in these specifications due to collinearity

**see note in Table 2.8

Table 2.10: LR Test For Presence of Stochastic Frontier

Null Hypothesis: gamma = 0*

Capital Measure	Net Haul (df=2) Log Revenue	Net Haul (df=2) Log Catch	Electronics (df=2) Log Revenue	Electronics (df=2) Log Catch
Model 1: full translog with technology interactions				
Net Length	15.68	4.86	27.60	4.80
Horsepower	18.20	6.02	14.30	5.67
Boat Shape	15.80	8.35	21.33	8.66
Model 2: Cobb Douglas with technology interactions				
Net Length	12.66	5.47	18.03	5.91
Horsepower	14.46	5.29	16.61	6.23
Boat Shape	13.75	5.39	18.32	5.24
Model 3: modified translog with technology interactions				
Net Length	14.47	5.15	*38.93***	6.39
Horsepower	14.75	6.21	17.93	6.45
Boat Shape	18.25	10.69	13.94	10.16

			Critical Value: 5%	Critical Value: 1%
Degrees of Freedom:	2		5.14	8.27

*compare to Kodde & Palm 1986, Table 1

**see note in Table 2.8

Table 2.11: LR Test For Presence of Stochastic Frontier

Null Hypothesis: d1 = ... = dN = 0

Capital Measure	Likelihood Ratio I = Net Haul	df*	Critical Value (5%)	Critical Value (1%)
Model 2: Cobb Douglas with technology interactions				
Dependent Variable: Log of Revenue				
Z=primary, secondary, # hauls, share, # adoptions				
Net Length	21.46	5	11.07	15.09
Horsepower	20.75	5	11.07	15.09
Boat Shape	22.34	5	11.07	15.09
Z=years experience, household size, primary, secondary, share, district, season, boat width class				
Net Length	47.89	13	22.36	27.69
Horsepower	36.86	13	22.36	27.69
Boat Shape	27.66	13	22.36	27.69
Dependent variable: Log of Catch				
Z=primary, secondary, # hauls				
Net Length	5.70	3	7.82	11.35
Horsepower	5.43	3	7.82	11.35
Boat Shape	6.14	3	7.82	11.35
Z=years experience, household size, primary, secondary, share, district, season, boat width class				
Net Length	46.86	13	22.36	27.69
Horsepower	42.47	10	18.31	23.21
Boat Shape	43.33	12	21.03	26.22

*MLE convergence was not obtained for all sets of inefficiency variables, so the Z vector was adjusted where necessary.

Table 2.12: LR Test For Presence of Stochastic Frontier

Null Hypothesis: d1 = ... = dN = 0

Capital Measure	Likelihood Ratio I = Electronics	df*	Critical Value (5%)	Critical Value (1%)
Model 2: Cobb Douglas with technology interactions				
Dependent Variable: Log of Revenue				
Z=primary, secondary, # hauls				
Net Length	3.47	3	7.82	11.35
Horsepower	4.64	3	7.82	11.35
Boat Shape	5.70	3	7.82	11.35
Z=years experience, household size, primary, secondary, share, district, season, boat width class				
Net Length	30.01	13	22.36	27.69
Horsepower	32.85	13	22.36	27.69
Boat Shape	31.47	13	22.36	27.69
Dependent variable: Log of Catch				
Z=primary, secondary, # hauls				
Net Length	6.04	3	7.82	11.35
Horsepower	6.35	3	7.82	11.35
Boat Shape	5.66	3	7.82	11.35
Z=years experience, household size, primary, share, district, season, boat width class				
Net Length	45.23	10	18.31	23.21
Horsepower	-	-	-	-
Boat Shape	28.62	10	18.31	23.21

*MLE convergence was not obtained for all sets of inefficiency variables, so the Z vector was adjusted where necessary.

Table 2.13: Coefficients on Z variables

Net Hauler, Model 2, t-statistics in italics

Dependent Variable: Revenue

	Capital Measure:					
	Net Length		Horsepower		Boat Shape	
constant	-1.60	1.93	-1.92	1.50	-1.52	1.16
	-0.89	*2.90*	*-1.02*	*2.38*	*-0.89*	*1.88*
# hauls	-0.79		-0.75		-0.82	
	-1.63		*-1.55*		*-1.69*	
# adoptions	-1.22		-1.16		-1.45	
	-1.45		*-1.36*		*-1.44*	
experience		-0.01		0.00		0.00
		-0.78		*-0.01*		*-0.13*
household size		0.02		0.03		0.01
		0.32		*0.51*		*0.24*
primary	1.37	0.47	1.29	0.73	1.40	0.83
	1.64	*1.82*	*1.60*	*2.38*	*1.67*	*2.53*
secondary	0.74		0.37	0.49	1.08	0.79
	0.77		*0.36*	*1.12*	*1.10*	*1.75*
share	2.48	0.48	2.75	0.62	2.32	0.50
	1.95	*0.82*	*2.00*	*1.39*	*1.96*	*1.20*
D1		-0.34		-0.53		-0.18
		-1.16		*-1.87*		*-0.64*
D2		-0.63		-0.81		-0.60
		-1.67		*-2.02*		*-1.60*
D3		-1.43		-1.60		-1.40
		-2.84		*-3.59*		*-3.03*
D4		-0.99		-1.01		-0.95
		-2.42		*-2.53*		*-2.37*
peak season		-0.26		-0.36		-0.19
		-1.18		*-1.65*		*-0.91*
w2		-0.62		-0.54		-0.50
		-1.91		*-1.70*		*-1.53*
w3		-0.38		-0.27		-0.12
		-1.26		*-0.92*		*-0.42*
w4		0.08		0.22		0.46
		0.22		*0.64*		*1.35*

Table 2.14: Coefficients on Z variables

Electronics, Model 2, t-statistics in italics

Dependent Variable: Revenue

	Capital Measure:					
	Net Length		Horsepower		Boat Shape	
constant	-1.60	0.41	-1.92	1.23	-1.52	1.68
	-0.89	*0.30*	*-1.02*	*1.60*	*-0.89*	*2.26*
# hauls	-0.79		-0.75		-0.82	
	-1.63		*-1.55*		*-1.69*	
# adoptions	-1.22		-1.16		-1.45	
	-1.45		*-1.36*		*-1.44*	
experience		0.00		0.00		0.00
		0.09		*-0.33*		*-0.34*
household size		0.04		0.07		0.06
		0.52		*0.89*		*0.78*
primary	1.37	0.96	1.29	0.73	1.40	0.74
	1.64	*1.86*	*1.60*	*1.91*	*1.67*	*1.93*
secondary	0.74	0.96	0.37	0.14	1.08	0.64
	0.77	*1.39*	*0.36*	*0.21*	*1.10*	*1.11*
share	2.48	1.37	2.75	0.80	2.32	0.14
	1.95	*1.55*	*2.00*	*1.53*	*1.96*	*0.28*
D1		-0.45		-0.52		-0.44
		-1.20		*-1.43*		*-1.23*
D2		-0.52		-0.50		-0.54
		-1.18		*-1.19*		*-1.33*
D3		-1.26		-1.99		-2.09
		-1.84		*-3.08*		*-3.22*
D4		-1.76		-1.39		-1.24
		-2.49		*-2.27*		*-2.20*
peak season		-0.56		-0.56		-0.40
		-1.86		*-2.09*		*-1.55*
w2		-0.83		-0.54		-0.73
		-1.94		*-1.27*		*-1.71*
w3		-0.15		-0.04		-0.17
		-0.41		*-0.11*		*-0.46*
w4		-0.25		0.15		0.06
		-0.53		*0.34*		*0.14*

Table 2.15: Correlation Matrix of Performance Measures

		TE: Net Hauler			TE: Electronics			Typical Revenue		Typical Catch	
		Lean	Peak	Recent	Lean	Peak	Recent	Lean	Peak	Lean	Peak
Technical	Lean	1.00									
Efficiency:	Peak	-0.05	1.00								
Net Hauler	Recent	0.30	0.28	1.00							
Technical	Lean	0.45	0.21	0.35	1.00						
Efficiency:	Peak	0.08	0.22	0.15	0.22	1.00					
Electronics	Recent	0.06	0.31	0.80	0.31	-0.03	1.00				
Typical	Lean	0.35	0.34	0.31	0.89	0.19	0.34	1.00			
Revenue	Peak	-0.08	0.76	0.21	0.38	0.17	0.36	0.50	1.00		
Typical	Lean	0.30	0.29	0.38	0.75	0.13	0.40	0.88	0.37	1.00	
Catch	Peak	-0.09	0.64	0.21	0.35	0.05	0.40	0.53	0.80	0.60	1.00

Table 2.16: Production Function Parameter Estimates
Net Hauler, Model 2
(Significance: **5%, *10%)

Dependent Variable:		Revenue			Catch	
Capital:	Net Length	Horsepower	Boat Shape	Net Length	Horsepower	Boat Shape
e(Y,K)	0.13	**0.52****	**1.18****	0.10	0.27	**1.42****
e(Y,L)	0.21	0.03	0.26	0.31	0.23	0.31
e(Y,F)	**0.49****	**0.40****	**0.49****	**0.69****	**0.68****	**0.71****
RTS	0.83	0.96	1.93	1.10	1.18	2.44
Technical Change	**-1.83****	-4.08	**-4.94****	*-2.10**	-5.09	**-3.94****
Input Bias (K)	**-4.17****	9.62	**32.37****	-2.94	16.64	15.05
Input Bias (L)	**-6.35****	-13.88	2.10	**-4.96****	-7.12	-2.17
Input Bias (F)	**9.45****	0.19	**-14.38****	**7.67****	-4.09	-8.82
Scale Bias	-1.07	-4.08	20.09	-0.23	5.43	4.06

