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

Ronald G. Felthoven

William C. Horrace
Syracuse University

Kurt E. Schnier
University of Rhode Island

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**Center for Policy Research
Working Paper No. 86**

ESTIMATING HETEROGENEOUS
CAPACITY AND CAPACITY UTILIZATION
IN A MULTI-SPECIES FISHERY

**Ronald G. Felthoven, William C. Horrace,
and Kurt E. Schnier**

**Center for Policy Research
Maxwell School of Citizenship and Public Affairs
Syracuse University
426 Eggers Hall
Syracuse, New York 13244-1020
(315) 443-3114 | Fax (315) 443-1081
e-mail: ctrpol@syr.edu**

November 2006

$5.00

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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. Furthermore, our new estimate of capacity enables *out-of-sample* production predictions predicated on either homogeneity or heterogeneity modeling which may be utilized to facilitate policy.

I. Introduction:

Efficient management of natural resources hinges on our ability to monitor and assess the status of resource stocks as well as the actions and economic performance of agents using these 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. Limitations and uncertainty associated with available data, particularly in the fishing industry, make estimating capacity and capacity utilization of these agents particularly difficult. Compounding these difficulties is the heterogeneous nature of agents using the resource. Heterogeneity implies that multiple production technologies may exist, which must be accounted for when trying 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 [13] 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 to investigate and control for production heterogeneity. Furthermore, it is important that we use measures that better incorporate information on the statistical reliability of our 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 uses information on the *stochastic dominance* 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 around the globe [13]. 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). The increased prevalence of these 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 in fisheries.

Input controls are often used to control overcapacity in a fishery, which in turn homogenize the effort exerted by members of the fleet and reduces their ability to fully use available technology and vessel capital. However, the success of input control regulations is contingent on the vessel's inability to

2

substitute out of the regulated input into another unregulated input [23]. 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 [17]. Alternatively, a transition to dedicated access privileges, such as individual transferable

fishing quotas, has been argued as a cost-effective solution to overcapacity as less efficient vessels are

bought out by more efficient vessels within the fleet [40, 22]. 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 a consensus on the definition of capacity,

or a means of estimating it, within the fisheries literature [20], and thus alternative and improved

definitions may be warranted.

However, one common thread among existing studies of fishery capacity is the need to estimate

production technology in a manner consistent with economic theory.[1] Currently, there are two primary

methods used to estimate fishery production technologies: data envelope analysis (DEA) [21, 19, 30] and

stochastic production frontier (SPF) models [31, 10, 39, 15, 22]. DEA does not assume a parametric form

for the production technology and is therefore a more general and flexible model. However, DEA models

used in fisheries measure a deterministic production frontier, whereas SPF estimates a stochastic frontier

which accounts for unexplained production variability, but in a less flexible, parametric framework.

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 vessel-specific component and random error component.[2] The

method adopted in this research is a latent class stochastic production frontier model (LSPF) [35], 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 [11]. This

measure defines capacity as the maximum feasible output that can be produced given the current level of

technological, 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 which incorporates behavioral assumptions such as cost minimization or profit maximization.

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[1] Ad hoc approaches such as the "peak to peak" method have been used in the past, which prompted many authors to
discuss their limitations and suggest more rigorous methodologies.

[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 [10] and [20].

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 unmeasurable, variation in environmental conditions. Addressing the former concern is readily achieved using ray production functions [10] or distance functions [26].[3] In our example, 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,[4] to control for unobservable variation in the production frontier, and to generate our new measure of fleet capacity. This new measure incorporates information on the second moment of a vessel's technical efficiency score to determine the probability of *stochastic dominance* of efficiency over other vessels within the fleet.

Another motivation for our work is that current estimates of capacity and capacity utilization assume that all agents operate with the same production technology. This presumes that each vessel possesses identical output elasticities, elasticities of substitution, marginal rates of transformation, and returns to scale (among other things). This implies that these 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) enacted to mitigate risks associated with excess capacity.[5] Obviously the output elasticity of a particular input is likely to be higher for a more productive vessel, *ceteris paribus*. However, if they have the same technology and we observe the same input bundles, we would incorrectly conclude that the addition of one input would have the same effect on output. This is an erroneous conclusion, 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 sub-fleets or groups of vessels. The latent class model used in this paper allows for both of these phenomena to be investigated and measured, 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 [37, 38]. In fisheries, random coefficient models have been used to investigate heterogeneity in site choice modeling for commercial fisheries [25, 36] as well as

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[3] For a comparison of the two methods used to estimate multi-species fishery production see [14].
[4] The modeling approach we propose can be utilized within a ray production function framework as well.
[5] 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.

recreational fisheries [29]. Although these models could be adapted to investigate heterogeneity in production technologies within fisheries, they do not allow the estimation of vessel-specific capacity and capacity utilization measures [6], which are necessary to inform policy in many contexts. To obtain vessel-specific measures of capacity we use the latent class regression method developed by El-Gamal and Grether [6,7], the EC algorithm. Alternatively, one could estimate the latent class production functions using finite mixture regressions [27]. 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

We define J different production technology groups (segments), indexed by $j = 1,...,J$. Within each segment operate N_j vessels, indexed by $i = 1,...,N_j$. Each vessel operates in weekly time periods $t = 1,...,T_i$. Therefore, a vessel's deterministic production function is:

$$ Y_{it|j} = Y_j(K_i, S_t, V_{it}, days_{it}, E_{it}, M_{it}, TE_i) , \quad j = 1,...,J , \quad i = 1,...,N_j , \quad t = 1,...,T_i . \quad (1) $$

Let K_i be a vector of quasi-fixed inputs of production, such as a vessel's horsepower and size, which are assumed to be fixed during the time horizon analyzed.[7] Let S_t be a vector of exogenous input stocks, such as the current stock level of the target species within a fishery. Let V_{it} be a vector of variable inputs and potentially the amount of time the fishing gear is deployed. Let $days_{it}$ be the number of 'days fished per week', also a variable input. We make 'days fished per week' explicit in our function, because this is the time-varying input that we adjust to calculate capacity for each vessel (any time-varying input or inputs would suffice). Let E_{it} be a vector of variables 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. Let M_{it} be a vector of other species harvested in conjunction with the target species in a multi-species fishery. Finally, let TE_i be a scalar measure of a vessel's level of technical efficiency normalized on the unit interval.[8]

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[6] A random coefficients stochastic frontier model has been developed by Greene [16].
[7] This assumption implies that the estimates of capacity we obtain are short-run estimates of *primal* capacity.
[8] In the empirical section we let vessel efficiency be stochastic. We also augment the production function with a random errors term independent of efficiency.

There are two measures of capacity we are interested in calculating: fleet capacity and a vessel-specific measure of capacity utilization. These measures are a function of the available inputs (both quasi-fixed and variable) and maximal output produced from these inputs. Assuming that there exist J distinct production technologies within the fishery, we define three different measures of fleet capacity, C, and one measure of capacity utilization, CU. The challenge of measuring capacity and capacity utilization is in defining the appropriate output measure for each vessel used in the capacity calculation. One common measure of fleet capacity is:

$$C^{MAX} = \sum_{j=1}^{J} C_j^{MAX} , \quad C_j^{MAX} = \sum_{i=1}^{N_j} \sum_{t=1}^{T_i} Y_{it|j}^{MAX} \tag{2}$$

where output is $Y_{it|j}^{MAX} = Y_j(K_i, S_t, V_{it}, days_i^{MAX}, E_{it}, M_{it}, TE_i)$, and $days_i^{MAX} = \max_t \{days_{it}\}$. The

$days_i^{MAX}$ is the maximal level of the primary variable inputs utilized by vessel i. The $Y_{it|j}^{MAX}$ is the level of output each vessel may derive from their quasi-fixed input base, given the *maximum* observed 'days fished per week.' Notice that $Y_{it|j}^{MAX} \geq Y_{it|j}$. Alternatively, one could substitute the technically efficient output,

$$Y_{it|j}^{TE} = Y_j(K_i, S_t, V_{it}, days_{it}, E_{it}, M_{it}, TE_i = 1) , \tag{3}$$

for Y_j^{MAX} in equation (2). Notice that $days_i^{MAX}$ is not used in this last formulation of maximal output. However, this measure would likely underestimate fleet capacity, since often $Y_{it|j}^{MAX} > Y_{it|j}^{TE}$.[9] A second commonly used measure of fleet capacity is,

$$C^{TE,MAX} = \sum_{j=1}^{J} C_j^{TE,MAX} , \quad C_j^{TE,MAX} = \sum_{i=1}^{N_j} \sum_{t=1}^{T_i} Y_{it|j}^{TE,MAX} \tag{4}$$

where,

$$Y_{it|j}^{TE,MAX} = Y_j(K_i, S_t, V_{it}, days_i^{MAX} E_{it}, M_{it}, TE_i = 1) , \tag{5}$$

which represents the technically efficient level of output producible by vessel i assuming maximum utilization of the primary variable input. Not only is the primary variable input at its maximal value, but vessels are assumed to be 100% efficient. Clearly, $Y_{it|j}^{TE,MAX} \geq Y_{it|j}^{MAX}$, so $C^{TE,MAX} \geq C^{MAX}$.

