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The Measurement of Capacity, Utilization, and Economic Performance: An Application to North Pacific Groundfish Fisheries

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An Application to North Pacific Groundfish Fisheries

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Abstract

The North Pacific groundfish fisheries (NPGF) of the Bering Sea and Aleutian Islands (BSAI) are among the largest and most valuable fisheries in the world. However, relatively little is known about the economic performance of the industry and concerns loom over the presence of excess fishing capacity. Aside from dissipating rents and shortening fishing seasons, excess capacity can pressure for managers to inadvertently keep the total allowable catch above sustainable levels in order to preserve employment.

In an attempt to address these problems Congress passed the American Fisheries Act (AFA) in 1998, which, among other things, represented an attempt to "rationalize" the pollock fishery (the most valuable of the NPGF fisheries). The AFA included regulations that instituted fishing rights, restricted access to certain parties, and allowed the formation of cooperatives that enabled eligible members to trade quota.

Initial reports indicate that there has been a decrease in fishing effort and an increase in season length for the BSAI pollock fishery since passage of the AFA. However, given that the quantity of pollock caught has not diminished and is still being taken in a few months time, it is unclear whether observed capacity reductions are sufficient to ease existing concerns.

In order to further our understanding of the issues discussed above, this dissertation provides estimates of harvesting capacity and utilization in the catcher-

processor sector of the BSAI pollock fishery, and analyzes many of the changes brought about by the AFA. Two proposed methods for measuring fishing capacity – stochastic production frontier (SPF) and data envelopment analysis (DEA) – are employed in multi-input, multi-output applications to the catcher-processor fleet. The resulting capacity estimates from the models are then compared and used to characterize the degree of excess capacity in this sector of the pollock fishery, and illustrate the substantial differences in capacity estimates that may arise when the stochastic aspects inherent in harvesting technologies are ignored. And, because DEA and SPF models allow one to analyze technical efficiency in production, the frameworks are also used to compare pre- and post-AFA technical efficiency among individual vessels and the pollock catcher-processor fleet as a whole.

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List of Acronyms

ADF&G – Alaska Department of Fish and Game
AFA – American Fisheries Act
BSAI – Bering Sea and Aleutian Islands
CDQ – Community Development Quota
CRS – Constant Returns to Scale
CU – Capacity Utilization
DEA – Data Envelopment Analysis
DRS – Decreasing Returns to Scale
EEZ – Exclusive Economic Zone
FAO – Food and Agricultural Organization of the United Nations
FGK – Färe, Grosskopf, and Kokkelenberg
H&G – Headed and Gutted
HSCC – High Seas Catchers' Cooperative
IFQ – Individual Fishing Quota
IRS – Increasing Returns to Scale
LRAC – Long-Run Average Costs
MLE – Maximum Likelihood Estimation
MRTS – Marginal Rate of Technical Substitution
NOAA – National Oceanic and Atmospheric Administration
NMFS – National Marine Fisheries Service
NPGF – North Pacific Groundfish Fisheries
OLS – Ordinary Least Squares
PCC – Pollock Conservation Cooperative
PPF – Production Possibilities Frontier
SPF – Stochastic Production Frontier
SRAC – Short-Run Average Costs
TAC – Total Allowable Catch
TE – Technical Efficiency
WPR – Weekly Processing Report
VRS – Variable Returns to Scale

Chapter 1
Introduction

1.1 Introduction

The North Pacific groundfish fisheries (NPGF) of the Bering Sea and Aleutian Islands (BSAI) are among the largest and most valuable in the world, generating two-thirds of a billion dollars per year in sales at first wholesale. Yet relatively little is known about the economic performance of the industry. In particular, concerns loom over the presence of excess fishing capacity.

Up until 1999, the NPGF was operated entirely as a regulated limited entry fishery wherein a total allowable catch (TAC) (and apportionments of the TAC) was set for each species or species group for specific times of year, areas, and gear types. Within these apportionments, vessels were allowed to fish until quotas for each species were met. It is widely accepted that when vessels compete in this manner for the TAC, the result is often larger and larger vessels that exhaust quotas in a very short amount of time as they "race" for fish. Such strategic behavior can lead to fishing capacity well in excess of the yearly TACs. The repercussions of such excess fishing capacity are typically dissipated rents and shortened fishing seasons.

Much of the rent is diminished in such a regulatory setting because of the decreased efficiency and/or productivity, and over-investment in vessel capital. In addition, excess fishing capacity may create pressure for managers to inadvertently keep the TACs above sustainable levels in order to preserve employment; this can be a particularly serious problem in fisheries where the underlying stock structure is not well known. And, with the already-dissipated economic rent spread among so many vessels, fishermen are more vulnerable to changes in regulations and TACs instituted to curb excess capacity. As a result, policy tools available to resource managers become more difficult to implement, both politically and socially (Kirkley and Squires, 1999).

In order to respond to these problems, policy changes have recently been implemented in the NPGF. In late 1998 Congress passed the American Fisheries Act (AFA), which, among other things, represented an attempt to "rationalize" the BSAI pollock fishery by instituting fishing rights and further restricting access. The pollock fishery was specifically targeted since a very contentious allocation conflict had occurred in the BSAI pollock fishery, and the associations representing most of the participants were able to agree on a plan to rationalize the fishery.

The AFA decommissioned a number of large catcher-processors that had been rebuilt overseas, but were operating in the BSAI pollock fishery (compensating them significantly) and imposed size limits on any vessels that may enter the fishery in the future. The Act, which runs through 2004, gave the remaining vessels sole harvesting rights to a specific portion of the pollock TAC. The Act also specified shares of pollock to be taken in the offshore and inshore sectors and allowed for the formation of harvesting and processing cooperatives. These cooperatives then assigned shares of their aggregate quota to individual members and allowed them to trade their fishing/processing rights to other cooperative members. This creates the ability to coordinate the harvesting and processing of pollock, to eliminate the race for fish, improve product quality, reduce costs, and thus enhance the profitability of harvesting and processing.

An initial report by the newly formed pollock cooperatives in the catcher-processor fleet indicates that there has been a decrease in fishing effort and an increase in season length for the BSAI pollock fishery. During certain times of the year as many as eight of the eligible catcher-processors were idled and their quota was used by other vessels (usually within the same company). However, given that the quantity of pollock caught has not diminished and is still being taken in a few months time, it seems there may still be excess capacity in the fishery – obviously a much smaller fleet could land the current yearly TAC available to the catcher-processors. Even now, with the fewer vessels fishing at a more reasonable pace, they are *still* able to easily catch as much as has historically been caught by a much larger fleet.

Thus, it remains unclear whether the observed capacity reductions in the pollock fishery are sufficient to ease existing concerns, and it may very well be the case that the current capacity still exceeds the sector's share of the TAC by a wide margin. Even the pollock cooperatives state that current capacity of the catcher-processor sector is probably three times greater than the TAC usually available to it (Pollock Conservation Cooperative and High Seas Catchers' Cooperative, 1999). In addition, the eleven or so other principal "target" species in the NPGF remain under limited license management, as the current AFA regulations ignore potential excess capacity in non-pollock fisheries[1].

One of the main obstacles in determining whether excess capacity persists (in the NPGF and elsewhere around the world), however, is a lack of a fully satisfactory method for assessing capacity. Much of the literature that does exist on determining the extent of overcapacity relies on the use of cost data (i.e. the "dual" approaches), which is not currently available in the NPGF or in a majority of other fisheries. As a result, much of the analysis must be undertaken in a primal framework, and recent efforts in this area have used data envelopment analysis (DEA) – a non-stochastic approach that is fairly easy to implement, but suffers from shortcomings that may be exacerbated when used in fisheries settings.

Therefore, this dissertation will provide an alternative primal method for measuring fishing capacity based on the stochastic production frontier (SPF) approach, as well as provide estimates of the fishing capacity for the BSAI catcher-processor fleet of the NPGF. In addition to suggesting a novel approach for measuring fishing capacity, a comparison between DEA and the SPF method allows for an indication of the degree to which capacity estimates may differ when alternative models are employed, and the stochastic nature of harvesting technologies is not accounted for. By focusing on the BSAI pollock catcher-processor fleet in particular, one can also use the models to analyze the effects that the AFA may have had on fishing capacity, efficiency, and productivity.

This dissertation contributes to the literature in at least five ways. First, the use of a SPF model to measure fishing capacity extends the empirical basis for capacity measurement, which has up to now primarily relied on DEA[2]. Second, while SPF and DEA have been compared in the past, a majority of studies have used simulated data, and have not compared capacity estimates (instead focusing on estimates of technical efficiency). Third, the use of a ray production function broadens the methodological foundations of the standard SPF model by utilizing a functional representation of a production technology that has yet to be used in fisheries application or capacity measurement. Fourth, there has yet to be a study to empirically estimate fishing capacity

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[1] The AFA does, however, include limits on the non-pollock catch of the pollock-based catcher-processors in an attempt to decrease spillover effects. Still, vessels that primarily target non-pollock species are not directly affected by the AFA, and potential excess capacity in these fleets has yet to be addressed.
[2] The peak-to-peak method has also been used in the past for capacity measurement (See Kirkley and Squires [1998] for a thorough literature review on the peak-to-peak method), but is subject to fairly severe limitations.

in the NPGF, nor has there been analysis of changes in capacity after passage of the AFA. Finally, the comparisons generated among eligible and ineligible vessels provide one of the first indications of the degree to which the AFA may have affected the relative efficiency of harvesting operations in the pollock fishery.

1.2 Background and General Methodological Approach

Worldwide concerns over excess fishing capacity have prompted recent policy initiatives focused on managing capacity, such as the Food and Agricultural Organization's (FAO) International Plan of Action for the Management of Fishing Capacity[3] (FAO, 1999). The FAO plan urges countries to develop national fishery management plans by 2002, which would include an assessment of domestic fishing capacity, and the introduction of measures to prevent or eliminate excess fishing capacity.

In response to this plan, the National Oceanic and Atmospheric Association (NOAA) has adopted a formal objective of reducing the number of overcapitalized fisheries by fifteen percent by 2004 (NOAA, 1999). The NOAA plan has led to the formation of the National Marine Fisheries Service (NMFS) Excess Capacity Task Force, which has recommended that capacity estimates be constructed for each of the U.S. federally managed commercial fisheries (NMFS, 1999).

To meet the guidelines of the plan, fishing capacity estimates must be generated and subsequently used to assign each fishery to one of the following three categories: "no appreciable excess capacity", "moderate excess capacity", and "substantial excess capacity." Because of the eventual comparisons and categorizations among the fisheries

[3] Other initiatives include the FAO Code of Conduct for Responsible Fisheries, the UN FAO Agreement on Compliance, and the United Nations Agreement on Highly Migratory and Straddling Fish Stocks.

based on their relative levels of excess capacity, it is important that the methods used to estimate capacity in each of the federally managed fisheries are consistent so as to generate comparable estimates. Unfortunately, this may be more difficult than it sounds, as there is still no consensus among researchers over the "best" method for generating such estimates.

In particular, most (if not all) of the recent studies that estimate fishing capacity have used DEA (Kirkley and Squires [1999], Kirkley et al. [1999], Squires et al. [1999]), which is non-stochastic approach based on mathematical programming. However, DEA's appropriateness in fisheries applications is unclear and it has been suggested that the SPF approach may be a more suitable and desirable way of generating such estimates (NMFS [1999], Morrison [2000], Lee and Holland (1999a)]. To this author's knowledge, very few (if any) other studies have yet to use SPF to estimate capacity in a fisheries setting[4].

Therefore, a central purpose of this dissertation is to develop an SPF model for use in estimating fishing capacity and to compare the results with those generated using DEA techniques. The results generated illustrate the marked differences in capacity estimates that can arise based on one's choice of modeling framework (as well as one's "definition" of fishing capacity, which will be discussed further in Chapter 3). To facilitate these comparisons, two suggested definitions of fishing capacity are estimated within each of the two alternative frameworks.

More specifically, estimates of individual vessel and aggregate fishing capacity are provided for the BSAI catcher-processor fleet, along with measures of capacity utilization (CU) and technical efficiency (TE). Capacity estimates are then compared to observed catch to gauge the extent of excess capacity, while CU estimates and TE scores are used to evaluate the relative performance of vessels and the performance of the fleet as a whole in different years.

The techniques used within this dissertation can be implemented using data that is routinely collected by NMFS, which is an important consideration, as often the data available for fisheries is limited. And, given that the institutional structure of the NPGF is fairly common and that excess fishing capacity has reached global proportions, the techniques developed within this dissertation will have relevance and applicability in many other settings.

Aside from providing estimates of fishing capacity, this dissertation also aims to provide a preliminary indication of the effects of the AFA on the BSAI pollock catcher-processor fleet. By changing the size and composition of the fleet operating in the fishery, the Act has likely affected the groups' economic performance; fewer boats are now harvesting the yearly TAC apportionment, and are doing so over a greater period of time. This change has occurred primarily because of the introduction of property rights, which diminishes the incentive to "race for fish." Thus, operations have slowed production and may be operating in a more profitable manner. Although profit data are not known outside the industry, the frameworks used in the capacity estimation do allow one to analyze the relative technical efficiency of vessels operating within the pollock fishery.

[4] Lee and Holland (1999a) compare the technically efficient output levels generated from two DEA and SPF models and draw inference on the bias that might occur in a similarly constructed capacity-measuring model.

Using such information, comparisons are made between the historical productive efficiency of the vessels decommissioned by the AFA with that of the vessels that were deemed eligible to continue. In addition, similar comparisons are conducted among the remaining eligible vessels, instead focusing on utilized versus idled vessels (which occurred when some vessels leased their fishing rights to others within the cooperative). Finally, comparisons are drawn between the efficiency of current eligible vessels before and after the AFA was passed, which provide an indication of how the new fishery structure may have augmented vessels' production plans and performance and changed their capacity.

1.3 Empirical Application

The research conducted in the dissertation focuses on the catcher-processors fishing in the BSAI. The catcher-processor fleet is of particular interest in the NPGF because it operates within the most highly valued fishery in the region; pollock landings alone account for a majority of the yearly 1st wholesale value generated in the BSAI groundfish complex.

In addition, the vessels in this catcher-processor fleet were affected by the AFA of 1998, which allows for an examination of the changes that occurred after the introduction of fishing rights and a harvesting/processing cooperative structure. Such a focus also allows for a preliminary indication of how effective (and rapid) such measures may have been in changing fishing capacity and efficiency.

As stated above, pollock is the primary target species for a majority of the BSAI catcher-processors. In fact, the pollock fishery is the largest of the BSAI groundfish fisheries, and the largest U.S. fishery by volume. Over two billion pounds of pollock are landed annually, accounting for over 20% of the total U.S. fishery landings (approximately 10 billion pounds each year), with an annual value after primary processing of roughly $700 million (At-Sea Processors Association, 1999).

1.4 Dissertation Organization

In the next chapter, a description of the NPGF is provided. The discussion focuses on the BSAI catcher-processor fleet, the pollock fishery, and the AFA. In Chapter 3, the theoretical foundation of the work that follows is presented, along with a review of the literature on capacity and capacity utilization. Chapter 4 presents, compares, and contrasts the techniques that are subsequently used to construct the capacity estimates, and Chapter 5 provides an application of these techniques to the BSAI catcher-processor fleet. The estimates are generated under alternative empirical frameworks (DEA and SPF) and different definitions of capacity, and the results are compared. Chapter 6 analyzes the implications of the AFA for the BSAI catcher-processors. Comparisons are drawn between vessels deemed eligible and ineligible by the AFA, and changes in efficiency are discussed with regard to continuing and exiting vessels. A comparison of the most technically efficient fleet and the observed eligible fleet is also provided. Chapter 7 concludes with a discussion on the research results and some final remarks on future extensions stemming from this dissertation.

Chapter 2

The BSAI Pollock Catcher-Processor Fleet and the American Fisheries Act

2.1 Introduction

The alternative capacity and TE models to be developed and estimated in the later chapters are applied using data from the BSAI catcher-processor fleet. This fleet is of particular interest in the NPGF for two primary reasons. First, this fleet operates within the largest and most valuable fishery in the BSAI groundfish complex; much of the significance associated with this fleet pertains to the notable size and value of its pollock landings. Secondly, this fleet was recently subjected to major changes in operational structure.

Up until 1998, the entire NPGF was managed as a license limited fishery, wherein the TAC for each species or species group was set and vessels competed for catch until the particular quotas were met. However, in late 1998 Congress passed the AFA, which altered the management characteristics of the *pollock* fishery (the primary fishery for many of the vessels in the BSAI catcher-processor fleet).

In short, the AFA provided incentives to "rationalize" the pollock fishery by further limiting access (decommissioning nine foreign-rebuilt vessels), specifying those within the BSAI catcher-processor fleet who may participate in the BSAI fishery, and by allowing these agents to form a cooperative. Before going into a more detailed discussion of the specific provisions that were introduced to achieve the aims of the AFA, a brief description of the pollock fishery will be provided.

2.2 The BSAI Pollock Fishery of the NPGF

The pollock fishery is the largest of the BSAI groundfish fisheries, as well as the largest U.S. fishery by volume. Over two billion pounds of pollock are harvested annually. As the largest of all U.S. fisheries, these landings account for over 20% of the total U.S. fishery landings (which are approximately 10 billion pounds each year), and have an annual value after primary processing of roughly $700 million (At-Sea Processors Association, 1999).

Pollock is the most abundant groundfish species in the BSAI, and swim in enormous, tightly packed schools. Harvesting of pollock is therefore most easily accomplished with large mid-water trawl nets, which are cone-shaped nets towed behind a vessel. Because the schools generally congregate off the ocean floor, there is little incidental catch of other groundfish in the fishery; in a typical tow, pollock comprise 98 or 99 percent of the catch. In addition, recent changes to the management system have prohibited bottom trawling for pollock and require retention of all pollock and cod harvested, which has further reduced discards (as well as increasing the utilization of the pollock catch). For these reasons, the Bering Sea pollock fishery is recognized as one of the "cleanest" fisheries in the world. However, despite low bycatch rates, it does account for a large proportion of the bycatch of some groundfish and non-groundfish species due to the size of the pollock fishery.

Upon catch, pollock are used in the production of three main products. Fillets (both standard and "deep skin") are key components of fish and chips, fish sandwiches, and frozen food products. These pollock fillets are consumed primarily in the U.S. and the catcher-processor fleet far exceeds other pollock sectors' production of fillets. A large proportion of pollock catch is also used in the production of surimi, a minced fish product used to make imitation crab and other similar products. The roe of the pollock is a very valuable product as well, and is processed almost exclusively within the winter/spring months (or the "A" season[5]). Surimi and pollock roe are largely produced for export, with Japan as the principal market. Once the primary products have been produced, fish meal is often generated as a secondary product, using predominantly the parts of pollock that are not used to produce fillets, surimi, or roe.

The North Pacific Management Council has allocated the pollock TAC in the BSAI to three specific groups: the inshore sector, the offshore sector, and the motherships. First, 10% of the total is given to the community development quota (CDQ), and about 5% is set aside for bycatch in other BSAI groundfish fisheries. The offshore pollock fishery (comprised of 16 U.S.-flag catcher-processor vessels and 7 catcher vessels that deliver their catch to catcher-processors) is then allocated 40 percent of the remainder, while the inshore processing sector is allocated 50 percent.

The inshore sector is comprised of seven processing facilities. Five plants are located onshore (three in Dutch Harbor and one each in Akutan and Sand Point) and the two others are floating processors, which by regulation must remain anchored at a single location during the pollock seasons. Approximately 100 catcher vessels deliver pollock to the inshore processing sector.

The mothership sector receives the remaining 10 percent, and is comprised of three processing vessels and a fleet of approximately 20 catcher vessels that deliver the pollock processed by the motherships.

[5] Recently, the season has been further subdivided in response to Steller sea lion concerns, to spread out the fishing in time and space.

Relative to many other U.S. fisheries, the BSAI groundfish stock is considered to be fairly stable and healthy. NMFS records and analysis indicates that few of the BSAI groundfish species are either overfished or approaching overfished status. One reason most groundfish stocks are in good condition is because of the information and controls given to resource managers and fisheries scientists in charge of assessing and managing the stocks. By setting a yearly TAC for each groundfish species or species group, managers can enforce their annual targets and adjust yearly groundfish harvest levels to account for population changes in previous years.

In order to ensure that actual catch is in line with the limits set by fisheries managers, efforts have been undertaken to accurately report weekly catch levels through mandatory weekly processing reports (WPR) and the federal fishery observer program (with participants of the fishery funding most of the program costs). The observer program is not perfect in all regards, but is one of the most comprehensive observer programs in the world. All groundfish-targeting vessels 125 feet in length or greater are required to carry onboard a federal fishery observer, while two fishery observers are stationed onboard every catcher-processor vessel in the BSAI pollock fishery.

While these observers are not able to sample every haul undertaken, the sampling rate is quite high; in 1999, observers sampled 4,704 of the 4,797 pollock hauls. And, to assure that the status of the fishery can be assessed and monitored on a timely basis throughout the season, the federal fishery observer program reports are filed electronically, and all fish caught (not just those retained) are then counted against the annually set TACs.

2.3 Effects and Origins of the AFA

The AFA decreased the number of catcher-processors operating in the BSAI pollock fishery by declaring ineligible nine large factory trawlers (but did give their owners significant compensation in the process). It also introduced new limits on the size of any replacement fishing vessel and limited replacement in other ways. Furthermore, the remaining vessels are now able to form harvesting and processing cooperatives, which allows members to establish and trade their fishing/processing rights within a season, which should serve to increase vessels' overall economic performance and processing efficiency (as opposed to the past emphasis on physical harvesting efficiency).

The basis for the legislation contained in the American Fisheries Act is linked to provisions included in the Magnuson-Stevens Fishery Conservation and Management Act, the current revision of the original Magnuson Act of 1976. The Magnuson Act for the first time established a law extending U.S. fishery management authority to 200 miles off U.S. coastal shores, creating the fishery consolidation zone, which became the Exclusive Economic Zone (EEZ). Congress enacted this law to preserve U.S. fisheries, which at the time were being prosecuted by a large number of foreign fishing fleets (in 1976, foreign-flag vessels were harvesting and processing nearly 90% of the fish in the BSAI groundfish fishery). Under the Magnuson-Stevens Act, American fishermen got first priority to catch the fish, and strict limits on total catch were introduced in an attempt to maintain healthy stocks and rebuild overfished stocks. The Act was generally successful in that the last two decades have seen a complete elimination of foreign fishing in the U.S. EEZ.

The Anti-Reflagging Act of 1987 mandated that all U.S.-flag fishing vessels must have been built or rebuilt in the U.S., and that all such vessels be at least 51 percent U.S. owned and controlled. The Act also included legislation designed to prohibit foreign-built vessels from reflagging as U.S. ships, thereby circumventing the Americanization policy. However, this Act included what some consider to be a "loophole" which allowed some vessels that were rebuilt in foreign shipyards to fish in U.S. waters (Comstock, 1998).

That is, in an attempt to accommodate U.S. fishermen who had already made commitments to rebuild U.S. built vessels for use in U.S. fisheries, and to protect jobs on U.S.-flag vessels that were not 51 percent U.S. owned and controlled when the anti-reflagging law took effect, Congress included "grandfather" provisions in the Act. One grandfather clause specifically allowed foreign-rebuilt U.S. ships to enter the North Pacific fishery if the ship had been purchased by July 28, 1987, entered a foreign shipyard contract within six months of the passage of the legislation (January 11, 1988) and was redelivered to the owner by July 28, 1990. These provisions were intended to protect the rights of individuals who had legitimately taken steps in good faith according to previous laws (Comstock, 1998).

The Anti-Reflagging Act did not work as planned and as a result, a flood of large factory trawlers rebuilt in foreign shipyards entered the fishery. Ultimately, 22 such foreign-rebuilt ships were allowed into U.S. fisheries under the grandfather clause, and have since captured a large proportion of the yearly pollock catch in the North Pacific. In an attempt to rectify the loopholes that allowed these vessels to participate in the U.S. fisheries, and to diminish the size and fishing power of the remaining catcher-processor fleet and transfer more of the BSAI pollock TAC to the inshore sector, the AFA was signed into law in 1998.

2.3.1 Specific Provisions of the AFA

The AFA is comprised of four principal components. The first component increases the amount of U.S. ownership and control that is required in order to obtain a Federal fishery license (from 51 percent to 75 percent – which is the same as the requirements for all fishermen in the U.S. EEZ).

The second major provision of the AFA prohibits the issuance of a fishery license after September 25, 1997 to any vessel greater than 165 feet long, or more than 750 gross tons, or that has a total of more than 3,000 shaft horsepower from all engines combined (and applies to all vessels within the U.S. EEZ). Existing fishing vessels that exceed these caps are allowed to continue to operate, but they cannot be expanded or replaced once taken out of service for a year or more (Public Law #105-277).

Though the historical effectiveness of input restrictions has been mixed, by limiting the length, tonnage, and horsepower of fishing vessels, the AFA has indeed made it more difficult for vessels to increase fishing capacity. The cap on length and weight may decrease the holding and processing capabilities of the vessels, and the cap on horsepower should limit the size of the trawl nets and the speed at which vessels can trawl. Still, given that remaining vessels appear to be harvesting in a slower, more deliberate manner (due to the fishing rights established by the cooperative), these restrictions may not represent a binding constraint for vessels that are currently eligible for the BSAI pollock fishery. Rather, the restrictions may serve more as a barrier for larger, more powerful vessels that may attempt to enter other U.S. fisheries.

The net outcome of the new restrictions on size, horsepower, and ownership was a group of 20 catcher-processors (owned by nine different companies) eligible to participate in the BSAI pollock fishery. The AFA also lists seven catcher vessels that remain eligible to fish and deliver a suballocation to the aforementioned catcher-processors. In addition, the Act specifically retires nine catcher-processors from further participation in this or any other U.S. fishery, offering a total of $90 million as compensation to the owners of such vessels. $20 million of the cost was borne by taxpayers, and the remainder is to be repaid by the inshore sector via a fee system amounting to .6 cents for each pound of pollock harvested under the inshore fishing allowance. The inshore sector is paying this portion because they received a substantial increase in their share of the BSAI pollock TAC. The Act also specifies three motherships, and 19 offshore catcher vessels that deliver to them, that may continue to operate in the pollock fishery.

For the inshore sector, the Act is a bit less specific with respect to which catcher vessels and processors would be eligible to participate in the BSAI pollock fishery. Rather than listing individual vessels or processors by name, the AFA stipulates the landing/processing history necessary for eligibility. NMFS has estimated that there are 92 catcher vessels and seven processing plants in the inshore sector that meet the criteria to be deemed "AFA eligible" (Oliver, 1999).

The third principal component of the AFA is a reallocation of the directed pollock fishery annual TAC. The AFA specifies that ten percent of the annual TAC will be allocated off the top to the Community Development Quota (CDQ) program, which is an increase from the previous allocation of 7.5%. After reserving about 5% for bycatch in other groundfish fisheries, the remaining TAC is divided among the inshore component, the offshore (catcher-processor) component, and the mothership component at 50%, 40%, and 10%, respectively (Public Law #105-277). This is a change from the previous allocation, which, after taking the CDQ and bycatch allowances, gave only 35% to the inshore sector and 65% to the catcher-processors and motherships combined.