Table 2.17: Production Function Parameter Estimates

Electronics, Model 2

(Significance: **5%, *10%)

Dependent Variable:	Revenue			Catch		
Capital:	Net Length	Horsepower	Boat Shape	Net Length	Horsepower	Boat Shape
e(Y,K)	-0.02	0.15	*0.78**	0.09	0.14	*0.96**
e(Y,L)	0.22	0.16	0.17	-0.05	-0.08	-0.01
e(Y,F)	**0.64****	**0.59****	**0.64****	**0.66****	**0.70****	**0.67****
RTS	0.85	0.90	1.59	0.71	0.76	1.62
Technical Change	0.57	**1.29****	**1.30****	*1.14**	*1.15**	**1.54****
Input Bias (K)	1.00	0.31	3.04	0.71	1.79	2.09
Input Bias (L)	2.78	0.80	-0.43	1.83	0.90	-0.31
Input Bias (F)	-0.28	-0.51	0.02	-0.14	-0.69	0.12
Scale Bias	3.50	0.60	2.63	2.40	2.00	1.90

Table 2.18: OLS of Technical Efficiency on Adoption
(Model 2)

	I = Net Hauler	I = Electronics
Capital Measure	Revenue TE	
Net Length	0.28***	0.13*
Horsepower	0.27***	0.11
Boat Shape	0.28***	0.09
	Catch TE	
Net Length	0.05	0.02
Horsepower	0.06	0.02
Boat Shape	0.05	0.03

legend: *p < 10%; **p < 5%; ***p < 1%

Table 2.19: OLS: Log Price

cellphone	*-0.02*
log of catch	-0.10***
peak	-0.04
kuantan	0.02
kemaman	-0.03
dungun	-0.43**
marang	-0.21
buyer	-0.11
primary	-0.02
log vessel tons	0.10**
constant	2.04***
N	108
F(10, 97)	3.58
Prob > F	0.0004
RSS	18.33
Adj R-squared	0.19

legend: *p < 10%; **p < 5%; ***p < 1%

Table 2.20: Mean Revenue (RM) by District, Boat Width and Technology

	Kuantan		Kemaman		Dungun		Marang		Setiu	
Width	**138**	*(43)*	**157**	*(11)*	**228**	*(15)*	**66**	*(20)*	**98**	*(31)*
1 **67** *(39)*	**63**	*5*	**81**	*4*	**143**	*6*	**40**	*9*	**50**	*15*
Net hauler							18	*1*		
Electronics	18	*1*	24	*1*					60	*1*
Cellphone	18	*1*	24	*1*						
GPS			24	*1*					60	*1*
Echo sounder										
Sonar										
2 **124** *(24)*	**88**	*10*	**150**	*1*	**NA**	*0*	**42**	*3*	**183**	*10*
Net hauler										
Electronics	103	*2*							100	*1*
Cellphone	103	*2*							100	*1*
GPS										
Echo sounder										
Sonar	100	*1*								
3 **140** *(29)*	**120**	*16*	**86**	*4*	**575**	*2*	**95**	*3*	**94**	*4*
Net hauler	54	*3*								
Electronics	580	*2*	30	*1*	575	*2*				
Cellphone	580	*2*	30	*1*	575	*2*				
GPS										
Echo sounder										
Sonar										
4 **208** *(28)*	**236**	*12*	**455**	*2*	**203**	*7*	**112**	*5*	**48**	*2*
Net hauler	497	*3*					107	*3*		
Electronics	505	*2*	310	*1*	200	*1*	105	*2*		
Cellphone	505	*2*			200	*1*				
GPS	650	*1*	310	*1*			110	*1*		
Echo sounder	650	*1*	310	*1*						
Sonar										

Revenue mean by category in bold, *N* in italics

Table 2.21: Signs on Coefficients for I = Net Hauler

Estimates for Largest Width Class Only

(++ or − implies significance)

Models: OLS

	Catch				Revenue			
	Net Length	Horse	Shape	Boat Length	Net Length	Horse	Shape	Boat Length
Group 1:								
I	+	+	+	+	+	+	+	+
Group 2:								
I	+	+	+	-	+	+	+	-
I*L	-	+	-	-	-	+	+	-
I*F	+	-	-	-	+	-	-	-
I*K	-	+	-	+	-	+	-	+

Models: Stochastic Frontiers

	Catch				Revenue			
	Net Length	Horse	Shape	Boat Length	Net Length	Horse	Shape	Boat Length
Group 1:								
I	-	-	+	-	-	−	-	-
Mean TE	80%	77%	71%	76%	86%	78%	84%	83%
Group 2:								
I	++	+	++	-	+	-	++	+
I*L	−	+	-	−	-	++	-	−
I*F	+	−	-	-	+	−	−	-
I*K	-	++	-	++	-	++	−	+
Mean TE	68%	75%	81%	71%	83%	83%	83%	83%

Table 2.22: Signs on Coefficients for I = Electronics
Estimates for Largest Width Class Only
(++ or − implies significance)

Models: OLS

	Catch				Revenue			
	Net Length	Horse	Shape	Boat Length	Net Length	Horse	Shape	Boat Length
Group 1:								
I	++	+	+	+	+	+	+	+
Group 2:								
I	+	+	+	+	+	+	+	+
I*L	-	-	-	-	-	-	-	-
I*F	+	-	-	-	-	-	-	-
I*K	-	-	-	+	-	-	-	+

Models: Stochastic Frontiers

	Catch				Revenue			
	Net Length	Horse	Shape	Boat Length	Net Length	Horse	Shape	Boat Length
Group 1:								
I	+	-	++	+	+	-	-	-
Mean TE	75%	71%	73%	71%	84%	80%	85%	80%
Group 2:								
I	++	+	++	++	++	+	+	+
I*L	−	-	-	−	-	-	-	-
I*F	+	-	−	+	+	-	-	-
I*K	−	-	−	+	-	-	-	+
Mean TE	71%	69%	82%	72%	80%	78%	85%	82%