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[9]This may not be true if a vessel is very inefficient and expending a lot of effort for their size. In this case the capacity utilization score could be high, and $Y_{it|j}^{MAX}$ could be less than $Y_{it|j}^{TE}$.

The previous measure of fleet capacity, $C^{TE,MAX}$, assumes that a vessel's technical efficiency is a fixed parameter in its production function. Ultimately, we assume in the modeling exercise that technical efficiency (or more precisely *inefficiency*) is a random draw from a positive distribution and estimate technical efficiency as the mean of this distribution [18,12]. This parameter estimate is then used for TE_i in the above formula. However, this procedure ignores that fact that efficiency is actually (by assumption) a random draw, and that for any given draw, the rank ordering of the vessel's efficiency may change. Therefore, our final estimate of fleet capacity incorporates the *probability* that a vessel is the most technically efficient vessel in the fleet. Call this probability,

$$F^{TE_i|j} = \Pr\{ \text{ inefficiency draw of vessel } i < \text{inefficiency draw of vessel } k, i \neq k \mid \text{segment } j \}$$

$$= \Pr\{ \text{ vessel } i \text{ is most efficient in segment } j \}.$$

The notation F is used because the probability is derived from a cumulative distribution function of a multivariate truncated normal distribution [18]. For details on the estimation of this probability in a SPF model see Horrace [18]. Then, our proposed measure of fleet capacity is defined as,

$$C^{P,MAX} = \sum_{j=1}^{J} C_j^{P,MAX} , \qquad C_j^{P,MAX} = N_j \sum_{i=1}^{N_j} F^{TE_i|j} Y_{it|j}^{TE,MAX} \qquad (6)$$

This last measure of fleet capacity refines the fleet-wide measure of capacity by assigning more weight to those vessels which possess a higher probability of being the most technically efficient. 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 in segment j is a statement on the extent to which the vessel *stochastically dominates* all other vessels in j.) The relative magnitudes of $C^{P,MAX}$ and $C^{TE,MAX}$ will depend on probability weights, $F^{TE_i|j}$, for each vessel in each segment. If the high-output vessels *stochastically dominate* other vessels in term of $F^{TEi|j}$, then $C^{P,MAX}$ will be greater than $C^{TE,MAX}$. If the low-output vessels *stochastically dominate* the other vessels, then $C^{TE,MAX}$ will be greater than $C^{P,MAX}$. Either way, estimates of $C^{P,MAX}$ will refine our capacity estimates by incorporating additional information contained in the efficiency probabilities.

Ultimately, all three measures will be estimated by estimating the production function $Y_j(K_i, S_t, V_{it}, days_{it}, E_{it}, M_{it}, TE_i)$ for different technologies $j = 1,2,3$ using the EC algorithm. (We will discuss the empirical differences in the capacity estimates in the sequel.) Furthermore, to investigate the sensitivity of our capacity analysis to the selection of the full capacity values of variable inputs, we use two additional measures which quantify capacity at 125% and 150% of current 'days fished per week.'

That is, we will substitute $\min(1.25 \cdot days_{it}, 7)$ and $\min(1.50 \cdot days_{it}, 7)$ for $days_i^{MAX}$ in equations 2, 4, and 6, where 'min' is the minimum of the two arguments in parentheses. This will produce measures, C^{25}, C^{50}, $C^{TE,25}$, $C^{TE,50}$, $C^{P,25}$, and $C^{P,50}$ respectively . For example,

$$C^{25} = \sum_{j=1}^{J} C_j^{25} , \qquad C_j^{25} = \sum_{i=1}^{N_j}\sum_{t=1}^{T_i} Y_{it|j}^{25} \tag{7}$$

where output is $Y_{it|j}^{25} = Y_j(K_i, S_t, V_{it}, \min(1.25 \cdot days_{it}, 7), E_{it}, M_{it}, TE_i)$.

Each vessel's *capacity utilization* is expressed as the ratio of their normal output to their capacity output level.[10] We select,

$$CU_i^{TE,MAX} = \frac{Y_{it|j}}{Y_{it|j}^{TE,MAX}} \leq 1, \quad i = 1,...,N_j, \; j = 1,...,J . \tag{8}$$

The closer $CU_i^{TE,MAX}$ is to one, the less excess capacity the vessel possesses. [11]   The inverse of $CU_i^{TE,MAX}$ indicates how much the vessel's production could increase were it to fully utilize inputs in the short-run, given technical efficiency and maximal 'days fished per week.' [12] We also specify capacity utilization at 125% and 150% of 'days fished per week,' producing $CU_i^{TE,25}$ and $CU_i^{TE,50}$, as with capacity. Since capacity utilization measures are vessel specific, we cannot incorporate the relative probabilities of efficiency, F^{TEi}, into their calculation in any practical way.[13]

The latent class model identifies differences in output elasticities among the J production technologies, leading to curvature differences between groups of vessels. The magnitude of these differences determines the degree to which a homogeneous estimate of capacity will over/under measure heterogeneous capacity for a given vessel. Figures 1 and 2 illustrate these differences when one assumes a homogeneous versus heterogeneous model and the degree of over/under measure of capacity generated by the homogeneous model assumption, when there exists two distinct production technologies, $J = 2$.

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[10] There are number of issues that must be addressed when defining capacity measures, for a more detailed discussion of these issues see [20].

[11] Alternatively, we could estimate capacity utilization $Y_{it|j}^{TE} / Y_{it|j}^{TE,MAX}$ as proposed by [9] which is 'unbiased' because it is not directly influenced by technical inefficiency.

[12] Ultimately, we estimate both the denominator *and* the numerator from a regression model, even though we have the *actual* data on the numerator. This is to ensure the capacity utilization is, indeed, less than 1.

[13] This is because the vessel specific probabilities in the numerator and denominator of capacity utilization would cancel.

Consider Figure 1, which graphs observations of output, Y, as a function of capital, K, assuming $J = 2$. That is, there are two different technologies generating the data; one technology is high-output (circles), while the other is low-output (diamonds). Estimation of a homogenous production function for these data might produce function Y. In this environment the two segments are evaluated as one and the production frontier is the average of the two technologies which lies predominately above the low-output technology (diamonds) and below the high-output technology (circles). Capacity output function might be $Y^{TE,MAX}$ (technically efficient, with maximal primary variable input, days fished). Then the homogenous capacity utilization at $K = K_i$ is $Y_i / Y_i^{TE,MAX}$. Figure 2, depicts the same observations but with different (heterogeneous) production functions estimated for each technology Y_1 and Y_2. Heterogeneity of the estimates produces a better fit for the two distinct production technologies (circles and diamonds). The technology-specific estimates of capacity utilization are $Y_{ji} / Y_{ji}^{TE,MAX}$, $j = 1, 2$, for the low-output (diamonds) and high-output (circles) technologies, respectively. These capacity utilization estimates appear to be larger than the homogenous capacity utilization estimate implied by Figure 1. This implies that there is less overcapacity in the heterogeneous model than the homogeneous model.

In general, aggregate 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 that the measures of 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 vessels possess this technology, then the increase in output associated with increased variable input (used for capacity output) will be also be large. Capacity output measures for this group of vessels will, in turn, be more precise than in the homogenous model, which would underestimate capacity. However, the total impact of model misspecification (mistaking a heterogeneous production for homogenous production) depends on the number of vessels which possess distinct technologies and the nature and extent of the differences between them. Presumably, the effects of misspecification will be lessened when the differences between technologies are symmetric, since the homogeneous model represents the average production process for the different segments. We also note that the issues discussed above also apply to measures of capacity utilization, since it is the ratio of capacity output to observed output.

