Estimating Heterogeneous Production in Fisheries

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Abstract

Stochastic production frontier models are used extensively in the agricultural and resource economics literature to estimate production functions and technical efficiency, as well as to guide policy. Traditionally these models assume that each agent's production can be specified as a representative, homogeneous function. This paper proposes the synthesis of a latent class regression and an agricultural production frontier model to estimate technical efficiency while allowing for the possibility of production heterogeneity. We use this model to estimate a latent class production function and efficiency measures for vessels in the Northeast Atlantic herring fishery. Our results suggest that traditional measures of technical efficiency may be incorrect, if heterogeneity of agricultural production exists.

Introduction

Production function estimation is important to the development and analysis of a wide range of agricultural and environmental policies. It can be used to identify areas of improvement in agricultural processes, to measure the value of production or input technology changes, or to assess producer response to new regulation or opportunities. Recent studies have focused on the role of agricultural policy (Paul et al. 2000), the accessibility to credit markets, and the use of new agricultural practices in developing nations (Bayarsaihan and Coeilli 2003; Hazarika and Alwang 2003; Kudaligama and Yanagida 2000; Liu and Zhuang 2000 to cite a few). In many applications, production function estimation is supplemented by producer-level technical efficiency estimates, which are used to identify the extent to which producers select inputs to make effective use of fixed resources. In many agricultural applications, efficiency analyses help extension agents identify resources that might aid farmers and help policymakers target resources for subsidy (Khairo and Battese 2004).[1]

When a production technology is used to exploit a common pool resource (such as a fishery) accurate characterization is particularly important. In this case, production estimates are often used to guide management policies aimed as reducing pressure on the resource and ensuring its future viability. For example, buyback programs are used in many over-exploited fisheries to reduce the amount of capital being applied to a dwindling stock. Buybacks have also been utilized in rationalizing so-called "derby fisheries," where the fishing season is open only until a set quantity of fish is harvested, providing an incentive to overcapitalize and catch as much as possible before others catch the limit. Therefore, an accurate picture of a fleet's production profile aids in identifying likely participants in buyback programs and in developing estimates of reservation prices that may be used to establish budgets for a successful program (Guyader et al. 2004).

Other fisheries are managed by input restrictions, such as maximum days-at-sea, gear restrictions or limits on the quantity of fixed gear (e.g., traps). However, experience shows that fishermen often respond to these restrictions by substituting unrestricted inputs, in some cases using more variable inputs (e.g., increasing crew size), or by investing in more fixed capital (e.g., purchasing a larger engine to reduce steam time or using a larger trawl device). Estimating production input elasticities helps managers predict the extent to which new input restrictions are likely to result in decreased stock pressure, or simply a substitution of other unrestricted inputs (Kompas et al. 2004). With both types of management measures, policymakers can use production functions to determine the technical efficiency of each operation. Furthermore, measures of technical efficiency can be used to determine the efficiency gains of switching from input regulations to property right management regimes, such as individual transferable quotas (Kompas and Che 2005; Weninger and Waters 2003).

Technical efficiency indicates how well vessels perform relative to the optimal use of their inputs, and provides a measure of excess harvesting capacity resulting from inefficiently managed or underutilized capital (Kirkley et al. 2002). This is of particular interest, because the excess capacity could be put into use in the event that part of the fleet were to be bought out, or it could reflect the potential for capital substitution in the event of new input restrictions.[2] Although production function and technical efficiency estimates are critical to assessing the likely effect of new policy, the traditional approach to production analysis develops a representative (homogenous) producer model. This approach is commonly employed even though there may be production heterogeneity among producers. In fisheries, this heterogeneity is often explained by the "good captain" hypothesis, which states that some captains possess skills, usually not directly measurable, which allow them to consistently outperform other captains with similar capital in the same fishery. This has lead economists to estimate the degree of technical efficiency possessed by captains within a number of different fisheries in an effort to determine the captain specific factors which determine their relative rates of inefficiency (Kirkley et al. 1998; Pascoe and Coglan 2002; Sharma and Leung 1998; Squires and Kirkley 1999; Viswanathan et al. 2002).[3]

The presence of "good" captains introduces latent heterogeneity in the production capabilities possessed by fishermen within a fishery because the determinants of a "good" captain are often unobservable. In addition, these differences may not be completely explained by differences in technical efficiency and the captain's managerial skill. For instance, Kirkley, Squires and Strand (1998) observed that two captains, using nearly identical vessels and possessing similar experience levels and backgrounds, possessed different measures of technical efficiency. Perhaps these differences were due to latent heterogeneity in the vessels' production functions, which when controlled for generates similar measures of technical efficiency. Recognizing this heterogeneity may not only improve the accuracy of production estimates, but it may also support more refined analysis and better-targeted policies.

In this paper, we use a latent class stochastic production frontier estimator to investigate the presence of latent heterogeneity in fisheries. The estimator is a statistical model that simultaneously estimates a set of distinct production functions *and* selects which producers use which function. The model generates a set of estimated production functions, along with a likelihood-based assignment of producers to each function. These different functions have the natural interpretation of reflecting different marginal productivities of both their fixed capital (e.g., vessel characteristics) and variable inputs (e.g., number of crew members and hours fished). These differences are not identified if we restrict the specification to a representative (homogenous) producer. Therefore, we employ latent class modeling to separate vessel production via explicit differences in their elasticities of input utilization.[4]

This latent class methodology has been used to investigate inefficiency heterogeneity in Turkish banking (El-Gamal and Inanoglu 2005), but to the best of our knowledge this is the first known application of this model to agricultural and resource production modeling. We demonstrate the value of latent class modeling in agricultural and resource production with an application to the Northeastern US Atlantic herring fleet. We identify three economically and statistically different production functions within the fishery. Technical efficiency analysis indicates that, within each production function, captains have a range of aptitude for selecting variable inputs to efficiently catch fish. However, relative to the traditional homogeneous model, they suggest dramatically different technical efficiency measures and marginal products of input utilization. These results highlight the importance of utilizing latent class modeling when heterogeneity is suspected.

The next section of the paper presents the latent class stochastic production frontier model. We then describe the data set, and present a three segment (heterogeneous) estimate of the fleet production function. We use these production functions to generate technical efficiency estimates, and compare the results across homogenous and heterogeneous specifications. These comparisons highlight the utility of estimating heterogeneous productions and provide some insight into the paired trawling practices within the Northeast Atlantic herring fishery. Finally, we discuss the pitfalls and policy implications of using a homogeneous analysis to interpret production measures in a heterogeneous environment.

Methodology

Latent class models posit that the population consists of several distinct types of producers with similar production functions, based on unobserved characteristics of the producers. The statistical task is to identify both which producers are of the same (unobserved) type *and* the parameters that represent each type's production function. Developing a latent class model requires two steps:

(1) specification of a parametric form for the production function of each type and (2) implementation of a method for determining the combination of parameters for each segment and assigning producers to each segment. We specify each type as having a partial trans-log functional form estimated within a stochastic production frontier model.[5] We then use El-Gamal and Grether's (1995; 2000) estimation-classification (EC) algorithm to simultaneously group producers into types and to estimate parameter values for each segment.

A stochastic frontier model has a composed error (Aigner et al. 1977; Meeusen and van den Broeck 1977), which is decomposed into an conventional random noise term and a random, firm-specific technical inefficiency term. The stochastic frontier model is specified as follows,

$$Y_{it} = f(X_{it};\beta)\exp\{\varepsilon_{it}\} \tag{1}$$

where Y_{it} is the production of producer $i = 1,...,N$ in period $t = 1,...,T_i$. The X_{it} is the level of inputs used in the production process, β is a parameter vector, and ε_{it} is a composed error term. The error term is linearly specified as

$$\varepsilon_{it} = v_{it} - \eta_i \tag{2}$$

where v_{it} is an independently and identically distributed $N(0,\sigma_v^2)$, and η_i is a non-negative, vessel-specific error term, distributed as the truncation below zero of a $N(\mu,\sigma_\mu^2)$ random variable. Further, the random variables v_{it} and the η_i are assumed to be independent of the inputs and of each other. For an unbalanced panel, the log-likelihood function is (Battese et al. 1989; Battese and Coelli 1995),

$$L(\theta; y) = -\frac{1}{2}\left(\sum_{i=1}^{N} T_i\right)\log(2\pi) - \frac{1}{2}\sum_{i=1}^{N}(T_i - 1)\log[(1-\gamma)\sigma_S^2] - \frac{1}{2}\sum_{i=1}^{N}\log\{\sigma_S^2[1+(T_i-1)\gamma]\}$$
$$- N\log[1-\Phi(-z)] + \sum_{i=1}^{N}\log[1-\Phi(-z_i^*)] - \frac{1}{2}Nz^2 - \frac{1}{2}(y-x\beta)'(y-x\beta)[(1-\gamma)\sigma_S^2] + \frac{1}{2}\sum_{i=1}^{N} z_i^{*2}$$

where,

$$z = \frac{\mu}{(\sigma_S^2 \gamma)^{0.5}}, \quad z_i^* = \frac{\mu(1-\gamma) - T_i\gamma(\bar{y}_i - \bar{x}_i\beta)}{(\gamma(1-\gamma)\sigma_S^2[1+(T_i-1)\gamma])^{0.5}}, \quad \bar{y}_i = \frac{y_i}{T_i}, \quad \text{and } \bar{x}_i = \frac{x_i}{T_i}. \tag{3}$$

T_i is the number of observations for each agent *i* and θ is the parameter vector to be estimated which consists of the coefficients for each segment, β_i, $\gamma = \sigma_\mu^2 / \sigma_S^2$, μ and $\sigma_S^2 = (\sigma_\mu^2 + \sigma_V^2)$.

