Estimating Measures of Spatial Efficiency for Highly-Mobile Production Technologies

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Abstract:

This paper considers the non-linear least squares (NLS) and generalized method of moments (GMM) estimation of a production function where inputs and outputs vary over time, space, and cross-sectional unit. We consider several flexible specifications for the space-time evolution of technical and spatial efficiency and derive their asymptotic distributions. Simulations are conducted to investigate the finite sample properties of the proposed estimators. Lastly, the method is applied to fishing vessel behavior within the Aleutian Islands where recent regulations have impacted the spatial production behavior of fishermen. Results indicate that regions where spatial production has been restricted in general possess the highest rates of spatial efficiency. However the distribution of spatial efficiency within these regions is not uniform, indicating that some regions within the protection zones are more adversely impacted by the policy than other nearby regions.

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I. Introduction

While most production technologies are fixed in the short-run, one can envision technologies that are not. For example, in the course of a year, a fishing boat will frequent different areas to maximize its catch. Over a month, a sales force can cover several different territories. In the course of a day, police cars are dispatched to various locations in a city to prevent or stop crime. Over a growing season, a large farming conglomerate will plant and harvest across several growing regions. Just as panel data have become more prevalent over time, so too has spatially oriented data (three-dimension panel data) with sufficient variability in the spatial dimension to identify time-varying technical inefficiency and/or measures of spatial efficiency. In fact, current research in the resource economics field is already exploiting these three-dimensional panel data sets to uncover the underlying spatial structure of the resource (Smith In press; Smith et al. 2009) and the presence of spatial congestion in fisheries (Hicks et al. 2008).

The purpose of this research is to expand on the contribution of Horrace and Schnier (2007) by relaxing the use of their data transformation to assure that all inputs are spatially varying and instead relying on the three-dimension nature of the panel data set to identify spatial efficiency. This achieved via alternative specifications of the individual, time and space specific constants within the production function and their corresponding first differences prior to estimation using either non-linear least squares (NLS) or generalized method of moments (GMM). Furthermore, by flexibly specifying the individual, time and space varying constants the methods developed within this research can be utilized to semi-parametrically investigate spatial measures of efficiency that, to the best of our knowledge, has never been conducted within the empirical production literature. To accomplish this, there must be sufficient variability in the spatial dimension over time. In other words, the production technology must be highly-mobile in the short-run. Therefore, to illustrate our empirical model we utilize data from Atka mackerel fishery in the Bering Sea and Aleutian Islands (BSAI) as these vessels are highly-mobile and there is sufficient spatial variation in the behavior to identify measures of spatial efficiency.

Between 1977 and 1983, the accepted treatment of the stochastic frontier model involved a cross section of data (e.g., firms in an industry) and a random error term for technical efficiency, characterized by a one-sided distributional assumption (e.g., half-normal or exponential). A seminar paper in the stochastic frontier literature was Schmidt and Sickles (1984), which considered the advantages of panel data over cross-sectional data in the estimation of stochastic production functions and firm-level technical inefficiency. Based on a simple, yet elegant, time-invariant specification of production technology, they demonstrated that production and time-invariant technical inefficiency are identified by exploiting variability in the time dimension of the panel.

The novelty of their fixed-effect procedure is that technical inefficiency is no longer a random variable (as it had been up to that point), but rather a parameter for estimation, so the usual parametric assumptions on the distribution of technical inefficiency are no longer necessary. In this sense, their fixed-effect estimator is semi-parametric and, consequently, a very popular procedure for understanding and estimating the inefficiency of economic units when a panel of data was available.[1] One drawback of the Schmidt and Sickles fixed-effect estimator of technical inefficiency was that it required inefficiency to be time-invariant. This was problematic, because the precision and asymptotic normality of their technical inefficiency estimates required large T (the time dimension). Unfortunately, it could easily be argued that over long periods (large T) technical inefficiency in competitive markets should change, as inefficient agents either improve their efficiency or drop out of the market.

The last 15 years of research has seen a myriad publications that attempt to relax this assumption and allow inefficiency to change with time. See, for example, Cornwell, Schmidt, and Sickles (1990), Kumbhakar (1990), Battese and Coelli (1992), Lee and Schmidt (1993), Cuesta (2000), Ahn, Lee, and Schmidt (2001, 2005), Han, Orea and Schmidt (2005), and Lee (2005). All these papers identify time-varying technical efficiency by linearly parameterizing it. Moreover, some of these papers make technical inefficiency random and re-impose the distributional assumptions that the Schmidt and Sickles paper endeavored to remove, when the fixed-effect specification was justified. [2]

Recently, Horrace and Schnier (2007) made a similar contribution to the stochastic frontier literature as Schmidt and Sickles (1984) using the spatial variation of highly mobile production technologies. They illustrated that if adding a time dimension to a

[1] At the time of this writing, the Social Science Citation Index showed 195 citations for the Schmidt and Sickles (1984) paper.
[2] Another common justification for the fixed-effect specification is that it does not require an assumption on the independence of inefficiency and the inputs to the production process

cross section of data identifies time-invariant technical efficiency, then adding a spatial dimension to a cross section of data identifies time-varying technical efficiency. This was achieved using a three dimensional panel of production behavior and transforming the production function to assure that all inputs of production spatially varied. This research will expand on Horrace and Schnier (2007) by utilizing the three-dimensional nature of spatial panel data sets to identify alternative specification of time-varying or spatially varying technical efficiency.

In the following section we outline our econometric specification and estimation procedure. In section III we conduct a series of Monte Carlos to investigate the properties of the estimators developed. In section IV we describe the Atka mackerel fishery operating within the Bering Sea and Aleutian Islands (BSAI) and the data used in our empirical application. Within this fishery management has implemented a series of spatial regulatory measures to protect Stellar sea lions and our estimator is used to investigate the spatial efficiency impacts of these measures. In section V we discuss the results from our application and the final section, section VI, summarizes our research.

II. Econometric Specification

The general production model we consider is,

$$Y_{its} = \alpha_{its} + X_{its}\beta + Z_{it}\gamma + W_i\delta + v_{its}, \quad i = 1,...,N, \; t = 1,...,T, \quad s = 1,...,S, \qquad (1)$$

where i indexes the individual, s indexes space, t indexes time, $\alpha_{its} = \eta - u_{its}$, and $u_{its} \geq 0$. The time- space- and individually varying production inputs are captured by X_{its}, the individual and time varying production inputs are Z_{it} and the space and time invariant variables are captured by W_i. In particular, we do not consider inputs that may vary over time and space, but not over the cross-sectional unit, nor do we consider inputs that vary only over time or only over space. The reason for this is that our asymptotics will be over the cross-sectional dimension, $i = 1,...,N$. Ultimately we will use a factorization of the model's heterogeneity term, and one factorization may lend itself to asymptotics in both i and t. Inference for factor models with large N and T has been consider by Bai (2003), and may apply for this special parameterization of α_{its}.

Considering the specification in equation (1) in more detail, let Y_{its} and v_{its} be scalars. Let X_{its}, Z_{it}, and W_i be $(1\times k)$, $(1\times g)$, and $(1\times d)$ row vectors, respectively. Let β, γ, and δ be $(k\times 1)$, $(g\times 1)$, and $(d\times 1)$ column vectors, respectively. Also define:

$$\underset{(S\times 1)}{Y_{it}} = \begin{bmatrix} Y_{it1} \\ \vdots \\ Y_{itS} \end{bmatrix}, \quad \underset{(TS\times 1)}{Y_i} = \begin{bmatrix} Y_{i1} \\ \vdots \\ Y_{iS} \end{bmatrix}, \ \underset{(Sx1)}{v_{it}} = \begin{bmatrix} v_{it1} \\ \vdots \\ v_{itS} \end{bmatrix}, \text{ and } \underset{(TSx1)}{v_i} = \begin{bmatrix} v_{i1} \\ \vdots \\ v_{iS} \end{bmatrix}$$

Now, define:

$$\underset{(S\times k)}{X_{it}} = \begin{bmatrix} X_{it1} \\ \vdots \\ X_{itS} \end{bmatrix}, \ \underset{(TS\times k)}{X_i} = \begin{bmatrix} X_{i1} \\ \vdots \\ X_{iS} \end{bmatrix}, \text{ and } \underset{(T\times g)}{Z_i} = \begin{bmatrix} Z_{i1} \\ \vdots \\ Z_{it} \end{bmatrix}.$$

We parameterize α_{its} in a variety of ways based on techniques designed for parameterizing α_{it} in the usual panel data literature. We concentrate this discussion on multiplicative parameterizations of technical efficiency. First, however we discuss the nature of α_{its} in the fisheries industry. Abstracting from time- and space-level technical efficiency, it seems reasonable that a fishing vessel captain would have a sense of her own vessel-level technical efficiency, if not by observing her own performance (*ceteris paribus*), then possibly by observing her performance relative to other vessels (*ceteris paribus*). It would also seam reasonable that there might be correlation between vessel-level efficiency and the inputs to the production process.

Within this research spatial efficiency will be estimated by assuming that vessel captains are unaware of any spatial efficiencies that are particular to their inherent skill level. Instead, they operate under the common knowledge available to all other captains on the spatial distribution of their target species. The implication of this assumption is that there is some spatial efficiency parameter, λ_s, which is common to all boats within the fishery targeting the same species. In particular, it is unnecessary to model NS

parameters, say α_{is}, when $N+S$ parameters, say $\lambda_s\alpha_i$, would suffice.[3] Under these conditions, it would also seems safe to assume that fleet-level spatial efficiency, λ_s, is uncorrelated with production inputs that vary over space and over boats, otherwise it would no longer be purely a function of space. It might be correlated with inputs that vary over space alone or over space and time alone, but we do not specifically include these variables in the model. Should the restrictive assumptions that all spatial information is common knowledge to each fishermen within the fleet seem too restrictive an alternative specification of α_{its} would be $\theta_t\alpha_{is}$ which implies that spatial efficiency can be further decomposed into an individual and spatially varying measure. This suggests that captains are aware of any spatial efficiencies that are particular to their inherent skill. That is, a captain is more inclined to look for spatial regions where they perform better than others within the fleet. However, this specification will not be investigated in this research effort and we leave it for future research.

Our interest in estimating fleet-level spatial efficiency, captured by λ_s, is similar in spirit to the pursuit of estimating site-specific baseline utility measures that control for the spatial characteristics of the resource (Smith In press; Smith and Zhang 2007; Hicks and Schnier In press; Hicks et al. 2008; Schnier 2009), following the methods developed by Berry et al. (1995) and Berry (1994). Whereas the baseline site-specific utility measures are estimated using alternative specific constants in a spatial discrete choice framework, our model estimates these latent factors via the decomposition of technical efficiency (α_{its}) into non-spatial varying and spatially varying components. Both methods provide an ordinal measure of the latent spatial information within the fishery, but utilize different methods. Therefore, our method could also be viewed as an alternative method for obtaining information on the spatial distribution of the resource utilizing production modeling versus spatial discrete choice modeling.