Calculation proceeds by the estimation of a latent class production function and estimation of vessel-specific technical (in)efficiency within each class. That is,

$$\hat{Y}_{it|j} = \hat{Y}_j(K_i, S_t, V_{it}, days_{it}, E_{it}, M_{it}, \hat{TE}_i), \quad j = 1, \ldots, J, \tag{9}$$

leading to output estimates,

$$\hat{Y}_{it|j}^{MAX} = \hat{Y}_j(K_i, S_t, V_{it}, days_i^{MAX}, E_{it}, M_{it}, \hat{TE}_i), \tag{10}$$

and

$$\hat{Y}_{it|j}^{TE,MAX} = \hat{Y}_j(K_i, S_t, V_{it}, days_i^{MAX}, E_{it}, M_{it}, TE_i = 1). \tag{11}$$

These are then plugged in our capacity and capacity utilization measures to produces corresponding estimates. For example,

$$\hat{C}^{25} = \sum_{j=1}^{J} \hat{C}_j^{25}, \quad \hat{C}_j^{25} = \sum_{i=1}^{N_j} \sum_{t=1}^{T_i} \hat{Y}_{it|j}^{25} \tag{12}$$

where output is $\hat{Y}_{it|j}^{25} = \hat{Y}_j(K_i, S_t, V_{it}, \min(1.25 \cdot days_{it}, 7), E_{it}, M_{it}, \hat{TE}_i)$.

ESTIMATION

To estimate the heterogeneous production technologies and determine the appropriate number of technologies, *J*, within the population, we emply a LSPF model [35]. The LSPF model is based on a *j*-technology production function with each technology possessing the following functional representation,

$$Y_{it|j} = f(X_{it}\beta_j)\exp\{\varepsilon_{it|j}\}, \tag{13}$$

where $X_{it} = [K_i, S_t, V_{it}, days_{it}, E_{it}, M_{it}]$ and β_j is the appropriately dimensioned vector of marginal products. The stochastic error $\varepsilon_{it|j}$ is composed of two components to generate the stochastic frontier model [1, 24] and is specified as,

$$\varepsilon_{it|j} = v_{it|j} - u_{i|j}. \tag{14}$$

The first error component, $v_{it|j}$ is an independently and identically distributed $N(0, \sigma_v^2)$ random variable, and $u_{i|j}$ is a one-sided, non-negative vessel specific error term drawn from a truncated $N(\mu, \sigma^2)$, with truncation below zero.[14] Let $v_{it|j}$ and $u_{i|j}$ be independent and uncorrelated with the inputs measures. Given these distributional assumptions, the log-likelihood function is [4,5],

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[14] Each of the *j* technologies share the same distributional parameters for $v_{it|j}$ and $u_{i|j}$. The model is 'ill-posed' without this assumption [8].

$$L(Y_{it}, X_{it}, \beta_j, \gamma, \sigma_S^2, \mu) = -\frac{1}{2}\left(\sum_{i=1}^{N} T_i\right)\log(2\pi) - \frac{1}{2}\sum_{i=1}^{N}(T_i - 1)\log[(1-\gamma)\sigma_S^2] - \frac{1}{2}\sum_{i=1}^{N}\log\{\sigma_S^2[1 + (T_i - 1)\gamma]\}$$

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

$$+ \frac{1}{2}\sum_{i=1}^{N}z_i^{*2}$$

where,

$$z = \frac{\mu}{(\sigma_S^2\gamma)^{1/2}}, \quad z_i^* = \frac{\mu_j(1-\gamma_j) - T_i\gamma_j(\bar{Y}_i - \bar{X}_i\beta_j)}{(\gamma_j(1-\gamma_j)\sigma_S^2[1+(T_i-1)\gamma_j])^{1/2}}, \quad \bar{Y}_i = \frac{\sum_{t=1}^{T_i}Y_{it}}{T_i}, \quad \bar{X}_i = \frac{\sum_{t=1}^{T_i}X_{it}}{T_i},$$

and where.

$$\gamma = \frac{\sigma_v^2}{\sigma_S^2}, \text{ and } \sigma_S^2 = (\sigma_v^2 + \sigma^2). \tag{15}$$

The EC algorithm proceeds by pre-specifying the number of production technologies within the data, J, and then obtaining parameter estimates assuming that 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 production technologies, given $(\beta_1,...,\beta_J)$. This is specified as follows,

$$L(Y_{it|j}, X_{it}, \beta_1,...,\beta_J, \gamma, \sigma_S^2, \mu) = \sum_{j=1}^{J}\arg\max_j \sum_{t=1}^{Ti}L(Y_{it}, X_{it}, \beta_j, \gamma, \sigma_S^2, \mu) \tag{16}$$

To determine the optimal number of latent production technologies, J^*, estimates are calculated assuming a number of different technologies, $j = 1,...,J^*$, and likelihood ratio tests, corrected Akaike Information Criterion (crAIC), and Bayesian Information Criterion (BIC) are used to determine the optimal number of latent types within the data set. This method is identical to that used by Schnier et al. [35] to identify heterogeneous measures of technical efficiency, but this is the first time it has been used to obtain capacity measures.[15]

Numerical maximization of this likelihood function returns consistent estimates $\hat{\beta}_j$, $\hat{\gamma}$, $\hat{\sigma}_S^2$, and $\hat{\mu}$. Equation 15 returns consistent $\hat{\sigma}_v^2$ and $\hat{\sigma}^2$. The distributional assumptions in the error components imply that the distribution of $u_{i|j}$ conditional on $\varepsilon_{it|j}$ $t = 1,...,T_i$ is that of a $N(\mu_i^*, \sigma_i^{*2})$ random variable truncated below zero [4,5], where,

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[15] This method is used in the experimental economics literature to investigate heterogeneity [6, 7, 2, 34].

$$\mu_{i|j}^{*} = \left\{ \mu\sigma_v^2 - \sigma^2 T_i \bar{\varepsilon}_{i|j} \right\} \Big/ \left\{ \sigma_v^2 + T_i \sigma^2 \right\} \tag{17}$$

$$\bar{\varepsilon}_{i|j} = \frac{1}{T_i} \sum_{t=1}^{T_i} \varepsilon_{it|j} \tag{18}$$

$$\sigma_i^{*2} = \frac{\sigma^2 \sigma_v^2}{\sigma_v^2 + T_i \sigma^2}. \tag{19}$$

This distribution has conditional mean [3],

$$E[u_{i|j} \mid \varepsilon_{it|j}, t = 1, ..., T_i] = \mu_{i|j}^{*} + \sigma_i^{*} \left\{ \phi\left(-\mu_{i|j}^{*}/\sigma_i^{*}\right)\left[1 - \Phi\left(-\mu_{i|j}^{*}/\sigma_i^{*}\right)\right]^{-1} \right\}, \tag{20}$$

where ϕ and Φ are the probability density and cumulative distribution of a standard normal random variable, respectively. In what follows, we will abbreviate the conditional mean as $E[u_{i|j} \mid \varepsilon_{i|j}]$ where

$\varepsilon_{i|j}$ is a $T_i \times 1$ vector. Estimates $\hat{\mu}_{i|j}^{*}$ and $\hat{\sigma}_i^{*}$ are calculated by substituting $e_{it|j} = Y_{it|j} - X_{it}\hat{\beta}_j$ for $\varepsilon_{it|j}$

in equation 18 (see [3] and [18]). Then $E[u_{i|j} \mid \varepsilon_{i|j}]$ in equation 20 is estimated by $E[u_{i|j} \mid e_{i|j}]$.

Estimates of efficiency probabilities, $F^{TE_i|j}$, are given in Horrace [18] and are based on $\hat{\mu}_{i|j}^{*}$ and $\hat{\sigma}_i^{*}$.

To generate output for our capacity and capacity utilization measure we use output estimates

$\hat{Y}_{it|j} = X_{it}\hat{\beta}_j$, but adjusted for differing values of the primary variable input (*days*) and also adjusted for

the conditional mean of efficiency, $E[u_{i|j} \mid e_{i|j}]$. That is,

$$\hat{Y}_{it|j} = X_{it}\hat{\beta}_j = \hat{Y}_j(K_i, S_t, V_{it}, days_{it}, E_{it}, M_{it}, TE_i = 1)$$

is the efficient output at nominal inputs. Then

$$\hat{Y}_{it|j}^{MAX} = \hat{Y}_j(K_i, S_t, V_{it}, days_i^{MAX}, E_{it}, M_{it}, TE_i = 1) - E[u_{i|j} \mid e_{it|j}],$$

is inefficient output at maximal primary variable input (maximal production with deviation from the

efficient frontier). Efficient output at maximal primary variable input is .

$$\hat{Y}_{it|j}^{TE,MAX} = \hat{Y}_{it|j}^{MAX} + E[u_{i|j} \mid \varepsilon_{i|j}].$$

These three output measure are used along with $F^{TE_i|j}$ to generate capacity and capacity utilization

estimates in equations 2, 4, 6, and 8.