Using this stochastic production frontier model as the functional form for each type, El-Gamal and Grether's estimation-classification (EC) algorithm performs the task of grouping producers into a pre-specified number of types, *H*, and estimating the unknown parameters, θ_h, for each segment. Each producer's contribution to the likelihood function is the maximum across the *H* segments of the joint log-likelihood of all their observations given $\Theta=(\theta_1, \ldots \theta_h)$ and may be expressed as[6],

$$\ln[L(Y_{it};Z_{it} \mid \Theta, H)] = \sum_{i=1}^{N} \operatorname{argmax}_h \sum_{t=1}^{T_i} \ln(L(Y_{it};Z_{it} \mid \theta_h)) \tag{4}$$

where $L(.)$ is the single-segment likelihood function. This method can be applied with a different number of segments, *H*, and statistical tests can be performed to determine the number of segments in the population (e.g., El-Gamal and Grether 1995). As mentioned earlier, El-Gamal and Inanoglu (2005) have used this methodology to investigate inefficiency in Turkish banking. This technique has also been used to analyze experimental data on individual and public good decision making problems (Anderson and Putterman 2006; El-Gamal and Grether 1995, 2000; Schnier and Anderson in press). This research illustrates the benefits of using this methodology within the agricultural and natural resource economics literature.

Technical efficiency of each vessel within a fishery is defined by the vessel ability to generate the maximum level of output (harvest) possible given a fixed level of inputs, the present stock level, and all other exogenously determined production factors. Measurements of technical efficiency are obtained from the vessel specific errors resulting from the stochastic frontier estimation. Since output is in logarithms, technical efficiency is expressed as $\exp\{-\eta_i\}$ for each vessel *i*. However, since η_i is unobserved, so we can only estimate its distribution (conditional on ε_{it})

and the mean of this distribution. The latter serves as an estimate of vessel *i*'s technical efficiency. In particular (per Battese et. al, 1989; Battese and Coelli 1992,1993),

$$TE_i = E[\exp\{-\eta_i\} \mid \varepsilon_{it}] = \frac{1-\Phi\left[\sigma_i^* - \left(\dfrac{\mu_i^*}{\sigma_i^*}\right)\right]}{1-\Phi\left(\dfrac{-\mu_i^*}{\sigma_i^*}\right)} \exp\left\{-\mu_i^* + \frac{1}{2}\sigma_i^{*2}\right\} \qquad (5)$$

where,

$$\mu_i^* = \frac{\mu\sigma_V^2 - \sigma_U^2 T_i \overline{E}_i}{\sigma_V^2 + T_i\sigma_U^2} \qquad (6)$$

$$\overline{E}_i = \frac{1}{T_i}\sum_{t=1}^{T_i}\varepsilon_{it} \qquad (7)$$

$$\sigma_i^{*2} = \frac{\sigma_U^2\sigma_V^2}{\sigma_V^2 + T_i\sigma_U^2}. \qquad (8)$$

These are the estimates used in the empirical section of the paper, but with the residual of the maximum likelihood estimation substituted for the composed error, ε_{it}, in the above formulae. The next section describes the data and provides a brief description of the Northeast Atlantic herring fleet.

Data Description and Fishery Background

We analyze production data from the Northeast Atlantic herring fishery. The data set utilized for this study was obtained from the National Marine Fisheries Service and consists of 2894 logbook entries for 39 vessels participating in the herring fishery during the years 2000 through 2003.[7] Each entry represents a single trip made by a vessel, and is considered the best available data for analyzing this fishery.[8] Each entry indicates the reporting vessel ID, tons of herring landed, the gear used, the crew size, the vessel characteristics (length, gross-tons, horsepower and hold capacity), home port, the time and date of departure and return to port, and the statistical reporting area fished (see Table 3 for descriptive statistics).

The Atlantic herring, *Clupea herengus*, is a pelagic species targeted by fishermen from Maine down to New Jersey along the New England seaboard. The primary products produced within the herring fishery are sardines (juvenile herring ranging from 1 to 3 years old), bait for the Maine lobster fishery, fishmeal used for livestock and aquaculture, smoked herring and a small market for large flavored and filleted "kippers." While landings were as much as 470,000 metric tons in the late 1960s, due to both stock and demand effects, current annual landings range from 81,000 to 124,000 metric tons. While the fishery is not currently heavily managed, there is discussion of implementing new management measures which divide the fishery into inshore and offshore management areas.[9]

The fishing fleet targeting Atlantic herring is relatively small, yet herring are captured in small quantities as bycatch by vessels targeting groundfish. However, we focus solely on those trips which herring were directly targeted. In addition, the fishery is primarily a single-species fishery with herring dominating the catch composition on those trips where fishing vessels are directly targeting herring.[10] There are three primary methods used to capture herring: mid-water trawl, purse seine, and paired mid-water trawl. Figure 1 contains a histogram of the landings for each of these gear types over the four years analyzed.[11] Our production estimates include only the purse seiners and mid-water trawlers. We do not investigate the production frontiers possessed by the paired-trawlers because we are interested in obtaining vessels specific measures of technical efficiency and paired-trawling involves two vessels towing a single trawl. However, because we often observe mid-water trawlers fishing alone and with another mid-water trawler while paired-trawling, we are able to determine with whom each vessel decides to pair up with and how this relates to the *H* production classes estimated. This is discussed further in the sequel.

There are five primary reasons why we suspect that heterogeneity may exist in the production technology of the Northeast Atlantic herring fishery: (i) purse seine and mid-water trawlers may possess different elasticities of input utilization, (ii) there exists a substantially large variance in the vessel characteristics, landings and trips conducted within the fleet targeting herring (see Table 3), (iii) landings are often pre-contracted before fishing and some vessels are predominately order filling vessels, (iv) herring is supplied to a number of different markets (e.g., bait and consumption markets) with vessels often pre-determining their intended market (v) the "good" captain hypothesis may be present. The later three forms of heterogeneity are truly unobserved within our data set. Determining the amount of pre-contracted fishing and the target market for each vessel would require contract data, which we do not possess. The "good captain" hypothesis could be investigated through inefficiency regressions but a rigorous investigation would require captain socioeconomic data (e.g., educational background, experience, see Kirkley et al., 1998) which we also do not possess. However, given that we suspect heterogeneity in the data (some of which we can directly observe and some which we cannot), the herring fishery data are well-suited to the investigation of heterogeneous production using the EC algorithm.

Estimation Procedure

The stochastic frontier model estimated for each $h = 1,..., H$ segment is specified as follows,

$$\begin{aligned}\ln(C_{it}) = {} & \beta_{0|h} + \beta_{1|h} * \ln(GRT_i) + \beta_{2|h} * \ln(HP_i) + \beta_{3|h} * \ln(Crew_{it}) + \beta_{4|h} * \ln(Hours_{it}) + \\ & \beta_{5|h} * \ln(GRT_i) * \ln(Crew_{it}) + \beta_{6|h} * \ln(Crew_{it}) * \ln(Hours_{it}) + \beta_{7|h} * DumNoCrew_{it} \\ & + \beta_{8|h} * DumSpWntInshore_{it} + \beta_{9|h} * DumSpWntOffshore_{it} \\ & + \beta_{10|h} * DumSumFallOffshore_{it} + v_{it} - \eta_i\end{aligned} \quad . \tag{10}$$

C_{it} represents the catch for vessel *i* on trip *t* expressed in metric tons of herring harvested. GRT_i and HP_i capture the fixed inputs of production for vessel *i* and represent the vessel's gross-registered tonnage and engine horsepower respectively.[12] $Crew_{it}$ and $Hours_{it}$ represent the number of crew members on board the vessel and the hours spent fishing on trip *t* respectively. We constructed the hours fished by calculating the difference in the departure and arrival time for each trip, and subtracting steam time.[13] Steam time was calculated by determining the distance between port and the centroid of the reported area fished and assuming a typical speed of 12 knots steaming to and from the fishing grounds.[14] $DumNoCrew_{it}$ is a dummy variable indicating whether or not the number of crew members on board the vessel was observed on trip *t*. In the case that no crew members were observed we substituted the mean number of crew members utilized by vessel *i* within the data set for the missing value.[15] The other three remaining variables, $DumSpWntInshore_{it}$, $DumSpWntOffshore_{it}$, and $DumSumFlOffshore_{it}$ are dummy variables indicating whether vessel *i* fished inshore during the Spring or Winter, offshore during the Spring or Winter or offshore during the Summer or Fall in time period *t* respectively.[16] The peak seasons for the inshore fishery are Summer and Fall, while they are the Spring and Winter for the offshore fishery. These peaks in the inshore and offshore activity correspond with the seasonal migration of herring from the inshore northern latitudes to the offshore southern latitudes within the year. Therefore, these dummy variables control not only for the respective inshore and offshore seasons but for the stock abundances present during these time periods.

