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FIXED-EFFECT ESTIMATION OF HIGHLY-MOBILE PRODUCTION TECHNOLOGIES

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Abstract

We consider fixed-effect estimation of a production function where inputs and outputs vary over time, space, and cross-sectional unit. Variability in the spatial dimension allows for time-varying individual effects, without parametric assumptions on the effects. Asymptotics along the spatial dimension provide consistency and normality of the marginal products. A finite-sample example is provided: a production function for bottom-trawler fishing vessels in the flatfish fisheries of the Bering Sea. We find significant spatial variability of output (catch) which we exploit in estimation of a harvesting function.

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JEL Codes: C23, D24, N50

Key Words: Panel data, time-varying individual effect, spatial econometrics, fisheries, agriculture, heteroskedasticity.

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1. Introduction

Consider the econometric fixed-effect model:

$$y_{it} = \alpha_{it} + x_{it}\beta + z_i\gamma + v_{it}\,, \qquad i = 1,\ldots,N\,,\ t = 1,\ldots,T\,,$$

where i indexes individual or cross-sectional unit, and t indexes time. Notice that the individual effects, α_{it}, vary over time. The earliest specifications of this model were identified by the restriction $\alpha_{it} = \alpha_i$ for all t, producing the common panel data specification (see Mundlak, 1978; MaCurdy, 1981; and Chamberlain, 1984). To relax this restriction a series of papers parameterize the time-varying effects into an individual component and a time component, so that the temporal pattern is fixed across individuals or groups of individuals. See Cornwell, Schmidt, and Sickles (1990), Kumbhakar (1990), Battese and Coelli (1992), Lee and Schmidt (1993), Cuesta (2000), Ahn, Lee, and Schmidt (2001), Han, Orea and Schmidt (2005), and Lee (2005).

An excellent discussion of time-varying individual effects models, their underpinnings, estimation, and applicability is provided in the introduction of Ahn, Lee, and Schmidt (2001). In particular they relate these models to the work of Kiefer (1980), Holtz-Eakin et al. (1988), and Chamberlain (1992). They also discuss their application to rational expectations models (Hall and Mishkin, 1982; Shapiro, 1984; and Keane and Runkle, 1992), production function estimation (Schmidt and Sickles, 1984; and Lee and Schmidt, 1993), and estimation of earnings equations where unobserved ability might vary with time due to a time-varying implicit price of ability. There is also a sizeable Bayesian literature that addresses panel data estimation of panel data models and production functions. However, Bayesian approaches are not directly comparable to

the frequentist approaches considered herein, so while the Bayesian literature is certainly important, it will not be discussed here.[1]

The intent of this research is to relax the parametric assumptions on time-varying individual effects, and exploit spatial variation of economics agents to identify and estimate the model with a 'within' transformation and ordinary least-squares. Our primary interest is production function estimation, but our results could also be applied in any of the aforementioned empirical settings, as long as agents are highly-mobile, location-specific data are observed, and the variability of output is statistically relevant along the spatial dimension.

While most production technologies are fixed (in the short-run), one can envision technologies that are not. The example we discuss in detail is the fishery, where fishing vessels harvest fish in different spatial locations of the sea and where spatial variability of harvest is statistically meaningful. Other examples of highly-mobile technologies are: police cruisers arresting criminals in different locations of a city, taxis competing for fares, sales forces mobilized to serve clients, farm combining operations that move from south to north over the course of a growing season, or natural gas and oil drilling operations.[2] Here, the dependent variable (production) may be observed over time, space, and individual (i.e., y_{its}). With adequate spatial variability in the factors of production (x_{its}) the time-varying individual effects (α_{it}) can be modeled without parameterization. In fact, β in the linear model,

$$y_{its} = \alpha_{it} + x_{its}\beta + z_{it}\gamma + w_i\delta + v_{its},$$

[1] For Bayesian treatments of panel data frontier models see, for example, Fernandez et al. (2002), Tsionas (2002), Kim and Schmidt (2000), and Koop et al. (1997).

[2] Frequent relocation of capital to maximize profits (or minimize cost) is an inevitability as the time dimension of a panel become large (in the long-run). Consider the flow of capital from the northern U.S. to the southern U.S. over the last twenty years. Of course, large *T* presents many challenges not addressed in this research, as we fix *T*.

can be estimated with a simple 'within' transformation, where within-cell averages are taken over the spatial dimension s (i.e., $y_{its} - \bar{y}_{it}$). In this paper, we consider only 'within' estimation and deal with several perplexing issues related to it. The most difficult of which is that the parameters of space invariant production factors, z_{it} and w_i, are not identified. This problem is tackled by recognizing that mobile technologies are usually engaged in the harvesting of some natural resource or moving to where the stock of raw materials of production are most abundant (e.g., fishing vessels harvest fish, police forces 'harvest' criminals, and taxis 'harvest' fares). If the resource stocks (fish, criminals, etc.) are observable within each spatial location and vary over space, then we posit a *harvesting function*, in the spirit of Schaefer (1957), which *interacts* space-varying stock with the factors of production. As such, all the factors of production are (effectively) space-varying and are, thus, identified. Identification hinges critically on the fact that individual effects do not vary over space (i.e., α_{it} remains fixed across s). Identification also hinges on the assumption that resource stocks are exogenous, which we assume throughout this paper. Of course, if stocks are endogenous then some form of instrumental variables estimation is needed.[3] For our example, the measure of resource stock is, indeed, exogenous. These complications are discussed in the sequel. Finally, we consider asymptotics in the spatial dimension, which is reasonable for highly-mobile technologies which are not limited to operating within a particular country, state, country, town or neighborhood. As such, the spatial resolution of the data in our model is not limited by physical constraints, as long as the technology moves rapidly and as long as data are observed at the finer spatial resolution.