III. Data and Econometric Specification

To illustrate our capacity and capacity utilization measures we use weekly 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 onboard for all trips. Data obtained from the federal observers were merged

12

with data from the weekly production reports filed by these vessels to create a dataset which includes vessel characteristics, the time period fished, the number of hauls made, the total length of time their gear was deployed (duration), crew size, and a complete characterization of their catch composition. Although other vessels 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 the predominance of their catch within the flatfish fishery, our data set represents the most coherent 'fleet' for investigating capacity and capacity utilization within the BSAI flatfish fishery. Additionally, the large number of vessels facilitates characterization of multiple production technologies, Y_j within the fishery. The primary flatfish species caught are yellowfin sole, rock sole, flathead sole, arrowtooth flounder, flounder, rex sole, and Greenland turbot.[16] Of these species, yellowfin sole comprises the largest percentage of total retained catch by the fleet, approximately 57%.[17] 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 the fish population. With the creation of the Exclusive Economic Zone (EEZ), these foreign vessels were eventually expelled in favor of a domestic fishery.

Our fixed input of production, K_i, is vessel gross-registered tonnage.[18] The vector of variable inputs is crew members per 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 weekly hauls was 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. Additionally, during the time period there was a shift in the way many of the vessels fish. Although total fishing/towing duration remained stable, vessels increased the number of hauls during the week (and thus decreased the average duration of each haul) in an attempt to decrease haul size and increase the quality of the deliverable product. It is possible that if we used the data on the number of hauls, the structural change in haul size could have impacted our ability to accurately characterize the contribution of hauls over the period and might provide misleading estimates. Dummy variables could have been used to capture such effects, but by using duration we avoid the need to estimate the additional parameters. The E_{it} input is the month

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[16] In addition, these vessels catch a fair amount of Pacific cod and pollock. These species compose about 8% and 6% of the total retained catch, respectively. However, we exclude then from the analysis since they are considered bycatch.

[17] We focus on retained catch in our analysis instead of total catch, since we believe it more closely reflects the targeting practices of the fleet. In the case that the retained amount of yellowfin sole was zero we substituted in a value of 0.0001 metric tons to facilitate the log-transformation of the production variables.

[18] We also investigated using each vessels horsepower but due to multicollinearity concerns it was eliminated.

(*Month*) that each vessel's fishing activity was reported in the weekly production reports. This control variable captures seasonal variation in the migration of flatfish, as well as the adverse climatic conditions present within the fishery. Finally, due to multicollinearity concerns we elected to not use information on the flatfish stock densities S_t.[19]

Given our multi-species application, the production specification is the *output distance function* of Shepard [32]. That is, we select yellowfin sole as are our primary output $(Y_{Ye,it|j})$.[20] Then rock sole $(Y^*_{R,it|j})$, flathead sole ,$(Y^*_{F,it|j})$ and all other flatfish species retained $(Y^*_{O,it|j})$, are contained in M_{it}. The superscript (*) represents scaling by $(Y_{Ye,it|j})$. Then our final translog specification of the output distance function is,

$$\ln Y_{Y,it|j} = \beta_{0|j} + \beta_{1j} \ln Nton_i + \beta_{2|j} \ln Duration_{it} + \beta_{3|j} \ln Crew_{it} + \beta_{4|j} \ln Days_{it} + \beta_{5|j} \ln Month_{it}$$
$$+ \beta_{6|j} \ln Y^*_{R,it|j} + \beta_{7|j} \ln Y^*_{F,it|j} + \beta_{8|j} \ln Y^*_{O,it|j} + \beta_{9|j} (Y^*_{R,it|j})^2 + \beta_{10|j} (\ln Y^*_{F,it|j})^2 + \beta_{11|j} (\ln Y^*_{O,it|j})^2$$
$$+ \beta_{12|j} \ln Nton_i \ln Duration_{it} + \beta_{13|j} \ln Nton_i \ln Days_{it} + \beta_{14|j} \ln Duration_{it} \ln Crew_{it}$$
$$+ \beta_{15|j} \ln Days_{it} \ln Month_{it} + \beta_{16|j} \ln Y^*_{R,it|j} \ln Y^*_{F,it|j} + \beta_{17|j} \ln Y^*_{R,it|j} \ln Y^*_{O,it|j} + \beta_{18|j} \ln Y^*_{F,it|j} \ln Y^*_{O,it|j} + v_{it|j} - u_{i|j}$$

(21)

To obtain the final specification we started with the full translog functional form for the homogenous model ($J = 1$) and eliminated interaction and squared terms that were highly collinear.[21] The homogeneous model was further refined by eliminating interaction parameters that were insignificant, using likelihood ratio tests, conditional on standard curvature conditions for the production possibilities frontier.[22] We then estimated a heterogeneous model ($J = 3$) based on the final specification of the homogenous model. Although it is possible for each segment $j = 1, 2, 3$ to possess its own functional form, we did not do this so that the homogenous and heterogeneous models can be directly compared. This also allows the resulting heterogeneous model to violate production curvature restrictions in each sector j, so, in a sense, we are allowing the heterogeneous model to identify any misspecification resulting from the restriction that it be the same as the homogenous model.

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[19] Initial investigations used S_t, but it was statistically insignificant and highly collinear with the constant term due its relative stability throughout the period studied.

[21] Our criterion for this selection was a collinearity estimate of 0.9 or greater.
[22] Restrictions on the coefficients were not implemented *a priori*, curvature restrictions were tested following estimation.

Equation (21) under the homogeneous assumption was estimated via maximum likelihood in GAUSS. Estimation under the heterogeneous assumption requires simulation techniques to maximize the likelihood function. This is because the likelihood function expressed in equation (16) is not smooth and may possess many local maxima. Therefore special maximization techniques are necessary such as repeated random starting points [2, 35], simulated annealing [34], or genetic algorithms. For this study we use random starting points to find the global maximum of the likelihood function, because the large number of parameters make the other techniques intractable.[23]

IV. Results, Capacity and Capacity Utilization Estimates

Estimation results assuming $J = 1$ and $J = 3$ are in Table 1.[24] To determine the appropriate number of production technologies we used likelihood ratio tests, the corrected Akiake Information Criterion (crAIC) and the Bayesian Information Criterion (BIC).[25] The results from these tests are in Table 2. Due to the large number of parameters, we were unable to estimate a $J = 4$ model. However, given the small number of vessels within the fleet (45 vessels), we believe that the $J = 3$ captures a majority of the production heterogeneity and expanding to $J = 4$ may over-fit the data. The production elasticities assuming a homogeneous versus heterogeneous production technologies are in Table 3.

In Table 1 for, $J = 1$ (homogenous), we see that the most important production inputs are a vessel's size (*Net-tons*) and the length of time a vessel deploys its gear (*Duration*). In addition, the complements in the multi-species production, variable M_{it}, are all of the expected sign and the second-order terms indicate that the presence of flathead sole, rock sole, and the other aggregated flatfish species decrease the portion of yellowfin sole caught at a decreasing rate. Furthermore, the production elasticities are all of the expected sign. Thus, our results indicate that the homogeneous model's curvature conditions are consistent with economic theory.

The empirical results for the heterogeneous production model in Table 1 generate distinctly different production profiles for each technology. The first production technology (Technology 1) contains the fewest vessels within the fleet (10 vessels), and their production is primarily determined by the level of variable inputs employed, *Duration* and *Crew*. A vessel's size and the number of days at sea within a week appear to have a much smaller role than the other technologies. In Table 3 we see that the elasticities of input utilization show one curvature violation for Technology 1 (*Net-tons*). However, the

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[23] We use 500 random starting points to determine the maximum likelihood function value.
[24] Estimation results assuming $J=2$ are available upon request from the author(s).
[25] The crAIC is -2ln(*L*)+G*(2+(2*(G+1)*(G+2)/(N-G-2))and the BIC is -2ln(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.

coefficient on *Net-tons* is insignificant in Table 1, so we conclude that this curvature violation is insignificant. Hence, the distance function for the first production technology is well-behaved.