The production function was determined by specifying the full trans-log production specification and then removing variables which were highly collinear. Any variable which possessed a linear correlation with *GRT, HP, Crew* or *Hours* greater then 0.90 was removed from the specification of the production function. Although this is an arbitrary rule for determining the specification of the model, it facilitates the estimation of the *H* production classes by reducing the probability of within segment multicollinearity.[17] For computational parsimony, we select the same number of production parameters for each segment.[18] Therefore, there are eleven parameters for each of the *H* segments within the latent class model. Denote each segment's $(J \times 1)$ parameter vector as $\lambda_h' = [\beta_{0|h}, \beta_{1|h}, ..., \beta_{11|h}]$, then there are *H*J*+3 parameters, $\Theta' = [\lambda_1', ..., \lambda_H', \gamma, \mu, \sigma_s^2]$, to estimate.[19]

The production function estimated for each segment was carefully selected to control for within segment multicollinearity. As mentioned earlier there exist two different fishing technologies in the North Atlantic herring fleet, purse seiners and mid-water trawlers. One obvious way to control for these technological differences would be to construct a dummy variable for one of the technologies. This dummy variable could also be interacted with the other variables within equation (10) to obtain two representative production functions within each of the *H* segments. This would imply that we would be (in essence) estimating *2*H* segments within the fishery. However, the EC algorithm aggregates agents into the *H* segments based on latent similarities in their production technology and one of these latent similarities is the marginal products possessed by these different fishing technologies. Therefore, this may increase the probability of within-segment multicollinearity, which could produce highly variable parameter estimates. Hence, we do not use a dummy variable to control for fishing technologies so as to obtain reliable parameter estimates and to investigate whether or not the EC algorithm is capable of partitioning the vessels according to their production similarities.[20] This serves as an *ex post* justification for using the EC algorithm in future production modeling where latent heterogeneity is believed to exist but is truly unobserved by the researcher.

Model Selection and Empirical Results

To select the appropriate number of segments, *H*, we appealed to likelihood ratio tests, the Bayesian Information Criteria (*BIC*), and the Akiake Information Criteria (*AIC*) tests. The likelihood ratio test in the context of the latent class regressions is $LR = -2[ln(L|H-1)-ln(L|H)]$, where the degrees of freedom for the test statistic is equal to *J*. The *BIC* and *AIC* tests are specified as follows, $BIC = -2ln(L)+J(ln(N))$ and $AIC = -2ln(L)+J2$ respectively, with lower values for the *BIC* and *AIC* supporting the further segmentation of the latent class model. All three test statistics support the segmentation of the model and indicate that the preferred number of segments is H=3.[21] Further segmentation of the data set was explored, H=4, however the log-likelihood estimates produced ill-conditioned Hessians, suggesting a high degree of within-segment multicollinearity. We, therefore, focus on the H=3 segmentation results in what follows. Additionally, given the small number of vessels on the data (39) and the estimated number of vessels within each of three segments, we believe that the four segment model is potentially asking too much of the data. Therefore, we present results for the one and three segment models to compare the model results under homogeneous and heterogeneous production assumptions.

In both the homogeneous and heterogeneous production models the variance parameter, γ, is close to one which indicates that the inefficiency effects are significant in our model (Battese and Coelli 1995). This was confirmed using a likelihood-ratio test on the null hypothesis that the inefficiency effects were absent in the homogeneous model, γ =0.[22] The magnitude of the variance parameter, γ, is reduced as we increase the number of segments in the model. This suggests that the heterogeneous production profiles generated by the EC algorithm reduce the explanatory power of the inefficiency effects relative to the homogeneous production model. However, the significance of this parameter across all the models estimated indicates that the inefficiency effects prevail.

The EC algorithm induces a small-sample classification bias in determining each vessel's segment membership (El-Gamal and Grether 1995; El-Gamal and Inanoglu 2005). To characterize the extent of this bias, El-Gamal and Grether (1995) introduce an "average normalized entropy" (ANE) statistic as a reliability measure of the segmentation algorithm. The ANE is based on the posterior probabilities for each vessel and is expressed as,

$$\kappa_{ik} = \frac{l_i(\theta_k)}{\sum_{j=1}^{H} l_i(\theta_j)} \qquad (12)$$

where $l_i(\theta_k)$ is vessel *i's* likelihood function value given parameter vector θ_k and j indicates the segment within the H segmented model. Using these posterior probabilities the ANE test statistic is constructed as,

$$ANE(H) = -\frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{H}\kappa_{ij}\log_2(\kappa_{ij})\,. \qquad (13)$$

The test statistic is bounded between zero and one, with lower values indicating a reliable segmentation of the data. El-Gamal and Inanoglu cite ANE values of 0.065 and 0.09 within their study of the Turkish banking as reliable measures of segmentation (El-Gamal and Inanoglu 2005). The ANE(3) value obtained in our research was 0.226. A four segment model could conceivably improve the statistic, but given the empirical intractability of the four segment model, this ANE value was the best we could obtain.

The estimation results are contained in Table 2. The first column of Table 2 shows the estimated homogeneous stochastic production frontier for the Northeast Atlantic herring fleet. This model indicates that production is primarily determined by the vessel's size and horsepower as well as the season and location. In addition, the elasticities of input utilization are all positive and satisfy the traditional monotonicity assumptions. Columns two through four of Table 2 show the estimated parameters for the three segment stochastic production frontier model. The results from the heterogeneous production frontier indicate that there exists substantial variation in input utilization across the segments (i.e., there are substantial differences in the elasticities across segments). Not all variables significant in the homogeneous model are significant in each of the heterogeneous segments, and visa versa. The most pronounced being the change in significance of *Hours* across the models. Additionally, there do exist a few statistically significant curvature violations (sign violations) within the heterogeneous model, which will be discussed in the next section. Fortunately, as we shall see, each segment possesses a set of unique features which may explain these violations once they are taken into consideration.

Before discussing how the three segment production functions differ, it is useful to characterize the producers in each of the three production segments. Table 3 shows the mean, standard deviation, maximum, and minimum values of the key production variables for both the homogeneous and heterogeneous production models. Vessels in segment 1 are predominately mid-water trawlers (% purse seiners = 7.69%); in fact, only one vessel is a purse seiner. Vessels in segment 1 possess the highest average catch per trip (109.70 metric tons), utilize the smallest vessels (as measured by average *GRT* = 91.38 tons and *HP* = 949.80 h.p.), fish the fewest number of days (average T_i = 36.85 days), and they fish longer (average *Hours* = 21.40 hrs) and farther from port (Distance = 98.55 km) than the other vessels. In addition, these vessels possess the greatest ratio of horsepower per a gross-registered tonnage (*HP/GRT*). Their ratio is 10.394 *HP/GRT*, while it is only 7.139 and 5.195 for segments 2 and 3, respectively, and 7.558 for the entire fleet. The most important descriptive statistic is the high variance this segment possesses. All of the aforementioned characteristics have the highest standard deviations in segment 1 except for the days fished.

The high variance for segment 1 results from the heterogeneity of the vessels in the segment: There are 9 small vessels and 4 very large vessels within this segment. The 9 small vessels possess an average catch per trip of 1.745 metric tons which is substantially lower than the 147.20 average metric tons harvested by the 4 large vessels. These size differences also manifest themselves as differences in vessel size and horsepower. The average *GRT* and *HP* for the 9 smaller vessels is 26.11 and 436.30 respectively, which is substantially different than the corresponding values of 238.30 and 2,105.00 for the 4 larger vessels. Although these differences may suggest that the segment be split into two segments (potentially resulting in a four segment model), there is a fundamental characteristic which all of these vessels possess that may be used to define the segment. These vessels are all opportunistic herring fishers. The smaller boats are vessels supplying small amounts of herring to the bait market for lobster, and the larger vessels participate in other fisheries (i.e., groundfish) throughout the year. Combined, these factors highlight two concerns in the estimation. First, it may be difficult to obtain reliable estimates of technical efficiency if vessels are constrained to possess the same production technology as other vessels which actively participate in the herring fishery. Two, the vessels in this segment may be thought as "fringe" participants in the fishery and not part of the "core" herring fleet from a policy perspective. (Not surprisingly, excluding these vessels from the analysis results in the exact two-tier segmentation implied by the three segment model, with the added benefit that the elasticity estimates for the two segments are very similar to the estimates obtain in the three segment model.)

