Estimating Heterogeneous Primal Capacity and Capacity Utilization Measures in a Multi-Species Fishery

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Abstract:

We use a stochastic production frontier model to investigate the presence of heterogeneous production and its impact on fleet capacity and capacity utilization in a multi-species fishery. Furthermore, we propose a new fleet capacity estimate that incorporates complete information on the stochastic differences between each vessel-specific technical efficiency distribution. Results indicate that ignoring heterogeneity in production technologies within a multi-species fishery, as well as the complete distribution of a vessel's technical efficiency score, may yield erroneous fleet-wide production profiles and estimates of capacity.

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Introduction:

Efficient management of natural resources hinges on our ability to monitor and assess the status of the resource stocks as well as the actions and economic performance of the agents utilizing such resources. The sustainability and viability (both in physical and economic terms) of our resource management plans can in part be assessed by estimating the extractive or productive capacity of economic agents relying on a given resource. However, because of the limitations and uncertainty associated with the available data, particularly in the fishing industry, estimating the capacity and capacity utilization of the agents using the resource can be a difficult endeavor. Compounding the difficulties of estimating capacity is the heterogeneous nature of the agents using the resource. Heterogeneity in the agents implies that multiple production processes may exist, which must be accounted for when attempting to measure capacity and capacity utilization. Otherwise, capacity estimates based on a homogeneous production model may be erroneous and yield inappropriate policy recommendations.

Given the ever-growing concern that excess capacity is prevalent in many natural resource environments and the need to assess capacity and its utilization to prioritize the settings in which direct problems exist, it is paramount that we develop methods which may be used to investigate and control for production heterogeneity in these environments. Furthermore, it is important that we utilize statistically reliable measures of fleet capacity. This research addresses these concerns by estimating heterogeneous capacity and capacity utilization in the context of a multi-species fishery and by proposing a new measure of fleet capacity which utilizes information on the statistical reliability of a vessel's technical efficiency score. Our results illustrate the complexities that arise in the presence of heterogeneous production technologies – a common situation in multi-species, multi-gear fisheries.

Estimates of capacity in fisheries are desirable because overcapacity is often cited as the most prevalent impetus for the overexploitation of fisheries across the globe (Food and Agricultural Organization 1998). Common symptoms of excess capacity are dwindling fish stocks, an accelerated "race for fish" resulting in a shorter fishing season, and excessive investment or input use ("capital stuffing") to increase one's odds of catching a larger share of the total catch (further exacerbating excess capacity in the fishery). Increased prevalence of such problems has stimulated a need to not only obtain reliable estimates of capacity and capacity utilization, but to develop management instruments to mitigate the rate of expansion in capacity and the effect of overcapacity within fisheries.

Input controls are often used to control overcapacity in fisheries, which in turn homogenize the effort that may be exerted by members of the fleet, and reduces their ability to fully utilize the currently available technology and vessel capital. However, the success of input control regulations is contingent on the vessel's inability to substitute out of the regulated input into another unregulated input (Kompas et al. 2004). Vessel buybacks are often conducted as well in an effort to remove vessels from the fleet and increase the rents of the remaining fishermen, thereby reducing the fleet's effective capacity and increasing the utilization of the remaining vessels (Guyader et al 2004). Alternatively, a transition to a well-defined property rights system, such as individual transferable fishing quotas, has been argued as a cost-effective solution to overcapacity as less efficient vessels are bought out by the more efficient vessels within the fleet (Weninger and Waters 2003; Kompas and Che 2005). Following this transition the property rights structure will reduce the incentives to "race for fish" and yield investments in capacity only when it is economically advantageous. This said, even with all the efforts to control excess capacity and recognition of the associated problems, there still does not exist an unequivocal definition of capacity, or a means of estimating it, within the fisheries literature (Kirkley et al. 2002).

However, one common thread among existing studies of fishing capacity is the need to estimate the fisheries production technology in order to be consistent with economic production theory.[1] Currently, there are two primary methods used to estimate production functions in fisheries: data envelope analysis (DEA) (Kirkley et al. 2001; Kirkley et al. 2003; Reid et al. 2003) and stochastic production frontier (SPF) models (Sharma Leung 1998; Felthoven 2002; Viswanathan et al. 2003; Garcia et al. 2005; Kompas and Che 2005). DEA does not assume a parametric form for the production technology and is therefore a more general and flexible model. However the DEA models used to date in fisheries estimate a deterministic production frontier, whereas SPF encompasses random variations along the production frontier to account for unexplained variability in production. Deterministic frontier models assume that an agent's inability to produce the maximum amount of output, given there current mix of inputs, is due to agent-specific technical inefficiency. On the other hand, SPF models decompose this inefficiency into a

[1] Alternatively, one could conduct a "peak to peak" production analysis. However, these estimates are not as rigorous as those explicitly based on production estimates.

vessel-specific component and random error component.[2] The method utilized in this research is a latent stochastic production frontier model (LSPF) (Schnier et al. 2006), which synthesizes latent class regressions with SPF models and allows for heterogeneity in the production frontiers within the fishery.

To define capacity we base our measure of capacity on the technological-economic approach (Felthoven and Paul 2004). This measure defines capacity as the maximum feasible output that can be produced given the current level of technology, and environmental and economic conditions. This approach provides a primal measure of capacity because it is based on the physical relationship between inputs and outputs, rather than a dual approach in which one also incorporates behavioral assumptions such as cost minimization or profit maximization. The latter approach is often infeasible given the lack of cost data for most fisheries. Therefore our definition of capacity is consistent with that conventionally used within the fisheries production literature. In fisheries the complexities of estimating capacity are often exacerbated by the multi-species nature of many fisheries as well as unexpected, and often times immeasurable, variation in environmental conditions. Addressing the former concern is readily achieved using ray (Felthoven 2002) or distance functions (Orea et al. 2005).[3] In our context, the flatfish fishery within the Bering Sea and Aleutian Islands (BSAI), we use distance functions to account for the multi-species nature of this fishery. The latter concern is controlled for using stochastic production frontier (SPF) models, which control for unobservable variation in the production frontier and allow us to generate a new measure of fleet capacity which incorporates information regarding the reliability of a vessel's technical efficiency.

Estimates of capacity and capacity utilization that have been derived in the literature to date embody the assumption that all agents operate with the same production technology. This assumption presumes, for example, that each vessel possesses identical output elasticities, elasticities of substitution, marginal rates of transformation, and returns to scale (among other things). This further implies that all vessels have the same ability to react and adapt their fishing strategies to regulatory measures (such as input controls or trip limits for particular species)

[2] The purpose of this paper is not to compare and contrast DEA and SPF models. For a more complete analysis and discussion of these alternative methods see Felthoven (2002) and Kirkley et al. (2002).
[3] For a comparison of the two methods used to estimate multi-species fishery production see Fousekis (2002).

enacted to mitigate risks associated with excess fishing capacity.[4] Presumably, this is a very strong assumption, as substantial variations in catch (for a given level of input use) often exist within the fleet. These differences may be explained either by differences in the technical efficiencies possessed by vessels using a common production technology, or by asymmetries in the production technologies employed by different fleets or groups of vessels. The latent class model used allows for both of these to be investigated and compared to the homogeneous production assumption.

Heterogeneity in behavior has received a fair amount of attention in the stated preference literature via the utilization of random coefficient models (Train 1998; Train 2003). In fisheries random coefficient models have been used to investigate heterogeneity in site choice modeling in commercial fisheries (Mistiaen and Strand 2000; Smith 2005) as well as recreational fisheries (Provencher and Bishop 2004). Although these models could be adapted to investigate heterogeneity in production technologies within fisheries, they do not facilitate the estimation of vessel-specific capacity and capacity utilization measures[5], which are necessary to inform policy. To obtain vessel-specific measures of capacity we use the latent class regression method developed by El-Gamal and Grether (1995; 2000), the EC algorithm. Alternatively one could estimate the latent class production functions using finite mixture regressions (Orea and Kumbhakar 2005). However, finite mixture models estimate the probability of participation in each of the respective classes whereas the EC algorithm restricts class participation probabilities to be either zero or one. This allows us to precisely identify class participation and therefore vessel-specific measures of capacity.