The second production technology (Technology 2) in Table 1 contains 16 vessels and its production is influenced more by the *Month* and the abundance of other flatfish species within the fishery than the other technologies. In fact, these variables have a larger marginal impact on output than changes in the quasi-fixed or variable inputs (many of which are statistically insignificant). Elasticities of production in Table 3 are all of the expected sign for this technology. Given the lack of statistically significant quasi-fixed and variable inputs and the low level of production possessed by this production technology, shown in Tables 8 through 10, this production segment may represent a "fringe" technology that is either not well represented by our specification of the distance function or is a portion of the fleet that possesses a different targeting strategy that the model does not capture. Alternatively, this result may be driven by reduced statistical significance of the parameter estimates as additional tiers in the latent class model are added, which has been observed in latent class models of recreational climbing [33]. Perhaps this technology represents the portion of the fleet that is "latent capacity," that is, vessels which are not extremely active in the fishery but could become more active if it were advantageous. Of course this conjecture requires further study, but this is beyond the scope of our analysis.

The third production technology (Technology 3) in Table 1 is similar to the homogeneous production technology. Production for these 19 vessels is primarily determined by *Net-tons*, and *Duration*. However, the elasticities for *Net-tons* and *Duration* (see Table 3) are substantially different than those in the homogeneous production model, with *Net-tons* being larger and *Duration* being smaller. This production technology also possesses a curvature violation for *Crew*, however given that *Crew* is insignificant we can conclude that this is an insignificant curvature violation and that this production technology is consistent with a well-defined distance function.

Tables 4 through 7 contain the vessel-specific inefficiency estimates $\hat{\mu}_i^*$ and $\hat{\sigma}_i^{*2}$. These are used to generate the vessel specific mean of technical inefficiency $E[u_{i|j} \mid e_{i|j}]$ and the probability of being efficient, $F^{TEi|j}$, as defined in [18] and [12]. Table 4 contains the results under a homogenous production technology, sorted on $F^{TEi|j}$. Notice that there are 45 vessels represented. In the homogeneous production model vessel 40 possess the largest probability that it is the most technically efficient vessel $(F^{TE_{40}|j} = 0.391)$. This is reflected in its relatively low mean technical efficiency (0.0648), caused by a relatively small mean (0.0307) and relatively tight variance (0.0042) prior to

truncation. The results for the next two vessels in the ranking are interesting. Vessel 15 has a *larger* mean of technical inefficiency (0.1286) than vessel 44 (0.0982), but vessel 15 possesses a *higher* probability of being efficient. This is due to the relatively large variance (prior to truncation) of vessel 15 (0.0236). High variance prior to truncation implies a high variance after truncation [18], so we cannot reject the hypothesis that vessel 15 is efficient relative to vessel 44. This result highlights the importance of using the efficiency probabilities over (or in conjunction with) the mean of technical inefficiency, because using the mean measures alone may produce erroneous policy recommendations if they are used for capacity estimation (as wee shall see).[26] Another interesting phenomenon occurs near the bottom of Table 4 (and 5, and 6, and 7). That is, as the $\hat{\mu}_i^*$ gets large (ceteris paribus) it begins to dominate $\hat{\sigma}_i^{*2}$ in the calculation of $E[u_{i|j} \mid e_{i|j}]$ from equation 20, so that $E[u_{i|j} \mid e_{i|j}] \rightarrow \hat{\mu}_i^*$.

Similar results are in Tables 5 though 7 but for *heterogeneous* production technologies. Table 5 contains the results for the 10 vessels employing Technology 1 ($j = 1$). Table 6 contains the results for the 16 vessels employing Technology 2 ($j = 2$). Table 7 contains the results for the 19 vessels employing Technology 3 ($j = 3$). In Table 5, vessel 22 possesses the highest ranked probability of being efficient ($F^{TE_{22|j}}$) for the first production technology. Notably, vessel 22's mean inefficiency estimate ($E[u_{22|j} \mid e_{22|j}]$) differs when we compare the homogenous model (0.6168) to the heterogeneous model (decreasing to 0.0491). A similar result arises for many other vessels possessing this production technology; the average mean inefficiency decreases from 1.0378 (homogeneous) to 0.6229 (heterogeneous). The reason is that homogenous estimation forces vessels with differing technologies to be benchmarked against one another, and large differences in vessels are attributed to inefficiency differences alone (and not to technological differences). Heterogeneous estimation mitigates differences due to technology, so benchmarking reveals only differences due to inefficiency. Another interesting result is that vessel 41, the fifth most inefficient vessel in this group (mean efficiency 0.3181), possesses the second highest $F^{TE_{41|j}}$ rank. This result is driven by the very large σ_{44}^{2*}, which make it difficult to reject the hypothesis that this vessel is efficient.

In Table 6 we see that the average mean inefficiency (for vessels possessing the second production technology) decreases more than any other technology when the assumption of a homogeneous production technology is relaxed. The mean inefficiency decreases from 1.299 to 0.5166, and vessel 3, a

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relatively inefficient vessel in the homogeneous model, has the highest mean inefficiency (0.0672) and

$F^{TE_3|j}$ rank. However, vessel 3's probability (0.36735) is lower than highest $F^{TEi|j}$ rank for the other

production technologies (0.73555 in Table 5 and 0.51379 in Table 7), indicating that the probability mass

of the distribution of relative efficiency is more spread out in the second technology that in the others.

Notice that in Table 7 none of the vessels have a zero probability of being efficient; this is not the case for

the other technologies in Tables 5 and 7. The final production technology in Table 7 parallels the

homogeneous results of Table 4 in that vessel 40 has the smallest mean inefficiency ($E[u_{22|j} \mid e_{22|j}] =$

0.0479) and the highest probability rank ($F^{TEi|j} = 0.51379$).

The estimates $E[u_{i|j} \mid e_{i|j}]$ and $F^{TEi|j}$ in Tables 4 though 7 are used to estimate capacity and capacity

utilization in Tables 8 and 9, respectively, based on equations 2, 4, 6, and 8. Consider the fleet capacity

estimates in Table 8. The first column contains the various technologies: the homogenous technology and

the heterogeneous technologies identified as " $j = 1$", " $j = 2$", and " $j = 3$". Consider the homogenous

technology in the first row. The capacity estimate $\hat{C}_j^{MAX}$ for the entire fleet is 898.3 thousand metric-tons

of yellowfin sole over the period. This estimate assumes that each vessel is operating at its mean level of

inefficiency ($E[u_{i|j} \mid e_{i|j}]$ in Table 4) and that it is operating at its maximum number of days fished per

week (not to exceed 7 days). We have subtracted $E[u_{i|j} \mid e_{i|j}]$ in Table 4 from the technically efficient

output in calculating this measure. Moving to the measure $\hat{C}_j^{TE,MAX}$ for the homogenous technology, we

add the mean inefficiency back into output and the fleet capacity increases to 1,697.4 thousand metric-

tons. This estimate assumes that all vessel are operating efficiently at the maximal days fished. The new

measure of capacity, $\hat{C}_j^{P,MAX}$, incorporates the probability that each boat is efficient into the capacity

calculation, and it is larger than the first two estimates (2,077.1 thousand metric-tons of fish) for the

homogenous technology. The fact that $\hat{C}_j^{P,MAX} > \hat{C}_j^{TE,MAX}$ implies that high-catch vessels have a higher

probability of being efficient than low-catch vessels. Continuing across the first row of Table 8 we see

that the relationship $\hat{C}_j^{P,MAX} > \hat{C}_j^{TE,MAX} > \hat{C}_j^{MAX}$ is maintained for the homogenous technology as we

vary the magnitude of the days fish from 125% to 150% (This is not always true in the heterogeneous

case, as we shall see.) In general, fleet capacity estimates for $\hat{C}_j^{P,k}$, $k = $ MAX, 20, 50 are approximately

1.22 times those obtained using $\hat{C}_j^{TE,k}$. The $\hat{C}_j^{TE,k}$ imply that fleet production could be approximately

doubled above $\hat{C}_j^k$, while $\hat{C}_j^{P,k}$ implies it could be more than doubled for each level of primary variable

input (k = MAX, 20, 50) once efficiency is taken into account. This result is challenged when we allow for heterogeneous production technologies.