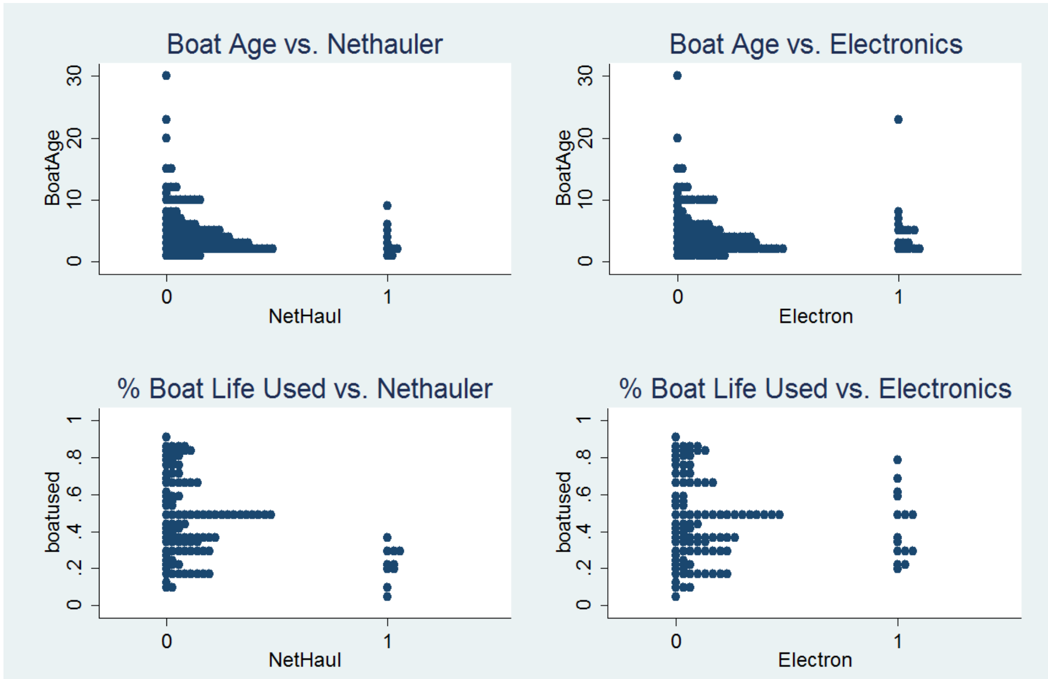

Figure 2.1: Vintage vs. Innovation

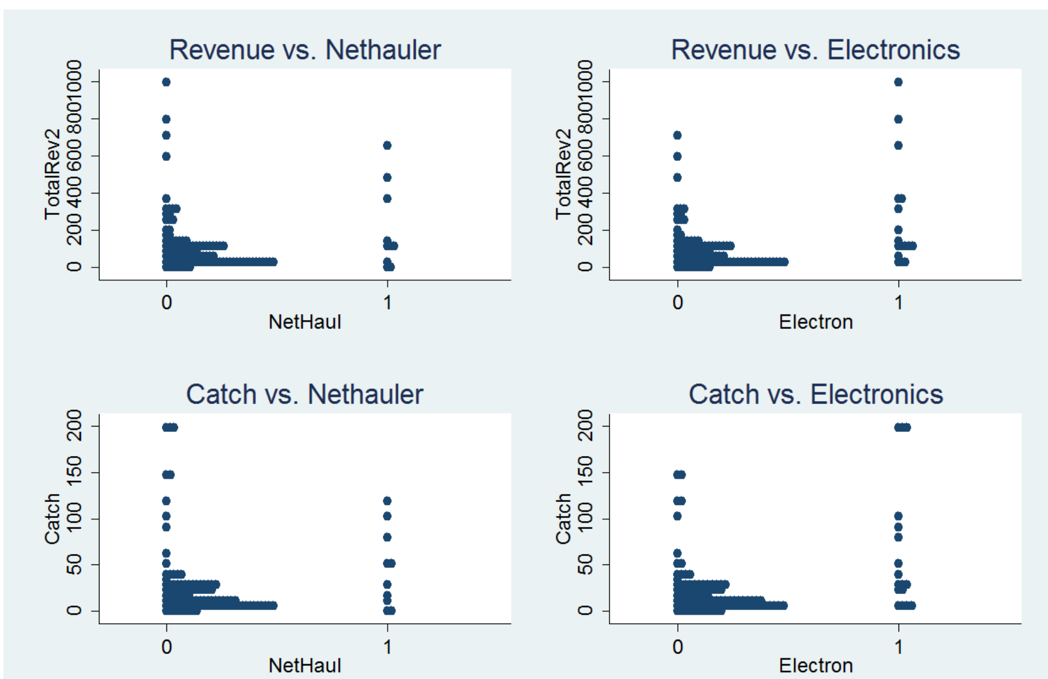

Figure 2.2: Output vs. Technology Adoption

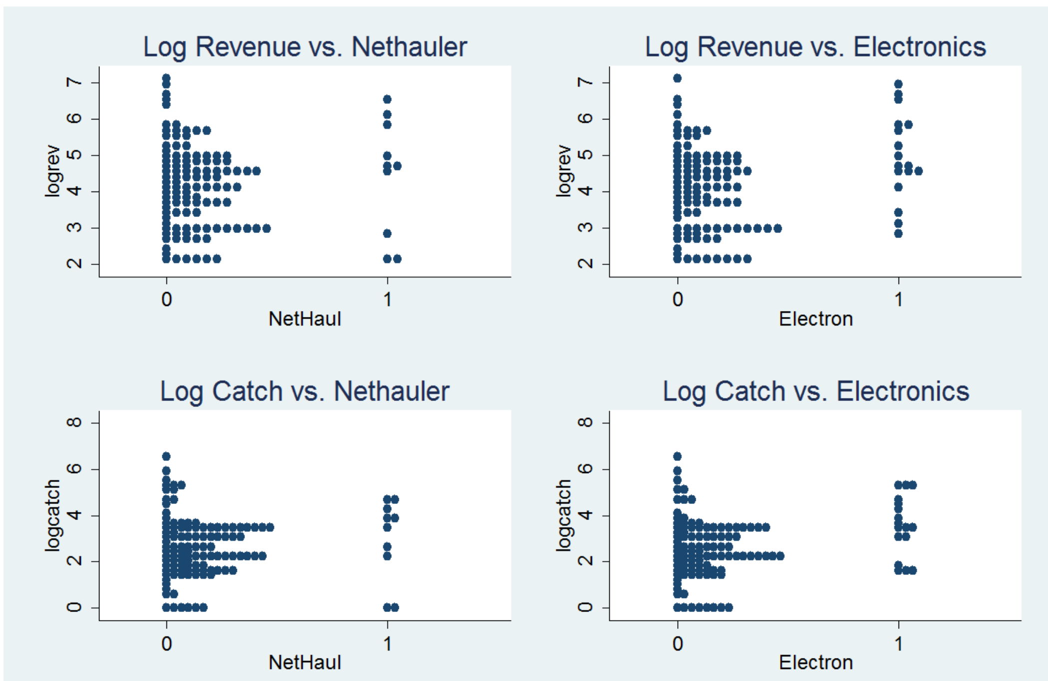

Figure 2.3: Log Output vs. Technology Adoption

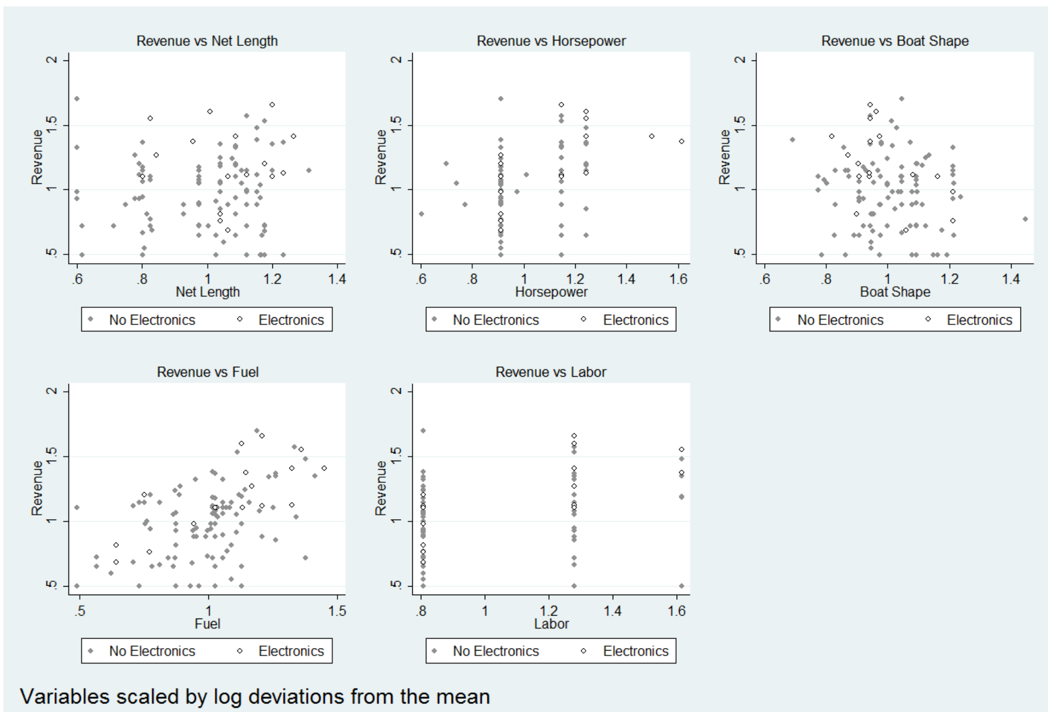

Figure 2.4: Electronics Frontiers

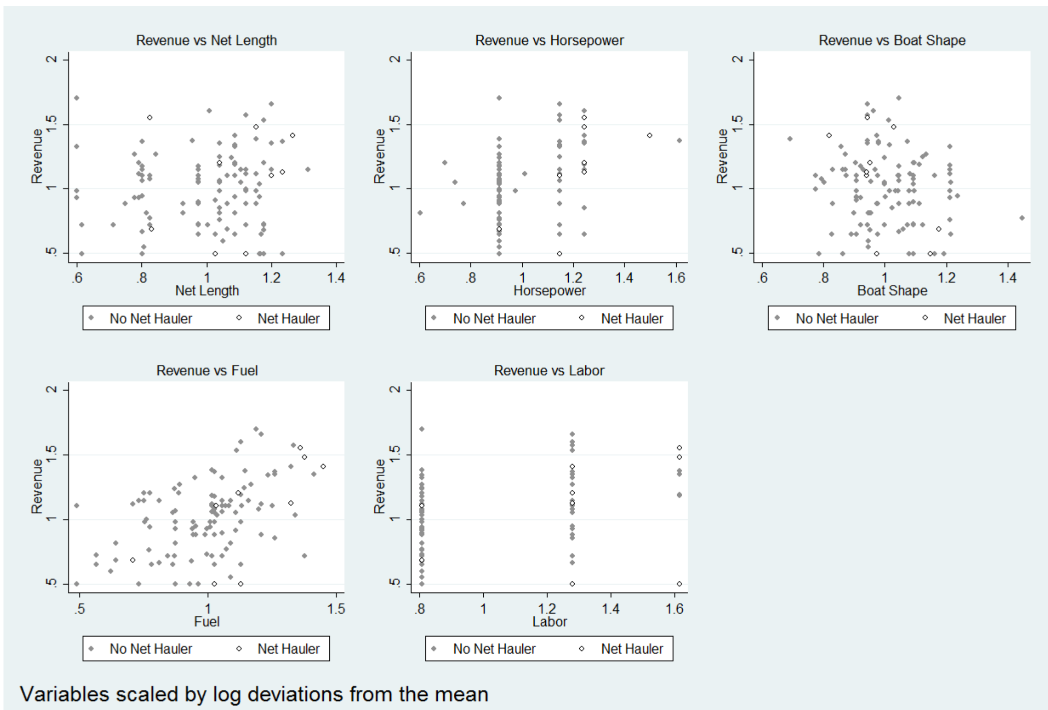

Figure 2.5: Net Hauler Frontiers

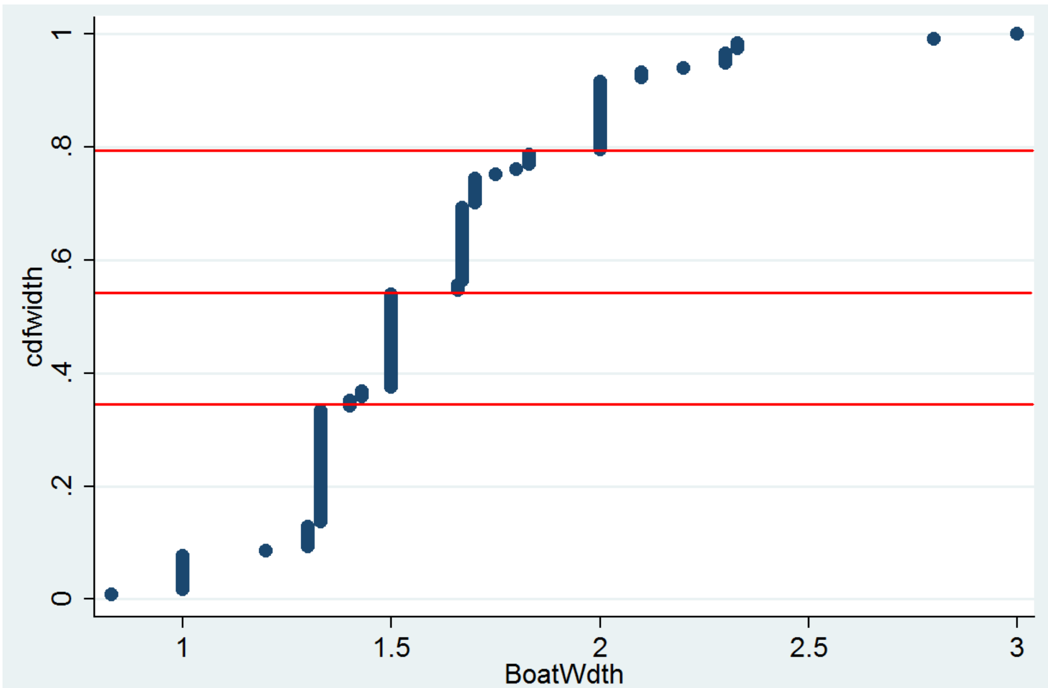

Figure 2.6: CDF of Boat Width

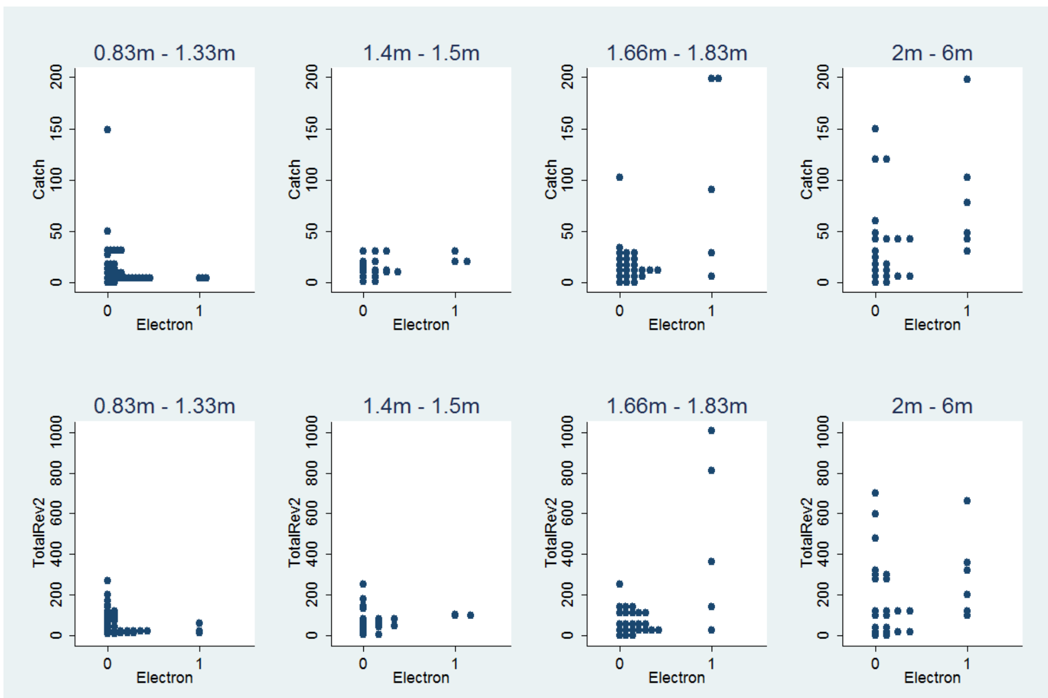

Figure 2.7: Output vs. Electronics Adoption by Size Class

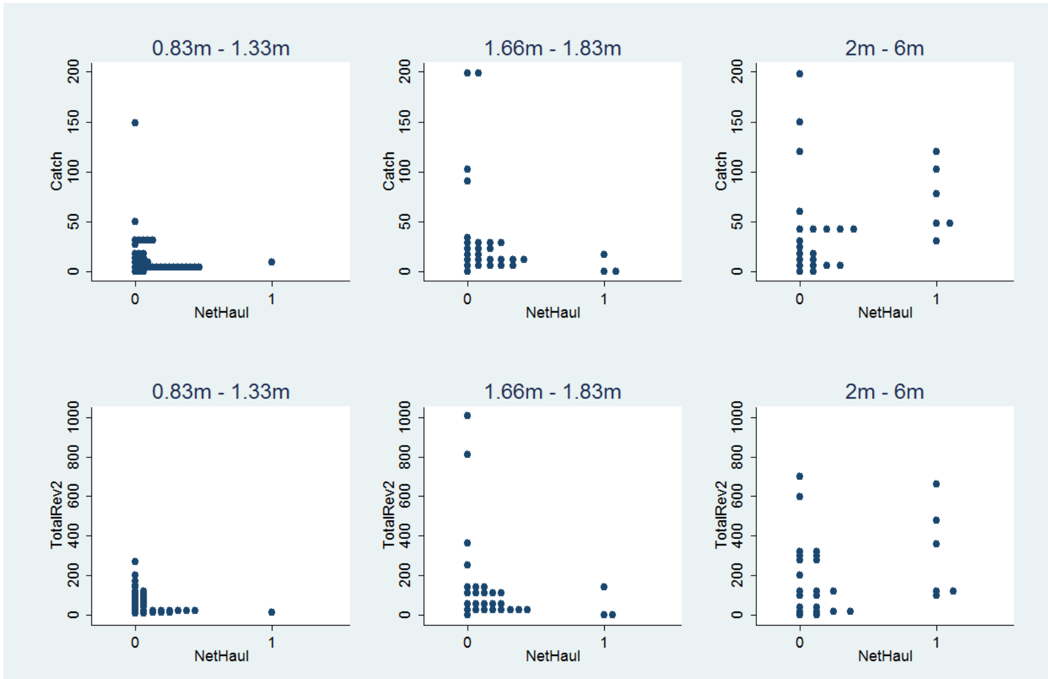

Figure 2.8: Output vs. Net Hauler Adoption by Size Class

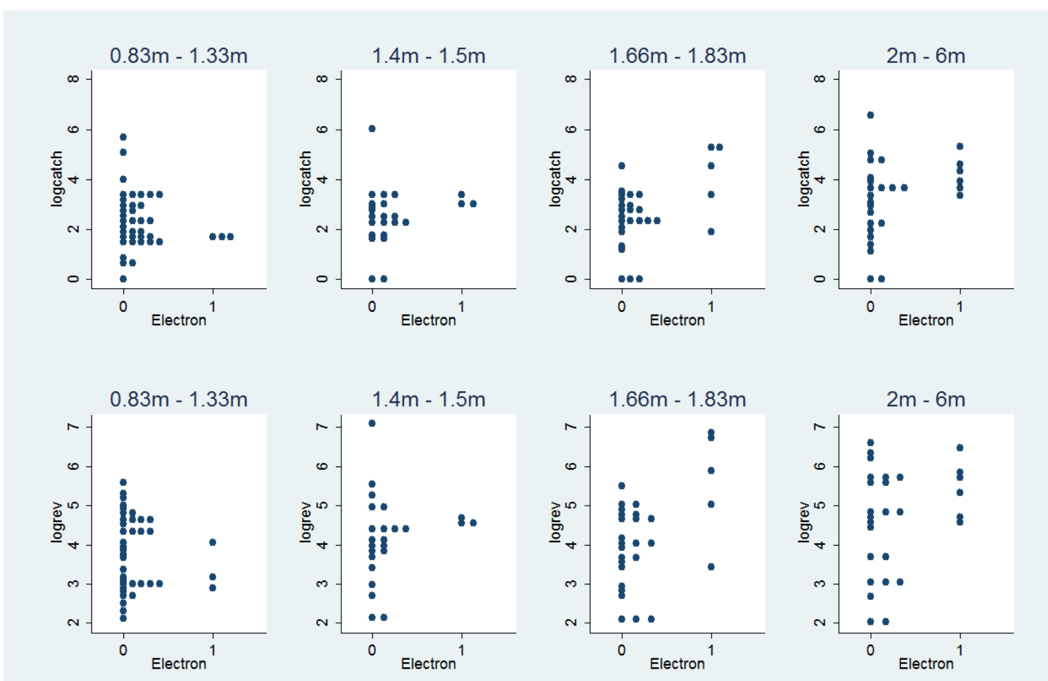

Figure 2.9: Log Output vs. Electronics Adoption by Size Class

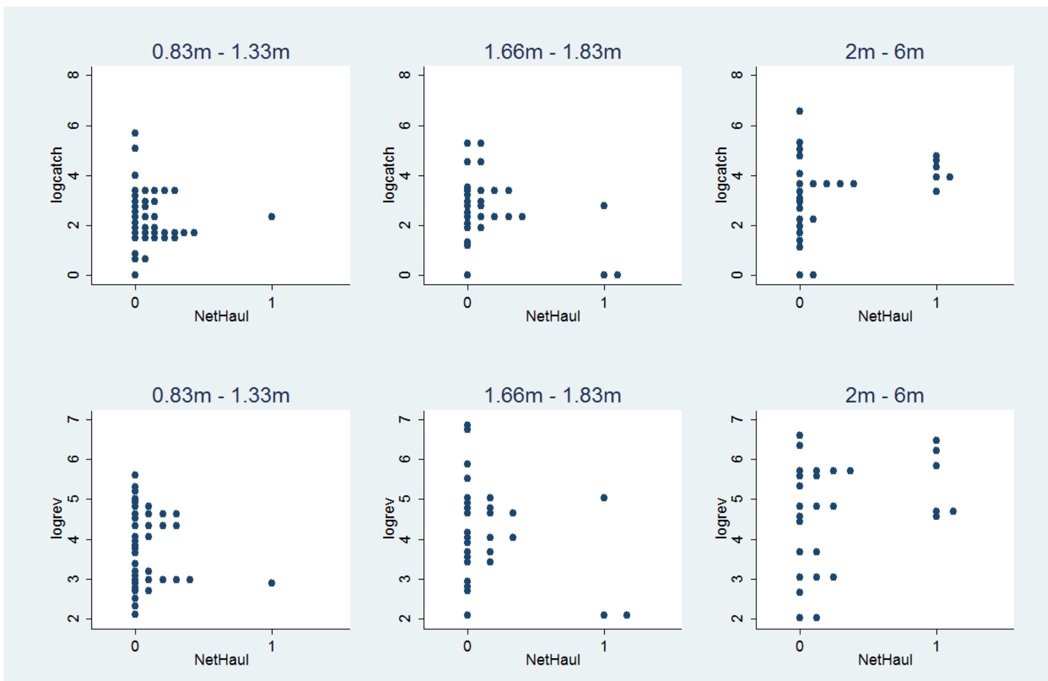

Figure 2.10: Log Output vs. Net Hauler Adoption by Size Class

Chapter 3

Exogenous Productivity Shocks and Capital Investment in Common-pool Resources

Abstract

We model exogenous technology shocks in common-pool industries using a compound Poisson process for total factor productivity. Rapid diffusion of exogenous innovations is typical in the commons, but technology is rarely modeled this way. Technology shocks lower the equilibrium resource stock while causing capital buildup based on transitory profits with myopic expectations. The steady state changes from a stable node to a shifting focus with boom and bust cycles, even if only technology is uncertain. A fisheries application is developed, but the results apply to many settings with discontinuous changes in value and open access with costly exit.

3.1 Introduction

Excess entry and investment are the hallmarks of congestible, common-pool resources. Symmetric externalities arise when resources are "rival" in consumption; when regulators or resource users are unable to effectively limit exploitation by other agents, the familiar "tragedy of the commons" arises, often manifest through overcapitalization. The result is that resource stocks are depleted and rents are dissipated. Yet why does capital investment often persist even as resource stocks shrink? This paper explores an additional explanation for excess investment in common-pool industries: discontinuous technological shocks.

Rapid diffusion of exogenously developed innovations is typical in common-pool resource industries, but technology is rarely modeled this way. Innovations can be developed in other industries and adapted to the common-pool resource (e.g., sonar in fisheries) or developed for similar resources elsewhere (e.g., better groundwater wells); in either case the technology is exogenous to the users of a given local resource. Improved groundwater wells allow access to deeper aquifers and the expansion of aquifer-dependent businesses. Better electronic fish-finders make all inputs more productive, raising the incentives for new vessels to enter. Until recently, research on technical change in fisheries has focused on identifying and measuring productivity growth and technical efficiency. In a normative, bioeconomic framework technology is often modeled as being time invariant or changing smoothly over time (Murray (2006); Squires and Vestergaard (2009)). While this approximation is convenient from a modeling perspective, in practice technology appears to move discontinuously. Jin et al. (2002), for example, find large year-to-year variation in total factor productivity change in the New England groundfish fishery. Some authors attribute this type of variation in productivity to a "ratchet effect" of capital investment driven by stock variability and government subsidies (Ludwig et al. (1993); Hennessey and Healey (2000)) while others point to exogenous development of technologies that are adapted to the fishery (Jin et al. (2002)). Because of the race to exploit, the adoption of new technologies tends to spread almost instantaneously throughout the industry. Our results show that the "ratchet effect" attributed to policy and stock fluctuations can be replicated in an open access model with exogenous technology shocks and costly entry and exit, even without stock uncertainty or policy actions.