II. Defining and Estimating Heterogeneous Capacity

Each technology's production function is defined as $Y_j = Y_j(F_j, S_j, V_j, C_j)$, where F_j is technology *j's* vector of fixed inputs of production, S_j is technology *j's* vector of exogenous input stocks, V_j is technology *j's* vector of variable inputs and C_j is technology *j's* vector of control variables. Variables contained in F are the long-run production control variables, such as

[4] This is true if we assume that fishermen do not alter their technological choice or targeting strategies for output, measured are the assemblage of species caught, within the fishery. Changes in regulatory measures will have all kinds of implications on people choice sets for inputs and outputs, which will not only reflect technological production possibilities but other factors not captured by the production function.

[5] A random coefficients stochastic frontier model has been developed by Greene (2005).

a vessel's level of horsepower and size, which are assumed to be fixed during the time horizon analyzed.[6] In a natural resource economics setting variables in S represent the current stock of resources used in production such as the current stock level of the target species within a fishery. The amount of time and labor devoted to production is captured in the vector V **,** which in a fishery is represented by the number of crew members on board the vessel, the number of days fished within a season, and potentially the amount of time the fishing gear is deployed. Variables contained in V represent short-run production inputs. The control variables captured in C may be used to control for differences in technology when multiple methods of production exist as well as to control for time, space and environmental factors such as El Nino and La Nina events.

Defining the production function as $Y_j = Y_j(F_j, S_j, V_j, C_j)$ we can further characterize the measures of Y_j and $Y_{C|j}$ used to define fleet capacity, C_J, and vessel specific measures of capacity utilization, CU_j. The observed output levels are used to determine Y_j^O, defined simply as $Y_j(F_j, S_j, V_j, C_j)$, hereafter denoted Y_j^O, whereas the technically efficient utilization of F_j, and V_j is defined as $Y_j^{TE} = Y_j^{TE}(F_j, S_j, V_j, C_j)$, hereafter denoted Y_j^{TE}. Should one assume a homogeneous production technology all subscript *j's* are removed.

There are two primary measurers of capacity we are interested in estimating: the fleet capacity and the vessel specific measures of capacity utilization. These estimates are contingent on the available inputs, both fixed and variable, and the maximum output which may be derived from these inputs. Assuming that there exist *J* separate production technologies within the fishery, we define three different measures of fleet capacity, C_J, and one measure of capacity utilization, CU_j. Our first measure of fleet capacity is defined as,

$$\hat{C}_J = \sum_{j=1}^{J} \sum_{i=1}^{N_j} Y_{C|j}^i \qquad (1)$$

[6] This assumption implies that the estimates of capacity we obtain are short-run estimates of primal capacity.

where N_j is the number of vessels possessing technology *j*, $Y_{C|j} = Y_j(F_j, S_j, C_j \mid V_j = V_j^{MAX})$ and V_j^{MAX} is the maximum level of variable inputs utilized by segment *j*. Estimates of $Y_{C|j}$ are defined as the level of output each technology may derive from their fixed input base, given the *maximum* observed level of variable input use and the exogenous stock variables. $Y_{C|j}$ therefore, in general, lies above both Y_j^O and Y_j^{TE} on technology *j's* production frontier and represents the *maximum* primal measure of output.[7] The second measure of fleet capacity is defined as,

$$\widetilde{C}_J = \sum_{j=1}^{J}\sum_{i=1}^{N_j} Y_{C|j}^{TEi} \qquad (2)$$

where $Y_{C|j}^{TE} = Y_j^{TE}(F_j, S_j, C_j \mid V_j = V_j^{MAX})$ which represents the technically efficient level of output producible by vessel *i* assuming maximum utilization of production technology *j's* variable inputs. The final estimate of fleet capacity incorporates the probability that a given vessel is technically efficient, F^{TEi}, which can be calculated using the vessel-specific distributions of technical efficiency derived in the stochastic frontier model (Horace 2005; Flores-Lagunas et al. In Press). The final measure of fleet capacity is defined as,

$$\overline{C}_J = \sum_{j=1}^{J} N_j \sum_{i=1}^{N_j} F^{TEi} Y_{C|j}^{TEi}. \qquad (3)$$

This last measure of fleet capacity refines the fleet-wide measure of capacity by assigning more weight to those vessel's which possess a higher probability of being technically efficient, indicated by F^{TEi}. It also incorporates all information on all *differences* between the technical efficiency distributions of all vessels. (That, is the probability that a vessel is efficient is a statement on the extent to which the vessel *stochastically dominates* all others.)

[7]This may not be true if a vessel is very inefficient, and expending a lot of effort for their vessel size. In this case their capacity utilization score could be quite high and $Y_{C|j}$ may be less than Y_j^{TE}. In addition, Y_j^{TE} will be greater than Y_j^O except when a vessel in segment *j* is technically efficient. When this is true $Y_j^O = Y_j^{TE}$.

For each specification of the production technologies that exist within the fishery, *J*, we will generate three different measures of fleet capacity, $\hat{C}_J, \tilde{C}_J$, and $\overline{C}_J$. Our new measure of fleet capacity, $\overline{C}_J$, emphasizes the reliability of our fleet capacity by utilizing information contained in the second moment of our stochastic frontier estimates. Furthermore to investigate the sensitivity of our analysis to the assumption that $V_j = V_j^{MAX}$ we use two additional specifications which estimate production when the variable inputs are 25% and 50% greater than current utilization levels, denoted $V_j = V_j^{25}$ and $V_j = V_j^{50}$ respectively.[8]

Each vessel's capacity utilization, CU_j, is expressed as the ratio of their output, assuming a production function *j*, Y_j, to the capacity output level, $Y_{C|j}$, $CU_j = Y_j / Y_{C|j}$. The closer CU_j is to one the less excess capacity each vessel possesses. The inverse of CU_j indicates how much each vessel's production could increase if they were to fully utilize their inputs in the short-run. To determine CU_j we must define how we will assess Y_j and $Y_{C|j}$.[9] To define Y_j we use the predicted production estimate generated from the stochastic frontier model, $\hat{Y}_j$, and we define $Y_{C|j} = Y_j(F_j, S_j, C_j \mid V_j = V_j^{MAX})$ to generate the following capacity utilization measure:

$$CU_j = \frac{\hat{Y}_j}{Y_{C|j}}. \tag{4}$$

Furthermore, we specific two alternative measures of CU_j which utilize V_j^{25} and V_j^{50} defined CU_j^{25} and CU_j^{50}, respectively.[10] Given that capacity utilization measures are vessel specific, we are not able to utilize the statistical information contained in the second moment of the

[8] In the application we use *Days* fished in a week as the variable input maximized. In the case that either 25% or 50% greater than current utilization exceeded seven days we capped it at seven days.
[9] There are number of issues that must be addressed when defining the measures used to estimate capacity, for a more detailed discussion of these issues see Kirkley et al. (2002).
[10] Alternatively we could estimate capacity utilization as $CU_j^{TE} = Y_j^{TE} / Y_{C|j}$ as proposed by Fare et al. (1989) which are "unbiased" because it is not directly influenced by technical inefficiency.

stochastic production function, reflective in our estimates of F^{TEi}, to generate another estimate of capacity utilization analogous to the fleet capacity measure defined above.[11]

By using the latent class model we can allow for differences in a given output elasticity among production technologies, representing potential differences in curvature among the production frontiers for groups of vessels. The magnitude of these differences will determine the degree to which a homogeneous estimate of primal capacity will over/under estimate the heterogeneous estimate of primal capacity for a given vessel. Figures 1 and 2 graphically illustrate these differences when one assumes a homogeneous versus heterogeneous model and the degree of over/under estimation of capacity generated by the homogeneous model assumption, when there exists two distinct production technologies within the population, *J=2.*

Capacity utilization estimates assuming a homogeneous production technology generates an estimate of V_{HA} / V_{HC} and V_{HB} / V_{HC} using observed production and technically efficient production respectively, assuming $K = K_1$. In this environment the two segments are evaluated as one and the production frontier is the average of the two technologies and predominately lies above one technology (depicted as the filled diamonds) and below the other technology (depicted as the open circles). Allowing for heterogeneity generates production frontiers which are a better fit for the two distinct groups. Similar estimates of capacity utilization are V_{1A} / V_{1C} and V_{1B} / V_{1C} for segment one (filled diamonds) and V_{2A} / V_{2C} and V_{2B} / V_{2C} for segment two (open circles). Because the production estimates of Y_j^O, Y_j^{TE} and $Y_{C|j}$ are tighter than the estimates assuming a homogeneous production technology the estimates of capacity utilization will be greater than those obtained under the homogeneous production model. This implies that there exists less overcapacity in the heterogeneous model than the homogeneous model.