[3] In some fisheries harvesting may serially deplete resource stocks, making resource stock exogenous. This is not a serious concern in the fishery we consider in the sequel, however serial depletion may be present in some of the aforementioned examples, such as policing where intensive criminal 'harvesting' may deplete resource stocks.

It should be noted that three-dimensional panels have been considered in empirical work in the past, but our model is unique in two ways. First, ours is the first to consider within estimation. Other papers have considered the " least squares dummy variable estimator" (LSDV) and ignore certain econometric nuances that we discuss in detail. For example, Parsley and Wei (2005) consider a LSDV regression of the variability of prices on traded goods (*i*), over time (*t*), and across cities (*s*) in the U.S. and Japan. Second, our three dimensions: cross-section, time, and space, are uniquely distinct features of the data. Other papers have added a third dimension to a panel that is not distinct from the others. For example, Davies and Lahiri (1995) consider a panel of forecasters (*i*), in time period (*t*), for forecast horizons (*h*). However, their third dimension (*h*) is merely a subdivision of time (*t*). Eilat and Einav (2004) develop a three-dimensional model of tourism flows over country of origin (*o*), destination country (*d*) and time (*t*). However, again the dimensions *o* and *d* are not uniquely distinct. When subdivisions of geographical entities are considered, the subdivisions are necessarily static. For example, there are many papers (e.g., Valletta, 1993 or Fleck, 1999) that analyze data over U.S. cities or counties, within states, over time. These are usually treated as a two-dimensional panels (cities or counties over time) with state dummies, because there is no sense in which cities or counties can move across states in they way that they 'move' across time. Our data are unique in that each cross sectional unit can move across both time and space.[4]

Most spatial econometric innovations in the last ten years are conceptualized for fixed (or nearly-fixed) economics agents. This is not entirely unrealistic since in the short-run economic agents and capital remain in a fixed location. For example, Conley's series of spatial econometric papers are all based on a one-shot view of space, where agents are not changing position. See Conley (1999), Conley and Dupor (2003), Conley and Ligon (2002), and Conley and Topa

[4] This is also a unique feature of Parsley and Wei (2001).

(2002). Also, papers based on fixed weighting matrices do the same. For example, see Kelijian and Prucha (1999 and 2001). In these papers, the presumption is that there is not enough mobility over time for space to be considered as another source of variability in the data. Indeed, we contend that they are either assuming that resources are fixed (e.g., immobile capital or natural resource), or that the time dimension is not large enough for mobility to be considered a reasonable assumption. Therefore, by relaxing the assumptions of spatially fixed inputs, our model makes a unique contribution to the literature on spatial econometrics.

Our analysis is an application of the spatial asymptotic theory of Pinkse, Shen and Slade (2007) and a special case Pinkse, Slade and Shne (2006). Both of these papers consider asymptotics across space, where the spatial location decision of economics agents is endogenous. However, their papers are conceptualized for asymptotics along the cross-sectional dimension, where each agent endogenously selects a position, and the number of agents and, hence, spatial locations grows. Our concept of a fixed number of agents moving over a growing number of spatial locations is slightly different, but all of their ideas still apply. The primary difference between our work and theirs is our indexing strategy, that allows us to specifically model time-varying heterogeneity. This could only be accomplished in a meaningful way using our idea of a fixed number of agents moving over ever-growing area. There are, however, certain practical drawbacks to this concept, and we discuss them in the sequel.

The paper is organized as follows. The next section defines the harvesting function, and discusses identification, estimation and asymptotic normality. Section 3 discusses practical issues concerning asymptotics and aggregation. In section 4, we present an example: estimation of a production function of bottom-trawler fishing vessels in the flatfish fisheries of the Bering Sea. The last section concludes and makes suggestions for future research.

2. Specification and Asymptotics

In what follows, we couch the discussion in terms of the example of interest, Bearing Sea flatfish fisheries. However, the discussion is relevant to all the aforementioned highly-mobile technologies. Define the Cobb-Douglas harvesting function:

$$y_{its} = A_{it}\{x_{its}^{\beta} z_{it}^{\gamma} w_i^{\delta}\}^{b_{ts}} \exp(v_{its}) \quad i = 1,...,N\ ,\ t = 1,...,T\ ,\ s = 1,...,S_{it}\ ,$$

where *s* indexes spatial location fished, i indexes the vessel, and *t* indexes time. Notice that we allow the number of spatial locations, S_{it}, to vary over i and t; this is the spatial equivalent of an unbalanced panel. We make explicit the fact that the exogenous inputs to the harvesting function may be space-invariant (z_{it}), or possibly space- and time-invariant (w_i). The b_{ts} is an *observed* time- and space-varying exogenous factor of harvesting, which does not vary over i. In our fisheries context this would be the fish density (biomass) in a given location and time period. The idea is that fishing stocks are exogenous (as we shall argue), and production efforts are only successful when fish are present. The exogeneity of b_{ts} may be called into question for many applications. In this context we think of endogeneity as coming from the decision of 'where to harvest.' That is, the location of the means of production is a key choice variable in the optimization problem. For example, cabbies elect to search for fares where population density is highest, and police forces patrol more in areas where the crime rate is highest, so production (output) effects the location decision, which is correlated with the stock of harvestable resources in each location.[5] Fortunately, in our example, there is a low correlation between our measure of fish stocks and the decision of where to fish, as we shall see in section 4.

[5] In particular we do not view the endogeneity as coming directly from the harvesting. That is aggressive harvesting does not lower the fish stocks in any appreciable way in the short-run. This may not be the case in all the examples we have suggested.