We model technological shocks using a Compound Poisson (CP) process in which the occurrence of a shock has a constant expected arrival rate and the size of the shock is determined by a random draw from the exponential distribution. The article characterizes the response of capital and resource stocks when investment is quasi-malleable. These technology shocks perturb the open access equilibrium, causing an increase in extraction ability for a smaller steady state resource stock. Temporarily positive profits result while the system is out of equilibrium; this paradoxically induces a buildup of the more productive capital when less capital is needed to achieve the new equilibrium extraction rate. With a logistic growth function for the resource stock, the nature of the steady state and the approach path change from a stable node to a stable vortex because highly productive harvesting outpaces the fleet's and the stock's ability to adjust. The result is that the fishery experiences boom and bust cycles as it attempts to adjust to the new steady state. We present simulations for a fishery example based on a modification of the myopic expectations case in Berck and Perloff (1984), hereafter referred to as BP, where we limit exit to a fixed rate of depreciation (this resembles Berck and Perloff (1984) as well as the quasi-malleable investment case in Clark et al. (1979)). We focus on a single aspect of capitalization, namely fleet size.

The remainder of the paper will proceed as follows: section 3.2 will discuss the empirical motivation and related literature. Section 3.3 will present the model. We will explain the CP process and how this process can be incorporated into the total factor productivity term of a production function (or the catchability coefficient of the Schaefer production function in the fisheries context). Section 3.4 presents the results of simulations from this model that replicate boom and bust patterns observed in fisheries. Section 3.5 concludes.

3.2 Empirical Motivation

Models of constant or continuously growing technology are not consistent with what is observed in practice, especially in industries with open access to the exploitation of a resource. Without positive profit margins or large dominant firms there is little incentive for investment in endogenous technical change; thus technology is developed exogenously and adopted or adapted to the open access resource. When a potential new application of an exogenously developed technology is realized by the resource exploiters, it is adopted by the entire industry almost immediately. Gordon and Hannesson (n.d.) documents the rapid fleetwide adoption of successive new technologies in the Norwegian winter herring fleet from 1937 to 1971 (figure 3.1); the pattern persisted even as the resource stock headed toward collapse and even if adopting the technology required reinvestment in the fleet. The rapid adoption is driven by the very nature of open access resources as impure public goods; they are diminishable (rival) and non-excludable. Competition over the impure public good produces the strong incentives leading to adoption of technologies as their effectiveness becomes realized. Rapid adoption is then necessary to remain an efficient competitor.

A precondition for rapid adoption is ready access to capital markets; the ability to adopt technologies when they are known, available, and the incentive is present. This condition is easily satisfied in developed countries where borrowing is relatively easy and fixed costs of adopting new technologies are typically small relative to returns. However, in less developed countries where there are significant borrowing constraints adoption may diffuse more slowly throughout the industry. Adapting our model to include various diffusion processes is straightforward. Simple extensions could include an empirically calibrated parameter that governs the adoption rate after the introduction of the technology. Because focus here is primarily on developed countries we will maintain the rapid adoption modeling approach.