In general, the total measures of overcapacity will be greater when homogeneity is assumed than when one allows for heterogeneous production. This is because the frontier in the homogeneous model can be thought of as the outer envelope for *all* observations, whereas in the heterogeneous model, there will be one frontier corresponding to each technology, some of which may lie below the uppermost frontier (representing the most productive technology). However, it is possible

[11] This is because F^{TEi} will be contained in both the numerator and denominator of CU_j and will cancel out.

that the measures of the overcapacity may be underestimated by the homogeneous model. For example, if the output elasticities are substantially different (and large) for one production technology and a large number of agents possess this technology, the increase in output associated with heightened variable input use at capacity output will be also be large. Capacity output estimates for this group of vessels will in turn be more precise than in the homogenous model, which would underestimate capacity. The total impact of model misspecification, however, depends on the number of agents which possess distinct technologies and the nature and extent of the differences among them. Presumably, the effects of misspecification will be lessened when the differences between technologies are symmetric, as the homogeneous model represents the average production process for the different segments. We should also note that the issues discussed above also apply to measures of capacity utilization, as it is merely a ratio of capacity output to observed output.

To estimate the heterogeneous production technologies and determine the appropriate number of technologies, *J**, within the population, we utilize a LSPF model. The LSPF model is based on a *j* segment production function with each segment possessing the following production function representation,

$$Y_{it|j} = f(K_i, S_{it}, V_{it}, C_{it}; \beta_j) \exp\{\varepsilon_{it|j}\}, \tag{7}$$

where, *i* indicates the agent, *t* the time period and *j* the segment assignment. The error structure is decomposed into two components to generate the stochastic frontier model (Aigner et al. 1977; Meeusen and van den Broeck, 1977) and is specified as follows,

$$\varepsilon_{it|j} = v_{it|j} - \eta_{i|j}. \tag{8}$$

The first error term, $v_{it|j}$ is independently and identically distributed $N(0, \sigma^2_{v|j})$ and $\eta_{i|j}$ is a one-sided, non-negative vessel specific error term drawn from a truncated $N(\mu_j, \sigma^2_{\mu|j})$. Given that the data set utilized is an unbalanced panel, the log-likelihood function is (Battese et al. 1989; Battese and Coelli 1995),

$$L(\theta_j;Y) = -\frac{1}{2}\left(\sum_{i=1}^{N} T_i\right)\log(2\pi) - \frac{1}{2}\sum_{i=1}^{N}(T_i-1)\log[(1-\gamma_j)\sigma_{s|j}^2] - \frac{1}{2}\sum_{i=1}^{N}\log\{\sigma_{s|j}^2[1+(T_i-1)\gamma_j]\}$$

$$-N\log[1-\Phi(-z)] + \sum_{i=1}^{N}\log[1-\Phi(-z_i^*)] - \frac{1}{2}Nz^2 - \frac{1}{2}(Y_{it}-X_{it}\beta_j)'(Y_{it}-X_{it}\beta_j)[(1-\gamma_j)\sigma_{s|j}^2] + \frac{1}{2}\sum_{i=1}^{N} z_i^{*2}$$

(9)

where,

$$X_{it} = (K_i, S_{it}, V_{it}, C_{it}),\ z = \frac{\mu_j}{(\sigma_{s|j}^2\gamma_j)^{0.5}},\ z_i^* = \frac{\mu_j(1-\gamma_j) - T_i\gamma_j(\overline{Y}_i - \overline{X}_i\beta_j)}{(\gamma_j(1-\gamma_j)\sigma_{s|j}^2[1+(T_i-1)\gamma_j])^{0.5}}$$

$$\overline{Y}_i = \frac{\sum_{m=1}^{T_i} y_{mi}}{T_i} \text{ and } \overline{X}_i = \frac{\sum_{m=1}^{T_i} x_{mi}}{T_i}.$$

T_i is the number of observations within the unbalanced panel for vessel *m* and θ_j is the parameter vector to be estimated for each segment and it consists of the following parameters,

$$\theta_j = \left\{\beta_j, \gamma_j = \frac{\sigma_{v|j}^2}{\sigma_{S|j}^2}, \sigma_{S|j}^2 = (\sigma_{v|j}^2 + \sigma_{\mu|j}^2)\right\}.$$

Using the likelihood function specified in equation (9) the EC algorithm is used to determine the number of vessels in each of the *j* types and to generate estimates of the segment-specific parameters, θ_j. The EC algorithm proceeds by first pre-specifying the number of types within the data, *J*, and then obtaining parameter estimates by assuming the each agent's contribution to the global likelihood function is the maximum joint likelihood of all their observations, T_i, across all the *J* pre-specified types, given $\Theta = (\theta_1,...,\theta_J)$. This is specified as follows,

$$L(Y_{it}; X_{it} \mid \Theta, J) = \sum_{m=1}^{N} \arg\max_j \sum_{t=1}^{Ti} L(Y_{it}; X_{it} \mid \theta_j) \qquad (10)$$

To determine the optimal number of latent types, *J**, estimates are conducted assuming a number of different type classifications, *J=1,2,…J**, and likelihood ratio tests are utilized to determine the optimal number of latent types within the data set. This method is identical to that used by Schnier et al. (2006) to identify heterogeneous measures of technical efficiency, but this is first time it has been used to obtain capacity measures.[12] Having outlined the motivation for investigating heterogeneous primal capacity measures, the following section describes the data used in our analysis and the econometric specification of $Y_{it|j}$ utilized.

III. Data and Econometric Specification

To illustrate our model we use data on catcher-processor vessels operating in the BSAI flatfish fishery for the years 1994 through 2004. The unbalanced panel data set consists of 4403 observations on 45 distinct vessels greater than 125 feet in length, which are required to have federal observers on board for all of their trips. Data obtained from the federal observers was merged with data from the weekly production reports filed by these vessels to create a dataset including vessel characteristics, the time period during which vessels fished, the number of hauls conducted, the total length of time their gear was in the water (duration), the number of crew members employed, and a complete characterization of their catch composition. Although there are other vessels that operate within the flatfish fishery, because they are smaller than 125 feet the observer data is incomplete (only 30% of trips include federal observers). However, given the size of this segment within the fleet and their predominance of their catch within the flatfish fishery, our data sets represents the most complete one which may be used to investigate capacity and capacity utilization within the BSAI flatfish fishery. In addition, the large number of vessels within this data set will facilitate the characterization of multiple production processes, Y_j within the fishery.

The primary flatfish species caught by the fleet are yellowfin sole, rock sole, flathead sole, arrowtooth flounder, flounder, rex sole and Greenland turbot.[13] Of these flatfish species, yellowfin sole comprises the largest percentage of total retained catch by the fleet, approximately 57%.[14] An almost exclusively foreign group of vessels began targeting flatfish in the BSAI in mid 1950s. However, extremely high catch rates from 1959-1962 caused a dramatic decline in

[12] This method has also been used in the experimental economics literature to investigate heterogeneity (El-Gamal and Grether 1995, 2000; Anderson and Putterman 2006; Schnier and Anderson In press).
[13] In addition, a fair amount of Pacific cod and pollock is caught by these vessels. These two species compose approximately 8% and 6% of the total retained catch by these vessels. However, we do not incorporate them in the analysis as they are considered a bycatch species.
[14] We focus on retained catch in our analysis instead of total catch as we believe it more closely reflects the targeting practices of the fleet.

the fish population. With the creation of the Exclusive Economic Zone (EEZ), these foreign vessels were eventually expelled in favor of a domestic fishery. Populations within the flatfish fishery have since rebounded.

To represent the fixed inputs in production, F_j, we will rely on each vessel's measure of gross-registered tonnage and horsepower. The vector of exogenous fish stocks, S_j, is represented by the estimates of stock densities within the BSAI for the entire flatfish assemblage. This variable was calculated by aggregating the stock densities for the three primary flatfish target species (yellowfin sole, rock sole and flathead sole) for each year over the years 1994 through 2004. These estimates were obtained from the NMFS stock assessment reports in 2004 for the three primary species used to construct the total stock variable. The aggregate stock density, denoted *Stock*, was normalized relative to the stock densities reported in 1994.[15]

The vector of variable inputs, V_j, is represented by number of crew members on board during the week (*Crew*), the number of days fished during the week (*Days)* and the amount of time the gear was used during the week to harvest flatfish (*Duration*). Although data on the number of hauls made during the week was also available, trawl duration provides a finer resolution of gear use and for parsimony (as well as collinearity concerns) we chose to use duration instead of hauls. In addition, during the time period analyzed there has been a shift in the way many of the vessels fish. Although total fishing/towing duration has remained stable, vessels have increased the number of hauls during the week (and thus the average duration of each haul) to decrease haul size and increase the quality of the deliverable product. It is possible that this structural change in haul size could have impacted our ability to accurately characterize the contribution of hauls over the sample period, and provide misleading estimates for this new environment. Dummy variables could have been used to capture such effects, but by using duration instead we can avoid the need to estimate additional parameters.