The fourth major provision of the AFA allows for the formation of cooperatives among catcher-processors, among the catcher vessels that deliver to the catcher-processors, among eligible motherships and catcher vessels in the mothership sector, and among the eligible catcher vessels in the inshore sector of the BSAI pollock fishery. Ideally, the vessel specific allocations within each cooperative will allow the vessels involved to coordinate their efforts, rather than race for fish. In accordance with the new AFA provision, and the catcher-processors in the catcher-processor sector formed the Pollock Conservation Cooperative (PCC), and the catcher vessel owners formed the High Seas Catchers' Cooperative (HSCC). An agreement called the "Cooperative Agreement Between Offshore Pollock Catchers Cooperative and Pollock Conservation Cooperative" was also formed to facilitate efficient management and accurate accounting between the HSCC and PCC.

Other provisions of the AFA limit the catch and bycatch of other groundfish and non-groundfish species that can be taken by BSAI pollock fishery eligible vessels. These provisions also impose limits on the percent of total catch that may be harvested by the BSAI pollock fishery eligible vessels.

2.3.2 Details of the PCC and the HSCC

The PCC is made up of nine companies that own the 20 catcher-processors eligible to fish in the pollock fishery (as specified in the AFA). Within the PCC, each member company is contractually allocated a percentage share of the catcher-processor allocation based on their historical catch levels. The percentage shares for each of the nine companies ranges from 44% (for the American Seafoods Company) to 4.17% (for the Starbound Ltd. Partnership).

The HSCC is comprised of seven companies that own seven catcher vessels eligible under the AFA to harvest pollock for the 20 catcher-processor vessels. Under the HSCC, each company is contractually allocated a percentage of the total catcher-vessel pollock allocation based on historical catch levels. The percentage shares vary from 24% (for Sea Storm, Inc.) to 7% (for Forum Star, Inc.).

The formation of the PCC and HSCC occurred during the last two months of 1998, and allowed members to coordinate plans for the fishing season beginning in January of 1999. Given the short amount of time the vessel owners had for developing new arrangements, it may be difficult to ascertain the long-term effects that may arise under the new regime by analyzing data from the 1999 season. However, the preliminary joint report of the PCC and HSCC indicates that "cooperative fishing was successful on many fronts." Daily catch rates reportedly declined significantly and product recovery rates increased by more than 20 percent. In addition, fewer vessels were used to harvest and process the catch in 1999, as some cooperative members opted to transfer or sell their harvesting or processing rights to others within the cooperative. Such transfers typically occurred within particular companies (which own multiple vessels), and some of the vessels idled in the pollock fishery continued to participate in the whiting fishery off Oregon and Washington.

In summary, there have been a number of changes introduced in the pollock fishery by the AFA. Both the size and structure of the fishery has been altered, as has the motivation underlying harvesting patterns due to the introduction of fishing rights established by the cooperatives. It remains to be seen, however, how such changes manifested themselves in the overall (and relative) performance of vessels operating in the pollock fishery.

2.4 The BSAI Catcher-Processor Data

The specific data used in the capacity and TE models is based on weekly harvesting and processing for 1991-1999, and comes primarily from Weekly Processor Reports (WPR) and observer data which are collected by NMFS are referred to as "blend data." The blend data for catcher-processors is constructed by first compiling weekly production reports for catcher-processors, which essentially report the weights of processed products and round weights of discards. Next, product weights are converted to equivalent round weights using standardized product recovery rates.

In addition to the weekly production reports, the blend data relies on information obtained from federal observers. The observers on catcher-processor vessels report groundfish species composition, total catch, and estimates of retention and discards. Such reports occur on a weekly basis for each separate reporting area and gear type, and the reported total catch used to be estimated using bin volume, scales, or conversion from production data. Now, scale weights are used for the AFA-eligible catcher-processors' catch. The species composition of the observed hauls is obtained by sampling the catch, with the total catch being apportioned by species based on that sampling.

Next, using the data from both weekly WPRs and observer reports, the total groundfish catch for all species combined is computed each week for each processor vessel. If by chance either report is missing, the report that is present is selected and used to characterize the weekly catch levels. If *both* reports are present, a blending process is used in order to compare the numbers from the two reports.

More specifically, if the WPR and observer total catch numbers are within 5 percent of one another, the WPR is selected as the source, and these values are recorded. If the WPR is greater than 30 percent higher than the observer total catch for pollock target fisheries (or more than 20 percent higher for all other target species), the WPR is again selected as the source. In all other cases, the observer report is selected as the source.

Once the source data has been identified through the blend selection process, the program then returns to the source data (either WPR or observer) and copies the detailed records, showing gear type, area and species, to the blend. Records from WPR are identified in the blend by a source field value of "W", and observer records are identified by a source field value of "O."

The aim of the blend process is to combine the data available in industry production reports and observer reports to make the best, comprehensive accounting of groundfish catch. Once compiled these data are used to manage quotas for groundfish in the Gulf of Alaska, and the Bering Sea and Aleutian Islands. The blend data are also used as the basis for computing estimates of prohibited species bycatch, which includes Pacific halibut, salmon, herring, and crabs. In addition, blend data are used for numerous regional and national reports, fishery stock assessments, and analysis of proposed fishery management actions.

The actual blend data used in this analysis includes a scrambled vessel id number, the data source, the week and year the catch occurred, the gear type used, the area the vessel fished in, the weight (in metric tons) of the various groundfish that were caught, as well as the level of bycatch[6] for halibut, bairdi crab, red king crab, Chinook salmon, all other species of salmon (collectively), herring, all other species of tanner crab (collectively), and all other types of king crab (collectively).

In addition to the catch data obtained from the blend, this research also uses information on vessel characteristics (coming from the Alaska Department of Fish and Game or [ADF&G] and Federal Vessel registration files), crew size (from WPRs after 1994), vessel effort (data on the number and duration of tows, and days at sea, from observer data), and finished product composition (from WPRs). The vessel registration files provide information on vessel length, vessel age, vessel tonnage (net and gross), vessel engine type (gas or diesel), vessel horsepower, hull type, and holding capacity.

The presence of scrambled vessel identification numbers makes it possible to track production by individual operators over time, as well as to separate the data into several modes of operation and fleets that are defined based on common production

[6] While the idea of including bycatch species in the production models is attractive, their inclusion in this particular application to the catcher processor fleet had very little impact in the initial model runs. Presumably because the fleet under study is one of the cleanest in the world (bycatch rates are around 1 to 2 percent), the bycatch parameters were invariantly insignificant in the SPF model, and were thus omitted from both the SPF and DEA model specifications.

patterns[7]. That is, commonality of production patterns in the data suggests commonality of production technology onboard, both in terms of fishing operations and processing. In addition, the way in which the data was broken into sub-samples is very similar to the breakdowns used by North Pacific Council and NMFS staff in their analyses of management issues involving groundfish. Such delineations will help ensure that the models characterize all vessels in each sample fairly well, and that any resulting comparisons are made among the appropriate agents.

2.5 Defining "Fleets" in the NPGF

While the specific composition of fishing gear and processing equipment may differ from boat to boat, development of tractable and representative models requires aggregating the data in a sensible manner. Not only does such a grouping make the analysis more manageable, it also improves the precision of model estimates by only grouping together vessels that share similar production technologies. As a result, the goal in many situations is to isolate the most natural and common groupings of production processes, such as vessels that use trawl gear and target similar species.

The first step in categorizing fleets (in an attempt to isolate the BSAI pollock catcher-processor fleet) was to recognize differences in mode of processing operation. The three basic modes are motherships, shoreside processors, and catcher-processors. This dissertation focuses solely on the catcher-processor sector of the industry for

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[7] The scrambled vessel id numbers also allow for the use of fixed-effect dummy variables in econometric specifications, which would allow one to compensate for producer-specific differences in mean output levels. However, since the same could not be done in the DEA models, and the goal was to attempt to construct equivalent models for comparison, this nuance was not incorporated (though it will be done in future analysis, where the focus will be more on constructing an "ideal" SPF model, rather than comparing standard DEA and SPF approaches).

purposes of model development and evaluation. Within the catcher-processor sector, three generally recognized fleets were identified: surimi and fillet fleet, freezer-longliners, and the headed and gutted (H&G) trawler fleet.

As the names suggest, there are some simple rules for classifying the catcher-processor operations into these fleets. The surimi and fillet fleet was identified as those vessels that used trawl gear (and produced surimi and fillets) during 1991-1999. The freezer-longliner fleet was those vessel operator id's for which longline gear was indicated as part of the production record. The H&G trawler fleet was given by those operator id's that used trawl gear but did not produce fillets or surimi.

The production possibilities exhibited by these three fleets (in terms of finished products) are quite diverse. The fillet and surimi fleet has the narrowest production focus, as many of these operations are almost exclusively single-species (pollock) operations, with only 2-3 products produced. Next in production diversity is the freezer longliner fleet, which principally produces two species (Pacific cod and sablefish) and two variations of a headed and gutted product. The H&G trawl fleet is probably the most diverse, comprised of vessels exhibiting substantial production of at least five different groundfish species through the year, principally into several headed and gutted product forms.

As mentioned above, this dissertation focuses solely on the BSAI catcher-processor fleet on the NPGF. The primary reason for such a focus is because its production is the most valuable in the NPGF, the vessels in this fleet participate in the pollock fishery, and it was a major focus of the 1998 AFA.

2.5.1 Species Selection and Data Characteristics

Once the observations from the BSAI catcher-processor fleet were selected from the data, the determination of which species to include as outputs in the empirical production models was made. It was necessary to narrow down the set of outputs because there are close to ten different groundfish species listed in the data set, many of which are caught incidentally as bycatch at very low levels, but are still reported.

In selecting the outputs, the goal was to incorporate data only on species that are a typical part of the production mix. This was done in order to conserve degrees of freedom (which would quickly disappear with 10 outputs and multiple inputs in a flexible functional form), and minimize the introduction of "noise" that would not add to the insight gained from the analysis (often the bycatch levels are measured less precisely or imputed). Therefore, for a species to be included in the models as an output, is had to represent a "substantial" fraction of catch (5% or more) during at least one year from 1994-1999.

The final set of data used in the capacity models is thus based on the species typically caught by the BSAI catcher-processor fleet, and comes primarily from WPRs and observer data for 1991-1999. The data includes 5974 observations on landings of groundfish, vessel characteristics, and variable input use. The data also includes a scrambled vessel id number for each vessel which allows one to track particular vessels over time.

It should be noted that the set of data used in each of the DEA and SPF models spans 1994-1999 (and not the entire 1991-1999 period previously discussed). The reason for this is that labor data was not available prior to 1994, and it was desirable to have a complete specification for all years, with a comparable set of inputs in all models.

Table 4.1 lists the mean yearly values of catch and vessel characteristics for the trawlers used in the analysis, while Table 4.2 shows the observed weekly values for each of the variables included in the SPF and DEA models. These tables illustrate that a majority of the catch is pollock and flatfish (followed by Atka mackerel, Pacific cod, sablefish, and rockfish), while much of this catch is used in the production of surimi (around 36%), followed closely by fillet products (approximately 32%), with the rest going primarily to H&G products. Generally, the vessels that target pollock as their primary catch are a more homogeneous group, and are larger than vessels that are less specialized in their catch composition.

One interesting and beneficial characteristic of the data used here is that it represents *total* catch for each season (both retained and discarded[8]), rather than just the catch that was retained and used in creating the resulting product forms (as is common in many other studies). As a result, capacity estimates better reflect the true technological fishing power of fishing vessels.

[8] Such discards occur because it may be more profitable to do so, because a fishery was closed and a maximum retainable bycatch limit is in place, or because the catch is so close to the TAC that retention is prohibited. Regardless of the reason, data structured in this format allows one a look at the actual amount that is caught in the harvesting operations.

Chapter 3
Theoretical Background and Literature Review

3.1 Introduction

Much of the work in the following chapters relies on representations of production technologies for different vessels within the BSAI catcher-processor fleet. Although the most well known and familiar primal form of production relationships is given by the production function, in many cases it does not provide a sufficiently general representation. This is particularly true in the applications contained in this dissertation, where multiple outputs as well as inputs are the norm.

Therefore, the basis for many of the production relationships used throughout this dissertation will be a technology set, which represents all of the technologically feasible combinations of inputs and outputs producible from a given technology. The advantage of defining a technology by its technology set is the ease with which one can handle multi-product technologies – which is not the case with the production function. While such a set representation is quite general and thus does not impose unnecessary restrictions on technologies, it is a bit more abstract than the familiar functional or parametric representations of technologies.

Fortunately, there are functional representations of production technologies that can be derived and used in empirical applications after one makes a few standard assumptions regarding the properties of the technology set – namely, the input and output distance functions. One of the greatest benefits of using distance functions is that they allow one to estimate primal models with multiple inputs *and* outputs, yielding a more realistic representation of the technology than a standard production function. And, aside from providing a complete characterization of the technological relationships among inputs and outputs, distance functions can be used to construct "efficiency scores" for each producer in the data set. This score essentially reflects the distance of a producer from a production isoquant (for the input distance function), or from a production possibilities frontier (for the output distance function). It yields a measure of one's relative technical efficiency, where optimal technical efficiency is such that the value of the input or output distance function equals one.

Parametric distance functions may be estimated empirically with a variety of flexible functional forms, and thus need not impose *a priori* restrictions on the curvature of the production relationships (e.g. Cobb-Douglas), which allows for a more complete and flexible model specification. Non-parametric distance scores may also be constructed through mathematical programming models (such as DEA), which more easily accommodate multiple inputs and outputs. In addition, as will be shown further below, distance functions can be used to derive shadow values for both inputs and outputs.

In this chapter, I will more formally introduce the notion of a technology set as well as the associated input and output distance functions. Once the distance functions have been introduced, it is fairly straightforward to show the duality between the input (output) distance function and the cost (revenue) function, which allows one to analyze production technologies by looking at the economic choices producers make under technological constraints.

Using a few standard assumptions over the production technology, one is then able to utilize a wide range of representations of the technology – both primal and dual. Primal representations (e.g., input and output distance functions) are more common/appropriate when the standard behavioral assumptions are questionable and only input/output data exists, while dual representations (e.g., cost, revenue, and profit functions) may be used when one assumes such behavioral objectives are appropriate, and the necessary price data is available.

3.2 Theoretical Background

More formally, a production technology transforming factors of production $\mathbf{x} = (x_1, x_2,\ldots,x_n) \in R_+^n$ into outputs $\mathbf{y} = (y_1, x_2,\ldots,y_m) \in R_+^m$ can be represented by the technology set, **T**. This set contains all technically feasible input and output bundles, i.e. $\mathbf{T} = \{\mathbf{x} \in R_+^n,\ \mathbf{y} \in R_+^m : \mathbf{x} \text{ can produce } \mathbf{y}\}$. From **T**, one can define the producible output set $Y(\mathbf{x}) = \{\mathbf{y}: (\mathbf{x},\mathbf{y}) \in T\}$ and the input requirement set $V(\mathbf{y}) = \{\mathbf{x}: (\mathbf{x},\mathbf{y}) \in T\}$, which are equivalent representations of the technology set, **T**, in that $\mathbf{x} \in V(\mathbf{y}) \Leftrightarrow \mathbf{y} \in Y(\mathbf{x})$. The boundaries of these two sets can loosely be thought of as the more common production possibilities frontier and the input isoquant, respectively.

Beginning in an output context, in order to characterize the producible output set $Y(\mathbf{x})$ with a well-defined output distance function, a set of four axioms regarding $Y(\mathbf{x})$ is required: (A.1) $0_m \in Y(\mathbf{x})\ \forall\ x$ in R_+^n; (A.2) $\forall\ (\mathbf{x},\mathbf{y})$ in R_+^{n+m}, if $\mathbf{y} \in Y(\mathbf{x})$ and $0< \theta \leq 1$ then $\theta y \in Y(\mathbf{x})$; (A.3) $\forall\ x$ in R_+^n, $Y(\mathbf{x})$ is a bounded set; (A.4) $\forall\ x$ in R_+^n, $Y(\mathbf{x})$ is a closed set.

Assumption (A.1) states that inaction is possible, while assumption (A.2) is referred to as weak disposability of outputs. This second assumption allows for the possibility of inefficient production; if a certain bundle of outputs is producible from a given bundle of inputs, then a smaller scalar proportion of the output bundle is producible from this same bundle of inputs. This assumption also allows for the possibility of "bad outputs." For example, if one wants to decrease the pollution output associated with production of electricity (for a given bundle of inputs), one must decrease both pollution *and* electricity generation. Assumptions (A.3) and (A.4) are essentially mathematical requirements that ensure that the producible output set is compact, allowing for the existence of a well-defined distance function.

Given these assumptions on the technology, as shown by Färe and Primont (1995), the output distance function is defined on the producible output set $Y(\mathbf{x})$ as

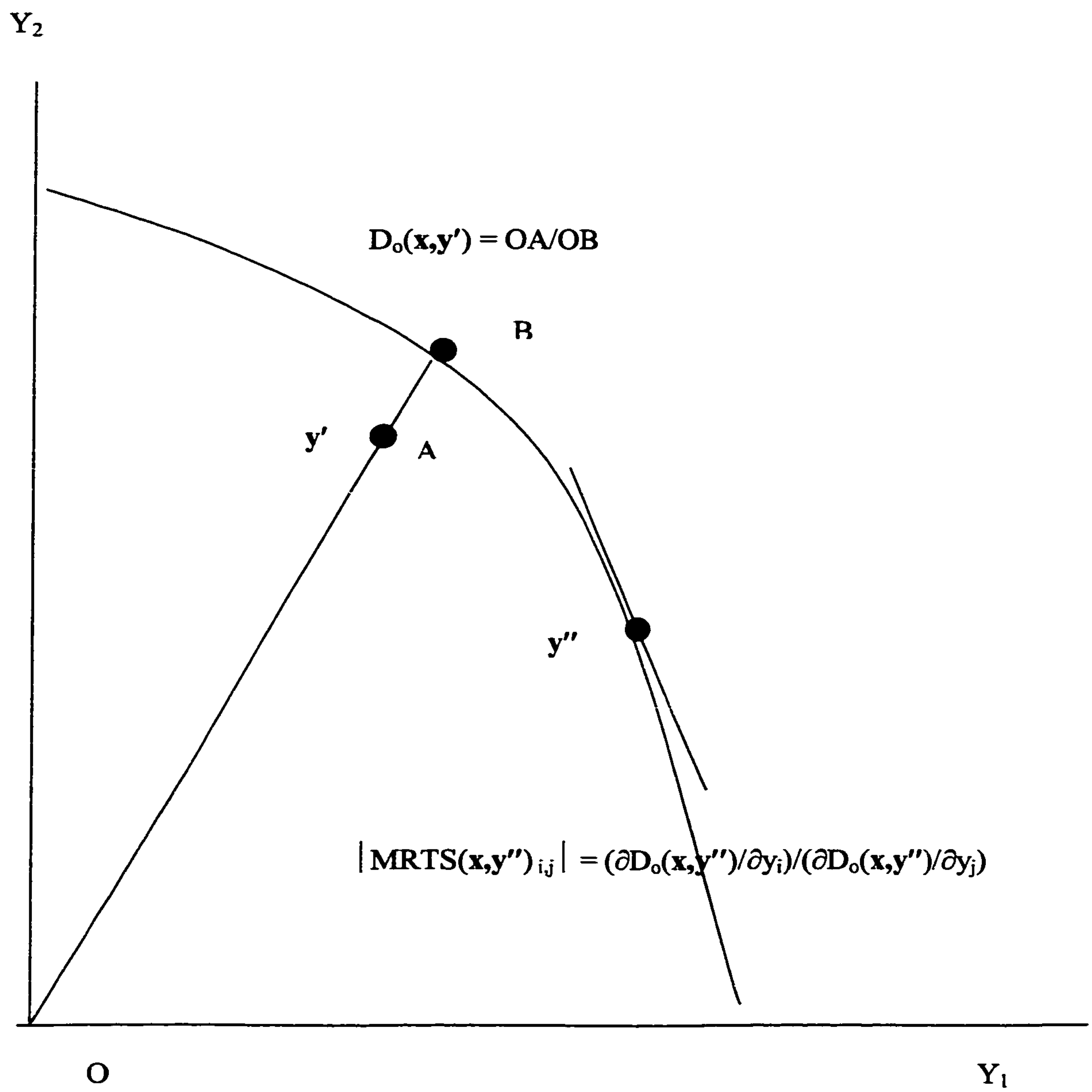
$$D_o(\mathbf{y},\mathbf{x}) = \min_\beta \{\beta: (\mathbf{y}/\beta) \in Y(\mathbf{x})\}. \tag{3.1}$$

Equation (3.1) gives the largest radial expansion of the output vector for a given input vector that is consistent with the output vector belonging to $Y(\mathbf{x})$. Figure 3.1 shows the producible output set, $Y(\mathbf{x})$, in two-dimensions and an element of $Y(\mathbf{x})$, y'. The value of $D_o(\mathbf{x},\mathbf{y})$ in Figure 3.1 at y' is given by the value OA/OB. The axioms given above regarding the output set $Y(\mathbf{x})$ imply the properties of the output distance function.

Namely, (1) $D_o(\mathbf{x},0_m) = 0\ \forall\ x$ in R_+^n, (2) $D_o(x, \theta y) = \theta D_o(\mathbf{x},\mathbf{y})$, (3) $D_o(\mathbf{x},\mathbf{y})$ is lower semi-bounded on R_+^m, and (4) $D_o(x,y)$ is lower semi-continuous on R_+^m. The first axiom implies that inactivity is possible, the second states that $D_o(\mathbf{x},\mathbf{y})$ is linearly homogeneous in outputs, and the third and fourth are the mathematical results of assumptions (A.3) and (A.4), which allow for the existence of a well-defined function.

It can easily be shown that the production function is a special case of $D_o(\mathbf{x},\mathbf{y})$ by examining the case of a scalar output. Since $D_o(y,\mathbf{x}) = \inf_\beta \{\beta: (y/\beta) \in Y(\mathbf{x})\}$, linear homogeneity in outputs implies that $D_o(y,\mathbf{x}) = y \cdot \min\{\beta/y: (y/\beta) \in Y(\mathbf{x})\}$, which equals

Figure 3.1 The Producible Output Set, Y(**x**), and the Output Distance Function



$y/\max\{y/\beta: (y/\beta) \in Y(\mathbf{x})\}$. If $D_o(\mathbf{x},\mathbf{y})=1$, however, then one is producing on the frontier, and $y= \max\{y/\beta: (y/\beta) \in Y(\mathbf{x})\}$. The value of $\max\{y/\beta: (y/\beta) \in Y(\mathbf{x})\}$ is by definition the familiar $f(\mathbf{x})$ given in the single output production function, implying that under full efficiency and a scalar output, $y=f(\mathbf{x})$.

The value of the output distance function at each observation can be used to give the Farrell output-oriented measure of technical efficiency (the Farrell output efficiency score is the inverse of the value of $D_o(\mathbf{y},\mathbf{x})$). By indicating the factor by which all outputs could be expanded proportionately (when using a given bundle of inputs), the distance function thus yields an indication of the relative efficiency of different agents given the current technology. In addition, the slope of the production possibilities frontier (the marginal rate of technical substitution, or MRTS) can be recovered at a point such as y'' in Figure 3.1 through the ratio of partial derivatives,

$$|\,\mathrm{MRTS}(\mathbf{x},\mathbf{y}'')_{i,j}\,| = (\partial D_o(\mathbf{x},\mathbf{y}'')/\partial y_i)/(\partial D_o(\mathbf{x},\mathbf{y}'')/\partial y_j) \tag{3.2}$$

While the minimal set of assumptions on $Y(\mathbf{x})$ given above is enough to guarantee the existence of a well-defined output distance function, there are further assumptions regarding $Y(\mathbf{x})$ that are typically made that impart further properties to the output distance function, and establish a duality relationship between it and the revenue function. More specifically, by further assuming that (A.5) $Y(\mathbf{x})$ is convex, and (A.6) $Y(\mathbf{x})$ exhibits strong disposability of outputs (if $\mathbf{y} \in Y(\mathbf{x})$ and $\theta \geq 1$, then $\mathbf{y} \in Y(\theta\mathbf{x})$), then $D_o(\mathbf{x},\mathbf{y})$ is increasing and convex $\mathbf{y}$, positively linearly homogeneous in $\mathbf{y}$, $\mathbf{y} \in Y(\mathbf{x})$ $\Leftrightarrow D_o(\mathbf{y},\mathbf{x}) \leq 1$, and $D_o(\mathbf{y},\mathbf{x})$ is dual to the revenue function $R(\mathbf{p},\mathbf{x})$.

Thus, through estimation of $D_o(\mathbf{x},\mathbf{y})$ one may compute many different measures to aid in assessing the relative performance of producers characterized by the same production technology. Some measures can be derived directly from $D_o(\mathbf{x},\mathbf{y})$ -- such as technical efficiency, capacity and capacity utilization, while others are obtained through use of the duality between $D_o(\mathbf{x},\mathbf{y})$ and revenue function. For example, Shephard (1970) shows that under the assumptions (A.1) – (A.6) given above, the following conditions hold:

$$R(\mathbf{p},\mathbf{x}) = \max_y \{ \mathbf{p}\cdot\mathbf{y}: D_o(\mathbf{x},\mathbf{y}) \le 1\} = \mathbf{p}\cdot\mathbf{y}^* / D_o(\mathbf{x},\mathbf{y}), \text{ for optimal } \mathbf{y}^*; \tag{3.3}$$

or equivalently,

$$D_o(\mathbf{x},\mathbf{y}) = \max_p \{ \mathbf{p}\cdot\mathbf{y}: R(\mathbf{p},\mathbf{x}) \le 1\} = \mathbf{p}^*\cdot\mathbf{y} / R(\mathbf{p},\mathbf{x}), \text{ for optimal } \mathbf{p}^*. \tag{3.4}$$

This relationship allows for alternative representations of the technology -- primal or dual -- depending on the available data and the appropriateness of the behavioral assumptions in one's particular application. One can also use the above relationship to derive shadow values for desirable *and* undesirable outputs (such as target species and bycatch, respectively) from $D_o(\mathbf{x},\mathbf{y})$ by solving the Lagrangian problem associated with (3.3)[9]. These results allow for the estimation of the implicit prices for products when markets or price data do not exist.