Notice that the inputs to fishing are affected by the biomass through the exponent b_{ts} and that technical change, A_{it}, is constant over all spatial locations and is, consequently, unaffected by the biomass in the spatial location (it is not raised to the b_{ts} power) . This is critical to identification for 'within' estimation of the model.[6] Taking logs yields the following log-transformed production function:

$$\ln y_{its} = \ln A_{it} + b_{ts} \ln x_{its}\beta + b_{ts} \ln z_{it}\gamma + b_{ts} \ln w_i\delta + v_{its} .$$

Let $\alpha_{it} = \ln A_{it}$, $Y_{its} = \ln y_{its}$, $X_{its} = b_{ts} \ln x_{its}$, $Z_{its} = b_{ts} \ln z_{it}$, and $W_{its} = b_{ts} \ln w_i$, then:

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

This is just a fixed-effect specification, but the beauty of it is that ALL the regressors vary over *s* (due to interactions with b_{ts}, which *does* vary over *s*). Therefore, all the parameters (β, γ, and, δ) are identified by 'within' estimation. The point is that inputs alone do not catch fish; it is the interaction of the biomass or density of fish with the production inputs that catch fish. As such, inputs that do not vary with spatial location (like vessel size) can be interacted with biomass in different locations to identify the parameters of the model. This is similar in spirit to Wooldridge's 'solution' to time invariant regressors in the usual fixed-effect model: they are not allowed "unless they are interacted with time varying variables, such as time dummies" (Wooldridge, 2002, p269). However, in this case the interactions are well-justified, as it would seem that the marginal products of fishing inputs would equal zero when there were no fish to catch but would be very large when there are many fish to catch (particularly when they are

[6] It is not critical if we assume a parametric form for lnA_{it} and perform GMM.

being caught in a trawl). Consequently, interaction of inputs with biomass makes sense both empirically and theoretically.[7]

One could also envision a specification where biomass (alone) enters the harvesting function log-linearly and is multiplied by a marginal product parameter for estimation. This presents no additional problems in the estimation. However, the specification would imply the Cobb-Douglas harvesting functions:

$$y_{its} = A_{it}\{x_{its}^{\beta} z_{it}^{\gamma} w_i^{\delta} b_{ts}\}^{b_{ts}} \exp(v_{its}) \text{ or } y_{its} = A_{it} b_{ts}\{x_{its}^{\beta} z_{it}^{\gamma} w_i^{\delta}\}^{b_{ts}} \exp(v_{its}),$$

which seems somewhat redundant because of b_{ts} occurring twice in the form. These functions are within the realm of possibilities, but are not considered in what follows. It should also be noted that the Cobb-Douglas harvesting function is easily generalized to a trans-log specification, with variable interactions across all three dimensions in the spatial panel.

Consider the specification in equation 1 in more detail. We have implicitly assumed that the inputs (X_{its}, Z_{its}, and W_{its}) and the parameters (β, γ, and, δ) are scalars. Let's make things more general. First, let Y_{its} and v_{its} be scalars. Let X_{its}, Z_{its}, and W_{its} 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. Let,

$$\underset{(1\times[k+g+d])}{\tilde{X}_{its}} = \begin{bmatrix} X_{its} & Z_{its} & W_{its} \end{bmatrix} \text{ and } \underset{([k+g+d]\times 1)}{\beta_*'} = \begin{bmatrix} \beta' & \gamma' & \delta' \end{bmatrix},$$

Then, our equation becomes

$$Y_{its} = \alpha_{it} + \tilde{X}_{its}\beta_* + v_{its}.$$

Defining the variables demeaned over the spatial dimension,

[7] We could also follow Wooldridge and interact all variables with location dummies. However, we desire asymptotics along the spatial dimension, so spatial dummies are infeasible due to incidental parameters.

$$Y_{its}^{+} = Y_{its} - S_{it}^{-1}\sum_{s=1}^{S_{it}} Y_{its}\ ,\quad \tilde{X}_{its}^{+} = \tilde{X}_{its} - S_{it}^{-1}\sum_{s=1}^{S_{it}} \tilde{X}_{its}\ ,\ \text{and}\ v_{its}^{+} = v_{its} - S_{it}^{-1}\sum_{s=1}^{S_{it}} v_{its}\ ,$$

our demeaned equation is,

$$Y_{its}^{+} = \tilde{X}_{its}^{+}\beta_{*} + v_{its}^{+}\ ,\ i = 1,...,N\ ,\ t = 1,...,T\ ,\ s = 1,...,S_{it}\ . \tag{2}$$

Under appropriate exogeneity assumptions and regularity conditions on the regressors (e.g., see White, 1984) ordinary least-squares (OLS) of this equation produces unbiased estimate,

$$\hat{\beta}_{*} = \left(\sum_{i}^{N}\sum_{t}^{T}\sum_{s}^{S_{it}} \tilde{X}_{its}^{+'}\tilde{X}_{its}^{+}\right)^{-1}\left(\sum_{i}^{N}\sum_{t}^{T}\sum_{s}^{S_{it}} \tilde{X}_{its}^{+'}Y_{its}^{+}\right).$$

Notice that all elements of $\hat{\beta}_{*}$ are identified, because all elements of $\tilde{X}_{its}^{+}$ are space-varying through interactions with biomass, b_{ts}.

We now provide conditions for asymptotic normality of $\hat{\beta}_{*}$ along the spatial dimension, based on the central limit theorem of Pinkse, Shen and Slade (2007) which accounts for spatial dependence and endogeneity of location choice. Their CLT results are based on the Bernstein (1927) grouping strategy, whereby spatial locations are partitioned in such a way that spatial dependence decreases as the number of locations increases. "Such partitioning does not actually have to take place; there merely must be the possibility to do so" (Pinkse, Shen and Slade, forthcoming p. 219). For notational simplicity we balance the panel in the spatial dimension, so let $S_{it} = S$ for all i,t. All our arguments will be based on $S \to \infty$. Further let $\tilde{X}_{s}^{+}$ be the matrix of observations of $\tilde{X}_{its}^{+}$ for all i,t in location s, so it is a $N \times T$ matrix. Similarly for v_{s}^{+} with covariance matrix Ω. Now assume the following.