The final input vector of production, C_j, is captured using the month (*Month*) that the fishing activity was reported in the weekly production reports. This control variable is used to capture seasonal variation in the migration of the flatfish species as well as the adverse climatic

[15] Initially we used each stock assessment for the three primary flatfish species as separate elements within S_j. However, we did not obtain substantially different results and given the high degree of collinearity possessed by these species, elected to aggregate the species into one index.

conditions present within the fishery. Yearly variations in the flatfish species composition are controlled for by the input vector S_j which varies over time.

Given that our application is a multi-species fishery, the output vector, Y_j, consists of all the flatfish species caught and described earlier. For parsimony we define four segment-specific output categories: catch of yellowfin sole $(Y_{Yellow|j})$, rock sole $(Y_{Rock|j})$, flathead sole $(Y_{Flat|j})$ and all other flatfish species caught and retained $(Y_{Agg|j})$. In addition to specifying the input and output vectors, we must also specify a functional representation of the production technologies. Here we will utilize the output distance function developed by Shephard (1970) and expand it to be segment specific. The segment-specific output distance function is predicated on the existence of a production transformation function for each segment *j*,

$$G_j(Y_j, F_j, S_j, V_j, C_j) = 0 \tag{6}$$

Furthermore the segment-specific output distance function represents the maximum proportional increase in the output vector that can occur to reach the production possibilities frontier, given the current level of inputs (F_j, S_j, V_j, C_j) for each segment. The output distance function is defined as,

$$D_j(F_j, S_j, V_j, C_j) = \min_{\lambda_j}\left\{\lambda_j > 0 : \left(\frac{Y_j}{\lambda_j}\right) \in Q_j(F_j, S_j, V_j, C_j)\right\} \tag{7}$$

where $Q_j(F_{j,}S_j, V_j, C_j)$ is the set of output vectors lying on or below the production possibilities frontier for segment *j* given the input vectors (F_j, S_j, V_j, C_j). If production within segment *j* is technically efficient the distance function, $D_j(\cdot)$, takes a value of 1. Otherwise, the distance function captures the degree of inefficiency possessed by the production process within segment *j*. The distance function can be directly related to the transformation function by scaling the output vector, Y_j, by $D_j(\cdot)$. This generates the following segment-specific transformation function,

$$G_j\left(\frac{Y_j}{D_j(F_j,S_j,V_j,C_j)},F_j,S_j,V_j,C_j\right)=0. \tag{8}$$

Conventionally, empirical applications of the distance production function normalize the distance function by dividing it through by one of the outputs within the vector Y_j (Paul et al. 2000), generating an observable left-hand-side variable. We have chosen to divide the output distance function by $Y_{Yellow|j}$, the species with the largest composition of retained catch. Therefore, the distance production function may be thought of as a ratio on outputs, $Y_j^* = Y_{-1|j} / Y_{Yellow|j}$, where $Y_{-1|j}$ are all the other outputs in vector Y_j. In addition, the output distance function is traditionally log transformed to the following,

$$-\ln(Y_{Yellow|j}) = G(\ln Y_j{*}, \ln F_j, \ln S_j, \ln V_j, \ln C_j) - \ln(D_j). \tag{9}$$

where $-\ln(D_j)$ represents the radial distance away from the production frontier and is captured by the error structure, $\varepsilon_{it|j}$, specified in equation (3). It is important to note, as discussed by Orea et al. (2005), that this assumption implies that the random component of production is symmetrically applied to all species within the output vector, Y_j. To further facilitate the interpretation of our econometric results we denote the dependent variable as $\ln(Y_{Yellow|j})$ instead of $-\ln(Y_{Yellow|j})$. Our econometric model is expressed as follows,

$$\begin{aligned}
\ln(Y_{Yellow|j}) &= \beta_{0|j} + \beta_{1|j}\ln(Nton_j) + \beta_{2|j}\ln(HP_j) + \beta_{3|j}\ln(Duration_j) + \beta_{4|j}\ln(Crew_j) + \beta_{5|j}\ln(Days_j) \\
&+ \beta_{6|j}\ln(Month_j) + \beta_{7|j}\ln(Y_{Rock|j}/Y_{Yellow|j}) + \beta_{8|j}\ln(Y_{Fsol|j}/Y_{Yellow|j}) + \beta_{9|j}\ln(Y_{Agg|j}/Y_{Yellow|j}) \\
&+ \beta_{10|j}\ln(Stock_j) + \beta_{11|j}(\ln(Y_{Rock|j}/Y_{Yellow|j}))^2 + \beta_{12|j}(\ln(Y_{Fsol|j}/Y_{Yellow|j}))^2 + \beta_{13|j}(\ln(Y_{Agg|j}/Y_{Yellow|j}))^2 \\
&+ \beta_{14|j}\ln(Nton_j)\ln(Duration_j) + \beta_{15|j}\ln(Nton_j)\ln(Days_j) + \beta_{16|j}\ln(Duration_j)\ln(Crew_j) \\
&+ \beta_{17|j}\ln(Days_j)\ln(Month_j) + \beta_{18|j}\ln(Y_{Rock|j}/Y_{Yellow|j})\ln(Y_{Fsol|j}/Y_{Yellow|j}) \\
&+ \beta_{19|j}\ln(Y_{Rock|j}/Y_{Yellow|j})\ln(Y_{Agg|j}/Y_{Yellow|j}) + \beta_{20|j}\ln(Y_{Rock|j}/Y_{Yellow|j})\ln(Stock_j) \\
&+ \beta_{21|j}\ln(Y_{Fsol|j}/Y_{Yellow|j})\ln(Y_{Agg|j}/Y_{Yellow|j}) + \beta_{22\,j}\ln(Y_{Fsol|j}/Y_{Yellow|j})\ln(Stock_j) \\
&+ \beta_{23|j}\ln(Y_{Agg|j}/Y_{Yellow|j})\ln(Stock_j) + \beta_{24|j}\ln(Month_j)\ln(Stock_j)
\end{aligned}$$

(10)

To obtain this specification we started with the full trans-log functional form of the model and due to multicollinearity concerns, eliminated interaction and squared parameters that were highly collinear.[16] This specification was further refined by eliminating interaction parameters that were insignificant using likelihood ratio tests, conditional on standard curvature conditions for the production possibilities frontier. All of the above mentioned restrictions were used to develop the homogeneous production function characterization, $J=1$. Furthermore, the functional form utilized in the heterogeneous production estimates is identical to the homogeneous model. Although it is possible for each segment j to possess its own functional form, we do not investigate this phenomenon. In addition, the specific curvature restrictions imposed on the homogeneous model were not imposed on the heterogeneous model, thereby allowing it to be mis-specified if the curvature restrictions are violated. The homogeneous model is a special case of the heterogeneous model, $J=1$, and therefore the restrictions that are appropriate for the homogeneous model may not be appropriate for the heterogeneous model.

Estimation of equation (10) is straight forward under the homogeneous assumption and was estimated via maximum likelihood in GAUSS. Estimating equation (10) in the context of heterogeneous production requires simulation techniques to obtain the parameter estimates which maximize the likelihood function. This is because the likelihood function expressed in equation (5) is not smooth and may possess a number of local maxima. Therefore, alternative techniques may be used to obtain the maximum such as using repeated random starting points (Anderson and Puttherman 2006; Schnier et al. 2006), simulated annealing (Schnier and Anderson in press) or genetic algorithms. For this study we use random starting points to generate the global maximum of our likelihood function.[17]

IV. Results, Capacity and Capacity Utilization Estimates

Estimation results assuming $J=1$ and $J=3$ are depicted in Table 1.[18] To determine the appropriate number of production technologies we utilized likelihood ratio tests, the Akiake Information

[16] Our criterion for this selection was a collinearity estimate of 0.9 or greater.
[17] We use 500 random starting points to determine the maximum likelihood function value.
[18] Estimation results assuming $J=2$ are available upon request from the author(s).