Similarly to the discussion of $Y(\mathbf{x})$, a production technology can also be represented in terms of the input requirement set, $V(\mathbf{y})$. This set contains all technically feasible input bundles $\mathbf{x}$ that can produce the output vector $\mathbf{y}$, i.e. $V(\mathbf{y}) = \{\mathbf{x} \in R_+^n: \mathbf{x} \text{ can produce } \mathbf{y}\}$. And, just as with the *output* distance function, four assumptions regarding

[9] Assuming the first-order necessary conditions are satisfied, the envelope theorem implies that $\mathbf{p} - \lambda(\mathbf{p},\mathbf{x}) \nabla_y D_o(\mathbf{x},\mathbf{y}) = 0$. By multiplying this condition by $\mathbf{y}(\mathbf{p},\mathbf{x})$ one gets $\mathbf{p}\mathbf{y}(\mathbf{p},\mathbf{x}) - \lambda(\mathbf{p},\mathbf{x}) \nabla_y D_o(\mathbf{x},\mathbf{y})\, \mathbf{y}(\mathbf{p},\mathbf{x}) = 0$. By H.O.D. one of $D_o(\mathbf{x},\mathbf{y})$ in outputs, $\nabla_y D_o(\mathbf{x},\mathbf{y})\, \mathbf{y} = 1$, and thus, $\lambda(\mathbf{p},\mathbf{x}) = \mathbf{p}\, \mathbf{y}(\mathbf{p},\mathbf{x}) = R(\mathbf{p},\mathbf{x})$. Plugging this in for $\lambda(\mathbf{p},\mathbf{x})$ in the FOC's implies that $\mathbf{p}/ R(\mathbf{p},\mathbf{x}) = \nabla_y D_o(\mathbf{x},\mathbf{y})$, or $\nabla_y D_o(\mathbf{x},\mathbf{y}) = \mathbf{p}^*(\mathbf{x},\mathbf{y})$. This implies that by taking the gradient of $D_o(\mathbf{x},\mathbf{y})$ with respect to $\mathbf{y}$, the result is a vector of revenue-deflated output shadow values, $\mathbf{p}^*(\mathbf{x},\mathbf{y})$. Or, looking at the i^{th} element of the gradient vector of $D_o(\mathbf{x},\mathbf{y})$ one sees $dD_o(\mathbf{x},\mathbf{y})/dY = p_i^*(\mathbf{x},\mathbf{y}) = p_i/R(\mathbf{p},\mathbf{x})$. Furthermore, by taking the ratio of such derivatives the relative output shadow values

V(**y**) (similar to those given above for Y(**x**) – see Färe and Primont [1995]) are necessary in order to assure the existence of a well-defined *input* distance function. Given these assumptions, the input distance function is defined on the input set V(**y**) as

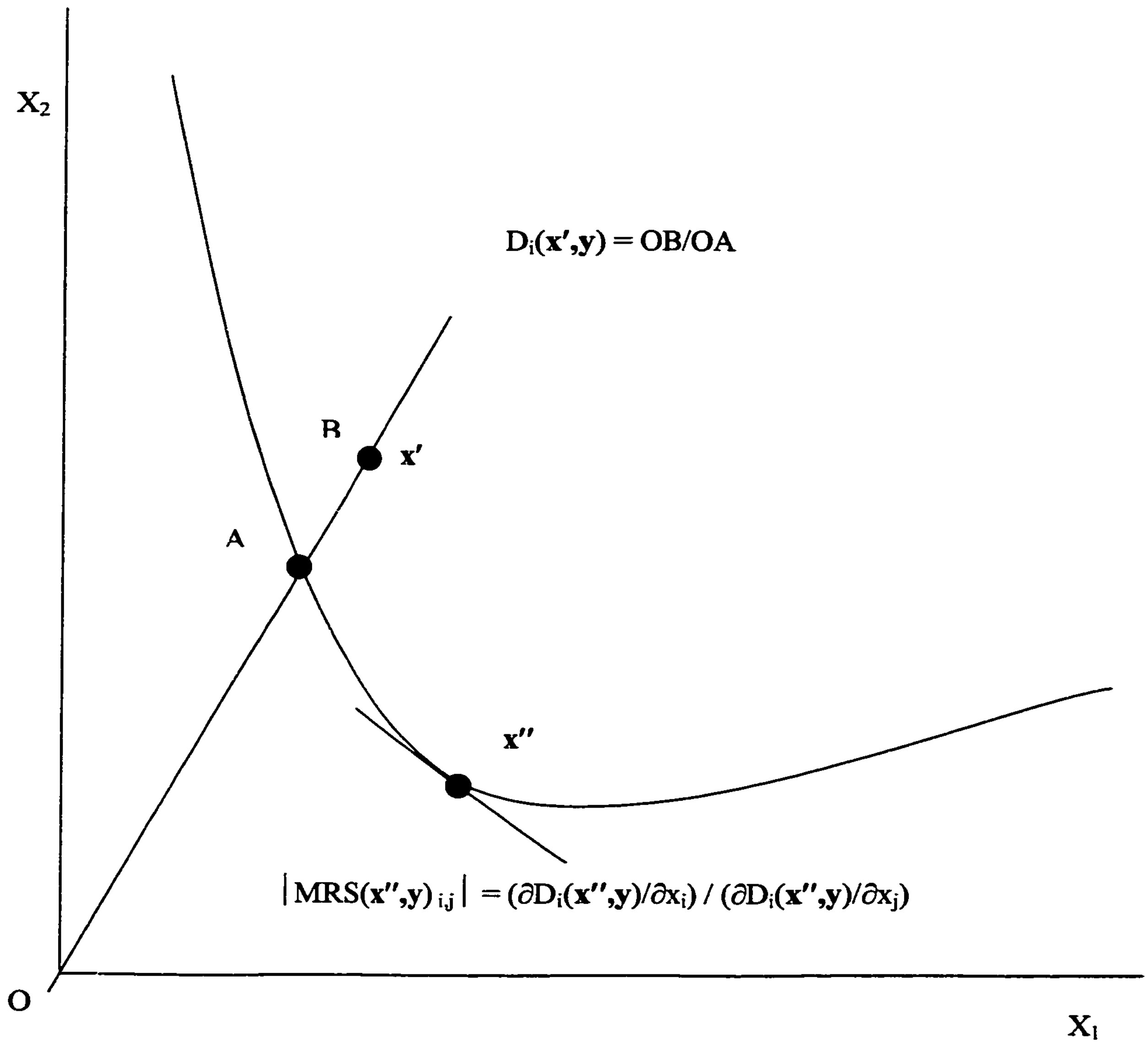
$$D_i(\mathbf{x},\mathbf{y}) = \sup_\beta \{\beta: (\mathbf{x}/\beta) \in V(\mathbf{y})\}. \tag{3.6}$$

Equation (3.6) gives the largest radial contraction of the input vector for a given output vector which is consistent with that input vector belonging to V(**y**). Figure 3.2 shows the input requirement set, V(**y**), in two-dimensional space, and an element of V(**y**), x′. Here, the value of the input distance function is given by the ratio OA/OB. As with the output distance function, a set of axioms regarding the input set V(**y**) imply the properties of the input distance: in short, $D_i(\mathbf{x},\mathbf{y})$ is continuous, non-increasing, concave, and positively linearly homogeneous in **x**, and quasi-convex and non-increasing in **y**. Note also that $\mathbf{x} \in V(\mathbf{y}) \Leftrightarrow D_i(\mathbf{x},\mathbf{y}) \geq 1$ (i.e., for a feasible input vector, $D_i(\mathbf{x},\mathbf{y}) \geq 1$).

The reason for interest in both input and output distance functions is that $D_o(\mathbf{x},\mathbf{y})$ and $D_i(\mathbf{x},\mathbf{y})$ provide slightly different notions of productive efficiency; the former indicates the possible radial increase in outputs obtainable from a given set of inputs, and the latter indicates the potential decrease in inputs for a given level of output. Depending on one's interest and which approach is more intuitive for the application at hand, one may prefer to use one versus the other. For example, the empirical applications in the following chapters rely on an output orientation. In the context of a constant returns to scale production technology, however, the efficiency scores of the two functions are inversely related ($D_o(\mathbf{x},\mathbf{y}) = 1/(D_i(\mathbf{x},\mathbf{y}))$, so either model yields equivalent results.

(the MRT) are obtained, which is illustrated in Figure 3.1. One can also generate ***absolute*** shadow values using this technique (Färe and Primont, 1995).

Figure 3.2 The Input Requirement Set, V(y), and the Input Distance Function



Further similarities between $D_o(\mathbf{x},\mathbf{y})$ and $D_i(\mathbf{x},\mathbf{y})$ exist as well; just as $D_o(\mathbf{x},\mathbf{y})$ is dual to $R(\mathbf{p},\mathbf{x})$ (see equation (3.3)), $D_i(\mathbf{x},\mathbf{y})$ is dual to $C(\mathbf{w},\mathbf{y})$. This implies that the input distance function can be used to estimate shadow values of inputs (analogous to the derivation above for outputs, but here using the input distance function and cost function). By comparing an input's shadow value to its market value, one can test if inputs are being used in an allocatively efficient manner. Under optimal input usage, the shadow value of x_i (its value of marginal product) should equal the market price of x_i. If the shadow value exceeds the market price, the input is being "underused", while the opposite condition would imply overuse. If one had information on costs, such analysis could be useful in examining the level of capacity or capital utilization, as one could then construct a measure $CU = C^*/C$, where C^* is shadow cost, and C is observed cost (to be discussed further in Chapter 4).

3.3 Literature Review on Capacity and Capacity Utilization

The term *capacity* is prevalent throughout much of the economics literature, and often there is little discussion of the foundations of the particular notion used in each context, as if there was agreement about its meaning. Generally, capacity may be thought of as either the maximal or optimal output level obtained from an endowment of fixed inputs. However, several different notions of capacity have been presented and developed over the years – each of which may correspond to entirely different levels of output.

Typically, differences arise in the definition of capacity depending on whether one is referring to a technical/physical notion of capacity or an economic notion, although there are even further subtle differences within each of these two groups (this will be discussed further soon). Regardless of one's chosen definition, capacity is a short-run concept in which firms and industry participants face short-run constraints, such as the stock of capital or other fixed inputs, existing regulations, and the state of the technology (Kirkley and Squires, 1999). As a result of the different notions of capacity, measures of *capacity utilization* (CU) differ as well. That is, since the definition of capacity output shares multiple interpretations, the standard primal measure of CU (given by the ratio of observed to capacity output[10], or Y/Y*) does too. Similarly, different economic measures of capacity lead to different measures of CU.

The notions of capacity that refer to some sort of physical maximum may be grouped together as primal-based capacity and CU measures. These measures are based solely on the production technology and typically define capacity output as the maximum potential output obtainable from a given set of fixed factors and the state of the technology (Johansen [1968], Corrado and Mattey [1997], Färe, Grosskopf, and Kokkelenberg [1989], Raddock [1990], Kalirajan and Salim [1997]).

As such, primal definitions of capacity are inherently short-run measures, as the fixed inputs are the factors of production that eventually limit potential output (regardless of the intensity of variable input use). Within the broad definition of primal-based measures, there are even further refinements based on different assumptions regarding the availability of variable inputs (ranging from freely available to "standard and customary" levels) that lead to upper and lower bounds on productive capacity.

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[10] Measures of CU may also differ depending on whether one uses a primal or dual framework. In the dual framework developed by Morrison (1985b), CU=C*/C, where C* is shadow costs and C is observed costs of production.

For example, the largest capacity estimate for a given technology would be constructed if one adopted an "engineering" definition of capacity. This would entail determining the maximum output obtainable when one uses variable inputs at their maximum possible levels in conjunction with the fixed inputs for a given period of time. Such estimates of capacity correspond to the full-input point on a production function and are unlikely to be observed in practice (as they are not economical in the presence of positive variable input prices). This is the output level corresponding to Y^{Max} in Figure 3.3[11].

Alternatively, the smallest primal-based notion of capacity would be generated if one were to consider the maximum output obtainable under *customary and usual operating procedures*. This estimate of capacity typically is interpreted as reflecting the output that is obtained when one operates under full technical efficiency, but with normal/standard variable input use. Such output levels correspond to the points on the production function in Figure 3.3 for each firm's variable input use (X_v^i), given the fixed input endowment.

Between these two extremes lies a third variation of the primal-based measures that can be thought of as a "technological-economic" approach. Capacity output in such a framework reflects the greatest output obtainable from a given set of fixed factors using *observed* levels of variable input use (and not the greatest output possible, as with the engineering definition). Thus, one is looking at the maximum possible output (hence "technological") given agents observed decisions over input use (hence economic). In deriving such a measure, one determines the output that could be produced if one

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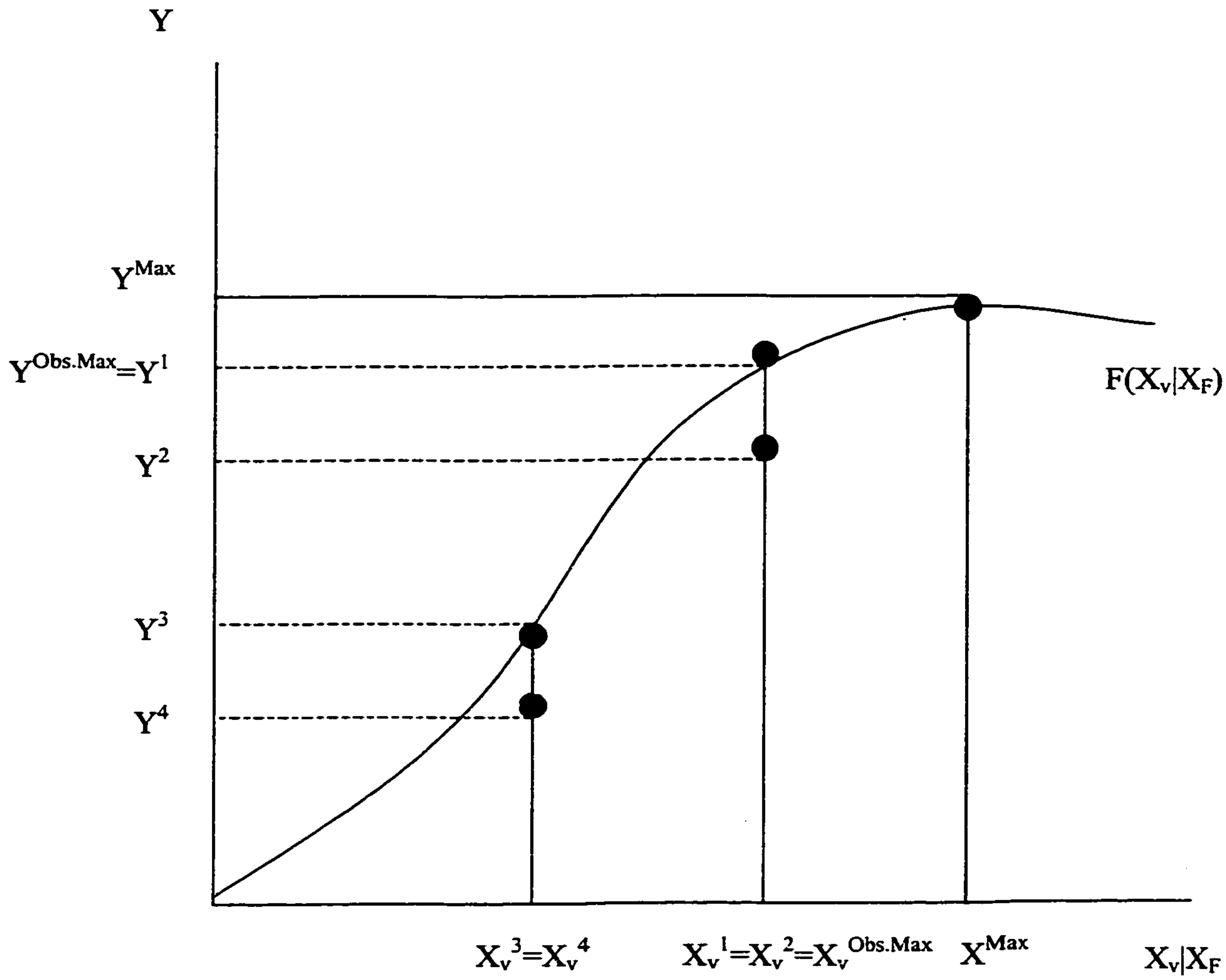
[11] For simplicity, Figure 3.3 utilizes a single output production function, but the same ideas may be generalized to the multi-output case without loss of generality.

Figure 3.3 Primal Capacity and Capacity Utilization Measures



Technological-Economic CU Scores:

Firm 1: $CU_1=Y^1/Y^{Obs.Max}=1$ Firm 2: $CU_2=Y^2/Y^{Obs.Max}<1$

Firm 3: $CU_3=Y^3/\ Y^{Obs.Max}< CU_2 < 1$ Firm 4: $CU_4=Y^4/\ Y^{Obs.Max} <CU_3<CU_2<1$

Note: Some of the CU scores are less than unity because of inefficiency, some because $X_v^{\,i} < X_v^{\,Obs.Max}$

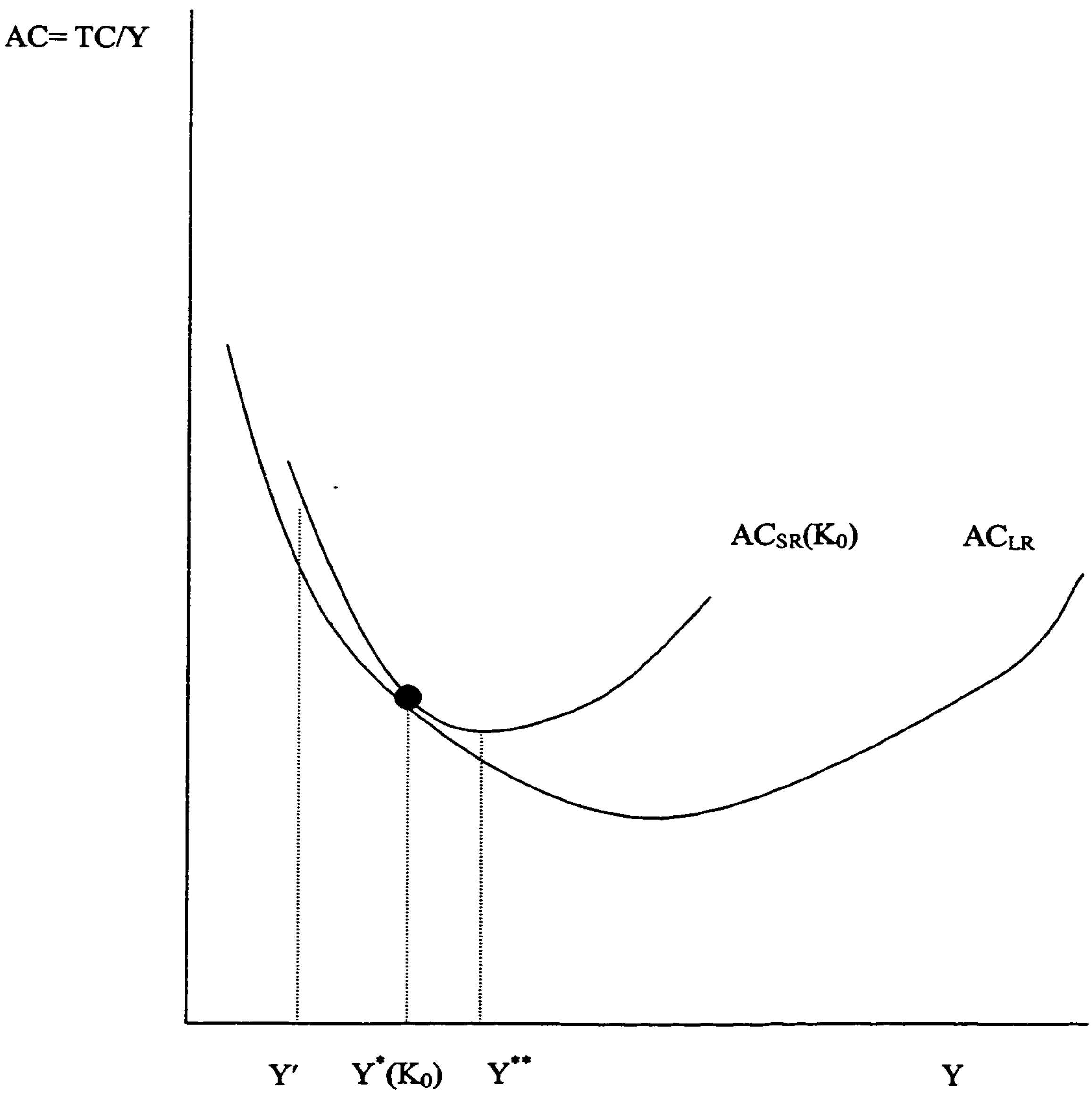
operated under full technical efficiency with the maximum observed variable input levels for a given set of fixed factors. So while these estimates of capacity do not correspond to the output observed under customary and usual operating procedures, they do rely on observed variable input use to help determine realistic "maximum" output levels.

An example of technological-economic capacity output is given by $Y^{Obs.Max}$ in Figure 3.3. This type of measure has recently been constructed in work by Squires *et al.* (2000), Grafton *et al.* (1999), and Kirkley and Squires (1999) by appealing to Johansen's (1968) explicit definition of capacity, or "the maximum amount that can be produced per unit of time with existing plant and equipment, provided the availability of factors of production is not restricted." While at first glance Johansen's definition may connote the engineering maximum discussed earlier, the empirical applications based on Johansen's definition have essentially been based on *observed* variable input use when determining the maximum potential output, and thus in practice correspond to technological-economic measures of capacity.

Given that the standard primal CU measure is constructed as $CU = Y^{Obs.}/Y^{Max.}$, the different primal notions of capacity ($Y^{Max.}$) obviously carry over into different notions of CU as well. As an illustration, in Figure 3.3, several CU scores are constructed using the technological-economic definition of capacity, $Y^{Obs.Max}$.

Turning the focus to economic-derived capacity and CU measures, there are essentially four main methods of defining capacity. The first economic approach, proposed by Klein (1960) and Friedman (1963), defines capacity output as that output corresponding to the tangency of the long-run average total cost (LRAC) and short-run average total cost (SRAC) curves, given by the point $Y^*(K_0)$ in Figure 3.4. The second

Figure 3.4 **Dual Measures of Capacity and Capacity Utilization**



economic approach developed by Cassels (1937) and Hickman (1964) instead defines capacity output as that corresponding to the minimum SRAC, given by the point Y^{**} in Figure 3.4. The first and second measures coincide for linearly homogeneous technologies (constant returns to scale, CRS), as the AC_{LR} curve is flat, and the point of tangency is also the minimum of the AC_{SR}. Note also that while these measures are derived within an economic-based framework (dual models), some authors have called them "primal" measures of capacity in that one determines the physical output levels corresponding to the relevant optimum under consideration.

The third economic approach is that of Morrison (1981, 1985b). This approach has been coined a "dual" approach because it does not directly compare physical output levels, but rather is defined in terms of firms' costs. More specifically, the shadow costs for fixed factors are computed and compared with the market prices for these factors in order to analyze the degree of divergence in cost between the short-run equilibrium and the long-run equilibrium. Here, $CU=C^*/C$, where C^* is the firm's shadow cost and C is the observed cost of production. Capacity output may then be computed by finding the output level at which costs equal C^*.

These first three economic measures are particularly well suited when output(s) is observed ex post, fixed or exogenously determined, or firms strive to minimize the costs of production. When such models are estimated at an industry level, they fit nicely into the context of predetermined TACs in fisheries, in which resource managers exogenously constrain catch levels. The use of an exogenous output contrasts with the endogenous output specified in the primal models discussed earlier, which may be more appropriate for firm level analysis. The fourth main economic approach is an extension of Morrison

(1985b) in which Segerson and Squires (1990) define capacity and CU in the context profit maximization. More specifically, CU is defined as CU= $(H(\mathbf{p},\mathbf{w}; z) - w_z z) / (H(\mathbf{p},\mathbf{w}; z) - w_z^* z)$, where H(•) is a restricted profit function, **p** is a vector of output prices, **w** is a vector of input prices, z is a quasi-fixed input, w_z is the observed price of the quasi-fixed input, and w_z^* is the shadow price of the quasi-fixed input. This formulation allows one to define capacity output for cases in which output is endogenously determined, and not given, as in the cost-minimization framework.

3.3.1 Choosing Among Capacity Models

None of the above measures should necessarily be considered "better" than another, but rather as representing different notions of capacity output. There may be instances in which one would rather have capacity estimates in terms of physical output, while in other circumstances one may desire measures that reflect deviations between actual costs and shadow costs.

Aside from one's preferences regarding the interpretation of the particular definition, the researcher is often at the mercy of the available data. Since the economic approaches generally have greater data requirements (cost-based models necessitate data on input prices and total production costs, while profit-based models require even further data on output prices and revenues), at times they may be unavailable or inappropriate for use in analyzing capacity. This may occur because the data simply does not exist, it exists but is of questionable quality, or the behavioral assumptions underlying the economic capacity measures appear inappropriate. For some purposes, primal models represent a satisfactory method for estimating capacity, but one must determine whether it is appropriate (and possible) in that particular setting to expand the model to generate economic-based measures[12].

For example, in situations in which a resource is managed under open access conditions, behavioral assumptions such as cost-minimization may not be relevant. Rather, economic agents may be attempting to extract as much of the resource as possible in the shortest amount of time. In such a case, resource managers may be concerned with the maximum amount of output that can be extracted/produced in a given period in order to determine how long the resource will last. Or, managers may seek to determine the extent of over-investment in a quota-constrained open access fishery by comparing the total allowable catch with the amount of catch possible with the current level of capital stock.

The following chapter presents an application using the theoretical constructs and functional representations described above. The approach taken will be a primal one (namely, an output distance function), and will utilize and compare parametric and non-parametric representations of the harvesting technologies for the catcher-processor fleet of the BSAI.

[12] If the data is available and of sufficient quality, the information contained from an economic measure of capacity can be more descriptive and informative. In addition, if one desires economic-based measures, but only physical measures can be computed, qualifications may be necessary when discussing the results.

Chapter 4
Two Empirical Capacity Measurement Techniques: A Comparison

4.1 Introduction

The presence of excess fishing capacity has become one of the most pressing problems facing fisheries throughout the world. Aside from dissipating rents, shortening fishing seasons, and diminishing efficiency and productivity, excess capacity can have other significant and detrimental effects on a fishery. First, it may create pressure for managers to inadvertently keep the TAC above sustainable levels in order to preserve employment. Second, with the few remaining economic rents spread among so many vessels, fishermen are more vulnerable to changes in regulations and TACs instituted to curb excess capacity. As a result, policy tools available to resource managers become more difficult to implement, both politically and socially (Kirkley and Squires, 1999).

Given the numerous negative effects of excess capacity on the world's fisheries, efforts have been undertaken to develop methods that aid in determining if excess capacity does exist in a particular fishery. Much of the literature that currently exists on estimating fishing capacity relies on the use of cost data (dual approaches), which is not currently available in the NPGF or in a majority of other fisheries. As a result, the analysis must often times be undertaken in a primal framework, and most of the recent efforts in this area have used DEA – a non-stochastic approach that is fairly easy to implement, but suffers from shortcomings that may be exacerbated when used in fisheries settings.

One aim of this chapter is to provide an alternative primal method for measuring fishing capacity, using an SPF approach. Next, capacity estimates will be constructed for the BSAI catcher-processor fleet (and the pollock fishery in particular) using both the SPF and DEA models. Such a comparison between DEA and SPF allows for an indication of the degree to which capacity estimates may differ when the stochastic nature inherent in harvesting technologies is ignored. And, by focusing on this fleet in particular, the models can also be used to analyze the effects that the AFA may have had on fishing capacity, efficiency, and productivity.

An additional purpose of this chapter is to illustrate the marked differences in capacity estimates that can arise based on one's choice over the "definition" of fishing capacity. To facilitate these comparisons, two definitions of fishing capacity are estimated within each of the two alternative frameworks (DEA and SPF[13]).

The possibility of generating substantially different estimates of fishing capacity (for a given data set) exists not only because of the inherent differences between the SPF and DEA models, but also because of the different estimates that can arise *within* each model (over definitional issues, model specification, spatial and temporal aggregation) that can impact capacity estimates greatly.