Feedback from technological progress has received relatively little attention in management models, especially regarding the perverse incentives for reinvestment by resource users. Exogenous technology shocks remain largely unexamined in this context, despite some empirical literature on discrete change and a growing theoretical literature on continuous technical change in renewable resources. Empirically, discontinuous change can be measured by using productivity residuals and index number methods (Squires (1992),Jin et al. (2002)), by estimating the general index of Baltagi and Griffin (1988) when sufficient data are available (Hannesson et al. (2010)), or by explicitly accounting for firm-specific adoption of particular technologies in the estimation of production (Kirkley et al. (2004)). Hannesson (2007) shows that productivity growth can mask stock declines. Murray (2007) demonstrates the consequences of managers overlooking technological change when estimating the stock and setting harvest limits. Squires and Vestergaard (2009) derive a modified golden rule for renewable resource harvest when productivity grows smoothly over time, demonstrating that technology can undo the so-called "stock effect", or the rising unit cost of harvest which normally acts as a brake on effort as the resource stock declines. Smith (1972b) examines endogenous technical change in common-pool resources.

There is a larger literature on entry and investment in renewable resources, but little overlap with the literature on technological change. Berck and Perloff (1984) model entry in a deterministic open access fishery and show that the equilibrium effort and stock levels are the same under myopic and rational expectations; both lead to overfishing and rent dissipation, but the approach paths are different. Homans and Wilen (1997) show that if total allowable catch and season length are the only regulatory controls, overcapitalization is exacerbated. These approaches rely on free entry and exit of capital, however. Models of irreversible investment in fisheries date back to Clark et al. (1979), who show that with non-malleable (or quasi-malleable) capital, the economically optimal harvest and investment policy may involve permanent (or at least prolonged) overcapitalization, depending on the size of the initial resource stock.

We develop a fisheries application, but the results apply to many settings with discontinuous changes in value and open access with costly exit. Many congestible, open access resources exhibit similar features that could be modeled using the Compound Poisson approach developed here. In addition to the groundwater example described above, many capacity-constrained network resources like broadband systems, freeways, and power grids have users that (i) often do not face the true social cost of entry, (ii) make quasi-irreversible investments that rely on the network to produce benefits, and (iii) can be expected to behave myopically because of limited information on the activity of other users. These resources also face discontinuous changes in the value of their use, such as viral news stories that crash web sites, traffic accidents that strand commuters, and the availability of waves of new electricity-intensive electronics. Siegel (1985) and Hendricks and Kovenock (1989) describe how the oil and gas industry can exhibit a "race to drill" when land tenure rules and locational information are imperfect. Dasgupta and Stiglitz (1980b), Dasgupta and Stiglitz (1980a), and Tandon (1983) explain how even the innovation process itself can behave like a common-pool resource inciting an inefficient "race to invent".