The heterogeneous fleet capacity estimates in Table 8 illustrate the advantages of using heterogeneous production technologies and the probability scores, F^{TEi}. Consider the traditional fleet capacity estimate, $\hat{C}_j^{TE,MAX}$, for the heterogeneous production technologies. For technologies 1, 2, and 3 the capacities are 457, 109, and 909.9 metric-tons of fish, respectively. These are naturally larger than the heterogeneous results for $\hat{C}_j^{MAX}$ (349, 91.7, and 549.4 metric-tons of fish, respectively), because they place all the vessels for each technology on the efficient frontier. (This pattern is also true for different levels of primary variable inputs, 125% and 150% of days fished.) The truly interesting and primary results of this paper occur onve we account for the probabilities of vessels being efficient in each technology group, using our new capacity measure $\hat{C}_j^{P,MAX}$. For Technology 1, our new capacity measure is actually lower than $\hat{C}_j^{TE,MAX}$ (391 metric-tons vs. 457 metric-tons). Apparently, for the first technology the efficient vessels tend to be those with *lower* catch. This is not the case for vessels using technologies 2 and 3, where high-catch vessels tend to be more efficient (compare 261.1 to 109 and 915.6 to 909.9). In particular this phenomenon of 'high-catch boats being more efficient' is more pronounced for technology 2 than for technology 3. Although we did not formally test it, it may be that case that the difference between 915.6 metric-tons and 909.9 metric-tons for technology 3 is statistically insignificant. In that case the heterogeneous production technologies have remarkably differentiated the vessel technology into groups of vessels that are marked by 1) low-catch efficiency, 2) high-catch efficiency, and 3) medium-catch efficiency. (This pattern is also repeated for different levels of primary variable inputs, 125% and 150% of days fished.)

In Table 8 the 'Total Heterogeneous Capacity' estimate is simple the sum of the capacity estimates for each technology (see equations 2, 4, and 6). These are to be compared with the (fleet) capacity estimates of the homogenous technology. For example, the three heterogeneous fleet capacities based on maximal primary variable inputs are 990.2 metric-tons, 1,475.9 metric-tons, and 1,566.7 metric-tons of fish. Compare these to the three homogenous estimates: 898.3 metric-ton, 1,697.4 metric-tons, and 2,077.1 metric-tons. When vessels operate at nominal efficiency levels ($\hat{C}_j^{MAX}$) the heterogeneous capacity estimate is approximately equal to the homogenous estimate (compare 990.2 to 898.3). However, the heterogeneous capacity estimate is smaller than the homogenous estimate once we allow vessels to move

to the frontier ($\hat{C}_j^{TE,MAX}$ and $\hat{C}_j^{P,MAX}$). The reason is that the homogenous production function overestimates inefficiency (underestimates efficiency), so when inefficient vessels are moved to the frontier we get a much larger increase in the homogenous case than in the heterogeneous case. The heterogeneous case makes economic sense, since we would expect many vessels to be close to the frontier, so moving them up does not drastically effect fleet capacity. This indicates that failing to properly account for heterogeneity in production technologies, when it exists, may inflate our traditional capacity estimates and lead to inaccurate policy advice. By accounting for both multiple production technologies we are able to obtain more reliable and realistic capacity estimates. Another interesting result is that as the number of production technologies estimated increases the estimates of $\hat{C}_j^{P,k}$ converge to the $\hat{C}_j^{TE,k}$ estimates. This is makes sense, because if the number of production technologies estimated equals the number of vessels within the fleet, $J = N$, then these two estimates will be identical.

An additional benefit of the $\hat{C}_j^{P,MAX}$ estimates 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 technologies. This is made clear by the fact that the estimate $C_j^{P,MAX}$ in equation 6, includes N_j, so it is simply the *expected efficiency output of a single vessel* which is then scaled up by the number of vessels, N_j. For instance, in the heterogeneous production model, we conclude that adding another (*out-of-sample*) vessel to the first production technology class would increase the expected production level by 39.1 thousand metric-tons of yellowfin sole over the period 1994-2004 (assuming $days^{MAX}$). If we added another vessel of similar production technology to the second production technology, we would increase flatfish production by 16.3 thousand metric-tons over the same time period, while if we do the same for the third production technology, output would increase by 48.2 thousand metric-tons. These are fairly large differences that highlighting the importance of heterogeneity modeling. The homogeneous production technology model generates an *out-of-sample* prediction of 46.2 thousand metric-tons. *Out-of-sample* prediction could be generated by dividing the total fleet capacity estimates $\hat{C}_j^{TE,k}$ by fleet size, but these estimates assign equal weight to each vessel and do not account for potential *stochastic dominance* of one vessel over another. Heterogeneity modeling aside, the representative-vessel, *out-of-sample* $\hat{C}_j^{P,k}$ estimates of fleet capacity substantially enhance a policy maker's ability to predict fleet expansion production as well as the reductions in production resulting from vessel buyback programs.

The vessel specific measures of capacity utilization ($\hat{C}U_i^{TE,k}$), k = MAX, 25, 50 are in Table 9 under the assumption of homogeneous and heterogeneous production. Since capacity utilization is a vessel-specific measure, we simple report the means and standard deviation (over vessels) within each technology for each estimate. Qualitatively the estimates for the homogeneous production model and the third technology ($j = 3$) of the heterogeneous model are similar (compare 0.4924 to 0.5132, and 0.5165 to 0.5768), while there are sizable divergence between the homogenous technology and the second ($j = 2$) and third ($j = 3$) technology of the heterogeneous model. The increases in vessel-specific capacity utilization as we move from a homogenous to a heterogeneous production function result from the decrease in the mean inefficiency estimates for each of the j production technologies as increasing levels of heterogeneity are incorporated. As illustrated in Figures 1 and 2, allowing for separate production frontiers refines the mean inefficiency estimates because technically efficient output is no longer defined by the outer envelope of all the observations, but by just those that are encompassed by the jth production technology. The most pronounced difference in the vessel-specific capacity utilization measures arises for the second production technology (j=2) in the heterogeneous model. As discussed earlier, the average mean inefficiency for this group decreased from 1.299 to 0.5166 when heterogeneous production technologies were incorporated, leading each vessel to be closer to its technological frontier and to exhibit larger capacity utilization measures. These results highlight the importance of heterogeneous technologies in production estimation.

Conclusion

Previous investigations of fleet capacity and vessel-specific measures of capacity utilization are based on a homogeneous production technology and measurement of inefficiency relative to a single production frontier. This research expands these investigations by incorporating a heterogeneous frontier. This research also informs previous work on heterogeneous production [35] by analyzing production in a multi-species fishery *and* by using the information contained in the simultaneous differences of the distributions of technical inefficiency. Our production technology estimates indicate that ignoring heterogeneity in production may overestimate a fleet's capacity. Furthermore, using complete distributional information of the fleet's technical efficiency distribution refines the fleet-wide estimates of capacity and suggests that traditional measures based on technically efficient production are unreliable. Combined, these results highlight the importance of incorporating production heterogeneity within fisheries – even when vessel characteristics or other measures often used to define "technology" may be quite similar. Results also show that gains may be obtained by incorporating measures on the statistical reliability of the technical efficiency scores using the efficiency probabilities from stochastic frontier models. These latter two results should be beneficial for policy development and for *out-of-sample* policy

responses, which are used to evaluate vessel buyback programs as well as fleet restructuring and expansion.

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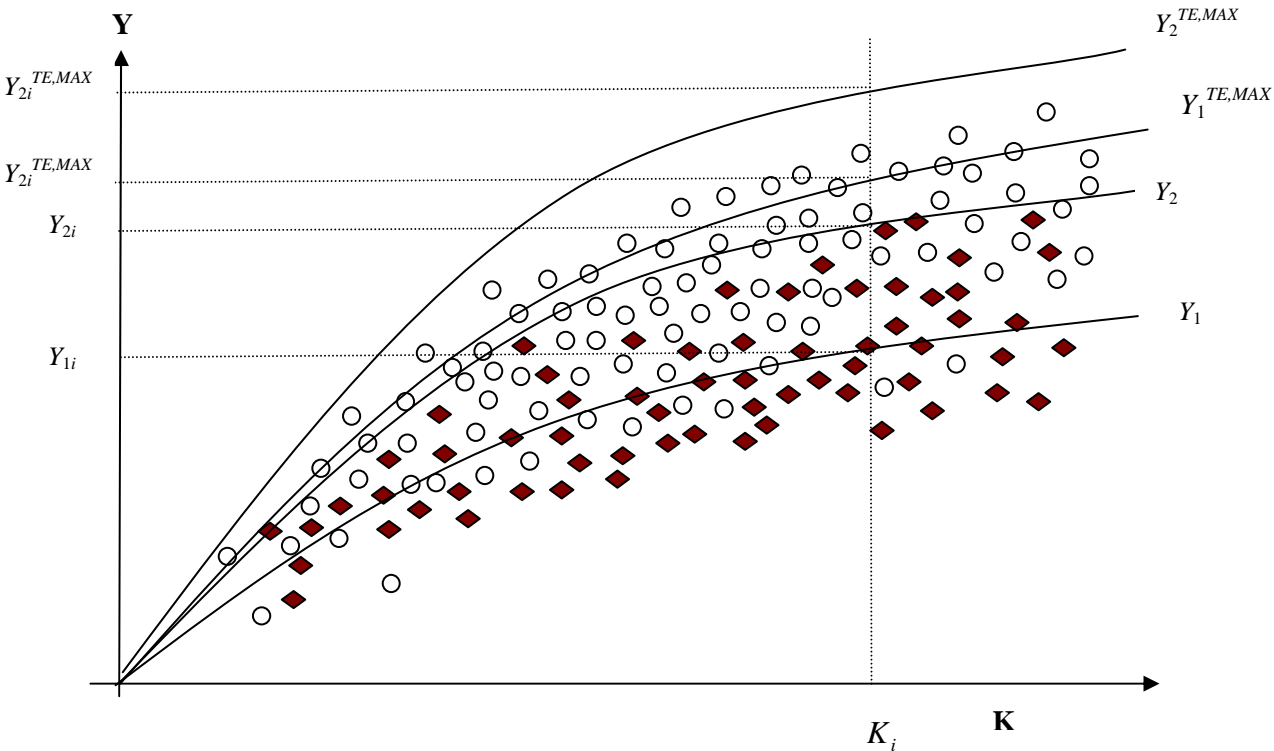
Tables and Figures:

Figure 1: Homogeneous Production Estimate on Heterogeneous Data.
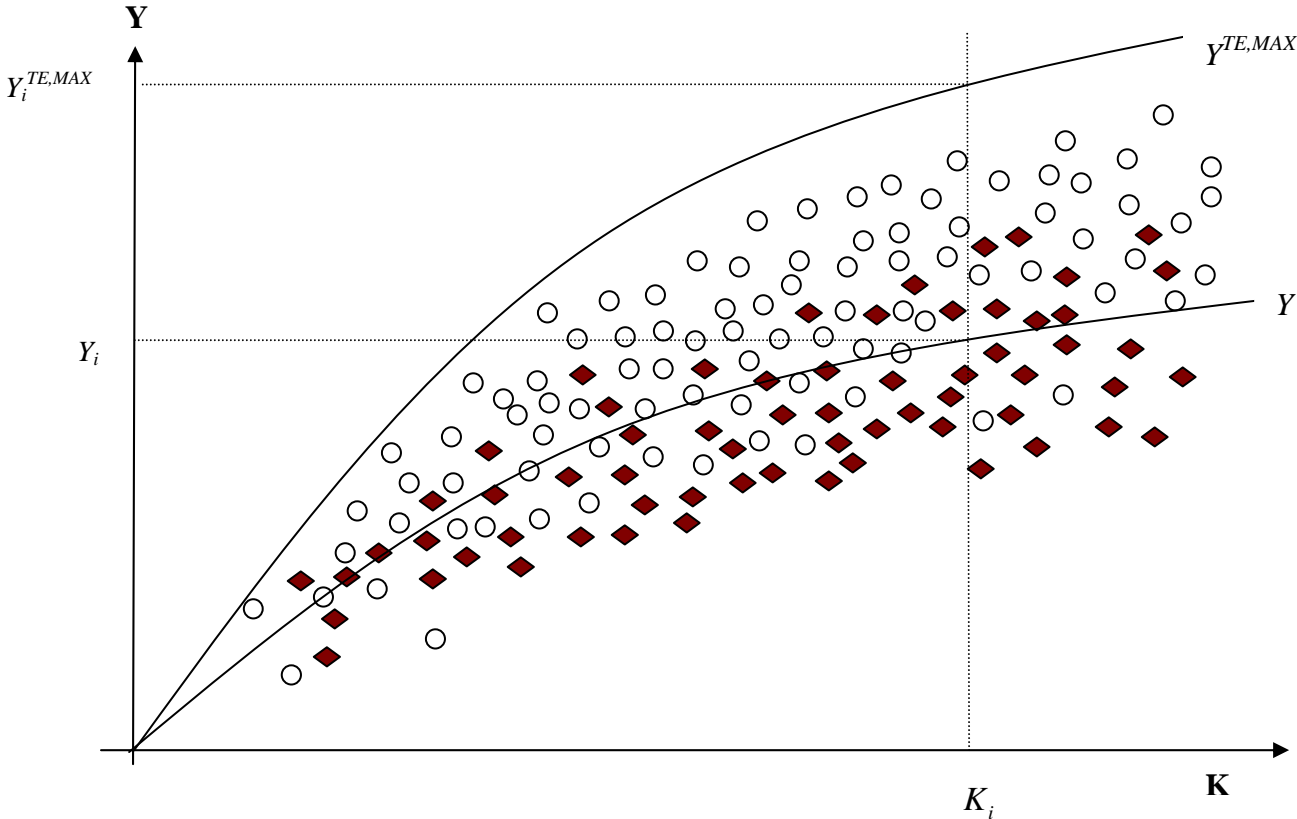
Circles = high-output technology
Diamonds = low-output technology

Figure 2: Heterogeneous Production Estimate on Heterogeneous Data.

Circles = high-output technology
Diamonds = low-output technology

Table 1: LSPF Regression Results

Coefficient	Homogeneous Technology	Heterogeneous Technology 1	Heterogeneous Technology 2	Heterogeneous Technology 3
Constant	-6.4834**	-10.5232**	5.1786	-5.0473**
	(-5.76)	(-2.95)	(0.98)	(-2.67)
Net Tons	0.6108**	-0.1759	-0.6731	0.7279**
	(2.81)	(-0.50)	(-0.70)	(1.96)
Duration	1.1721**	1.8079*	-3.1188	2.0011**
	(2.94)	(1.86)	(-1.52)	(3.17)
Crew	0.5524	2.7112**	-0.8964	0.3960
	(1.42)	(2.25)	(-1.05)	(0.64)
Days	0.9826	1.0198	4.4097	-0.4097
	(1.50)	(1.10)	(1.54)	(-0.39)
Month	0.6959	0.8138**	0.7108**	0.1287
	(5.98)	(4.87)	(2.74)	(0.72)
Rock Sole	-0.1146	-0.2003**	-0.0477**	-0.1029**
	(-18.62)	(-20.80)	(-3.60)	(-9.96)
FlatHead	-0.1764**	-0.2360**	-0.0101	-0.0319*
	(-19.68)	(-23.27)	(-0.32)	(-1.69)
Other	-0.3435**	-0.3000**	-0.5256**	-0.4675**
	(-37.73)	(-27.76)	(-16.17)	(-25.48)
(Rock Sole)^2	-0.0144**	-0.0282**	-0.0020	-0.0119**
	(-14.61)	(-18.24)	(-0.99)	(-7.91)
(FlatHead)^2	-0.0246**	-0.0364**	-0.0055	-0.0045*
	(-17.67)	(-20.04)	(-1.15)	(-1.67)
(Other)^2	-0.0756**	-0.0794**	-0.0534**	-0.0661**
	(-52.31)	(-38.04)	(-12.24)	(-26.39)
(Net Tons)(Duration)*	-0.0778	0.0189	0.5089	-0.1394
	(-1.06)	(0.25)	(1.46)	(-1.28)
(Net Tons)(Days)*	0.0759	0.0390	-0.5718	0.2664
	(0.75)	(0.26)	(-1.24)	(1.71)
(Duration)(Crew)*	-0.00579	-0.3661	0.2707	-0.1813**
	(-0.63)	(-1.34)	(1.35)	(-1.16)
(Days)(Month)*	-0.3226**	-0.2770**	-0.3398**	-0.2478
	(-4.81)	(-2.91)	(-2.26)	(-2.39)

Table 1: :LSPF Regression Results (cont.)