Two additional alternative specification of efficiency which will be considered in the Monte Carlo, but not in the empirical application, are the fully decomposed $\alpha_{its}=\theta_t\lambda_s\alpha_i$ and time-level efficiency $\alpha_{it}=\theta_t\alpha_i$, the later possessing no spatially varying component of efficiency. However, given the spatial dimension of our data we can achieve identification of the NT parameters, so interactions between vessel-level

[3] The results in this paper could be adapted to the case of $\boxed{\alpha_{is}}$ with only minor modifications to the models.

and time-level efficiencies can be captured with out any particular structural form. This is a truly unique feature of this data and one that was similarly exploited by Horrace and Schnier (2007). We purposely avoid additive specifications, which will generally not identify all the parameters in the model, and concentrate on multiplicative specifications which identify all parameters thought the nonlinear transformations they imply. The following sub-sections will outline the three models and the empirical estimation of each using NLS or GMM estimation techniques.

Given that our empirical models is an expansion of the one-factor parameterization model developed by Ahn, Lee and Schmidt (2001), we will first present our empirical frame work for a non-spatial efficiency model and then expand it to the spatial efficiency context.

Model 1: Time-Varying Technical Efficiency $\alpha_{its} = \theta_t \alpha_i$

Let $M_i = \left[X_{i11},...,X_{iTS},Z_{i1},...,Z_{iT},W_i\right]$ be a $1\times\{T(Sk+g)+d\}$ vector of the inputs used in the production model and factorize $\alpha_{its} = \alpha_{it} = \theta_t \alpha_i$ with the first measure of time-varying efficiency being normalized to one, $\theta_1 = 1$. Using a generalized within transformation in the spirit of Chamberlain (1984), equation (1) can be written as

$$Y_{its} = \theta_t Y_{i1s} + (X_{its} - \theta_t X_{i1s})\beta + (Z_{it} - \theta_t Z_{i1})\gamma + (W_i - \theta_t W_i)\delta + (v_{its} - \theta_t v_{i1s}), \quad (2)$$

$t = 2,...,T$; $s = 1,...,S$. This is similar to the one-factor model of Ahn, Lee and Schmidt (2001), hereafter ALS (2001), and can be expanded to the *p*-factor model of Ahn, Lee and Schmidt (2004) at the cost of requiring $\delta = 0$. It can also be modified to fit the technique of Kneip, Sickles and Song (2005). These modifications and their effects on estimation will be considered in future research. For obvious reasons we assume there is no spatial correlation in the error structure but subsequent research will investigate spatial dependence in the error variance structure. Under appropriate assumptions (Amemiya, 1985. p. 129), the model in (2) can be consistently estimated with two-stage, non-linear least squares, using instruments

$$H_{1i} = \begin{bmatrix} X_{i11} & \dots & X_{iTS} & Z_{i1} & \dots & Z_{iT} & W_i \\ \vdots & & \vdots & \vdots & & \vdots & \vdots \\ X_{i1S} & \dots & X_{iTS} & Z_{i1} & \dots & Z_{iT} & W_i \end{bmatrix} \qquad S \times [T(k+g)+d]$$

in a first-stage regression for Y_{i1s} in (2). This is slightly different from the results of Ahn, Lee and Schmidt (2001) where the instrument set is M_i. Equivalently, one can perform GMM using the $S(T-1)\{T(Sk+g)+d\}$ unique moment conditions embodied in $E[M_i'(v_{its} - \theta_t v_{i1s})] = 0$, $t = 2,\ldots,T$; $s = 1,\ldots,S$.[4]

Notice that when $k = 0$ and $s = 1$, we get the Ahn, Lee and Schmidt (2001) result of $(T-1)\{Tg+d\}$ moment conditions. Here, it may be empirically easier to implement nonlinear least squares than GMM, when $S(T-1)\{T(Sk+g)+d\}$ is large (which it typically will be, even for moderate values of N, T, and S), because the optimal weighting matrix for GMM will necessarily be of dimension NTS. Alternatively, Ahn, Lee and Schmidt (2001) propose methods for reducing the number of moments without loss of efficiency in the GMM estimator. These methods will be explored in future research. All the results of GMM1 of ALS (2001) follow as $N \to \infty$ for the specification in (2), if their basic assumptions, BA.1 – BA.5, hold with slight modification. These modifications are, $\alpha_{its} = \theta_t \alpha_i$, $\theta_1 = 1$; $[M_i, \alpha_i, v_i']$ is iid over i; v_{its} has finite 4th moment and zero mean; $E[M_i'(W_i, \alpha_i)]$ is full-rank; and $[M_i, \alpha_i]$ is uncorrelated with v_i, and its second moment matrix is non-singular.

In particular, the parameters will be consistent. Similar to Ahn, Lee and Schmidt (2001) identification of θ_t is ensured through no multicollinearity between α_i and W_i, and a nonzero correlation between α_i and M_i. Also, it is easy to show that our moment condition $E(M_j' v_{jt}) = 0$ is equivalent to the moment conditions associated with GMM1 in Ahn, Lee and Schmidt (2001). Let $\Gamma_{1i}(\xi_1) = \Gamma_i(\beta, \gamma, \delta, \theta)$, where $\theta' = [\theta_2, \ldots, \theta_T]$ and $\xi_1' = [\beta', \gamma', \delta', \theta']$, be the non-linear regression function implied by (2). Stacking s and then t, we get:

[4] Notice that $\boxed{E[H_{1i}'(v_{its} - \theta_t v_{i1s})] = 0}$ could be used, but then there would be redundant moment conditions.

$$\underset{[S(T-1)\times 1]}{\Gamma_{1i}(\xi_1)} = G_1^*(\theta)Y_i + G_1(\theta)\left[X_i\beta + (Z_i \otimes e_S)\gamma + (W_i \otimes e_{ST})\delta\right],$$

where e_j is a j- dimensional column vector of ones, $G_1(\theta) = \left[\theta \otimes I_s \quad : \quad I_{TS-S}\right]$, and $G_1^*(\theta) = \left[\theta \otimes I_s \quad : \quad 0_{TS-S}\right]$. The derivative of $\Gamma_{1i}(\xi_1)$ with respect to ξ_1 is:

$$\frac{\partial \Gamma_{1i}(\xi_1)}{\partial \xi_1'} = \underset{\{S(T-1)\times[k+g+d+(T-1)]\}}{\left\{G_1(\theta)\left[X_i, (Z_i \otimes e_S), (W_i \otimes e_{ST})\right], I_{T-1} \otimes Q_1\left[Y_i - X_i\beta - (Z_i \otimes e_S)\gamma - (W_i \otimes e_{ST})\delta\right]\right\}}$$

Where $Q_1 = \left[I_s \quad : \quad \underset{S\times S(T-1)}{0}\right]$. Let the GMM estimator of ξ_1 be $\hat{\xi}_1$, Then the asymptotically efficient covariance of $N^{1/2}(\hat{\xi}_1 - \xi_1)$ for GMM is:

$$\sigma_v^2 \; \underset{N\to\infty}{p\lim}\left[\frac{1}{N}\sum_{i=1}^{N}\left(\frac{\partial \Gamma_{1i}(\xi_1)}{\partial \xi_1'}\right)'\left(\frac{\partial \Gamma_{1i}(\xi_1)}{\partial \xi_1'}\right)\right]^{-1}.$$

Model 2: Spatial-Varying Technical Efficiency $\alpha_{its} = \lambda_s \alpha_i$

Assume $\alpha_{its} = \lambda_s \alpha_{it}$, $\lambda_1 = 1$; $[M_i, \alpha_{i1}, \ldots \alpha_{iT}, v_i']$ is iid over i; v_{its} has finite 4$^{\text{th}}$ moment and zero mean; $E[M_i'(Z_{i1}, \ldots, Z_{it}, \alpha_{i1}, \ldots, \alpha_{it})]$ is full-rank; and $[M_i, \alpha_{i1}, \ldots \alpha_{iT}]$ is uncorrelated with v_i, and its second moment matrix is non-singular.

Under these assumptions equation (1) can be re-written as,

$$Y_{its} = \lambda_s Y_{it1} + (X_{its} - \lambda_s X_{it1})\beta + (Z_{it} - \lambda_s Z_{it})\gamma + (W_i - \lambda_s W_i)\delta + (v_{its} - \lambda_s v_{it1}), (3)$$

which is another one-factor model, similar to Ahn, Lee and Schmidt (2001). Under appropriate assumptions, this model can be estimated with two-stage non-linear least squares, using instruments:

$$H_{2i} = \begin{bmatrix} X_{i11} & \dots & X_{i1S} & Z_{i1} & W_i \\ \vdots & & \vdots & \vdots & \vdots \\ X_{iT1} & \dots & X_{iTS} & Z_{iT} & W_i \end{bmatrix} \qquad T \times \{Sk + (g+d)\}$$

in a first-stage regression of Y_{it1} in (3). Notice that the shape of the moment matrix is different here than in *Model 1*. Alternatively, *Model 2*, can be estimated by GMM using the $T(S-1)\{T(Sk+g)+d\}$ unique moment conditions embodied in $E[M_i'(v_{its} - \lambda_s v_{it1})] = 0$, $t = 1,\dots,T$; $s = 2,\dots,S$. If $S > T$, then there are more moment conditions here than in *Model 1*. The obvious trade-off is that when $S > T$, there are $S - T$ more parameters to estimate here than under assumption *Model 1*.

All the asymptotic results of Ahn, Lee and Schmidt (2001) for their GMM1 estimator follow, as $N \to \infty$. A nice feature of this specification is that asymptotics can be for S fixed, $N \to \infty$, and $T \to \infty$, so that the asymptotic results of Bai and Ng (2002) may be applicable in this context. The estimator under *Model 2* can be recast as the estimator under *Model 1*.