Therefore, if a common/consistent capacity estimation method is *not* used for each of the fisheries to be compared, classified, and ranked, it is likely that researchers may mischaracterize the relative levels of excess capacity in those fisheries. In addition, given the range of capacity estimates that may be generated by alternative specifications and assumptions, it may be more prudent for researchers to derive a *distribution* of capacity estimates for each fishery, rather than just one number.

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[13] The peak-to-peak method is also considered an option by NMFS, though it has been the subject of much criticism. It is somewhat of a "last resort" option for fisheries in which data is lacking for a satisfactory DEA or SPF model. Given that existing data for the federally managed fisheries is sufficient to construct DEA models (NMFS, 1999), the peak-to-peak method will not be discussed further in this paper.

An additional issue that will be addressed is the task of modeling multi-output production settings with primal models; a majority of the fishing effort in the BSAI catcher-processor fleet is geared toward harvesting pollock, but multiple species are caught throughout the year. To appropriately characterize the production technology without unnecessary *a priori* restrictions, a multi-output framework must be used. However, the presence of multiple outputs poses significant problems for the standard SPF framework, and possibly because of these difficulties, no study has yet to use SPF techniques to measure capacity in a multi-output fishery[14].

The approach taken here to accommodate multiple outputs is to augment the standard SPF framework through use of a stochastic ray production function. This application represents one of the first uses of the ray production function to measure capacity and technical efficiency (TE) in a fisheries setting.

4.2 Approaches for Capacity Measurement: Primal and Dual

Although the available data necessitates a primal-based model, and the DEA and SPF approaches have been suggested by NMFS for measuring capacity in federally managed fisheries, there are also a variety of dual measures of capacity. As discussed in the previous chapter, dual models explicitly build upon an economic foundation and incorporate hypotheses regarding agents' objectives. Morrison (1985a,b; 1986), Nelson (1989), Berndt and Fuss (1989), and Segerson and Squires (1990, 1992, 1995) all offer economic approaches for defining and measuring capacity. Alternatively, primal models

[14] A September 1999 draft by Dupont, Grafton, Kirkley and Squires using the DEA approach claims to be the first capacity study for a multi-species fishery.

(Färe, Grosskopf, and Kokkelenberg [1989], (Kalirajan and Salim [1997]) focus solely on the production technology.

When choosing between the two frameworks in a fishery application, one's choice really comes down to two main trade-offs: the interpretability of the resulting capacity estimates and the appropriateness of the underlying assumptions in the model. For example, dual models give a more economic interpretation of capacity -- comparing current levels to "optimal" levels -- but do so at the expense of behavioral assumptions that may not be accurate (cost minimization in a race for fish?)[15]. Alternatively, primal models of capacity say nothing about the economic "optimality" of a particular fleet size and only indicate the maximum output that could be produced with the observed fixed factors of production, resource stock, state of technology, etc. However, they do allow one to relax behavioral assumptions that may not hold. This may be particularly important in fisheries, as the presence of regulations may cause standard optimization behavior to be an inappropriate assumption (Coelli *et al.*, 1998).

Regardless of the theoretical merits of either framework, it is the available data that ultimately determines which approach one must take. Even though economists may inherently prefer the use of economic notions of capacity for capacity management, these approaches are often not feasible tools for fisheries. The data required for these approaches is typically unavailable, and is currently lacking in most of the federally managed fisheries[16]. In addition, fishery managers seeking to restrict capacity as a means of limiting catch are also interested in estimates of the maximum a fleet can catch, and not just how current catch levels compare to "optimal" levels (Lee and Holland [1999a]).

[15] Such models also rely on price data, which is often of questionable quality in many fisheries settings.

Therefore, the NMFS capacity management plan will rely, in the near term, on technical (primal) rather than economic (dual) definitions and measures of fishing capacity. This implies that researchers will be faced with choosing among competing estimators of technical fishing capacity: namely, DEA and SPF models.

4.3 Alternative Definitions of Fishing Capacity in Primal Models

Both SPF and DEA models were originally developed for estimating the frontier of a technology and then comparing the observed output to the technically efficient output (yielding a TE score). In more familiar terms, these TE scores indicate the amount by which output levels could be increased under technically efficient production, which for a given input endowment is the quantity given by the production possibilities frontier (PPF) (or a production function, in a single-output context). Therefore, in order to use these models to generate estimates of *capacity* (which in some contexts may require not only estimating the PPF, as in the TE models, but also estimating how far out it can shift), one must make some adaptations.

The changes one makes to each of the standard DEA and SPF models depends upon one's interpretation of capacity. The different definitions of technical capacity that have been suggested in the literature essentially differ in their views regarding variable input use. Some authors claim that technical capacity should be based on some maximal level of variable input use (Johansen [1968], Färe, Grosskopf, and Kokkelenberg [1989], Kirkley and Squires [1999]), while others suggest a more sustainable, "normal" notion of capacity (NMFS, 1999).

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[16] Recent changes in data collection, however, may allow for cost-based models to be estimated in the near future.

More specifically, the definition offered by Johansen[17] is " the maximum amount that can be produced per unit of time with existing plant and equipment, provided the availability of variable factors of production is not restricted." This definition of capacity corresponds to the output that could be produced under technically efficient production with variable inputs fully employed, but constrained by the fixed factors and the state of technology. As will be shown shortly, when the Johansen notion is employed in an empirical setting, one essentially obtains capacity output levels representing the most output obtainable from a set of fixed factors and the maximum observed variable input use (for that fixed endowment).

In contrast, the National Excess Capacity Taskforce has suggested that capacity be defined relative to more "normal" output levels: "the output that a fleet could reasonably expect to catch if variable inputs are utilized under normal operating conditions, for a given resource condition, state of technology, and other constraints." Use of this definition in capacity estimation would lead to smaller capacity estimates than Johansen's definition, due to relaxation of Johansen's unrestricted use of variable inputs.

That is, the requirement of "normal" variable input use seems to imply that the capacity output specified in the NMFS definition corresponds to the maximum output obtainable when vessels operate is in their normal or typical manner. Such levels may thus be thought of as a point along a production function (in the case of a single output, for ease of exposition) at a normal or customary level of variable input use. Because a production function does not allow for the possibility of inefficient production (it reflects the maximum amount of output obtainable from a bundle of inputs), the NMFS capacity

[17] Johansen's definition is equivalent to the current FAO definition of capacity agreed upon by researchers representing forty nations at a Technical Working Group meeting. It is also equivalent to that offered by

levels will therefore be interpreted in the current study as the technically efficient output levels given by the SPF and DEA models (and *not* the levels that would be produced with maximum variable input use).

Given these two proposed definitions it is fairly straightforward to adapt each of the standard DEA and SPF models to generate estimates of capacity that correspond to these notions of capacity. This is particularly true for the NMFS Excess Capacity Taskforce definition, which again, seems to reflect the TE output producible from each vessel as its "capacity" (implying no changes in the variable input levels, and thus, use of the standard DEA and SPF TE models). Alternatively, the Johansen definition requires that each of the DEA and SPF capacity models be formulated so as to find the maximum level of output obtainable for a given set of fixed factors when variable factors are unrestricted.

The DEA model of Färe, Grosskopf, and Kokkelenberg (1989, hereafter referred to as "FGK") to be introduced in Section 4.4 was constructed so as to directly correspond to Johansen's definition. As a result, it is easier to implement than SPF when one is seeking a Johansen-based measure of capacity. SPF is more difficult because one is required to choose/specify the unrestricted variable input levels corresponding to each endowment of fixed inputs, while in the DEA model the choice is made internally through the selection of "peers", wherein the maximum observed variable input use for each fixed input endowment is used in the determination of capacity.

In the SPF approach it is not entirely clear how to determine the appropriate unrestricted variable input levels for each vessel. That is, should one use the maximum *possible* variable input levels, the maximum *observed* levels for each *individual* vessel, or

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Christy (1996), Prochaska (1978), and the Federal Fisheries Investment Task Force Report to Congress.

maximum *observed* variable input levels of *all vessels* with similar fixed input endowment (as with the FGK DEA model)? The approach taken here is to make the determination of the relevant maximum variable input use for each vessel as similar to the DEA model as possible (to facilitate a more reasonable comparison of the results of the two models – a goal pursued throughout the following chapters). Thus, vessels will be grouped according to their size, and the maximum variable input use for each group of "peers" will be used as the maximum for each vessel in that group. The exact details of the selection process for the BSAI catcher-processor fleet will be discussed further in Chapter 5.

4.4 An Introduction to Data Envelopment Analysis

Both DEA and SPF approaches attempt to identify a best-practice frontier for a group of producers characterized by a particular technology. However, DEA and SPF models differ in the way in which they generate the frontiers.

DEA is a non-parametric method that uses mathematical programming to construct a piece-wise linear representation of the frontier of technology. In an output orientation, those who get the most output from a particular set of inputs define the frontier of the output set. Deviations from the frontier are interpreted as evidence technical inefficiency, as other vessels produced more output from a given level of inputs.

The following output-oriented linear program computes the technically efficient output levels by finding the maximum amount by which each observed output bundle could be radially increased (θ), given the best practice technology:

$$Max_{(\theta,z,\lambda)}\ \theta \tag{4.1}$$

subject to the following restrictions:

$$\theta\, y_{j_m} \le \sum_{j=1}^{J} z_j\, y_{jm},\ m = 1,2,\ldots M$$

$$\sum_{j=1}^{J} z_j x_{jn} \le x_{jn}\ , \quad n = 1,2,\ldots N$$

with $z_j \ge 0$, $j = 1,2,\ldots,J$

$$\sum_{j=1}^{J} z_j = 1$$

The "activity levels" (z_j) of y and x are the weights for the points that define the frontier. The first three constraints ensure that the observed output bundles stay on or within the feasible set, while the last constraint allows for variable returns to scale (VRS). A VRS approach ensures that each vessel is only benchmarked against vessels of similar size, as projected points for vessels below the frontier are formed as a convex (rather than linear) combination of frontier observations (Coelli *et al.*,1998).

The value of the parameter θ is the reciprocal of the output distance function and therefore provides a measure of the possible (radial) increase in outputs under full technical efficiency. Using the results from the program above, one can thus determine the technically efficient output for each vessel by scaling observed output levels by θ. For example, an objective value of θ =1.1 indicates that the capacity output equals 1.1 times the current observed output vector.

Although DEA models were originally designed to measure TE, FGK proposed a variation of the standard DEA model given above that was explicitly designed to provide measures of capacity output and utilization corresponding to Johansen's definition of capacity[18]. To implement the FGK DEA model, one computes the maximum proportionate increase in outputs, ϕ, (using ϕ instead of θ to distinguish this distance measure from the standard TE model distance measure) when variable inputs are allowed to vary, but fixed inputs are held at observed values. The following output-oriented linear program also allows for VRS:

$$Max_{\,(\phi, z, \lambda)}\ \phi \tag{4.2}$$

subject to the following restrictions:

$$\phi\, y_{j_m} \le \sum_{j=1}^{J} z_j\, y_{jm},\ m = 1,2,...M$$

$$\sum_{j=1}^{J} z_j x_{jn} \le x_{jn}\,, \quad for \quad n \in \alpha\,;$$

$$\sum_{j=1}^{J} z_j x_{jn} \le \lambda_{jn}\, x_{jn}\,, \quad for \quad n \in \hat{\alpha}\,;$$

with $z_j \ge 0$, $j = 1,2,...,J$

$\lambda_j \ge 0, \quad for \quad n \in \hat{\alpha},$

and $\sum_{j=1}^{J} z_j = 1$

The variable factors are denoted by $\hat{\alpha}$, the fixed factors are denoted by α. As stated, in the FGK specification the use of variable inputs is not restricted to observed levels. As such, the third constraint involving λ tells one the necessary variable input use required to achieve frontier output levels, and thus serves a check on the sensibility of

[18] Strictly speaking, capacity estimates generated with observed data will correspond to Johansen's theoretical notion of capacity to the extent that maximum *observed* variable input use (for a given fixed input bundle) is similar to maximum *possible* variable input use.

capacity estimates[19]. As in the TE DEA model, the "activity levels" (z_j) of y and x are the weights for the points that define the frontier, the first three constraints ensure that such projections stay on or within the feasible set, and the last constraint allows for VRS.

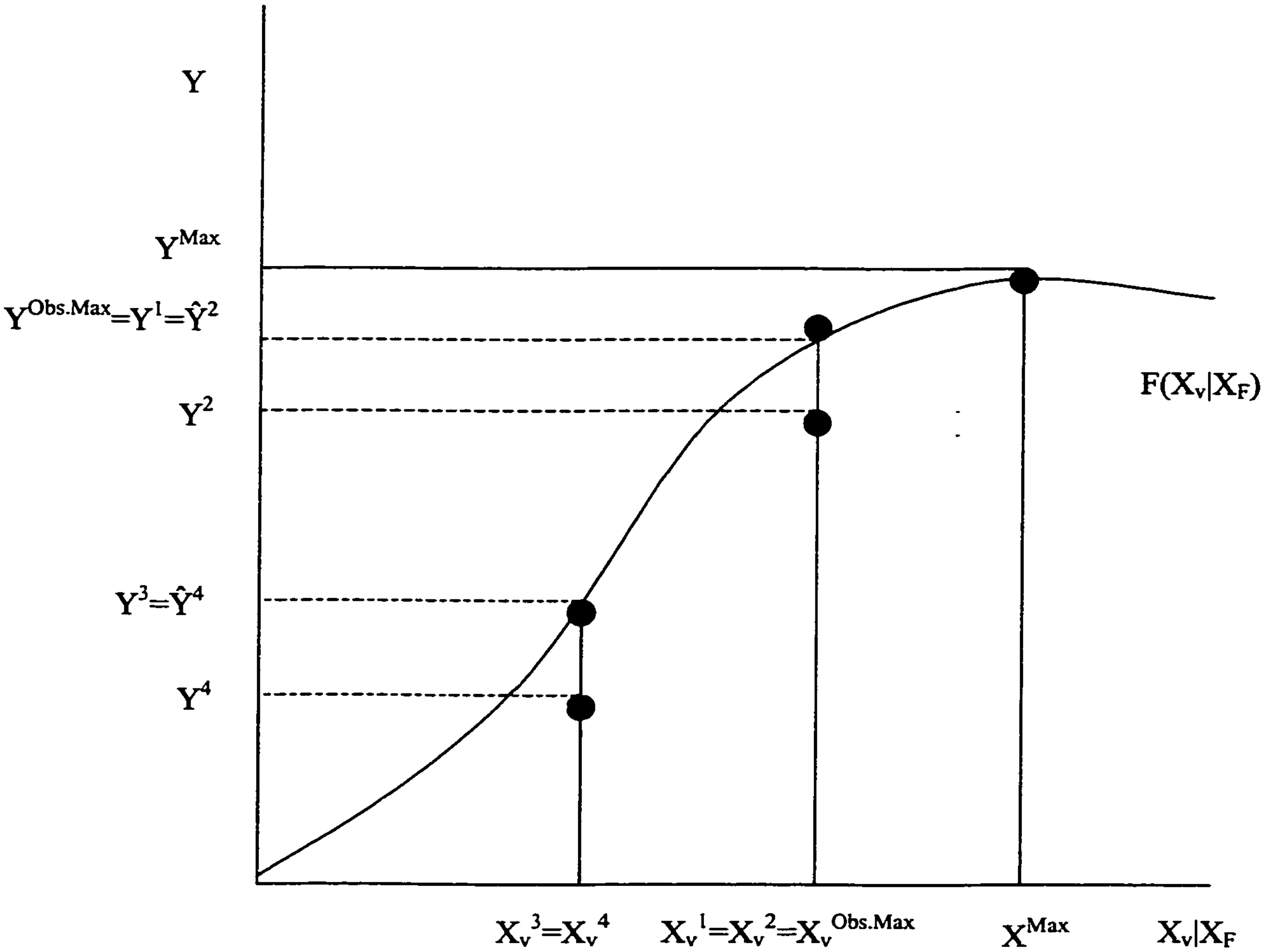
Using the results from the program above, one can determine fishing capacity by analyzing each vessel's frontier output levels. One merely scales each vessel's observed output vector by the value of ϕ -- here termed a "capacity score", and is analogous to θ in the standard TE model -- which yields an estimate of the Johansen-based fishing capacity for that vessel. Next, one sums the capacity output for all vessels in a particular fleet or fishery and an estimate of total fishing capacity is obtained.

Note that to be on the frontier in the FKG model, vessels must have produced the most output for a given level of *fixed* inputs. Firms that are not on the frontier may be below it because they are either using fixed inputs inefficiently, or because they are using lower levels of variable inputs than frontier vessels (or both). Regardless, their production levels do not represent maximal capacity, as others have been observed to produce more with a similar endowment of fixed inputs.

To illustrate these ideas, Figure 4.1 shows output bundles from four firms with identical fixed-input endowments, graphed in two dimensions (input and output space). Firms 3 and 4 would not be on the frontier in the FGK model because their output is less than that of firms 1 and 2. Firm 3's output falls short of capacity solely because it is using lower levels of variable inputs in conjunction with its fixed input endowment,

[19] For example, use of variable inputs such as fishing time (or days at sea) at full capacity should not exceed the maximum fishing time possible. Such input use would be unrealistic, as would the associated capacity estimates. Typically, however, the implied unrestricted variable input levels correspond to the maximum observed variable input use from a set of peers.

Figure 4.1 A Comparison of Capacity Utilization Measures



FGK CU Scores:

Firm 1: $CU_1=Y^1/Y^{Obs.Max}=1$ Firm 2: $CU_2=\hat{Y}^2/Y^{Obs.Max}=1$

Firm 3: $CU_3=Y^3/Y^{Obs.Max}<CU_2$ Firm 4: $CU_4=\hat{Y}^4/Y^{Obs.Max}=CU_3<CU_2$

Note: No CU scores are affected by inefficiency; only by $X_v^i < X_v^{Obs.Max}$

Standard DEA CU Scores:

Firm 1: $CU_1=Y^1/Y^{Obs.Max}$ Firm 2: $CU_2=Y^2/Y^{Obs.Max}<1$

Firm 3: $CU_3=Y^3/Y^{Obs.Max}<CU_2<1$ Firm 4: $CU_4=Y^4/Y^{Obs.Max}<CU_3<CU_2<1$

Note: Some CU scores are less than unity because of inefficiency and/or $X_v^i < X_v^{Obs.Max}$

while firm 4 has underutilized variable inputs *and* exhibited technical inefficiency. Firm 2 has fully utilized its variable inputs, but has produced less output because of technical inefficiency.

In addition to computing capacity, the DEA model can also be used to construct measures of capacity utilization (CU), typically computed in DEA models as $CU=Y^{Obs.}/Y^{Obs.Max.}$, where $Y^{Obs.}$ corresponds to observed output, and $Y^{Obs.Max}$ corresponds to the maximum output possible from observed input use (which should be contrasted with the maximum theoretical [unobserved] or "engineering" notion of capacity output, Y^{Max}, which is not computed in DEA analysis). There are however, some concerns that have been raised in the literature about this measure. The first concern is that one may want a CU measure that is purged of any current technical inefficiency. FGK show that the measure above may be downward biased because the numerator in this traditional CU measure, observed output, could be inefficiently produced.

To see why one may want to account for technical inefficiency, it helps to think of an "economic" or "dual" interpretation of full capacity utilization, described by Morrison (1999) as a tangency between the SRAC and LRAC curves (see Figure 3.4). Under full CU, fixed inputs are at the levels that would be optimally chosen if they were fully variable. Deviations from full CU occur as a result of a sub-optimal input mix, not because of technical inefficiency. In a primal analysis, one seeks to identify the repercussions of a sub-optimal input mix on *output* (rather than on costs). So while the potential technical inefficiency has been accounted for when estimating capacity output, inefficiency in the *observed* output bundle may introduce potential problems.

To accommodate these concerns, FGK suggests computing CU as the ratio of TE scores from the two output-oriented DEA programs, CU = θ / ϕ, where the numerator is the TE score from a standard output-oriented DEA model in equation (4.1), and the denominator is the TE score from the capacity-based DEA program in equation (4.2). While this CU measure may look quite a bit different than the typical CU= $Y^{Obs.}$/ $Y^{Obs.Max.}$ measure (assuming a technological-economic formulation, which is computed in the DEA and SPF models included in this dissertation), it merely represents the ratio of the *technically efficient* output (rather than observed output) to the technological-economic maximum output, or CU = Y^{TE} / $Y^{Obs.Max}$ = ($Y^{Obs.}$ $\cdot\theta$) / ($Y^{Obs.}$ $\cdot\phi$) = θ / ϕ. Note that in addition to the "unbiasedness" pointed out by FGK, this alternative CU measure has the benefit of giving a single CU measure even in the case of multiple outputs[20]. For these reasons, the FGK CU measure will be constructed in the applications in Chapters 5 and 6 (as opposed to the more standard CU=$Y^{Obs.}$/$Y^{Obs.Max.}$).

Figure 4.1 presents some examples of the "standard" and FGK CU measures for four hypothetical observations in which firms share identical fixed input endowments. Note that the FGK CU scores differ from the standard measures for two of the four observations, reflecting potential increases in output from increased variable input use.

4.5 An Introduction to Stochastic Production Frontiers

An alternative to the DEA methodology is the SPF approach, which is a parametric model that econometrically "fits" the frontier of technologies. Loosely

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[20] Fare's CU measure incorporates CU with respect to all outputs jointly (while the CU=$Y^{Obs.}$/$Y^{Max.}$ must be computed for each output individually). However, since the TE scores are computed for *radial* expansions of output vectors, one is essentially creating a composite output and thus, strictly speaking, computing a single output CU measure.

speaking, the SPF framework uses a functional representation to model the technology while simultaneously disentangling observed deviations from the frontier into two parts: random variation/noise and productive inefficiency.

The functional representation of the technology has historically been limited to single output production functions, but can be expanded to accommodate multiple output technologies through the use of distance functions and ray production functions.

The familiar single output SPF model (see Kumbhakar and Lovell, 2000) typically expresses production technologies in terms of

$$y = f(\mathbf{x};\boldsymbol{\beta})\cdot\exp\{e\} \; ; \qquad (4.3)$$

$$e = -u + v$$

Here, y is the output, f(•) is a functional form of the production technology, **x** is a vector of inputs, $\boldsymbol{\beta}$ is a vector of parameters to be estimated, and e is a random error term. Note that actual output, y, may differ from potential output due the observed error term, e. This error is usually specified as including two components.

The first component represents differences between observed and potential output due to inefficient input use, and is denoted by u. The second component, denoted by v, is attributed to purely random variations in output (unrelated to inefficient factor use), analogous to the error term in standard regression models. In fisheries contexts, such random errors are often attributed to weather conditions, variations in stock conditions, luck, or possibly introduced by measurement errors. It is usually assumed that v is an independent and identically distributed (i.i.d.) N(0, σ_v^2) random variable and u is distributed as an i.i.d. half-normal random variable[21], where u ~ N(0, σ_u^2).

An additional parameter (γ) is typically introduced as well, in order to ease the maximum likelihood estimation (MLE) of the variance parameters. First, a "combined" variance is constructed in terms of the random error and inefficiency term, given by $\sigma_s^2 = \sigma_v^2 + \sigma_u^2$. Next, the parameter γ is defined as $\gamma = \sigma_u^2 / \sigma_s^2$. This reparameterization allows one to undertake a grid search for γ, which by definition must lie between 0 and 1, which is much easier than attempting to estimate σ_v^2 and σ_u^2 individually (which may lead to negative variances in some cases).

Given these distributional assumptions, Battese and Corra (1977) showed that the log-likelihood function for the stochastic frontier may be expressed as

$$\ln(L) = -\frac{N}{2}\ln(\pi/2) - \frac{N}{2}\ln(\sigma_s^2) + \tag{4.4}$$

$$\sum_{i=1}^{N}\ln[1-\Phi(z_i)] - \frac{1}{2\sigma_s^2}\sum_{i=1}^{N}(\ln y_i - x_i\beta)^2$$

where $z_i = \frac{(\ln y_i - x_i\beta)}{\sigma_s}\sqrt{\frac{\gamma}{1-\gamma}}$; and $\Phi(\bullet)$ is the distribution function of the standard normal random variable.

The MLE estimates of β, γ, and σ_s^2 may then be found by maximizing the log-likelihood given in (4.4). However, since the ordinary least squares (OLS) estimator of the slope parameters of β has been shown to be unbiased by Aigner *et al.*, (1977), the usual practice is to first find the OLS estimates of β, and then use MLE to find consistent

[21] The truncation ensures that the inefficiency term takes only positive values, thus putting vessels *below* the production frontier in cases of inefficient production.

estimates of the intercept (β_0) and σ_s^2. Once consistent estimates of all parameters are found, an iterative MLE procedure is performed, and consistent and asymptotically efficient estimates are obtained.

With the estimates of the model parameters in hand, one may then go about constructing estimates of technical efficiency. These TE scores represent the (inverse of the) proportional increase in output that would be obtained under full technical efficiency. However, there are two distinctly different ways of analyzing technical efficiency; one can construct the mean levels for the *sample as a whole* or alternatively, compute *firm-level* efficiency scores. The former may be of interest if one is not interested in singling out a particular firm or vessel, and only overall performance is the focus, while the latter is useful in facilitating vessel-by-vessel comparisons or rankings.

To construct the mean level of technical efficiency for a *sample as a whole*, one must take the mathematical expectation of the technical efficiency term, or $TE_i=\exp(-u_i)$. If, as discussed above, the u_i's are i.i.d. half-normal random variables, then as shown by Coelli *et al.* (1998),

$$E[\exp(-u_i)] = 2[1-\Phi(\sigma_s\sqrt{\gamma})]\exp(-\gamma\sigma_s^2/2), \qquad (4.5)$$

and the MLE estimator of mean technical efficiency for the sample is obtained by evaluating this expression with the values of the MLE parameter estimates.

Alternatively, one can obtain estimates of each *individual vessel's* mean technical efficiency score by computing the conditional expectation of u_i given the observed error, $e_i = v_i + u_i$, as shown by Jondrow *et al.* (1982):

$$E[u_i \mid e_i] = -\gamma e_i + \sigma_A\{\frac{\phi(\gamma e_i/\sigma_A)}{1-\Phi(\gamma e_i/\sigma_A)}\}, \qquad (4.6)$$

where $\sigma_A = \sqrt{\gamma(1-\gamma)\sigma_s^2}$; $e_i = y_i - x_i\beta$; *and* $\Phi(\bullet)$ is the density function of a standard normal random variable. However, since the magnitude of the expectation of the residual u_i itself provides little intuition on the relative performance of different firms, Battese and Coelli (1988) suggest constructing a predictor of $\exp(u_i)$ rather than a predictor of u_i. Their suggested TE measure is bounded between zero and one, and thus interpretable as the value of the distance function, given by the following:

$$E[\exp(-u_i)|e_i] = \frac{1-\Phi(\sigma_A + \gamma e_i/\sigma_A)}{1-\Phi(\gamma e_i/\sigma_A)}\exp(\gamma e_i + \sigma_A^2/2). \qquad (4.7)$$

These technical efficiency scores can be computed manually with programs such as Gauss, or by using the MLE routines in packages such as FRONTIER or Limdep.