Vessels in segment 2 are predominately mid-water trawlers, except for one purse seine vessel. These vessels also use the fewest number of crew members on average, and are the oldest and largest vessels within the fleet. These vessels also have the lowest average catch rates. Segment 3 contains the largest concentration of purse seiners, containing 90% of the entire purse seine fleet, which account for 64.29% of the vessels within segment 3 and 85.30% of the observations. Segment 3 also uses the largest and most stable work force, fish the largest number of days, T_i, and they possess the newest vessels. The most significant factor is that this segment predominately participates in the summer and fall inshore fishery, which accounts for 82.60% of their days-at-sea. This substantially exceeds the 49.70% and 48.80% for segments 1 and 2, respectively.

Given these segmentation results, it is evident that the EC algorithm successfully partitioned the data set into three distinct segments. The most remarkable segmentation result was the EC algorithms ability to group nearly all of the purse seiners within the data set into the third segment (table 3, segment 3, % purse seiners = 64.29%). Although this is a factor which could presumably be controlled for in a homogeneous production model, it does suggest that, if there exists truly latent heterogeneity in the data (that which can not be directly observed), the EC algorithm is capable of accounting for its existence in the grouping of the segments. In fact, conducting a chi-squared test of the frequency of vessel technologies within the three segments rejects the null hypothesis that the assignment of vessel technologies across the three segments is uniformly distributed.[23] The improvement in fit and increase in statistical efficiency that comes from capturing this heterogeneity is of limited interest if modeling heterogeneity does not also yield a different profile of production in the fishery. Examination of the production coefficients (table 2) indicates that the aggregate estimation does in fact mask differences in production functions, predominately identifying the season fished and vessel size as significant factors which are not always consistent with the results generated by the heterogeneous model.

Table 4 contains the segment specific marginal products under both homogeneity and heterogeneity assumptions, as well as each segments implied returns-to-scale.[24] Comparing the marginal products and returns-to-scale for each segment under the homogeneous and heterogeneous models it is clear that there exists a high degree of heterogeneity. In addition, the increasing returns to scale observed under the homogeneous model appears to be driven by the exceptionally high returns-to-scale possessed by segment 1 in the heterogeneous model, which we have already labeled as the "fringe" segment within the herring fishery. When controlling for this segment of the fleet, one can conjecture that the herring fleet possesses decreasing returns-to-scale. This is an interesting discovery because increasing returns-to-scale has often been observed in many fisheries (Felthoven 2002; Felthoven and Paul 2004; Kirkley, Squires and Strand 1995; Sharma and Leung 2002 to cite a few), and the results from the EC algorithm suggest that this may be due to latent heterogeneity in the production functions. Of course, this is something that would need to be empirically investigated on a case by case basis since the high degree of heterogeneity observed in the herring fishery may not exist in other fisheries.

Continuing in table 4, the largest determinants of production for vessels in segment 1 are their size (*HP* = 0.1414 and *GRT* = -0.1638) and hours fished (*Hours* = 1.3888). However, the negative and significant coefficient on *GRT* suggests a production theory curvature violation. Based on the production segmentation of the fishery, there are two potential explanations for this anomaly. The linear correlation of *HP* and *GRT* within segment 1 is 0.9813, which is substantially larger than the 0.5768 and -0.1630 correlations for segments 2 and 3 respectively. This could presumably be controlled for by restricting this segments production function to contain only *HP* or *GRT*, however this is not something we explore since our standard errors are relatively small. Alternatively, this phenomenon may be a result of the opportunistic nature of this segment. Vessels in segment 1 fish the fewest number of days (about half the days fished by segment 2 and about one third the days fished by segment 3, in table 3). This suggests that they participate in the herring fishery to "fill the season," when herring fishing is advantageous relative to the other fisheries in which they are geared to participate. This would indicate that the fixed inputs these vessels select, *HP* and *GRT*, may be optimal for alternative fisheries. Therefore, they may be using a vessel which has a substantially different returns-to-scale within an alternate fishery, which is more economically important for the bulk of the season.

To further investigate whether or not vessels in segment 1 opportunistically participate in the herring fishery, we calculated the average annual percentage of their fishery-wide returns that consisted of herring for 11 of the 13 vessels in segment 1.[25] Of these 11, 6 vessels possessed percentages below 10%, with 4 of them below 2%, indicating that these vessels predominately participate in other fisheries throughout the year. Comparing this with a similar calculation for 12 of the 14 vessels in segment 3, we found that 5 of the 12 possessed percentages greater than 95%

and 3 of these 5 received all of their revenues from the herring fishery. Furthermore vessels in segment 1 are not as dramatically affected by the season in which they fish. Combined, these results support the hypothesis that segment 1 contains vessels which opportunistically fish in the herring fishery and are "fringe" participants, whereas those in the other segments represent the stronger "core" of the herring fleet. This may explain not only the high returns-to-scale possessed by this segment but also the curvature violation.

In table 4, herring production for segment 2 is predominately determined by the size of their vessels (*GRT* = 0.00619), the number of crew members (*Crew* = 3.0050), and the hours spent fishing (*Hours* = 0.1820). This segment possesses two unique production attributes, a small marginal product for *GRT* and a very high marginal product for *Crew*, relative to the other segments. In addition, vessels in segment 2 have the lowest returns-to-scale. The last segment within the fleet, segment 3, is primarily influenced by their mobility (*HP* = 0.0393) size (*GRT* = 0.1761), the number of hours fished (*Hours* = -0.6649), and the season in which they fish. This is reflected by the highly significant coefficient on *HP*, the marginally significant coefficient on *GRT* and the negative and statistically significant coefficient on *Hours*.[26] Given that this segments *HP/GRT*, discussed earlier, is the lowest in the fleet, the empirical results indicate that this segment could enhance their catch by increasing their vessel's horsepower.

The curvature violation in the third segment for *Hours* results from the mixed technologies within the herring fleet. Segment 1 and 2 are predominately mid-water trawlers, while vessels in segment 3 are both purse seiners and mid-water trawlers. These two technologies possess substantially different returns to hours fished. The average returns per an hour fished for a mid-water trawler within segment 3 is 3.005 metric tons/hour fished. This stands in stark contrast with the 6.781 metric tons/hour fished. Therefore, from an empirical stand point the purse seine vessels within segment 3, which account for over 85% of the observations, are being controlled for via the negative coefficient on *Hours*. Presumably, we could have corrected for this using a dummy variable for purse seiners but, as discussed earlier, we were unable to do so, given the high degree of within-segment multicollinearity which would result. Alternatively, the negative coefficient on *Hours* may result from the fact that herring are a schooling pelagic species. With a schooling pelagic species the most difficult factor is locating a school of fish, which when found are easily captured. Presumably, a longer time spent fishing would indicate either a small school of herring resulting in increased fishing time spent to locate more fish nearby or an increase in search time.[27] This negative impact of *Hours* will be greater for segment 3 because segment 2 contains more mid-water trawlers. Mid-water trawlers require more time to catch herring as they must trawl through the herring school and therefore we observe a positive and significant coefficient on *Hours* within segment 2.

Aside from the properties of the production function possessed by segment 3, these vessels also consistently fish the largest number of days within the fishery and predominately fish inshore during the summer and fall. Although vessel characteristics do explain some of this segments production, the highly significant coefficients on *DumSpWintInshore*, *DumSpWintOffshore* and *DumSumFallOffshore* indicate that this segment of the fishery generates most of its output during the summer and fall inshore season, which corresponds to the seasonal migration patterns of the herring. Given the recent proposed amendments to the Herring Fishery Management Plan, which may potentially restrict access of mid-water trawlers to the inshore fishery, the EC algorithm has determined which vessels are most likely to be adversely effected by this new policy; the mid-water trawlers in segment 3.

Since segment 1 represents an opportunistic and "fringe" segment of the herring fishery, it is possible that this segment should not be considered when conducting policy analysis.[28] To further investigate this we eliminated vessels in segment 1 and re-estimated a two segment latent class model. The results are in Table 5, hereafter denote Model 2. Comparing these results with those in Table 2 (denoted Model 1), it is evident that the coefficients are similar and in many cases not statistically significant from one another. In addition, the most remarkable result is that the segmentation in the data set is identical to that obtained in the three segment model. The primary difference between model one and model two is that model two generates substantially different parameter estimates for γ and σ^2_S. This suggests that vessels in segment 1 were driving the higher variance, σ^2_S, and the relative importance of σ^2_μ (reflected by the higher value for γ).