Let $\Gamma_{2i}(\xi_2) = \Gamma_i(\beta,\gamma,\delta,\lambda)$, where $\lambda' = [\lambda_2,\dots,\lambda_S]$ and $\xi_2' = [\beta',\gamma',\delta',\theta']$, be the non-linear regression function implied by (4). That is, stacking s and then t, we get:

$$\underset{[S(T-1)\times 1]}{\Gamma_{2i}(\xi_2)} = G_2^*(\lambda)Y_i + G_2(\lambda)\left[X_i\beta + (Z_i \otimes e_S)\gamma + (W_i \otimes e_{ST})\delta\right],$$

where $G_2(\lambda) = I_T \otimes \left[-\lambda \quad : \quad I_{S-1}\right]$, and $G_2^*(\lambda) = I_T \otimes \left[\lambda \quad : \quad 0_{S-1}\right]$, with derivative:

$$\frac{\partial \Gamma_{2i}(\xi_2)}{\partial \xi_2'} = \underset{\{T(S-1)\times[k+g+d+(S-1)]\}}{\left\{G_2(\lambda)\left[X_i,(Z_i \otimes e_S),(W_i \otimes e_{ST})\right] I_{S-1} \otimes Q_2\left[Y_i - X_i\beta - (Z_i \otimes e_S)\gamma - (W_i \otimes e_{ST})\delta\right]\right\}}$$

where 0_j is a $(j \times j)$ matrix of zeroes, and $\underset{T\times TS}{Q_2} = I_T \otimes \left[1 \quad : \quad \underset{1\times(S-1)}{0}\right]$. Let the GMM estimator of ξ_2 be $\hat{\xi}_2$, Then the asymptotically efficient covariance of $N^{1/2}(\hat{\xi}_2 - \xi_2)$ for GMM is:

$$\sigma_v^2 \ \underset{N\to\infty}{p\lim}\left[\frac{1}{N}\sum_{i=1}^{N}\left(\frac{\partial\Gamma_{2i}(\xi_2)}{\partial\xi_2'}\right)'\left(\frac{\partial\Gamma_{2i}(\xi_2)}{\partial\xi_2'}\right)\right]^{-1}.$$

Model 3: Spatial-and Time-Varying Technical Efficiency $\alpha_{its} = \theta_t\lambda_s\alpha_i$

Assume that $\alpha_{its} = \theta_t\lambda_s\alpha_i$ with the first year and spatial location parameter normalized to unity, $\lambda_1 = \theta_1 = 1$; $[M_i, \alpha_i, v_i']$ is iid over i; v_{its} has finite 4th moment and zero mean; $E[M_i'(W_i, \alpha_i)]$ is full-rank; and $[M_i, \alpha_i]$ is uncorrelated with v_i, and its second moment matrix is non-singular. These assumptions generate a two-factor model which re-specifies equation (1) as,

$$Y_{its} = \theta_t\lambda_s Y_{i11} + (X_{its} - \theta_t\lambda_{s\,t} X_{i11})\beta + (Z_{it} - \theta_t\lambda_s Z_{i1})\gamma + (W_i - \theta_t\lambda_s W_i)\delta + (v_{its} - \theta_t\lambda_s v_{i11}) \quad (4)$$

This model can be estimated with two-stage non-linear least squares, using instruments M_i in a first-stage regression of Y_{i11} in (5). Alternatively, under a generalization to the basic assumption in Ahn, Lee and Schmidt (2001), this can be estimated by GMM using the $(T-1)(S-1)\{T(Sk+g)+d\}$ unique moment conditions embodied in $E[M_i'(v_{its} - \theta_t\lambda_s v_{i11})] = 0$, $t = 2,\ldots,T$; $s = 2,\ldots,S$.

Let $\Gamma_{3i}(\xi_3) = \Gamma_i(\beta,\gamma,\delta,\theta,\lambda)$, where $\xi_3' = [\beta',\gamma',\delta',\theta',\lambda']$, be the non-linear regression function implied by (4). That is, stacking s and then t, we get:

$$\underset{[S(T-1)\times 1]}{\Gamma_{3i}(\xi_3)} = G_3^*(\theta,\lambda)Y_i + G_3(\theta,\lambda)\left[X_i\beta + (Z_i \otimes e_S)\gamma + (W_i \otimes e_{ST})\delta\right],$$

where

$$\underset{(S-1)(T-1)\times TS}{G_3(\theta,\lambda)} = \left[-\underset{(S-1)(T-1)\times 1}{\theta\otimes\lambda} \ : \ \underset{(S-1)(T-1)\times(S-1)}{0} \ : \ I_{T-1}\otimes[\underset{(S-1)\times 1}{0}, I_{S-1}]\right], \text{ and}$$

$$\underset{S-1)(T-1)\times TS}{G_3^*(\theta,\lambda)} = \left[\underset{(S-1)(T-1)\times 1}{\theta\otimes\lambda} \ : \ \underset{(S-1)(T-1)\times(TS-1)}{0}\right], \text{ with derivative:}$$

$$\frac{\partial \Gamma_{3i}(\xi_3)}{\partial \xi_3'} = \begin{cases} G_3(\theta,\lambda)\left[X_i, (Z_i \otimes e_S), (W_i \otimes e_{ST})\right] \\ \qquad \underbrace{\left(I_{T-1} \otimes \lambda, \theta \otimes I_{S-1}\right)}_{\{(S-1)(T-1)\times[k+g+d+(S-1)+(T-1)]\}} \otimes Q_3\left[Y_i - X_i\beta - (Z_i \otimes e_S)\gamma - (W_i \otimes e_{ST})\delta\right] \end{cases}$$

where $Q_3 = \left[1 \;\; : \;\; \underset{1\times(TS-1)}{0}\right]$. Let the GMM estimator of ξ_3 be $\hat{\xi}_3$, Then the asymptotically efficient covariance of $N^{1/2}(\hat{\xi}_3 - \xi_3)$ for GMM is:

$$\sigma_v^2 \; \underset{N\to\infty}{p\lim}\left[\frac{1}{N}\sum_{i=1}^{N}\left(\frac{\partial \Gamma_{3i}(\xi_3)}{\partial \xi_3'}\right)'\left(\frac{\partial \Gamma_{3i}(\xi_3)}{\partial \xi_3'}\right)\right]^{-1}.$$

Having outlined the three empirical specifications and estimation methods used to recover measures of efficiency using a three-dimension panel data, the following section conducts a series of Monte Carlo experiments to investigate the performance of each estimator.

III. Monte Carlo

Given that the data set used is structured as a three dimensional panel over the dimensions of time, space and individuals, there are a number of different dimensional combinations that can be investigated in our Monte Carlo analysis. To simplify these dimensions we have elected to fix the number of time periods to be five years for each model. The Monte Carlo data generation process for each model is specified as,

Model 1

$$Y_{its} = \theta_t\alpha_i + X_{its}1 + Z_{it}1.5 + W_i 2 + v_{its} \qquad \theta' = [1.5, 2.0, 2.5, 3.0]$$

Model 2

$$Y_{its} = \lambda_s\alpha_i + X_{its}1 + Z_{it}1.5 + W_i 2 + v_{its} \qquad \lambda' = [1.5, 2.0, 2.5, \ldots.., 0.5S + 0.5]$$

Model 3

$$Y_{its} = \lambda_s\theta_t\alpha_i + X_{its}1 + Z_{it}1.5 + W_i 2 + v_{its} \quad \lambda' = [1.5, 2.0, \ldots, 0.5S + 0.5],\; \theta' = [1.5, 2.0, 2.5, 3.0]$$

For all the models $i = 1,...,N$ $N \in \{10,50,100\}$; $s = 1,...,S$ $S \in \{5,10\}$; and $t = 1,...,5$ and each model is simulated 100 times. The independent variables X_{its}, Z_{it} and W_i are drawn from an iid uniform distribution on [0, 1], and the errors are drawn from an independent normal distribution, $v_{its} \sim N(0,1)$. Furthermore, to reduce the computational requirements of the Monte Carlo (see discussion of moment conditions) we utilize NLS to estimate the models.[5] The results are expressed in Tables 1, 2 and 3 for each respective model.

Monte Carlo Results: Model 1

Model 1 is an N asymptotic model and we would likely expect the biases and RMSE of our parameter estimates to decrease as this dimension increases. This is predominately what we observe in our Monte Carlo analysis. The bias and RMSE for the production input variables (β, γ and δ) for the most part decrease as the number of firms, N, and/or the number of spatial locations, S, increases. The only cases for which increasing the number of firms does not reduce the bias occurs when $\{N,T,S\} = \{50,5,10\}$ for all the production input variables and when $\{N,T,S\} = \{50,5,5\}$ for γ. The former result indicates that increasing N from 10 to 50, holding T and S constant at 5 and 10 respectively, has a negative effect on both the bias and the RMSE for all parameters. However, this increase in the bias and RMSE is offset when N increases from 50 to 100. This is further exacerbated by the increase in the bias for γ when N increases from 10 to 50 holding T and S constant at 5 and 5 respectively. Despite the negative results for this one interval within the Monte Carlo, the results readily indicate that the bias and RMSE decrease when N and/or S increase which is consistent with our *a priori* expectations.

Another interesting result is illustrated by comparing the relative biases and RMSEs across the production input coefficients. For four of the six models the bias and RMSE for β is lower than any of the other production input coefficients. Furthermore, in the other two cases where this is not true the bias and RMSE is lower for γ than any of the other coefficients. This result is interesting because β is the coefficient on those production inputs which vary across time, individual and space and γ varies across the

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[5] Using smaller sample sizes our preliminary results indicated that our results are robust to using either GMM or NLS estimation techniques.

individual and time. This additional dimension of variability, relative to the individual variability captured by δ, appear to enhance the fit of these parameters. This suggests that the estimator is able to provide good estimates for parameters that vary across multiple dimensions simultaneously even when the sample sizes are small.

Model 1 closely resembles the model of Horrace and Schnier (2007), and like Horrace and Schnier (2007) provides the first step forward in using the spatial dimension of the data set to recover estimates of time varying technical efficiency. This information is captured by the coefficients $\theta_2, \theta_3, \theta_4$ and θ_5. Focusing on these coefficients it is evident that increasing the spatial dimension of the data set decreases the bias and RMSE for all of these coefficients. However, increasing the number of firms does not reduce the bias and RMSE when N increases from 10 to 50, but it does decrease both measures when N increases from 50 to 100. The former result is not what we expected to occur and it warrants further investigation. However, given that the biases and RMSEs are at there lowest when N is equal to 100, the results generally indicate that increasing N will reduce the bias and RMSE of Model 1.

Monte Carlo Results: Model 2

As was the case with Model 1, Model 2 is an N asymptotic model and we would expect the bias and RMSE of our parameters to decrease as we increase the number of firms.[6] This is precisely what we observer in our Monte Carlo results, in all cases the bias and RMSE decreases as N increase for the primary production inputs, β, γ and δ. This is not true when S increases, keeping N and T fixed. In all cases increasing S increases the bias and the RMSE for β. For γ increasing S also increases the bias when N is equal to 50 and 100, however in both cases this change also reduces the RMSE. Given that these increases in bias are much smaller than with β, this does suggest that as S increases the empirical fit for γ increases as well. The final production input variable, δ, is the only coefficient for which increasing S unilaterally decreases the bias and RMSE, indicating that the empirical fit of this parameter increases in both N and S. However, it is important to note that the model is not an S asymptotic model and these results may not consistently hold across other parameterizations.

[6] As mentioned earlier, Model 2 may also be N and T asymptotic following Bai and Ng (2002), but we do not formally investigate this dimension in our analysis and leave this for future research.