One important limitation of the standard SPF framework as usually employed is that it does not allow one to specify multiple outputs, which are common in many of the federally managed fisheries where capacity assessment will be undertaken. And, if one chooses to include data on multiple species in this specification, one must aggregate the outputs into a composite output. Aside from the restrictive assumptions implied by aggregating outputs in such a way, one also loses much of the information contained in a parametric specification, such as the cross-terms between multiple inputs and outputs (which aid in determinations of jointness, substitutability, etc.). To avoid such undesirable compromises, the following section expands the standard SPF framework to accommodate multi-output, multi-input specifications.

4.5.1 Multi-Output Functional Representations of SPF Technologies

Two alternative functional representations that allow for multiple-output SPF specifications are the distance function and the ray production function. In addition to accommodating multi-input, multi-output specifications, they also allow for the two-part error decomposition discussed in the previous single output model. While these two functions differ in the way they are implemented, either can be used to estimate TE output and construct estimates of capacity. However, difficulties arise when using the stochastic output distance function in applications in which there are zero-valued outputs.

These problems occur primarily because a lack of data on the dependent variable (D_o) prohibits one from directly estimating the model. The approach typically used to overcome this problem is to utilize the linear output homogeneity of the distance function, which generates the following equality:

$$D_o(\mathbf{x},\lambda\mathbf{y}) = \lambda\ D_o(\mathbf{x},\mathbf{y}) \tag{4.8}$$

Next, λ is specified as the inverse of either one of the outputs, y_i^{-1}, or the Euclidean norm of the output vector, $||\mathbf{y}||^{-1}$, and logs are taken. The result is an equality that now has an observable left-hand-side variable for estimation:[22]

$$-\ln||\mathbf{y}|| = \ln D_o(\mathbf{x},\mathbf{y}/||\mathbf{y}||) - \ln D_o(\mathbf{x},\mathbf{y}) \tag{4.9}$$

Note, however, that for any observation in which y_i is equal to zero, the logarithm of the right-hand side variable is undefined, precluding estimation of the model.

One can avoid such problems by utilizing a different, but equivalent[23], representation of the technology that is not subject to problems with zero-valued outputs:

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[22] The right-hand side value of $\ln D_o(\mathbf{x},\mathbf{y})$ is then interpreted as an inefficiency term, u, a random error term v is appended, and $\ln D_o(\mathbf{x},\mathbf{y}/||\mathbf{y}||)$ is typically parameterized as a translog functional form. See Morrison and Johnson [1999] for a further discussion.

[23] Both the distance function and the ray production function construct TE scores using radial expansions of the observed output vector.

the stochastic ray production function (Löthgren, 1997). The ray production function model is derived by augmenting the standard, single output production given by

$$f(\mathbf{x}) = \max \{y \in R_+ : y \in Y(\mathbf{x})\}. \tag{4.10}$$

This single-output representation is transformed into a multiple-output generalization of the production function by expressing the output vector of a multi-output technology in polar-coordinate form:

$$\mathbf{y} = \|\mathbf{y}\| \cdot m(\boldsymbol{\theta}), \tag{4.11}$$

This form for y implies that the multiple-output ray production function[24] takes the form:

$$f(\mathbf{x},\boldsymbol{\theta}) = \max \{\|\mathbf{y}\| \in R_+ : \|\mathbf{y}\| \cdot m(\boldsymbol{\theta})) \in Y(\mathbf{x})\} \tag{4.12}$$

Here, $\|\mathbf{y}\|$ is the Euclidean norm of the output vector, $\|\mathbf{y}\| = (\sum_{i=1}^{m} y_i^2)^{1/2}$, $\boldsymbol{\theta}$ represents the polar-coordinate angles of the output vector (rather than the standard rectangular coordinates in "x-y" space), and the function m: $[0, \pi/2]^{m-1} \rightarrow [0,1]^m$ is defined in terms of the output polar-coordinate angles as

$$m_i(\boldsymbol{\theta}) = \cos\theta_i \prod_{j=0}^{i-1} \sin\theta_j, \; i=1,\ldots m, \tag{4.13}$$

where $\sin\theta_0 = \cos\theta_m = 1$. The vector of polar-coordinate angles $\boldsymbol{\theta}$ (which are used in estimation) are easily obtained from the inverse transformation of (4.13), $m^{-1}(\mathbf{y}/\|\mathbf{y}\|)$, or

$$\theta_i(\mathbf{y}) = \cos^{-1}(y_i / \|\mathbf{y}\| \prod_{j=0}^{i-1} \sin\theta_j), \; i=1\ldots m-1 \tag{4.14}$$

While the conventional single-output production function given in (4.10) represents the maximum output obtainable from a given bundle of inputs, the multiple

[24] The polar coordinate angles, θ, represent the curvature of the production frontier, which may be derived from the partial derivatives of the ray function with respect to the polar-coordinate angles, $\partial f(x, \theta)/\partial\theta_i$, $i=1,\ldots m-1$.

output ray production function in (4.12) represents the maximum output *norm* obtainable given inputs and the observed output mix (as represented by the output polar coordinates).

In addition, if Y($\mathbf{x}$) satisfies strong disposability of inputs (which may or may not hold in one's particular application), the ray function is positively monotonic in inputs, or $f(\mathbf{x}'', \theta(\mathbf{y}), \omega) \geq f(\mathbf{x}', \theta(\mathbf{y}), \omega), \forall\ \mathbf{x}'' \geq \mathbf{x}'$.

To model the technology in the context of the SPF framework discussed earlier, the link between the ray production function and the output distance function can be exploited to allow for a natural decomposition of inefficiency and random error. This relationship is easily derived by recognizing that, by definition, the output distance function represents the ratio of the observed output norm to the frontier output norm (Shephard, 1970). Thus, in the context of the ray production frontier this relationship implies

$$D_o(\mathbf{x},\mathbf{y}) = ||\mathbf{y}|| \,/\, f(\mathbf{x}, \theta) \tag{4.15}$$

Which can be rearranged to yield

$$||\mathbf{y}|| = f(\mathbf{x}, \theta) \cdot D_o(\mathbf{x},\mathbf{y}). \tag{4.16}$$

One may then the specify (4.16) as in the standard SPF framework in (4.3) by including a symmetric multiplicative random error term, exp(v), and representing the output distance function as $D_o(\mathbf{x},\mathbf{y}) = \exp(-u)$ (which as required by theory, is bounded between zero and one):

$$||\mathbf{y}|| = f(\mathbf{x}, \theta) \cdot \exp\{-u + v\} \tag{4.17}$$

Estimation may then proceed just as with the single-output framework once a suitable flexible functional form is chosen for $f(x, \theta)$. If one chooses to use a logarithmic form for (4.17), there will still be no problems in the case of zero-valued outputs, as θ evaluated at $y_i=0$ is well defined (see (4.14)).

Once the ray frontier model has been estimated, one may then generate capacity estimates by evaluating the efficient frontier at the levels of variable input use commensurate with one's chosen definition of capacity.

The capacity estimates corresponding to the NMFS-based definition of capacity are obviously the easiest to construct, as this definition is based on *observed* variable input use. Therefore, one just uses the model's TE scores to compute the capacity output levels. Constructing Johansen-based capacity estimates, however, requires that one evaluate the efficient frontier at unrestricted levels of variable input use.

As discussed earlier, unrestricted variable input levels in the FGK DEA model often coincide with the maximum observed levels of each variable input for a given endowment of fixed inputs[25]. Thus, when constructing Johansen-based capacity estimates in the SPF approach, one must manually determine the maximum observed variable input use for each set of producers with a similar set of limiting fixed inputs.

Once the technically efficient output with *given* input levels and the technically efficient output with *maximum variable* input utilization (the Johansen-based capacity measure) are determined, one can then construct CU scores in a manner analogous to the DEA models. Given that the FGK CU measure is interpreted/constructed as either a ratio of distance scores or as a (possibly more familiar) ratio of output levels (see page 59), this CU measure can be easily constructed in the SPF approach. One simply computes the technically efficient output and then divides it by the technically efficient output under maximum observed variable input use. This measure would yield a technological-economic CU measure, as in the FGK DEA approach.

The resulting CU scores (from either the SPF or DEA models) can then be used in at least two ways. The first approach would be to compare the CU scores from each vessel in order to infer which vessels have more fully utilized their fixed input endowments. A CU score less than one indicates that vessels have the potential for greater production without having to incur major expenditures for new capital or equipment (Klein and Summers, 1960). Thus, greater deviations from one imply greater potential production from utilization of the fixed inputs.

Alternatively, one could use the CU scores to construct capacity estimates that do not incorporate or reflect any potential observed technical inefficiency. Since these FGK CU scores are purged of any current technical efficiency, their values reflect only the relative intensity of variable input employment used in conjunction with the fixed inputs. Thus, by scaling observed output by the CU scores, one obtains capacity estimates that represent the maximum output obtainable from the fixed input endowment, irrespective of any technical inefficiency. Since some opponents of the frontier approach to capacity estimation in fisheries claim that the technically efficient output levels are unrealistic, or that vessels are operating as efficiently as possible already, such estimates may be more appealing to some (but are not pursued here).

Regardless of whether one constructs capacity estimates from the DEA approach or an SPF model, the individual vessel results from either method can also be used to specify *total* fleet capacity. Such a measure is constructed by summing the capacity

[25] Maximum *observed* variable input levels (as opposed to the *theoretical* maximum at which marginal products are jointly zero) are used in order to more accurately reflect the observed technology exhibited in

output levels for each vessel in the fleet for each species caught. These computations result in an estimate of the fishing capacity for each different species in the fishery. If instead one were looking for an estimate of the total amount of biomass than can be caught, this would entail summing the capacity output for each species over all species in the data[26].

It is also possible to use the model output to specify the efficient number and composition of vessels for landing a given TAC in a fishery, as suggested by Kirkley and Squires (1998). To do this, one first orders the vessels' capacity estimates by their respective TE scores, and then sums over the ranked capacity estimates until the cumulative output level equals a given TAC. This resulting group of vessels represents the most relatively technically efficient fleet for catching the particular TAC. However, given that the technical efficiency is only part of the "economic picture" (as information regarding costs or profits is not incorporated in the model), this ranking/selection process will not be advocated or pursued further in this dissertation.

4.6 Issues in Modeling Technical Capacity with DEA and SPF

To this point the structures of the DEA and SPF models have been discussed, but without much emphasis on the pros and cons of using either approach. The literature on capacity estimation provides comparisons of the DEA and SPF models in general applications (Fried, Lovell, Schmidt [1993], Kalaitzondonakes and Dunn [1995], Sharma, Leung and Zaleski [1997], Hjalmarsson, Kumbhakar, and Heshmati [1996], Coelli

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the fishery, which will lead to more realistic estimates of capacity.

[26] It should be noted that this measure of fleet capacity is a short-run measure. In the long run, if inputs can be reallocated among the vessels, leading to a different fleet configuration, then it can be shown that fleet capacity may exceed the sum of the individual short-run vessel capacities (Färe et al., 2000).

[1998], Cummins and Zi [1998]), but much of the focus is on theoretical properties of the estimators and makes little mention of adaptations to resource applications. Therefore, a further discussion of the relative merits of the two approaches in the context of fisheries applications and capacity estimation is useful here.

One strength of the DEA approach is that it easily accommodates multiple inputs and outputs (common in fisheries), while use of SPF in multi-output contexts necessitates restrictive aggregation assumptions or the development of more complicated multiple output models (as illustrated in Section 4.5.1). Another strength of DEA is that is does not impose an arbitrary functional form on the technology, while SPF models require that the researcher assume a particular form. And, as noted by Färe et al. (1989), some functional forms are theoretically inconsistent with a maximum level of output, which may make their use inappropriate for measuring technical capacity[27].

DEA also easily accommodates zero valued outputs, which are common in fisheries data due to seasonal and geographical fishing patterns; fishermen will often target one species at a time, but land multiple species throughout a season. In contrast, when SPF models are used in conjunction with data that exhibits frequent zero valued left-hand-side variables, the model estimates may suffer from censoring problems (Tobin, 1958). Lastly, DEA allows one to include inequality constraints for stock levels, bycatch or other fishing restrictions, which cannot be said for the SPF models. Rather, one must rely on the use of dummy variables or the estimation of environmental variables in order to account for constraints that may directly affect the technological possibilities.

[27] However, one may not be seeking capacity estimates that correspond to a *theoretical* maximum (where marginal products are all jointly zero). Rather, one may want estimates of the output levels that would be generated under technically efficient production using *realistic* (or observed) input levels (which may fall well below the point of zero-valued marginal products).

Note, however, that there are caveats to DEA's "ease" with multiple inputs and outputs and zero-valued observations in that one must be selective in choosing the appropriate variables to include in the analysis (in order to facilitate the appropriate "peer" comparisons). For example, in analyzing a multi-species fishery there are often many species that comprise "incidental catch", but are still incorporated in the data for completeness. If all of these species were included as outputs in the models output vector, a majority of observations for the incidental species would be zero, and would give rise to a large number of permutations of output composition.

Since DEA relies on making comparisons among peers who use similar bundles of inputs and outputs, a large number of permutations of output composition may nullify potential efficiency comparisons among vessels whose primary outputs (target species) and input use are quite similar. Thus, many of the observations will be unique in that they have no peers, and will form a unique segment of the production frontier. When this occurs, no comparisons are made and an observation is deemed relatively efficient by default[28]. However, it may actually be the case that when these vessels are compared to others who harvest the same composition of target species, the vessels appear to be relatively *inefficient.*

As for the strengths of SPF models, their most appealing trait is the ability to account for random variations and data noise, which are both common in fisheries data. Random variations in output may occur because of the inherent variability of the fishing industry; for a given level of input use, output levels may differ from trip to trip or week

[28] The same result may occur if one has too few observations. A lack of sufficient number of observations may occur not only because of pure data scarcity, but also through lost observations due to temporal aggregation (say, using yearly totals or averages rather than daily or weekly observations) in order to "smooth" potential noise in the observed daily/weekly data.

to week due to random factors such as weather, luck, resource conditions, etc. Similarly, data noise may be present in fisheries data because of the susceptibility of data collection to reporting errors; the size of the some of the operations and the amount of fish harvested often makes it necessary for data recorders to provide "rough" estimates of catch levels and composition.

Recent Monte Carlo analysis by Lee and Holland (1999b) provides empirical evidence of the differences that may arise when one uses DEA and SPF models with "noisy" data. The authors generate observations using a Cobb-Douglas production function and examine the effects of introducing various levels of noise. They show that when the SPF model is specified correctly (i.e., proper choice of functional form and distribution of the error components), the mean bias in TE scores is often substantially larger for DEA than SPF. And, as noise levels increase, the bias in DEA models tends to rise quite rapidly relative to SPF[29]. For these reasons, SPF's ability to account for noise is attractive and may be valuable in fisheries applications.

An additional benefit of the SPF error structure is the ability to conduct conventional statistical tests on the parameter estimates and other technological characteristics of interest (such as substitution elasticities, scale economies, or scope economies). Statistical tests can provide an indication of the robustness of one's results and may be especially important if capacity estimates are to be used for policy-related decisions.

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[29] However, one could argue that this exercise systematically puts DEA at a disadvantage. While SPF does have the ability to handle random errors, its performance will suffer if one mis-specifies the form of the technology or the distribution of the error term. Given that the authors have eliminated a potentially significant source of bias in SPF models (by using a Cobb-Douglas specification for both the data generating process and in their SPF model), one might expect *a priori* for the SPF method to out-perform DEA.

To investigate the range of "capacity" estimates that may be generated by employing the two notions of capacity discussed above in the SPF and DEA frameworks, an empirical application will be performed in Chapter 5 using data from the multi-output BSAI catcher-processor fleet of the BSAI.

Chapter 5
An Application to the BSAI Catcher-Processor Fleet

5.1 Introduction

The previous chapters have discussed the theoretical and empirical foundations underlying the current state of fishing capacity measurement, and broadened the methodological basis by suggesting an alternative approach for capacity measurement in fisheries. The aim of this chapter is to provide an application of the novel SPF approach and compare it to the more standard DEA approach. In addition to comparing the capacity estimates that are generated from similarly constructed DEA and SPF model, the analysis also examines the effects of adopting different (but reasonable) "definitions" of capacity, which differ according to alternative assumptions regarding variable input use. The resulting capacity models are applied using data on the pollock catcher-processor fleet of the BSAI, as outlined in Chapter 2.

5.2 Model Specifications and Results

Using the catcher-processor data, capacity estimates were computed for the four following specifications:

(1) DEA with a NMFS-based definition of capacity (assumed to be represented by the TE model in equation (4.1))

(2) DEA with a Johansen-based definition of capacity (as given by the FGK model with unrestricted variable input use – equation (4.2))

(3) SPF with a NMFS-based definition of capacity (assumed to be represented by the TE model in equation (4.17))

(4) SPF with a Johansen-based definition of capacity (constructed by scaling up the variable inputs in the fitted frontier from equation (4.17)).

Each of the models was specified with 6 outputs (pollock, Pacific cod, flatfish, sablefish, rockfish, and Atka mackerel), 3 fixed inputs (vessel length, vessel tonnage, and vessel age [representing the vintage/quality of the vessel's technology]), and 2 variable inputs (crew size and the number of tows).

Attempts were made throughout the analysis to make the corresponding DEA and SPF specifications ((1) and (3), and (2) and (4), respectively) as similar and comparable as possible. This was accomplished by specifying the same set of inputs and outputs in each model, allowing for non-constant returns to scale in all specifications, not including constraints in the DEA model that could not be incorporated into the SPF model, and not including explanatory variables in the SPF model to help explain observed inefficiency. While such a structure does make for a more natural and justifiable comparison of the two approaches, the trade-off is that both have their hands somewhat "tied" in that some of the aspects that are unique to each approach are not incorporated.

It should also be noted that each DEA model was estimated one year at a time (using weekly observations from each particular year) to avoid the implicit assumption of a constant technology over the six-year period. While Malmquist index DEA models can accommodate technological change and be estimated over multiple years, they typically require a "balanced panel" (which is not the case with the data used here), have yet to used for capacity measurement, and are beyond the scope of the current comparison. Alternatively, the SPF models were estimated using all six years of data, as a time variable representing technological change can be directly incorporated into SPF models, which allows one to avoid the potentially restrictive assumptions of no technological change over the six-year period.

One result of the chosen temporal specifications is that some of the efficiency comparisons that can be made within the SPF models will not be made within the DEA models. The reason for this incongruity is because the TE calculations made within the SPF and DEA models are *relative* scores (relative to the best-practice technology exhibited in time period(s) spanned by the data), and so comparisons are only appropriate between observations included in that model. In the context of the yearly DEA models, this factor rules out comparisons of the efficiency scores from different years. Such comparisons *are* valid, however, within the multi-year SPF specification, and will be elaborated upon later. Numerous other comparisons will be made in this chapter and Chapter 6 using results of the SPF and DEA models.

Another result of the temporal specifications is that yearly stock levels were not incorporated into the DEA models (as they exhibit no variation within each model year and make no contribution). As a result, stock levels were omitted from the SPF specification as well (continuing with the attempt to keep the models as similar as possible). While at first glance yearly stock levels may seem important in the analysis, the explanatory relevance of *yearly* stock levels in the models of weekly production would be minimal in this fishery -- especially since it is stock abundant and quota constrained; for this application, it is the *density* of the fish in different weeks of the season that determines the ease/difficulty with which fish are caught.

The DEA models (1) and (2) were estimated for each year using the DEAP package (Coelli, 1996) and a VRS specification. The yearly average distance score for each vessel in the fleet and the fleet as a whole (for models (1) and (2)) are given in Tables 5.3 and 5.4, respectively. In addition, CU scores were computed and averaged within each year, as seen in Table 5.5[30].

The results from models (1) and (2) were then used to scale each weekly observation by its corresponding distance score and to thus compute the NMFS- and Johansen-based capacity output levels. The capacity estimates for each observation were then summed up over all species in order to compute the NMFS- and Johansen-based capacity estimates for the fleet as a whole. The fleet-wide capacity estimates for each species based on the two DEA models (1) and (2) are given in Table 5.6.

Turning the focus to the SPF model and results, the original specification was assumed to take the form of the translog:

$$\ln \|y_t\| = \beta_0 + \beta_1 DUM99 + \sum_{j=1}^{(m+n)} \beta_j \cdot \ln(z_{jt}) \tag{5.1}$$

$$+ \sum_{j \le k} \sum_{k=1}^{(m+n)} \beta_{jk} \cdot \ln(z_{jt}) \cdot \ln(z_{kt}),$$

where DUM99 is a dummy variable equal to one for the year after the AFA was passed, the vector z includes each of the *m-1* polar coordinate angles (θ's), the *n* fixed and variable inputs (length, tonnage, year built, tows, and crew), a time variable (t) to capture/represent potential technological change, and the full set of squared and cross terms associated with these variables, as given by the translog specification.

[30] The CU scores constructed here and in other parts of this dissertation are the FGK $CU=Y^{TE}/Y^{Max.}$, where Y^{TE} is the technically efficient output, and $Y^{Max.}$ is the Johansen-based measure of capacity output. The motivation for this choice is provided in Section 4.4.

However, after testing several restricted forms of the translog model[31] with generalized likelihood ratio tests, the null hypothesis of a restricted version of the full translog specification could not be rejected as an appropriate representation of the ray frontier function. This restricted specification included only the linear and squared terms, omitting the cross-terms among the θ's, inputs, and t. The resulting model was thus given by:

$$\begin{aligned} \ln\|y_t\| = {} & \beta_0 + \beta_1 DUM99 + \beta_2 \ln(\theta_{1t}) + \beta_3 \ln(\theta_{2t}) \\ & + \beta_4 \ln(\theta_{3t}) + \beta_5 \ln(\theta_{4t}) + \beta_6 \ln(\theta_{5t}) + \beta_7 \ln(\text{length}_t) \\ & + \beta_8 \ln(\text{tonnage}_t) + \beta_9 \ln(\text{tows}_t) + \beta_{10} \ln(\text{crew}_t) \\ & + \beta_{11} \ln(\text{yr.built}_t) + \beta_{12}\, t + \beta_{13} \ln(\theta_{1t})\ln(\theta_{1t}) + \beta_{14} \ln(\theta_{2t})\ln(\theta_{2t}) \\ & + \beta_{15} \ln(\theta_{3t})\ln(\theta_{3t}) + \beta_{16} \ln(\theta_{4t})\ln(\theta_{4t}) + \beta_{17} \ln(\theta_{5t})\ln(\theta_{5t}) + \beta_{18} \ln(\text{length}_t)\ln(\text{length}_t) \\ & + \beta_{19} \ln(\text{tonnage}_t)\ln(\text{tonnage}_t) \\ & + \beta_{20} \ln(\text{tows}_t)\ln(\text{tows}_t) + \beta_{21} \ln(\text{crew})\ln(\text{crew}) \\ & + \beta_{22} \ln(\text{yr.built}_t)\ln(\text{yr.built}_t) + \beta_{23}\, t^2. \end{aligned} \tag{5.2}$$

The SPF model was estimated using an MLE procedure in FRONTIER and was based on the time-varying error components model[32] (Coelli, 1997). The procedures used to calculate the MLE estimates are based on a 3-stage method in which OLS estimates of the mean and variance parameters (β and σ_s^2) are first constructed, then used as starting values over a grid search for $\gamma = \sigma_u^2 / \sigma_s^2$ (see Section 4.5 for details). Finally, the parameter values for β and γ resulting from the grid search are used as starting values in a

[31] The restricted forms that were tested were a purely linear relationship, a form with only linear and cross terms, and a form with only linear and squared terms included.

[32] The preferred model (in the author's opinion) would have been the "technical efficiency effects" model (in which explanatory variables are included to help explain any observed inefficiency in the data), but it

Davidson-Fletcher-Powell maximization routine. Once a solution is found, the resulting parameter estimates are then used to create distance scores in FRONTIER, as given by equation (4.7). The parameter estimates, standard errors, and t-ratios for the final MLE estimates for the catcher-processor fleet are given in Table 5.7.

A majority of the model parameters (24 out of 27) are statistically significant at the α=.05 level, including γ, which indicates a rejection of the null hypothesis that all vessels are technically efficient. In addition, inputs satisfy the relevant monotonicity conditions (with the exception of "year built"[33]).

In order to derive estimates of the technically efficient output (the NMFS-based capacity estimates), the parameter estimates from the model were first used to generate conditional technical efficiency expectations ("TE scores") for each observation in the data, using equation (4.7). The average yearly TE score for each vessel in the fleet is given in Table 5.8, along with the yearly mean for the fleet as a whole. Next, each vessel's observed output was scaled up by the inverse of the corresponding conditional technical efficiency expectation (since these scores correspond to the value of the output distance function, which is bounded between zero and one) in order to compute each vessel's NMFS-based capacity estimates for each of the six species.

In order to determine the Johansen-based estimates of capacity (model (4)), the technically efficient frontier was evaluated at the maximum levels of variable input use. The relevant maximum variable input levels for each vessel were chosen in such a way as to ensure that the values corresponded to reasonable levels that could be used by each

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was not used due to data limitations and a desire to keep the DEA and SPF models as similar as possible to facilitate appropriate comparisons.

vessel of a given size (as vessel size was thought to provide an indication of the maximum amount of variable inputs that may be employed).

In particular, three fairly equally sized groups of vessels were delineated: vessels under 200 ft., vessels between 200 and 250 ft., and vessels over 250 ft. Within each group the maximum observed level of variable input usage was recorded (for tows and crew) and subsequently evaluated in the estimated frontier (along with the observed *fixed input* levels) to construct Johansen-based estimates of capacity.

Just as in the DEA models, the NMFS- and Johansen-based capacity estimates for the fleet as a whole were obtained by summing over each of the individual vessels in the BSAI catcher-processor fleet. Both the NMFS- and Johansen-based capacity estimates for the SPF model are given in Table 5.10. In addition, FGK-based CU scores were constructed (following the approach outlined on page 59) for each observation using the results from models (3) and (4). The average CU score for each vessel (and the entire fleet) in each year is given in Table 5.9.

5.3 Comparisons of Capacity Estimates from DEA and SPF Models

The results of the DEA and SPF models show that the capacity estimates derived under both the NMFS- and Johansen-based definitions of capacity output differ markedly between the two frameworks, as seen in Tables 5.6 and 5.10. In particular, for the years 1994-1996 the DEA capacity output estimates (under both definitions) for the catcher-processor fleet exceeded the SPF analogs for all 6 species by approximately 40%; in some years the differences amounted to almost 40,000 metric tons. This pattern also

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[33] This finding is not too surprising, considering that this variable serves only as a proxy for the vintage of the technology on board, as many vessels have been rebuilt since their original build date. However, given

continues through 1997 and 1998 for the pollock and Pacific cod Johansen-based capacity estimates, though DEA estimates are only around 20% greater than their SPF analogs on average. However, after 1997, the SPF NMFS-based capacity estimates generally exceed the corresponding DEA estimates (and SPF exceeds DEA for *all* species in 1999).

Turning the focus to pollock, the most significant species in terms of catch and value, Table 5.11 analyzes the percent differences between the DEA and SPF estimates in each year. For nine of twelve capacity estimates computed, DEA estimates are larger than SPF; DEA estimates exceed SPF estimates by an average of 23.5% for the NMFS-based capacity models, and by an average 35.5% for Johansen-based models.