The comparison of these two models (Models 1 and 2) highlights an additional advantage of using the EC algorithm, it not only produces consistent latent segmentation but it generates reliable within segment parameter estimates. Therefore, following estimation a policy maker can decide to focus on one or more of the segments obtained and ignore the vessels in other segments they deem to be "fringe" segments or irrelevant from a policy perspective. This could be potentially advantageous from a policy perspective if one of the segments possess a substantially different marginal product for an input undergoing policy reform. Presumably it is possible to obtain similar estimates using a prespecified data filter (i.e., focusing vessels which catch more than a certain amount), but this would be an *ad hoc* way of segmenting the data and may ignore latent heterogeneity in the data. Although the coefficients are similar, from a policy perspective it would still be important that the technical efficiency measures under the two models be similar because different estimates for γ and σ^2_S may yield different technical efficiency measures. This is investigated further when we analyze the technical efficiency measures generated using the homogeneous and heterogeneous production models (both Model 1 and Model 2).

Implications of Heterogeneity for Technical Efficiency

Stochastic production frontier models are often used to derive measures of technical efficiency to characterize industry capacity (Felthoven 2002; Kirkley et al. 2002). These measures are used, in turn, to determine the nature and extent of effort reduction programs, such as the creation of fishing cooperatives in the Alaskan pollock fishery, following the inception of the American Fisheries Act (Felthoven 2002; Felthoven and Morrison Paul 2004). [29] Technical efficiency measures the degree to which a vessel obtains the maximum level of production implied by their production technology. Table 6 shows the technical efficiency measures for vessels in each segment, calculated under the two different assumptions. The left-most column of each segment shows the technical efficiency for each vessel in the sample based on the heterogeneous model, and the right-most column is based on the homogeneous model. For segments 2 and 3, two heterogeneous technical efficiency measures are provided, corresponding with the Model 1 (Table 2) and Model 2 (Table 5) estimates.

The homogenous production model leads to substantially different measures of technical efficiency than the heterogeneous model.[30] There are many sizable differences in estimated technical efficiencies between these models, especially for vessels in segment 1. Therefore, assuming homogeneity in the production technology may yield substantially different results than if one allows for production heterogeneity, yet when one allows for production heterogeneity the distribution of technical efficiency measures becomes more homogeneous (within segments). The most profound difference in technical efficiency measures occurs in segment 1 were the efficiencies are abysmally low for the homogenous model. This illustrates that failure to account for heterogeneity leads to a statistically and economically significant underestimation of the technical efficiency of these vessels. In many cases, the homogeneous model underestimates technical efficiency by a factor of 10 or more. This may lead policymakers to generate fallacious estimates of excess capacity for this segment, leading to improperly guided management measures.[31] However, given that this segment has been labeled our opportunistic "fringe" segment of the fleet, these results should be interpreted with caution. Since these vessels primarily participate in other fisheries during the year, increasing there effort in the herring fishery may not be economical given their capital stock. Another interesting result from the EC algorithm is illustrated in Table 6. As mentioned earlier, 9 vessels in segment 1 possessed catch rates indicative of supplying herring to the bait market. Using a production filter of average catch less than or equal to 3 metric-tons to indicate a "bait-market" vessel (indicated with BM in table 6), the EC algorithm has grouped nearly all of them into segment 1. Only one other "bait-market" boat exists and that is a mid-water trawler in segment 2. This further highlights the EC algorithms ability to capture latent heterogeneity in the data set.

Comparing the technical efficiency measures obtained using Models 1 and 2 for segments 2 and 3 it is evident that these alternative specifications (Models 1 and 2) generate similar technical efficiency measures. However, the results from Model 2 are slightly lower than those obtained from Model 1, but they are both superior to the homogeneous model estimates (in the sense that they both result in *higher* efficiency measures than the homogenous production model). In addition, the ordinal ranking of the technical efficiency measures do change for a few vessels in each segment, but they are otherwise consistent with the results generated using Model 1. It is possible to determine whether or not this change in ordinal ranking is statistically significant using a minimal subset ranking approach (implied by Horrace 2005), but this is beyond the scope of this investigation. Figure 2 illustrates the impact of heterogeneous modeling on the cumulative density of technical efficiency in the herring fishery. For the homogeneous model ($H=1$) a substantial portion of the cumulative density lies below a technical efficiency measure of 0.50, which is not the case for the two-segment ($H=2$) and three-segment ($H=3$(Mod1) and $H=3$(Mod2)) models. Increasing the number of segments in the model causes a rightward shift in the cumulative density of technical efficiency measures.

Who Pairs with Whom?

In addition to challenging accepted notions of homogeneous production frontiers, our latent class analysis can be used to provide some initial insight into a trend which has not been previously analyzed within the herring fishery. Figure 1 illustrates that while mid-water trawling and purse seining are the most common gear types, they have steadily declined in recent years with the rise of paired-trawling. This reflects vessels switching from individual fishing to paired-trawling, giving us the opportunity to identify the characteristics of vessels that pair with one-another.

Specifically we can determine whether vessels pair with other vessels in the same segment when they switch to paired-trawling or vessels in an alternate segment. Although the logbook data does not contain precise information on which vessels paired up with each other, many pairings can be recovered by matching the port, date and time of return. Vessels that returned to the same port within an hour of each other reporting a paired-trawl gear type were considered to have paired up. This resulted in 277 pairings for the 39 vessels analyzed. Of these 277 only 7 pairing involved a vessel from segment 1. Therefore, the opportunistic vessels in segment 1 rarely participate in paired-trawling activities.

To determine with whom vessels in each segment pair up with, the 277 pairings were further analyzed to determine unique pairings between vessels in the data set. A unique pairing is defined as a pairing between vessels that occurred at least once during the 277 pairings observed. Given this definition there were 11 unique vessel pairings with the pairing frequencies defined over segments illustrated in Figure 3.[32] From the figure, it is apparent that vessels in segment 2(three) and three predominantly pair up with vessels in segment 3(two), occasionally with a same-segment vessel, but almost never pair up with a vessel from segment 1.

These pairing practices indicate that vessels which utilize different production function while fishing alone often pair up with each other while paired-trawling. The vessel characteristics for segments two and three may influence the pairing process. Vessels in segment 2 are on average larger and more powerful than those in segment 3. Focusing on the observed cross segment pairings indicates that often these pairings involve two vessels with substantially different measures of horsepower per a meter of vessel length.[33] Perhaps these differences complement each other while paired-trawling. Therefore, the pairing of these two segments is either driven by the fact that they possess similar levels of productivity, that there are returns-to-scale from using a less powerful and a more powerful vessel together in paired-trawling, or that there exist alternative social arrangements which determine paired-trawling in this fishery (e.g., family relationships). The most remarkable result is the low frequency of pairings involving vessels in segment 1, further highlighting the opportunistic and "fringe" production segment they represent.[34]

Conclusion

The notion of heterogeneity in production is an obvious extension given the increasing concern of addressing heterogeneity in preferences and individual decision making within economics (Train

2003). The latent stochastic production frontier model developed within this research illustrates how heterogeneity can be introduced and investigated. Our results support the hypothesis that there exists production heterogeneity in the Northeast Atlantic herring fleet which is reflected in the different marginal products of input utilization. In addition, our model illustrates that if one ignores the presence of heterogeneity it is quite possible that erroneous policy recommendations may be made.

Although this model is applied to a fisheries production process it invariably may prove to be beneficial within the agricultural literature focusing on crop selection and policy response. In essence the homogeneous model discussed within this paper straightjackets agents to follow the same production practices, which in turn may yield inaccurate measures of technical efficiency. This is well illustrated in the Northeast Atlantic herring fishery were we observe a substantial difference in a vessel's technical efficiency measure assuming a homogeneous versus heterogeneous production technology. Whereas if we allow for heterogeneity to exist, we obtain a flatter distribution of technical efficiency because inter vessel differences are better explained by alternative production functions not technical efficiency.

Within the fisheries literature, the methods outlined within this paper may be extremely beneficial to researchers interested in fishery capacity or the ability of vessels to compensate for management instruments that effect their rate of efficiency (eg.. gear and area restrictions). Should heterogeneity exist within a fishery, any policy which restricts input utilization will yield asymmetric impacts due to the differences in the returns-to-scale and marginal product of input utilization within the fleet. Therefore these methods have not only been able to segment a fleet into different latent groups, they have illustrated a potentially useful methodology to facilitate policy development. This may be of increasing concern to resource managers who are now faced with more complex management goals, and the regimes to achieve these goals, within fisheries.

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[1] For a more detailed review of applications in agriculture see the articles written by Battese (1992) and Coelli (1995b). For applications in aquaculture see Irz and McKenzie (2003), Sharma and Leung (2003) and Dey et al. (2000) to cite a few.