A1. $E(\tilde{X}_{s}^{+'}v_{s}^{+}) = 0$.

A2. $\Gamma = V\left(S^{-1/2} \sum_{s=1}^{S} \tilde{X}_s^{+'} v_s^{+} \right) = S^{-1} \sum_{s=1}^{S} \tilde{X}_s^{+'} \Omega \tilde{X}_s^{+}$ is $O_p(1)$ and uniformly positive definite.

A3. For any vector λ with $\lambda\lambda' = 1$, assumptions A-C of Pinkse , Shen and Slade (2007) are satisfied for:

$$\lambda \left(\sum_{s=1}^{S} \tilde{X}_s^{+'} \Omega \tilde{X}_s^{+} \right)^{-1/2} \left(\sum_{s=1}^{S} \tilde{X}_s^{+'} v_s^{+} \right).$$

Letting the kth element of vector $\tilde{X}_{its}^{+}$ be the scalar $\tilde{X}_{its;k}^{+}$,

A4. $\left| Cov(\tilde{X}_{its;k}^{+} \tilde{X}_{i^*t^*s;k^*}^{+}, \tilde{X}_{jmr;g}^{+} \tilde{X}_{j^*m^*r;g^*}^{+}) \right| \le \rho_{sr} \sqrt{V(\tilde{X}_{its;k}^{+} \tilde{X}_{i^*t^*s;k^*}^{+})} \sqrt{V(\tilde{X}_{jmr;g}^{+} \tilde{X}_{j^*m^*r;g^*}^{+})}$ where

$$\mathrm{P} = \max_{s \le S} \sum_{r=1}^{S} \rho_{sr} \text{ and } \lim_{S \to \infty} \frac{\mathrm{P}}{S} = 0, \text{ for all } i,\ j,\ t,\ m,\ k,\ g,\ i^*,\ j^*,\ t^*,\ m^*,\ k^*,\ g^*,\ s,\ r.$$

A5. $V\left(S^{-1} \sum_{s=1}^{S} \tilde{X}_s^{+'} \tilde{X}_s^{+} \right)$ is $O_p(1)$ and uniformly positive definite.

A6. $M = E\left(S^{-1} \sum_{s=1}^{S} \tilde{X}_s^{+'} \tilde{X}_s^{+} \right)$ is $O_p(1)$ and uniformly positive definite.

Assumption A1 is a standard exogeneity assumption. A sufficient condition for A1 is $E(v_s \mid \tilde{X}_s) = 0$. Assumption A2 allows for arbitrary covariance structure for the error (this is important not only for spatial dependence but for aggregation issues that we discuss in the sequel). The conditions necessary for A3 to hold are those that ensure spatial 'mixing' for sums of the $\tilde{X}_s^{+'} v_s^{+}$. The most important condition is a covariance-variance inequality with mixing constants similar to A4, but for the elements of the product of $\tilde{X}_{its}^{+}$ and v_{its}^{+}.

The spatial mixing condition in A3 is based on a blocking strategy (Bernstein, 1927), which partitions the sample into groups (blocks) and subgroups (sub-blocks), such that as the sample size grows, dependence between subgroups within a group becomes negligible. First, it

is important to note that the blocking strategy is not limited to partitioning physical space; it is more general. Indeed, Pinkse, Shan and Slade (2007) state that the blocks "do not have to be blocks; they are judiciously chosen subsets of observations." Second, the blocking "does not actually have to take place; there merely must be the possibility to do so." For our application we think of the blocks as a partitioning of the sea and the asymptotics are for an "expanding sea" (i.e., as the number of spatial locations, S, grows, the sea expands), the implications of which we discuss in the next section.

Assumptions A1, A2 and A3 ensure that, $S^{-1/2}\sum_s \tilde{X}_s^{+'} v_s^+ \xrightarrow{d} N(0,\Gamma)$. Assumption A4 is the linear version of equation 25 of Pinkse, Slade and Shen (2006) and is a spatial mixing condition. The constants ρ_{sr} limit the amount of spatial dependence to ensure convergence of the second moment matrix. A5 and A6 are standard. Together A4, A5 and A6 ensure that $S^{-1}\sum_2 \tilde{X}_s^{+'}\tilde{X}_s^+ - M \xrightarrow{p} 0$. To see this, notice that A4 implies:

$$
\begin{aligned}
&S^{-1}\sum_s E\left[\tilde{X}^+_{its;k}\tilde{X}^+_{i^*t^*s;k^*} - E\left(\tilde{X}^+_{its;k}\tilde{X}^+_{i^*t^*s;k^*}\right)\right]^2 \\
&\quad \le S^{-2}\sum_{s,r}\left|Cov(\tilde{X}^+_{its;k}\tilde{X}^+_{i^*t^*s;k^*}, \tilde{X}^+_{jmr;g}\tilde{X}^+_{j^*m^*r;g^*})\right| \\
&\quad\quad \le S^{-2}\rho_{sr}\sqrt{V(\tilde{X}^+_{its;k}\tilde{X}^+_{i^*t^*s;k^*})}\sqrt{V(\tilde{X}^+_{jmr;g}\tilde{X}^+_{j^*m^*r;g^*})} \\
&\quad\quad\quad \le \frac{\mathrm{P}}{S}\sum_{s,r}\sqrt{S^{-1}V(\tilde{X}^+_{its;k}\tilde{X}^+_{i^*t^*s;k^*})}\sqrt{S^{-1}V(\tilde{X}^+_{jmr;g}\tilde{X}^+_{j^*m^*r;g^*})} = o_p(1).
\end{aligned}
$$

The first summation is simply the S element-by-element variances in each spatial location; the equation shows that this is bound in probability by zero. The second summation consists of the S variances plus the absolute value of the covariances. The second and third inequality hold due to A4. The last equality follows from $\lim_{S\to\infty}\mathrm{P}/S = 0$ along with A5 and A6. The asymptotic normality result, $\sqrt{S}(\hat{\beta}_* - \beta_*) \xrightarrow{d} N(0, M^{-1}\Gamma M^{-1})$, follows from White (1984, Theorem 4.25).