Figure 5.1 shows a graphical depiction of the different estimates of capacity output for pollock. It again highlights that DEA estimates systematically exceed the SPF estimates for each given definition of capacity (though there appears to be some convergence of estimates in 1999).

For other species comprising a lower proportion of total catch, the number of years in which SPF estimates exceed DEA estimates (and vice versa) is more evenly divided. DEA capacity estimates (for both definitions) generally exceed the SPF estimates for 1994-1996, while the opposite holds fairly true for 1997-1999. However, this pattern is not entirely stable. The relative magnitude of the estimates generated by the SPF and DEA models often differs from year to year (for both definitions of capacity) for species such as rockfish and Atka mackerel.

Looking at each framework individually, one can instead examine the extent to which alternative *definitions* of capacity lead to different results. In doing so, it is

that the data does not give information on rebuild dates, the original build dates were used in the analysis.

important and instructive to recall *why* the two definitions differ: the assumptions regarding variable input use. That is, if for the same framework (DEA or SPF), estimates from the two definitions are quite different, there must be a wide range between the *observed* variable input use in each observation and the *maximum* observed for that particular level of capital. This finding would suggest that the corresponding CU scores are relatively low, as these CU measures (to be discussed shortly) indicate the additional output that could be had from a given input endowment if variable inputs were scaled up to full utilization levels.

Table 5.6 shows the extent to which the DEA Johansen-based estimates of capacity exceed the NMFS-based DEA capacity estimates. The differences between the two definitions are quite substantial in all years (differing anywhere from 30% to 50%), with the largest differences occurring for species comprising the greatest share of the total catch (pollock, flatfish, and Atka mackerel).

Table 5.10 shows a similar comparison of the two definitions within the SPF models, but with noticeably different results than those of the DEA models. In each year, the capacity estimates based on the NMFS and Johansen definitions of capacity output are much more similar, and fairly consistent for all species, only differing by about 10% to 13% on average.

Again turning to pollock, Table 5.11 shows that the differences between SPF Johansen- and NMFS-based capacity estimates are much smaller (averaging 12%) than those of the DEA model, in which the Johansen-based capacity estimates exceed the NMFS-based estimates by an average of 34.1% for the 1994-1999 period. In addition, the amount by which the Johansen-based capacity output exceeds the NMFS-based estimates barely differs from year to year for the SPF model (the minimum difference is 11%, the maximum is 13%), while the difference between the DEA capacity estimates shows a great deal of variation (ranging from a 23% difference in 1998 to a 45% difference in 1995).

These results indicate that the implied increase in output from enhanced capacity utilization is greater in the DEA models than in the SPF models (since as discussed, the differences between the two definitions are based on assumptions regarding variable input use). This can be seen more closely by examining the CU scores from the DEA and SPF models, as given in Tables 5.5 and 5.9, respectively. The mean CU score over the range of the data is approximately .83 for the SPF model, but only around .77 for the DEA models. These scores imply that output could be increased by between 17 and 23 percent (depending on which model one employed) solely from increased variable input use, with no changes in technical efficiency or the fixed input endowment.

Aside from the previous DEA and SPF comparisons, an additional question of interest is whether changes in the AFA led to a significant decline in capacity in the BSAI pollock fishery in 1999. As discussed in Chapter 2, in 1998 25 vessels in the current data set targeted pollock as their primary catch[34]. Of these vessels, only 14 participated in the fishery in 1999. Regardless of the reason for decreased participation (some left voluntarily, others were decommissioned), the results are clear under all model specifications.

According to the SPF model results in Table 5.10, the NMFS-based estimates indicate that pollock capacity decreased by 265,722 metric tons in 1999, while the

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[34] For a week of fishing activity to be classified as targeting on midwater pollock, the catch must exceed 95% pollock by weight.

Johansen-based estimates show a decrease of 294,862 metric tons (or a 28% decline for both). The DEA results in Table 5.5 indicate that NMFS-based estimates of pollock capacity fell by 413,043 metric tons from 1998 to 1999, while Johansen-based estimates were reduced by 434,944 metric tons (or by 42% and 44%, respectively). Therefore, regardless of model selection, one can safely assume that capacity did indeed fall in the pollock fishery.

It should also be noted that the reduced capacity in the pollock fishery was not accompanied by increases in estimated capacity output levels for the other five groundfish species. The results indicate that capacity output fell for *all* species from 1998 to 1999 for both the DEA and SPF specifications under both definitions of capacity.

5.4 Summary

This chapter has discussed two potential definitions of technical fishing capacity and two proposed frameworks for estimating either of the definitions. The aim of the analysis was to compare the range of capacity estimates that arise under the alternative definitions and capacity estimation models. To this end, an application to the pollock catcher-processor fleet of the Bering Sea and Aleutian Islands groundfish fisheries was presented.

The application to the trawler fleet represents a novel use of a multi-output SPF model in a fishery setting, and of the ray production function to estimate capacity. This approach will ultimately be quite useful for such endeavors, as it allows one to model multi-output technologies, include zero-valued outputs, and can be implemented using commonly available econometric packages.

The results of the analysis indicate that at least for the pollock catcher-processor fleet of the BSAI, the two empirical frameworks suggested by NMFS can lead to significantly different estimates of capacity within a given fishery (for both proposed definitions of capacity). These differences underscore the problems that can arise by making comparisons across fisheries with differently constructed models. Only with a consistent estimation process will the capacity estimates generated within different fisheries allow for the subsequent categorizations NMFS has adopted[35].

Regardless of how the capacity estimates from the different frameworks differ in magnitude, some common patterns emerged. First, both models indicate that increases in technical efficiency could increase the fleet's output by at least 30% (according to the observed best-practice technologies in the data). However, given that differences in catch for a given vessel and crew size might be attributable to skipper skill, or fortuitous unobserved weather or stock conditions, such increases may not be realistically possible.

Second, both the SPF and DEA models show that even when inefficiency in production is accounted for, there are still substantial potential output increases from increased variable input use. The CU scores from the DEA (SPF) models indicate that output could be increased by at least 20 percent (12 percent) from increased utilization of fixed inputs.

[35] Strictly speaking, the SPF and DEA TE measures are "relative" (to the best practice technology in that particular model), and therefore should not be compared between different fisheries. For example, if one fishery had a mean TE score of .6, this would imply that many of the vessels in that fishery are underproducing relative to the best vessels. And if a different fishery had an average TE score of .9, this would imply that all vessels are producing similar output levels from a given bundle of inputs. What these findings would *not* suggest, however, is that the second fishery is more efficient than the first; it could be the case that every vessel in the first fishery is outperforming those in the second. But, since the vessels in the second fishery are all equally as bad, it appears as though efficiency is high. Thus, the efficiency scores are more an indicator of the degree of homogeneity of a fleet, and not of absolute performance. However, once the observed output is scaled up by the inverse of the TE/capacity scores (to get capacity output), these estimates do provide an indication of the amount that could be caught in that fishery, which can then

Table 5.1 Mean Values of the BSAI Catcher-Processor Data, by Year, 1994-1999

	1994	*1995*	*1996*	*1997*	*1998*	*1999*
No. Vessels	48	56	60	54	51	40
Pollock (tons)	14935.4	12598.9	11455.1	11992.2	12296.7	11064.4
Pacific Cod (tons)	1061.3	1186.2	989.9	1125.6	968.5	971.1
Sablefish (tons)	9.7	4.8	2.4	1.3	2.9	7.4
Flatfish (tons)	4085.7	2958.7	3416.3	5039.9	3593.5	3676.6
Atka Mackerel (tons)	1336.2	1385.1	1727.0	1216.4	1111.4	1399.9
Rockfish (tons)	319.8	230.9	385.6	299.9	279.0	485.2
Vessel Length (feet)	226.1	217.2	221.3	219.3	222.9	218.1
Vessel Tonnage (tons)	1040.1	939.5	988.5	982.5	997.5	965.0
No. Tows	516.5	443.4	480.1	501.7	467.8	489.2
No. Crew (man weeks/yr.)	1400.6	1202.0	1356.8	1356.8	1396.7	1408.3
Yr. Vessel Built	1976	1977	1977	1977	1977	1977
Surimi Percentage	29.33	34.14	36.16	39.82	39.31	42.04
Fillet Percentage	29.40	32.26	34.10	28.71	37.80	32.79

be compared to stock levels (or desired catch levels) to provide an indication of which fishery has more excess capacity.

Table 5.2 Summary Statistics of Variables Included in the Study, by Week, 1994-1999 (5974 Obs.)

	Mean	*Std. Deviation*	*Minimum*	*Maximum*
$\|\|y\|\|$[36]	769.60	782.92	0.10	6,413.91
θ_1	0.93	0.68	0.00	1.57
θ_2	1.43	0.30	0.00	1.57
θ_3	1.57	0.01	1.24	1.57
θ_4	1.01	0.62	0.00	1.57
θ_5	1.53	0.19	0.00	1.57
Pollock (tons)	550.27	875.84	0.00	6,413.89
Pacific Cod (tons)	45.41	93.97	0.00	1,193.63
Sablefish (tons)	0.18	1.41	0.00	45.37
Flatfish (tons)	161.03	224.99	0.00	2,454.06
Atka Mackerel (tons)	63.59	196.69	0.00	2,306.62
Rockfish (tons)	15.00	70.80	0.00	950.12
Vessel Length (feet)	218.75	60.18	98.00	376.00
Vessel Tonnage (tons)	915.06	789.43	69.00	3,546.00
No. Tows	22.09	11.44	1.00	77.00
No. Crew	60.60	33.62	13.00	146.00
Year Built	1977	1061	1941	1989

[36] The description and interpretation of $||y||$, θ_1, θ_2, θ_3, θ_4, and θ_5 is given in Section 4.5.1.

Table 5.3 DEA Technical Efficiency Scores, by Vessel, Year, 1994-1999

Vessel	*1994*	*1995*	*1996*	*1997*	*1998*	*1999*
1	0.422	0.582	0.411	0.368	0.512	N/A[37]
2	N/A	0.769	0.583	0.505	0.577	N/A
3	N/A	0.464	0.685	0.761	0.776	0.774
4	0.592	0.761	0.636	0.617	0.663	N/A
5	0.790	0.859	0.838	0.546	0.695	N/A
6	0.555	0.572	0.617	0.592	0.652	0.614
7	0.551	0.774	0.716	0.738	0.595	0.609
8	N/A	0.786	0.785	N/A	N/A	N/A
9	0.561	0.605	0.599	0.566	0.532	0.563
10	N/A	0.601	N/A	N/A	0.337	N/A
11	N/A	N/A	0.334	0.452	N/A	N/A
12	N/A	1.000	0.846	N/A	N/A	1.000
13	N/A	N/A	0.427	0.393	0.392	0.524
14	0.857	0.886	0.888	0.907	0.808	0.842
15	0.401	0.527	0.476	0.387	0.368	N/A
16	0.607	0.632	0.610	0.491	N/A	N/A
17	0.460	0.549	0.713	0.657	0.681	0.668
18	1.000	0.905	0.877	0.779	0.949	0.885
19	0.976	0.528	0.586	0.555	0.734	0.805
20	N/A	N/A	0.650	0.590	0.578	0.767
21	0.500	0.562	0.591	0.583	0.513	0.476
22	0.576	0.749	0.726	0.626	0.721	0.623
23	N/A	N/A	0.530	0.614	0.506	0.427
24	0.622	0.638	0.683	0.614	0.646	N/A
25	N/A	N/A	0.641	0.651	0.595	N/A
26	0.827	0.491	0.453	0.670	0.679	0.695
27	0.572	0.742	0.716	0.747	0.504	0.520
28	N/A	1.000	0.921	0.998	1.000	N/A
29	0.388	0.417	N/A	N/A	N/A	0.417
30	N/A	N/A	0.370	0.465	0.343	N/A
31	N/A	N/A	N/A	N/A	0.666	0.701
32	0.552	0.678	0.454	N/A	N/A	N/A
33	0.618	0.667	0.533	0.521	0.504	0.558

[37] N/A implies that this vessel did not participate in the fishery in this year.

Table 5.3 DEA Technical Efficiency Scores, by Vessel, Year, 1994-1999 (cont.)

Vessel	*1994*	*1995*	*1996*	*1997*	*1998*	*1999*
34	0.655	0.701	0.790	N/A	N/A	N/A
35	0.431	0.542	0.500	0.523	0.451	0.439
36	0.613	0.507	0.506	N/A	N/A	N/A
37	0.757	0.704	0.550	0.631	0.689	0.714
38	0.409	0.555	0.439	0.401	0.374	N/A
39	0.794	0.792	0.736	0.680	0.660	0.699
40	0.550	0.732	0.730	0.744	0.678	0.648
41	0.598	0.534	0.563	0.632	0.543	0.786
42	0.507	0.610	0.699	0.574	0.496	0.529
43	0.327	0.515	0.527	0.594	0.474	0.533
44	0.906	0.717	0.703	0.597	0.756	0.637
45	0.527	0.671	0.596	0.491	0.477	N/A
46	0.498	0.556	0.599	0.704	0.686	N/A
47	N/A	0.743	0.850	0.758	0.788	0.609
48	0.572	0.646	0.623	N/A	N/A	N/A
49	0.691	0.754	N/A	N/A	N/A	N/A
50	0.587	0.615	0.613	0.633	0.522	0.616
51	0.530	0.504	0.493	0.442	0.463	N/A
52	0.508	0.610	0.638	0.526	0.496	0.493
53	N/A	N/A	0.608	0.702	0.595	0.665
54	N/A	N/A	N/A	0.731	0.832	0.777
55	0.387	0.464	0.549	0.486	0.461	0.390
56	0.506	0.612	0.586	0.579	0.525	0.609
57	0.449	0.648	0.607	0.602	0.472	0.417
58	0.402	0.533	0.618	0.431	0.506	0.657
59	1.000	0.739	1.000	0.952	0.457	0.989
60	N/A	N/A	0.371	0.660	N/A	N/A
61	1.000	0.975	N/A	N/A	N/A	N/A
62	0.597	0.617	0.584	0.548	0.485	0.606
63	0.494	0.517	0.437	0.555	N/A	N/A
64	0.680	0.717	0.590	0.572	0.566	0.534
65	N/A	0.481	0.448	N/A	N/A	N/A
Fleet Mean	0.604	0.658	0.620	0.606	0.587	0.636

Table 5.4 DEA "Capacity Scores", by Vessel, Year, 1994-1999

Vessel	*1994*	*1995*	*1996*	*1997*	*1998*	*1999*
1	0.41133	0.45883	0.356	0.301	0.37417	N/A[38]
2	N/A	0.58381	0.49433	0.42264	0.53131	N/A
3	N/A	0.1276	0.4728	0.55047	0.58267	0.54771
4	0.56952	0.70845	0.60456	0.55073	0.60844	N/A
5	0.61793	0.61881	0.65684	0.40183	0.51421	N/A
6	0.36489	0.39771	0.48433	0.49709	0.58694	0.48116
7	0.43949	0.58979	0.52569	0.5939	0.48068	0.53091
8	N/A	0.37833	0.4152	N/A	N/A	N/A
9	0.47468	0.51083	0.49688	0.4473	0.4698	0.53092
10	N/A	0.381	N/A	N/A	0.26891	N/A
11	N/A	N/A	0.21225	0.32129	N/A	N/A
12	N/A	1	0.57171	N/A	N/A	0.68833
13	N/A	N/A	0.34731	0.31978	0.29367	0.42648
14	0.69081	0.64026	0.66626	0.80656	0.59006	0.58483
15	0.37	0.42943	0.43163	0.31571	0.32111	N/A
16	0.5688	0.52009	0.50943	0.40549	N/A	N/A
17	0.28268	0.37234	0.4684	0.51183	0.52802	0.51668
18	0.7425	0.6767	0.65369	0.60689	0.735	0.63171
19	0.66485	0.37638	0.39909	0.38486	0.58357	0.67263
20	N/A	N/A	0.49046	0.39218	0.49508	0.529
21	0.3482	0.38741	0.49005	0.45093	0.47039	0.38683
22	0.3839	0.5681	0.50011	0.48908	0.50633	0.5508
23	N/A	N/A	0.42942	0.46009	0.4476	0.3891
24	0.54214	0.53385	0.58675	0.54238	0.60374	N/A
25	N/A	N/A	0.40677	0.34925	0.44953	N/A
26	0.41013	0.377	0.32335	0.43206	0.50727	0.54607
27	0.37562	0.45183	0.60446	0.595	0.45791	0.42167
28	N/A	0.854	0.6972	0.59014	0.804	N/A
29	0.32177	0.3204	N/A	N/A	N/A	0.32028
30	N/A	N/A	0.28209	0.33225	0.28508	N/A
31	N/A	N/A	N/A	N/A	0.53685	0.63187
32	0.44076	0.54622	0.38883	N/A	N/A	N/A
33	0.55285	0.58663	0.42159	0.40549	0.4165	0.43346
34	0.55765	0.51806	0.58175	N/A	N/A	N/A

[38] N/A implies that this vessel did not participate in the fishery in this year.

Table 5.4 DEA "Capacity Scores", by Vessel, Year, 1994-1999 (cont.)

Vessel	*1994*	*1995*	*1996*	*1997*	*1998*	*1999*
35	0.31617	0.37303	0.3198	0.34408	0.29519	0.34284
36	0.52044	0.43032	0.48467	N/A	N/A	N/A
37	0.5161	0.57928	0.46014	0.40031	0.64163	0.66122
38	0.39246	0.46444	0.38589	0.273	0.31847	N/A
39	0.55914	0.66575	0.659	0.50118	0.59521	0.66039
40	0.42331	0.54972	0.54165	0.58753	0.56721	0.55226
41	0.51306	0.48035	0.52663	0.59736	0.49241	0.7166
42	0.40934	0.46241	0.48866	0.43541	0.37	0.44007
43	0.283	0.40247	0.47537	0.507	0.40259	0.45983
44	0.66616	0.58613	0.64223	0.51383	0.71194	0.60624
45	0.42412	0.42136	0.4585	0.3595	0.44285	N/A
46	0.45895	0.49815	0.56715	0.61108	0.60194	N/A
47	N/A	0.50507	0.7205	0.67105	0.7595	0.5385
48	0.49111	0.50514	0.5665	N/A	N/A	N/A
49	0.32392	0.3302	N/A	N/A	N/A	N/A
50	0.51246	0.46695	0.51511	0.47445	0.3914	0.47315
51	0.46013	0.4071	0.43759	0.40279	0.44263	N/A
52	0.47195	0.4642	0.57288	0.4264	0.46144	0.44291
53	N/A	N/A	0.42082	0.40513	0.50071	0.45247
54	N/A	N/A	N/A	0.45372	0.6686	0.72107
55	0.35858	0.42207	0.42171	0.36066	0.37053	0.34342
56	0.39624	0.3983	0.46916	0.358	0.43114	0.46332
57	0.35589	0.375	0.36148	0.44474	0.38527	0.30282
58	0.28311	0.34736	0.47195	0.37067	0.46442	0.46229
59	0.87413	0.5734	0.574	0.638	0.4065	0.793
60	N/A	N/A	0.30391	0.46667	N/A	N/A
61	0.52533	0.82986	N/A	N/A	N/A	N/A
62	0.508	0.49529	0.50843	0.38929	0.43325	0.53954
63	0.30657	0.41689	0.28969	0.27744	N/A	N/A
64	0.57027	0.46043	0.45588	0.44243	0.52808	0.405
65	N/A	0.3347	0.17175	N/A	N/A	N/A
Fleet Mean	0.494	0.479	0.456	0.493	0.518	0.493

Table 5.5 DEA Capacity Utilization Scores, by Vessel, Year, 1994-1999

Vessel	1994	1995	1996	1997	1998	1999
1	0.974	0.787	0.848	0.756	0.801	N/A[39]
2	N/A	0.732	0.788	0.781	0.843	N/A
3	N/A	0.337	0.632	0.711	0.733	0.685
4	0.943	0.886	0.913	0.894	0.899	N/A
5	0.786	0.731	0.769	0.704	0.737	N/A
6	0.605	0.669	0.755	0.761	0.867	0.762
7	0.773	0.737	0.732	0.784	0.800	0.840
8	N/A	0.452	0.534	N/A	N/A	N/A
9	0.843	0.819	0.803	0.761	0.858	0.901
10	N/A	0.615	N/A	N/A	0.755	N/A
11	N/A	N/A	0.611	0.656	N/A	N/A
12	N/A	1.000	0.660	N/A	N/A	0.688
13	N/A	N/A	0.779	0.764	0.731	0.764
14	0.779	0.711	0.763	0.889	0.714	0.685
15	0.887	0.801	0.878	0.731	0.791	N/A
16	0.928	0.814	0.842	0.788	N/A	N/A
17	0.650	0.685	0.662	0.745	0.756	0.787
18	0.743	0.736	0.745	0.770	0.771	0.720
19	0.677	0.704	0.650	0.672	0.842	0.805
20	N/A	N/A	0.741	0.618	0.815	0.669
21	0.661	0.655	0.789	0.748	0.839	0.770
22	0.675	0.750	0.678	0.744	0.696	0.866
23	N/A	N/A	0.767	0.722	0.834	0.850
24	0.862	0.783	0.841	0.833	0.902	N/A
25	N/A	N/A	0.616	0.499	0.724	N/A
26	0.524	0.761	0.643	0.620	0.752	0.796
27	0.602	0.597	0.803	0.760	0.869	0.801
28	N/A	0.854	0.757	0.592	0.804	N/A
29	0.811	0.705	N/A	N/A	N/A	0.779
30	N/A	N/A	0.714	0.676	0.788	N/A
31	N/A	N/A	N/A	N/A	0.806	0.895
32	0.762	0.794	0.835	N/A	N/A	N/A
33	0.864	0.846	0.759	0.739	0.794	0.798
34	0.811	0.721	0.671	N/A	N/A	N/A
35	0.728	0.681	0.628	0.631	0.640	0.783
36	0.825	0.797	0.940	N/A	N/A	N/A

[39] N/A implies that this vessel did not participate in the fishery in this year.

Table 5.5 DEA Capacity Utilization Scores, by Vessel, Year, 1994-1999 (cont.)

Vessel	*1994*	*1995*	*1996*	*1997*	*1998*	*1999*
37	0.678	0.814	0.812	0.626	0.909	0.903
38	0.949	0.816	0.849	0.672	0.847	N/A
39	0.706	0.835	0.842	0.694	0.874	0.925
40	0.758	0.740	0.705	0.776	0.830	0.849
41	0.843	0.858	0.917	0.904	0.866	0.910
42	0.794	0.753	0.695	0.726	0.733	0.796
43	0.815	0.742	0.829	0.851	0.815	0.802
44	0.734	0.784	0.878	0.832	0.930	0.921
45	0.747	0.624	0.749	0.683	0.846	N/A
46	0.892	0.877	0.913	0.854	0.841	N/A
47	N/A	0.647	0.818	0.876	0.940	0.871
48	0.816	0.760	0.883	N/A	N/A	N/A
49	0.481	0.444	N/A	N/A	N/A	N/A
50	0.806	0.727	0.824	0.725	0.698	0.719
51	0.896	0.778	0.857	0.924	0.898	N/A
52	0.917	0.753	0.843	0.699	0.814	0.870
53	N/A	N/A	0.665	0.584	0.801	0.684
54	N/A	N/A	N/A	0.620	0.782	0.917
55	0.921	0.856	0.716	0.701	0.781	0.861
56	0.765	0.609	0.771	0.587	0.781	0.747
57	0.782	0.557	0.580	0.734	0.772	0.722
58	0.688	0.656	0.742	0.778	0.820	0.734
59	0.874	0.737	0.574	0.676	0.877	0.804
60	N/A	N/A	0.756	0.744	N/A	N/A
61	0.525	0.849	N/A	N/A	N/A	N/A
62	0.832	0.752	0.847	0.684	0.869	0.852
63	0.700	0.779	0.634	0.514	N/A	N/A
64	0.804	0.638	0.705	0.781	0.910	0.752
65	N/A	0.623	0.529	N/A	N/A	N/A
Fleet Mean	0.775	0.730	0.754	0.728	0.812	0.802

Table 5.6 DEA Capacity Estimates for the BSAI Catcher-Processor Fleet, by Year, Species, 1994-1999

Observed Catch (tons):

	1994	*1995*	*1996*	*1997*	*1998*	*1999*
Pollock	593,582	495,297	551,560	587,005	618,871	440,978
Pacific Cod	40,633	47,502	47,701	52,279	47,341	35,793
Sablefish	293	159	133	52	136	283
Flatfish	146,453	111,589	167,030	235,283	168,013	133,610
Atka Mackerel	52,764	63,579	93,706	57,695	56,581	55,576
Rockfish	107,87	10,926	20,180	14,147	14,212	19,353
No. Vessels	48	56	60	54	51	40

NMFS-based Capacity Estimates (tons):

	1994	*1995*	*1996*	*1997*	*1998*	*1999*
Pollock	1,219,462	1,062,398	1,133,001	1,102,359	1,147,686	734,593
Pacific Cod	88,755	95,639	100,342	96,235	98,101	67,911
Sablefish	526	369	382	63	192	407
Flatfish	297,539	230,778	309,108	406,061	290,120	244,670
Atka Mackerel	93,758	94,297	127,913	73,978	76,804	89,786
Rockfish	22,122	16,697	28,750	18,245	20,474	27,337

Johansen-based Capacity Estimates (tons):

	1994	*1995*	*1996*	*1997*	*1998*	*1999*
Pollock	1,607,943	1,545,185	1,468,072	1,569,833	1,408,494	973,550
Pacific Cod	122,047	135,829	133,978	123,033	121,220	83,771
Sablefish	667	404	864	66	195	452
Flatfish	400,372	309,397	427,764	564,151	363,486	285,650
Atka Mackerel	111,392	128,062	192,053	92,037	108,779	107,783
Rockfish	24,584	22,268	39,173	22,280	26,217	33,130

Table 5.7 Ray Production Function Parameter Estimates

Parameter	*Coefficient*	*Standard-Error*	*T-Ratio*
β_0; intercept	-108	1.01	**-106.9**[40]
β_1; DUM99	0.082	0.025	**3.22**
β_2; $\ln(\theta_{1t})$	-0.14	0.011	**-12.4**
β_3; $\ln(\theta_{2t})$	0.388	0.026	**14.8**
β_4; $\ln(\theta_{3t})$	-12.7	0.891	**-14.3**
β_5; $\ln(\theta_{4t})$	0.111	0.014	**8.11**
β_6; $\ln(\theta_{5t})$	0.071	0.036	**1.98**
β_7; $\ln(\text{length}_t)$	0.862	1.52	0.566
β_8; $\ln(\text{tonnage}_t)$	0.825	0.3	**2.75**
β_9; $\ln(\text{tows}_t)$	1.12	0.044	**25.3**
β_{10}; $\ln(\text{crew}_t)$	0.218	0.192	1.14
β_{11}; $\ln(\text{yr.built}_t)$	-8.35	1.44	**-5.79**
β_{12}; t	2.49	0.124	**20**
β_{13}; $(\ln(\theta_{1t}))^2$	-0.002	0.001	**-3.2**
β_{14}; $(\ln(\theta_{2t}))^2$	0.043	0.003	**14.3**
β_{15}; $(\ln(\theta_{3t}))^2$	11.1	0.728	**15.3**
β_{16}; $(\ln(\theta_{4t}))^2$	0.016	0.002	**10.1**
β_{17}; $(\ln(\theta_{5t}))^2$	0.02	0.005	**4.1**
β_{18}; $(\ln(\text{length}_t))^2$	-0.022	0.069	-0.313
β_{19}; $(\ln(\text{tonnage}_t))^2$	-0.025	0.011	**-2.21**
β_{20}; $(\ln(\text{tows}_t))^2$	-0.022	0.005	**-4.87**
β_{21}; $(\ln(\text{crew}_t))^2$	0.013	0.012	1.08
β_{22}; $(\ln(\text{yr.built}_t))^2$	0.497	0.088	**5.67**
β_{23}; t^2	-0.013	0.001	**-20.4**
σ^2	0.399	0.032	**12.6**
γ	0.415	0.045	**9.33**
μ	0.814	0.121	**6.7**
η	-0.003	0	**-9.95**

[40] Bold type indicates a P-value < .05

Table 5.8 SPF Technical Efficiency Scores, by Vessel, Year, 1994-1999

Vessel	*1994*	*1995*	*1996*	*1997*	*1998*	*1999*
1	0.613	0.584	0.542	0.501	0.449	N/A[41]
2	N/A	0.632	0.593	0.552	0.501	N/A
3	N/A	0.501	N/A	0.396	0.342	0.297
4	0.780	0.760	N/A	0.695	0.657	N/A
5	0.761	0.732	0.702	0.666	0.627	N/A
6	0.696	0.656	0.623	0.581	0.537	0.489
7	0.890	0.875	0.859	0.841	0.819	0.797
8	N/A	0.419	0.376	N/A	N/A	N/A
9	0.769	0.739	0.710	0.677	0.637	0.596
10	N/A	0.575	N/A	N/A	0.421	N/A
11	N/A	N/A	0.382	0.334	N/A	N/A
12	N/A	0.586	0.530	N/A	N/A	N/A
13	N/A	N/A	0.373	0.327	0.277	0.233
14	0.655	N/A	N/A	N/A	0.493	0.444
15	0.564	0.500	0.457	0.414	0.361	N/A
16	0.724	0.692	0.661	0.623	N/A	N/A
17	0.887	0.872	0.855	0.837	0.815	0.790
18	0.671	0.661	0.616	0.573	0.530	0.482
19	0.751	0.719	0.688	0.652	0.609	0.566
20	N/A	N/A	0.719	0.688	0.648	0.614
21	0.580	N/A	N/A	0.446	0.393	0.341
22	0.851	0.832	0.811	0.786	0.760	0.730
23	N/A	N/A	0.560	0.516	0.480	0.415
24	0.778	0.749	0.721	0.691	0.652	N/A
25	N/A	N/A	0.827	0.808	0.781	N/A
26	0.758	0.724	0.691	0.655	0.622	0.572
27	0.681	0.642	0.602	0.565	0.510	0.468
28	N/A	0.556	0.529	0.475	0.418	N/A
29	0.498	N/A	N/A	N/A	N/A	0.250
30	N/A	N/A	0.493	0.450	0.392	N/A
31	N/A	N/A	N/A	N/A	0.814	0.792
32	0.660	N/A	N/A	N/A	N/A	N/A
33	0.580	0.534	0.488	0.444	0.389	0.348
34	0.830	0.806	0.791	N/A	N/A	N/A
35	0.675	0.642	0.601	0.560	0.513	0.467
36	0.624	0.580	0.553	N/A	N/A	N/A
37	0.720	0.688	N/A	0.611	0.574	0.527
38	0.585	N/A	N/A	0.433	0.399	N/A

[41] N/A implies that this vessel did not participate in the fishery in this year.