In addition to the above mentioned bias and RMSE results, the coefficients for β, γ and δ possess a similar comparative fit as indicated by our results in Model 1. For four of the six models the bias for β is lower than all of the other coefficients and for all six models its RMSE is lower than the other production input coefficients. Furthermore, in the two cases where the bias for β is not the lowest, it is marginally beat by the γ coefficient. These results further illustrate that the additional variability generated by the individual-, spatial-,and time-varying production inputs as well as individual- and time-varying production inputs increases the relative fit for the parameters in small samples.

Increasing N predominately reduces the bias and RMSE for the measures of spatial production, λ. The only exception occurs when N increases from 50 to 100 fixing S and T at 5 and 5 respectively, where the bias increases. However, in this case the RMSE does decrease and the increases in the bias are very marginal. Therefore, increasing N does appear to increase the fit of these parameters, which accords with the N asymptotic nature of the model. Increasing S has a mixed effect on the parameter estimates. When N is less than 100, the biases predominately increase and the RMSE decreases. When N reaches 100, both the bias and the RMSE decrease as S increases. Presumably the later reduction in bias and RMSE when S increases results from the substantial increase in the number of observations within the data set. Increasing S from 5 to 10, holding N and T at 100 and 5 respectively, increases the size of the data set by 2500 observations and only increases the number of parameters to estimate by 5. This tradeoff is lower at smaller sample sizes, which generates the increase in bias.

Although increasing S when N and T are small does increase the bias, it is important to note that the bias and RMSE for the spatial production measures are low for even small sample sizes. In fact in a number of cases the bias and RMSE for these parameters (spatial production measures captured by λ) are lower than the primary production inputs within the model. Given that the primary objective of our empirical application is to estimate the policy impacts of spatial production restrictions, this result is encouraging because we will employ this model in our empirical application.

Monte Carlo Results: Model 3

Model 3 is also an N asymptotic model and we would similarly expect the bias and RMSE to go down as we add additional firms. This is in fact true, the bias and RMSE for the production input variables decrease as S and N increase, indicating that increasing either dimension of the data set increases the statistical fit of the model. This said, it is important to note that when N is small (10 versus 50) the bias and RMSE often times exceed the parameter coefficients, with the largest differences occurring for the parameter δ. This implies that with a low number of firms (as is the case in our empirical application) the statistical fit of Model 3 is very weak and one can not reliably estimate the production coefficients. This is presumably due to the time and space varying parameters, λ_s and θ_t, which makes it more difficult for the empirical model to capture the production inputs that vary along these dimensions as well. This hypothesis is supported when we investigate the impact that increasing N and S has on the bias and RMSE for λ_s and θ_t.

Holding T and S constant at 5, increasing the number of firms lowers the bias and RMSE of θ for nearly all the parameters except when N equals 100 where the RMSE for θ_4 and θ_5 is higher than when N equals 50. However, this increase is marginal and the results indicate that for small T and S, increasing N increases the statistical fit of the model. These conditions similarly hold when S equals 10, except for when N equals 100, where the bias and RMSE predominately increases. Furthermore, the increase in bias is nearly three times what it was when N equals 50, which further compromises the performance of the estimator.

Comparing the performance of λ_s and θ_t when the number of spatial locations increases illustrates the true weakness in this estimator. Increasing S, holding all else constant, unilaterally compromises the performance of the estimator by increasing the bias and RMSE, except for when N and T are small. However, this exception should be cautiously noted because the bias and RMSE for the other production variables (β, γ and δ) are extremely high. In general, these results illustrate that larger data sets are required to generate reliable parameter estimates and that increasing N increases the statistical fit of the model. Given that in our empirical application N is small (10 vessels) we will not utilize this estimator to obtain estimates of spatial efficiency. However, this empirical model may be suitable for other data sets with larger N.

IV. Fishery and Data Description

The data set used within our empirical analysis consists of fishermen targeting Atka mackerel within the BSAI. Atka mackerel is found throughout the numerous islands within the Aleutian Island chain as well as within the Gulf of Alaska (GOA). Research has indicated that the stocks residing in these two regions are distinct populations, and they are managed separately with a bulk of the commercial activity focused in the BSAI (Lowe et al. 2006). Therefore, we have elected to focus solely on the fishing activity within the BSAI. The Atka mackerel fishery is predominately executed along the numerous island seamounts and rocky outcroppings within the Aleutian Island chain, which is the preferred habitat for the species while spawning. Fishing for Atka mackerel began in the early 1970's when they were primarily targeted by a foreign fleet from Russia, Japan and Korea. However following the Magnuson-Stevens Fishery Conservation and Management Act of 1978, the fishery gradually shifted over to a domestic venture with all current harvesting activities being dominated by U.S. flagged fishing vessels (Lowe et al. 2006). Commercial catches have recently stabilized at around 60,000 metric tons a year, following the peak of nearly 104,000 metric tons in 1996. Although Atka mackerel are of a sufficient size to market to their meat, their most valuable product is their roe, which is a delicacy in many fresh fish markets.

Atka mackerel is an integral feed stock for Steller sea lions that are protected under the Endangered Species Act (ESA) (Merrick et al. 1997; Guenette et al. 2006). Therefore, the North Pacific Fisheries Management Council (NPFMC) is tasked with the responsibility to maintain a healthy stock of Atka Mackerel near the Steller sea lion breeding "rookeries" within the BSAI. The NPFMC achieves this goal using spatially and temporally defined total allowable catches (TACs). The utilization of spatially defined TACs began in 1993 under Amendment 80 to the BSAI Fishery Management Plan. This amendment divided the fishery into three separate spatially defined regions within the BSAI consisting of the western (543), central (542) and eastern (541) management zones. These management zones are illustrated in Figure 1. Each of these regions possesses its own TAC and the primary purpose for dividing up the regions was to prevent localized stock depletions (Lowe et al. 2006).

Further stock protection measures were instituted in 1998, when the fishing season was divided into an A and B season. Season A runs from January 1st through April 15th and season B runs from September 1st through November 1st. The annual TAC was evenly divided between the two seasons and it was stipulated that no more than 40% of the TACs could be harvested within the Steller sea lion harvest limitation areas (HLAs) contained in the western and central regions of the BSAI (see Figure 1). HLAs were not created in the eastern region because critical habitat zones were in existence that precluded fishing effort from taking place near the islands within this region (Lowe et al. 2006). In 2002 the 40% restrictions were increased to 60% to allow fishermen access to these high productivity zones. However, a lottery system was utilized to temporally spread out the harvest within the HLAs. The lottery system randomly assigned vessels participating in this fishery to one of two "platoons" and each platoon was randomly assigned to begin fishing in either the western or central zone. The regional TACs were also equally divided up between the "platoons" and after each platoon had caught there assigned TAC they could switch locations. Given that the HLAs within the western and central regions are some of the most productive waters within the BSAI for Atka mackerel these restrictions had a substantial impact on the fisheries spatial and temporal production activity.

Given the complexity of the spatial and temporal regulations implemented within the Atka mackerel fishery, there are a number of different policy questions that can be addressed. This research will focus on the spatial production restrictions that have been implemented in order to determine the gradient of spatial efficiencies that exist within the fishery and to compare spatial efficiency measures inside and outside of the HLA regions within the western and central regions. This will be achieved using the spatial production models outlined earlier, *Model 2*, to estimate measures of λ_s. Estimating these models will allow us to determine the degree to which the Steller sea lion protection measures have impacted the spatial production of fishermen participating in the Atka mackerel fishery.

Production data for this analysis comes from Alaska Fisheries Science Center's Fisheries Monitoring and Analysis Division that collects data on the BSAI fisheries. Two primary data sources were used to construct our panel data set, the observer data program and the weekly production reports. The observer data program contains 100 percent coverage on those vessels which are greater than 125 feet in length and 30 percent coverage for those vessels less than 125 feet. All vessels which actively participate within the Atka mackerel fishery are greater than 125 feet in length; therefore we completely observe their spatial production activities. Data from the observer program contains information on the individual, time and space varying production variables (hauls and duration). This information is merged with the weekly production reports that contain information on non-spatial varying production variables (crew size and measures of vessel capital). Merging these two data sources provides a complete profile of the production inputs utilized as well as their spatial output.

Our data set contains 10 vessels that are the core fleet targeting Atka mackerel within the BSAI from 1999 through 2006.[7] Table 4 illustrates the descriptive statistics for the vessels utilized within the empirical analysis, which indicate that there exists a high degree of heterogeneity in the fixed capital inputs employed within the fishery despite the fact that there are only 10 vessels. For instance, among the 10 vessels within our data set the net-tonnage and horsepower of the smallest vessel is over 60% less than the largest vessel within the data set. This high degree of heterogeneity maps over to the variable inputs of production as well. The largest vessel within the Atka mackerel fleet employs nearly 4 times as many crew members as the smallest vessel. Atka mackerel production within and outside of the HLA indicates that catch rates are roughly 17% greater within the HLA regions (see Table 4). This corresponds with the spatial aggregation of Atka mackerel. However, given that the standard deviation of catch within and outside of HLA is high, we can not confidently conjecture whether or not production is higher within the HLA regions.

For each vessel over the time period studied we observe the latitude and longitude of each haul made while on their fishing trip. Using ArcGIS we determined whether or not a haul was conducted within a HLA zone as well as which region (543, 542, and 541) and six-digit Alaska Department of Fish and Game statistical reporting zone (6-digit zone defined over ½ degree latitude and 1 degree longitude) the haul was conducted within. This information was used to construct three different data sets used in the analysis. The first data set contains six unique spatial identifiers by dividing both regions 542 and 543 into non-HLA and HLA regions and including region 541 and all other production activity. The non-HLA regions of zones 542 and 543 are defined as 5420 and 5430 respectively and the HLA regions are defined as 5421 and 5431. Region 541 is defined as

[7] There are 11 vessels that participate in the Atka mackerel fishery but we have elected to focus on the 10 vessels that are the most temporally stable participants within the fishery.

zone 5410 and all other production activity is defined as zone 5000. The second data set contains 11 spatial zones which further divides regions 5410, 5000, 5431 and 5421. Region 5410 is divided into two regions depending on whether or not they are east or west of 174 degrees latitude. The western zone is defined as spatial location 1, and the eastern zone is defined as location 2. Region 5000 is divided into two regions depending on whether or not activity took place east or west of 168 degrees latitude. The western zone is spatial location 3, and the eastern zone is spatial location 4. Regions 5420 and 5430 were not further sub-divided and represent spatial locations 5 and 6 respectively. Furthermore, the two HLA zones, regions 5431 and 5421, were sub-divided into two and three different spatial locations respectively. Region 5431 was divided using the 185 degrees latitude line, with the western region defined as location 7 and eastern region defined as location 8. Region 5421 is divided using the 179 degree west and 179 degree east latitude lines. Those HLA hauls that took place west of the 179 degree west were defined as spatial locations 9, those between 179 degree west and 179 degrees east were defined as location 10 and those east of 179 degrees east were defined as location 11. These definitions of space were utilized to further sub-divide the fishing effort within each region into roughly equal partitions of effort, in order to determine whether or not sub-regions of the macro definitions utilized within the first data set possessed asymmetric measures of spatial efficiency, λ_s.