3.3 Modeling Technical Change with Compound Poisson Processes

The Compound Poisson Process

We will start by briefly outlining some of the properties of the CP process as it will be used here. The CP process has a variety of applications. It is often used to capture random events where the time interval between events is independent from one occurrence to the next. Let $q(t)$ be the technology parameter in a standard production function which we model as being time-dependent. We model $q(t)$ here as a simple CP process.

$$dq(s) = \phi(s)d\lambda(s) \qquad P(d\lambda(s) = 1) = \gamma ds$$

The CP process has a constant intensity parameter γ and the exponential distribution $\phi(s) \sim exp(1/\xi)$ is used as the compounding distribution. The exponential distribution is used because we assume only positive shocks to technology occur - that is, technology is only improving over time. As a result $q(t - \Delta) \leq q(t)$ for $\Delta \geq 0$. We assume the $\phi(s)$ is independent of $\lambda(s)$ for all $s \in [0, t]$. Having defined $dq(s)$ in this manner we can recover $q(t)$ as the integral from 0 to t.

$$q(t) = \int_0^t dq(s) = \int_0^t \phi(s)d\lambda(s) = \sum_{i \in N_t} \phi(s_i)$$

$$N_t \equiv \{i : d\lambda(s_i) = 1, s \in [0, t]\}$$

Here, $\lambda(t)$ serves as a counting measure, keeping track of each time the Poisson process receives a shock. The jump size is then given by the exponential distribution. Thus, $q(t)$ is simply the accumulation of the exponential shocks over time. The bottom right panel of figure 3.6 shows an example of the evolution of the process $q(t)$.

Poisson processes are within the family of Lévy processes which are càdlàg, meaning right continuous with left limits. Because of the lack of right continuity we introduce the notation $q(t_-) = \lim_{\Delta \to 0} q(t - \Delta)$ to indicate the left limit. This allows us to write the derivative of the composition of two functions $y = g(q(t))$, with the nested function CP, as Sennewald and Walde (2006)

$$\frac{dy(t)}{dq(t)} = g(q(t_-) + \phi(t)d\lambda(t)) - g(q(t_-))$$

The expected change in the technology parameter at any instant is defined simply as the interaction of the expectation of the exponential distribution and the expected arrival rate of the Poisson process over an increment of time. The expected value for the technology parameter at any time is defined as the expected number of arrivals times the expectation of the exponential distribution at each arrival.

$$E[dq(s)] = E[\phi(s)d\lambda(s)] = E[\phi(s)]E[d\lambda(s)] = \xi\gamma ds$$
$$E[q(t)] = E[\sum_{i \in N_t} \phi(s_i)] = E[\#N_t]\xi = t\gamma\xi$$

Where $E[\#N_t]$ is the expected cardinality of the set N_t. Having modeled $q(t)$ in this way carries with it the implication that technological progress is unbounded as t increases. Note however that this is also true for cases in which technological progress is assumed to be a linear or exponentially growing trend, as is often the case. Thus, having unbounded technological progress is not without precedent from a modeling standpoint. An interesting extension of our modeling approach would be to make technological progress dependent upon returns to the fishery. This could be used to bound the technological progress either through the jump size, intensity parameter, or both. Unbounded technological growth also implies that any open access resource, renewable or otherwise, will eventually be completely depleted. The intuition behind this is that in an open access setting the cost of exploitation is the only binding constraint on the industry. Unbounded technological progress drives costs to virtually nothing, simultaneously driving the resource to commercial exhaustion.

Technology Shocks in the Bioeconomic Model

We now wish to incorporate the CP into the bioeconomic framework through the technology parameter of the standard Schaefer production function. This new technology-dependent production function can be written as

$$h(t) = q(t)s(t)x(t)$$

Where $s(t)$ captures the size of the fleet and $x(t)$ gives the size of the stock. Consistent with Berck and Perloff (1984) and Clark et al. (1979), $s(t)$ and $x(t)$ will be treated as continuous despite their discrete nature.

In order to bring this into the bioeconomic framework we must couple the biological growth function with the economic production function and specify the rent. Following Berck and Perloff (1984), the present value of quasi rents per vessel and the its equation of motion are given by

$$\begin{aligned} y(t) &= \int_t^{\infty} e^{-r(z-t)}(pq(z)x(z) - c)dz \\ \frac{dy}{dt} &= ry - (pq(z)x(z) - c) \end{aligned} \tag{3.1}$$

Assuming that entrants base their entry decision on the present value of expected rents using current profits as an adaptive, or myopic estimate of future profits, Berck and Perloff (1984) arrive at an equation of motion for the stock that asserts that the change in the size of the fleet is proportional to the present value of rents

$$\frac{ds}{dt} = \delta y = \frac{\delta}{r}(pq(t)x(t) - c) \tag{3.2}$$

This is an equilibrium expression for the vessel construction market. Berck and Perloff (1984) assume that vessel construction costs are quadratic in the rate of entry, $\frac{ds}{dt}$, and entry occurs until the marginal cost of vessel construction equals the present value of expected rents, which is the expression in equation 3.2 where δ is a parameter of the entry cost function. The only obvious difference between our framework and that of Berck and Perloff (1984) is the insertion of the technology parameter. The biological equation of motion is given by the growth function less the amount that is harvested each period.

$$\frac{dx}{dt} = \Gamma(x(t)) - q(t)s(t)x(t) \tag{3.3}$$

The model has been set up in the standard continuous time, surplus production framework. The system is in equilibrium when $\frac{ds}{dt} = 0$ and $\frac{dx}{dt} = 0$, i.e., when the change in the stock is zero so that the surplus growth is exactly equal to the harvest, and the fleet size is no longer in flux. Solving the system of equations defined by equations 3.2 and 3.3 in equilibrium

$$\begin{aligned} \frac{ds}{dt} &= \frac{\delta}{r}(pq(t)x(t) - c) = 0 \\ x^*(t) &= \frac{c}{pq(t)} = f_x(q(t)) \end{aligned} \tag{3.4}$$

$$\begin{aligned} \frac{dx}{dt} &= \Gamma(x(t)) - q(t)s(t)x(t) = 0 \\ s^*(t) &= \frac{\Gamma(x^*(t))}{q(t)x^*(t)} \\ &= \Gamma(\frac{c}{pq(t)})p/c = f_s(q(t)) \end{aligned} \tag{3.5}$$

The focus of this paper is on the response of the system to changes in the technology. The system can change in two ways: the equilibrium levels will change, and the nature of the approach path to the equilibrium can change. First, the change in the equilibrium stock level is characterized by the differential

$$\begin{aligned} \frac{dx^*(t)}{dq(t)} &= f_x(q(t_-) + \phi(t)d\lambda(t)) - f_x(q(t_-) \\ &= \frac{c}{p(q(t_-) + \phi(t)d\lambda(t))} - \frac{c}{p(q(t_-))} \end{aligned} \tag{3.6}$$

Intuitively, the equilibrium stock size will be smaller as fishermen are capable of harvesting more fish for any given fleet size. This can be seen here clearly as $\frac{dx^*(t)}{dq(t)} \leq 0$ since $\phi(t)d\lambda(t) \geq 0$. That is to say, the new equilibrium stock size is always smaller following a technology shock. This is consistent with the basic result of Squires and Vestergaard (2009), who show that equilibrium stock size shrinks smoothly with a continuously growing technology parameter. Recall that $d\lambda(t)$ is a random variable and $P(d\lambda(s) = 1) = \gamma ds$ or $P(d\lambda(s) = 0) = (1-\gamma)ds$, thus, $\frac{dx^*(t)}{dq(t)} = 0$ most of the time for γ small, as we would expect.

The change in the equilibrium fleet size will not be unambiguous like the change in the stock size. This is because the $f_s(q(t))$ is dependent upon the growth function, which is nonlinear. The equilibrium fleet size will depend on how the growth changes at the new equilibrium.

$$\begin{aligned} \frac{ds^*(t)}{dq(t)} &= f_s(q(t_-) + \phi(t)d\lambda(t)) - f_s(q(t_-)) \\ &= [\Gamma(\frac{c}{p(q(t_-) + \phi(t)d\lambda(t))}) - \Gamma(\frac{c}{p(q(t_-))})]p/c \end{aligned} \tag{3.7}$$

Equilibrium fleet size will be larger following the technology shock if the new equilibrium fish stock increases surplus growth. The equilibrium fleet size will be smaller when growth is reduced. This says nothing, though, about the initial response of the fleet to the technology shock. To say something about initial responses to shocks, we must further investigate the off-equilibrium dynamics.

Characterizing the Equilibrium

Growth functions for biological processes are nonlinear; even the simplest logistic growth function is a nonlinear differential equation. As long as the surface is sufficiently smooth we can characterize the local behavior of the system by linear approximation. In particular, the system can be linearized around the critical point, or equilibria. The nature of the equilibrium at a given point of the linearized system will be the same as that of the nonlinearized system under standard continuity and differentiability assumptions. This is the approach followed here. The linearization of equations 3.2 and 3.3 about the equilibrium yields the following system of equations relating s to x.

$$\begin{pmatrix} \Delta\dot{x} \\ \Delta\dot{s} \end{pmatrix} \approx \begin{pmatrix} \Gamma'(x^*) - q(t)s^* & -q(t)s^* \\ q(t)\delta p/r & 0 \end{pmatrix} \begin{pmatrix} x - x^* \\ s - s^* \end{pmatrix} = A \begin{pmatrix} x - x^* \\ s - s^* \end{pmatrix} \tag{3.8}$$

To determine the nature of the equilibrium we can analyze the determinant of the eigenvalue matrix $A - \mu I$. After plugging in the equilibrium condition the determinant will be

$$\Rightarrow \mu^2 - \left(\Gamma'\left(\frac{c}{q(t)p}\right) - q(t)\frac{p}{c}\Gamma\left(\frac{c}{q(t)p}\right)\right)\mu + q(t)\frac{c\delta}{r} = 0 \tag{3.9}$$

$$\mu^2 + b\mu + c = 0$$

The eigenvalues of the system will then be given by the roots

$$\mu = \frac{-b \pm \sqrt{b^2 - 4c}}{2}$$

and the discriminant will be

$$\left(\Gamma'\left(\frac{c}{q(t)p}\right) - q(t)\frac{p}{c}\Gamma\left(\frac{c}{q(t)p}\right)\right)^2 - 4q(t)\frac{c\delta}{r}$$