Table 5.8 SPF Technical Efficiency Scores, by Vessel, Year, 1994-1999 (cont.)

Vessel	*1994*	*1995*	*1996*	*1997*	*1998*	*1999*
39	0.766	0.738	0.708	0.673	0.635	0.595
40	0.956	N/A	0.944	0.936	0.927	0.917
41	0.663	0.623	0.583	0.543	0.493	0.459
42	N/A	0.777	0.749	0.719	0.684	0.650
43	0.695	0.647	0.608	0.570	0.521	0.472
44	0.691	0.660	0.620	0.577	0.523	0.489
45	0.692	0.662	0.622	0.584	0.533	N/A
46	0.704	N/A	0.630	0.594	0.549	N/A
47	N/A	0.677	0.634	0.597	0.549	0.501
48	0.691	N/A	N/A	N/A	N/A	N/A
49	0.682	0.647	N/A	N/A	N/A	N/A
50	0.715	0.677	0.640	0.605	0.557	0.510
51	0.591	0.552	0.508	0.465	0.415	N/A
52	0.619	0.583	0.555	0.500	0.449	0.396
53	N/A	N/A	0.713	0.682	0.646	0.608
54	N/A	N/A	N/A	0.761	0.729	0.699
55	0.483	0.436	0.388	0.340	0.288	0.243
56	0.744	0.714	0.681	0.645	0.603	0.558
57	0.612	N/A	0.531	0.484	0.434	0.401
58	0.607	0.560	0.521	0.477	0.424	0.372
59	0.654	0.614	0.585	0.528	0.467	0.413
60	N/A	N/A	0.515	0.467	N/A	N/A
61	0.784	0.764	N/A	N/A	N/A	N/A
62	0.696	0.657	0.618	0.580	0.537	0.491
63	0.444	0.412	0.367	0.334	N/A	N/A
64	0.663	0.623	0.580	0.544	0.490	0.446
65	N/A	0.540	0.518	N/A	N/A	N/A
Fleet Mean	0.689	0.648	0.611	0.577	0.547	0.512

Table 5.9 SPF Capacity Utilization Scores, by Vessel, Year, 1994-1999

Vessel	*1994*	*1995*	*1996*	*1997*	*1998*	*1999*
1	0.896	0.861	0.877	0.872	0.832	N/A[42]
2	N/A	0.865	0.887	0.879	0.886	N/A
3	N/A	0.661	N/A	0.775	0.752	0.702
4	0.883	0.887	N/A	0.880	0.857	N/A
5	0.778	0.756	0.792	0.795	0.778	N/A
6	0.881	0.892	0.890	0.895	0.905	0.896
7	0.799	0.800	0.786	0.816	0.797	0.790
8	N/A	0.708	0.718	N/A	N/A	N/A
9	0.846	0.853	0.836	0.840	0.844	0.850
10	N/A	0.830	N/A	N/A	0.827	N/A
11	N/A	N/A	0.834	0.817	N/A	N/A
12	N/A	0.697	0.722	N/A	N/A	N/A
13	N/A	N/A	0.824	0.845	0.830	0.809
14	0.867	N/A	N/A	N/A	0.830	0.850
15	0.894	0.886	0.874	0.861	0.848	N/A
16	0.845	0.816	0.813	0.847	N/A	N/A
17	0.781	0.797	0.799	0.815	0.795	0.778
18	0.733	0.806	0.824	0.769	0.806	0.743
19	0.752	0.761	0.709	0.792	0.746	0.723
20	N/A	N/A	0.872	0.866	0.878	0.852
21	0.881	N/A	N/A	0.888	0.916	0.896
22	0.774	0.758	0.778	0.799	0.779	0.779
23	N/A	N/A	0.804	0.813	0.820	0.810
24	0.857	0.840	0.862	0.872	0.884	N/A
25	N/A	N/A	0.832	0.828	0.850	N/A
26	0.705	0.763	0.758	0.805	0.726	0.758
27	0.871	0.890	0.888	0.902	0.893	0.902
28	N/A	0.723	0.753	0.733	0.670	N/A
29	0.861	N/A	N/A	N/A	N/A	0.835
30	N/A	N/A	0.850	0.858	0.835	N/A
31	N/A	N/A	N/A	N/A	0.804	0.816
32	0.747	N/A	N/A	N/A	N/A	N/A
33	0.813	0.826	0.829	0.834	0.811	0.804
34	0.817	0.829	0.780	N/A	N/A	N/A
35	0.798	0.821	0.817	0.815	0.790	0.815
36	0.878	0.892	0.919	N/A	N/A	N/A
37	0.824	0.832	N/A	0.807	0.831	0.831
38	0.917	N/A	N/A	0.886	0.868	N/A

[42] N/A implies that this vessel did not participate in the fishery in this year.

Table 5.9 SPF Capacity Utilization Scores, by Vessel, Year, 1994-1999 (cont.)

Vessel	*1994*	*1995*	*1996*	*1997*	*1998*	*1999*
39	0.799	0.816	0.817	0.815	0.822	0.832
40	0.813	N/A	0.782	0.819	0.800	0.785
41	0.850	0.850	0.872	0.872	0.867	0.836
42	N/A	0.813	0.791	0.808	0.795	0.782
43	0.873	0.871	0.856	0.874	0.866	0.838
44	0.823	0.811	0.824	0.853	0.842	0.849
45	0.887	0.886	0.899	0.897	0.909	N/A
46	0.861	N/A	0.882	0.884	0.855	N/A
47	N/A	0.742	0.828	0.846	0.825	0.809
48	0.782	N/A	N/A	N/A	N/A	N/A
49	0.702	0.693	N/A	N/A	N/A	N/A
50	0.863	0.855	0.874	0.884	0.856	0.863
51	0.863	0.837	0.873	0.864	0.846	N/A
52	0.906	0.898	0.878	0.880	0.869	0.889
53	N/A	N/A	0.873	0.878	0.887	0.869
54	N/A	N/A	N/A	0.786	0.764	0.788
55	0.857	0.846	0.840	0.835	0.843	0.840
56	0.868	0.871	0.841	0.871	0.858	0.864
57	0.860	N/A	0.850	0.862	0.865	0.843
58	0.882	0.886	0.904	0.895	0.916	0.883
59	0.769	0.746	0.718	0.785	0.748	0.767
60	N/A	N/A	0.813	0.805	N/A	N/A
61	0.675	0.673	N/A	N/A	N/A	N/A
62	0.885	0.874	0.883	0.871	0.881	0.861
63	0.731	0.818	0.810	0.769	N/A	N/A
64	0.882	0.903	0.886	0.895	0.918	0.879
65	N/A	0.751	0.672	N/A	N/A	N/A
Fleet Mean	0.829	0.815	0.827	0.841	0.834	0.824

Table 5.10 SPF Capacity Estimates, by Year, Species, 1994-1999

Observed Catch (tons):

	1994	1995	1996	1997	1998	1999
Pollock	593,582	495,297	551,560	587,005	618,871	440,978
Pacific Cod	40,633	47,502	47,701	52,279	47,341	35,793
Sablefish	293	159	133	52	136	283
Flatfish	146,453	111,589	167,030	235,283	168,013	133,610
Atka Mackerel	52,764	63,579	93,706	57,695	56,581	55,576
Rockfish	10,787	10,926	20,180	14,147	14,212	19,353
No. Vessels	48	56	60	54	51	40

NMFS-based Capacity Estimates (tons):

	1994	1995	1996	1997	1998	1999
Pollock	891,464	774,603	910,814	1,044,749	1,206,835	941,113
Pacific Cod	58,190	74,655	81,031	94,199	89,213	79,900
Sablefish	404	236	213	80	239	710
Flatfish	211,266	174,230	291,285	421,209	315,210	273,819
Atka Mackerel	66,348	82,785	122,733	79,455	78,079	90,830
Rockfish	13125	13736	27939	20241	19295	30078

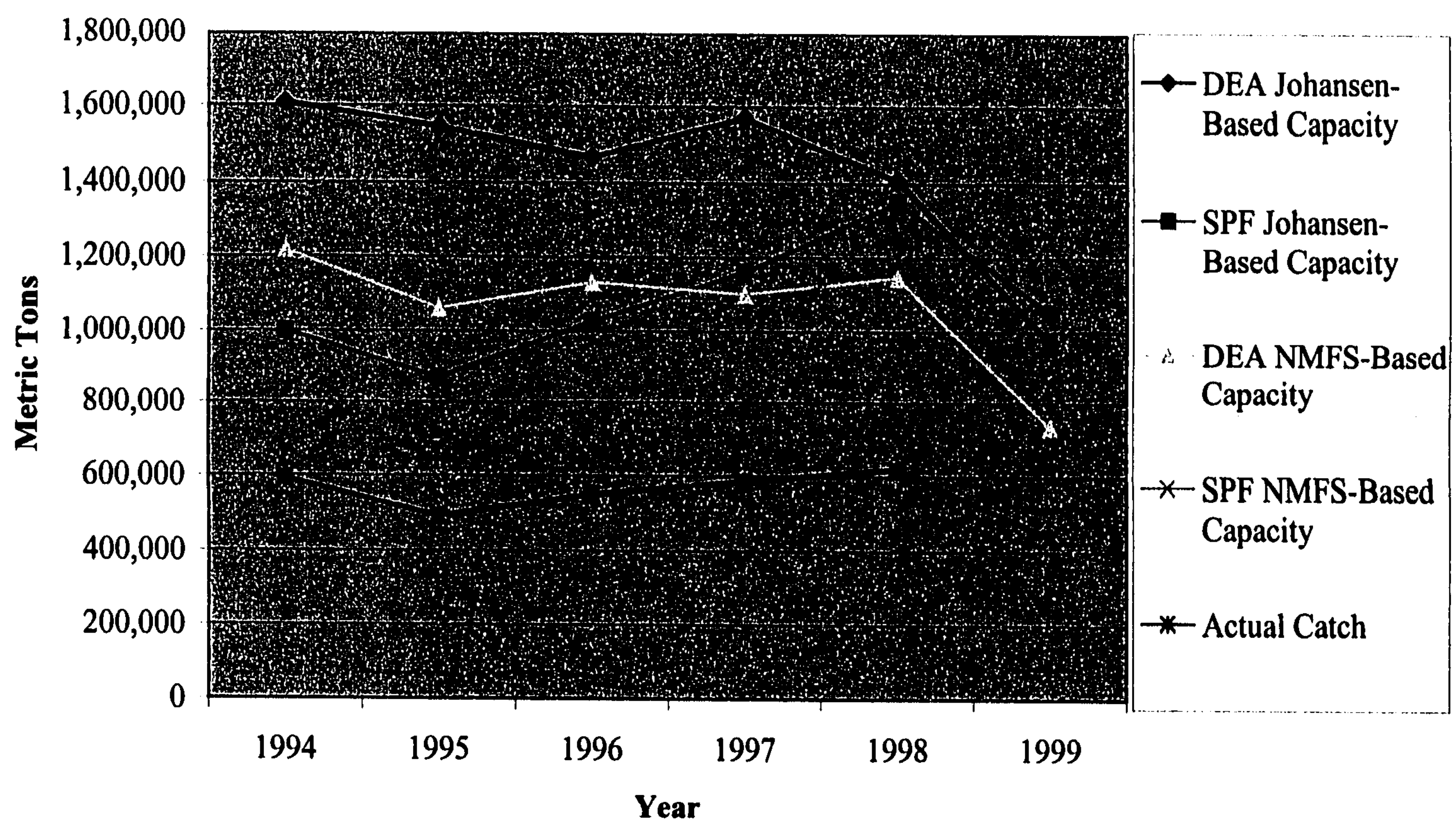
Johansen-based Capacity Estimates (tons):

	1994	1995	1996	1997	1998	1999
Pollock	1,001,132	870,469	1,026,539	1,160,738	1,349,546	1,054,684
Pacific Cod	68,678	87,244	95,615	110,196	106,501	95,900
Sablefish	505	308	253	93	286	844
Flatfish	248,788	204,253	337,573	491,961	370,963	321,340
Atka Mackerel	81,063	101,087	150,201	95,671	95,959	112,550
Rockfish	16,177	16,688	33,913	24,431	24,181	37,168

Table 5.11 Differences in DEA and SPF Capacity Estimates for Pollock (in tons)

	SPF	DEA	% Diff. In DEA vs. SPF: (DEA-SPF)/SPF	% Diff. in SPF: $(SPF_{JOHANSEN}-SPF_{NMFS})$ / SPF_{NMFS}	% Diff. in DEA: $(DEA_{JOHANSEN}-DEA_{NFMS})$ / DEA_{NMFS}
1994					
NMFS-Based Output	891,464	1,219,462	0.27	0.12	0.32
Johansen-Based Output	1,001,132	1,607,943	0.61		
1995					
NMFS-Based Output	774,603	1,062,398	0.37	0.12	0.45
Johansen-Based Output	870,469	1,545,185	0.78		
1996					
NMFS-Based Output	910,814	1,133,001	0.24	0.13	0.30
Johansen-Based Output	1,026,539	1,468,072	0.43		
1997					
NMFS-Based Output	1,044,749	1,102,359	0.06	0.11	0.42
Johansen-Based Output	1,160,738	1,569,833	0.35		
1998					
NMFS-Based Output	1,206,835	1,147,686	-0.05	0.12	0.23
Johansen-Based Output	1,349,546	1,408,494	0.04		
1999					
NMFS-Based Output	941,113	734,593	-0.22	0.12	0.33
Johansen-Based Output	1,054,684	973,550	-0.08		

Figure 5.1 BSAI Catcher-Processor Pollock Capacity Estimates, 1994-1999



Chapter 6
Effects of the American Fisheries Act on the At-Sea Alaskan Pollock Fishery

6.1 Introduction

As mentioned in earlier chapters, Congress passed the AFA in 1998 in part to further Americanize the pollock fishery of the North Pacific, and to encourage the remaining pollock fishermen to harvest in a more efficient and less derby-like manner. The result of the provisions included in the AFA was a change in the structure of the fleet that harvests and processes pollock – nine vessels were decommissioned, and the introduction of a cooperative structure with tradable harvest shares led to the possibility of eligible, continuing vessels sitting idle. As a result, a year after the AFA was passed, the size and composition of the catcher-processors harvesting pollock changed markedly.

Many interesting questions naturally arise when considering the potential effects of such an act. One such question is whether the decommissioned boats were more or less efficient than those that remained, which may be of particular interest to many of the AFA's opponents, who claimed that it was wasteful and politically motivated. Such claims could be partially[43] legitimated if the results indicate that the decommissioned vessels were far outperforming similar remaining vessels.

A second question is whether, after passage of this Act, fishing capacity has been substantially reduced. An initial report by the newly formed cooperatives indicates that there has been a decrease in fishing effort (in terms of fishing intensity) and an increase in season length for the pollock fishery. During certain times of the year as many as eight of the eligible vessels were idled, and their quota was used by other vessels (usually within the same company). However, given that a TAC similar to the pre-AFA TACs is still being taken in just a few months time, it seems there may still be excess capacity in the fishery. Even now, with the remaining vessels fishing at a more reasonable pace, they are still able to easily catch as much as has historically been caught by a much larger fleet. Even the pollock cooperatives state that current capacity is probably three times greater than the usual TAC (Pollock Conservation Cooperative and High Seas Catchers' Cooperative, 1999). Thus, it remains unclear whether the observed capacity reductions in the pollock fishery are sufficient to ease existing concerns.

A third question that naturally arises upon obtaining capacity estimates is "what to do now?" If there is in fact substantial excess capacity in a fishery, how might one curb or eliminate it? One suggested approach is to decommission the most technically inefficient vessels (Kirkley and Squires, 1998, 1999), while another is to introduce transferable fishing rights (NMFS, 1999). The AFA of 1998 used a combination of both vessel decommissioning *and* fishing rights in the BSAI pollock fishery analyzed here. As a result, the effectiveness of such tools in decreasing capacity can be analyzed in the context of the pollock fishery.

In order to address these questions, this chapter will compute the differences in capacity between the pre- and post-AFA BSAI pollock catcher-processor fleet and compare the relative efficiency (and vessel characteristics) of AFA-eligible and -ineligible vessels. Similar comparisons will also be made within the subset of eligible vessels among boats that either fished or were idled. Through use of data spanning the period before and after the AFA was passed, one can investigate the degree to which the provisions of the AFA affected both capacity and relative efficiency. Additional

[43] I say "partially" because the relative technical efficiency of a fishing vessel is only one of many factors describing the overall performance of a vessel.

information (such as estimates of scale economies and data on vessel characteristics) will also be used to aid in determining if criteria other than technical efficiency seemed to drive the cooperative's choices over use of the remaining AFA-eligible vessels.

6.2 Pre- and Post-AFA Comparisons

The changes brought about by the AFA had impacts on several aspects of the pollock fishery. One of the goals of this chapter is to analyze such impacts by focusing on three main areas. The first area relates to changes in fishing capacity after passage of the AFA. The combined effects of decommissioning nine catcher-processors and limiting the length, size, and horsepower of the remaining vessels *should* have led to a fairly significant decrease in capacity in the offshore pollock fishery.

It is theoretically possible, however, that capacity may not have fallen, as capacity reflects use of *all* inputs, and the AFA restrictions were aimed at only capital inputs. If, for example, variable input use was to increase substantially, or "capital stuffing"[44] was to occur, it is possible that the fall in capacity in the pollock fishery would be negligible. Therefore, SPF and DEA models will be used to compute capacity for the BSAI pollock catcher-processor fleet before and after passage of the AFA.

The second and third areas of focus involve analyzing the changes in efficiency that may have occurred after implementation of the AFA, and whether the vessels that were decommissioned due to the AFA regulations were relatively more or less technically efficient than those vessels that remained eligible to harvest pollock. Or, put another way, did the AFA regulations increase the efficiency of each vessel in 1999 from

[44] Capital stuffing refers to the process of increasing the effective amount of certain types of unregulated capital on board during times when restrictions place limits on other types of capital.

past levels, and did the most (historically) efficient group of catcher-processors remain in the fishery?

Some opponents of the AFA have argued that the AFA didn't allow the market to decide which vessels are the most efficient and which should stay in the fishery, but rather decided vessels' fates based on the where the vessel had been rebuilt. Although this position does have some merit (in that the competition for fish may drive the less efficient vessels out of business), the public-good aspect of the regulated open access fishery leads to a market failure in which the usual efficiency notions associated with competitive markets may not apply. To examine this question, a comparison of the decommissioned and continuing vessels will be provided.

A separate but related question pertains to the relative efficiency of the vessels that traded their fishing rights to other vessels within the newly formed cooperative, which has been called a "quasi-IFQ." Part of the motivation for IFQ's (individual fishing quota) is that economic theory dictates that under freely transferable quota rights (and price-taking behavior), the vessel operators with the highest marginal profits will end up owning the fishing rights, leading to the greatest amount of producer surplus.

While the data available does not allow one to compare or analyze producer surplus, one can compare the relative efficiency of idled and continuing vessels to see if the transfer of quota from idled to continuing vessels represents a gain in efficiency or if the transfer occurred for other reasons. That is, if the group of continuing eligible vessels is found to have been *less* efficient than those that were idled, this finding may indicate that criteria other than harvesting efficiency were more important in determining which vessels continued to fish. Possible reasons may include vessel size or age, an inflexible platform (in terms of product mix capabilities), lack of a meal plant onboard, etc.

6.3 Model Specification and Results

In order to address the questions discussed above, the models specified and discussed in Chapter 5 to estimate capacity for the BSAI catcher-processor fleet were used. For a discussion of the model setups, parameter estimates (for the SPF model), and basic results, see Section 5.2.

The first set of questions that will be addressed here with the results from the DEA and SPF models pertains to comparisons of producer efficiency before and after passage of the AFA. However, an issue that arises when comparing efficiency between years and vessels is that two main changes have been brought about by the AFA -- vessels were decommissioned and fishing rights were introduced -- and different effects can be attributed to either parts of the Act. Therefore, in the discussion that follows, changes in fleet efficiency will be examined in two contexts.

The first context involves differences in fleet efficiency that are due to the change in fleet composition resulting from decommissioning the nine vessels. Such a focus allows one to infer how the expulsion of the vessels would have affected fleet efficiency. For example, if the decommissioned vessels happened to be the most historically inefficient group of vessels in the fleet, their exclusion would increase the efficiency of the overall fleet. This area will be analyzed by comparing the historical, pre-AFA efficiency (from 1994-1998) of the *AFA-eligible* and *AFA-ineligible* vessels.

The second context involves looking at the overall effect (or gross result) of the AFA decommissionings *and* property right scheme on fleet efficiency. That is, the observed changes in fleet efficiency can be attributed to both, and thus by comparing efficiency of the fleet before and after the AFA was passed, one is capturing both effects. These overall effects will be analyzed by looking not at just AFA-eligible vs. AFA-ineligible vessels, but instead focusing on the historical efficiency (from 1994-1998) of the vessels that *continued* participating in the pollock fishery in 1999 (and were thus AFA-eligible) versus those that *exited* in 1999 (due to either AFA-ineligibility or being eligible but idled). Or, put another way, this second focus looks at the final outcome in order to examine whether the most efficient boats continued or exited the pollock fishery after the AFA was passed.

Although at first glance it may seem more natural to instead compare the efficiency of the observed fleet in 1998 versus that of the observed fleet in 1999, such an approach gives rise to two significant problems. First, changes in efficiency between years can be attributed to many different technological, biological, and managerial conditions, which makes it difficult to infer what portion of any observed change was a result of the AFA (and thus even more difficult to break changes in efficiency into "decommissioning effects" and the "overall" AFA effect).

Second, since the *DEA* models were estimated one year at a time, efficiency comparisons among years are inappropriate, as the TE scores are relative to the best practice technology for each year. Comparisons *can* be drawn between years in the SPF model constructed here, but any comparisons would be subject to the first problem listed above[45]. For these reasons, the analysis instead focuses on the efficiency characteristics of the vessels and how the inclusion/exclusion of different vessels altered the overall performance of the fleet.

A related question that will also be addressed is if managers had used a TE criterion to decommission vessels (say, in order to decrease capacity), as suggested by Kirkley and Squires (1998, 1999), would the resulting fleet have been similar to what was observed in the harvesting cooperative? In order to address this question, comparisons will be made between the observed fleet and the group of vessels that results when one sorts the vessels in the fleet by their DEA or SPF TE scores.

As an aid in evaluating the efficiency of AFA-eligible and AFA-ineligible vessels, Table 6.1 shows the mean TE scores from DEA and SPF models for the groups of eligible and ineligible vessels over the 1994-1998 period (the time leading up to the decommissioning of ineligible vessels). The results from DEA and SPF models indicate that on average, the decommissioned vessels' TE scores were approximately 11% lower than the vessels eligible in 1999.

As for the exiting versus continuing vessels over the 1994-1998 period, DEA results indicate that exiting vessels' mean TE scores were 9.8% lower than the continuing vessels. The SPF model finds exiting vessels' TE scores to be only .5% lower than those vessels that continued to fish in 1999. In addition, the parameter β_1 on the variable DUM99 was positive and statistically significant, implying that output levels were higher in 1999 for a given bundle of inputs (and output mix) than in previous years. However,

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[45] The interested reader can make such comparisons, however, by referring to Table 4.8 and examining the changes in mean vessel and fleet-wide efficiency from 1998 to 1999.

this result applies to all vessels in the BSAI catcher-processor fleet, and not just those specifically targeting pollock.

While the results discussed above do indicate that, on average, the boats that were decommissioned or idled were not as technically efficient as those who continued in the pollock fishery, Table 6.2 shows that there is no clear ordering of TE levels for both eligible/ineligible vessels or the continuing/exiting vessels. This finding suggests that, according to these measures, some of the vessels that were decommissioned or idled may have actually been more technically efficient than other vessels that continued to fish.