The third data set utilized divides the fishery into 15 different spatial locations. Region 5420 is divided into two locations depending on whether or not it is east or west of 180 degree latitude. The western region is defined as spatial location 1 and the eastern is spatial location 2. Region 5410 is divided into three different sub-regions depending on whether or not the activity took place west of latitude 173, location 3, between latitude 173 and latitude 175, location 4, and locations east of latitude 175, location 5. Region 5000 is sub-divided into two sub-regions centered at 167 degree latitude, those locations west of 167 degree latitude are location 6 and those east are location 7. Region 5430 is divided into two sub-regions depending on whether or not the area is east or west of the 174 degrees latitude east. Those regions to the west are location 8 and those to the east are location 9. The HLA region 5421 is divided identically as it was within the second data set, with the three sub-regions being redefined as locations 10, 11 and 12 (previously locations 9, 10 and 11 respectively). The last three sub-regions are obtained by partitioning the HLA region 5431 into three sub-regions using 176 and 174 latitude east. Spatial locations west of 176 latitude are defined as location 13, those between 176 and 174 east latitude is defined as location 14, and the those locations east of this region are location 15.

The final data set was created to increase the spatial resolution of the data in an effort to further investigate sub-regional differences in spatial efficiency. An additional factor which must be addressed within this research is that the data set must be balanced across at least two dimensions of the data set to conduct our analysis. Given that we are primarily interested in measures of spatial efficiency we have elected to allow the data set to be unbalanced across space, but force it to be balanced across time and the number of participating vessels. Furthermore, our definition of time is achieved by summing up all production output obtained within our spatial definitions at the yearly level. The details of the data restrictions will be discussed in more detail in the upcoming section. However, our empirical Models 1-4 use our first data set; Models 5 and 6 use our second data set and the final data set is used in Model 7.

The redefinition of the spatial locations increases the number of spatial locations visited by each vessel. This can be readily observed in Table 5 which reports the descriptive statistics for each of the empirical models estimated. The mean number of spatial sites visited within each year using our first data set (Models 1-4) is slightly over 5, with a maximum equal to the number of locations utilized in the empirical analysis. Our use of the second data set increases the mean number of sites visited by roughly 2.5, and the maximum number of sites visited within a year is 11. The final data set increases the number of spatial locations visited by 2, and the maximum number of locations by 3.[8] Having defined the data set utilized and our definitions of space the following section outlines our empirical results.

V. Empirical Results

The econometric model estimated is,

$$\begin{aligned}\ln(Y_{its}) = {} & \lambda_S \alpha_{it} + \beta_0 + \beta_1 \ln(Hauls_{its}) + \beta_2 \ln(Duration_{its}) + \beta_3 \ln(rock_{its}) \\ & + \beta_4 \ln(other_{its}) + \gamma_1 \ln(crew_{it}) + \delta_1 \ln(gtons_i) + v_{its}\end{aligned} \quad (5)$$

[8] Further refinements of our spatial identifiers were experimented with in our analysis, but we were unable to obtain parameter estimates.

The dependent variable (Y_{its}) is the Atka mackerel fisherman $i's$ catch in time period t within location s. The individual- time- and space varying inputs of production (X_{its}) consist of two variables: $Hauls_{its}$ and $Duration_{its}$. $Hauls_{its}$ is the number of times that a vessel deploys its trawl (fishing gear) into the water in location s in time period t. $Duration_{its}$ is the total length of time that a fisherman's trawl device was deployed in the water in location s in time period t. The individual and time varying production inputs (Z_{it}) are captured by $Crew_{it}$, the number of crew members on board the vessel during time period t. The time- and space- invariant variables (W_i) captures the vessel's fixed capital inputs of production. Due to a high degree of correlation among the different fixed inputs possessed by a vessel, we have elected to use a vessel's gross-registered tonnage (GRT_i) to capture their time and space invariant production inputs.

Given that there does exist bycatch within this fishery, we have created two additional production factors that will serve to control for the compliments and substitutes of production using an output distance production function (Shephard 1970; Felthoven et al. 2008). The first aggregates all other rockfish species which may be caught in conjunction with Atka mackerel because they often reside in similar locations, this variable is defined as $rock_{its}$, our *a priori* expectation is that these are compliments of production and should have a positive impact on production. The second aggregate is all other non-rockfish species, $other_{its}$, (i.e., pollock, Pacific cod and flatfish) which may have been caught. Our *a priori* assumption is that these are substitutes of production and that they will have a negative impact on the production of Atka mackerel.

The empirical results using our first data set are contained in Table 6. There are four different models investigate which partition the complete data set different ways to preserve the balancing of the data set across time and individuals. Model 1 eliminates two vessels who did not fish in location 5410, model 2 eliminates two vessels who did not fish in location 5421, model 3 removes data from 2003 and 2006 because not all vessels visited location 5410 in those years and finally model 4 eliminates 1999 and 2000 because not all the vessels visited location 5421 in those years. Combined, all of these restrictions ensure that all the vessels contained in the data set fished in one location for each year in the analysis, a necessary restriction to implement the empirical model discussed earlier.

Across Models 1 through 4 the results illustrate that *hauls*, *crew* and the spatial measures of production $\lambda_{5410}, \lambda_{5420}, \lambda_{5421}, \lambda_{5430}$ and λ_{5431} are the primary determinants of spatial production. Furthermore, the fixed inputs of production, captured by *gtons*, do not have a significant impact on production except within Model 4, where the coefficient is statistically significant at the 90% level. Combined these results illustrate that the time and space varying inputs of production are a stronger determinant of production than time and space invariant inputs. The results also illustrate that the spatial production of Atka mackerel increases with the production of rockfish species, *rock*, and decreases with the production of other fish species, *other*, which is consistent with our *a priori* expectations. Although these results do not contain any violations of production theory the exceptionally large coefficient on *crew* should be noted. This is due to the high degree of heterogeneity within the number of crew members employed within the fishery (see Table 4) and the high degree of correlation between production output and crew members utilized.

The primary purpose of this research is to investigate the spatial efficiency of vessels operating within the Atka mackerel fishery. Location specific measures of spatial efficiency are estimated using the following transformation of the spatial production constants,

$$SE_s = \exp\left(\lambda_s - \max\left\{\lambda_j \, j \in S\right\}\right). \tag{6}$$

SE_s is the spatial efficiency measure for location s and λ_s is the location specific constant of production. Before discussing the relative spatial efficiencies of different regions within the Atka mackerel fishery it is important to note that our notion of spatial efficiency should not be confused with technical efficiency. Technical efficiency defines the degree to which a vessel optimally utilizes its production inputs and their distance from the production frontier, spatial efficiency defines the regions where the physical and biological inputs of production are greatest. More specifically suppose there are two locations, one possessing a spatial efficiency measure of 1 (on the spatial production frontier) and the other possessing a spatial efficiency measure of 0.9. This indicates that holding all other production inputs constant, as well as there respective marginal products, a vessel will only catch 90% of location ones output in location two. Given that the other production factors are under the control of the fishermen via their fixed and variable inputs the spatial efficiency measures capture productive efficiency beyond the immediate control of the fishermen and associated with the physical and biological characteristics of the region. These facts further highlight the similarity between our model and the utilization of alternative specific constants in the spatial discrete choice literature (Hicks et al. 2008; Smith In press; Schnier 2009).

Figure 2 graphically illustrates the spatial efficiency measures for Models 1 through 4. For all four models region 5421, the HLA portion of zone 542, possesses the highest spatial efficiency. The second highest ranked location is region 5431, the HLA portion of zone 543. The remaining sequential rankings are 5420, 5410, 5430 and 5000. These spatial efficiency rankings indicate that the HLA regions are the best locations for fishermen to target Atka mackerel and when they are forced to fish outside of the HLA, per the spatial regulations currently implemented, they must fish more intensively to obtain the same level of catch outside of the HLA zones. However, it is important to note that on average the spread in spatial efficiency, not including region 5000 which lies outside of the primary fishery, is between 1.00 and 0.88 and therefore the fishermen may not have had to exert an exorbitant degree of extra effort to compensate for the spatial regulations. To investigate this further, the second data set further partitions the HLA regions, as well as some of other regions, to determine which sub-regions within the HLA zones possessed a higher degree of spatial efficiency.

The results using the second data are contained in Table 7 for Model 5 and 6. The results generate a very similar profile of significant time and space variant inputs of production as Models 1-4 (see Table 6). The number of hauls a vessel executes in a given location as well as the number of crew members on board are the primary variable inputs of production, whereas the fixed inputs of production are statistically insignificant. The impact that rockfish and other species bycatch have on production is similar to the profile generated in Models 1-4, with rockfish being a compliment and other species being a substitute of production. Furthermore, nearly all of the spatial measures of production are statistically significant except for λ_{S1} and λ_{S2} in Model 5. The spatial efficiency measures for Models 5 and 6 are illustrated in Figure 3.

The locations with the two highest spatial efficiency rankings are locations 10 and 11 that are contained in region 5421. This is consistent with our findings in Models 1-4, however location 9 possesses a substantially lower spatial efficiency measure. This indicates that those regions of 542 that are within the HLA and east of the Delarof Islands, located near 179 degrees latitude, are the most spatially efficient regions of 5421. Therefore, spatial production restrictions west of the Deralof islands within the HLA zones do not have as significant an impact on spatial production as those east of the Deralof islands. The third highest ranked location is spatial location 1, which is a sub-region of 5410. The other region of 5410 (location 2) is actually the lowest spatially ranked location which indicates that those locations west of 174 degree latitude (location 1) possess a spatial efficiency measure similar to that obtained within the HLA zones of 542. The forth-highest ranked spatial location on average is location 8, which is contained in region 5431, and represents those regions in the vicinity of Attu and Kohi Island in the far eastern side of the Aleutian Island chain. Given that the average measure of spatial efficiency for this region is 0.85 and the that the other HLA regions of 543 possess an average spatial efficiency measure of 0.70, this indicates that spatial regulations surrounding Attu and Kohi islands have a more adverse impact on spatial production than those implemented in the Kisha and Bat island region (contained in location 7). Beyond the spatial efficiency rankings of the HLA regions the results indicate that spatial efficiency measures for those locations contained in 5420 and 5430 (locations 5 and 6 respectively) still exceed those contained in 5000 (locations 3 and 4),which is consistent with the results obtained using our first data set, Models 1-4.