[2] It should be noted that data envelop analysis (DEA) is often used to generate estimates of excess capacity and this paper utilizes a stochastic frontier model. Both methods can be used to generate estimates of

excess capacity and there have been a number of papers which discuss the advantages and disadvantages of these methods. See Kirkley et al. (2002) for a more detailed discussion.

[3] The presence of a "good" captain has also been investigated by cultural anthropologists. Acheson (1981) and Thorlindsson (1988) provide a more detailed discussion of the human dimensions influencing the presence of "good" captains within fisheries.

[4] We acknowledge that a fairly rich specification can be achieved (without latent class regression) by including sets of interacted dummy variables, which represent *observed* classes of heterogeneity. An added benefit is that these specifications often imply traditional pooling tests for the vessels in the sample. However, the goal here is account for latent (unobserved) heterogeneity which, if ignored, may bias marginal product estimates in the production function.

[5] The rationale for the functional form is discussed in the estimation procedure section.

[6] All segments share common parameters for the distribution of the vessel-specific error term, a truncated $N(\mu, \sigma^2_\mu)$. El-Gamal and Inanoglu (2005) claim that without common μ and σ^2_μ the econometric model is "ill-posed." A latent class production model with an exponential distribution for efficiency could also be investigated.

[7] The complete data set contains 3004 observations. However, we use a production filter of 0.10 metric tons of herring landed per a trip and eliminate observations for which vessel characteristics were not recorded. In addition, two boats within the data set were sold during the time period analyzed and have been treated as separate distinct vessels due to the change in ownership.

[8]The catch data contained in the logbook data set is provided by the captain of the vessel. It should be noted that any form of catch estimate may be subject to measurement error.

[9] For a more detailed discussion of the proposed management changes see NEFMC (2005).

[10] Given the technologies (mid-water trawl and purse seine), there are two primary species caught within this fishery, herring and mackerel. Vessels in the data set predominately caught herring with a small number of observations possessing positive amounts of mackerel. In order to focus solely on herring catch we eliminate all observations for which the herring composition did not exceed 90% of the total catch.

[11] All other landings recorded by other gear accounted for between 0.02% and 0.05% of the total metric tons landed from 2000 through 2003. Therefore, all other gears are not illustrated in Figure 1.

[12] The vessel's gross-registered tonnage and horsepower were selected to represent the vessel's fixed inputs because they possessed the lowest degree of linear correlation (0.4809) of all the available fixed inputs.

[13] In the case that our steaming time calculations exceeded the hours spent on the trip we set the number of hours fished to one. The total trip time consists not only of steaming time and fishing time but also search time, therefore the construction of this variable does introduce an estimation bias due to heterogeneous nature of the fleet's technology.

[14] The distance measures were calculated using the earth model distance conversions developed by C.G. Carlson and D.E. Clay for site-specific management guidelines available at www.ppi-far.org/ssmg and programmed in MATLAB 7. The average travel speed was provided by contacts at Woods Hole Oceanographic Institute.

[15] There were two vessels in the data for which we did not observe any crew data on and we set $\ln(Crew_{it})$ equal to zero for these boats.

[16] Initial investigations partitioned these dummy variables into the four seasons and inshore and offshore regions. The results indicated a high degree of multicollinearity within the segments so we aggregated the Spring and Winter seasons as well as the Summer and Fall.

[17] Using a linear correlation filter of 0.95 was also investigated. In models with $H > 1$ the production estimates indicated a high degree of within segment multicollinearity.

[18] A likelihood ratio test was conducted on the homogeneous model restricting $\beta_5 = \beta_6 = 0$. The test statistic of 2.497 does not exceed the 95% level critical value of 5.99 for a χ_2^2. This indicates that we could have used the Cobb-Douglas functional form of equation 10. However, we elected not to because we suspected that these variables could be significant determinants for one segment and not another in the EC algorithm. Therefore, eliminating these variables from the model would further homogenize our results. This suspicion was confirmed in our final results.

[19] Estimation of equation (10) does raise the question of endogenous explanatory variables. However, if we assume that the choice of inputs used to maximize catch is subject to "human error" and that these errors are uncorrelated with the error specification in the stochastic frontier model the endogeneity concerns are addressed (Kirkley et al. 1998).

[20] Initially we selected a dummy variable for the purse seine gear, *Pseine*, which was used as a intercept shifter as well as interacted with the other inputs in the production function. However, this produced and ill-conditioned Hessian and explosive standard errors; a sign that multicollinearity may be a problem.

[21] Because the likelihood function may have many local maxima we used 500 different random starting points to obtain the maximum log-likelihood value using the Constrained Maximum Likelihood (CML) algorithm in GAUSS. To obtain values for γ and σ_s we transformed them so that γ lied on the interval [0,1] and σ_s was non-negative. Following the 500 random starting points, the best estimates for γ and σ_s were transformed back and the model was re-estimated to obtain standard-errors.

[22] The likelihood ratio statistic was 1936.73 which is greater than the 95% critical value of 7.82.

[23] The chi-squared test statistic is 11.635, which is greater than the critical value of 5.99 for a chi-squared random variable with two degrees of freedom.

[24] The vessel elasticities of input utilization were calculated as follows, $\varepsilon_{k|h} = \partial C_h / \partial Z_{k|h}$. The marginal products were calculated as follows, $MP_{k|h} = \varepsilon_{k|h}(\overline{C}_h / \overline{Z}_{k|h})$, where $\overline{C}_h$ is the average catch for segment h and $\overline{Z}_{k|h}$ is the average level of the k^{th} input for segment h.

[25] We thank Andrew Kitts at the National Marine Fisheries Service for providing us with this information. This data was unavailable for 2 of the boats in segment 1 and segment 3.

[26] The coefficient on *GRT* is significant at the 84% level and *GrtCrew* is significant at the 73% level.

[27] This does suggest and is consistent with the two-stage production process investigated in Campbell (1991) but we do not investigate this form of production.

[28] It is possible that this “fringe” segment possesses some latent capacity which would be utilized if current management policies changed, but we ignore this given the low percentage of revenues derived from herring. However some caution should be used, given that in other fisheries latent capacity is a significant management issue.

[29] Felthoven and Morrison Paul (2004) do not utilize a stochastic production frontier model to estimate efficiency and capacity in the Alaskan pollock fishery. They utilize a GLS estimation of a multi-output

production function. However, there objective, measures of capacity, is motivated by the same concerns as researchers utilizing stochastic production frontier models.

[30] Since these are efficiencies measured in an *absolute* sense, the differences are not being driven by the fact that there are few boats for comparison in the heterogeneous models.

[31] In the fisheries literature inefficiency is usually removed before estimating excess capacity. Therefore, the homogeneous model could either over-estimate or under-estimate the degree of excess capacity, relative to the heterogeneous production model. What is important is that the homogeneous model generates an inaccurate production profile which if used to generate measures of excess capacity will be erroneous.

[32]Segment 1 is omitted because only 2 unique pairings involved a vessel from segment 1 and they were evenly split between pairing up with a boat in segment 2 and three. This pairings are implicitly realized in Figure 2.

[33] Looking at all 11 unique pairings this is true for 9 of them.

[34] It is important to note that we are not characterizing all paired-trawling activities in the herring fishery. We are only looking at those vessels for which we observe individual fishing activity as well as paired-trawling. We are not looking at all paired-trawling activities within the fleet; therefore, what we observe may not be true for all other vessel pairings.

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Figures and Tables

Figure 1: Metric tons landed by gear type and year.

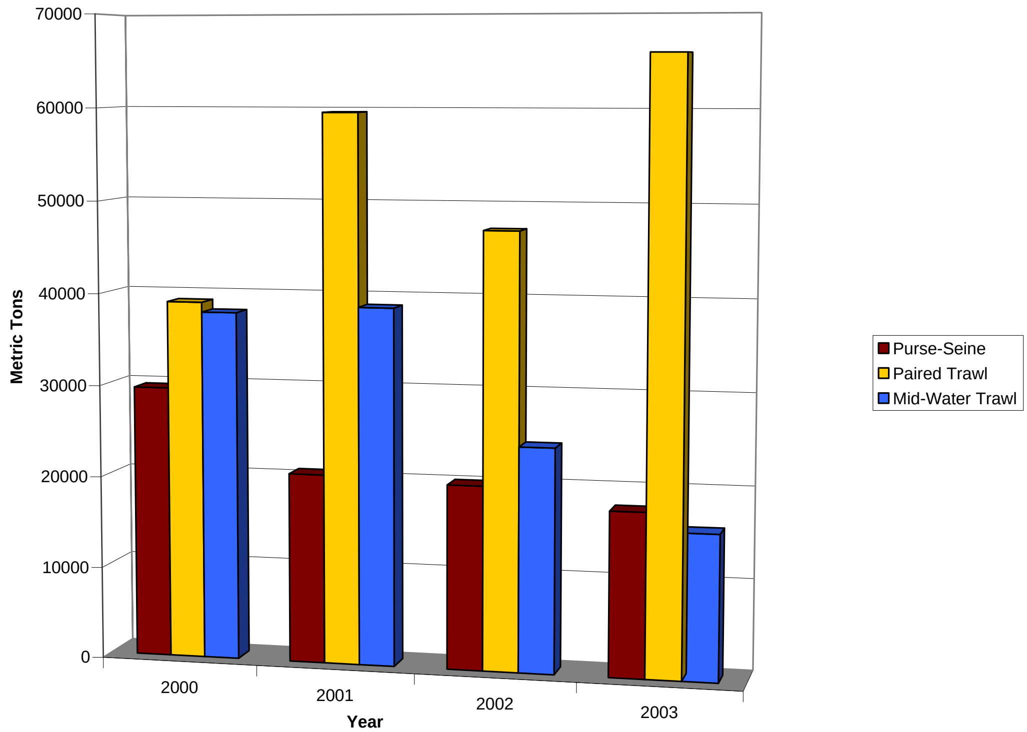


Figure 2: Cumulative Density Estimates of the Technical Efficiency (*H* defines the segment assumptions).