Criterion (AIC) and the Bayesian Information Criterion (BIC).[19] The results from these tests are depicted in Table 2. Due to the large number of parameters estimated per production technology (25) we were unable to estimate a *J=4* model. However, given the small number of vessels within the fleet (45) we believe that the *J=3* captures a majority of the production heterogeneity within the fleet and expanding to *J=4* may over-fit the data. The production elasticities assuming a homogeneous versus heterogeneous production technologies are depicted in Table 3.

The homogeneous production model, *J=1*, indicates that the most significant fixed input of production, F , is a vessel's size (*Net Tons*). In addition, all the variable inputs, V , are significant determinants of production. The most significant variable input in production is amount of time a vessel deploys their gear, *Duration.* The complements in the multi-species production vector are all of the expected sign and the second-order terms indicate that the presence of flathead sole, rock sole, and the other aggregate species decrease the portion of yellowfin sole caught at a decreasing rate. The only variable which is significant and not of the expected sign is the elasticity of flatfish stock densities within the Eastern Bering Sea, which is negative and statistically significant. Given that stock density estimates are the best available population densities for the entire fishery and not for the location a vessel fishes within, nor based on the temporal resolution of our data, weekly production, the interpretation of this result is not clear. However, given that it is the most resolute data available, and that a negative stock elasticity has been observed in other empirical applications in the Bering Sea (Felthoven 2002), we felt compelled to keep it in the model.

The empirical results for the heterogeneous production model, *J=3*, generate distinctly different production technology profiles within the flatfish fishery. The first production technology contains the largest number of vessels within the fleet, 30 of the 45 analyzed, and their production is primarily determined by the level of fixed inputs employed, *Horsepower* and *Net- tons*, as well as the amount of time their gear is deployed, *Duration.* The number of crew members employed and the number of days at sea within a week appear to have a minimal effect on their production technology.

[19] The Akiake Information Criterion (AIC) is $-2\ln(L)+2G$ and the Bayaesian Information Criterion (BIC) is $-2\ln(L)+G(\ln(N))$, where G is the number of parameters estimated in the model and N is the number of vessels in the fishing fleet.

These results stand in contrast to technologies two and three within the flatfish fishery. Both of these technologies possess a negative and statistically significant elasticity associated with *Horsepower* and an insignificant elasticity of *Net-tons.* This suggests that for these groups of vessels, greater output is associated with lower levels of horsepower. Close examination of the data reveals that each segment possesses a vessel with a very high ratio of average productivity to vessel horsepower (likely due to a high degree of skipper skill). However, when all vessels are lumped together in one representative technology, *J=1*, these anomalies tend to wash out and generate a well-behaved aggregate production technology.[20] This result is a direct violation of production theory and could either be generated by outliers in the data set or the misspecification of the production technology possessed by boats in the second and third technology profile. This could potentially be rectified by allowing for an alternative functional form to be possessed by each segment, for instance using only one fixed input of production in the estimation, but this generates an exorbitantly large number of production profiles which would be prohibitive to estimate given the time required to estimate the model using the EC algorithm.[21]

Aside from this similarity the production profiles possessed by these two technologies are substantially different. Technology two possesses a very high *Crew* influence whereas the third technology is strongly influenced by *Duration* and the number of *Days* in the week that they fish for flatfish. Furthermore technology two is differentiated from the other two technologies via the high impact of the *Month* in which they fish relative to the other vessels within the flatfish fishery. This suggests the vessels possessing technology two are strongly influenced by the season in which they chose to fish. This could either reflect the seasonality of their production behavior as they shift across fisheries or the limitations of their production technology to fish in the inclement weather in the early months of the year.

Tables 4 through 7 illustrate the vessel specific technical efficiency estimates generated as well as the resulting F^{TEi} measure proposed by Horrace (2005) and Flores-Lagunes et al. (2006) used to generate our new fleet capacity estimate $\overline{C}_j$ sorted on F^{TEi}. In the homogeneous production

[20] Within the two production technology model, *J=2*, this negative curvature violation arose as well. Both of the vessels possessing the high ratio of average productivity to horsepower were lumped together. In this model 36 vessels possessed a well-behaved production technology and 9 vessels possessed the negative curvature violation, two of which are driving the result in the *J=3* model.

[21] Alternative a research could utilize a more generalized finite mixture model which does not restrict the technology probabilities to be 0 or 1. This would presumably be able to capture the outliers in production by creating a technology which possesses this curvature violation yet assigns marginal weight to the probability of its occurrence.

model vessel 44 is the most technically efficient vessel, yet the probability that they are the most technically efficient vessel, F^{TEi}, is very small. Furthermore, the second most technically efficient vessel, vessel 40, possesses a zero probability of being the most technically efficient vessel. Vessel 15 possesses the highest probability of being the most technically efficient vessel within the fleet, despite that their ordinal technical efficiency ranking is third within the fleet. This result highlights the importance of using the efficiency probabilities over (or in conjunction with) the usual point estimate of technical efficiency, because using the technically efficiency measures alone, may produce erroneous policy recommendations. This can be seen looking at Tables 8 through 10 where the three measures of fleet capacity are estimated under the assumption of homogeneous, *J=1*, and heterogeneous, *J=2* and *3*, production technologies.

Under the homogeneous production technology assumption the measures of technically efficient fleet capacity, $\widetilde{C}_j$, are substantially greater than our revised measure of fleet capacity, $\overline{C}_j$. Fleet capacity estimates for $\widetilde{C}_j$ are between 1.74 and 1.84 times greater than those obtained using $\overline{C}_j$ depending on the assumptions regarding the amount of days fished within the fleet, V^{MAX}, $V^{0.25}$ and $V^{0.5}$. Both of these estimates utilize a vessel's technical efficiency score to predict their capacity. $\overline{C}_j$ utilizes the additional information contained in the second moment of a vessel's technical efficiency to generate a more statistically reliable measure of capacity, which not only controls for technical inefficiency but the variance in the technical efficiency measure as well. Comparing these results to those obtained without controlling for technical inefficiency, $\hat{C}_j$, illustrates that $\overline{C}_j$ provides a very close estimate to $\hat{C}_j$. In fact, $\overline{C}_j$ is below $\hat{C}_j$ in the homogeneous production technology model. However, given that both of these are based on predicted harvest rates, $\hat{Y}_j^O$, instead of the truly observed production levels these marginal differences could be explained by statistical noise in the econometric modeling. Where the relative differences in the three fleet capacity estimates become more interesting is when we begin to control for heterogeneity in the production technologies within the flatfish fishery.

In the heterogeneous production model, vessel 15 retains their top F^{TEi} ranking for vessels possessing the first production technology and their TE_i measure increases. Furthermore, vessel 40 which was the second most efficient vessel in the homogeneous production model possesses a much larger F^{TEi} score and possesses the largest TE_i measure. For the second and third production technologies the most technically efficient vessels, vessels 2 and 32 respectively, also possess the largest F^{TEi} scores within their respective production technologies. Both of these vessels were toward the bottom of the ordinal TE_i rankings and F^{TEi} scores in the homogeneous production model, suggesting that the homogeneous model did not accurately capture their respective production profiles.

Fleet capacity estimates in the heterogeneous production case further illustrate the advantages of utilizing heterogeneous production technologies as well as their respective F^{TEi} scores. Focusing on the fleet capacity estimates generated by $\widetilde{C}_j$ illustrate the differences between homogeneous and heterogeneous production technologies. In all three variable input utilization cases, V^{MAX}, $V^{0.25}$ and $V^{0.5}$, increasing the number of production technologies reduces the fleet capacity measure $\widetilde{C}_j$. This is a direct result of the increases in vessel specific technical efficiency which result from controlling for production heterogeneity. This is most pronounced with production technologies two and three, which possessed mean technical efficiency scores of 0.3350 and 0.5390 in the homogeneous case, whereas they increase to 0.6251 and 0.6693 in the heterogeneous production model, respectively. This resulted in a reduction of total $\widetilde{C}_j$ by roughly 35% for the *J=2* model and 37% for the *J=3* model. Therefore, relying on the homogeneous production measures of technically efficient capacity may yield incorrect estimates when heterogeneity exists.

The fleet capacity estimates generated using $\overline{C}_j$ under the heterogeneous production model yield slightly higher capacity estimates than in the homogeneous production model, yet share the same qualitatively differences with the $\widetilde{C}_j$ estimates. In both the *J=2* and *J=3* production model the measures of $\overline{C}_j$ where greater than those obtained using $\hat{C}_j$ and less than those obtained using $\widetilde{C}_j$. However, this does not hold within each production technology modeled. The second production technology in both the *J=2* and *J=3* model generated lower estimates of $\overline{C}_j$ than $\hat{C}_j$. The most dramatic difference occurs in the *J=3* model and is a direct result of the high TE_i and F^{TEi} measure possessed by vessel 2 and a correspondingly low level of flatfish production. The simultaneous occurrence of all three generates an anomalous fleet capacity estimate and should be cautiously interpreted.