The last data set expands our spatial definition of regions 5410, 5420, 5430 and 5431 to further investigate the relative spatial efficiency measures within the fishery. The results for Model 7 are contained in Table 8 with the corresponding measures of spatial efficiency illustrated in Figure 3. The location with the largest spatial efficiency is no longer within region 5421, it is now location 3 that is contained in region 5410. This corresponds with the spatial area east of Umnak Island and west of Atka Island in the vicinity of the Sequam and Amukta Passes, indicating that this is an area with similar spatial productive capacity to those within the HLA zones that is not impacted by the Steller sea lion protection measures. The location with the second highest spatial efficiency measure is location 11 which is identical to the location 10 in Models 5 and 6, in which models it was the most spatially efficient location. The third most spatially efficient location is location 9 which is contained in 5430 and represents the spatial regions the Attu and Bat Island area lying outside of the HLA. Beyond these rankings the results are generally consistent with those in Models 5 and 6, which further illustrates that the HLA zones possess a high spatial efficiency ranking relative to the other non-HLA zones (locations 2, 4, 5 and 6).

VI. Conclusion

Within this research we developed three different empirical models which utilize the addition of a spatial dimension in our panel data sets to estimate measures of technical and spatial efficiency using NLS or GMM estimation techniques. Monte Carlo analysis indicated that empirical models which endeavor to estimate time-varying technical efficiency or spatial measures of efficiency can be estimated using small panel data sets, whereas those which estimate both time and spatially varying measures of efficiency require large samples which increase in N. Therefore, caution and further econometric theory is required before we can confidently utilize this empirical model in applied research with small sample sizes.

Applying these methods to a data set on Atka mackerel fishermen we determined which regions within the Aleutian Island chain possess the highest measures of spatial efficiency and their degree of correlation with the recent spatial regulatory measures sought to protect the Steller sea lion populations. Results indicate that regions where spatial production has been restricted in general possess the highest rates of spatial efficiency. However the distribution of spatial efficiency within these regions is not uniform, indicating that some regions within the protection zones are more adversely impacted by the policy than other nearby regions. Most notably the spatial regions surrounding the Delarof Islands in region 5421 and Attu and Kohi Island in region 5431 are the most spatially efficient regions within the HLA protection areas. In addition, the islands Umnar and Atka Island possess a high spatial efficiency ranking which indicates that not all of the high productivity regions were restricted under the HLA regulations.

These results suggest that it may be possible to restrict effort in those HLA regions with a lower degree of spatial efficiency in an exchange for an increase in effort within those regions with a relative higher degree of spatial efficiency and perhaps create a win-win situation for fishermen and the Steller sea lions being protected. However, considerable research effort needs to conducted on both the welfare implications of further spatial restrictions and the biological response of the Steller sea lion population being protected within the HLA zones to confidently confirm this hypothesis.

References

Ahn, S.C., Lee, Y.H. and P. Schmidt. 2001. GMM estimation of liner panel data models with time-varying individual effects. *Journal of Econometrics* 101: 219-55.

Ahn, S.C., Lee, Y.H. and P. Schmidt. 2005. Panel data models with multiple time-varying individual effects, unpublished manuscript, Department of Economics, Hansung University.

Bai, J. 2003. Inferential theory for factor models of large dimensions. *Econometrica* 71: 135-71.

Bai, J. and S. Ng. 2002. Determining the number of factors in approximate factor models. *Econometrica* 70: 191-221.

Battese, G.E. and T.J. Coelli. 1992. Frontier production functions, technical efficiency and panel data. *Journal of Productivity Analysis* 3: 153-169.

Berry, S. 1994. Estimating discrete choice models of product differentiation. *RAND Journal of Economics* 25: 242-262.

Berry, S., Levinson, J. and A. Pakes. 1995. Automobile prices in market equilibrium. *Econometrica* 63(4): 841-90.

Chamberlain, G. 1984. Panel data, In: Griliches, Z. and Intrilligator, M.D. (Eds.) Handbook of Econometrics, Vol. 2.

Cornwell, C., Schmidt, P., and R. Sickles. 2000. Production frontiers with cross-sectional and time-series variation in efficiency levels. *Journal of Econometrics* 46: 185-200.

Cuesta, R.A. 2000. A production model with firm specific temporal variation in technical inefficiency: with application to Spanish dairy farms. *Journal of Productivity Analysis* 13: 139-49.

Felthoven, R.G., Horrace, W.C. and K.E. Schnier. 2008. Estimating heterogeneous capacity and capacity utilization in a multi-species fishery. *Working Paper, Department of Economics, Georgia State University.*

Guenette, S., Heymans, S.J.J., Christensen, V. and A.W. Trites. 2006. Ecosystem models show combined effects of fishing, predation, competition and ocean productivity on Stellar sea lions (*Eumetopias jubatus*) in Alaska. *Canadian Journal of Fisheries and Aquatic Science* 63: 2495-2517.

Han, C., Orea, L. and P. Schmidt. 2005. Estimation of panel data model with parametric temporal variation in individual effects. *Journal of Econometrics* 126: 241-67.

Hicks, R.L. and K.E. Schnier. In press. Spatial regulations and endogenous consideration sets in fisheries. Forthcoming in *Resource and Energy Economics.*

Hicks, R.L., Horrace, W.C. and K.E. Schnier. 2008. Congestion externalities and fishing vessels: the game of "where to fish?" *Working Paper, Department of Economics, Syracuse University*.

Horrace, W.C. and K.E. Schnier. 2007. Fixed-effects estimation of highly-mobile production technologies. *Working Paper, Department of Economics, Syracuse University.*

Kneip, A., Sickles, R.C. and W. Song. 2005. A new panel data treatment for heterogeneity in time trends . *Unpublished Manuscript, Department of Economics, Rice University*.

Kumbhakar, S.C. 1990. Production frontiers, panel data, and time-varying technical inefficiency. *Journal of Econometrics* 46: 201-11.

Lee, Y.H. 2005. A stochastic production frontier model with group-specific temporal variation in technical efficiency. *European Journal of Operational Research*

Lee, Y.H. and P. Schmidt. 1993. A production frontier model with flexible temporal variation in technical inefficiency, In: Fried, H., Lovell, C.A.K., Schmidt, P. (Eds.) The measurement of productivity efficiency: techniques and applications, Oxford University Press, Oxford.

Lowe, S., Ianelli, J., Wilkins, M., Aydin, K., Lauth, R. and I. Spies. 2006. BSAI Atka mackerel *In* Stock assessment and fishery evaluation report for the groundfish resources of the Bering Sea/Aleutian Islands regions. *North Pacific Fisheries Management Council*, P.O. Box 103136, Anchorage, AK.

Merrick, R.L., Chumbley, M.K. and G.V. Byrd. 1997. Diet diversity of Stellar sea lions (*Eumetopias jubatus*) and their population decline in Alaska: a potential relationship. *Canadian Journal of Fisheries and Aquatic Science* 54: 1342-1348.

Schmidt, P. and Sickles, R. 1984. Production frontiers and panel data. *Journal of Business and Economic Statistics* 2: 367-374.

Schnier, K.E. 2009. Estimating heterogeneous alternative specific constants: an application to regional delivery requirements in fisheries. *Working Paper, Department of Economics, Georgia State University.*

Shephard, R.W. 1970. *Theory of Cost and Production Functions*. Princeton University Press, Princeton, New Jersey.

Smith, M.D. In press. Towards an econometric foundation for marine ecosystem-based management. *Bulletin of Marine Science.*

Smith, M.D. and J. Zhang. 2007. Sorting models in discrete choice fisheries analysis. *selected paper,* American Agricultural Economics Association, Portland, OR.

Smith, M.D., Sanchirico, J.N. and J.E. Wilen. 2009. The economics of spatial-dynamic processes: applications to renewable resources. *Journal of Environmental Economics and Management* 57: 104-21.

Tables and Figures

Table 1: *Model 1 Results* ($\alpha_{it} = \theta_t \alpha_i$) : Bias and RMSE for each parameterization {N,T,S}

Model	{10,5,5}		{10,5,10}		{50,5,5}		{50,5,10}		{100,5,5}		{100,5,10}	
Parameter	Bias	RMSE	Bias	RMSE	Bias	RMSE	Bias	RMSE	Bias	RMSE	Bias	RMSE
β	-0.0303	0.4806	-0.0401	0.1711	-0.0058	0.1935	-0.0274	0.2757	0.0007	0.1396	0.0168	0.1008
γ	-0.0263	0.4899	-0.0140	0.1906	-0.0272	0.2575	-0.0735	0.3470	-0.0118	0.1369	-0.0013	0.0942
δ	-0.3187	1.0272	-0.0178	0.3552	-0.0929	0.4142	-0.2146	0.6765	-0.0526	0.2521	-0.0029	0.2041
θ_2	-0.0215	0.0786	-0.0045	0.0300	-0.0465	0.2585	-0.0168	0.0568	-0.0044	0.0283	-0.0006	0.0176
θ_3	-0.0311	0.1244	-0.0078	0.0506	-0.0616	0.3428	-0.0286	0.0899	-0.0082	0.0444	0.0019	0.0293
θ_4	-0.0456	0.1738	-0.0144	0.0716	-0.0760	0.4256	-0.0413	0.1233	-0.0100	0.0656	0.0027	0.0412
θ_5	-0.0620	0.2228	-0.0167	0.0924	-0.0892	0.5080	-0.0611	0.1580	-0.0148	0.0830	0.0027	0.0533

Table 2: *Model 2 Results* $(\alpha_{its} = \lambda_s \alpha_{it})$: Bias and RMSE for each parameterization {N,T,S}

{N,T,S}	**{10,5,5}**		**{10,5,10}**		**{50,5,5}**		**{50,5,10}**		**{100,5,5}**		**{100,5,10}**	
Parameter	**Bias**	**RMSE**	**Bias**	**RMSE**	**Bias**	**RMSE**	**Bias**	**RMSE**	**Bias**	**RMSE**	**Bias**	**RMSE**
β	**-0.0608**	**0.4895**	**-0.1668**	**0.5755**	**-0.0335**	**0.1832**	**-0.0437**	**0.1999**	**-0.0101**	**0.1317**	**0.0163**	**0.1520**
γ	**-0.1828**	**0.7513**	**-0.1109**	**0.6387**	**0.0216**	**0.3694**	**-0.0760**	**0.3099**	**-0.0202**	**0.2707**	**-0.0164**	**0.1977**
δ	**-0.5043**	**1.2057**	**-0.3696**	**0.7395**	**-0.0398**	**0.4074**	**-0.0716**	**0.2619**	**-0.0582**	**0.3106**	**-0.0401**	**0.2037**
λ_2	**-0.0282**	**0.0795**	**-0.0312**	**0.0739**	**0.0015**	**0.0401**	**-0.0150**	**0.0361**	**-0.0060**	**0.0303**	**-0.0033**	**0.0245**
λ_3	**-0.0629**	**0.1442**	**-0.0636**	**0.1347**	**0.0011**	**0.0712**	**-0.0258**	**0.0566**	**-0.0086**	**0.0520**	**-0.0069**	**0.0411**
λ_4	**-0.0900**	**0.1980**	**-0.0959**	**0.1830**	**-0.0030**	**0.1023**	**-0.0378**	**0.0820**	**-0.0127**	**0.0760**	**-0.0100**	**0.0554**
λ_5	**-0.1276**	**0.2647**	**-0.1231**	**0.2420**	**-0.0021**	**0.1324**	**-0.0494**	**0.1047**	**-0.0184**	**0.0981**	**-0.0110**	**0.0716**
λ_6	**----**	**----**	**-0.1546**	**0.2957**	**----**	**----**	**-0.0562**	**0.1274**	**----**	**----**	**-0.0134**	**0.0899**
λ_7	**----**	**----**	**-0.1855**	**0.3579**	**----**	**----**	**-0.0686**	**0.1510**	**----**	**----**	**-0.0168**	**0.1043**
λ_8	**----**	**----**	**-0.2160**	**0.4195**	**----**	**----**	**-0.0819**	**0.1756**	**----**	**----**	**-0.0184**	**0.1207**
λ_9	**----**	**----**	**-0.2453**	**0.4725**	**----**	**----**	**-0.0922**	**0.1998**	**----**	**----**	**-0.0232**	**0.1383**
λ_{10}	**----**	**----**	**-0.2771**	**0.5320**	**----**	**----**	**-0.1015**	**0.2210**	**----**	**----**	**-0.0254**	**0.1551**