With regard to idled vessels, one explanation for this result is that some companies own multiple vessels and may have chosen to consolidate their operations, idling one or more of their boats. However, their idled vessel may have still exhibited a higher level of TE than other boats (owned by different companies) that continued to fish. Table 6.3 groups the vessels owned by companies with multiple vessels according to their DEA and SPF TE scores. What one finds is that in general, for 3 out of 4 companies, their ineligible boats were among their least technically efficient vessels.

What is somewhat surprising, however, is that often times the *eligible* vessels *chosen* to be idled (by companies owning multiple eligible vessels) were relatively more efficient than other participating vessels within the same company, as seen in Table 6.4. The reason for this may be related to the size of these vessels (and thus the type and variety of processing equipment that can be accommodated).

That is, TE may not have been the primary factor considered when determining which boats to continue to use (which is, admittedly, not a shocking result). Table 6.1 shows the mean vessel characteristics for the eligible/ineligible and exiting/continuing groups, and there are some striking differences. The eligible boats are 18% longer than the decommissioned boats, possess 121% more metric tonnage, and have 43% greater horsepower. Similarly, the continuing vessels are on average 22% longer than exiting vessels, almost 53% larger (in metric tonnage), have 34% greater horsepower, employ 17.5% more labor, and are 5 years older.

It turns out that these vessel characteristics also seem to be a fairly good predictor of the continuing/exiting and eligible/ineligible patterns that are observed in the pollock fishery – much more so than when looking at the same patterns based on TE scores. If one ranks the vessels by their respective characteristics, one typically sees that the "larger" vessels remain, and the smaller vessels have exited.

Table 6.5 shows vessels ranked by length and tonnage, and the eligible/ineligible vessels tend to break up into two fairly distinct groups. The same can also be said for exiting/continuing vessels, but to a lesser extent. Generally, the longest/largest boats using the most crew continued in the fishery, while the smallest vessels were those that were often idled.

Table 6.6 ranks the vessels within each company by length and tonnage. One finds that for companies with multiple eligible vessels, it is the smaller sized boats that are typically idled (when any are idled at all).

It should be remembered when comparing the eligible and ineligible boats, however, that the ineligible vessels were decommissioned because they were foreign rebuilt vessels that some argue should have been ineligible under the Anti-Reflagging Act. Thus, any size differences between the eligible and ineligible vessels may be coincidental.

The preceding discussion regarding vessel characteristics indicates that continuing vessels appear to be chosen more on their size and "fishing power" than on their TE. Discussions with the At-Sea Processors Association economist have also led this author to a similar conclusion. It seems that some of the smaller, shorter vessels are unable to accommodate meal plants (necessary to meet requirements banning discard of bycatch), and are less flexible in terms of creating the variety of product forms changing market prices may dictate (indicating such vessels may exhibit economies of scope in the revenue sense). It may also be the case that the movement toward fewer, larger vessels may reflect agents' beliefs over the presence of economies of scale. Table 6.7 shows the proportion of observations (by vessel) that exhibited increasing, constant, or decreasing returns to scale in the DEA models. Most vessels exhibit increasing returns over the range of the data in all years, which may provide even further evidence that many vessels are under-producing relative to their capacity.

One other interesting result of the models is that although the mean TE of the decommissioned and idled vessels was generally lower than the vessels that continued in 1999, the mean TE score for the remaining BSAI pollock catcher-processors dropped in 1999 relative to previous years. This seemingly paradoxical finding can be attributed to two separate but equally plausible factors.

First, since the remaining vessels fished at a slower, more sustainable, and presumably more cost-effective manner after the AFA was passed (due to the introduction of fishing rights), the data indicates *lower* average output per week for a given vessel size. The result of this is a decrease in the fleet-wide TE scores in 1999 relative to previous years, as the vessels are getting less output from a similar input composition. Even though the value of the catch has improved (through increased quality and product recovery rates), and the decrease in output may have been profitable, the purely technological/primal analysis does not account for such factors. It may also be true that some harvesting efficiency gains are ignored because a more favorable size composition (afforded by the slower pace) is not reflected by simply measuring output in terms of catch weight.

Second, this analysis focuses on the harvesting technology and not the processing technology where a majority of the quality and raw product recovery gains have occurred. It may be the case that the efficiency with which vessels harvest fish has been sacrificed in order to reap benefits in the processing portion of production.

Still, the finding of a *decrease* in technical efficiency when vessels are operating at what appears to be a more cost-effective and sustainable production schedule overall, points to a limitation to the primal-based model. These results also necessitate a more careful interpretation of results – especially in attempting to compare TE scores among Pre- and Post-AFA periods. For this reason, I have purposely avoided making comparisons of the vessels' TE in different years. Rather, I have focused on the relative efficiency of vessels within each year, and analyzed whether the most relatively efficient vessels participated in the pollock fishery after the AFA was passed, or if these boats were idled or decommissioned.

A second main focus of this chapter is whether the AFA decreased the fishing capacity of the pollock fishery. The results from both the DEA and SPF models, using both the NMFS- and Johansen-based definitions, indicate that it did. Even before turning to model results, one preliminary indication that capacity may have decreased is the observed decrease in the number of vessels that targeted pollock in 1999. In 1998, 25 vessels in the current data set targeted pollock as their primary catch[46]. Of these vessels, only 14 participated in the fishery in 1999. As mentioned earlier, this decrease can be attributed to restricting vessels from the fishery and because some AFA-eligible vessels were purposely idled (trading their fishing rights to other vessels in the cooperative).

According to the SPF model results in Table 5.10, the NMFS-based estimates indicate that pollock capacity decreased by 265,722 metric tons in 1999, while the Johansen-based estimates show a decrease of 294,862 metric tons (or a 28% decrease for both). The DEA results in Table 5.6 indicate that NMFS-based estimates of pollock capacity decreased by 413,043 metric tons from 1998 to 1999, while Johansen-based estimates were reduced by 434,944 metric tons (or by 42% and 44%, respectively). It should be noted that the decreased capacity in the pollock fishery was not accompanied by increases in capacity output levels for the other five groundfish species. The results suggest that capacity output fell for all species from 1998 to 1999 for both the DEA and SPF specifications under both definitions of capacity.

6.4 Summary

This chapter has discussed the specific provisions of the AFA and provided a description of the BSAI pollock fishery, which is the primary target of AFA legislation and the largest, most valuable of the NPGF fisheries. The analysis has focused on how the provisions of the AFA have affected the fleet composition, technical efficiency, and fishing capacity of the pollock fishery. In doing so, vessel comparisons were made in

[46] For a week of fishing activity to be classified as targeting on pollock, the catch must exceed 95% pollock by weight.

two different contexts; namely, comparisons between the AFA-eligible vessels and the AFA-ineligible vessels (to solely analyze the TE effects of decommissioning the nine vessels) and also between the "exiting" and "continuing" vessels (to look at the overall effect of the AFA on the TE of the pollock fishery).

Results from both the DEA and SPF models indicate that mean TE scores from 1994-1998 for AFA-eligible vessels exceeded those of the AFA-ineligible vessels, and the same result held for continuing versus exiting vessels. However, it was not the case that when ranked by their respective TE scores, the AFA-eligible vessels were the most efficient and the AFA-ineligible vessels were least efficient (nor were the continuing vessels all more efficient than the exiting vessels). These findings suggest that the effect of decommissioning the foreign rebuilt vessels was not efficiency increasing with respect to all vessels, that the overall effects of the AFA led to the exit (either permanently or idled for 1999) of some relatively efficient and inefficient vessels, but the overall effect change in fleet efficiency was positive.

The results also suggest that with respect to the AFA-eligible vessels, vessel TE may not have been the primary factor in determining whether eligible vessels were idled or utilized. Rather, vessel characteristics such as length and tonnage appear to be better indicators. A similar pattern exists when comparing the AFA-eligible vessels with AFA-ineligible vessels and when comparing exiting vessels with continuing vessels; that is, generally speaking the longer, larger boats had a higher incidence of remaining in the pollock fishery.

The analysis of this chapter also showed that the AFA did serve to substantially decrease fishing capacity *for all species* caught by the BSAI catcher-processors – a result that held in both the DEA and SPF capacity models and under two alternative definitions of "capacity." In particular, the SPF model estimates implied a 28% decrease in pollock fishing capacity, while the DEA models estimated the decrease to be approximately 43%. These findings can most likely be attributed to two main provisions of the AFA: the decommissioning of nine foreign-rebuilt vessels, and the introduction of fishing rights, which left 3 eligible vessels idled for the entire 1999 season, and also led to lower weekly harvesting rates and levels.

Table 6.1 Mean Technical Efficiency Scores and Characteristics of At-Sea Pollock Fleet, 1994-1998

	DEA TE Score	*SPF TE Score*	*Age*	*Length (feet)*	*Tonnage (m.tons)*	*HP*	*Crew*
Eligible Vessels	0.587	0.611	25.2	286.8	1823	5794	99.7
Ineligible Vessels	0.525	0.552	19.5	232.3	823	3914	84.5
% Difference	11.7%	10.6%	29.4%	18.1%	121.5%	48%	23.4%

	DEA TE Score	*SPF TE Score*	*Age*	*Length (feet)*	*Tonnage (m.tons)*	*HP*	*Crew*
Continuing Vessels	0.590	0.544	25.9	293.7	1771.3	5814.1	100.9
Exiting Vessels	0.538	0.541	20.3	240.4	1158.1	4338.4	85.8
% Difference	9.80%	0.50%	27.5%	22%	52.90%	34%	17.50%

Table 6.2 Mean DEA and SPF Technical Efficiency Rankings, Eligibility, and Entry/Exit for Pollock Fleet, 1994-1998

ID	*Eligibility*[47]	*In/Out*	*DEA TE Score*	*ID*	*Eligibility*	*In/Out*	*SPF TE Score*
14	E	I	0.865	25	E	O	0.804
20	E	I	0.661	9	E	I	0.707
53	E	I	0.647	20	E	I	0.686
27	E	I	0.631	53	E	I	0.679
25	E	O	0.627	56	E	I	0.676
2	I	O	0.614	16	I	O	0.674
64	E	I	0.605	50	E	I	0.630
46	I	O	0.604	45	E	O	0.627
6	E	I	0.600	6	E	I	0.623
50	E	I	0.598	46	I	O	0.621
16	I	O	0.584	62	E	I	0.615
56	E	I	0.572	27	E	I	0.603
62	E	I	0.572	43	E	I	0.596
9	E	I	0.571	14	E	I	0.588
45	E	O	0.554	64	E	I	0.583
21	E	I	0.536	2	I	O	0.574
58	E	I	0.533	52	E	I	0.537
52	E	I	0.531	1	I	O	0.531
43	E	I	0.515	58	E	I	0.523
1	I	O	0.475	21	E	I	0.480
38	I	O	0.445	38	I	O	0.473
15	I	O	0.432	15	I	O	0.442
10	E	O	0.369	10	E	O	0.440

[47] "I" indicates that a vessel is ineligible, while "E" indicates eligibility.

Table 6.3 Mean DEA and SPF Technical Efficiency Rankings, Eligibility, and Entry/Exit, by Owners with Multiple Vessels, 1994-1998

ID	*Eligibility*	*In/Out*	*DEA TE Score*	*Owner ID*	*ID*	*Eligibility*	*In/Out*	*SPF TE Score*	*Owner ID*
64	E	I	0.605	3	45	E	O	0.627	3
46	I	O	0.604	3	6	E	I	0.623	3
6	E	I	0.600	3	46	I	O	0.621	3
45	E	O	0.554	3	64	E	I	0.583	3
21	E	I	0.536	3	52	E	I	0.537	3
58	E	I	0.533	3	58	E	I	0.523	3
52	E	I	0.531	3	21	E	I	0.480	3
62	E	I	0.572	6	9	E	I	0.707	6
9	E	I	0.571	6	62	E	I	0.615	6
1	I	O	0.475	6	1	I	O	0.531	6
38	I	O	0.445	6	38	I	O	0.473	6
15	I	O	0.432	6	15	I	O	0.442	6
16	I	O	0.584	8	56	E	I	0.676	8
56	E	I	0.572	8	16	I	O	0.674	8
20	E	I	0.661	9	25	E	O	0.804	9
53	E	I	0.647	9	20	E	I	0.686	9
25	E	O	0.627	9	53	E	I	0.679	9
2	I	O	0.614	9	2	I	O	0.574	9
10	E	O	0.369	9	10	E	O	0.440	9

Table 6.4 Mean DEA and SPF Technical Efficiency Rankings of Eligible Vessels and Entry/Exit by Owners with Multiple Vessels, 1994-1998

ID	Eligibility	In/Out	DEA TE Score	Owner ID	ID	Eligibility	In/Out	SPF TE Score	Owner ID
64	E	I	0.605	3	45	E	O	0.627	3
6	E	I	0.600	3	6	E	I	0.623	3
45	E	O	0.554	3	64	E	I	0.583	3
21	E	I	0.536	3	52	E	I	0.537	3
58	E	I	0.533	3	58	E	I	0.523	3
52	E	I	0.531	3	21	E	I	0.480	3
62	E	I	0.572	6	9	E	I	0.707	6
9	E	I	0.571	6	62	E	I	0.615	6
20	E	I	0.661	9	25	E	O	0.804	9
53	E	I	0.647	9	20	E	I	0.686	9
25	E	O	0.627	9	53	E	I	0.679	9
10	E	O	0.369	9	10	E	O	0.440	9

Table 6.5 Vessel Characteristics, Eligibility, and Entry/Exit in 1999 for Vessels Targeting Pollock

ID	*Eligibility*	*In/Out*	*Length*	*ID*	*Eligibility*	*In/Out*	*Tons*
27	E	I	376	21	E	I	3546
21	E	I	341	58	E	I	3546
58	E	I	341	45	E	O	3471
6	E	I	336	27	E	I	2542
14	E	I	334	6	E	I	2282
2	I	O	306	53	E	I	2262
53	E	I	304	64	E	I	1932
64	E	I	285	14	E	I	1773
62	E	I	276	56	E	I	1553
20	E	I	275	52	E	I	1303
50	E	I	275	20	E	I	1190
45	E	O	272	25	E	O	1139
25	E	O	270	1	I	O	1097
43	E	I	270	50	E	I	1058
52	E	I	256	15	I	O	945
56	E	I	240	38	I	O	945
15	I	O	236	43	E	I	940
38	I	O	236	62	E	I	937
10	E	O	224	2	I	O	898
46	I	O	217	10	E	O	897
1	I	O	209	9	E	I	620
9	E	I	201	16	I	O	611
16	I	O	190	46	I	O	442

Table 6.6 Vessel Characteristics, Eligibility, and Entry/Exit in 1999 by Owners with Multiple Vessels

ID	Eligibility	In/Out	Owner ID	Length	ID	Eligibility	In/Out	Owner ID	Tons
21	E	I	3	341	21	E	I	3	3546
58	E	I	3	341	58	E	I	3	3546
6	E	I	3	336	45	E	O	3	3471
64	E	I	3	285	6	E	I	3	2282
45	E	O	3	272	64	E	I	3	1932
52	E	I	3	256	52	E	I	3	1303
62	E	I	6	276	62	E	I	6	937
9	E	I	6	201	9	E	I	6	620
53	E	I	9	304	53	E	I	9	2262
20	E	I	9	275	20	E	I	9	1190
25	E	O	9	270	25	E	O	9	1139
10	E	O	9	224	10	E	O	9	897

Table 6.7 Percentage of Observations Exhibiting IRS, CRS, and DRS, by Vessel, from DEA Models

Vessel	%IRS 1994-1998	%CRS 1994-1998	%DRS 1994-1998	% IRS 1999	% CRS 1999	% DRS 1999
1	**0.901**[1]	0.074	0.025	N/A	N/A	N/A
2	**0.810**	0.155	0.034	N/A	N/A	N/A
6	0.271	0.140	**0.589**	0.316	0.158	**0.526**
9	**0.951**	0.042	0.007	**1.000**	0.000	0.000
10	**0.920**	0.000	0.080	N/A	N/A	N/A
14	**0.824**	0.176	0.000	**0.870**	0.130	0.000
15	**0.760**	0.040	0.200	N/A	N/A	N/A
16	**0.914**	0.079	0.007	N/A	N/A	N/A
20	**0.870**	0.111	0.019	**0.944**	0.056	0.000
21	0.075	0.108	**0.817**	0.087	0.174	**0.739**
25	**0.975**	0.025	0.000	N/A	N/A	N/A
27	0.066	0.105	**0.829**	0.067	0.000	**0.933**
38	**0.819**	0.083	0.097	N/A	N/A	N/A
43	**0.745**	0.122	0.133	**0.833**	0.125	0.042
45	**0.857**	0.071	0.071	N/A	N/A	N/A
46	**0.893**	0.080	0.027	N/A	N/A	N/A
50	**0.746**	0.097	0.157	**0.926**	0.074	0.000
52	**0.740**	0.160	0.100	**0.913**	0.087	0.000
53	**0.897**	0.052	0.052	**1.000**	0.000	0.000
56	**0.839**	0.024	0.137	**0.960**	0.000	0.040
58	0.261	0.143	**0.597**	0.238	0.286	**0.476**
62	**0.659**	0.167	0.175	**0.583**	0.208	0.208
64	**0.817**	0.161	0.022	**0.773**	0.182	0.045

[1] Bold type indicates the category into which the majority of each vessel's observations fell.

Table 6.8 SPF Technical Efficiency Scores for Vessels Participating in the Pollock Fishery in 1999

Vessel	*1994*	*1995*	*1996*	*1997*	*1998*	*1999*
6	0.696	0.656	0.623	0.581	0.537	0.489
9	0.769	0.739	0.710	0.677	0.637	0.596
14	0.655	N/A	N/A	N/A	0.493	0.444
20	N/A	N/A	0.719	0.688	0.648	0.614
21	0.580	N/A	N/A	0.446	0.393	0.341
27	0.681	0.642	0.602	0.565	0.510	0.468
43	0.695	0.647	0.608	0.570	0.521	0.472
50	0.715	0.677	0.640	0.605	0.557	0.510
52	0.619	0.583	0.555	0.500	0.449	0.396
53	N/A	N/A	0.713	0.682	0.646	0.608
56	0.744	0.714	0.681	0.645	0.603	0.558
58	0.607	0.560	0.521	0.477	0.424	0.372
62	0.696	0.657	0.618	0.580	0.537	0.491
64	0.663	0.623	0.580	0.544	0.490	0.446

Chapter 7
Conclusion

7.1 Summary

This dissertation examines alternative methods for defining and estimating fishing capacity, and evaluating performance when cost and revenue data do not exist, or standard behavioral assumptions are not appropriate. The insights that were gained from comparing capacity estimates generated by two competing empirical methods (SPF and DEA) underscore the difficulty of a generating a consistent or "correct" estimate of technical fishing capacity, as capacity estimates for a given fishery can differ greatly if different models or assumptions are employed. Such consistency may be especially important if the levels of excess capacity are to be compared across different fisheries.

The source of this variation in capacity estimates can be attributed to two main factors. The first factor is the inherent difference between the SPF and DEA approaches – namely the stochastic nature of SPF models versus the deterministic DEA. The results of an application to the BSAI catcher-processor fleet indicate that when random variations in output (due to weather, biomass density fluctuations, mechanical breakdowns, etc.) are not treated as such, but instead lumped together with "inefficiency" (as in the DEA approach), the efficiency scores for vessels in any given week tend to be lower than in a similarly constructed stochastic model.

The result of the lower scores is a greater implied increase in output corresponding to technically efficient production, and therefore a greater estimate of the potential capacity for individual vessels and the fleet as a whole. Thus, one consequence of the inherent differences in the models is that capacity estimates for the BSAI catcher-processor fleet (and the pollock fishery in particular) were found to differ markedly between the DEA and SPF models in any given year for all species included in the analysis, with DEA estimates systematically exceeding SPF estimates.

A second reason for potential differences in the primal models' estimates of capacity lies in the different definitions of capacity that have been suggested. The analysis undertaken here compares estimates corresponding to Johansen's suggested definition of capacity with those implied by NMFS. Capacity estimates corresponding to the two definitions (which essentially differ over assumptions regarding the intensity of variable input use) are found to differ substantially within a given year – especially when DEA is used for the analysis. That either definition may be assumed to be reasonable by the practitioner, and such a decision can lead to drastically different results, underscores the repercussions generated by one's assumptions.

While the capacity estimates from the SPF and DEA models do differ in magnitude, results from both models support the hypothesis that significant excess capacity has existed since at least 1994 (the starting point of this analysis) in the pollock fishery, and persists to this day. The estimates from the DEA and SPF models both indicate that even the current post-AFA fleet is outfitted to catch around twice the TAC, even under the assumption of no increase in season length.

The reason current catch levels have not reached such levels may be attributed to two main factors. First and foremost, the TAC has been set exogenously and season lengths have adjusted accordingly to achieve the desired TAC (Homans and Wilen, 1997). This obviously serves as a limitation on the amount that can be caught, regardless of the number and size of vessels. Second, even though the current investment in vessel capital may be capable of supporting twice the current TAC apportionment, varying levels of other essential inputs (fish stock/density, or variable inputs such as labor) during certain parts of the season and differences in skipper skill restrict the utilization of the capital. The relatively low CU scores exhibited in the DEA and SPF models (as seen in Tables 5.5 and 5.9, respectively) serve as further support of such factors.

With respect to the effects of the AFA, the results presented in Chapter 6 showed that fishing capacity decreased in the pollock fishery by an estimated 30% to 40% (according to the SPF and DEA estimates, respectively) after the AFA was passed. Therefore, it appears that the net effect of the AFA has moved capacity in the desired direction. Probably the most significant reason for the decline was the decrease in the number of vessels operating within the pollock fishery. Prior to passage of the AFA, 25 BSAI catcher-processors targeted pollock, while in 1999, only 14 of these vessels participated in the pollock fishery. A second reason for the decrease in capacity was the decrease in weekly output in 1999, wherein vessels slowed production in order to increase product recovery rates and generate higher quality products – yielding them greater returns in the market.

One somewhat paradoxical effect of the slower operations was a slight decrease in the measures of technical efficiency in harvesting for most operations, as vessels used crews similar to pre-AFA sizes, yet generated less output per week. In most instances, however, the fall in output was accompanied by decreases in other "inputs." For example, the average tow duration fell in the post-AFA periods, as did the average number of tows. Thus, it appears that sacrifices in *harvesting* efficiency were made in an attempt to increase the efficiency and value of *processing* activities (which essentially dictate the rate at which fish are harvested).

The finding of a *decrease* in technical efficiency when vessels are operating at what appears to be a more cost-effective and sustainable production schedule points to a limitation of primal-based models – a point emphasized by Wilen (1979). This finding also necessitates a more careful interpretation of results – especially in attempting to compare TE scores among pre- and post-AFA periods. For this reason, comparisons of vessels' TE scores in different years were avoided. Rather, the discussion focused on the relative efficiency of vessels within each year, and analyzed whether the most relatively efficient vessels participated in the pollock fishery after the AFA was passed, or if these boats were idled or decommissioned.

Results from both the DEA and SPF models suggest that the mean technical efficiency of the AFA-eligible group was marginally greater than the decommissioned vessels, although no clear pattern emerged when vessels were ranked by their average TE score. If a clear pattern *had* immerged, it might have, for example, indicated that the most technically efficient boats remained eligible and the least technically efficient boats were decommissioned – a possible justification for certain boats' exclusion. Results also indicate that TE scores did not consistently indicate which of the *eligible* vessels might be idled (with the owner using another one of her more technically efficient vessels to catch the quota typically caught by the idled vessel).

The lack of correlation among TE scores and idled or decommissioned vessels suggests that the vessels that were chosen to exit the fishery were likely chosen according to a different criterion. It was shown that vessel size, and in particular, vessel length, does a much better job of predicting which vessels were idled or exited the fishery, and which continued to operate.

One reason that vessel length represents an important factor is because the length of a vessel often dictates the number of processing lines that may be accommodated onboard. After passage of the AFA, when vessels slowed operations and chose their product mix more according to market prices than by a desire to maximize total catch and keep production lines moving, the ability to produce a variety of products is believed to be paramount. Thus, it appears that longer vessels have the ability to accommodate a greater variety of processing equipment, as well as meal plants, which have recently been necessary due to mandatory retention and utilization of all pollock and cod.

7.2 Extensions

As one of the primary aims of this research was to compare the differences in capacity estimates that may arise from similarly constructed SPF and DEA models, many of the model extensions that are possible only in one of the two frameworks were not fully developed. For example, the SPF framework allows one to include potential determinants of the technical efficiency term, which can allow for a useful decomposition/explanation of deviations from the frontier output (such as biomass and weather effects), rather than lumping everything together as "inefficiency." Alternatively, the DEA approach can be modified to include relevant constraints that may have been in place during the period in which the landings occurred (such as constraints on aggregate catch, bycatch, etc.). Because some of the "strengths" inherent to each individual model were not included (in order to facilitate the most similar model comparisons), I believe that it may be possible to improve somewhat on the results generated within each of the respective frameworks.

Within the SPF model, there are some extensions that may warrant further examination. First, a translog functional form was employed in estimating the ray production frontier, and nested tests were performed until the most appropriate final specification was determined. There may, however, be other functional forms that could effectively be used within the SPF model, though this author is unaware of any previous applications. The reason for the scarcity of alternative forms in SPF applications most likely lies in the difficulties and non-linearities that arise when non-logarithmic forms are used in conjunction with the multiplicative error structure commonly assumed in the standard SPF model.

As for changes to the current DEA model, the use of some form of stochastic DEA may have promise. It was shown earlier that large differences arise when one uses the SPF model instead of the deterministic DEA, and many of the discrepancies seem to have arisen because the basic DEA model ignores random noise in the data. Therefore, a DEA model that accounts for such shocks would be more desirable than that used here, though the current stochastic DEA models are difficult to implement, and have data requirements beyond those presently obtainable in the BSAI.

A more "standard" econometric model may also represent a promising extension to the approach developed within this dissertation. For example, if one were to look at the average production relationships (rather than the frontier-based approach used in SPF models), one would be able to more easily implement alternative non-logarithmic functional forms for the production technology. In such a model, one could construct the average output levels for each vessel within a season and compare such levels to their capital stock. Vessels that are catching much more fish than the average for a given level of capital may be thought of as over-utilizing their capital (potentially implying further capital investment may help to diminish costs), while those that catch less than the average may have excess capital for their typical output levels. Such an approach would allow one to make inferences typically reserved for dual models (in which opportunity/shadow costs of capital are compared to factor costs), though some qualifications would certainly be necessary when interpreting the results.

In terms of models that could be constructed if further data existed, the obvious extension would be a static dual approach, as discussed in Chapter 2, which would allow one to say a bit more about allocative efficiency and evaluate more of the economics underlying changes brought about by the AFA. If a panel of profit data were available, a promising and potentially illuminating approach would be a long-term dynamic model that sought to maximize the net present value of the fishery and endogenously determined the optimal capacity for the fishery, subject to relevant constraints. In addition, information relating to the biological factors and externalities present in harvesting technology would be a welcome inclusion, as the current data only avails yearly biomass estimates.

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