In general the $\widetilde{C}_j$ fleet capacity estimates are substantially greater than the $\overline{C}_j$ estimates and the $\overline{C}_j$ estimates are greater than the $\hat{C}_j$ estimates, with the few exceptions noted earlier. This generalized result suggests that fleet capacity estimates generated using $\widetilde{C}_j$ overestimate the excess capacity possessed within the flatfish fishery because the $\overline{C}_j$ estimates utilize the same information contained $\widetilde{C}_j$ as well as the statistical reliability of the TE_i measures used to generate $\widetilde{C}_j$.

One additional benefit of using the $\overline{C}_j$ estimates of fleet capacity is its ability to provide an *out-of-sample* analysis of the expected production, generated by adding a vessel or vessels with similar characteristics to one of the production profiles. For instance, in the *J=3* production technology model, we conclude that adding another (out-of-sample) vessel to the first production technology class would generate an expected production level of 46,226 metric-tons of yellowfin sole over the time period 1994-2004 assuming that $V^{MAX} = days$. This expectation is based on the statistical estimation of all vessels possessing the first production technology and is obtained by multiplying each vessels $\widetilde{C}_j$ measure by their corresponding F^{TEi} and aggregating across all the vessels possessing the first production technology. This *out-of-sample* prediction of a representative vessel is not feasible using the $\widetilde{C}_j$ measures and is based on the statistical reliability of each vessel's TE_i. This result could be used to facilitate policy development by predicting future production levels given a change in regulatory policy.

The final measures of capacity analyzed, the vessel specific measures of capacity utilization, are depicted in Table 11 under the assumption of homogeneous, *J=1*, and heterogeneous, *J=2* and 3, production assumptions. Qualitatively the estimates for the homogeneous production model and those vessel possessing the first production technology in both the *J=2* and *J=3* model are very similar. However, the capacity utilization measures obtained under the heterogeneous production profiles indicate that vessels possessing production technology two in the *J=2* and technologies two and three in the *J=3* model on average operate closer to their productive capacities. In fact vessel's possessing the second production technology in the $J=3$ model are on average operating closer to capacity than any other production class within the flatfish fishery. This result further highlights the importance of utilizing heterogeneous production technologies because the fleet wide capacity utilization measures depicted are substantially different than those obtained in the homogeneous production model.

Conclusion

Many previous investigations into fleet capacity and vessel specific measures of capacity utilization have been based on estimating a homogeneous production technology and extrapolating a vessel's efficiency relative to a homogeneous production frontier. This research expands previous investigations in heterogeneous production (Schnier et al. 2006) by analyzing production in a multi-species fishery and utilizing the information contained in the simultaneous differences of the distributions of technical inefficiency for each vessel to construct an alternative measure of fleet capacity. Our production technology estimates indicate that ignoring heterogeneity in production may overestimate a fleet's capacity. Furthermore, utilizing complete distributional information of the fleets technical efficiency refines the fleet-wide estimate of capacity and suggests that traditional measures based on technically efficient production may generate substantially higher estimates which may be unreliable. Combined, these results highlight the importance of focusing on both production heterogeneity within fisheries as well as the statistical reliability of the technical efficiency measures generated using stochastic frontier models. Both of which should be beneficial for future policy development and especially for *out-of-sample* policy responses.

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Tables and Figures:

Figure 1: Homogeneous Production Model. Open circles represent one segment and the filled diamonds represent another production segment.

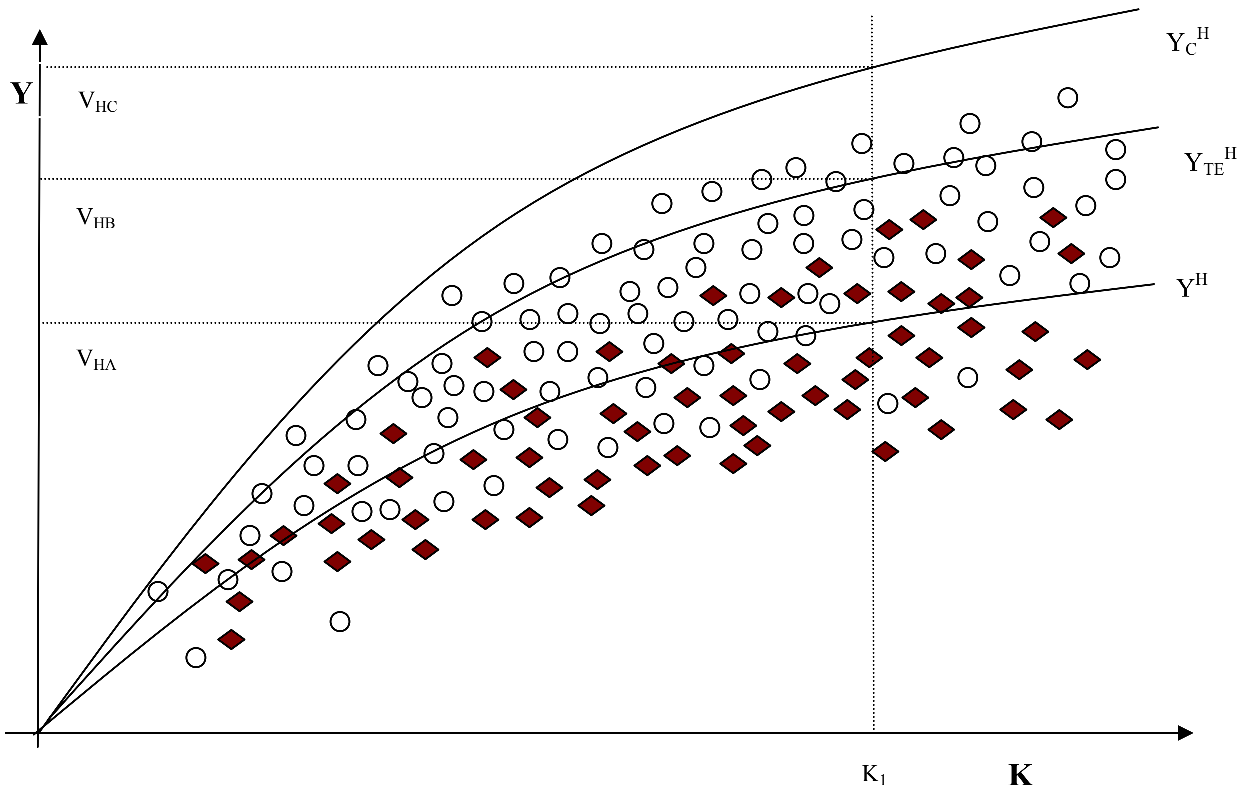

Figure 2: Heterogeneous Production Model. Open circles represent one segment and the filled diamonds represent another production segment.