Table 3: *Model 3 Results* $(\alpha_{its} = \lambda_s \theta_t \alpha_i)$: Bias and MSE for each parameterization {N,T,S}

{N,T,S}	**{10,5,5}**		**{10,5,10}**		**{50,5,5}**		**{50,5,10}**		**{100,5,5}**		**{100,5,10}**	
Parameter	**Bias**	**RMSE**	**Bias**	**RMSE**	**Bias**	**RMSE**	**Bias**	**RMSE**	**Bias**	**RMSE**	**Bias**	**RMSE**
β	**-2.8168**	**4.5012**	**-2.4862**	**4.1302**	**-0.3228**	**0.5380**	**-1.5212**	**1.8027**	**-0.1800**	**0.3557**	**-0.2530**	**0.3978**
γ	**-3.4477**	**4.7956**	**-2.5408**	**4.4283**	**-0.2929**	**0.5768**	**-1.2789**	**2.0248**	**-0.2199**	**0.4054**	**-0.3646**	**0.5193**
δ	**-4.8255**	**6.1978**	**-3.9795**	**5.5935**	**-0.5164**	**0.7948**	**-1.5271**	**2.3203**	**-0.3777**	**0.5795**	**-0.4745**	**0.6261**
θ_2	**-0.8313**	**1.2410**	**1.3450**	**3.8369**	**-0.0771**	**0.1938**	**0.3119**	**2.6337**	**-0.0472**	**0.1716**	**0.7415**	**0.8967**
θ_3	**-1.2679**	**1.3718**	**-1.0893**	**1.1456**	**-0.1067**	**0.2396**	**0.3929**	**0.7386**	**-0.0700**	**0.2301**	**0.9834**	**1.1842**
θ_4	**-1.5564**	**1.8016**	**-1.4852**	**1.5485**	**-0.1329**	**0.2819**	**0.4764**	**1.1827**	**-0.0935**	**0.2892**	**1.2271**	**1.4716**
θ_5	**-1.8935**	**2.1651**	**-1.8739**	**1.9501**	**-0.1573**	**0.3268**	**0.5569**	**1.4056**	**-0.1169**	**0.3484**	**1.4718**	**1.7582**
λ_2	**-0.8923**	**1.1096**	**0.6612**	**1.2453**	**-0.0786**	**0.2686**	**-0.6027**	**0.6415**	**-0.0460**	**0.2567**	**-0.5902**	**0.6072**
λ_3	**-1.2361**	**1.3766**	**0.7467**	**1.5006**	**-0.1154**	**0.3583**	**-0.8419**	**0.8830**	**-0.0697**	**0.3097**	**-0.7916**	**0.8124**
λ_4	**-1.5821**	**1.7466**	**0.8148**	**1.7867**	**-0.1512**	**0.4477**	**-1.0779**	**1.1287**	**-0.0921**	**0.1716**	**-0.9922**	**1.0166**
λ_5	**-1.9257**	**2.1235**	**0.9251**	**2.1669**	**-0.1861**	**0.5361**	**-1.3139**	**1.3782**	**-0.1149**	**0.2301**	**-1.1918**	**1.2199**
λ_6	**----**	**----**	**1.0028**	**2.4669**	**----**	**----**	**-1.5462**	**1.6246**	**----**	**----**	**-1.3908**	**1.4224**
λ_7	**----**	**----**	**1.1028**	**2.8322**	**----**	**----**	**-1.7832**	**1.8824**	**----**	**----**	**-1.5884**	**1.6245**
λ_8	**----**	**----**	**1.1638**	**3.1206**	**----**	**----**	**-2.1029**	**2.1320**	**----**	**----**	**-1.7858**	**1.8268**
λ_9	**----**	**----**	**1.2400**	**3.4699**	**----**	**----**	**-2.2406**	**2.3811**	**----**	**----**	**-1.9822**	**2.0290**
λ_{10}	**----**	**----**	**1.3450**	**3.8369**	**----**	**----**	**-2.4677**	**2.6337**	**----**	**----**	**-2.1777**	**2.2314**

Table 4: Descriptive Statistics for Atka Mackerel Fishery

Variable	Average	Standard Dev.	Minimum	Maximum
Length (ft.)	227.10	28.79	185.00	295.00
Net-tonnage	868.10	212.72	426.00	1162.00
Gross-tonnage	1470.20	218.91	1027.00	1658.00
Horsepower	3525.20	964.15	2250.00	6000.00
Hold Capacity	30760.80	9856.14	16000.00	42880.00
Crew Members	47.35	8.77	20.00	79.00
HLA harvest (mt.)	18.05	15.46	0.00	74.70
Non-HLA harvest (mt.)	14.93	15.40	0.00	84.65

Table 5: Spatial Locations Visited Within a Year by Model Assumption:

Model	Average	Standard Dev.	Minimum	Maximum
Model 1	5.42	0.69	3.00	6.00
Model 2	5.45	0.66	4.00	6.00
Model 3	5.00	1.26	2.00	6.00
Model 4	5.25	1.05	2.00	6.00
Model 5	7.78	1.68	3.00	11.00
Model 6	7.68	1.69	3.00	11.00
Model 7	9.61	2.68	3.00	14.00

Table 6: Atka Mackerel Production Model Results –3-digit locations

Parameter	Model 1 Results	Model 2 Results	Model 3 Results	Model 4 Results
β_0	-15.9249 (11.59)	-14.8925 (10.06)	-5.4092 (4.64)	-9.6263 (4.45)
$\beta_1(duration)$	0.0074 (0.021)	0.0029 (0.02)	---- (----)	0.0469* (0.02)
$\beta_2(hauls)$	1.3785** (0.07)	1.4199** (0.07)	1.3852** (0.05)	0.9074** (0.07)
$\beta_3(rock)$	0.0881** (0.03)	0.0804** (0.03)	0.1350** (0.02)	0.1027** (0.03)
$\beta_4(other)$	-0.2871** (0.03)	-0.2844** (0.03)	-0.3176** (0.03)	-0.2139** (0.04)
$\gamma_1(crew)$	1.6146* (0.83)	3.0205** (0.78)	1.2193** (0.56)	0.2820 (0.69)
$\delta_1(gtons)$	1.1220 (1.37)	0.2054 (1.32)	0.0811 (0.61)	1.2592* (0.68)
λ_{5000}	0.2392 (0.24)	0.2612 (0.23)	-0.2840 (0.32)	-0.2935 (0.72)
λ_{5410}	1.0000 (---)	0.9529** (0.03)	1.0000 (---)	0.7410** (0.15)
λ_{5420}	0.9509** (0.03)	0.9432** (0.03)	0.9938** (0.04)	0.9169** (0.06)
λ_{5421}	1.0016** (0.02)	1.0000 (---)	1.1105** (0.05)	1.0000 (---)
λ_{5430}	0.9053** (0.04)	0.9146** (0.04)	0.9227** (0.05)	0.8567** (0.10)
λ_{5431}	0.9801** (0.03)	0.9867** (0.03)	1.0175** (0.05)	0.8365** (0.10)
# Obs.	347	349	313	317
Sigma (Variance)	0.5991	0.7717	0.7233	0.8026

(**indicates statistically significant at the 95% level: * indicates statistical significance at the 90% level)

Table 7: Atka Mackerel Production Results – Sub-division of regions 5000, 5410, 5420, 5421, 5430, 5431 indicated.

Parameter	Model 5 Results	Model 6 Results
β_0	-22.2716**	-14.2812**
	(6.49)	(2.88)
$\beta_1(duration)$	-0.0058	0.0213
	(0.02)	(0.01)
$\beta_2(hauls)$	1.600**	1.3594**
	(0.05)	(0.04)
$\beta_3(rock)$	0.0179	0.1117**
	(0.02)	(0.02)
$\beta_4(other)$	-0.2524**	-0.2278**
	(0.03)	(0.02)
$\gamma_1(crew)$	4.7464**	2.6534**
	(0.52)	(0.37)
$\delta_1(gtons)$	0.2297	0.6185
	(0.81)	(0.33)
λ_{S1} (5410)	1.0000	1.1603**
	(---)	(0.06)
λ_{S2} (5410)	0.0669	-1.4319**
	(0.13)	(0.38)
λ_{S3} (5000)	0.4303**	-0.4797**
	(0.07)	(0.24)
λ_{S4} (5000)	0.3119**	-0.9490**
	(0.09)	(0.33)
λ_{S5} (5420)	0.9026**	1.0000
	(0.02)	(---)
λ_{S6} (5430)	0.8760**	0.9320**
	(0.03)	(0.06)
λ_{S7} (5431)	0.8300**	0.7581**
	(0.03)	(0.09)
λ_{S8} (5431)	0.9161**	1.0664**
	(0.03)	(0.07)
λ_{S9} (5421)	0.8169**	0.4164**
	(0.04)	(0.13)
λ_{S10} (5421)	1.0019**	1.3110**
	(0.02)	(0.08)
λ_{S11} (5421)	0.9287**	1.1288**
	(0.02)	(0.07)
N Obs.	489	542
Sigma (Variance)	1.3407	1.5335

(**indicates statistically significant at the 95% level: * indicates statistical significance at the 90% level)

Table 8: Atka Mackerel Production Results – Aggregated 6-digit locations

Parameter	Model 7 Estimates	Parameter	Model 7 Estimates
β_0	15.1307 (9.95)	$\lambda_{S5}(5410)$	0.5345** (0.16)
$\beta_1(duration)$	0.0343** (0.01)	$\lambda_{S6}(5000)$	0.5998** (0.14)
$\beta_2(hauls)$	1.3478** (0.04)	$\lambda_{S7}(5000)$	0.5285** (0.16)
$\beta_3(rock)$	0.0270** (0.02)	$\lambda_{S8}(5430)$	0.9290** (0.03)
$\beta_4(other)$	-0.2131** (0.02)	$\lambda_{S9}(5430)$	1.0435** (0.02)
$\gamma_1(crew)$	0.0281 (0.03)	$\lambda_{S10}(5421)$	0.8687** (0.05)
$\delta_1(gtons)$	-2.6765* (1.58)	$\lambda_{S11}(5421)$	1.0723** (0.03)
$\lambda_{S1}(5420)$	1.0000 (---)	$\lambda_{S12}(5421)$	1.0144** (0.02)
$\lambda_{S2}(5420)$	0.7010** (0.10)	$\lambda_{S13}(5431)$	0.9482** (0.03)
$\lambda_{S3}(5410)$	1.1094** (0.04)	$\lambda_{S14}(5431)$	0.9543** (0.02)
$\lambda_{S4}(5410)$	0.2600 (0.25)	$\lambda_{S15}(5431)$	0.9116** (0.03)
N Obs.		662	
Sigma (Variance)		1.7996	

(**indicates statistically significant at the 95% level: * indicates statistical significance at the 90% level)

Figure 1: Graphical illustration of the management zones utilized within the Atka mackerel fishery. Steller sea lion HLAs are indicated by the shaded in zones along the numerous islands within the Aleutian island chain residing within management zones 543 and 542. Shaded in regions within 541 indicate the critical habitat zones.