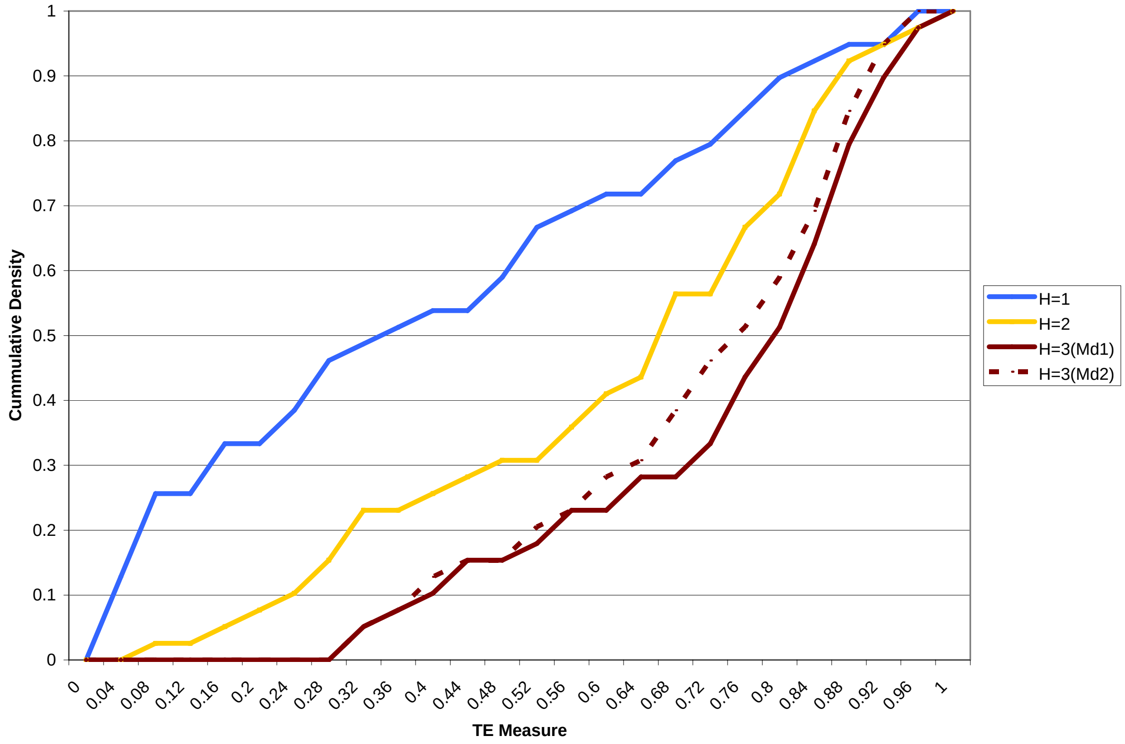
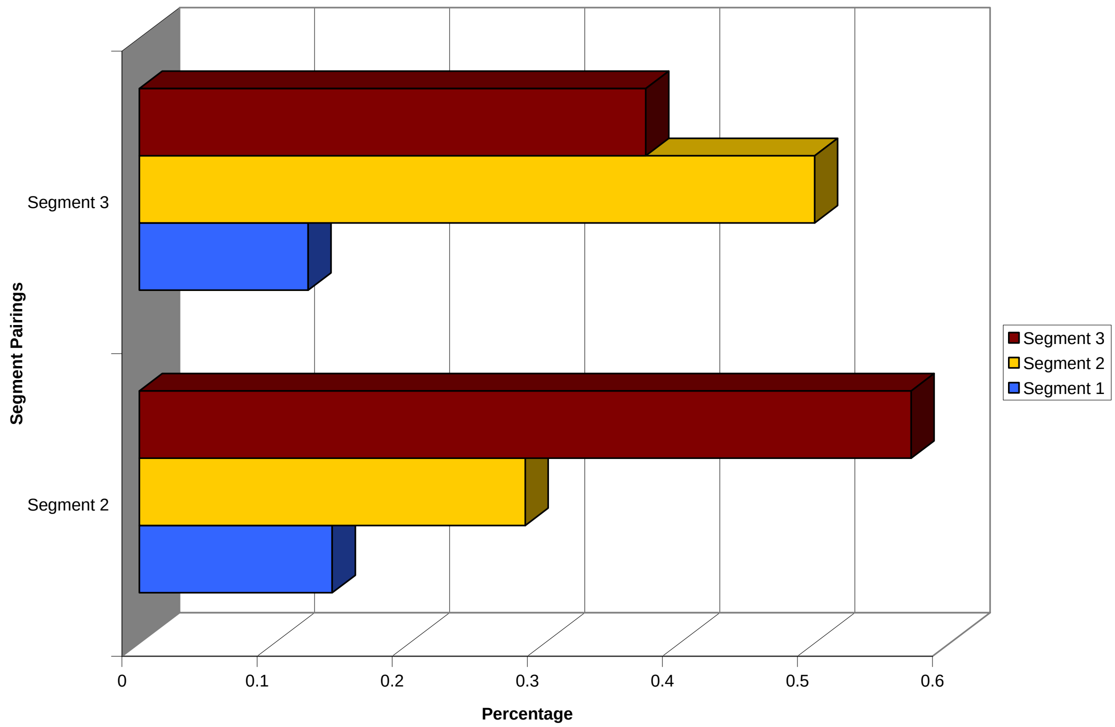


Figure 3: Paired-trawling behavior by segment.



(**Segment 1 is not include in this figure because there existed only two paired-trawling observations, both of which were paired with a vessel in segment 2.)

Table 1: Model Selection Tests

Classes	Parameters	Mean Ln(L)	LR Test	BIC	AIC
1	14	-1.00957	-------	5894.68	5871.39
2	25	-0.97883	177.92	5757.06	5715.47
3	36	-0.96396	86.07	5711.29	5651.40

Table 2: Latent Class Regression - Stochastic Frontier Results(t-stats)

Variable	No Segments	Segment 1	Segment 2	Segment 3
Constant	-2.2913	-16.0335**	-10.1388**	1.8865*
	(-1.62)	(-11.03)	(-3.88)	(1.67)
GRT	0.2653*	-0.5028**	2.7700**	0.1658
	(1.71)	(-3.26)	(6.91)	(1.42)
HP	0.7781**	2.8326**	0.1254	0.3249**
	(3.57)	(10.85)	(0.38)	(2.16)
Crew	0.2679	0.4373	9.8811**	-0.4213
	(0.62)	(1.06)	(4.06)	(-1.05)
Hours	0.1130	0.4405**	-0.2826**	-0.3380**
	(1.20)	(2.99)	(-2.28)	(-2.24)
GRT*Crew	0.0184	-0.0146	-2.0462**	0.0845
	(0.17)	(-0.13)	(-4.36)	(1.10)
Crew*Hours	-0.0668	-0.1457	0.2823**	0.1414
	(-1.04)	(-1.32)	(3.08)	(1.49)
No-Crew	-0.1314**	0.0081	-0.1752**	-0.0605
	(-2.95)	(0.08)	(-2.86)	(-0.79)
Sp. Wint. Insh.	-0.3221**	-0.0486	-0.0183	-0.5759**
	(-6.93)	(-0.53)	(-0.22)	(-9.25)
Sp. Wint. Off.	0.3829**	0.6814**	0.3106**	-0.1518*
	(7.70)	(7.24)	(3.94)	(-1.66)
Sum. Fall Off.	0.2094**	-0.0314	0.3870**	-0.2274*
	(4.51)	(-0.31)	(6.88)	(-1.83)
γ	0.9597**	-------	-------	0.8807**
	(25.19)			(13.88)
σ^2_S	10.3535	-------	-------	3.2835*
	(1.06)			(1.88)
μ	-3.9023	-------	-------	-6.9310
	(-0.61)			(-1.34)
Number of Vessels	39	13	12	14
Mean Log-Likelihood	-1.00957	-------	-------	-0.96396

** indicates significance at the 95% level; * indicates significance at the 90% level
Segmentation determined by EC algorithm.