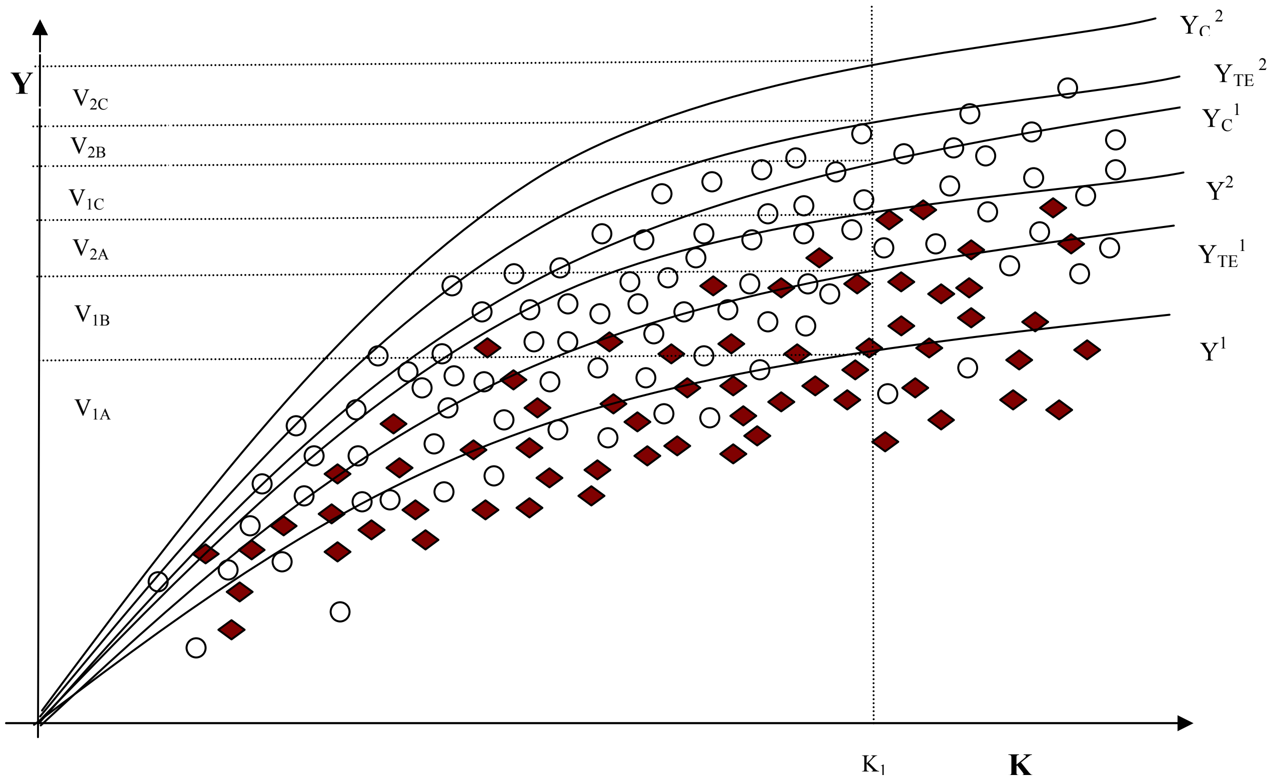

Table 1: Regression Results

Coefficient	Homogeneous Technology	Heterogeneous Technology 1	Heterogeneous Technology 2	Heterogeneous Technology 3
Constant	-5.8227**	-14.0679**	-2.5578	10.0996**
	(-3.19)	(-6.59)	(-0.35)	(2.91)
Net Tons	0.5759**	1.3500**	-0.1392	-0.1012
	(2.75)	(4.06)	(-0.09)	(-0.39)
Horse Power	-0.0973	0.9081**	-3.3821**	-1.3895**
	(-0.41)	(3.63)	(-2.89)	(-3.11)
Duration	0.8452**	2.3703**	3.5337*	-1.1919**
	(1.99)	(4.35)	(1.67)	(-2.05)
Crew	0.5258*	-0.5250	7.0358**	0.0183
	(1.84)	(-1.03)	(2.52)	(0.09)
Days	1.0680*	-0.9027	3.8060	1.8625**
	(1.65)	(-0.99)	(1.24)	(2.11)
Month	0.8432**	0.3421**	1.4978**	0.6880**
	(6.95)	(2.22)	(3.86)	(3.89)
Rsol/Ysol	-0.1086**	-0.0800**	-0.2074**	-0.1183**
	(-14.88)	(-8.65)	(-11.96)	(-9.20)
Fsol/Ysol	-0.1630**	-0.0260*	-0.2984**	-0.1612**
	(-18.10)	(-1.68)	(-17.07)	(-11.02)
Agg/Ysol	-0.3716**	-0.4955**	-0.3567**	-0.4082**
	(-38.61)	(-32.04)	(-19.49)	(-24.53)
Flatfish Stock	-3.4794**	-1.5382**	-5.8063**	-2.9828**
	(-6.13)	(-1.97)	(-3.41)	(-3.54)
$(Rsol/Ysol)^2$	-0.0131**	-0.0073**	-0.0302**	-0.0162**
	(-13.74)	(-6.20)	(-10.72)	(-8.77)
$(Fsol/Ysol)^2$	-0.0230**	-0.0043**	-0.0464**	-0.0264**
	(-16.50)	(-1.97)	(-14.83)	(-11.11)
$(Agg/Ysol)^2$	-0.0724**	-0.0594**	-0.0683**	-0.0676**
	(-50.06)	(-28.56)	(-19.26)	(-26.25)
(Net Tons)*(Duration)	-0.0584	-0.3659**	0.2453	0.1230
	(-0.92)	(-3.58)	(0.69)	(1.44)
(Net Tons)*(Days)	0.0559	0.3410**	-0.5061	-0.1336
	(0.56)	(2.51)	(-0.96)	(-0.93)
(Duration)*(Crew)	-0.0060	0.1251	-1.1122*	0.2779**
	(-0.96)	(1.01)	(-1.71)	(4.04)
(Days)*(Month)	-0.2971**	-0.2575**	-0.4191*	-0.1460
	(-4.53)	(-3.11)	(-1.88)	(-1.49)

Table 1: Regression Results (cont.)

(Rsol/Ysol)*(Fsol/Ysol)	0.0027**	0.0016**	0.0055**	0.0064**
	(4.82)	(2.30)	(3.27)	(6.34)
(Rsol/Ysol)*(Agg/Ysol)	0.0081**	0.0024**	0.0243**	0.0096**
	(9.02)	(2.25)	(9.87)	(5.10)
(Rsol/Ysol)*(Stock)	0.0055	0.0251	0.1531*	0.0180
	(0.15)	(0.64)	(1.73)	(0.40)
(Fsol/Ysol)*(Agg/Ysol)	0.0163**	0.0017	0.0346**	0.0162**
	(12.52)	(0.83)	(11.65)	(7.22)
(Fsol/Ysol)*(Stock)	0.0351	0.0544	-0.0582	0.0728
	(1.12)	(1.38)	(-0.59)	(1.36)
(Agg/Ysol)*(Stock)	-0.1105**	-0.1176**	-0.1231	-0.2014**
	(-2.53)	(-2.25)	(-0.81)	(-3.03)
(Stock)*(Month)	0.9362**	-0.1233	2.6454**	0.8259*
	(2.92)	(-0.30)	(2.83)	(1.77)
γ	0.4919**	-------	0.4894	-------
	(3.27)		(1.07)	
σ_S^2	1.9457**	-------	1.6382	-------
	(3.38)		(1.12)	
μ	0.5356	-------	-0.4701	-------
	(0.93)		(-0.18)	
# of Vessels	**45**	**30**	**6**	**9**
Mean Log-Likelihood	**-1.42755**		**-1.34046**	

(** indicates significant at the 95% level; * indicates significant at the 90% level.)

Table 2: Model Specification Tests

Classes	Parameters	Mean Ln(L)	LR Test	BIC	AIC
1	28	-1.42755	-------	12677.592	12627.005
2	53	-1.36536	547.645	12225.113	12129.360
3	78	-1.34046	219.269	12101.010	11960.091

Table 3: Elasticities of Production

Model/Parameter	Homogeneous	Heterog. j=1	Heterog. j=2	Heterog. j=3
Net-tons	0.4213	0.3723	0.0478*	0.2814*
Horsepower	-0.0973*	0.9081	-3.382	-1.389
Duration	0.4608	0.4670	1.300	0.5121
Crew	0.5005	0.0010*	2.253	1.214*
Days	0.9194	0.8853*	0.2039*	0.8418

(* indicates not statistically significant)

Table 4: Homogeneous Vessel Efficiency Results Sorted on F^{TEi}

Vessel Number	μ_i^*	σ_i^*	TE_i	F^{TEi}
15	-0.0193	0.0225	0.8966	0.58101
43	-0.0153	0.0274	0.8850	0.39426
41	-0.4978	0.4863	0.6982	0.02506
28	1.3759	0.4863	0.2968	0.00012
44	0.0526	0.0030	0.9340	0.00001
16	1.0476	0.2451	0.3823	0.00000
38	1.6840	0.3260	0.2169	0.00000
35	2.1173	0.3260	0.1416	0.00000
13	1.1020	0.1639	0.3580	0.00000
14	1.1062	0.1639	0.3566	0.00000
19	0.5996	0.0822	0.5620	0.00000
40	0.0860	0.0040	0.9088	0.00000
39	1.9372	0.1964	0.1590	0.00000
29	2.9775	0.2451	0.0576	0.00000
30	1.0069	0.0089	0.3670	0.00000
42	0.4548	0.0329	0.6425	0.00000
34	1.4593	0.1094	0.2455	0.00000
6	0.1270	0.0033	0.8803	0.00000
33	0.8635	0.0519	0.4327	0.00000