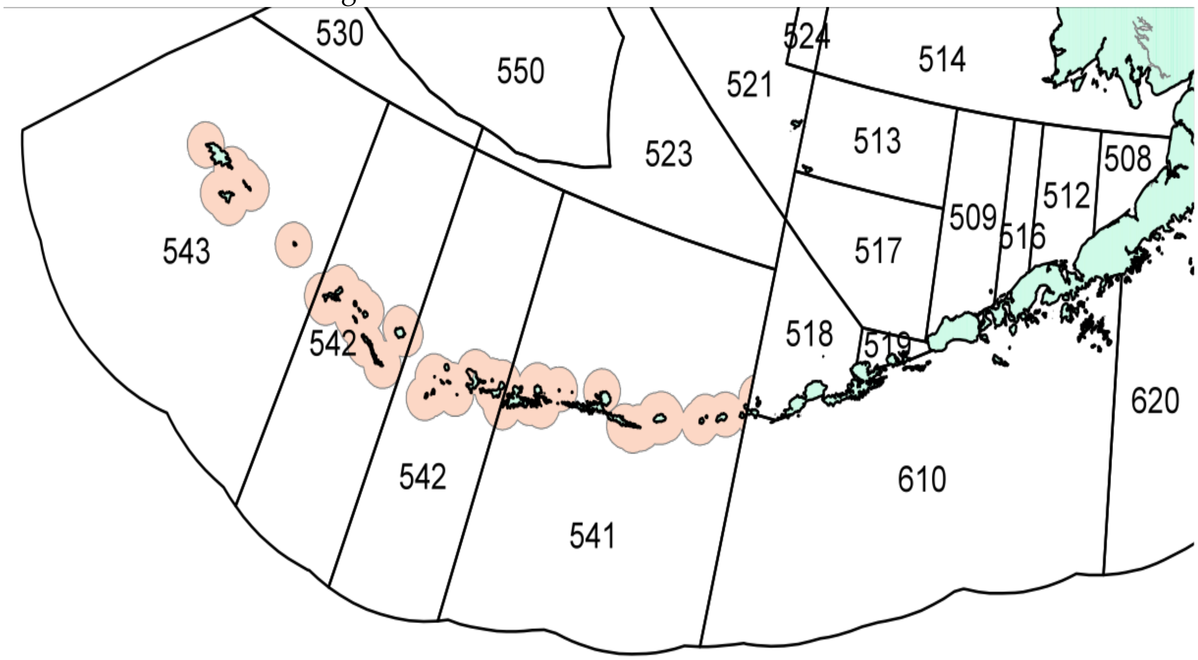

Figure 2: Spatial Efficiency Measures Models 1-4.

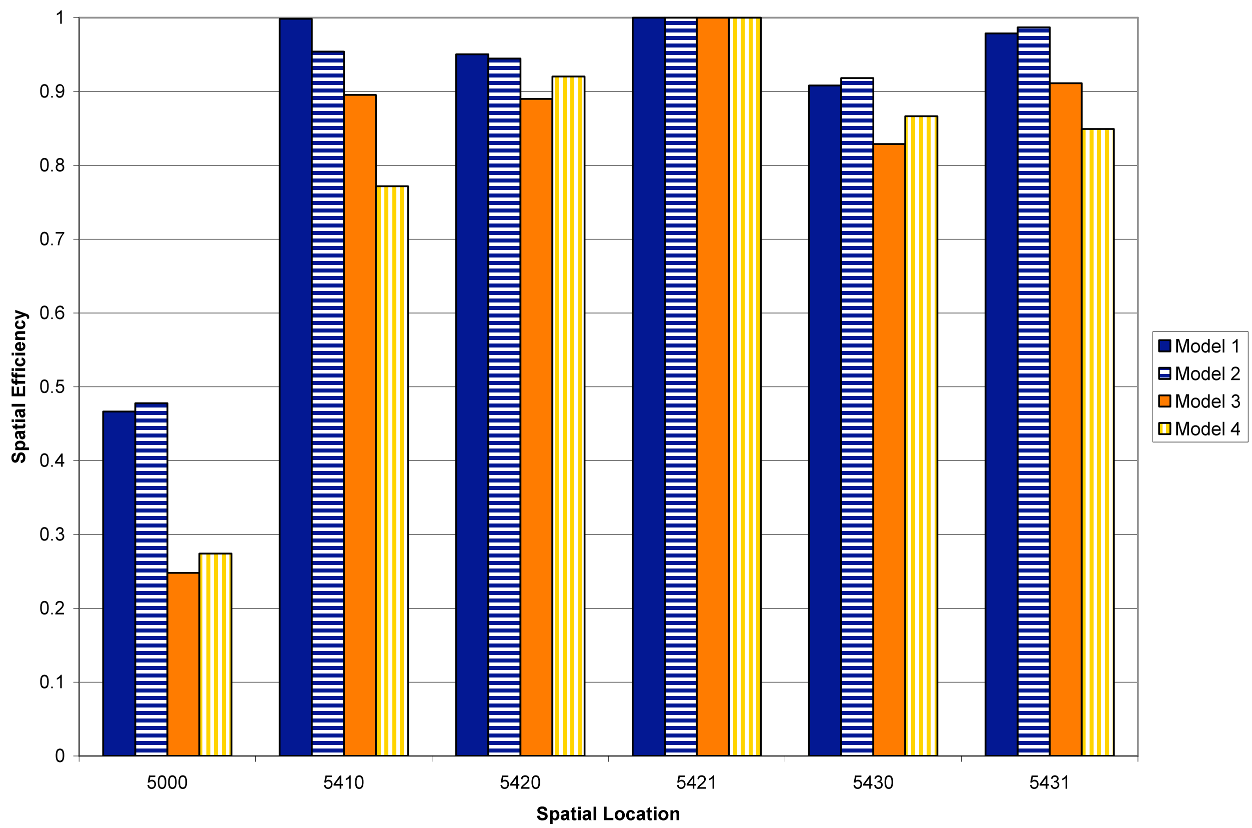

Figure 3: Spatial Efficiency Measures Model 5 and 6.

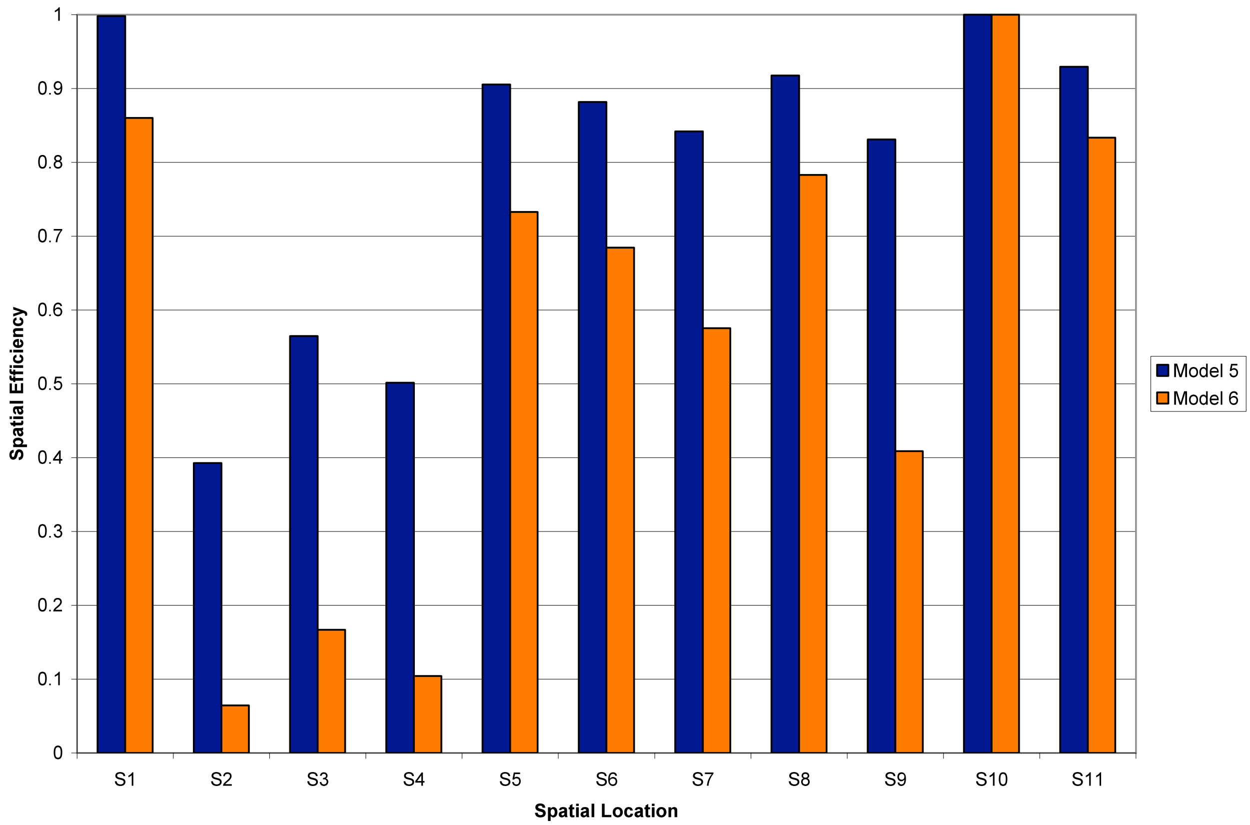

Figure 4: Spatial Efficiency Measures Model 7.