Together A1-6 are a linear version of the assumptions for asymptotic normality in Pinkse, Slade and Shen (2006) with some noticeable simplifications caused by (among other things) the linear form in (2) and the closed-form of the estimator. Therefore, $\hat{\beta}_*$ is asymptotically normal with $\sqrt{S}$ convergence rate. The blocking strategy also accommodates asymptotic normality as $N \to \infty$, $NS \to \infty$, $TS \to \infty$ or as $NTS \to \infty$, so the aforementioned asymptotics could be adjusted to accommodate a variety of convergence rates, as long as the dependences in the alternative dimensions can be adapted to those implied by A3 and A4. In cases where the time dimension grows, the usual temporal mixing conditions (e.g., White 1984, Definition 3.42) are essentially replaced with the spatial mixing conditions. Consistency of $\hat{\beta}_*$ is implied by the conditions for asymptotic normality (White, 1984, Theorem 2.28). Finally, for inference let the residual be $\hat{v}_s^+ = Y_s^+ - \tilde{X}_s^+ \hat{\beta}_*$. Then a robust variance estimate in the spirit of White (1980) and Arellano (1987) is:

$$V(\hat{\beta}_*) = \left(\sum_{s=1}^{S} \tilde{X}_s^{+'} \tilde{X}_s^+ \right)^{-1} \left(\sum_{s=1}^{S} \tilde{X}_s^{+'} \hat{v}_s^+ \hat{v}_s^{+'} \tilde{X}_s^+ \right) \left(\sum_{s=1}^{S} \tilde{X}_s^{+'} \tilde{X}_s^+ \right)^{-1}. \tag{3}$$

We now discuss some practical issues related to asymptotics along the spatial dimension and a blocking strategy that ensures weak dependence along the spatial dimension.

3. Spatial Asymptotics and Aggregation

Our discussion of asymptotics is intended to facilitate inference when the errors are non-normally distributed or when robust inference is necessary. The latter situation may arise (in part) from data aggregation. Aggregation may be necessary for data from highly-mobile technologies, as we will see below.

Asymptotics in Physical Space

The asymptotic normality of $\hat{\beta}_*$ along the spatial dimension is a nice feature of the model, but how are asymptotics even conceptualized in physical space? [8] If we think of the physical space (say, the sea) as a two-dimensional rectangular integer lattice, then production can move to any of spatial regions within a given time period. Given this, we can think of asymptotics in two extreme ways: either a) the surface area of the lattice (domain) expands and the area of the individual locations is fixed , or b) the area of the lattice (domain) is fixed, and the number of spatial locations increases while their area size decreases. Following Cressie (1993) we call the former "increasing-domain asymptotics" and the latter "infill asymptotics." Theoretically, if we can let N and T be fixed, then $S \to \infty$ as either an expanding lattice or as a finer spatial resolution, and the asymptotics presents no additional problems.[9] However, practically speaking both concepts of asymptotics present aggregation issues and these are discussed in what follows.

Spatial Aggregation

The increasing-domain asymptotics are problematic in a practical sense. To see this, we only need realize that as the lattice gets larger, there will not be enough time in period t to move production to all (or a large number) of the spatial locations; there is just not enough time to travel the large distances. For example, if we are discussing fishing vessels, and the unit of t is one week, and one vessel can fish a maximum of 25 different locations in one week, then expanding the number of locations above 25 for asymptotics is impractical. To remedy this we could expand the unit of observation for t by aggregating across t. To continue the example, suppose we aggregated 52 weeks of weekly data into 12 months of monthly data, then over the

[8] Note that *s* can also represent subdivisions of time for each *t*, but we will not consider this here.

[9] Infill asymptotics can be motivated by recent advancements in the resource economics literature which divide a fishery into spatially distinct “patches” (Sanchirico and Wilen, 1999, 2005). Each patch is defined by the ecological characteristics of the resource and the degree of resource heterogeneity present.

course of a month a vessel may be able to visit four times as many spatial locations, so we could expand the maximal number of locations to 100. Now, we effectively have $S \to \infty$ while $T \to 0$ as our asymptotic argument. However, as $T \to 0$, we still have a problem, since, $\alpha_{it} \to \alpha_i$, and the model will be misspecified, as individual effects are no longer time-varying. We can also think of this as a violation of the fact that over large units of time, it is not practical to think of individual effects as be time-invariant.[10] The infill asymptotics approach is less problematic, but there are still practical difficulties associated with it. If we divide the lattice into smaller and smaller spatial areas while keeping its total area fixed, then the lattice becomes a spatial continuum of fixed size in s. Unfortunately, production data are inherently discrete in s, so increasing S will eventually cause the production data at each location at be unmeasurable (in a discrete sense).

Another practical problem with data aggregation over time concerns the measurement of the biomass. If we have weekly biomass measures and aggregate them to the year, how does one interpret the aggregate measure? Perhaps *average* yearly biomass would be a more suitable measure, but this average is not what the vessels truly face over the course of the year, particularly when fish exhibit annual migratory patterns. Alternatively, if the biomass is measured only once a year and we aggregate catch up to a year, the same problem ensues: the measure is not indicative of what the vessels face. In either case this can loosely be interpreted as a measurement error problem created by aggregation.