23	1.2530	0.0759	0.2967	0.00000
10	1.4112	0.0822	0.2538	0.00000
11	0.3811	0.0043	0.6846	0.00000
37	0.9089	0.0449	0.4121	0.00000
25	0.5687	0.0230	0.5728	0.00000
27	0.4612	0.0040	0.6318	0.00000
36	0.4833	0.0042	0.6180	0.00000
31	0.5207	0.0055	0.5958	0.00000
26	0.5565	0.0055	0.5748	0.00000
9	1.8449	0.0704	0.1637	0.00000
24	1.1751	0.0411	0.3152	0.00000
22	0.6192	0.0031	0.5392	0.00000
12	1.3382	0.0470	0.2686	0.00000
45	0.6519	0.0039	0.5225	0.00000
7	1.332	0.0095	0.4928	0.00000
5	1.6606	0.0519	0.1950	0.00000
4	0.8053	0.0122	0.4497	0.00000
32	0.7232	0.0029	0.4859	0.00000
18	2.4554	0.0759	0.0891	0.00000
1	0.7955	0.0034	0.4521	0.00000
21	0.8865	0.0048	0.4131	0.00000
3	0.9137	0.0076	0.4026	0.00000
2	1.3393	0.0267	0.2655	0.00000
8	1.0471	0.0049	0.3518	0.00000
17	1.7510	0.0395	0.1771	0.00000
20	1.3757	0.0274	0.2562	0.00000

Table 5: Heterogeneous Vessel Efficiency Sorted on F^{TEi} ; ***J=3; j=1***

Vessel Number	μ_i^*	σ_i^*	TE_i	F^{TEi}
15	-0.0886	0.0190	0.9222	0.90130
40	-0.0284	0.0034	0.9635	0.14784
19	-0.0670	0.0695	0.8374	0.07518
41	-1.0990	0.4094	0.7892	0.02492
14	0.4805	0.1384	0.6035	0.00002
35	1.1342	0.2749	0.3558	0.00000
13	0.6711	0.1384	0.5248	0.00000
39	1.0775	0.1659	0.3667	0.00000
27	0.0871	0.0033	0.9106	0.00000
23	0.6629	0.0641	0.5297	0.00000
34	0.9868	0.0925	0.3900	0.00000
9	0.6469	0.0596	0.5373	0.00000
11	0.2129	0.0036	0.8097	0.00000
43	0.3203	0.0232	0.7286	0.00000
20	0.3335	0.0232	0.7200	0.00000
42	0.4098	0.0278	0.6703	0.00000
21	0.2653	0.0041	0.7685	0.00000
10	1.0227	0.0695	0.3723	0.00000
31	0.2869	0.0046	0.7523	0.00000
12	0.7551	0.0397	0.4794	0.00000
37	0.7678	0.0379	0.4729	0.00000
1	0.4057	0.0029	0.6675	0.00000
5	0.9580	0.0439	0.3922	0.00000
25	0.5502	0.0194	0.5824	0.00000
17	0.8306	0.0334	0.4431	0.00000
3	0.4846	0.0064	0.6180	0.00000
45	0.5067	0.0033	0.6034	0.00000
24	1.0357	0.0348	0.3612	0.00000
36	0.8206	0.0035	0.4410	0.00000
30	0.9410	0.0075	0.3917	0.00000

Table 6: Heterogeneous Vessel Efficiency Sorted on F^{TEi} ; ***J=3; j=2***

Vessel Number	μ_i^*	σ_i^*	TE_i	F^{TEi}
2	-0.0172	0.0226	0.8957	0.98270
28	0.3570	0.4094	0.5640	0.01091
38	0.4180	0.2749	0.5829	0.00669
22	0.1191	0.0027	0.8876	0.00000
29	1.2435	0.2069	0.3172	0.00000
4	0.6914	0.0103	0.5035	0.00000

Table 7: Heterogeneous Vessel Efficiency Sorted on F^{TEi} ; ***J=3; j=3***

Vessel Number	μ_i^*	σ_i^*	TE_i	F^{TEi}
32	0.0382	0.0025	0.9451	0.96290
16	0.2778	0.2069	0.6472	0.03710
44	0.0799	0.0025	0.9185	0.00000
33	0.4689	0.0439	0.6340	0.00000
26	0.2701	0.0046	0.7650	0.00000
7	0.3212	0.0080	0.7282	0.00000
8	0.3624	0.0042	0.6975	0.00000
6	0.5727	0.0028	0.5648	0.00000
18	2.1220	0.0641	0.1237	0.00000

Table 8: Fleet Capacity Estimates ($V^{MAX} = days$)

	$\hat{Y}_j(F_j, S_j, V_j)$	$\hat{C}_j$	$Y_j^{TE}(F_j, S_j, V_j)$	$\widetilde{C}_j$	$\overline{C}_j$
J=1	1,434,210	1,737,207	3,422,634	4,167,582	1,525,143
J=2; j=1	931,136	1,152,410	1,652,989	2,060,881	1,386,766
J=2; j=2	332,593	376,680	585,942	641,737	335,048
Total	1,263,729	1,529,090	2,238,931	2,702,618	1,721,814
J=3; j=1	796,307	990,832	1,359,849	1,696,781	1,412,682
J=3; j=2	260,174	270,449	299,389	311,124	18,763
J=3; j=3	263,017	312,223	492,228	600,923	402,190
Total	1,319,498	1,573,504	2,151,466	2,608,828	1,833,635

Table 9: Fleet Capacity Estimates ($V^{0.25} = days$)

	$\hat{Y}_j(F_j, S_j, V_j)$	$\hat{C}_j$	$Y_j^{TE}(F_j, S_j, V_j)$	$\widetilde{C}_j$	$\overline{C}_j$
J=1	1,434,210	1,568,064	3,422,634	3,762,251	1,322,635
J=2; j=1	931,136	1,023,671	1,652,989	1,823,842	1,130,229
J=2; j=2	332,593	353,804	585,942	611,691	329,477
Total	1,263,729	1,377,475	2,238,931	2,435,633	1,459,706
J=3; j=1	796,307	874,607	1,359,849	1,495,596	1,129,345
J=3; j=2	260,174	266,800	299,389	306,705	19,348
J=3; j=3	263,017	285,310	492,228	534,204	381,503
Total	1,319,498	1,426,717	2,151,466	2,336,505	1,530,196

Table 10: Fleet Capacity Estimates ($V^{0.50} = days$)

	$\hat{Y}_j(F_j, S_j, V_j)$	$\hat{C}_j$	$Y_j^{TE}(F_j, S_j, V_j)$	$\tilde{C}_j$	$\overline{C}_j$
J=1	1,434,210	1,642,848	3,422,634	3,952,422	1,401,642
J=2; j=1	931,136	1,076,517	1,652,989	1,922,685	1,215,709
J=2; j=2	332,593	376,604	585,942	640,301	335,048
Total	1,263,729	1,453,121	2,238,931	2,562,986	1,550,757
J=3; j=1	796,307	992,635	1,359,849	1,701,740	1,412,682
J=3; j=2	260,174	270,272	299,389	310,637	19,083
J=3; j=3	263,017	298,266	492,228	561,566	394,419
Total	1,319,498	1,561,173	2,151,466	2,573,934	1,826,184

Table 11: Capacity Utilization Measures CU

Model/CU measure	Mean	Std. Dev.
J=1		
CU^{Days}	0.8156	0.2054
$CU^{0.25}$	0.8990	0.0874
$CU^{0.5}$	0.8567	0.1334
J=2		
CU^{Days}; $j=1$	0.8100	0.2140
$CU^{0.25}$; $j=1$	0.9008	0.0880
$CU^{0.5}$; $j=1$	0.8563	0.1365
CU^{Days}; $j=2$	0.8892	0.1505
$CU^{0.25}$; $j=2$	0.9346	0.0702
$CU^{0.5}$; $j=2$	0.8892	0.1505
J=3		
CU^{Days}; $j=1$	0.8090	0.2137
$CU^{0.25}$; $j=1$	0.9014	0.0880
$CU^{0.5}$; $j=1$	0.8082	0.2137
CU^{Days}; $j=2$	0.9668	0.1359
$CU^{0.25}$; $j=2$	0.9794	0.0533
$CU^{0.5}$; $j=2$	0.9726	0.0799
CU^{Days}; $j=3$	0.8408	0.1834
$CU^{0.25}$; $j=3$	0.9084	0.0796
$CU^{0.5}$; $j=3$	0.8727	0.1196