Since $4q(t)c\delta/r$ is strictly positive the eigenvalues will either both be negative and real, or imaginary with a negative real term. When the eigenvalues are both negative and the surface is a sink, approach paths to the equilibrium are direct. However, when the discriminant is less than zero the eigenvalues will be imaginary and the approach path will be a vortex with the equilibrium as its focus. As a concrete example consider the case where the growth is given by the logistic growth function in equation 3.10 where g is the intrinsic growth and k is the carrying capacity.

$$\Gamma(x) = gx(1 - x/k) \tag{3.10}$$

The discriminant of the system with logistic growth will then be less than zero when

$$\left(g\left(1 - \frac{2c}{q(t)pk}\right) - q(t)\frac{p}{c}g\left(\frac{c}{q(t)p}\right)\left(1 - \frac{c}{q(t)pk}\right)\right)^2 - 4q(t)\frac{c\delta}{r} < 0$$

$$\left(\frac{gc}{pk}\right)^2 - q(t)^3 4c\frac{c\delta}{r} < 0$$

$$\sqrt[3]{\frac{g^2cr}{4\delta p^2k^2}} < q(t) \tag{3.11}$$

Since $q(t)$ is unbounded it will eventually exceed the threshold established by equation 3.11. In our experience under most reasonable parameterizations of the growth function the threshold is exceeded quite early on the exploitation path. Figure 3.2 shows the phase plane gradients of the resource stock and the fleet when the threshold has been exceeded, with arrows indicating the spiraling direction of convergence from off-equilibrium points. Consequently, with increasing technology we will eventually see a fishery in which the fleet size is oscillating as it attempts to approach the steady state.

Notice that this threshold contains an expression for the intrinsic growth rate of the fish stock relative to the entry cost parameter δ, as well as other economic parameters and the carrying capacity. This threshold describes a point where the ability of entry costs to act as a break on rising harvest pressure and protect stock recovery is exceeded by the ability of each existing vessel to deplete the stock. In other words, technology makes entry continue to appear profitable even as the harvest capacity exceeds the stock's ability to replenish itself.

Figure 3.3 illustrates this point more clearly by redrawing the stock-fleet phase plane and illustrating example approach paths on either side of the transition threshold. The black arc represents the locus of equilibrium points in the stock-fleet plane, at different values of $q(t)$, with the transition threshold marked in red. A smoothly changing $q(t)$ would trace out this arc over time. Perturbations on either side of the threshold result in very different dynamics.

Technology Shocks with Rational Expectations

We now temporarily relax the assumption of myopic expectations and examine the case where agents form and respond to rational expectations about the future. In a rational expectations framework, agents will consider expected future changes in technology, stock, and fleet size when making entry and exit decisions. In particular, the present value of quasi rents in the system described above is augmented by consideration of the expected time path of technology, given by

$$\begin{aligned} y &= \int_t^\infty e^{-r(z-t)}(pE_t[q(z)]x(z) - c)dz \\ &= \int_t^\infty e^{-r(z-t)}\left(p[q(t) + (z-t)\xi\gamma]x(z) - c\right)dz \qquad (3.12) \end{aligned}$$

The equation of motion for expected quasi rents is given by

$$\frac{dy}{dt} = ry - (pq(t)x(t) - c) + p(\phi(t)d\lambda(t) - \xi\gamma)\int_t^\infty e^{-r(z-t)}x(z)dz \tag{3.13}$$
$$= ry - (pq(t)x(t) - c) + p(\phi(t)d\lambda(t) - \xi\gamma)B(t)$$

The first two terms are identical to equation 3.1 and is simply the change in the present value of rents. The final term on the right hand side of equation 3.13 accounts for long run revenue adjustments when current technology shocks (today's draw from the CP process) deviate from their expected value. The impact of today's deviation on the resource stock at every subsequent moment is then factored into the evolution of expected rents. In this case, $s^*(t) = \Gamma(x^*(t))/q(t)x^*(t)$ as before and additionally $y^*(t) = 0$, but the expression for $x^*(t) = 0$ is given by

$$x^*(t) = \frac{c + p(\phi(t)d\lambda(t) - \xi\gamma)B(t)}{pq(t)} = \tilde{f}_x(q(t)) \tag{3.14}$$

Repeating the analysis of section 3.3, the change in the equilibrium stock size is now

$$\begin{aligned}\frac{dx^*(t)}{dq(t)} &= \tilde{f}_x(q(t_-) + \phi(t)d\lambda(t)) - \tilde{f}_x(q(t_-)) \\ &= \frac{c + p(\phi(t)d\lambda(t) - \xi\gamma)B(t)}{p(q(t_-) + \phi(t)d\lambda(t))} - \\ &\qquad \frac{c + p(\phi(t)d\lambda(t) - \xi\gamma)B(t)}{pq(t_-)}\end{aligned} \tag{3.15}$$

Two observations are worth noting here. First, the equilibrium stock size is smaller than under myopic expectations because firms expect future productivity gains, which induces more entry earlier and thus more depletion earlier. Second, the effect of a shock on the equilibrium stock size is dampened by the continual adjustments to the evolution of expected rents in response to deviations from the expected path. The equilibrium fleet size is then given by

$$\begin{aligned}A(t) &= p(\phi(t)d\lambda(t) - \xi\gamma)B(t) \\ s^*(t) &= \Gamma\left(\frac{c + A(t)}{pq(t)}\right)\frac{p}{c + A(t)}\end{aligned} \tag{3.16}$$

The change in fleet size now becomes

$$\begin{aligned}\frac{ds^*(t)}{dq(t)} &= f_s(q(t_-) + \phi(t)d\lambda(t)) - f_s(q(t_-)) \\ &= \Gamma\left(\frac{c + A(t)}{p(q(t_-) + \phi(t)d\lambda(t))}\right)\frac{p}{c + A(t)} - \Gamma\left(\frac{c + A(t)}{p \cdot q(t_-)}\right)\frac{p}{c + A(t)} \qquad (3.17)\end{aligned}$$

Again, the effect of a technology shock is less dramatic than in the myopic case because of the expected long run revenue adjustments. In this sense, the rate of entry and stock drawdown following a major technology shock could be considered indicators of the extent of myopia in the industry.

3.4 Simulation

The theoretical results from the myopic expectations case of section 3.3 make two points that we wish to emphasize and show through simulation. The first is to propose and characterize the CP process as a model of technological change that mirrors empirical findings from open access resources, where shocks accrue to the system randomly and irregularly and the adoption of technology into the fishery is nearly instantaneous. The second point of our theoretical analysis is that as technology increases it surpasses a threshold, beyond which the approach paths to the equilibrium switch from stable convergence to spiraling convergence, or boom and bust cycles. Discontinuous shocks produce off equilibrium dynamics that make the approach path relevant and observable. The cyclicality of the approach path means that we would expect to see boom and bust cycles, particularly in the years following a technology shock.

The simulations focus on the case of myopic expectation because it is our belief that this is a fairly close approximation to behavior in many open access scenarios. We simulate the system defined by the two differential equations 3.2 and 3.3. For the growth function $\Gamma(\cdot)$ we use the logistic growth function defined by equation 3.10. The parameters of the simulation can be found in table 3.1. The process is simulated over 100 years on daily time intervals $dt = 1/365$ and then sampled annually at the end of the simulated year. The simulation is initialized using a technology parameter of $q(0) = 1$ and with the stock and fleet at their equilibrium values $x(0) = \frac{c}{pq(0)}$, $s(0) = \frac{\Gamma(x(0))}{q(0)x(0)}$.

Boom and Bust Cycles

Figures 3.4 and 3.5 plot the time path of variables for the two approach paths illustrated in the phase plane in figure 3.3, demonstrating shocks that lead to two different sides of the transition threshold. In figure 3.4, the fishery begins in equilibrium and after a small technology shock, adjusts smoothly to a larger equilibrium fleet size (implying larger surplus growth) and lower fish stock. Profits are quickly dissipated by entrants. In figure 3.5, on the other hand, a large shock moves the fishery beyond the transition point. Profits, fleet size, and fish stocks fluctuate for about 30 years before settling down.

Compound Poisson Technology Simulation

While the system begins with stable convergence to the equilibrium, the technology shocks quickly change the nature of the equilibrium to one of boom and bust cycles. This produces the erratic fluctuations in the stock, fleet size and profits that appear in figure 3.6. This pattern closely resembles the time path of stocks and yields reported by Hennessey and Healey (2000) as a "ratchet effect" of stock variability and government policy. Technology shocks induce transitory periods of growth, but the fish stocks remain in long run decline despite relatively steady per-vessel profits that could hide the severity of stock depletion.

3.5 Conclusion

This article proposes a useful modeling tool for open access resource dynamics that more closely reflects observed patterns of innovation and adoption, and explores the consequences for renewable resource use. Discontinuous technological processes can have significant economic and resource impacts. Although smooth measures of growth based on long run expectations may be accurate over decades, short run dynamics will differ markedly from the long run forecast when discrete shocks are present. Economic resources will be suboptimally allocated through dimensions such as overcapitalization and resource depletion.

In the fishing context, overfishing for a short time may push resource stocks below their sustainable limits. Previous explanations of excess capacity and stock declines in de facto open access fisheries, such as the ratchet effect, ignore this important driver of observed outcomes. Accurate technological accounting could be built directly into catch-per-unit effort measures which are often used by regulators as an indicator of stock abundance.