One could also envision some combination of these two form of spatial asymptotics. The spatial lattice is expanding while the spatial resolution is simultaneously increasing. This may provide some empirical benefits. For a particular data set, we may have large enough S to

[10] This is particularly relevant when individual effects are viewed as technical efficiency (see Schmidt and Sickles, 1984). In the long-run technical efficiency (or inefficiency) should be time varying.

appeal to asymptotics, where the lattice is not too big, so as to force T to be too small to preclude time-varying individual effect, *and* where the spatial resolution is not too fine, so as to preclude data collection in each spatial location or to cause inputs to be fixed over space. Ultimately, adjusting the data through aggregation, disaggregation, or spatial normalization are empirical decisions that must balance time and space. Of course aggregation in any dimension, may induce heteroskedasticity in the aggregate errors, so robust variance estimation is required.

Spatial Asymptotics and the Blocking Strategy

Our blocking strategy is based on the concept of expanding domain asymptotics. Generally speaking, the blocking should be designed "[s]o the 'distance' between subgroups in the same group increases" with the sample size (Pinkse, Shen and Slade, 2007 p. 219). There are many ways that one could envision this, and we present two. If we think of the sea as the pie in Figure 1, then "spatial location zero" is the center of the pie. As the pie expands, spatially-correlated realizations of $\{X_s, v_s\}$ are generated at different locations, such that locations that are closer together have larger spatial correlation. (This is the same correlation scheme as Pinkse, Slade and Shen, 2006.) We partition the sea with radii originating at the center of the pie, so blocks are pie slices. In the figure, the numbers represent the group (first number) and subgroup (second number), so we have two groups and four subgroups. If we think of new realizations as occurring farther from the center than old realizations (vessels moving away from port), then the physical distances between new realizations in subgroups within a group are increasing as the sea expands. For example, realizations in 1.1 and 1.2 become farther apart as the sea expands. As the sea expands, the number of subgroups is also increasing (the pie is cut into more slices), but so are the distances between them. It is in this sense that the blocking strategy creates independence between subgroups within a group. If the number of observations in group 2 is a

negligible fraction of the those in one (in the limit), then sums over the subgroups in group 1 will satisfy the weak dependence assumption in Pinkse, Shen and Slade (2007).

An alternative blocking strategy is depicted in Figure 2. This is the two-dimensional equivalent of the one-dimensional blocking strategy discussed in Pinkse, Shen and Slade (2007) and requires four groups. Group 1 is the dominant group and groups 2, 3, and 4 are the asymptotically negligible groups. The square is the sea, that is expanding in two dimensions, and we think of the expansion starting from the center of the square. The size of the subgroups and the distance between subgroups are increasing in the limit, just as in the first blocking strategy, but here the infinitely large domain is partitioned as a grid rather than infinitely large pie slices. Neither blocking strategy is entirely satisfying in any practical sense, as they are technically irrelevant for empirics. However, they are necessary for conceptualizing notions of weak dependence in stochastic limit theory.

4. Application to Bearing Sea Flat Fisheries

To illustrate our fixed-effect method, we use data on 12 bottom-trawlers targeting yellowfin sole in the Bering Sea flatfish fishery from 2002 through 2004. The data come from three sources. The spatial dimension of the data set is defined by the Alaska Department of Fish and Games (ADF&G) spatial locations, which partition the Bering Sea into grids that are one-half degree latitude by one-degree longitude in dimension. This produces approximately 95 spatial locations in the sea, but the average vessel in our data visits only about 12 of these in a given year.[11] Production data (catch), $Y_{its} = \ln Catch_{its}$, is obtained from the National Marine Fisheries Service (NMFS) "observer program," which requires all vessels longer than 125 feet to have an observer

[11] The 12 vessels were selected using a spatial site and production filter. This filter required a vessel to visit at least 5 spatial locations within each year of the data set and to catch at least 10 metric tons of fish in each site. Therefore, our analysis is only for the most mobile and productive vessels in the fleet.

onboard to record catch size, composition, and geographic position. On any given fishing trip, not all the catch is recorded, because observers take periodic breaks for sleep and hygiene, but we can only assume that these missing records are random. Weekly catch data for the twelve vessels were aggregated to annual data, resulting in 436 observations. That is, 12 vessels, over 3 years, each visiting on average a little over 12 spatial locations per year.

A quick experiment demonstrates that there is considerable variability in $\ln Catch_{its}$ over the spatial dimension. Different aggregation schemes reveal that: the average catch for each of the 12 vessels was 7,926 metric-tons with a standard deviation of 2,390; the average catch in each of the three years was 31,704 metric-tons with a standard deviation of 3,350; and the average catch in each of the spatial locations was 2,438 tons of fish with a standard deviation of 2,866. The spatial dimension of the data possesses the highest coefficient of variation (117.5%), so the spatial panel specification of equation 1 is well-justified.

Observations in X_{its} (also from the observer program data) are $\ln Hauls_{its}$ and $\ln Duration_{its}$, where $Hauls$ is the number of times the gear (the trawl) is deployed and $Duration$ is the total length of time that the gear is deployed. The spatially invariant inputs, Z_{it} and W_i, are from the weekly production reports collected by NMFS as well as the United States Coast Guard vessel registry database, which records vessel characteristics. The Z_{it} variable is $\ln Crew_{it}$, which is the logarithm of the total number of crew members employed during the year divided by the number of weeks fished. The W_i variable is $\ln NetTons_i$ which is the logarithm of the ratio of net-tonnage to horsepower for each vessel. The data set is balanced across vessels and time but unbalanced across space.