(Rock Sole)(FlatHead)*	0.005**	0.0027**	0.0027**	0.0010
	(4.40)	(2.14)	(2.14)	(1.14)
(Rock Sole)(Other)*	0.0089**	-0.0034*	-0.0034*	0.0061**
	(9.78)	(-1.77)	(-1.77)	(4.65)
(FlatHead)(Other)*	0.0187**	0.0008	0.0008	0.0040
	(14.34)	(0.19)	(0.19)	(1.64)
γ	0.4692**	-------	0.8287**	-------
	(3.12)		(4.92)	
σ_S^2	1.9655**	-------	5.2632	-------
	(3.53)		(1.01)	
μ	0.6017	-------	-5.8657	-------
	(0.51)		(-0.69)	
# of Vessels	**45**	**10**	**16**	**19**
Mean Log-Likelihood	**-1.45408**		**-1.37883**	

(** 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	crAIC
1	22	-1.45408	-------	12888.38	12851.40
2	41	-1.39270	540.51	12420.19	12363.10
3	60	-1.37883	61.07	12370.38	12314.25

Table 3: Elasticities of Production

Model/Parameter	*Homogeneous*	*Heterog. j = 1*	*Heterog. j = 2*	*Heterog. j = 3*
Net-tons	0.1231	-0.0280*	0.5199*	0.5782
Duration	0.5133	0.6454	1.0070*	0.3687
Crew	0.6684*	1.1330	0.2386*	-0.3679*
Days	0.8984*	0.7903*	0.3111*	0.9459*
Number of Vessels	**45**	**10**	**16**	**19**

(* indicates that the elasticity measure is statistically insignificant)

Table 4: Homogeneous Vessel Efficiency Results Sorted on $F^{TE_i|j}$

Vessel Number	$\hat{\mu}_i^*$	$\hat{\sigma}_i^{*2}$	$E[u_{i|j} \mid e_{i|j}]$	$F^{TE_i|j}$
40	0.0307	0.0042	0.0648	0.39057
15	0.0158	0.0236	0.1286	0.18669
44	0.0919	0.0032	0.0982	0.14813
43	0.0721	0.0289	0.4832	0.12745
6	0.1187	0.0034	0.1218	0.07853
41	-0.3331	0.4895	0.4530	0.05614
16	1.0241	0.2525	1.0498	0.00387
42	0.4806	0.0346	0.4832	0.00378
28	1.4629	0.4895	1.4949	0.00241
13	1.1816	0.1702	1.1843	0.00063
14	1.1981	0.1702	1.2004	0.00058
25	0.5267	0.0242	0.5269	0.00053
38	1.7064	0.3332	1.7093	0.00033
19	0.9896	0.0086	0.9900	0.00021
11	0.2982	0.0045	0.2982	0.00015
35	2.0989	0.3332	2.0992	0.00004
31	0.3696	0.0058	0.3696	0.00002
37	0.9005	0.0471	0.9005	0.00002
39	1.9123	0.2033	1.9123	0.00001
23	1.3645	0.0794	1.3645	0.00000
34	1.5789	0.1143	1.5789	0.00000
1	0.7694	0.0036	0.7694	0.00000
2	1.5448	0.0281	1.5448	0.00000
3	0.6518	0.0081	0.6518	0.00000
4	1.1475	0.0129	1.1475	0.00000
5	1.2121	0.0545	1.2121	0.00000
7	0.8271	0.0100	0.8271	0.00000
8	0.9400	0.0052	0.9400	0.00000
9	1.8226	0.0738	1.8226	0.00000
10	1.7337	0.0860	1.7337	0.00000
12	1.3790	0.0494	1.3790	0.00000

17	1.8863	0.0415	1.8863	0.00000
18	2.3698	0.0794	2.3698	0.00000
20	1.3123	0.0289	1.3123	0.00000
21	0.7140	0.0051	0.7140	0.00000
22	0.6168	0.0033	0.6168	0.00000
24	1.4785	0.0432	1.4785	0.00000
26	0.5054	0.0058	0.5054	0.00000
27	0.3852	0.0041	0.3852	0.00000
29	2.7632	0.2525	2.7632	0.00000
30	1.1045	0.0094	1.1045	0.00000
32	0.7393	0.0031	0.7393	0.00000
33	1.2083	0.0545	1.2083	0.00000
36	0.4820	0.0044	0.4820	0.00000
45	0.5967	0.0041	0.5967	0.00000

Table 5: Heterogeneous Model Sorted on $F^{TE_i|j}$; $J = 3$; $j = 1$

Vessel Number	$\hat{\mu}_i^*$	$\hat{\sigma}_i^{*2}$	$E[u_{i|j} \mid e_{i|j}]$	$F^{TE_i|j}$
22	0.0160	0.0029	0.0491	0.73555
41	-1.7690	0.7472	0.3181	0.11251
44	0.1246	0.0027	0.1258	0.08104
32	0.1284	0.0026	0.1294	0.07074
6	0.2724	0.0030	0.2724	0.00010
26	0.3307	0.0050	0.3307	0.00010
8	0.3983	0.0045	0.3983	0.00001
2	1.2387	0.0249	1.2387	0.00000
4	0.7919	0.0112	0.7919	0.00000
29	3.1898	0.2812	3.1898	0.00000

Table 6: Heterogeneous Model Sorted on $F^{TE_i|j}$; $J = 3$; $j = 2$

Vessel Number	$\hat{\mu}_i^*$	$\hat{\sigma}_i^{*2}$	$E[u_{i|j} \mid e_{i|j}]$	$F^{TE_i|j}$
3	0.0014	0.0070	0.0672	0.36735
1	0.0664	0.0031	0.0789	0.22935
7	0.1088	0.0087	0.1304	0.11102
21	0.1231	0.0044	0.1280	0.07375
16	0.0750	0.2812	0.4515	0.04310
14	0.2137	0.1732	0.4227	0.03967
12	0.2490	0.0446	0.2967	0.03916
5	0.3039	0.0495	0.3421	0.02845
23	0.3502	0.0739	0.4026	0.02521
28	0.2605	0.7472	0.7934	0.02265
35	0.9277	0.4086	1.0237	0.00774
38	0.9494	0.4086	1.0403	0.00734
33	0.5200	0.0495	0.5258	0.00484
10	0.8965	0.0805	0.8972	0.00040
24	0.7368	0.0389	0.7369	0.00010
17	0.9282	0.0373	0.9282	0.00001

Table 7: Heterogeneous Model Sorted on $F^{TE_i|j}$; $J = 3$; $j = 3$

Vessel Number	$\hat{\mu}_i^*$	$\hat{\sigma}_i^{*2}$	$E[u_{i|j} \mid e_{i|j}]$	$F^{TE_i|j}$
40	-0.0014	0.0037	0.0479	0.51379
43	-0.1204	0.0256	0.2047	0.25729
15	0.0544	0.0209	0.1374	0.13233
42	0.1397	0.0309	0.2047	0.07019
13	0.5443	0.1732	0.6223	0.01397
25	0.3497	0.0214	0.3531	0.00693
39	0.9724	0.2144	0.9931	0.00308
37	0.5477	0.0425	0.5502	0.00228
34	1.0770	0.1099	1.0777	0.00023
11	0.3165	0.0039	0.3165	0.00002
9	1.0455	0.0683	1.0455	0.00002
20	0.7259	0.0256	0.7359	0.00001
19	1.3370	0.0805	1.3370	0.00000
18	2.0008	0.0739	2.0008	0.00000
27	0.4302	0.0036	0.4302	0.00000
30	1.0187	0.0082	1.0187	0.00000
31	0.6226	0.0050	0.6226	0.00000
36	0.5078	0.0038	0.5078	0.00000
45	0.7136	0.0036	0.7136	0.00000

Table 8: Fleet Capacity Estimates, thousands of metric-tons of Yellowfin Sole.

	$\hat{C}_j^{MAX}$	$\hat{C}_j^{TE,MAX}$	$\hat{C}_j^{P,MAX}$	$\hat{C}_j^{25}$	$\hat{C}_j^{TE,25}$	$\hat{C}_j^{P,25}$	$\hat{C}_j^{50}$	$\hat{C}_j^{TE,50}$	$\hat{C}_j^{P,50}$
Homogeneous	898.3	1,697.4	2,077.1	811.1	1,530.7	1,861.6	848.3	1,603.7	1,955.0
Heterogeneous									
$j = 1$	349.0	457.0	391.0	321.6	421.4	366.8	349.1	457.9	391.0
$j = 2$	91.7	109.0	261.1	90.5	107.6	257.9	91.1	108.3	259.6
$j = 3$	549.4	909.9	915.6	483.0	800.8	807.4	508.2	843.0	850.0
Total Heterogeneous Capacity	990.2	1,475.9	1,566.7	895.1	1,329.8	1,432.1	948.4	1,409.2	1,500.6

Table 9: Capacity Utilization Measures

	$\hat{CU}_i^{TE,MAX}$		$\hat{CU}_i^{TE,25}$		$\hat{CU}_i^{TE,50}$	
	Mean	Std. Dev	Mean	Std. Dev.	Mean	Std. Dev.
Homogeneous	0.4924	0.2097	0.5165	0.1925	0.5415	0.1890
Heterogeneous						
$j = 1$	0.6850	0.1853	0.7309	0.1449	0.6850	0.1853
$j = 2$	0.7956	0.1695	0.8223	0.1409	0.8098	0.1460
$j = 3$	0.5132	0.2048	0.5768	0.1710	0.5459	0.1785