Management systems should be designed to anticipate and deal with sudden changes in exploitation power, particularly in cases when its not feasible to regulate or ban specific technologies. Requiring ex ante public disclosure of investment plans and announcing real-time resource limitations may dissuade myopic behavior, leading to fewer wasted inputs and dampening the wide capacity swings that could lead to resource collapse. When output taxation is feasible and productivity levels are stationary, it is well known that regulators can achieve optimum rent even though individual agents face open-access incentives; with technology shocks, an adaptive system of graduated taxes may be required to reduce expected quasi-rents for myopic actors following a shock.

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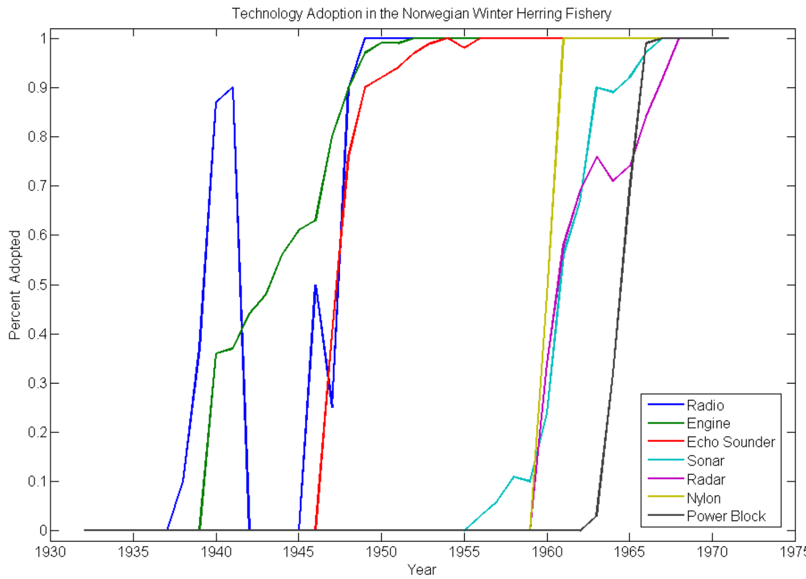

Figure 3.1: Technology Adoption in the Winter Herring Fishery

3.7 Figures and Tables

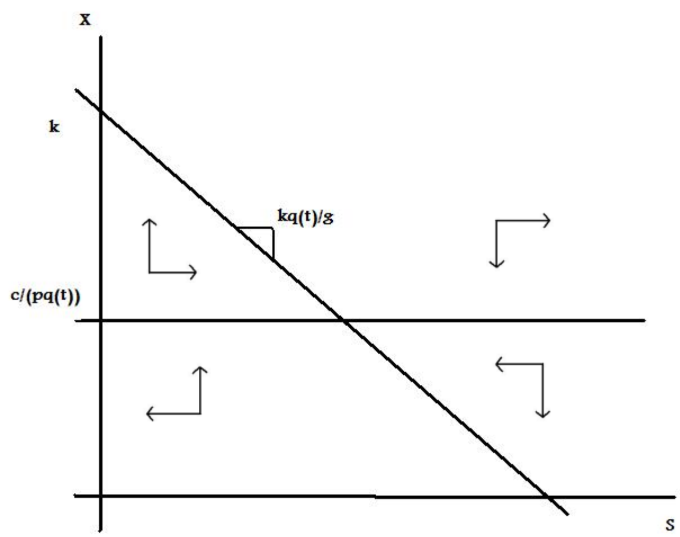

Figure 3.2: Dynamics in the stock-fleet plane

Table 3.1: Productivity Shock Simulation Parameter Values

Growth Parameters	
Intrinsic growth	$g = 0.75$
Carrying capacity	$k = 1$
Economic Parameters	
Interest rate	$r = 0.05$
Price	$p = 3.5$
Operating costs	$c = 2.33$
Entry Proportion	$\delta = 0.001$
Technology Parameters	
Poisson intensity	$\gamma = 0.1$
Jump size	$\beta = 0.5$

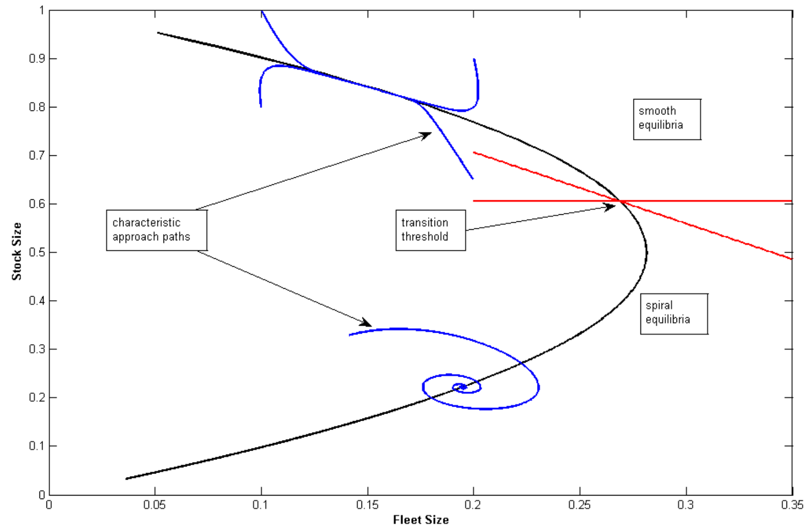

Figure 3.3: Differences in approach path for changing technology

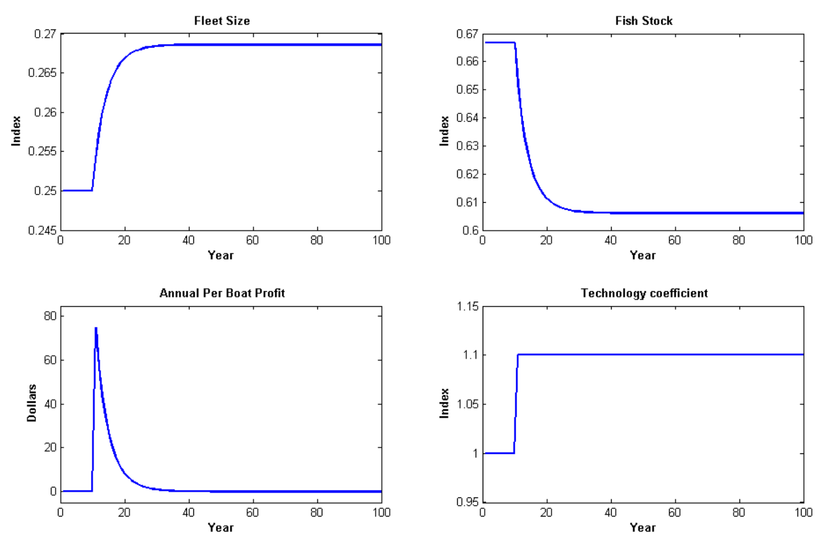

Figure 3.4: Small shock with smooth transition to equilibrium

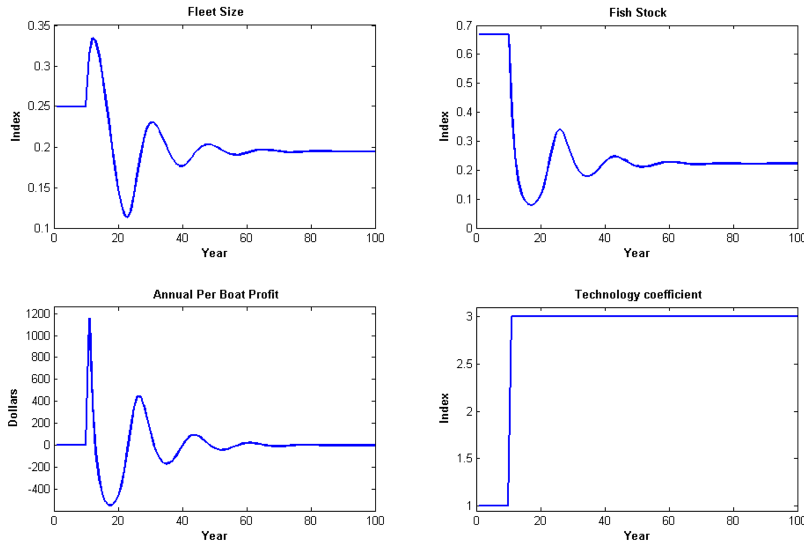

Figure 3.5: Big shock inducing oscillating equilibrium

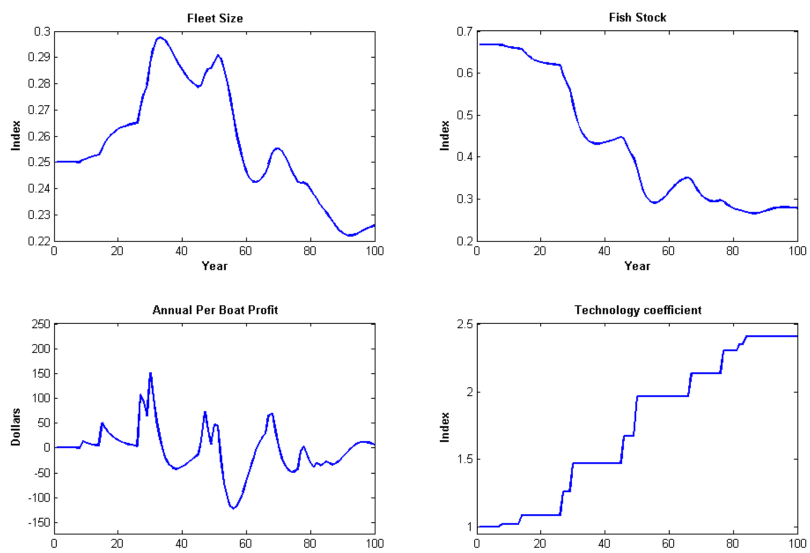

Figure 3.6: Compound Poisson Process Simulation

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