Biomass densities, b_{ts}, are from the annual NMFS "biomass trawl survey," which biologist at the Alaska Fisheries Science Center use to calculate stock estimates. Annual stock assessment studies are conducted independently of the fishery (i.e., are not based on fishery output) and are the best available estimates of the spatial distribution of the stock density. Over the three years of data the biomass survey was conducted from June 2 – July 24 in 2002, June 2 – July 22 in 2003, and June 5 – July 25 in 2004. Since this is roughly in the middle of the yellowfin sole season (February to October), we limited the analysis to $Catch_{its}$ targeting yellowfin sole.[12] The idea is that the survey is a simple "snapshot" during a particular time of year and may not represent the biomass faced by vessels throughout the *entire* year. By limiting the analysis to within approximately 3 months before and after the survey (the yellowfin sole season) we minimize the extent to which this simplification may cause errors. Yellowfin sole is the largest portion of flatfish harvest within the Eastern Bering Sea, so limiting the analysis to this species does not ignore vast quantities of useful information nor does it grossly underestimate the behavioral patterns of the vessels. Ideally, we would have biomass data at various points during a year, but these data are simply unavailable. In the case that $Catch$ is observed but b_{ts} is not, then the mean biomass density within a given year is imputed.[13]

We believe that our biomass data are exogenous, because a vessel captain's decision of "where to fish" is not based on this particular survey.[14] That is, catch incentives do not feedback into biomass through the harvest location decision. First, the biomass trawl surveys are conducted independently of the fishery (i.e., the survey is not based on commercial catch). Also,

[12] We use the North Pacific (NORPAC) targeting rule where yellowfin are targeted if more than 50% of the total catch are flatfish and 70% of the flatfish are yellowfin sole.
[13] This occurred in roughly 9% of the observations.
[14] It may also be worth noting that if choice variables are endogenous by definition, then labor and capital are also endogenous, and the entire exercise of estimating a production function is not identified.

Holland and Sutinen (2000) suggest that captains are "creatures of habit," tending to fish the same spatial pattern from year to year, regardless of survey data. Smith (2000) suggests that factors in the location decision are largely not observed by the analyst. Wilson (1990) suggests that fisheries have complex unobservable "informational networks" in which captains share location/catch information on a daily basis. Since stock measurements are taken annually, correlations between our biomass patterns and daily or hourly location decisions are perhaps negligible. [15] Finally, and perhaps most compelling, the sample correlations between biomass and aggregate catch across space are not consistently positive across years. The same is true for the correlations between biomass and the aggregate number of vessels visiting each spatial location ($Vessels_t$). They are:

$$Corr(Catch_{2002}, b_{2002}) = -0.1580, \qquad Corr(Vessels_{2002}, b_{2002}) = 0.0013,$$

$$Corr(Catch_{2003}, b_{2003}) = 0.5426, \qquad Corr(Vessels_{2003}, b_{2003}) = 0.0590,$$

$$Corr(Catch_{2004}, b_{2004}) = -0.0717, \qquad Corr(Vessels_{2004}, b_{2004}) = -0.0888.$$ [16]

Clearly, flatfish captains are not precisely following the biomass survey map, so biomass can be treated as exogenous in this exercise. There are other unobserved factors in the flatfish location decision. However, our biomass measures are *legitimate* space- and time-varying features of the different locations in the sea, and once a vessel visits one of the locations, the biomass measures are relevant to the vessels ability to harvest fish. Therefore, we are not merely adding noise to the model by interacting this measure.[17]

[15] There are bycatch biomass surveys conducted in this particular fisheries that *are* known to be used by captains in their location decisions. These surveys are based on vessel catch and are designed to help captains avoid bycatch species. In this case, the biomass readings are certainly endogenous. It is not clear that this has been recognized in the fisheries literature.

[16] We suspect these correlations are spurious, particularly since some of the signs are not what we would expect if vessels location decisions were based on biomass data. This feature could, however, be induced by measurement error in the biomass, as discussed in section 3.

[17] Flatfish vessels may also be fishing to the south to follow flatfish migratory patterns or to avoid certain bycatch.

The basic Cobb-Douglas harvesting function is:

$$\ln Catch_{its} = \alpha_{it} + b_{ts} \ln Hauls_{its} \beta_1 + b_{ts} \ln Duration_{its} \beta_2 + b_{ts} \ln Crew_{it} \gamma_1 + b_{ts} \ln NetTons \delta_1 + \varepsilon_{its}$$

Notice that each variable in interacted with biomass, b_{ts}, making them all space-varying (effectively). The basic model was estimated and subjected to specifications test. We also experimented with models that ignored spatial variation or that set $\alpha_{it} = \alpha_i$ and found that the marginal effects and elasticities did not make sense (e.g., elasticities were negative or much greater than 1). Experimentation with interaction terms and a series of specifications tests led to the augmented Cobb-Douglas specification in Table 1, which includes interactions of $NetTons$ with both $Hauls$ and $Duration$.[18]

The results in Table 1 imply the relationship between the number of hauls and production is nonlinear, and that crew size (t-stat = 0.18) is not an important input to production.[19] *Duration* (t-stat = -1.21) is only important insofar as it is interacted with vessel size. Even though the coefficients on *Duration* and its interaction with *NetTons* are negative, their elasticities are positive once we account for biomass, their interactions, and the fact that $\overline{\ln NetTons}$ is negative (it is negative, since it is first scaled by vessel horsepower which, on average, exceed the vessel tonnage.)

Elasticity estimates are contained in Table 2 , and are transformed by average biomass over t and s, $\bar{b} = 1.3257$. For example, the marginal product of *Hauls* is:

$$\varepsilon_{Hauls} = \frac{\partial \ln Y_{its}}{\partial \ln Hauls_{its}} = \bar{b}\left[0.9768 + 0.4515 \cdot \overline{\ln NetTons}\right],$$

[18] We experimented with a full trans-log production function, but it was rejected by specification tests. Some of the less parsimonious specifications had problems with highly collinear interactions. In cases where correlations exceeded 0.975, some interactions were eliminated from the specification.