Table 3: Segment Characteristics

Variable	Mean (st.dv.) Homog.	Max. (Min.) Model	Mean (st.dv.) Hetero.	Max. (Min.) Seg. 1	Mean (st.dv.) Hetero.	Max. (Min.) Seg. 2	Mean (st.dv.) Hetero.	Max. (Min.) Seg. 3
Catch (tons)	67.59 (59.62)	447.10 (0.12)	109.70 (107.30)	447.10 (0.12)	53.91 (43.61)	311.60 (0.23)	61.96 (36.95)	224.50 (0.45)
GRT (tons)	118.90 (106.30)	476.00 (5.00)	91.38 (130.40)	476.00 (7.00)	137.00 (76.93)	199.00 (5.00)	128.90 (105.70)	394.00 (5.00)
Horse Power	898.70 (678.50)	2985.00 (150.00)	949.80 (937.30)	2985.00 (300.00)	1002.00 (586.30)	2100.00 (150.00)	762.40 (459.60)	2000.00 (333.00)
Number of Crew	4.45 (1.45)	15.00 (1.00)	3.86 (1.91)	15.00 (1.00)	3.63 (1.13)	12.00 (2.00)	5.04 (1.13)	12.00 (2.00)
Hours Fished	15.26 (17.43)	220.40 (1.00)	21.40 (24.38)	214.60 (1.00)	20.34 (21.98)	220.40 (1.00)	20.84 (9.08)	101.40 (1.00)
Distance (km)	87.09 (67.86)	542.40 (67.86)	98.55 (93.08)	329.80 (4.64)	83.44 (78.58)	542.40 (4.44)	85.52 (50.51)	494.90 (5.56)
Vessel Age	17.13 (9.63)	53.00 (1.41)	17.31 (12.76)	53.00 (1.41)	18.01 (8.07)	41.66 (11.00)	16.21 (7.98)	27.39 (2.00)
T_i	74.21 (119.70)	499.00 (1.00)	36.85 (87.76)	327.00 (1.00)	67.92 (142.90)	499.00 (1.00)	114.30 (119.80)	339.00 (3.00)
Obs. No Crew	0.148	-------	0.079	-------	0.261	-------	0.063	-------
% Purse Seiners*	28.21	-------	7.69	-------	8.33	-------	64.29	-------
% of All P.S.	100.00	-------	9.09	-------	9.09	-------	81.82	-------
Obs. P.S.	0.476	-------	0.021	-------	0.002	-------	0.853	-------
Sum/Fall Inshore	0.675	-------	0.497	-------	0.488	-------	0.826	-------
Sp/Wint Inshore	0.092	-------	0.167	-------	0.087	-------	0.071	-------
Sum/Fall Offshore	0.085	-------	0.196	-------	0.119	-------	0.034	-------
Sp/Wint Offshore	0.148	-------	0.140	-------	0.306	-------	0.069	-------

*The percentage of purse seine boats in each segment is not precise due to a small degree of gear switching over the four year time period analyzed occurring within each segment.
Homog. Model = Homogenous production model.
Hetero. Seg. 1 = Segment 1 results for the 3-segement heterogeneous production model.
Hetero. Seg. 2 = Segment 2 results for the 3-segement heterogeneous production model.
Hetero. Seg. 3 = Segment 3 results for the 3-segement heterogeneous production model.
Segmentation determined by EC algorithm.

Table 4: Marginal Product (metric-tons) and Returns-to-Scale

Variable	Homo. Model	Heterog. Seg. 1	Heterog. Seg. 2	Heterog. Seg. 3
GRT	0.1208**	-0.1638**	0.0619**	0.1761
Horse Power	0.0584**	0.1414**	0.0075	0.0393**
Crew	2.9520	-0.7963	3.0050**	2.9910
Hours	0.0714	1.3888**	0.1820**	-0.6649**
Returns-to-Scale	1.2807	2.5424	0.6210	0.7485

** indicates that the marginal product is statistically significant.
Homo. Model = homogenous production model
Heterog. Seg. 1 = Segment 1 results for the 3-segement heterogeneous production model.
Heterog. Seg. 2 = Segment 2 results for the 3-segement heterogeneous production model.
Heterog. Seg. 3 = Segment 3 results for the 3-segement heterogeneous production model.
Segmentation determined by EC algorithm.

Table 5: Latent Class Regression (Model 2) - Stochastic Frontier Results(t-stats)

Variable (*t-stat*)	**Segment 2 Model 2**	**Segment 3 Model 2**
Constant	-10.3427**	1.9373
	(-3.80)	(1.62)
GRT	2.7608**	0.1506
	(6.40)	(1.15)
HP	0.1710	0.3337**
	(0.54)	(2.01)
Crew	10.1429**	-0.4767
	(3.86)	(-1.18)
Hours	-0.2894**	-0.3424**
	(-2.30)	(-2.21)
GRT*Crew	-2.0994**	0.0948
	(-4.15)	(1.25)
Crew*Hours	0.2881**	0.1451
	(3.08)	(1.49)
No-Crew	-0.1751**	-0.0633
	(-2.85)	(-0.83)
Sp. Wint. Insh.	-0.0144	-0.5792**
	(-0.19)	(-9.26)
Sp. Wint. Off.	0.3081**	-0.1516*
	(3.91)	(-1.65)
Sum. Fall Off.	0.3889**	-0.2129*
	(6.91)	(-1.71)
γ	-------	0.3910**
		(2.31)
σ^2_s	-------	0.6496** (3.60)
μ	-------	0.1836
		(0.42)
Number of Vessels	12	14
Mean Log-Likelihood	-------	-0.96396

** indicates significance at the 95% level
* indicates significance at the 90% level
Quantities in parenthesis are t-stats.
Segmentation determined by EC algorithm.

Table 6: Measures of Technical Efficiency

Rank in Segment	Segment1 Model 1	Segment1 Homog.	Segment2 Model 1	Segment2 Model 2	Segment2 Homog.	Segment3 Model 1	Segment3 Model 2	Segment3 Homog.
1	0.9281	0.2421	0.9074	0.8617	0.5126	0.9710^{PS}	0.9582^{PS}	0.9564^{PS}
2	0.9049^{BM}	0.0749^{BM}	0.9028	0.8740	0.7455	0.9338^{PS}	0.9075^{PS}	0.9334^{PS}
3	0.8810^{BM}	0.0284^{BM}	0.8638	0.8140	0.5092	0.9295	0.9033	0.4693
4	0.8586^{BM}	0.0739^{BM}	0.8625	0.8115	0.7936	0.8250^{PS}	0.8022	0.8642^{PS}
5	0.8464^{BM}	0.0157^{BM}	0.8139	0.7462	0.2618	0.8174^{PS}	0.7735^{PS}	0.7950^{PS}
6	0.8444	0.5859	0.7680^{BM}	0.6586^{BM}	0.0224^{BM}	0.8080^{PS}	0.7754^{PS}	0.8086^{PS}
7	0.8413	0.6595	0.7583	0.6610	0.6842	0.7827	0.7179	0.2898
8	$0.8167^{PS,BM}$	$0.0210^{PS,BM}$	0.7434^{PS}	0.6510^{PS}	0.6481^{PS}	0.6106^{PS}	0.5959^{PS}	0.7408^{PS}
9	0.7806^{BM}	0.0553^{BM}	0.7054	0.6318	0.3335	0.6061^{PS}	0.5828^{PS}	0.5135^{PS}
10	0.7308	0.1207	0.5008	0.4824	0.3813	0.5550	0.5030	0.1308
11	0.7246^{BM}	0.0633^{BM}	0.3818	0.3710	0.2134	0.5495^{PS}	0.5320^{PS}	0.5514^{PS}
12	0.6849^{BM}	0.0518^{BM}	0.3566	0.3368	0.1582	0.4349	0.4159	0.2119
13	0.2979^{BM}	0.0074^{BM}				0.4032^{PS}	0.3961^{PS}	0.4641^{PS}
14						0.2931	0.2881	0.2487
Average TE	0.7800	0.1537	0.7137	0.6583	0.4387	0.6800	0.6537	0.5699

^{PS} indicates a purse seine vessel.
^{BM} indicates “bait market” vessels with average landings ≤ 3 metric tons.
Homog. = homogenous production model
Model 1 = three segment heterogeneous production model
Model 2 = two segment heterogeneous production model (without segment 1 vessels from 3-segment model).
Technical efficiencies lower in general in the homogenous model.
Segmentation determined by EC algorithm.