[19] Since the average number of spatial sites visited in a given year is roughly 12, we are not invoking asymptotic normality for inference. We have to assume normality of the regression errors in this example. We are, however, estimating robust standard errors based on equation (3)

where $\overline{\ln NetTons}$ is the average over i. The results imply that $Hauls$ and $Duration$ contribute more on the margin then any of the other inputs (elasticities of 0.3105 and 0.4295, respectively). $NetTons$ provides the least (0.0150). However, all elasticities are positive, so our production model does not violate any of the traditional production theory assumptions. These results make sense. The acts of deploying the nets (*Hauls*) and dragging the nets (*Duration*) are the most important inputs to harvesting fish. (Clearly, if this does not happen there will be zero output!) The next most important productive input to harvesting fish (in terms of elasticity) is crew size (elasticity of 0.0873); crews deploy and retrieve the nets. The size of the vessel is only important for speed and storage capacity, which are meaningless without a good crew and efficient deployment of the nets. Finally, returns to scale (the sum of the elasticities) for the 12 vessels are 0.8423. The decreasing returns to scale may be from eliminating smaller vessels (below 125 feet), if these vessels exhibit constant or increasing returns.

5. Conclusions

This research makes direct contributions to the panel data econometrics literature and the spatial econometrics literature. Highly-mobile technologies represent a very clean extension to the usual panel data results and add a degree of flexibility to asymptotic arguments on model parameters. Our contribution to the spatial econometrics literature is clear. However, the results have implications for the estimation of spatial weighting matrices. It would be interesting to use the panel structure to estimate a spatial weighting matrix and compare it to the usual spatial weight matrix based on physical distance (e.g., Kelijian and Prucha, 1999 and 2001). Also, our discussion of spatial asymptotics is quite basic; a more complete exploration of these concepts is currently a high priority on our research agenda. Finally, our results may inform the location

choice literature. For example, there are growing literatures on location choice in fisheries (e.g., Hick and Schnier, 2006; Holland and Sutinen, 1999, 2000), agglomeration economies (e.g., Lovely, Rosenthal and Sharma, 2005), and migration (e.g., Dahl, 2002), that may benefit from the discussions herein.

Two weaknesses of the results are that resource stocks must be exogenous and that the individual effects cannot be space-varying. In the case that stocks are endogenous through the location decision, then appropriate instruments for stocks are necessary. In the case of U.S. fisheries, over the last few years, there have been important policy changes that have impacted the behavior of fishing vessels. Perhaps the timing of these exogenous policy changes could be used as instruments. In fact, there are certain weekly or daily stock measures that are known to be used by vessel captains in their search for target fish species (i.e., bycatch signals provide by SeaState Inc. in the Bering Sea). Exploring policy changes as instruments for these stocks would be interesting. In the case where individual effects vary over both time and space our results do not apply, but an extension to the results of Ahn, Lee, and Schmidt (2004) would identify the model in a GMM framework. Also, the model could be identified with 'within' estimation if the individual effects were *time-invariant* but *space-varying*. In this case, interaction with resource stocks would be unnecessary, and the usual demeaning along the time dimension would produce the usual panel results. Finally, a referee pointed out that a theoretically interesting question is whether the model's parameters are efficiency estimated? Clearly, a GLS-type adjustment could be employed based on the non-spherical error, but perhaps asymptotic efficiency could be explored in greater depth. For examples, Park, Sickles and Simar (1998) consider semi-parametric efficiency bounds in a panel framework. What can be done here remains to be seen. These points are left for future research.

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Table 1: Model Parameter Estimates

Variable	Coefficient (t-statistic)
$b_{ts} \ln Hauls_{its}$	0.9768** (3.02)
$b_{ts} \ln Duration_{its}$	-0.2925 (-1.21)
$b_{ts} \ln Crew_{it}$	0.0659 (0.18)
$b_{ts} NetTons_{i}$	1.9096** (2.48)
$b_{ts} \ln Hauls_{its} * \ln NetTons_{i}$	0.4515** (2.73)
$b_{ts} \ln Duration_{its} * \ln NetTons_{i}$	-0.3749** (-2.82)

**indicates significance at the 95% level.
t-statistics are robust.

Table 2: Elasticities and Returns to Scale

ε_{Hauls}	$\varepsilon_{Duration}$	ε_{Crew}	$\varepsilon_{NetTons}$	Returns-to-scale (RTS)
0.3105	0.4295	0.0873	0.0150	0.8423

Figure 1. Spatial Blocking Strategy.

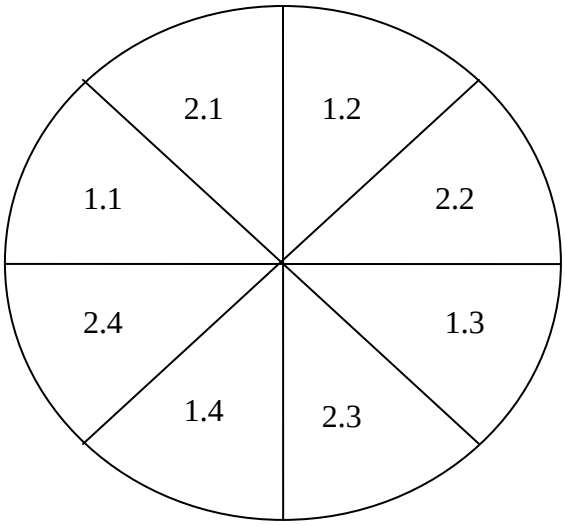

Figure 2. Alternative Blocking Strategy.

1.1	2.1	1.2	2.2	1.3
3.1	4.1	3.2	4.2	3.3
1.4	2.3	1.5	2.4	1.6
3.4	4.3	3.5	4.4	3.6
1.7	2.5	1.8	2.6	1.9